

Swarm –Based Truck-Shovel Dispatching System in Open Pit Mine Operations

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Abstract

The dispatch of trucks and shovel has always been an important component in the success of open pit mine operations. Dispatch systems have evolved from manual to today automatic with almost no human intervention. Although dispatching systems available today are “pseudo real time” and efficient, the optimal dispatching is realized over subsets of the fleet when dealing with large fleets. This approach certainly raises the question of optimality. In fact decomposing the fleet into sub-fleets and then optimizing each one does not guarantee optimality for the entire fleet. Moreover the system is not flexible to changes in the operation environment such as emergency breakdowns and anticipated down times.

The swarm intelligence approach introduced in this paper is a new technique that uses the behaviour of social insects to model and simulate a dispatching system. Social insects are flexible in that they respond to any change in their environment, particularly those that threaten their survival. This flexibility occurs in response to chemical or physical cues produced in the environment either by the insects themselves or by external influences. Using analogies to these chemical and physical cues, a flexible dispatching system can be developed that can efficiently dispatch trucks of the entire fleet and that can adapt to changes in the truck/shovel/maintenance environment. Simulations of dispatching systems based on those concepts are presented and described.

Introduction

Dispatching systems for open pit mines have attracted considerable attention in the last years due to substantial gains in productivity achieved through their implementation. Haul trucks and shovel are one of the key resources, which represent a significant capital and operating cost, of surface mining. Due to the high operating and maintenance cost, a lot of effort has been directed to cost savings in shovel-truck haulage which has proven to be improving in terms of reliability over the time. But the increase of equipment and fleet size has reduced the flexibility of the shovel-truck haulage procedure. The allocation of the equipment becomes more delicate as a decision on one piece of equipment can have a huge impact on the entire operation. For example when should one decide to send a shovel or a truck to maintenance with respect to constraints such as target requirement (mill requirement), equipment scheduled and/or unscheduled maintenance, tires wear off, etc. With the advent of larger size equipment coupled with increasing haul distances, deepening pits and a more competitive mineral market, there is an urgent need to develop a dispatching procedure that is not only reliable in terms of allocating resources in real time but can also be flexible and adapt to any changes that occur within the operation environment.

Dispatching procedures available today range from simple heuristic rules to complex mathematical programming based methods. Mathematical programming (more often linear programming) based dispatching systems have mostly been in two parts. The first part is normally based on the short range planning objectives, and the second part is used to implement the first part in real time [1].

Today many authors agree that heuristic dispatching procedures are formulated rules that do not guarantee optimality, especially when dealing with large fleets. The heuristic sets of rules consist generally of maximizing truck and shovel use based on “nearest available truck to dispatch”. Bonates [2] and Lizotte [3] observed that not only optimality is not guarantee, but also grade requirements cannot be met by this approach.

The general approach of mathematical procedures are based on using mathematical tools such as linear or a non-linear programming that are used to optimize truck or tonnage flow rate between shovel and crusher/dump with respect to some quality constraints and the trucks are dispatch accordingly [4]. In order to account for uncertainties that may occur during, some mathematical methods use stochastic linear or non-linear programming or genetic algorithm. The later models although efficient do not guarantee adequate adaptability when something goes wrong during operation. Stochastic linear programming for instance couples linear programming methods with simulation techniques that may not describe the real environment in which the equipment are operated. Genetic algorithm uses the process of mutation and crossovers to determine a set of population within which the problem should be optimize. But because of the high costs related to the equipment, omitting a part of the entire population may have an impact on the optimization procedure.

The procedure proposed in this paper is based on the behaviour of social insect such as ant colonies. The procedure uses local optimization approach while guaranteeing a real time dispatch system that adapt to variations within the operation environment to ensure that optimization is satisfied. Like ants react to any changes within their environment to guarantee their survival by adopting flexible behaviours, the method proposed in this paper leads to a procedure that make trucks and shovels react to any unforeseen changes (such as extreme weather conditions, breakdowns, etc) and take action to ensure that the targets are met under any given constraints.

