Improvements to Production Planning in Oil Sands Mining Through Analysis and Simulation of Truck Cycle Times

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ABSTRACT

A theoretical framework based on a detailed analysis of mine operations data from an oil sands mine in northern Alberta and the static simulation of truck cycle times is developed, verified and validated in this paper. Implementation of this framework provides better results than existing in-house tools, which rely solely on manufacturer data, and thus aids in efficient equipment planning for life of mine plans. The use of this framework to modify existing productivity curve estimation methods currently in use at the mine site is also proposed. This method replaces "loaded flat haul" with "effective loaded flat haul" in the estimation of productivity. Validation of the model presents an over estimation of productivity by 4% against an underestimation of over 10% by the existing in-house method.

1. Introduction

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

The research presented in this paper has direct application in the areas of predicting truck requirements for budgeting and life of mine (LOM) planning. There have been insufficient advances in the research of shovel-truck simulation or estimation methods that produce reliable results for LOM planning. Whereas 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 are usually not representative of the complex nature of large-scale, real-world mining operations. These limitations hinder reliable predictions as these software packages fail to capture varying site specific characteristics. Talpac (RungePincockMinarco, 2015), which is one of the most widely used fleet performance software packages, possess a comprehensive library of equipment and their characteristics as provided by the manufacturers. It captures the variability in truck speeds based on gradients, rolling resistance and adjustment factors based on the haulage path between a source and a destination. However, the amount of site specific details that is

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incorporated is limited. Chanda and Gardiner ((2010)) claim that Talpac (RungePincockMinarco, 2015) underestimates and overestimates short and long haul times, respectively. Manyele (2017) claims that loaded haul times are usually longer than empty haul times because of the difference in the weights resulting in slower speeds of loaded trucks, and that empty haul times are usually more variable due to the dispatching logic.

Production rates in an open pit mine operation are affected by the project complexity, traffic flow, accessibility, road condition, gradient, rolling resistance, size of equipment, match factor, operator competency, weather and disruptions, as noted by Kuo (2004). Burt and Caccetta (2014) consider appropriate representation of the associated variability in truck cycle times extremely important as it affects the feasibility of the fleet and the match factor in addition to predicting productivity. Moreover, as noted by Burt (2008), the number of trucks can also affect the truck cycle times due to bunching and excessive queuing. A detailed simulation modeling of the production operations (S. P. Upadhyay*, et al.*, 2013; Shiv Prakash Upadhyay & Askari-Nasab, 2018) bears the capability to account for all the factors and provide more precise results. However, building and running detailed simulation models for site specific operations are time consuming and undesired unless a detailed scenario analysis of the production operations is required.

Bozorgebrahimi, Hall, and Blackwell (2003) emphasize the importance of the haul road network and its characteristics, which have a direct bearing on the truck performance. Rolling resistance of haul roads is an important characteristic affecting cycle times and haulage costs, as observed by Dotto (2014), Thompson and Visser (1997; 2003) and Joseph and Szymanski (2013).

Effective flat haul (EFH) is another metric often used to measure haulage distances and predict haul times (Curi*, et al.*, 2014; Sheremeta, 2015). Curi et al. (2014) define EFH as 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". Campbell and Hagan (2012) used ranges of EFH values for different gradient ranges as modifying factors to develop an equipment selection model. Similarly, Hargroves, Gockowiak, McKeague, and Desha (2014) used EFH to normalize elevation changes. Newmont mining has implemented EFH as one of their key performance indicators (KPIs) in order to better categorize and account for production and equipment usage figures (Newmont, 2014).

Although it has been established that truck cycle time is one of the most important parameters in measuring LOM productivity, efficient prediction tools for estimating this parameter do not exist. A review of existing research shows the need to solve the problem of inaccurate cycle time estimations in open pit mining systems. Poor cycle time estimations may lead to poor LOM planning and, in-turn, deviations from planned production targets. Overestimation of truck requirements may lead to increased costs. On the other hand, underestimation may lead to a shortfall in production. It is thus considered important in this research to develop a tool that can provide cycle time estimations and truck requirements as accurately as possible.

Cycle time is the single most important parameter of a mining operation, as it is a key parameter in estimating maximum achievable production rate between a source and destination. In addition to being dependent on the type and capability of equipment used, cycle time is also impacted by other controllable and external factors. Relevant controllable factors 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.

