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Equipment Selection for Surface Mining: A Review

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One of the challenging problems for surface mining operation optimization is choosing the optimal truck and loader fleet. This problem is the Equipment Selection Problem (ESP). In this paper, we describe the ESP in the context of surface mining. We discuss the related problems and applications. Within the scope of both the ESP and related problems, we outline modeling and solution approaches. Using the state-of-the-art operations research literature as a guide, we conclude by pointing to future research directions to improve both the modeling and solution outcomes for practical application of this problem.

Key words: Equipment Selection, Surface Mining, Shovel-Truck Productivity, Mining Method Selection, Multi-Commodity Network Flow

Introduction

The general Equipment Selection Problem (ESP) is to choose a collection of compatible, but not necessarily homogeneous (i.e. not mixed type), vehicles and ancillary equipment to perform a task at minimum cost. Different equipment types have attributes that can interact in a complex way with respect to productivity. In the surface mining application, the ESP addresses the selection of truck and loader fleets to move mined material, including both waste and ore. Mine planners divide the mining schedule, which may run for multiple decades, into planning periods [Figure 1]. The size of these periods may differ depending on the planning task: typically a year for mine scheduling decisions (Gleixner 2008), more frequently for fleet scheduling decisions and less frequently for equipment purchasing decisions. Mining companies can consider long schedules (e.g. up to 25 years) in strategic planning of this nature (Epstein et al. 2003).

In surface mining, the tasks that the equipment must perform are loading and transporting material. Once multiple origins, destinations, or routes are considered, the underlying problem becomes a multi-commodity flow problem. For example, there may be multiple pits supplying one

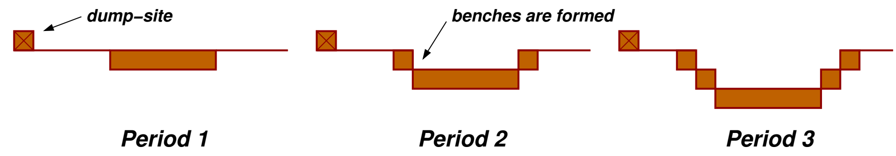

Figure 1 **A mining schedule is divided into planning periods. In each period, the decisions include material to be moved, excavation locations and dumpsites.**

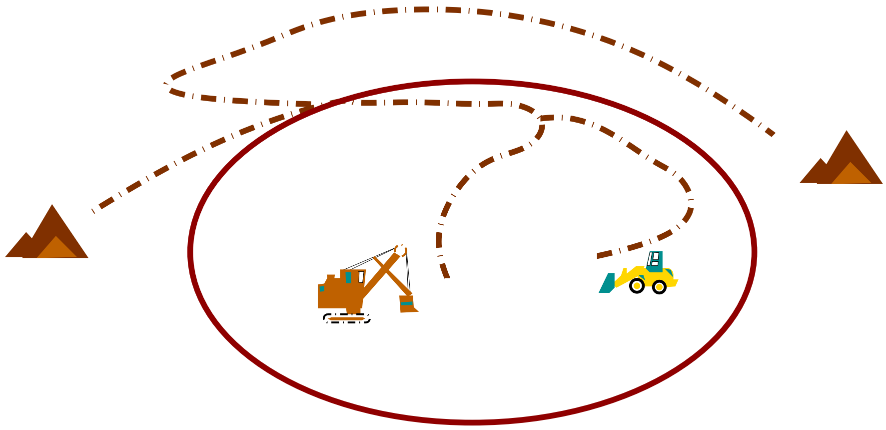

Figure 2 **Within a surface mine there may be more than one loading location with differing requirements such that different loader types are necessary. There may also be multiple dumpsites.**

or more dumpsites with the truck fleet moving material between the sites [Figure 2]. Since there may be several loading locations with different loading requirements, different loader types may be required. The selected trucking fleet must be compatible with the loaders assigned in each period. This issue of compatibility is a complicating characteristic of surface mining equipment selection. A partial fleet may exist at an equipment purchase point, and due to supercession of particular models (since the last purchase took place, as in Cebesoy (1997)) or due to other optimization criteria, this may also lead to mixed-type (i.e. heterogeneous) fleets including mixed truck types.

Due to improved efficiencies after maintenance and overhauls, the operating costs of the equipment are non-linear functions of the age of the equipment (or equipment utilization) [Figure 3]. They typically include uncertain costs such as fuel prices and transit times. The productivity of equipment also changes over time, usually due to maintenance, equipment overhauls, size of operating fleet and driver competence.

