APPLICATION OF AGENT-BASED MODELING TO TRUCK-SHOVEL DISPATCHING SYSTEMS IN OPEN PIT MINES

By

YASSIAH BISSIRI

B.Sc., Universite de Ouagadougou, Burkina Faso, 1993
M.A.Sc., University of British Columbia, Canada, 2000

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Department of Mining Engineering
The University of British Columbia
Vancouver, Canada

Date Dec 09, 2002
Abstract

Various computer-based dispatching systems have been developed for managing truck and shovel pairing in surface mining operations and are being used to varying degrees of success. Systems have shown the ability to increase production and maintain ore quality within prescribed upper and lower limits provided there is a stable operational environment. However, operational environments in mining are uncertain and highly variable. Upsets such as equipment breakdowns, or changing weather conditions often occur and no claims have been made about the success of these systems to react to these upsets and successfully adapt to new operational conditions generated by upsets.

In an ant colony different activities are performed simultaneously by specialized individuals. However when the environment with an ant colony changes or experiences a major upset, the configuration of task allocations within the colony change to adapt to the new conditions.

In this thesis, the task allocation model developed for ant colonies was modified and used to develop a dispatch algorithm, the Agent Based Model, which reacts reliably to changes and upsets in surface mining operations. The algorithm was simulated over a twelve-hour shift using AUTOMOD®, a discrete event simulation program. The simulation results of the Agent Based Model are compared to that of the Fixed Assignment Method used by current dispatch systems in which each truck is permanently assigned to a particular shovel. The total production of ore and waste from the Agent Based Model is consistently greater than that from the Fixed Assignment Method because an Ant Based system allows re-assignment (task reallocation). The simulations also show that the Agent Based system reliably adapts and limits the impact of upsets on a mining operation.
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1 INTRODUCTION

The ability to make effective use of trucks and shovels in an open pit mining operation will have a major impact on the profitability of the overall mining operation. There are many factors that contribute to the effectiveness of this equipment including availability, reliability and operating performance. The focus of this work is on how the operating equipment is used, specifically the dispatch of trucks. At this point a distinction must be made between two functions 1) allocation which is the distribution of trucks to shovels or routes based on steady state planning information and 2) dispatch which is the real time control of the trucks in the face of minor and major changes in the operating environment.

The methodology used to dispatch trucks has evolved from manual decisions made by a dispatcher to computerized dispatch systems where a computer makes the dispatch decisions. Computerized dispatch systems were introduced to improve dispatch systems for large scale open pit mines, these systems have brought more flexibility to operations and increased their overall productivity [Bonates, 1992]. However, these systems have limitations when dealing with complex operational environments that change unpredictably and frequently.

Manual systems work well for small systems where the dispatcher can make effective decisions based on all the information without being overwhelmed. Optimization or model based systems work well in static operations where the model is valid over a wide range of conditions and the system is well measured. However in a mine the operating environment is continually changing which requires model updates and a large amount of information to react properly based on model results and this is a difficult system to build and maintain. Experience of current dispatchers is that the existing systems are not robust enough to allow full automation of the dispatch function\(^1\).

\(^1\) Based on conversations with dispatchers at Syncrude Canada Ltd.
Social insects are capable of adapting to almost any changes within their environment that threaten their survival. They are able to do this with only limited intelligence and information about their surroundings. The purpose of this work is to draw analogies between the behaviours of social insects and mine operations to develop an Agent Based Model for Truck-Shovel Dispatch System (ABM DISPATCH). There are significant differences in the behaviour of an ant colony and an open pit mining operation; however, there are also similarities in the type of tasks that must be performed. The current models for ant behaviour will need to be extended to account for the differences in numbers and cost of individuals. However, the ability to adapt to changing operational environments using only simple but widely applicable rule sets is a valid goal for a new dispatch system. If successful developed, ABM DISPATCH could achieve the benefits of both manual and computerized dispatch systems.

1.1 Statement of the Problem

Most mine managers with large-scale surface mining operations agree that dispatching shovels and trucks is a very complex man-machine system [Temeng, 1997]. Like other industries that purchase and work up raw materials, a mine operates in the midst of its raw material (the ore in situ). In mining this raw material is not as well characterized as those of other industries. The ore grades and mechanical properties, which determine an important part of the mining cost, are highly variable and encumbered with estimation errors. Further, production planning in other industries is a cyclic process with small changes from one cycle to the next, conversely in the mining industry this activity is an ever changing process as mining progresses through the ore body [Soumis and Elbrond, 1987].

The central issue in this work is to develop an alternate dispatch system that will be able to react appropriately to the changing environment of an open pit mining operation. This dispatch algorithm will implement a truck allocation based on the result of a Linear Program, which satisfies short-term objectives and constraints. This dispatch system will need to be flexible because there are many ways that the mining environment can change including:
• The varying topography of the pit and the associated complex network of haul routes.
• Weather conditions (road conditions, visibility).
• The variability in the status of operating equipment, including breakdowns.
• Limited and variable capacity of crushers and waste dumps.
• The spatial grade variability of the orebody.

These factors are critical to the dispatch decision-making process. Any single decision to dispatch a truck to a given location should be made in conformity with the operational constraints and objectives. These objectives include maximizing production, minimizing shovel and truck waiting time, minimizing delays, minimizing operation costs within operational constraints such as production rate, mill capacity, ore processability (ore quality requirements) and road conditions.

By monitoring the operating environment and the distribution of resources (trucks to shovels) the algorithm dispatches trucks to shovels when they have dumped their loads. The proposed algorithm works to make the best use of a limited set of trucks in the face of minor variations and to reallocate individual trucks in the face of major changes.

1.2 Objectives

The objectives of this research are to extend the analogy between the behaviour of ants within their colonies and surface mining operations, formulate, develop and simulate a simple and robust two-stage truck-shovel dispatching system model that is able to adapt to new operational environments should any serious upsets occur in order to satisfy the operational objectives and constraints set by mine planners. The goal is to demonstrate the stability of the “ABM DISPATCH” for truck-shovel dispatching in the mining industry using a discrete simulation of an open pit mine.

The models for social insect behaviour proposed in the literature are not adequate for ABM DISPATCH. These models need to be extended to account for the fact that there are many fewer trucks and each truck costs much more than an ant. These models will be
the basis of the ABM DISPATCH, which will act as a control system for the mining operation. This control system needs to be responsive to minor changes and major upsets.

It is unrealistic to test a proof-of-concept on a working mine, therefore a discrete simulation of a mining operation needs to be developed. This simulation must be representative of a simplified mining operation and allow the incorporation of different dispatch systems.

The final objective is to develop two case studies that will be used to test the ABM DISPATCH and compare it to a traditional strategy. These case studies need to be simple enough to clearly demonstrate how the system is behaving but complex enough to reflect real operation and to show the advantages of the algorithm.

1.3 Limitations of this Study

- This research does not determine the optimal number of trucks, shovels, crushers and waste dumps for a given mining operation. This is the work of mine planners. This research focuses instead on how to use the available resources efficiently to meet operational objectives and constraints.
- The locations of shovels are determined by mine planning and are not treated in this research.
- This study does not explicitly select the shortest path between a shovel and a crusher/dump. It is assumed during the design of the haulage network, roads are built in such a way that routes represent optimal mine development.
- This is a deterministic study that does not address issues of missing or uncertain information. Further, this study does not predict travel times of trucks. Their locations would be provided by global positioning systems (GPS). Grade information is assumed to be known and provided by the orebody model.

1.4 Contributions of the Thesis

The two central contributions of this work are
• the extension of the existing models for social insect behaviour so that they can be applied to the dispatch of trucks in an open pit mining operation, and
• the demonstration of the stability of the ABM DISPATCH strategy and its ability to respond to upsets in a simulated environment.

1.5 Organization of the Work

This thesis is organized in six chapters. Chapter 1 has presented a brief introduction, the statement of the problem, and the objectives, limitations and contributions of this work. Chapter 2 reviews the literature on existing dispatch strategies. Chapter 3 introduces a model for social insect behavior and the concept of “Swarm Optimization” and agent based modeling. The analogy between an ant colony and mining operations is established. The dispatch system model is formulated in Chapter 4. The existing social insect models presented in Chapter 3 are extended so that they can be used in a truck-shovel dispatching system. The development of the shovel-truck haulage simulation model is presented in Chapter 5 along with its application in two case studies. The results for the ABM are compared with results obtained by a traditional strategy, the fix assignment model. Chapter 6 summarizes the conclusions and the recommendations made as a result of this work.
2 REVIEW OF TRADITIONAL DISPATCH STRATEGIES

2.1 Introduction

Truck-shovel systems have become the most common means of transportation of material in open pit mines today because of the large operational flexibility and versatility they offer [Bonates, 1992]. The first truck-shovel system was introduced in an open pit mine operation in the late 1930s in the USA with truck capacity ranging from 15 to 20 tons [Whitney et al, 1939]. Since the early 1950s, the capacity of trucks and shovels has been increasing at a steady rate due to increasing demand for resources and the scarcity of high-grade deposits. Depletion of high-grade deposits created the incentive to mine lower grade deposits. Hence, it has become necessary for the mining industry to invest in large size equipment with larger fleets and develop larger scale operations. Although larger and more efficient fleets are an apparent solution to the ever-increasing need for more production from low-grade, low-profit-margin ore deposits, the next challenge faced by many mining companies is to continue to reduce their total costs. Indeed truck/shovel systems represent 50% or more of operating costs in most surface mines [Kennedy, 1990]. The acquisition of larger size equipment necessitates a large capital investment. Also the size of the fleets makes the management of surface mining operations more complex. Managers are faced with challenging decisions to be made at every stage of operation. Until recently, the allocation of trucks and shovels were made by a dispatcher who uses his/her experience and past histories to make critical decisions about where a truck is to be dispatched. But with a large fleet and a more uncertain environment, the dispatcher might not be able to deal with major upsets that happen.

Efforts have been made in the past to limit and reduce haulage costs. These include improving operating performance of the trucks, resulting in better reliability; capitalizing on developments made in truck technology which made larger payloads possible; employing truck haulage with in pit crusher and conveyor systems. One of the main opportunities for large-scale surface mining dwells in improving the allocation of
resources on site. The interaction between orebody, shovels, trucks and the maintenance system is becoming more important.

The earliest dispatching systems were manual. In these systems, a dispatcher, from a strategic location in the mine, kept track of the status of various resources visually and/or through radio communication and reassigned trucks to shovels, solely based on their own judgment. By the late 1970's these systems evolved into semi-automatic systems where the dispatchers were aided by microcomputers to allocate trucks to shovels [Munirathian et al, 1994]. But the dispatchers remained totally in charge as they could override whatever the computer suggested. Since the late 1970s, fully automated real time computer-based systems have been developed, which have the ability to directly assign trucks to shovels, overcoming the limitations of dispatchers needing to handle large amounts of information, in a short time, which is necessary for an efficient dispatch system.

Today, mine management widely believes in investing in computerized truck dispatching system [Munirathian et al, 1994]. Many mine operators, [Barnum, 1987; Clevenger, 1983; Himebaugh, 1980], have reported that computer-based dispatching systems are gaining popularity and acceptance, and unquestionably result in increasing productivity. Table 1 [White and Olson, 1996] shows productivity improvements that have been reported in the literature due to the implementation of DISPATCH®, a computer-based truck dispatch system developed by Modular Mining Systems Inc., a mining software company.
Table 2.1. Reported Productivity Improvement from Implementations of DISPATCH®

[White and Olson, 1996]

<table>
<thead>
<tr>
<th>Mine</th>
<th>Location</th>
<th>Type</th>
<th>Productivity increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barrick</td>
<td>Nevada</td>
<td>Gold</td>
<td>15%</td>
</tr>
<tr>
<td>Bong Mine</td>
<td>Liberia</td>
<td>Iron</td>
<td>10%</td>
</tr>
<tr>
<td>El Cerrejon</td>
<td>Colombia</td>
<td>Coal</td>
<td>13%</td>
</tr>
<tr>
<td>Empire</td>
<td>Michigan</td>
<td>Iron</td>
<td>10%</td>
</tr>
<tr>
<td>Palabora</td>
<td>South Africa</td>
<td>Copper</td>
<td>7%</td>
</tr>
<tr>
<td>IOC</td>
<td>Newfoundland</td>
<td>Iron</td>
<td>23%</td>
</tr>
</tbody>
</table>

These reported results make computer-based dispatch systems attractive, but they are capital intensive especially for small mines.

Computerized dispatching systems available today range from simple heuristic rules to complex mathematical programming based methods. Mathematical programming-based dispatching systems have mostly been implemented in two parts [Barnum, 1987]. The first part is based on short range planning objectives, and the second is used to implement the first part in real time. The first part usually consists of a linear programming algorithm used to determine initial operational objectives such as tonnages or trucks flow rates between shovels and dumps/crushers under operational constraints such as ore quality and resources availability. Different authors have used different objectives to optimize their dispatching procedures. The objectives vary from maximizing the utilization of resources (trucks and shovels) [Kolonja et al, 1993] to maximizing production with the available resources, or minimizing the operating costs of the resources [Lizotte and Bonates, 1987; Forsman and Vagenas, 1992; Wenco International Mining Systems Ltd., 2001; Bonates and Lizotte, 1988]. The operational constraints have ranged from quality constraints, stripping ratios, availability of resources, shovel-truck constraints, truck route restriction and production flow rates. Various procedures have also been used for real time dispatch decisions ranging from heuristics (procedures that do not guarantee optimality) to mathematical procedures that provide guarantees of optimality.
While there are many dispatching systems available today, a good dispatching system should be evaluated by its ability to meet mine planning objective in the long term and short horizons under the operational constraints. It should also be very easy and cheap to implement.

Dispatching systems are generally classified according to level of computerization. There exist three categories of dispatch systems:

- Manual dispatching systems. In this method, trucks are allocated to various shovels by a dispatcher stationed at a strategic location in the pit. Dispatch decisions are made based on his/her best judgments with no intervention of computer applications. This type method of dispatching is suitable for small mines with up to 10 operating trucks [Tu et al, 1985; Lizotte and Bonates, 1986].

- Semi-automated dispatching systems. As the size of different fleets (trucks and shovels) grows larger, the flow of information becomes too complex for a dispatcher to handle and make proper dispatching decisions. Semi-automatic dispatching systems consist of systems where the dispatcher is assisted by a computer that is programmed to provide him/her with information necessary to make dispatch decisions. The computer processes, reports and records information that may be useful for future operations. This type of method is suitable for medium size mines.

- Fully automated dispatching systems. Information in such systems is generated by a computer and sent directly to trucks and shovels by the medium of control panels mounted on each truck and shovel. The sole task of the dispatcher is to monitor the entire operation and make adjustments according to changes in the operational environments.

Note that both semi-automated and fully automated dispatching systems involve a dispatcher observing and making adjustments. The distinction between the two systems is therefore one of degree rather than category.
2.2 Existing Dispatching Procedures

The efficiency of a dispatching system depends on the procedure used to implement it. Procedures used in most dispatching systems are either heuristic or mathematical programming-based procedures, except for manual dispatching system where no computers are involved. Mathematical programming based procedures were introduced in the early 1970's as alternatives to heuristic based procedures that usually lead to shortsighted decision making [Munirathian et al, 1994]. Heuristic dispatching procedures consists of a set of non-optimal rules for real time dispatching [Temeng, 1997]. Mathematical programming based dispatching generally consist of a two-part procedures with the first part comprising an optimization method and the second part a real time dispatching method.

2.1.1 Heuristic Based Procedures

For heuristic dispatching systems, at the time of making a dispatch decision, the procedure will invoke a chosen heuristic rule. The heuristic is usually applied to one-truck-at-a-time. The current assignment decision is made with indifference to the assignments of other trucks that will be made in the near future [Munirathian et al, 1994]. Dispatching algorithms based on heuristic procedures are easy to implement and do not require exorbitant computations. However, many authors [Kennedy, 1990; Munirathian et al, 1994; Kolonja et al, 1993; Lizote and Bonates, 1987; Forsman and Vagenas, 1992], agree that heuristic dispatching procedures often lead to shortsighted decisions that may maximize the immediate effectiveness of truck being assigned, but may reduce the net effectiveness of truck assignments over the long term. Most heuristic rules ignore essential constraints, or secondary goals, of system operation, such maintaining product grade requirements by balancing production ratios among the available loader [Soumis and Elbond, 1987]. Among the heuristic rule-based procedures, the following can be cited:

- Fixed truck Assignment rule: each truck is assigned to a shovel and remains with that shovel during a shift. The number of trucks that are assigned to a shovel is based on its performance variables, its production level and the expected travel and wait time.
of trucks in the haulage network. The problem with this procedure is that because of the stochastic nature of haulage operations and the random occurrences of downtimes, the formation of long queues at a specific shovel occurs with some frequency [Kolonja et al, 1993; Tan et al, 1992].

- Minimizing Truck waiting time rule: an empty truck is assigned to the shovel that is expected to result in the least waiting time for the truck to be dispatched. This strategy may cause under-utilization of shovels located farther from dumpsites creating difficulties for the operation to achieve production targets and maintain grade control [Tan et al, 1992; Kolonja et al, 1993].

- Maximize truck rule: an empty truck is assigned to the shovel where it is expected to be loaded at the earliest future point in time. Although this rule tends to reduce truck idle time and prevent long waiting lines, it might also produce unbalanced production among shovels, especially for undertrucked systems [Lizotte and Bonates, 1987; Kolonja et al, 1993].