Many companies have ceased using standard software programs, and, in place, have developed site-specific in-house methods for predicting productivity through cycle times, often with unreliable results due to the low-detail and fast-paced nature of their development. The in-house method evaluated in this paper involves relating the historical loaded haul distances to a productivity performance indicator: tonnes per gross operating hour (TPGOH) through a line of best fit. This line of best fit is then used to predict LOM productivity based on distance between scheduled mining locations and respective dump destinations. TPGOH for each truck cycle is calculated as the ratio of truck payload and the cycle time plus any related delays. The activities that make up the cycle time are: idling at dump, dumping, loading, time in queue, spotting, waiting to spot, loaded hauling and empty hauling. A plot of normalized TPGOH versus loaded haul distance, as shown in Fig. 1 for the mine site evaluated, reveals how inadequate the line of best fit method can be due to high variability in TPGOH. A detailed study of the data revealed that one of the reasons for this variability is the assumption that same distance over different haulage paths shall yield the same haul time, which is not the case. Two paths with same distance but different haul road profiles and surface characteristics cannot be assumed equivalent. Fig. 2 shows how much variability there is in terms of haul time for specific loaded haul distances.

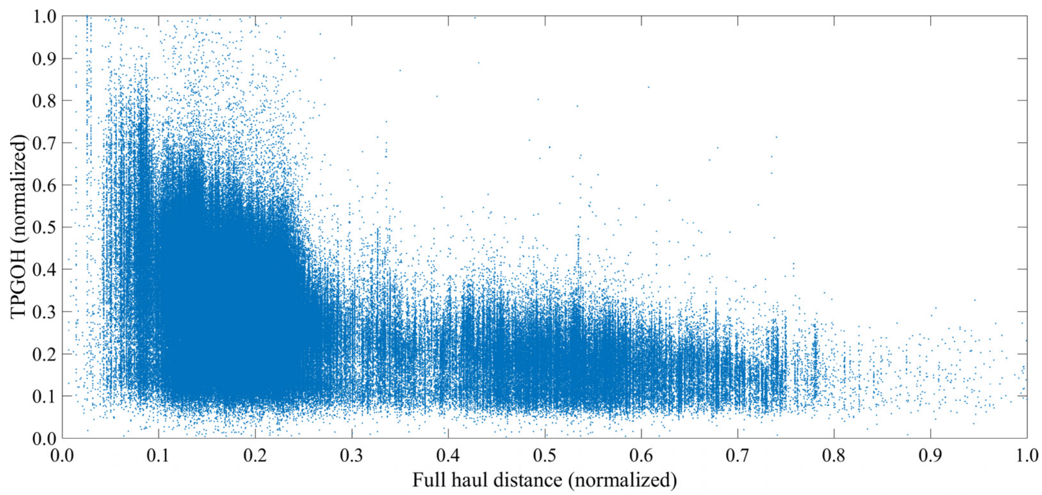

Fig. 1. Tonnes per gross operating hour (TPGOH) vs full haul distance variability (normalized) - company database

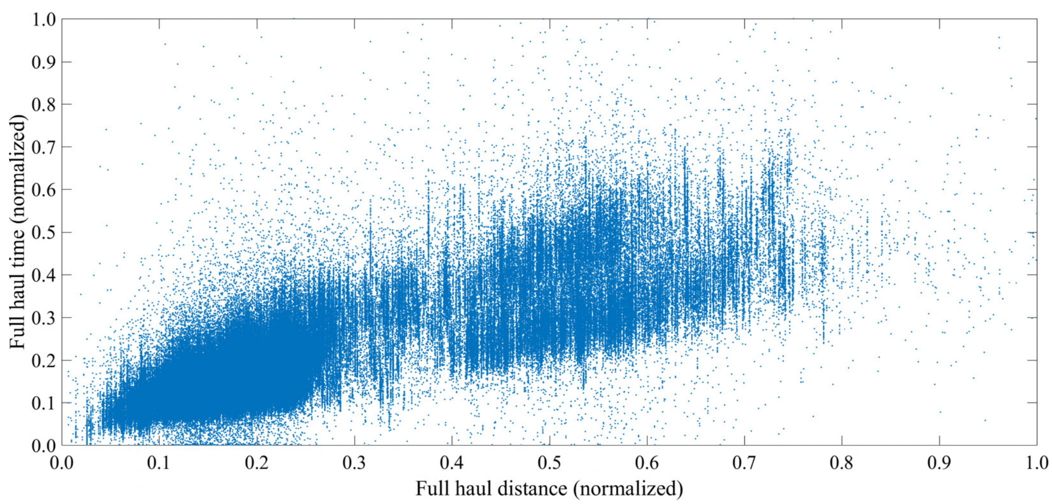

Fig. 2. Full haul time vs. full haul distance variability (normalized) - company database

This paper focuses on generating accurate and reliable estimates of loaded truck travel times through simulation so that productivity figures, such as TPGOH, can be accurately estimated. A comparison of predictions over short, medium and long hauls is presented to show the strength of proposed method (Method 2 in this paper) in comparison to the rimpull method (Method 1 in this paper) which strictly follows the manufacturers' truck performance data. This paper also aims to improve the company's in-house method of deriving productivity curves by replacing the relation of TPGOH to loaded haul with a relationship of TPGOH to loaded EFH (estimated by proposed Method 2 in this paper) in order to reduce the variability in TPGOH, as shown in Fig. 1. To validate this proposition, a comparison of the output of the current in-house method with that of the proposed framework is also presented.

