doi:10.36487/ACG_repo/2063_42

Development of a discrete event simulation model for cave mining ore handling systems with open source tools

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Abstract

The ore handling systems represent one of the largest expenses in cave mining, while the productivity and cost of a given production system can significantly impact the value of mining projects and operations. Moreover, in recent years the increase in mineral production using mass mining methods has led to significant progress in extraction techniques as well as equipment and technologies. Simulations are used to mimic real situations of production systems to aid in the design of new concepts and make engineered decisions. Discrete event simulation (DES) techniques can be applied to a wide range of analyses in cave mining, from refinement of cost and feasibility of plans or schedules to understanding the system behaviour for better decisions before expenses. This paper discusses the foundations to build a simulation model, while presenting the development of a discrete event simulation code using the R-Simmer package for the R language, to estimate productivity and capacity of an underground mining production system. Models using open source tools are intended to be an alternative to commercial simulation software, which can be onerous and restricted to specific settings. The outcome of this work constitutes a novel contribution to the simulation field, with the benefit to help design and assess cave mining ore handling systems but also create the basis of a future fully open-source simulation tool for cave mining.

1 Introduction

Simulations are widely used in the industry to mimic real situations with the purpose of describing and analysing the behaviour of production systems and to aid in the design of new concepts for more accurate results. Simulations have been used in mining for more than 50 years, originally on mainframe computers, but more recently on powerful desktop packages with sophisticated 3-D visualization complements for better understanding and validation. However, the real benefit of simulations is for analysing the results of a vast number of replications, identifying variability in outputs, and responses to changes with a sensitivity analysis (Hall 2015). On the other hand, simulation is much more meaningful when we understand what it is doing and how it works in order to know whether we are applying it correctly and what the output results mean. In that context, this paper aims to show the development of a discrete event simulation model for cave mining ore handling systems through a worked example and using a fully open-source tool, as an alternative to commercial simulation software.

2 Simulation basics

2.1 Simulation types

The way a simulation works is based largely on the kind of simulation used. In general, simulations can be classified by time (i.e.: static or dynamic), randomness (i.e.: stochastic or deterministic) and state change (i.e.: discrete or continuous). Although there are many ways to categorise simulation, an accepted classification for mining is shown in Table 1. Despite that in the literature, production systems or material handling system simulations are referred to as discrete event simulation (DES), it is common practice to combine both discrete event simulation with stochastic simulation.

Table 1 Simulations types (Brunner 2001; Barraza et al. 2004; Harrell et al. 2011)

Simulation Types	Description
Static	The static simulation does not consider the time and often involves drawing random samples to generate a statistical outcome, being the effect observed only at a single moment. For instance, static simulation modelling would be able to calculate the expected travel time from one location to another using Monte Carlos simulation with random samples to estimate an average travel time.
Discrete Event (DES)	The DES or dynamic simulation includes time, model systems whose states change at discrete points, triggered by events. Typical simulation events might be the arrival of equipment, the failure of a resource, the completion of an activity or the end of a shift. The simulation of rock movement systems are a typical case, where bulk solids move at constant rates (e.g.: ore extraction with LHD from a drawpoint, a skip reaching the surface or the content of an ore pass).
Continuous	The continuous simulation is targeted to model systems with states change uninterruptedly, the reason for what is referred to as continuous change state variables. They are used to model nonlinear behaviour based on either differential equations or difference equations, to define the rates of change in the state of variables over time (e.g.: chemical reactions or heat transfer).
Stochastic	The stochastic simulation also called probabilistic or non-deterministic, is based on random variables, hence producing random outputs. This method runs several replications to get an accurate performance estimate as variables fluctuate statistically. The most common stochastic and static simulation is Monte Carlo, for instance where the failure probability of various loader components is given, it is possible to estimate the likelihood that the entire LHD will fail. DES can also have stochastic behaviour if such inputs are used.

2.2 Discrete event simulation packages

There are multiple software to run discrete event simulations, as well as open-source packages for specific programming languages (e.g.: R-Simmer, SimPy or SimJulia), however, the final decision will depend on the know-how with previous tools, programming skills, support and training available, and licensing cost. Nonetheless, the best way to assess software is using their trial versions despite it is time-consuming and the outcomes for the project are generally expected with readiness. A review of available packages applied to cave mining is summarised in Table 2. Similarly, an extensive review of open-source DES tools has been carried out by Dagkakis, Heavey and Byrne, focusing on decision support in operations research and modelling (Dagkakis & Heavey 2015; Byrne, Heavey et al. 2010).

