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Simulation of Payload Variance Effects on Truck Bunching to Minimise Energy Consumption and Greenhouse Gas Emissions

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SIMULATION OF PAYLOAD VARIANCE EFFECTS ON TRUCK BUNCHING TO MINIMISE ENERGY CONSUMPTION AND GREENHOUSE GAS EMISSIONS

Ali Soofastaei, Saiied Mostafa Aminossadati, Mehmet Siddik Kizil and Peter Knights

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 and greenhouse gas emissions. 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, minimise energy consumption and reduce greenhouse gas emissions. 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 rate of greenhouse gas emissions corresponding to diesel consumption by haul trucks is calculated according to global warming potential guidelines. 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. The validated model has been utilised in a real mine site in central Queensland, Australia as a case study. The focus of this case study has been on the relationship between the trucks bunching due to payload variance with average cycle time, average hauled mine materials, fuel consumption and greenhouse gas emissions. The results have indicated that there is a non-linear correlation between the payload variance and the mentioned parameters. In this case study, the simulation results indicate that a reduction of up to 15 minutes on average cycle time is possible if the standard deviation of payload is reduced from 30 down to 5 tonnes. By reducing the payload variance, the average of hauled mine materials can be increased up to 35 kt per day. Moreover, the fuel consumption and greenhouse gas emissions can be reduced dramatically by reducing the payload variance.

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 the mining industry (Ercelebi and Bascetin, 2009; Limsiri, 2011).The main effective parameters on material transport when the 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 (Raj, Vardhan and Rao, 2009). Based on the literature, among all the above mentioned parameters, truck payload variance is one of the most important parameters in this field (Schexnayder, Weber and Brooks, 1999). 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 (Singh and Narendrula, 2006). 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 (Paton, 2009).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 (Knights and Paton, 2010). 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 operation parameters. The study conducted by Hewavisenthi, Lever and Tadic(2011) is concerned with using a Mont-Carlo simulation to study the effect of bulk density, fill factor, bucket size and a number of loading passes on the long term payload distribution of earthmoving systems. The focus of their study is on simulation of payload distribution and variance in large surface mines. The study conducted by Knights and Paton(2010) is concerned with the truck bunching due to load variance.

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This study was conducted to provide an analysis of the effect of load variance on truck bunching. Webb(2008) investigated the effect of different bucket load sizes on truck cycle times and the inherent costs. The research project being undertaken will focus primarily on the effect of load variance on truck bunching. The payload variance not only affects the production rate, but also it is an important parameter in the analysis of energy consumption and gas emissions.

The trucks utilised in the haulage operations of surface mines use a great amount of energy (DOE, 2002) and this has encouraged truck manufacturers and major mining corporations to carry out a number of research projects on the energy efficiency of haul trucks (EEO, 2012).There are many factors that affect the rate of fuel consumption for haul trucks such as payload, truck velocity, haul road condition, road design, traffic layout, fuel quality, weather conditions and driver skill(Cetin, 2004). 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 (White and Olson, 1992).

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 time, the rate of loading materials, fuel consumption and greenhouse gas emissions.

PAYLOAD VARIANCE

Loading performance depends on different factors such as bench geometry, blast design, muckpile fragmentation, operators' efficiency, weather conditions, utilisation of trucks and shovels, mine planning and mine equipment selection (Schexnayder, Weber and Brooks, 1999; Hewavisenthi, Lever and Tadic, 2011). 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 (Knights and Paton, 2010). 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 (Paton, 2009). 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 Equation 1.

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

Where N is the number of available data for each parameter, i is a counter of data, x is the value of parameter and μ can be calculated by Equation 2.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (2)$$

Figure 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).

The GVW is the total weight of empty truck and payload. Based on the CAT 793D technical specifications, the range of Gross Vehicle Weight GVW () variation is between 165 tonnes (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.

