Modelling open pit shovel-truck systems using the Machine Repair Model

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Transaction Paper

Synopsis

Shovel-truck systems for loading and hauling material in open pit mines are now routinely analysed using simulation models or off-the-shelf simulation software packages, which can be very expensive for once-off or occasional use. The simulation models invariably produce different estimations of fleet sizes due to their differing estimations of cycle time. No single model or package can accurately estimate the required fleet size because the fleet operating parameters are characteristically random and dynamic. In order to improve confidence in sizing the fleet for a mining project, at least two estimation models should be used. This paper demonstrates that the Machine Repair Model can be modified and used as a model for estimating truck fleet size in an open pit shovel-truck system.

The modified Machine Repair Model is first applied to a virtual open pit mine case study. The results compare favourably to output from other estimation models using the same input parameters for the virtual mine. The modified Machine Repair Model is further applied to an existing open pit coal operation, the Kwagga Section of Optimum Colliery as a case study. Again the results confirm those obtained from the virtual mine case study. It is concluded that the Machine Repair Model can be an affordable model compared to off-the-shelf generic software because it is easily modelled in Microsoft Excel, a software platform that most mines already use. This paper reports part of the work of a MSc research study submitted to the University of Witwatersrand, Johannesburg, South Africa.

Keywords: simulation, bunching, probability distributions, cycle time, queuing, matching, shovel-truck, OEM.

Introduction

Shovel-truck systems are a prevalent loading and hauling system in surface mining operations. The loading units are typically wheel loaders (WL), hydraulic excavators (HEX) or rope excavators. The trucks can be off-highway trucks (OHT), articulated dump trucks or coal haulers as in coal mining. Generally truck fleet sizes increase with progressive mining or when expansion projects are envisaged. Haulage distances invariably increase with increasing pit depth as mining progresses, consequently reducing individual truck productivity and demanding more trucks to maintain the same level of production. Expansion projects require higher production rates, and with same level of truck productivity, it means more trucks will be required to meet the increased production rate.

The stochastic-dynamic nature of shovel-truck production cycle variables renders deterministic calculations inadequate to estimate the required shovel-truck fleet sizes. Consequently, simulation models are used to estimate the additional truck requirements. Several simulation models or software packages are available for this purpose. However, these models yield different fleet sizes for the same input parameters. The main reason why these different models each yield unique results is based on the assumed probability distributions fitted to the main cycle variables and the corresponding calculation of waiting time for both trucks and loaders.

Of-the-shelf simulation software packages can be very expensive for once-off use and mines would need to be able to analyse their new truck requirements using affordable and reliable models. Consequently, most mines have to rely on the original equipment manufacturers' (OEM) fleet size recommendations. Mines can increase their confidence in the OEM estimations by using simple models to substantiate the estimations. The modified Machine Repair Model based on Markov chains and running on an MS Excel platform, can used for this purpose because mines have computers that run MS Excel. The Machine Repair Model can therefore be used as an affordable model for checking OEM recommendations.

The shovel-truck sizing problem is a two-stage problem even for a shift start-up (Ta *et al.*, 2005). The first stage is truck resource

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allocation or fleet size estimation. The second stage, which is a truck dispatching stage, is a real-time implementation of the estimated truck resource and is done either manually or using computerized truck dispatch systems such as Dispatch®. Truck allocation is critical because if it is incorrectly done then the dispatch stage inherently carries over errors made in the first stage, resulting in sub-optimal truck dispatching decisions. This is the reason why at project inception the fleet size has to be estimated as accurately as possible. Two extreme undesirable trucking conditions can exist if truck allocation is done incorrectly. These are an 'over-equipped' condition where there are more trucks than are required or an 'under-equipped' condition when there are fewer trucks than required. There are consequences associated with these conditions. For example over-estimating truck fleet size by one extra CAT 777D truck implies about R10 million (in 2006 monetary terms) unnecessary extra capital expenditure, while under-estimating truck fleet size carries the risk of loss of potential revenue due to production shortfalls.

