Journal of Sustainable Mining 15 (2016) 85–94

HOSTED BY

ELSEVIER

Contents lists available at ScienceDirect

Journal of Sustainable Mining

journal homepage: http://www.elsevier.com/locate/jsm

Reliability effect on energy consumption and greenhouse gas emissions of mining hauling fleet towards sustainable mining

Salvatore Peralta, Agus Pulung Sasmito, Mustafa Kumral*

Mining and Materials Engineering Department, McGill University, 3450 University Street, Montreal, Quebec, H3A 0E8, Canada

ARTICLE INFO

Article history:
Received 30 June 2016
Accepted 12 August 2016
Available online 20 August 2016

Keywords:
Mining fleet
Energy consumption
Greenhouse gas emission
Sustainable production
Reliability and maintenance

ABSTRACT

Mineral commodity prices have decreased swiftly since 2012. For example, gold price, which was above $1800 per ounce, is currently about $1250 per ounce. Price slumps were even more severe in the base metals. Furthermore, the resource degradation and complex geologic conditions give rise to operation costs. As a result, many mining operations and development projects were eventually suspended, cancelled or ceased. Environmental compliance is also another challenge to the mining industry. The fuel consumed by diesel trucks emits greenhouse gases, which are one of contributors to the global warming. In Canada, the provinces of Quebec, British Columbia and Alberta introduced carbon taxes with the objective of reducing gas emissions in attempt to mitigate climate change. In this scope, only way to stay in business for a mining company is to invest more efficient and environmental friendly production practices such that operation costs are reduced. Given that maintenance costs and energy consumption are the largest contributors to operation costs, the minimization of carbon emissions and the maximization of equipment availability would be beneficial. This paper addresses to quantify the relationship between equipment reliability and energy consumption through a case study. It shows that a maintenance policy based on equipment reliability can significantly reduce energy consumption and its associated gas emissions.

© 2017 Central Mining Institute in Katowice. Production and hosting by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. Introduction

In 1983 the Brundtland Commission defined sustainable development as development "that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland, Khalid, Agnelli, Al-Athel, Chidzero, Fadika, Hauff, Lang, Shijun, & de Botero, 1987). The live standards of human being are based on the infrastructure constructed by raw materials of the mineral industries. Furthermore, the mineral industries also significantly contribute to local and national economies in form of tax and royalty incomes, and employment opportunities (Onn & Woodley, 2014). On the other hand, mining operations lead to a series of environmental problems such as landscape deterioration, acidic water generation, soil pollution and greenhouse gas (GHG) emissions. In other words, mining is an industry placed into intersection of economic, environmental and social aspects (Moran, Lodhia, Kunz, & Huisingh, 2014). There is significant literature on mining and its sustainability. It has proposed sustainable developments and sustainability management strategies for the mining industry (Caron, Durand, & Asselin, 2016; Lodhia & Hess, 2014). Burchart-Korol, Krawczyk, Czaplicka-Kolarz, Turek, and Borkowski (2014) proposed a developed algorithm suitable to evaluate coal mine functioning aspects and coal production influence on environmental, economic and social efficiency. One of important criteria regarding performance of a mining operation is to what extent mining process is sustainable (Gomes, Kneipp, Kruglianskas, da Rosa, & Bichueti, 2014) and socially acceptable (Dubiński, 2013).

About 50% of the operating costs of open pit mine is related to material loading and haulage (Topal & Ramazan, 2010). The decline of loader and hauler efficiencies associated with equipment aging results in significant increases in energy consumption. The energy expenditure for hauling material from the pit to the stockpile or dump could be over a hundred dollar per kiloton of material removed. Furthermore, greenhouse gas (GHG) emissions increase proportionally with respect to the fuel consumed (Soofastaei, Aminossadati, & Kizil, 2008). On the other hand, as equipment reliability decreases, its fuel consumption and GHG emissions will

* Corresponding author.
E-mail address: mustafa.kumral@mcgill.ca (M. Kumral).
Peer review under responsibility of Central Mining Institute in Katowice.

http://dx.doi.org/10.1016/j.jsm.2016.08.002
2300-3960/© 2017 Central Mining Institute in Katowice. Production and hosting by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

increase. In this scope, a maintenance policy that ensures equipment reliability at required level will help to reduce gas consumption and emissions. At the same time, equipment life can be maximized. Thus, equipment capital and operation costs can be reduced.

Energy efficiency is an important factor contributing to sustainable management. According to Kaarsberg, HuangFu, and Roop (2007), mining operations are intensive energy consumers. Mining companies have the potential to save about 61% of their energy consumption if they improve the efficiency of their operations (US Department of Energy, 2007). This can be achieved by introducing an energy-efficient production styles such that material energy demand is minimized (Awuah-Offei, 2016). Since the hauling equipment used in mining is generally powered by diesel engines (Norgate & Haque, 2010), the energy efficiency of mining haulers is generally evaluated in terms of fuel consumed by the haulers. Giannelli et al. (2005) proposed the approaches to estimate energy consumption of heavy-duty diesel vehicles determining diesel engine efficiency. Soofastaei, Aminossadati, Arefi, and Kizil (2016) developed a model estimating the variation of dump truck specific fuel consumption (fuel consumption per ton transported) with respect to input parameters such as payload, materials handling rate, vehicle speed, distance etc. Sahoo, Bandyopadhyay, and Banerjee (2014) compared the payload variance effect with the specific fuel consumption. In this study, the fuel consumption is investigated in relation to the power demand of the vehicle and it is evaluated through the correlation between vehicle tractive power and vehicle specific power. The second approach considers the major power consumption components.

Diesel equipment is also responsible for the emission of greenhouse gases into the atmosphere (Norgate & Haque, 2012). The greenhouse gases include carbon dioxide (CO_2) and non CO_2-greenhouse gases such as methane (CH_4), nitrous oxide (N_2O), ozone-depleting substances (ODSs), hydrofluorocarbons (HFCs), sulphur hexafluoride (SF_6) and perfluorocarbons (PFCs) (Montzka, Dlugokencky, & Butler, 2011). According to the Global Warming Potential, which is the relative measure of how GHG and heat are trapped in the atmosphere, total GHG emissions are expressed in CO_2 equivalent (CO_2-eq) (Carmichael, Bartlett, & Kaboli, 2014). Greenhouse gases absorb infrared radiation and re-emit it. The absorbed and reflected energy trap heat in the atmosphere and maintain a warmer temperature inside the cap that they create. The greenhouse effect is a natural process that allows for life on the planet; however, the GHG emissions have increased compared to the pre-industrial era. Production activities including mining release a large quantity of GHGs into the atmosphere. To mitigate the effects of global warming, various countries have requested controls and limits in the emissions of GHGs and promoted studies to monitor this behavior (Meinshausen et al., 2009). The Canadian target according to the Copenhagen Accord (2009) is to reduce its GHG emissions to below 17% of the 2005 levels by 2020; however, the emissions from 2013 to 2014 show an upward trend, with 2013 only 3% below the 2015 levels (Government of Canada, 2015). In order to monitor emissions in the mining industry, Wang et al. (2015) measured emissions of Caterpillar 797B haulers and calculated real world fuel emission factor. The calculated emission factors were compared with haulers activities. Environmental protection procedures and their implementations affect the mining projects profitability by increasing the total cost (Tuusjarvi et al., 2014). However, non-regulating fuel emissions would also reflect on major energy expenditure and taxes. According to Tuusjarvi et al. (2014) modelling the effect of environmental regulation beside the economical factor, would bring cost minimization with a successful corporate strategy oriented toward maintaining the social licence to operate.

