International Journal of Mining Science and Technology 26 (2016) 745–752

Contents lists available at ScienceDirect

International Journal of Mining Science and Technology

journal homepage: www.elsevier.com/locate/ijmst

A discrete-event model to simulate the effect of truck bunching due to payload variance on cycle time, hauled mine materials and fuel consumption

A. Soofastaei *, S.M. Aminossadati, M.S. Kizil, P. Knights

School of Mechanical and Mining Engineering, The University of Queensland, Brisbane, QLD 4072, Australia

ARTICLE INFO

Article history:
Received 29 November 2015
Received in revised form 13 January 2016
Accepted 28 March 2016
Available online 8 June 2016

Keywords:
Discrete-event model
Simulation
Truck bunching
Payload variance
Cycle time
Fuel consumption

ABSTRACT

Data collected from truck payload management systems at various surface mines shows that the payload variance is significant and must be considered in analysing the mine productivity, energy consumption, greenhouse gas emissions and associated cost. Payload variance causes significant differences in gross vehicle weights. Heavily loaded trucks travel slower up ramps than lightly loaded trucks. Faster trucks are slowed by the presence of slower trucks, resulting in 'bunching', production losses and increasing fuel consumptions. This paper simulates the truck bunching phenomena in large surface mines to improve truck and shovel systems' efficiency and minimise fuel consumption. The study concentrated on completing a practical simulation model based on a discrete event method which is most commonly used in this field of research in other industries. The simulation model has been validated by a dataset collected from a large surface mine in Arizona state, USA. The results have shown that there is a good agreement between the actual and estimated values of investigated parameters.

1. Introduction

Improving the efficiency of haulage systems is one of the great challenges in mining engineering and is the subject of many research projects undertaken in both study and industry [1–9]. For mining, it is important that haulage systems are designed to be as efficient as possible, in order to minimise haulage cost, improve profitability and increase the total mine value. Haulage system inefficiency is typically derived from inadequate engineering, which results in poor haul road design, machinery standby and downtime, and circuit traffic [10–12]. According to the literature, haulage costs can be some of the largest in a mining system [13,14]. In various case studies it was found that material transportation represents 50% of the operating costs of a surface mine [15].

The main effective parameters on material transport when a truck and shovel system is used in surface mines are mine planning, road condition, truck and shovel matching, swell factors, shovel and truck driver's ability, weather condition, payload distribution and payload variance [16–19]. Based on the literature among all above mentioned parameters, truck payload variance is one of the most important parameters in this field [7,20,21]. The payload variance not only affects the production rate, but also it is an important parameter in the analysis of fuel consumption. The main source of the payload variance in truck and shovel mine operation is the loading process. Loading is a stochastic process and excavator performance is dependent on factors such as swell factor, material density and particle size distribution [22]. Variation of these factors causes variation of bucket and consequently truck payloads, affecting productivity. Reducing truck payload variance in surface mining operations improves productivity by reducing bunching effects and machine wear from overloaded trucks [23]. In large surface mines having long ramps, bi-directional traffic and restrictions on haul road widths negate the possibility of overtaking. Overloaded trucks are slower up ramp in comparison to under-loaded trucks. Thus, faster trucks can be delayed behind slower trucks in a phenomenon known as truck bunching [20]. This is a source of considerable productivity loss for truck haulage systems in large surface mines.

There are some investigations about the payload variance simulation and the effect of this event on other mining operational parameters. A project completed by Hewavisenthi, is about using a Monte-Carlo simulation to investigate the effect of bulk density, fill factor, bucket size and number of loading passes on the long term payload distribution of earthmoving systems [21]. The focus of their study is on simulation of payload distribution and variance in large surface mines. A study conducted by Knights and Paton

* Corresponding author. Tel.: +61 7 33658232.
E-mail address: a.soofastaei@uq.edu.au (A. Soofastaei).

http://dx.doi.org/10.1016/j.ijmst.2016.05.047
2095-2686/

concerned with truck bunching due to load variance [20]. This study was conducted to provide an analysis of the effect of load variance on truck bunching. In this project, a GPSS/H model was constructed which simulates a haulage circuit designed using data inputs from a real mine site. The model was used to run haul circuit simulations with different levels of payload variance. From empirical data, haul route travel times were estimated to be dependent on payload based on a linear relationship with an additional stochastic component modelled by a normal distribution. The data was insufficient to determine the dependence of changes in haul route travel time on changes in payload variance. In this project, a simulation was also conducted to investigate the haul circuit throughput difference if single truck overtaking was permitted. Webb investigated the effect that different bucket load sizes had on truck cycle times and the inherent costs [24]. The research project being undertaken will focus primarily on the effect of load variance on truck bunching.

Based on the condition of truck and shovel mining operations in surface mines, the best simulation for this event can be simulated by discrete event methods. Discrete event simulation can be used to model systems which exhibit changes in state variables at a discrete set of points in time [26]. The models can be static or dynamic. Static models represent a system at a specific time, while dynamic models represent a system as it evolves over a period of time [26]. A mining operation is a dynamic system which is very difficult to model using analytical methods. When simulation is used, the model input can be based on probabilistic data which better characterise the input variables and a given number of variables can be described by selecting appropriate distributions [27].