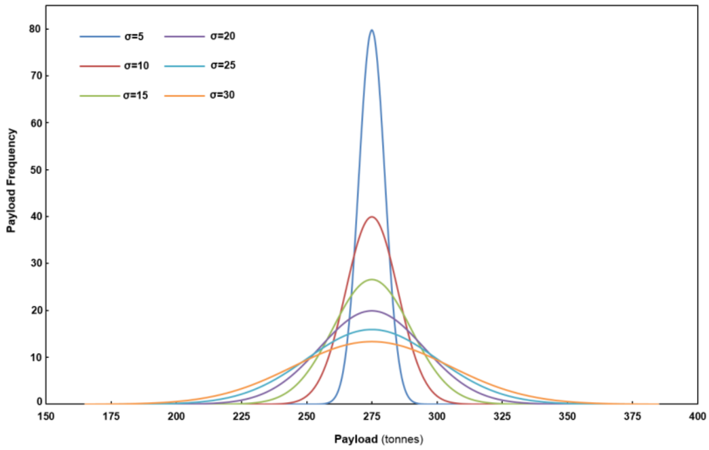


Figure 1:Normal payload distribution for difference standard deviations (σ) (CAT 793D)

Simulation Models

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(Banks *et al.*, 2010).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 (Byoung and Donghun, 2013). 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(Muller, 2011). It can be used for 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.

The second studied model is SIMUL8. This model is a graphically oriented simulation package developed by the SIMUL8 Corporation (Concannon, Hunter and Tremble, 2003). 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. This model was released in 1977 by Wolverine Software Corporation who still develop and sell this model today (Stout *et al.*, 2013). 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.

The fourth observed model in this project is WITNESS. This model is a discrete event simulation suite developed by Lanner (Paton, 2009). Witness is capable of producing haulage system simulations in a dynamic animated computer model.

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 (Kamrani, Hashemi and Rahimpour, 2014). SIMAN is a Discrete Event Simulation package which can be used in a process or event scheduling mode. SIMAN is most commonly used in conjunction with Arena in the industry today. The ARENA system can produce scale models of circuits and other simulations.

TRUCK BUNCHING MODEL

Developed algorithm

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

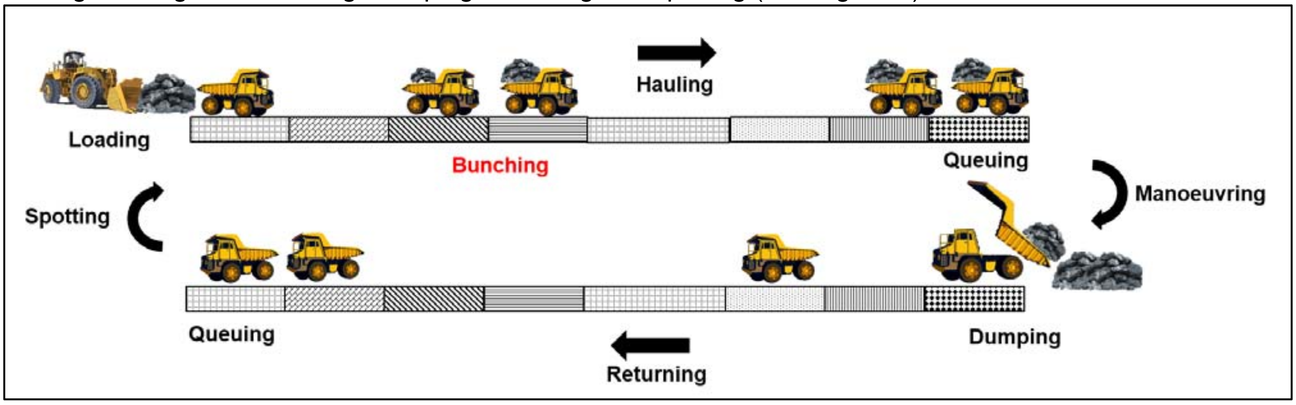


Figure 2: Schematic of hauling operation in surface mines

In the standard hauling operation loading time is the time taken to load the truck, hauling and returning time are traveling 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 the sum of loading, spotting and dumping 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 in a 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 fixed, travel and wait time.

