An Improved Approach to Production Planning in Oil Sands Mining Through Detailed Analysis and Simulation of Cycle Times

By

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ABSTRACT

The objective of this thesis is to develop, implement and verify a theoretical framework based on detailed analyses and simulation of truck and shovel cycle times in open pit mining, placing an emphasis on the hauling component of the cycle. The goal is to improve the generation of accurate and reliable cycle time estimates to aid in the production planning stages and ongoing performance evaluation. The literature review showed that there is a void in this area of research. In order to achieve this, analyses on a major oil sands operation in Northern Alberta were performed, identifying the source of variability within the cycle time as the truck hauling component. The shortcomings of current commercially available estimating tools are mostly attributed to their overly simplistic assumptions in using truck manufacturers' performance data, which indicated operating parameters under ideal conditions that are not indicative of those in practice. In addition, most digital models of mine haul road networks are overly simplistic and lack detail. The main factors affecting the performance of the haul trucks are over or under loading (payload variability), total resistance due to gradients and road conditions, and other hindrances in the haulage such as traffic interactions. This framework introduces two methods for producing cycle time estimates; one that mimics the currently available software packages which solely use manufacturer-supplied data and serves as a benchmark, and another method that is probabilistic and historical data-driven. The main data requirements are outlined and include a detailed model of the mine's road network, dispatch production records, truck velocity data and other operational parameters such as operating guidelines and rolling resistance values. The concept of EFH is introduced due to a need to categorize different haul routes of equal distances based on how inclined or declined they are, and how rolling resistance varies; which affect truck performance. A computer program was generated using MATLAB, and the algorithm is thoroughly explained. Efforts were made to ensure the flexibility and wide-ranging applicability of this framework to other mining operations. A case study is presented in order to validate the model, and a more advanced application of this new approach is displayed. The data acquisition activities for the mine in the case study are outlined. The framework is validated on four haulage profiles of varying lengths, showing accurate predictions of cycle times. The more advanced application of the framework shown in the case study consists of a productivity and production rate estimate for a period of three months at the oil sands operation. The results are compared to the database in order to assess the framework's prediction accuracy, and to the old method adopted by the staff at the mine to show the superiority of this approach. This framework generates TPGOH productivity estimates that are within 0.1% accuracy of the database records, while the old method generated estimates that were up to 18% off. Due to the probabilistic nature of this simulation method, several replications are run. The program in this thesis is found to achieve desired accuracy and confidence levels for complex scenarios in a matter of seconds. Using EFH, a planning tool similar to the old method is produced, and yields results with an error of less than 4%. Recommendations for future work are provided, and center around two topics: properly characterizing the details of mine advancement within bench faces and movement of dump locations, as well as properly characterizing the dispatch logic in order to be able to correctly predict empty truck travel times.

This Thesis is Proudly Dedicated:

To my grandmother, Yolanda

For her unconditional love and support, and for always believing in me

To the memory of my grandfather, Jorge

For loving me like a son, for being my first and most important teacher, and for being a great source of inspiration in my life

And to my mother

For her boundless love and for the influence her continued guidance has had on my life and career. Without your presence, I would not be a fraction of the man I am today. I thank you for teaching me to always place my trust in God.

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Eduardo, January 2018

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GLOSSARY OF TERMS

LOM: Life of mine, a term used to refer to long-term planning that spawns for several years and may approach the entire productive term of a mine.

EFH: effective flat haul or equivalent flat haul, a distance measure that accounts for the time effects of gradients and rolling resistance in truck hauling.

TPGOH_A: tonnes of material produced per equipment gross operating hour. This the includes empty haul time from the calculation

TPGOH_B: tonnes of material produced per equipment gross operating hour. This excludes empty haul time in the calculation

Cycle time: refers to the conventional truck cycle time in mining, composed of loading, loaded hauling, dumping and empty hauling.

Loading: first component of the truck cycle time where a shovel transfers material from a source such as the ground (or stockpile) onto a haul truck.

Dump location: place where the third component of the truck cycle time occurs, and material is transferred from the truck to usually a crusher, a stockpile or others.

Loaded haul: the second component of the truck cycle time, it occurs after the truck has been loaded at a material source, and heads towards the dump location

Empty haul: the last component of the truck cycle time, it occurs after the truck dumps a load at the destination, and heads towards a new source of material

Cycle delay: a field in the mine dispatch system that records the extra time in the cycle time caused by unexpected factors or circumstances.

Rolling resistance: force exerted against the tire of a vehicle by the conditions of the surface on which it travels.

Total resistance: rolling resistance plus gradient resistance, expressed as a percentage.

Rim pull: the measurable mechanical force applied through the wheels and tires of a truck, based on payload and other factors.

Oil sands: refers to the unconventional petroleum deposits in the Athabasca region of northern Alberta, in Canada.

Segments: parts between two points within the road network, of predefined and constant length.

Path: the route selected by the program as being the shortest and defined by the intersections which it crosses.

Distribution: refers almost exclusively to a probability distribution fitted to a set of data.

KPI: key performance indicator. A quantity or measure that represents the performance of a specific area of the operation.

1. INTRODUCTION

1.1 INTRODUCTION

Open pit mining is the most widely used method of mineral extraction in the world due to its associated low operational and capital costs, when compared to underground mining methods. While the selection of mining and processing methods is very much dependent on the characteristics of the orebody (dimensions, grade, geology and depth), lower costs in open pit mining are possible due to the highly-mechanized nature of its operations. In addition, open pit mines are generally less operationally complex, and therefore safer and less capital intensive (on a per-ton basis) than underground mines.

In open pit mining, cash flows are generated much earlier in the life of the project due to shorter development and ramp-up periods, and the fact that the mineralization can be reached faster due to its proximity to the surface. The operating cost advantages attributed to open pit mining are achieved, in part, through economies of scale. Open pit mining is well suited to massive ore deposits, with high tonnages and production rates, which in turn makes lower grade deposits economically feasible to mine.

Some of the core elements to consider when planning an open pit mining operation are the mine sequencing and equipment selection. These elements are highly correlated, leading mining engineers to iteratively search for the optimal plan. Of special importance is the correct selection of a materials-handling system. The most commonly used system is, by and large, the use of mobile excavators (also referred to as shovels) and haul trucks. These two types of equipment result in low operating costs but more importantly, their performance is predictable and highly reliable. This is due in part to the fact that excavators and trucks, as a combination, have been used extensively in the construction industry. In addition, the underlying mechanisms of shovels (usually hydraulic machines) and haul trucks (mostly diesel internal combustion engines) are mature technologies that have been extensively studied, researched and improved over several decades. It is because of the reasons outlined in the above paragraphs that the near-surface volume of the economically extractable oil in the Western Canadian Sedimentary Basin is extracted via open pit mining, using truck and shovel operations.

However, the extractive/natural resources sector is highly cyclical due to the variable nature of commodity prices. This variability in prices can be attributed to factors such as speculative investors in an unstable markets environment around the globe, uncertainty in economic growth in developing countries, and irregular supply and demand of various commodities. As such, it is important for mining companies to be able to reliably plan near-optimal schedules, and strive achieve said targets, so that their overall solvency and liquidity remain unthreatened.

The prices of crude oil fluctuate significantly on a daily basis, and there have been some wild price cycles and adjustments in the last 10 years that have seen the benchmark WTI price on the NYMEX at a high of over $140US/barrel in July of 2008 plummet to just over $30US/barrel a short six months later, in December of the same year. The WTI then climbed to a high of over $110US/barrel in Q2 2011, to then plunge heavily to just over $26US/barrel in February of 2016 (NASDAQ).

These oil price fluctuations have posed significant risk to Canadian oil sands producers and, by extension, the economy of the country. With other types of conventional oil having lower unit costs of production, there is currently an oversupply that has kept prices relatively low. Therefore, there has been a significant drive for cost cutting in the industry to keep operations profitable. This has been exacerbated in recent years as overall costs to mining companies have risen due to increasing environmental regulations, taxation regimes, royalties and public scrutiny. Cost cutting by making the operation leaner has a practical limit, and therefore investing in research and development of better planning strategies, and more advanced data analysis is important, as it ensures the long-term sustainability, and prepares companies to take advantage of the next upcycle in prices.

One area that differentiates oil sands mining in Northern Alberta to conventional hard-rock mining is the environment in which they operate in. Due to the characteristics of the ground, producers in the region experience very high rolling resistance values that, in turn, negatively affect haul truck performance, and greatly increase their fuel consumption and emissions. Oil sands mining companies employ some of the largest and most capable haul trucks in the world. In addition, oil sands mines are much more extensive in area than hard rock pits, therefore introducing much longer haul distances on roads of comparatively viscous material.

A review of available literature (detailed in later sections of this thesis) suggests that there is an opportunity to improve operational efficiency in the truck-shovel activities of mining operations. At the center of this opportunity for improvement, is the accurate prediction of production rates – which is entirely dependent on the accurate prediction of cycle times.

1.2 PROBLEM STATEMENT

The proposed research lies squarely in the areas of operations research, optimization and simulation. More specifically, the research presented in this thesis has intended direct applications in the areas of optimization and planning of mining operations.

There have been insufficient advances in the research area of shovel-truck simulation or estimation methods that produce reliable results. While there are various software packages dedicated to this purpose, they are limited in their level of detail, as they solely rely on equipment manufacturers' performance data that is usually not representative of the complex nature of a large-scale, real-world mining operation. As such, many companies have ceased using these programs, and have developed other site-specific "in-house" methods for predicting productivity through cycle times (the essence of productivity in shovel-truck operations), often with unreliable results due to the low-detail, fast-paced nature of their development.

For this particular case study, the "in house" method involved relating the loaded haul distance to a productivity performance indicator, Tonnes Per Gross Operating Hour (TPGOH) through a line of best fit. TPGOH is calculated as follows:

$$TPGOH = \frac{Tonnage\ of\ Material\ Moved}{Cycle\ Time + Cycle\ Delays}$$

There are several time items or activities that make up Cycle Time:

- Idling at dump
- Dumping
- Loading
- Time in queue
- Spotting
- Waiting to spot
- Loaded hauling
- Empty hauling

A simple plot of TPGOH versus loaded haul distance in Figure 1 reveals how inadequate the line of best fit method is. The data in this and other figures has been normalized.

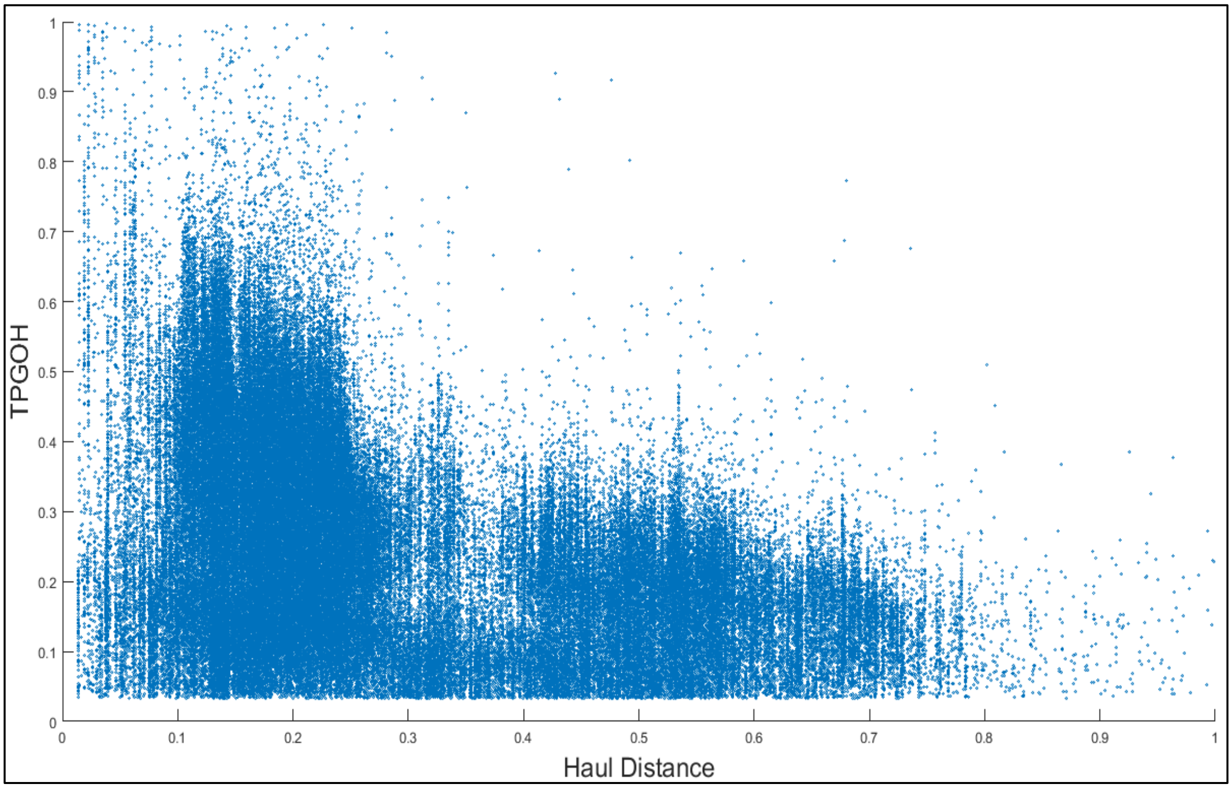

Figure 1: TPGOH vs Haul Distance variability (normalized)

Cycle time is the single most important parameter of a mining operation, as it dictates the maximum achievable production rate. Cycle time is dependent on the type and capability of equipment used, but is also controlled by other controllable and external factors. Controllable factors influencing cycle times include the mining sequence (schedule), road design, road construction, safety guidelines, maintenance of roads and equipment, as well as operator proficiency and behavior. External factors include unexpected equipment downtime and weather events that affect the characteristics of the road and performance of the equipment.

Weather events such as large amounts of rainfall or thawing snow make the material on oil sands haul roads even softer and can create ruts on the surface that increase rolling resistance and therefore cycle times. Similarly, but to a lower extent, typical Northern Albertan low temperatures during winter can harden the oil sands, making it harder for shovels to retrieve material from the mine benches.

The reliable estimation of shovel-truck cycle times is also essential for future production planning and definition of equipment requirements. In addition, a reliable estimate of cycle times can be used to assess the relative performance of a mining operation against a theoretical ideal value. As a planning tool, a link needs to be established between productivity and a parameter that is known in the planning stage; such as the estimated haul distance from a new dig location to a specified source. Figure 2 below shows how much variability there is in terms of haul time for specific loaded haul distances. This variability is, as described above, due to a combination of complex factors.

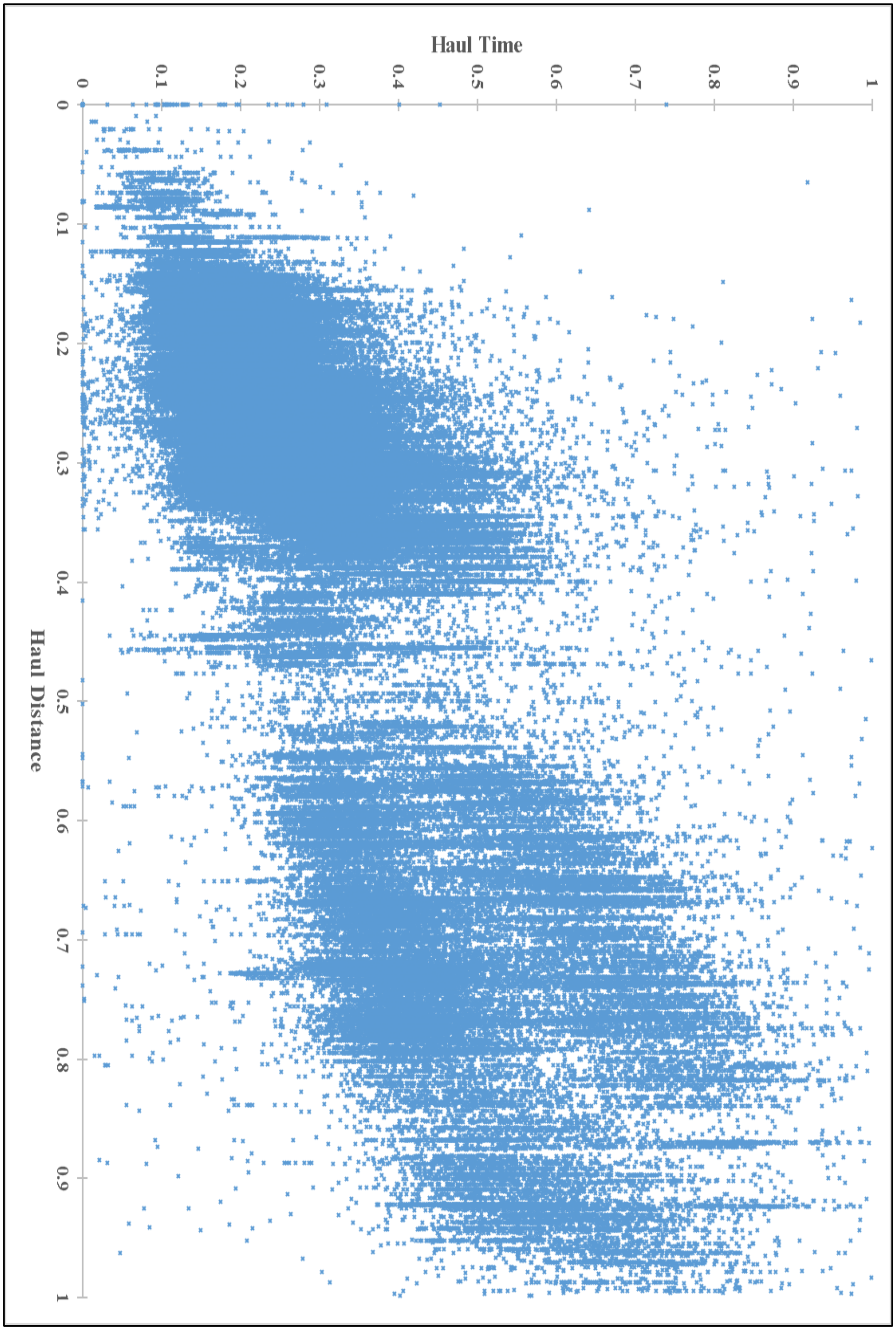

Figure 2: Loaded Haul Distance vs. Loaded Haul Time variability (normalized)

1.3 SUMMARY OF LITERATURE REVIEW

Table 1 features a summary of some of the relevant and available literature in the field of production planning, equipment selection, operations research and simulation of mining operations. In addition, a review of literature pertaining to rolling resistance in Canadian oil sands operations was performed. Lastly, papers in the area of EFH (effective flat haul) were evaluated.

These papers range widely in scope and in how relevant they are to this thesis and to the type of mining operation presented in the case study. Chapter 2 presents a more complete review of the literature, outlining their relation to this thesis.

Table 1. Key points of literature review

Author(s)	Summary/Key Points
(Chanda & Gardiner, 2010)	Compare three methods for cycle time estimation (TALPAC simulation, artificial neural networks and multiple regressions). Simulation tends to underestimate short hauls and overestimate longer ones. The other two methods are more complex. One of the shortcomings of TALPAC is that the performance of the trucks is based on manufacturer data, and it doesn't account for random events during the cycle.
(Bozorgebrahimi, Hall, & Blackwell, 2003)	Loading machine selection affects selectivity, hauling machine influences mine layout and design, both should be appropriately matched. Capital and operating costs of hauling equipment are much greater than loading equipment. Roads are one of the most important infrastructure elements at the mine since they affect the operation of trucks.

(Hardy, 2007)	Outlines the effect of external factors in the overall wellbeing and efficiency of the mine. It provides a thorough review of performance characteristics of loading and hauling machines. Mechanical (diesel) are therefore relatively more reliable and predictable. Equipment selection and productivity estimates are entirely dependent on the truck cycle time; for which loading and travel are the most variable elements. Looked at truck travel time case studies using CAT FPC and outlined factors affecting it such as road conditions and operator efficiency, Study did not consider bunching, traffic and queueing. Productivity tends to increase with truck size. Author notes that return hauls (empty hauls) are more variable due to operators. Payload variation has significant effects on truck performance. Overloading increases productivity but decreases performance. The paper provides guidelines on equipment selection and matching, based mostly for hard rock, open pit mines that may not be entirely applicable to oil sands mining.
(Burt & Caccetta, 2013)	A paper relating to equipment selection. States that the truck cycle time is particularly important and variable, since this is where factors external to the fleet can affect the operation. Considering the variability in cycle times is required, since it affects the feasibility of the fleet and the match factor.
(Burt C. N., 2008)	The number of trucks can affect cycle time due to bunching and queueing. Gives an overview of other techniques for equipment selection, including heterogeneous and homogeneous fleets. The study focused on minimizing costs. For this study, it was assumed that truck cycle time was constant, since there

	was only one source and one destination. To make study more realistic, the author assumed that truck cycle times increased linearly with time and proportionally to bench depth. The author concludes that variability comes from two main sources: cycle time and loss in performance from ageing equipment. This thesis is focused heavily on the former.
(Doig & Kizil, 2013)	A study that outlines the importance and complexity of detailed haulage analyses in coal mining operations. More specifically, the impact on budgets and production planning. It was found that total distance had a greater effect on cycle times than elevation changes. This study used average cycle times; results were unsatisfactory due to limited data and numerous assumptions.
(Manyele, 2017)	Finds that small improvements in truck cycle time can result in significant productivity and efficiency gains. Recommends "stringent control of driver behavior" to ensure efficiency. As expected, loaded hauls are longer than empty hauls because of payload effects on performance, and road conditions affect hauling times greatly. Empty haul times were more variable than loaded haul ones due to dispatching logic.
(Ta, Kresta, Forbes, & Marquez, 2005)	Stochastic approach to truck allocation and dispatch problems, it features a probabilistic simulation of haulage times; not detailed enough. Also outlines the increased complexity of dispatching and how it adds variability to cycle times.
(Kaboli & Carmichael, 2014)	Conducted an analysis that outlines the effects of varying grades along hauling routes on dozer fuel consumption and emissions. Finds distance and resistance as the main

	factors that adversely affect them.
(Carmichael, Bartlett, & Kaboli, 2014)	Formulated an analysis that examined and quantified the influence of various operational parameters (including cycle time) on unit costs and emissions. However, it uses average travel times.
(Hargroves, Gockowiak, McKeague, & Desha, 2014)	EEERE project in Australia, Explains the use of EFH as a normalizing metric to accurately measure energy requirements.
(Sheremeta, 2015)	MBA Thesis, talks about increasing productivity and its importance in the oil sands industry. Identifies recent trends of increasing distances and uses EFH and talks about the impact of road conditions and cycle times from a cost perspective.
(RungePincockMinarco, 2015)	TALPAC is one of the most widely used commercially available haul fleet planning applications. It calculates productivity metrics based on manufacturers' equipment data. It carries out calculations for single haulage routes. It can incorporate some variability for parameters like bucket cycle time and bucket payload, travel time, dumping time and availability. It is assumed that road segments are homogenous.
(Campbell & Hagan, 2012)	Study that uses an EFH-based equipment selection. It notes that EFH is helpful in planning since it relates directly to road gradient and conditions. Their study used average factor ranges for different scenarios thus eliminating detail in calculations.
(Vasquez Coronado, 2014)	Master's thesis that presents a novel alert system for truck/shovel inactivity. Characterization of hauling activities was performed using arena input analyzer and arena for simulation – proving sufficient and adequate for

	distribution fitting.
(Krzyzanowska, 2007)	Studied impact of a heterogeneous mine fleet at hard rock mine, and the impact on cycle times from road conditions. Cycle times were calculated using TALPAC but are oversimplified.
(Soofastaei, 2016)	Investigates the effects of loading performance in trucks, which in turn affects hauling, from an energy perspective. Also highlights effect of payload variance on maintenance requirements. Did not need retarding. Also investigates explores effects of rolling resistance on performance.
(Choi, Park, Sunwoo, & Clarke, 2009)	Developed an algorithm for optimal route selection – find that distance is usually main controlling factor, but high gradients can have even greater effects.
(Hui, 2012)	Identifies load distribution and road conditions as a parameter that increases haulage costs. Provides operational guidelines to keep these under control.
(Alarie & Gamache, 2002)	Provide an overview of truck dispatching solutions. They highlight that the common goal is to try to maximize production and minimize downtime, yet everything depends on the hauling conditions.
(Krause A. J., 2006)	Provides an overview of cycle time simulation and analysis tools. Distributions are given for hauling times. A case study is presented. Probability distributions for elements of the cycle time vary in time. Case study calculates TPH to match requirements. Three main components that affect productivity are: payload, cycle time and operator proficiency (8% decrease).
(Kecojevic & Komljenovic, 2010)	Correlate higher CO2 emissions and fuel consumption to higher engine load factors originated from higher

	resistance. Overloading leads to significantly higher fuel consumption.
(Awhua-Offei, Osei, & Askari-Nasab, 2011)	Simulation study on truck energy usage. Recommends shortening haul distances – and controlling road conditions for better truck performance.
(Upadhyay & Askari-Nasab, 2012)	Simulation study on the detailed behavior of haul trucks in mines. It identifies and characterizes the behavior of truck interaction (bunching) in mining operations. Case study assumed flat roads of fixed length only. Shows MATLAB can be appropriate and matches output with TALPAC.
(Ercelebi & Bascetin, 2009)	They present a linear programming approach to the optimization of truck and shovel systems. They identify hauling as one of the major cost items in mining.
(Edwards & Holt, 2000)	Developed a regression model for predicting productivity and costs for excavators. Cycle times were estimated using geometric operational parameters as inputs. They found correlation between these input variables and cycle times. Considered not user-friendly nor flexible.
(Alhasan & White, 2016)	Conduct a cycle time analysis and assess productivity at an earthmoving operation. Somewhat difficult since they did not have a dispatching system and had to define geographical boundaries to mark the start and end of the cycle. Cycle times were assumed not to experience any delays. Equipment interaction is documented as having significant effects on productivity.
(Thomas, et al., 1990)	Describe various methods for measuring productivity in heavy industries. The Activity model is the one that measures output/hours and is proven to be an appropriate metric for productivity. Direct working hours can't be a

	measure of productivity since it ignores the quantification of output.
(Krause & Musingwini, 2007)	Simulated shovel-truck system using the machine repair model. Describes various methods of simulation: iterative models, regressive models, stochastic Monte Carlo simulation and stochastic graphical, identifying simulation as being superior. It used exponential distributions for all fields.
(Curi, Schmidt Felsch, Cunha Rodovalho, & Prado Meireles, 2013)	Used EFH to quantify and describe the characteristics of particular haul routes in an open pit mine.
(Newmont, 2014)	They adopted EFH in their main KPIs, as "tonnesEFH" to better categorize and describe their production data.
(Dotto, 2014)	Graduate thesis investigates the relative impact of haul truck size in mine planning. Of special relevance to this thesis, the author states that the progression of rolling resistance through road usage is minimal (when inside of regular maintenance intervals).
(Thompson & Visser, 2003)	Found that reducing rolling resistance has significant effects on operating costs as well as capital costs.
(Tannant & Regensburg, 2001)	Give a range of road design parameters for rolling resistance of 1 to 10+%. It states that at Syncrude operations, the rolling resistance is approximately 5% or more during the winter. Also characterizes the effects of increased resistance on tire life.
(Morton, 2017)	A research journalistic article that examines the need and use for extremely large haul trucks in mining. Identifies high rolling resistances in oil sands mining as one of the reasons why these trucks need to be overdesigned.
(Firmin, 2012)	Oil sands mining historically has experienced very high

	rolling resistance values, and road conditions usually put a lot of strain on the trucks causing failure.
(Topf, 2010)	Mentions that operating in the oil sands is tough on equipment. Describes oil sands roads as being very soft and malleable, leading to high rolling resistance.
(Adair, Soofastaei, Aminossadati, Kizil, & Knights, 2015)	Describe various factors that control rolling resistance and its variance. These factors are put into four main categories: design, construction, operational and maintenance.
(Kuo, 2004)	Provides a thorough explanation and delineation of factors affecting productivity in excavations, which is directly applicable to open pit mining and especially oil sands mining.
(Thompson & Visser, 1997)	Presents an overview on principles for road material selection and developed a maintenance system that optimizes equipment efficiency and cost.
(Joseph, Curley, & Anand, 2017)	A very detailed study finds that rolling resistance is a material property independent of truck size. Main haul roads in Canadian oil sands operations range from 5.5% in winter to 11% in summer. Off main roads it is as high as 13.5%.
(Anand, 2012)	Conducted scaled test to find rolling resistance values in oil sands, agrees with above.
(Joseph & Szymanski, 2013)	Describe the importance of reducing rolling resistance, and its impact on fuel usage; fuel efficiency is not linearly proportional. Also mentions that under certain conditions, roads can become nearly liquefied. Quantifies costs savings from reducing rolling resistance.
(Bonates, 1996)	Examines the effect of rolling resistance and gradient on productivity. Its objective is to estimate the performance

	of a truck along a single route. States that there are many assumptions and simplifications, reducing its flexibility. Assumed one single value for mechanical efficiency. Calculates speed for each segment through a formula rather than with rim pull curves.
(Dindarloo, Osanloo, & Frimpong, 2015)	A stochastic discrete event simulation was successfully developed and implemented at a large open pit mine in Iran. It also provides excellent guidelines for simulation model developments to which the model in this thesis adheres.
(Dindarloo & Siami-Irdemoosa, 2016)	Delineate some advantages of simulation: allows for test and analysis of changes without spending capital resources. It also allows for the detailed study of processes that may be too short, or too long to observe in reality. Disadvantages include: simulation results may be difficult to interpret since they are based on random variables, thus it may be hard to determine if an observation is a result of the randomness or some more complex system trait.
(Moradi Afrapoli, Upadhyay, & Askari-Nasab, 2017)	Present a novel dispatch logic model that is linked to a simulation model, where probabilistic distributions of truck velocity and other parameters are used.
(Ben-Awuah & Hosseini, 2017)	A comparative study between truck hauling and conveyor material handling at a bauxite mine. Features the use of rim pull curve velocity values. Average gradients and average distances between source and destination are used.
(De Werk, Ozdemir, Ragoub, Dunbrack, & Kumral, 2017)	Comparative analysis and simulation study of truck/shovel operations vs. in-pit crushers and conveyor systems for materials handling. Find in-pit crushers and

	conveyors more cost effective. Used single values for operational parameters, and simulation is used as a sensitivity analysis of certain parameters, where they find the project to be most sensitive to production rate.
(Tabesh, Upadhyay, & Askari-Nasab, 2016)	Present a simulation model where the speed of the trucks at each segment is adjusted based on rim pull curves, with the total resistance as the controlling parameter. It incorporates safety parameters and traffic interactions (using guided transporter modules in Arena) making it a better characterization of reality. Like this thesis, it builds confidence intervals around the output of several simulation replications.
(Sturgul & Harrison, 1987)	Presents some of the early applications of simulation in mining, in the late 60s FORTRAN was used but was impractical. It outlines the advantages of simulation: programs can be quickly written, easily modified, are inexpensive. The case studies presented express their main data requirement were the cycle time records.
(Vagenas, 1999)	A review of simulation applications in the Canadian mining industry in the 1990s. Simulation has been primarily focused on materials handling systems (for open pit), whereas underground mines focuses also on extraction rates. The author touts the potential of simulation in the mining industry.
(Askari-Nasab, Frimpong, & Szymanski, 2007)	Present a simulation model applied to pit expansion geometry (and the Lerchs Grossman algorithm), not to haulage systems. It is a precedent for other uses of simulation. Finds production rate as one of the most important parameters.