Central to the estimation of shovel-truck fleet size is the determination of the load-and-haul cycle time. The number of cycles a haulage unit can complete per hour are then determined. Subsequently, the system's productivity in tons per hour is determined as the aggregate of the productivity of all haulage units, hence sizing the shovel-truck fleet system. However, in any load-and-haul system there exist variations in the cycle variables such as loader bucket payload, truck payload, haul road distances, haul road conditions, operator proficiency, truck waiting times and truck loading time, to name but a few. Variations in these variables and their subsequent interaction contribute to the complication in the estimation of real-time waiting time, hence the estimation of the cycle time in real-time. Waiting time is an inherent but undesirable part of any load-and-haul system because it represents real-time equipment mismatch and ultimately production loss from idling equipment. Any shovel-truck analysis must therefore include estimation of waiting time. Accordingly, optimization of shovel-truck systems must aim to minimize or eliminate the total waiting time for both shovels and trucks (Temeng, Francis and Frendewey, 1997).

Models for analysing shovel-truck systems

To date, a number of off-the-shelf commercial simulation software packages have been developed to estimate shovel-truck fleet size requirements for given mining production rates and conditions. The various models associated with these packages and considered in this study can be broadly classified as:

- Iterative models that fit discrete empirical values to cycle variables. Examples are the Elbrond (1990) model and Machine Repair Model (Winston, 2004). In this paper, the Machine Repair Model is also alternatively referred to as the Winston model
- Regressive models that treat waiting time as a function of fleet matching and bunching correction factors. These models are based on static simulation algorithms that are driven by prescribed processing flow that is not dependent on time or interaction of resources. An example is the Fleet Production and Cost model (FPC®) developed by Caterpillar Inc. and discussed in detail by Morgan (1994)
- Stochastic Monte Carlo type models which fit probability distributions to cycle variables. An example is the Talpac® model developed by Runge Software Ltd
- Stochastic graphic simulation methods in which trucks and shovels (or loaders) are represented by physical entities (icons) within a virtual environment following probability distributions within a Monte Carlo simulation environment. The simulation progress can be viewed as an animation. An example is the Arena® model developed by Rockwell Software Inc.

The reasons for the choice of the above models are firstly, that the Elbrond (1990) and Winston (2004) models are iterative models, which can easily be programmed in MS Excel. The Talpac and FPC models were chosen because they are commonly used in the mining industry for shovel-truck analysis although they are limited to fitting probability distributions to a maximum of five major shovel-truck cycle variables. Lastly, Arena was chosen because it can be programmed with any number of probability distribution models fitted to an unlimited number of cycle variables and is therefore a very flexible model for use in analysing several variables in shovel-truck analysis. This characteristic of Arena gives it the potential to closely imitate real systems and was therefore chosen as the benchmark model in this study to compare the output from other simulation models.

Other useful models that were not considered in this study, due to reasons of non-availability and financial constraints, include Shovel Truck Analysis Package (STRAPAC®), General Purpose Simulation System (GPSS/H®) developed by the Wolverine Software Corporation, and Vehicle Simulation (VEHSIM®). Panagiotou and Michalakopoulos (1994) discussed the STRAPAC framework and its application to a shovel-truck system in a bauxite open pit mine. Today the STRAPAC® name is associated with plastic holding ties produced by Sublett Co. The GPSS/H® program, which has been used for both surface and underground mine simulations, is discussed in detail both in terms of architecture and application by Sturgul (2000). Dowborn and Taylor (2000) successfully used GPSS/H® to simulate a production system for an underground narrow reef platinum mine on the Bushveld Complex in South Africa. Other mining applications of GPSS/H® are reported by Sturgul, Jacobsen and Tecsa (1996), Sturgul and Jacobsen (1994), and Sturgul and Tecsa (1996). VEHSIM® was developed by Caterpillar Inc. in the late 1960s primarily for sales and technical support of the CAT 779 (85 ton) electric drive OHT truck, but was discontinued due to the decline in the truck's use. FPC® has essentially the same program setup and functionality as VEHSIM®.