Background

Studies conducted by entomologists have shown that ants taken individually are almost blind with no memory and they do not have direct communication within their colony. Ant yet taken together, these insects are able to performed amazing things such finding the shortest path from their nest to a food source illustrated by Fig. 1, finding their way back to nest after a long trip that ranges from kilometers, harvesting leaves to produce fungus that is used for their nutrition, organizing themselves in a well structured manner, etc. The very question one might ask is if ants do not have direct communication and are not intelligent in the human sense, how do they organized themselves and perform all these amazing tasks?

The same studies have confirmed that ants communicate indirectly through a chemical hormone, called pheromone, which they release on their route. An ant traveling from a point A to another point B will release a trail of pheromone that is sensed by other ants preceding him (This procedure is called “recruitment”). The preceding ants will follow path AB if its pheromone concentration is the highest among the other paths. The process of recruiting and successfully responding to the recruitment is called stigmergy. In Fig. 1A describes ants traveling between a food source and their nest. Suddenly and obstacle is placed in their path (Fig. 1B). At first they react quickly by going randomly around the obstacle (Fig. 1C), after a short period of time, the ants successfully figure out the shortest path between the food source and their nets (Fig. 1D).

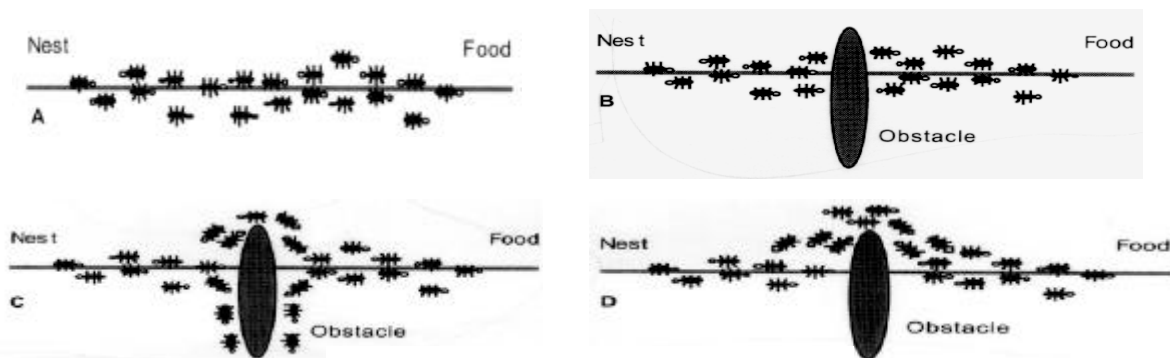


Fig. 1. Illustration of pheromone trails

The pheromone concentration became stronger on the shortest as it takes less time for ants on that portion of the path to travel. The first ants that traveled on the upper portion of Fig. 1D have therefore recruited the rest of the ants in a very random way.

Another behaviour of ants that are used in the proposed model is their ability to react to any conditions new to their environment. Wilson (5) conducted an experiment that supports the idea and proposed a theory that explains the adaptable nature of ants. The experiment consists of two categories (majors and minors) of ants within the same colony, each performing a task allocated to its category. The ratio of major to minor was altered. After a short period of time, some majors joined the remaining minors to perform task that were initially allocated to minors. The Wilson experiment is well illustrated by Fig. 2.

