Models for Mining Equipment Selection

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EXTENDED ABSTRACT

In many industries, materials handling represents a significant component of the operational cost, making equipment selection an important challenge to management. To meet this challenge, extensive research has taken place in the mining and construction industries which are heavily dependant on equipment. Yet this research effort has not resulted in an acceptable solution strategy for these industries. The complexity of the problem is due to the many factors that contribute to the operating expense of equipment. Consequently, available methods can only consider a small subset of the possible combinations of trucks and loaders.

This paper addresses equipment selection for surface mines. Given a mine plan, the ultimate objective is to select the trucks and loaders such that the overall cost of materials handling is minimised. Such a fleet must be robust enough to cope with the dynamic nature of mining operations where the production schedule can sometimes be dependent on refinery requirements and demand. Due to the scale of operations in mining, even a small improvement in operation efficiency translates to substantial savings over the life of the mine.

There is a considerable amount of literature concerning shovel-truck productivity for construction equipment selection and shovel-truck equipment selection for surface mines. Although a variety of modelling methods have been applied, such as Queuing Theory, Bunching Theory, Linear Programming and Genetic Algorithms, the solutions obtained are consistently inadequate. In the mining industry current methods use spreadsheets and are heavily dependent on the expertise of a specialist consultant.

Classical Methods include concepts such as match factor, bunching theory and productivity curves. These methods often rely on brute force to achieve a feasible solution, where a handful of truck types may be enumerated by hand for the minimum cost fleet size. Operations Research techniques such as Integer Programming (IP) and Nonlinear Programming have been applied in a bid to achieve an optimal solution. Current IP solutions tend to oversimplify the model or rely on excessive assumptions. More complex constraints can be included in these formulations, which help to describe a more realistic idea of the performance of a particular fleet. Artificial Intelligence techniques such as expert systems, knowledge based methods and genetic algorithms have been applied to equipment selection with some success, although optimality has not been demonstrated in the literature.

Common weaknesses amongst all of these models are fleet homogeneity, loader (or truck) type pre-selection and restricted number of passes (from loader to truck). Fleet homogeneity assumes that the truck fleet should only consist of one type of truck. Yet there is no reason to believe that a mixed-type fleet underperforms a homogeneous-type fleet. Loader (or truck) type pre-selection requires a highly skilled and experienced engineer to select a loader type based on geographical and geological information. This can be a time consuming task and a demonstration of optimality is unlikely. Although there is a general preference for restricting the maximum passes from loader to truck, there is also no evidence in literature to support this constraint. The equipment type selection should occur alongside fleet size selection if a bid at optimality is desired. Models that consider the condition of pre-existing equipment do not exist in the literature. Some research has modeled the equipment replacement problem but focuses on replacement time rather than optimising the type and number of trucks/loaders replacements.

This paper provides a critical analysis of the various models for surface mining operations, identifying important constraints and suitable objectives for an equipment selection model. A new Mixed Integer Linear Programming model is presented that makes use of a linear approximation of the cost function. This model allows for mixed-type fleets and selects the truck and loader types within the solution. The results demonstrate that heterogeneous fleets can result in savings for the mining operation. Problems arising from IP formulations are discussed.

1 Introduction

The problem of equipment selection in a surface mine is complex. Many features, restrictions and criteria need to be considered (Naoum and Haidar 2000). The model must reflect the important constraints of the mining operations to a level that is acceptable and used by mining engineers. Martin consultants (Martin et al. 1982) list the selection considerations for a truck as follows:

- Material characteristics of the mine
- Loading equipment
- Haul route requirements
- Maneuvering space
- Dumping conditions
- Capacity
- Engine power and altitude limitations
- Final drive gear ratios for mechanical drives
- Two axle or three axle configuration
- Mechanical or electrical drive system
- Tires size, tread and ply rating

However the problem is much more complex than these points convey. Literature has clearly demonstrated that the speed that a haul truck can travel is heavily influenced by rolling resistance (Gove, 1994). Research also indicates that truck bunching can severely affect productivity (Smith 2000). Other parameters include:

