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Approach to solving mining machine selection problem by using grey theory

The selection of a mining machine is a multiple-attribute problem that involves the consideration of numerous parameters of various origins. A common task in the mining industry is to select the best machine among several alternatives, which are frequently described both with numerical variables as well as linguistic variables.

Numerical variables are mostly related to the technical characteristics of the machines, which are available in detail in most cases. On the other hand, some equally important parameters such as price, reliability, support for service and spare parts, operating cost, etc., are not available at the required level for various reasons; hence, these can be considered uncertain information. For this reason, such information is described with linguistic variables.

This paper presents research related to overcoming this problem by using grey theory for selecting a proper mining machine. Grey theory is a well-known method used for multiple-attribute selection problems that involves a system in which parts of the necessary information are known and parts are unknown.

Key words: *machine selection, grey theory, multiple-attribute, uncertain information, mining industry*

1. INTRODUCTION

The selection of a mining machine is a multi-attribute decision-making problem that is an important issue for an effective production system. The most common approach is to evaluate several alternatives that should be ranked according to various criteria or attributes. For evaluating mining machines, several factors should be taken into consideration. The purpose of this task is to acquire the best possible alternative for the given restrictions.

The most common recent approach is the use of operational research methods such as the Analytical Hierarchical Process (AHP), Analytical Network Process (ANP), and Preference Ranking Or-ganization Method for Enrichment Evaluations (PROMETHEE) [1–5]. Some papers also suggested the application of fuzzy sets [6–7] or a more general approach to machinery selection [8].

However, there is still a difficulty when the criteria for selecting a machine are completely known or partially known; i.e., when some of the criteria or attributes can only be described by linguistic variables. The mining machine selection methodology presented in this paper incorporates both numerical and linguistic variables based on grey theory.

2. METHODOLOGY

The most common situation for decision makers in the mining industry is to act according to information based on some level of accuracy. The problem of selecting a machine based on its technical characteristics is the easiest one, since all the variables are defined with numerical values. In conventional multi-attribute selection methods, the attribute ratings and attribute weights are precisely known [9–11].

In this case, the variables are easily transformed, compared, normalized, or evaluated. However, comparing some alternatives and their attributes can only be performed by linguistic variables. For example, an accurate performance comparison of machines from different manufacturers can only be done if the machines are operating under the same conditions with the same rock materials and with equal maintenance policies, etc. (which is seldom the case). Hence, mining industry professionals are constantly debating which machine is “better” or “poorer.”

Adding to this, the confidentiality policies of mining companies furthermore reduce the accuracy of the information. Nevertheless, even reduced accuracy can generate some information such as some supplier who is “more” agile in after-market support (the delivery of spare parts) or some machine has “poorer” reliability in hard rocks. Again, an evaluation of such attributes can be done with linguistic variables.

Keeping in mind that the selection of machines is most often based on partially completely known information and partially on information with reduced accuracy, we have developed an approach based on grey theory. Grey theory is one of the methods used to study uncertainty problems with discrete data and incomplete information. In the theory, if the system information is fully known, the system is called a white system; if the information is totally unknown, the system is called a black system. A system with partially known information is called a grey system. Definitions, grey number operations, and procedures are described in detail and are well-known [12], and this system is used in similar research such as [13, 14].

The main concept of the grey system is to reduce the uncertainty based on the available information as shown in Figure 1 to allow for a more reliable ranking of the alternatives.

The procedure for determining the rank of alternatives comprises of several steps (according to common grey system nomenclature) are as follows:

- allocation of weights (Tab. 1) and ratings (Tab. 2) to each of the attributes by a panel of experts and calculating the average value of these,
- establishment of grey decision matrix (D),
- normalizing the grey decision matrix (D*) to compare the different evaluation measures,
- establishment of weighted normalized grey decision matrix (V) to indicate the contiguous grades between the comparative series,
- composing the ideal alternative,
- calculation of grey possibility degree between alternatives and ideal alternative,
- ranking of alternatives according to grey possibility degree.