The fleet selection problem is of striking importance in surface mining, where the cost of operating the equipment over long-term schedules is anecdotally between 40-60% of the overall cost of materials handling (Alarie and Gamache 2002): robust equipment selection solutions is a driving

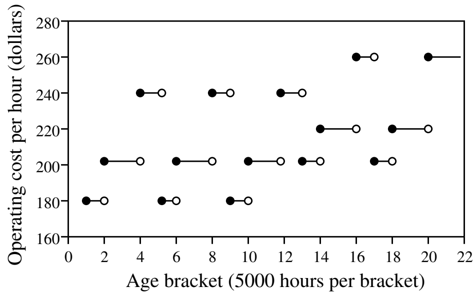

Figure 3 **Discretized operating cost function against age brackets. The rise in operating cost reflects the increased maintenance expense; large drops in the expense occur when a significant maintenance, such as overhaul, has taken place.**

factor for the profitability of mining operations. In the context of surface mining, a "robust" fleet selection will be able to perform the required tasks on time.

A *fixed-charge* objective function results from considering purchase, salvage and service decisions in a cost minimization scenario. Fixed-charge represents an incremental (disjoint) jump in the objective function and is usually due to purchase or other binary decisions. There are limitations to productivity at the loader and carrying capacity of the trucks, which can be dependent on the combined choice of equipment since a loader will not pass a half or partial scoop to a truck just to fill the truck. These factors, in combination with the multiple flow paths the equipment may take in transit (see Figure 2), results in a problem with structure similar to the *fixed-charge capacitated multi-commodity flow problem*. However, the network is often very simple. A chief difficulty lies in tying the strategic and tactical decisions of equipment types and numbers, and time of purchase, to the operational scheduling decisions over a long-term mining schedule. This disparity in time scale, between strategic, tactical and operational decisions, has an enormous affect on the effectiveness of a chosen modeling and solution approach.

The input to the ESP is generally: (i) a long-term mining schedule including production requirements at a number of loading and dumping locations; (ii) a set of loaders and trucks that may be purchased; (iii) equipment productivity information; and, (iv) cost information (including interest and depreciation rates, purchase, maintenance, and operating costs). The output from the ESP is a purchase and salvage policy over the entire mining schedule and proof that a feasible fleet schedule exists. We consider the "fleet schedule" to be daily task allocation decisions for the equipment, whereas the "mining schedule" determines the mid-term production requirements of the mine including the excavation and dumping locations.

In the literature, there are two approaches to solving this problem: (i) to simplify the problem; and, (ii) to develop extensive solving strategies hand-in-hand with the modeling process. The most common approach in the mining equipment selection literature has been to simplify the problem.

However, by observing recent advancements in related literature, where the problem structure is similar or identical, the mining industry may be able to solve larger scale, and more difficult instantiations of the problem.

In this paper, we review the literature directly addressing mining applications with related technical literature from the operations research community. In the construction industry, truck and loader equipment selection is very similar to surface mining equipment selection, although the scale of material and the nature of the job due dates is very different. Two other strikingly similar applications, with respect to problem structure, are Manufacturing Production research (including Equipment Selection and Allocation problems) and Capacitated Network Design (in the presence of multi-commodity flow). To help bring together theoretical advancements that are of practical use to the surface mining community, we include literature from these applications here where it is appropriate. However, our primary focus is the mining and construction literature. We endeavor to state which paper addresses which problem, since the arising assumptions and complexity of the models depends on the precise problem addressed within each paper.

We first provide a background to the problem in the next section. Then we outline some related problems, and proceed with a review of modeling and solution methods in both the mining and operations research literature. Using the state-of-the-art operations research literature as a guide, we conclude with future directions for research in the context of the surface mining application.

Background

A surface mine is an open pit style of mine for extracting mineral endowed rock (or ore) from the earth to a depth of 500m. We extract minerals such as iron, copper, coal and gold in this way. This method is superior, as an alternative to underground mining, when the ore is close to the surface ($<$ 500m); the overlaying soil (or overburden) is shallow; or, the surrounding environment is too unstable for tunneling. There are several methods of surface mining including open-pit, stripping, dredging and mountain-top removal. This paper will focus on open-pit surface mining, which involves removing ore from a large hole in the ground (sometimes referred to as a borrow-pit).

A combination of explosives and excavating equipment create surface mines by sequentially removing small vertical layers (or benches) of material at a time [Figure 1]. Over time, these benches are removed and the borrow pit becomes wider and deeper. Mining engineers categorize the mined material into ore and waste material, with sub-categories depending upon their quality or grade. Trucks sort these materials o a number of dumpsites, which can include mills and stockpiles. The ore will be refined at the mill, while the stockpiles are important for ensuring that the mill receives the correct mixing of ore grades to meet market demands. The mining schedule optimizes the related productivity requirements. The schedule, alongside the pit optimization (the optimization of the shape of the pit), provides required productivities, bench sequences and the shape of the mine (including bench heights). The height of the bench can vary from 4m to 60m and will dictate the type of equipment that can remove it. For large scale open pit mining in particular, trucks and loaders are the preferred method of materials handling (Czaplicki 1992, Ta et al. 2005).