Review of the machine repair model

In queuing theory, models in which arrivals (or customers) are drawn from a small population are called finite source models (Winston, 2004). The Machine Repair Model is an example of a finite source model. The model or system consists of K machines and R repair bays. The length of time that a machine spends away from the repair bays before coming back for repair follows an exponential distribution with rate λ and the time to repair a broken down machine at a repair bay follows an exponential distribution with rate μ. In other words, λ is the inter-arrival rate and μ is the service rate. Using the Kendall-Lee notation (Winston, 2004), the Machine Repair Model can be described as an M/M/R/GD/K/K model, where the first *M* is the inter-arrival rate, the second *M* is the service rate, *R* represents the number of repair bays, *GD* states that the machines are serviced following some general queue discipline, the first *K* is the number of machines being serviced in the system, and the last *K* states that the machines are drawn from a population of size *K*.

Typical queue disciplines include first-come, first-served (FCFS), last-come, first-served (LCFS), service in random order (SIRO) and priority queuing disciplines. In FCFS customers are serviced in the order of their arrival, in LCFS the most recent arrivals are serviced first, and in SIRO the order in which customers arrive has no effect on the order in which they are served. In priority queue discipline, each arrival is classified into one of several categories, each category is allocated a priority level, and within each priority level, customers are serviced on an FCFS basis. For most shovel-truck systems, trucks are serviced on an FCFS basis.

When arrivals to a system are drawn from a small population, the arrival rate may depend on the state of the system. For example, if the Machine Repair Model is in a state where $j \leq R$ machines are broken down, then a machine that has just broken down will be assigned for repair immediately, and if in a state where $j > R$ machines are broken down, then $j - R$ machines will have to queue in a line waiting for the next available repair bay. The state of a system can be described as stable or unstable. Winston (2004) describes the conditions under which a system will be stable or unstable, as explained below.

Let ρ represent the traffic intensity for an M/M/1/GD/∞/∞ system with exponential inter-arrival and service rates.

$$\text{Then, } \rho = \frac{\lambda}{\mu} \qquad [1]$$

where λ is the number of machines arriving for repair per unit time and μ is the number of machines successfully repaired per unit time. Further, an M/M/1/GD/∞/∞ can be modelled as a birth-death process with parameters as described in Equations [2] to [4].

$$\lambda_j = \lambda \quad (j = 0,1,2,\ldots) \qquad [2]$$

$$\mu_0 = 0 \qquad [3]$$

$$\mu_j = \mu \quad (j = 1,2,3,\ldots) \qquad [4]$$

These equations describe the flow balance of a birth-death process where: expected no. of departures from state *j* per unit time = expected no. of entrances to state *j* per unit time

The steady state probabilities that j machines will be present are given in Equation [5].

$$\pi = \frac{\lambda\pi_0}{\mu},\ \pi_2 = \frac{\lambda^2\pi_0}{\mu^2},\ldots,\pi_j = \frac{\lambda^j\pi_0}{\mu^j} \qquad [5]$$

where π is described as the probability that at a future instant, *j* machines will be present or may be perceived as the fraction of time that the *j* machines are present in the distant future. The sum of the probabilities should be equal to unity as indicated in Equation [6], since at any given time the system must be in some state.

$$\pi\left(1 + \rho + \rho^2 + \ldots\right) = 1 \qquad [6]$$

This infinite sum will diverge to infinity should $\rho \geq 1$ and no steady state will exist, resulting in an unstable system.

Adapting machine repair model to shovel-truck system analysis

In this study the Machine Repair Model was modified to model shovel-truck systems and the modelling results obtained compared to output from other simulation models/packages. The Machine Repair Model equivalents are shown in parenthesis. A truck is sent for loading (repair) every cycle with the number of shovels or shovel loading sides or number of tipping bins (repair bays) being equal to *R* and the inter-arrival and service times both assumed to have an exponential distribution. Therefore, a shovel-truck system can be described as M/M/R/GD/K/K, where the first *M* is truck arrival rate, the second *M* is loader service rate, *R* is the number of shovels or shovel loading sides that are loading *K* trucks drawn from a population of size *K*, whereby the loading follows some general queue discipline, *GD*.

As with the Machine Repair Model, trucks are drawn from a finite population and their arrival pattern will therefore depend on the state of the system. For example, should all the trucks within a particular circuit be present at the loading unit, such as when a loading unit is experiencing an unexpected breakdown, then the truck arrival rate will be zero. At any other instant when there is less than the maximum number of trucks at the loading unit, the arrival rate will be positive. Under steady state conditions, the length of time that a truck spends away from the shovel follows an exponential distribution with rate λ, and the length of time that a shovel takes to load a truck follows an exponential rate μ.