In conclusion, the literature review indicates that there is an existing gap in current research to solve the problem of inaccurate cycle time estimations. Since the cycle time is one of the central and most important parameters of any mining operation, any gaps and insufficiencies within the realm of cycle time prediction and simulation have an aggregated effect on the estimation and simulation of productivity and other performance indicators.

Since oil sands mines are more extensive in area than other traditional (hard-rock) mines, the haul times represent a greater portion of the cycle time. This thesis will focus on accurately predicting this specific component of the cycle time.

The literature review also points out that the current problem is partly rooted in the lack of models that are driven by operational data, therefore relying on ideal-conditions performance parameters such as those provided by the equipment manufacturers.

1.4 OBJECTIVES

The objective of this research is to develop a framework that can accurately and reliably produce estimates of the truck-shovel cycle time through simulation, at an oil sands mining operation, so that productivity figures, such as TPGOH (tonne per gross operating hour) can be calculated.

In addition, this framework must be validated and verified to prove its superiority to the current method used at the mine in the case study. Other detailed objectives in the development of this thesis include:

- Adequately analyze the operation to properly characterize its behavior and identify the main sources of data that will be used as inputs
- To define the sources of data and the level of detail needed to achieve satisfactory results. In addition, the road characteristics and resulting truck performance will be analyzed in detail
- To develop a simulation framework that is data-driven, so that it serves as an accurate predictor of cycle times
- To use the simulation model to define realistic ideal levels of productivity by identifying potential areas of improvement
- To use the simulated cycle times for more practical and advanced applications such as short- and long-term planning
- To use the simulation model framework as a tool that will allow for testing other types of equipment and will correctly predict the reaction of the mining operation
- To use the simulation as a tool that will allow for the analysis of changes to other operational parameters
- To compare the results of this framework to those produced by the alternative current method (based on a line of best fit on a plot of TPGOH vs haul distance), and to evaluate the accuracy of both estimates by comparing them to real production data
- To achieve the above objectives by using widely-available development tools and software such as MATLAB, creating a computer program that is user-friendly, yet

robust enough to handle large amounts of data, and is flexible so that it can be applied at most open pit mines

- To achieve these objectives in relatively short run-times and with user-defined levels of detail
- To provide a "theoretical" estimate that mimics the currently available cycle time estimation tools, which use equipment manufacturers' data and allows for the comparison of the more realistic simulated output versus ideal values, thereby quantifying opportunities for improvement
- To provide outputs that are easy to interpret. To achieve this, the output will be manipulated so that this framework results in a TPGOH vs distance relationship, same as the in-house method in the case study

1.5 SCOPE AND LIMITATIONS

The scope of this study is mainly restricted by the availability of data to correctly characterize the mining operation. This framework was developed with the availability of dispatch system production data that had detailed information of every cycle within a two-year period. While this is a very significant amount of data, much of the time and effort in this research was spent making sure that all the errors in the database were corrected and omitted from further use in the model.

There were also instances where large portions of dispatch data were incorrectly recorded, which required supplementation with other data sources Another limitation is the inability to ensure the proper calibration of GPS trackers in the mobile equipment, which record important cycle time data as well as velocities.

In general, it is hard to characterize the individual components of a complex operation such as a mine, therefore this study is heavily focused in the analysis of haul-truck behavior, and as such, there is a disproportionate amount of detail in this area compared to others such as shovel movement, equipment matching, etc. With this in mind, it is worth mentioning that a very detailed virtual surface of the mine was provided, and this made the characterization of road features, such as lengths and gradients, possible.

One important consideration that was revealed during the development of this framework was that one component of the truck-shovel cycle time is very hard to validate/verify for correctness. This is the empty haul time of the truck after dumping its payload at a dump location. While the simulation could assume that it goes back to the same shovel or dig location, in practice this is not the case. Dispatching techniques are very well researched and a very complex area of mining operations, and is therefore outside the scope of this study. Therefore, when generating simulations for TPGOH, and trying to validate them against the production/dispatch database, it is hard to know that the dispatch logic was for assigning routes to trucks after dumping, especially considering that at any given time there are more than 10 active shovels, as well as stockpile locations.

Another limitation was the fact that the dispatch data did not categorize the mine areas in the classical method of other open pit mines, by polygons, with defined boundaries and locations. Instead, these were categorized by benches that varied greatly in location from record to record, due to the advancement of mining. Therefore, advanced manipulation using coordinates in the records was necessary, and it resulted in a very flexible program. This entire framework was developed using generally available software such as MATLAB, Excel GEMS and AutoCAD, among others. Data requirements are more thoroughly discussed in Chapter 3. This framework works best when applied to existing mines for which operational data records exist, but its use is also applicable in the planning of new mines. In its simplest form, the framework in this thesis generates estimates for components of the cycle time between distinct sources and destinations within the mine's haul road network.

1.6 RESEARCH METHODOLOGY

Seeing as the objective of this study was well-established since the beginning, and reinforced due to a review of the literature, the focus shifted towards developing a robust framework that would solve the problem(s) in a reasonable computer run-time. During the development of this research, one theme was kept constant: only generalist software and applications were used, in order to ensure the future flexibility and application capabilities of the framework. The steps taken in the development of this research and in the achievement of the above goals can be categorized into three main areas:

1. Careful and detailed analysis of dispatch data from the mine in the case study, and subsequent review of relevant literature
    - Site visits to the mine in the case study were made, in order to become familiar with the operation and understand the basic logic in its processes, namely the shovel and truck behavior and utilization

- The dispatch data was analyzed extensively to characterize the overall behavior of the mine and identify trends that would pinpoint the areas with the most potential improvement
- Having identified these areas, a thorough review of available solutions and literature was performed, revealing a gap in research and an opportunity to innovate and improve in this field
- The performance of the available solutions was evaluated and studied so that a comparison could be made between those and the outputs generated by this framework. This program can generate estimates like those obtained in TALPAC and CAT FPC, which are based on manufacturers' performance data

2. Definition and delineation of data requirements, as well as manipulation of the available data to generate the model
    - The most important input to the framework and program is a digital model of the mine's road network. The accuracy of the estimates is dependent on the quality of the network model – namely the correct distances and gradients
    - Other main data inputs needed for hauling simulation were identified as velocity records from GPS trackers in the haul trucks, and manufacturers' performance data such as rim-pull curves for the desired model of truck
    - For complete cycle time simulation, dispatch data with detailed timestamps delineating loading, spotting, queueing, dumping and delay times are necessary, as well as a defined dispatch logic for assigning empty trucks from dump locations to new dig locations

    - For productivity parameter estimation, such as TPGOH, payload measurements within the dispatch records are necessary, so that the variance in weight can be accounted for. The weight is a direct component that affects truck performance
    - Fitting probability distributions to the aforementioned parameters, using statistical methods and goodness-of-fit tests is imperative for simulation
    - Accurate coordinates for mining polygons are necessary
    - Other miscellaneous pieces of information within the operation were needed, such as general traffic rules like speed limits, or behavior at intersections. These were noted by communicating with the mine staff. It is important to accurately model the small-scale behavior of the equipment within the network for increased certainty
- The implementation of the EFH parameter is explored and analyzed, and is deemed useful in properly categorizing haul data based on the effects of gradients and rolling resistance

3. Development, validation, verification and application of the framework
    - Several algorithms and functions in MATLAB were developed, starting with one that would import and read the characteristics of the network, and prepare it for subsequent calculations
    - A method that uses manufacturer performance data to calculate cycle times was developed, yielding results like those of widely used commercially available software, to establish a baseline and for calibration purposes

- A more advanced simulation method that is more data-driven is developed, and its outputs are compared to the records in the database for validation and verification
- A complex case study is presented, showcasing a more advanced application of this framework. The outputs are compared to the records in the production database, and compared to the predictions generated by the old method
- The implementation of EFH allows for the simplification of this program's output, by maintaining the operators' desire to establish a relationship between TPGOH and a distance metric

While these main steps are in chronological order, some of the steps in the first category, and most of those within the second and third categories occurred concurrently, since the development of this framework was mostly driven and shaped by the constraints presented due to the form of the available data and the desired outputs, of which the characteristics were not initially revealed.

1.7 INDUSTRIAL SIGNIFICANCE OF THE RESEARCH

It is important to note that this research was directly driven by a real necessity in the industry (and more specifically, the mining operation to which the case study refers) for a more accurate method of estimating productivity, in order to better plan in both short- and long-terms, as well as define equipment requirements in the future.

This is also a conclusion drawn from the literature review in the following chapter. As such, the development of the program presented in this thesis was initially well suited exclusively to this operation, but at later stages, efforts were made to ensure that it is flexible and general enough so that it can be applied at other oil sands mining operations, and almost any open pit mine where trucks are used as the main hauling unit.

The direct effects of improved cycle time estimation are parallel to those of optimization in any heavy industry; reduced operational uncertainty leads to lower risk of unexpected inefficiency in the short and long-term plans. Similarly, by utilizing a prediction method that is more detailed than what is currently available, optimal solutions can be achieved, therefore minimizing costs.

These costs are both operational and capital. Operational costs can be optimized with this tool by selecting the most fuel-efficient routes, for example, also leading to reduced emissions, which is a very important goal. In addition, capital costs can be mitigated by selecting routes that are less punitive on the trucks, therefore delaying the need for replacement or costly repairs of equipment.

1.8 ORGANIZATION OF THESIS

The main sections in this thesis, after this first and introductory chapter, are in the following order: Chapter 2 provides a thorough review of the available literature pertaining to the central topics to this project, outlining the need for a tool like the one presented in this thesis. The chapter starts by examining the uses of simulation in the mining industry chronologically and continues to review more recent studies in other areas of mining and in material transport systems.

The shortcomings in the approaches in some of these studies are explicitly noted to create a contrast that highlights the merits of this thesis.

In Chapter 3, the theoretical framework of the approach and the program is outlined, and a detailed step-by-step explanation is provided. The general data requirements are outlined, showing the flexibility of this approach. Several alternate uses and potential applications of the program are then proposed.

Then, in Chapter 4, the results from the application of this approach at a major Canadian oil sands mining operation are presented as a case study. The real-world data acquisition tasks performed are outlined. The model was validated against the mine's production and dispatch data using several scenarios. Lastly, a more advanced application of this program and framework is presented, comparing its outputs and estimates to those of previous methods used at the operation, and to the records in the database.

In Chapter 5, a summary and a few conclusions are offered, outlining the key findings and valuable insights revealed through the development of this study. In addition, recommendations for future work and advancement in this area of research are provided. The code is shown in the appendices.

2. LITERATURE REVIEW

This chapter presents a comprehensive review of the available literature relevant to the areas of research that are central to this project. More specifically, the chapter starts by reviewing some of the published applications of simulation in the mining industry, further sorting these based on their intended area of use within the operation, all while identifying their significance and shortcomings.

Then, an overview of published research on analyses and simulation relating to productivity and efficiency of shovel and truck operations in mining is presented, highlighting the importance and necessity of a framework that can lead to more accurate estimates of cycle times, such as the one presented in this thesis.

Simultaneously, the literature points to rolling resistance as one of the main parameters affecting truck performance, and several papers investigating and quantifying the high rolling resistances in the Athabasca oil sands mining operations are reviewed. Lastly, literature and documentation relating to the concept of equivalent (or effective) flat haul (EFH) is reviewed and summarized.

2.1 SIMULATION IN THE MINING INDUSTRY

While simulation in mining has been around for several years now, it is still one of the most recent and promising tools in the industry, and presently, its full potential remains unexplored. In addition to its ample current capabilities, simulation methods benefit directly from the relentless technological advancement in the computing and software industry.

Sturgul and Harrison (1987) mention and review some of the earliest practical applications of simulation in mining. In their paper, the authors mention that the FORTRAN coding language was used for most simulation studies starting in the late 1960s, noting that the resulting codes were quite long, and thus impractical when considering that their intended use was for rather simple simulations. At the time of writing, two decades after the first applications, the authors mention that the GPSS (general purpose simulation system) coding language is comparatively superior than what was previously used, resulting in worthwhile simulation efforts.

Sturgul and Harrison (1987) elaborate further, stating that since its earliest applications in the industry, the intended uses of simulation models have always been, essentially, the determination of optimal parameters at the mine. For example, by correctly simulating the operation, one could generate production estimates for new mine zones, or assess the behavior of the operation using different equipment, amongst many other applications. They proceed to mention that the main advantage of simulation is that codes can be written quickly, inexpensively and can be easily modified and further refined.

Vagenas (1999) presents a thorough review of the applications of simulation in the Canadian mining industry in the 1990s, stating that it has been primarily focused on materials handling systems for open pit mines, whereas applications in underground mines focus also on extraction rates. Vagenas (1999) agrees with Sturgul and Harrison (1987), touting the use of computer simulation in the industry by emphasizing that its main advantage is rooted in that the virtual model "…allows rapid manipulation of the major parameters of functions of system without the need of real-life experimentation”. Due to this, the correct application of simulation directly yields operational improvements (and thus, advantages over rival companies), and therefore many of its more advanced and substantial applications are not publicly available. In his concluding remarks, Vagenas (1999) correctly predicts that “…simulation analysis will be an indispensable scientific methodology for mine engineers in the coming decade”.

Dindarloo and Siami-Idermoosa (2016) echo the thoughts of Vagenas (1999) nearly two decades later, identifying simulation in mining as a tool that allows for the testing, implementation and analysis of the effects of major changes on the operation, but without the need to commit significant capital or resources. In other words, the value of simulation comes from the fact that it allows operators to explore the inherent behavior of their operation at a miniscule fraction of the cost of making that change, therefore minimizing operational risk. Another important advantage of simulation outlined in Dindarloo and Siami-Idermoosa (2016) is that it also allows the detailed study of processes that may be too short or too long to observe in real life, in a time that is appropriate for decision making. They also identify one major potential disadvantage: since this method involves the use of random variables, the interpretation of simulation results may be hard to properly interpret; it is often difficult to discern between normal variability from the random inputs, and inherent behavior of the complex system.

Dindarloo, Osanloo, & Frimpong (2015) describe mining operations as a series of random discrete events. This is particularly true when considering the truck cycle. It consists of sequential activities, namely loading, hauling, dumping and travelling to a new destination. Their paper presents a stochastic discrete event simulation study that was developed and implemented at a large open pit mine in Iran. The goal of this study, like many others and including this thesis, was to generate productivity estimates that would allow for the optimal selection of equipment. The authors state that a 10% improvement in productivity was achieved upon the implementation of their model. They provide an overview of other methods for achieving this, and mention that other researchers have tried using linear, non-linear and mixed integer programming, queuing theory, analytical hierarchy processes, genetic algorithms, as well as simple calculations based on manufacturer-supplied equipment performance data. However, the authors say that simulation in general is a superior method due to its relative ease of use and accuracy. In addition, they also provide a set of excellent guidelines for simulation modeling, chief among which is making sure that the input data is a result of detailed observation (or recording) and careful analysis of field parameters in loading and haulage operations, so that interrelated processes can be characterized. They also present different sets of guidelines for new mines and for existing mines, based on the availability of field data. The model in this thesis follows, to a certain extent, the best practices proposed for existing mines by Dindarloo, Osanloo, & Frimpong (2015).

An example of an alternative to simulation for productivity estimation is presented by Edwards & Holt (2000), as they developed a regression model called ESTIVATE, with the goal of predicting productivity and cost parameters for excavators in the construction industry in the United Kingdom. Machine cycle times were estimated using equipment manufacturer's equipment operational parameters (namely machine weight, digging depth and swing angle) as inputs to the model, and multiple regression as the specific calculation method. In the model, they were able to determine and quantify the correlation between these input variables and the geometry of the desired operation, and use it to predict the cycle times. While the authors conclude that their regression model is robust and yields acceptable results, they also mention that, due to its complex mathematical nature, it is not user friendly nor flexible.

Askari-Nasab, Frimpong, & Szymanski (2007) present an example of an advanced application of simulation in the mining industry, as they developed a predictive stochastic model for the expansion of open pit mines, founded on geometrical calculations based on an elliptical frustum. One of the main goals of the model is to try and correctly characterize the randomness and behavior of the operations at the mine and then use these as inputs to try to define the newly expanded pit limits. As such, one of the main data inputs into the model is the production rate, which is almost entirely dependent on the selection of equipment and therefore their capacity and resulting cycle times. In the 2007 paper, these production rates were obtained deterministically by using the outputs generated in Whittle, one of the most widely used mine optimization programs. In contrast, this thesis recognizes and stresses the importance of accurate estimates of cycle times as, and thus generates them in a more detailed manner by focusing in the intricacies of truck activity.

De Werk et al (2017) conducted a comparative cost analysis that investigates in-pit crusher and conveyor systems versus traditional truck and shovel operations for materials handling at open pit mines. They present a case study for an open pit iron ore mine, applying their framework and concluding that, for that specific scenario, in-pit crushers and conveyors more cost effective than trucks and shovels. This conclusion was reached by using single and average values for cycle times and other important operational parameters, which may be an oversimplification. The authors, however, do conduct a sensitivity analysis through Monte Carlo simulation of some parameters, namely the prices of both fuel (for trucks and shovels) and electricity (for crushers and conveyors), as well as equipment availability. The results of the sensitivity analysis show that both methods are most significantly affected by variations in production rates. By extension, production rates in typical truck/shovel operations are governed by cycle times, the estimation of which is the focus of this thesis.

Alarie & Gamache (2002) provide an excellent overview of various truck dispatching solutions in open pit mining, also outlining the common problems encountered in the industry. They highlight that operators and planners, in essence, all aim to maximize production and minimize downtime. However, it is stressed that the productivity and performance of the system is significantly dependent on the hauling conditions in which the trucks operate.

Ta et al (2005) present a stochastic approach to remediating truck allocation and dispatch problems, and it features a probabilistic simulation of cycle times and payloads, which is not detailed enough and identified to be a potential area of improvement of their proposed approach. The authors also mention that the cycle times can be greatly affected by the decision-making process in dispatch, more specifically, the time haul trucks spend travelling empty after dumping material to a new destination. Since this thesis is not focused on developing a better dispatch solution, some of the productivity indicators in the case study do not include that component of the truck cycle time.

Moradi Afrapoli, Upadhyay, & Askari-Nasab (2017) developed a novel fleet management system for open pit mines which minimzes deviations from the original mine plan. The new system was validated by linking it to an Arena simulation model. In order to correctly simulate the major uncertain variables at the operation, they fit probability distributions to field data for spotting, loading and dumping times, separately. In addition, they fit probabiltiy distributions to the data for the loaded velocity of trucks. It is important to mention that they fit individual distributions for every combination in their heterogeneous fleet. The simulation framework presented in this thesis is similar in approach to Moradi Afrapoli, Upadhyay, & Askari-Nasab (2017) in that it tries to capture the randomness of the original system variables in the operation to generate estimates that are closer to reality.

Vasquez Coronado (2014) presents an approach to improving productivity via a novel system that alerts operators of truck/shovel inactivity. In his model, he characterized and modelled the operation's hauling activities by fitting distributions and using the Arena input analyzer, which allows for statistical hypotheiss testing, and Arena for simulation. This sets one of the only precedents for data analysis and probability distribution fitting using that specific program. This thesis employs the same technique and software for statistical modeling. However, the case study presented in his dissertation is simplistic in that there are only a couple of sources and destinations, requiring only a few distributions for travel times between them. While it sets a good precedent for simulation of cycle times, it is not flexible, nor is it intended to be a tool that can easily be applied elsewhere.

Krzyzanowska (2007) uses the widely popular haulage simulation program, TALPAC (which will be discussed more in detail below), to simulate haul times for a study that characterizes the relative disadvantage of using mixed (or heterogeneous) fleets in open pit mining operations. The author recognizes truck performance and road conditions as the main parameters affecting overall productivity, but also describes the negative effects of poor equipment matching in a case study. It is concluded that using trucks and shovels of varying capacity and performance results in increased delays, poor matching and bunching within the mine's road network. The inputs used in Krzyzanowska's study assume ideal (uninterruped) hauling conditions. Such assumption must not be made when the focus of the study is to quantify productivity, rather than measure relative performance in two mining scenarios.

Awhua-Offei, Osei, & Askari-Nasab (2011) conducted a study on truck energy usage at a mining operation. The inputs to their simulation were probability distributions for shovel and truck activities, separately. The authors recommend increasing shovel size slightly while maintaining compatibility in the system, and identify haul distance and road gradient as very important elements. They recommend shortening haul distances and maintaining gradients to relatively low levels to achieve maximum efficiency levels. This thesis agrees with those recommendations in most cases, as it implements a shortest-path algorithm to minimize travel distances and recognizes resistance (both rolling and gradient) as a factor that should be kept to a minimum through proper design and maintenance of the road network.

In one of the most interesting truck-shovel simulation approaches is presented by Krause & Musingwini (2007). These authors modelled a mining operation using an adaptation of the Machine Repair model in Arena. Cycle times were represented as inputs using exponential distributions within their model, and the authors were able to generate similar productivity outputs to that of TALPAC and other widely used tools. The authors note that the differences in the outputs from the various methods in their study are rooted in how the input data is manipulated in each approach, and therefore suggests that proper statistical analysis and probability distribution fitting is paramount in simulation.

Bonates (1996) presents one of the earliest haul-time simulation models. The author examines the effects of rolling resistance and gradient on productivity. The core objective of his study is to estimate the performance of a truck along a single haul route. He states that many assumptions were made to make the model simpler and thus cannot be universally applicable. Some of these assumptions include assuming one single value for mechanical efficiency and calculating truck speed for each road segment via a power/weight formula rather than with rim pull curves that take into account the mechanical characteristics of the truck's drivetrain.

Ben-Awuah & Hosseini (2017), much like De Werk et al (2017) conducted a comparative analysis between truck and shovel hauling and in pit crushers with conveyors, this time at a bauxite mine. In this paper, Ben-Awuah & Hosseini utilize a single assumed value for rolling resistance, and average values for gradients along selected routes of fixed length. With this information, they use the truck manufacturer's rim pull performance curve to determine the speed (and thus, the time) that it will take to haul from point to point. The authors also find that major cost savings are possible using the conveyor system, but point out that truck and shovel operations are better understood in the industry as a more mature technology.

Doig & Kizil (2013) present a haulage analysis study that aims to identify the value drivers of materials handling operations using trucks and shovels. It outlines the importance and complexity of detailed haulage analyses in coal mining operations. More specifically, it analyzes the impact of hauling on budgets and variability in production planning. The study found that total distance had a greater effect on cycle times than elevation changes at their analyzed mine. The authors express that increasing detail in haulage analysis is crucial, calling for a program such as the one in this thesis. The authors' study used average cycle times and yielded unsatisfactory results which were attributed to a lack of data and numerous assumptions in the methodology.

In an excellent paper that has been cited by many in this area of research, Chanda & Gardiner (2010) compare three existing methods for cycle time estimation: TALPAC simulation, artificial neural networks and multiple regressions. After a thorough review, they conclude that simulation is the most commonly used method. The authors also find that this method, in general, underestimates short hauls and overestimates long ones. They also find that artificial neural networks and regression are more complex methods that require greater levels of effort and data and are not as flexible. The paper states that one of the shortcomings of TALPAC simulation is that the behavior and performance of the trucks is solely based on manufacturer data (i.e. rim-pull curves) which are assumed to be under ideal conditions; it doesn't account for random events during the cycle. The framework presented in this thesis does, as it incorporates distributions that are representative of said events. The authors also found abnormally low variation in cycle times with TALPAC, due to the nature and form of its inputs. This is overcome in this thesis' proposed framework by using full probability distributions and true random number generation, as opposed to a "spread" of values as used in TALPAC.

TALPAC (RungePincockMinarco, 2015) is one of the most widely used commercially available haul fleet planning applications. It calculates productivity metrics based on manufacturers' equipment performance data, both for loading and hauling equipment, either separately or working in conjunction. It extends its estimates into costing and economic areas that are quite important in the planning stage. It features a massive equipment library with many models of trucks and shovels. It carries out time calculations for single haulage routes. TALPAC can incorporate variability for a few operational parameters such as bucket cycle time, bucket payload, travel time, dumping time and availability. It is assumed that road segments are homogenous. Thanks to this, there is the possibility to simulate and generate variable output travel times, but as mentioned earlier in this chapter, TALPAC does not allow users to fully capture the variability of factors. The framework in this thesis is comparatively more detailed yet flexible. Both TALPAC and the program in this thesis vary the payload and adjust performance accordingly.

Hardy (2007) outlines the importance of other mine elements and external factors in the overall efficiency of the mine. In his paper, he provides a thorough review of performance characteristics of loading and hauling machines. He also notes that mechanical (diesel-powered) haul trucks present very mature technology and are therefore relatively more reliable and their operation is more predictable. He states that equipment selection and productivity estimates are entirely dependent on the truck cycle time; for which loading and travel times are the most variable elements. He conducted research on case studies in deep pits using CAT FPC software, and outlined the main factors affecting productivity, such as road conditions and operator efficiency. The framework in this thesis accounts for both, as well as speed limits by fitting distributions as opposed to assuming best-case values. Hardy did not consider the effects of bunching, traffic and queueing. The case study in this thesis does, since its data-driven. Hardy states that productivity tends to increase with truck size, thus the recent preference for using larger trucks when possible. He notes that return hauls (empty hauls) are more variable due to operator behavior, even when eliminating the variability of dispatching systems. He also mentions that variations in payload have significant effects on truck performance. He then investigates the effect of truck overloading, finding that it increases productivity but decreases performance and efficiency. He also mentions that haul road maintenance at mining operations is essential, since resistance affects the trucks' ability to perform, but maintenance often results in traffic interactions that slow trucks down. This was found to be true in this thesis and case study.

Tabesh, Upadhyay, & Askari-Nasab (2016) present a truck-shovel simulation model, in which, like this thesis, the speed of the trucks at each segment is adjusted based on the rim pull curves, with the sum of rolling resistance and gradient as the controlling parameter. The simulation study goes a step beyond others, as it incorporates and models behavior at the mine that brings the simulation to a closer representation of reality. These include safety parameters (such maintaining minimum following distances between trucks), yielding the right of way at intersections, and traffic interactions (slower trucks holding faster ones, possible thanks to the guided transporter modules in Arena). Like the framework in this thesis, it builds confidence intervals around the output of several replications, yielding a probabilistic estimate of the KPI of interest.

Continuing within the topic of detailed simulation of haulage systems, Upadhyay & Askari-Nasab (2012) provide a simulation study on the detailed behavior of haul trucks in mines, accounting for the acceleration, deceleration and other traits of the system. It identifies and quantifies the behavior of truck interaction (bunching) in mining operations. Their case study assumes flat roads of fixed length only. Their study is carried out in MATLAB and shows that it can be an appropriate tool for simulation coding by matching its output with the one determined in TALPAC. The program presented in this thesis was coded in MATLAB.

In summary, one can observe that one of the most important inputs to the model has always been properly fitted probability distributions for cycle time data, as well as a detailed profile of the haul route(s), regardless of the intended goal of the simulation study. Therein lies the motivation to develop a framework that accurately predicts this.

2.2 PRODUCTIVITY ANALYSES

Maximizing productivity in the mining industry is of paramount importance and is the second greatest value driver after increased resource discoveries, and the one that operators can control. Thomas et al (1990) provide a thorough overview and description of various methods for measuring productivity in heavy industries. The authors note that working hours cannot alone be a measure of productivity, since it ignores the quantification of output. The "activity model" is an approach that measures productivity as a desired unit of measurable output, normalized by the working hours put in to achieve said production. As the authors mention, it is proven to be an appropriate metric for productivity in industries like mining.

The cost of using trucks to haul material in open pit mines is the highest operating expense, representing approximately 50 to 60% of the total, according to Ercelebi & Bascetin (2009). This fact motivated them to develop a linear programming approach to optimizing their operations and to increase productivity. When considering these high operating costs, one must also take into account the very high capital costs associated with the purchase of mining equipment, such as shovels, trucks, dozers and other auxiliary equipment. The push for peak productivity at mines around the glove is easily justified.

Alhasan & White (2016) present a study of an earthmoving operation where GPS records were used to conduct cycle time analysis and assess productivity. The analysis of cycle times in the case study was difficult since they did not have a dispatching system on site, and thus had to define geographical boundaries to mark the start and end of cycle times. The cycle times were calculated by removing the delays from the records – this may not be ideal since there are ramifications and interrelations on the entire cycle due to these delays, and thus should have been accounted for. Equipment interactions such as bunching and traffic is documented as having significant effects on productivity. The authors note that more refined systems for monitoring truck activity would be useful in properly capturing other factors that affect productivity.

Kuo (2004) provides a very detailed look at the factors that can affect productivity in excavations and earthworks, and how they are interrelated. These are directly applicable to open pit mining and especially oil sands mining. Kuo lists project complexity, traffic flow, accessibility, road/soil condition, gradient, rolling resistance, size of equipment, match factor, operator competency, weather and disruptions and as some of the main factors that ultimately affect production rates. The framework in this thesis successfully encompasses data from all of the aforementioned sources to produce accurate estimates of productivity.