2. Theoretical framework

The framework/tool proposed in this paper assumes the travel component of trucks as the only component contributing to changes in truck cycle times and productivity over the LOM. Other components of cycle time, such as loading time, dumping time, queuing time and spotting time remain independent of the schedule and should follow a fixed distribution over the LOM. For this study, historical data recorded by the company dispatch system are used to fit distributions on each component of cycle time except loaded haul time. It is important here that the distributions are representative of the system for a true representation of the environment. This framework features full integration with the company's SQL database to access historical dispatch records. Other potentially useful information recorded by the company includes operator ID, equipment ID (both for excavators and trucks) and a timestamp (or shift number), which could be used for further classification at higher resolutions.

A digital model of the mine's haul road network is also required. The accuracy of the outputs produced by this program is, to a large extent, dependent on the accuracy and precision of the road network model. A proper characterization of distances within segments is important, but properly capturing changes in elevation is essential, since these directly affect the speed of the truck. The framework/tool reads in the drawing exchange format (dxf) input of the haul road network from any modeling software to characterize the paths and gradient of segments.

Historical truck speed records on haul roads are also required to model flat haul speed distributions. Usually such data are recorded periodically as velocity maps from the global positioning systems within the trucks. For this study, this information was provided, which included coordinates of trucks with time stamp, velocity, and corresponding shovel and dump names. However, these records were not explicitly segregated, so further manipulation using timestamps and shift identifiers was performed to characterize loaded and empty speed records. A long flat haul section of the road network was chosen to filter out loaded and empty flat haul speeds. A distribution was then derived for flat haul speeds while empty and loaded. This ensures that the variability and characteristics of the truck/network interactions are captured. Moreover, while calculating these data points, an effort was made to exclude areas where the trucks may be accelerating or decelerating. This was accomplished by selecting coordinates of flat haul roads well within the flat section of the road, choosing limits that are not close to where the flat road starts or ends.

To mimic the changes in truck speed with varying resistance values (gradient plus rolling resistance), the rimpull curves for each specific truck type is used in this framework. Rimpull curves are not used to assign speeds as in Talpac (RungePincockMinarco, 2015), but rather to examine the relative changes in velocity based on varying payload and total resistance of segments of haulage paths. It is also essential to properly characterize the rolling resistance of the haul roads, the data for which usually remain unavailable. 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.

The framework/tool presented in this paper is written in MATLAB. This framework presents two distinct methods of calculating haul times. Method 1,based entirely on performance data provided by the truck manufacturer (similar to Talpac and CAT FPC), serves as a benchmark for comparison with proposed Method 2. Method 2 is a data-driven simulation of haul times that incorporates data from the mine site and dispatch, yielding much more accurate and realistic outputs. These two methods are described in more detail below. 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 capability to a company database through direct querying, operating under the assumption that the intended application of this framework is for existing operations with a significant amount of dispatch data recorded and available within the database. Fig. 3 provides an overview of the framework, showing the various steps required to complete the analysis. Step 1provides the assumed rolling resistance of the haul network, truck types and corresponding rimpull curve characteristics and the number of replications required for the desired confidence interval. In Step 2, the framework reads in the road network of the mine and checks for errors. This stage also refines the road network from native resolution to a desired resolution, i.e. it manipulates the segments to have desired lengths to minimize computational burden. Moreover, it eliminates high fluctuations in gradients that may be observed due to the close proximity of two points showing aberrations on haul road characteristics.