An appropriate maintenance plan has potential to reduce energy consumption of the mining fleet. However, according to Topal and Ramazan (2010), maintenance costs can represent about 30–50% of the overall haulage operating costs for an open-pit mining operation. The engineering problem will be to find minimum fuel consumption with the most effective maintenance policy. The maintenance cost optimization can be achieved by a reliability-based maintenance plan (Rahimdel, Ataei, Khalokakaei, & Hoseinie, 2013).

Hauling equipment is repairable and non-renewable system. A system being restored for satisfactory operation after a failure are called repairable systems, which are complex systems where the repair of a part does not assure the complete restoration of the system. (Tobias & Trindade, 2011). This paper takes a further step and investigates effect of equipment reliability on fuel consumption. In other words, trade-off between cost of maintenance that ensures pre-specified reliability level and extra fuel consumption associated with the reliability below pre-specified level is explored through a case study using the equipment fleet of a Turkish mine.

2. Methodology

In mining operations, trucks are assigned to loaders and destinations (waste dump or processing plants). When a truck is loaded, its task is to transport the material to a destination. It offloads its material and then returns empty. This cycle is repeated from the beginning to the end of each shift (Fig. 1). The fuel consumed by the truck varies according to the distance travelled, the payload, speed and time to complete each phase. The cycle time of a truck is the sum of the time it takes to go from the destination to the loader, the time to go from the loader to the destination, loading time, unloading time and waiting time. As the equipment ages, its efficiency is progressively lowered according to the decrees of its reliability. The reliability represents the probability of a system to perform its task efficiently. Thus, the decrease in reliability could be directly related with the energy consumption of the machine.

The estimate of the energy consumption is formulated according to the speeds of the truck, the power requirements, the mine characteristics and the weight in question. The balance of the mass transported is expressed with the gross mass weight (*GW*) as the sum of the weight of the truck empty (*EW*) with the payload transported (*PW*). This formula is expressed (Equation (1))

$$GW = PW + EW \tag{1}$$

The velocities of the truck are calculated using the rimpull-speed-gradeability curves or the retarder curves. "*Rimpull is the driving force developed by a wheel as it acts upon a surface*" (Caterpillar Inc., 2015). The rimpull-speed-gradeability curves are used to determine the maximum speed attainable, the rimpull and the gear range. The calculated velocities are then used to derive the power required for maintaining that specific speed. The power required at this gradeability performance (*grade P*) (in Kw) is expressed (Equation (2)) as (Caterpillar Inc., 2015):

$$grade\ P = \left(\frac{GW \cdot TR \cdot V}{273.75}\right) 0.7457 \tag{2}$$

Where TR is the total resistance and V is the truck velocity. The total resistance or total effective grade of a truck moving uphill is calculated (Equation (3)) as:

$$TR = Rolling\ resistance + Grade\ resistance \tag{3}$$

The rolling resistance is the force that must to be overcome to pull a wheel over the ground. The grade resistance is the force that

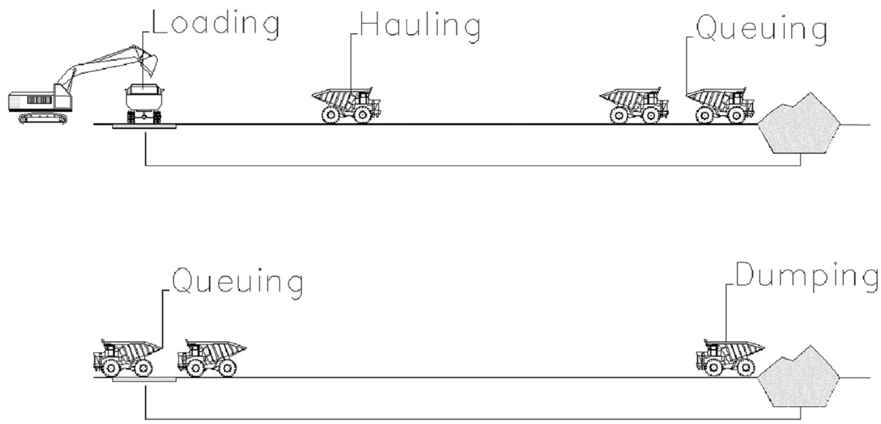


Fig. 1. Hauling operations cycle.

must be overcome to move a truck ascending a grade. Similarly, the retarder curves are used to determine the speed that can be maintained when a truck is descending a grade with retarder. The calculated velocities are then used to derive the power required for maintaining that specific speed without the use of service brakes. The retarding power demand (*retarding P*) required at this retarder or brake performance is given below in Equation (4) (Caterpillar Inc., 2015):

$$retarding\ P = \left(\frac{GW \cdot TR \cdot V}{273.75}\right)0.7457 \tag{4}$$

The total resistance or total effective grade of a truck moving downhill is calculated in Equation (5) as:

$$TR = Grade\ asssistance - Rolling\ resistance \tag{5}$$

The rolling resistance is always the force opposing the truck movement. The grade assistance is the force that assist truck movement on favorable grades.

The fuel consumption of a truck moving from loader to destination is calculated considering the load factor in relation to the power demand. The load factor is the ratio of the average payload to the maximum load in an operating cycle. The load factor of an empty truck is 20% while that of a loaded truck is 50% (Soofastaei et al., 2008). The power demand for the truck going from a loader to destination is calculated from Equation (2), whilst on its way back the power demand is calculated from Equation (3). Therefore, the fuel consumption can be calculated (Equation (6)) as (Runge, 1998):

$$FC = P \cdot 0.3 \cdot LF \tag{6}$$

Where *FC* is the fuel consumption, *P* is the power demand and *LF* is the load factor. The travel times from a loader *l* to destinations *d* (Equation (7)) and vice-versa (Equation (8)) are calculated as:

$$t_{ld} = \frac{d_{ld}}{V_{ld}} \tag{7}$$

$$t_{dl} = \frac{d_{dl}}{V_{dl}} \tag{8}$$

The cycle time (t_{cycle}) is the sum of the times to go from a loader *l* to destinations *d* and vice-versa, the loading and unloading time. The cycle time is expressed by Equation (9) as

$$t_{cycle} = t_{ld} + t_{dl} + t_{load} + t_{uload} \tag{9}$$

Where t_{load} and t_{uload} are the loading and the unloading time, respectively. As a result, the quantity of litres of fuel consumed per trip (*VF*) for a truck moving from a loader to destinations and vice-versa is (Equation (10)):

$$VF = FC_{ld}t_{ld} + FC_{dl}t_{dl} + FC_{idle}(t_{load} + t_{uload} + t_{wait}) \tag{10}$$

Where F_{ld} and F_{dl} are the fuel consumption from the loading point to the destination and from the destination to the loader, respectively. F_{idle} is the fuel consumption at idle, and t_{wait} is the waiting time.

