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 related problems and applications. Within the scope of both the ESP and related problems, we outline modeling and solution approaches. Using operations research literature as a guide, we conclude by pointing to future research directions to improve both the modeling and solution outcomes for practical applications of this problem.

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

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Introduction

The general Equipment Selection Problem (ESP) is to choose a collection of compatible, but not necessarily homogeneous, items of equipment to perform a specified task. In many applications, the task is to move a volume of material from a set of locations to a set of destinations. However, different equipment types have attributes that can interact in a complex way with respect to productivity. In surface mining applications, the ESP addresses the selection of equipment to extract and haul mined material, including both waste and ore, over the lifetime of the mining pit. In this paper, we focus specifically on the truck and loader equipment selection problem for surface mines. Before we discuss the literature on this problem, or even define the problem and its solution formally, we provide a general background on surface mining and the parameters that are important in the quest to find a good ESP purchase policy.

A surface mine contains pits with mineral endowed rock (or ore). We extract ore that lies within the upper layer of the earth, from surface mines (Fricke, 2006) . This ore can include metals such as iron, copper, coal and gold. There are several methods of surface mining, including open-pit, stripping, dredging and mountain-top removal. This paper focuses on open-pit surface mining, which involves removing ore from a large hole in the ground (sometimes referred to as a borrow-pit).

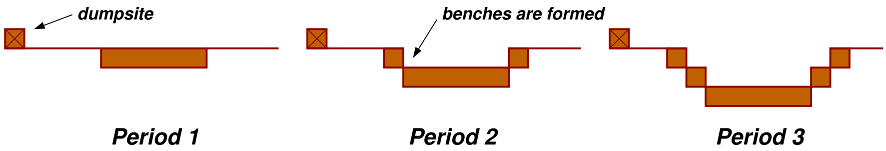

Figure 1 **A mining schedule is divided into planning periods. In each period, the mine planning decisions include which material will be excavated, and where the excavating equipment and stockpiles will be located. For a long-term schedule, these periods could be one year in length.**

The process for creating a borrow-pit is sequential: first explosives loosen the earth; then, excavating equipment removes small vertical layers (or benches) of material, as illustrated in Figure 1. Over time, these benches themselves are blasted, excavated and removed, making the borrow-pit wider and deeper. Mining engineers categorize the mined material into ore and waste material, with sub-categories depending upon the quality or grade of the ore. Trucks transport this material to a number of dumpsites, which can include mills for crushing or refining the ore, stockpiles, and waste dumpsites. The ore is refined at the mill, while the stockpiles store supplementary material for ensuring that the mill receives the correct mixing of ore grades to meet market demands. The long-term mine plan optimizes the timing of bench development, such that market demand is met and the value of the mine is maximized. The plan, alongside the optimization of the shape of the pit, provides required productivity rates, bench sequences, and the shape of the mine (including bench heights). The height of the bench can vary from 4m to 60m and dictates the type of equipment that can remove it. There are alternate practices for conducting material movement in mines; however, for large-scale open pit mining in particular, the "truck and loader" material movement practice is 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 for removal from the mine. In an open-pit mine, loader types can include electric rope, hydraulic excavators including backhoe excavators, and front-end loaders (also called wheel loaders) (Erçelebi and Kırmanlı, 2000). Figure 2 illustrates these varieties, which differ significantly in terms of:

- availability (Hall and Daneshmend, 2003)—the proportion of time the equipment is available to work;
- maintenance needs (Topal and Ramazan, 2010)—the proportion of time required for general maintenance, overhauls and unexpected maintenance;
- compatibility with different truck types (Morgan, 1994b)—the suitability of loader to truck height and loader bucket to truck tray size;

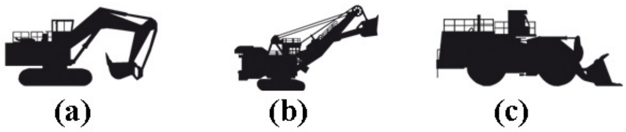

Figure 2 **Excavating equipment may include (a) hydraulic, (b) rope and (c) front-end loaders. Images from Immersive Technologies (2012)**

- volume capacity (Caterpillar, 2003); and,
- cost per unit of production (Bozorgebrahimi et al., 2005).

These characteristics affect the overall possible utilization of the loading equipment and also impact utilization of the trucking fleet.

The type of loader selected for use in a surface mine depends on the type of mineral to be extracted and specifications of the environment, such as the bench height. We must also consider other factors in the equipment selection process, particularly, 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 to find the best truck and loader set, then we must model the problem such that we select the truck and loader types simultaneously.

Mining trucks, also called haul trucks or off-road trucks, haul the ore or waste material from the loader to a dumpsite. More commonly, these vary from 36 tons to 315 tons. The size and cost of operating mining trucks is directly proportional to its tray capacity, while the speed at which 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. For example, “rimpull” 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 product of the torque of the wheel axle and 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).

Also, the softness of the road soil creates an effect of rolling resistance (against the truck tires) that reduces the efficiency of the truck in propelling itself forward. Rolling resistance varies significantly across the road and over time, and is notoriously difficult to estimate (Dunston et al., 2007). Watering and compressing the roads regularly can control and reduce the effects of rolling resistance. Haul grade, which is the incline of the haul road, can exacerbate the effects of rolling resistance and rimpull. These parameters, in addition to distance traveled, are crucial for the accurate calculation of the truck cycle time (Zhongzhou and Qining, 1988).