Burt & Caccetta (2013) wrote what is one of the most complete papers relating to equipment selection and the calculation of the match factor. The authors state that the truck-shovel cycle time is extremely important, and usually quite variable. It is variable, according to the authors, because it is at the shovel-truck operating cycle where factors that external to the fleet and inherent performance can affect the operation. It is therefore necessary to appropriately represent the variability in cycle times during calculations, or simulation, since it affects the feasibility of the fleet and the match factor. Along the same lines, Burt (2008) states that the number of haul trucks can affect cycle time, due to bunching and excessive queueing. She also provides an overview of techniques to select equipment with heterogeneous and homogeneous truck fleets. For this study, it was assumed that truck cycle time was semi-constant since the trucks left the centroid of the mine and went to a single dump location. In order to make her study more realistic, the author assumed that truck cycle times increased linearly with time as mining progressed, since the pit deepened. The author identifies two main sources of variability in productivity estimates: loss of performance from ageing equipment, and variations in cycle time due to external factors and the respective responses in equipment performance. This thesis is focused heavily on the latter.

Bozorgebrahimi, Hall, & Blackwell (2003) reached the conclusion that loading machine selection (such as shovels and excavators) affects mining selectivity, while hauling equipment mainly influences mine layout and design, and both should be appropriately matched. However, capital and operating cost of hauling equipment are often much greater than those of loading equipment, and often the highest single-cost item at a mining operation. They go on to say that haul roads are one of the most important infrastructure elements at the mine, since they directly affect the performance of trucks.

This has motivated studies like the one presented by Choi, Park, Sunwoo, & Clarke (2009) who developed an algorithm for optimal route selection in which they focused to minimize costs. They found that distance is usually the main controlling factor for cost, but recognize that extreme gradients can have even greater effects.

Kaboli & Carmichael (2014) conducted an analysis that described the effects of varying grades along hauling routes on fuel consumption and emissions. While this study did not look at haul trucks specifically, it examined dozers, and the principle is the same. They indicate that the cycle time and emissions are very sensitive to the hauling distance and resistance. They express the need for further studies into hauling analysis and simulation, which this thesis answers.

Kecojevic and Komljenovic (2010) characterized the effects of positive gradient resistance on fuel consumption and emissions. In their study, they set out to investigate variation in these parameters under various engine load conditions. Higher gradients and rolling resistance values result in greater engine loads and, as expected, they are correlated to higher CO2 emissions and fuel costs. These authors also mention the effect of overloading, which leads to much higher than expected fuel consumption, in line with the conclusions from other literature.

Carmichael, Bartlett, & Kaboli (2014) formulated an analysis that examined and quantified the influence of various operational parameters (including cycle time) on operating costs and truck emissions. Longer cycle times due to longer distances or higher resistances were directly associated with higher costs and emissions. However, the analysis uses average travel times. The authors revealed that the optimal point in unit costs is, theoretically, coincident with optimum unit emissions, both relating to lower resistances.

Manyele (2017) conducted a material flow data analysis study at an open pit mine. He found that even minute improvements in truck cycle time can result in significant positive effects on the operation and its productivity levels. Manyele strongly recommends "stringent control of driver behavior" to ensure that the mine adheres to the planned production levels. As expected, loaded haul times were longer than empty hauls because of the effect of weight on truck performance. The author also mentions that poor road conditions and high gradient affect times greatly. Haul times are considered by Manyele to be the most important components of the cycle time. Empty haul times were found to be more variable due to the dispatching logic at the site.

Krause (2006) provides an investigation into the factors that control cycle times in mining operations, presenting also an overview of various simulation and analysis tools. A case study is presented, where probability distributions for elements of the cycle time are used for simulation. The KPI of the case study is TPH (tonnes per hour) and is used to calculate equipment requirements. Three main components that affect productivity are identified: payload variance, cycle time and operator proficiency. Krause finds that operator proficiency is a factor that decreases optimal productivity by approximately 8%.

Hui (2012) identifies two aspects of truck hauling that affect performance and drive up operating and maintenance costs: load distribution and road conditions Hui provides operational guidelines to control and avoid unnecessary costs. Soofastaei (2016) investigates the effects of variable loading performance from shovels to trucks, which has a chain reaction, as affects the payload distribution of the truck, which in turn affects its performance during hauling. Soofastaei's doctoral dissertation analyses the system from an energy (rather than productivity) perspective. In his dissertation, the author also highlights effect of payload variance on maintenance requirements. Like the approach in this thesis, simulation is used to generate samples of payload tonnages, and they are then used to determine the performance of the truck based on manufacturers' rim pull curves. The author did not use retarder curves for truck performance calculations, and examines the effects of rolling resistance on hauling energy

Adair et al (2015) investigate the origin and mechanisms involved in rolling resistance in haul truck operations. They recognize it as a major hindrance to productivity and safety. The authors categorize these factors into four main categories: design, construction, operational and maintenance. They cross-examine them against four major components of an operation, based on where they originate: road, tire, system and weather. Most factors are of the operational kind, meaning that they can be corrected and rolling resistance can be somewhat avoided.

Dotto (2014) investigates and reports the relative impact of haul truck size in mine planning. Of special relevance to this thesis, the author states that the progression of rolling resistance through road usage is minimal (when inside of regular maintenance intervals). Dotto states that the increase in rolling resistance due to use-related road degradation is minimal, if the road maintenance intervals are kept to under 12 days. Thompson & Visser (1997) present an overview on principles for road material selection and developed a maintenance system that optimizes equipment efficiency and cost. These guidelines center around minimizing rolling resistance and high gradients. Thompson & Visser (2003) also found that reducing rolling resistance has significant effects on operating costs as well as capital costs. Trucks incur in more wear and therefore mine operators need to look into replacing the equipment before their expected service life.

Several companies have pioneered research into the area of mine haul road maintenance and design, claiming that a limestone cap layer can reduce rolling resistance by up to 55% (Hammerstone Corporation), thus reducing fuel costs and increasing tire and frame life. Joseph & Szymanski (2013) describe the importance of reducing rolling resistance and its impact on fuel usage.

The authors determine that fuel efficiency is not linearly related to rolling resistance. They also mention that under certain conditions, such as the summer months in North America, the road material can become nearly liquefied. The authors quantified the average costs savings stemming from reductions in rolling resistance and provide a figure of $350 per shift, per 400-tonne truck. This figure results in very significant savings through LOM when considering the scale of some of the major mining operations, and the number of trucks they employ.

2.3 ROLLING RESISTANCE IN OIL SANDS MINING OPERATIONS

Oil sands mining operations in Northern Alberta have, historically, experienced very high rolling resistance values. Since trucks often operate on sand-like surfaces, held together by bitumen, the addition of moisture in the form of rain or melting snow makes the ground and roads turn very soft. According to Firmin (2012), during the early days of oil sands mining, the commercially available trucks were designed for hard rock mining, and when tried at the very soft ground, they were not sufficient. The problem was that the rolling resistances were much higher than those experienced in hard rock mining, so modifications had to be made; much larger and more powerful engines were fitted to overcome the resistance. Another issue that presented itself, apart than larger engine requirements, was that the roads in oil sands mines induced a lot more stresses and caused more flex on the bodies of the trucks, which motivated the application of finite element analysis for more durable chassis design (Firmin, 2012). Morton (2017) investigates the need and the current use of extremely large haul trucks in mining. The author identifies high rolling resistances in oil sands mining as one of the reasons why these trucks need to be overdesigned, and the parallel growing concern for fuel efficiency and emissions control.

Joseph, Curley, & Anand (2017) conducted a very detailed study, and found that rolling resistance is a material property, and therefore independent of truck size. The authors mention that the rolling resistance values of main haul roads in Canadian oil sands operations range from 5.5% in winter to 11% in summer, while the values off the main roads is as high as 13.5%. These estimates are in line with the scale-test research performed by Anand (2012). These values agree also with the estimates generated by Tannant and Regensburg (2001), which state that rolling resistances of 5% or more are present at Syncrude operations. They also mention that tire life is diminished due to such high resistance levels.

Topf (2010) describes overall operating conditions in oilsands mining as being unforgiving, which require truck manufacturers to design equipment that can withstand high stresses. The author also comments on the consistency of the roads being very soft, therefore leading to high rolling resitance vaues. Therefore, in the oil sands mining industry, it is essential to accurately predict cycle times by accounting for these high resistance values and their effects on performance.

2.4 EFFECTIVE FLAT HAUL (EFH)

Sheremeta (2015) mentions that the oil sands mining industry has experienced rapid growth in the past, and now that mines are starting to become more mature, average haul distances have been increasing, along with costs and recent shrinking profits due to depressed commodity prices. The author also comments on the effects of increased costs due to poor road conditions. Sheremeta suggests using the often-overlooked metric of EFH, or effective flat haul, to better analyze and categorize haul data.

As Curi et al (2013) put it, EFH is a “calculated parameter that accounts for both the distance from the source to the destination, and the elevation change from the source to the destination. The EFH normalises the elevation changes and distance travelled” which then “enables a comparison of the energy consumed and tonnage moved for a mining activity.”

Campbell & Hagan (2012) developed an equipment selection model based on the characterization of the road network and EFH. Several ranges for EFH values were assigned to different gradient ranges as modifying factors. Because these values were assigned as averages, lots of potential detail was lost but it made the approach easier to understand and implement. Hargroves et al (2014) have also mentioned the use of EFH in order to normalize elevation changes and account for large impacts on fuel/energy consumption.

EFH has been proven useful, and some large mining companies have found ways to benefit from such a metric, like Newmont mining has implemented it as one of their KPIs in order to better categorize and account for their production and equipment usage figures. (Newmont, 2014)

2.5 SUMMARY OF LITERATURE REVIEW

A review of literature in the areas of simulation, productivity, operational parameters and EFH was performed. The chapter started by reviewing some of the published applications of simulation in the mining industry, further sorting these based on their intended area of use within the operation. The literature review indicates that there is an existing gap in current research to solve the problem of inaccurate cycle time estimations. Then, an overview of published research on analyses and simulation relating to productivity and efficiency of shovel and truck operations in mining is presented, highlighting the importance and necessity of a framework that can lead to more accurate estimates of cycle times, such as the one presented in this thesis.

The literature review also points out that the current problem is partly rooted in the lack of models that are driven by operational data, therefore relying on ideal-conditions performance parameters such as those provided by the equipment manufacturers. Since the cycle time is one of the central and most important parameters of any mining operation, any gaps and insufficiencies within the realm of cycle time prediction and simulation have an aggregated effect on the estimation and simulation of productivity and other performance indicators.

Since oil sands mines are more extensive in area than other traditional (hard-rock) mines, the haul times represent a greater portion of the cycle time. This thesis will focus on accurately predicting this specific component of the cycle time. Simultaneously, the literature points to rolling resistance as one of the main parameters affecting truck performance, and several papers investigating and quantifying the high rolling resistances in the Athabasca oil sands mining operations are reviewed. Lastly, literature and documentation relating to EFH is summarized.

3. THEORETICAL FRAMEWORK

The main goal of the approach presented in this thesis, and thoroughly described below, is to accurately generate estimates of cycle times by capturing the operational characteristics of the mine's material handling systems, namely those of the shovels, trucks and their interaction with the road network. By appropriately doing so, the framework can then result in a simulation tool that mimics the behavior of the operation, allowing planners to examine the outcomes of proposed changes to the mine schedule. In addition, the correct application of this framework can result in a very useful tool for production forecasting, planning and ongoing performance evaluation.

This program, at its most basic level, generates estimates for cycle times between discreet pairs of sources (dig locations where the shovel is extracting material) to destinations (a crusher, processing facility, stockpile or other dump type). After careful review of the dispatch data of the mine within the case study, it was determined that a disproportionate amount of variability within the cycle time comes from the loaded haulage component. In turn, there are three main factors that contribute to said variability in the haul time. From most to least influential:

1. The trucks' variable performance in relation to the changing characteristics of the road (gradients and rolling resistance)
2. Hindrances in the haulage of material, attributed to the microscopic behavior of the operation (traffic, bunching, operator proficiency, equipment malfunctions and loss of performance due to age)
3. The trucks' variable performance in relation to the inconsistency in payload quantities (loading variability and its effects on rim pull)

Having identified the haulage component as being the culprit of inaccuracy, this framework places relatively more weight into the correct analysis and simulation of haul times than the rest of the other parameters within the cycle time. This is reasonable since there are many more varying parameters in truck performance and road interactions than within shovel performance and operations, which are fairly constant. The non-haul factors of the cycle time, however, are stochastically simulated from probability distributions fitted to dispatch data, therefore generating very reliable estimates.

The superiority of this framework's outputs and subsequent applications over other commercially available or in-house estimation tools is rooted in the fact that this model is data-driven, meaning that most of its inputs come from operational records from the mine. As expected, this leads to results that more closely resemble the reality of the operation, whereas other approaches are simplistic in that they rely on manufacturers' performance data, which assumes ideal working conditions. In an environment as complex as a mining operation, this is an oversimplification.

The sections within this chapter outline the data requirements for the application of this framework, followed by a thorough explanation of the logic implemented to produce quality results. Since this is a probabilistic approach, confidence intervals are built around the mean value of several replications. This is beneficial since it helps establish the quality of the outputs and can be easily compared to historical data for validation and verification. It is in Chapter 4 where this framework is applied, validated and verified with actual data from a mining operation.

3.1 DATA REQUIREMENTS

3.1.1 Road Network

A digital model of the mine's haul road network is required for the use of this framework. The accuracy in the outputs produced by this program is, to a large extent, dependent on the accuracy and precision of the road network model. The proper characterization of distances within segments is important, but properly capturing the changes in elevation is essential, since these directly affect the performance of the truck.

For use within the proposed framework, individual roads are called segments, and intersecting roads should have a common node. In addition, if two or more roads come together to form a single road, these should all end or begin at the intersecting node (see Figure 3).

Efforts should also be made to avoid sharp turns (which is often unrealistic), and model the actual curvature of non-straight roads (see Figure 4).

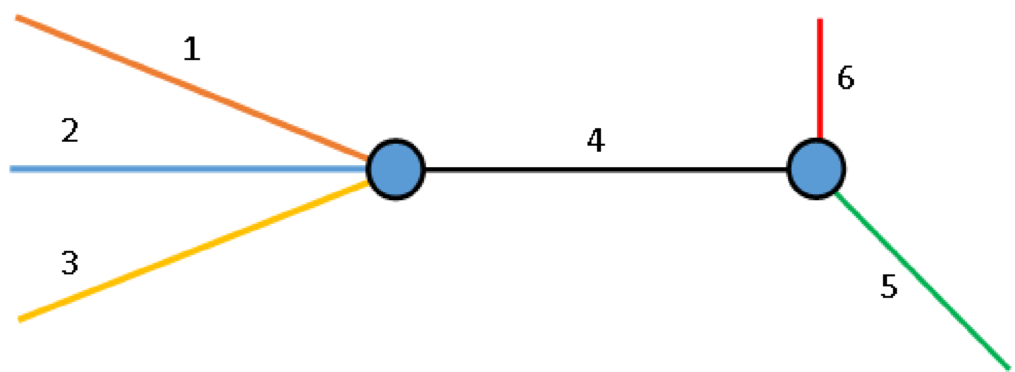

Figure 3: Node and segment logic

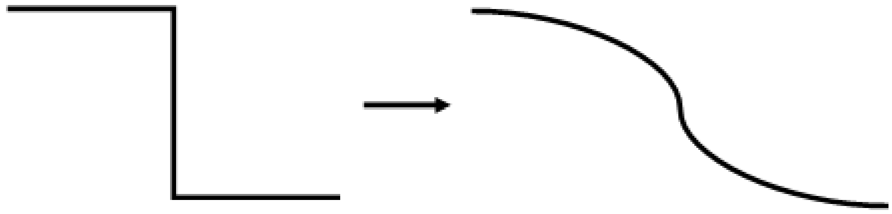

Figure 4: Curvature detail

In addition to the above, both main and temporary roads should be modelled to make sure that sources and destinations are located on the network itself, or in close proximity to a node within a segment so as to not have any gaps in detail (see Figure 5).

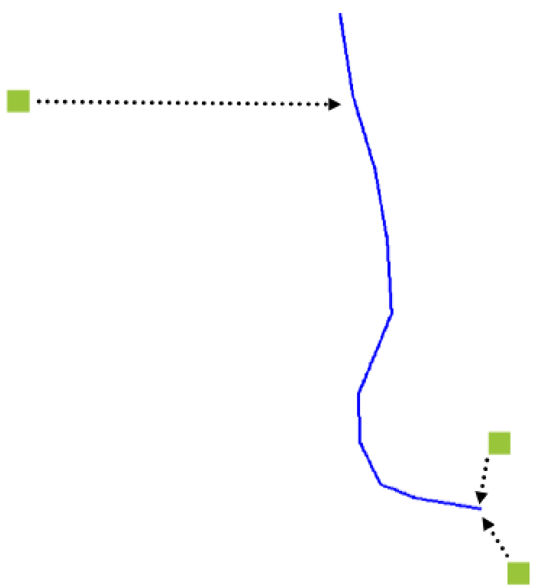

Figure 5: Proximity of sources/destinations to road network

3.1.2 Dispatch Data

Mine dispatch systems record vital information that is necessary in this framework, pertaining to the individual elements of cycle time as well as payload. This framework features full integration with SQL databases, so it is beneficial to link dispatch records to a local database.

To provide an estimate of the complete cycle time, probability distributions will be fitted to the following:

- Payload (tonnage)
- Spotting time
- Wait to spot time
- Time in queue
- Loading time
- Idle time at dump
- Dumping time
- Other delays
- Empty haul time (this parameter can be simulated using the program, but historical averages are used when no information about dispatching logic is available)

In addition, it is useful if the records for every cycle include information such as dates, load and dump coordinates, distances travelled and identifiers pertaining to specific dig and dump locations. Other potentially useful information includes operator ID, equipment ID (both for excavators and trucks) and a timestamp (or shift number).

Other more advanced applications of the framework may require additional data to the listed above and varies case by case. In the absence of the above data, such as the case of planning for new mines, distributions can be theorized or adopted from similar mines (benchmarking).

3.1.3 GPS velocity records

Usually separate from database records, but almost always readily available, are records from GPS trackers in the trucks. Often, these data logs include latitude, longitude and elevation coordinates, along with an instantaneous velocity. These parameters are usually recorded periodically at specific time intervals.

It is important for these records to differentiate between loaded and empty trucks, since they behave differently because of payload effects on performance. In this case study, the records were not explicitly segregated, so further manipulation using the timestamps and shift identifiers was performed to accomplish this.

Having obtained said records, it is imperative to find a long section of haul road that is mostly flat, and extract those records, while differentiating between loaded and empty. Once extracted, a probability distribution will be fitted to the data sets for subsequent calculations in the algorithm. This ensures that the variability and characteristics of the truck/network interactions are captured.

3.1.4 Manufacturer performance data

To be able to mimic the changes in truck speed with varying resistance values, the rim-pull curves for the specific truck type(s) should be obtained and put into table format, with one column being total rim pull force and the other being the corresponding speed.

For the main method of cycle time simulation in this thesis, this information will not be used to assign speeds like in TALPAC, but rather to examine the relative changes in velocity between rim pull values encountered when varying payload and total resistance in the simulation.

Knowing the weight and dimensions of the truck is also necessary information that is readily available from manufacturers' literature and specifications. The rimpull curve for a CAT797F mining truck is presented below (Caterpillar Inc., 2013):

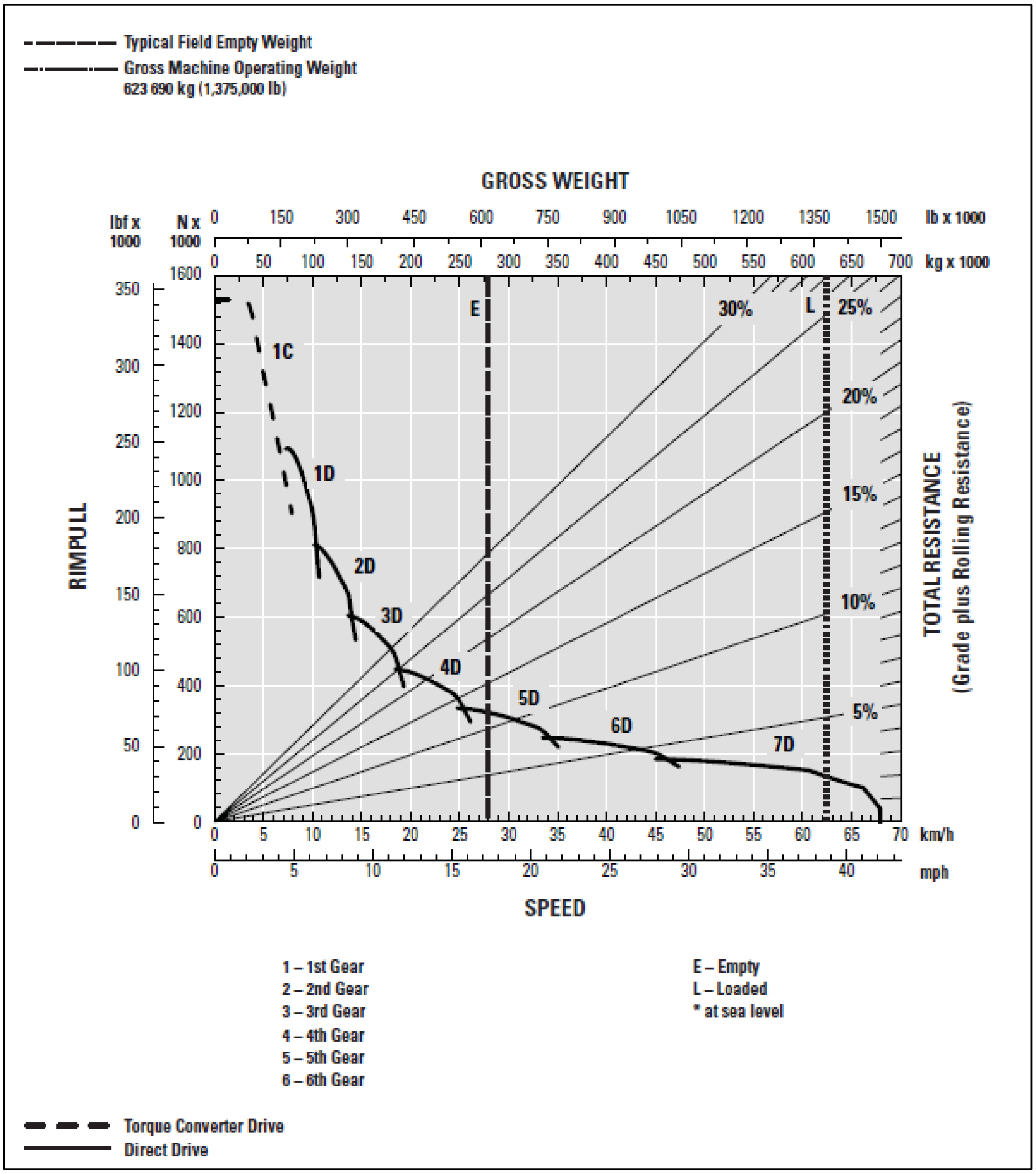

Figure 6: Gradeability/Speed/Rimpull curve for CAT797F (Caterpillar Inc., 2013)

Note that the use of retarder curves is not necessary within this framework.

3.1.5 Mine-specific operational parameters

Mine-specific parameters should be defined, as they have significant effects on the truck-shovel system. These include safety guidelines such as:

- Imposed speed limits (often lower than the truck's maximum achievable speed)
- Actions at intersections
- Actions in proximity of other equipment
- Actions in proximity of workers on foot
- Minimum safe following distances on various road features like sharp turns, or downhill

In addition, the proper characterization of rolling resistance values within the mine's roads should be performed. Joseph, Curley and Anand (2017) provide excellent guidelines and insights into rolling resistance measurements and typical values within oil sands mining operations, stressing that seasonal weather changes affect RR significantly.

This framework allows for the assignment of individual RR values to specific segments of roads, and for changing values for different seasons (when water creates ruts and increases resistance).

3.2 STRUCTURE AND LOGIC

The following code was written in MATLAB and consists of a main script (aptly called ‘MAIN’) that prompts the user for various parameters necessary for calculations, and then calls other functions that perform specific tasks in the overall logic of the algorithm.

This framework has two distinct methods of calculating haul times. ‘Method 1’ is based entirely on performance data from the trucks’ manufacturer – similar to TALPAC and CAT FPC, serving as a benchmark for comparison with the second method. ‘Method 2’ is a data-driven simulation of haul times that incorporates data from the site and dispatch, yielding much more accurate and realistic outputs. The remaining parameters of the complete cycle time are calculated in the same manner, regardless of the method.

In addition, there is another important distinction in the algorithm. This code was developed with high integration ability to a database through direct querying, operating under the assumption that the intended application of this framework is for an existing operation with a significant amount of dispatch data recorded and available within the database.

In addition, this was performed in order to avoid ‘hard-coding’ and making it more flexible with changing outputs. However, this framework also allows users to explicitly feed data into the model in the absence of historical dispatch data – using benchmarking from other operations, which is often the case with new mines.

Figure 7 below provides an overview of the entire framework, showing the order in which the sub-functions are called and a summary of what they do. The following subsections of this chapter go into more detail.

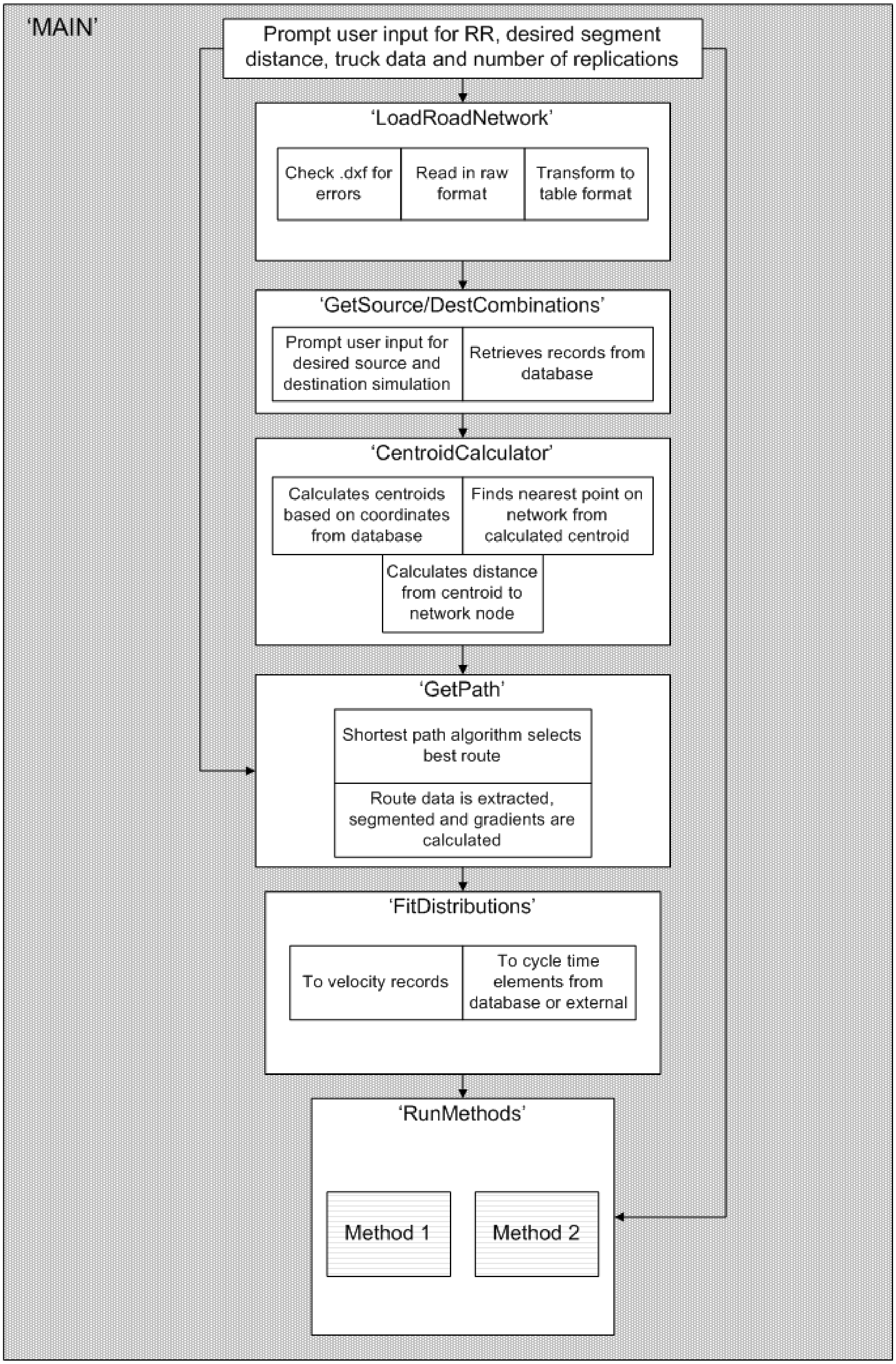

Figure 7: High-level algorithm flowchart

3.2.1 Main

This is the primary script of the code, since most of the initial input parameters and data sources are defined here. In addition, this main function calls, controls and receives output from other sub-functions. The main inputs that are asked of the user in MAIN are:

- File path or location of the digital model of the road network
- Locations of Sources/Destinations, or time period to be used for querying into the database
- Desired output: complete cycle time simulations, haul times only, or more advanced KPI's (user defined)
- Desired segment length for subsequent calculation (also a control for resolution/precision and directly related to run time)
- Truck type(s)
- Rolling resistance values (if using a single value for desired analysis)
- Number of replications and desired confidence intervals

Additionally, the final outputs and results from the simulation are recorded here in the user's preferred format. Other more advanced applications of the framework can also happen here, as illustrated in the case study.