- Minimizing shovel waiting time or maximize shovel rule: Assign the truck to the shovel that been waiting the longest or shovel expected to become available soonest. The risk associated with this rule is that trucks will be allocated to shovels located far away ignoring nearby shovels that have not waited long enough, thus creating a decrease in production [Lizotte and Bonates, 1987; Kolonja et al, 1993].

- Minimizing shovel saturation rule: assign truck to the shovel that has the least degree of saturation. This rule however is applicable only for systems that have adequate number of trucks to satisfy the requirements of shovels [Tan et al, 1992; Kolonja et al, 1993].

- Minimizing deviation of shovel production from target rule: Assign the truck to the shovel that is most behind schedule. A formula is used to determine the most lagging shovel but fails to consider the random nature of the network. For example total production may be affected if a shovel was not in operation during a period of time, as all the trucks will be sent to that shovel, creating a lengthy queue [Kolonja et al, 1993; Zang et al, 1991].
• Mixed heuristic rules: a combination of one or more of the above rules. Crosson [1991] used a relative priority number calculated for each shovel to make truck assignments. They defined the priority number as \( P = 3600 \times \text{truck factor (tons)/shovel digging rate (tons/hour)} \). They reported better grade control, reduced truck queuing time and improved recording and reporting as the gains resulting from their dispatching system.

In minimizing deviation from Shovel Production Target [Tan et al, 1992], a truck is assigned to a shovel, which is furthest behind schedule (i.e. this schedule might be provided by a LP model or any optimization process). In order to identify the most lagging shovel, the following basis was used:

\[
k = \text{Arg} \left[ \max \left( \frac{T_{NOW} \times P_{O_i}}{T_{SHIFT}} - P_i \right) \right]
\]

where:
- \( \text{Arg} \) = Argument of the component of a vector
- \( k \) = shovel to which truck is to be dispatched
- \( T_{NOW} \) = time elapsed from start of the shift
- \( T_{SHIFT} \) = total shift time
- \( P_i \) = actual production of \( i \) th shovel by time \( T_{NOW} \)
- \( P_{O_i} \) = targeted production of \( i \) th shovel

The above formula fails to take uncertainties, such as breakdowns, into consideration and does little to improve production efficiency. For example in the event that more than one shovel breaks down during operations in a random manner and is brought back in operation in a random order, the method could trigger instability to which shovel to focus more despite ore quality requirements. To illustrate this claim, imagine a fleet of trucks serving a surface mine operating with two shovels (A and B) and two dumpsites (C and D) as shown in Figure 2.1.
Suppose that the travel time between shovel B and dumpsite C is at least one minute more than travel time between Shovel A and dump D. If shovel B is the neediest shovel at present, the one-truck-at-a-time decision to assign a truck that has just dumped at dumpsite C is undesirable if 30 seconds from now a truck completes a dump at dumpsite D. This approach might however be suitable if the objective is to rigorously enforce production targets in order to meet production constraints (such as blending).

Heuristic based dispatching procedures do have some positive sides. These procedures have brought improvement in production by reducing waiting times of resources. For example, when improving production, minimizing truck waiting times seems to help undertrucked shovels while minimizing shovel waiting times seems to perform better for overtrucked systems. It is certain is that heuristic procedures work better than “fixed assignment” methods. Therefore if quality constraints are not a concern, heuristic based procedures may be acceptable in today’s context. But with the need to perform better due to high costs associated with open pit mining methods and equipment, and due to the steady increase in operation costs, searching for new procedures that will reduce costs and increase efficiency is justified.
It is clear from the description of these heuristic based procedures that the main problem of heuristic algorithms, although easy to implement, is that they fail to account for the random nature of the system and the quality constraints imposed by the geometry of orebodies. In some cases this approach may generate more problems such as overtrucking or undertrucking a shovel. The rationale behind one-truck-at-a-time assignment cannot be justified, as the decision made for the current situation ignores entirely the assignment of the next truck. Mathematical programming based procedures were introduced to reduce the insufficiencies that appear in heuristic rule-based dispatching procedures.

2.1.2 Mathematical Programming Based Dispatching Procedures

There exist two types of mathematical programming based dispatching procedures: the plan-driven procedures and constrained assignment approach. But both procedures use optimization tools such as linear programming (LP), integer programming (IP), non-linear programming, stochastic linear programming (SLP), dynamic programming or queuing theory techniques to optimize operational objectives such as production or operation costs.

Plan-driven procedures are comprised of two components. The first deals with the short term production planning, and the underlying basis for generating the plan is a mathematical programming formulation. This formulation attempts to optimize total production subject to operational constraints such as ore blending targets. The second deals with the real-time dispatching. It uses the solutions provided by the first component to make assignment decisions in real time. The goal of this second component is to realize the target set by the first component in a way to insure that deviations of haulage operations from the ones set by the mathematical model are minimized [Munirathian et al, 1994].

In contrast, constrained assignment procedures achieve the same goals as the plan-driven procedures by assigning trucks directly in real time. The operational constraints are embedded in the assignment formulation and constrain therefore each assignment decision [Munirathian et al, 1994].
White and Olson [1989] formulated two linear programs for their two stage dispatching procedure. The first stage consisted of minimizing a sum of pseudo-cost functions associated with the processing rate, the cost of operating the shovels and penalties for quality requirements. The pseudo costs are judgment-based weights established by mine management depending on their relative importance. The optimization is achieved under three constraints. The first constraint makes sure that the desired production from each shovel does not exceed their maximum possible digging rate, the second constraint requires that total material feed does not exceed the plant’s processing capacity and the third constraint ensures that the quality of the plant feed is within acceptable bounds.

The second stage of the dispatching procedure is also an LP problem and requires prior knowledge of the haulage network characteristics and the shortest routes between all the stations involved in operation. It is in fact a classical problem of finding the shortest path or a vehicle routing problem. The system constructs a graph of the haulage network by representing stations with nodes and applies Dijkstra’s algorithm to find the paths of interest. Given time estimates for travel and dumping, the second LP problem attempts to maximize mine production by minimizing the haulage capacity needed for shovel coverage. The solution of the LP problem is a vector, whose components are haulage capacity assignment to paths, and is used to make real time decisions. The two LP problems are linked by one of the constraints of the second stage LP, which guarantees that the optimum production rate from a shovel is effectively distributed amongst the paths leaving it. The two LP problems establish a new short-term plan in the event of a major disturbance in operations. In the absence of disturbances, re-planning is performed after a control interval, chosen by the planners, expires to ensure that operational objectives are on the right track.

Bonates et al. [1988] proposed a simplified approach to the White and Olson’s approach. In their approach a LP formulation used to solve the production rate of all operating shovels in order to achieve maximum production is run once a shift (usually a twelve hour operation). The formulation takes into account grade requirements. The objective
function in the LP formulation is the sum of the production from shovels working on ore and waste. There are four constraints in the formulation of the LP problem. The first constraint ensures that ore production rate does not exceed processing rate of the crusher, the second one guarantees targeted ore grade and the third constraint makes sure that the production rate from each shovel falls within the acceptable range. Finally the fourth constraint ensures that desired production can be accomplished using the available truck fleet. However the final solution is built on the assumption that each additional truck will lead to a linear increase in shovel production and this may be very difficult to justify.

Three stage dispatching procedures have also been formulated. Most of them employ optimal routing in the first stage [Temeng, 1997; White and Olson, 1989, 1992], linear or non-linear programming model in the second stage and a real time dispatching algorithm in the third stage. Soumis and Elbrond [1987] however employed a different approach in the first stage of their three stage-dispatching model. They used a combinatorial programming approach to select the best shovel locations that optimizes production under quality constraints. Their approach consists of a three factor non-linear objective function in the second stage. The three objectives are maximize shovel production, minimize the sum of the squared difference between computed truck hours and available truck hours, and minimize the deviation of each ore quality objective by introducing the concept of penalty functions. It was observed that despite its complexity, non-linear programming has fewer tendencies towards extreme values compared to linear programming methods. They also reported a gain of 2% in production and better control of blending. Temeng [1997] also develop a three-stage model where the optimal routing approach is used in the first stage. The first part of his model consists of a vehicle routing model. But in addition to time study input, he introduced a multiple regression model used to predict travel time, based on rimpull-gradeability charts (a chart provided by the trucks’ manufacturer to choose a safe speed with respect to the condition of roads). According to Temeng [1997] the prediction model is intended to facilitate the use of performance and retarder chart based data in cases of inadequate or lack of input data. The second part is developed to ensure that shovel selection and truck assignment to such shovels match
truck flow to various shovels as close as possible to the flow rates of the optimal solution to a goal-programming model. Finally, the third part, a transportation model, is used to minimize the waiting time of selected shovels and assigned trucks for each assignment in real time. In this third stage, the decision criteria for assigning trucks to shovel is based on the deviation (computed) of shovel route cumulative tonnage ratios from current mean ratio. All routes with deviations below zero are considered needing assignment at current time. The number of trucks required per route is deduced from the corresponding deviation and route tonnage per shift. In the model, the results of the first and second stages are determined and then input to a shovel-truck haulage simulation. The third part of the model (the real time assignment tool) is incorporated directly in the simulation model as a subroutine so that anytime there is a demand for a truck, it will execute and return the optimal assignment. Although the model developed by Temeng [1997] seems to have improved slightly the performance of math-based dispatching system, the fact that he uses three mathematical-based algorithms makes its model very complicated and risky in terms of feasibility. It is well known that not all the LP problems have solutions and for a changing environment like in mining, scenarios where these LP may not have solutions should not be neglected. Its prediction algorithm based on regression analysis may be attractive in terms of mathematical manipulations with respect to its accuracy but a prediction model is not accurate all the time.

Although mathematical based procedures theoretically outperform heuristic based procedures, some problems arise. Large fleet truck/shovel systems represent complex stochastic networks that are very difficult to model analytically. In fact most models assume linear relationships assignment level to haulage circuit and production from that circuit. Also in order to counter the complexity of problems, many assumptions are made and as direct result the performance of these systems may be limited [Temeng, 1997]. The other major problem in these procedures is the fact that the systems always try to solve optimization problems in any run. Because of the stochastic nature of the haulage network, some runs may not necessarily have solutions causing the procedures to look for solutions that are only feasible. But although feasible solutions satisfy operational conditions, they may not necessarily be optimum. In order to resolve the infeasibility
problem, Hauck [1973] suggested that the problems be divided into sub-problems that can easily be solved using dynamic programming techniques. Although this approach seems to be attractive, its major risk is that once a problem is decomposed into sub-problems, the flow of information linking these sub-problems may be lost, causing the solution of this approach to be the solution of anything but the solution of the initial problem. This situation is mainly caused by the inflexibility of the constraints in the event of changes in the haulage network, the ore configuration, and quality control requirements.

Some authors [White and Olson, 1989, 1992; Xi and Yegulap, 1994] used dynamic programming models to assign trucks to shovels based on the optimal linear programming solution. For instance the “assign best truck (truck with the minimum lost tons) to the neediest path” dynamic programming was used [White and Olson, 1989, 1992].

The dispatch model in this research consists also of two parts. The first part is an optimization algorithm that allocates resources (trucks) to shovels based on operational targets and objectives. The optimization algorithm consists of minimizing a cost function that is a sum of traveling, mining and loading costs. The solution of the optimization algorithm is a vector whose components are production rates of each available shovel in order to satisfy production requirements under ore quality requirements. The second part of the model, the agent-based dispatching algorithm, consists of a real time dispatch algorithm inspired by the self-organization behaviour of social insects within their colony. The results (production rates) from the optimization algorithm are formulated as demand functions for shovels in the agent-based model. A demand function represents the intensity with which a shovel needs a truck under operational objectives and constraints. A truck will respond (positively or negatively) to that demand based on its status (loaded vs. unloaded), its position (located by GPS), its capacity (plasticity) and the road conditions formulated into a function, the threshold function. The response of a truck to the demand of a shovel is quantified by a function, the response function, that suggests the decision to make regarding assigning a truck. In the event of major upsets,
the system is not adjusted by any external intervention but instead readjusts itself as a part of a normal operational condition with new information provided by the status of the crushers and dumps. The demand and the threshold functions are formulated in such a way that the queue length and the waiting times of shovels and the deviations from targets set by planners are kept to acceptable levels under the same constraints. In the agent-based model, there is no need to identify the causes of upsets. The system has the ability to recognize its limitation under the current operational environment and may suggest compromises to be made to obtain results that are acceptable to operation (this involves defining relative importance given to ore zones). Unlike the previous models, the proposed algorithm does not use prediction models (such as equipment failure models) but it instead allows the operation system to adapt to the new environment in order to provide the "best" solutions under new constraints.

It is clear that mathematical based procedure for truck/shovel dispatch systems theoretically satisfy operational objectives and constraints such as those related to ore quality. In practice however they are difficult to implement [Munirathian et al, 1994]. Because of the changing nature of operational conditions, mathematical based procedures that use linear programming methods run the risk of not being feasible. Evidence [Munirathian et al, 1994; Kennedy, 1990; Kolonja et al, 1993; Lizotte and Bonates, 1987; Forsman and Vagenas, 1992] described above suggests that heuristic procedures have serious limitations with respect to operational constraints and objectives. Another alternative that can circumvent or mitigate these limitations is the subject of the proposed research.
3 SOCIAL INSECT MODEL

3. Introduction

Insects that live in colonies such as ants, bees, wasps and termites, have fascinated naturalists as well as poets for many years. There are many examples showing the incredible abilities of these insects to master their environment, perform complex tasks, and organize themselves to guarantee the survival of their colonies in the event of threats (Examples that show the capabilities of social insects are shown in Figures 3.1-3.3). However, each individual insect has limited cognitive abilities. Indeed researchers who study social insects have shown that every single insect in the social insect colony seems to have its own agenda and behaves in a random fashion [Maeterlink, 1927; Holldobler and Wilson, 1978; Holldobler and Wilson, 1990]. What is it that governs here? What is it that issues orders, foresees the future, elaborates plans, and preserves equilibrium? These are puzzling questions.

![Figure 3.1. Ant nest cleaning.](image)

1500 corpses of the ant species Messor sancta were placed randomly in a circular arena 25 cm in diameter. Live worker ants of the species were then placed in the arena. Four successive stages of the state of the arena are shown: the initial state, 3 hours, 6 hours, and 36 hours after the beginning of the experiment. (Courtesy and © Guy Theraulaz, CNRS, Université Paul Sabatier, Toulouse, France)
Figure 3.2. Termite tower in Australia

Approximately 6m in height. These are the tallest structures on Earth made by a non-human. They are also sophisticated structures. Tunnels and arches in the towers allow air to flow into the dark cooler interior and cause moisture to collect in certain areas so that the termites can farm a fungus required for digestion. (Source: http://web.onetel.net.uk/~rcplatts/aust/index.htm)

Figure 3.3. Weaver ants forming long chains

Weaver ants (Oecophyla) form long chains with their own bodies, allowing them to cross wide gaps. Such chains create enough force to pull leaf edges together to form a nest. Once the leaves are in place the ants connect both edges with a continuous thread of silk emitted by a mature larva held by a worker [Holldobler and Wilson, 1978].

Other examples of the capabilities of social insects are described below.

- Honeybees build a series of parallel combs by forming chains that induce a local increase in temperature. The wax combs can be more easily shaped thanks to the temperature increase. With the combined forces of individuals in the chains, wax
combs can be untwisted and be made parallel to one another. Each comb is organized in concentric rings of brood, pollen, and honey.

- In some species of ants, two (or more) physically different types of workers coexist; the majors and the minors who are smaller and morphologically distinct from the majors. Majors cut large prey with large mandibles whereas minors feed the brood and clean the nests. Removal of minor workers stimulates major workers into performing tasks usually carried out by minors and this reorganization takes place within two hours of removal of minors [Wilson, 1975]. The ants have adapted to the new situation in order to complete tasks necessary for their survival.

Studies of these processes have revealed that each individual insect acts randomly with no direct communication with the others [Bonabeau et al, 1999]. Although insects are considered to be amazingly adaptable creatures with their sensing ability and their ability to react to stimuli and make decisions, these abilities alone cannot explain the complexity of their behaviour. How do individual behaviours connect to collective performance? How does the cooperation arise if it is assumed that there is no direct communication or supervision?

### 3.1 Self-Organization

The concept of self-organization was originally developed in the context of physics and chemistry to describe the emergence of macroscopic patterns out of processes and interactions defined at the microscopic level [Nicolis and Prigogine, 1977]. It can be extended to social insects to show that complex collective behavior may emerge from interactions among individuals that exhibit simple behavior. Self-organization theories do not preclude individual complexity but show instead that at some level it is possible to explain complex collective behaviour by assuming that insects are relatively simple interacting entities [Bonabeau et al, 1999].

Self-organization requires direct or indirect interactions among insects. Direct interactions are antenna and mandibular contacts or chemical releases in close proximity. Indirect interactions occur when one individual insect modifies the environment (for
example, by laying down a pheromone trail) and the other insects respond to the new environment at a later time. This is called *stigmergy*, a term introduced by the French entomologist P.-P. Grassé. Bonabeau et al (1999, p 16) describe stigmergy by the following statement:

"Individual behavior modifies the environment, which in turn modifies the behavior of other individuals."

Stigmergy provides a mechanism to relate individual behavior to colony-level behaviours. The details of the mechanism must be determined by individual experiments with social insects. The concept of stigmergy is best explained by example. Bonabeau et al (1999, p 16) describe several examples of stigmergic activities in social insect colonies, some of which are given below.