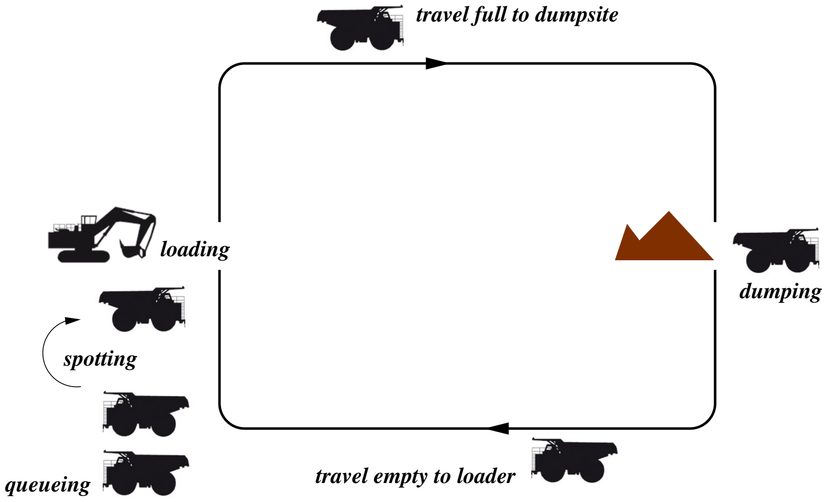

Figure 3 **The truck cycle time is measured from the time the truck is filled at the loader, travels full to the dumpsite, dumps the load, and travels empty to the loader to join a queue and positions itself for the next load (spotting). The truck cycle time includes queuing and waiting times at the dumpsite and loader. Images adapted from Immersive Technologies (2012)**

The *truck cycle time* itself comprises load time, haul time (full), dumping time, return time (empty), queuing (and other delays) and spotting times [Figure 3](Kennedy, 1990). A cycle may begin at a loading site where the truck receives its load from the excavating equipment. The truck then "travels full" to the dumpsite via a designated route along a haul road. The dumpsite may be a stockpile, waste 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 20-30 minutes in total, and can vary significantly over time if the stockpiles move and as the mine deepens.

The truck cycle time is an important parameter because related parameters, particularly those which are not dependent on the final selected fleet, can be absorbed into it. Ultimately, we wish to include details of the mine, such as topography and rolling resistance, in the model for selecting equipment. Mining engineers can make reasonable estimates of these parameters before modeling and incorporate 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. In industry, the common method of truck cycle time estimation is to divide the speed of the trucks obtained from manufacturer performance guidelines into the approximate travel distance (Smith et al., 2000). These guidelines arise from extensive simulations that take into consideration engine power, engine transmission efficiency, truck weight, capacity, rimpull and road gradients and conditions (Blackwell, 1999). Smith et al. (2000) provides a method for determining a rolling resistance estimate.

Çelebi (1998) calculates truck cycle time estimates using regression models. However, the level of queuing that occurs in a fleet is dependent on the number of trucks operating with each loader. This makes it difficult to accurately estimate truck cycle times before the fleet is determined. This aspect of truck cycle time estimation is largely undiscussed in the ESP literature.

Loading locations include any part of the mine that provides a source of material, such as pit locations where primary excavations occur and stockpiles where reserve material is temporarily stored. Destinations include any site where material can be dumped, such as material processing locations (including crushers), stockpiles and waste dumpsites. However, multiple origins, destinations or pits often occur in the mine design, and the complication here is that equipment (particularly trucks) may work on any of the adjoining routes of these locations. 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, since the trucking fleets may switch task assignments from period to period. Additionally, a partial fleet may exist at the time of equipment purchase, and due to supercession of particular models since the partial fleet was purchased (as in Cebesoy (1997)) or some optimization criteria, this may also lead to mixed-type (i.e., heterogeneous) fleets.

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 4] (Burt et al., 2011). The productivity of equipment also changes over time, usually because of maintenance, equipment overhauls, size of operating fleet and driver competence. The costs themselves are uncertain (Zhang, 2010) as they typically encapsulate uncertain interest rates (Wiesemann et al., 2010), depreciation (Burt, 2008) and revenue (Bodon et al., 2011). The presence of uncertainty makes the overall problem more difficult and can lead to infeasibility of implemented policies. Uncertain inputs include truck cycle time (Cebesoy et al., 1995; Ta et al., 2005), equipment availability, truck bunching (described later) and truckload variability (Newman et al., 2010).

In the context of surface mining, a "robust" selection of equipment can perform the required tasks on time, without compromising the mine planning. That is, we require a sufficient quantity of equipment to maintain expected productivity rates even when truck cycle times are large, some equipment is down for maintenance, or an unplanned event has taken place. Since the cost of purchasing and operating mining equipment is so high—anecdotally between 40-60% of the overall cost of materials handling (Alarie and Gamache, 2002)—robust equipment selection is a driving factor for the profitability of mining operations.

Mine planners subdivide the long-term plan (or mining schedule) 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. The mine plan dictates both the timing and manner of material movement over the strategic time horizon. Mining companies can consider long schedules (e.g., up to 25 years) in strategic planning of this nature (Epstein et al., 2003). In this time frame, replacement equipment may include types other than the original selection as a reflection of emergent technologies. Typically, equipment reaches replacement age after approximately 5 years for trucks and 10–15 years for loaders (depending on the type and usage). The trucks may be selected from a pool of 5–25 types (Burt et al., 2011; Topal and Ramazan, 2010), whereas loaders could be chosen from a larger pool (e.g., 26 loader types (Burt, 2008)) due to the different variants including rope and hydraulic, back-hoe and front-end loaders.

