Multi-attribute fuzzy methodology for the selection of mining shovels

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Abstract

Mining shovels or excavators are basic equipment designed to dig and load material in surface mines. They are often considered the major material-handling equipment for high-production, low-cost operations (HPLC). The selection of an appropriate shovel for any HPLC operation is of critical importance because the overall production of the mine is measured in terms of material handled by a principal digging and loading equipment. A new multi-attribute fuzzy methodology for the selection of mining shovels for HPLC operations was developed. The fuzzy analysis included eight shovel selection categories with almost 60 objective and subjective attributes. The weight of each attribute was obtained by employing a pair-wise comparison. The final result of this fuzzy analysis is an overall fuzzy membership value or fuzzy score (FUZ-SCO). The methodology was incorporated in an expert system called shovel selection fuzzy expert system (SHS-FES) developed in Java and HTML programming languages. The SHS-FES allows for the assignment of an overall membership value to each of the shovel options and suggests to the mining experts a specific shovel that will satisfy given project requirements. A developed SHS-FES system was used to conduct a case study at an operating surface mine.

Introduction

There are two basic types of shovels: the hydraulic mining shovel (HMS) and the electric mining shovel (EMS). They have similar characteristics and routines when performing at a mine; however, there are few differences that could give an advantage to one over the other. These shovels require a high capital cost investment and could represent the costliest asset for mining operations (Agarwal, 1994; P&H MinePro, 2003).

In an equipment selection process, in most cases, shovels are selected as a member within a fleet. Authors such as O’Shea (1964), Morgan and Peterson (1968), Mayer and Stark (1981), Easa (1988), Karshenas (1989), Jayawardane and Harris (1990), Huang and Kumar (1994) and Nagatani (2001) focused their efforts on the selection of a fleet rather than the sole selection of the excavator.

The optimal shovel selection requires in-depth analysis of a series of characteristics or attributes that define both the excavator and the specific operation (Haidar et al., 1999). In other words, the excavator selection problem must be primarily approached by a comprehensive analysis of various equipment selection methodologies. Some of these methodologies consider selection attributes, which are linguistically focused and subjectively weighted, i.e., these attributes are not perfectly defined and are difficult to weigh (Kesimal and Bascetin, 2002). The identification of the factors or attributes affecting the excavator selection becomes important. Touran (1990) added that the selection methodology must be flexible and applicable to most types of problems directly related to surface mine machine selection. Most of the time, methodologies related to equipment selection lack flexibility when dealing with problems such as data transferring, process interaction, and specific input data change.

Xing Xie (1997) indicated that the “type of operation” is the most significant concern when selecting any type of mining equipment. Mozumdar and Tiwari (1980) specified that the main mining considerations are mine planning, mine scheduling, supervision, mine design and marketing and noted that these are the drivers for equipment selection. Haidar et al. (1999) listed variables affecting equipment selection for surface mines in seven categories:
P&H MinePro (2003) identified and evaluated several excavator selection attributes. These attributes were classified into the following eight categories:

- technical,
- machine operation,
- geology and deposit characterization,
- digging and loading,
- productivity,
- maintenance,
- environmental impact and
- commercial considerations.

The selection of the appropriate type of excavator is a complex problem, and it is often performed by qualified mine planning engineers or by people with vast equipment selection experience. Such people are called “experts.” Most of these experts frequently base their selection criteria on intuition, judgment of knowledge, rules of thumb, and past successful and unsuccessful experiences (Xing Xie, 1997; Kesimal and Bascetin, 2002). The P&H MinePro (2003) stated that the identification of the attributes on which experts base their selection criteria is particularly important because it implies the correct definition of the characteristics and abilities of each and every one of the pieces of equipment. Ranking each attribute in any equipment selection system by its importance or relevance can become a difficult task; however, the most challenging task is to assign a membership score to each of these attributes. The fuzzy set methodology can be used for evaluating individual membership functions for each of the selection criteria. A pairwise comparison of various criteria is a useful tool utilized to facilitate the weight of each criterion. In other words, the pair-wise comparison can generate a weighting value or factor that represents the importance of each attribute for the final equipment selection (Kesimal and Bascetin, 2002).