- Worker ants clean their nests by forming piles of dead ants. An example of nest-cleaning behavior is shown in Figure 3.1. At any time the distribution of dead ants governs the behavior of the ants. If a worker ant encounters a dead ant, it picks it up if there are few dead ants in the vicinity. While carrying a dead ant, the worker will deposit it in an area where the density of dead ants is high. Thus placement of dead ants in a pile is a behavior that results from simple rules involving environmental cues that control the behavior of a single ant. Nest-cleaning behavior does not require communication between the ants.

- Worker ants arrange larvae in concentric rings depending on their stage of development. The smaller (younger) larvae are deposited closer to the center of the rings. This behavior also emerges from distinct cues, i.e., the developmental stage of the larvae.

- Ants will attempt to transport an item by positioning and aligning themselves with respect to the item. This causes a redistribution of forces within the item that stimulates other ants to change position or alignment and effect transport. In contrast to distinct environmental cues, the redistribution of forces is almost continuous.
- Social insect colonies are composed of various types of insects that normally perform specialized tasks, such as reproduction, cleaning, defense, or food storage. However, depending on conditions within the colony, tasks may be re-allocated among all worker insects so that those tasks required for survival of the colony are performed. The colony conditions are the cues that trigger the division of labor and task re-allocation.

- Nest-building activity by termites (see Figure 3.2) is triggered by both pheromone deposition and the current structure of the nest. Pheromone deposition by the queen termite dictates the size of the nest. However, over time, a particular nest configuration (including the absence of a nest) triggers the response of a worker termite to perform certain construction activities using soil pellets. In turn, the results of these activities trigger another set of construction activities.

- The foraging nature of social insects governs their behavior when seeking for food. Studies have shown that ants always find the shortest paths between food sources and their nests. Their ability to find the shortest path is due their ability to lay trails of pheromones. The reinforcement of the pheromone on the shorter path allows the preferential selection of this route. This ability to choose the shortest path is described in an experiment Figure 3.4.

![Figure 3.4. Illustration of the use of pheromone to find the shortest path](image)

A) Ants travel in a direct line from their nest to a food source B) An obstacle is placed on their path. C) The ants travel randomly around the obstacle with equal probability of traveling on the upper or lower path around the obstacle. D) The ants have found the shortest path from their nest to the food source (upper path around the obstacle). (Source: Bonabeau et al, 1999)
3.2 Applications of Self-Organization

Self-organization within social insect colonies provides engineers with a model for intelligent system design in which autonomy, emergence, and distributed functioning replace centralized control and pre-programming. An important feature of social insect colonies is that they are robust and flexible. Flexibility allows adaptation to changing environments while robustness endows the colony to function even though some individuals may fail to perform their tasks. For this reason, the daily problems “solved” by social insects such as finding food, building nests, and efficient division of labor have been used as models in robotics engineering and computer science.

In the case of robotic engineering, based on studies of insect colonies or animal groups, groups of robots have been either constructed or simulated to carry out the following tasks [Arkin, 1998, p. 361]:

- Foraging – where items distributed randomly throughout an area are returned to a central location
- Consuming – where the robots are required to perform work on a desired object in situ, rather than transport them to a home base
- Transport – where the robots are distributed around an object and move it to a desired location. (This may be a subtask of foraging.)
- Grazing – where a group of robots is required to traverse an area in some fashion
- Formations or flocking – where the robots are required to assume and maintain a geometrical pattern as they move

What is interesting is that these tasks have analogies in mining and mineral processing and could be the basic building blocks for more complicated tasks required in mineral extraction. Thus foraging is seeking mineralized zones, consuming would be processing ore in-situ, and transport is transport. These analogies are discussed later in this chapter.
The foraging behavior of ants and their ability to find the shortest path to a source of food has inspired a novel approach to optimization. The basic idea behind this approach is to use a form of positive feedback based on the analogy with the trail-laying, trail-following behavior of ants. Paths in solution space to good solutions of the optimization problem are reinforced by laying "digital pheromone" that effectively stores these paths in memory and allows them to be used as the basis for better solutions. Dorigo et al [1991, 1997] described the development of ant-based optimization algorithms and applied them to the classical Traveling Salesman Problem. They also showed how the new approach can be applied to problems such as the Asymmetric Traveling Salesman Problem, the Quadratic Assignment Problem, and job-shop scheduling. Complete formulae and details can be found in Bonabeau et al [1999]. The performance of these ant-based optimization algorithms is generally better than conventional algorithms [Bonabeau et al, 1999, p.65, p.70]. Ant-based optimization has been applied to call routing in telecommunication networks [Schonderwoerd et al, 1996].

3.3 Division of Labor in Ant Colonies

In social insect colonies, different activities are performed simultaneously by specialized individuals. However division of labour is rarely rigid. The ratios of workers performing the different tasks that maintain the colony’s viability and reproductive success can vary in response to internal perturbations or external challenges. The resilience of task allocation exhibited at the colony level is connected to the elasticity of individual workers, which represent the ability of individuals to perform tasks other than those that they are generally pre-assigned to do. Factors such as food availability, predation, climatic conditions, phase of colony development, or time of year influence the size and structure of a colony’s worker population in natural conditions. The work force must be allocated to tasks according to changing conditions.

The changes in the pattern of task allocation in an ant colony were experimentally illustrated by Wilson [1984]. The Wilson experiment is illustrated in Figure 3.5. Wilson put together two categories of ants of the same species in a laboratory environment: minor ants (minors) and major ants (majors). Each category of ants started to perform a
task. Minors were searching for and carrying food (task T1) while majors were building a nest and grinding food (task T2). At the beginning of the experiment, the number of minors exceeded that of majors as shown in Figure 3.5a.

In the second part of the experiment, the ratio of minors to majors was altered by removing some minors and increasing the number of majors (Figure 3.5b). The colony reacted quickly to the new environment and some majors went to help the minors in performing T1 (Figure 3.5c). The colony adapted to the new environment imposed by the experimental conditions. T1 consists of providing food to the colony and the colony is threatened anytime food is not provided. The ants have therefore responded to the threat of not having food by using the elastic behaviour of majors with respect to task T1.

![Figure 3.5. The Wilson experiment](image)
Bonabeau et al. [1996] have developed a simple model to explain Wilson's observations. The model assumes that a series of tasks must be performed in order for the colony to thrive and survive. Tasks essential to the survival of the colony demand ants and ants respond to the demands based on their characteristics (age, morphology, caste, sex, etc). The demand of tasks for ants and the ability of ants to react to these demands are characterized by two functions: the stimulus and the threshold functions.

The interpretation of Wilson's observations to explain the adaptive behaviour of ants is shown in Figure 3.6. At the beginning of the experiment, minor and major ants are allocated to T1 and T2 according to their size and this is called specialization. Owing to specialization, major ants will preferentially perform T2 before performing T1.

![Figure 3.6. Interpretation of the Wilson model](image)

In Figure 3.6a, the demand or stimulus of T2 is initially greater than the stimulus of T1 ($s_2 > s_1$). To explain what happened in the Wilson experiment, Bonabeau et al [1996] proposed the concept of threshold $\theta$, a characteristic of an ant's ability to respond to a demand. Thus minors and majors have different thresholds, $\theta_1$ and $\theta_2$ with respect to T1.
and T2. An ant *may* perform a task if the stimulus of that task exceeds the ant’s threshold with respect to that task. The initial state of the system is

\[
\begin{align*}
  s_2 &> s_1 \\
  s_1 &> \theta_1 \\
  s_2 &> \theta_2
\end{align*}
\]

This implies that \( s_2 > \theta_1 \) so that major ants might be attracted to T1. However, due to specialization, the major ants perform T2 before performing T1.

Bonabeau et al [1996] believe that once some minors are removed from the experiment, the stimulus of T1 increases from \( s_1 \) to \( s_1 + \Delta s_1 \) to approach that of T2 \( (s_1 + \Delta s_1 \rightarrow s_2) \) (Figure 3.6b). The reason for this increase is that not performing T1 may threaten the survival of the colony. Thus the stimulus of T1 exceeds the threshold for major ants that begin to perform T1, due to their elasticity with respect to T1.

3.3.1 The Response Threshold Model

The response threshold model is a mathematical model proposed by Bonabeau et al [1996] and is used to describe Wilson’s observations. Let \( s \) be the intensity of stimulus (or demand) associated with a particular task and let \( \theta \) be the threshold of an individual with respect to this task. The probability of this individual responding to a stimulus at any time \( t \) is given by

\[
r(t) = \frac{s^n(t)}{s^n(t) + \theta^n(t)}
\]

(3.1)

The parameter \( n > 1 \) represents the steepness of the threshold. For \( n=2 \) the sensitivity of the response function is shown in Figure 3.7. From this graph it can be seen that for \( \theta \leq s \) the probability of an individual engaging in a task approaches 100% whereas for \( s \leq \theta \) the probability approaches 0.
According to Wilson [Bonabeau et al 1996], an ant engages in task performance if its response value is greater than 50% (the value of the stimulus is greater than the threshold). If its response value is less than 50% (the value of the stimulus is less greater than the threshold), the ant waits or searches for another task that causes a response greater than 50%.

![Response function versus stimulus and threshold](image)

**Figure 3.7.** Response function versus stimulus and threshold.

The threshold model proposed by Bonabeau et al [1996] was based on a fixed threshold and was designed to simulate the specialization observed in the behaviour of social insects. Indeed the simple threshold model assumes that individual insects are differentiated and their roles pre-assigned. However, a fixed threshold cannot account for elasticity of ants with respect to tasks and is valid only over a short period of time.

The simple threshold model was improved by introducing the variable threshold method to refer to the likelihood of reacting to task-associated stimuli [Theraulaz, 1998]. The improved version of the model is based on the fact that performing a given task induces a
decrease in the corresponding individual threshold whereas not performing a task induces an increase in threshold, as observed earlier by Wilson [1994].

Theraulaz et al [1998] extended the model to a situation where multiple tasks need to be performed. The response, the stimulus and the threshold functions are now vectors for each individual insect. Unlike the first model, the threshold is not a fixed parameter regardless of the category of individual selected. Furthermore, the concept of learning and forgetting is introduced to take into account the dynamic, flexible nature of ant-based problem solving abilities.

The division of labor model has been successfully applied to a number of problems. Bonabeau et al [1997] applied it to a mail delivery service. This has revealed how the model can be used to allocate tasks in a multi-agent system in a flexible and robust way. Agassounou et al. [2001] used the threshold model to develop the worker allocation algorithm that allocates workers to tasks whose demand evolves dynamically over time. Some of the characteristics of this algorithm are that it is fully distributed, flexible and efficient. Murciano et al. [1997] have used the threshold model combined with a simple reinforcement learning procedure to achieve specialization in a multi-robot system composed of robots with identical capabilities which do not communicate directly with each other, resulting in a cost saving. Cicirello et al. [2001] introduced a new approach to dynamic shop floor routing based on the method of task allocation in a colony of wasps. Their approach successfully allocates jobs to various machines, constrained by the job mix in factory environments comprised of multipurpose machines and sequence-dependent setups. The required setup time accrued by the system was limited and thus the throughput performance of the system was optimized on a current product demands basis.

3.4 Summary of Self-Organization Models

The foraging and the task allocation behaviour in social insects have inspired researchers to produce successful optimization algorithms in telecommunication, manufacturing and combinatorial optimization problems. The characteristics of these models are that they allow flexibility, they are robust, and they perform better than the existing problem
solving tools. Other industries have successfully developed applications based on these algorithms and therefore an attempt to apply the same approach to mining problems (at least at research level) is encouraging and justified for the following reasons:

- Other fields that have problems similar to the ones encountered in mining operations have successfully applied the self-organization concept of social insects that generated good algorithms [Colorni, 1994; Bullnheimer, 1997; Schonderwoerd, 1996; Bonabeau, 1996]. There is therefore an incentive to begin investigating how algorithms based on social insects can be applied to problems encountered during mining operations.

- The environments in which social insects evolve in are very similar to those of open pit mining operations. Social insects such as ants are constantly dealing with disturbances that threaten their survival and ants have to perform multiple tasks to ensure that their colony thrives. Similarly an open pit mining operation, a multiple-task dispatching system, faces multiple challenges due to constant changing operating environment and constraints. Therefore chances of developing successful tools and acquiring new information on how to understand the complexity of mining operations are greater.

3.5 Ant Colonies and Mining-Mineral Processing Operations – an Analogy

Mining operations consist of tasks that are performed in a very uncertain environment. For the mine to be viable, not only do the resources to perform tasks have to be sufficient but also these tasks have to be performed in an efficient and economic manner. The essential tasks at a mine site consist of:

- Building access roads to the sites
- Mining ore and waste blocks
- Maintaining equipment
- Processing and/or re-handling the materials that have been mined.
Tasks usually performed by ants within their colony in order to guarantee their survival are:

- Foraging
- Grinding
- Feeding the larvae and the queen
- Nest cleaning

Analogies can be drawn between mining and mineral processing operations and division of tasks within an ant colony. As ants adopt a foraging behaviour by swarming for food, grinding food to sustain their colonies, trucks and shovels also swarm to ore blocks that are sent to the mill (grinding and processing). As ants clean their nest by removing dead ants and unwanted items from their nest, in open pit mining operations, maintenance of mining equipment occurs. These analogies are illustrated in Figure 3.8.

![Figure 3.8: Description of the analogies between an ant colony and a mining system](image)

Given these analogies, the behaviour and threshold models described by Wilson [1994] and Bonabeau et al [1996] can be used to build a model for the interactions between an orebody, shovels, trucks, the mill, waste dumps, crushers and the maintenance operations. In particular, the threshold model seems to be applicable to the problem of dispatching trucks to shovels under variable and uncertain conditions.
The proposed dispatch model is shown in Figure 3.9. In this model, parts of the orebody (ore zones or blocks) compete for shovels in order to satisfy production and ore quality requirements set by mine planners. Shovels compete for trucks in order to guarantee that the operational objectives are met. The whole system uses positive feedback where information relative to operational objectives is assessed and sent back to the shovel fleet. To achieve operational objectives, changes may occur in the assignment of shovels to ore blocks or in the assignment of trucks to shovels. Meanwhile, the maintenance section will compete for both trucks and shovels. The next chapter describes the development of this model in detail.

![Figure 3.9. Representation of the ABM dispatch model](image)

The concept of using artificial insects and simulating their behaviour for the purpose of solving an industrial problem is called Agent Based Modeling. An Agent Based Model is composed of agents that compete for resources. In the proposed model, ore blocks are agents that demand for shovels and shovels are resources for ore blocks. Similarly, shovels are agents with respect to trucks and trucks are resources for shovels. Finally
trucks and shovels are resources for the maintenance module that acts as an agent. The model can therefore be classified as an Agent Based Model.
4 FORMULATION OF THE AGENT-BASED TRUCK-SHOVEL DISPATCH MODEL

4.1 The Agent-Based Truck Dispatch Model

Analogies between activities in an ant colony and activities in a typical mining operation were described in Chapter 3. Provided with these analogies, the behaviours adopted by ants within their colony when faced with threats [Wilson, 1984] can be applied to dispatching trucks to shovels in an open pit mining operation. This application is embodied in a model, called the Agent Based Model (ABM), and is shown in Figure 4.1.

![Figure 4.1. Illustration of a simple agent-based dispatch model](image)

The agent-based model shown in Figure 4.1 can be described as follows:

- Based on the long-term plan imposed by the geometry and grade distribution of the orebody, blocks (waste and ore) within the orebody demand shovels at different times and rates.
Once the shovels have been assigned to the blocks, a number of trucks is allocated to each shovel based on the relative importance of the ore or waste blocks. The relative importance of the blocks represents the tonnage that should be mined out of the blocks in order to meet production goals.

Once the trucks are allocated to the shovels they are dispatched in a way that the number of trucks initially allocated to each shovel remains unchanged until upsets occur. At that time the second part of the model, the dispatching algorithm, dispatches or re-dispatches the trucks in order to minimize the impacts of these upsets on the entire system.

During operation, trucks or shovels may break down or be sent to maintenance for scheduled maintenance (Maintenance demands a truck and/or a shovel). Such scenarios may result in a significant decrease in production depending on their frequencies indicating that operational objectives are not met.

When the objectives are met, no changes to the truck-shovel-maintenance interaction occur in the next time step. However if the objectives are not met, the truck-shovel-maintenance interaction module is rearranged in a way to respond to the new environment.

It is common in mining to divide portions of a mine site into ore and waste zones. At the beginning of each shift the quantity of material to be removed from each zone is set by mine planners to meet short-term and long-term requirements. Because of the continuously changing operational conditions, these quantities, although constant on a long-term horizon may change during a shift because of upsets. Mine planners have to decide what the new objectives are to meet short-term plans. They may decide for instance that for a given shift, ore production is more important than waste production (the ore zone has a higher relative importance) or vice versa. The same criteria are applied to ore blocks that are also characterized with a relative importance factor. Either way, one zone (or ore block) may borrow trucks allocated to another until the immediate objectives are met.
In the ABM, demands are characterized by stimulus functions \(s\) and the reaction to demands is characterized by a threshold function \(\theta\) and a response function \(r\) at any given time. Figure 4.1 illustrates the proposed dispatch decision framework for the shovel-truck interaction for two ore zones, one waste zone, three shovels, and five trucks. At any time \(t\), shovels bid on trucks (bid = generate a stimulus – a numerical value). The demand of a shovel \(i\) for a truck \(j\) at time \(t\) is characterized by the stimulus \(s_{ij}(t), 1 \leq i \leq 3, 1 \leq j \leq 5\). The ability of trucks and shovels to respond to a certain demand is characterized by a threshold value, \(\theta_{ij}, 1 \leq i \leq 3, 1 \leq j \leq 5\). Stimuli are defined in order to satisfy the mill and/or dump requirements characterized by the relative importance of material to be sent to the mill and the waste dump in order to meet operational objectives. (This is not the only criterion for stimulus generation – queue length, etc are also involved as discussed in Section 4.3.1) The relative importance is interrelated in such a way that when mining ore is more important than mining waste, the relative importance of the crusher increases and the relative importance of the waste dumps decreases. The opposite is true if mining waste is more important than mining ore.

