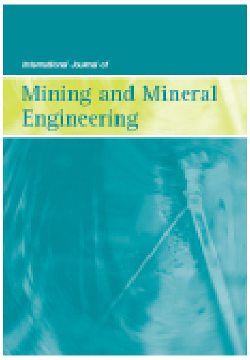

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Characteristics and models for energy improvements of cyclic transport operations in mining

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Abstract: There is a large potential for automation and optimisation of transports within quarrying and mining, but operational models and characteristics for this purpose are lacking. This paper aims to provide insight into cyclic transports and the parameters that affect energy consumption and productivity. Detailed operational data from machines has been collected and analysed through automatic logging of the machine's internal communication network. The paper presents and discusses the characteristics of the operation identified, develops models for energy consumption and productivity, and discusses their relation for optimisation and automation purposes. A conclusion is that stochastic fluctuations in activity times need continuous real-time control for an optimisation system to be effective. The method used in the paper resulted in regression models for cycle energy cost and hauler fuel rate, which provide both correlation and significance, which is promising for future validation and use in energy optimisation control systems.

Keywords: mining characteristics; transport optimisation; energy model; fuel model; energy optimisation; energy improvements; surface mining; lean construction; cyclic transport operations; fleet optimisation; automated machine guidance; AMG.

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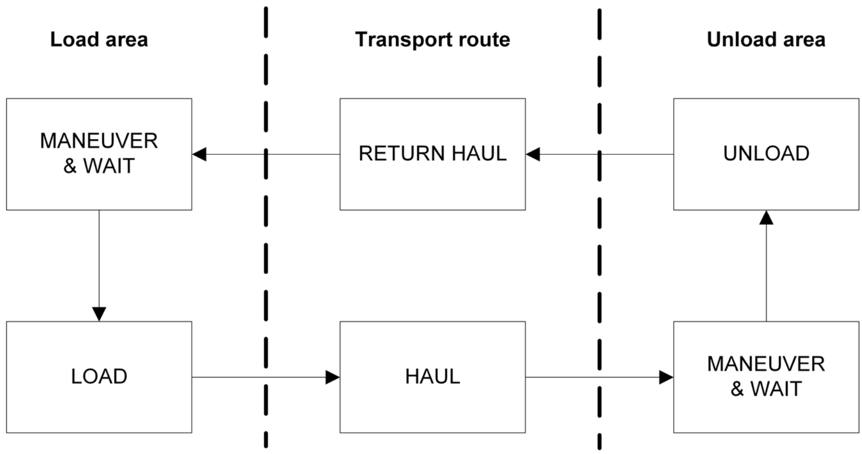
1 Introduction

Cyclic transport operations are common in the quarry and mining domain. In surface mines, transports consume about 30% of the energy and are the primary source of greenhouse gas emissions (Siami-Irdemoosa and Dindarloo, 2015). Research has shown that transport operations include a large amount of lean waste, (e.g., waiting) and have a great potential for automation and optimisation to improve productivity and reduce energy consumption (Rylander and Axelsson, 2013). To optimise, control, and eventually effectively automate, the operation's characteristics need to be known and their models need to be developed. As stated by Azar and Kamat (2017) "most of the recent research efforts highlight the lack of in-depth knowledge-based application of the captured data for modelling and controlling the cyclic operations". Golbasi and Kina (2022) conclude that surprisingly little research is available concerning fuel consumption behaviour of haul trucks including kinematic factors.

This paper presents the operational parameters and characteristics of the earthmoving transport processes in mining environments. Furthermore, it provides a method and models for fuel consumption of transport operations. The models are based on detailed machine data and its kinematic parameters. The method utilised and the knowledge presented in the paper is intended to be used to innovate several phases of asset management in mining including strategic and tactical planning as well as operation improvements including automation and productivity optimisation.

Figure 1 The transport work step cyclic activities



1.1 The quarry and mining process

The primary operation of quarries and mines consists of a set of sequential and potentially parallel subprocesses, (e.g., blast, transport, sort, and screen) that can be referred to as work steps. These work steps depend on each other since each sequential subprocess relies on the deliveries of the preceding subprocess. The throughput of the system is limited by the subprocess with the least throughput, referred to as the bottleneck. In a dynamic environment, a subprocess's production rate and capacity vary over time, which may move the bottleneck.

The transport work step can be described by its activities, see Figure 1. The transport work step's overall capacity depends on loading and unloading capacity and its availability (input and output to the subprocess). Due to the continuous capacity variations over time, there are no static states. Instead, an effective and sustainable control system needs to continuously detect and manage the changes to minimise operational waste and improve the operation.

Simultaneously there is a low tolerance of delays in the production. The overall production of the site is often depending on the uptime and deliveries of the transport work step. Significant downtime in the transport operation causes loss of production for the entire site. Such loss is a considerably higher cost than the benefits achievable by limiting waste in the transport process. Therefore, operative waste reductions need to be at a level where there still is a low risk of production loss effects from operative changes and variations.

1.2 Optimisation and control

In any production system including sequential processes and activities, there exists at least one bottleneck (Goldratt, 1990). While the maximum production is achieved, the capacity available in non-bottlenecks can be used to minimise operative costs. When a fleet of vehicles, routes, and drivers is defined, the main possibility of minimising cost relates to energy consumption. The operation's main target is to maintain the required productivity (ton/h) with the assets available. Thus, cost optimisation efforts need to manage risks of decreasing production, affecting the bottleneck and, consequently, the site's productivity. Therefore, changes in the operation need to be identified and managed to prevent loss in production capacity. While turning operational wastes into, e.g., decreased speed and later arrivals to destinations than theoretically possible, trade-offs for production loss risks and energy optimisation need to be considered.

To partly or fully automate the transport work step or at least the haulers in the transport work step, the design parameters to configure and execute the operation need to be known. To design and choose optimisation and control algorithms, the characteristics of the parameters need to be modelled based on reliable data. For this purpose, it needs to be known what parameters to consider and what boundaries, variation, and dependencies the parameters include. Finally, as the environment is changing, the optimisation and control approaches need to be dynamic and real-time.

1.3 Purpose and research questions

This research aims to improve productivity for both the planning and execution of cyclic earthmoving operations within the transport work step. Productivity can be described as the relation between output and input over time. To be able to improve productivity, the output value produced can be increased or input cost reduced. To reduce input cost through enhanced energy efficiency, the flow in operation and bottlenecks respectively need to be identified. To identify the bottleneck, waiting times, setup times, and activity times are crucial and need to be monitored. By identifying activity times, the bottleneck can be identified, and control and automation of operation can be facilitated. An important factor is then how the activity times vary over time. How large are the operative variations, and how are they distributed over the different activities in a transport work step? To define and understand this, both the design and execution parameters need to be presented and analysed.

The main research questions addressed are:

RQ1 What are the main operational characteristics and parameters required to schedule, control, and automate transport work steps for earthmoving machines in a quarry/mining operation?