Table 2 Comparison of commercial simulation packages (Puhakka & Kainulainen 2000; Botha et al. 2008; Codelco 2014; RPM 2015)

Package	Method	Mine	Purpose	Input	Visual	Focus
Arena	Block Cave	Grasberg	Mine Performance	Pre-processed data	2D/3D	General
Promodel	Panel Cave	El Teniente	Haulage Capacity	Pre-processed data	2D/3D	General
Haulsim	Panel Cave	Cadia Valley	-	Raw data	3D	Mining
Optimine	Open Stopes	Avesta Polarit	Fleet sizing	Raw data	3D	Sandvik Equipment

2.3 Data and frameworks

Simulations, as a group of data, can be organized in frameworks that describe the operation of a system and its components in order to make it sound and logical. In a simulation-oriented system, attributes or entities (e.g. ore tonnage or cycles quantity) flow through a series of resources (e.g. equipment with its cycle time components or capacity) in the context of a defined trajectory (e.g. one trajectory for each loader). Attributes are units of work or traffic, and they queue to use resources according to logical rules and constraints (e.g. dumping into a crusher with limited tipping accesses).

Likewise, discrete event simulations can capture interaction in a way that no static simulations techniques can, given a large number of dynamic events that can happen in an underground mine. Fortunately, DES can incorporate a stochastic component through the use of random variables instead of deterministic or fixed inputs. More evident is the case of the cycle-time variabilities, such as speed, loading time, and dumping time, but also failure modelling and many other aspects of mine behaviour that can be represented by sampling from a probability distribution.

Data for mining models is often hard to gather and to bring to a usable scale. The extent of available data may be difficult to understand by an individual or a team, struggling to agree on what practices, criteria or ways of doing things to follow. However, when creating a model, the classification of inputs must be unanimous in order to clarify the assumptions and criteria used. Table 3 proposes four main categories to classify the inputs.

Table 3 Simulation Inputs of mining systems (After Brunner 2001)

Logic Data
It includes all the rules for operating the system. Some examples are the definition of the effective operating time, the number of shifts, the allocation of different equipment at various tasks, sequences that need to be followed or whether the model makes sequencing decisions dynamically.
System Data
It represents the physical system. This input includes mine design and layout, material properties, and the equipment list. If the information is available, it might be useful to break different geometries onto separate blocks that may have unique properties.
Process Data
It includes all the rates and speeds that constrain the system. Equipment capacity and performance, equipment failure, utilisation, availability, conveyor speeds, and similar data fall into this category.
Demand Data
It drives the model regarding the goal that needs to be achieved, for instance, the production schedule of a mine. Demand data may not be a major factor when the goal is to estimate the maximum system capacity, given the other constraints in place. However, there may be cases when the model is configured to start at certain producing zones at certain times or to stop before the end of the shift once a certain tonnage is drawn (e.g. drawpoint call to mimic the hang-up frequency).

The outputs of simulations are not always statistical, mainly for two reasons. First, a significant benefit of a well-constructed simulation project is the insights gained by describing the system in the framework of simulation. It means gathering and analysing the data as well as developing the logical rules for the system operation. Second, if the simulation package has visualization, it can be used to reveal system constraints or bottlenecks, anticipate improvements and validate the analysis. However, most open source packages have the disadvantage that computer graphics are not available or require the use of additional packages.

The statistical output from simulations can be derived from a standard report or customised to suit the user. Typical outputs include a list of arrivals, attributes and resources, as well as queuing statistics. The model can also produce measurable statistics that are consistent with the level of detail in the model. A model is not going to be considered useful unless everyone understands and believes it is valid. Although most decision-makers have got no insight into what is involved in the simulation, they have the capacity to determine whether the outcomes are sound. Calibration and validation are crucial to make a model representative.

There are many ways simulation can be used in the design and assessment of cave mining ore handling systems. Thus it is fundamental to define the framework of the simulation, as a response to the goals. Brunner describes a practical framework (Brunner 2001), as shown in Table 4. Such a framework delineates the time scope or horizon, the model focus and the model objective. For instance, a longer-term model usually requires proportionally less detail than shorter-term models. At the same time, on the model focus, the challenge is to limit the focus without sacrificing the desired level of fidelity, as it may complicate the model validation.