The trucks utilised in the haulage operations of surface mines consume a great amount of fuel and this has encouraged truck manufacturers and major mining corporations to carry out a number of research projects on the fuel consumption of haul trucks [28]. There are many factors that affect the rate of fuel consumption for haul trucks such as payload, velocity of truck, haul road condition, road design, traffic layout, fuel quality, weather conditions and driver skill [1]. A review of the literature indicates that understanding of energy efficiency of a haul truck is not limited to the analysis of vehicle-specific parameters; and mining companies can often find greater energy saving opportunities by expanding the analysis to include other effective factors such as payload distribution and payload variance [29].

This paper aims to present a new simulation model based on the discrete event methods to investigate the effect of truck bunching due to payload variance on average cycle times, the rate of loading materials and fuel consumption.

2. Payload variance

Loading performance depends on different factors such as bench geometry, blast design, muck pile fragmentation, operators' efficiency, weather conditions, utilisation of trucks and shovels, mine planning and mine equipment selection [21,30]. In addition, for loading a truck in an effective manner, the shovel operator must also strive to load the truck with an optimal payload. The optimal payload can be defined in different ways, but it is always designed so that the haul truck will carry the greatest amount of material with lowest payload variance [20]. The payload variance can be illustrated by carrying a different amount of overburden or ore by the same trucks in each cycle. The range of payload variance can be defined based on the capacity and power of the truck. The increase of payload variance decreases the accuracy of the maintenance program. This is because the rate of equipment wear and tear is not predictable when the mine fleet faces a large payload variance [23]. Minimising the variation of particle size distribution, swell factors, material density and fill factor can decrease the payload variance but it must be noted that some of the mentioned parameters are not controllable. Hence, the pertinent methods to minimise the payload variance are real-time truck and shovel payload measurement, better fragmentation through optimised blasting and improvement of truck-shovel matching. The payload variance can be shown by variance of standard deviation σ. Standard deviation measures the amount of variation from the average. A low standard deviation indicates that the data points tend to be very close to the mean; a high standard deviation indicates that the data points are spread out over a large range of values. This parameter can be calculated by

$$\sigma = \sqrt{\frac{1}{Z}\sum_{i=1}^{Z}(x_i-\mu)^2} \tag{1}$$

where Z is the number of available data for each parameter; i the counter of data; x the value of parameter; and μ the mean which can be calculated by following equation.

$$\mu = \frac{1}{Z}\sum_{i=1}^{Z}x_i \tag{2}$$

Fig. 1 shows the different kinds of normal payload distribution (the best estimation function for payload distribution) based on the difference σ for one type of the mostly used truck in surface mines (CAT 793D).

In Fig. 1, gross vehicle weight (GVW) is the total weight of empty truck and payload. Based on the CAT 793D technical specifications, the range of GVW variation is between 165 (empty truck) and 385 tonnes (maximum payload). Hence, the maximum σ for this truck can be defined as 30; that is because for higher standard deviations, the minimum GVW is less than the weight of empty truck and the maximum GVW is more than the maximum capacity of truck.

3. Discrete simulation modelling

Based on the condition of truck and shovel mining operation in surface mines, the best simulation for this event can be by discrete event methods. Discrete event simulation can be used to model systems which exhibit changes in state variables at a discrete set of points in time [25,31]. The models can be static or dynamic. Static models represent a system at a specific time, while dynamic models represent a system as it evolves over a period of time [32]. A mining operation is a dynamic system which is very difficult to model using analytical methods. There are different kinds of discrete simulation models used for modelling the systems in industrial projects. In this study, some of the most popular models have been investigated and a new model to simulate the truck bunching event in surface mining operation has been developed.

The first investigated model is AutoMod. This model is a simulation system which is designed for use in material movement systems developed by Applied Materials, USA [33]. It can be used for

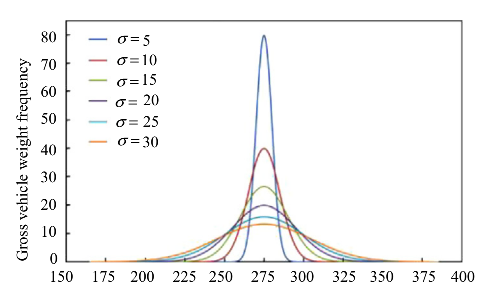


Fig. 1. Normal payload distribution for different standard deviation σ (CAT 793D).

simulation of truck haulage circuits and transport circuits, conveyors, load dumping and retrieval, cranes and robots. Simulations with AutoMod have the ability for simulation of complex movement with stochastic inputs. AutoMod models can contain multiple systems (e.g. interacting truck and shovel circuits). To produce a simulation, the user constructs a series of action statements which allow the incorporation of elements such as machinery, queues, loading, delays and input values/variables. Simulations also allow the use of conditional tests. Load inputs can be deterministic or stochastic. AutoMod offers control variables for queuing, wait times and traffic which are crucial for haul circuit simulation bunching analysis. Visualisation of simulation is powerful and extensive in AutoMod. Graphical model outputs can be represented in three dimensions and is industry leading in terms of animation and realism.

The second studied model is SIMUL8. This model is a graphically oriented simulation package developed by the SIMUL8 Corporation [34]. This software is a discrete event simulation package, meaning it simply executes tasks in queue based on time, which then triggers the activity of new tasks. SIMUL8 can be used in simulation of multiple haulage systems, but is more effective at single circuit simulations.