Table 1
Scale of attribute weights

Very Low	0	0.1
Low	0.1	0.3
Medium Low	0.3	0.4
Medium	0.4	0.5
Medium High	0.5	0.6
High	0.6	0.9
Very High	0.9	1

Table 2
Scale of attribute ratings

Very Poor	0	1
Poor	1	3
Medium Poor	3	4
Fair	4	5
Medium Good	5	6
Good	6	9
Very Good	9	10

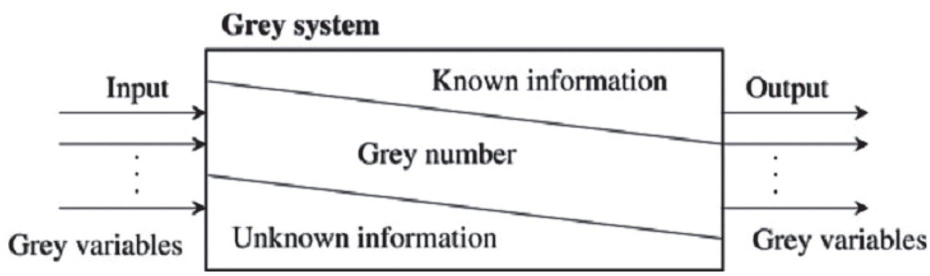

Fig. 1. Concept of grey system

Having in mind all of the above, we are suggesting a different approach in the first step of the procedure for cases when alternatives are described by white and grey numbers. The panel of experts should not be included in the attribute ratings for white attributes. Ratings for white attributes should be allocated according to the scale given in Table 2 and by taking into account the location of a specific value within the range of alternatives (maximum and minimum) – direct ratings.

In this way, subjective judgement is further reduced, since complete information on a specific attribute is available. However, it should be noted that the panel of experts is included in the allocation of weights for all of the attributes regardless if they are white or grey.

An example of the described procedure is given below as a case study for ranking Load-Haul-Dump (LHD) machines.

3. CASE STUDY – EXAMPLE

In this example, we are considering five Load-Haul-Dump machines whose nine characteristics that will be used for ranking are given in Table 3. The same problem is considered in one of the previous research, such as [15].

For ranking these machines, their technical characteristics are categorized into four attributes (A1 through A4), as elaborated in Table 4. These attributes will be considered as white attributes, and ratings of these attributes will be done in relation to one of the others instead of by the panel of experts.

Besides these, a further three grey attributes (A5, A6, and A7) will also be used for ranking the LHD machines (which are also elaborated in Table 4).

Table 3

Underground loaders and characteristics

Machine	Bucket volume [m^3]	Engine power [kW]	Payload [kg]	Machine mass [t]	Loading cycle [s]	Velocity max. [km/h]	Outside turning radius [mm]	Inside turning radius [mm]	Bucket width [mm]
Atlas Copco ST 3.5	3.4	136	6000	17.10	12.6	21.0	5446	2620	1956
Sandvik Tamrock Toro 006	3.0	142	6700	17.20	12.9	26.0	5600	3030	2100
GHH Fahrzeuge LF/6	3.0	136	6000	19.50	12.5	23.0	6022	3247	2040
Caterpillar R1300	3.4	123	6800	20.95	9.3	24.0	5741	2825	2400
Wuhan KHD-3	3.0	112	6500	17.20	13.5	23.0	6060	3274	2110

Table 4

Attributes for ranking LHD machines

Attribute	Type	Description
Material handling (A1)	gain	This attribute combines the bucket volume and payload capability of the LHD machine. In this case study, these are combined into a single attribute by multiplying these characteristics
Power to weight (A2)	gain	This is a common parameter obtained by dividing the engine power [kW] with the mass of the machine [t]
Machine swiftness (A3)	gain	This attribute is obtained by dividing the maximal velocity of the machine (km/h – bigger is better) by the loading cycle ([s] – smaller is better), providing a parameter for evaluating the swiftness of a machine to achieve high production rates
Maneuverability (A4)	loss	This attribute is obtained by summing the inside and outside turning radii as well as the bucket width. The smaller the value, the better, since the machine can turn in narrower roadways
Acquisition cost (A5)	loss	This is the price of the machine; hence, is the loss attribute – the smaller, the better
Service support and availability of spare parts (A6)	gain	This attribute is envisaged for evaluating the manufacturer's presence on the market in terms of the expertise of its staff, the quality of its, workshops, its storage facilities, etc.
Reliability of machine (A7)	gain	This attribute is used for evaluating the operational capabilities of the machine; i.e., evaluation of machine performance in actual operation

Ratings for these attributes will be established by the panel of experts as well as the attribute weights for all seven attributes.