Throughout this paper, we consider a “loader” to be any type of high productivity excavating equipment, which may include a mining loader, shovel or excavator. Loaders lift the ore or waste material onto the trucks or other equipment for removal from the mine. In an open-pit mine, loader types can include electric rope and hydraulic excavators, the hydraulic backhoe excavator, and front-end loaders (also wheel loaders) (Erçelebi and Kırmanlı 2000). This variety of machines differs significantly in terms of reliability (Hall and Daneshmend 2003), maintenance needs (Topal and Ramazan 2010), compatibility with different truck types (Morgan 1994b), volume capacity (Caterpillar 2003), and cost per unit of production (Bozorgebrahimi et al. 2005).

The type of loader selected for use in a surface mine depends on the type of mineral to be extracted and other environmental conditions, such as the bench height. We must also consider other factors in the equipment selection process. In particular, the compatibility of the loaders with selected truck fleets. For example, some loaders cannot reach the top of the tray on the larger trucks. Conversely, some loader capacities exceed the capacity of the truck. If we are determined not to underpin the optimization process, then we must model the problem such that we select the truck and loader types simultaneously.

Mining trucks (also off-road trucks or haul trucks) haul the ore or waste material from the loader to a dumpsite. More commonly, these vary from 36 tonnes to 215 tonnes. The size and cost of operating mining trucks is directly proportional to its tray capacity, while the speed the truck can travel is inversely proportional to its capacity. As with loaders, the variety of truck types differs according to their reliability, maintenance requirements, productivity and operating cost.

The mine environment greatly affects the performance of a truck (Bennett and Yano 2004). For example, the softness of the road soil creates an effect of rolling resistance that reduces the efficiency of the truck in propelling itself forward. Wetting and compressing the roads regularly can control and reduce the effects of rolling resistance. Rolling resistance varies a lot across the road and over time, and is notoriously difficult to estimate (Dunston et al. 2007).

Rimpull also affects the forward motion of the truck. Rimpull is the natural resistance of the ground to the torque of the tire; and, is equal to the torque of the wheel axle multiplied by the wheel radius. Manufacturers supply pre-calculated rimpull curves for their trucks to enable a satisfactory calculation of truck cycle times. The rimpull curves map the increase in road resistance as the truck increases speed (Caterpillar 2003). Haul grade (that is, the incline of the haul road) exacerbates the effects of rolling resistance and rimpull. These parameters, alongside haul distance, are crucial for the accurate calculation of the truck cycle time (Zhongzhou and Qining 1988).

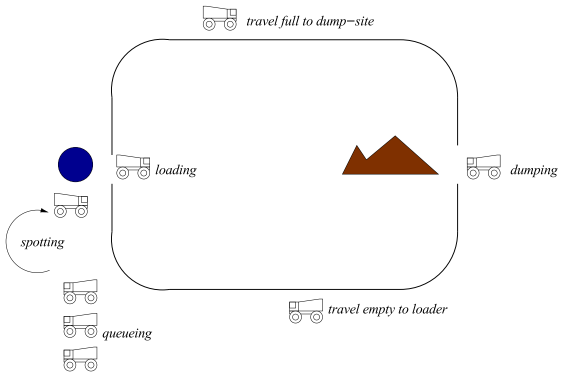

Figure 4 **The truck cycle time is measured from the time the truck is filled at the loader, travels full to the dumpsite, dumps the load, and travels empty to the loader to join a queue and positions itself for the next load (spotting). The truck cycle time includes queuing and waiting times at the dumpsite and loader.**

Definition 1. The *truck cycle time comprises of load time, haul time (full), dump time, return time (empty), queuing and spotting [Figure 4].*

A cycle may begin at a loader where the truck receives its load. The truck then "travels full" to the dumpsite via a designated route along a haul road. The dumpsite may be a stockpile, dumpsite or mill. After dumping the load, the truck turns around and "travels empty" back to the loader. "Spotting" is the act of maneuvering the truck under the loader for serving. This can take several minutes. In a large mine the truck cycle time may be around 20-30 minutes in total, and can vary a lot over time if the stockpiles move and as the mine deepens.

The truck cycle time is an important parameter because related parameters (that are not dependent on the final selected fleet) can be absorbed into it. Ultimately, we wish to include intimate details of the mine, such as topography and rolling resistance, in the modeling process. Mining engineers can make reasonable estimates of these parameters before modeling and incorporating them into the truck cycle time. In a similar way, the truck cycle time can absorb other parameters such as rimpull, haul grade and haul distance into one estimate. However, the level of queuing that occurs in a fleet is dependent on the number of trucks operating against each loader. This makes it difficult to accurately estimate truck cycle times before the fleet is determined.