Based on the experience of many researches, the application of both a multi-attribute selection methodology and an expert system becomes the preferred approach to enhance the shovel-selection problem.

**Literature review**

Equipment selection methodologies focus primarily on the application of the appropriate tools for specific mining environments. Several equipment attributes for selection were identified and various methodologies were utilized and developed to select the most productive combination of equipment for a given surface mining operation. Burt et al. (2005) indicated the classification of equipment selection techniques into three categories: classical methods, operations research techniques and artificial intelligence techniques.

Some of the classical methods utilized for equipment selection are the match factor, the bunching theory, the productivity curves and the queuing theory. Morgan and Peterson (1968) explored the match factor methodology. The main idea behind the match factor was the assumption that “the most economical fleet will also be the most productive and efficient fleet.” Burt et al. (2005), for example, incorporated an efficiency expression to turn the match factor methodology into a non-linear formulation. Nagatani (2001) studied bunching theory. The main purpose was to capture and understand the tendency of moving objects to bunch together. O’Shea (1964), Karshenas (1989), and Huang & Kumar (1994) explored the application of queuing theory.

The operation research techniques utilized for equipment selection are: linear programming, integer programming, non-linear programming, fuzzy theory, analytical hierarchy process and multi-attribute decision making techniques. Mayer and Stark (1981), Easa (1988) and Jayawardane and Harris (1990) explored linear programming models for equipment selection. They focused their efforts on minimizing the cost of the operating fleet. Cebesoy et al. (1995) used integer programming and considered the cost to be a constant; therefore, much of the focus of integer programming was placed on project completion, dispatching and scheduling.

Professor Lotfi Zadehn was the creator of fuzzy logic (FL), also called fuzzy set theory. Some applications of FL methodology related to the mining industry include the development and selection of post-mining utilizations of the land by Bandopadhyay (1987a), the partial ranking of primary stripping equipment by Bandopadhyay (1987b) and the selection of an optimal transportation system by Bascetin and Kesimal (1999).

Saaty (1980) developed a methodology called analytical hierarchy process (AHP). This technique was adapted and applied for numerous purposes, including equipment selection processes. Komljenovic and Kecojevic (2006) utilized the coefficient of technical level (CTL) and AHP to develop a methodology for the selection of mining trucks. Komljenovic et al. (2003) determined the relationship between comparative coefficient and truck size utilizing the least-squares-estimator method. Bascetin (2003) used a multiple attribute decision making (MADM) for the selection among a group of equipment alternatives.

Atkinson (1992) developed the procedure known as mining method selection (MMS). This approach focuses on the idea that a particular mining method would be the most appropriate under particular environmental circumstances. As a result, the selection of any equipment is an intuitive consequence of the particular environmental conditions of a given mine.

Some of the artificial intelligence techniques used for equipment selection are expert systems, knowledge-based methods, genetic algorithms and simulation. Fisher et al. (1988) indicated that when constructing an expert system (ES), certain basic steps must be followed: “knowledge base construction, expert system implementation, system refinement and validation.” Clarke et al. (1990) developed an ES called the knowledge base decision support system (KBDS), which utilized a rule-based approach. Another example of an ES, utilized in mining, is the material handling equipment selection system (MATHES) developed by Fisher et al. (1988). Gershon et al. (1993) studied the selection of mining equipment utilizing a decision support system. Amirkhanian and Baker (1992) and Alkass and Harris (1988) developed knowledge based systems (KBES) for the selection of equipment for earthmoving operations. Some researchers used genetic algorithms for the selection of surface mining equipment (Haidar and Naoum, 1996; Haidar et al., 1999). Genetic algorithms were utilized in equipment selection to acquire or arrive at an optimal combination in terms of number and types of equipment.

A large variety of equipment selection methodologies, from very simple ideas to complex systems, were encountered through the literature review. A special interest was developed when researching fuzzy logic, pair-wise comparison of attributes and
The authors believe that an integrated approach in developing a multi-attribute fuzzy methodology would be useful in the selection of mining shovels for HPLC operation.