The third analysed model is GPSS/H. The general purpose simulation system (GPSS) language was originally released in 1961 and became a popular means of simulation since it could be operated without the requirement for the user to be knowledgeable in programming. GPSS/H was derived from the evolution and expansion of GPSS and became the more widespread and superior package. GPSS/H was released in 1977 by Wolverine Software Corporation who still develops and sells GPSS/H today [20]. GPSS/H can be used with a wide range on models due to its simplicity and flexibility. It is based on a flowchart type system using "transactions" which move between "blocks". It involves the creation of blocks and controls statements to generate a system. Transactions move throughout the system based on the tick of an internal clock. Each tick of the clock corresponds to one-time unit worth of action. GPSS/H is stochastic in nature, such that it can execute Monte Carlo style randomisation to apply statistical distributions. GPSS/H is particularly adept at simulating queuing and bunching. GPPS/H can be applied to several systems including haulage circuits, data flow or a production line. The language is based on text entry, and does not provide visualisation without the use of proof animation.

The fourth studied model in this project is WITNESS. This model is a discrete event simulation suite developed by Lanner. Witness is capable of producing haulage system simulations in a dynamic animated computer model [35]. The suite consists of four separate modules, the main WITNESS simulation module, an experimentation optimiser, a scenario manager for analysis and a three dimensional visual output.

The last but not least inspected model is Arena. This model is a simulation software package developed by Rockwell Automation based on the SIMAN programming language [36]. SIMAN is a discrete event simulation package which can be used in process or event scheduling mode. SIMAN is most commonly used in conjunction with Arena in industry today. SIMAN can alternatively be used in conjunction with CINEMA, a visualisation package. The ARENA system can produce scale models of circuits and other simulations.

4. Truck bunching model

4.1. Developed algorithm

Hauling operations in surface mines consists of different kinds of components. These components are loading, hauling, manoeuvring, dumping, returning and spotting (Fig. 2).

In the standard hauling operation, loading time is the time taken to load the truck, and hauling and returning time are travelling time for each truck between loading zone and dumping area. Spotting time is the time during which the loading unit has the bucket in place to dump, but is waiting for the truck to move into position. Spotting time will depend on the truck driver's ability and the loading system. Double-side loading should almost eliminate spot time. Dumping time is the time taken for the truck to manoeuvre and dump its payload either at a crusher or dump.

Based on the above mentioned hauling operation components, four main times can be defined; fixed time, travel time, wait time and cycle time.

Fixed time is sum of the loading, manoeuvring, dumping and spotting time. It is called 'fixed' because it is essentially invariable for a truck and loading unit combination. Travel time is the time taken to haul and return the payload. Wait time is the time the truck must wait before being served by the loading unit, waiting in a queue for dumping and the waiting time in line behind the overloaded trucks in large surface mines (truck bunching). Cycle time is the round trip time for the truck. It is the sum of the fixed, travel and wait times.

Fig. 3 illustrates the proposed algorithm to complete a discrete event model in this project.

This algorithm consists of four main subroutines to cover all processes in the hauling operation. These main components are loading, hauling, dumping and returning. Based on the developed model, each component has a waiting time. The main reason for waiting time in hauling is payload variance.

4.2. Payload distribution and variance simulation

A main part of the truck bunching model is simulating the payload distribution and variance. In this study, a simulation model was designed to estimate the distribution of truck and bucket payloads based on several of input parameters. These parameters are bucket size, number of loader passes (to fill the truck tray), distribution of bucket bulk density and distribution of bucket fill factor.

This simulation was implemented as a MATLAB workbook and a commercially available Monte-Carlo simulation engine was used to run the simulation. In this model, the truck payload is calculated by

$$m_k = \rho_k \sum_{q=1}^{P} v_b f_q \tag{3}$$

where m_k is the truck payload (for the kth truck); V_b the bucket rated capacity; f_q the fill factor; ρ_k the bucket density (one value for all of the passes in one truck); q the bucket pass; and P the maximum bucket passes to fill the truck tray. In this simulation bucket bulk density (ρ_k) and fill factor (f_q) are randomly selected by the Monte-Carlo simulation engine.

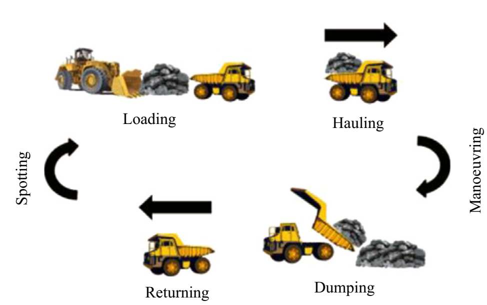


Fig. 2. Schematic of hauling operation in surface mines.

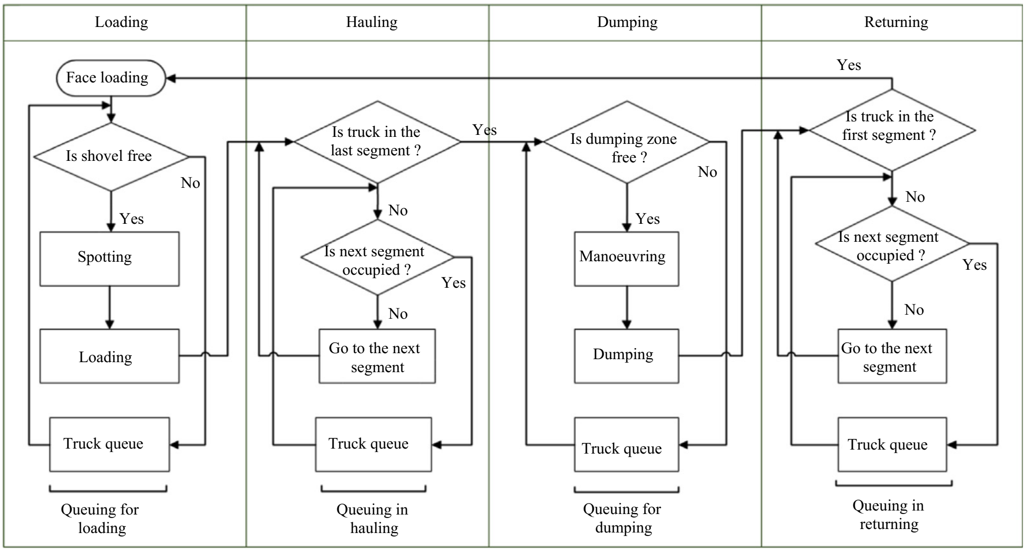


Fig. 3. Truck bunching algorithm.