Table 4 Simulation Frameworks of a mining systems (After Brunner 2001)

Time
Short-term models (i.e.: days to a month) are used to evaluate operational conditions, to assess the schedule or the impact of exception conditions such as the impact of components downtimes or deficit of catch-up capacity of components.
Medium-term models (i.e.: months to years) are used to evaluate equipment plans, medium term schedules and operating policies.
Long-term models (i.e.: a few decades or more) are used to assess long-range mine plans, look for development bottlenecks or assess long-term strategies.
Focus
The development processes.
The production processes.
Supporting processes such as services, logistics and maintenance.
Materials handling; ore flow with: ore passes, crushers, hoppers and other system components.
Operator training.
Objectives
Equipment type comparisons.
Specific capital purchase decisions.
Mine plan analysis (discussion of integrated planning and modelling).
Mining method comparisons.
Operating policy evaluation and improvement (equipment deployment decisions, equipment and crew assignment decisions, sequencing).

2.4 Simulation steps

A typical simulation project consists of successive steps that guide a model builder in developing a simulation study. As shown in Figure 1, the process covers areas from the early problem formulation to the implementation, passing through verification and validation stages that ensure a model will represent the reality. The whole process has to be consistent with the simulation framework, following the time scope, model focus and model objectives.

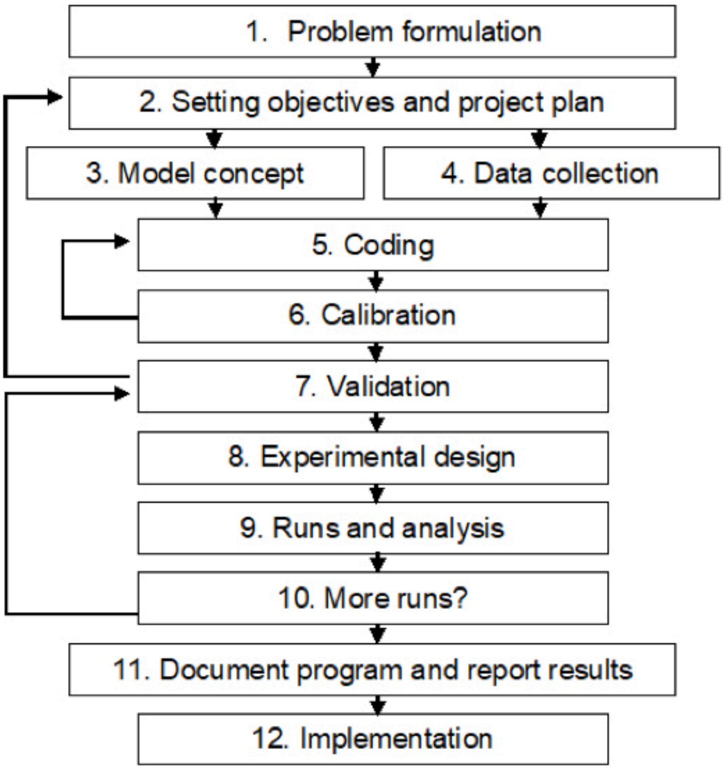

Figure 1 Steps to build a model (After Banks, Carson et al. 1996)

3 Simulation model construction

3.1 In-built speed model

Based on the terminology used to describe simulations with open source packages, some attributes were used to control throughput and capacity (i.e.: tonnage) and some resources to discretise the components of the rock flow (i.e.: loading, tramming and dumping). Since attributes and resources are controlled by time, there is a necessity to assist the model in the calculation of such time using average speed and tramming distance.

In that context, a speed model for mobile equipment was built, capable of estimating average speeds as a function of the tramming distance and accelerations of loaders or trucks using the physics of rectilinear motion with uniform acceleration, described in the formulas (1), (2) and (3), where "V" is the final speed, "Vo" the initial speed, "a" the acceleration, "d" the final distance, "do" the initial distance and "t" the time.

$$V^2 - Vo^2 = 2 * a * d \tag{1}$$

$$V - V_o = a * t \tag{2}$$

$$d = d_o + V_o * t + 0.5 * a * t^2 \tag{3}$$

For instance, an LHD has different acceleration and speeds when it moves forward and reverse, and most importantly, when it is loaded or empty; thus, it has four combinations of movement. Table 5 shows the inputs for the speed model of an LHD and Figure 2 illustrates the average speed that the simulation model estimates given a distance and direction of movement.

