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Equipment Selection for Surface Mining

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We consider the equipment selection problem in a surface mining context. This problem involves choosing a fleet of trucks and loaders and designing a long-term mining schedule that minimizes transportation and other fixed costs. The arising problem has an underlying fixed-charge capacitated multi-commodity network flow structure. Considering purchase and salvage of equipment; compatibility of arising fleets; utilization of equipment over time; long term schedule; and Net Present Value analysis are important in this application. In this paper, we review the literature that addresses this and related problems. We especially consider problems in which the structure is similar but where there have been more methodological advances.

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

1. Introduction

In the surface mining application, the Equipment Selection Problem (ESP) addresses the selection of truck and loader fleets to move mined material, including both waste and ore. The mining schedule, which may run for multiple decades, will be divided into planning periods. Typically fleet planning occurs in quarters (of a year), with equipment purchase decisions occurring less frequently at 1–2 year intervals. Long schedules, up to 20 years, are preferred considerations. There may be several loading locations with different loading requirements, resulting in different loader types assigned. Furthermore, 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) or due to other optimization criteria, this may also lead to heterogeneous fleets including mixed truck types. The operating costs are non-linear functions of the age of the equipment (or equipment utilization). They also typically involve uncertainties such as fuel prices and transit times. The productivity of equipment also changes over time, usually due to maintenance and equipment overhauls. The fleet selection problem is of striking importance in surface mining, where the cost of operating the equipment over long term schedules is significant enough (anecdotally between 40-60% of the overall cost of materials handling (**?**)), that obtaining robust equipment selection solutions is a driving factor for improving the profitability of mining operations.

The input to the ESP is generally a long-term mining schedule including production requirements at a number of loading and dumping locations; a set of loaders and trucks that may be purchased; equipment productivity information; and 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 some indication that feasible schedules may be generated with the available fleets.

The general ESP is to choose a collection of compatible but not necessarily homogeneous vehicles and other equipment, to perform a task at minimum cost. Different equipment types have attributes that can interact in a complex way. In Surface Mining however, the task that the equipment must perform is a transportation task. However, 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 or more dumpsites with the truck fleet moving material between the sites. Considering purchase, salvage and the provision of service results in a *fixed charge* objective function if we wish to minimize the cost of the operation. There are limitations to productivity at the loader and carrying capacity of the trucks (which can be dependent on the combined choice of equipment), resulting 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. Depending on the modeling approach used, the fleet planning period chosen for the equipment selection model is important in determining the size of the underlying model.

There are two approaches in the literature to handle this: to simplify the problem and 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, great advancements could be made.

Two 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 two 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 being addressed.

In this paper, we review the literature directly addressing mining applications with related technical literature from the operations research community. We begin with a description of related problems in the mining industry and other applications of the ESP in Section **??**, and then provide modeling and solution approaches in Section **??**. We outline some recommendations for future research focus in Section **??**, and conclude briefly in Section **??**.

2. Related Problems

In this section we outline problems in mining that are closely related to the ESP, and also other applications of ESP in the wider literature. In the mining literature, Equipment Selection is closely related to *Mining Method Selection* and *Shovel-Truck Productivity.* Solution of the mining method selection problem is a preliminary step to equipment selection, whereby an appropriate excavation method is chosen based on environmental conditions. In early times, this approach in combination with Match Factor (described in Section **??**), a product of shovel-truck productivity research, was deemed sufficient for selecting equipment (**???**).

Dispatching and Allocation are also related topics in the mining literature. Allocation focuses on the satisfaction of productivity requirements, often with complex features such as bottleneck prevention; dispatch optimization seeks to maximize the efficiency of the fleet at hand (**?**). Truck dispatch systems typically apply Match Factor or mathematical programming approaches to determine the minimum number of trucks required for a schedule (see **?**) and then use dynamic programming to determine allocation to mining locations (see **?**). Truck allocation is complicated by the presence of uncertainty in some parameters, such as plant downtime and truck loading and cycle times. **?** developed a stochastic model that incorporates real-time data for allocation of the fleet. **?** addressed the uncertainty in parameters with a fuzzy optimization allocation model. In another example, **?** 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.

There are many other related problems, such as mine production scheduling (**???**), pit optimization (**?**), equipment costing (**???**), production sequencing (**?**), and equipment replacement (**??**). The influence of all of these problems on the equipment selection problem in surface mining is clear: typically, they are addressed using discrete optimization methods, such as integer programming.