4.3. Model considerations

In the model, the total length of haul and return road is divided in segments based on the variation of total resistance (TR). TR is equal to the sum of the rolling resistance (RR) and grade resistance (GR). The haul and return road are analysed using the same approach. However, on haul roads, the grade resistance is positive and on the return road it is negative (Fig. 4). The main reason for truck bunching on haul road is payload variance and the reason for truck bunching on return roads is the driver's supposed ability and mine traffic management.

4.4. Decision variables

In completed discrete event model three decision variables have been defined. The variables are U_k, S_k and $n_{i,k}$.

$$U_k = \begin{cases} 1 & \text{If Truck } k \text{ is in first segment} \\ 0 & \text{Otherwise} \end{cases} \tag{4}$$

$$S_k = \begin{cases} 1 & \text{If Truck } k \text{ is in last segment} \\ 0 & \text{Otherwise} \end{cases} \tag{5}$$

$$n_{i,k} = \begin{cases} 1 & \text{If } V_{i,k} > V_{i,(k-1)} \\ 0 & \text{Otherwise} \end{cases} \tag{6}$$

To create a practical model, it is necessary to define some functions based on the above mentioned decision variables.

4.5. Objective functions

In this section, the objective functions for cycle time, travel time and hauled mine materials have been presented in following equations.

$$(\text{Cycle time})_k = t_S + t_L + \sum_i t_{(T)_i} + t_M + t_D + (t_S + t_L)W_{okj}U_k + (t_M + t_D)W_{Lkj}S_k \tag{7}$$

where t_s is the spotting time; t_L the loading time; t_T the travel time; t_M the manoeuvring time; t_D the dumping time; W_{0kj} the number of trucks at queue in front of truck k at time j in the first segment; W_{Lkj} the number of trucks at queue in front of truck k at time j in the last segment; U_k the first decision variable; and S_k the second decision variable.

$$(\text{Travel time})_{i,k} = t_{(T)_{i,k}} = \sum_i \frac{2l_i\left(V_{(i+1),(k-1)} - V_{(i-1),k}\right)}{V^2_{(i+1),(k-1)} - V^2_{(i-1),k}} n_{i,k} + \frac{2l_i\left(V_{i,k} - V_{(i-1),k}\right)}{V^2_{i,k} - V^2_{(i-1),k}}(1 - n_{i,k}) \tag{8}$$

where $t_{(T)i,k}$ is the travel time for truck k in segment i; l_i the length of segment i; $V_{i,k}$ the velocity of truck k in segment i; $V_{(i-1),k}$ the velocity of truck k in segment $i-1$; and $n_{i,k}$ the decision variable.

$$\text{Hauled mine materials} = \sum_r \sum_k \text{payload}_{k,r}/\text{shift time} \tag{9}$$

where payload$_{k,r}$ is the payload of truck k in cycle r.

4.6. Constraints

There are three main constraints in the presented model.

$$\sum_i l_i = 2L = \text{Lengh of haul road} + \text{lenght of return road} \tag{10}$$

$$n_{i,k} = n_{k,i} \tag{11}$$

$$W_{i,j,k} = W_{i,k,j} \tag{12}$$

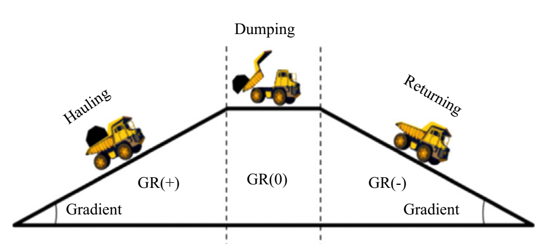


Fig. 4. Grade resistance (GR).

Table 1
A simplified version of the payload matrix ($P_{k,r}$).

Cycle (r)	Truck (k)	k = 1	k = 2	...	k = N
r = 1	→	$P_{1,1}$	$P_{2,1}$	...	$P_{N,1}$
r = 2	→	$P_{1,2}$	$P_{2,2}$	...	$P_{N,2}$
...	...	...	...	...	...
r = M	→	$P_{1,Z}$	$P_{2,Z}$	...	$P_{N,Z}$

Table 2
A simplified version of velocity matrix ($P_{k,i}$, V_{ki} & $t_{(T)k,i}$).