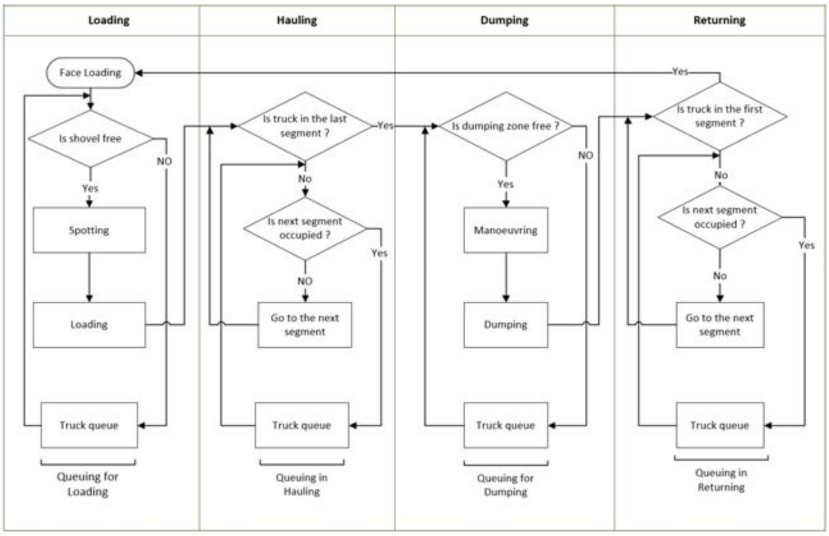


Figure 3: Truck bunching algorithm

Figure 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.

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 variations 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 Equation 3.

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

Where m_k is truck payload (for the k^{th} truck), V_b is bucket rated capacity, f_q is fill factor, ρ_k is bucket density (one value for all of the passes in one truck), q is bucket pass and p is the maximum bucket pass to fill the truck tray. In this simulation bucket bulk density (ρ_k) and fill factor (f_q) are randomly selected by the Mont-Carlo simulation engine.

Decision variables

In completed discrete event model three decision variables have been defined. These variables are u_k, s_k and $n_{i,k}$.

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

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

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

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

Objective functions

In this section, the objective functions for cycle time and traveling time have been presented in Equation 7 and Equation 8.

$$(\mathrm{Cycle\ Time})_k = t_S + t_L + \sum_i t_{(T)_i} + t_M + t_D + (t_S + t_L)W_{okj}u_k + (t_M + t_D)W_{Lkj}s_k \tag{7}$$

Where:

t_s : Spotting time;

t_L : Loading time;

t_T : Travel time;

t_M : Manoeuvring time;

t_D : Dumping time;

W_{0kj} : Number of trucks at queue in front of truck k at time j in the first segment;
W_{Lkj} : Number of trucks at queue in front of truck k at time j in the last segment;
u_k : First decision variables; and
s_k : Second decision variables.

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

Where:

$t_{(T)i,k}$: Travel time for truck k in segment i;

X_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
$n_{i,k}$: Decision variable.

The effect of truck bunching on hauled mine materials in each shift can be estimated by Equation 9.

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

Where:
Payload $_{k,r}$:The payload of truck k in cycle r.

Fuel Consumption simulation

Haul truck fuel consumption is a function of various parameters. The key parameters that affect the energy 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(EEO, 2012). In the present study, the effects of the GVW, the truck velocity and the Total Resistance (TR) on the energy consumption of the haul trucks were examined. The TR is equal to the sum of the Rolling Resistance (RR) and the Grade Resistance (GR) when the truck is moving against the grade of the haul road.

$$TR = RR + GR \tag{10}$$

Figure 4 presents a schematic diagram of a typical haul truck and the key factors that affect the performance of the truck such as the GVW, RR, gradient, friction force and Rimpull Force (RF).

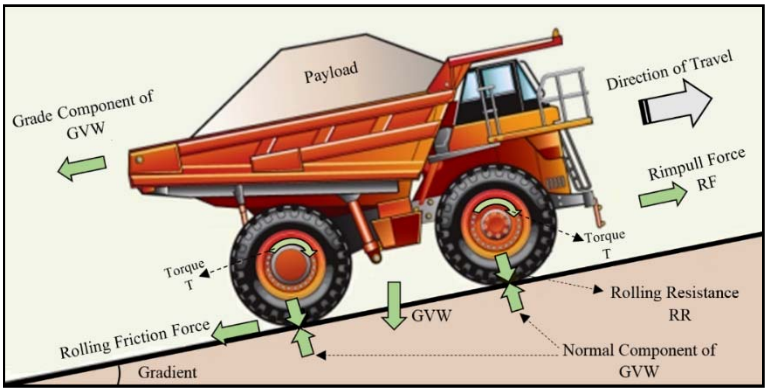


Figure 4: A schematic diagram of a typical haul truck

RF is the force available between the tyre and the ground to propel the machine. It is related to the Torque (T) that the machine is capable of exerting at the point of contact between its tyres and the ground and the truck wheel radius (r).