The inputs to the ESP are generally: (i) a long-term mining schedule, including production requirements at a number of loading and dumping locations; (ii) a set of loader and truck types that may be purchased; (iii) equipment productivity information and how this changes when equipment operates with different types of equipment; and (iv) cost information, including interest and depreciation rates, purchase, maintenance and operating costs. The output from an ESP is a purchasing strategy or *policy*, as well as ancillary information such as how the equipment should be used with respect to defined tasks. A specific example of such ancillary information is a job allocation schedule for equipment over the defined period. We now define the ESP formally.

Equipment Selection Problem (mining) *Consider the set of all truck and loader purchase policies that are feasible with respect to period demand, productivity balancing requirements between trucks and loaders and compatibility constraints (with the environment and between equipment types). Then the Equipment Selection Problem is to select the minimum cost policy from this feasible*

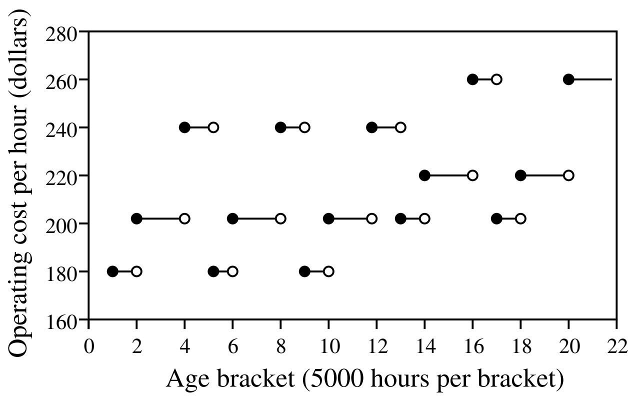

Figure 4 **This figure describes the discretized operating cost function over time. The rise in operating cost reflects the increased maintenance expense; large drops in the expense occur when a significant maintenance, such as overhaul, has taken place.**

set.

This problem can be solved during strategic planning, in which case the input is a long-term mine plan, or later during mining operations when new equipment is required. In the latter case, medium-term production schedules may be used as input instead of the larger resolution long-term plan. In either case, the cost of operating the equipment is dependent on the tasks the equipment must perform. A dimensionality 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 effect on the effectiveness of a chosen modeling and solution approach.

In the literature, there are two approaches to solving this problem: (i) to partition the problem and solve each partition sequentially; and, (ii) to develop holistic computational models. The most common approach in the mining equipment selection literature has been to take a sequential approach (such as, e.g., first selecting loader type, then truck type and finally determining fleet sizes). However, by observing recent advancements in related research in mathematical programming, especially in applications with similar problem structure, the mining industry may be able to solve larger scale, and more difficult, instantiations of the problem. In particular, these advancements could lead mine planning away from sequential decision-making for problems that are essentially interdependent and should therefore be solved holistically.

In the Appendix, we provide an example of a mixed-integer programming formulation of the ESP to illustrate the following description of the general structure of the problem. 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 capacity of the loaders and trucks; the productivity of the loaders can be dependent on the pairing with particular truck types, and the productivity of both trucks and loaders is influenced by the number of bucket loads required to fill the tray. These factors, in combination with the multiple flow paths the equipment may take in transit, results in a problem with structure similar to the *fixed-charge capacitated multi-commodity flow problem.* However, the underlying transportation network and arising transportation problem is often very simple, composed of a small number of excavation and dumping locations, often with some shared routes.

In the construction industry, truck and loader equipment selection is very similar to surface mining equipment selection. The principal problem involves selecting appropriate loading and trucking equipment and, here, the transportation networks are also very simple. The key difference lies in the objective of the operations—in the construction industry, the *earliest finish time* of the project (i.e., shortest make-span) is very important. The objective function is not the only difference: the scale of material moved is significantly smaller in construction operations compared to mining operations. Two other 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 apply 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 first outline some related problems, and proceed with a review of modeling and solution methods in both the mining and Operations Research (OR) literature. Using the operations research literature as a guide, we conclude with future directions for research in the context of surface mining applications.

Related Problems

In this section, we outline problems in mining that are similar to the ESP. We provide a summary of these papers in Tables 1–2. 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. We defer discussion of other applications of ESP (i.e., outside of the mining application) and similarly structured problems from the wider OR literature, where modeling and solution approaches may prove relevant, to the Modeling and Solution Approaches section.

In the literature on mining, Equipment Selection is a similar problem to *Mining Method Selection*; and in the literature on construction, it is similar to *Shovel-Truck Productivity.* The mining method selection problem is an approach to equipment selection that is based on the premise that the environmental conditions dictate the mining method used, and that the selection of truck and loader types follows intuitively from the adopted mining method. To simplify the task of selecting equipment while also selecting the mining method, solution approaches to this problem generally focus 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 notion that improving productivity translates into cost reductions (Schexnayder et al., 1999). However, the number of trucks performing the materials handling task affects the efficiency of the truck fleet (Alarie and Gamache, 2002). Therefore, these methods extend in a simple way to find feasible solutions for the equipment selection problem.

Solution of the mining method selection problem is a preliminary step to solving the equipment selection problem, whereby mining engineers choose an appropriate excavation method based on environmental conditions. Early work on this problem, (e.g., Tan and Ramani, 1992; Kesimal, 1998) and Blackwell (1999), describes this approach in combination with a “match factor” (described in *Modeling and solution approaches*), as part of the procedure to select equipment.