RQ2 What is the potential of energy optimisation of a transport work step?

RQ3 How can an optimisation model be constructed to optimise the transport work step cycle and machine energy consumption?

To address the research questions the paper presents a model whose purpose is to assist in the different phases of asset management for the site and its operation. Typical target roles in a site would be site managers, fleet managers, or operations managers. It is intended to help calculate the benefits of performing construction work to, e.g., widen the route to allow for meetings at higher speed or to assess the need to perform route maintenance to increase traction or visibility. The model is also intended to be used for mission management for the operators to decide behaviours in a cycle as conditions for performing meetings or driving through intersections. Further, it is meant to be assistive in the lean analysis of throughput, machine configuration, and bottlenecks in the operation.

The paper's structure is as follows: first, we present the related work followed by the research methodology used in this study. Then we present our result, which is followed by a discussion and conclusions.

2 Related work

Within quarry and mining, several disciplines are working with Lean thinking and optimisation theories. The related research can be divided into two areas:

1 site planning and configuration

2 automation and coordination.

Both areas are relevant since they have the potential for optimisation and automation.

2.1 Site planning and configuration

A large field of research tackles the site fleet planning and configuration problem (Burt and Caccetta, 2018). Several methodologies and approaches have been presented. Hoła and Schabowicz (2010) present a methodology for determining earthworks execution time and cost to select the optimal set of machinery. It concludes that researchers often find that earthworks' actual productivity is considerably lower than the theoretical productivity values. Several methods have been presented for how to configure an operation efficiently, and it is concluded to be crucial for the cost and duration of the project (Smith et al., 2000). Burt and Caccetta (2018) present many variables that affect the configuration of a site operation and fleet used and present approaches for how to manage them. For optimal productivity, it is described how the total cost of ownership is affected by having the right size and type of machine for specific tasks (Uhlin, 2012). What can be concluded is that a set of machines is discrete; an optimum is not half a vehicle but can be theoretically defined as the size and capacity of vehicles in fleets. Different sizes and characteristics of a machine can be utilised. Still, the need for a site continuously changes as, e.g., the distance, traction, and loading and unloading capacity vary over time.

Site configuration is essential, but sites may not instantly change the fleet configuration or acquire new machines based on a new optimum. Instead, most are forced to use what they have at hand. Many sites change operations daily or even several times per day or shift based on operative needs and physical requirements. The optimum for one distance and fleet configuration may not be the optimum for another. These factors lead to varying capacities within the operations over time. Therefore, there is a need to handle fluctuations in production and manage the site assets to balance the production chain's capacities and deviations.

2.2 Automation and coordination

In larger mining operations, there can be multiple loading and dump locations and numerous paths in between. Different dispatching optimisation algorithms have been presented where the aim is to minimise the avoidable non-productive time of loaders and trucks and deviation from the target feed rate of the processing plant. Sofranko et al. (2015) proposed a solution using a personal digital assistant (PDA) mounted for monitoring time and spatial use and optimisation of productive time. Additional machine sensors were not presented in the monitoring or optimisation approach, and instantaneous energy consumption was not given as a parameter.

Moradi-Afrapoli and Askari-Nasab (2020) present algorithms considering stochastic behaviours during operation and focus on the key performance indicators (KPIs): plant feed rate (ton/hr), shovel utilisation, truck queue length, and queue time (minutes). The approach seems very successful for its purpose, but the work does not present KPIs of how energy consumption is minimised.

There is additional research in the automation and optimisation domain focusing specifically on the loader, hauler, or crusher machines and related processes. The loading subprocess often uses excavators or wheel loaders to load earthmoving haulers. The wheel loader short cycle defined by Dadhich et al. (2016) is research where productivity and energy efficiency have been investigated. Frank et al. (2012) used 80 operators in an empirical study on operator behaviour to identify the potential for fuel and productivity improvements. The results show a large difference in operators' productivity but do not present the variations over time per cycle. The paper by Guevara et al. (2020) identifies several variables, of which the amount of moved, loaded, and unloaded material is the main operational target. The paper proposes a point cloud approach to estimate the effective payload volume for loaders. Volume estimations are central but need to be correlated to the density and shape of the material. For a transport optimisation application, the variations in loader short cycle times (CTs) and volume/weight are important for arrival time estimations. For that reason, this variability data is needed, and current research does not present such data concerning a transport work step operation.

Further, there is rigorous work to optimise the crusher facility where the main task is to keep production on a desired level and to protect the crusher from overload and fatigue failures (Bhadani et al., 2020). The work shows how KPIs, as defined by ISO (2014) can be used to identify improvement opportunities for an aggregate production plant. The KPIs selected include equipment utilisation, availability, and throughput rate, but Bhadani et al. (2020) have limited their research to four primary units in aggregate production: crusher, screen, bin, and conveyor. Other equipment such as material handling trucks and loaders are excluded in this work.

Dadhich et al. (2016) identify the key challenges in automation and teleoperation of earthmoving machines and provide a survey of different areas of research. They conclude that fully autonomous systems for the loading procedure that can perform equally well as manual operations are still far-fetched based on the current state of the art. Instead, it is argued that manual operation with the technical assistance of loaders will continue to be the norm for the foreseeable future. This means that transport operation optimisation should continue to consider the manually operated machines and their behaviour as its primary loading procedure for the years to come, even though the haulers may become autonomous. Autonomous loaders are expected to have lower CT variance than manually operated. But as it is indicated that manual loaders will be the norm in the coming years, these loading procedures need to be assessed for their influence on transport work step optimisation and automation.

Recent research regarding transport operations has shown that quarry operations can have operative waste due to uneven overcapacity in production. 20%–30% waiting time at loading and unloading has been observed during time studies at real-world quarries, identifying an occasional overcapacity in the transport operation (Rylander and Axelsson, 2013). According to interviews made with quarry site managers, the observed effects are not uncommon and may vary during a workday depending on driver skills, environmental influences, and operational variations. How this can be quantified is however not presented.

On energy consumption explicitly, Siami-Irdemoosa and Dindarloo (2015) conclude that few studies have been published on fuel prediction in mining operations. The paper presents a cycle energy prediction using payload and activity times as variables. They conclude that mining truck idling time has a significant effect on energy consumption but do not explain why they idle or what effect driving style and fleet coordination would have on the consumption. Furthermore Golbasi and Kina (2022) conclude that most studies offer macroscale or regression-based models without including vehicle-related kinematic factors. In addition, they present models and simulations of fuel consumption as a function of several factors including payload, distance, speed, and road characteristics. The study does not include the effects of driver performance, vehicle deterioration, or traffic influence on speed, accelerations, overall throughput behaviour, diversity, and resultant fuel consumption.