$$RF = \frac{T}{r} \tag{11}$$

The truck fuel consumption can be calculated from Equation 3(Filas, 2002):

$$FC = \frac{SFC}{FD}(LF.\,P) \tag{12}$$

Where SFC is the engine specific fuel consumption at full power (0.213–0.268 kg/kw.hr) and FD is the fuel density (0.85 kg/L for diesel). The simplified version of Equation 3 is presented by Runge(2005):

$$FC = 0.3\,(LF.\,P) \tag{13}$$

Where LF is the engine load factor and is defined as the ratio of average payload to the maximum load in an operating cycle(Kecojevic and Komljenovic, 2011). P is the truck power (kW). For the best performance of the truck operation, P is determined by:

$$P = \frac{1}{3.6}\,(RF.V) \tag{14}$$

Where the RF is calculated by the product of Rimpull (R) and the gravitational acceleration (g). V is calculated by Equation 15.

$$V = a - b \times \exp(-c \times R^{d}) \tag{15}$$

Where a= 53.867, b= 54.906, c= 37.979 and d= -1.309.

In this paper, DataThief 5.6 and Curve Expert 2.1 were used to find an equation for R as a function of TR and GVW based on the Rimpull-Speed-Grade ability curve.

$$R = 0.183\,GVW\,(0.006 + 0.053\,TR) \tag{16}$$

The developed model, in this project, can simulate the fuel consumption by haul trucks based on the above mentioned formulas.

Greenhouse gas emissions

Diesel engines emit both Greenhouse Gases (GHG_S) and Non-Greenhouse Gases ($NGHG_S$) into the environment(Aziz and Kecojevic, 2008). Total GHG emissions are calculated according to the Global Warming Potential (GWP) and expressed in CO_2 equivalent or CO_2 - e.
The following equation can be used to determine the haul truck diesel engine GHG_S emissions(ANGA, 2013).

$$GHG_{Emissions} = (CO_2 - e) = FC \times EF \tag{17}$$

Where FC is the quantity of fuel consumed (kL) and EF is the emission factor. The emission factor for haul truck diesel engines is 2.7 t.

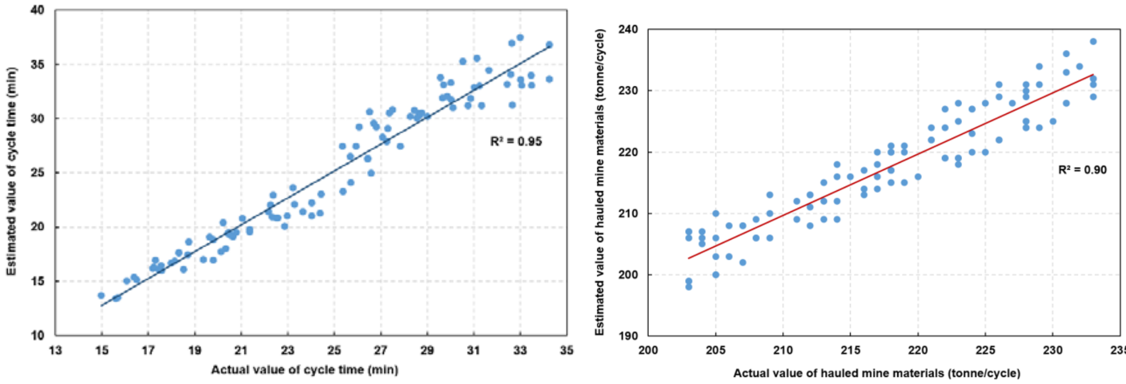
Model Validation

Model validation is a main part of this project. To validate the developed model a dataset collected from a large open pit mine in the central part of Arizona State, USA has been applied. This dataset included measuring loader payloads, truck payloads, bucket bulk density, fill factors and swell factors (Table 1).

Table 1: A sample of data collected for model validation

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

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 model has been completed for average cycle time and the average of mine material hauled by one type of truck (CAT 793D) after truck bunching. The test results of the developed model are shown in Figure 5.



Figures 5a & 5b: Comparison of actual values of cycle time and hauled materials with model outputs

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

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. In this case study, Talpac^{TM} and MATLAB software have been used to develop the model. The effect of truck bunching due to payload variance on average cycle time and average hauled materials are illustrated in Figure 6. In this figure, the standard deviation indicates the payload variance changes from 5 to 30.