In first step, a group of five experts allocated the weights for each attribute as given in Table 1, thus highlighting the importance of each specific attribute. These marks are used for calculating the range of the weights (min and max) for each attribute (Tab. 5). Further on, the same panel of experts assigned attribute ratings according to Table 2 for Attributes 5, 6, and 7. Ratings for the first four attributes (A1–A4) are assigned in a process of "direct rating," meaning that these are established by comparing the attributes among themselves (thus eliminating subjectivity). For this reason, each rating for the first four attributes is an integer value, while the ratings for the remaining three attributes are calculated as average values (Tab. 6, grey decision matrix – D). A normalized grey decision matrix is given in Table 7, which is established by taking into account that Attributes 4 and 5 are loss attributes (the smaller, the better), while all of the other attributes are gain attributes (larger values are better).

Multiplying the attribute weights (Tab. 5) and normalized grey decision matrix (Tab. 7) provides Weighted normalized grey decision matrix (V), which is given in Table 8. The values from this matrix are used to compose the Ideal referential alternative, which is given in Table 9.

Finally, the grey possibility degree is calculated for each attribute as related to the Ideal referential alternative. The grey possibility degrees are given in Table 10. The average values of the grey possibility degrees are given in the last column of Table 10.

Table 5

Attribute weights

	E1	E2	E3	E4	E5	min	max
A1	medium	medium	medium high	medium	medium	0.42	0.52
A2	medium high	medium	high	medium high	medium high	0.50	0.64
A3	high	medium high	medium high	very high	medium high	0.60	0.74
A4	medium	medium low	medium	medium low	medium high	0.38	0.48
A5	medium high	high	high	medium high	medium high	0.54	0.72
A6	high	medium	very high	medium	high	0.58	0.76
A7	very high	very high	medium	medium high	high	0.66	0.80

Table 6

Grey decision matrix (D)

	A1		A2		A3		A4		A5		A6		A7	
M1	6.0	9.0	6.0	9.0	4.0	5.0	4.0	5.0	5.4	7.2	5.4	7.2	5.6	7.8
M2	6.0	9.0	6.0	9.0	5.0	6.0	5.0	6.0	5.8	8.4	5.0	6.4	5.4	7.2
M3	5.0	6.0	5.0	6.0	4.0	5.0	6.0	9.0	5.6	7.8	4.8	5.8	5.4	7.2
M4	9.0	10.0	4.0	5.0	6.0	9.0	5.0	6.0	7.2	9.4	6.4	8.6	5.8	8.4
M5	5.0	6.0	5.0	6.0	4.0	5.0	6.0	9.0	4.0	5.0	4.4	5.8	3.6	4.6

Table 7

Normalized grey decision matrix (D*)

	A1		A2		A3		A4		A5		A6		A7	
M1	0.600	0.900	0.667	1.000	0.444	0.556	0.800	1.000	0.556	0.741	0.628	0.837	0.667	0.929
M2	0.600	0.900	0.667	1.000	0.556	0.667	0.667	0.800	0.476	0.690	0.581	0.744	0.643	0.857
M3	0.500	0.600	0.556	0.667	0.444	0.556	0.444	0.667	0.513	0.714	0.558	0.674	0.643	0.857
M4	0.900	1.000	0.444	0.556	0.667	1.000	0.667	0.800	0.426	0.556	0.744	1.000	0.690	1.000
M5	0.500	0.600	0.556	0.667	0.444	0.556	0.444	0.667	0.800	1.000	0.512	0.674	0.429	0.548

Table 8

Weighted normalized grey decision matrix (V)

	A1		A2		A3		A4		A5		A6		A7	
M1	0.252	0.468	0.333	0.640	0.267	0.411	0.304	0.480	0.300	0.533	0.364	0.636	0.440	0.743
M2	0.252	0.468	0.333	0.640	0.333	0.493	0.253	0.384	0.257	0.497	0.337	0.566	0.424	0.686
M3	0.210	0.312	0.278	0.427	0.267	0.411	0.169	0.320	0.277	0.514	0.324	0.513	0.424	0.686
M4	0.378	0.520	0.222	0.356	0.400	0.740	0.253	0.384	0.230	0.400	0.432	0.760	0.456	0.800
M5	0.210	0.312	0.278	0.427	0.267	0.411	0.169	0.320	0.432	0.720	0.297	0.513	0.283	0.438