- Mine and dump plan restrictions
- Truck and loader availability restrictions
- Truck queuing effect
- Truck and Loader life constraints

A clear and simple method of determining the optimal truck and loader has not yet presented itself in the literature. Current industry practice relies heavily on an equipment selection expert to enter data and interpret solutions. These solutions do not select from the entire set of available truck and loader types, but rather select from a small hand-picked subset. Additionally, these methods only allow for homogeneous fleets in the solution space. Optimal heterogeneous fleets are possible where production requirements must be met almost exactly. In an industry where even a small increase in efficiency can translate to huge savings, optimality or near optimal solutions are important (Naoum and Haidar 2000).

Feasible solutions to the equipment selection problem exist under a number of related industry canopies: Mining Method Selection (MMS), Equipment Selection (ES) and Shovel-Truck Productivity (STP) [Figure 1]. This paper brings together these seemingly disparate streams of work.

The literature survey that follows demonstrates that a wide variety of technical and classical modelling approaches have been applied to the problem of equipment selection in surface mines. Those methods deemed classical include “match factor” and “bunching theory”. Shovel-truck productivity methods incorporate both match factor and bunching ideas into the solution. However, much of the literature on STP exists for construction case studies and little published researched applies to surface mining. Nonetheless these methods must be addressed here as they represent the core ideas behind current industry practice (Smith 2000).

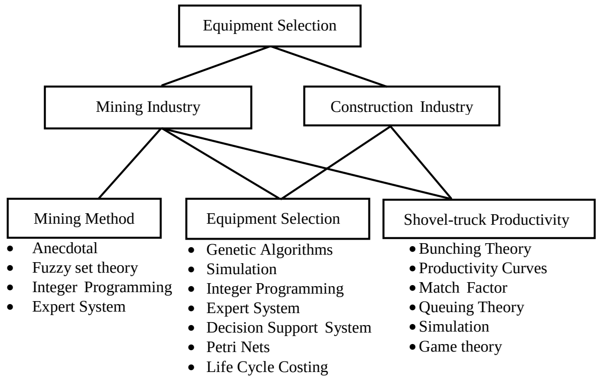

Figure 1. Distribution of literature for ES.

The Mining Method selection problem focuses on choosing the correct excavation method for the given mining conditions. Generally, this research is based on anecdotal methods, where a feasible solution is sought, rather than an optimal solution. Much of the literature on mining method selection does not discuss equipment selection modelling in enough detail to be discussed here, but is nonetheless an important area to research when considering pre-selection procedures.

The Shovel-truck Productivity problem has been well established in construction and earthmoving literature (Kesimal 98). Even though limited literature exists that specifically applies these methods to select equipment for surface mines, these methods are commonly applied to the equipment selection problem in the mining industry. This work uses many assumptions, considerable expert knowledge/experience and relies on heuristic solution methods to achieve a solution. The inability to demonstrate optimality and also the desire to consider larger truck and loader sets has spawned the search for a program-aided solution. These more advanced formulations fall into the category of Equipment Selection.

The inclusion of sensible ownership, operating (and maintenance) costs may play a crucial role in the solution. Yet in integer programs the costs are often accepted as a constant input to which no further calculations are performed. This highlights an important area of research for equipment selection in surface mines.

The Equipment Selection problem work has focused on achieving optimal or near optimal solutions and relies on computer generated solutions. The most logical way to categorise the literature is in terms of the method applied. Within these sections, the problem definitions and assumptions can be discussed in a clear manner.

There are many closely related problems such as mine production scheduling, truck dispatching, equipment costing, and equipment replacement. These works are not within the scope of this study and will not be discussed here.

2 Literature Survey

2.1 Mining Method Selection

The Mining Method Selection (MMS) problem is an approach to Equipment Selection that stems from the logic that the environmental conditions will imply a particular mining method, and that the selection of loader and consequently trucks follows intuitively from there.