3.2.2 Load Road Network

This is the first sub-function called from MAIN, and its main purpose is to read the .DXF file containing the digital model of the network. In addition, it manipulates the read data and places it into table/matrix format by assigning it an individual node identifier at the network's original resolution. This initial table contains information of all the points in the network model; it stores its 3D coordinates and node IDs in separate columns.

The next step within this function is to logically re-arrange the individual points into segments, maintaining the raw resolution. The table gets altered based on the points' coordinates and the code identifies nodes within the same lines (as explained in chapter 3.1), ultimately defining the road network's segments, within the native resolution – which means that often these are uneven in length.

At this point, the data matrix has twice the number of columns, containing information of the 'From' node, and the 'To' node, each with unique identifiers. Having this information, the Euclidean distance of each segment between points is calculated using the coordinates in 3D, yielding a new column for segment length. Similarly, the gradients between points are calculated in 3D, and put into a new column for each segment.

The final step within this sub-function involves checking the gradient values of each and every segment and capping it to user-defined limits. This step is necessary to make sure that errors in the digital model are eliminated, especially at native resolution before further manipulation. Often times, there may be a very short segment (for example, of no more than a couple of meters in length) with a gradient value that is unreasonable (i.e. 20%). This scenario is common when, as in the case study in the next chapter, the surface of the roads was scanned by laser and the digital line representing the road goes over imperfections or other features. This function also allows users to establish limits on the relative change of gradients from one segment to the next and requires a more advanced knowledge of the characteristics of the mine's road network.

The flow chart in Figure 8 below shows a summary this function's main actions.

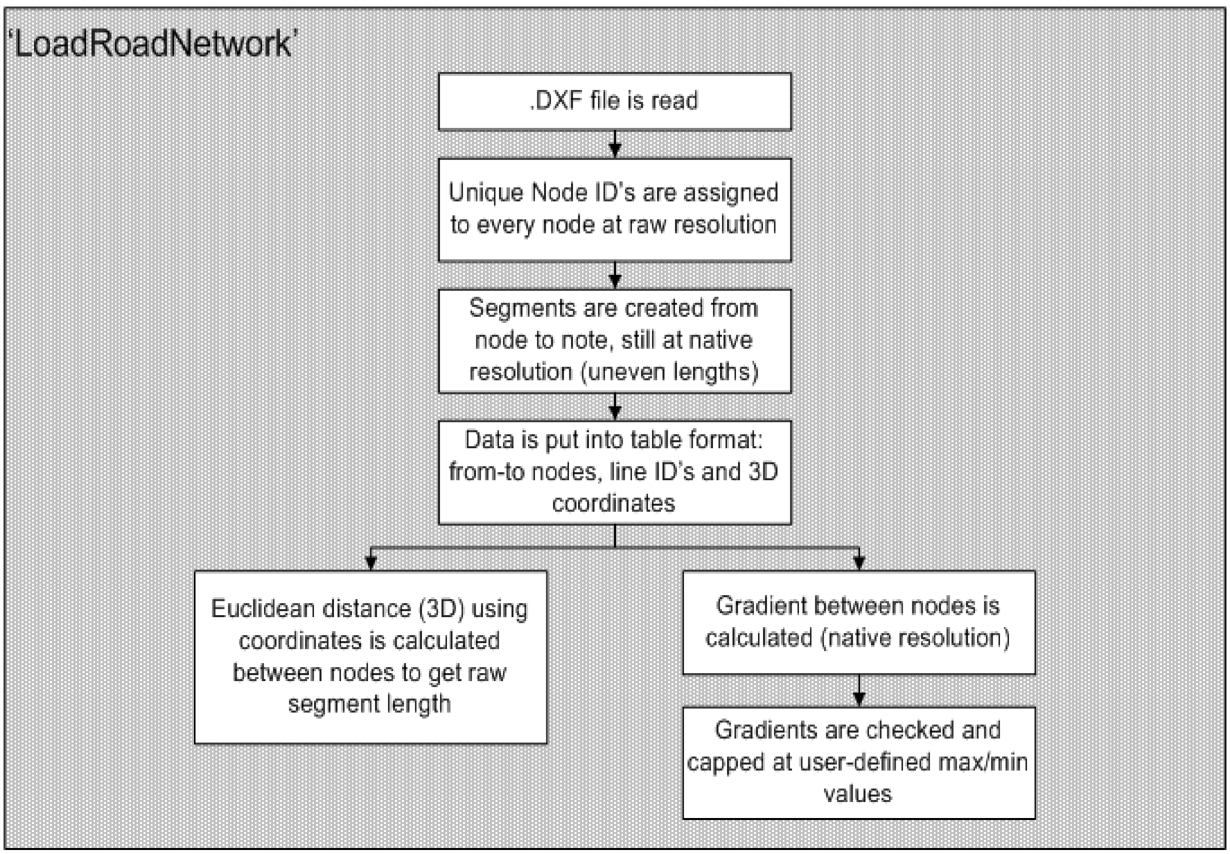

Figure 8: LoadRoadNetwork function flowchart

3.2.3 Get Sources/Destination

If the user's routes of interest already exist and are in operation, using the user inputs from MAIN, this sub-function can connect to the database and retrieve the dispatch records for a number of source and destination combinations either based on coordinate ranges, time periods, or by polygon IDs and dump locations. Having extracted the desired data, the code can then call a subsequent function for further manipulation.

In the absence of historical data, which is the case of new proposed haul routes or new mines, this function allows users to select specific coordinates in proximity to the network. Both cases above lead to the CENTROID CALCULATOR function. Figure 9 below outlines this function's logic.

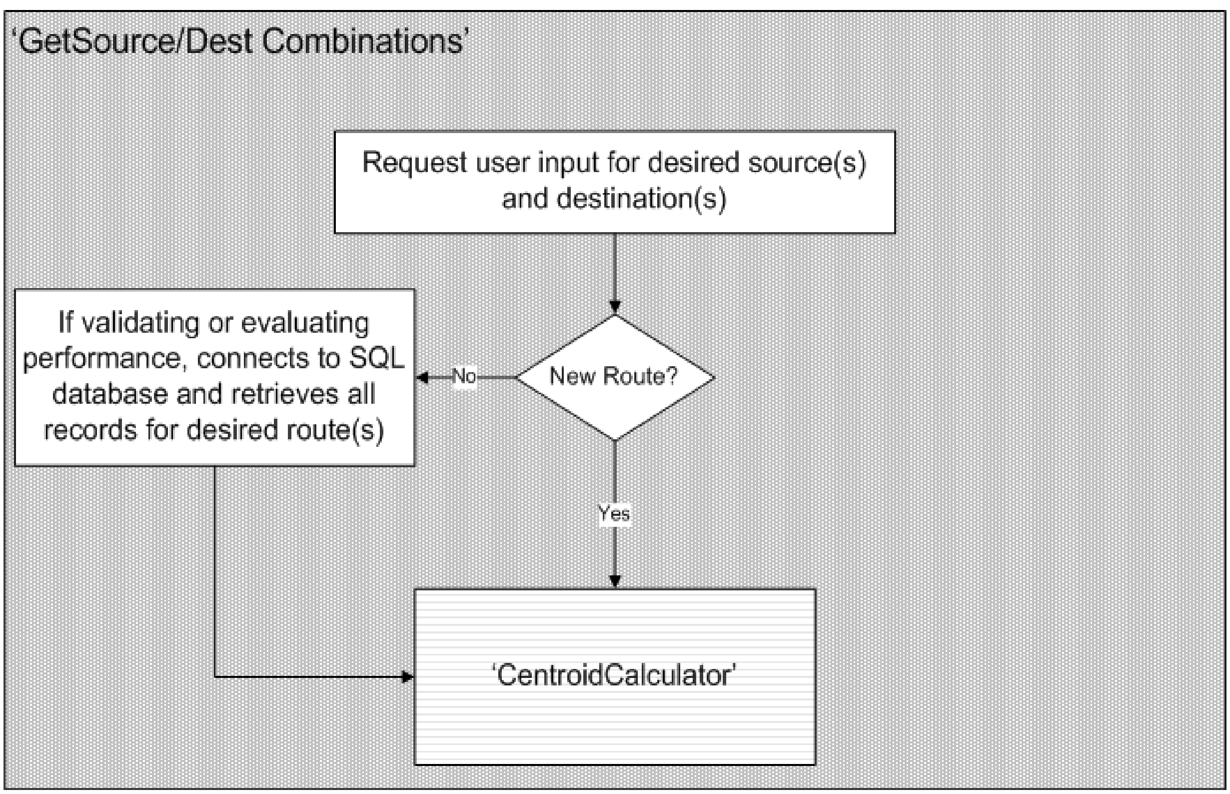

Figure 9: Get Source/Dest Combinations function flowchart

3.2.4 Centroid Calculator

This function receives the dispatch records extracted from the database in the previous function and, using the coordinate for every record, defines the sources' centroids by calculating the arithmetic mean of its coordinates. For new routes, the coordinates that were input in the previous step are brought over. In both cases, the centroids or the user-defined locations undergo a 'nearest-neighbor search' that identifies the closes point to the network from these locations. In addition, the distance from centroid to the node on the network is recorded.

It is important to note that this nearest-neighbor search algorithm is aware of changes in elevation coordinates from the centroids to the nodes in the network. This ensures correctness in choosing a nearest network node. Problems could arise if changes in elevation are ignored, as the roads are often in select benches that may not be accessible from all areas. Figure 10 below shows this function's logic:

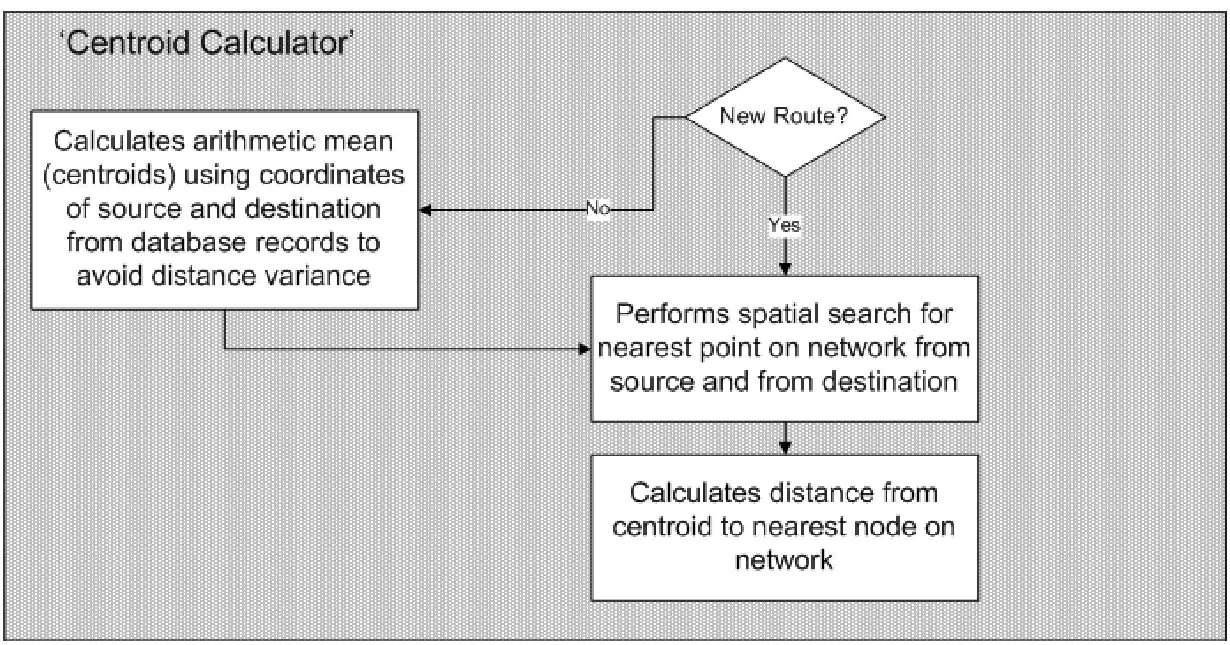

Figure 10: Centroid Calculator function flowchart

3.2.5 Get Path

Having established a source and a destination within the network in the previous step, an algorithm that finds the shortest possible path between these is implemented. All possible paths are evaluated, and one is selected based on shortest distance. A more advanced version of this algorithm can also add an elevation change criterion in selecting an optimal route, but is very site-specific.

Once the optimal route is selected and delineated, all the data relating to these segments is extracted from the main matrix and put into a new table, conserving the native resolution from the original .DXF file. The lengths of all these segments are added and compared to the distance found by the shortest-path algorithm as a check for correctness. This new matrix will go on to subsequent functions and calculations, and serves as one of the main elements within this framework.

The next step within this function is to merge (or divide) the segments of native resolution to create segments of the user-defined length (in MAIN). In order to preserve the characteristics of the original file, the gradient and length of each original segment is used in a weighted average calculation, in order to obtain a correct gradient in the newly merged segment of predefined length. This “smoothens” the variability of the gradients within the selected path and establishes the desired resolution for subsequent calculations.

As a rule of thumb, the user defined segment length is the minimum allowable following distance between two trucks in a haul cycle. In the mining industry, this is often a multiple of the overall truck length. Merging and smoothening cuts down significantly on run time while preserving the original behavior of the network. Figure 11 shows the order in which these actions are performed:

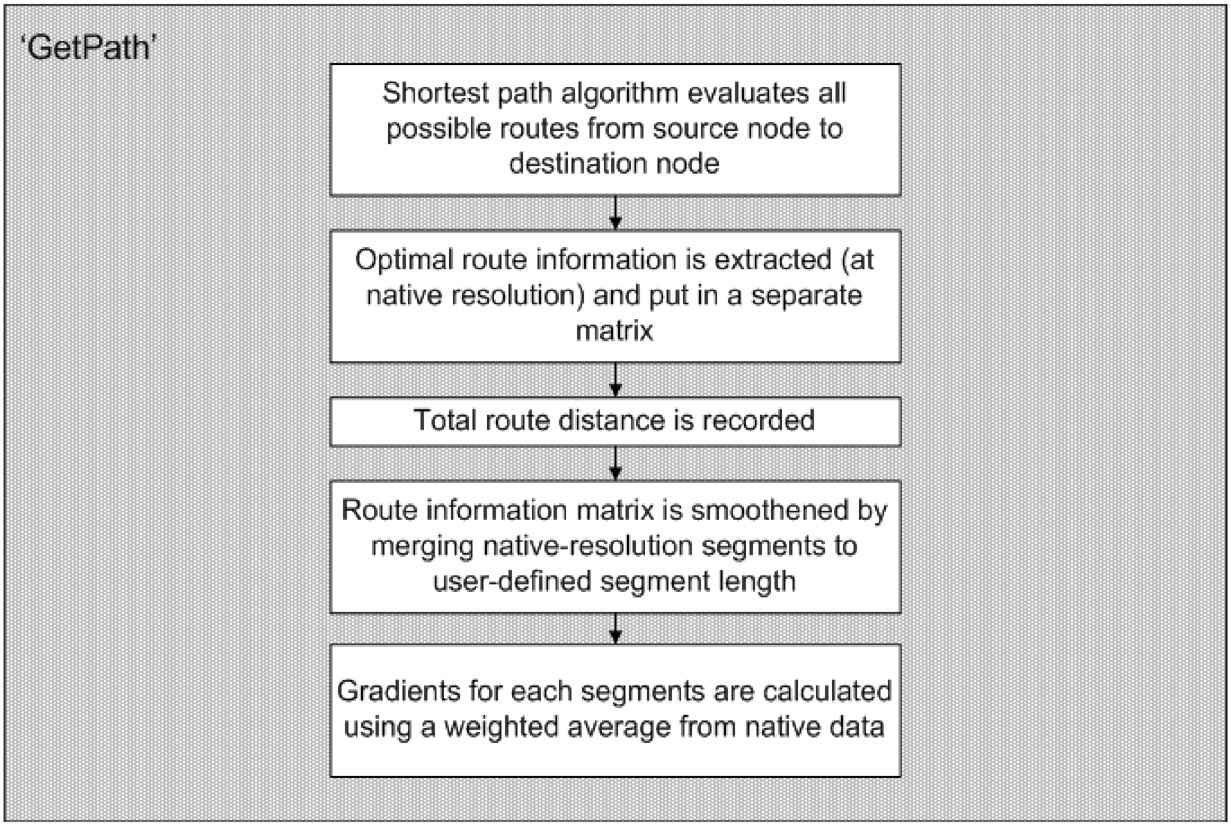

Figure 11: GetPath function flowchart

3.2.6 Fit Distributions

In preparation to calculate haul and cycle times, an SQL query with user-defined parameters is performed, extracting data relating to the following fields:

- Payload tonnage
- Flat haul velocity

And, if performing a complete cycle time simulation,

- Cycle time elements

Having extracted the desired historical data, the code then fits various probability distributions to the data, finding the one that best represents each parameter. A probability distribution element is created in MATLAB, allowing for random sampling in later steps. The user can implement other more advanced criteria into this step, such as capping values or handling the SQL query.

The code also allows users to upload external files, or explicitly feed the code distribution parameters, in the absence of historical data. Figure 12 below shows the steps within this function:

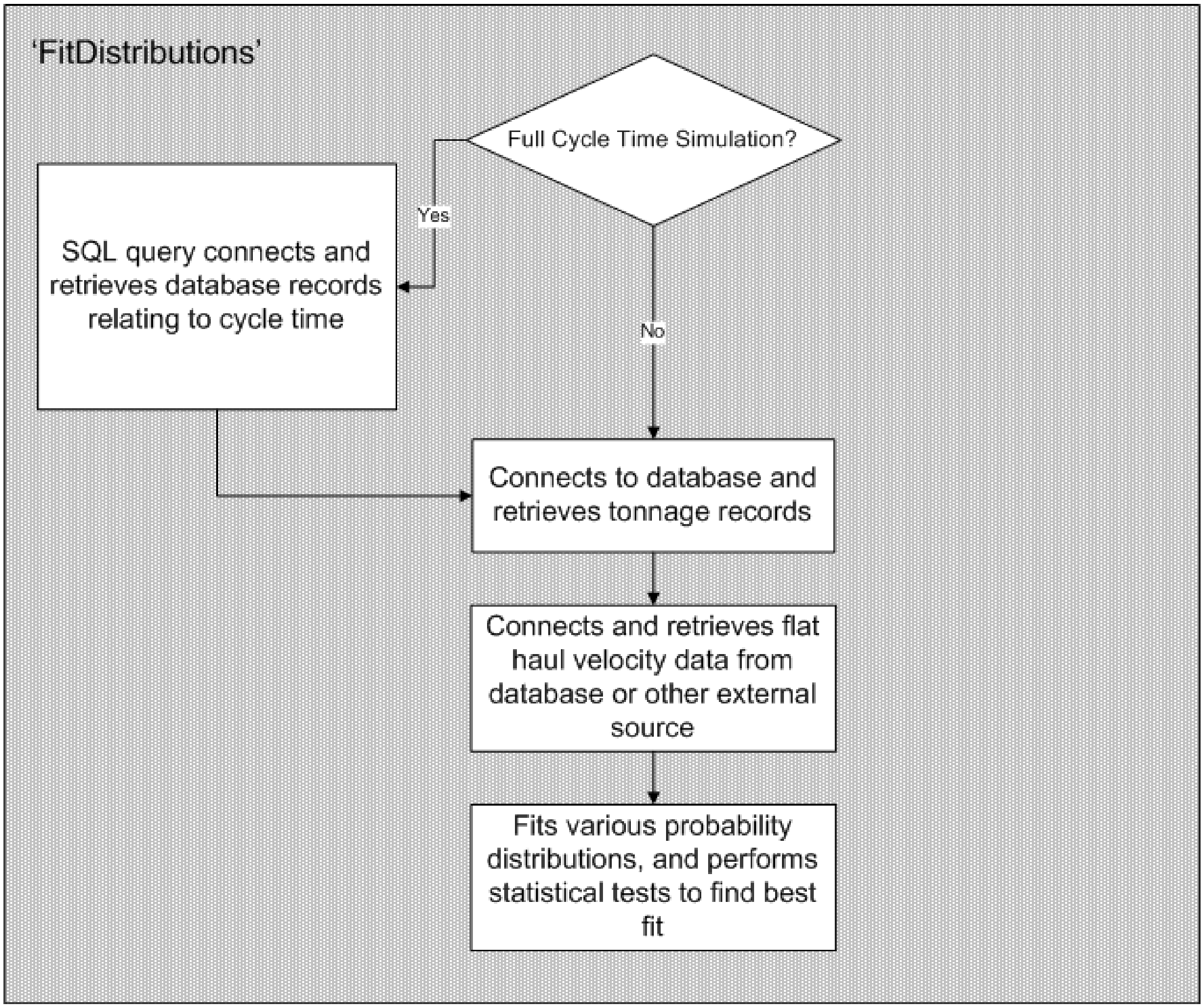

Figure 12: FitDistributions function flowchart

3.2.6.1 Dispatch fields

For complete cycle time distributions, data relating to the complete cycle time activities is extracted. These vary from operation to operation, but in general include loading time, dumping time, spotting time, time in queue, idle time, delays, etc.

Both for haul time simulation and complete cycle time simulation, the variability in the payload tonnage must be captured. This can be included in the original SQL query, uploaded externally, or explicitly input as a distribution or a fixed value. The payload tonnage affects the performance of the truck directly.

3.2.6.2 Flat haul velocity

These records are based on instantaneous velocity records situated within coordinates near known road segments with flat roads. This eliminates the variability of gradient resistance and captures the behavior of trucks within the system.

An effort should be made to record these data points excluding areas where the truck may be accelerating, or decelerating – this is accomplished by selecting coordinates well within the flat section of road, choosing limits that are not close to where the flat road starts or ends. A probability distribution that is capped at a known top speed must be fitted in order to avoid unrealistically high velocity samples which would, in turn, lead to underestimating the haul time.

3.2.7 Run Methods

This framework presents two methods of calculating haul times (the complete cycle time calculation is the same for both). The first method, 'Method 1' is, in its entirety, based on truck manufacturers' performance data, which assumes ideal conditions and some other simplifying assumptions. As such, Method 1 serves as a benchmark to evaluate the historical performance against what could be considered a theoretical maximum. In contrast, 'Method 2' is data-driven and it captures the variability and behavior of the trucks within the mine and their interactions within the network. In general, Method 1 underestimates the haul times, and Method 2 provides much more accurate and realistic estimates. Figure 13 and Figure 14 show their overall logic.

3.2.7.1 Method 1 - Benchmark

This method evaluates the total resistance at each segment, by adding the previously defined rolling resistance to the gradient of each segment. Then, a random sample is generated from the payload tonnage distribution (if available), and calculates the rim pull force - which is based on the total weight of the loaded truck.

Having calculated a rim pull value for each segment, the algorithm then performs an interpolation of the manufacturer's rim pull data to assign a speed to each segment. This manufacturer-supplied data assumes ideal conditions. The segment length is then divided by this corresponding speed in order to find the time it takes to travel through said segment. The sum of all segment times results in the total hauling time between source and destination.

This method then calculates the time it takes for the loaded truck to travel the total path distance, assuming it is flat. The EFH factor is found by and dividing the actual rim pull estimate by this.

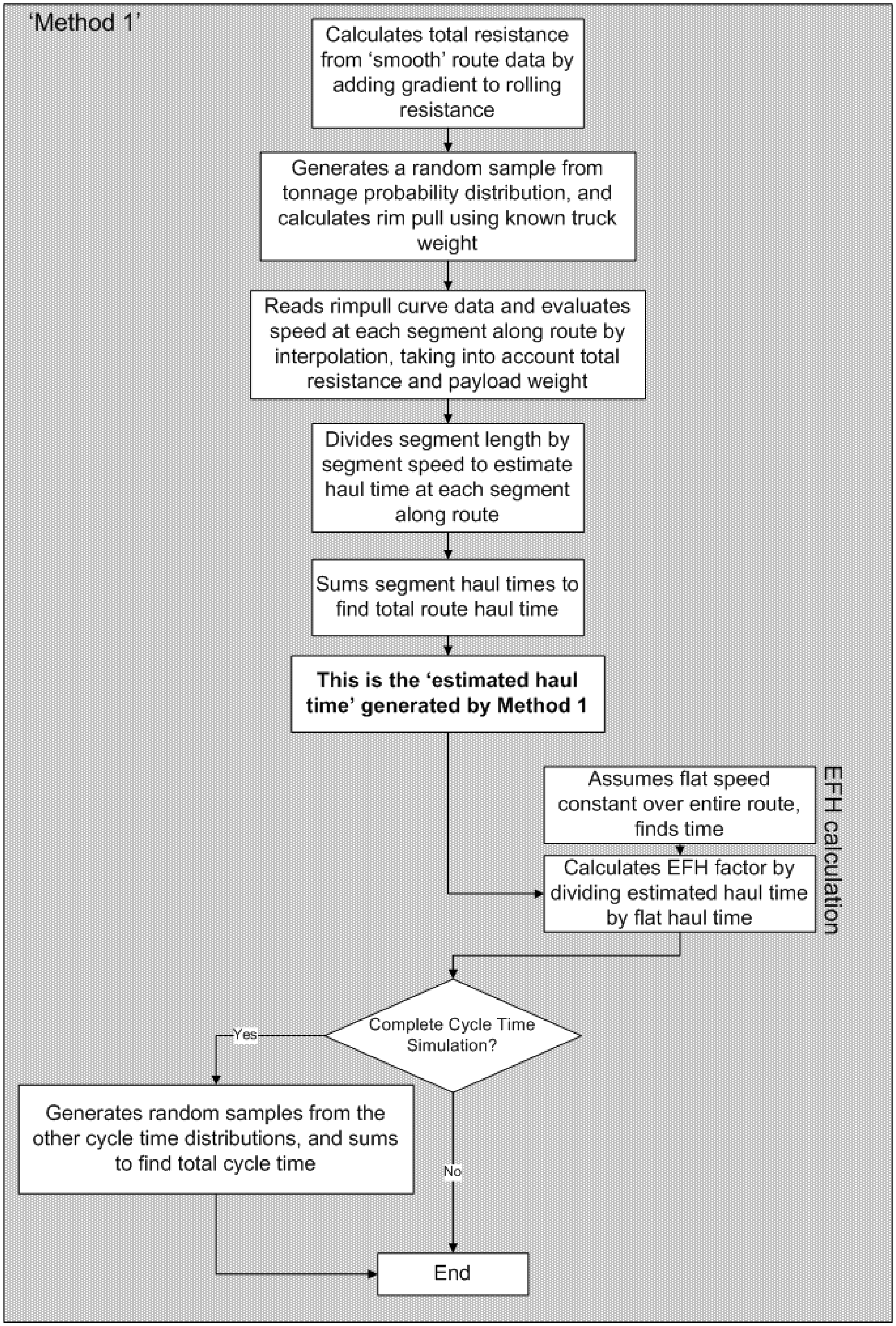

Figure 13: Method 1 flowchart

3.2.7.2 Method 2 - Simulation

This method is very similar to Method 1, with the exception that instead of using the manufacturer-defined performance specifications, this method uses data from the operation itself, and focuses on finding the relative behavior of the truck with changing resistance values.

Instead of finding the speed corresponding to a rim pull value for every segment, this method generates a random sample from the velocity probability distribution. This value is then used to normalize all the velocity values within the manufacturer's rim pull curve – instead focusing on the relative velocity change with each increment or decrement in rim pull force (in this case, varies due to total resistance). The algorithm then continues to apply the appropriate changes to the originally sampled velocity for every segment. Time at each segment is calculated in the same manner as Method 1, and total time is the sum of time at every segment within the route or path. The EFH factor is calculated in the same manner as in Method 1, but instead of assuming the manufacturers' top speed, the initially sampled flat haul velocity is used.

Using data from the operation ensures that the variability in performance of the trucks within the network, due to weather events, road conditions, traffic or other hindrances is accounted for, leading to more accurate estimates of haul and cycle times. In addition, users can implement time penalties to account for acceleration, deceleration and other truck behavior.

The haul time estimates and outputs generated from this simulation are, generally, higher than those of Method 1 due to the incorporation of real-world behavior, moving away from ideal conditions and other such assumptions.

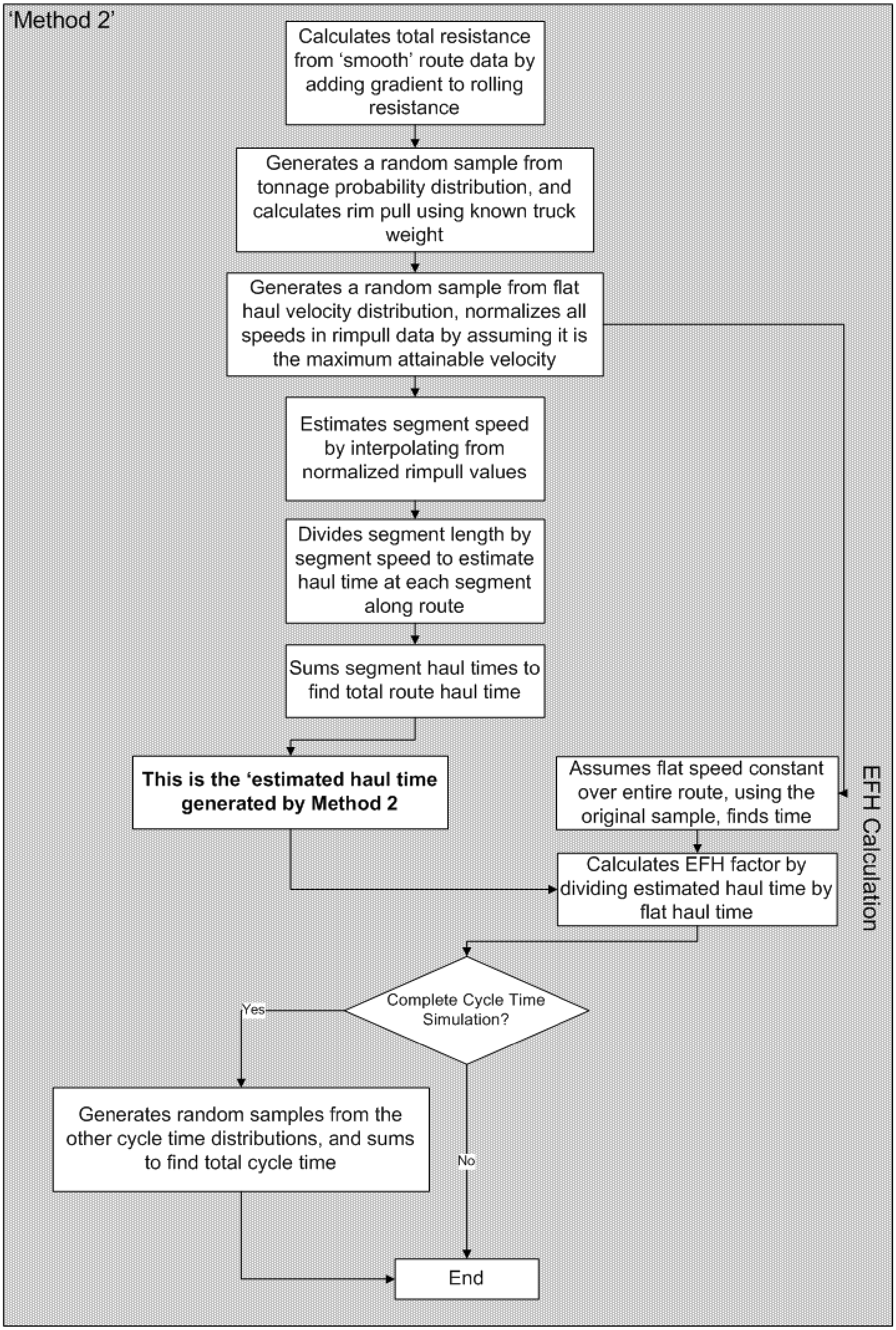

Figure 14: Method 2 flowchart

3.3 REPLICATIONS

Due to the probabilistic nature of these simulation methods, several replications must be generated in order to quantify the variability of the outputs. From these replications, a half width is defined at a desired confidence interval. This helps in the validation/verification stages and for comparing different proposed operational changes. The code is capable of automatically sending queries to the database to automatically compare outputs from the simulation to historical averages.