Methodology
This section presents a new selection methodology for mining shovels based on a multi-attribute fuzzy approach. Its basic concept is shown in Fig. 1. A shovel database was created and features different shovel models from various manufacturers. It includes 40 different types of mining shovels, both HMSs and EMSs. A database on shovel specifications was gathered from various sources, including Hartman (1992), P&H MinePro (2003), Western Mining Engineering (2006) and manufacturer brochures encountered throughout the research. A technical analysis including production and economic evaluation was carried out. This evaluation is not presented in this paper because it is covered in many well-known mining reference textbooks (Kennedy, 1990; Hartman, 1992; Caterpillar, 2000). The shovels that fulfilled basic criteria, such as the production requirements, the project lifetime requirements and the cost per unit loaded, were further evaluated by fuzzy analysis. The latter analysis included eight shovel selection categories with 60 objective and subjective shovel attributes. Each of the evaluated attributes was assigned a membership value. These membership values represent how well the shovels fit the requirements of the given attribute. The weight of each attribute was obtained by employing a pair-wise comparison. The final result of this fuzzy analysis is an overall fuzzy membership value or fuzzy score (FUZ-SCO), which indicates the overall appropriateness of a shovel to a given project and serves as a selection scale for comparison. The methodology was incorporated in an expert system called shovel selection fuzzy expert system (SHS-FES).

The base of this study represents detailed analysis on shovel selection for HPLC mining operations carried out by the P&H MinePro (2003). In that study, specific selection variables and attributes are assigned to HMS and EMS shovels to help in the selection process. The key selection criteria are classified into the eight categories. Specific attributes of both hydraulic and electric shovels as they relate to the selection criteria describe the various features and characteristics that make the machine more or less appropriate for a given situation. In terms of importance in the selection process, each attribute is ranked as low, high or very high. However, the selection attributes in P&H study are linguistically focused and subjectively weighted. The lack of "preciseness" for these attributes makes it impossible to measure certain information, differing from objective attributes, where there is a general acceptance about an evaluation statement being either true or false. This was the fundamental principle of classic logic; nevertheless, research
of discourse is a collection of fuzzy numbers with similar boundaries within the same universe of discourse, where the universe of discourse encounters intersections with different variables or elements than numbers. Their boundaries are often imprecise and may be perceived as linguistic variables rather than numbers. Non-numerical values. Its values represent "appropriateness." A discrete number with non-numerical values. Its values represent the appropriateness level that an element has for a given attribute. The values are: very high, high, fair, low and very low. Their defined membership values are 1, 0.75, 0.50, 0.25 and 0, respectively. To evaluate attributes of TYPE 1, the basic "appropriateness" fuzzy number must be defined. In most cases, this number will indicate the appropriateness of a HMS over an EMS (or vice versa) for a given situation. "Appropriateness" is a discrete number with non-numerical values. Its values represent the appropriateness level that an element has for a given attribute. The values are: very high, high, fair, low and very low. Their defined membership values are 1, 0.75, 0.50, 0.25 and 0, respectively. To evaluate attributes of TYPE 2, a composition of a fuzzy relationship must be established. Several methods of composition of fuzzy relationships exist; however, the main two utilized in literature are the max-min and the max-product composition relationships. These composition methods deal with the ability of analyzing fuzzy numbers from two or more universes of discourse simultaneously (Iphar and Goktan, 2006). To find the membership value for each mining shovel and each attribute of TYPE 2, it is necessary to identify the two fuzzy numbers to be employed. Usually, the first fuzzy number will be "appropriateness" and will cover different advantages or disadvantages that a HMS and an EMS bring to the selection process. The second fuzzy number is a property closely related to the quality evaluation of the attribute. Some examples of this type of shovel property are the weight, boom length, height, power, etc.

Table 1 — Technical attributes (P&H MinePro, 2003) along with the authors’ assignment of “appropriateness.”