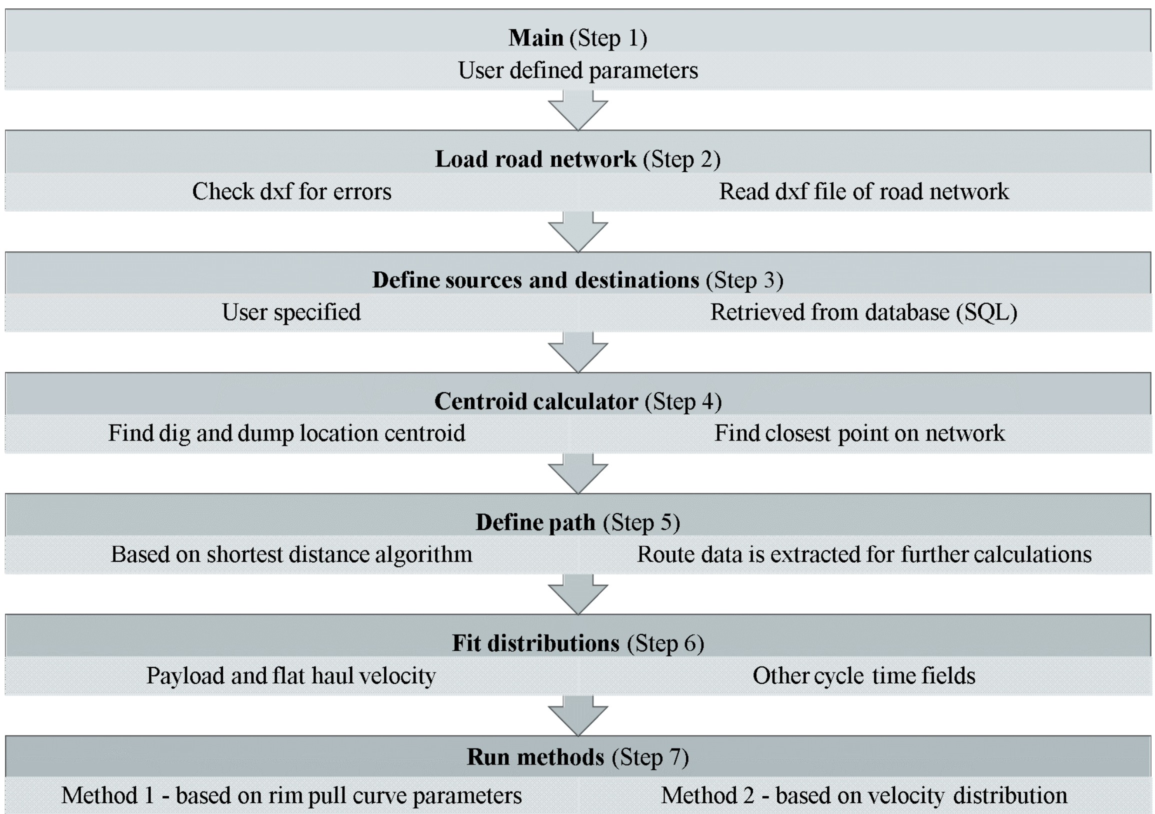

Fig. 3. High level flow chart of the framework

Step 3 provides the dig location and corresponding dump location names. If the tool is used for prediction, this input corresponds to the schedule; otherwise, a SQL query is used to retrieve historical data from a company database for validation and calibration purposes. As the dig and dump locations do not correspond to a single point but an area, Step 4 estimates the centroids for each dig location and dump location and determines the closest point on the haul road network from these centroids. Based on the shortest path algorithm, a path following the haul road network is established in Step 5, constituting segment lengths, gradients and rolling resistance in the direction from dig location to dump location for the loaded haul. Step 6 is a parallel step which provides flat haul velocity distributions for each truck type as well as payload distributions and other cycle time components. Finally the simulation replications are executed in Step 7, using the paths and distributions generated by two methods (Method 1 - benchmark and Method 2 - simulation). The simulation output includes cycle times, payload, EFH and TPGOH. The derived EFH values are proposed to replace corresponding full haul values in company's in-house method to derive productivity curves. The two methods used in this framework to estimate loaded haul times comprise the following.

2.1. Method 1 –benchmark

This method evaluates the total resistance of each segment, by adding the previously defined rolling resistance to the gradient of the segment. Then, a random sample is generated from the payload tonnage distribution and the rimpull force is calculated, based on the weight of the empty truck plus the payload tonnage. Having calculated a rimpull value for each segment, the algorithm then performs an interpolation of the manufacturer's rimpull characteristic data to assign a speed to each segment which is the maximum possible speed at the given conditions. The segment length is then divided by its corresponding speed to determine the time the truck takes to travel through said segment. The sum of all segment travel times results in the loaded haul time between source and destination. The method then calculates the time it takes for the loaded truck to travel the path assuming it is flat. The EFH factor is found by dividing the rimpull based estimate by the flat haul estimate.

2.2. Method 2 –simulation

This method is similar to Method 1 with the exception that rimpull characteristics are used to estimate only the relative changes in velocity instead of velocity itself. Instead of directly finding the speed corresponding to a rimpull value, for each road segment, this method generates a factor which equals the ratio of the rimpull velocity estimate for a given segment to the rimpull velocity estimate for an equivalent flat haul segment. This factor works as an adjustment factor to the flat haul velocity of the truck. Velocity is then sampled from the flat haul velocity distribution for the truck type and multiplied by the rimpull factor to estimate the velocity corresponding to each segment. The remaining estimation of loaded haul time and EFH remains same as in Method 1.