If only the haul time is desired, Method 1 does not need to generate replications as the inputs are fixed and are deterministic. However, for complete cycle time determination, the variability in the other fields will be captured and will require multiple replications.

3.4 OTHER USES

The cycle time is the essential parameter of all mining operations. Having simulated these accurately, many other applications can be developed. Apart from helping planners assess the impact of changes to the system, this simulation framework can serve in estimating and predicting productivity measures that relate to production rates and equipment utilization.

The case study in the following chapter presents a more advanced application of this framework that focuses on long-range planning and estimation of various KPIs, all rooted within the appropriate estimation and simulation of cycle times.

4. CASE STUDY AND DISCUSSION OF RESULTS

4.1 OVERVIEW

The framework presented in this thesis was developed using data from a major oil sands mining operation in Northern Alberta. This section presents the results of applying the framework to said operation, which utilizes several CAT 797F trucks and multiple excavators. This operation operates year-round and is very extensive in area, and the range in hauling distance is quite wide.

The current method for estimating productivity was developed ‘in-house’ and is, in its most basic form, implementing a line of best fit on a graph containing loaded haul distance in the abscissa, and TPGOH_A (tonnes per gross operating hour, including empty hauls) in the ordinate. Figure 1 shows how unreliable this method can be. Figure 2 shows that there is not a reliable relationship between cycle time and haul distance.

This was the motivation for the development of this framework – a new method for calculating cycle times that accurately accounts for all sources of variability within the operation.

4.2 DATA ACQUISITION

Two years’ worth of dispatch data were made available for this study, but the data in the first year was not entirely useful due to the fact that this was a development-heavy period that introduced unusual variability to the operation.

Similarly, weekly velocity reports for trucks, shovels, dozers and other auxiliary equipment from year 2 were made available, although the records did not differentiate between loaded and unloaded trucks. In order to solve this, the timestamps from these records were cross-referenced to the dispatch records in order to differentiate between loaded and unloaded trucks, also taking their direction of travel in consideration.

The most important piece of information in this framework, the digital haul road network, was not explicitly available as the mine planning teams use different methods. However, a laser scan of the entire property was made available in the form of a digital three-dimensional surface. This file contained extreme detail of the gradients, features and relief of an extensive area.

In order to define where the roads were, the velocity records were overlain onto this surface, and the lines were drawn manually in GEMS. Since the velocity records did not contain an elevation coordinate, the manually drawn network was ‘pressed’ onto the detailed surface, thus capturing the gradients and elevations in great detail.

Figure 15 shows the GPS records from the trucks, which were used to obtain the rough shape of the network. Figure 16 shows the provided surface file with the correct and detailed elevations, and Figure 17 shows the finalized version of the road network model, which was based on a combination of the velocity records for X and Y coordinates, and the surface for the Z coordinates.

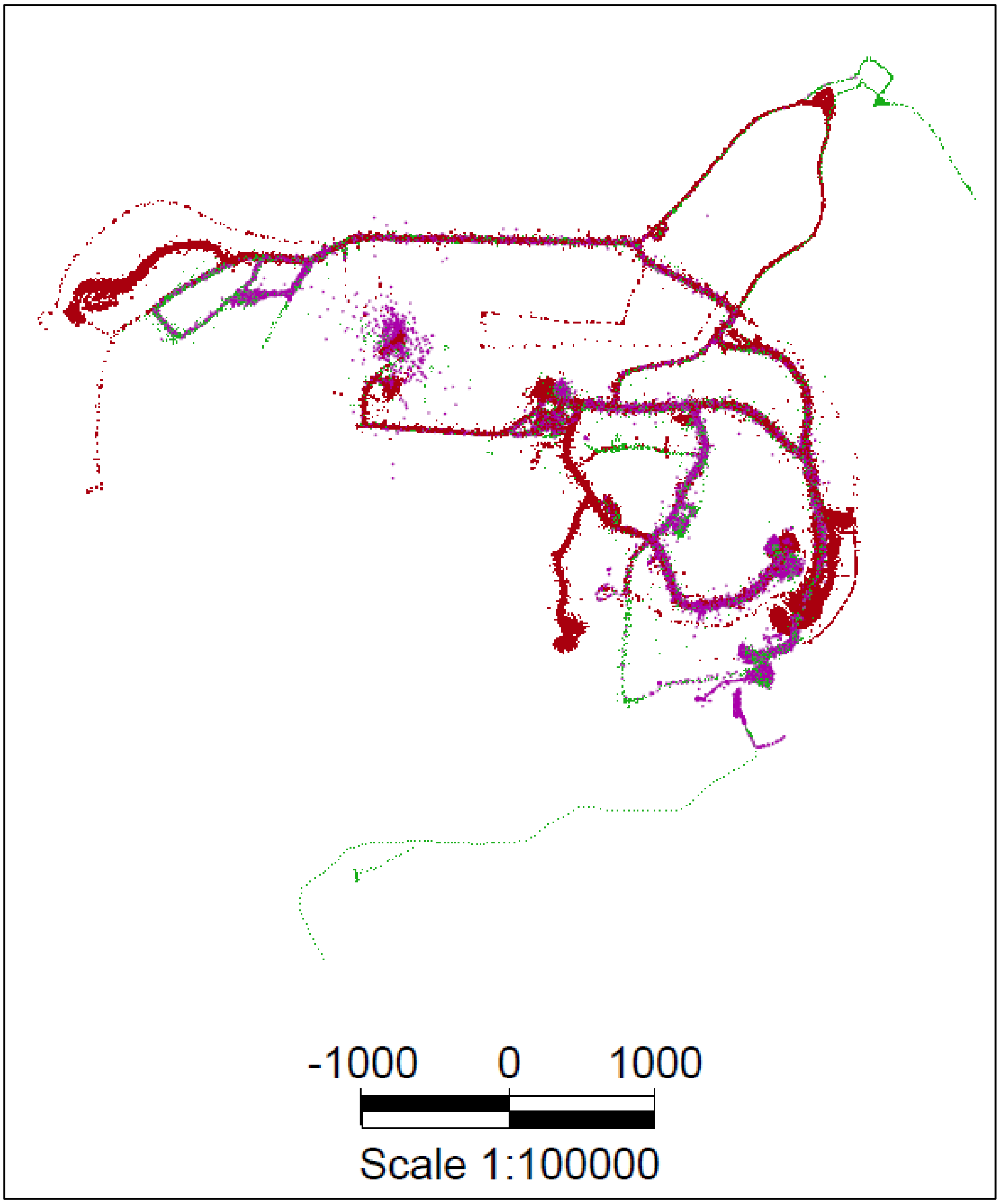

Figure 15: GPS velocity points

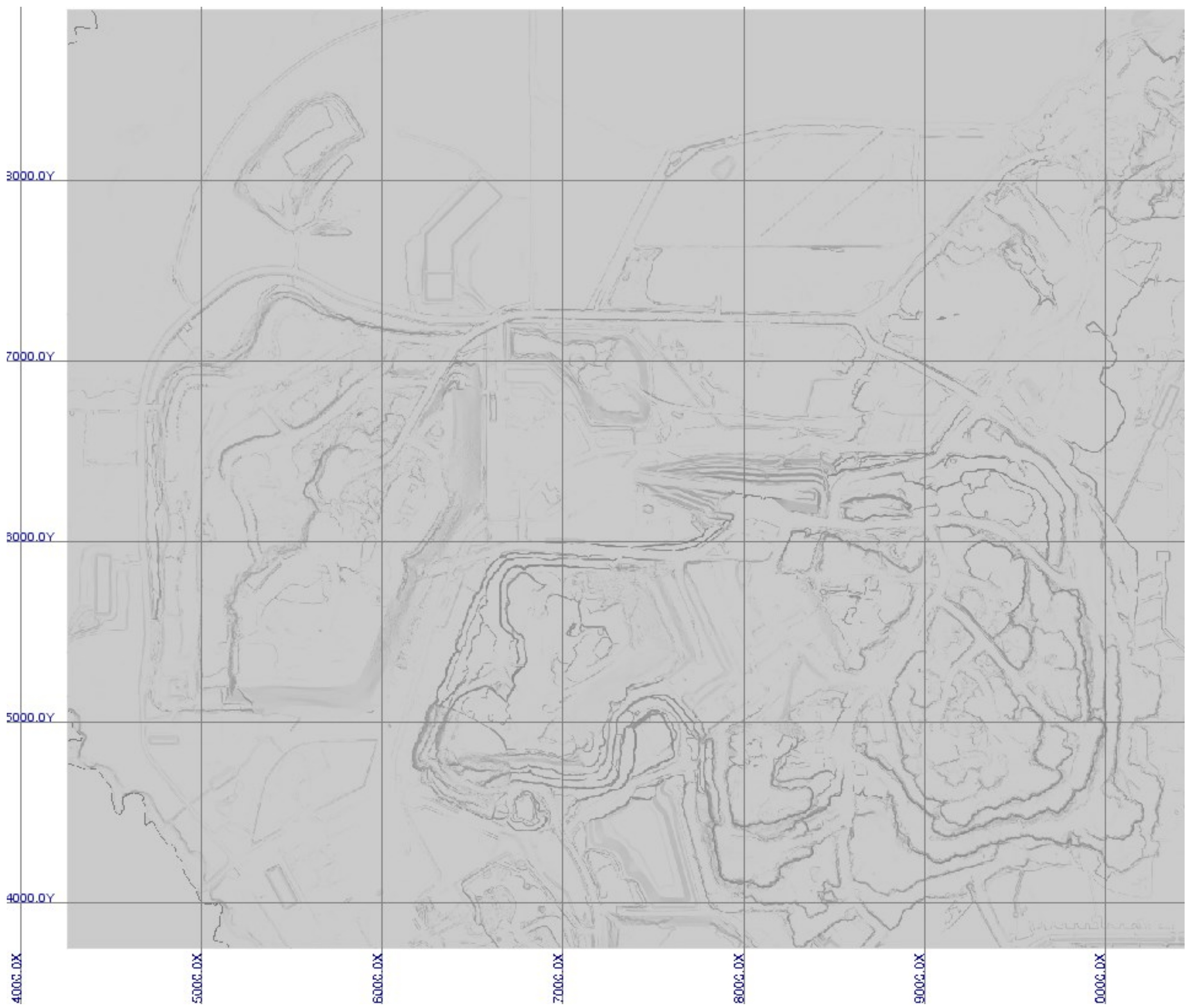

Figure 16: Topographic surface

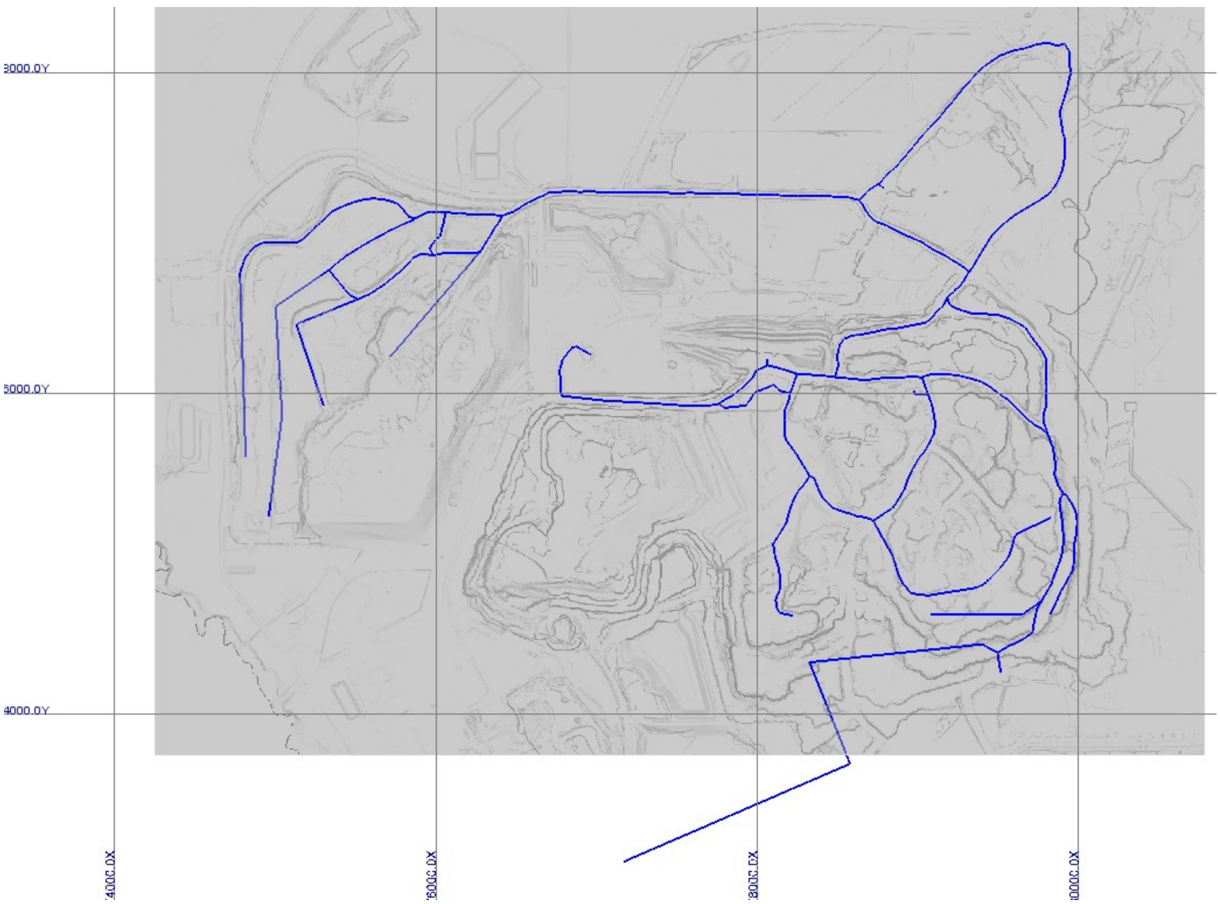

Figure 17: Resulting road network model

In this specific case study, mine polygons were not available as such, since the mine planners defined their ore sources as benches, resulting in high variability in hauling distances for the records within the same "bench ID". In order to account for this variability correctly, extensive manipulation of the coordinates in the dispatch records was necessary. The centroids for every individual group of dig and dump locations (possessing the same Dig/Dump Location ID) were found and used, making the calculations simpler but maintaining the original characteristics of the operation. Figure 18 shows what a typical cluster of records within the same dig location ID looks like.

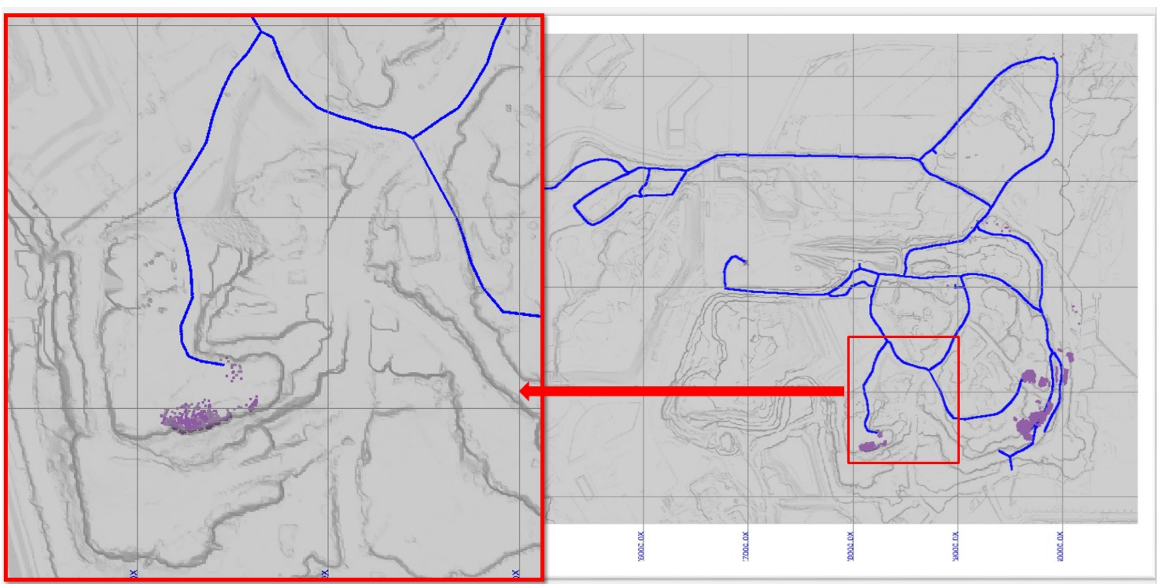

Figure 18: Dig Locations

A significant effort and amount of time was spent working around these deficiencies in data sources, but ultimately allowed for the identification of important data sources for future applications.

4.3 INPUTS TO MODEL

A quarterly simulation is presented in chapter 4.5. The rolling resistance varies in different areas of the mine, but for simplicity, a weighted average value was used and produced correct results: 5.5%. This value is in line with available literature. The segment length was defined as 35 metres. The road network consists of 47 separate lines that represent more than 35 total kilometers of haul roads. The distributions used in this specific case study are listed in Table 2 below.

Table 2: Probability distributions for quarterly simulation

Parameter	Distribution	Mean	Std. Deviation	Count
Loaded Flat Haul Velocity	10 + BETA(4.19, 1.92)	51.2 km/h	10.2	36480
Tonnage	175 + WEIBULL(9.57, 208)	380 tonnes	25.2	162337
Cycle Delay	60 * BETA(0.0923, 1.73)	3.04 min.	7.8	212842
Idle at Dump	EXPONENTIAL(0.869)	0.869 min.	1.93	213155
Dumping Time	TRIANGULAR(0, 1.43, 1.5)	1.23 min.	0.32	198238
Loading Time	GAMMA(0.935, 3.93)	3.68 min.	1.96	212842
Time in Queue	60 * BETA(0.168, 2.69)	1.17 min.	2.39	213002
Spotting Time	20 * BETA(1.63, 26.3)	1.14 min.	1.05	213134
Wait to Spot	WEIBULL(0.0542, 0.81)	0.06 min.	0.42	211731
Empty Haul Time*	GAMMA(4.2, 1.85)	7.68 min.	3.59	67987

One of the most important distributions input to this model is the one for loaded flat haul velocity. Several thousands of records were available to use and were extracted from a portion of road network that is several kilometers long and remarkably flat. The histogram is shown in Figure 19.

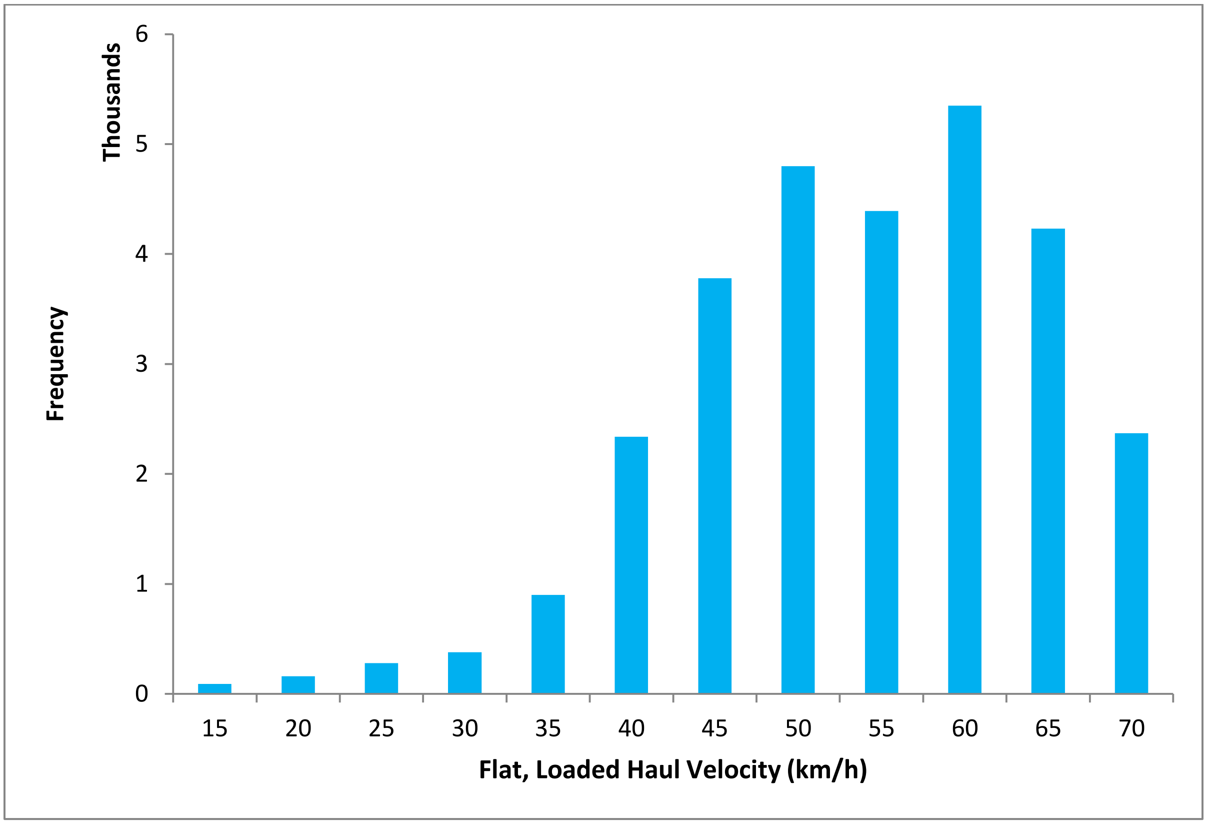

Figure 19: Loaded Flat Haul Velocity distribution

4.4 VALIDATION

The validation and verification of the model was performed by examining the haul time estimates produced by this framework over several haul routes that vary in distance. During the literature review stage of this study, it was identified that one of the shortcomings of available programs was that the estimates were not accurate for either short hauls or long hauls.

A short haul of 1.3 km, a short/medium haul of 2.6 km, a medium length haul of 4 km and a long haul of 8 km are presented below. The outputs from both Method 1 and Method 2 are compared against the records in the database.

As predicted earlier, Method 2 is much more accurate since it is data-driven, while Method 1 serves as a benchmark value where all conditions are ideal. The difference between Method 1 and the data records or the estimates produced by Method 2 can be thought of as how much the operation can be optimized.

For each of these cases, a table summarizing the statistics and accuracy of all methods is shown, along with histograms presenting the records in the database, and the outputs of the Method 2 simulation. It is important to note that the minimum haul time value in the Method 2 output histogram is equal to the unique estimate generated by Method 1 – as it is the best-case scenario.

The database records histogram shows that there are values smaller than this theoretical value, and it can be attributed to recording errors within the dispatch system. 500 replications were performed for each of these cases – taking only a few seconds of run time.

Table 3: Short Haul output summary

<table>
<tr><th>Short Haul
(1.3 km average)</th><th>Database</th><th>Method 2</th><th>Difference</th><th>Method 1</th><th>Difference</th></tr>
<tr><td>Mean</td><td>5.58</td><td>5.52</td><td rowspan="4">-1%</td><td rowspan="7">4.19</td><td rowspan="7">-24.9%</td></tr>
<tr><td>CI</td><td>0.11</td><td>0.12</td></tr>
<tr><td>UB</td><td>5.69</td><td>5.64</td></tr>
<tr><td>LB</td><td>5.48</td><td>5.40</td></tr>
<tr><td>Median</td><td>5.27</td><td>5.16</td><td>-2.1%</td></tr>
<tr><td>Std. Dev.</td><td>1.67</td><td>1.35</td><td>-19.2%</td></tr>
<tr><td>Variance</td><td>2.80</td><td>1.82</td><td>-35%</td></tr>
</table>

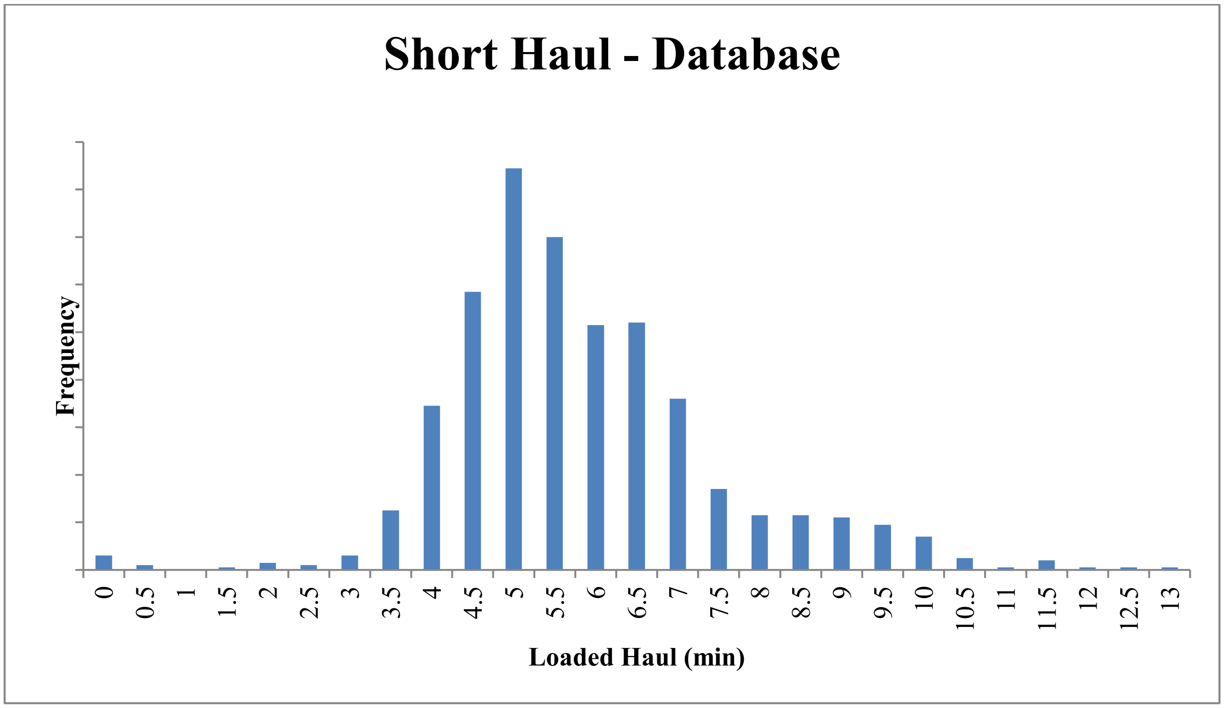

Figure 20: Short Haul database histogram

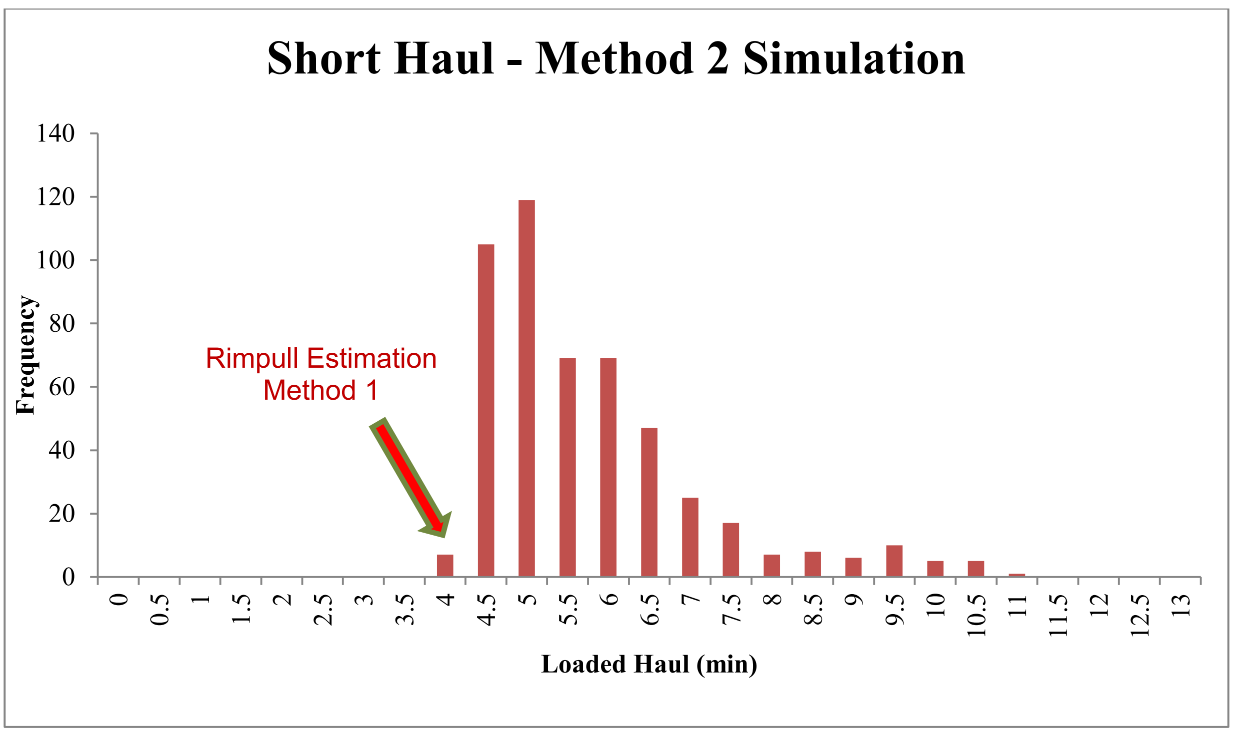

Figure 21: Short Haul simulation output histogram

Table 4: Short/Medium Haul output summary

Short/Medium Haul (2.6 km average)	Database	Method 2	Difference	Method 1	Difference
Mean	8.96	9.08	+1.3%	6.86	-23.4%
CI	0.14	0.21			
UB	8.99	9.29			
LB	8.92	8.87			
Median	8.83	8.50	-3.7%		
Std. Dev.	2.10	2.40	+14.3%		
Variance	4.42	5.61	+26.9%		