<table>
<thead>
<tr>
<th>Index</th>
<th>Attribute</th>
<th>HMS appropriateness</th>
<th>EMS appropriateness</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>Ambient and temperature adaptability</td>
<td>Low when below -34°C (-29°F)</td>
<td>High if within the range</td>
</tr>
<tr>
<td>A2</td>
<td>Digging forces</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>A3</td>
<td>Ground bearing pressure</td>
<td>Very high</td>
<td>High</td>
</tr>
<tr>
<td>A4</td>
<td>Machine assembly time</td>
<td>Very high</td>
<td>Fair</td>
</tr>
<tr>
<td>A5</td>
<td>Machine weight</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>A6</td>
<td>Mobility</td>
<td>Very high</td>
<td>Fair</td>
</tr>
<tr>
<td>A7</td>
<td>Power selection options</td>
<td>Very high</td>
<td>Very low</td>
</tr>
<tr>
<td>A8</td>
<td>Power supply requirements</td>
<td>Very high</td>
<td>High</td>
</tr>
<tr>
<td>A9</td>
<td>Technology change adaptability</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>A10</td>
<td>Trail cable</td>
<td>Very high (if electric: Very low)</td>
<td>Very low</td>
</tr>
</tbody>
</table>

Table 2 — Machine operation attributes (P&H MinePro, 2003) along with the authors’ assignment of “appropriateness.”

<table>
<thead>
<tr>
<th>Index</th>
<th>Attribute</th>
<th>HMS appropriateness</th>
<th>EMS appropriateness</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
<td>Cab location</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>B2</td>
<td>Digging phase control</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>B3</td>
<td>Ergonomics</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>B4</td>
<td>Use of propel to maximize fill factor</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>B5</td>
<td>Visibility</td>
<td>High</td>
<td>Very high</td>
</tr>
</tbody>
</table>
is utilized only as an illustrative approach. The methodology developed through this research offers the flexibility of a potential modification of weights and membership values for attributes based on experts’ self-preferences and experience.

The importance of each and every one of the attributes presented for the selection of a mining shovel must be distinguished. Each of the considered attributes has different principles and characteristics than the others and must be treated individually. The importance or weight behind each attribute is the logical result of asking: “How much does each attribute affect the final selection of a shovel?”

The subjective attributes are capable of receiving a membership value depending on their suitability for a given situation. The membership value for each attribute is a number between 0 and 1, which represents the percentage of suitability of a shovel for a given task under certain attribute. This membership value can be treated as a score for a given attribute; furthermore, the weight or importance of this score can be applied to its evaluation. In order to obtain such weight, a “pair-wise comparison of attribute importance” can be employed.

Several techniques for attribute weight acquirement are utilized throughout the literature; however, the one that is mostly used for multi-attribute analysis is Saaty’s (1980) “method for pair-wise comparison of the criteria” or analytic hierarchy process (AHP). In this methodology, the decision maker or expert is asked to judge the importance of each of the attributes and compare it to all of the others. Throughout this research, five levels of comparison are considered to be sufficient: 1/5 = much less important, 1/3 = less important, 1 = equally important, 3 = more important, 5 = much more important. The original AHP scale is not utilized because a lower judgment scale is needed for the “importance” differences among the encountered attributes.

After assigning the shovel’s membership values for each of the attributes, these are combined with the attributes’ weights, to obtain the partial membership value for the category, as follows

\[
A = \left[\mu_{A_1} \cdot w_{A_1} + \mu_{A_2} \cdot w_{A_2} + \mu_{A_3} \cdot w_{A_3} + \ldots + \mu_{A_n} \cdot w_{A_n}\right]
\]

where

\[A = \text{the partial membership value of the category (value between 0 and 1)},\]

\[\mu_{A_i} = \text{the membership value of the attribute } A_i \text{ that belongs to category } A,\]

\[w_{A_i} = \text{the weight of attribute } A_i,\]

\[n = \text{the number of subjective attributes in category } A.\]

### Table 3 — Geology and deposit characterization attributes (P&H MinePro (2003) along with the authors’ assignment of “appropriateness.”