Mining and Construction related literature						
	Background	*Equipment Selection*	*Mining Method Selection*	*Shovel-truck Productivity*	*Scheduling*	*Dispatching & Allocation*
Alarie and Gamache (2002)	×					
Amirkhanian and Baker (1992)		×				
Başçetin and Kesimal (1999)		×				
Başçetin (2004)		×				
Başçetin et al. (2004)		×				
Bandopadhyay and Nelson (1994)		×				
Bandopadhyay and Venkatasubramanian (1987)		×				
Bazzazi et al. (2009)		×				
Bitarafan and Ataei (2004)			×			
Blackwell (1999)	×			×		
Bozorgebrahimi et al. (2005)	×					
Burt (2008)		×				
Burt et al. (2011)		×				
Burt and Caccetta (2007)	×					
Caccetta and Hill (2003)					×	
Çelebi (1998)		×				
Cebesoy (1997)	×					
Cebesoy et al. (1995)		×				
Czaplicki (1992)	×					
Denby and Schofield (1990)		×				
Douglas (1964)				×		
Dunston et al. (2007)	×					
Easa (1988)						×
Edwards et al. (2001)		×				
Eldin and Mayfield (2005)		×				
Epstein et al. (2003)					×	
Erçelebi and Kırmanlı (2000)	×					
Farid and Koning (1994)		×				
Fricke (2006)	×				×	
Frimpong et al. (2002)					×	
Ganguli and Bandopadhyay (2002)		×				

Table 1 **Categorization of the problems solved in the related mining and construction literature, A–G.**

Dispatching and allocation are also related topics in the literature on mining. The problem is to allocate tasks to equipment [Figure 5], which is a component of the ESP. In the scope of timed services, this becomes the dispatching problem. The key difference between dispatching and equipment selection problems is that dispatching concerns generating a feasible online schedule for daily operational decisions, while the ESP concerns generating a purchase and salvage policy that is robust to the tactical planning level. The literature on allocation focuses on the satisfaction of productivity requirements, often with complex features such as bottleneck prevention; the literature on dispatch optimization seeks to maximize the efficiency of the fleet at hand (Newman et al., 2010).

The ESP is related to *Asset Management*, where related sub-problems in this category include equipment costing (O'Hara and Suboleski, 1992; Morgan, 1994a; Leontidis and Patmanidou, 2000), production sequencing (Halatchev, 2002), facility equipment and machine selection in manufacturing systems (Chen, 1999), network planning (Derigs et al., 2009) and equipment replacement (Rajagopalan, 1998; Tomlingson, 2000; Nassar, 2001).

Mining and Construction related literature						
	Background	*Equipment Selection*	*Mining Method Selection*	*Shovel-truck Productivity*	*Scheduling*	*Dispatching & Allocation*
Gleixner (2008)					×	
Griffis, Jr (1968)				×		
Halatchev (2002)					×	
Hall and Daneshmend (2003)	×					
Hassan et al. (1985)		×				
Huang and Kumar (1994)		×				
Ileri (2006)		×				
Karimi et al. (2007)						×
Karshenas (1989)				×		
Kesimal (1998)				×		
Kumral and Dowd (2005)					×	
Leontidis and Patmanidou (2000)	×					
Markeset and Kumar (2000)		×				
Marzouk and Moselhi (2002a)		×				
Marzouk and Moselhi (2004)						×
Michiotis et al. (1998)		×				
Morgan (1994a)	×					
Morgan (1994b)	×					
Moselhi and Alshibani (2009)		×				
Naoum and Haidar (2000)		×				
Newman et al. (2010)	×					
O'Hara and Suboleski (1992)	×					
O'Shea (1964)				×		
Schexnayder et al. (1999)	×					
Smith et al. (1995)				×		
Smith et al. (2000)	×					
Ta et al. (2005)						×
Tan and Ramani (1992)					×	
Tomlingson (2000)		×				
Topal and Ramazan (2010)		×				
Wei et al. (2003)			×			
Xinchun et al. (2004)		×				
Zhongzhou and Qining (1988)	×					

Table 2 **Categorization of the problems solved in the related mining and construction literature, G–Z.**

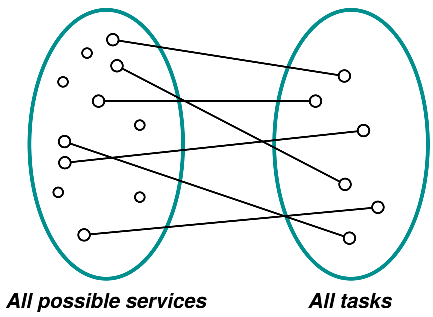

Figure 5 **The allocation and dispatching problems are concerned with matching services (e.g., provided by equipment) to tasks (e.g., moving ore).**

Studying the similarity between various problems (or the structure they exhibit) is important in order to adequately solve a difficult problem such as the ESP. In the next section, we review both modeling and solution approaches for the ESP in mining, construction and wider literature, as well as those approaches for similarly structured problems (or sub-problems of the ESP).

Modeling and Solution Approaches

The problem structures that we address in this section include Equipment Selection, Network Design, Vehicle Routing, Hub Location, Scheduling and Allocation. We provide a table of the problem structure in the related literature in Table 3. However, we have organized the literature into modeling and solution approach sub-categories to illustrate the success of some approaches (in some applications) and to highlight the arising opportunity, in some cases, to apply these advancements to the ESP for surface mining. The order of the text is as follows: we begin by discussing the least sophisticated approaches, move toward exact approaches and search techniques that can complement or enhance exact solution and finish with solution verification approaches.