Scheduled maintenance or maintenance due to random failures, may exercise a stimulus on the shovels and/or the trucks, although recommended for future work. Trucks may also be parked to avoid traffic congestion.

### 4.2 Differences between Social Insect Colony and Mining Operation

A major difference exists between an insect colony and a mining operation. Insects (e.g. ants) are favored by high numbers and high birthrates to deal with their environment. Because of the random nature of their behaviour at the individual level and because of the fact that they communicate indirectly through the deposition of pheromone, their large numbers guarantees their success (survival) through a trial and error process that emerges from these random behaviours. In Wilson’s experiment for instance [Wilson, 1984], some ants became idle as a result of all the tasks being assigned sufficient resources. Furthermore, some ants may never perform any task as they move indefinitely from one task to another.
In mining however, resources are limited and need to be used efficiently. Shovels do not enjoy the flexibility of moving randomly in the orebody because of their size and the costs associated with their relocation. Instead shovels are assigned to ore blocks or zones based on a combination of a long-term and short-term schedule decided in advance by mine planners and remain in these locations until work at these locations is completed or until the planners decide otherwise. Trucks may move randomly and this adds flexibility to mining operations. However, mining operations cannot afford to have idle trucks or trucks that travel from one shovel to the other without performing any haulage task unless major upsets such as breakdowns occur. Therefore, unlike an ant colony, which can tolerate idle ants, each truck must be dispatched to a shovel and should not be re-dispatched to another shovel or parked unless required by operational objectives.

In direct analogy with an insect colony, trucks would seek shovels much like insects forage for food. This analogy could be implemented by having the trucks drop “pheromone” on their way to the “food sources” (the shovels). Eventually, the trucks would assign themselves to shovels in some optimum manner. However, this would not be realistic or efficient. An optimum allocation of trucks to shovels can be done by minimizing transport costs or minimizing queue length at the shovel subject to constraints. This allocation can be formulated as a linear programming problem, as described below.

Despite the differences mentioned previously, the social insect model inspired by the Wilson [1984] experiment with ants and developed by Bonabeau et al [1996] can still be applied to a truck-shovel dispatching system provided that additional intelligence is added to the formulation.

4.3 Initial Truck Assignment Using Linear Programming

The sole purpose of the linear programming algorithm is to start the dispatch algorithm by providing initial conditions to the ABM at the beginning of a shift.
There are many ways to formulate the specific problem depending on the operating and business conditions of a specific mine operation. The one used in this thesis looks to minimize the cost of satisfying both the ore and waste movement over a shift and is formulated as follows:

Minimize \[ z = \sum_{i=1}^{n_o} c_i^o T_i^o + \sum_{j=n_o+1}^{n_o+n_w} c_j^w T_j^w \]  

\[ (4.1) \]

where

- \( n^o \) and \( n^w \) represent, respectively, the number of shovels in ore and waste
- \( T_i^o \) is the tonnage of ore from ore-shovel \( i \) in a shift
- \( T_j^w \) is the tonnage of waste from waste-shovel \( j \) in a shift
- \( c_i^o \) and \( c_j^w \) are respectively the mining costs (\$/ton) for ore-shovel \( i \) and waste shovel \( j \)

In the event that costs are not well known, the objective function needs to be reformulated in another measurable metric. However minimizing costs or maximizing profit is always at the root of these objectives.

At the beginning of a shift, data such as production targets, upper and lower limits of ore quality (or grade), resources available, stripping ratios, and mining layout are provided by mine planners. This information is converted into constraints as described in the following paragraphs.

The constraint given in (4.1a) ensures that the blended material at the crusher satisfies processing requirements.

\[ a \leq \frac{\sum_{i=1}^{n_o} g_i T_i^o}{\sum_{i=1}^{n_o} T_i^o} \leq b \]  

\[ (4.1a) \]
where $g_i$ is the ore quality parameter (e.g., grade) of the material mined by shovel $i$, $a$ is the lower limit of the ore quality parameter, and $b$ is the upper limit of ore quality parameter.

Total ore production is constrained by a minimum production requirement and the capacity of the crusher:

$$MINT^o \leq \sum_{i=1}^{n^*} T_i^o \leq CC$$

where $MINT^o$ is the minimum tonnage required for ore and $CC$ is the capacity of the crusher.

There is a lower bound to total waste production

$$MINT^w \leq \sum_{j=n^*+1}^{n^*+n^w} T_j^w$$

where $MINT^w$ is the minimum tonnage required for waste. The stripping ratio constraint is

$$SR1 \leq \frac{\sum_{j=n^*+1}^{n^*+n^w} T_j^w}{\sum_{i=1}^{n^*} T_i^o} \leq SR2$$

where $SR1$ is the lower limit of the stripping ratio and $SR2$ is the upper limit of the stripping ratio. Constraint (4.1d) ensures that the balance between ore and waste is maintained and the lower and upper limit stripping ratios imposed by the planners are satisfied. In many mines these limits may change during operation if for instance the limit of the crusher is reached forcing a choice between parking some trucks or sending them to waste zone for an aggressive waste removal process that may guarantee access to ore in the future. The opposite may also happen and less waste is moved to manage a production requirement.

Additional constraints for the problem are:

- Trucks assigned must be less than the number of available trucks
The LP formulation presented here is based on a period of time (a shift). This assumes that there is a storage capacity for delivered material. The problem is easily reformulated for operations, like those at Syncrude's oil sands mines where mining and processing are closely coupled and there is no capacity for long-term storage of material, by expressing rates over a shorter time period (e.g., tonnes/hr rather than tonnes/shift).

4.4 Conceptual Approach

The relative suitability of a shovel-truck pairing can be defined as the response value of a truck to a demand from a shovel. The value of this decision-making parameter is a function of the level of demand, the ability of the truck to respond and the status of the truck. This relationship is inspired from the fixed threshold model [Bonabeau et al, 1996] and can be expressed as:

\[ r_{ij}(t) = \frac{[s_i(t)]^n}{[s_i(t)]^n + [\theta_j(t)]^n} \times status_j(t) \quad 1 \leq i \leq N \quad \text{and} \quad 1 \leq j \leq M \quad (4.2) \]

where

- \( s_i(t) \) = demand of shovel \( i \) for trucks
- \( \theta_j(t) \) = ability of truck \( j \) to respond to the demand of shovel \( i \) (expressed in units of stimulus).
- \( N \) = total number of shovels during operation.
- \( M \) = total number of trucks during operation.
- \( n > 1 \) = steepness of the stimulus and threshold.
- \( status_j(t) = \begin{cases} 1 & \text{if truck } j \text{ is empty} \\ 0 & \text{if truck } j \text{ is loaded} \end{cases} \) = load status of truck \( j \).

As discussed in Chapter 3, the fixed threshold model is limited in its application to dispatching systems because it does not allow a truck to be dispatched to another shovel throughout operation and also does not take into account that trucks operating in a mine...
are usually of different sizes. To overcome these limitations the concept of variation of threshold is introduced.

4.4.1 Variation of Threshold Method

The threshold has been defined as the predisposition of a resource to respond to the demand of an agent. The sensitivity analysis conducted on the response function in Chapter 3 (Figure 3.7) showed that the response function is a decreasing function of increasing threshold value. Therefore, favorable truck-shovel pairings will have low thresholds and unfavorable pairings will have high thresholds. Unfortunately, the operating environment is continuously changing and the favorability of truck-shovel pairing is affected by the changing environment. Therefore the threshold needs to be expressed as a function of parameters describing the best the operating environment.

The variation of threshold method occurs in the model in two ways. When a decision is made to dispatch a truck to a shovel the threshold of the truck with respect to that shovel is decreased by a certain value (the reinforcement parameter). This action ensures that the truck, during its trip from the decision point to the shovel, is not easily reassigned to another shovel. In the event that the truck successfully reaches the shovel without being reassigned, its threshold with respect to that shovel is decreased by another value (the previous assignment or learning parameter) so that the truck has better chances of returning to the same shovel at the next decision point unless the operational environment changes.

A truck may be reassigned to another shovel before it reaches its final destination if and only if it is justified to do so and this may be the case if another shovel shows interest in the truck with a rapid increase of its stimulus (or demand for trucks). In this case, the threshold of the truck with respect to the previous shovel is incrementally increased by a certain value (the forgetting parameter) and its threshold with respect to the new shovel incrementally decreased (the assignment to the new shovel is reinforced). This action causes the truck to ignore the decision made at the decision point (dump or crusher).
The reinforcement, learning and forgetting parameters reduce the risks of instability described previously where a truck may be assigned and then reassigned many times. Despite the introduction of these parameters, instabilities may occur if the environment is highly volatile. If this is the case, points of no return (points beyond which a truck cannot be re-assigned) need to be inserted in the haulage circuit.

The threshold of a truck can be expressed as a function of four important factors that influence the response to a shovel:

$$\theta = f(\text{Truck capacity, Distance to shovel, Previous assignment, Road conditions})$$

Threshold as a function of truck capacity
In mine operations, several types of trucks are often used along with several types of shovels. The allocation of small trucks to large shovels is not generally preferred and may occur only when there are no other alternatives. Therefore the threshold should be defined in a way that when there is a mismatch, the magnitude of the threshold increases so that mismatch situations are reduced to a minimum.

Distance to shovel
When an available truck is close to a shovel and the shovel needs a truck, this truck may be a candidate to be dispatched to that shovel. Thus the distance between the shovel and the truck should be taken into account.

Previous assignment
A truck tends to return to a shovel it was previously assigned to as the previous dispatch decision was made under “near” optimum conditions. However, if the demand of another shovel for that truck is significantly higher, the truck may be re-dispatched. However, if the demand of another shovel for that truck is significantly higher, the truck may be re-dispatched.
Road conditions

The road conditions will affect the travel time of a truck and therefore another truck, although far from a shovel, may be preferred.

4.4.2 Dispatching Decisions

In open pit mines, trucks move between shovels, dumps, crushers and maintenance. Normally once a truck is assigned to a shovel, it returns to the same shovel until the dispatcher decides otherwise. In this model however, a truck does not necessarily return to the same shovel. A truck is dispatched to a shovel if that decision would guarantee that the operational goals will be met. The decision to dispatch a truck occurs when it becomes available (at a crusher or a dump). At this time $t$ the response functions $r_{ij}(t)$ are evaluated with respect to each shovel. The truck is awarded to the shovel whose response value is the highest. At that time, the threshold of the truck with respect to that shovel is decremented while the thresholds with respect to the other shovels remain the same. By decrementing the threshold function with respect to the shovel that is awarded the truck, the procedure avoids unstable situations where a truck is dispatched many times without actually being productive. In this condition, a truck may be re-dispatched only if the operating conditions change significantly. This may be caused by sudden changes in ore requirements or breakdowns. The decision to re-dispatch the truck may occur at a second decision point that is general located at an intersection because under normal operation a truck enroute to a shovel is rarely reassigned to another. However, this may occur when shovels breakdown.

Consider a simple scenario where $n$ shovels bid on a truck as shown in Figure 4.2.
At the time of decision, a response vector $r = (r_{ij})$ is computed. Truck $j$ is awarded to shovel $i_0$, such that:

$$r_{ij} = \max_{1 \leq i \leq n}(r_{ij}) \quad \text{or} \quad i_0 = \arg\max_{1 \leq i \leq n}(r_{ij})$$

(4.3)

Once the decision is made to dispatch truck $j$ to shovel $i_0$, the threshold of truck $j$ with respect to shovel $i_0$, $\theta_{i_0}$, is decremented for the remaining of the time until the truck reaches the shovel. The algorithm can be formulated in the following form:

$$\theta_{i_0}(t + \Delta t) = \begin{cases} \theta_{i_0}(t) - \varepsilon_{kj}(t) & \text{if} \quad r_{ij}(t) = \max_{1 \leq i \leq n}(r_{ij}(t)) \\ \theta_{i_0}(t) & \text{otherwise} \end{cases}$$

(4.4)

$\varepsilon_{kj}(t)$ is the reinforcement factor of truck $j$ with respect to shovel $k$ to which it is assigned. However, if truck $j$ is reassigned to another shovel (shovel $l$) during its trip to shovel because operating conditions have changed that made $r_{lj}$ the new maximum value of the response value, the new thresholds are:

\[2^\text{The 50\% rule used in the fixed threshold model to characterize idle and busy ants (refer to chapter 3) is not applicable in truck dispatch systems because trucks are not allowed to be idle during operation.} \]
\[ \begin{align*}
\theta_j(t) &= \theta(t) - \varepsilon_j(t) & \text{if } r_j(t) = \max_{1 \leq i \leq n} r_i(t) \\
\theta_{kj}(t) &= \theta(t) - \varepsilon_{kj}(t) + \gamma_{kj}(t) & \text{otherwise}
\end{align*} \]  

(4.5)

where \( \gamma_{kj}(t) \) is the forgetting parameter. The forgetting parameter increases the threshold value of truck \( j \) with respect to shovel \( k \) and as a result its equivalent response decreases to allow shovel \( l \) to be the successful bidder. All the parameter functions introduced in Equations 4.3 and 4.4 are explicitly defined in the next sections.

The proposed time history of a truck threshold and its corresponding response functions are shown in Figure 4.3. Note that all dispatching decisions are made after a truck has dumped its load.

Figure 4.3 shows that when a truck is traveling from a shovel to a crusher or a waste dump, its response value to the demand of any working shovels is zero, indicating that no decisions can be made about a loaded truck until it is empty. Once the truck becomes available (empty and at a crusher or a dump), it becomes receptive to the demands of working shovels. At a crusher or a dump a decision is made regarding which shovel should be awarded the truck. Once a decision is made, the threshold of the truck with respect to the shovel it is dispatched to decreases (this is the reinforcement) and its threshold with respect to the remaining shovels remain unchanged so that the chances of having other shovels successfully bid on it is reduced. This reduces the chance of instability. Note that shovels keep on bidding on a truck until the truck is assigned. Continuous generation of stimulus guarantees that the status of each item involved in the dispatch decision is updated and takes into account the changing nature of the operational environment.
Even when a truck is assigned to a shovel, the other shovels keep on bidding on it as the truck can be re-assigned anytime if it is justified to do so, between the time it dumps its load and the time it reaches its next destination. This means that if a truck is enroute to a shovel that breaks down, it automatically looks for work elsewhere.

A simulation was conducted for three shovels competing for one truck using a Microsoft EXCEL spreadsheet in order to demonstrate the expected behaviours when applying the variation of threshold method to the dispatch model. In order to avoid any bias in the results, the stimulus of each shovel is chosen randomly (Although in real operations, the variation of the stimulus is less severe). The results of the simulation are shown in Figures 4.4-4.6.

Figure 4.4 is a plot of the stimulus of each shovel, the corresponding thresholds, and the response values of the truck to their demand when the fixed threshold method is applied. At the first decision point (time $t = 10$) the response of the truck to shovel 1 is the highest and it should theoretically be awarded to that shovel. But at time $t = 17$ and 19, the...
response of the truck to the shovels cross over each over so that it becomes unclear which shovel should the truck be awarded to. This is an unstable situation. The same scenario occurs at the next decision point (time \( t = 30 \)) where the response of the truck to shovel 1 is the highest. But at time \( t = 34 \), the response of the truck to shovel 1 and shovel 2 are equal so that it is difficult to decide which shovel should be awarded the truck. Furthermore at time \( t = 38 \), the response of the truck shovel 2 is the highest and theoretically should be dispatched to shovel 2. Thus in the fixed threshold model, a truck faces the risk of being re-dispatched continuously between its dumping and loading point without being productive. The arrows in Figures 4.4, 4.5 and 4.6 show the zones of instability.

Figure 4.4. Simulation results-fixed threshold method
Instability causes a dispatch system to be inefficient. A truck may be re-assigned to another shovel only if the decision to do so is entirely justified and the reassignment should not occur several times.
The simulation results for the model with the variation of threshold model are shown in Figures 4.5 and 4.6. The two graphs show the plot of the thresholds and responses of the truck with respect to the three shovels. Figure 4.5 is a common case in the dispatching where a truck is favored to return to the shovel it came from. In this case, at the time of decision-making (time = 10 units), the truck is awarded to shovel 1 (highest response value).

At the first decision making point (time t = 10) the truck is awarded to shovel 1 and its threshold with respect to the shovel 1 is decremented (by a reinforcement factor) whereas its thresholds with respect to the other shovels remain unchanged. As a consequence, unless a new factor affects the decision (such as urgent need for another shovel due to very high waiting time for instance), the response function of the truck with respect to shovel 1 is the highest. At the next decision point (time t = 30) the truck is re-dispatched.

**Figure 4.5.** Simulation results. Variation of threshold method
to another shovel. The previous assignment may have been a factor in that decision provided that the stimuli of the shovels did not vary much from their previous values.