<table>
<thead>
<tr>
<th>Index</th>
<th>Attribute</th>
<th>HMS appropriateness</th>
<th>EMS appropriateness</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>Bench height&lt;br&gt;Priority: High</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>C2</td>
<td>Digging material layer by layer&lt;br&gt;Priority: Low</td>
<td>Very high</td>
<td>If need for this task: Low; else: Very high</td>
</tr>
<tr>
<td>C3</td>
<td>Drilling and Blasting (D&amp;B) Requirements&lt;br&gt;Priority: High</td>
<td>Very high (if good D&amp;B)</td>
<td>High (if good D&amp;B)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Low (if poor D&amp;B)</td>
<td></td>
</tr>
<tr>
<td>C4</td>
<td>Following layers up a grade&lt;br&gt;Priority: Low</td>
<td>Very high</td>
<td>High</td>
</tr>
<tr>
<td>C5</td>
<td>Material abrasiveness&lt;br&gt;Priority: High</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>C6</td>
<td>Selective mining face digging&lt;br&gt;Priority: Low</td>
<td>Very high</td>
<td>Very low</td>
</tr>
</tbody>
</table>

### Table 4 — Digging and loading attributes (P&H MinePro, 2003) with the authors’ assignment of “appropriateness.”

<table>
<thead>
<tr>
<th>Index</th>
<th>Attribute</th>
<th>HMS appropriateness</th>
<th>EMS appropriateness</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>Cycle time&lt;br&gt;Priority: Very high</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>D2</td>
<td>Debris removal&lt;br&gt;Priority: Low</td>
<td>Very high</td>
<td>Very low</td>
</tr>
<tr>
<td>D3</td>
<td>Digging below ground level&lt;br&gt;Priority: Low</td>
<td>High for a regular HMS; Very high for a backhoe HMS</td>
<td>Fair</td>
</tr>
<tr>
<td>D4</td>
<td>Fill factor&lt;br&gt;Priority: Very high</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>D5</td>
<td>Floor cleanup&lt;br&gt;Priority: Low</td>
<td>Very high</td>
<td>Fair</td>
</tr>
<tr>
<td>D6</td>
<td>Floor level digging reach&lt;br&gt;Priority: High</td>
<td>Very high</td>
<td>Very high</td>
</tr>
<tr>
<td>D7</td>
<td>Material discharge&lt;br&gt;Priority: High</td>
<td>Very high</td>
<td>High</td>
</tr>
<tr>
<td>D8</td>
<td>Proximity to face&lt;br&gt;Priority: High</td>
<td>Fair</td>
<td>Very high</td>
</tr>
<tr>
<td>D9</td>
<td>Reach&lt;br&gt;Priority: Very high</td>
<td>Fair</td>
<td>Very high</td>
</tr>
<tr>
<td>D10</td>
<td>Removal of large rocks from the digging face&lt;br&gt;Priority: Low</td>
<td>Very high</td>
<td>High</td>
</tr>
<tr>
<td>D11</td>
<td>Removal of obstructions from the floor&lt;br&gt;Priority: Low</td>
<td>Very high</td>
<td>High</td>
</tr>
<tr>
<td>D12</td>
<td>Rock handling capability&lt;br&gt;Priority: Low</td>
<td>Very high</td>
<td>Fair</td>
</tr>
<tr>
<td>D13</td>
<td>Truck compatibility&lt;br&gt;Priority: Very high</td>
<td>High</td>
<td>Very High</td>
</tr>
<tr>
<td>D14</td>
<td>Truck loading&lt;br&gt;Priority: Very high</td>
<td>High</td>
<td>Very high</td>
</tr>
<tr>
<td>D15</td>
<td>Working dimensions&lt;br&gt;Priority: High</td>
<td>High</td>
<td>Very high</td>
</tr>
</tbody>
</table>
Finally, the overall fuzzy subjective score or overall membership value (FUZ-SCO) is calculated by utilizing all partial category membership values and their corresponding category weight. This FUZ-SCO is calculated as follows

\[
FUZ-SCO = [A \cdot w_A] + (B \cdot w_B) + \ldots + (N \cdot w_N) \]

(2)

where

- \( A \) is the number of categories considered for the fuzzy analysis.