If we define $\rho = \frac{\lambda}{\mu}$ as in Equation [1], the steady-state probability distribution will be given by Equations [7] and [8].

$$\begin{aligned}\pi_j &= \left(K_j\right)\rho^j\pi_0 \qquad (j = 0,1,\ldots,R)\\ &= \frac{\left(K_j\right)\rho^j j!\,\pi_0}{R!\,R^{j-R}} \qquad (j = R+1,\ R+2,\ldots,K)\end{aligned} \qquad [7]$$

$$\text{where } \left(K_j\right) = \frac{K!}{j!(K-j)!} \qquad [8]$$

For any queuing system under steady-state conditions, Little's queuing formulae can be applied to the system (Winston, 2004). Under steady-state conditions, an analogy of the shovel-truck system and the Machine Repair Model (Winston model) is illustrated in Table I.

By applying Little's queuing formulae, the model parameters are obtained from the calculations in Equations [9] to [12].

$$L = \sum_{j=0}^{j=k} j\pi_j \qquad [9]$$

Table I

An analogy of shovel-truck system and Machine Repair Model

Notation	Machine Repair Model Description	Repair model adjusted for load and haul
L	Expected number of broken trucks or destination server (plant or dump)	Expected number of trucks at the loading unit
L_q	Expected number of trucks waiting for service at the workshop repair bays	Expected number of trucks waiting for service at the loading unit or dumping distination
W	Average time a machine spends broken (down time)	Average time a truck spends at the loading unit or dump destination
W_q	Average time a truck spends waiting for service	Average time a truck queues at the loading unit or the plant/dump

$$L = \sum_{j=0}^{j=K} \lambda(K-j)\,\pi_j = \lambda(K-L) \qquad [10]$$

$$L = \lambda W \qquad [11]$$

$$L_q = \lambda W_q \qquad [12]$$

The average number of arrivals per unit time is given by $\bar{\lambda}$, where:

$$\bar{\lambda} = \sum_{j=0}^{j=K} \pi_j \lambda_j = \sum_{j=0}^{j=K} \lambda(K-j)\pi_j = \lambda(K-L) \qquad [13]$$

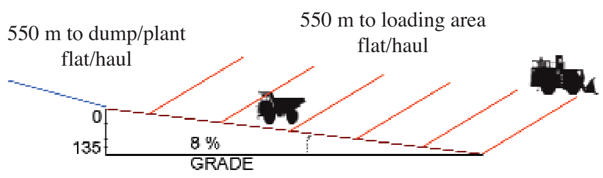
If Equation [11] is applied to trucks being loaded or trucks tipping at a bin, then the trucks that are waiting for service, W, are given by Equation [14].

$$W = \frac{L}{\bar{\lambda}} \qquad [14]$$

If Equation [12] is applied to trucks waiting to be loaded, W_q, we obtain the relationship shown in Equation [15].

$$W_q = \frac{L_q}{\bar{\lambda}} \qquad [15]$$

The inter arrival time $\frac{1}{\lambda}$ at the loading unit is thus a function of the truck's waiting time at the dumping destination, W_q (and vice versa for trucks at the dumping destination). This system of equations defining the Machine Repair Model was then programmed into MS Excel.



Bench height:	10 m (depth: 10–135 m)
Ramp length:	168–2828 m
Half cycle distance:	1268 m–2932 m
Rolling resistance:	4% constant

Figure 1—Layout of the virtual mine

Application of Machine Repair Model to virtual mine

The virtual mine has 10 m benches that extend from surface to a depth of 135 m (Figure 1). The ramp is constructed at 8% up-grade (GR) with a 4% rolling resistance (RR) kept constant throughout the haul route. A wheel loader loads OHT trucks that dump material at either a plant tipping bin or waste dump. For the virtual mine three loader cycle times were simulated, these being 3 minutes (for Caterpillar 777 OHT), 4 minutes (for CAT 777 OHT) and 5 minutes (for CAT 793 OHT). The dump and manoeuvre time was kept constant at 2.5 minutes, assuming a consistent operator proficiency.