Table 5 Inputs for the speed model for an LHD in a Block Cave mine

Heading	Acceleration (m/s²)	Deceleration (m/s²)	Maximum Speed (m/s)
Loaded Forward	0.42	0.57	4.72
Loaded Reverse	0.53	0.61	4.72
Empty Forward	0.62	0.62	4.72
Empty Reverse	0.59	1.13	5.56

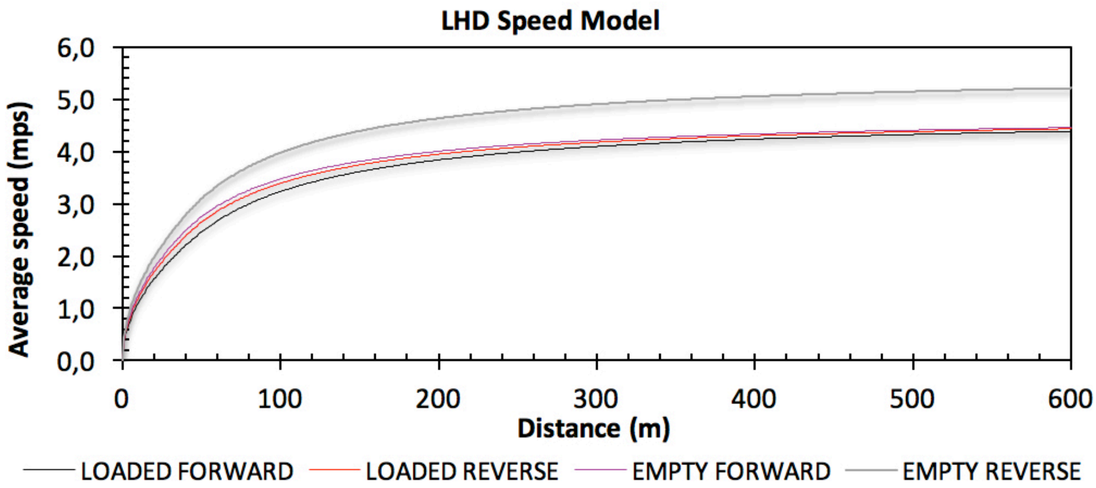

Figure 2 In-built speed model for R-Simmer of an LHD in a Block Cave Mine

3.2 In-built time usage model

Regarding the frameworks theory previously described, simulation-oriented systems use attributes that flow through a series of resources in the context of a defined trajectory, being dynamically regulated by interaction; in other words, including the run of time. For this reason, it is crucial to incorporate a time usage model, so the effective operating time or the total time that the simulation will run can be estimated.

Different organisations may have different time usage models or time arrangements, however, utilisation and availability are commonly accepted concepts across the industry. Availability represents the impact of planned and unplanned downtimes, while utilisation embodies the effect of delays and idle time that the system experiences as interruptions of the effective operating time.

Finally, a simple time usage model is shown in Table 6, which considers availability as the loss of planned and unplanned downtime, and utilisation as the operational loss given delays and idle time. Similarly, other availability factors are used in cave mining, such as drawpoint or tipping point availability, although the way that they are applied varies, from affecting the cycle time efficiency to the number of simultaneous active drawpoints. Ultimately, the important edge condition is not to double count the loss time and being able to determine the effective time that the simulation will run as a whole or per units operating simultaneously in the model.

Table 6 Example of a time usage model for an LHD in a Block Cave mine

Hours per Month (α)			
744			
Available Hours (β)		Downtime Hours	
590		154	
Utilised Hours (Ω)	Unutilized Hours	Planned Hours	Unplanned Hours
463	127	88	66

Summary		
Availability (%)	A = β / α	79%
Utilization of Availability (%)	B = Ω / β	78%
Effective Utilization (%)	A X B or Ω/ α	62%

3.3 In-built fragmentation model

The fragmentation is one of the areas with a major impact on equipment performance in current production systems. It determines the equipment and infrastructure sizing requirements while impacting on the drawpoint availability (i.e. hang-ups), loading time and the fill factor. Having reliable fragmentation estimates, allows for better designs and plans, anticipating current and future materials handling requirements.