In industry, the common method of truck cycle time estimation is to estimate the speed of the trucks using manufacturer performance guidelines (Smith et al. 2000). These guidelines are simulation results that take into consideration engine power, engine transmission efficiency, truck weight, capacity, rimpull, and road gradients and conditions (Blackwell 1999). Mining engineers may then combine these guidelines with topographical information to provide an estimate of the hauling route. Smith et al. (2000) provides a method for determining a rolling resistance estimate. Çelebi (1998) calculate truck cycle time estimates using regression models.

Figure 5 **Mining method selection is the process of choosing a particular style of mining, e.g. open-pit, dredging or stripping. Once the method is chosen, the set of equipment to choose from is reduced. Heuristic or exact methods can then be applied to choose the fleet.**

Related Problems

In this section, we outline problems in mining that are similar to the ESP. We also describe other applications of ESP in the wider literature. We defer discussion of similarly structured problems, where modeling and solution approaches may prove relevant, for the Modeling and Solution Approaches section.

In the mining literature, Equipment Selection is a similar problem to *Mining Method Selection*; and in the construction literature, *Shovel-Truck Productivity* is a similar problem. The mining method selection problem is an approach to equipment selection that reasons that the environmental conditions will imply a particular mining method, and that the selection of loader and truck types will follow intuitively from there [Figure 5]. This problem then focuses on choosing the correct excavation method for the given conditions. The shovel-truck productivity research area focuses on estimating and optimizing the productivity of a truck and loader fleet. This literature generally relies on the intuitive notion that improving productivity will translate into cost reductions (Schexnayder et al. 1999). Often these productivity optimization methods extend in a simple way to become an equipment selection solution. The number of trucks performing the materials handling task affects the efficiency of the truck fleet (Alarie and Gamache 2002).

Solution of the mining method selection problem is a preliminary step to equipment selection, whereby mining engineers choose an appropriate excavation method based on environmental conditions. In early work on this problem, Tan and Ramani (1992), Kesimal (1998) and Blackwell (1999) (for example) describe this approach in combination with match factor (described in *Modeling and solution approaches*), a product of shovel-truck productivity research, to select equipment.

Dispatching and Allocation are also related topics in the mining literature. The basic problem here is to allocate tasks to equipment [Figure 6]. In the scope of timed services, this becomes the dispatching problem. The allocation literature focuses on the satisfaction of productivity requirements, often with complex features such as bottleneck prevention; the dispatch optimization literature seeks to maximize the efficiency of the fleet at hand (Newman et al. 2010).

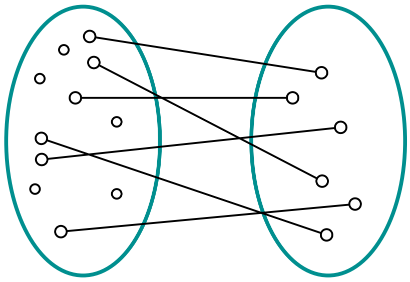

Figure 6 The allocation and dispatching problems are concerned with matching services to tasks.

Other related problems include mine production scheduling (Caccetta and Hill 2003, Kumral and Dowd 2005, Gleixner 2008), pit optimization (Frimpong et al. 2002), equipment costing (O'Hara and Suboleski 1992, Morgan 1994a, Leontidis and Patmanidou 2000), production sequencing (Halatchev 2002), and equipment replacement (Tomlingson 2000, Nassar 2001).

In other applications areas of the operations research literature, the ESP is synonymous with *Asset Management*: facility material handling equipment selection and machine selection in manufacturing systems (Bennett and Yano 2004, Chen 1999), network planning (Derigs et al. 2009), and equipment replacement (Rajagopalan 1998).

This broad range of applications illustrates the importance of the ESP in industry. We note, however, that this list of other applications of the ESP is far from exhaustive.

Modeling and solution approaches

In this section, we outline modeling and solution approaches applied to the ESP in the context of surface mining. We also outline the solution approach of some similarly structured problems in the OR literature.

Markeset and Kumar (2000) and Bozorgebrahimi et al. (2005) each presented *life cycle costing* (LCC) as an equipment selection method. LCC is a method for determining the cost per utilized hour of equipment if the equipment operates for its entire life span. A basic comparison can be made between each equipment utilized cost to determine the cheapest equipment, although these comparisons don't tend to take into account the task to be performed or the time required to perform it. This type of analysis may be useful in determining a cost per hour for equipment, especially in a model that does not permit salvage. Some literature also uses cost estimation for truck transportation problems where the focus on uncertain parameters aims to improve robustness of the solutions, e.g. see Zhang (2010).

Heuristic methods and their use persist in industry, with spreadsheets employed to aid hand iteration over a small subset of possibilities rather than optimization (see Eldin and Mayfield (2005)).