Simulations were performed using the five models described earlier on. The Arena model was used as the benchmark model for the reason stated in Section 2.0 of this paper. The shovel-truck model created in Arena for this study is illustrated by the screen snapshot in Figure 2. By using different loader service times of three minutes, four minutes and five minutes, the five estimation models were run to produce estimates of attainable loads per shift. A comparison of the Winston (Machine Repair Model), FPC, Elbrond and Talpac to Arena in terms of the loads per shift is shown in Figure 3.

Several observations and accompanying explanations can be made in relation to Figure 3. Generally, the loads per shift obtained from the models are quite close to those obtained using Arena, with estimates from the other models ranging between 97% and 99.7% of the Arena estimates. The Talpac model with predominantly lognormal distributions fitted to cycle variables (standard distribution spreads embedded in program) produced estimates that were very close to those obtained from the Machine Repair Model, which has predominantly exponential distributions. Although FPC does not specify its embedded distributions, its estimates were closer to the estimates produced from lognormal and exponential distribution based models and appears to produce intermediate estimates compared to estimates from the other two models. The Elbrond (1990) model produced estimates that had the lowest percentage in comparison to Arena estimates compared to the rest of the models. This is primarily due to underestimation of waiting time by the FPC model when compared to the other models. By increasing the standard deviation of service time to return time ratios by 0.2 to 0.5, the difference of the Elbrond from with other models decreases, improving its percentage estimation compared to the other models. With an increase in service time the estimates of loads per shift deviate further away from Arena