3. Implementation and results

The framework is implemented using data from a large scale oil sands open pit mine in Northern Alberta. At these operations an in-house method is used to derive a productivity curve, i.e. the relationship between TPGOH and loaded haul distance. This, in-turn, is used to predict truck requirements over the LOM for budgeting purposes. The operation employs Cat 797F trucks to haul material from the mine with large haul distances. Although the rolling resistance varies in different areas of the mine and varies based on changing conditions, seasons etc., it is hard to find. For simplicity and in accordance with the literature, a representative equivalent rolling resistance value of 5.5% is used in this implementation for the entire mine haulage road network. This value is determined during calibration of the model, which provided reasonable results. The segment lengths in the road network are defined as 35 m. The road network consists of 47 separate roads between intersections and the end nodes, representing more than 35 km in total length. Due to confidentiality requirements, most of the data presented in this paper are normalized.

A literature review identified that one of the shortcomings of available commercial programs is that cycle time estimates are not accurate for either short hauls or long hauls. Thus, the verification and validation of the model was performed by examining haul time estimates produced by this framework over several haul routes of varying distances. The outputs from both Methods 1 and 2 are compared against records in the company database for four cases consisting of a short haul of 1.3 km (Fig. 4 and 5), a short/medium haul of 2.6 km (Fig. 6 and 7), a medium haul of 4 km (Fig. 8 and 9) and a long haul of 8 km (Fig. 10 and 11). Corresponding statistics and percentage difference from historical data is presented in Table 1, 2, 3 and 4, respectively.

It is important to note that the minimum haul time value on the histogram generated by Method 2 is equal to the unique estimated haul time generated by Method 1, which is the best-case scenario using the maximum velocity possible at the given total resistance. It should also be noted that, although the histograms generated from the company database records show values smaller than this theoretical value, this can be attributed to recording errors within the dispatch system. A total of 500 replications were performed with less than 20 seconds of run time for each case.

Table 1. Short haul output summary

Short haul (1.3 km average)	Database	Method 2	Difference (%)	Method 1	Difference (%)
Mean	5.58	5.52	–1	4.19	–24.9
95% confidence interval	0.11	0.12			
Upper bound	5.69	5.64			
Lower bound	5.48	5.40			
Median	5.27	5.16	–2.1		
Standard deviation	1.67	1.35	–19.2		
Variance	2.80	1.82	–35.0		

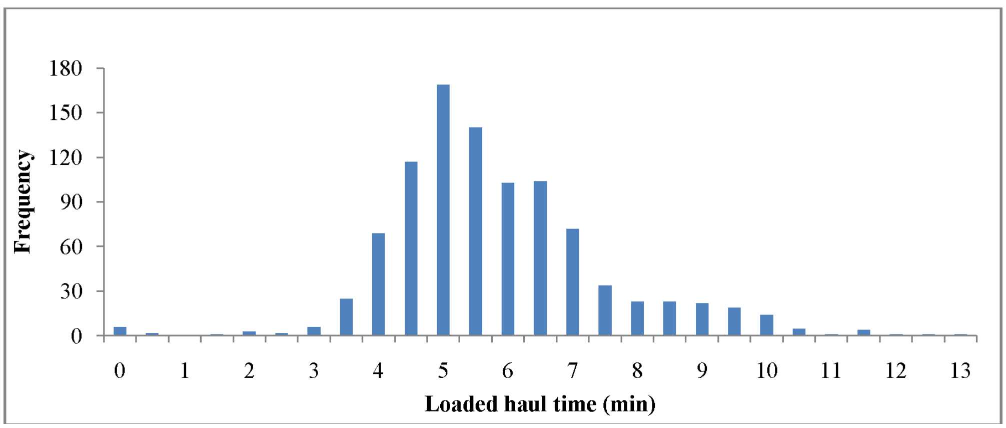

Fig. 4. Short haul histogram, company database

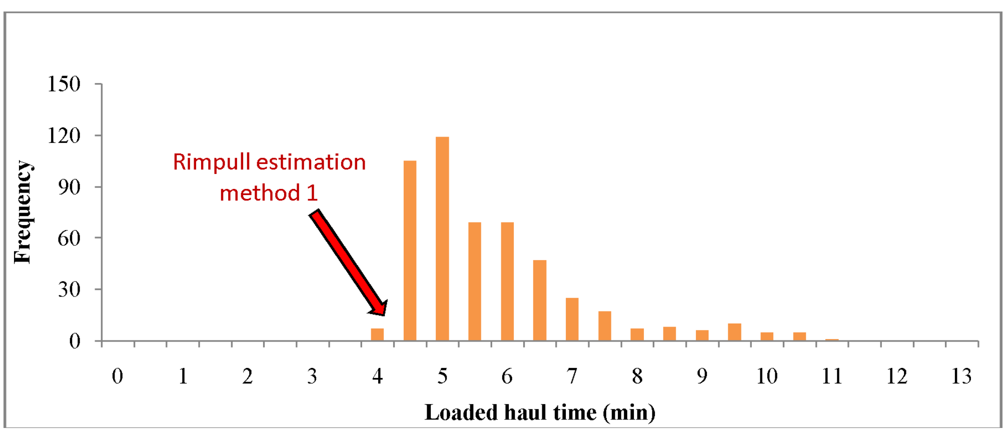

Fig. 5. Short haul simulation output histogram, Methods 1 and 2

Table 2. 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
95% confidence interval	0.14	0.21			
Upper bound	8.99	9.29			
Lower bound	8.92	8.87			
Median	8.83	8.50	–3.7		
Standard deviation	2.10	2.40	14.3		
Variance	4.42	5.61	26.9		