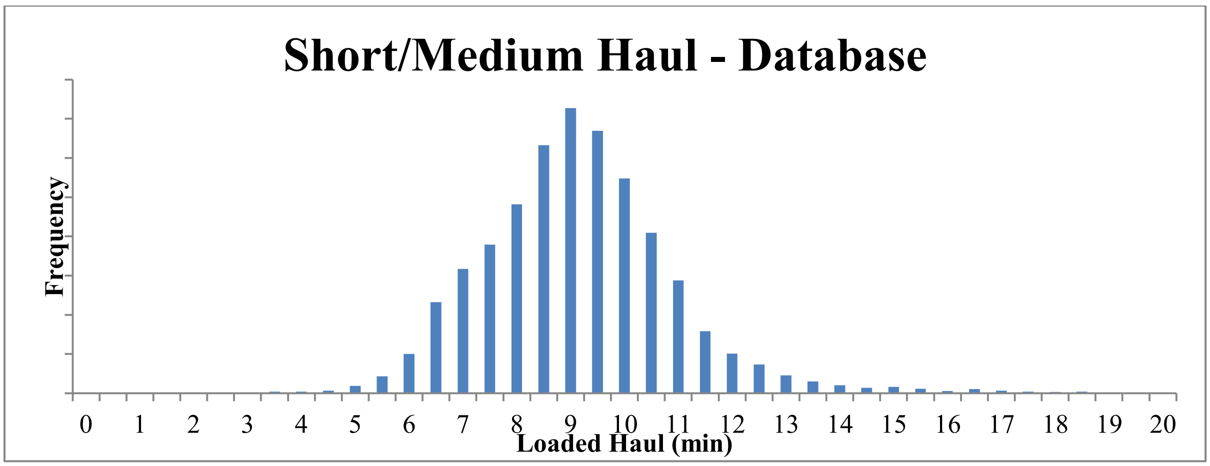

Figure 22: Short/Medium database histogram

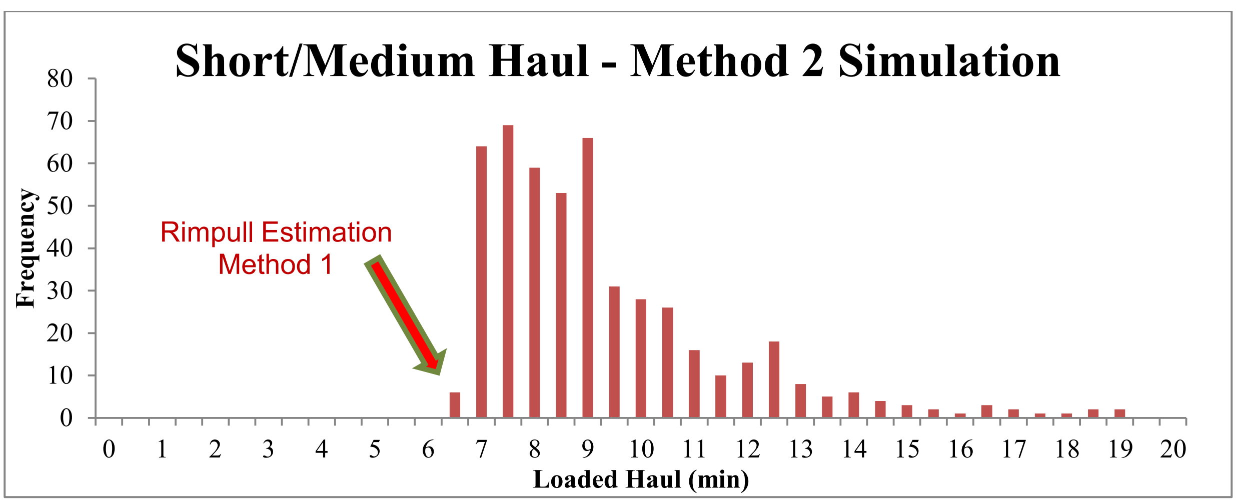

Figure 23: Short/Medium simulation output histogram

Table 5: Medium Haul output summary

Medium Haul (4 km average)	Database	Method 2	Difference	Method 1	Difference
Mean	15.62	15.60	-0.12%	11.59	-25.8%
CI	0.09	0.37			
UB	15.71	15.97			
LB	15.52	15.23			
Median	15.58	14.38	-7.7%		
Std. Dev.	3.24	4.20	+29.6%		
Variance	10.21	18.01	+71%		

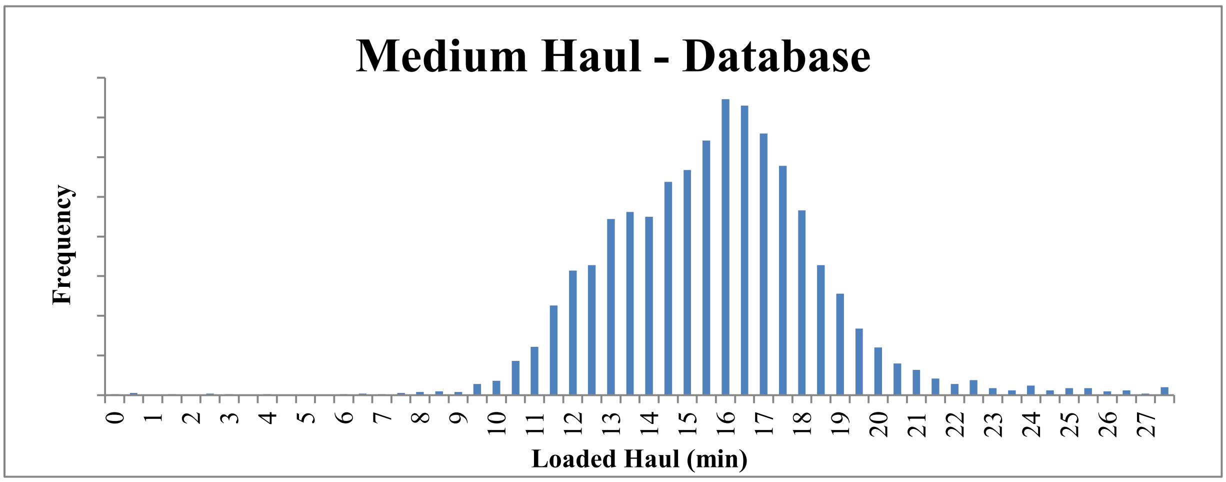

Figure 24: Medium Haul database histogram

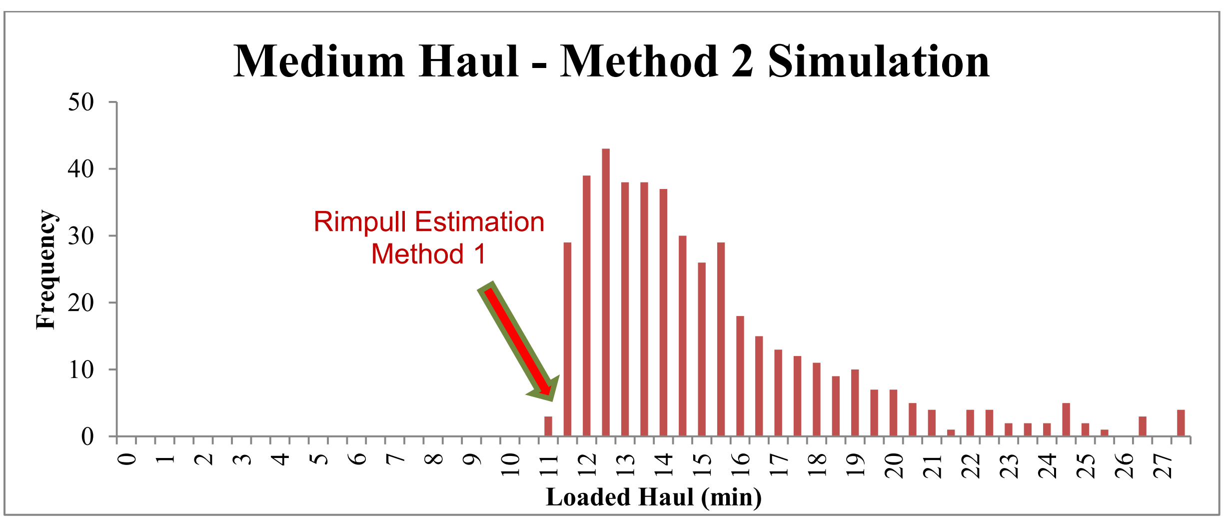

Figure 25: Medium Haul simulation output histogram

Table 6: Long Haul output summary

Long Haul (8 km average)	Database	Method 2	Difference	Method 1	Difference
Mean	23.20	23.09	-0.5%	17.2	-25.9%
CI	0.22	0.37			
UB	23.42	23.46			
LB	22.98	22.72			
Median	22.78	21.41	-6.0%		
Std. Dev.	4.5	6.0	+33.3%		
Variance	20.0	36.5	+82.5%		

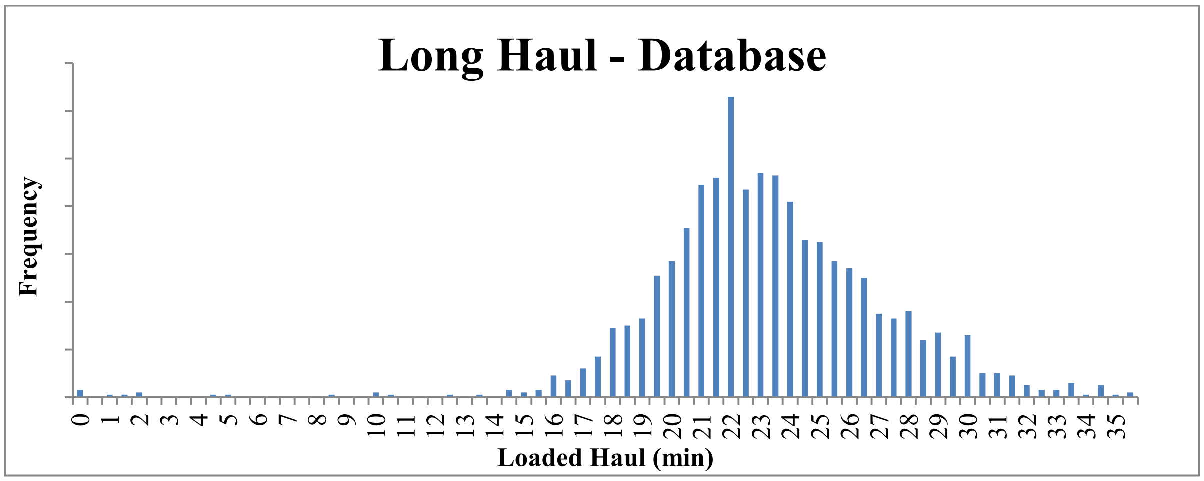

Figure 26: Long Haul database histogram

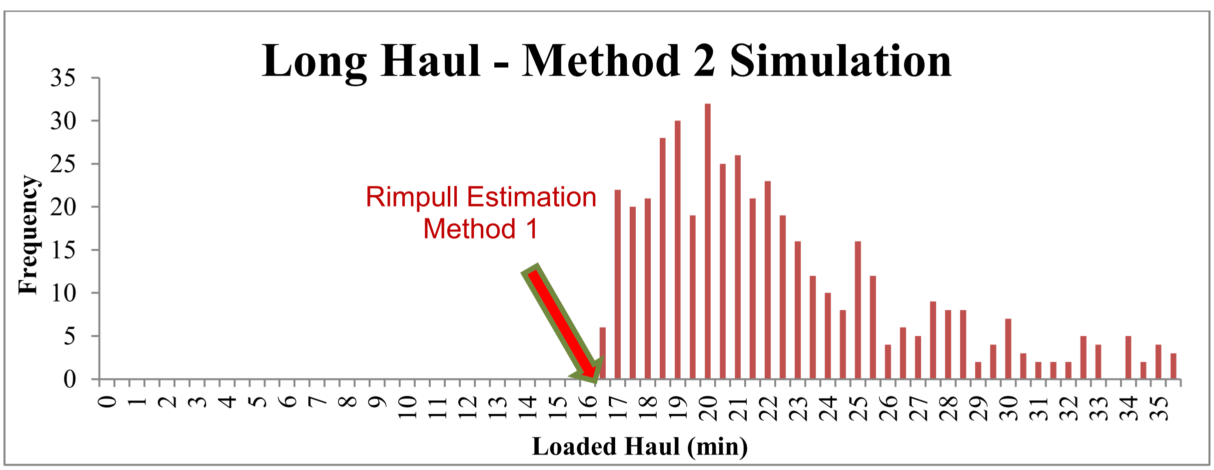

Figure 27: Long Haul simulation output histogram

Even with a relatively low number of replications (500), excellent results were achieved by Method 2. All scenarios presented above are within 1.5% of accuracy compared to the database, and their confidence intervals are very close. As expected, Method 1 overestimates the performance of the trucks by underestimating the haul times, consistently, by about 25%. Comparing the output in the histograms suggests that the model is simulating the operation correctly. Each 500-replication process took the program no longer than 20 seconds to produce.

4.5 ADVANCED APPLICATIONS

In order to display the potential of this framework, a more advance application was developed. A quarterly (3-month) simulation of TPGOH was performed, and the outputs were compared to the records in the database. The outputs are divided in the following subsections based on the metric they compare. TPGOH was calculated by using the same sample for payload tonnage and dividing it by the cycle time. Within the cycle time, the loaded haul time is simulated with Method 1 and 2, and the rest of the parameters are simulated from probability distributions. Since the dispatch logic at the mine is unknown, it was incorrect to assume that the trucks travelled empty back to the same dig locations they came from.

Chapter 4.5.1 compares a variation of TPGOH, where the return travel time is not included. In chapter 4.5.2 the return travel was simulated from a probability distribution generated with data from those months. Excellent results were obtained in both cases. The correctness of the TPGOH (with return times) can be rooted in the fact that the data used in the probability distribution for return travel time was specific to those months only – meaning that trucks would only go to the specific polygons of that quarter rather than to other mine locations.

During these three months of production, 11 distinct dig locations were identified, with most of the material going to the crusher for further processing, and only a small fraction going to waste dumps. This finite number of source and destination combinations were assigned weights based on their available material tonnage, and then several replications were performed for each. After establishing the TPGOH values for each source/destination combination, these were multiplied by the aforementioned weights, yielding a single value within a 95% confidence interval that could be compared to the database.

For both TPGOH cases, a table summarizing the output and comparing to the database for validation is included, along with histograms for the database records, and for Methods 1 and 2 in raw resolution (all outputs without calculating the weighted average) and a weighted average value. During the development of these results, it was noted that there is a 2% difference in productivity (TPGOH_A) in the day and night shifts – with the night shift being more productive. This may be attributed to the fact that some of the auxiliary equipment in the road network is usually operated by contractors, who mostly work during the day. Without them creating traffic interactions with the trucks, cycle times are shorter and the operation more productive.

4.5.1 TPGOH no return

Table 7: Quarterly Simulation output summary – no empty haul time

	Database	Method 2	Difference	Method 1	Difference
Mean	**0.52877**	**0.53188**	**0.58%**	0.60813	15.1%
95% CI	0.00577	0.00238	-58%	0.00272	-52.8%
Median	0.5365	0.5399	0.63%	0.6068	13.1%
Std. Dev.	0.1744	0.0857	-50.9%	0.0981	-43.6%

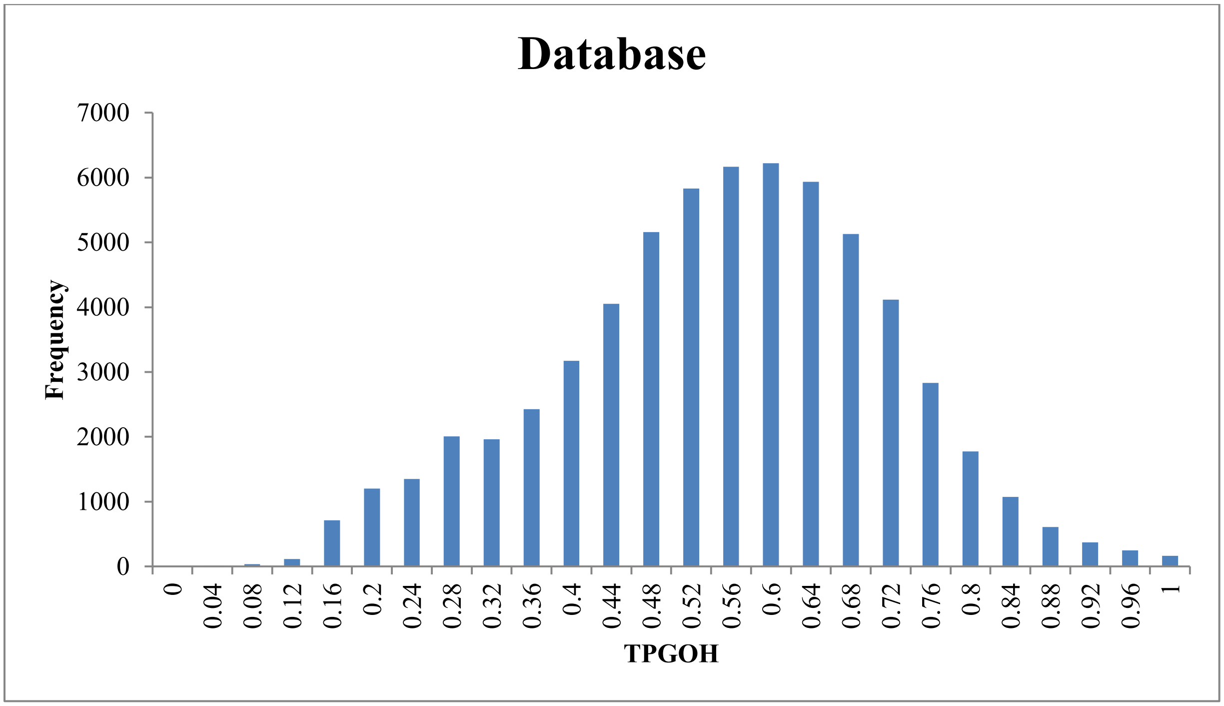

Figure 28: Quarterly TPGOH database histogram – no empty travel

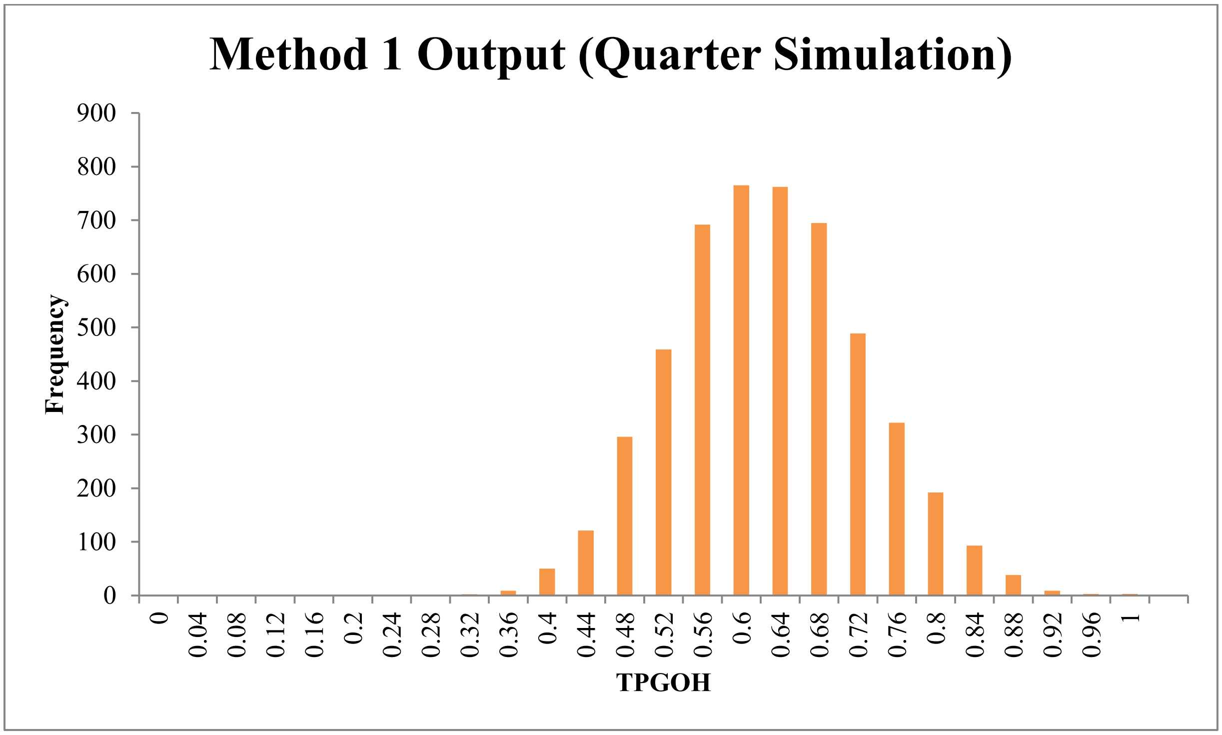

Figure 29: Quarterly TPGOH Method 1 output – no empty travel

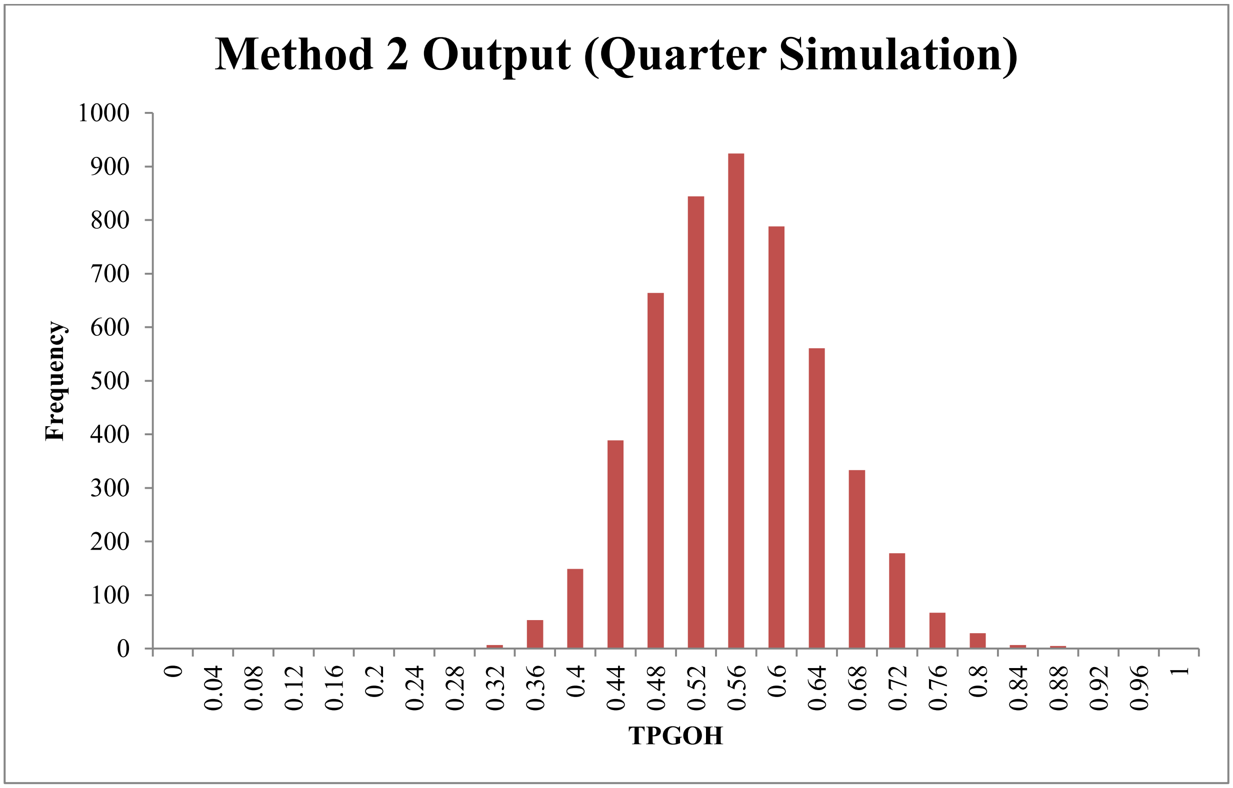

Figure 30:Quarterly TPGOH Method 2 output – no empty travel

4.5.2 TPGOH with return

Table 8: Quarterly Simulation output summary – with empty haul time

	Database	Method 2	Difference	Method 1	Difference
Mean	**0.3654**	**0.36505**	**-0.09%**	0.39514	8.14%
95% CI	0.00086	0.00136	58.6%	0.00152	76.27%
Median	0.3739	0.3629	-2.9%	0.3929	5.1%
Std. Dev.	0.1139	0.0491	-56.8%	0.0547	-52%