The shovel selection fuzzy expert system (SHS-FES) is developed and the “multi-attribute fuzzy methodology for the selection of mining shovels” is applied. The SHS-FES is written in Java, as a collection of modules or Java applets, utilizing the Eclipse 3.2 compiler. The graphic user interface of this expert system is designed in a combination of Java applets and HTML code written in MS FrontPage 2003. One of these applets is shown in Fig. 2.

The first component for the creation of an ES is the knowledge base (KB). A knowledge base is defined as a collection of facts, heuristics and models that can be used for problem solving. There are three types of knowledge bases: database, dynamic knowledge bases and calculated knowledge bases (Kumara, 2006). Database is a collection of information stored in the KB in a systematic way. A dynamic knowledge base or “input” is the information provided to the ES by the user. Finally, the calculated knowledge base contains a collection of information calculated or inferred from both the database and the dynamic knowledge base.

The knowledge base layout for this ES is presented in Table 9. The information contained in this KB makes it possible for the ES to perform the selection of a mining shovel for a given case, as long as the case represents a HPLC operation situation.

The second component of an ES is called an “inference engine.” The inference engine for this ES is composed of the technical analysis and the fuzzy analysis. The technical analysis is used to lower the number of shovel alternatives. This technical inference engine takes four requirements into consideration: the required production, the project lifespan, the prechoice of a shovel type and the cost per unit loaded. The inference engine for the technical analysis of SHS-FES is presented in Table 10.

The mining shovels that produce between 100% and 120% of the required production are further considered by the ES, while others are eliminated from the search. The reason for considering some mining shovels that do not fulfill the lifespan expectations is that these shovels are still options. If the project life is shorter than the expected life of the shovel, then there is a possibility of resale. If the expected life of the shovel is less than that of the project, then there is the possibility of acquiring an additional shovel. Some users might have a preference for a particular type of shovel (HMS or EMS), given the characteristics of the project, such as the availability or not of certain power source, etc. This feature is included in the ES. Finally, the cost per unit loaded for each of the shovels is the sorting agent. Each shovel option suggested by the ES will appear sorted by cost per unit loaded.

The logic behind this inference engine is mathematically explained in Table 11. It is based on the flow of the inference engine, which is graphically presented in Fig.

<table>
<thead>
<tr>
<th>Table 5 — Productivity attributes (P&amp;H MinePro, 2003) along with the authors’ assignment of “appropriateness.”</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Index</strong></td>
</tr>
</tbody>
</table>
| E1 | Availability  
*Priority: Very high* | High | Very high |
| E2 | Capacity  
*Priority: Very high* | Depends on bucket size | Depends on bucket size |
| E3 | Reliability  
*Priority: Very high* | High | Very high |

<table>
<thead>
<tr>
<th>Table 6 — Maintenance attributes (P&amp;H MinePro, 2003) along with the authors’ assignment of “appropriateness.”</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Index</strong></td>
</tr>
</tbody>
</table>
| F1 | Ease of maintenance  
*Priority: Very high* | High | Very high |
| F2 | Fueling  
*Priority: Very high* | Very high if electric; Very low if Diesel | Very high |
| F3 | Planned comp. replacement  
*Priority: Very high* | High | Very high |
| F4 | Preventive maint. schedules  
*Priority: Very high* | High | Very high |
| F5 | Reliability indicators  
*Priority: High* | Fair | Very high |

<table>
<thead>
<tr>
<th>Table 7 — Environmental impact attributes (P&amp;H MinePro, 2003) along with the authors’ assignment of “appropriateness.”</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Index</strong></td>
</tr>
</tbody>
</table>
| G1 | Cleanliness  
*Priority: High* | Fair | Very high |
| G2 | Fluid disposal  
*Priority: High* | Low | Very high |
| G3 | Greenhouse gas emissions  
*Priority: Very high* | Fair | Very high |
| G4 | Spillage  
*Priority: High* | Fair | Very high |
3. In SHS-FES, this section of the ES is called “shovel search.”