Since oversize and drawpoint blockages exert a major constraint on production build-up, there is a necessity to simulate models that consider the drawpoint yield, representing a hang-up frequency or drawpoint availability, which affects the ability to mine as per the schedule (Pretorius & Nigidi 2008). Following a sizing distribution example at PT Freeport Indonesia (Botha et al. 2008), the following formulas were used to define a sizing criteria for the discrete event simulation model:

$$\text{Long Side} = \sqrt[3]{(Rock\ Aspect\ Ratio^2 * Volume)} \tag{4}$$

$$Rock\ Aspect\ Ratio = Long\ Side\ /\ Short\ Side \tag{5}$$

$$Volume = Short\ Side^2\ x\ Long\ Side \tag{6}$$

$$Volume = Short\ Side^3\ /\ Rock\ Aspect\ Ratio^2 \tag{7}$$

As a result, taking as an input the fragmentations curves for different years and caving heights, Table 7 shows the results of the in-built fragmentation model, being able to limit the fractions of production that will create rock flow detentions due to the lack of availability for hang-ups or blockages in the components of a given production system.

Table 7 Example of a fragmentation model sourced from fragmentation curves in a Block Cave

Description	Long side criteria (m)				Volume (m^3)		
Passing Crusher	0.3				0.003		
Passing LHD Oversize	2.3				2.0		
Passing Hang-up	4				10		
Passing Grizzly	1.0				0.2		
Caving height (m)	**20**	**50**	**100**	**150**	**200**	**300**	**400**
Year of predicted height	**1**	**1**	**2**	**3**	**4**	**6**	**8**
Passing crusher (%)	2%	5%	7%	10%	14%	18%	22%
Passing LHD oversize (%)	44%	52%	58%	70%	80%	90%	100%
Passing hang-Up (%)	68%	78%	78%	87%	92%	97%	100%
Passing grizzly (%)	17%	25%	36%	50%	65%	82%	96%

3.4 Model development

R-Simmer is a process-oriented and trajectory-based Discrete-Event Simulation (DES) package for R, designed to be a generic framework, just as SimPy is for Python. R-Simmer exploits the concept of trajectory as a common path for entities of the same type. Programmers recognise it as a flexible and straightforward package. Nevertheless, it may be difficult to learn for people without previous experience in programming.

Having reviewed the simulation basic required to build a model, Table 8 shows an example of a simplified general simulation model in R-Simmer, being in this case applied to a system of LHDs within the production level in a block cave mine, as result of the overall system utilisation and availability. Since the raw data from this model includes a list of every activity completed during the simulation time, an assorted battery of results can be drawn, including, performance, capacity, productivity to distance and average time spent on every activity during a cycle, as some examples.

Table 8 Simplified general simulation model of an LHD in R-Simmer (After Silva 2017)

Trajectory		LHD_x<-create_trajectory("drive_y")%>%
Attribute of tonnes		set_attribute("tonnage_dp_i",0)%>%
Attribute of travels		set_attribute("travels_dp_i",0)%>%
Cycle Iteration at drawpoints "i"	Stay or continue?	branch(function(attrs) ((attrs[["tonnage_dp_i"]]>Production)+1),c(T,T),
	Stay	create_trajectory("stay") %>%
	Travels counter	set_attribute("travels_dp_i" ,function(attrs) attrs[["travels_dp_i"]] + 1)%>%
	Tonnes counter	set_attribute("tonnage_dp_i",function(attrs)attrs[["tonnage_dp_i"]]+Capacity*FF)%>%
	Loading time	seize("loading_dp_i",1)%>%
		timeout(function() loading_time)%>%
		release("loading_dp_i",1)%>%
	Tramming time	seize("tramming_dp_i",1)%>%
		timeout(function() tramming_time)%>%
		release("tramming_dp_i",1)%>%
	Inversion	seize("inversion1_dp_i",1)%>%
		timeout(function() change_direction_time)%>%
		release("inversion1_dp_i",1)%>%
	Dumping	seize("dumping_access_n",1)%>%
		timeout(function() dumping_time)%>%
		release("dumping_access_n",1)%>%
	Inversion	seize("inversion2_dp_i",1)%>%
		timeout(function() change_direction_time)%>%
		release("inversion2_dp_i",1)%>%
	Return	seize("return_dp_i",1)%>%
		timeout(function() return_time)%>%
		release("return_dp_i",1)%>%
	Iterate for cycles	rollback(amount="drawpoint call",check=function(attrs) attrs[["travels_dp_i"]]<10),
	Continue	create_trajectory("continue")%>%
	Reset travels	set_attribute("travels_DP_i",0))%>%set_attribute("travels_DP_i",0)%>%
Iterate for production		rollback(amount="No_dp*2",check=function(attrs) attrs[["tonnage_dps_i"]]<"production_dp_i" &
		attrs[["tonnage_dp_i+1"]]<Production_dp_1+1
Open project		Name%>%
Resources "i"		add_resource("loading_dp_i",1)%>%
		add_resource("tramming_dp_i",1)%>%
		add_resource("inversion1_dp_i",1)%>%
		add_resource("return_dp_i",1)%>%
		add_resource("inversion2_dp_i",1)%>%
		add_resource("dumping_access_i",1)%>%
LHD units generator		add_generator("drive_y",LHD_x,at(1), mon=2)%>%
Run operating time		run(until="time of simulation")