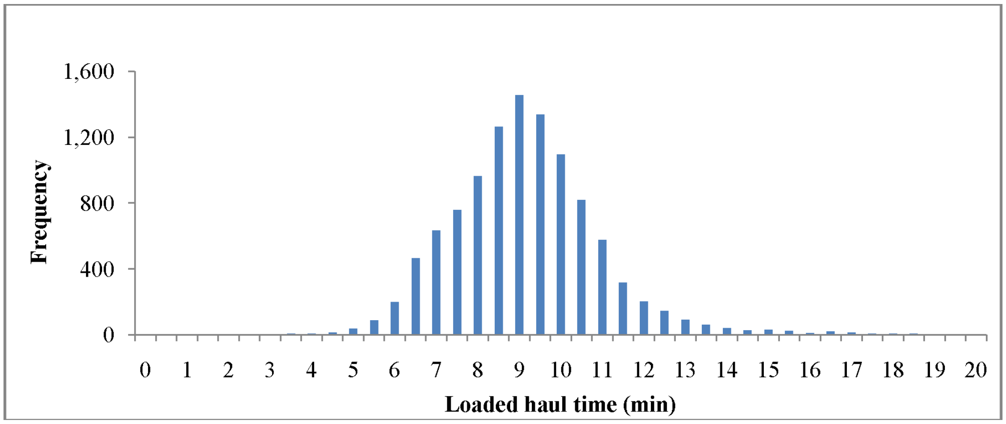

Fig. 6. Short/medium histogram, company database

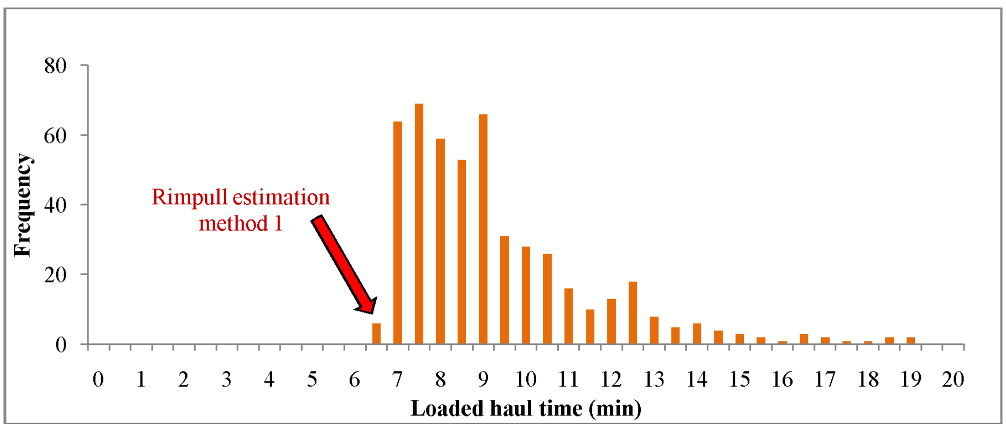

Fig. 7. Short/medium simulation output histogram, Methods 1 and 2

Table 3. 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
95% confidence interval	0.09	0.37			
Upper bound	15.71	15.97			
Lower bound	15.52	15.23			
Median	15.58	14.38	–7.7		
Standard deviation	3.24	4.20	29.6		
Variance	10.21	18.01	71.0		