The number of trips (N_{trips}) per hour is expressed in Equation (11) as:

$$N_{trips} = \frac{1}{t_{cycle}} \tag{11}$$

The specific fuel consumption (*SFC*) which defined as the quantity of litres of fuel consumed per tonne transported is calculated in Equation (12) as:

$$SFC = \frac{H \cdot N_{trips} \cdot VF}{Q} \tag{12}$$

Where *H* represents the working hours in a year and *Q* is the yearly material handled.

The GHG emission of diesel engine of a mining truck is expressed (Equation (13)) in terms of $CO_2\text{-}eq$ (Kecojevic & Komljenovic, 2010) as:

$$CO_{2-eq} = FC \cdot EF \tag{13}$$

Where the *FC* is the fuel consumption and *EF* stands for emission factor. The emission factor of a diesel mine truck was found to be 2.7 tonnes of $CO_2\text{-}eq$ per KL of fuel (Australian Government, 2012; United States Environmental Protection Agency (EPA), 2008).

Trucks are complex systems with great number of components. The repair of a truck does not assure the restoration of the system to al level as good as new. This process is known as non-renewal process and the frequency of repair varies in time. The model describing this behavior is the power law model, which is also known as Crow-AMSAA model (Crow, 1975). The failure intensity at time t $u(t)$ for the Power Law is expressed in Equation (14) as

$$u(t) = \lambda\beta t^{\beta-1} \tag{14}$$

Where λ represents the scale parameter, β represents the shape parameter of the power law. When $\beta > 1$ the failure intensity is increasing, decreasing if $\beta < 1$ (infant mortality) and constant for $\beta = 1$ (useful life). The power law model is a generalization and describe both renewal and non-renewal processes for repairable systems. In fact, when the system has a constant failure intensity ($u = \lambda$) then the process described is renewal (the repair rate does not change with time).

Goodness of fit of the power law is tested by a Kramer-Von Mises test, and the parameters λ and β of the power law are in this study estimated with a maximum likelihood estimation. With the estimation of the scale and the shape parameters is possible to describe the reliability behavior of a truck.

The power law model can describe the system under the minimal repair condition. However, in a complex system, a repair is never perfect nor always minimal. The system age is never completely restored but rather decreases (Kijima & Sumita, 1986). The restoration of the system is expressed by the restoration or the maintenance effectiveness (Kijima, 1989). The restoration factor is the percentage of a component's restoration after a repair and is used to describe the virtual age of the machine consequent to a maintenance action. The virtual age of the machine is described in Equation (15) by the following model of (Kijima, 1989):

$$V_n = V_{n-1} + (1 - RF)T_n \tag{15}$$

Where V is the virtual age at a certain time n, RF is the restoration factor and T_n is the nth failure time. Knowing the virtual age of a truck, its reliability is a function of the truck age.

In this study a sensitivity analysis was done to evaluate the specific fuel consumption, and GHG emission with respect to the reliability change over time. Reliability, working hours, distance and gross mass weight are considered as variables of the fuel consumption in multiple regression analysis that estimates the contribution of each variable to the specific fuel consumption change. A positive value of the estimated variable means a positive change in specific fuel consumption whereas a negative value represents its negative change contribution.

3. Results

Fleet data gathered from six trucks used in an open pit mining operation were analyzed in this study. The data contain the times between failures and time to repair for each truck. A reliability model for each truck was independently developed using the power law model. Fig. 2 shows the evolution of reliability over the time for trucks. Average reliability of the fleet is provided in the figure. The average reliability represents the behavior of a generic truck working in the mine. The model parameters, the scale (λ) and shape (β) of the power law, are given in Table 1. The other input parameters regarding the trucks and the mine site parameters are given in Table 2 and Table 3, respectively. In Table 3 are showed the actual values of fuel cost and Carbon Tax for the Province of British Columbia (Government of British Columbia, 2012). These costs are useful to compare maintenance with fuel and Carbon Tax expenditures.

The restoration factors of the trucks were calculated using the Reliasoft software. The average reliability was calculated according to the reliability behavior of all 6 trucks.

The power demand of the average truck was calculated subsequently and the performances of three different truck sizes A, B and C compared. The power demand was calculated based on the maximum speed obtained from the rimpull curve of each truck model (A, B and C). The fuel consumptions for truck models A, B and C are shown on Table 4 when they are empty. Furthermore, fuel consumption of the trucks associated with cycle times were also calculated. In Table 5, specific fuel consumptions are given for different hauling distances, truck size and number of trucks. In that table, the SFC are calculated by comparing the results of trucks operating in outstanding working conditions with those of defective trucks. The results show that the specific fuel consumption of truck models A, B and C working in outstanding conditions is respectively 32%, 33% and 33% lower than that of the same models working in suboptimal conditions (Table 5). This table shows that a poor maintenance schedule reduces truck efficiency. Similarly, Table 6 shows the emissions of truck models A, B and C in terms of CO_2-eq. The proportions remain the same since the emissions are linearly related to the fuel consumed.

4. Discussions

To assess the factors affecting special fuel consumption, a multiple regression model was developed. In preliminary analysis, independent variables, reliability (R), working hours (H_w), distance

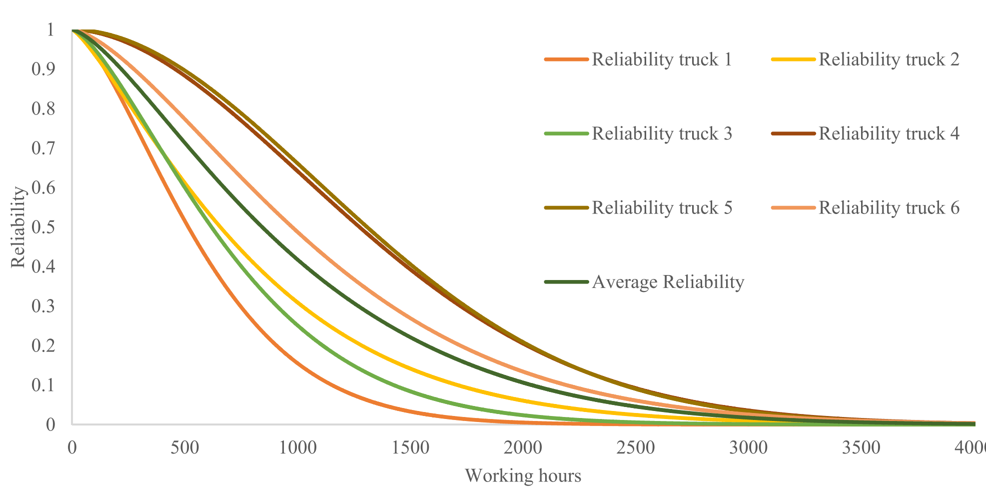


Fig. 2. Reliability behavior of each truck and their average reliability.

Table 1
Parameters λ and β for the power law model.

Distribution parameters	Truck 1	Truck 2	Truck 3	Truck 4	Truck 5	Truck 6
Lambda	$6.28 \cdot 10^{-5}$	$7.68 \cdot 10^{-5}$	$1.44 \cdot 10^{-5}$	$6.14 \cdot 10^{-5}$	$6.03 \cdot 10^{-5}$	$9.9 \cdot 10^{-5}$
Beta	1.49	1.45	1.64	1.95	2.22	1.51

Table 2
Input parameters.