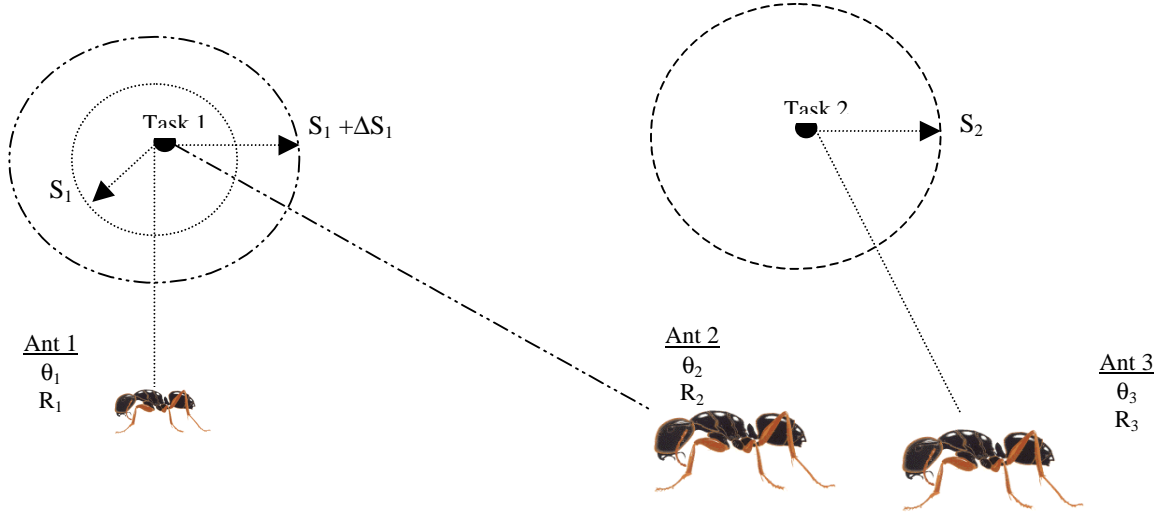


Fig. 2. Illustration of the Wilson experiment

According to Wilson, every task releases some pheromone, called stimulus S , which determines the intensity with which it needs to be performed in order to guarantee the survival of the ants in the short term. An ant will then perform a task based on its age, morphology and/or cast identified as the threshold level θ . An ant is candidate to perform a given task if the stimulus intensity S is greater than its threshold θ . In the Wilson experiment the fact of reducing minors performing task 1 created a demand for that task translated into the increase in its stimulus intensity ($S_1 + \Delta S_1$). Provided with a higher stimulus, task 1 can now attract majors that were not previously engaged in performing task 2.

A mathematical model was developed by Wilson to support his experiment. Given a task with a stimulus intensity S and given ant with a threshold θ , the likelihood of the ant performing the task is given by a function called the response function $R(s, \theta)$. The response function illustrates the fact even though the stimulus intensity of task is greater than the threshold of ant, that ant will not necessarily perform the task but is a candidate to perform the task. The ant will perform the task if and only if its response function is the greatest among the other ants. The dynamic response function is given below

$$R_{ij}^n(t) = \frac{s_i^n(t)}{s_i^n(t) + q_{ij}^n(t)} \quad 1.$$

$q_{ij}^n(t)$ = threshold of j th ant with respect to i th task at time t

s_i = stimulus intensity displayed by i th task at time t

n = sensitivity factor

The response represents in fact the probability that an ant that is candidate for performing a task will perform the task. It generates value between 0 and 100%.

The sensitivity of the response function is described in Fig. 3 and Fig. 4.

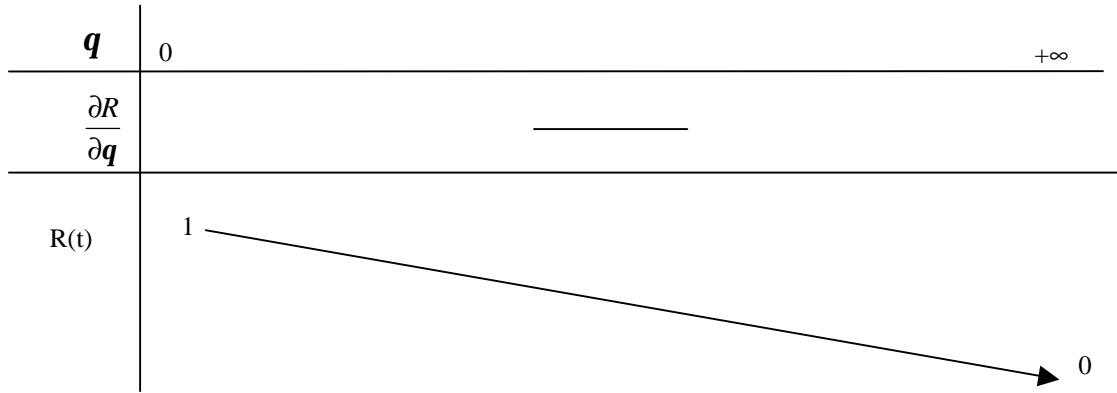


Fig. 3. Sensitivity with respect to threshold

Fig. 3 shows that the response function decrease from 0 to 1 as the value of the threshold increases. This suggests that ants with low threshold values are more likely to perform a given task at a given time