Controlling the speed of a production process includes lowering the speed of machines and haulers toward the site's throughput and bottlenecks. By reducing mobile machines' speed, several values are obtained, such as increased safety, decreased maintenance, decreased wear on tires and machine mechanical components such as engines, and decreased fuel consumption. It has been shown that lowering the speed and simultaneously reducing unnecessary stops in a cyclic work cycle can decrease fuel consumption by up to 42% (Rylander et al., 2014). Such a decrease in fuel consumption assumes a poorly coordinated site operation where haulers stop two times every lap due to e.g., meetings at narrow road segments or intersections, and otherwise drive fast and near full capacity and speed. The amount of productivity gains that can be obtained is not trivial and depends on several factors. White et al. (2018) present indicative productivity gains from vendors of around 40% and potential cost savings of about 25% to 40% using automated machine guidance (AMG) technologies. Contractors have a more conservative view of the gains that can be obtained using AMG. When a human interface has been used to provide speed-optimised advisory feedback to a manual operator of haulers, energy savings have also been identified (Albrektsson and Åslund, 2017).

Reducing waste by controlling speed to avoid unnecessary movements from a value flow perspective can decrease costs such as energy without necessarily decreasing the operation's production rate and outcome. While production can be obtained with less cost, the result will be increased productivity, measured as ton produced per cost item (e.g., ton/$). As has been presented in Rylander et al. (2016), the actual savings by a speed optimisation system through an operator assist function applied to a cyclic transport operation can vary between the machines in operation. Rylander et al. (2016) also conclude that the operator's skills and capacity to follow advice vary. These are relevant aspects and can be summarised as that optimisation and automation of the transport work step include a considerable improvement potential. However, the parameters need to be presented and understood to design and develop optimisation and automation systems efficiently.

3 Method

To address the research questions and collect data on the transport work step operations, quantitative empirical methods have mainly been used. Data has been collected through a case study from real-world earth-moving activities in quarry and mining operations to understand the characteristics and their parameters.

3.1 Case description

The majority of the quantitative data presented was collected from a real-world site operation in England. The main reason for this choice of site was the availability of new machines equipped with, e.g., a weighing system enabling data accessibility, which seemed representative of many sites and their willingness to be part of the study. The site's main flow was to load mass from the face transport it to designated unloading positions and dump it onto stockpiles for further transport and processing. The pit's transport can vary from some 100 m to 2 km depending on the current flow.

The operation was conducted with several parallel processes. Machines could be moved between the processes to balance the capacity. The operation characteristics of loading, unloading, route, and distance could change daily, sometimes several times per day. The data collection was performed by logging data from six haulers simultaneously for two weeks. Since the operation changed often, and logging failures occurred; all data could not be used. For the work cycle analysis, the dataset with the longest continuous cyclic operation was selected. The selected operation includes 20 work cycles of one machine. Figure 2 show the cyclic route used with elevation marked as colour code between the two destinations, load and unload. The transport route distance used in the analysis according to the odometer in the haulers was ~1,270 m. Excavators performed the loading procedure at the site.

3.2 Data collection

Professionals performed all machine operations. The data collection was carried out by equipping a set of machines with a data logger connected to the machine's internal data network. Data parameters were selected based on the availability and need for basic potential and kinetic energy of motion principles, including mass, altitude change, velocity, and acceleration. Additional sensors such as tipping body movements were added to be able to identify unloading activity. Time was used for synchronisation, and the geographical position was needed for referencing as well as for defining the activity and machine states. The following data items were collected at 5 Hz, which we assumed to be sufficient for the purpose:

- timestamp (UTC)
- speed (km/h)
- fuel (l/s)
- odometer (m)
- load (kg)
- tipping body angle (%)
- lat, long, altitude (WGS84 GPS, using local dedicated RTK for the data collection purpose).

Figure 2 Map over route including colour marked work step activities for eight cycles (see online version for colours)

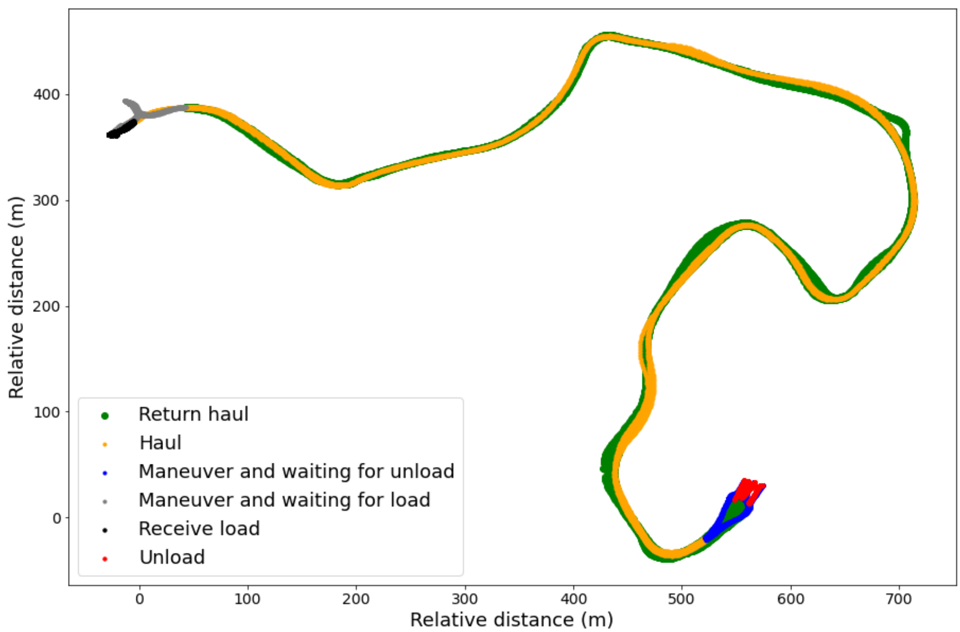
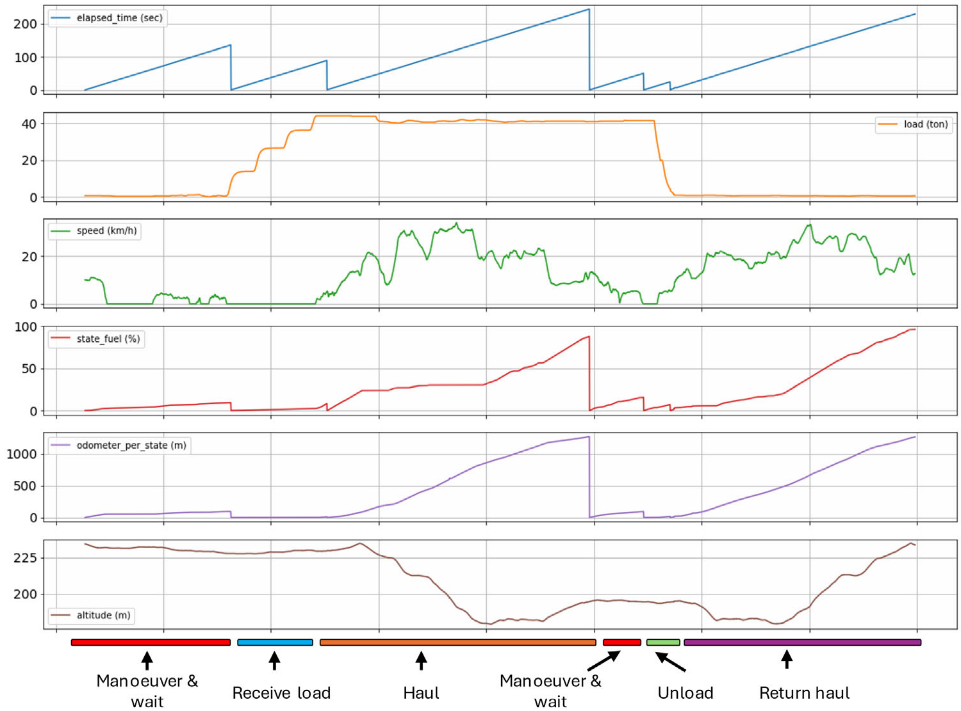