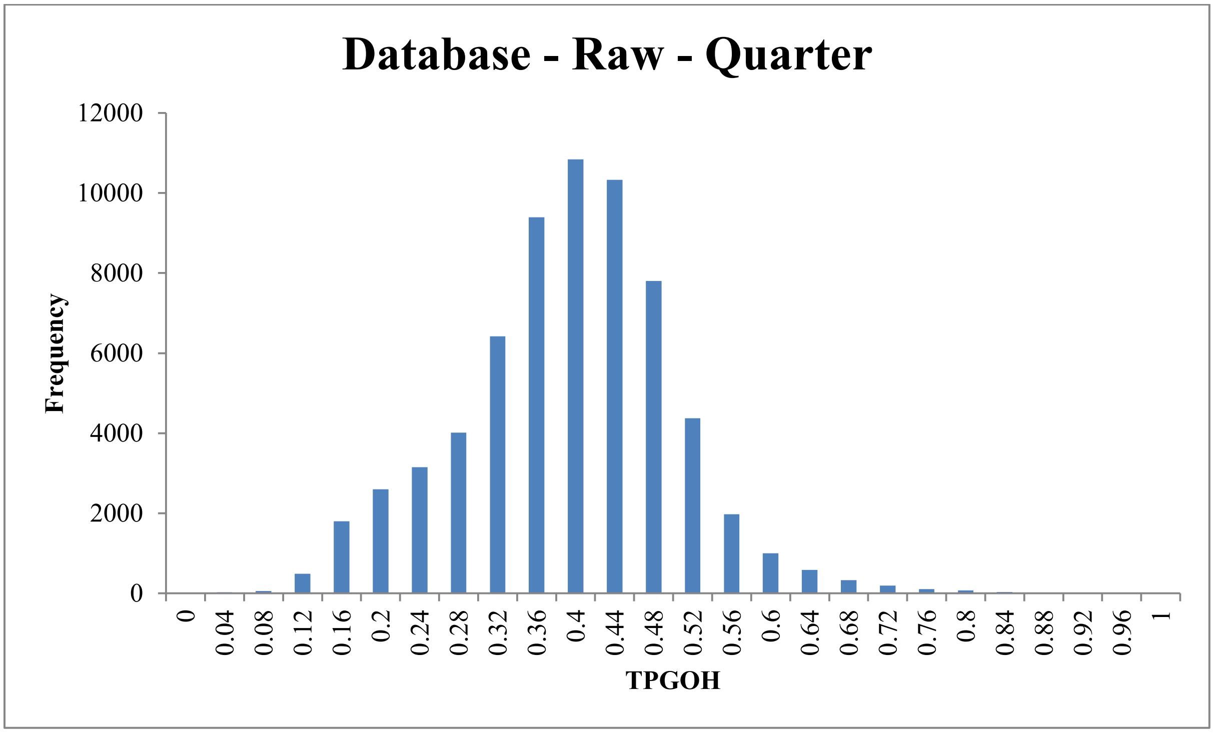

Figure 31: Quarterly TPGOH database histogram – with empty travel

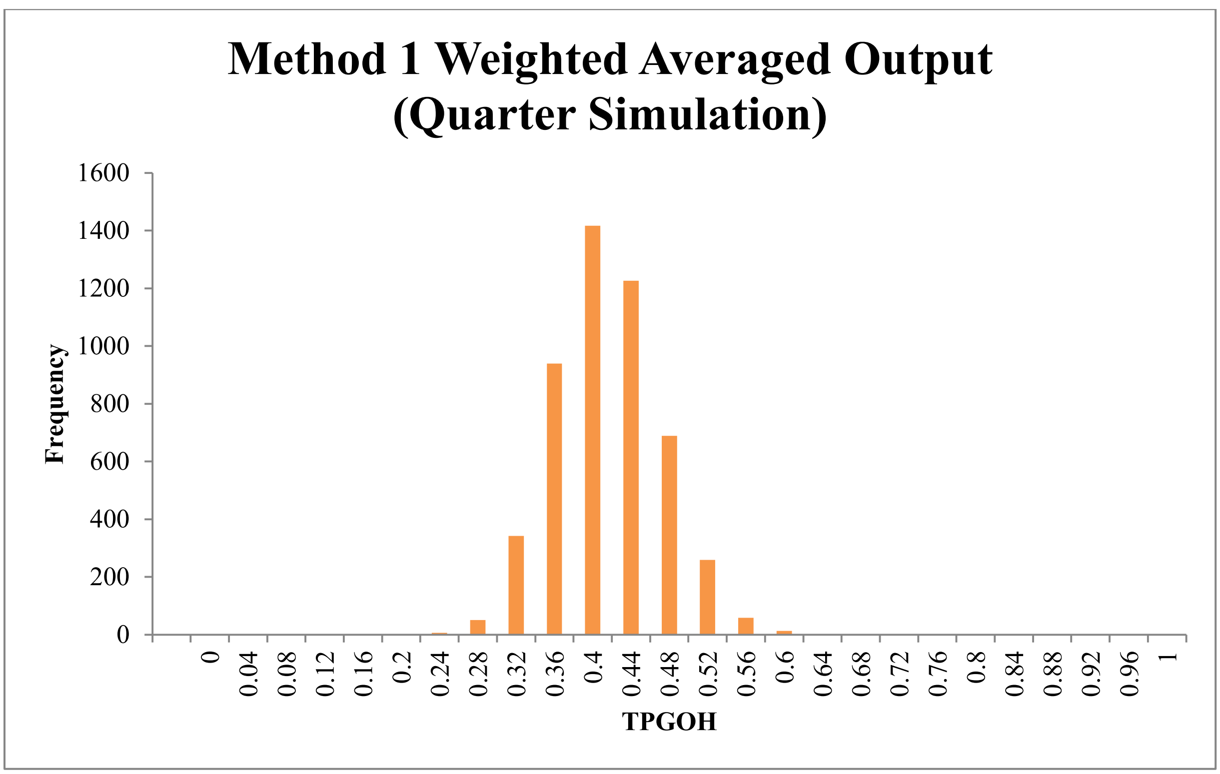

Figure 32: Quarterly TPGOH Method 1 averaged output – with empty travel

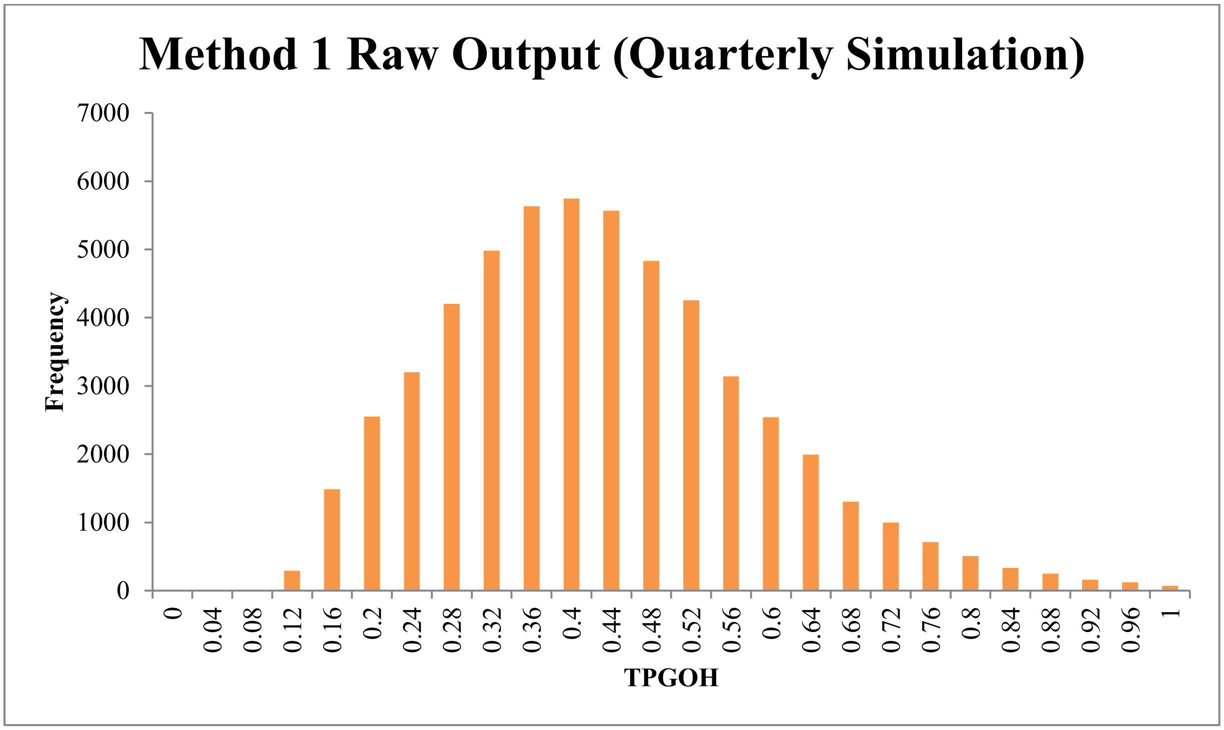

Figure 33: Quarterly TPGOH Method 1 raw output – with empty travel

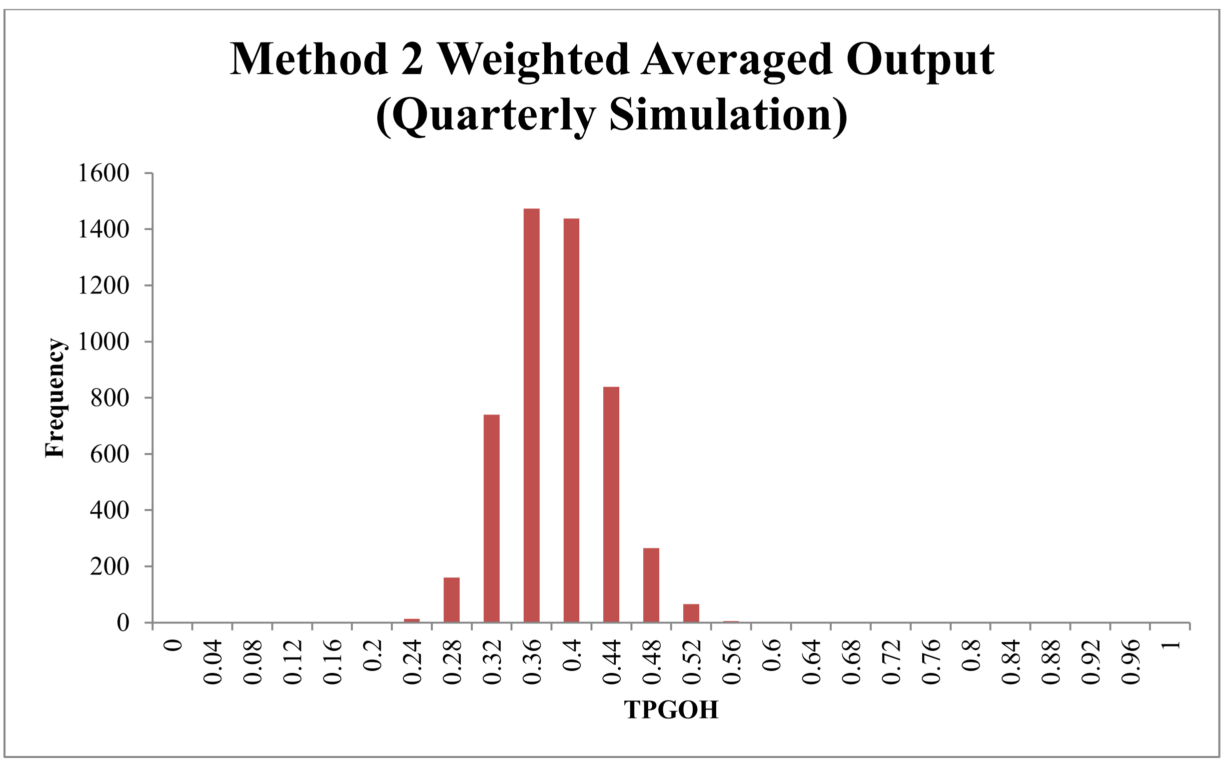

Figure 34: Quarterly TPGOH Method 2 averaged output – with empty travel

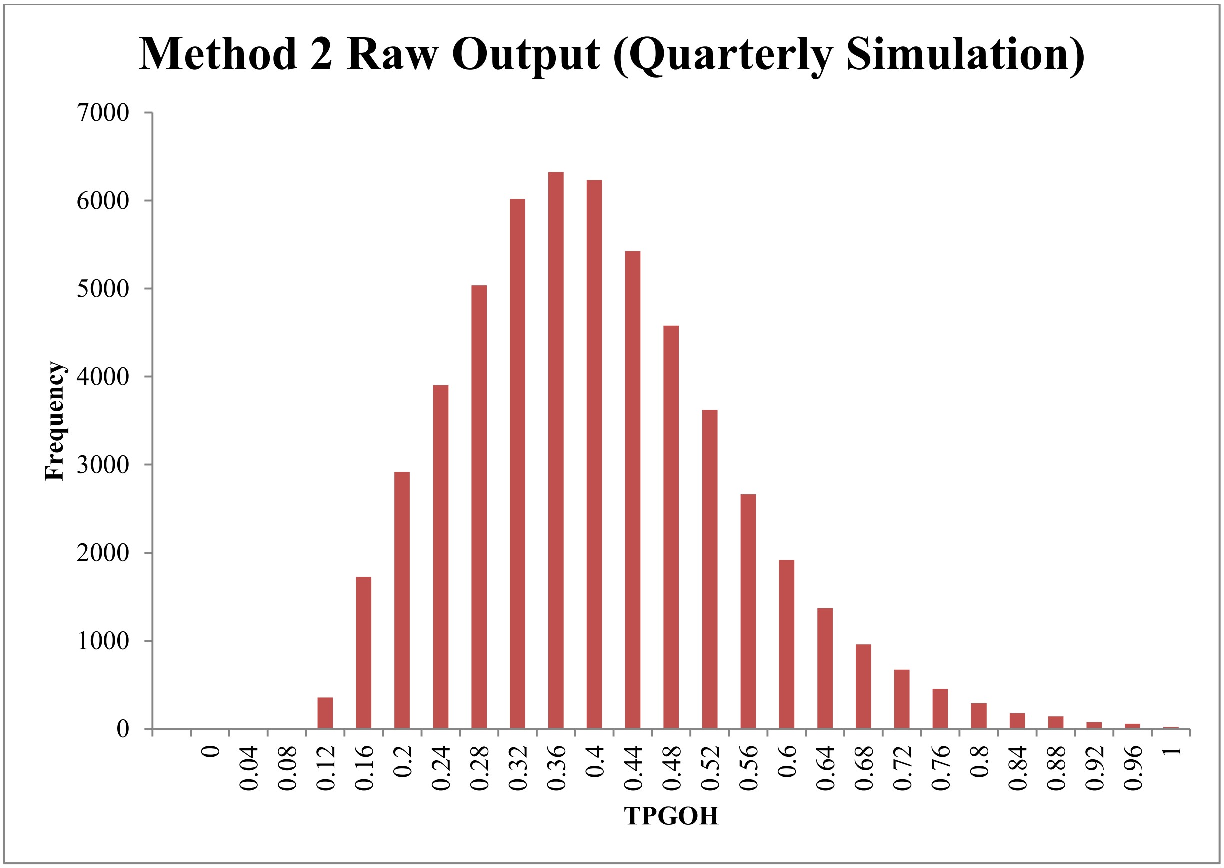

Figure 35: Quarterly TPGOH Method 2 raw output – with empty travel

As expected, the outputs from Method 1 overestimate the productivity by underestimating the cycle times, compared to Method 2, which results in extremely accurate outputs.

The summary statistics are very close to those of the database, and the histograms show that the output is extremely similar to the records in the database – suggesting that the model is not only well-calibrated, but is correct.

4.5.3 Comparison to Old Method

The old 'in house' method consists in fitting a negative exponential line of best fit to the distance-sorted historical data, by minimizing the squared error (distance from line to points). This line of best fit is in the following form:

$$Ax^{-B}$$

Where A and B are varied non-linearly to minimize the squared error from the line to the data points. Three scenarios were generated and differ only on the data used: case A utilizes data from the entire year of operation. Case B uses two years' worth of data and case C uses data from the specific quarter which this study simulates. Table 9: Comparison of Old Methods presents a summary of these cases and their comparison to the records in the database.

Table 9: Comparison of Old Methods

	TPGOH	Difference from Database
Database	0.3654	-
Old Method A	0.3278	-10.28%
Old Method B	0.3206	-12.27%
Old Method C	0.2988	-18.24%

The framework presented in this thesis proves to be superior. In addition, due to the old method's form, the only way to quantify its overall intrinsic error is to look at the distances from the line of best fit to the data points (standardized squared error) which does not translate to a particularly usable parameter. In contrast, this new framework produces an output that establishes a half width at 95% confidence interval of TPGOH units itself.

Having calculated EFH factors for every source and destination combination, it is then possible to compare the TPGOH plots. The old method plots TPGOH against loaded haul distance and fits a line of best fit. Having used the framework in this thesis, the loaded haul distance gets replaced by EFH (which accounts for the effects of changing gradients and rolling resistances). Figure 36 below shows a series of boxplots using loaded haul distance. The bulk of the data occurs in the area indicated by the yellow rectangle:

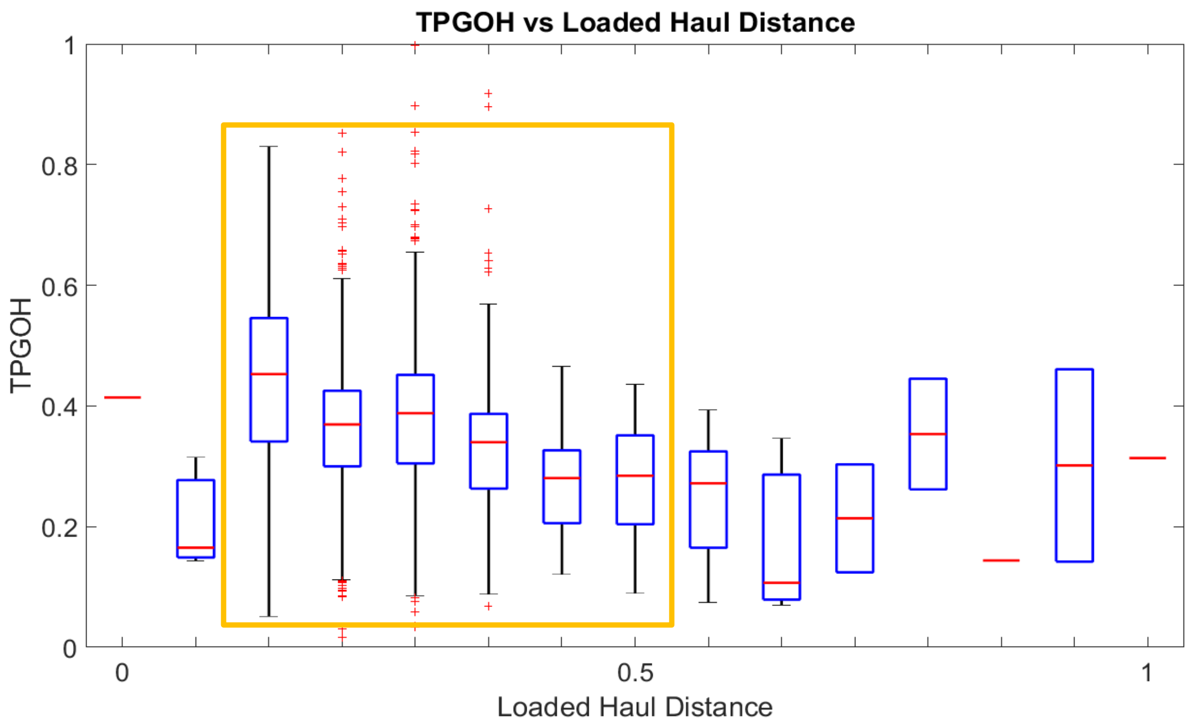

Figure 36: BoxPlots for Old Method

Figure 37 below shows a plot of the same data but is categorized based on the records' corresponding EFH values instead of loaded haul distance. The bulk of the data is within the range shown by the orange rectangle:

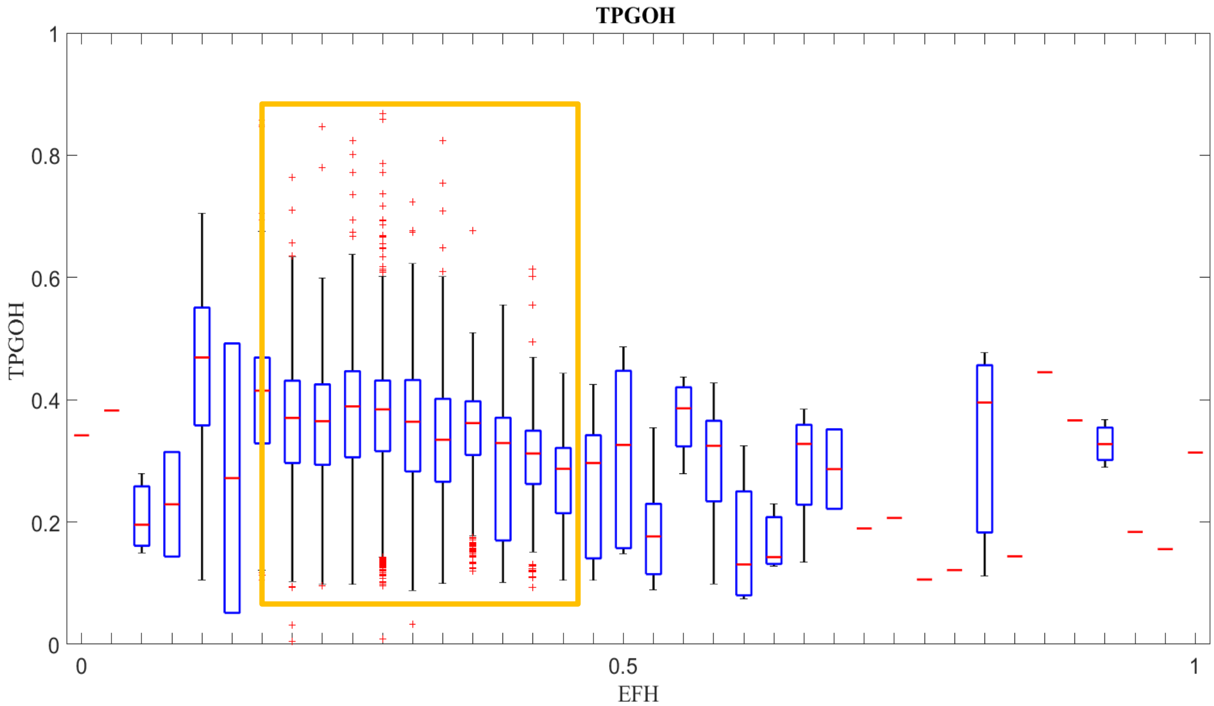

Figure 37: EFH BoxPlots

The standard deviation for both curves was calculated by estimating a weighted average of each bin. The EFH categorization of the data showed a reduction in standard deviation of 25.3%. The 'Old Method' was performed using the TPGOH vs EFH data, and yielded a quarterly TPGOH estimate of 0.3797, which is an overestimation of **4%** over the database records. While this figure is not as accurate as the simulation in this framework, it is a very significant improvement over the old method. In addition, it is in the same form of the old method, which involves relating productivity levels to a measure or function of distance via a line of best fit.

5. CONCLUSIONS AND RECOMMENDATIONS

The framework presented in this thesis has proven to be a definite improvement over existing methods for estimating truck/shovel cycle times at operating mines, which were identified as insufficient during the literature review.

This improvement is rooted in the fact that the framework is driven by operational data within historical records, instead of relying only on standardized and simplified performance parameters. This approach also allows for the evaluation of operational performance, since it is able to produce reliable estimates through simulation and the comparison to historical production records. This is of great value for mine planning staff in order to detect trends and identify opportunities for improvement.

In addition to these advantages, there are other potential uses within this framework. In its current form, the optimal path selection algorithm is based on the criterion of shortest distance, but for specific applications, this objective could be altered to find the most fuel-efficient route, perhaps to the detriment of production rates. In any case, a cost-benefit analysis should be performed in order to maximize NPV.

This framework also allows for more advanced applications, such as the productivity analysis shown in the case study. This may be a helpful tool for mine planners in aiding their estimates of production both in the short- and long-term. In addition, it solves the problem of estimating future equipment requirements, as the TPGOH metric is a production rate which is directly related to the number of shovels and trucks operating at any one time.

The algorithm presented within is the result of thorough investigation of the oil sands mine in the case study. A great effort was made to ensure that the proposed framework is flexible and easy to implement at other operations. During the development of this approach, the main data sources were identified and limited to being readily available at almost every mine, since they come from the dispatch system. Very tight half widths and high confidence intervals were achieved in short computation times in the validation/verification and case study, adding to the positive features of this framework.

There are two areas of improvement possible within this framework: linking it to the dispatch logic for more accurate simulation, and conducting a more thorough simulation study where the rim pull curves are not used, instead obtaining velocity records for every increment of gradient or rolling resistance and sampling from each. This was not possible in this case study due to a lack of data, and it would involve making this framework inflexible and very specific to this operation.

In addition, another area for future work and improvements over the framework presented in this thesis would be to accurately capture the advancement of the bench face in order to avoid having to calculate a centroid for each dig location. The same should be performed for dump locations. Both of these actions would result in more accurate and realistic results.

WORKS CITED

Adair, L., Soofastaei, A., Aminossadati, S., Kizil, M., & Knights, P. (2015, February). Rolling Resistance in Haul Truck Operations. *Australian Mining*.

Alarie, S., & Gamache, M. (2002). Overview of Solution Strategies Used in Truck Dispatching Systems for Open Pit Mines. *International Journal of Surface Mining, Reclamation and Environment, 16*(1), 59-76.

Alhasan, A., & White, D. J. (2016). *Earthwork Haul-Truck Cycle-Time Monitoring - A Case Study.* Institute for Transportation Iowa State University.

Anand, A. (2012). Scaled test estimation of Rolling Resistance. Edmonton: University of Alberta.

Askari-Nasab, H., Frimpong, S., & Szymanski, J. (2007). Modelling open pit dynamics using discrete simulation. *International Journal of Mining, Reclamation and Environment, 21*(1), 35-49.

Awhua-Offei, K., Osei, B., & Askari-Nasab, H. (2011). *Modeling Truck-Shovel Energy Efficiency Under Uncertainty.* University of Alberta. Edmonton: Mining Optimization Laboratory ISBN: 978-1-55195-281-9.

Ben-Awuah, E., & Hosseini, N. S. (2017). *An economic evaluation of a primary haulage system for a bauxite mine: load and haul versus in-pit crushing and conveying.* University of Alberta. Edmonton: Mining Optimization Laboratory ISBN: 978-1-55195-383-0.

Bonates, E. J. (1996). Interactive truck haulage simulation program. In W. T. Hennies, L. Azuaga Ayres Da Silva, & A. Pinto Chaves (Ed.), *5th International Symposium on Mine Planning and Equipment Selection 1996* (pp. 51 - 57). Sao Paulo: A. A. Balkema / Rotterdam / Brookfield.

Bozorgebrahimi, E., Hall, R., & Blackwell, G. (2003, December). Sizing equipment for open pit mining - a review of critical parameters. *Mining Technology (Trans. Inst. Min. Metall. A), 112*, A171 - A179. doi:10.1179/037178403225003591

Burt, C. N. (2008, August). An Optimisation Approach to Materials Handling in Surface Mines. Curtin University of Technology.

Burt, C. N., & Caccetta, L. (2013). Equipment Selection for Surface Mining: A Review. *Interfaces, 44*(2), 143-162.

Campbell, S., & Hagan, P. (2012). Selection of an Optimum Truck and Shovel Fleet Based on Effective Flat Haul and Capacity Constraint Modelling. *8th AusIMM Open Pit Operators' Conference*, (pp. 19-25). Perth.

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. doi:10.1080/17480930.2013.772699

Caterpillar Inc. (2013). 797F Mining Truck Specifications.

Chanda, E. K., & Gardiner, S. (2010). A comparative study of truck cycle time prediction methods in open-pit mining. *Engineering, Construction and Architectural Management, 17*(5), 446-460.

Choi, Y., Park, H.-D., Sunwoo, C., & Clarke, K. C. (2009, December). Multi-criteria evaluation and least-cost path analysis for optimal haulage routing of dump trucks in large scale open-pit mines. *International Journal of Geographical Information Science, 23*(12), 1541-1567.

Curi, A., Schmidt Felsch, W., Cunha Rodovalho, E., & Prado Meireles, B. (2013). Evaluation of Haul Trucks Performance in a CSN Mine. In C. Drebenstedt, & R. Singhal (Ed.), *Mine Planning and Equipment Selection - Proceedings of the 22nd MPES Conference* (pp. 1143-1150). Dresden: Springer.

De Werk, M., Ozdemir, B., Ragoub, B., Dunbrack, T., & Kumral, M. (2017). Cost analysis of material handling systems in open pit mining: Case study on an iron ore prefeasibility study. *The Engineering Economist, 62*(4), 369-386.

Dindarloo, S. R., & Siami-Irdemoosa, E. (2016). Merits of discrete event simulation in modeling mining operations. *SME Annual Meeting.* Phoenix.

Dindarloo, S. R., Osanloo, M., & Frimpong, S. (2015, March). A stochastic simulation framwork for truck and shovel selection and sizing in open pit mines. *The Journal of The Southern African Institute of Mining and Metallurgy, 115*, 209-219.

Doig, P., & Kizil, M. S. (2013). Improvements in truck requirement estimations using detailed haulage analysis. *13th Coal Operators' Conference* (pp. 368-375). University of Wollongong.

Dotto, M. (2014). Impact of hauler scale in mine planning. Edmonton: University of Alberta.

Edwards, D. J., & Holt, G. D. (2000). ESTIVATE: a model for calculating excavator productivity and output costs. *Engineering, Construction and Architectural Management, 7*(1), 52-62.

Ercelebi, S. G., & Bascetin, A. (2009). Optimization of truck-shovel system for surface mining. *South African Institute of Mining and Metallurgy, 109*(7), 433-439.

Firmin, K. (2012, June 1). Principal Consultant with Snowden Mining Consultants. (B. Brennan, Interviewer) Calgary.

Hammerstone Corporation. (n.d.). *Hammerstone Haul Roads.* Retrieved from Hammerstone Corporation: www.hammerstonecorp.com

Hardy, R. J. (2007, July). Selection Criteria For Loading and Hauling Equipment - Open Pit Mining Applications. Curtin University of Technology.

Hargroves, K., Gockowiak, K., McKeague, F., & Desha, C. (2014). *An Overview of Energy Efficiency Oportunities in Mining and Metallurgy Engineering.* Canberra: The Univeristy of Adelaide and Queensland University of Technology (The Natural Edge Project).

Hui, V. (2012, June). Paying Attention to Load Balance and Road Repairs for Haulage Cost Reduction. *Engineering & Mining Journal*, 144-146.

Joseph, T. G., & Szymanski, J. (2013). Roads Make Loads - Rolling Resistance Saves Emissions. *Journal of Civil & Environmental Engineering, 3*(1).

Joseph, T. G., Curley, M., & Anand, A. (2017). Operational Methodologies for Rolling Resistance Evaluation. *Geotech GEol Eng, 35*, 2935-2946.

Kaboli, A. S., & Carmichael, D. G. (2014). Optimum scraper load time and fleet size for minimum emissions. *International Journal of Construction Management, 14*(4), 209-226.

Kecojevic, V., & Komljenovic, D. (2010, December). Haul truck fuel consumption. *Mining Engineering Magazine*, pp. 44-48.

Krause, A. J. (2006). Shovel-Truck Cycle Simulation Methods in Surface Mining. Johannesburg, South Africa: University of the Witwatersrand.

Krause, A., & Musingwini, C. (2007). Modelling open pit shovel-truck systems using the Machine Repair Model. *The Journal of The Southern AFrican Institute of Mining and Metallurgy, 107*, 469-476.

Krzyzanowska, J. (2007, April). The impact of mixed fleet hauling on mining operations at Venetia mine. *The Journal of the Southern African Institute of Mining and Metallurgy, 107*, 215-224.

Kuo, Y.-c. (2004, August). Highway earthwork and pavement production rates for construction time estimation. Austin, Texas: The University of Texas at Austin.

Manyele, S. V. (2017). Analysis of Waste-Rock Transportation Process Performance in an Open-Pit Mine Based on Statistical Analysis of Cycle Times Data. *Engineering*, 649-679.

Moradi Afrapoli, A., Upadhyay, S., & Askari-Nasab, H. (2017). *A Multi Objective Multi Stage Mining Fleet Management System Linking Dynamic Operation to Short-Term Plan.* University of Alberta. Edmonton: Mining Optimization Laboratory ISBN: 978-1-55195-383-0.

Morton, J. (2017, September). Is the Ultra-class Truck Dream Dead? *Engineering and Mining Journal*, 32-36.

NASDAQ. (2018, 1 2). *Crude Oil Markets*. Retrieved from NASDAQ: http://www.nasdaq.com/markets/crude-oil.aspx?timeframe=10y

Newmont. (2014, December 12). *Full Potential.* Retrieved from Newmont Newsroom: http://www.newmont.com/newsroom/newsroom-details/2014/Full-Potential/default.aspx

RungePincockMinarco. (2015). TALPAC help files. Brisbane, Queensland, Australia.

Sheremeta, R. (2015). Truck Shovel Productivity: The Historical and Future Strategic Advantage for Teck Coal. Simon Fraser University.

Soofastaei, A. (2016). Development of an Advanced Data Analytics Model to Improve the Energy Efficiency of Haul Trucks in Surface Mines. Queensland, Australia: The University of Queensland.

Sturgul, J. R., & Harrison, J. F. (1987). Simulation models for surface mines. *International Journal of Surface Mining, Reclamation and Environment, 1*(3), 187-189.