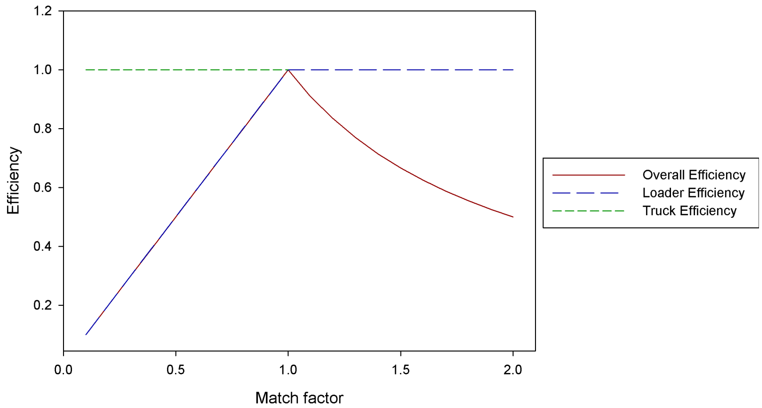

Figure 7 **The Match Factor is the ratio of loader productivity to truck productivity. A low MF ($<$ 0.5) suggests that the loader is not working to capacity, whereas a high MF ($>$ 1) suggests the truck fleet is smaller than necessary.**

The match factor ratio is an important productivity index in the mining industry (see Figure 7). The match factor is simply the ratio of truck arrival rate to loader service time. Construction literature, in particular, uses match factor to determine a suitable truck fleet size. Smith et al. (2000) recommended using the match factor formula as a means of determining the appropriate fleet size. However, an expert must select the best types of equipment before applying the formula. Burt and Caccetta (2007) extended the formula to account for heterogeneous fleets and multiple truck cycle times. Smith et al. (2000) reported that, at the time of publication, the earthmoving industry still used this ratio to determine an appropriate truck fleet size once the loader fleet and truck type has been established. In research for truck dispatch systems, researchers typically apply match factor or mathematical programming approaches to determine the minimum number of trucks required for a schedule (see Alarie and Gamache (2002)) and then use dynamic programming to determine allocation to mining locations (see Blackwell (1999)).

Uncertainty in some parameters, such as plant downtime and truck loading and cycle times, can complicate truck allocation. Ta et al. (2005) developed a stochastic model that incorporates real-time data for allocation of the fleet. Karimi et al. (2007) addressed the uncertainty in parameters with a fuzzy optimization allocation model. In another example, Easa (1988) developed two quadratic programming models for earthwork allocation. These models only allow for linear unit cost functions, as opposed to the more common piece-wise linear cost functions. Chen (1999) looks at a multi-period equipment selection model without transportation and develops a heuristic to deal with the difficulty arising from the multi-period nature of the model. They use Lagrangian relaxation to provide bounds on solution quality.

A number of models incorporate Net Present Value (NPV) analysis to allow comparisons between present and future cash flow. However, future interest rates are uncertain and difficult to predict. Yet, they are a critical part of the objective function for these models. Wiesemann et al. (2010) proposed a global optimization model for accurate NPV under uncertainty, and also, a heuristic solution approach based on branch-and-bound.

Edwards et al. (2001) used a *linear programming* model for selecting hire equipment. However, the authors neglected to define the variables and explain how continuous variables could lead to integer values of equipment as a solution. Land and Doig (1960) established that continuous optimal solutions may be very far away from integer optimal solutions, and therefore rounding methods can lead to violation of important discrete variable constraints or far from optimal solutions.

Queuing theory was first notably applied to shovel-truck productivity by O'Shea (1964). In this work, they used queuing theory to predict the productivity of trucking fleets in an attempt to account for productivity lost when the trucks queue at a loader. Much later, Karshenas (1989) outlined several improvements and subsequently incorporated them into an equipment capacity selection model. This is a non-linear optimization model with a single constraint, and can be solved using direct search. Since the model requires the times between any arrivals as an input, it is restricted to selecting homogeneous fleet capacity.

Griffis, Jr (1968) developed a heuristic for determining the truck fleet size using queuing theory. This extended the work by O'Shea (1964) for calculating the productivity of different fleet options by modeling the truck arrival rates as a Poisson process. Here, the authors assume the time between arrivals follows an exponential distribution. Independence between arrivals is also a key assumption. Later, Farid and Koning (1994) used simulation to verify the effectiveness of the equipment selection results of Griffis and O'Shea. However, equipment bunching may violate the independence assumption. Bunching theory is the study of the jamming effect that can occur when equipment travel along the same route. Douglas (1964), Morgan (1994b), Smith et al. (1995) and Smith et al. (2000) describe equipment bunching. However, the literature has thus far not included bunching in the modeling process in a satisfactory way. The aforementioned mining literature adopted shrinking factors to account for bunching, although bunching is a function of the number of equipment, the type of road, and many other factors.