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 (i.e., equipment utilized cost) 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 piece of equipment, although these comparisons do not 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 (i.e., the equipment is kept for its entire life cycle). Some literature also uses cost estimation for truck transportation problems in which the focus on uncertain parameters aims to improve robustness of the solutions, (see Zhang, 2010).

Heuristic or approximate methods and their use persist in industry. Heuristics can find feasible solutions quickly. However, in some examples, spreadsheets are employed to aid manual iteration over a small subset of possibilities (see Eldin and Mayfield, 2005). Another heuristic is an extension of the match factor ratio. The match factor ratio is an important productivity index in the mining industry (see Figure 6). The match factor is simply the ratio of truck arrival rate to loader service time. Literature for the construction industry, 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. 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 have been established. Complete ESP solutions are typically obtained

Problem structure	*Network Design*	*Vehicle Routing Problem*	*Equipment Selection*	*Hub Location*	*Scheduling*	*Assignment Problem*
Anderson et al. (2009a)	×					
Anderson et al. (2009b)	×					
Armacost et al. (2002)	×					
Baldacci et al. (2008)		×				
Barnhart et al. (2002)	×					
Barnhart and Schneur (1996)	×					
Baxter et al. (2010)			×			
Bennett and Yano (2004)			×			
Bienstock and Günlük (1995)	×					
Bienstock and Günlük (1996)	×					
Bienstock and Muratore (2000)	×					
Boland et al. (2004)				×		
Büdenbender et al. (2000)	×					
Caramia and Guerriero (2009)	×					
Chen (1999)			×			
Cohn (2002)	×					
Cordeau et al. (2007)		×				
Crainic et al. (2000)	×					
Croxton et al. (2003)	×					
Dahl and Derigs (2009)	×					
Derigs et al. (2009)					×	
Equi et al. (1997)					×	
Frangioni and Gendron (2009)	×					
Galiano et al. (2010)	×					
Gambardella et al. (2002)					×	
Gendron et al. (1998)	×				×	
Hane et al. (1995)	×					×
Khan (2006)			×			
Kim (1997)	×				×	
Mirhosseyni and Web (2009)			×			
Mitrović-Minić et al. (2004)	×	×				
Moccia et al. (2011)		×				
Montemanni and Gambardella (2005)	×			×		
Nassar (2001)			×			
Pedersen and Crainic (2007)	×				×	
Powell and Sheffi (1989)	×					
Raack et al. (2011)	×					
Rajagopalan (1998)			×			
Raman et al. (2009)			×			
Savelsbergh and Sol (1998)		×				
Sung and Song (2003)	×					
van Dam et al. (2007)				×		
Webster and Reed (1971)			×			
Zhang et al. (2010)					×	

Table 3 This table categorizes the problem structure in related OR literature.

by applying match factor or mathematical programming approaches to determine the minimum number of trucks required for a mine plan (see Alarie and Gamache, 2002) and then using dynamic

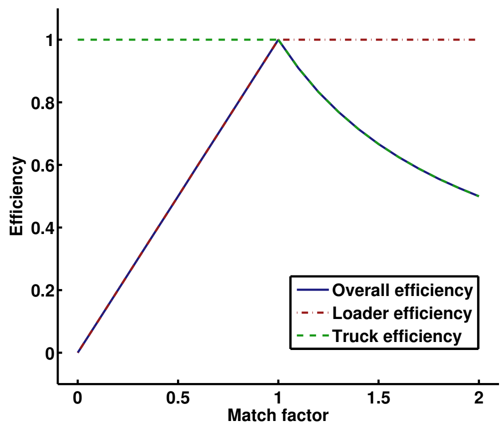

Figure 6 **The Match Factor (MF) is the ratio of loader productivity to truck productivity. A low MF (< 0.5) suggests that the loader is not working at capacity, whereas a high MF (> 1) suggests the truck fleet is smaller than necessary to maintain a productivity balance between truck and loader fleets.**

programming to determine allocation to mining locations (see Blackwell, 1999). Burt and Caccetta (2007) extended the formula to account for heterogeneous fleets and multiple truck cycle times.

Uncertainty in some parameters can lead to infeasibility of the truck allocation solution. 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, but their approach ignores the fixed charge (incurred at purchase), and thereby does not address the equipment selection problem as we have defined it here. In another example, Easa (1988) developed two quadratic programming models for earthwork allocation. These models only allow for linear cost functions, as opposed to the more common piece-wise linear cost functions. Chen (1999) examines a multi-period equipment selection model without transportation and develops a heuristic to address the difficulty arising from the multi-period nature of the model. They use Lagrangian relaxation to provide bounds on the quality of their heuristic solutions.

A number of models incorporate Net Present Value (NPV) analysis to allow comparisons between present and future cash flow. Typically, a multiplier (incorporating interest rates and depreciation) as a function of time can be appended to a cost-based objective function (Burt et al., 2011). However, future interest rates are uncertain and difficult to predict. Wiesemann et al. (2010) proposed a global optimization model for accurate NPV under uncertainty, and solve it using a branch-and-bound based heuristic.

Edwards et al. (2001) used a *linear programming* model for selecting equipment in which the equipment is to be hired instead of purchased. However, the authors neglected to define the variables and explain how continuous variables could lead to integer values of equipment as a solution. That is, equipment is discrete in nature and a fraction of a piece of equipment cannot be hired. Land

and Doig (1960) established that simply rounding discrete variables from a linear program can lead to violation of important discrete variable constraints or a solution in which the rounded variable values are vastly different to their optimal integer values.