Table 9

Ideal referential alternative

A1		A2		A3		A4		A5		A6		A7	
0.378	0.520	0.333	0.640	0.400	0.740	0.304	0.480	0.432	0.720	0.432	0.760	0.456	0.800

Table 10

Grey possibility degree

	A1	A2	A3	A4	A5	A6	A7	Avg.
M1	0.749	0.500	0.977	0.500	0.806	0.660	0.557	0.678
M2	0.749	0.500	0.813	0.739	0.878	0.760	0.621	0.723
M3	1.000	0.795	0.977	0.951	0.843	0.844	0.621	0.862
M4	0.500	0.949	0.500	0.739	1.000	0.500	0.500	0.670
M5	1.000	0.795	0.977	0.951	0.500	0.852	1.000	0.868

These values are used for ranking the machines:

M4 < M1 < M2 < M3 < M5.

Therefore, it can be said that the fourth machine is the best among the considered five LHD machines.

4. CONCLUSIONS

Grey theory can be used for the selection or quality assessment of an arbitrary number of mining machines according to their technical characteristics. The introduction of the proposed approach further reduces subjectivity in the process, offering a more precise selection of the best solution. The presented procedure for the selection of a mining machine provided similar outcomes with the results of previous research. Therefore, combining grey and white numbers for the selection of machines as presented in this paper is justifiable and suitable for ranking an arbitrary number of alternatives/machines according to their technical characteristics and grey attributes. The next step of the research will be to compare the results of a grey analysis with the results achieved using other decision-making methods.

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References

[1] Dagdeviren M.: *Decision making in equipment selection: an integrated approach with AHP and PROMETHEE*, “Journal of Intelligent Manufacturing” 2008, 19: 397–406.

[2] Lin Z.C., Yang C.B.: *Evaluation of machine selection by the AHP method*, "Journal of Materials Processing Technology" 1996, 57: 253–258.

[3] Paramasivam V. et al.: *Decision making in equipment selection: an integrated approach with digraph and matrix approach*, *AHP and ANP*, "International Journal of Advanced Manufacturing Technology" 2011, 54: 1233–1244.

[4] Bascetin A.: *A decision support system for optimal equipment selection in open pit mining: analytical hierarchy process*, "Istanbul Üniversitesi, Mühendislik Fakültesi Yer Bilimleri Dergisi" 2003, 16, 2: 1–11.

[5] Mohamadabadi H.S. et al.: *Development of a multi-criteria assessment model for ranking of renewable and non-renewable transportation fuel vehicles*, "Energy" 2009, 24, 1: 112–125.

[6] Cebesoy T.: *Hydraulic Excavator Selection Using Improved Quality Comparison Method*, "Journal of Engineering Sciences (Mühendislik Bilimleri Dergisi)" 1999, 5, 1: 1001–1008.

[7] Hadi-Vencheha A., Mohamadghasemi A.: *A new hybrid fuzzy multi-criteria decision-making model for solving the material handling equipment selection problem*, "International Journal of Computer Integrated Manufacturing" 2015, 28, 5: 534–550.

[8] Basu A.S., Lineberry G.T.: *Selection of Mobile Equipment for Underground Coal Mining: An Expert System Approach*, "Mineral Resources Engineering" 1995, 4, 1: 71–88.

[9] Delgado M., Verdegay J.L., Vila M.A.: *Linguistic decision-making models*, "International Journal of Intelligent Systems" 1992, 7: 479–492.

[10] Hwang C.L., Yoon K.P.: *Multiple Attributes Decision Making: Methods and Applications*, Springer, Berlin – Heidelberg 1981.

[11] Kaufmann A., Gupta M.M.: *Introduction to Fuzzy Arithmetic, Theory and Applications*, Van Nostrand Reinhold, New York 1991.

[12] Liu S., Lin Y.: *Grey systems Theory and Applications*, Springer, Berlin – Heidelberg 2010.

[13] Bhattacharyya R.: *A Grey Theory Based Multiple Attribute Approach for R&D Project Portfolio Selection*, "Fuzzy Information and Engineering" 2015, 7: 211–225.

[14] Li G-D. et al.: *A grey-based decision-making approach to the supplier selection problem*, "Mathematical and Computer Modelling" 2007, 46: 573–581.

[15] Milisavljević V., Medenica D., Čokorilo V., Ristović I.: *New Approach to Equipment Quality Evaluation Method with Distinct Function*, "Thermal Science" 2015, 20, 2: 743–752.

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