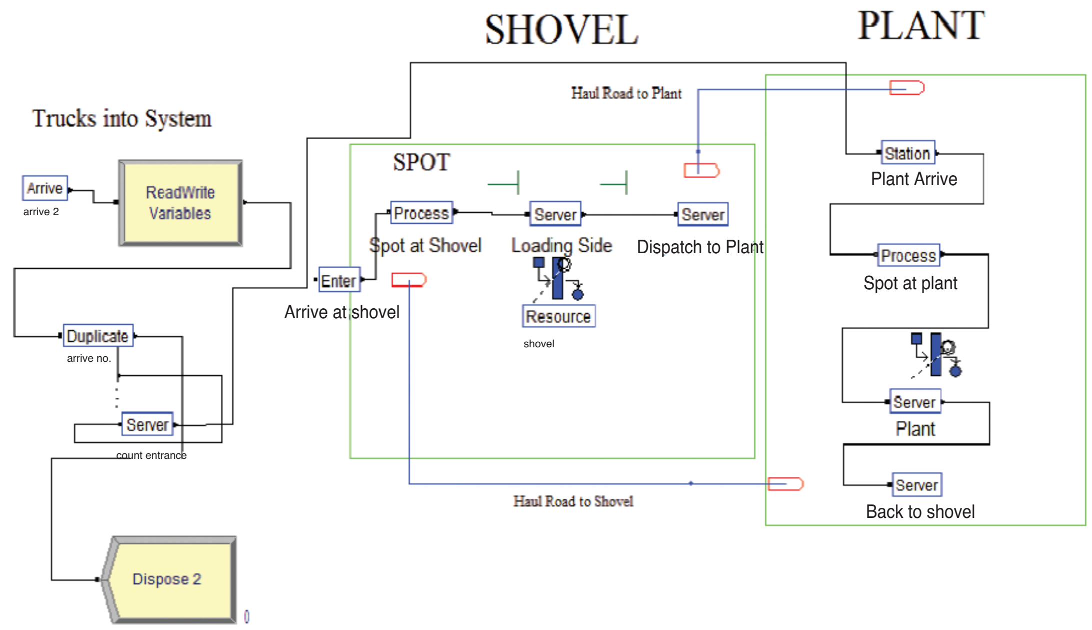


Figure 2—Screen snapshot of shovel-truck simulation process in Arena

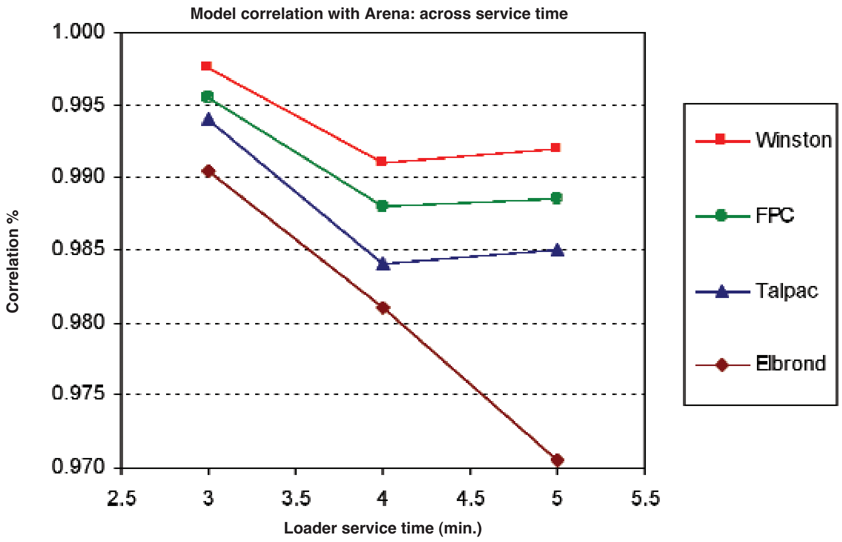


Figure 3—Comparison of loads per shift of other models with arena for virtual mine

estimates. Arena reported slightly higher loads per shift with a possible explanation that the other models are more conservative, which could be a benefit to the user because the risk of potential loss of planned production is reduced. The slight improvement in the estimates from the Winston, FPC and Talpac models compared to those from the Arena model with the increase in service time from four minutes to five minutes can partly be explained by the difference in machine characteristics between the CAT 777D and CAT 793D OHT trucks. The reason why Talpac does not show this improvement can partly be explained by the tendency of the Talpac program to underestimate the performance of Caterpillar trucks. Overall, the results show that the Winston (Machine Repair) model produces productivity estimates in terms of loads per shift that closely match those of the other models.

Application of machine repair model to Optimum Colliery's Kwagga section

Optimum Colliery is a surface coal mine owned by Ingwe Coal Corporation and BHP Billiton. Kwagga section is part of Optimum Colliery. Coal from Kwagga section is mined from three areas namely the North (or Rail), Central and South sections. The haulage routes for all three areas were considered in the study. Figures 4 depicts the haulage routes for the North (or Rail) section to show a typical haul route layout for the mine. The general geology of the North section is illustrated by a geological section (Figure 5). The strata consist mainly of a relatively thick, white, coarse grained massive sandstone layer followed by a thick shale layer below. Thinner alternating shale and sandstone bands occur