Parameters	Truck model A	Truck model B	Truck model C
Total resistance	0.1	0.1	0.1
Grade resistance	0.06	0.06	0.06
Payload	44 tonnes	183 tonnes	363 tonnes
Truck weight	38 tonnes	141 tonnes	260 tonnes
Gross weight	82 tonnes	324 tonnes	623 tonnes
Loading time	0.06 h	0.06 h	0.06 h
Unloading time	0.01 h	0.01 h	0.01 h
Waiting time	0.04 h	0.04 h	0.04 h

Table 3
Mine site parameters. The carbon tax is relative to Province of British Columbia and applies to the fuel used.

Parameters	Values
Distance [km]	1.5, 2, 3 km
Working days in a year	365
Yearly production	1,264,506 tonnes
Daily operating hours	16.50 h
Fuel cost	0.795 $/liter
Carbon tax	0.0767 $/liter

Table 4
Net power demand and fuel consumption at idle for each truck model.

Truck model	Fuel consumption at idle [l/h]	Net power [kw]
A	4.67	415
B	16.52	1468
C	31.85	2830

Table 5
Comparison of different specific fuel consumption (SFC) between three truck's capacities (A, B and C), three different distances and n-trucks for each fleet when the truck is working in perfect working conditions and when the defective truck is working not efficiently.

n	Truck A			Truck B			Truck C		
	1.5 km	2 km	3 km	1.5 km	2 km	3 km	1.5 km	2 km	3 km
	SFC [l/t]	SFC [l/t]	SFC [l/t]	SFC [l/t]	SFC [l/t]	SFC [l/t]	SFC [l/t]	SFC [l/t]	SFC [l/t]
Trucks in perfect working conditions									
6	0.93	1.21	1.78	1.58	1.84	2.36	1.57	1.839	2.34
12	1.85	2.42	3.56	3.17	3.69	4.72	3.15	3.65	4.67
24	3.71	4.85	7.12	6.34	7.37	9.44	6.3	7.32	9.35
Suboptimal trucks									
6	1.23	1.61	2.37	2.11	2.13	3.13	2.09	2.43	3.11
12	2.47	3.22	4.73	4.21	4.25	6.27	4.19	4.86	6.21
24	4.94	6.44	9.46	8.43	8.51	12.53	8.37	9.72	12.42

(*D*), gross mass weight (*GW*) and payload (*PW*), were considered in the analysis. The results showed that working hours has no significant influence on SFC. This is clear because working hours do not effect hourly fuel consumption. Also, there was a collinearity between GW and PW. Therefore, PW was removed the multiple regression model. As can be seen from ANOVA (Table 7) the model is valid. Final model is given in Table 8. The model explains 87.5% of total variability ($R^2 = 87.5\%$) As can be seen from the model, *D* is certainly the most significant factor. As can be seen beta value (−0.48), *R* is also a significant factor. This important finding that a maintenance plan keeping equipment in pre-specified reliability level will contribute to SFC reduction. *GW* is also almost an equally significant parameter for SFC.

The p-values of the second model are reasonably low, therefore, the model is acceptable on a first step. The second step is the analysis of beta coefficients of the model. Beta or standardized coefficients are the slopes we would get if all the variables were on the same scale, which is done by converting them to z-scores before doing the regression. So an increase of one standard deviation in the reliability is associated with a drop of 0.4787 standard deviation in SFC, if all the other variables are held constant. In this model (model 2), GMW is the most important predictor of SFC beside the payload (*PW*).

Finally, the third step is the analysis of the variance inflation factors. Variance inflation factors (VIF) measure how much the variances of the estimated regression coefficients are inflated compared to when the predictor variables are not linearly related. The variance inflation factors of the model show that *GW* and *PW* contribute to each other, which suggests that one of them should be eliminated. *GW* contains information about the payload and the weight of the truck, which calls for the removal of payload from the model.

Thus, whether all variables are maintained constant, an increase of one standard deviation in the reliability rate is associated with a decrease of 0.48 standard deviation in SFC. It is possible to see that reliability and *GW* are of roughly the same importance in predicting SFC. The distance D have almost the same importance although it is slightly higher in value.

The variance inflation factors for the three predictors show that the variance for the estimated coefficient is inflated by a factor of 1. Therefore, *R*, *D* and *GW* are not correlated with each other. As confirmed from the multiple R-squared of 0.88 and the adjusted R-squared of 0.87, dropping the two factors *PW* and H_w and considering model 3 instead of model 1 is reasonable. The model representing the SFC is model 3 with the reliability *R*, the distance *D* and the gross weight of the truck *GW* as variables.

Effect of maintenance on energy consumption and GHG emissions is also discussed. The reliability of a generic truck was expressed as the average of the reliabilities of all the trucks. Every peak in the average reliability graph corresponds to a maintenance action. Four types of time-based maintenance policies were compared with four other reliability-based maintenance

Table 6
Comparison of different CO2-eq emissions between three truck's capacities (A, B and C), three different distances and n-trucks for each fleet when the truck is working in perfect working conditions and when the defective truck is working not efficiently.

n	Truck A			Truck B			Truck C		
	1.5 km	2 km	3 km	1.5 km	2 km	3 km	1.5 km	2 km	3 km
	CO_2-eq [kg/t]	CO_2-eq [kg/t]	CO_2-eq [kg/t]	CO_2-eq [kg/t]	CO_2-eq [kg/t]	CO_2-eq [kg/t]	CO_2-eq [kg/t]	CO_2-eq [kg/t]	CO_2-eq [kg/t]
Trucks in perfect working conditions									
6	2.51	3.27	4.81	4.28	4.98	6.37	4.25	4.94	6.31
12	5.02	6.55	9.61	8.56	9.95	12.74	8.51	9.88	12.62
24	10.03	13.10	19.23	17.13	19.91	25.47	17.01	19.75	25.24
Suboptimal trucks									
6	3.33	4.35	6.39	5.69	5.74	8.46	5.65	6.56	8.38
12	6.66	8.70	12.77	11.38	11.49	16.92	11.30	13.12	16.77
24	13.33	17.40	25.54	22.75	22.97	33.84	22.60	26.25	33.54

Table 7
ANOVA table of the model.

	Df	Sum Sq	Mean Sq	F Value	Pr(>F)
Regression	3	0.88	0.29	237.43	4.08E-46
Residual	103	0.13	0.0012	–	–
Total	106	1.01	–	–	–

truck's reliability level progressively lower each successive time interval. With the reliability decreasing, the fuel consumption is expected to increase according to the model (Table 7). The GHG emissions are linearly related to the fuel consumption (13), therefore, they are also expected to increase beside the fuel consumption. The performances of the four time-based maintenance approaches. The four types of time-based maintenances were effectuated respectively every 737, 663, 617 and 590 h according to the different time-based policy chosen. On a reliability-working hours graph the four approaches denote a similar downward trend over time (Fig. 3). The differences noticeable on Fig. 4 are the higher frequency in maintenance while the number of hours between two maintenance actions decreases. Paying attention to each peak of a particular function on the graph (Figs. 3 and 4), the successive maintenance action is never completely effective according the estimated restoration factor of 98%.

Table 8
Regression results for model 3. Multiple R-squared: 0.8775, Adjusted R-squared: 0.874.