The report generated by the “shovel search” applet has two sections: the “Project Input Data” and the “Recommended Shovels.” The “Project Input Data” section contains the user-defined material, project and schedule characteristics. The “Recommended Shovels” section lists the shovels, if any, chosen as alternatives or options for the current project. These are sorted by their cost per unit-loaded value. This section also lists the manufacturer, model, type (HMS/EMS), attachment type (front shovel/backhoe), energy type, bucket volume, bucket payload, recommended truck payload, yearly production, ownership cost, operating cost, total hourly cost, cost per unit loaded and lifespan recommendations of each shovel option.

The final part of the SHS-FES enables the calculation of an overall Fuzzy Score (FUZ-SCO) to each of the shovel options. This FUZ-SCO is the overall membership value of a shovel for a given project. In other words, it represents “how well a shovel fits the requirements of a project.” The FUZ-SCO is also utilized as a point of comparison among the shovel options presented by the technical inference engine.

Application of the methodology — data collection, results and analysis

An operating copper mine was used to collect data related to the production and material properties. The highest elevation of the mine is 1,950 m (6,400 ft) above sea level. The temperature ranges from 2°C (36°F) in February to 37°C (99°F) in July, while the rainfall averages 33 cm (13 in.) per year. The remaining mine lifespan is expected to be 13.2 years, and a new shovel needs to be acquired. This lifespan indicates the possibility of acquiring either an electric mining shovel for the full lifespan of the mine or a hydraulic mining shovel for the next 8 to 9 years of operations. The average bank density of copper ore is 2.55 t/m$^3$, the average swell factor is 1.50, and the digging conditions are medium-hard (M-H). The drilling and blasting conditions are good. Moreover, the mine plan requires front shovels for the operations; therefore, digging below ground level and digging material layer by layer are not requirements. The work schedule of mine is three 8-hour shifts per day, 7 days a week. It is reasonable to assume 40 minutes of non-operating delays and 30 minutes of operating delays. It is assumed that there will be 15 scheduled lost shifts, 15 unscheduled lost shifts and 15 maintenance shifts per year.

The shovel database is created and features different shovel models from different manufacturers. It includes 40 different types of mining shovels, both HMSs and EMSs. Table 12 shows the list of shovels included in a database. It should be noted that each shovel manufacturer is given an arbitrary identification, such as A, B, C, D, E and F.

The outputs of the reports generated by SHS-FES are shown...
The shovel options that produce 100% to 120% of the required production, i.e., 15 to 18 Mt (16 to 20 million st) of material per year, are listed. For this specific mine, the report introduces five mining shovels as options along with their production and cost characteristics. The first two options are EMSs. The last three options are fuel-powered HMSs. HMSs have a productive life of 7 to 9 years; on the other hand, EMSs have a productive life of more than 20 years.

Recommendations related to the shovel’s life are presented for each of the options. Because of the lifespan of shovels, the hourly ownership cost of EMSs is significantly lower than that of HMSs. The tax rate is assumed to be 6%, the interest rate...
as 1% and the insurance rate as 3% for a HMS and 1% for an EMS. However, these rates are of lesser importance because they have been applied equally to all the analyzed options. Also, the differences in operating costs appear due to the higher costs for fuel and maintenance for HMSs.

The mine has a lifespan of 13.2 years, which means that an EMS would have to be sold to the used equipment market at the end of the mine’s life. SHS-FES suggests that, given the mine lifespan, the shovel’s resale value approximates 35% of the original machine price. On the other hand, HMSs will not fulfill the mine’s lifespan; thus, two HMSs must be purchased during the life of the project. It should be noted that there is no certainty on purchasing the same HMS at the end of the life of the first shovel. The EMS shovels have a lower total hourly cost than hydraulic mining shovels; this lowers their cost per unit loaded. In the first two options (EMSs), the cost per unit loaded is about 19 cents per metric ton. The fuel-powered HMSs have a cost per unit loaded of about 45 cents per metric ton.