Segment (i)	Truck (k)	$k = 1$	$k = 2$		$k = N$
$i = 1$	→	$P_{1,1}$ $V_{1,1}$ $t_{(T)1,1}$	$P_{2,1}$ $V_{2,1}$ $t_{(T)2,1}$	... ...	$P_{N,1}$ $V_{N,1}$ $t_{(T)N,1}$
$i = 2$	→	$P_{1,2}$ $V_{1,2}$ $t_{(T)1,2}$	$P_{2,1}$ $V_{2,1}$ $t_{(T)2,1}$	... ...	$P_{N,2}$ $V_{N,2}$ $t_{(T)N,2}$
...	...	... ...	... ...	... ...	... ...
$i = 2L$	→	$P_{1,2L}$ $V_{1,2L}$ $t_{(T)1,2L}$	$P_{2,1}$ $V_{2,1}$ $t_{(T)2,1}$	... ...	$P_{N,2L}$ $V_{N,2L}$ $t_{(T)N,2L}$

Table 3
Data collected for model validation (sample).

No.	Average loader payload (tonne/pass)	Truck payload (tonne)	Average bucket bulk density (tonne/m^3)	Loader bucket fill factor	Average swell factor
1	47.23	218.21	2.01	0.937	1.25
2	45.12	217.46	1.98	0.978	1.22
3	38.14	209.42	1.96	0.919	1.18
4	42.15	210.36	2.03	0.954	1.27
5	46.58	216.78	2.14	0.984	1.19
6	47.56	217.96	1.86	0.927	1.26
7	39.87	218.04	2.07	0.946	1.24
8	38.47	218.43	2.18	0.992	1.25
9	42.58	217.69	2.05	0.957	1.20
10	40.59	216.97	1.99	0.939	1.25

4.7. Data processing

The developed truck bunching model uses two matrices at the same time (parallel processing) to create and process data. The first matrix is used to generate the truck payload based on Eq. (3). In this process the truck payload in all steps of the model will be generated randomly by a Monte-Carlo simulation engine. A simplified version of payload matrix is presented in Table 1. In Table 1, k represents the number of trucks and r represents the number of cycles in each shift; and $P_{k,r}$ is the payload of truck k in cycle r.

The presented model calculates the best performance velocity of each truck in each segment based on the payload generated by the payload matrix and truck rim pull curve. This model can apply the truck bunching effects on the velocity and hauled mine material by trucks in each cycle and each segment. A very simplified version of velocity matrix is presented in Table 2.

In Table 2, k is the number of trucks in the fleet; i the number of segments in haul and return roads; $P_{k,i}$ the payload of truck k in segment i; $V_{k,i}$ the velocity of truck k in segment i; and $t_{(T)k,i}$ the travel time for truck k in segment i.

The developed parallel data processing in this model can simulate complicated fleets in large surface mines.

4.8. Fuel consumption simulation

Haul truck fuel consumption is a function of various parameters. The key parameters that affect the fuel consumption of haul trucks include the payload management, the model of the truck, the grade resistance and the rolling resistance, according to a study conducted by the Department of Resources, Energy and Tourism [28]. In the present study, the effects of GVW, the velocity of truck (V) and the TR on the fuel consumption of the haul trucks were examined. The truck fuel consumption can be calculated from Eq. (13) [37].

$$FC = 0.3(LF \cdot PW) \tag{13}$$

where LF is the engine load factor and is defined as the ratio of average payload to the maximum load in an operating cycle; and PW the truck power, kW [18]. The developed model, in this project, can simulate the fuel consumption by haul trucks based on Eq. (13).

Table 4
Sample values of estimated (model) and independent (tests) cycle time and hauled mine materials.

(a) Values of estimated (model) and independent (tests) cycle time (sample)

No.	Estimated value of cycle time (model) (s)	Independent value of cycle time (tests) (s)	Absolute error (%)
1	1520	1560	2.56
2	1650	1680	1.78
3	1410	1380	2.17
4	1620	1680	3.57
5	1990	2040	2.45
6	1910	1860	2.69
7	1465	1500	2.34
8	1350	1380	2.17
9	1910	1860	2.69
10	1390	1440	3.48

(b) Values of estimated (model) and independent (tests) hauled mine materials (sample)

No.	Estimated average value of hauled mine materials (model) (tonne/cycle)	Independent average value of Hauled mine materials (tests) (tonne/cycle)	Absolute error (%)
1	203	198	2.46
2	205	200	2.44
3	207	202	2.42
4	209	206	1.44
5	212	208	1.89
6	214	218	1.87
7	214	209	2.34
8	223	228	2.24
9	229	224	2.18
10	233	238	2.15

Table 5
A sample of real mine site parameters (a case study).

(a) Material		
Parameter		Value
Insitu bank density (tonne/m^3)		2.5
Swell factors (tonne/m^3)	Bank to loader bucket	1.25
	Bank to loader bucket	1.25
Lose density (tonne/m^3)	Bank to truck tray	2
	Bank to loader bucket	2
Product ration (tonne of product per tonne hauled)		1
Loader bucket fill factor	Heaped	0.978
	Struck	0.978
(b) Roster for 5 day week-8 h shifts		
Parameter		Value
Mon–Fri (daily)		3 Shift
Total shift (shifts/year)		783
Scheduled lost shifts (shifts/year)		27
Scheduled shifts (shifts/year)		756
Loading unit maintenance (shifts/year)		113
Unscheduled lost shift (shifts/year)		42
Fleet operating shifts (shifts/year)		601
Shift duration (hh:mm:ss)		08:00:00
Non-operating shift delays (hh:mm:ss)		01:00:00
In shift operating time (hh:mm:ss)		07:00:00
Operating shift delays (hh:mm:ss)		00:30:00
In shift working time (hh:mm:ss)		06:30:00
(c) Loading		
Parameter		Value
Bucket capacity (m^3)		25.2
Bucket cycle time (min)		0.5
Mechanical availability		85%
Truck positioning		Single sided
Bucket fill factor		0.98
First bucket pass delay (min)		50%
Payload distribution (right skewed)		Normal
(d) Truck		
Parameter		Value
Spot time at loader (min)		0.5
Spot time at dump (min)		0.5
Dumping time (min)		0.5
Mechanical availability		80%
Motor power (kW)		1743
Transmission speed factor		1:00
Standard body capacity (m^3)		129
Empty truck weight (tonne)		165.75
Actual truck payload (tonne)		218
Full truck weight (tonne)		383.75
Operating hours per year		4799.2
Average payload (tonne)		221.53
Production per operating hour (tonne)		560.21
Production per loader operating shift (tonne)		3137.17
Production per year (tonne)		2688552.13
Queue time at loader (min/cycle)		2.71
Spot rime at loader (min/cycle)		0.5
Average loading time (min/cycle)		1.95
Travel time (min/cycle)		15.94
Spot time at dump (min/cycle)		0.5
Average dump time (min/cycle)		0.5
Average cycle time (min/cycle)		22.11
Fleet size		8
Average No. of bucket passes		5