Besides, the simulation requires the distances from each source (e.g.: drawpoints) to its destination in the system (e.g.: ore passes, bins or a crusher), so the speed model can get such information to estimate the travel time. Similarly, the production schedule and drawpoint call are required to represent the conditions of the mine best, unless it is set to produce at maximum capacity. Finally, the number of loaders available and their allocation to specific extraction drives should be defined as logic inputs that have to be considered to set the model layout, bearing in mind that R-Simmer reads the code as a sequence of iterative activities.

4 Application to a Block Cave mine

4.1 Mine setting

As part of the prefeasibility studies of a block cave mine expansion using El Teniente layout, the R-Simmer Package was used to determine what production level design (expansion zone in green) matched the existing ore handling systems best, connecting the ore flow to the current macroblock infrastructure. As illustrated in figure 3, the base case design, involves 20-tonne capacity loaders tramming from drawpoints to a new ROM bin, which in turn feeds a single jaw-gyratory crusher located outside of the footprint. On the other hand, the alternative design pursues to save CAPEX despite the longer distances, making the 20-tonne loaders tram directly from the drawpoints to the existing crushed ore bin using three tipping accesses.

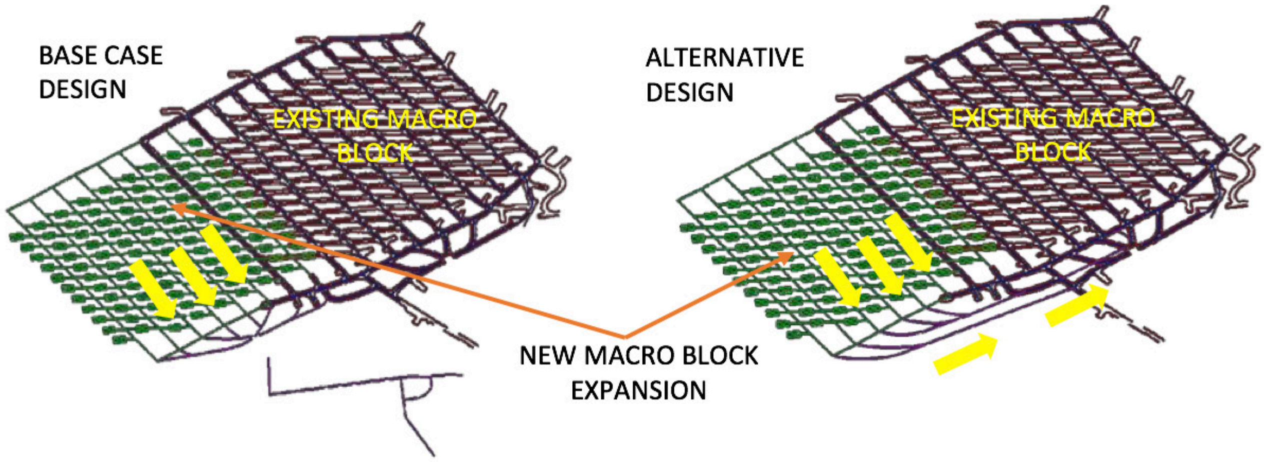

Figure 3 Base case versus alternative design of a block cave mine expansion

4.2 Inputs

The model accepts some deterministic and probabilistic values to assess the interaction of these parameters thoroughly. For this paper, the simulation is set to estimate the system throughput as the result of the average loader performance, based on the entire system availability and utilisation. In that context Table 9 summarises the main inputs of the model.