Atkinson (1992) acknowledges the interdependency of ground preparation, excavation and loading, transport and mineral treatment: that "the optimum cost per ton may not be obtained by attempting to minimize each of the individual operational costs". It is the complexity of combining these factors into one problem that has led many engineers to the primarily anecdotal and knowledge based solution methods applied to the mining method selection problem. As each step is completed these methods assume that all other steps logically follow. In this way, the loader type and loader fleet size is selected based on diggability studies; the truck type is selected based on the loader; and, the truck fleet size is selected based on all the above information.

2.2 Equipment Selection

The Equipment Selection (ES) problem aims to select an appropriate set of trucks and loaders subject to various objectives and constraints. The methods applied to this problem are varied, as are the assumptions and types of constraints that are included in the models.

2.2.1 Integer Programming

The use of integer programming methods is well established in both the mining and construction operations. However much of the focus is on project completion, dispatching or scheduling. The models tend to assume given equipment type, rather than allowing the models to select these with the fleet size. Fleet homogeneity and restricted passes between loader and truck are also common constraints (Celebi 1998) that have not been demonstrated to be sensible.

Jayawardane and Harris (1990) place importance on early project completion time for earthwork operations. While this is important for the construction industry, the mining production schedule should take into account any project completion dates and early completion is not often a consideration due to milling constraints. The production schedule is assumed to be provided for equipment selection models and this is incorporated into the constraints.

In other formulations, "budgeting constraints" have been considered where the maximum permissible budget cash outlay for a given time period is an upper bound (Cebesoy et al. 1995). This constraint can be applied to both ownership costs and operating costs. "Mutual Exclusivity" is a common constraint that restricts the choice of equipment type to one. Cebesoy et al. (1995) describes heterogeneous fleets as "unacceptable or even unthinkable" although only anecdotal evidence has supported these claims to date.

2.2.2 Simulation

Simulation is a well used and notably powerful tool for the mining industry. Although simulation is most effectively used in mining equipment selection to analyse the earth-moving system, some equipment selection solutions exist that use simulation models. Kannan et al. (2000) recognise that despite the complementary role of academic research and industry applied simulation models, a gap exists between the two: academia follow "opportunity driven" models and industry aims for "need-based" models. The authors provide some defined requirements and "success factors" for simulation programming. A short but directed literature survey of simulation modelling in the construction industry is also included.

Hrebar and Dagdelen (1979) developed a simulation method for dragline stripping equipment selection. This model provides dragline reach and bucket capacity as output to create a subset of considered equipment; further equipment selection can then be made analytically from this reduced set of equipment.

2.2.3 Artificial Intelligence

The most common methods among the literature are the expert system and decision support system methods (Bascetin 2004). The expert systems approach is often preferred for complex systems: it is a structured attempt to capture human expertise into an efficient program (Welgama and Gibson 1995). Amirkhanian and Baker (1992) developed an expert system for equipment selection in construction incorporating 930 rules. These rules interpret "information concerning a particular project's soil conditions, operator performance, and required earth-moving operations". Although this method does not claim optimality of its solutions, it does highlight an important aspect of modelling equipment selection: the equipment subset to be considered in the model will be dependent on the soil and mining conditions. In this sense, rule-based pre-selection is a logical pre-process to any equipment selection model (Bascetin 2004).

Naoum and Haidar (2000) have developed a genetic algorithm model for the equipment selection problem. Although their model satisfies the requirements for an integer programming solution, the authors pursued a genetic algorithm solution. The solution incorporates the lifetime discounted cost of the equipment, which is formally attached to the assumption that the equipment is used from purchase until official retirement age, and not sold or replaced before that time. The authors argue that intelligent search techniques are necessary because integer programming is incapable of solving a problem with more than one type of independent variable. While this is not true, intelligent search techniques are certainly required when constraints become nonlinear. Nonlinearities in the constraints arise due to queuing, and have not yet been sufficiently modelled using integer programming or genetic algorithms.