Figure 4.6 however shows that at the next decision point, the truck can ignore the previous assignment rule.

![Graph](image)

**Figure 4.6.** Simulation results. Variation of threshold method with an upset scenario

At the first decision point (time = 10) the truck is awarded to shovel 3. But it is awarded to shovel 1 at the next decision point (time = 30). New information since the previous decision caused the truck to forget the previous dispatch decision. The plot of the corresponding stimulus shows that at the second decision point, the stimulus of shovel 1 grew very fast to indicate its need for a truck. This is an upset situation, defined as a change of operational environments necessitating readjustment of parameters involved in the dispatching model.
4.5 Stimulus, Threshold and Response Functions

The scenario used for the formulation of the agent-based algorithm consists of trucks of the same capacity, shovels of the same size, one crusher and one dump. A simple scenario is used to facilitate the understanding of the stimulus, threshold and response functions developed. The model will be extended to multiple equipment size and multiple crushers and dumps. The three key functions are:

- The stimulus of a shovel $s_i(t)$
- The threshold value of a truck $\theta_j(t)$
- The response function $r_{ij}(t)$

Although the model proposed in this chapter does not need to identify upsets in order to reduce their impacts on operations, it is instructive to identify the most common ones in a typical mining operation:

- Breakdowns (most common upset in any mine); breakdowns change the availability of resources and therefore the entire operational environment
- Not meeting mill capacity
- Crusher waiting for ore (as a result, ore zones get higher priority)
- Severe weather conditions; may cause a significant decrease in productivity.

4.5.1 Shovel Stimulus

For a particular shovel, the stimulus changes with the following:

- Production rate from the shovel
- Deviation from crusher tonnage requirements
- Queue length
- Number of trucks en route to shovel
- Shovel idle time

The instantaneous sensitivity of the stimulus function of a shovel $i$ can be formulated in general form as follows:
\[ s_i(t + \Delta t, q_i, e_i, d_i, w_i) = s_i(t, q_i, e_i, d_i, w_i) + \left( -k_1 \frac{\partial (q_i + e_i)}{\partial t} + k_2 \frac{\partial d_i}{\partial t} + k_3 \frac{\partial w_i}{\partial t} \right) \Delta t \quad (4.6) \]

where,

- \( d_i \) is the deviation factor of shovel \( i \)
- \( q_i \) is the queue length at shovel \( i \)
- \( e_i \) is the number of trucks en route to shovel \( i \)
- \( w_i \) is the waiting time factor of shovel \( i \)

\( \frac{\partial}{\partial t} \) is the partial derivative operator used here to express rates

\( k_i \) are positive coefficients

Each parameter in equation (4.6) is assumed to be a function of time and also a function of the other parameters. For example by the parameter \( d_i \) is expressed as \( d_i(t, q_i, e_i, w_i) \). If a clear relationship can be established between each variable, it will be possible to solve the differential equation (at least numerically) and the solution will better reflect the stimulus function. In reality however, it is impossible to establish such relationships among the variables. Thus, it is assumed that the parameters in equation (4.6) are only time dependent.

Equation (4.6) leads to the following differential equation:

\[ \frac{\partial s_i}{\partial t} = -k_1 \frac{\partial (q_i(t) + e_i(t))}{\partial t} + k_2 \frac{\partial d_i(t)}{\partial t} + k_3 \frac{\partial w_i(t)}{\partial t} \quad (4.6a) \]

The general solution of this equation is:

\[ s_i(t) = k_2 d_i(t) - k_1 q_i(t) - k_2 e_i(t) + k_3 w_i(t) + K \quad (4.6b) \]

where \( K \) is an integration constant. It may be assumed that the initial stimulus \( s_i(0) = 0 \) and that the remaining parameters in equation (4.6b) are equal to zero. It follows from
these assumptions that \( K = 0 \). For simplicity, \( k_1 = k_3 = 1 \) and \( k_2 = k \). Thus the solution to the differential equation is:

\[
 s_i(t) = kd_i(t) - q_i(t) - e_i(t) + w_i(t)
\]  

(4.6c)

\( k \) is a stabilizing parameter whose sole purpose is to give the deviation the same weight in the function as the remaining variables. The deviation factor is defined as follows:

\[
d_i(t) = \frac{E(T) - T}{c}
\]  

(4.6d)

where,

\( E(T) \) is the expected production rate at the time the deviation is calculated

\( T \) is the actual production rate at the time the deviation is calculated

\( c \) is the capacity of the trucks available during operation (assuming one category of truck)

In the event that different categories of trucks are used, the deviations are divided by the average capacity of the trucks.

The expected production rates are calculated from the initial values provided by the LP algorithm assuming that there is no disruption of the operation. The production rates are divided by the capacity of the trucks to keep consistency in the variables’ unit (number of loads per unit of time). Because the deviation factor is smaller in magnitude than the other active variables, \( k \) is used as a stabilizing parameter to allow the deviation factor to have the same weight as the remaining variables.

The waiting time is converted into the number of loads as follows:

\[
w_i(t) = \frac{\text{shovel waiting time}}{\text{truck travel time}}
\]  

(4.6e)
The function defined in Equation (4.6c) contains all the variables necessary to formulate the stimulus function of a shovel. However in order to avoid dealing with negative values during the simulation, the stimulus of a truck can be redefined as follows:

\[ s_i(t) = \exp[k.d_i(t) - q_i(t) - e_i(t) + w_i(t)] \] (4.6f)

The exponential function, a monotonous function, possesses the same sensitivity as the initial stimulus function (derived from the differential equation) with the advantage that it varies very quickly and is always positive.

The sensitivity of the stimulus function is shown in Figures 4.7, 4.8 and 4.9. Figure 4.7 indicates that the stimulus function increases rapidly with increasing deviation factor (showing that the stimulus react faster to changes observed during operation). As the deviation factor decreases to negative values, the stimulus function decrease to values closer to zero, indicating that trucks are not needed for a certain period. Figure 4.8 shows the behaviour of the stimulus function for smaller deviation factors that could not clearly be seen in Figure 4.7 (the remaining variables are arbitrary chosen). It shows the rapid decrease of the function to zero indicating a quick response guaranteeing better adaptability.

![Graph](image.png)

**Figure 4.7.** Sensitivity of the stimulus function with respect to the deviation factor
Figure 4.8. Illustration of Figure 4.7 for smaller deviation factor

Figure 4.9 shows that the stimulus function decreases rapidly with increasing queue and enroute. In practice this is justified as larger queue length or enroute may indicate that a shovel is well served and may not need more trucks and therefore its demand for trucks should decrease.

Figure 4.9. Sensitivity of the stimulus function with respect to queue and enroute
4.5.2 Illustration of the Deviation Factors

Consider a group of shovels operating in an ore zone as shown in Figure 4.10. Provided with the calculations of the production rates for each shovel assigned to the ore zones, trucks travel between the ore shovels and the dump.

\[ \bar{g} = \frac{\sum_{i=1}^{n} g_i T_i^o}{\sum_{i=1}^{n} T_i^o} \quad \text{and} \quad T^o = \sum_{i=1}^{n} T_i^o \]  \hspace{1cm} (4.7)

\( T_i^o \) represents the actual production of ore from ore shovel \( i \)

These two variables represent the control variables for the dispatching system. The system compares these control variables to the given values,
\[ a \leq g_{\text{actual}} \leq b \]  
\[ MINT^0 \leq T_{\text{actual}} \leq CC \]

The system calculates the actual production vector \((T_i^0)_{1 \leq i \leq n_i}\) and compares it to the expected production vector \([E(T_i^0)]_{1 \leq i \leq n_i}\) (determined by the LP). The deviation factor is therefore defined as follows.

\[ d_i^0 = \frac{E(T_i^0) - T_i^0}{c} \]

where \(c\) is the capacity of the \(i\)th truck (assuming one category of trucks).

In practice, constraint 4.7a is considered satisfied as grade distribution is assumed to be known with some degree of confidence. The stimulus of each ore-shovel is therefore:

\[ s_i^o(t) = \exp[kd_i^o(t) - q_i^o(t) + e_i^o(t) + w_i^o(t)] \]

The variables defined in (4.7d) are similar to those defined in Equation (4.7) except that the superscript in Equation (4.7d) indicates that the material moved is ore. The same definition can be extended to the waste zone.

4.5.3 Maintenance

Maintenance of resources is introduced into the dispatch model in the form of a “maintenance indicator”. The characteristic of the “maintenance indicator” is that it causes the algorithm to ignore all the commands in the code except the command that dispatches the trucks or shovels to maintenance shops in the event of breakdowns. The “maintenance indicator” causes only breakdowns and scheduled maintenance commands to be executed. The model does not predict when breakdowns will occur, but instead deal
with them as they occur. An example of how the “maintenance indicator” is shown in the code below (extracted from the simulation code):

```
begin camion:crusher task search procedure
if V_maintenance = 0
begin
    dispatch this vehicle to camion:Wshovel
    print this vehicle " is going to Ore from crusher" to message
    increment C_Wshovel_queue by 1
    increment V_Wshovel_queue by 1
end
else if V_maintenance = 1 then
begin
    dispatch this vehicle to camion:maintenance_shop
    increment V_maintenance_queue by 1
end
end
```

In this code, the algorithm dispatches a truck to a waste shovel when its “maintenance indicator” is zero. When its maintenance indicator is one, the truck is dispatched to the maintenance shop.

### 4.5.4 Crossing from an Ore Zone to a Waste Zone

At the initial phase of operation, shovels and trucks are assigned to a specific zone (ore or waste) until operation in that zone is achieved. However in the event of major upsets that may cripple the operational objectives, these standings may change. A truck may cross from a waste zone to an ore zone if the fleet of trucks initially assigned to the ore zone suffers repeated breakdowns preventing the operational objectives to be met and if these operational objectives put the production of ore material at a higher priority or relative importance.
In the agent-based model a truck crossing from one zone to another zone is achieved by “borrowing” trucks from one zone to replace the inoperative trucks in the other zone. The algorithm below (from the simulation model) shows how the “cross over” is achieved for an ore zone:

\[
\text{if } V_{\text{total deviation}} > \text{const. Then} \begin{align*}
& \text{begin} \\
& \text{set } V_{\text{cross}} = 1 \\
& \text{increment } V_{\text{cross}} \text{ by 1} \\
& \text{set } V_{\text{cross}} = 0 \\
& \text{Call break\_procedure} \\
& \text{end} \\
& \text{begin camion:dump task search procedure} \\
& \text{if } V_{\text{cross}} = 1 \text{ then dispatch this vehicle to camion:Junction} \\
& \text{else dispatch this vehicle to camion:normal} \\
& \text{end}
\]

In this algorithm, $V_{\text{total deviation}}$ is the variable deviation factor of the total ore production. The algorithm suggests that when the deviation is greater than a certain value (const.) set by the planners and usually determined empirically, the “cross over indicator” variable is set to one and a truck that arrives at the dump is dispatched to a junction point between the two zones and later dispatched to a shovel in the ore zone. The “break\_procedure” is a programming language procedure that allows the code to break the algorithm so that trucks cross over to the other zone only if needed to avoid having too many trucks in one zone creating therefore the risk of congestion.

4.5.5 Outlets or parking areas

If it is important to keep all the equipment active during operation, it is also very important to use them in an efficient manner. Sometimes, it is worth parking a truck rather than keeping it active. In the event for instance that a waste-shovel or ore-shovel breaks down during operation, what should be done with the trucks that were supposed to go to that shovel? Assigning these trucks to other shovels is an option and parking them
or sending them to early maintenance is another viable option. Trucks may be parked because of the congestion they may create if they are left in the haulage circuit. However, the problem is to balance the need to park a truck and the need to keep it busy to satisfy truck usage parameters such as efficiency.

In the ABM, when a shovel breaks down its trucks are either sent to early maintenance (if possible), to other shovels or simply parked. These three options are called “outlets” In the event that early maintenance is not an option, the trucks are distributed to the remaining shovels if needed or parked. The approach used in this model is to dispatch the trucks to zones that suffered breakdowns as replacements. The maintained trucks once ready to resume operation are sent to the shovel that was initially down (if it resumed operation) or parked.

4.5.6 Threshold

For a given truck, the threshold changes with the following parameters:

- Previous assignment
- Distance to a shovel
- Capacity
- Road condition

Similar approaches used to derive the stimulus function (Equation 4.6) is used to derive threshold function and its time dependence of the threshold function can be formulated as follows:

\[
\theta_{ij}(t + \Delta t) = \theta_{ij}(t) + \left[ \frac{\partial}{\partial t} (\gamma_{ij}(t) - p_{ij}(t) - e_{ij}(t)) \right] \Delta t
\]

(4.8)

where,

- \( p_{ij}(t) \) is the previous assignment status factor of truck \( j \) with respect to shovel \( i \)
- \( e_{ij}(t) \) is the reinforcement or learning factor
- \( \gamma_{ij}^0(t) \) is the forgetting factor
\[ p_{ij}(t) = \begin{cases} 
1 & \text{if truck } j \text{ was previously assigned to shovel } i \\
0 & \text{otherwise} 
\end{cases} \]

\[ \varepsilon_{ij}(t) = \begin{cases} 
\frac{d_{ij}(t)}{d_i} & \text{if truck } j \text{ is assigned to shovel } i \text{ at the time of decision} \\
0 & \text{otherwise} 
\end{cases} \]

\[ \gamma_{ij}(t) = \begin{cases} 
0 & \text{if truck } j \text{ is assigned to shovel } i \\
\frac{d_{ij}(t)}{d_i} & \text{otherwise} 
\end{cases} \]

\( d_{ij}(t) \) is the distance between truck \( j \) and shovel \( i \) as a function of the time.

\( d_i \) is the fixed distance between shovel \( i \) and the crusher.

\( \alpha \) is the road condition factor \((0 \leq \alpha \leq 1)\), with 1 considered as the best road condition.

Equation 4.8 leads to the following differential equation for the threshold function:

\[
\frac{\partial \theta_{ij}(t)}{\partial t} = \frac{\partial}{\partial t} \left[ \gamma_{ij}(t) - p_{ij}(t) - \varepsilon_{ij}(t) \right] \tag{4.8a}
\]

The general solution of this equation is:

\[
\theta_{ij}(t) = -p_{ij}(t) + \gamma_{ij}(t) - \varepsilon_{ij}(t) + K
\]

where \( K \) is an integration constant. At the time of decision making, the threshold is equal to the matching parameter of the truck with respect to the shovel and \( K \) could be defined as follows:

\[
K = \frac{c_i^j}{c_i^i}
\]

where \( c_i^j \) is the bucket capacity of the shovel \( i \) and \( c_i^j \) is the capacity of truck \( j \). The matching parameter gives better chances of trucks being paired with "right" shovels with respect to the concept of truck/shovel matching factor.
The threshold function is finally formulated as follows:

\[ \theta_{ij}(t) = -p_{ij}(t) + \gamma_{ij}(t) - \varepsilon_{ij}(t) + \frac{c_x^i}{c_i^j} \quad (4.8b) \]

As for the stimulus function, the threshold function can be replaced with the following formula:

\[ \theta_j(t) = \exp \left[ -p_j(t) + \gamma_j(t) - \varepsilon_j(t) + \frac{c_x^j}{c_j^i} \right] \quad (4.8c) \]

This reformulation ensures that the threshold is dimensionless similar to the stimulus and that it remains positive throughout a simulation.

Figure 4.11 shows the threshold functions for two trucks that a shovel is trying to acquire. One truck is successfully assigned to the shovel. The two functions are different in that the one for the assigned truck is learning with time (decreasing threshold) whereas the other is forgetting about the shovel to allow other shovels to compete for it.

![Graph](image)

**Figure 4.11.** Threshold function for two different trucks

Figure 4.12 shows how the road condition factor \( \alpha \) affects the threshold function and therefore the decision-making process. Better road conditions (higher values of \( \alpha \))
increase the ability of a truck to respond to a shovel infers lower threshold values and therefore better responses.

Figure 4.12. Sensitivity of the threshold function with respect to road conditions

4.5.7 The Response Function

The response function is formulated as follows:

\[ r_j(t) = status_j \times \frac{s_i(t)^2}{s_i(t)^2 + \theta_j(t)^2} \]  \hspace{1cm} (4.9)

where

- \( s_i(t) \) is the stimulus or demand of shovel \( i \) at time \( t \)
- \( \theta_j(t) \) is the threshold of truck \( j \) with respect to shovel \( i \) at time \( t \)
- \( status_j \) is the load status of truck \( j \) at time \( t \)

\[ status_j = \begin{cases} 
1 & \text{if truck } j \text{ is empty} \\
0 & \text{if truck } j \text{ is loaded} 
\end{cases} \]
The response function ensures that dispatch decisions are made only on loaded trucks and that in order for trucks to be dispatched to a shovel, not only that shovel should have a high stimulus to show that it is interested in getting a truck but also the truck should first show its availability to respond to that shovel and this ability is summarized in its threshold.

### 4.6 Multiple Crushers and Dumps

The multiple crushers and dumps scenario is illustrated in Figure 4.12. The difference between the single dump and crusher and the multiple crushers and dumps scenario lies in the number of routes available for each truck to dump its load. Trucks will be sent to crushers or dumps where they can dump their loads quickly and return and therefore dumps and crushers’ characteristics such as distance and queue length will certainly influence the decisions to be made. Similarly to the single crusher and dump case, the queue length at a crusher or dump will have an influence on the stimulus of a shovel. Thus, like the threshold function of a truck is defined with respect to a shovel, the stimulus of a shovel is defined with respect to a dump or a crusher.