	Coefficients	Standard error	t value	Pr(>|t|)	VIF	Beta coefficients
Intercept	$1.79\cdot10^{-1}$	$1.67\cdot10^{-2}$	10.77	$<2\cdot10^{-16}$	–	–
R	$-1.88\cdot10^{-1}$	$1.35\cdot10^{-2}$	−13.95	$<2\cdot10^{-16}$	1	−0.48
D	$1.03\cdot10^{-1}$	$5.41\cdot10^{-3}$	19.04	$1.03\cdot10^{-1}$	1	0.65
GW	$2.09\cdot10^{-4}$	$1.52\cdot10^{-5}$	13.71	$2.09\cdot10^{-4}$	1	0.47

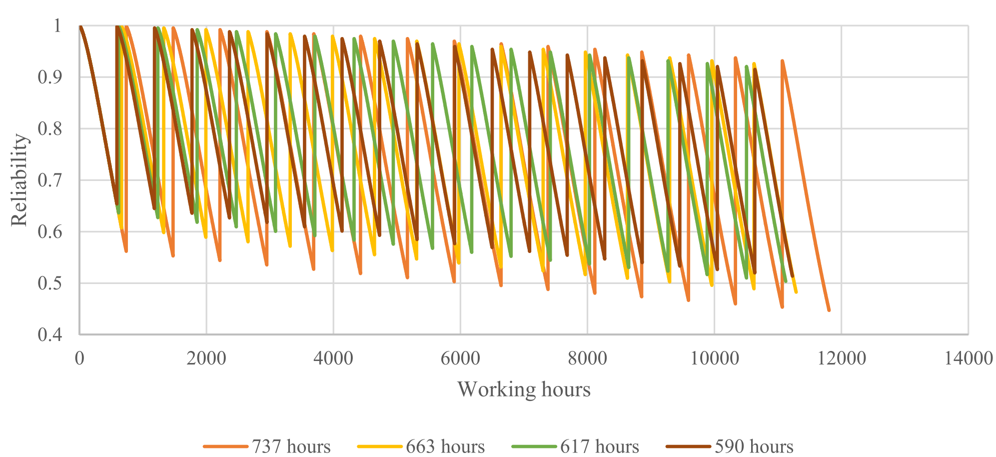


Fig. 3. Average reliability behavior of a truck in 1-years with four different time-based scheduled maintenance approaches. The fluctuating four different time-based maintenance approaches show a downward trend over time.

In addition, as a consequence of the time-based policy chosen, the local minima show a successive decreasing behavior due to the approaches for truck A are compared in Fig. 5. This histogram shows the cost per tonne of the maintenance (SMC), fuel consumption (SFCC) and GHG emissions (SGTC). Overall, the maintenance cost decreased with the number of hours whilst the fuel consumption and emissions costs increased. The lowest cost was the 15,397 $/t of the maintenance policy for the 617 h approach, where the maintenance, fuel consumption and emissions tax accounted for 29.9 percent, 65.4 percent and 4.7 percent of the total cost, respectively. Comparing 617 h approach with the 737 h approach the latter showed 1.5 percent increase in maintenance cost whereas the fuel consumption and emission tax growth for 9 percent. According to these results, the fuel consumption cost had

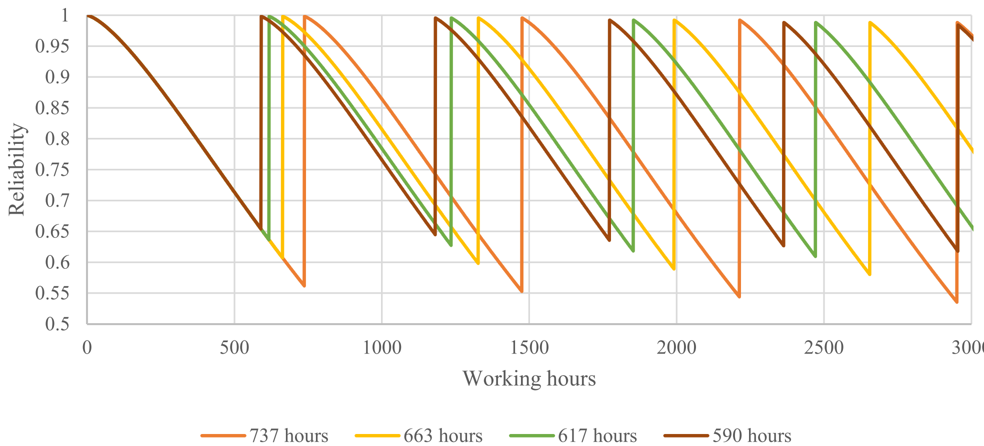
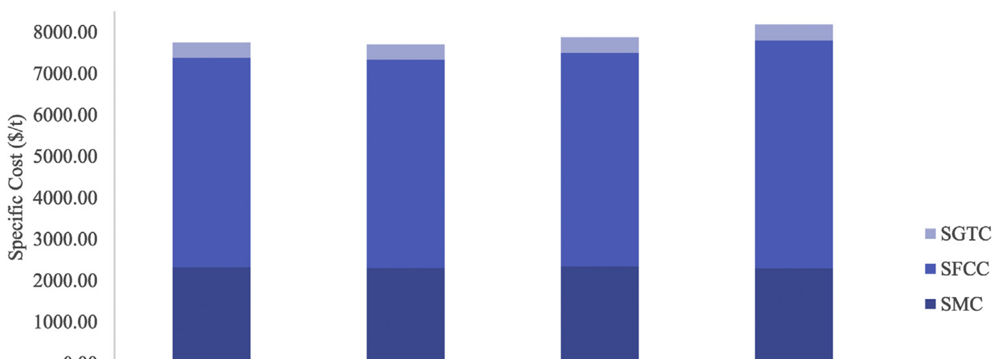


Fig. 4. Particular of the Average reliability behavior of a truck for 3000 h. Among the four different time-based maintenance approaches, the one considering a repair every 590 h shows best results in term of reliability but at the price of a higher repair frequency.



	Truck A 590h	Truck A 617h	Truck A 663h	Truck A 737h
SGTC	362.16	360.56	369.71	393.94
SFCC	5054.98	5032.66	5160.96	5498.58
SMC	2327.18	2305.42	2339.41	2294.23

Time-based maintenance approaches

Fig. 5. Yearly specific cost ($/t) of maintenance (SMC), fuel consumption (SFCC) and GHG emissions tax (GHGT) comparison for the four time-based maintenance approaches.

an important effect on the total cost. Although the maintenance cost decreased with the number of hours between maintenance actions (lower repairs frequency), the fuel consumption cost grew beside the emissions' cost because of the decline on the reliability level. The previous result suggests that to control the reliability level of a machine, evaluating the costs of maintenance, fuel consumption and emissions is needed.

The results of a reliability-based approach are showed on Fig. 6, Fig. 7 and Fig. 8. The four reliability-based maintenance approaches were constrained respectively to 60, 65, 70 and 75 percent reliability level where the maintenance action was effectuated according to the specific reliability-based policy chosen. On a reliability-working hours graph the four approaches denote a similar downward trend over time whether the peaks of the reliability functions are considered (Fig. 6). As a matter of fact, the detected restoration factor of 98 percent confirmed that the repairs effectuated keep a certain level of imperfection since the machine system is never fully renovated at each repair. However, on the reliability based approach the local minima of the reliability functions were constant because the repairs were constrained to the reliability level and effectuated each time this value was reached (Fig. 7).