Figure 3 presents a complete work step cycle highlighting the main sensor data collected. The plot starts from one vehicle load activity, as highlighted at the bottom of the graph. Each bucket load from the excavator is registered as the load indicator on the machine is instantaneous. In the example presented in Figure 3, four loader short cycles were performed to fill the hauler. Vehicle speed is 0 during load and unloads as expected and fluctuates during operation. The odometer presenting the distance travelled shows roughly similar values during the haul and on the return haul. The tipping body is used during unloading and the load measure goes down to roughly 0, seen 2,200 seconds into the test. Figure 3 presents the CT, distance travelled (odometer), and fuel consumed accumulated per activity and reset to 0 for every activity and state change.

Figure 3 Data plot from an example log of a complete transport work step cycle (see online version for colours)



3.3 *Analysis*

To create the results, data was filtered. We had to remove cycles that was not complete, and we had deviating patterns due to breaks, start or end of work shift. Cycles that did not consist of all work steps or had substantial disruptions have been excluded from the analysis. The logging equipment also had disturbances where sensor data was not available; these have also been excluded from the analysis.

After the filtering was completed, a statistical analysis was performed to provide an overview of the dataset and to describe the characteristics of the operation. The statistical analysis was followed with regression model development, where both simple linear and multiple linear regression methods were used. We used all different combinations possible with the data set at hand to develop the final regression models.

4 Results

The results presented in this paper aim to be useful both for planning and maintenance and in the execution phases of the transport work step. In the planning phase, the main tasks are to design and configure the operation work step and its targets as origin, destination, route, mass amount over time, and assign fleet machines (e.g., type and quantity) and operators. Decisions to improve the route could, for instance, be to perform construction or maintenance activities. Construction work decisions could widen the route to allow for random meetings without speed adjustments or maintenance to improve traction, visibility, or road surface quality. In the operation execution phase, the main purpose is to control and optimise the fleet and assets' utilisation to ensure productivity at a minimum cost.

The contribution and structure of the results are the presentations of:

- Transport work step characteristics of real-world quarry site operations.
- Insight in cost and productivity benefits of removing route bottlenecks.
- A model to calculate fuel consumption for a quarry transport work step cycle.
- A model for instantaneous fuel rate to be used for haulage machine fleet optimisation and automation.

4.1 Transport work step characteristics

The characteristics of the site transport work step can be described by its activities and their activity times. The main activities presented in Figure 1 can be described as states that a hauler can be in during a cycle, and they are sequential. The activity characteristics are:

- Load manoeuvring: in the loading zone, situation dependent manoeuvring (e.g., reversing) may be required before loading is initiated. As such, manoeuvring may be dependent on operator skills and machine external factors such as loader availability, queue, etc. Load manoeuvring activity may also include waiting and queuing: waiting and queuing may be required due to that the loading position and/or loader being occupied. This activity time is separated from the actual loading as this is a relevant indicator of capacity differences between the work steps.
- Receive load: receive load activity time mainly depending on the loader performance including the amount of loader cycles, loader capacity, and operator skills.
- Haul: the activity time depends not only on the speed and distance but also on route characteristics. In some cases, unplanned stops or major retardations may be required at intersections or narrow road segments for meetings, etc. affecting the load time.
- Unload manoeuvring: in an unloading zone, specific manoeuvring usually takes place to reverse into the unloading position. For the same reason as load zone manoeuvring, it is beneficial to sort out this part of the work step from the unloading, haul, and return haul activities as the time variation between cycles is affected by different parameters. While in the unloading zone, waiting may be required before the unloading activity starts. The reason can be that the unloading position is occupied, or the unloading area is full.
- Unload: the unload activity time varies depending on machine capacity, amount of mass, and operator skills.
- Return haul: this is required to move the empty hauler back to the loading position. Similar to haul activity, operator skills affect the time and fuel consumption. Additionally, external factors such as route bottlenecks also play a role.

By monitoring identified activity types over time, the statistical characteristics can be described, which indicates their distribution and if there are potential bottlenecks. Table 1 presents the characteristics of the studied site operations, from which several conclusions can be drawn.

As unloading has only a few factors that affect it and the tipping is done by a machine in a single movement, it can be assumed to have a comparatively small standard deviation (SD). This is also the case as presented in the table. The slight difference in the mean and median value of the activities indicates the homogeneous conformity of the values with few or no extreme values.

Table 1 Characteristics of the site operation studied

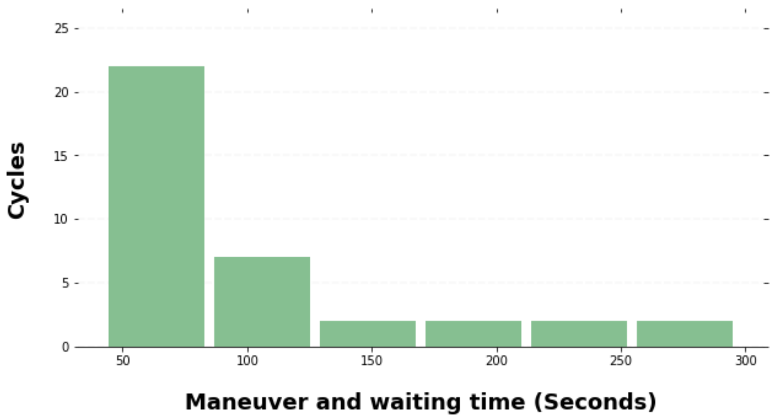
	Complete cycle using excavator for loading					
	Load manoeuvre time (sec)	*Receive load time (sec)*	*Haul time (sec)*	*Unload manoeuvre time (sec)*	*Unload time (sec)*	*Return haul time (sec)*
Mean value	82.3	123	233.1	59.3	14.9	246.9
Standard deviation	42.6	30.4	15	16.7	2.2	29.6
Median value	63.3	114	229.0	60.8	15	240
Relative SD	51.8%	24.7%	6.4%	28.2%	14.5%	12%
Skewness	1.25	2.18	1.06	–0.17	–0.26	0.38

When comparing the different activities, we find that manoeuvring time at loading is where the largest SD and the largest SD part of the mean value are found. This is also expected as the loading was considered the bottleneck in the operation used for data collection. The load manoeuvring time includes both the actual manoeuvring and the waiting time. But as operators may observe queuing before arrival, they may adapt speed during transport. For this reason, the waiting time in the load zone is not a complete measure of overcapacity and is not presented separately in the table.