Huang and Kumar (1994) have extended this work in an attempt to select the size of the trucking fleet using a more accurate productivity estimate. They developed a fleet size selection queuing model to minimize the cost of idle machinery. Their model recommended that fleet sizes matching the maximum efficiency for both location and haulage equipment. Although this objective function may not improve the economic result, it is useful to consider the variability in some of the parameters of the equipment selection problem, such as truck cycle times and queue length.

In production materials handling research, Raman et al. (2009) used queuing theory to determine the optimal quantity of equipment in a transportation context, given a schedule.

Exact methods, such as integer programming, have been an important modeling and solution approach for equipment selection in surface mining. Network design models, in particular, capture the selection and flow aspects that are crucial to a good equipment selection model. In the mining literature, basic integer programming models are common. Simplifying assumptions reduce the problem instantiations to easily solvable cases. For example, non-linear operating costs can be discretized to piecewise linear functions using age brackets, as in Burt et al. (2010) and Topal and Ramazan (2010). Cebesoy et al. (1995) developed a systematic decision making model for the selection of equipment types, using a binary integer program in the final step of their heuristic. This model considers a single period, single location mine with homogeneous fleets. Suitability matching of the equipment occurs before the solving of this model.

In another example, Michiotis et al. (1998) used a pure binary programming model for selecting the number, type, and locality of excavating equipment to work in a pit. The authors ignore the transportation aspect of the problem by looking only at the excavators. The model minimized the time to extract. It was constrained by knapsack-based constraints that ensured that equipment was feasible for the type of bench and that all production requirements are satisfied. Burt et al. (2010) developed a mixed-integer programming model for equipment selection with a single source and destination. This model focused on the complex side constraints arising from heterogeneous fleets and the compatibility of the equipment. Outside of mining, Baxter et al. (2010) considered the equipment selection problem in the context of the forestry harvesting, also with a mixed-integer programming approach. This problem is essentially the same as the surface mining problem, whereby the model selects the equipment and the number of hours of operation for a given harvesting schedule with respect to an underlying transportation problem. The authors have modeled the number of hours of operation so that the objective function is more accurate. That is, since the efficiency and cost of operating equipment changes with the age of the equipment (e.g. the number of hours the equipment has been used), then it is practical to include the age of the equipment in the objective function.

Since part of the underlying structure is a *multi-commodity network flow* problem, it is useful to consider literature focusing on this problem. Papers that provide a deep discussion of the structure, computational issues, solution approaches and application of capacitated multi-commodity network flow include Bienstock and Günlük (1995), Bienstock and Günlük (1996), Gendron et al. (1998), Barnhart et al. (2002) and Moccia et al. (2011). Anderson et al. (2009b) incorporated equipment selection into their intermodal transportation problem quite simply by adding variables as well as re-indexing the flow variables.

In the OR literature, Equi et al. (1997) model the scheduling problem in the context of transportation using mixed-integer programming, and develop a Lagrangian relaxation solution approach. Other examples of Lagrangian relaxation in the context of network planning include Gendron et al. (1998), Galiano et al. (2010) and Zhang (2010).

Since including a time step as a variable index is important for the NPV costing, the quantity of variables in discrete models can sometimes become overwhelming. In the OR literature, reformulation is common in a bid to find a smarter, less inhibitive way to capture the problem. Good examples of network reformulations in this context include Cohn (2002), Armacost et al. (2002) and Frangioni and Gendron (2009). These papers each used composite binary variables to represent multiple decisions in a bid to simplify the model and reduce its size. The papers then exploit the composite variable formulation for a decomposition approach, since the problem is in natural partitions whose solution may help to reduce the solution space or add rows/columns to the problem. The composite variables capture overarching decisions and a linear program may solve the underlying transportation problems. Kim (1997) provides a discussion and comparison of some types of reformulation, such as node-arc versus path and tree formulations. Another possible approach is to use a set-partitioning model, such as in Baldacci et al. (2008). The authors consider the set of all possible routes, $\mathcal{R}$, and construct constraints to select m routes for a minimum cost function.