2.3 Shovel-truck Productivity

The ability to accurately predict the productivity of a truck and loader fleet is an important problem to mining and construction and is intrinsically linked to equipment selection. In particular we are interested in "predicting the travel times on the haul and return portions of the truck cycle... and the prediction of the interaction effect between the shovel and truck at the loading point" (Morgan and Peterson 1968).

2.3.1 Match Factor

Consider Figure 2: the productivity of the truck and loader fleet cannot exceed the lowest capacity of the trucks or the loader. That is, before the intersection the productivity of the fleet is limited by the capacity of the truck fleet, and the loader will have additional waiting periods. After the intersection the productivity of the fleet is limited by the capacity of the loader, and the trucks will have additional waiting periods. The intersection itself is the theoretical "perfect match point" (Morgan and Peterson, 1968).

This match point is also influenced by the natural variation in haul cycles which can lead to further queuing. This is known as bunching and is discussed further in the proceeding section.

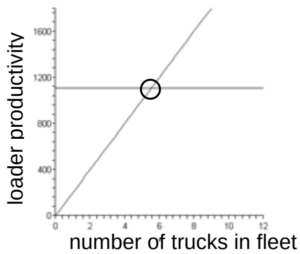

Figure 2. Theoretical "match point" occurring at the intersection.

Match Factor operates under the assumption that the most economical fleet will also be the most productive and efficient fleet (corresponding to the intersection). The results in section 4 demonstrate that this is not the case, and that optimal cost fleets can have efficiency as low as 50%. In Figure 2 this efficiency could correspond to 4 trucks operating with 1 loader.

The Match Factor has a dual purpose: it is indicative of the suitability of the size of the truck fleet; it is used to determine the efficiency of the fleet which can be fed back into performance calculations. The Match Factor itself is a simple calculation:

$$MF = \frac{\text{trucks}}{\text{loaders}} \times \frac{\text{loading cycle}}{\text{load/haul/dump cycle}} \tag{1}$$

The theoretical perfect match occurs at an MF of 1. This formula clearly only considers homogeneous fleets. Due to the assumption of maximum efficiency, the match factor can be misleading when determining the lowest cost fleet.

2.3.2 Bunching Theory

Bunching models capture the tendency of moving objects to bunch together when moving in a line. This is usually due to some of the objects being operated or moving more efficiently than others. It can also be due to small unpredictable delays. Bunching is known to reduce a fleet's ability to meet its maximum capacity. Nagatani (2001) has studied into the problem of modelling bunching transitions in general traffic flow and bus routes. The bunching transition in the truck cycle may be modeled in the same manner. In the bus model, bunching of the buses is exacerbated by an increase in the number of passengers the 'slower' buses are required to pick up. That is, if for some reason a bus is delayed the time gap between it and the bus in front can only become greater as it must stop to pick up more passengers than if it were on time (Nagatani 2001).

Bunching certainly occurs in a system of a loader and its correlating fleet of trucks. The relationship is not as complex as that of buses and passengers; if a truck has a greater cycle time due to some delay this time is absorbed by either the queue or the fleet cycle time. That is, the slowest truck will cause the trucks that follow to wait. In this manner, the cycle times of all of the trucks approaches the cycle time of the slowest truck. This is a conservative measure and is not adopted in practice: industry generally adopts the average cycle time. The use of slowest cycle time provides an interesting study for the effect of truck ordering in the fleet.

2.3.3 Queuing Theory

Queuing theory is the study of the waiting times, lengths, and other properties of queues. Waiting time for trucks and loaders has been the focus of some shovel-truck productivity research. Although this has not resulted in good ES solutions, it may provide a suitable upper bound for an IP model. Queuing Theory was first notably applied to shovel-truck productivity by O'Shea in 1964. Further to this study, Karshenas (1989) has outlined several improvements that were incorporated into an equipment selection program.