The distribution should not be considered as a normal distribution. The skewness for load manoeuvre time is 1.65 while considering 40 cycles with different loading positions and 1.25 when we analyse 20 cycles with the same loading position. When considering different positions, it can be expected to get a higher SD and skewness as the physical limitations and possible fastest way to perform the activity likely are different. Anyhow the overall pattern is the same. Activity times within a defined space have a minimum possible duration, constrained by physical limitations. However, this duration can vary based on geographical location, performance, and specific situations.

As shown in Figure 4, which presents the manoeuvre time for 40 cycles, the operation often nears this minimum time but frequently deviates due to waiting periods and performance variations. In practice, the loader occasionally had to handle larger shot stones that were not meant for loading onto the haulers, moving them aside instead. Additionally, the loader needed to reposition for optimal loading and reach, and there were instances where other haulers were queued up. Additionally, operator performance varied over time, contributing to the variation in manoeuvring time. These factors collectively result in a longer manoeuvring time than the shortest possible.

Figure 4 Histogram distribution of load manoeuvre time based on data from 40 cycles (see online version for colours)



The waiting time is rather stochastic and fluctuates over time. To fully understand the reasons, a more in-depth flow analysis must consider the entire fleet and map out the relations and consequences the individual behaviours have for the flow.

The loader capacity depends not only on the machine CT to load. A loader may also be required to move and clean the ground surface from overburdens that have fallen off the haulers, or it merely must physically move to be able to fill the bucket to load the hauler. Such activities take time and instantly affect the capacity and consequently the loading time. Such extra occasional activities may immediately move the bottleneck to the delayed activity from other production activities.

Table 2 Activity energy consumption comparisons

	Receive load	*Haul*	*Unload*	*Return haul*	*Full cycle*
% of total fuel consumption	7%	38%	10%	45%	100%
Max fuel consumption compared to mean (normalised)	35%	8%	27%	3%	5%
Min fuel consumption compared to mean (normalised)	–39%	–10%	–52%	–3%	–5%
Max fuel consumption compared to min (normalised)	123%	19%	164%	6%	10%

On an overall level, the difference in fuel consumption per cycle is significant. Table 2 presents the measured energy characteristics, showing the dispersion in energy consumption for various activities and indicating potential savings. The table includes the fuel consumption for each activity within a complete cycle, comparing the highest (max) recorded fuel consumption per activity with the lowest (min) and the average (mean). The conclusion is that the return haul activity has the highest fuel consumption, while the load and unload activities exhibit the largest statistical variation.

4.2 Route bottlenecks

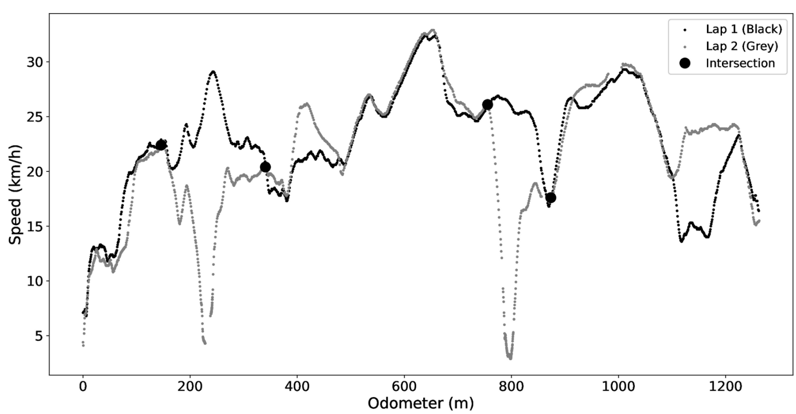
When comparing cycles, the characteristic that differentiates the cycles is the occasional decrease in speed during the route. It is caused by route bottlenecks such as meetings in narrow route segments. They are instantaneous and cause a penalty in time, leading to a decrease in mean speed for the route segment and an increase in fuel consumption.

Based on earlier research, it has been shown that lowering speed provides lower fuel consumption while higher speed ranges (Rylander et al., 2014). It has also been presented that additional stops for meetings on the route cause additional accelerations, increasing overall fuel consumption. These parameters are instantaneous and applicable for the part of the route where these are applied. While analysing an entire cycle or an activity, both the lowering of speed and extra stop has the same effect on the average speed over a cycle. However these features have the opposite impact on fuel consumption. Therefore, average speed and travel times over a cycle are insufficient to analyse fuel consumption in a real-world drive cycle. The outcome is highly dependent on the details of the driving characteristics.

What is common to both the lowering of speed for meetings and the aggressive driving with a higher max speed is that it deviates from the mean value over a specific route segment and hence increases SD. High fluctuations cause a high SD during operation, and a low SD indicates calmer driving with fewer changes.

Looking at the fuel consumption in the same process, the four cycles with the least fuel consumed had on average 7% lower consumption than the four cycles with the most consumed fuel. When comparing the SD average for speed over the same cycles, it was 22.1% lower. This strongly indicates that having a calmer drive style has a measurable positive effect on fuel consumption.

Figure 5 Two laps of return haulage including two route segments that fulfil the energy, position and speed drop criteria used for segment comparison analysis



To accurately quantify the cost of route bottlenecks and the resulting speed adaptations, we need comparable data points. The energy cost difference between cycles is best calculated using data points with the same potential and kinetic energy. These points are identified when the same vehicle has an equivalent mass and velocity at the same geographical position. This allows for direct comparison of data without adjusting for potential and kinetic energy differences before and after the segment. For reliable results, six different example segments were used. Bottlenecks were identified by speed drops of more than 50% compared to the segment mean or an absolute speed difference of 15 km/h. These cycles were then compared to cycles without speed drops where comparable data points were found, see Figure 5. Based on these comparisons, the average distance measured between measure points was 254 m, and the average fuel difference was 19%.

The absolute cost for fuel per measurement was 1.33% of the total fuel consumed for a work cycle. As the occurrence of meetings on average was 1.6 times per work cycle, the total cost for each speed drop was 1.7% of the total fuel consumption for the cycle operations in the analysis.