Queuing theory was first notably applied to shovel-truck productivity by O'Shea (1964). In this work, O'Shea used queuing theory to predict the productivity of trucking fleets in an attempt to account for the 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 algorithms for global optimization.

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 that 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 bunching effect that can occur when equipment travels along the same route. Since trucking equipment does not travel at precisely the same speed (and therefore maintain uniformly distributed cycle times), equipment may cluster behind slower trucks, creating the bunching effect. Douglas (1964); Morgan (1994b) and Smith et al. (1995) describe equipment bunching in the context of a surface mine. However, the literature has thus far not included bunching in the modeling process. Instead, 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 recommends the selection of fleet sizes that matches the maximum efficiency for both location and haulage equipment. Although using a productivity-focused objective function may not improve the economic result (e.g., by lowering the overall cost of materials handling), 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 provided important methodology 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 (2008) and Topal and Ramazan (2010). Cebesoy et al. (1995) developed a systematic decision-making model for the selection of equipment types. They solved their model with a heuristic that makes use of a binary integer program in the final step. This model considers a single-period, single-location mine with homogeneous fleets. They perform compatibility matching of the equipment separately before solving the 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 therefore ignore the transportation aspect of the problem. The model minimizes the time to extract the material. In this model, the solution space is restricted by knapsack-based constraints that ensure that equipment is suitable for the size and shape of the bench; and, production requirements. Burt et al. (2011) 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 forestry harvesting, also using mixed-integer programming. This problem is similar to 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 than the current standard in surface mining. 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 an aspect of the Equipment Selection Problem 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), Barnhart et al. (2002) and Moccia et al. (2011). In an example of a combined network design and equipment selection problem, Anderson et al. (2009b) incorporated equipment selection into their intermodal transportation problem quite simply by adding variables to select equipment, as well as re-indexing the flow variables to account for the different types of possible equipment.

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 index on a variable is important for the NPV costing, the quantity of variables in discrete models can sometimes become overwhelming. Reformulation is common in a bid to find a less naive and inhibitive way to capture the problem than, for example, the most obvious formulation. Good examples of network reformulations in this context include Armacost et al. (2002), Cohn (2002) and Frangioni and Gendron (2009). These papers each used composite binary variables to represent multiple decisions to simplify the model and to reduce its size. The papers then exploit the composite variable formulation in a decomposition approach, the latter which we describe in the next paragraph. The composite variables capture overarching decisions, and a linear program can 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 feasible routes and partition them into sets that cover each customer's demand. They then construct heuristics to find good bounds on the optimal solution and use exact methods (such as branch-and-bound) to try to improve on the resulting optimality gap.

Decomposition approaches are widely used in the broader literature for problems that are too difficult to solve in complete form or for problems that are naturally composed of easy-to-solve sub-problems. Dynamic programming, branch-and-bound, Dantzig-Wolfe and Bender's decomposition are classic examples of decomposition approaches. Papers related to network planning that employ decomposition include Powell and Sheffi (1989), Barnhart and Schneur (1996), Mamer and McBride (2000) 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 choice and service provision to satisfy the flow of product. Derigs et al. (2009) address air cargo network planning which involves flight selection, aircraft rotation and cargo routing. This application is closely related to the service selection, service frequency and equipment allocation aspect of equipment selection in surface mining. However, this problem involves additional complexities, such as crew scheduling and maintenance scheduling. The authors develop a column generation solution approach to combat the size of the problem (i.e., the number of variables required to express a practical instance). In a column generation approach, the columns represent feasible solutions 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 search space 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 a quadratic integer programming model that allocates material handling tasks to a single piece of equipment. This model allocates equipment rather than selecting the types and number of equipment, 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 context of mining. They developed a specialized branch-and-cut algorithm based on the structure of the problem.

Preprocessing techniques are an important part 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), who provide multiple properties for preprocessing flow variables as well as constraint reduction.

In the OR literature, there is an increasing number of cases of *local search* techniques used to improve the efficiency of exact algorithms, and as stand-alone heuristics. 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 than is common in the literature to reduce the variance in travel times. Other local search techniques in the context of the 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 in the literature are the *decision support system* methods (Bandopadhyay and Venkatasubramanian, 1987; Denby and Schofield, 1990) and *genetic algorithms* (Naoum and Haidar, 2000; Marzouk and Moselhi, 2002a,b; Xinchun et al., 2004; Moselhi and Alshibani, 2009). 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 evolve 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). Fuzzy programming approaches may help to combat the uncertain nature of some of the data.

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. 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 for surface mining applications).

Finally, *simulation* approaches can not only verify solutions (obtained from other methods) for robustness and quality, they can be used to obtain solutions themselves. For example, Marzouk and Moselhi (2004) designed a model using simulation and genetic algorithms to trade off two objectives, time and cost, for the construction industry.

We provide a summary of these modeling and solution approaches in Tables 4–5.

Discussion

Heuristic methods, including life-cycle costing, are the simplest 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. Practicability is a desirable attribute, since the quantity of parameters necessary to construct the problem and the different time scales in decisions makes the problem seem overwhelmingly complicated. Queuing theory, artificial intelligence and simulation literature try to address these complexities in an efficient and easy to understand way, but are lacking the solving power to deal with the number of decisions that must be made across different time horizons. It is clear in the literature that there is a preference for exact approaches, and in particular, mixed-integer linear programming (MIP). This may be because MIP is capable of handling larger scale models of the problem, such as multiple scheduling and purchasing periods, heterogeneity of fleets and other complex side constraints. The treatment of the ESP in the context of these methods has, however, been weak. The mining literature addresses only overly simplified instantiations of the problem and fails to sufficiently address the need for robustness in the solution. However, the OR literature has many modeling and solution tools that may improve solution of the ESP. Many difficult, similarly structured and large-scale problems have been solved using exact methods. Furthermore, computationally difficult methods, such as MIP approaches, can provide measurably good quality solutions efficiently.