4.9. Model validation

To validate the developed model, a dataset collected from a large open pit mine in central Arizona, USA has been applied. This dataset included measuring average loader payloads, truck payloads, average bucket bulk density, loader bucket fill factor and average swell factor (Table 3).

In this mine, the volume of material loaded into the bucket was determined by comparing loaded and empty laser scan profiles of the buckets. Fill factors were calculated by dividing the material volume by the rated volume of the bucket and bulk densities were calculated by dividing the payload by the loaded volume. On-board payload monitoring systems were used to measure payloads. The validation of the model was completed for average cycle times and the average mine material hauled by one type of truck (CAT 793D) after truck bunching. Table 4 and Fig. 5 present sample values for the estimated (using the developed model) and the independent (tested) cycle time and hauled mine material in order to highlight the insignificance of the values of absolute error in the analysis.

The results indicate good agreement between the actual and estimated values of average cycle time and average hauled mine materials.

5. A case study

In this project, a real mine site dataset that was collected from a large surface mine in central Queensland, Australia has been analysed. A sample of real mine site parameters is tabulated in Table 5. Production per year for haulage system is 21,508,417 tonnes.

The effect of truck bunching due to payload variance on average cycle time and average hauled materials for one mostly used model of haul truck in studied surface mine is illustrated in Fig. 6.

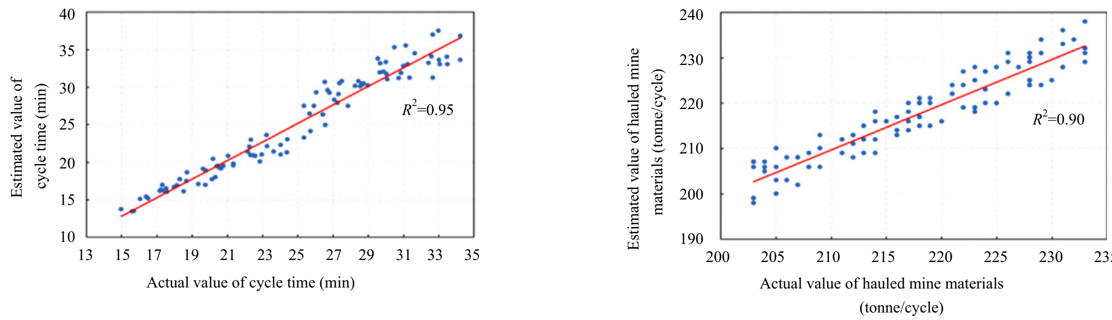
Fig. 6 demonstrates that, there is a non-linear relationship between payload variance/standard deviation and average cycle time in the fleet. Based on the presented results of analysed data in Fig. 6, it is clear that by increasing the payload variance the average cycle time increases dramatically. By maximum reducing of standard deviation from 30 to 5 tonnes, reducing average cycle time up to 15 min is possible. Other main effective parameters on mine productivity are average hauled materials. Fig. 7 illustrates the relationship between the payload variance/standard deviation and average hauled materials. The correlation between mentioned parameters in Fig. 7 is non-linear. The minimum average hauled mine is obtained with maximum payload variance. The presented relationship between payload standard deviation and average hauled materials in studied mine shows that there is a great opportunity to improve productivity by reducing payload variance.

In this case study, the effect of payload variance on haul truck fuel consumption in different haul road conditions for three models of haul truck has been investigated. It is noted that, to have a better understanding in this study, a fuel consumption index (FC_{Index}) has been defined. This index presents the quantity of fuel used by a haul truck to move one tonne of mine material (ore or overburden) in an hour. Truck specifications for studied haul trucks are presented in Table 6.

Haul trucks were selected based on their capacity and engine power. The maximum GVW for trucks is 160, 249 and 383 tonnes respectively. The results of completed investigation by developed truck bunching model are tabulated in Table 7.

In Table 7, FC_{Index} was calculated for three payload standard deviations (σ = 5, 10 and 15 tonnes) in three different road conditions (TR = 5, 10 and 15%). The results show that FC_{Index} increases not only by increasing the TR but also by increasing the payload variance for each truck. Fig. 8 presents the FC_{Index} versus payload standard deviation for three studied models of trucks in same road condition (TR = 10%).