In the multiple crushers and dumps scenario, the crushers and dumps become agents that bid for loaded trucks. A loaded truck when leaving a shovel should choose a crusher or dump for its next destination which should reflect “optimum conditions” of the entire operation. Thus, the concept of demand or stimulus of crushers and dumps is introduced similarly to that of shovels. The decision to dispatch a loaded truck to a crusher or a dump occurs exactly after the last shovel’s pass. The loaded truck responds to a crusher or a dump based on its demand or stimulus and its distance to the crusher or dump (representing its threshold). In Figure 4.12 for example, three ore-shovels are mining ore that can be sent either to crusher1 or crusher2. The loaded trucks move into point B, which represents the junction between the paths from the three shovels and the decision point in the process. Once at point B, a truck chooses to go to a crusher provided that such decision meets operational requirements and objectives such as shorter queue, capacity problems, maintenance situation or blending. The ideal situation is for a truck to dump as quickly as possible its load and return to active status (hauling material).
4.6.1 Stimulus function for a crusher

The stimulus of a crusher (in the multiple crusher case) will primarily be based on the queue length at that crusher level and the distance of a truck to that shovel as the goal of introducing this part of the model is to stimulate the trucks to choose crushers that allow them to dump quickly and return to a shovel.

The stimulus for a crusher can be formulated as follows:

\[ S^c_i(t) = e^{-q^c_i(t) + d^c_i(t)} \]  (4.10)

**Figure 4.12.** Illustration of the multiple crushers and dumps scenario
where $q_i^c$ is the queue at crusher $i$ and $d_i^c$ is the deviation factor from the expected target at crusher $i$

$$d_i^c = \frac{E(T_i^c) - T_i^c}{c}$$

where,

$E(T_i^c) = $ expected tonnage received by crusher $i$ (rate)

$T_i^c = $ actual tonnage received by crusher $i$

$c = $ average capacity of trucks

Equation (4.10) indicates that the demand of a crusher increases with the crusher’s rate and its positive deviation factor but decreases with increasing queue length and its negative deviation factor. A negative deviation factor indicates that the crusher is receiving more material than projected at the time of decision-making but a positive deviation factor indicates the need to send more trucks to the crusher.

4.6.2 Threshold of a truck with respect to a crusher

The demand of a crusher for a truck is not the only element considered in the decision to send a loaded truck to it. The distance of the truck to a crusher and road conditions are equally important as a given crusher may have a greater demand than another crusher but based on its distance to the truck or the road conditions, the truck may be awarded to this other crusher. The threshold of a truck with respect to a crusher may be defined as follows:

$$\theta_i^c(t) = \exp\left[\alpha \frac{l_{ij}^c}{l_i^c}\right]$$

(4.11)

where,

$l_{ij}^c$ is the distance between crusher $i$ and truck $j$ at the time of decision

$l_i^c$ is the fixed distance between the shovel where the truck came from and crusher
No reinforcement or forgetting factors are need for the threshold of a truck with respect to a crusher because a loaded truck does not enjoy the flexibilities of movement an empty truck have. Once loaded and a decision to dump is made, the truck travels to that location and dumps its load.

4.6.3 Response Function of a Truck With Respect to a Crusher

The response function of truck to a crusher is formulated like the one with respect to a shovel.

\[ r_j^c(t) = status_j^c \times \frac{[S_j^c(t)]^2}{[S_j^c(t)]^2 + [\theta_j^c(t)]^2} \]  \hspace{1cm} (4.12)

where

- \( S_j^c(t) \) is the stimulus or demand of crusher \( i \)
- \( \theta_j^c(t) \) is the threshold of truck \( j \) with respect to crusher \( i \)
- \( status_j^c \) is the status (loaded or empty) of truck \( j \) with respect to crushers’ demand

\[ status_j^c = \begin{cases} 
0 & \text{if truck } j \text{ is empty} \\
1 & \text{if truck } j \text{ is loaded} 
\end{cases} \]

The same remarks made for the response function with respect to the demands of shovels remain valid for the response function with respect to the demands of the crushers. The only difference is that crushers compete for loaded trucks unlike shovels that compete for empty trucks.

The stimulus and threshold functions for dumps and waste zones are formulated in a manner similar to the case of crushers and ore zone.
5 SIMULATION, RESULTS AND DISCUSSION

Simulation is defined as the imitation of a real-world process or system over time [Banks, 1998]. It involves the generation of an artificial history of the system and the use of that artificial history to draw inferences concerning the operating characteristics of the real system being represented. Simulation is often used to describe and analyze the behaviour of a system, ask “what if” questions about the real system, and to aid in the design of real systems. Both existing and conceptual systems can be simulated.

In this chapter the simulation program AUTOMOD® is used to simulate mining scenarios. The first scenario, called the Z-model, is a simple mining configuration used to test dispatch systems at Wenco International Mining Systems Ltd. The second scenario, the Two Zones model, represents part of the mining operation at SYNCRUDE. The simulation is used to test the ABM dispatch strategy. The results of the simulation and a comparison to a traditional FAM strategy are presented in this chapter.

5.1 Description of the AUTOMOD Simulation Program

AUTOMOD® can simulate discrete events and continuous models in a dynamic environment. The simulation environment within AUTOMOD® is controlled by entities, representing objects that require explicit definitions. Changing the status of one these entities will change the outcome of a simulation. An entity can be dynamic (moves through the system) or static (serves other entities). The following are entities found in the AUTOMOD® environment:

- Loads - represent the dynamic entities of any systems.
- Queues – are placed where loads reside physically and graphically and are static
- Resources – represent entities that provide service for other entities (can be static or dynamic)
- Activities – represent a period of time that is known prior to the commencement of an event.
AUTOMOD® offers two types of environments: a default environment that consists of using the default status and attributes and a user-defined environment controlled by a programming window that allows the user to define his/her own environment. The programming language used in the user-defined environment is a mix C++, Quick Basic and FORTRAN language. The attributes of the entities can be either defined by the user directly in the program or set in windows provided. The user defined environment can be somewhat unstable when one is interested in knowing when events occur with accuracy as user-defined functions and calculations may change the operating environment.

AUTOMOD® can perform many functions such as statistical analysis of results or optimization of systems. The results of an AUTOMOD® simulation model are dumped into files that can be imported to other spreadsheet programs such as MS-EXCEL or to plotting programs.

In this thesis, the AUTOMOD® environment has been deactivated and loads and entities were controlled by the computer program available in the software. The threshold and stimulus functions were defined as C++ functions. The activities of trucks at the shovels were defined in a combination of modules and subroutines.

Production rates are sampled every 30 minutes and (queue + enroute) sampled every six minutes. The duration of each simulation is 12 hours. Two maintenance shops (one shop near the dump and another near the crusher), where trucks can exit the haulage circuit, are incorporated in the simulation model.

5.2 Description of the Problems Used

Two models with different configuration were used in this research and detailed explanations about these models are provided in Appendix A.
5.2.1 The Z-Model

The Z-model, proposed during a brainstorming session with researchers at Wenco International Mining Systems LTD, was used as a calibration model for the simulations. The objective was to test the new dispatch model against a well-known and simple problem prior to modeling more complex systems. The model is shown in Figure 5.1. The model consists of two shovels, one mining ore and one waste, a crusher and a waste dump. Ore is hauled from ore-shovel to the crusher and waste from the waste shovel to the dump.

![Figure 5.1. The Z-model](image-url)
The following parameters are used in the simulation for the Z-model:

<table>
<thead>
<tr>
<th>Truck Speed (km/hr)</th>
<th>Capacity (tons)</th>
<th>Loading Time (sec)</th>
<th>Emptying Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loaded: 20</td>
<td>240</td>
<td>120</td>
<td>40</td>
</tr>
<tr>
<td>Empty: 25</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The travel, loading and dumping times are displayed in parentheses in Figure 5.1. During a brainstorming session with Wenco International Mining Systems Ltd., it was proposed that trucks are dispatched on the circuit using the “minimize shovel waiting time criteria”.

A single truck travels to the ore-shovel, loads and then travels to the crusher where it dumps its load then travels to the waste-shovel to load waste to be transported to the dump. The truck has then completed a cycle. Provided with the durations given in parentheses in Figure 5.1, the total cycle time will take 19.73 minutes.

**Calculation of the optimum number of trucks**

The best number of trucks to allocate to the Z-model is computed as follows. If the shovel loading time is 2 minutes and the truck capacity is 240 tons, then the maximum number of tons per hour that the shovel can move is \( P_{\text{max}} = \frac{60}{2} \times 240 = 7200 \) tons/hour.

The cycle time for the Z model is 19.73 minutes so that the maximum number of tons per hour that a truck can move is \( R_{\text{max}} = \frac{60}{19.73} \times 240 = 729.9 \) tons/hour. The nominal number of trucks is therefore \( n = \left\lfloor \frac{P_{\text{max}}}{R_{\text{max}}} \right\rfloor = 9 \) where \( \lfloor \cdot \rfloor \) denotes the integer part of the argument. However, given the relative capital costs of trucks and shovels, it is usually desirable to have trucks waiting to be loaded rather than shovels waiting to load. The best number of trucks is therefore given as the minimum number \( n \) such that \( n \times R_{\text{max}} \geq P_{\text{max}} \).

---

3 In AUTOMOD one can model only a one way road and therefore, a two way road is modeled using two “one way roads”. As a result, the distances between traveling to and away a shovel may be different. This does not however change the goal of the simulation as it consists in comparing two strategies in the same system.
With this condition, a queue will form at a shovel. The best number of trucks for the Z-model is \( n = 10 \).

5.2.2 The Two-Zone Model

The Two Zone problem is based on operations similar to that practiced at Syncrude Canada Ltd. The problem consists of four shovels, a crusher and a dump. Two shovels are located in ore zone and the two in waste zone. At the beginning of a shift, the production target for each zone is determined by mine planners. The production targets are set to satisfy operational objectives and constraints. An LP problem (discussed in detail in Appendix A) is solved to determine what quantity of material each shovel should produce in order to meet operational requirements and objectives. The production targets and haul distances are used to determine the number of trucks allocated to each ore zone. The configuration of the operation is described in Figure 5.2 along with the travel times, loading and dumping times shown in parentheses. The travel times when trucks are load are represented in bold.

Each shovel is allocated a certain number of trucks so that the operational constraints and objectives are met at the end of the shift. In the Fixed Assignment Method (FAM) for dispatching trucks to shovels, each truck remains with the shovel it was initially allocated to until the end of a shift or until the dispatcher decides to re-allocate it\(^4\). In the Agent Base Model (ABM) a truck does not necessarily return to a shovel it was initially allocated but is instead dispatched to the other shovel if that is required by the ABM algorithm.

---

\(^4\) The scenario proposed in the Z-Model where trucks maintain a fixed route (ore shovel-crusher-waste shovel-dump-ore shovel) is also termed “Fixed Assignment Method” for further reference in the discussions that follow.
The following parameters are used in the simulation for the Two Zone Model:

<table>
<thead>
<tr>
<th>Truck Speed (km/hr)</th>
<th>Capacity (tons)</th>
<th>Loading Time (sec)</th>
<th>Emptying Time (sec)</th>
<th>Strip Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loaded: 20</td>
<td>240</td>
<td>120</td>
<td>60</td>
<td>0.7 ≤ strip ratio ≤ 1.2</td>
</tr>
<tr>
<td>Empty: 25</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 5.2. The Two Zone problem

The cycle times and the solutions of the LP problem are presented in Table 5.1 and these parameters are used to determine the optimum number of trucks needed in each zone for each shovel.
Table 5.1. Parameters of the Two Zone Model

<table>
<thead>
<tr>
<th></th>
<th>Cycle time $T_c$ (minutes)</th>
<th>Optimum production rates $P_{opt}$ (tons/hr)</th>
<th>Nominal number of trucks</th>
<th>Best number of trucks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ore shovel1</td>
<td>12</td>
<td>5714.3</td>
<td>$[5714.3/1200] = 4$</td>
<td>5</td>
</tr>
<tr>
<td>Ore shovel2</td>
<td>12.56</td>
<td>5714.3</td>
<td>$[5714.3/1146.5] = 4$</td>
<td>5</td>
</tr>
<tr>
<td>Waste shovel1</td>
<td>12.34</td>
<td>6765.7</td>
<td>$[6765.7/1166.9] = 5$</td>
<td>6</td>
</tr>
<tr>
<td>Waste shovel2</td>
<td>12.5</td>
<td>5805.7</td>
<td>$[5805.7/1152.0] = 5$</td>
<td>5</td>
</tr>
</tbody>
</table>

The best number of trucks to allocate to each shovel in the Two-Zone model is computed as follows. The maximum number of tons per hour that a truck can move is $R_{\text{max}} = 60/T_c \times 240$, where $T_c$ is the cycle time for a truck assigned to a shovel. Given the optimum production rates, $P_{opt}$, for each shovel from the LP model, the nominal number of trucks to assign to each shovel is $n = \lceil P_{opt} / R_{\text{max}} \rceil$ where $\lceil \cdot \rceil$ denotes the integer part of the argument. However, given the relative capital costs of trucks and shovels, it is usually desirable to have trucks waiting to be loaded rather than shovels waiting to load. The best number of trucks is therefore usually given as the minimum number $n$ such that $n \times R_{\text{max}} \geq P_{opt}$. The best number of trucks for each shovel is shown in Table 5.1. The total number of trucks in the system is 21.

5.3 Scope of the Simulation

This simulation is a discrete deterministic event simulation. All speeds, loading times and dump times are known and invariant. However, any occurrence that causes a time delay is interpreted as an “upset” by the model. Time delays are caused by 1) collision avoidance, wherein if two trucks reach the intersection, one will be slowed down to avoid a collision; and 2) truck breakdowns.

In the Z model the ABM dispatch can send a truck back to the shovel rather than continuing through the cycle (ore_shovel-crusher-waste_shovel-dump-ore_shovel) if that

75
improves performance. One truck was also allowed to start at the waste shovel at the beginning of the simulation because of the requirement of the AUTOMOD software.

In the Two Zone Model, neither dispatch strategy can dispatch trucks across zone boundaries so that ore trucks cannot be used in the waste zone. This is a departure from the ant colony task allocation analogy, but is done to reduce the scope of the simulation. However trucks can be assigned to any one of two shovels located in the same zone.

In both models the only dispatch point is when the truck has finished dumping.

5.4 Simulation Results

The purpose of the simulation is to compare the ABM and FAM dispatch strategies in the presence of truck breakdowns. The following convention is used in the figures in this chapter, arrows pointing upward represent the breakdowns of trucks and a dashed arrows pointing downward represents the returns of trucks after maintenance.

5.4.1 Simulation Results for the Z-Model

Simulations were performed on the Z-model for no truck breakdowns, two and four truck breakdowns to compare the performance of the ABM with the FAM. The no upset and four upset scenarios are presented in detail in the next sections.

Z-model with no upset

Data obtained from the simulation, presented in Table 5.2, indicates that in the no upset situation, the ABM DISPATCH performs slightly better than the FAM DISPATCH. The total production (ore + waste) from the ABM DISPATCH is 166,080 tons whereas it is 164,640 tons for the FAM DISPATCH. This is increase in production of 1,440 tons, corresponding to 6 truckloads. The production rates of both systems are shown in Figure 5.3.

---

5 In AUTOMOD, a load has to be physically present in a process for calculations to take place.
Table 5.2. Production of ore and waste, Z-model, no upsets

<table>
<thead>
<tr>
<th></th>
<th>FAM DISPATCH</th>
<th>ABM DISPATCH</th>
<th>FAM – ABM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ore production (tons)</td>
<td>82800</td>
<td>83040</td>
<td>-240</td>
</tr>
<tr>
<td>Waste production (tons)</td>
<td>81840</td>
<td>83040</td>
<td>-1200</td>
</tr>
</tbody>
</table>

The variations (the graphs are not smooth) observed in the production rates in Figure 5.3 are not the results of upsets (trucks breakdowns) but they are due to blocks (a procedure written in AUTOMOD to slow down trucks) placed at the intersections in order to avoid trucks colliding with one another. The blocks cause the trucks to slow down as they approach the intersections creating a variation of speed and therefore of travel times. Trucks slowing down may later create longer queue at shovels.

![Z-Model, no upset](image)

**Production rate of shovels for the ABM strategy**

![Production rates of shovels for the FAM](image)

**Production rates of shovels for the FAM**

**Figure 5.3.** Production rates for FAM DISPATCH, Z-Model with no upsets
In theory, the production for both ore and waste should be the same. However in the simulations the production from both shovels may be different because the simulation may stop just before trucks reach the next shovel.

The activities of trucks at shovels are shown in Figure 5.4 after four hours of simulation. The comparison of these activities indicates that the dispatching strategies of both systems are different throughout the simulation.

The gain in production observed for the ABM DISPATCH is due to two main reasons:

- Figure 5.5 (an expanded version of Figure 5.4) shows that the sum of the queue and enroute for the FAM DISPATCH is on average equal to nine trucks and occasionally 10 whereas the same sum taken sampled at the same time is on average between eight and nine trucks for the ABM DISPATCH. This means that after slowing down, trucks may arrive almost at the same time at a shovel generating longer queue for the FAM DISPATCH. The ABM DISPATCH recognizes the queue and because shovels compete for trucks based on their stimulus (a decreasing function of increasing queue and enroute), trucks are distributed evenly between shovels. Unlike the activities of trucks for the FAM DISPATCH where the distribution of trucks among the shovels becomes even after a longer period, the ABM DISPATCH tries to distribute the trucks evenly at the beginning of the simulation.