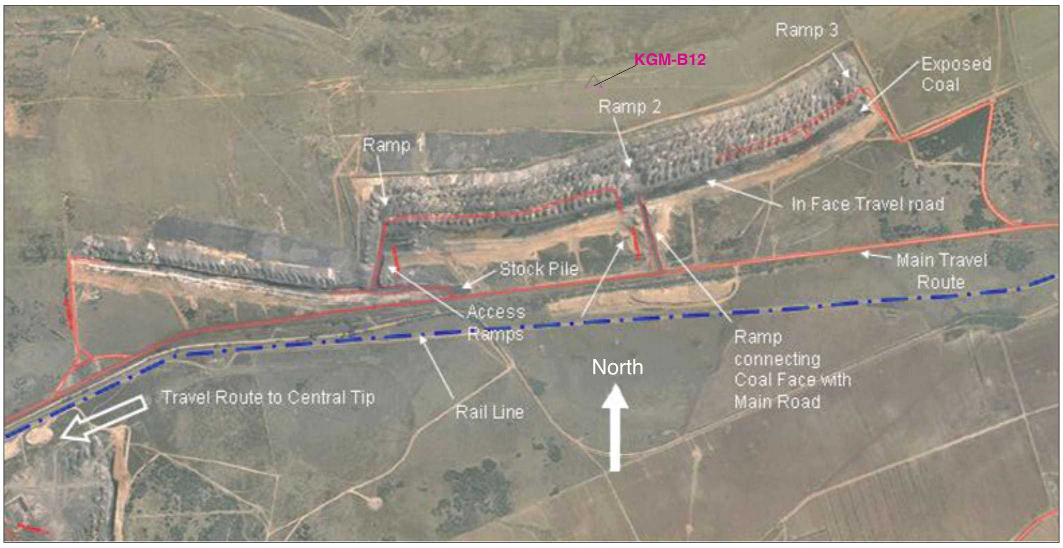


Figure 4—Aerial photograph showing haulage routes for the North (Rail) section

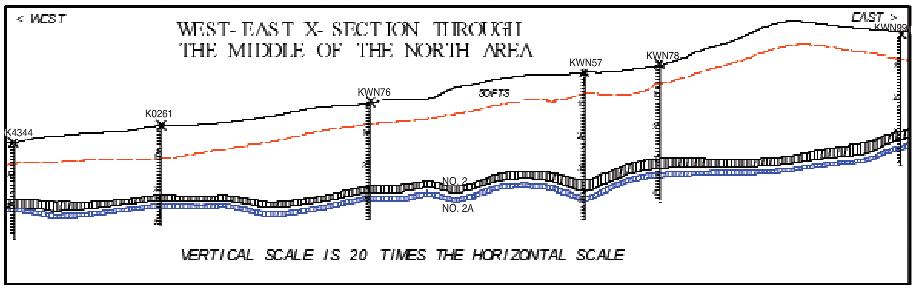


Figure 5—Section through North (Rail) section

in places. The top 8 metres consist of soft unconsolidated material. The geology illustrated in Figure 5 dictates that the general mining direction should be up-dip so that the gradient can be used to drain water away from the loading operations. Consequently, in-face haulage roads on the mine are developed with a slight dip. Major segments constituting the haulage profiles and their associated haulage resistances, for the three sections are presented in Table II.

Prior to the study, the haulage equipment fleet complement for Kwagga section was constituted as follows:

- 4 x Caterpillar 776D coal haulers (CAT 776D)
- 7 x Caterpillar 777D OHT (CAT 777D)
- 2 x Caterpillar 992G Wheel Loader (WL) with a high lift (HL) design (CAT 992 G WL HL)
- 1 x Caterpillar 992D WL HL (CAT 992D WL HL).

At the North section one CAT 992D WL and four Caterpillar 776D coal haulers are used. At the Central and South sections seven Caterpillar 777D OHT and two Caterpillar 992G WL are used. The travel distances are moderate for the Central and South sections while the North (or Rail) section has longer haul routes. It is for this reason that the CAT 776D coal haulers are predominantly confined to the North (Rail) section since they are more suited for longer hauls. Three Marion draglines are used for overburden stripping. Front end wheel loaders load blasted coal into the OHT trucks and coal haulers. The trucks haul the coal to two tips situated at the Central and South sections from where two main conveyors feed the washing plant that delivers coal to the Hendrina Power Station.

The above equipment suite hauls about 10.5 million tons of run-of-mine (ROM) coal per annum with the distribution by section as shown in Table III for a planned 8 322 site-scheduled hours per year. As can be derived from Table III, the fleet has a scheduled production rate of about 1 260 t per site-scheduled hour. It was required to estimate the additional trucks required to raise the production rate to 3 022 t per scheduled site hour. Simulation runs were performed using five different models including the Machine Repair Model. The simulated truck fleet requirements for a production rate of 3 022 t per site-scheduled hour are presented in Table IV.

From Table IV it can be seen that the Arena and Winston models, which are both modelled on exponential cycle time variable distributions, yield the same truck requirement. The Elbrond model also yields the same truck requirement as the Arena and Winston models. Although the Elbrond model yields the same result as the Arena and Winston models, the difference between its estimation of tons per hour (THP) and the required TPH is double the difference between estimated TPH and required TPH for other models. This can be directly attributed to the Elbrond model reporting zero waiting time for the coal haulers at the loaders. The FPC and Talpac