4.3 Cycle fuel consumption model for site optimisation

Different measures can be taken to improve the site operations planning and configuration. Measures such as the removal of route bottlenecks and improved road layout and road surface conditions are included, but the gain of performing a measure needs to be quantified. Several route condition factors can negatively impact speed, CT, and productivity. CT is relatively easy to measure and monitor. Aside from the loss in speed and throughput, the main cost is energy consumption. Increasing speed in non-bottleneck subprocesses offers no particular benefit, as it may lead to unnecessary waiting and higher costs without improving throughput. For these subprocesses, energy consumption can be minimised as long as the bottleneck's throughput is maintained. Energy consumption is influenced by several parameters and predicting and measuring each parameter's effect in every condition of a work cycle is highly complex. Therefore, a model of fuel (energy) consumption based on relevant cycle parameters is needed. From a cycle perspective, the following parameters have been identified as possible independent variables affecting the dependent fuel variable and are assessed in this study:

- CT is a relevant variable to include as the route and distance are constant in a cyclic operation.
- Load (L) is a factor to include while loaded. In the 19 cycles used for the cycle cost model analysis, the load mean was 39,900 kg with a SD of 1,900 kg. While operating unloaded in return trip activity, the load is not a parameter in the function as it should continuously be 0.
- SD of speed is a relevant variable as continuous acceleration and retardation cause energy-consuming variations of speed in operation. A measure of the variation is the SD.
- The number of stops (NS), the amount of significant fluctuating retardations and accelerations compared to the route's mean is an indication of route bottlenecks. As identified during operation, the machines performed speed adaptations while unloaded to adapt for meetings with loaded machines. For this reason, the amount of stops and decelerations during operation is only a parameter in the function for return transport activities for the operation analysed.

As distance in the cycle is static, it is not included in the model. Otherwise, distance, e.g., the elevation would be relevant additional variables to consider.

The highest level of correlation for the hauling activity was found using CT, L, and SD of speed in the regression analysis. But as the significance provided by SD of speed was low, and the effect of including it only improved R2 with 0,001, we excluded it from the final function presented. With more data, this variable could provide added value to the function.

The function is then modelled as a multiple regression model (Myers et al., 2010) using the least square method for the cycle where fuel consumption ($\dot{y}$) is a function of CT and load (L).

The model for fuel consumption ($\dot{y}$) in haul activity, (i.e., while loaded) shows both correlation $R^2 = 0.479$ and significance (Pearson correlation) $p = 0.006$ with low correlations between all independent variables where the highest calculated variance inflation factor (VIF) was 1.18.

The function for haul activity developed is $\dot{y} = 0.3973 + 0.0037*CT + 0.0252*L$.

The highest level of correlation for return haul was found using CT, NS, and SD of speed as independent variables. Still, as NS and SD of speed had a significant correlation, we chose to exclude SD of speed in the final model. The final model developed for fuel consumption ($\dot{y}$) of a cycle while unloaded in return haul activity shows both correlation $R^2 = 0.694$ and significance $p = 0.0001$ with low multi correlations where the highest calculated VIF was 1.12.

The function developed for return haul is $\dot{y} = 2.4852 + 0.0009*CT + 0.0218*NS$.

4.4 Hauler fuel rate model for machine fleet optimisation

As described in the work step operation characteristics, there are stochastic variations in the operation that require instant control and operational adaptations for continuous improvement and optimised utilisation. When the input (loading) or output (unloading) activity throughput changes, the transport activity's required throughput also changes. For this reason, instantaneous control of speed is needed to minimise energy and fuel consumption. While a fleet of machines is utilised in a cyclic transport operation, the speed and travel time can be distributed unevenly to different machines to minimise overall energy consumption and manage the risk of arriving too late to destinations. To be able to perform energy predictions and optimisation of fleet behaviour, a model for energy consumption and fuel rate of a machine is required.

For this reason, we have used the data collected during operation and developed a multiple regression model. In the analysis to create a model for fuel rate $\dot{y}$, acceleration (A), slope (S), load (L), and speed (V) were included. The best model was achieved while having different functions while loaded during haul activity and unloaded in the return haul activity. The best correlations were found, including L in the hauling activity, but as it only improved the model R^2 with 0.01, we excluded the variable from the final function.

The function for return haul is then modelled for the cycle where the fuel rate ($\dot{y}$) of a cycle while unloaded shows both correlation $R^2 = 0.578$ and significance $p = 0.001$ with low multi correlations where the highest calculated VIF was 1.01.

The fuel rate function developed for return haul is $\dot{y} = 0.0003 + 0.0022*A + 0.0418*S + 0.0005*V$.

The model for haul fuel rate ($\dot{y}$) of a cycle while loaded also shows both correlation $R^2 = 0.563$ and significance $p = 0.001$ with low multi correlations where the highest calculated VIF was 1.4.

The fuel rate function developed for haul with load is $\dot{y} = 0.0195 + 0.0008*A + 0.0377*S - 0.0005*V$.

5 Discussion and validity

We performed quantitative measures on a cyclic transport work step in a mine operation with the aim of describing the characteristics and models for optimisation and control. While analysing the data several conclusions can be made. One of the main results is that the cycle with the highest energy consumption was 10% higher than the lowest, performing the same work. This is significant and indicates a large saving potential for the entire operation. The largest percentage difference was in the loading area even though the largest absolute difference was in the return haul activity. This overall characteristic shows that it is not only during the mass transport activity that fuel can be saved.

Another important result is the understanding of the stochastic behaviour in the operation and the energy consumption it causes. An unbalanced workflow results in occasional waiting, which causes a stop-and-go behaviour. This is also observed during manoeuvring within the load and unloads activity areas. These behaviours cost energy to perform, and as a percentage of the whole activity, extra manoeuvring or stop-and-go cause significant extra fuel consumption. The analysis results show that significant retardation during transport on average costs an additional 1.3% of total cycle fuel consumption per occasion. The cost per occasion part of the total cost can be higher while in shorter transport distances. The cost of a meeting is expected to be depending on the amount of speed adaptation required. The speed adaptation is a floating scale, and somehow a classification and criteria are required. We used rather prominent threshold criteria to get the data that can be used as indicative reasoning for the cost and benefits they include. Real-world operations as analysed include a wide range of different behaviours, and different thresholds for the criteria result in different conclusions. Even smaller deviations below our threshold include a cost that is not included in the analysis. We see from the analysis that driving uphill and downhill is very different, and different variables are applicable. While the load is a burden uphill, it is a forced asset of energy downhill. When breaks driving downhill are released, there is no need to increase fuel consumption to accelerate. Other categories to narrow down the models may be needed depending on the characteristics of the route, and it could be of benefit to further break down the route and apply different models depending on the topography of the route segment.

5.1 Automated machine guidance

To automate the operation, either through operator-assistive functions or fully autonomous, several factors need to be considered. Regarding operator assistive functions, it would not be possible to effectively assist the operators while only considering one hauler in a fleet of haulers. It can also be concluded that in operations where multiple destinations exist and a sorting, mechanism is performed by the loader; the loader also needs to be connected to such an assistive function as it has a significant role in defining the throughput of the entire process. Based on the variance and SDs presented, which is a consequence of the operation's fluctuations, continuous activity measurements and feedback loops are required. It may be possible to automate part of the operation, but it would need to connect the machines that are not automated in that case.