Table 9 General inputs for the model

Parameter	Value	Parameter	Value
Drawpoint call (cycles/shift)	10	Equipment length (m)	11.2
Payload (t)	20	Speed	As per model
Fill factor (%)	rnorm(1,0.9,0.05)	System availability (%)	77%
Loading time (s)	rnorm(1,10,2)	System utilisation (%)	74%
Dumping time (s)	rnorm(1,5,1)	Tip availability (%)	81%

Note: rnorm(x, y, z) = generate "x" normally distributed values, with mean "y" and standard deviation "z".

The drawpoint call is meant to mimic the effect of drawpoint availability due to hang-ups, while the equipment length is used by the model to estimate inversion times during the cycle. The loading and dumping times are indexed as probability distributions after measurement on-site, as well as the time usage parameters. Depending on the level of interferences as logic information some factors should be adjusted in order not to double penalize the effective operating time. At last, some logic rules were also considered, as the allocation of loaders to certain drifts.

4.3 Outcomes

The simulation results for the base case are shown in Figure 4, sensitizing the loaders productivity to the number of units used. It can be seen that as tramming distances get longer, consequently the productivity decreases, as well as when more units are introduced due to interferences in traffic. Likewise, Figure 5 shows the alternative design with a limited number of tip accesses and even longer distances, as shown in Figure 3, resulting in a lower productivity per unit in the fleet. Particularly, it can be seen in the alternative design that beyond the 400 m, the productivity tends to stabilize when increasing the number of loaders, showing that the system has touched the threshold of traffic interferences or queuing for tipping accesses.