- Since theoretically the amount of ore and waste should be equal and because the stimulus is a function of the deviation factor, ABM DISPATCH tries to ensure that at the end of the simulation this condition is satisfied.
Figure 5.4. Queue + enroute, Z-Model with no upset

Figure 5.5. Queue + enroute, Z-Model with no upset (expanded)
Validation of the Z-model

With a loading time of two minutes, it is determined that the maximum number of trucks a shovel can load per hour is 30. This is equivalent to a maximum 86,400 tons of material that each shovel can remove over a 12-hour shift (or 172,800 tons in total). With 10 trucks in the fleet, it is determined that all the trucks will be moving a total of 87264 tons of material from each shovel and therefore a total of 174,528 tons of material.

The simulation for the scenario where no breakdown occurs shows that the total production for the ore shovel is 83,040 tons for the ABM DISPATCH and 82,800 tons for the FAM DISPATCH which is less than the maximum production by almost 3,500 tons. The fact that the total production from the simulation is less than the maximum total production is expected and is largely attributed to the initial conditions of the simulations where trucks wait in line before starting to load whereas the calculations for the maximum production assume steady state. Furthermore the difference in production between the ABM DISPATCH and the FAM DISPATCH is due to the variation of travel times mentioned for the simulation at intersections causing one of the shovels to be waiting longer and the other being serviced with a longer queue. The actual configuration, copied from an interface of the simulation, of the Z-model is shown in Figure 5.6.

Figure 5.6. Actual configuration of the Z-Model
The actual configuration also shows that there are more intersections in the ABM DISPATCH than in the FAM DISPATCH and that explain why there is more variability in the production rates of ABM DISPATCH than that of the FAM DISPATCH.

If the objective of this simulation was to meet a production requirement, more than 10 trucks may have been needed, but again there is a need to balance shovel wait time and truck wait time as these two parameters vary in opposing directions.

**Z-Model with four upsets**

Four trucks are taken out of operation and sent to maintenance, two at the time at respectively time $t = 2$ hours and 3 hours. In order to ensure that the way trucks breakdown is unbiased, two trucks are taken down respectively after leaving the crusher and after leaving the waste dump. The production of ore and waste for both systems is presented in Table 5.3.

<table>
<thead>
<tr>
<th></th>
<th>FAM DISPATCH</th>
<th>ABM DISPATCH</th>
<th>FAM-ABM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ore production (tons)</td>
<td>76800</td>
<td>77520</td>
<td>- 720</td>
</tr>
<tr>
<td>Waste production (tons)</td>
<td>75840</td>
<td>77040</td>
<td>- 1200</td>
</tr>
</tbody>
</table>

The total production is 152,640 tons from the FAM DISPATCH and 154,560 tons from the ABM DISPATCH. The ABM DISPATCH has produced 1,920 tons more than the FAM DISPATCH, corresponding to eight trucks (240 tons). The production rates of both systems are compared in Figure 5.7 where the gain of ABM DISPATCH over FAM DISPATCH is shown.

Figure 5.8 shows the behaviour of the production rates of both systems. The variability in the case of the ABM DISPATCH appears less frequently but last a little longer. The recovery after the upsets occur seems to be longer because trucks are shared equally between both shovels.
Figure 5.7. Comparative production rates, Z-model – four upsets

Figure 5.8. Production rates, Z-model – four upsets
Table 5.3 shows that the difference in production between ore and waste shovels is 480 tons for the ABM DISPATCH and 960 tons for the FAM DISPATCH. These differences are attributed to the fact that the simulation ends before trucks reach shovels. However it important to point the fact that unlike the FAM DISPATCH which configuration was designed to achieve the same production for both shovels, the ABM DISPATCH with a different configuration has managed to satisfy this constraint despite being subjected to more intersections and therefore more travel time variations.

The activities of trucks at shovels when the trucks breakdown and when they return from maintenance are shown in Figures 5.9 and 5.10.

![Graph](image)

**Figure 5.9.** Queue + enroute, Z-model- four upsets (trucks leaving for maintenance)

The pattern of the activities of trucks before the trucks breakdown, shown in Figure 5.9, indicates that the dispatching strategies used by both systems are different. When the first two trucks broke down at time $t = 2$ hours, the sum of the queue and enroute in both
systems decreased. However the distribution of trucks to shovels was more even in the ABM DISPATCH than in the FAM DISPATCH. Figure 5.10 shows the dispatching patterns after the trucks have returned from maintenance.

Figure 5.10 shows that after the trucks have returned from maintenance, the ABM DISPATCH always attempted to keep a balanced distribution of trucks among shovels. The pattern of the dispatching strategies in both systems resumed to that of the no upsets situation after all the trucks have returned.

Figure 5.11 shows an expanded version of the queue and enroute for both systems between t = 3 hours and t = 4.5 hours. The purpose of this graph is to detail the behaviour of the truck activities patterns after four trucks broke down. Figure 5.11 emphasizes the difference in dispatching strategies. Shovel waiting time (queue + enroute = 0) for the
FAM DISPATCH is longer than that of the ABM DISPATCH. The distribution of trucks in the ABM DISPATCH remains balanced because of the constraint imposed by the configuration of the Z-model (production of waste = production of ore). Also the fact that the sum of queue and enroute equals five does not mean that trucks are either queued or traveling but is instead due to a coordination between the simulation time and the time the data are sampled. In our case for example, the queue and enroute are sample every 6 minutes and therefore a truck has enough time to travel from one point to the other, as the average travel time is 5 minutes.

![Z-Model, queue + enroute - four upsets](image)

**Figure 5.11.** Queue + enroute, Z-Model – four upsets (expanded version)

The results for the simulation of the Z-Model in the event of two upsets are shown in Table 5.4 and the graphs are available in Appendix B.

**Table 5.4.** Production of ore and waste, Z-model, two upsets

<table>
<thead>
<tr>
<th></th>
<th>FAM DISPATCH</th>
<th>ABM DISPATCH</th>
<th>FAM - ABM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ore production (tons)</td>
<td>80640</td>
<td>81120</td>
<td>-480</td>
</tr>
<tr>
<td>Waste production (tons)</td>
<td>79680</td>
<td>81120</td>
<td>-1440</td>
</tr>
</tbody>
</table>
The total production is 160,320 tons from the FAM DISPATCH and 162,240 tons from the ABM DISPATCH. The ABM DISPATCH has produced 1,920 tons more than the FAM DISPATCH, corresponding to five trucks. Table 5.4 shows that the production of ore and waste are equal in the ABM DISPATCH whereas in the FAM DISPATCH, this criterion is not maintained.

The ABM DISPATCH has foreseen the risk of having longer queues caused by the variation of travel times and has therefore reacted to even the distribution of trucks by reducing the queue length at the shovels and therefore increasing the overall productivity.

The simulations performed on the Z-Model for both systems suggest that the ABM DISPATCH outperformed the FAM DISPATCH most of the time. The Z-Model is not a realistic model as far as mining operations are concerned. In most mine operations, the current practices impose a certain number of trucks to be assigned to a shovel or group of shovels until the end of a shift. The production for both ore and waste may not necessarily be the same. In the next section, the more realistic Two Zone model is simulated. Also, the dispatching strategies used by both systems make the configuration of their haulage circuits different from one another. However, the ABM occasionally follows the dispatching strategies of the FAM. If the dispatching strategies of the FAM can be predicted because it is not variable, the dispatching strategies for the ABM cannot be predicted because it reacts to parameters within its environment which may be very variable and this is a good indication that the ABM follows the methodologies it was designed for: react to changes within its operating environment.

The Z-Model is not a realistic model as far as mining operations are concerned. In most mine operations, the current practices impose a certain number of trucks to be assigned to a shovel or group of shovels until the end of a shift. Also, the production for both ore and waste may not necessarily be the same. In the next section, the more realistic Two Zone model is simulated.
5.4.2 Simulation Results for the Two Zone Model

Simulations were performed on the Two Zone model for no upset, four upsets and seven upsets scenarios to compare the performance of the ABM model with the FAM model. The layout of the mine in this case consists of two zones (ore zone and waste zone) with two shovels in each zone (see Figure 5.2). Two maintenance shops are created for both zones. The production rates of both ore shovels were deliberately set to be equal as a constraint in the LP problem. This is a way to verify how the ABM is capable of maintaining ore quality within prescribed limits.

The efficiency of the ABM DISPATCH over the FAM DISPATCH is measured by its ability to satisfy the constraints such as strip ratio and ore quality. The ore quality constraint can be verified during the simulation with either the production rate from both ore shovels or the deviation factor defined in Chapter 4. For example a simulation will meet the ore quality constraints if the production rate or if the deviation factor of both ore shovels are identical during the simulation.

The simulations results for the no upset, two and seven upsets scenarios are discussed in the next sections. The results for the two upset scenario are presented in Appendix B.

Two Zone Model, no upset

The Two Zone-Model was simulated with no upset. The results for the ABM and FAM Dispatch are presented in the following sections and the production of waste and ore are for both systems are presented in Table 5.5

<table>
<thead>
<tr>
<th></th>
<th>FAM DISPATCH</th>
<th>ABM DISPATCH</th>
<th>FAM - ABM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total production of ore (tons)</td>
<td>135360</td>
<td>137280</td>
<td>- 1920</td>
</tr>
<tr>
<td>Total production of waste (tons)</td>
<td>151440</td>
<td>151680</td>
<td>- 240</td>
</tr>
<tr>
<td>Ore production1 (tons)</td>
<td>67680</td>
<td>68880</td>
<td>- 1200</td>
</tr>
<tr>
<td>Ore production2 (tons)</td>
<td>67680</td>
<td>68400</td>
<td>- 720</td>
</tr>
<tr>
<td>Waste production1 (tons)</td>
<td>82560</td>
<td>78960</td>
<td>+ 3600</td>
</tr>
<tr>
<td>Waste production2 (tons)</td>
<td>68880</td>
<td>72720</td>
<td>-3840</td>
</tr>
</tbody>
</table>

Table 5.5. Production of ore and waste, Two Zone Model, no upset
Table 5.5 shows that the ABM DISPATCH has produced more material (2,160 tons) than the FAM DISPATCH when no upsets are applied to the simulation. Although the production of waste shovel1 for the FAM DISPATCH is greater than that of waste shovel1 for the ABM DISPATCH, the system was able to recover later with waste shovel2 in ABM DISPATCH producing more than that of FAM DISPATCH. This is due to the fact that there is no quality requirement for waste.

Although it appears from the results from Table 5.5 that in the case of ABM DISPATCH production of ore1 is not equal to production of ore2, the difference (440 tons or two truck loads) can be attributed to the fact the simulation stopped before the trucks reached ore shovel2.

Similarly to the case of the Z-model, the configuration of the Two Zone Model contains blocks at its intersection that prevents trucks from colliding. This latter may explain why the ABM has produced more that the FAM as trucks slowing down may later line up and form longer queue at shovels. The ABM DISPATCH was capable of recognizing these queues and thus reacted in a way that decreases and balances the queues at each shovel. In the absence of these constraints at the intersections, the ABM DISPATCH and the FAM DISPATCH would have produced the same amount of material.

Comparative production rates of both systems are shown in Figure 5.12. It is apparent that the production rates from the ABM DISPATCH are always above that of the FAM DISPATCH. The small variation observed in the graphs is not the result of upsets but instead is related to blocks placed at the intersections in the haulage.
The activities of trucks at shovels for both strategies are shown in Figures 5.13 and 5.14. The two dispatch strategies are very different in a sense that the patterns observed for the FAM DISPATCH is more regular and uniform. This is justified by the fact that it is a fixed assignment method where trucks remain with shovels they were initially allocated to. The patterns for the ABM DISPATCH however are not uniform and regular and this is because dispatching decisions vary with the environment and could not be predicted.
**Figure 5.13.** Queue + enroute, Two Zone Model – FAM (no upset)

**Figure 5.14.** Queue + enroute, Two Zone Model – ABM (no upset)
Validation of the Two Zone Model

The solutions of the LP problem, the cycle times and the number of trucks shown in Table 5.1 are used to check the reliability of the simulation and the validation for the FAM is shown below.

Ore shovel 1
With 5 trucks and a cycle time of 12 minutes, the expected production of ore 1 is 
\[5 \times \left(\frac{60}{12}\right) \times 12 \times 240\] = 72000 tons in the event that operation occurs smoothly. Table 5.5 suggests however that the production is 67680 tons which is almost 4000 tons lower than the expected production. These differences are the results on the constraints imposed on operation. For example a production of 72000 tons is equivalent to a production rate of 6000 tons/hour, which is above the production rate of 5714.286 tons/hour, which is the solution of the LP problem. A production of 67680 tons from the simulation is equivalent to 5640 tons/hour, which is closer to the result suggested by the LP problem. The same method of validation can be extended to Ore shovel 2 as the same number of trucks and the same production rate are used.

Waste shovel 1
With 6 trucks and a cycle time of 12.34 minutes, the expected production of waste 1 is 
\[6 \times \left(\frac{60}{12.34}\right) \times 12 \times 240\] = 84019.45 tons in the event that operation occurs smoothly. Table 5.5 suggests however that the production is 82560 tons which is almost 1459.45 tons lower than the expected production. However, 84019.45 tons is equivalent to \(84019.45 / 12\) = 7001.62 tons/hour whereas 82560 tons is equivalent to \(82560 / 12\) = 6880 tons/hour. The solution proposed by the LP is about 6765.714 tons/hour. The simulation result is therefore valid as its production rate for waste 1 is close to the LP solution.

Waste shovel 2
With 5 trucks and a cycle time of 12.5 minutes, the expected production of waste 1 is 
\[(60/12.5) \times 12 \times 240\] = 69120 tons in the event that operation occurs smoothly. Table 5.5 suggests however that the production is 68880 tons which is 240 tons lower than the
expected production. This may be the result of a truck stopping before the end of the simulation. A production of 68880 tons is equivalent to 5740 tons/hour and this result is very close to the production suggested by the LP problem and found in Table 5.1.

As stated in the case of the Z-model, the difference observed between the maximum production rate and the production rates of the simulations is mainly attributed to the initial conditions where trucks wait in line before starting to load. Blocks located at intersections to prevent collisions also contribute to the difference in production rate.

Because of the slight differences in production with the FAM, the validation procedure described above can be extended to the ABM strategy.

**Two Zone Model, 7 upsets**

The model was stressed in order to see the effects that multiple breakdowns may have on both systems. For this simulation, seven upsets (three in the ore zone and four in the waste zone) were created at times t = 2, 3, and 4 hours for each zone. Two trucks are sent to maintenance at the same time at time t = 4 for the waste zone. The productions from each shovel are presented in Table 5.6.

<table>
<thead>
<tr>
<th></th>
<th>FAM DISPATCH</th>
<th>ABM DISPATCH</th>
<th>FAM – ABM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total production of ore (tons)</td>
<td>126720</td>
<td>126240</td>
<td>+ 480</td>
</tr>
<tr>
<td>Total production of waste (tons)</td>
<td>139920</td>
<td>143280</td>
<td>- 3360</td>
</tr>
<tr>
<td>Ore production1 (tons)</td>
<td>64800</td>
<td>63120</td>
<td>+ 1680</td>
</tr>
<tr>
<td>Ore production2 (tons)</td>
<td>61920</td>
<td>63120</td>
<td>- 1200</td>
</tr>
<tr>
<td>Waste production1 (tons)</td>
<td>76800</td>
<td>74640</td>
<td>+ 2160</td>
</tr>
<tr>
<td>Waste production2 (tons)</td>
<td>63120</td>
<td>68400</td>
<td>-5280</td>
</tr>
</tbody>
</table>

The results from Table 5.6 show that the ABM DISPATCH system produced more material than the FAM DISPATCH system overall (a gain of 2,880 tons). The variability in the difference in production observed in Table 5.6 results from the fact the ABM DISPATCH system allow shovels to borrow trucks from one another in order to satisfy operational requirements in the ore zone. For example in order to keep production from
the shovels located in ore zone identical as required by the LP problem, ore shovel1 sacrifices its production to satisfy ore shovel2 (difference = + 1680 and − 1200 tons). The total production of ore for the ABM is less that that of the FAM by as much as 480 tons. The ABM DISPATCH has thus sacrificed production for quality. The ore quality requirement imposed upon the system is quite tight and that explain why the ABM has sacrificed it total ore production. The ABM did very well in waste zone because the requirement for the production of waste is only limited to production and therefore the two systems are faced with less stress in the waste zone.

A comparison of the total production for the two systems is shown in Figure 5.15.

![Figure 5.15. Comparative Total production rate, Two Zone Model (seven upsets)](image)

The production rates of ore and waste for both systems are shown in Figures 5.16 and 5.17. The graphs show the behaviour of the production rates for the two systems when faced with truck breakdowns. The ABM strategy tries to balance the production rates of the two shovels located in ore zone in order to satisfy the ore quality constraints. There is more variability in the production rates of the FAM strategy, indicating longer travel or
waiting times. If the identity of the trucks that breakdown in the FAM is important (to find for example which shovel is affected), it can be seen from the graphs that it is not the case for the ABM where a truck does not belong to a particular shovel. For example ore shovel1 lost two trucks at respectively $t = 2$ and 4 hours and ore shovel2 lost just one truck at $t = 3$ hours for the FAM.