Fig. 4 however suggests that ants exposed to tasks with larger stimulus intensity are more likely to perform the tasks at a given time because the response is an increasing function of increasing stimulus.

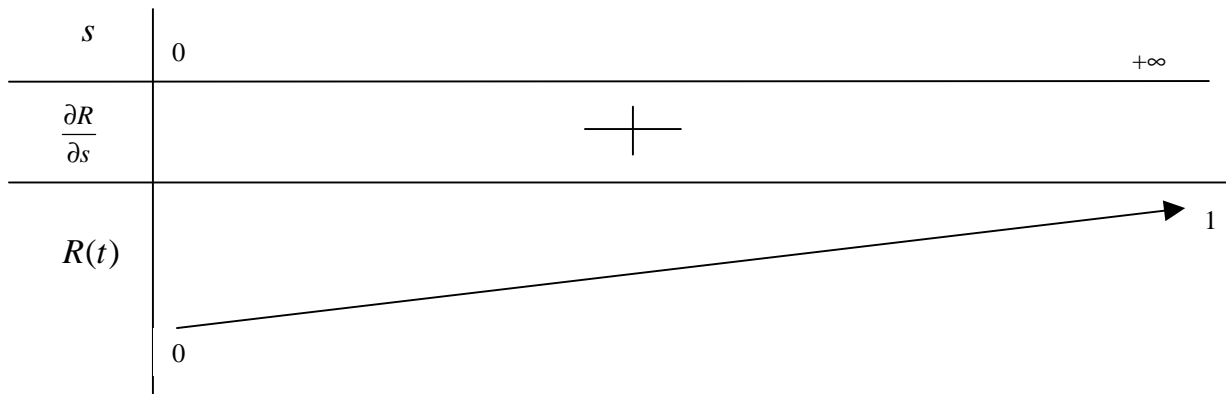


Fig. 4. Sensitivity with respect to Stimulus

In the case of ants however, the notion of specialization is added to the model to justify why the stimulus intensity of task 2, the highest, did not attract minors. In ant colonies some members can perform tasks allocated to others. It is called “resilience or elasticity” of ants. For example majors that usually perform grinding tasks can carry food and mud initially allocated to minors. The elasticity factor can be accounted in the model as follow:

$$R_{ij}(t) = e_{ij}(t) \frac{s_{ij}^n(t)}{s_{ij}^n(t) + q_{ij}^n(t)} \quad 2.$$

$e_{ij}(t)$ is the elasticity factor of the j^{th} with respect to the i^{th} task.

In the Wilson experiment, the elasticity factor can be chosen to 1 when a task associated to an ant category bids on an ant of that category and 0 otherwise.

It is this concept that is applied to the truck-shovel dispatch procedure to develop a system of trucks and shovels that capable of recognizing future upsets during operation and react to suppress them.

Analogy of ore body-truck-shovel-maintenance with Ant colony

The model proposed in this paper is described in Fig. 5. Ore blocks bid on shovels based on their priority on the short term. Shovels bid on trucks based on the short-term production requirement (target) and finally maintenance and emergency repair bids on both shovels and trucks based on scheduled and/or anticipated maintenance programs. In this paper however, focus will be on the interaction between a fleet of shovels and trucks. By analogy with an ant colony, shovels are compared to tasks and trucks to ants. The same approach can be extended to other components of the module.