Outside of mining, the equipment selection problem has been considered in the forestry harvesting industry, also with a mixed integer programming approach (**?**). This problem is essentially the same as the surface mining problem, whereby one must select the equipment and the number of hours of operation for a given harvesting schedule with respect to an underlying transportation problem.

In the operations research literature, the ESP is also related to *Asset Management*: facility material handling equipment selection and machine selection in manufacturing systems (**??**), network planning (**?**), and equipment replacement (**?**). **?** 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. In **?** the authors 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.

In **?** the authors 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.

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.

3. Modeling and solution approaches

In this section we outline modelling and solution approaches that have been applied to the ESP in the context of surface mining. We also outline some similarly structured problems in the OR literature.

Heuristic methods and their use persists in industry, with spreadsheets employed to aid hand iteration over a small subset of possibilities rather than optimization (see **?**). **?** recommended the construction industry Match Factor formula as a means of determining the appropriate fleet size. However, selecting the best equipment types must be performed by an expert before applying the formula. As defined by **?**, the match factor ratio, $MF_{i,i'}$, for trucks of type i working with loaders of type i' is given as:

$$MF_{i,i'} = \frac{t_{i,i'} x_i}{\bar{t}_X x_{i'}},$$

where x_i is the number of trucks of type i, $x_{i'}$ is the number of loaders of type i', $t_{i,i'}$ is the time taken to load truck type i with loader type i', and $\bar{t}_X$ is the average cycle time for all trucks (i.e., time taken to travel with a full load to the dumpsite and return empty to the loader). **?** provided extensions to heterogeneous fleets and multiple truck cycle times. **?** 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.

Life cycle costing was presented by **?** as an equipment selection method. This is a method for determining the cost per utilized hour of equipment use if the equipment is kept for its entire life span. A basic comparison can be made to determine the cheapest operating cost, 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. Cost estimation has also been developed for truck transportation problems where the focus on uncertain parameters aims to improve robustness of the solutions, e.g. see **?**.

A number of models incorporate Net Present Value (NPV) analysis to allow comparisons between present and future cash flow. However, future interests rates are clearly uncertain and difficult to predict. Yet, they are a critical part of the objective function for these models. **?** proposed a model for accurate NPV under uncertainty.

Linear programming was used in a model by **?** as an approach for selecting hire equipment. However, the authors neglected to define the variables and explain how linear variables could lead to integer values of equipment as a solution. It is well-known 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 **?**. 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, **?** outlined several improvements that were incorporated into a equipment capacity selection model. This was a non-linear optimization model with a single constraint, and could 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.

? developed a heuristic for determining the truck fleet size using queuing theory. This extended the work by **?** for calculating the productivity of different fleet options by modeling the truck arrival rates as a Poisson process. Later, **?** used simulation to verify the effectiveness of the equipment selection results of the Griffis and O'Shea.

? have continued 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 $M_1\backslash M_2\backslash N\backslash FIFO\backslash n_1\backslash n_2$ model to minimize the cost of idle machinery. Here, M_1 and M_2 assert that the customer arrival rate and service rate are exponentially distributed. There are N parallel servers and the service discipline is First-In First-Out. The upper bound on customers allowed in the system is n_1, while n_2 is the maximum number of potential customers. 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, **?** used queuing theory to determine the optimal quantity of equipment in a transportation context where a schedule is known.

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. 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 **?**, **?** and **?**. These papers each used composite binary variables to represent multiple decisions in a bid to simplify the model and reduce its size. The composite variable formulation can then be exploited for a decomposition approach; the composite variables capture overarching decisions and the underlying transportation problems can be solved separately as a linear program. A discussion and comparison of some types of reformulation, such as node-arc versus path and tree formulations can be found in **?**. Another possible approach is to use a set-partitioning model, such as in **?**.

In the mining literature, simple integer programming models in which assumptions are made to simplify the model, are common. The reduced problem is simple but can be solved efficiently. For example, non-linear operating costs are typically discretized to piecewise linear functions using age brackets, as in **?** and **?**. **?** 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 prior to the solving of this model.

In another example, **?** used a pure binary integer programming model for selecting the number, type, and locality of excavating equipment to work in a pit. The transportation aspect of the problem was removed by looking only at the excavators. The model minimized the time to extract and was constrained by knapsack-based constraints that ensured that equipment was feasible for the type of bench and that all production requirements were met. **?** developed a mixed integer programming model for equipment selection with a single source and destination. This model focussed on the complex side constraints arising from heterogeneous fleets and the compatibility of the equipment.