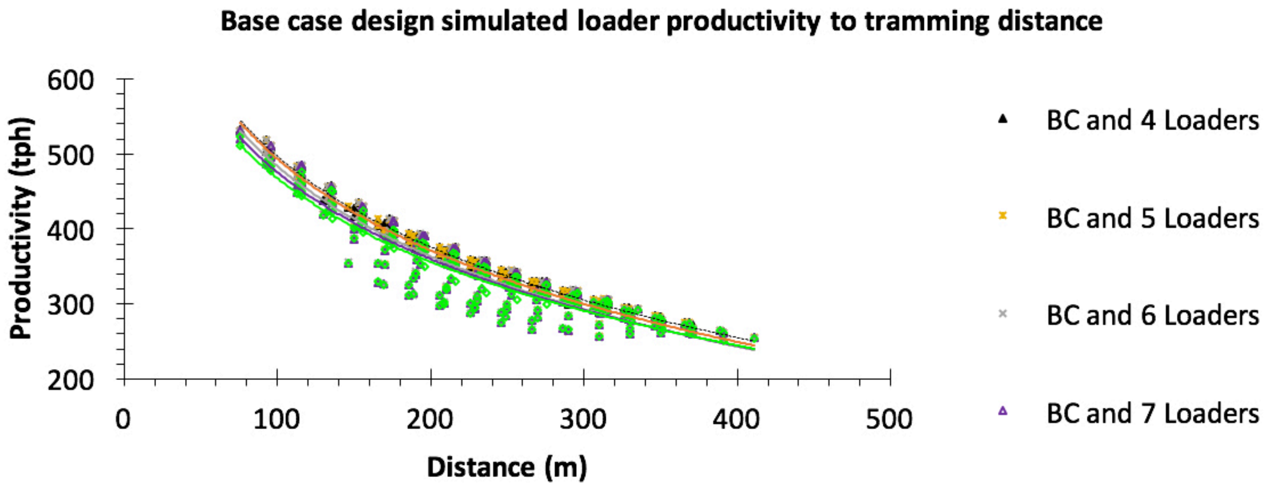

Figure 4 Base case - Simulated productivity to tramming distances

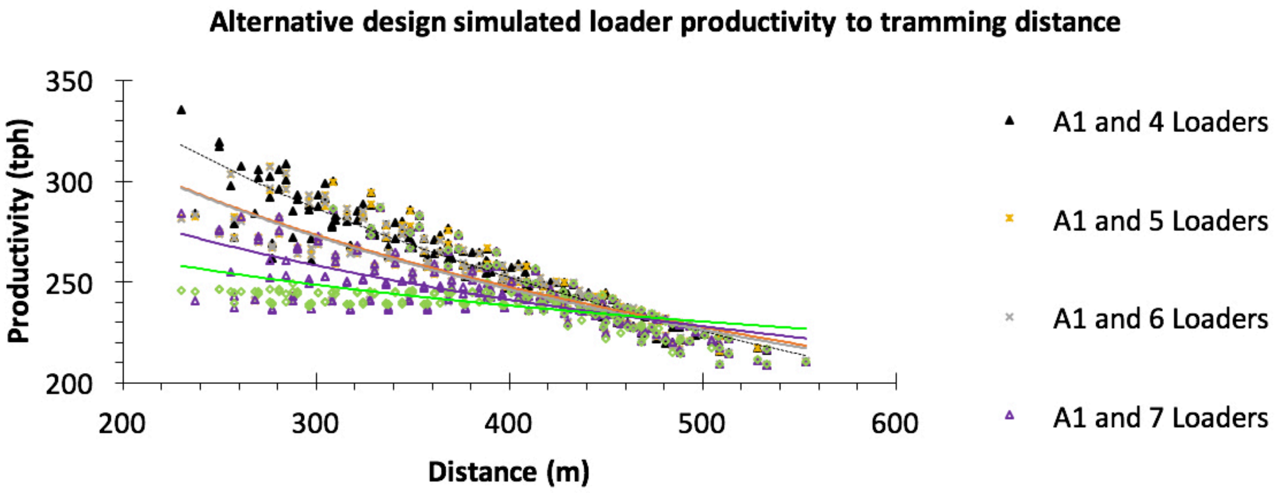

Figure 5 Alternative - Simulated productivity to tramming distances

Ultimately, Table 10 shows the simulated system throughput as the result of the average loader performance, based on the entire ore handling system (i.e.: drawpoint to crusher) availability and utilisation. It can be seen that as more loaders are added to the fleet, the productivity decreases and so the system throughput. Most importantly, the results suggest that even when the alternative design brings simplicity and saving of CAPEX by not requiring additional excavation and facilities for a new crusher station, the new macroblock would be limited by the ore handling system to a maximum of 9.6 Mtpa, while the base case design can achieve more than 13.4 Mtpa.

Table 10 Simulated system throughput as the result of the average loader performance

Alternative	Number of Loaders	4	5	6	7	8
Base Case	Capacity (Mtpa)	7	8.5	9.8	11.6	13.4
	Productivity (tph)	359	354	346	343	340
Alternative	Capacity (Mtpa)	5.2	6.3	7.5	8.6	9.6
	Productivity (tph)	258	252	251	244	240

As for validation, and based on the average tramming distances, these simulations indicate that the base case could achieve average productivities per LHD between 340 tph to 360 tph depending on the number of loaders used, mainly given the constraint of queueing at tip accesses. This data was contrasted with samples of the existing macroblock, where the loaders productivities had similar values.

5 Conclusions

During the last decade, Discrete Event Simulations (DES) have been used in cave mining to simulate ore-flow, however, open source simulation have not been found in the literature. For these reasons, an open-source simulation tool using the R programming environment was selected to code a simulation model, taking advantage of the R-Simmer package specifically for DES.

An expandable simulation model of loaders at the extraction level was constructed in R-Simmer, being flexible and expandable enough to simulate different scenarios with different inputs, following the model framework (i.e.: time, focus, and objectives). The model also includes an implicit speed sub-model prototype to estimate the average speed and time as a function of the measured tramming distance, as well as a drawpoint yield to mimic the occurrence of hang-ups due to the expected fragmentation.

For the worked example, it can be concluded that the construction of a new crusher station, as defined in the base case, allows the macroblock to achieve higher system capacity, although it comes at a higher cost. Meanwhile, the alternative design provides a lower capacity but low-cost option with relatively rapid construction to enable the material handling system of the new macroblock, assuming that it would be available by the time the new production sector commences. Nonetheless, different upgrades to this design have the potential to improve productivity, for instance, building more tip accesses to reduce queuing, improvements on tip availability, and estimation of the optimum ROM bin capacity.

Acknowledgement

The author of this paper would like to acknowledge the contribution made to the completion of the Master thesis that originated this publication: Professor Gideon Chitombo from The University of Queensland, Doctor Germán Flores from Newcrest Mining Limited, the material handling systems senior consultants Mr Peter Choules and John Spreadborough. Likewise, the author acknowledges Doctor Juan Ossa, whose R coding expertise contributed to the development of this simulation modelling code with R-Simmer.

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