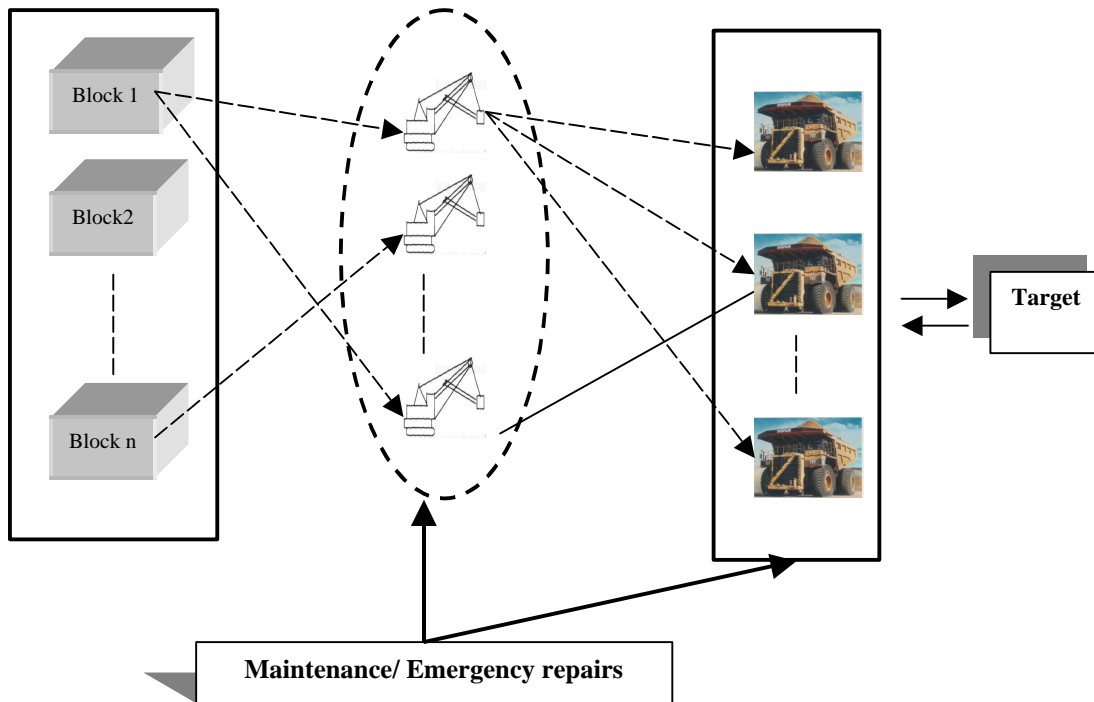


Fig. 5. Model description

The main challenges in using the behaviour of ants to model the interaction between shovels and trucks are to define what a stimulus is for a shovel, what a threshold consists of for a truck and finally how a truck reacts to the bid of a shovel. These functions are defined with only three purposes that are:

- Satisfaction of operation requirements
- Be as "real time as possible"
- Guarantee optimality

Shovel-truck interaction

The interaction between shovels and trucks is described in Fig. 6. Shovels are initially sent to different locations (ore blocks) of the ore body based on the short term mine plan and trucks swarm between shovels, stockpiles, crusher and waste dumps. A shovel's demand or bid for trucks will depend on the geometry of the ore body, the nature of the block the shovel is allocated to, the priority given to the block in the short term plan, the loading time of the shovel and the length of the queue at the shovel. The response of a truck to a shovel demand will depend on the location of the truck to that shovel, the truck capacity if different types of trucks are used, the speed of the truck the dumping time of the truck and the status of the truck (loaded versus unloaded).