Future Research Directions and Conclusions

Clearly, in the literature there are very broad definitions of the truck and loader equipment selection problem for surface mining. In some research, the truck and loader types are selected deterministically and the fleet sizes implied from production requirements. In more recent work, the complex interplay between different types of equipment is addressed. The gap between these two solution formats indicates an evolution in what could be considered a suitable definition of the problem. However, there is still progress that can be made on this problem, as the uncertain input parameters have not yet been properly addressed. While some uncertainty may only affect the optimality of a solution, such as depreciation, interest rates and fuel prices, other inputs affect the feasibility of the fleet, such as truck cycle time, availability, bunching and truckload variability. The uncertainty

Methods					
	Mixed integer & Linear Programming	*Artificial Intelligence*	*Heuristic*	*Simulation*	*Queueing*
Anderson et al. (2009a)	×				
Anderson et al. (2009b)	×				
Armacost et al. (2002)	×				
Başçetin et al. (2004)		×			
Baldacci et al. (2008)	×				
Bandopadhyay and Nelson (1994)		×			
Bandopadhyay and Venkatasubramanian (1987)		×			
Barnhart et al. (2002)	×				
Barnhart and Schneur (1996)	×				
Baxter et al. (2010)	×				
Bazzazi et al. (2009)		×			
Bennett and Yano (2004)	×				
Bienstock (2001)	×				
Bienstock and Günlük (1995)	×				
Bienstock and Günlük (1996)	×				
Bienstock and Muratore (2000)	×				
Bitarafan and Ataei (2004)		×			
Boland et al. (2004)	×				
Büdenbender et al. (2000)	×	×			
Burt (2008)	×				
Burt et al. (2011)	×				
Caccetta and Hill (2003)	×				
Caramia and Guerriero (2009)			×		
Cebesoy et al. (1995)		×			
Chen (1999)			×		
Cohn (2002)	×				
Cordeau et al. (2007)	×				
Crainic et al. (2000)		×			
Croxton et al. (2003)	×				
Dahl and Derigs (2009)		×		×	
Denby and Schofield (1990)		×			
Derigs et al. (2009)		×			
Easa (1988)			×		
Edwards et al. (2001)	×				
Eldin and Mayfield (2005)			×		
Equi et al. (1997)	×				
Farid and Koning (1994)				×	
Frangioni and Gendron (2009)	×				
Frangioni and Gendron (2010)	×				
Fricke (2006)	×				
Frimpong et al. (2002)		×		×	
Galiano et al. (2010)	×				
Gambardella et al. (2002)		×		×	

Table 4 This table categorizes the OR methods used in each paper, A–G.

Methods					
	Mixed integer & Linear Programming	*Artificial Intelligence*	*Heuristic*	*Simulation*	*Queueing*
Ganguli and Bandopadhyay (2002)		×			
Gendron et al. (1998)	×				
Gleixner (2008)	×				
Griffis, Jr (1968)		×			
Hane et al. (1995)	×				
Hewitt (2009)			×		
Huang and Kumar (1994)					×
Ileri (2006)			×		
Irnich (2002)	×				
Karimi et al. (2007)		×			
Karshenas (1989)					×
Khan (2006)			×		
Kim (1997)	×				
Kumral and Dowd (2005)		×			
Land and Doig (1960)	×				
Lübbecke and Desrosiers (2005)	×				
Mamer and McBride (2000)	×				
Marzouk and Moselhi (2002b)		×			
Marzouk and Moselhi (2004)		×		×	
Michiotis et al. (1998)	×				
Mirhosseyni and Web (2009)		×			
Mitrović-Minić et al. (2004)			×		
Moccia et al. (2011)	×				
Montemanni and Gambardella (2005)	×				
Moselhi and Alshibani (2009)		×			
Naoum and Haidar (2000)		×			
Nassar (2001)				×	
O'Shea (1964)					×
Pedersen and Crainic (2007)	×				
Powell and Sheffi (1989)	×				
Raack et al. (2011)	×				
Raman et al. (2009)					×
Sung and Song (2003)			×		
Tan and Ramani (1992)	×				
Topal and Ramazan (2010)	×				
van Dam et al. (2007)		×			
Webster and Reed (1971)	×				
Wei et al. (2003)		×			
Xinchun et al. (2004)		×			
Zhang et al. (2010)			×		
Zhongzhou and Qining (1988)					×

Table 5 This table categorizes the OR methods used in each paper, G–Z.

of the latter set of parameters must be addressed first in new research. In order to achieve this using the exact algorithmic approach, the problem and subsequent model must be controlled by complementary techniques, such as those described in the following paragraphs.

Preprocessing is of clear benefit due to the dependency of solutions on previous periods, but one must avoid destroying structure that could be exploited in 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 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 have some of these implemented for the general case.

Due to the issues arising from the time fidelity, a rolling horizon could be practical. Mitrović-Minić et al. (2004) provide such an example for network planning. The time fidelity discrepancy may reduce if the schedule is cyclic, 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 is 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 the need 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).