The lower the reliability, the more fuel consumption increases. The cost per tonne of the maintenance (SMC), fuel consumption (SFCC) and GHG emissions (SGTC) is shown on Fig. 8. Overall, the maintenance cost decreased whilst the reliability level threshold increased. Besides the maintenance specific cost, the fuel consumption and GHG emissions specific costs showed an inverse tendency with respect to the reliability level. The lowest specific cost was the 13,272 $/t of the maintenance policy at 75% reliability threshold, where the maintenance, fuel consumption and emissions tax accounted for 31.4 percent, 64 percent and 4.6 percent of the total cost, respectively. Comparing 75 percent reliability threshold approach with the 60 percent reliability threshold approach the latter showed 9.7 percent increase in maintenance cost whereas the fuel consumption and emission tax growth by 15.6 percent. According to these results the fuel consumption cost had an important effect on the total costs. However the maintenance cost decreased while the reliability threshold increased. In fact, the investment on the repair with a higher level of reliability resulted less expensive than a repair at a lower reliability level. As expected, the fuel consumption cost grew beside the emissions' cost because of the decline of the reliability level. In light of this result, the best maintenance policy was the reliability-based at a 75 percent reliability threshold. In fact, comparing the 75 percent reliability threshold approach with the 737-h approach the former showed a 10 percent reduction in maintenance cost whereas the

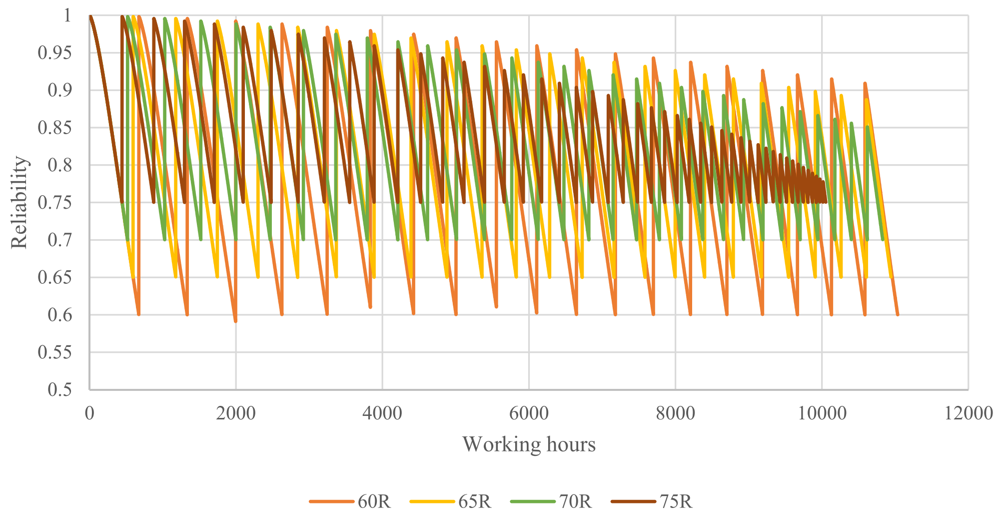


Fig. 6. Average reliability behavior of a truck in 1-years with four different reliability-based maintenance approaches. The fluctuating four different reliability based maintenance approaches show a downward trend for the reliability peack after each repair. The bottom values are instead constant because the method has a reliability threshold.

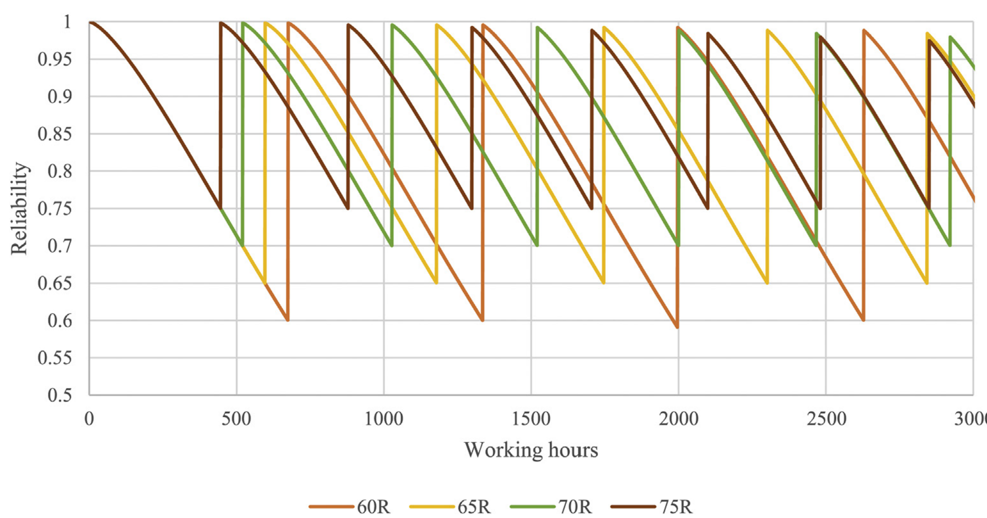


Fig. 7. Particular of the Average reliability behavior of a truck for 3000 h. Among the four different time-based maintenance approaches, the one considering 75% reliability threshold shows best results in term of reliability but at the price of a higher repair frequency. The 75% reliability-based method fluctuate with higher frequency because of the higher number of repairs.

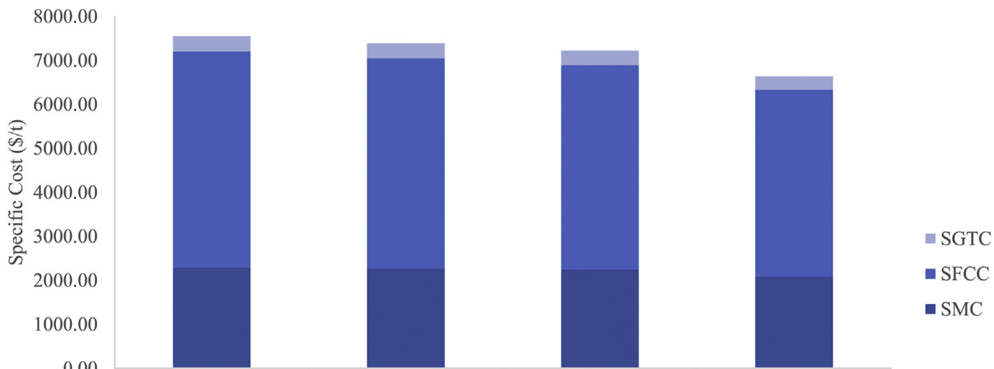
fuel consumption and emission tax decreased by 29.5 percent. The performance of the 617-h approach respect the 75 percent reliability threshold was not competitive since the latter showed 11, 19 and 19 percent savings for the maintenance cost, fuel consumption and emission tax respectively.