Table II

Distances, grade and rolling resistance of the haulage profiles

Section	Face to ramp Ramp to haulage			Haulage to tip Total						
	Distance	Grade %	RR%	Distance	Grade %	RR%	Distance	Grade %	RR%	distance
North										
Ramp 1	1 050	5%	4%	800	9.5%	4%	4 100	0%	3%	5 950
Ramp 2	400	5%	4%	500	9.5%	4%	8 715	0%	3%	9 615
Ramp 3	Load from stockpile		6 800	9.5%	4%	10 000	0%	3%	10 600	
	26 165									
Central										
Ramp 1	200	5%	4%	400	9.5%	4%	2 000	0%	3%	2 600
Ramp 2	350	5%	4%	450	9.5%	4%	1 300	0%	3%	2 100
Ramp 3	400	5%	4%	400	9.5%	4%	700	0%	3%	1 500
Ramp 4	650	5%	4%	5 800	9.5%	4%	400	0%	3%	1 500
	7 750									
South										
Ramp 2	500	5%	4%	1 000	9.5%	4%	1 000	0%	3%	2 500
Ramp 3	450	5%	4%	700	9.5%	4%	400	0%	3%	1 550
Ramp 4	350	5%	4%	700	9.5%	4%	400	0%	3%	1 450
Ramp 5	300	5%	4%	400	9.5%	4%	1 100	0%	3%	1 800
Ramp 6	250	5%	4%	600	9.5%	4%	1 500	0%	3%	2 350
Ramp 7	350	5%	4%	700	9.5%	4%	1 900	0%	3%	2 950
	12 600									

Distance = travel in metres (one way)
Grade % = grade resistance %
RR% = rolling resistance %

Table III

Planned production distribution by section

Section	Site schedule hours	Tons per annum planned
North		
Ramp 1	3 177	1 046 093
Ramp 2	2 951	971 373
Ramp 3	2 194	722 303
Sub-total	8 322	2 739 769
Central		
Ramp 1	1 040	598 357
Ramp 2	1 820	1 047 125
Ramp 3	2 081	1 196 714
Ramp 4	3 381	1 944 661
Sub-total	8 322	4 786 857
South		
Ramp 2	1 891	663 278
Ramp 3	1 702	596 951
Ramp 4	1 324	464 295
Ramp 5	1 135	397 967
Ramp 6	946	331 639
Ramp 7	1 324	464 295
Sub-total	8 322	2 918 425
Total	8 322	10 445 051

Table IV

Simulated truck fleet size estimates from the five models

Model	Section	Truck type		Total truck no.	
	776D	777D	776D	777D	
Elbrond	North Central South	6 - -	- 5 4	6	9
FPC	North Central South	6 - -	- 6 4	6	10
Winston	North Central South	6 - -	- 5 4	6	9
Arena	North Central South	6 - -	- 5 4	6	9
Talpac	North Central South	7 - -	- 6 4	7	10

models estimate one additional truck requirement compared to the other models for the Central section. The Talpac model estimates an additional coal hauler for the North section compared to the other models. This can be attributed to Talpac reporting higher truck travel times, which result in higher waiting times at both loader and dumping tips. Consequently, individual truck total cycle times are higher compared to other models. Ultimately, in order to meet the required TPH, more trucks are required compared to other models. Overall, it can be seen again that the Winston (Machine Repair) model produces truck fleet size estimates that closely match those from other models.

Subsequent to this study the mine decided to purchase two extra CAT 777D OHT trucks to bring the total CAT 777D fleet size to six. They also decided not to supplement the coal hauler fleet due to a change in the North section mining strategy. This decision was supported by a road improvement strategy using mobile crushers to provide sound underfoot conditions. This improvement will result in a reduction of rolling resistance and travel time and thus total cycle time and the number of coal haulers required.

Concluding remarks

Each of the five truck fleet size estimation models produced different estimates for the same project input parameters. The underlying reason for the differences, as was observed from the two case studies, derives from the way the models assign probability distributions to the individual cycle time components. The simulations showed that the Arena model with exponential distributions fitted to the cycle time components yielded similar results to the Winston model. The Elbrond and FPC programs, which do not have a specified underlying distribution model and can be described as field models, yielded similar results compared to that of Arena and Winston (Machine Repair) models. The case studies demonstrate that the Winston (Machine Repair) model produces truck fleet size estimates that closely match the estimates produced by other models. The Winston (Machine Repair) model is an affordable model, even for once-off use, for mines needing to estimate project truck requirements because it can be programmed on an MS Excel platform, a software package that most mines already use.

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