Fig. 8 shows that by increasing the capacity of truck, FC_{Index} can be reduced. In this case the maximum reduction of FC_{Index} can be



(a) Comparison of actual values of cycle time with model outputs for test data

(b) Comparison of actual values of hauled mine materials with model outputs for test data

Fig. 5. Comparison of actual values of cycle time and hauled mine materials with model outputs for test data.

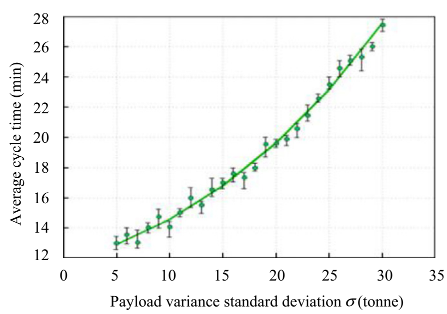


Fig. 6. Variation of average cycle time with payload variance, standard deviation (a case study).

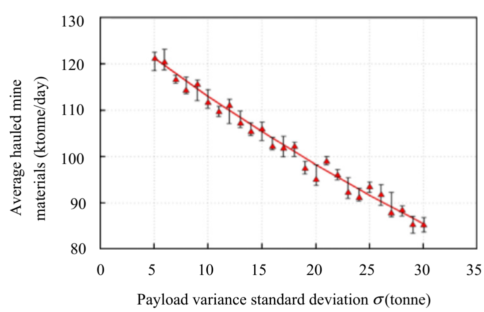


Fig. 7. Variation of average hauled materials with payload variance/standard deviation (a case study).

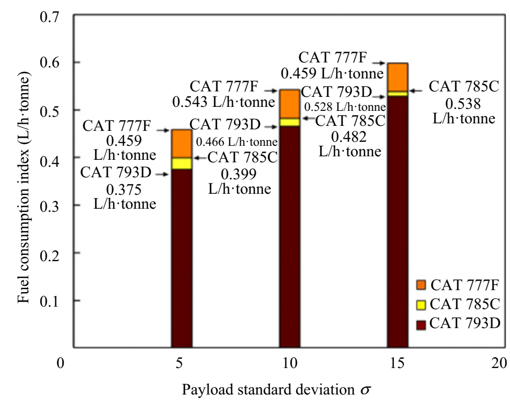


Fig. 8. Fuel consumption index for three models of haul trucks, TR = 10% (a case study).

Table 6
Truck specification (a case study).

Truck specification		CAT777F	CAT785C	CAT793D
Engine	Model	C32 ACERT™	3512B EUI	3516B HD EUI
	Gross power	758 kW	1082 kW	1801 kW
	Net power	700 kW	1005 kW	1743 kW
Weight	Total empty operating weight	64 tonnes	105 tonnes	165 tonnes
	Nominal payload class	96 tonnes	144 tonnes	218 tonnes
	Gross machine operating weight	160 tonnes	249 tonnes	383 tonnes

achieved by changing the model of truck from CAT777F to CAT793D.

6. Conclusions

This paper aimed to develop a discrete event model to simulate the effect of payload variance on truck bunching to improve productivity and energy efficiency in surface mines. There is a significant payload variance in the loading process in surface mines. The main reason for truck bunching in this type of mine is the variance of payload. In this paper, an innovative simulation model was developed to investigate the effects of payload variance on truck bunching, mine operation efficiency and decreasing the fuel consumption by haul trucks. To validate the developed model a dataset collected from a large surface mine in the central part of Arizona State, USA was used. Validation of the model was completed for the cycle time and the hauled mine materials by one type of truck (CAT 793D) after truck bunching. The results indicated a good agreement between the actual and estimated values of cycle time and hauled mine materials. The model was utilised in a real mine site in central Queensland, Australia as a case study.

Table 7
Fuel consumption index for three models of studied haul truck (a case study) (L/h·tonne).

Standard deviation σ (tonne)	CAT 777F			CAT 785C			CAT 793D		
Total resistance (%)	TR = 5 %	TR = 10%	TR = 15%	TR = 5%	TR = 10%	TR = 15%	TR = 5%	TR = 10%	TR = 15%
σ = 5 tonnes	0.361	0.459	0.540	0.321	0.399	0.479	0.300	0.375	0.455
σ = 10 tonnes	0.456	0.543	0.619	0.416	0.482	0.563	0.399	0.466	0.546
σ = 15 tonnes	0.523	0.598	0.671	0.483	0.538	0.618	0.471	0.528	0.608

The results of this project showed that there is a non-linear relationship between payload variance and cycle time in the fleet. In this case study, a correlation between the payload variance and hauled mine materials was developed and the effect of truck bunching due to payload variance on energy consumption for three models of haul truck was studied.

Acknowledgments

The authors would like to acknowledge CRC Mining and The University of Queensland for their financial support for this study.