4.1. Effect of distance on energy consumption and GHG emissions

The 75 percent reliability threshold was defined as the best reliability approach considering the effect of distance on energy consumption and GHG emissions (c.f. Fig. 9). The histogram shows the specific cost of SMC, SFCC and GHG emission tax for three different distances. Considering truck A and a reliability-based maintenance at 75% reliability threshold, the result is that the fuel consumption and GHG emission specific cost increase with the distance. The lowest cost of 13,272 $/t was registered at 1.5 km with a proportional contribution of 31.4 percent for SMC, 64 percent for the SFCC cost and 4.6 percent for the SGTC. The performance over 1.5 km with respect to the 3 km resulted in the latter showing a 20 percent increase for the fuel consumption cost and the emission tax while the maintenance cost was not influenced and stayed stable.

4.2. Effect of truck capacity on energy consumption and GHG emissions

Fig. 10 shows the effect of three different truck capacities (trucks A, B and C) on energy consumption and GHG emissions. The figure shows the specific cost of SMC, SFCC and GHG emission taxes for the three truck capacities and the four different reliability-based maintenance approaches over a distance of 1.5 km. The most important noticeable result from the histogram is that the specific costs of maintenance, fuel consumption and GHG emissions increased as capacity grows. For truck A, over a distance of 1.5 km and a reliability of 75 percent, the contribution of each variable to the overall specific costs was 29.9 percent for SMC, 65.4 percent for SFCC and 4.7 percent for SGTC. Comparing truck A with the truck C, over a distance of 1.5 km and a reliability of 75 percent, the latter showed 60.7 percent increase in maintenance cost

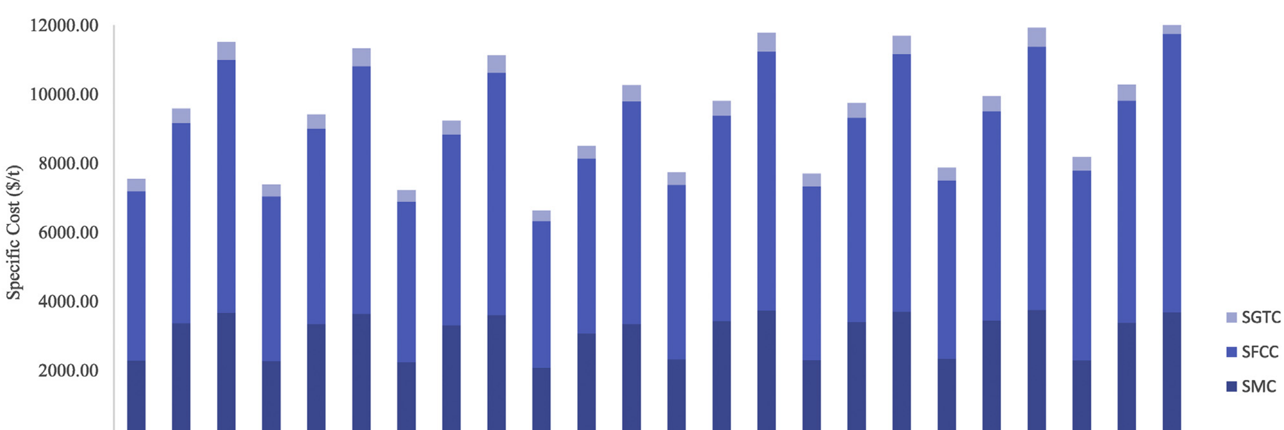


	Truck A 60	Truck A 65	Truck A 70	Truck A 75
SGTC	351.84	342.36	333.05	304.31
SFCC	4910.93	4778.63	4648.70	4247.61
SMC	2286.77	2268.32	2243.04	2084.08

Fig. 8. Yearly specific costs ($/t) of maintenance (SMC), fuel consumption (SFCC) and GHG emissions tax (SGTC) comparison for the four reliability-based maintenance approaches.

	Truck A 75 1.5 km	Truck A 75 2 km	Truck A 75 3 km
SGTC	304.31	329.94	363.96
SFCC	4247.61	4605.35	5080.12
SMC	2084.08	2084.08	2084.08

Fig. 9. Yearly specific costs ($/t) of maintenance (SMC), fuel consumption (SFCC) and GHG emissions tax (SGTC) comparison for three different distances.



Truck capacities	Truck A	Truck B	Truck C	Truck A	Truck B	Truck C	Truck A	Truck B	Truck C	Truck A	Truck B	Truck C	Truck A	Truck B	Truck C	Truck A	Truck B	Truck C	Truck A	Truck B	Truck C	Truck A	Truck B	Truck C
Maintenace type	60	60	60	65	65	65	70	70	70	75	75	75	590h	590h	590h	617h	617h	617h	663h	663h	663h	737h	737h	737h
Distance	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
SGTC	351.8	415.1	524.5	342.3	405.4	513.9	333.0	395.8	503.0	304.3	362.8	462.3	362.1	426.3	537.7	360.5	424.0	534.4	369.7	433.8	545.9	393.9	460.6	578.0
SFCC	4910.	5794.	7321.	4778.	5659.	7173.	4648.	5525.	7022.	4247.	5064.	6453.	5054.	5950.	7505.	5032.	5918.	7459.	5160.	6056.	7620.	5498.	6430.	8067.
SMC	2286.	3375.	3675.	2268.	3348.	3645.	2243.	3311.	3605.	2084.	3076.	3349.	2327.	3435.	3740.	2305.	3403.	3705.	2339.	3453.	3760.	2294.	3386.	3687.

Fig. 10. Yearly specific cost ($/t) of maintenance (SMC), fuel consumption (SFCC) and GHG emissions tax (SGTC) comparison for three different (A, B and C) truck capacities, four different maintenance approaches and 1.5 km distance.

whereas the fuel consumption and emission tax growth for 52 percent.

In conclusion, the results suggest that an increase of truck capacities does not seem to be a good solution for decreasing operating costs. In fact, in light of previous results, the cost of maintenance, fuel consumption and GHG emissions (due to the taxation proportional to fuel consumption) increase accordingly with the dimension of the truck.

5. Conclusions

The crisis affecting the mining sector leads to an effort to reduce operating cost. Energy consumption related to material haulage is a major contributor of total energy expenditures. Therefore, it represents one of the most important factors that can be optimized. Increased production demands also contribute to an increase in energy consumption and greenhouse gas emissions. The relationship between energy consumption and GHG emissions with regards to the age of the equipment, has not been studied yet. The aim of this paper is to evaluate the effect of truck maintenance on the energy consumption and greenhouse gas emissions in mining trucks. In doing so, a regression analysis was used to estimate the reliability contribution on the specific fuel consumption variations. Regression analysis showed that truck reliability, distance and weight were equally important parameters affecting fuel consumption. This study benchmarked the results of three different trucks, three different distances, and three different fleet sizes. Given that truck reliability is an important parameter affecting energy consumption and GHG emissions, a reliability-based maintenance plan can reduce this consumption and emissions. Furthermore, specific energy consumption increases equipment capacities. There is trade-off between energy and maintenance costs. It is concluded that these costs will minimized at approximately 75% of truck reliability. A follow-up of this research will be a robust optimization of the energy consumption of a truck fleet considering uncertainties associated with variations of speed, payloads and road conditions. Thus, sensitivities affecting fuel consumption and reliability can be further quantified. Furthermore, being hauling equipment performance affected by loading operations, the research would consider the analysis of a larger system of truck and loaders and their interaction. A critical comparison of electric versus diesel equipment will also be implemented.