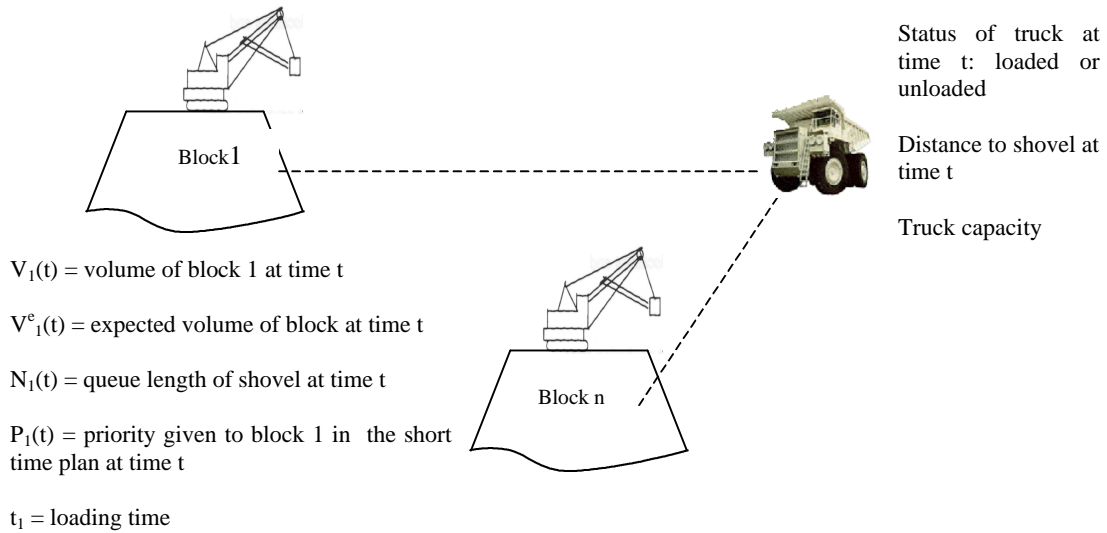


Fig. 6. Shovel-truck interaction

In this model, each individual shovel bids on each trucks at any time and a decision to dispatch a truck to a given shovel will depend on how justified, in terms of target and requirements satisfaction, this shovel need a truck. A shovel with a higher stimulus (demand) does not necessarily bid successfully on a truck, only the value of the response function of the truck with respect to the shovel determines whether or not a bid is successful.

Fig. 7 shows a shovel bidding on different trucks. Assuming the truck have the highest stimulus intensity it will successfully bid on the truck with the highest response value at the time the bidding occurs.