These models use the inter-arrival time of one truck instead of the inter-arrival time of the entire fleet. However the model requires the times between any arrivals. No justification for this change in the theory is given in any literature. Huang and Kumar (1994) developed a case study using the queuing theory method. Their definition of arrival time is not provided in the paper. Further application of queuing theory exists in the development of an upper bound on the truck fleet size.

3 Linear Program with approximate cost function [single period]

The choice of objective function is paramount to the type of solution produced. For this model we wish to minimise the cost of operating the fleet and are not concerned with how profit varies from fleet to fleet. It is important to recognise the distinction between these two ideas: although a tonnage requirement has been placed in the constraints, some fleets will produce more tonnes in the same time as other fleets. If the model were to maximise profit, greater detail of the production schedule would need to be included in the model. This objective function will not be discussed further here, and instead we pursue minimising the cost of operating the fleet.

Creating a linear program of the equipment selection problem presents an issue with the linearity of the cost function. The actual cost function is unlikely to be linear for at least the following reasons:

- Cost of unit operation will increase as the machine ages,
- Cost of unit repairs and maintenance will increase as the machine ages,
- Unit productivity will decrease as the unit ages,
- Cost of operation is dependent on the unit's surrounding fleet and its corresponding efficiency.

Two clarifications must be made if we are to find a linear approximation for the cost function: the bunching effect must be absorbed by the slowest cycle time; and a flat cost per tonne per unit must be accepted as a fair cost comparison for the lifetime of the machines (although demonstrating this is beyond the scope of this study). For a multi-period IP model the cost assumption can be softened. In order to take advantage of some of the new ideas discussed in this paper, the decision variables, duly defined as the number of units of machine type per fleet, must also define which loader the truck is working with and vice versa. For example, a CAT789 truck may operate more efficiently and cost effectively with an EX3600 loader. The variables should reflect this complexity of decision making, as should their related costs and cycle times.

$x_{i,j}$: the number of trucks of type i working with loader type j,

$y_{i,j}$: the number of loaders of type j working with truck type i.

With these decision variables the model includes the opportunity to select heterogeneous fleets. The data should also echo this additional dimension: loaders will have a different cycle times with different trucks, and vice versa.

A useful objective function is the overall cost per tonne of the operating fleet. For this to be linear we must accept the assumption that the operating fleet will only extract the required production of the production schedule, and will not do any more (or less) work in spite of its maximum capacity. In this manner the actual fleet capacity is the production requirement and thus is the same for all feasible solutions. For simplicity of the example, the objective function will minimise the overall cost per hour of the operating fleet, which is equivalent to cost per tonne under the above assumption.

In order to create effective constraints that act as lower bounds on truck and loader fleets, a suitable estimate of unit productivity must be obtained. Traditionally this is a combination of unit availability (percentage of time that the unit is available to work), capacity, cycle time and fleet efficiency. Fleet efficiency may incorporate the effects of match factor, bunching and queuing. This component has a tendency to create nonlinearities in the model if integrated in its truest form. However, as previously discussed, the efficiency of the fleet can be absorbed conservatively but effectively into the cycle time. The lower bound on the loader fleet is constructed in the same way.

Due to difference in size, some machines simply cannot work together. Truck and loader compatibility is an important inclusion in the model. This can be reflected in the cost matrix where incompatible machines *i* and *j* can be allocated an arbitrarily large cost.

Additional constraints include non-negativity constraints on both the truck and loader variables, and also pair-wise selection. That is, if truck *i* is selected because it works cheapest with loader *j*, then loader *j* should also be selected (corresponding to $\rho_{i,j} = 1$).

$$\text{Minimise} \quad \sum_{i,j} C^x_{i,j} x_{i,j} + \sum_{i,j} C^y_{i,j} y_{i,j} \tag{2}$$

$$\text{subject to} \quad \sum_{i,j} P^y_{i,j} y_{i,j} \geq T \tag{3}$$

$$\sum_{i,j} P^x_{i,j} x_{i,j} \geq T \tag{4}$$

$$x_{i,j} + y_{i,j} \leq M\rho_{i,j} \tag{5}$$

$$x_{i,j} \geq \rho_{i,j} \tag{6}$$

$$y_{i,j} \geq \rho_{i,j} \tag{7}$$

where

$C^x_{i,j}$ is the cost per hour of operating truck type *i* with loader type *j*,