In conclusion, open-pit mining involves the removal of a large quantity of material, requiring extraction and hauling equipment. The 50 years of publications on this problem demonstrate a colored and adventurous collection of modeling and solution approaches. In spite of this, satisfactory robust solutions are missing from the literature. To direct future applied research, we have highlighted OR literature illustrating advancements that may aid in efficient solution of the ESP.

Ultimately though, the goal is to embed the equipment selection problem into the long-term mine plan such that they can be optimized holistically.

Appendix. A

We present a simplified mixed-integer programming formulation of the ESP, adapted from Burt et al. (2011) and Burt et al. (2013), to illustrate the components and structure of the problem. The variables and parameters in this model are:

$\lambda,\ \tau$: indicate loader or truck types, respectively.

$e^\lambda,\ e^\tau$: index for specific loader and truck, respectively.

$j^\lambda,\ j^\tau$: index for loader locations and truck routes, respectively.

$\mathcal{E}^\lambda,\ \mathcal{E}^\tau$: sets of loader and truck types, respectively.

$\mathcal{J}^\lambda,\ \mathcal{J}^\tau$: sets of loader locations and truck routes, respectively.

$\mathcal{J}^\tau_{j^\lambda}$: the set of truck routes that connect uniquely to a loader location, j^λ.

$\mathcal{A}'$: subset of the superset of loader types.

$\mathcal{E}^\tau_{\mathcal{A}'}$: the set of truck types that are compatible with a subset of loader types.

$\mathcal{P}$: the set of pre-existing equipment.

F_e : fixed cost of purchasing equipment type e.

$V_{e,l,t}$: variable cost for equipment e, aged l in period t.

δ^1_t : discount factor in period t.

$\delta^2_{l,t}$: combined discount factor and depreciation factor for equipment aged l in period t.

$P_{e,l,t}$: production of equipment e, aged l in period t.

$D_{j,t}$: demand at location j in period t.

$x_{e,l,t}$: number of equipment of type e owned in period t which are in age bracket l (integer variable).

x^P_e : number of pre-existing equipment type e.

$s_{e,l,t}$: number of equipment of type e salvaged in period t which are in age bracket l (integer variable).

$f_{e,j,l,t}$: portion of equipment of type e, in age bracket l, that are allocated to route j in period t, where $f_{e,j,l,t} \in [0, x_{e,l,t}]$ (continuous variable).

$$\min \quad \sum_{e,t} F_e \delta^1_t x_{e,0,t} + \sum_{e,j,l,t} V_{e,l,t}\delta^1_t f_{e,j,l,t} - \sum_{e,l,t} F_e \delta^2_{l,t} s_{e,l,t}$$

$$\text{subject to} \quad \sum_{e^\lambda,l} P^{t,l}_{e^\lambda} f_{e^\lambda,j^\lambda,l,t} \geq D^t_{j^\lambda} \qquad \forall \quad j^\lambda \in \mathcal{J}^\lambda, t, \tag{1}$$

$$\sum_{e^\tau,l} P^{t,l}_{e^\tau} f_{e^\tau,j^\tau,l,t} \geq D_{j^\tau,t} \qquad \forall \quad j^\tau \in \mathcal{J}^\tau, t, \tag{2}$$

$$\sum_{e^\tau,l;j^\tau\in\mathcal{J}^\tau_{j^\lambda}} P_{e^\tau,l,t} f_{e^\tau,j^\tau,l,t} \geq D_{j^\lambda,t} \qquad \forall \quad j^\lambda \in \mathcal{J}^\lambda, t, \tag{3}$$

$$\sum_{e^\tau\in\mathcal{E}^\tau_{\mathcal{A}'},l} P_{e^\tau,l,t} f_{e^\tau,j^\tau,l,t} \geq \sum_{e^\lambda\in\mathcal{A}',l} P_{e^\lambda,l,t} f_{e^\lambda,j^\lambda,l,t} \qquad \forall \quad \mathcal{A}' \subset \mathcal{E}^\lambda, j^\lambda, t \tag{4}$$

$$x_{e,l,t} \geq \sum_j f_{e,j,l,t} \qquad \forall \quad e,l,t, \tag{5}$$

$$x_{e,l,t} = x_{e,l-1,t-1} - s_{e,l,t} \qquad \forall \quad e, l>0, t>0, \tag{6}$$

$$x_{e,l-1,t-1} \geq s_{e,l,t} \qquad \forall \quad e, l>0, t>0, \tag{7}$$

$$x_{e,l,t} + s_{e,l,t} = x^P_e \qquad \forall \quad e\in\mathcal{P}, t=0, \tag{8}$$

$$x_{e,l,t}, s_{e,l,t} \in \mathbb{Z}^+,$$

$$f_{e,j,l,t} \in \mathcal{R}^+.$$

The objective function captures purchase, variable expense and salvage of equipment. The latter is important for the consideration of heterogeneous fleets in the case where there is pre-existing equipment that are expected to retire within the considered time horizon. Constraints (1)–(2) are *demand* constraints on the loading locations and dumpsites. Constraints (3)–(4) ensure that the trucking fleet is capable of *matching* loader productivity, even in the case of heterogeneous fleets. Constraint (5) *couples* the selection variables $x_{e,l,t}$ to the allocation variables $f_{e,j,l,t}$. Constraints (6)–(7) capture the *flow* of equipment, or precedence, over time. Constraint (8) allows for the inclusion of pre-existing equipment in this model.

Acknowledgments

The authors wish to thank the editors and anonymous reviewers for their insightful comments that lead to significantly improved revisions of this paper.

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