To understand the most important technical parameters for the selection of a mining shovel, Fig. 7 shows the sensitivity analysis of technical parameters with respect to Option 1. This sensitivity analysis shows that if the bucket volume, mechanical availability, working hours per year, fill factor or operating efficiency were increased by a slight percentage, the cost per unit loaded would decrease. The increase in bucket size is a very sensitive variable because the cycle time and the production of the shovel are functions of the bucket volume.

Figure 8 shows the final report generated by the SHS-FES fuzzy analysis of the shovels identified by the technical evaluation. The first two identified options are recognized as the electric mining shovels. These shovels have a higher fuzzy score (0.857 and 0.846) than the hydraulic shovels (overall MV: FUZ-SCO). The differences in the FUZ-SCO between these two options come from the MVs for the machine attribute category (0.97 for the first option and 0.93 for the second option) and the digging and loading attribute category (0.68 for the first option and 0.60 for the second option). These differences are related to attributes such as visibility, cab location, working dimensions, proximity to face and reach, where the first option has a slight advantage over the second option in properties such as boom length, height and weight. Figure 8 shows the results that indicate that the best solution is shovel Model 2 by Manufacturer F. Once again, it is important to note that the most influential attributes for shovel selection in the current case study are utilized by the technical analysis; thus, the weight for the commercial attributes is lower.

The sensitivity analysis shown in Fig. 9 indicates that the weight of the attributes is one of the major factors for the calculation of the FUZ-SCO. The change in the MV of an attribute category with a higher weight will result in a larger change in the FUZ-SCO. This means that attributes in the productivity and maintenance categories are key factors of the fuzzy evaluation of shovels. Figure 9 shows that a positive 50% change in MV for a category with a low weight will result in a positive
It should be noted that all attributes or their values used in this research work are not prescriptive and may be subject of change in order to adequately reflect specific circumstances. Other attributes, such as the time associated with shovel delivery/mobilization, compatibility with existing mine infrastructure and existing shovels and access to service and spare parts, can also be included in the analysis. The proposed methodology is flexible enough to take into consideration such changes.

Conclusions

The methodology presented in this paper identifies a number of attributes related to the selection of a mining shovel, such as technical, machine operation, geology and deposit characterization, digging and loading, productivity, maintenance, environmental impact and commercial aspect. The ranking or weighting of attributes was performed by utilizing a pair-wise comparison of attributes. The membership value and the weight for each attribute were utilized in equations developed for the evaluation by category and in a unique equation developed for the overall evaluation. The latter equation's result was called the FUZ-SCO (fuzzy score), and it 2% change in the FUZ-SCO. Similarly, the same change in a category with a high weight will result in a positive 5% change in the FUZ-SCO. Finally, this change in a category with a very high weight will result in a 12% change in the FUZ-SCO.

It should be noted that all attributes or their values used in this research work are not prescriptive and may be subject of change in order to adequately reflect specific circumstances. Other attributes, such as the time associated with shovel delivery/mobilization, compatibility with existing mine infrastructure and existing shovels and access to service and spare parts, can also be included in the analysis. The proposed methodology is flexible enough to take into consideration such changes.

Figure 4 — Production and economics for Options 1 and 2.

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represented the overall membership value of each shovel with respect to the project characteristics.

The final results of the SHS-FES system are limited to the identified shovel database. SHS-FES could be highly enriched with the identification of every single machine available in the market and its characteristics. In other words, a step forward from this research would be the enrichment of the shovel database.

This study was based on a deterministic approach. The methodology can be significantly improved if a probabilistic approach were introduced, which would take into consideration uncertainties related to cycle times, efficiencies, availabilities, etc. This probabilistic approach would result in more accurate confidence intervals. Simulation tools with the introduction of haul truck queuing theory would push the accuracy of this expert system even further. The fuzzy analysis could also improve with the introduction of several possible results, similar to PERT theory (pessimistic, normal and optimistic).

The desired future of SHS-FES is to become a website. Users could enter this website to perform the selection of a wide variety of equipment with up-to-date database and information, such as state taxes, interest rates, insurance rates and site temperatures.

References


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