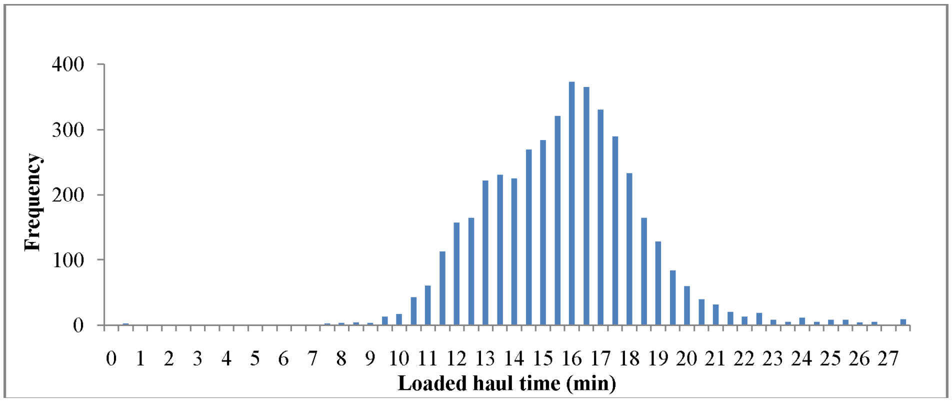

Fig. 8. Medium Haul histogram, company database

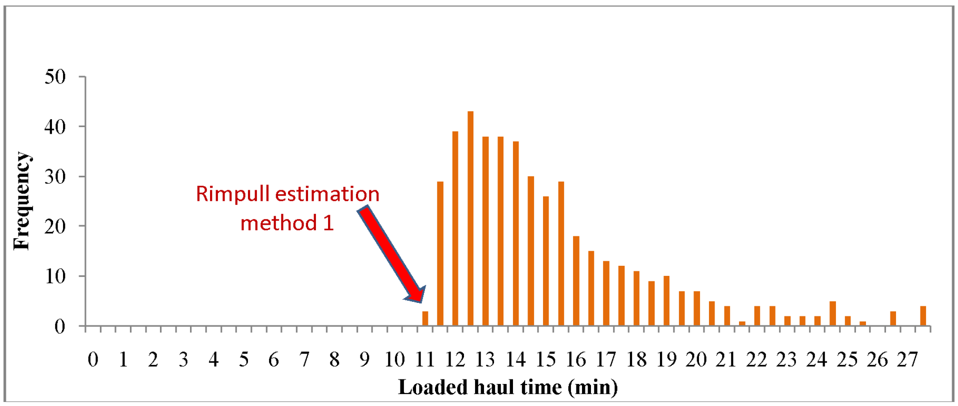

Fig. 9. Medium haul simulation output histogram, Methods 1 and 2

Table 4. 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
95% confidence interval	0.22	0.37			
Upper bound	23.42	23.46			
Lower bound	22.98	22.72			
Median	22.78	21.41	–6.0		
Standard deviation	4.5	6.0	33.3		
Variance	20.0	36.5	82.5		