The drops in production observed in the graphs are not the result of breakdowns only, as observed in the graphs. For example in Figure 5.16, the FAM production rate of ore shovel2 decreased for a duration of 0.5 hour at $t=5.5$ hours despite the fact that it was not subjected to an upset after $t=4$ hours. These drops that are not the result of upsets are attributed to the effects of blocks placed at each intersection to avoid collisions. This is also a sign of longer waiting times for the shovels as trucks break down and their travel times change.

![Figure 5.16. Production rates, Two Zone Model (Three upsets in ore zone)](image)

**Figure 5.16.** Production rates, Two Zone Model (Three upsets in ore zone)
Figure 5.17. Production rates, Two Zone Model (Four upsets in waste zone)

Figure 5.17 shows that unlike in the ore zone, the variations in production rate for both systems is moderate. If in the case of the ABM DISPATCH a truck does not belong to a particular shovel, in the case of the FAM DISPATCH waste shovel1 has lost two trucks at times $t = 2$ and 3 hours whereas waste shovel2 has lost two trucks at time $t = 4$ hour. The activities of trucks at shovels before and after the breakdowns occur are shown in Figures 5.18, 5.19, 5.20 and 5.21 and may explain the observation made on the production rates of both systems.

Figures 5.18 and 5.19 show that the sum of queues and enroutes for the FAM DISPATCH drops to zero more frequently than that of the ABM DISPATCH. This observation suggests that shovels wait longer in the FAM DISPATCH than in the ABM DISPATCH and last longer as the number of upsets increases. The differences observed are due to the fact that in the ABM DISPATCH, the demand (or stimulus) of a shovel for trucks is a increasing function of decreasing queue + enroute and therefore when shovels
are not awarded trucks, their stimulus increases such that at the next decision point they may claim the next trucks.

Figure 5.18. Queue + enroute, Two Zone Model – FAM (when upsets occur)

Figure 5.19. Queue + enroute, Two Zone Model – ABM (when upsets occur)
Figures 5.20 and 5.21 show the activities of trucks after the broken ones return from maintenance.

Figure 5.20. Queue + enroute, Two Zone Model – FAM (when trucks are leaving)

Figure 5.21. Queue + enroute, Two Zone Model – ABM (when trucks are returning)
Figures 5.20 and 5.21 show that as the trucks are returning from maintenance, the queue and enroute of the ore shovels for the FAM DISPATCH increases rapidly and reach a high of 4 trucks with an average of 3 trucks. The queue and enroute graph of ore shovel for the ABM DISPATCH has a maximum of 3 trucks and an average of 2 trucks. This an indication that trucks in the ABM DISPATCH are more productive than that of the FAM DISPATCH as most of the trucks in this case are either traveling or queued at the shovels in the ore zone. Also trucks are evenly distributed among shovels in the ore zone throughout the simulation and that explain why the ore quality constraint is satisfied. The same remarks are applicable to the waste zone with the only difference that the quality of waste is not an issue.

When mixing ore from two different locations for example, the grade of the final material is determined as follows:

\[
g = \frac{x_1 g_1 + x_2 g_2}{x_1 + x_2} \Rightarrow \bar{g} = \frac{1}{\left(1 + \frac{x_2}{x_1}\right)} g_1 + \frac{1}{\left(1 + \frac{x_1}{x_2}\right)} g_2
\]

\(\bar{g}\) = ore grade  
\(g_1\) = ore grade from location1  
\(g_2\) = ore grade from location2  
\(x_1\) = production rate from location1  
\(x_2\) = production rate from location2

Equation 5.1 shows that the grade of the final mixture is a function of the production rates of both locations.

In this simulation the production rate each shovel located in the ore zone was constrained to be equal and therefore the grade of ore delivered is half of the sum of the grades from both shovels. In order to satisfy this constraint, the deviation of the production rates of both shovels from their expected value should remain the same. The deviation factor defined in Chapter 4 of this thesis is proportional to the deviation from their expected value. The deviation factors from both systems are shown in Figure 5.22.
Figure 5.22. Deviation factors, Two Zone Model – seven upsets

Figure 5.22 shows that the deviation factors of both local shovels remain identical for the ABM DISPATCH whereas it is not the case for the FAM DISPATCH. That explains why the ABM DISPATCH was able to satisfy the ore quality constraint.

Two Zone Model, Two Upsets

The two strategies were also applied to a two upset scenario (one in each zone) and the results of the simulations are presented in Table 5.7.
Table 5.7. Production of ore and waste, Two Zone Model, eight upsets

<table>
<thead>
<tr>
<th></th>
<th>FAM DISPATCH</th>
<th>ABM DISPATCH</th>
<th>FAM – ABM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total production of ore (tons)</td>
<td>132480</td>
<td>133920</td>
<td>-1440</td>
</tr>
<tr>
<td>Total production of waste (tons)</td>
<td>148560</td>
<td>149280</td>
<td>-720</td>
</tr>
<tr>
<td>Ore production1 (tons)</td>
<td>64800</td>
<td>66960</td>
<td>-2160</td>
</tr>
<tr>
<td>Ore production2 (tons)</td>
<td>67680</td>
<td>66960</td>
<td>+720</td>
</tr>
<tr>
<td>Waste production1 (tons)</td>
<td>79680</td>
<td>77760</td>
<td>+1920</td>
</tr>
<tr>
<td>Waste production2 (tons)</td>
<td>68880</td>
<td>71520</td>
<td>-2640</td>
</tr>
</tbody>
</table>

Table 5.7 shows that not only the ABM DISPATCH has produced more material than the FAM DISPATCH but it also managed to satisfy the ore quality constraint. The graphs of the production rate and queue and enroute are displayed in Appendix B.

5.5 Summary of the Simulation Results

The simulation results are summarized in Table 5.8 below and it shows the gain of the ABM DISPATCH over the FAM DISPATCH.

Table 5.8. Gains realized by the ABM DISPATCH over the FAM DISPATCH

<table>
<thead>
<tr>
<th>Simulation scenario</th>
<th>Gain (tons)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total ore</td>
</tr>
<tr>
<td>Z-Model, no upset</td>
<td>240</td>
</tr>
<tr>
<td>Z-Model, two upsets</td>
<td>480</td>
</tr>
<tr>
<td>Z-Model, four upsets</td>
<td>720</td>
</tr>
<tr>
<td>Two Zone Model, no upset</td>
<td>1920</td>
</tr>
<tr>
<td>Two Zone Model, two upsets</td>
<td>1440</td>
</tr>
<tr>
<td>Two Zone Model, seven upsets</td>
<td>-480</td>
</tr>
</tbody>
</table>

Table 5.8 suggests that the gain of the ABM DISPATCH strategy over the FAM DISPATCH increases as the number of upsets increase for ore and remain constant for waste in the Z-Model except for total waste in the two upset scenario. However, this can be attributed to the fact the last truck has stopped before the end of the simulation.

For the Two Zone Model, the gain in the production of waste increases with increasing number of upsets whereas the gain in the production of ore decreases with increasing number of upsets. The difference is attributed to the fact that there are more constraints to
the production of ore than that of waste. The ABM DISPATCH sacrifices production for ore quality. Thus, the gains realized in the waste zone suggest that if the ore quality constraints were a little relaxed, the gains realized in by the ABM DISPATCH will have increased with increasing number of upsets until the system reaches an optimum number of upsets where the gains will decrease.
6 CONCLUSIONS AND RECOMMENDATIONS

6.1 CONCLUSIONS

On the basis of results obtained from this study, the following conclusions are made:

1) With no upsets the ABM and the FAM showed equivalent results. This is to be expected because with a deterministic simulation and no upsets there is no reason to reallocate trucks. This does show that the ABM is stable and will reallocate only in the even of upsets.

2) With upsets in the system, both the Z-model and the two zone model, showed that the ABM reallocated trucks or changed routes to balance the system and load trucks according to the plan.

3) One of the significant advantages of this system is that it identifies the upsets but does not need to predict their occurrences before adapting to new operational environments. For example longer delay and waiting times caused by trucks meeting at intersection were identified. However, predicting with great accuracy the upsets may add valuable information to the dispatch system in terms of lessening the stress faced by operation.

4) The upset cases showed that ABM DISPATCH is stable and that it smoothly adapts to upsets, which is one of the shortcomings of current algorithms. The ore quality resulting from the simulation was always within prescribed limits.

5) The algorithms used in ABM DISPATCH are much simpler than those used in general LP-based truck/shovel dispatch systems. The LP problem used to solve the initial allocation problem is very simple and its sole purpose is guide the system to closer dispatch decision solutions.
6) The overall difference in production is very small. It would be interesting to see under what conditions the impact is really significant.

7) The model relies heavily on information updates. Decisions are made in a fraction of second and when the data are not transferred on time, the model may miss an important decision point and bypass the current situation. This is acceptable if the current and previous environments do not differ too much. When the differences are important, data transfer in the simulation may likely cause problems in the real implementation of the model.

6.2 Recommendations

The following recommendations are made based on this work:

1) That the ABM DISPATCH model developed in this study be used in addition to existing tools. This model has the capability to reduce the effect of upsets within a dispatching system and maintain the ore quality within prescribed limits, assuming that ores do not react chemically.

2) The simulations in this research were performed on a single decision point (crusher and dumps). In order to improve the performance of the ABM DISPATCH model, it is suggested that haulage circuits be designed to circumvent the limitations of multiple decision points.

3) The stimulus and response functions developed in this research were simple and based on simple approaches. Detailed studies of these functions such as finding the relationships between the variables and solving the differential equation for the stimulus and the threshold functions may help enhance the performance of the ABM DISPATCH model.
4) Expand the simulation to include maintenance as an agent with stimuli with respect to both shovels and trucks. Thus maintenance and shovels can compete for trucks based on scheduled maintenance plans.

5) Expand the simulation to incorporate uncertainties and mistakes.

6) Expand the upsets to include shovel breakdowns.

7) It is suggested that the performance of ABM DISPATCH system be compared with decisions made by a human operator on a smaller scale. Human operators, based on their personal experiences, may have developed a natural aptitude of reacting to upsets that may be perhaps have some similarities with what the ABM DISPATCH system does. This will require individual mines to document decisions made by dispatchers in the event of upsets. This sequence of events would then be “hard-wired” into the ABM DISPATCH simulation model.
REFERENCES


Temeng, A., 1997, A Computerized Model for Truck Dispatching in Open Pit Mines, PhD Dissertation, Michigan Technological University, USA.


APPENDIX A

PRODUCTION AND NUMBER OF TRUCKS

Solution of the Linear Programming Problem

The linear programming problem for the simulations of the Two Zone Model is simplified to two ore shovels and two waste shovels located respectively in ore and waste zones. The problem is biased from its original form in order to highlight the behaviour of the ABM DISPATCH system in upset situations. For example the production of ore from both ore shovels was forced to be equal in order to track how ore the quality requirement is satisfied. Furthermore, waste production from both waste shovels was chosen to be different.

Owing to the difficulty of obtaining haulage cost data, pseudo costs were used in the objective function in reference to the work of White and Olson [1986]. The pseudo costs represent in fact the relative weight of the production of ore and waste. For example ore was given a higher relative weight because it is assume that the operation involves blending that is more important than just moving waste from shovels to a crusher. The linear programming problem for the Two Zone Model is formulated as follows:

The following parameters are used in the simulation for the Two Zone Model:

<table>
<thead>
<tr>
<th>Upper limit of ore (tons/hour)</th>
<th>Lower limit of ore (tons/hour)</th>
<th>Upper limit of waste (tons/hour)</th>
<th>Lower limit of ore (tons/hour)</th>
<th>Strip Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>14400</td>
<td>10000</td>
<td>144000</td>
<td>11000</td>
<td>0.9 ≤ strip ratio ≤ 1.2</td>
</tr>
</tbody>
</table>

Minimize \( C_0 (T_{1o} + T_{2o}) + C_w (T_{1w} + T_{2w}) \)

subject to

\[ 10000 \leq T_{1o} + T_{2o} \leq 14400 \]

\[ T_{1w} \geq T_{2w} \]

\[ 0.9 \leq \frac{T_{1w} + T_{2w}}{T_{1o} + T_{2o}} \leq 1.2 \]

\[ 11000 \leq T_{1w} + T_{2w} \leq 14400 \]
where,

\[ C_o = \text{pseudo cost of moving ore} = \$1.5/\text{hour} \]

\[ C_w = \text{pseudo cost of moving waste} = \$1/\text{hour} \]

\[ T_i^o = \text{production rate of ore shovel } i \, (\text{tons/hour}) \]

\[ T_j^w = \text{production rate of waste shovel } j \, (\text{tons/hour}) \]

The linear programming problem was solved in Excel Solver and the solutions expressed in tons are shown in Table A.1.

**Table A1. Solutions of the LP problem**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ore1</td>
<td>5714.286</td>
</tr>
<tr>
<td>ore2</td>
<td>5714.286</td>
</tr>
<tr>
<td>waste1</td>
<td>6765.714</td>
</tr>
<tr>
<td>waste2</td>
<td>5805.714</td>
</tr>
<tr>
<td>sum of ore</td>
<td>11428.57</td>
</tr>
<tr>
<td>sum of waste</td>
<td>12571.43</td>
</tr>
<tr>
<td>sum</td>
<td>24000</td>
</tr>
<tr>
<td>stip ratio</td>
<td>1.1</td>
</tr>
</tbody>
</table>

**Constraints**

<table>
<thead>
<tr>
<th>strip ratios</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>upper</td>
<td>1.1</td>
</tr>
<tr>
<td>lower</td>
<td>0.7</td>
</tr>
</tbody>
</table>

| max prod of ore    | 14400     |
| Min ore            | 10000     |
| max prod of waste  | 14400     |
| Min waste          | 11000     |
| Sum                | 28800     |
|                    | 24000     |

**Cost Function**

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>26285.71</td>
</tr>
</tbody>
</table>

The cycle times and the solutions of the LP problem are presented in Table A.2. These parameters are used to determine the best number of trucks needed in each zone for each shovel.
The best number of trucks to allocate to each shovel in the Two-Zone model is computed as follows. The maximum number of tons per hour that a truck can move is $R_{\text{max}} = 60/T_c \times 240$, where $T_c$ is the cycle time for a truck assigned to a shovel. Given the optimum production rates, $P_{\text{opt}}$, for each shovel from the LP model, the nominal number of trucks to assign to each shovel is $n = \lfloor P_{\text{opt}} / R_{\text{max}} \rfloor$ where $\lfloor \cdot \rfloor$ denotes the integer part of the argument. However, given the relative capital costs of trucks and shovels, it is usually desirable to have trucks waiting to be loaded rather than shovels waiting to load. The best number of trucks is therefore usually given as the minimum number $n$ such that $n \times R_{\text{max}} \geq P_{\text{opt}}$. The best number of trucks for each shovel is shown in Table 5.1. The total number of trucks in the system is 21.

### Table A2. Optimum number of trucks

<table>
<thead>
<tr>
<th>Shovel</th>
<th>Cycle time $T_c$ (minutes)</th>
<th>Optimum production rates $P_{\text{opt}}$ (tons/hr)</th>
<th>Nominal number of trucks $n$</th>
<th>Best number of trucks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ore shovel1</td>
<td>12</td>
<td>5714.3</td>
<td>$\lfloor 5714.3/1200 \rfloor = 4$</td>
<td>5</td>
</tr>
<tr>
<td>Ore shovel2</td>
<td>12.56</td>
<td>5714.3</td>
<td>$\lfloor 5714.3/1146.5 \rfloor = 4$</td>
<td>5</td>
</tr>
<tr>
<td>Waste shovel1</td>
<td>12.34</td>
<td>6765.7</td>
<td>$\lfloor 6765.7/1166.9 \rfloor = 5$</td>
<td>6</td>
</tr>
<tr>
<td>Waste shovel2</td>
<td>12.5</td>
<td>5805.7</td>
<td>$\lfloor 5805.7/1152.0 \rfloor = 5$</td>
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APPENDIX B

Z-Model, Two Upsets

Figure B.1. Production rate, Z-Model – two upsets
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Z-Model, Two Upsets

Figure B.1. Production rate, Z-Model – two upsets
Figure B.2. Queue + enroute, Z-Model – two upsets (trucks leaving for maintenance)

Figure B.3. Queue + enroute, Z-Model – two upsets (trucks returning from maintenance)
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Figure B.3. Queue + enroute, Z-Model – two upsets (trucks returning from maintenance)
Two Zone Model, Two Upsets

Figure B.4. Total production rates, Two Zone Model – two upsets

Figure B.5. Total production rates, Two Zone Model – two upsets
Two Zone Model, Two Upsets

Figure B.4. Total production rates, Two Zone Model – two upsets

Figure B.5. Total production rates, Two Zone Model – two upsets
Figure B.6. Production rates, Two Zone Model – two upsets in ore zones

Figure B.7. Production rates, Two Zone Model – two upsets in waste zones
Figure B.6. Production rates, Two Zone Model – two upsets in ore zones

Figure B.7. Production rates, Two Zone Model – two upsets in waste zones
**Figure B.8.** Queue + enroute, Two Zone Model – FAM (two upsets)

**Figure B.9.** Queue + enroute, Two Zone Model – FAM (two upsets)
Figure B.8. Queue + enroute, Two Zone Model – FAM (two upsets)

Figure B.9. Queue + enroute, Two Zone Model – ABM (two upsets)
Figure B.10. Deviation factors, Two Zone Model – two upsets
Figure B.10. Deviation factors, Two Zone Model – two upsets