Acknowledgement

The authors thank to the Natural Sciences and Engineering Research Council of Canada for supporting this research (Fund number: 236482).

References

Australian Government. (2012). *National pollutant inventory emission estimation technique manual for mining (NPI). Department of Sustainability, Environment, Water, Population and Communities*.

Awuah-Offei, K. (2016). Energy efficiency in mining: A review with emphasis on the role of operators in loading and hauling operations. *Journal of Cleaner Production, 117*, 89–97.

Brundtland, G., Khalid, M., Agnelli, S., Al-Athel, S., Chidzero, B., Fadika, L., et al. (1987). *Our common Future: Report of the world commission on environment and development*. USA: Oxford University Press.

Burchart-Korol, D., Krawczyk, P., Czaplicka-Kolarz, K., Turek, M., & Borkowski, W. (2014). Development of sustainability assessment method of coal mines. *Journal of Sustainable Mining, 13*(4), 5–11.

Carmichael, D. G., Bartlett, B. J., & Kaboli, A. S. (2014). Surface mining operations: Coincident unit cost and emissions. *International Journal of Mining Reclamation and Environment, 28*(1), 47–65.

Caron, J., Durand, S., & Asselin, H. (2016). Principles and criteria of sustainable development for the mineral exploration industry. *Journal of Cleaner Production, 119*, 215–222.

Caterpillar Inc. (2015). *Caterpillar performance handbook* (44 ed.). Caterpillar.

Crow, L. H. (1975). *Reliability analysis for complex, repairable systems*. Retrieved June 29, 2016, from https://pdfs.semanticscholar.org/e176/06aeb2e7c003ad1b7610006bbb27ac622a10.pdf.

Dubiński, J. (2013). Sustainable development of mining mineral resources. *Journal of Sustainable Mining, 12*(1), 1–6.

Giannelli, R. A., Nam, E., Helmer, K., Younglove, T., Scora, G., & Barth, M. (2005). *Heavy-duty diesel vehicle fuel consumption modeling based on road load and power train parameters* (0148–7191). Retrieved January 12, 2016, from http://collaboratory.ucr.edu/files/Diesel_Vehicle_Fuel_Consumption.pdf.

Gomes, C. M., Kneipp, J. M., Kruglianskas, I., da Rosa, L. A. B., & Bichueti, R. S. (2014). Management for sustainability in companies of the mining sector: An analysis of the main factors related with the business performance. *Journal of Cleaner Production, 84*, 84–93.

Government of British Columbia. (2012). *How the carbon tax works*. Retrieved February 22, 2015, from http://www.fin.gov.bc.ca/tbs/tp/climate/A4.htm.

Government of Canada. (2015). *Canada's greenhouse gas emissions*. Retrieved 16 September, 2015, from http://www.ec.gc.ca/indicateurs-indicators/default.asp?lang=en&n=FBF8455E-1.

Kaarsberg, T. M., HuangFu, E. P., & Roop, J. M. (2007). *Extreme energy efficiency in the U.S.: Industrial, economic and environmental impacts*, 2007 ACEEE Summer Study on Energy Efficiency in Industry, 4-24-24-35.

Kecojevic, V., & Komljenovic, D. (2010). Haul truck fuel consumption and CO2 emission under various engine load conditions. *Mining Engineering, 62*(12), 44–48.

Kijima, M. (1989). Some results for repairable systems with general repair. *Journal of Applied Probability, 26*(1), 89–102.

Kijima, M., & Sumita, U. (1986). A useful generalization of renewal theory: Counting processes governed by non-negative markovian increments. *Journal of Applied Probability*, 71–88.

Lodhia, S., & Hess, N. (2014). Sustainability accounting and reporting in the mining industry: Current literature and directions for future research. *Journal of Cleaner Production, 84*, 43–50.

Meinshausen, M., Meinshausen, N., Hare, W., Raper, S. C., Frieler, K., Knutti, R., et al. (2009). Greenhouse-gas emission targets for limiting global warming to 2 C. *Nature, 458*(7242), 1158–1162.

Montzka, S. A., Dlugokencky, E. J., & Butler, J. H. (2011). Non-CO2 greenhouse gases and climate change. *Nature, 476*(7358), 43–50.

Moran, C. J., Lodhia, S., Kunz, N. C., & Huisingh, D. (2014). Sustainability in mining, minerals and energy: New processes, pathways and human interactions for a cautiously optimistic future. *Journal of Cleaner Production, 84*, 1–15.

Norgate, T., & Haque, N. (2010). Energy and greenhouse gas impacts of mining and mineral processing operations. *Journal of Cleaner Production, 18*(3), 266–274.

Norgate, T., & Haque, N. (2012). Using life cycle assessment to evaluate some environmental impacts of gold production. *Journal of Cleaner Production, 29–30*, 53–63.

Onn, A. H., & Woodley, A. (2014). A discourse analysis on how the sustainability agenda is defined within the mining industry. *Journal of Cleaner Production, 84*, 116–127.

Rahimdel, M. J., Ataei, M., Khalokakaei, R., & Hoseinie, S. H. (2013). Reliability-based maintenance scheduling of hydraulic system of rotary drilling machines. *International Journal of Mining Science and Technology, 23*(5), 771–775.

Runge, I. C. (1998). *Mining economics and strategy*. SME.

Sahoo, L. K., Bandyopadhyay, S., & Banerjee, R. (2014). Benchmarking energy consumption for dump trucks in mines. *Applied Energy, 113*, 1382–1396.

Soofastaei, A., Aminossadati, S. M., Arefi, M. M., & Kizil, M. S. (2016). Development of a multi-layer perceptron artificial neural network model to determine haul trucks energy consumption. *International Journal of Mining Science and Technology, 26*(2), 285–293.

Soofastaei, A., Aminossadati, S. M., & Kizil, M. S. (2008). *The effects of payload variance on mine haul truck energy consumption, greenhouse gas emission and cost*. Retrived October 7, 2015 from irannec.com/GetFile.aspx?FilePrm=ETE-144_172302286.pdf.

Tobias, P. A., & Trindade, D. (2011). *Applied reliability*. CRC Press.

Topal, E., & Ramazan, S. (2010). A new MIP model for mine equipment scheduling by minimizing maintenance cost. *European Journal of Operational Research, 207*(2), 1065–1071.

Tuusjarvi, M., Maenpaa, L., Vuori, S., Eilu, P., Kihlman, S., & Koskela, S. (2014). Metal mining industry in Finland - Development scenarios to 2030. *Journal of Cleaner Production, 84*, 271–280.

United States Environmental Protection Agency (EPA). (2008). *Average annual emission and fuel consumption for gasoline-fueled passengers cars and light trucks*. Retrieved September 7, 2105, from https://www3.epa.gov/otaq/consumer/420f08024.pdf.

US Department of Energy. (2007). *Mining industry energy bandwidth study*. Retrieved November 12, 2015, from http://energy.gov/sites/prod/files/2013/11/f4/mining_bandwidth.pdf.

Wang, X., Chow, J. C., Kohl, S. D., Percy, K. E., Legge, A. H., & Watson, J. G. (2015). Real-world emission factors for Caterpillar 797B heavy haulers during mining operations. *Particuology*. http://dx.doi.org/10.1016/j.partic.2015.07.001.