Ta, C. H., Kresta, J. V., Forbes, J. F., & Marquez, H. J. (2005). A stochastic optimization approach to mine truck allocation. *International Journal of Surface Mining, Reclamation and Environment, 19*(3), 162-175. doi:10.1080/13895260500128914

Tabesh, M., Upadhyay, S., & Askari-Nasab, H. (2016). *Discrete Event Simulation of Truck-Shovel Operations in Open Pit Mines.* University of Alberta. Edmonton: Mining Optimization Laboratory ISBN: 978-1-55195-367-0.

Tannant, D., & Regensburg, B. (2001). *Guidelines for Mine Haul Road Design.* Retrieved from https://www.researchgate.net/publication/277759950

Thomas, H. R., Maloney, W. F., Horner, R. W., Smith, G. R., Handa, V. K., & Sanders, S. R. (1990). Modeling Construction Labor Productivity. *Journal of Construction Engineering and Management, 116*(4), 705-726.

Thompson , R. J., & Visser, A. T. (1997). An introduction to the integrated design of surface mine haul roads. *International Journal of Surface Mining, Reclamation and Enironment, 11*, 115-120.

Thompson, R., & Visser, A. T. (2003). Mine haul road maintenance management systems. *Journal of the Southern AFrican Institute of Mining and Metallurgy, 103*(5), 303-312.

Topf, A. (2010, September 1). *Oil Sands Mining Equipment Built Tough.* Retrieved from MINING.com: http://www.mining.com/oil-sands-mining-equipment-built-tough/

Upadhyay, S., & Askari-Nasab, H. (2012). *Micro-Simulation of Mine Haulage Systems.* University of Alberta. Edmonton: Mining Optimization Laboratory ISBN: 978-1-55195-301-4.

Vagenas, N. (1999). Applications of discrete-event simulation in Canadian mining operations in the nineties. *International Journal of Surface Mining, Reclamation and Environment, 13*(2), 77-78.

Vasquez Coronado, P. P. (2014). Optimization of the haulage cycle model for open pit mining using a discrete-event simulator and a context-based alert system. Arizona, USA: The University of Arizona.

APPENDIX I

Main

```
[Nodes, Segments, Lines] = LoadRoadNetwork();
%Segments: 1.LineID, 2.x1,3.y1,4.z1,5.NodeID1,6.x2,7.y2,8.z2,9.NodeID2,
10.Length, 11.Gradient
%Lines:    1.LineID, 2.NodeID1,3.NodeID2, 4.Length
%Nodes:    1.LineID, 2.X, 3.Y, 4.Z, 5.NodeID
% SmoothPathMat columns: 1= LineID, 2=FromNode, 3=ToNode, 4=SegmentLength,
    % 5=Gradient, 6=EffectiveGrade, 7=Rimpull (if flat or uphill),
    % 8=SegmentVelocityRimpull


% % %%%%%%%%%%%%%%%%                             Plot RoadNetwork raw %
% for iLoop=1:size(Segments,1)
% p1=plot([Segments(iLoop,2),Segments(iLoop,6)],
[Segments(iLoop,3),Segments(iLoop,7)]);
% p1.Color='b';
% hold on
% end
% %

%% Get all the source destination combinations querying database %
[Source, Dest] = GetSourceDestCombinations();

TPGOHsim = cell(size(Source,1),1);
EFHFactor = cell(size(Source,1),1);
FullHaulTime=[];

for rLoop=1:size(Source,1) %for all the paths
    [PathMat, PathDistance] =
GetPath(Source(rLoop),Dest(rLoop),Lines,Segments);

    PathMat(:, 12) = PathMat(:,10) .* PathMat(:, 11); %length weighted
gradient value for average gradient in SmoothPathMat

    % % %%%%%%%%%%%%%%%%%                             Plot RoadNetwork route
%
    % for iLoop=1:size(PathMat,1)
    % p2=plot([PathMat(iLoop,2),PathMat(iLoop,6)],
[PathMat(iLoop,3),PathMat(iLoop,7)]);
    % p2.Marker='.';
    % p2.Color='r';
    % % xlabel(['Haul Length: ' num2str(PathDistance) ' m']);
    % hold on
    % end


    %%%%%%%%%%%%%%%%%%                             Smooth/Merge Route
Information %
```

```
    SmoothPathMat=[];
    toldist= 35;
%     tolgrad=7;

    row=1;

SmoothPathMat(row,:)=[PathMat(1,1),PathMat(1,5),PathMat(1,9),PathMat(1,10),
1];
    for iLoop=2:size(PathMat,1)
        if PathMat(iLoop,1)==SmoothPathMat(row,1) && SmoothPathMat(row,4) <
toldist
            SmoothPathMat(row,3)=PathMat(iLoop,9);
            SmoothPathMat(row,4)=SmoothPathMat(row,4) + PathMat(iLoop,10);
            SmoothPathMat(row,5)=iLoop;
        else
            row=row+1;

SmoothPathMat(row,:)=[PathMat(iLoop,1),PathMat(iLoop,5),PathMat(iLoop,9),Pat
hMat(iLoop,10),iLoop];
        end
    end

    %%%%%%%%%%%%%%%%%%                            Calculate and add
weighted average gradient to SmoothPathMat %
    SmoothPathMat(1, 6) = sum(PathMat(1:SmoothPathMat(1, 5),
12))/(SmoothPathMat(1, 4));
    for iLoop=2:size(SmoothPathMat,1)
        SmoothPathMat(iLoop, 6) = (sum(PathMat(SmoothPathMat(iLoop-1,
5)+1:SmoothPathMat(iLoop, 5), 12)))/(SmoothPathMat(iLoop, 4));
    end
    SmoothPathMat(:,5) =[]; %clear indexing

    %%%%%%%%%%%%%%%%%%                            Calculate Effective grade
and Rimpull Value for flat and uphill %
    LoadedWeight = 623690;
    RollingRes = 5.5;




    for iLoop=1:size(SmoothPathMat,1)
        SmoothPathMat(iLoop,6) = (SmoothPathMat(iLoop,5) + RollingRes);
        if SmoothPathMat(iLoop,6) >= 0    % checks if uphill or flat
            SmoothPathMat(iLoop,7) = ((SmoothPathMat(iLoop,6)/100) *
LoadedWeight);
        else
        end
    end



    %% ------------------------------- Travel Time Estimations -------------
-----------------%%
```

```
    % Determine Rimpull Velocities for each segment based on the gradient
    RimpullData = xlsread('RimpullRetardCurves.xlsx', 'Rimpull-Cat 797B',
'B4:C75');

    FlatSpeed_Rimpull =RimpullData(find(RimpullData(:,1)==0,1),2); %at zero
TR, rimpull=0

    InterpolateMat = [];
    for iLoop=1:size(SmoothPathMat,1)
        if SmoothPathMat(iLoop,7) >= 10000
            InterpolateMat=RimpullData(find(SmoothPathMat(iLoop,7)>=
RimpullData(:,1),2)-1,1:2);
            SmoothPathMat(iLoop,8) =
(((InterpolateMat(2,2))*(InterpolateMat(1,1)-
SmoothPathMat(iLoop,7)))+((InterpolateMat(1,2))*(SmoothPathMat(iLoop,7) -
InterpolateMat(2,1))))/ (InterpolateMat(1,1) - InterpolateMat(2,1));
            clear InterpolateMat;

        else SmoothPathMat(iLoop,8) = FlatSpeed_Rimpull;
        end
    end


    %% Run Methods
    NRep=1; % number of replications
    TPGOHmean=[];

    for repLoop=1:NRep
        [TPGOHsim{rLoop}(repLoop,:), EFHFactor{rLoop}(repLoop,:)] =
RunMethods(SmoothPathMat, PathDistance, FlatSpeed_Rimpull);
        %[FullHaulTime{rLoop}(repLoop, 1), FullHaulTime{rLoop}(repLoop,2)] =
RunMethods(SmoothPathMat, PathDistance, FlatSpeed_Rimpull);
    end

%     for mLoop=1:11
%
%     TPGOHmean(mLoop,  1:3) = mean(TPGOHsim{mLoop});
%     end
%

end
```

APPENDIX II

Run Methods

```
function [TPGOHsim, EFHFactor] = RunMethods(SmoothPathMat, PathDistance,
FlatSpeed_Rimpull)




%% Velocity Distribution Sampling
VelocitySamplesVector = VelocityDistGrad();


%% METHOD1
[PathTravelTime1, EFHFactor1] = HaulTime_Full_Method_1(SmoothPathMat,
PathDistance, FlatSpeed_Rimpull);

%% METHOD2
NormalizingVel= FlatSpeed_Rimpull;
SampledVelocity = VelocitySamplesVector(1); %flat haul  velocity
[PathTravelTime2, EFHFactor2] = HaulTime_Full_Method_2(SmoothPathMat,
PathDistance, SampledVelocity, NormalizingVel);

%% METHOD3
if SmoothPathMat(1,6) >= 1.5
    SampledVelocity = VelocitySamplesVector(round(SmoothPathMat(1,6))+1);
    NormalizingVel= SmoothPathMat(1,8);
else SampledVelocity = VelocitySamplesVector(1); %flat haul velocity
     NormalizingVel=  VelocitySamplesVector(1);
end

[PathTravelTime3, EFHFactor3] = HaulTime_Full_Method_3(SmoothPathMat,
PathDistance, SampledVelocity, NormalizingVel);

%%%%%%%%%%%%%%%%%% TPGOH Simulation%%%%%%%%%%%%%%%%%%%%%%%%
[tCycleTimes, rMeasuredTonnage] = CycleTimeDistributions();
TPGOHsim(1)= (rMeasuredTonnage * 60)/(PathTravelTime1  + tCycleTimes);
TPGOHsim(2)= (rMeasuredTonnage * 60)/(PathTravelTime2 + tCycleTimes);
TPGOHsim(3)= (rMeasuredTonnage * 60)/(PathTravelTime3 + tCycleTimes);

EFHFactor = [EFHFactor1,EFHFactor2,EFHFactor3];

end
```

APPENDIX III

Distributions

```
function [tCycleTimes, rMeasuredTonnage] = CycleTimeDistributions()


%%%%MeasuredTonnage%%%%%%
pdMeasuredTonnage = ProbDistUnivParam('Normal', [380, 21.9]);
rMeasuredTonnage  = random(pdMeasuredTonnage);

%%%%CycleDelay%%%%%%%
pdCycleDelay = ProbDistUnivParam('Beta', [0.0923, 1.73]);
tCycleDelay = 60 * random(pdCycleDelay);

%%%%DumpIdle%%%%%%%
pdDumpIdle = ProbDistUnivParam('Exponential', [0.869]);
tDumpIdle = random(pdDumpIdle);

%%%%DumpingTime%%%%%%%
pdDumpingTime = makedist('Triangular','a', 0, 'b', 1.43, 'c', 1.5);
tDumpingTime = random(pdDumpingTime);

%%%%LoadingTime%%%%%%%
pdLoadingTime = ProbDistUnivParam('Gamma', [0.935, 3.93]);
tLoadingTime = random(pdLoadingTime);

%%%%QueueTime%%%%%%%
pdQueueTime = ProbDistUnivParam('Beta', [0.168, 2.69]);
tQueueTime = 60 * random(pdQueueTime);

%%%%SpotTime%%%%%%%
pdSpotTime = ProbDistUnivParam('Beta', [1.63, 26.3]);
tSpotTime = 20 * random(pdSpotTime);

%%%%WaitToSpot%%%%%%%
pdWaitToSpot = ProbDistUnivParam('weibull', [0.0542, 0.81]);
tWaitToSpot = random(pdWaitToSpot);

%%%%%%%%%%%EMPTY HAUL%%%%%%%%
pdEmptyHaul = ProbDistUnivParam('Gamma', [4.2, 1.85]);
%ProbDistUnivParam('BETA', [5.03, 14.5]);
tEmptyHaul =  random(pdEmptyHaul);                    %30 *
random(pdEmptyHaul);

tCycleTimes = tCycleDelay + tDumpIdle + tDumpingTime + tLoadingTime +
tQueueTime + tSpotTime + tWaitToSpot + tEmptyHaul;
```

APPENDIX IV

DXF read

```
function [poly3dlines] = dxfRead()


[filename, pathname] = uigetfile('*.dxf'); % choose file to open
% addpath(pathname); % add path to the matlab search path
fid=fopen(strcat(pathname,filename));%('JPMRoadNetq678ore.dxf'); % open file
C=textscan(fid,'%s'); % read dxf file as cell array of strings C
fclose(fid); % close file to accelerate further computation
C=C{1,1}; % reshape array

% %%%%%%%%%%%%%%%%%%%%%%%%%% case point
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%get some markers and help variables
indpoint=strcmp('AcDbPoint', C); % get line no. of points
pointnum=sum(indpoint); % get total number of lines
indpoint=find(indpoint == 1); % get line no. of lines
points=zeros(pointnum,4); % preallocate variable to increase speed

for i=1:pointnum
    points(i,1)=i; % id of line
    points(i,2)=str2double(C(indpoint(i)+2)); % x start
    points(i,3)=str2double(C(indpoint(i)+4)); % y start
    points(i,4)=str2double(C(indpoint(i)+6)); % z start
end
clear indpoint pointnum  % delete garbage from workspace
%%%%%%%%%%%%%%%%%%%%%%%%%%%% end case point %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%% case line %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%get some markers and help variables
indline=strcmp('AcDbLine', C); % get line no. of LW polylines
linenum=sum(indline); % get total number of lines
indline=find(indline == 1); % get line no. of lines
lines=zeros(2*linenum,4); % preallocate variable to increase speed

for i=1:linenum % some funny indexing
    ten=strcmp('10',C(indline(i):indline(i)+2));
    ten=find(ten == 1);
    lines(i+(i-1),1)=i;
    lines(i+(i-1),2)=str2double(C(indline(i)+ten)); % x start
    lines(i+(i-1),3)=str2double(C(indline(i)+ten+2)); % y start
    lines(i+(i-1),4)=str2double(C(indline(i)+ten+4)); % z start
    ten=strcmp('10',C(indline(i):indline(i)+2));
    ten=find(ten == 1);
    lines(i+i,1)=i;
    lines(i+i,2)=str2double(C(indline(i)+ten+6)); % x end
    lines(i+i,3)=str2double(C(indline(i)+ten+8)); % y end
    lines(i+i,4)=str2double(C(indline(i)+ten+10)); % z end
end
```

```
clear cont indline indnum ten k linenum % delete garbage from workspace
%%%%%%%%%%%%%%%%%%%%%%%%%% end case line %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%% case polyline %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%get some markers and help variables
indpoly=strcmp('AcDbPolyline', C); % get line no. of LW polylines
polynum=sum(indpoly); % get total number of polylines
indpoly=find(indpoly == 1); % get line no. of polylines
vertices=zeros(polynum,1); % detto
vertices=str2double(C(indpoly+2)); % the number of vertices is 2 lines after
'AcDbPolyline'
polylines=zeros(sum(vertices),4); % preallocate variable to increase speed,
closed polys excluded
    for i=1:polynum % begin coordinate extraction for every single polyline,
see !readme.m or dxf reference for details and group codes
        clear id xpoly ypoly zpoly  % clear to avoid error
        null=strcmp('0',C(indpoly(i):(indpoly(i)+(4*vertices(i)+10)))); %
find next 0 after last 10...=end of entity
        null=max(find(null == 1)); % max(null)=end of entity polyline(i)
        ten=strcmp('10',C((indpoly(i)+4):(indpoly(i)+null))); % find 10 in C
(10 is group code for x-coords)
        ten=find(ten==1); % reshape ten
        NUM=str2double(C(indpoly(i):(indpoly(i)+null-1))); % get subset of
numeric values of entity polyline(i), strings are nan's
        xpoly=NUM(ten+5);ypoly=NUM(ten+7); % x- & y- coords
        threight=find(NUM(4:10)==38); % find '38' in NUM (38 is group code
for z-coords)
            if isempty(threight) % check out elevation
                zpoly=zeros(vertices(i),1); % elevation =0
            elseif threight~=0
                zpoly(1:vertices(i))=NUM(threight+4);zpoly=zpoly'; % get
elevation if exists
            end
        id(1:vertices(i))=i; % id of polyline
        polyline=[id' xpoly ypoly zpoly]; % create polylinesubset
        seventy=find(NUM(3:6)==70); % find 70 (70 is group code for closed
polylines)
            if NUM(seventy+3)==1 % if polyline is closed...
                polyline(vertices(i)+1,:)=polyline(1,:); % ... add first row
as last one
            end
        [posin(i),z]=size(polyline);
        posout=cumsum(posin);
                if i==1 % save subset to matrix 'polylines'
                    polylines(1:posin(i),:)=polyline;
                else
                    polylines(posout(i)-posin(i)+1:posout(i),:)=polyline;
                end

        clear polyline % clear to avoid error
    end % end case polyline
clear i id indpoly null polynum seventy ten threight vertices
clear xpoly ypoly zpoly NUM posin posout z % delete garbage
%%%%%%%%%%%%%%%%%%%%%% end case polyline %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%% case 3d polyline %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%get some markers and help variables
indpoly3d=strcmp('AcDb3dPolyline', C); % get line no. of 3d polylines
poly3dnum=sum(indpoly3d); % get total number of 3d polylines
indpoly3d=find(indpoly3d == 1); % detto
vert3d=strcmp('AcDb3dPolylineVertex', C); % get line no. of vertices of 3d
polylines
verttotal=sum(vert3d); % total amount of vertices
vert3d=find(vert3d == 1); % detto
poly3dlines=zeros(verttotal,4); % preallocate 3dpolys

    for i=1:poly3dnum % begin coordinate extraction for every 3d polyline
        if i<poly3dnum
            idmax=max(find(vert3d<indpoly3d(i+1)));
        else
            idmax=find(vert3d==max(vert3d));
        end
            idmin=min(find(vert3d>indpoly3d(i)));
            sub=vert3d(idmin:1:idmax); % get indices of coords
            x3d=str2double(C(sub+2));
            y3d=str2double(C(sub+4));
            z3d=str2double(C(sub+6));
            id=zeros(1,length(x3d)); % to avoid error
            id(1:length(x3d))=i;
            ddpoly=zeros(length(sub),4);
            ddpoly=[id' x3d y3d z3d];
            seventy=strcmp('70',C(indpoly3d+6:indpoly3d+11)); % find out if
polyline is closed
            seventy=find(seventy==1);

            closed=str2double(C(indpoly3d(i)+seventy+6)); % get value of
'70'+1 line
            closed=dec2bin(closed,8);closed=closed(:);closed=closed(8); %
because group code '70' is binary coded

            if closed=='1' % if polyline is closed
                [x,y]=size(ddpoly);
                ddpoly(x+1,:)=ddpoly(1,:); % ... add first row as last one
            end

            [posin(i),z]=size(ddpoly); % find out positions to save
            posout=cumsum(posin);

            if i==1 % save subset to matrix 'polylines'
                poly3dlines(1:posin(i),:)=ddpoly;
            else
                poly3dlines(posout(i)-posin(i)+1:posout(i),:)=ddpoly;
            end

    end

clear closed ddpoly i id idmax idmin indpoly3d poly3dnum x3d y3d z3d
clear posin posout seventy sub vert3d verttotal x y z % delete garbage

%%%%%%%%%%%%%%%%%%%%%%%%%% end case 3d polyline %%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%% case 3d faces %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%get some markers and help variables
face3d=strcmp('AcDbFace', C); % get line no. of 3d faces
face3dnum=sum(face3d); % get total number of 3d faces
face3d=find(face3d == 1); % detto
faces3d=zeros(4*face3dnum+1,4); % preallocate, +1 to enable resizing at the
end

for i=1:face3dnum
    fac3d=zeros(4,4);
    fac3d(1,1)=i; % again(id,x-coord,y-coord,z_coords)
    fac3d(1,2)=str2double(C(face3d(i)+2));
    fac3d(1,3)=str2double(C(face3d(i)+4));
    fac3d(1,4)=str2double(C(face3d(i)+6));
    fac3d(2,1)=i;
    fac3d(2,2)=str2double(C(face3d(i)+8));
    fac3d(2,3)=str2double(C(face3d(i)+10));
    fac3d(2,4)=str2double(C(face3d(i)+12));
    fac3d(3,1)=i;
    fac3d(3,2)=str2double(C(face3d(i)+14));
    fac3d(3,3)=str2double(C(face3d(i)+16));
    fac3d(3,4)=str2double(C(face3d(i)+18));
    fac3d(4,1)=i;
    fac3d(4,2)=str2double(C(face3d(i)+20));
    fac3d(4,3)=str2double(C(face3d(i)+22));
    fac3d(4,4)=str2double(C(face3d(i)+24));

        if fac3d(4,2)==fac3d(3,2) % find out if 4th coord pair == 3rd
            fac3d=fac3d(1:3,:); % if so, delete 4th coord pair
        end

    [posin(i),z]=size(fac3d); % find out positions to save
    posout=cumsum(posin);

        if i==1 % save subset to matrix 'polylines'
            faces3d(1:posin(i),:)=fac3d;
        else
            faces3d(posout(i)-posin(i)+1:posout(i),:)=fac3d;
        end
end

faces3d=faces3d(1:min(find(faces3d(:,1)==0))-1,:); % resize face3dmatrix
clear posin posout face3d face3dnum fac3d i z % finished so far
%%%%%%%%%%%%%%%%%%%%%%%%%% end case 3d faces %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%% case circles %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%get some markers and help variables
cir=strcmp('AcDbCircle', C); % get line no. of 3d faces
cirnum=sum(cir); % get total number of 3d faces
cir=find(cir == 1); % detto
circles=zeros(cirnum,5); % preallocate (id x y z radius)

for i=1:cirnum
    circ=zeros(1,5);
```

```
    threenine=strcmp('39',(C(cir(i):cir(i)+1))); % '39' is the group code of
entity thickness
    threenine=find(threenine==1);
        if isempty (threenine) % get coordinates and radii
            circ=zeros(1,5);
            circ(1,1)=i;
            circ(1,2)=str2double(C(cir(i)+2)); % x-coord of center
            circ(1,3)=str2double(C(cir(i)+4)); % y-coord of center
            circ(1,4)=str2double(C(cir(i)+6)); % z-coord of center
            circ(1,5)=str2double(C(cir(i)+8)); % radius of circle
        else
            circ=zeros(1,5);
            circ(1,1)=i;
            circ(1,2)=str2double(C(cir(i)+4)); % x-coord of center
            circ(1,3)=str2double(C(cir(i)+6)); % y-coord of center
            circ(1,4)=str2double(C(cir(i)+8)); % z-coord of center
            circ(1,5)=str2double(C(cir(i)+10)); % radius of circle
        end

    circles(i,:)=circ; % save to matrix

end

clear threenine i cirnum circ cir  % delete garbage


%%%%%%%%%%%%%%%%%%%%%%%%%%%% end case circles %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

APPENDIX V

Get Path

```
%Segments: 1.LineID, 2.x1,3.y1,4.z1,5.NodeID1,6.x2,7.y2,8.z2,9.NodeID2,
10.Length, 11.Gradient
%Lines:    1.LineID, 2.NodeID1,3.NodeID2, 4.Length
%Nodes:    1.LineID, 2.X, 3.Y, 4.Z, 5.NodeID


function [PathMat, PathDistance] = GetPath(Source,Dest,Lines,Segments)

% G=graph(Lines(:,2),Lines(:,3),Lines(:,4));
% [PathNodes, PathDistance] = shortestpath(G,Source,Dest);

G=graph(Segments(:,5),Segments(:,9),Segments(:,10));
[PathNodes, PathDistance] = shortestpath(G,Source,Dest);

PathMat=[];
for kLoop=1:size(PathNodes,2)-1
%     if~isempty(find(Lines(:, 2) == PathNodes(kLoop) & Lines(:,3) ==
PathNodes(kLoop + 1)))
%         LineID(kLoop) = Lines(find(Lines(:, 2) == PathNodes(kLoop) &
Lines(:,3) == PathNodes(kLoop + 1)), 1);
%         temp=find(Segments(:,1)==LineID(kLoop));
%         PathMat_temp=Segments(temp,:);
%     else
%         LineID(kLoop) = Lines(find(Lines(:, 3)==PathNodes(kLoop) &
Lines(:, 2)==PathNodes(kLoop+1)), 1);
%         temp=find(Segments(:,1)==LineID(kLoop));
%         PathMat_temp = [Segments(temp(end:-1:1),1),Segments(temp(end:-
1:1),6:9),Segments(temp(end:-1:1),2:5),Segments(temp(end:-1:1),10:11)];
%     end
%
    if~isempty(find(Segments(:, 5) == PathNodes(kLoop) & Segments(:,9) ==
PathNodes(kLoop + 1)))
        temp = find(Segments(:, 5) == PathNodes(kLoop) & Segments(:,9) ==
PathNodes(kLoop + 1));
        PathMat_temp=Segments(temp,:);
    else
        temp = find(Segments(:, 9) == PathNodes(kLoop) & Segments(:,5) ==
PathNodes(kLoop + 1));
        PathMat_temp =
[Segments(temp,1),Segments(temp,6:9),Segments(temp,2:5),Segments(temp,10), -
Segments(temp,11)];
    end

    PathMat=[PathMat;PathMat_temp];
end

end
```

APPENDIX VI

Load Road Network

```
function [Data, Segments, Lines] = LoadRoadNetwork()
%Data/Nodes: LineID, X, Y, Z, NodeID
%Segments: 1.LineID, 2.x1,3.y1,4.z1,5.NodeID1,6.x2,7.y2,8.z2,9.NodeID2,
10.Length, 11.Gradient
%Lines:    1.LineID, 2.NodeID1,3.NodeID2, 4.Length

Data =dxfRead();
Data(:,2:4) = round(Data(:,2:4),2);

Nodes=unique(Data(:,2:4),'rows'); %Nodes: x, y, z
Data(1,5)=find(Nodes(:,1)==Data(1,2)& Nodes(:,2)==Data(1,3) &
Nodes(:,3)==Data(1,4));
for iLoop=2:size(Data,1)
    Data(iLoop,5)=find(Nodes(:,1)==Data(iLoop,2)& Nodes(:,2)==Data(iLoop,3)
& Nodes(:,3)==Data(iLoop,4));
end


% Set up matrix
Segments = [Data(1:end-1, :) , Data(2:end,:)];
Segments(Segments(:,1) ~= Segments(:,6),:)=[];


Segments(:,6)=[];
% Calculate distance using difference matrix
diffMat=Segments(:,6:8)-Segments(:,2:4);
Segments(:,10)= sqrt(diag(diffMat*diffMat'));

clear diffMat
diffMat=Segments(:,6:7)-Segments(:,2:3);
Segments(:,11)= 100*(Segments(:,8)-
Segments(:,4))./sqrt(diag(diffMat*diffMat'));

%%%%%%%%%%%%%%%%%% Cap Gradients of segments within route to
GradientUpperCap and GradientLowerCap

GradientUpperCap = 15;
GradientLowerCap = -15;

Segments(Segments(:, 11) > GradientUpperCap,11)=GradientUpperCap;
Segments(Segments(:, 11) < GradientLowerCap,11)=GradientLowerCap;


%%%%%%%%%%%%%%%%%%                              Plot RoadNetwork raw %
% for iLoop=1:size(Segments,1)
```

```
%
plot([Segments(iLoop,2),Segments(iLoop,6)],[Segments(iLoop,3),Segments(iLoop
,7)]);
% hold on
% end


%%%%%%%%%%%%%%%%%%       Simplify network for Paths, by removing segments.
%%%%%%%%%%%%%%%%%%       Lines are one segment between junctions

row=1;
Lines(row,:)=[Segments(1,1),Segments(1,5),Segments(1,9),Segments(1,10)];
for iLoop=2:size(Segments,1)
    if Segments(iLoop,1)==Lines(row,1)
        Lines(row,3)=Segments(iLoop,9);
        Lines(row,4)=Lines(row,4) + Segments(iLoop,10);
    else
        row=row+1;

Lines(row,:)=[Segments(iLoop,1),Segments(iLoop,5),Segments(iLoop,9),Segments
(iLoop,10)];
    end
end


%%%%%%%%%%%%%%%                                Plot simplified RoadNetwork %
%  for iLoop=1:size(Lines,1)
%
plot([Nodes(Lines(iLoop,2),1),Nodes(Lines(iLoop,3),1)],[Nodes(Lines(iLoop,2)
,2),Nodes(Lines(iLoop,3),2)]);
%  hold on
%  end
```

APPENDIX VII

Run Methods

```
function [PathTravelTime, EFHFactor] = HaulTime_Full_Method_1(SmoothPathMat,
PathDistance, FlatSpeed_Rimpull)



%%%%%               Determine Time Elapsed per segment and total %%%%%%%

PathTravelTime = (60/1000)*sum(SmoothPathMat(:,4)./SmoothPathMat(:,8));

%%%%%%%%%%%%%%%%%%%%%%%%%mean(FlatSpeedSamples) or topspeed rimpull

FlatTravelTime = 60*PathDistance/(FlatSpeed_Rimpull*1000);

%%%%%%% Calculate EFH Factor
EFHFactor = PathTravelTime/FlatTravelTime;

end



function [PathTravelTime, EFHFactor] = HaulTime_Full_Method_2(SmoothPathMat,
PathDistance, rflat, NormalizingVel)


temp_Factors = SmoothPathMat(:,8)/NormalizingVel;
temp_Velocities = rflat*temp_Factors;


PathTravelTime = sum((60/1000)*SmoothPathMat(:,4)./temp_Velocities);

%%%%%               Calculate EFH %%%%%%%

FlatTravelTime = 60*PathDistance/(rflat*1000);

%%%%%%% Calculate EFH Factor
EFHFactor = PathTravelTime/FlatTravelTime;

end



function [PathTravelTime, EFHFactor] = HaulTime_Full_Method_3(SmoothPathMat,
PathDistance, SampledVelocity, NormalizingVel)
```

```
temp_Factors = SmoothPathMat(:,8)/NormalizingVel;
temp_Velocities = SampledVelocity*temp_Factors;


PathTravelTime = sum((60/1000)*SmoothPathMat(:,4)./temp_Velocities);

%%%%%               Calculate EFH %%%%%%%

FlatTravelTime = 60*PathDistance/(SampledVelocity*1000);

%%%%%%% Calculate EFH Factor
EFHFactor = PathTravelTime/FlatTravelTime;

end
```