The data that we have collected is based on deep insight into the machine sensors and behaviour, which is usually exclusive to the machine manufacturer. Mixed brand fleets are, for this reason, a challenge where standards need to evolve for this purpose. Fully automated machines are expected to lower the variance since a robotic operator does things consistently. Several parameters are independent of the operator's skills and input as human operators have physical limitations and cannot see and adapt to what happens while obstructed. These need to be considered, and from the flow perspective, the entire fleet operation still needs to be connected to avoid production loss and low productivity and efficiency.

A challenge of automation besides the actuator controls and safety is the lack of accurate and reliable digital representation of the work step. Route and topography are constantly changing, the locations of loading and unloading change over time as mass is removed. To digitalise and automate the site representation and its processes is not trivial. Even in the data collection process such aspects were challenging to identify. Haulers perform more than the actual cycle work as the operators need to take breaks and start and stop the shifts. Additionally, machines need maintenance and repairs. Such events and behaviours needed specific manual work for the analysis to be accurate. In a real-world scenario where such aspects need continuous updates and available and reliable data. It requires additional resources, skills, and associated costs compared to current operations. The benefit of the improvements then needs to be greater than the overall costs for the solution.

Finally, as observed, operator skills and incentives play a crucial role in the performance of the operation. Even in cyclic operations where similar activities and routes are used, operators behave differently between cycles. As shown by Rylander et al. (2016) operators perform very differently when not provided with a guiding system. Additionally, the paper (Rylander and Axelsson, 2021) presents data from hauler operators based on an anonymous questionnaire. Not all operators agree that a coordination system would be useful, indicating that there may be incentives and willingness to be part of and use a central coordination and automation system. Such factors would be relevant for further research.

5.2 Asset management

Asset management involves optimally and sustainably managing assets and asset systems throughout their life cycle. Effective asset management ensures a clear connection between the organisation's desired outcomes, purpose, strategies, plans, and daily activities (The Institute of Asset Management, 2024).

Continuous access to the data and models presented in this paper can be beneficial for asset management across various phases, from strategic planning of the overall mine design to dispatching vehicles for specific processes and missions, as well as in operational performance. Komljenovic et al. (2015) present a global model of strategic planning and asset management in the mining industry, which relies on several sub-models where the models presented in this paper, can be useful.

The level of data, extracted from the machine internal network, and used in this paper is typically not available for commercial use. Additionally, it requires specific data extraction techniques and site connectivity for real-time control and optimisation. Instead, more heuristic approaches are commonly used. Further development of tools supporting asset management based on continuous data, providing predictive, accurate, and reliable models, is an important area for future research.

5.3 Model validity

The haulage cycle model presented can be derived from the physical laws that apply. The energy cost is a function of mass and force. As we include the potential energy as well as the kinetic energy in the model, it should be sufficiently accurate. Known factors that we lack in the model are road friction, air drag, and heat costs. That fuel is also used to heat the engine is known but can be assumed to be included in the model as a constant factor. Friction could be a relevant factor if the route includes different friction factors over time. In the data used to provide the model, the weather and route conditions were fairly constant, and the machine was the same, so these conditions in the analysis, should be a small variable to consider. But for other weather and route conditions, friction could be a relevant factor to include and something to consider for a future improvement of the model. An interesting result is that the dependent variable fuel rate is higher with higher speed in the haul activity model. The assumed explanation for this is that the hauling activity was operating downhill. While operating at higher speeds downhill, assumed with less utilisation of the retarder, less energy is required to climb. In the return haul activity, the opposite applies, and lower speed is beneficial.

The hauler fuel-rate model is intended to be used for the optimisation of a fleet in operation. While an overall model calculates the throughput and available time to arrive just in time to destinations, a model is needed to distribute the time over a path and route. The model provided is a candidate for such calculations. Further trade-offs as discussed can be made to decide that one vehicle should adapt to another, e.g., meetings. Individual haulage costs for such trade-offs can be calculated with the model provided.

In current manual operations, speed adaptations are performed by a human. The model presented can be utilised both to calculate advice and present it to the human operator or directly control the drivetrain as for automated driverless operations. One could argue that for driverless operations, the need for the model is more significant as a human often can assess and control the hauler concerning the environment. In contrast, a driverless machine does not have this capability.

The numerical factors in the model presented are based on the characteristics of the site and operation as it was operated while data was recorded. The model itself is probably not very useful in other conditions; instead, the method presented should be used for continuous use to recalibrate the model. The analysis of how the model is developed is intended as a machine learning algorithm, where new data for the condition of the operation is changed continuously for it to be accurate.

The R-square values provided with the method show correlation of up to 0.713, which we believe is very promising for optimisation purposes. A factor that influences the theoretical maximum of R-squared is the human factor. Since it is a human operating the machines in the analysis, it can be assumed that there are errors and noise in the models developed. But in the end, how well the model needs to reflect reality comes down to how and in what context the models are used and implemented.

The models are all significant. The correlation matrices and VIF calculations show low multicollinearity in between the variables. This provides confidence in the model's usability for the site operation analysed.

The known limitations of the models are that the characteristics of the operation analysed in this paper reflect one specific type of operation where the main bottleneck is in the loading procedure. This may not always be the case, and several factors influence the overall characteristics. In some transport work cycles, the loading procedure may be performed using silos. Silos may provide less variance in activity time and give a less stochastic behaviour. In theory, the bottleneck can be elsewhere in the work cycle, changing the operation's conditions. Such other factors would be relevant to validate the method. Further, while the machines use different drivelines, especially electric drivetrains, the method usability would be of interest to assess.

6 Conclusions and future work

In this paper, we address the main operational characteristics and parameters required to schedule, control, and automate a hauling work step in a quarry/mining operation (RQ1).

The operational characteristics are described using the sequential activities performed by haulers in earthmoving operations. The attributes in terms of activity times and variation by SD are presented. Real-world operation includes waiting and speed adjustments due to meetings and capacity changes causing throughput variations. These data are represented in the overall characteristics by the variation in activity times but also presented by the measured occurrence of major speed adjustments or stops during operation. The activities measured and presented include large stochastic variations. Several significant parameters affecting energy cost and throughput are identified. The variations in fuel and energy costs between cycles show considerable potential for improvements through coordination and optimisation. The loading manoeuvring procedure, including the loading's waiting times, had a SD of up to 52% of the mean, which is a large variance and instantaneous overcapacity.

The paper contributes to productivity improvement potentials and energy consumption data and analytics for how specific operational characteristics such as retardations caused by meetings affect energy cost (RQ2).