Since part of the underlying structure is a *multi-commodity network flow* problem, it is useful to consider literature focussing on this problem. Important papers on capacitated multi-commodity network flow include **?**, **?**, **?**, **?** and **?**. **?** 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, **?** models 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 **?**, **?** and **?**.

Decomposition approaches are widely used in the broader related literature, primarily due to the size of the problem (in terms of binary variables) in combination with inherent structure. Examples of such papers related to network planning include **?**, **?**, **?**, **?**, and **?**. 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. Also, the equipment solution can be inferred from the material flows. A typical approach in network planning applications is to develop a custom *branch-and-cut* algorithm, as in **?**, **?**, and **?**.

Fleet assignment or allocation has been widely considered in the mining literature, mostly due to the ease of the heuristic approach of first determining the equipment types, then the fleet size, and subsequently the fleet assignment. This problem is closely related to the ESP when an existing schedule is assumed (with the difference lying in the purchase and salvage requirements of the ESP). **?** proposed an allocation model for general materials handling as a quadratic integer program for a single piece of equipment. This quadratic integer program is intended for allocation rather than equipment selection and is restricted to a single period. However, **?** 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 other words, it selects the type and size of the fleet when the schedule is already known, there are no demand or production requirements, and no transportation is required. In the broader literature, **?** 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.

Artificial intelligence techniques are prevalent in large-scale mining applications due to their ability to find feasible solutions within a comparatively short time (**?**). The most common methods among the literature are the *decision support system* methods (**???**) and *genetic algorithms* (**????**).

Various decision support tools, such as the analytical hierarchy process (**?**) and expert systems (**?**), 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 equipment pairs can be ranked by suitability in a pre-processing step.

Genetic algorithms are a heuristic solution technique that selects 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. **?** developed a genetic algorithm model for the equipment selection problem. Their model incorporates the lifetime discounted cost of the equipment, which arises from the assumption that the equipment will be used from purchase until its official retirement age and not sold or replaced before that time. **?** 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 focussing on attribute matching, such as **?** in the production research literature and **?** in the mining literature. Attribute-based selection methods include multi-attribute decision making modeling (**??**) and fuzzy set theory (**????**). Fuzzy programming approaches have been suggested as a way to combat the uncertain nature of some of the data, such as interest rates, depreciation, and cycle times. **?** 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 be extended to select the equipment over multiple periods. Here, a schedule must be generated that takes into account the possible deterioration in performance of equipment as it ages. **?** 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. **?** developed a knowledge-based heuristic to focus on attribute matching without incorporating the transportation and multi-period aspect of the problem. **?** presented a combined expert system and genetic algorithm approach for the selection and assignment of equipment for materials handling (not only surface mining application).

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 **?** provides a brief description of variable and constraint reduction. Other preprocessing examples in related literature include **?**, who preprocesses by observing dominance among route assignments; and **?** provide multiple properties for preprocessing flow variables as well as constraint reduction.

In the OR literature, *local search* techniques have been employed to improve the efficiency of algorithms and can also be used as heuristics on their own. **?** 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 a fine granularity of time step to account for steep changes in delivery times over time. Other local search techniques in the context of capacitated network planning problem include **?**, **?**, **?** and **?**.

Finally, solutions can be verified for robustness and quality using *simulation* approaches. Simulation can also be used, however, to obtain solutions. **?** 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 **?**, and **?**.

4. 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 also be used to obtain good initial solutions that can be used to 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 **?**. Alternative heuristics include **?**, **?**, and **?**. Tabu-search and agent-based methods may also provide good starting solutions, as in **?** and **?**.

Separation procedures available in the literature could be computationally advantageous in a branch-and-cut approach, such as those in **?**, **?** and **?**. Computational improvements may also be obtained by constructing minimal cover cuts from the productivity constraint (in knapsack constraint form, such as in **?**); cut-sets on the flow (as in **?**); reachability sets on the flow (as in **?**); and, lifting on precedence constraints (as in **?**). 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 also be considered. **?** provide such an example for network planning. The time-step complexity can also be reduced by assuming that the equipment forms a cyclic schedule, as in **?** and **?**, 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 can be interpreted to mean taking uncertain parameters into account, or generating solutions that are robust against unlikely events. Of particular importance is to account for uncertainty in the key parameters. Starting points include **?**. Other approaches include scenario generation, as in **?** and **?**.

5. 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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