Decomposition approaches are widely used in the broader but related literature, primarily due to the size of the problem (in terms of binary variables) in combination with inherent structure. Decomposition is a solution approach that breaks the problem down into logical partitions, and solve them iteratively. Dynamic Programming, branch-and-bound, Dantzig-Wolfe and Bender's decomposition are classic examples. Papers related to network planning that employ decomposition include Powell and Sheffi (1989), Barnhart and Schneur (1996), Mamer and McBride (2000), Irnich (2002), and Frangioni and Gendron (2010). Customizing the branching process is sensible for a problem with such inherent structure as the ESP. Notably, the solution from one period is dependent on the solution from a previous period. In addition, the material flows imply the equipment solution. A typical approach in network planning applications is to develop a custom branch-and-cut algorithm, as in Croxton et al. (2003), Baldacci et al. (2008), and Cordeau et al. (2007). Bennett and Yano (2004) describe a single-period equipment selection model with an underlying transportation problem. They adopt a Benders decomposition approach by observing the natural partitioning of the problem into equipment/fleet choice and service provision to satisfy the flow of product. Derigs et al. (2009) address air cargo network planning but this problem involves flight selection, aircraft rotation and cargo routing, which is closely related to the service selection, service frequency, and equipment allocation aspect of equipment selection in surface mining. However, the problem involves additional complexities, such as crew scheduling and maintenance scheduling. The authors develop a column generation solution approach to combat the problem difficulty. In a column generation approach, the columns represent variables in the problem. The key to this approach is to devise efficient heuristics for adding columns to the model. The overarching goal is to keep the number of variables minimal—and therefore this approach can be effective for problems that have an overwhelming number of variables or have an exploitable structure. Lübbecke and Desrosiers (2005) provide a review of relevant techniques in column generation.

Fleet assignment or allocation has been widely considered in the mining literature, mostly due to the ease of the heuristic approach of (i) determining the equipment types, then (ii) the fleet size, and subsequently (iii) the fleet assignment. This problem is similar to the ESP when a mining schedule already exists (with the difference lying in the purchase and salvage requirements of the ESP). Webster and Reed (1971) proposed an allocation model for general materials handling as a quadratic integer program for a single piece of equipment. This quadratic integer program allocates equipment rather than selecting, and is restricted to a single period. However, Hassan et al. (1985) extended Webster and Reed's model to combine the equipment selection problem with the allocation problem. This model minimizes the cost of operating the fleet subject to a knapsack and linking constraint set. In the broader literature, Hane et al. (1995) provide another example of fleet assignment in the context of complex networks. They model a fleet assignment problem as a multi-commodity flow problem with side constraints. Some considerations in their paper, such as defining the problem on a time-expanded network, are particularly relevant for the ESP in the mining application. They developed a specialized branch-and-cut algorithm based on the structure of the problem.

Preprocessing techniques are an important aspect of solving mixed-integer programs, particularly in the presence of symmetry (arising, for example, from representing identical equipment with separate variables) and excessive quantities of binary variables in the discrete description of the problem. These techniques are not common in the mining literature, although Burt (2008) provides a brief description of variable and constraint reduction. Other preprocessing examples in related literature include Ileri (2006), who preprocesses by observing dominance among route assignments; and Boland et al. (2004) provide multiple properties for preprocessing flow variables as well as constraint reduction.

The OR literature uses *local search* techniques to improve the efficiency of algorithms and as heuristics on their own. Zhang (2010) considered a Less-Than-Load planning problem with the assumption that freight flow patterns repeat, thus reducing the number of commodity variables considerably. However, the author also argued for smaller time steps to account for differences in travel times. Other local search techniques in the context of capacitated network planning problem include Büdenbender et al. (2000), Sung and Song (2003), Hewitt (2009) and Caramia and Guerriero (2009).

Artificial intelligence techniques are prevalent in large-scale mining applications due to their ability to find feasible solutions within a comparatively short time (Clément and Vagenas 1994). The most common methods among the literature are the *decision support system* methods (Bandopadhyay and Venkatasubramanian 1987, Başçetin 2004, Denby and Schofield 1990) and *genetic algorithms* (Naoum and Haidar 2000, Marzouk and Moselhi 2002, Xinchun et al. 2004, Moselhi and Alshibani 2009). Bazzazi et al. (2009) introduce various decision support methods in the context of equipment selection. Various decision support tools, such as the analytical hierarchy process (Başçetin 2004) and expert systems (Amirkhanian and Baker 1992), apply priority to decisions for logic-based heuristic solutions. These methods consider the entire process of equipment selection holistically, including site conditions, geology and environment, as well as equipment matching. Equipment matching is a step beyond merely considering compatibility, where ranks (formed in a pre-processing step) represent the suitability of pairs.

Genetic algorithms are a heuristic solution technique that select a solution after several generations of stochastic selection based on a fitness criterion. There are numerous examples of the application of genetic algorithms to the equipment selection problem. Naoum and Haidar (2000) developed a genetic algorithm model for the equipment selection problem. In their model, they incorporate the lifetime-discounted cost of the equipment, which arises from the assumption that the equipment operates from purchase until its official retirement age and is not sold or replaced before that time. Moselhi and Alshibani (2009) developed a genetic algorithm to choose equipment for a single location, single period mining schedule.