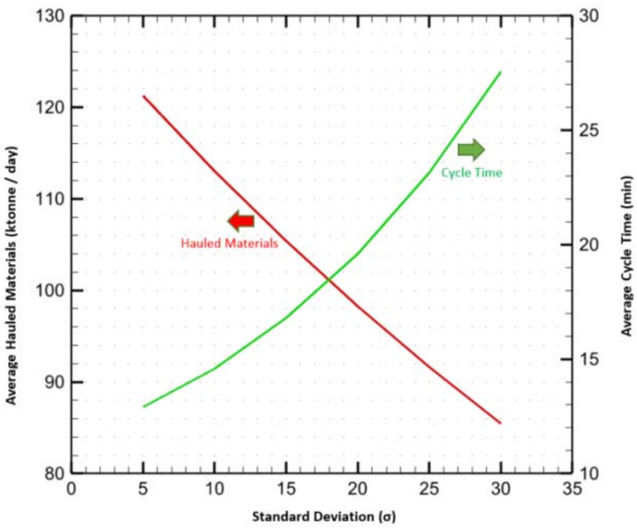


Figure 6: The effect of payload variance on average cycle time and average hauled materials

Figure 6 demonstrates that, there is a non-linear relationship between standard deviation and average cycle time in the fleet. This figure also illustrates the relationship between the standard deviation (σ) and average hauled materials. Finding the best correlation between the standard deviation and average hauled materials can be very important in calculation of the effect of truck bunching due to payload variance on productivity and production cost. Hence, the following equation has been developed to estimate the hauled mine materials based on the payload variance.

$$\text{Hauled Materilas} = 130 \times \exp(-0.014\sigma) \quad (18)$$

The effect of payload variance on haul truck fuel consumption in different haul road conditions is illustrated in Figure 7. In this figure, the total resistance has been changed from 5% to 30% and the payload standard deviation is varied between 0 and 30. It is noted that, to have a better understanding, 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.

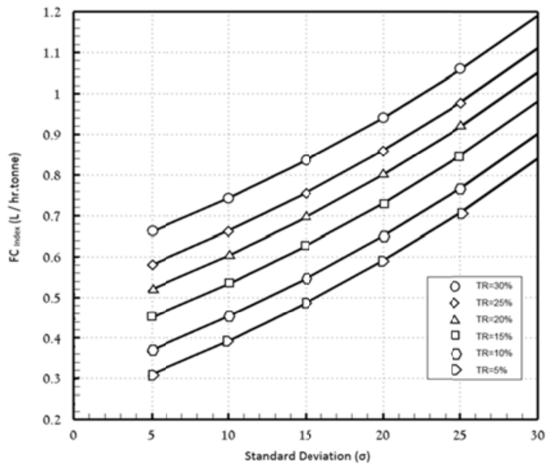


Figure 7: The effect of payload variance on haul truck fuel consumption in different haul road conditions (TR= Total Resistance)

Figure 7 demonstrates that there is a non-linear relationship between the standard deviation and the fuel consumption for all haul road total resistance. Moreover, the FC_{Index} rises with increasing the total resistance.

The variation of CO_2-e with standard deviation for CAT 793D is presented by CO_2-e_{Index} in Table 2. In this table CO_2-e_{Index} presents the amount of GHG emission generated by truck to haul one tonne of ore or overburden in an hour.

Table 2: The variance of CO_2-e $_{Index}$ (kg/hr. tonne) with standard deviation (CAT 793D)

σ \ TR	5%	10%	15%	20%	25%	30%
5	0.83	0.99	1.21	1.40	1.56	1.78
10	1.06	1.22	1.43	1.62	1.78	2.00
15	1.31	1.47	1.68	1.87	2.04	2.25
20	1.59	1.75	1.97	2.16	2.32	2.53
25	1.91	2.07	2.29	2.47	2.64	2.85
30	2.27	2.43	2.64	2.83	2.99	3.21

Based on the tabulated results, it is obvious that there is a non-linear relationship between the CO_2-e_{Index} and the standard deviation for each haul road total resistance. The minimum greenhouse gas is emitted for the minimum total resistance (TR=5%) when the standard deviation has been zero (σ=0) and the maximum pollution is generated for the maximum total resistance and standard deviation (TR=30% and σ=30).

CONCLUSIONS

This paper aimed to develop a discrete event model to simulate the effect of payload variance on truck bunching to minimise energy consumption and greenhouse gas emissions. 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, decreasing the fuel consumption and reducing greenhouse gas emissions 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 Australia as a case study. The results of this project showed that there is a non-linear relationship between standard deviation and cycle time in the fleet. In this case study, a correlation between the standard deviation and hauled mine materials was developed and the effects of truck bunching due to payload variance on energy consumption and greenhouse gas emission were studied.

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