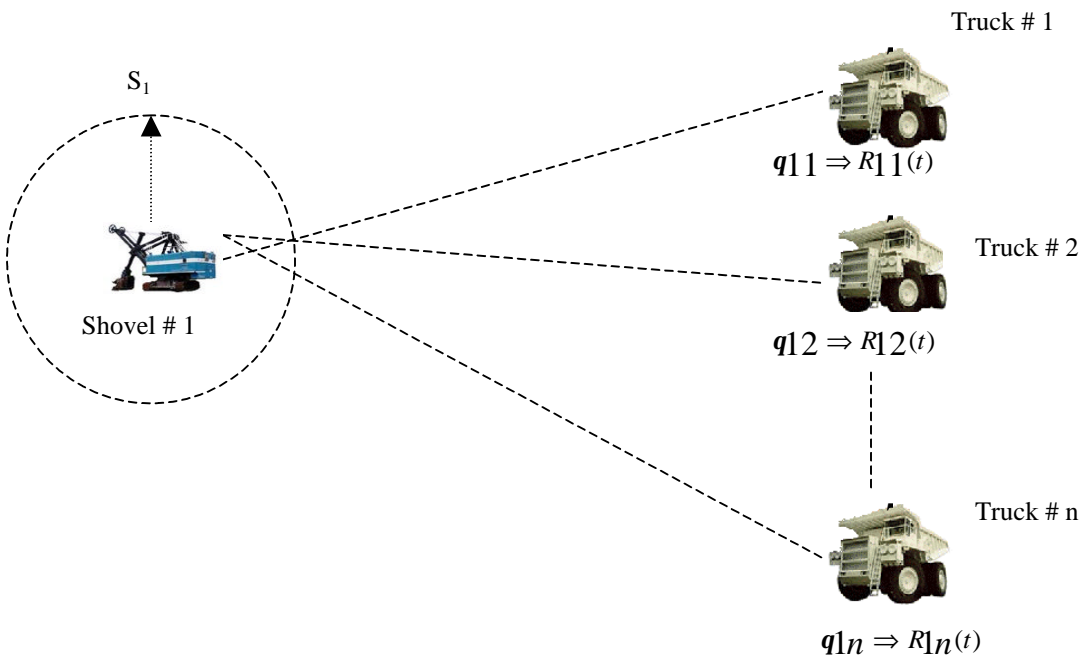


Fig. 7. Representation of the bidding process of a shovel

The bidding process described in Fig. 7 is duplicated by each shovel and for a given shovel that has to acquire a truck, the successful candidate satisfies the following condition:

$$l \text{ such that } R_{il}(td) = \max_j (R_{ij}(td))$$

td = dispatch time

3.

Stimulus intensity of a shovel

The stimulus intensity of a given shovel should be dynamic and reflect the behaviour of the target (optimization). The following parameters described below are used in the definition of the dynamic stimulus intensity. The update function ensures that the system dispatches a truck to shovel based on a real need to meet the target while satisfying the constraints. Its value is positive if no truck is dispatch and negative when a truck is successfully dispatched.

Assuming the following parameters:

- $V_i^e(t)$ = expected cumulative volume of material removed by shovel # i at time t
- $V_i(t)$ = actual cumulative volume of material removed by shovel # i at time t
- $n_i(t)$ = number of trucks queued at shovel i at time t
- C = capacity of trucks queued at shovel i (assuming same trucks)
- $p_i(t)$ = priority given to material mined by shovel i

The stimulus intensity of shovel # i can be defined as:

$$S_i(t) = p_i(t) \frac{[V_i^e(t) - V_i(t)]}{f(n_i(t), C)}$$

where $f(n_i(t), C)$ is a function of the queue length and the capacity assumed to be non zero.

4.

Example: $f(n_i(t), C) = (n_i(t) \times C + \mathbf{x})$ where $0 < \mathbf{x} \ll 1$

The stimulus intensity defined above ensures that the tonnage requirement is met given the priority of each block within the short-term plan. However the dynamic of the stimulus requires it be updated in order to reinforce an on going bidding procedure. An update function is added as follow:

$$S_i(t + \Delta t) = S_i(t) + \Psi(t)$$

where $\Psi(t)$ is the update function

5.

The goal of the update function is to maintain dispatch stability during operation. For example if after a certain period, another truck has already been dispatched to the shovel, the update function triggers its stimulus intensity to decrease, freeing the truck for another shovel. If however not truck has previously dispatched to the shovel, then the update function will increase the value of the stimulus to ensure that the truck is effectively claimed by that shovel unless a dramatic change occurs. The update function gives a better chance to a shovel that has successfully claimed previously to hold on to its claim, unless major changes happen.

Threshold value of a truck

The dynamic threshold function of a truck is described in Fig. 8. The threshold value is a function of the status of a truck (loaded or unloaded), the distance between the truck and the shovel. Intuitively it can be seen from the response function in the Wilson's model that for a given stimulus intensity, the response function increases with decreasing threshold value. Fig. 8 show that a loaded truck has a very high initial threshold value (lower response) when it is at the shovel level. As the truck drive toward a crusher or a waste dump its threshold value decreases (higher response) to reflect the fact it may be available soon.