The complex interplay between types of equipment has led to literature focusing on attribute-matching, such as Abdel-Malek and Resare (2000) in the production research literature and Bazzazi et al. (2009) in the mining literature. Attribute-based selection methods include multi-attribute decision making modeling (Bandopadhyay and Nelson 1994, Başçetin et al. 2004) and fuzzy set theory (Başçetin and Kesimal 1999, Wei et al. 2003, Bitarafan and Ataei 2004, Başçetin 2004). Fuzzy programming approaches combat the uncertain nature of some of the data, such as interest rates, depreciation, and cycle times. Karimi et al. (2007) provides a discussion of this uncertainty but their approach ignores fixed-charge by neglecting indicator variables and thereby does not address the equipment selection problem as we have defined it here.

The basic attribute-matching problem can select the equipment over multiple periods. Ganguli and Bandopadhyay (2002) also developed an expert system for equipment selection. However, their method requires the user to input the "relative importance of the factors", which is typically difficult to quantify and substantiate. Khan (2006) developed a knowledge-based heuristic to focus on attribute-matching without incorporating the transportation and multi-period aspect of the problem. Mirhosseyni and Web (2009) presented a combined expert system and genetic algorithm approach for the selection and assignment of equipment for materials handling (not only surface mining application).

Finally, *simulation* approaches can verify solutions for robustness and quality. Additionally, simulation can obtain solutions. Marzouk and Moselhi (2004) designed a model using simulation and genetic algorithms to trade-off two objectives, time and cost, for the construction industry. Other examples in the OR literature include Dahl and Derigs (2009), and Gambardella et al. (2002).

Discussion

Heuristic methods, including LCC, are the most easy to implement of all the approaches. The solution process is also typically easy to understand. From this standpoint, these approaches are practical for mining engineers to use in practice. This is a desirable attribute, since the quantity of parameters feeding into the problem and the different time scales in decisions makes the problem seem overwhelmingly complicated. The queuing theory, artificial intelligence and simulation literature try to deal with these complexities in an efficient and easy to understand way, but are lacking the power to deal with the number of decisions that must be made across different time scales. It is clear in the literature that there is a preference for exact approaches, and in particular, mixed-integer programming. This may be because MIP is capable of handling larger scale models of the problem, such as multiple scheduling and purchasing periods, heterogeneous fleets and other complex side constraints. The treatment of the ESP in the context of these methods has, however, been weak. The literature addresses only overly simplified instantiations of the problem and fails to sufficiently deal with the need for robustness in the solution. However, the OR literature has many hints to offer to improve on this case. Many difficult, similarly structured and large scale problems have been solved using exact methods—even if the solution approach falls short of providing an 'optimal' solution. In this sense, there is still much that advances in the OR literature can achieve for the ESP.

Future Research Directions

Preprocessing is of clear benefit due to the dependency of current period solutions on previous periods, but one must avoid destroying structure that may be of benefit for decomposition techniques. Approximation algorithms and heuristics can obtain good initial solutions that can then initialize a branch-and-bound algorithm in order to improve computation time. One approach could be to focus on solving the underlying transportation problem (with approximation heuristics) and then infer the required selection. To this end, one could use the approximation algorithm in Bienstock (2001). Alternative heuristics include Mitrović-Minić et al. (2004), Savelsbergh and Sol (1998), and Zhang et al. (2010). Tabu-search and agent-based methods may also provide good starting solutions, as in Crainic et al. (2000) and van Dam et al. (2007).

Separation procedures available in the literature could be computationally advantageous in a branch-and-cut approach, such as those in Bienstock and Muratore (2000), Irnich (2002) and Raack et al. (2011). Constructing minimal cover cuts from the productivity constraint (in knapsack constraint form, such as in Boland et al. (2004)); cut-sets on the flow (as in Bienstock and Muratore (2000)); reachability sets on the flow (as in Montemanni and Gambardella (2005)); and, lifting on precedence constraints (as in Cordeau et al. (2007)), could lead to computational improvement. Commercial solvers will have some of these implemented for the general case.

Due to the issues arising from the time step, a rolling horizon could be practical. Mitrović-Minić et al. (2004) provide such an example for network planning. The time-step complexity may reduce if the equipment forms a cyclic schedule, as in Zhang (2010) and Anderson et al. (2009a), although this might lead to loss of detail in the model that is important.

The most important focus for future research will be to generate robust solutions. This could mean considering uncertain parameters in the modeling process, or generating solutions that are robust against unlikely events. Of particular importance is to account for uncertainty in the key parameters. Starting points include Ileri (2006). One other potential aspect is incorporating bunching into future modeling approaches. Other approaches include scenario generation, as in Pedersen and Crainic (2007) and Preuss and Hellingrath (2010).

Conclusion

In this paper, we have described the literature on the ESP in surface mining. We have also briefly outlined closely related problems in mining and applications of ESP outside of mining, and literature related to the problem structure in the wider OR literature.

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