References

[1] Cetin N. Open-pit truck/shovel haulage system simulation, vol. 1. Ankara: Middle East Technical Universality; 2004. p. 147–56.
[2] Carter T. Failures in a load–haul–dump vehicle axle used in deep mining operations. Eng Fail Anal 2008;15(7):875–80.
[3] Ghojel J. Haul truck performance prediction in open mining operations. In: Proceedings of the national conference publication. Australia: Institution of Engineers; 1993.
[4] Soofastaei A, Aminossadati SM, Arefi MM, Kizil MS. Development of a multi-layer perceptron artificial neural network model to determine haul trucks energy consumption. Int J Min Sci Technol 2016;26(2):285–93.
[5] Soofastaei A, Aminossadati SM, Kizil MS. Development of an artificial intelligence model to determine trucks energy consumption. In: Proceedings of energy future conference. Future energy, 1. p. 178–9.
[6] Soofastaei A, Aminossadati SM, Kizil MS, Knights P. Payload variance plays a critical role in the fuel consumption of mining haul trucks. Aust Resour Invest 2014;8(4):64.
[7] Soofastaei A, Aminossadati S, Kizil MS, Knights P. Simulation of payload variance effects on truck bunching to minimise energy consumption and greenhouse gas emissions. In: Proceedings of the 2015 coal operators' conference. Australia: The University of Wollongong; 2015.
[8] Guo WB, Xu FY. Numerical simulation of overburden and surface movements for Wongawilli strip pillar mining. Int J Min Sci Technol 2016;26(1):71–6.
[9] Benton DJ, Iverson SR, Martin LA, Johnson JC, Raffaldi MJ. Volumetric measurement of rock movement using photogrammetry. Int J Min Sci Technol 2016;26(1):123–30.
[10] Eskandari H, Darabi H, Hosseinzadeh SA. Simulation and optimization of haulage system of an open-pit mine. In: Proceedings of simulation series, 37. Society for Modeling & Simulation International; 2013.
[11] Leonardi K. Mining and haulage systems-new challenges and new strategy of DFM ZANAM-LEGMET Spólka z o.o. J Mines Met Fuels 2008;56(11):223–7.
[12] Cardu M, Lovera E, Patrucco M. Loading and haulage in quarries: criteria for the selection of excavator–dumper system. In: Proceedings of the 14th international symposium on mine planning and equipment selection, MPES 2005 & the 5th international conference on computer applications in the minerals industries. CAMI; 2005.
[13] Benito R, Dessureault SD. Estimation of incremental haulage costs by mining historical data and their influence in the final pit limit definition. Min Eng 2008;60(10):44–9.
[14] Yuan DC, Yue XG. SVMR model for coal mine cost management prediction. Appl Mech Mater 2014:608–11.
[15] Curry JA, Ismay MJL, Jameson GJ. Mine operating costs and the potential impacts of energy and grinding. Miner Eng 2014;56:70–80.
[16] Chironis NP. Coal age operating handbook of coal surface mining and reclamation. Coal Age Min Inf Serv 1978(2).
[17] Beckman R. Haul trucks in Australian surface mines 2012:87–96.
[18] Kecojevic V, Komljenovic D. Haul truck fuel consumption and CO_2 emission under various engine load conditions. In: SME annual meeting and exhibit, CMA 113th national western mining conference, USA. p. 186–95.
[19] Fiscor S. Improving haul truck productivity. Coal Age 2007:31–6.
[20] Knights P, Paton S. Payload variance effects on truck bunching. In: Proceedings of the seventh large open pit mining conference. Melbourne: The Australasian Institute of Mining and Metallurgy; 2010.
[21] Hewavisenthi R, Lever P, Tadic D. A Monte Carlo simulation for predicting truck payload distribution. In: Proceedings of the 2011 Australian mining technology conference, Sydney.
[22] Singh S, Narendrula R. Productivity indicators for loading equipment. CIM Magazine; 2006.
[23] Paton S. Truck bunching due to load variance. Australia: The University of Queensland; 2009.
[24] Webb B. Effects of bucket load distribution on performance. Australia: The University of Queensland; 2008.
[25] Nelson BL, Carson JS, Banks J. Discrete event system simulation.. USA: Prentice Hall; 2001.
[26] Basu AJ, Baafi EY. Discrete event simulation of mining systems: current practice in Australia. Int J Surf Min Reclam Environ 1999;13(2):79–84.
[27] Hu LP, Wang DM, Zuo L. Event step method on computer simulation of discrete event system. Appl Mech Mater 2014;543:1848–51.
[28] EEO. Analyses of diesel use for mine haul and transport operations. Australian Government, Energy and Tourism Editor; 2012. p. 1–22.
[29] White JW, Olson JP, Vohnout SI. On improving truck/shovel productivity in open pit mines. In: Bandopadhyay PS, editor. Proceedings of the 23th application of computers and operations research in the mineral industry. Fairbanks: Department of Mining and Geological Engineering University of Alaska Fairbank; 1992. p. 739–46.
[30] Schexnayder C, Weber S, Brooks B. Effect of truck payload weight on production. J Constr Eng Manage 1999;125(1):1–7.
[31] Jerry B. Discrete-event system simulation. India: Pearson Education; 1984.
[32] Choi BK, Kang D. Modeling and simulation of discrete event systems.. USA: John Wiley and Sons; 2013.
[33] Muller D. AutoMod™-providing simulation solutions for over 25 years. In: Proceedings of the 2011 winter simulation conference (WSC). IEEE; 2011. p. 39–51.
[34] Concannon KH, Hunter KI, Tremble JM. Dynamic scheduling II: SIMUL8-planner simulation-based planning and scheduling. In: Proceedings of the 35th conference on winter simulation: driving innovation. Winter simulation conference. p. 1488–93.
[35] Runciman N, Vagenas N, Corkal T. Simulation of haulage truck loading techniques in an underground mine using WITNESS. Simulation 1997;68(5):291–9.
[36] Kamrani M, Abadi SMHE, Golroudbary SR. Traffic simulation of two adjacent unsignalized T-junctions during rush hours using Arena software. Simul Model Pract Theory 2014;49:167–79.
[37] Runge I. Mining economics and strategy. Co (USA): Littleton; 2005.