$C^y_{i,j}$ is the cost per hour of operating loader type *j* with truck type *i*,

T is the required tonnage per second for the given period,

$P^x_{i,j}$ is the productivity of truck type *i* working with loader type *j*,

$P^x_{i,j}$ is the productivity of loader type *j* working with truck type *i*,

$\rho_{i,j}$ is a binary variable where 1 defines the pair *i,j* is selected; 0 not selected,

M is an arbitrarily large number.

4 Results

A linear version of the match factor method was compared to the presented linear model. The purpose of this comparison is to demonstrate that the linear program opens opportunities to select heterogeneous fleets which may be chosen as the optimal fleet for minimised cost. The linear match factor (LMF) method was employed through a Microsoft Excel spreadsheet. The mixed integer linear program (MILP) was solved using Ilog CPLEX v.9.0. Both methods incorporated 7604 operating hours per one year period; production requirements ranging from 10Mt – 50Mt; cycle times of trucks and loaders; capacity of trucks and loaders; and the percentage availability of the machines after maintenance. The comparison was made on a cost per hour basis, which increases as a piecewise linear function as the fleet size increases.

The brute force LMF method requires a full enumeration of fleet combinations to determine the best solution. This enumeration includes fleets with 1 loader, 2 loaders and so forth, and a spreadsheet function is required to determine the lowest cost fleet from all of these combinations, which can take a lot of time to set up properly. Also, tedious changes to these calculations may occur if a simple change in mine parameters is necessary.

At this stage it is not known how much more realistic the solutions from a nonlinear model that formalizes efficiency losses will be. The MILP solution is generated within seconds using CPLEX, and optimality is guaranteed subject to said assumptions. Other advantages include opportunity for heterogeneous solutions and changes to mining parameters are easily incorporated into the program.

The comparison can be made in two ways: pre-selecting the loader and allowing both methods to choose the optimal truck fleet; allow both methods to select both the truck and loader fleets.

Model	Required Production	Loaders	Trucks	Cost per hour ($)	Max Cap (Mt)
MILP preselected loader	**20**	1 O&K RH170	1 CAT 785C ; 3 Komatsu 830E	**2054.97**	20.05
LMF preselected loader	20	1 O&K RH170	4 Komatsu 830E	2115.07	20.5
MILP	**47**	1 Hitachi EX3600; 1 P&H 4100A	7 Dresser 830E	**3188.62**	47.5
LMF	47	2 Hitachi EX3600	8 Dresser 830E	3327.91	51.0

Table 1. Selected results from MILP and LMF.

The results demonstrate that optimal heterogeneous solutions are possible. All optimal homogeneous solutions are identical for the two methods, although the time to find the optimal solution is not. The time taken to complete a full enumeration of solutions is subject to the complexity of the spreadsheet user interface, and has not been approximated here.

5 Conclusions and Recommendations

The given linear program is able to quickly search the entire set of available trucks and loaders for an optimal solution set subject to the defined assumptions.

Industry standards incorporate match factor and bunching concepts into the solution. The inclusion of an efficiency expression turns the current MILP formulation into a nonlinear formulation. The nonlinearity issue can be solved using constraint programming methods.

Several extensions to this work and further studies have arisen and include:

- The full effect of bunching in haul trucks is not well recognised.
- It would be a useful study to develop a bunching transition model to determine the effect of bunching and match factor.
- The effect of including rolling resistance in the equipment selection model can be studied.
- Derive new models using different objective functions such as maximising profit.
- The incorporation of equipment usage may be important.

The linear program may also be extended to include multi-periods so that the aim to optimise the materials handling over the life of the mine may be realised.

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