In between the work step cycles, the transport activity had a fuel consumption difference of up to 19%. The mean for the fuel consumption per work step cycle was 5% higher than the best work cycle. This indicates how the same work can be done with different costs and highlights the optimisation's benefit potential. The work cycle's total fuel consumption increases by 1.33% for every occasion of meeting in the return transport activity.

Finally, the paper contributes to models that can be used to plan and design real-time optimisation and automation (RQ3). The models provide functions for how to calculate fuel consumption for a cycle and instantaneous fuel consumption for earthmoving machines. The linear least square multi-regression models that we developed do provide statistical correlation and significance for the operation studied, which is promising for a larger-scale adoption and use of the methodology. The models can preferably be utilised in continuous machine learning applications as they are tailored specifically towards the same cycle that is performed in the studied case.

The specific results show that removing route bottlenecks, improving road conditions, and further coordinating and controlling the operation would significantly impact energy costs, still with sustained throughput of the operation that was analysed. From the characteristics that we present, we conclude that the earthmoving operation includes sequential activities with stochastic behaviours, including loading time, waiting times, and transport times. These behaviours need to be measured in real-time to predict and optimise the operation reliably.

Future work includes the assessment, scaling, and usability validation of the approach and characteristics of:

- hybrid or electric drive trains in the earthmoving machines
- autonomous vehicles (removing the human operator parameter)
- optimisation and control functionality validation in real-world operation
- system of systems architectures for how to create an interoperable solution considering the multi-brand and vehicle type and capacity variations (different sizes of machines).

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References

Albrektsson, J. and Åslund, J. (2017) 'Fuel optimal control of an articulated hauler utilising a human machine interface', *Smart Cities, Green Technologies, and Intelligent Transport Systems*, Springer, DOI: 10.1007/978-3-030-02907-4_10.

Azar, E.R. and Kamat, V.R. (2017) 'Earthmoving equipment automation: a review of technical advances and future outlook', *Journal of Information Technology in Construction*, Vol. 22, No. 13, pp.247–265.

Bhadani, K., Asbjörnsson, G., Hulthén, E. and Evertsson, M. (2020) 'Development and implementation of key performance indicators for aggregate production using dynamic simulation', *Minerals Engineering*, Vol. 145, No. 1, p.106065.

Burt, C.N. and Caccetta, L. (2018) *Equipment Selection for Mining: With Case Studies*, Vol. 150, Springer International Publishing.

Dadhich, S., Bodin, U. and Andersson, U. (2016) 'Key challenges in automation of earth-moving machines', *Automation in Construction*, Vol. 68, pp.212–222, https://doi.org/10.1016/j.autcon.2016.05.009.

Frank, B., Skogh, L., Filla, R. and Alaküla, M. (2012) 'On increasing fuel efficiency by operator assistant systems in a wheel loader', *2012 International Conference on Advanced Vehicle Technologies and Integration (VTI 2012)*, Changchun, China.

Golbasi, O. and Kina, E. (2022) 'Haul truck fuel consumption modeling under random operating conditions: a case study', *Transportation Research Part D: Transport and Environment*, Vol. 102, p.103135, https://doi.org/10.1016/j.trd.2021.103135.

Goldratt, E.M. (1990) *Theory of Constraints*, North River Croton-on-Hudson, NY.

Guevara, J., Arevalo-Ramirez, T., Yandun, F., Torres-Torriti, M. and Cheein, F.A. (2020) 'Point cloud-based estimation of effective payload volume for earthmoving loaders', *Automation in Construction*, Vol. 117, p.103207, https://doi.org/10.1016/j.autcon.2020.103207.

Hoła, B. and Schabowicz, K. (2010) 'Estimation of earthworks execution time cost by means of artificial neural networks', *Automation in Construction*, Vol. 19, No. 5, pp.570–579, https://doi.org/10.1016/j.autcon.2010.02.004.

ISO (2014) *ISO22400-1: Automation Systems and Integration – Key Performance Indicators (KPIs) for Manufacturing Operations Management Part 1: Overview, Concepts and Terminology*, International Standard Organization.

Komljenovic, D., Abdul-Nour, G. and Popovic, N. (2015) 'An approach for strategic planning and asset management in the mining industry in the context of business and operational complexity', *International Journal of Mining and Mineral Engineering*, Vol. 6, No. 4, pp.338–360.

Moradi-Afrapoli, A. and Askari-Nasab, H. (2020) 'A stochastic integrated simulation and mixed integer linear programming optimisation framework for truck dispatching problem in surface mines', *International Journal of Mining and Mineral Engineering*, Vol. 11, No. 4, pp.257–284.

Myers, J.L., Well, A. and Lorch, R.F. (2010) *Research Design and Statistical Analysis*, Routledge, New York.

Rylander, D. and Axelsson, J. (2013) 'Lean method to identify improvements for operation control at quarry sites', *International Symposium on Automation and Robotics in Construction (ISARC) Conference*, Montreal, Canada.

Rylander, D. and Axelsson, J. (2021) 'Design and evaluation of a system of systems architecture for the optimization of a cyclic transport operation', *2021 16th International Conference of System of Systems Engineering (SoSE)*, IEEE, pp.114–119.

Rylander, D., Axelsson, J. and Wallin, P. (2014) 'Energy savings by wireless control of speed, scheduling and travel times for hauling operation', *Intelligent Vehicles Symposium Proceedings, 2014 IEEE*, IEEE, pp.1115–1120.

Rylander, D., Fryk, J., Wallin, P. and Axelsson, J. (2016) 'Lean speed optimization applied to a cyclic haul operation', *24th World Mining Congress*, Rio de Janeiro, Brazil.

Siami-Irdemoosa, E. and Dindarloo, S.R. (2015) 'Prediction of fuel consumption of mining dump trucks: a neural networks approach', *Applied Energy*, Vol. 151, pp.77–84, https://doi.org/10.1016/j.apenergy.2015.04.064.

Smith, S.D., Wood, G.S. and Gould, M. (2000) 'A new earthworks estimating methodology', *Construction Management*, Vol. 18, No. 2, pp.219–228, DOI: 10.1080/014461900370843.

Sofranko, M., Wittenberger, G. and Skvarekova, E. (2015) 'Optimisation of technological transport in quarries using application software', *International Journal of Mining and Mineral Engineering*, Vol. 6, No. 1, pp.1–13.

The Institute of Asset Management (2024) *Asset Management – An Anatomy, Version 4* [online] https://www.theiam.org/ (accessed 11 December 2024).

Uhlin, E. (2012) 'Microsimulation of total cost of ownership in quarries', *17th International Conference of Hong Kong Society for Transport Studies*.

White, D.J., Jahren, C.T., Vennapusa, P., Westort, C., Alhasan, A.A., Turkan, Y., Guo, F., Hannon, J., Dubree, A. and Sulbaran, T. (2018) *Use of Automated Machine Guidance within the Transportation Industry*, National Academies of Sciences, Engineering, and Medicine.