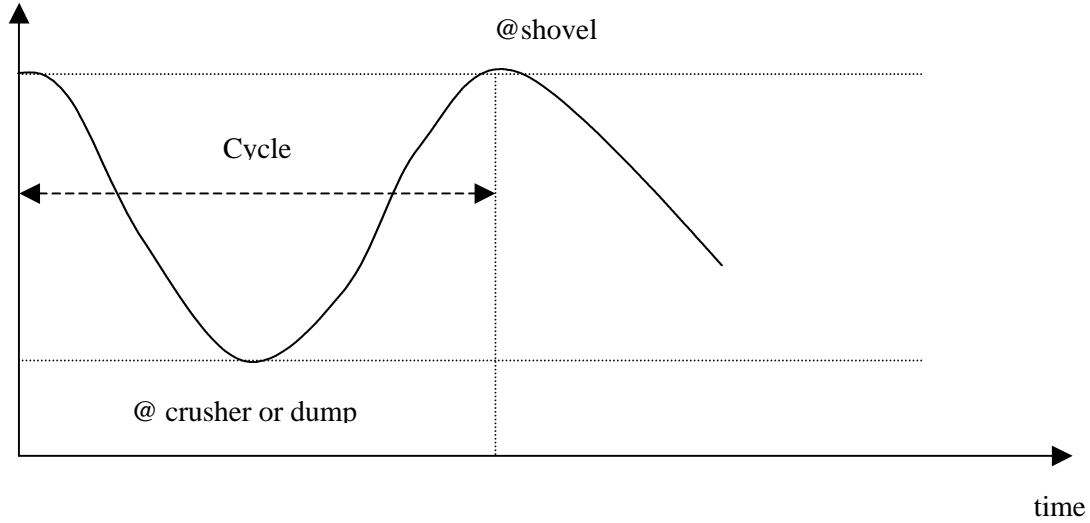


Fig. 8. Profile of threshold function for a loaded truck

An unloaded truck however will have a lower threshold value at the crusher or waste dump level to reflect its availability. The threshold value will then increase the truck is returning to the same shovel or is reallocated to another one. Unlike the standard definition of a cycle for a truck, a cycle in the model is defined as the time span between the beginning of its first dispatch and the end of the next one. A truck does not necessarily have to return to the same shovel.

$$e_j(t) = \text{status of truck } j \text{ at time } t = \begin{cases} 1 & \text{if truck is loaded} \\ -1 & \text{if truck is unloaded} \end{cases} \quad 6.$$

$$d_{ij}(t) = \text{distance of truck } j \text{ to shovel } i \text{ at time } t \quad 7.$$

The threshold function can be defined as :

$$q_{ij}(t) = e^{-\left[\frac{d_{ij}(t)}{\sum_k d_{ik}(t)}\right]} e_j(t) \quad 8.$$

Although the profile indicates that the threshold is continuous, it suffices for the function to be piecewise continuous to satisfy the modeling requirements with discontinuity points at each end of the cycle time (When a truck changes status).

Conclusion

A new model for truck-shovel dispatch procedure is developed in this paper. The model adapts the equipment to the environment of the operation. Unlike the previous models, it is simple and takes into account every aspect of the operation. However, the success of the model relies on the definition of the threshold and stimulus functions that constitute the main challenges of this model. The use of simulation techniques can be helpful in determining new functions that can lead to better optimization of the interactions between shovels and trucks.

The model presented in this paper assumes that the optimality of trucks and shovel fleet size are predefined and therefore focuses more on the efficient use of the equipment. However, the model can further be adjusted to take into account the target. The target, which in most operations is to optimize the tonnage of ore delivered to the crushers, can play a very important role in reinforcing the stimulus generated by each shovel. For example the demand for more loads at the crusher level can force trucks that were assigned to ore groups operating in a waste zone to join the ones that operate in an ore zone. This later remark will be elaborated in a future paper.

References

1. Temeng Victor A., 1997, A computerize Model For Truck Dispatching In Open Pit Mines, PhD dissertation, Michigan Technological University.
2. Lizotte Y. and Bonates E., 1986, Truck and shovel dispatch rules and Assessment Using Simulation, Mining Science and Technology, 5, Elsevier, Amsterdam, 45- 58.
3. Bonates E. and Lizotte Y., 1988, A combined Approach to solve Truck Dispatching Problems, Computer Application in the Mineral Industry, Fystas, Collins & Singhal (eds), Balkema, Rotterdam, 403-412.
4. Bonates E., 1992, PhD thesis. Universidade Federal Da Paraiba. Departamento De Mineracao Geologia.
5. Bonabeau, Eric et al, 1999, Swarm Intelligence, from natural to artificial systems, 109-147.