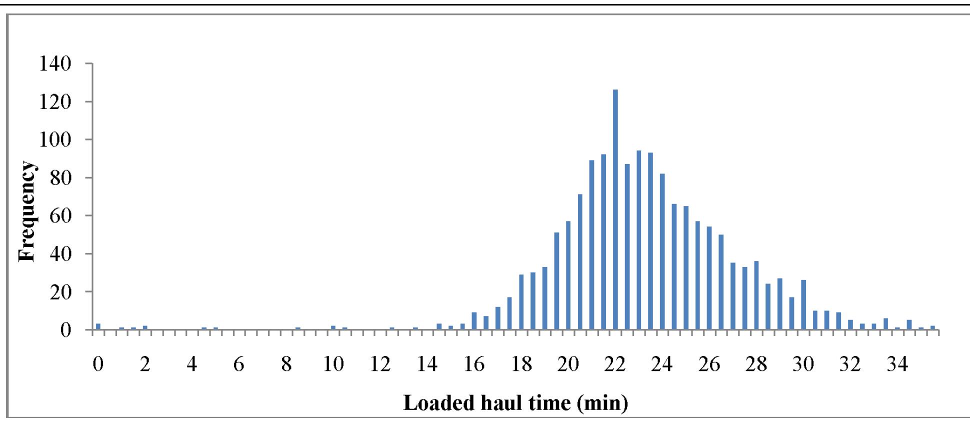

Fig. 10. Long haul histogram, company database

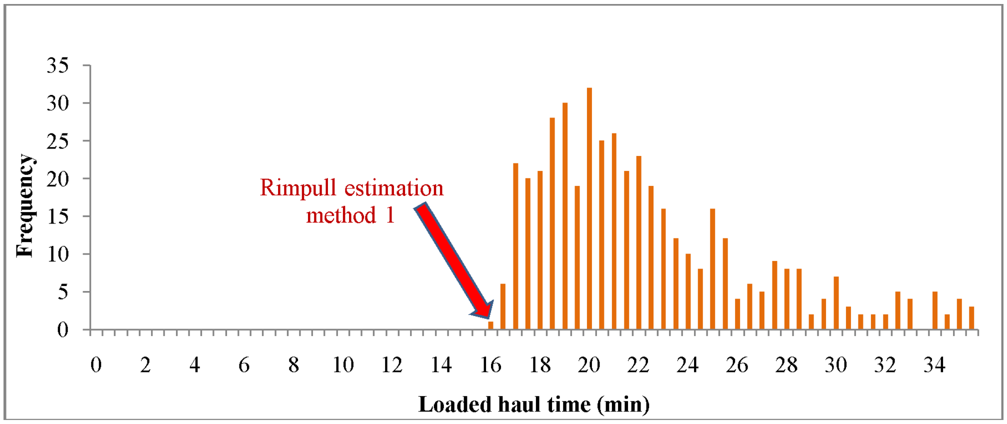

Fig. 11. Long haul simulation output histogram, Methods 1 and 2

It can be concluded from this study that Method 2 is much more accurate in its predictions over all distance ranges in comparison to Method 1. For the four cases, the maximum percentage difference of the mean values of loaded haul times between Method 2 and recorded company data is 1.3% for short/medium haul and the minimum difference is 0.12% for medium haul. For all the cases, Method 2 provided haul times within 1.3% of accuracy compared to the database. As expected, Method 1 overestimates the performance of the trucks by consistently underestimating haul times by about 25%. Comparisons of the histograms generated by the model to those generated from company data for the four cases suggest that the model is simulating the operation correctly.

After the model is verified, it is extended to estimate TPGOH and the results compared against historical data. For this, a quarterly (3-month) simulation of TPGOH was performed. TPGOH is calculated by dividing the payload tonnage 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 directly from their probability distributions. Since the empty return trip time remains unknown due to the possibility of a truck returning from a combination of various dump locations, two scenarios have been analyzed. The first scenario does not incorporate return trip time to estimate TPGOH (scenario 1) whereas the second scenario does (scenario 2). For the second scenario, return trip time is assumed to follow a probability distribution similar to other cycle time components. This is considered a valid assumption at this stage of the study, as data are taken directly from the company database for the given time period being simulated and thus represent reality. Further study is proposed to eliminate this assumption and develop an accurate prediction model for both loaded and empty haul times.

Eleven distinct dig locations with corresponding scheduled production tonnage over the 3 month quarter from 2016 production year are selected. These combinations of dig locations and corresponding dump locations are fed into the model, the corresponding centroids estimated and connected to the network (Fig. 3) and multiple replications run. The resulted TPGOH values for each source/destination combination are then multiplied by corresponding weighting factors. A weighting factor here is the fraction of tonnage scheduled for the dig location/dump location combination as compared to the total scheduled tonnage in the quarter. This process yielded a single TPGOH value estimate to be compared against the database.

3.1. Scenario 1 (return trip not included)

Fig. 12, 13 and 14 show the histograms of TPGOH values for scenario 1 derived from the historical recorded data and the predictions from Method 1 and Method 2, respectively. A statistical comparison of results is presented in Table 5. It can be observed that Method 2 overestimates the mean value of the TPGOH by only 0.58% as compared to 15% for Method 1. Moreover, standard deviation is observed to be fairly small in the prediction methods in comparison to reality. The reason for this variance may be attributed to the variability in truck speeds due to interactions with other trucks and systems on the haulage paths. During the development of these results, it was also noted that there is a 2% difference in productivity during day and night shifts, with the night shift being more productive in reality, which is not accounted for in the current scenario comparison.

Table 5. Quarterly TPGOH simulation output summary (normalized) – scenario 1

	Database	Method 2	Difference (%)	Method 1	Difference (%)
Mean	0.5288	0.5319	0.58	0.6081	15.1
95% confidence interval	0.0058	0.0024	–58	0.0027	–52.8
Median	0.5365	0.5399	0.63	0.6068	13.1
Standard deviation	0.1744	0.0857	–50.9	0.0981	–43.6

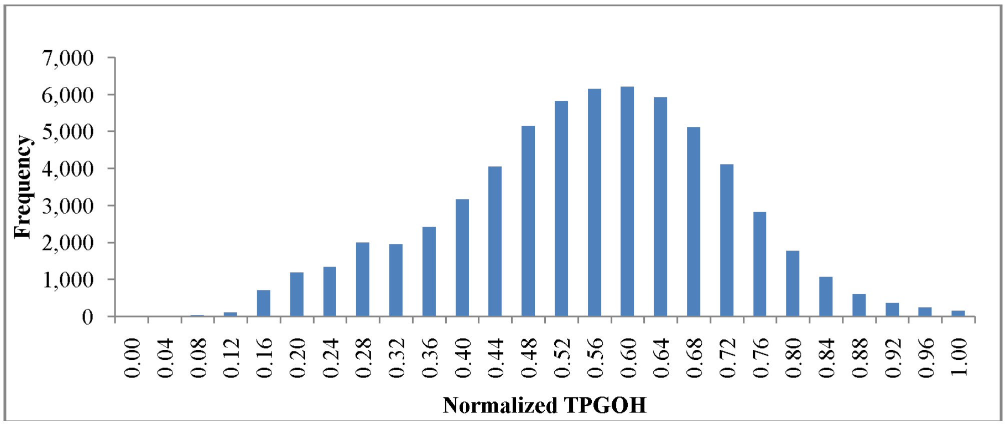

Fig. 12. Quarterly tonnes per gross operating hour (TPGOH)company database histogram – scenario 1

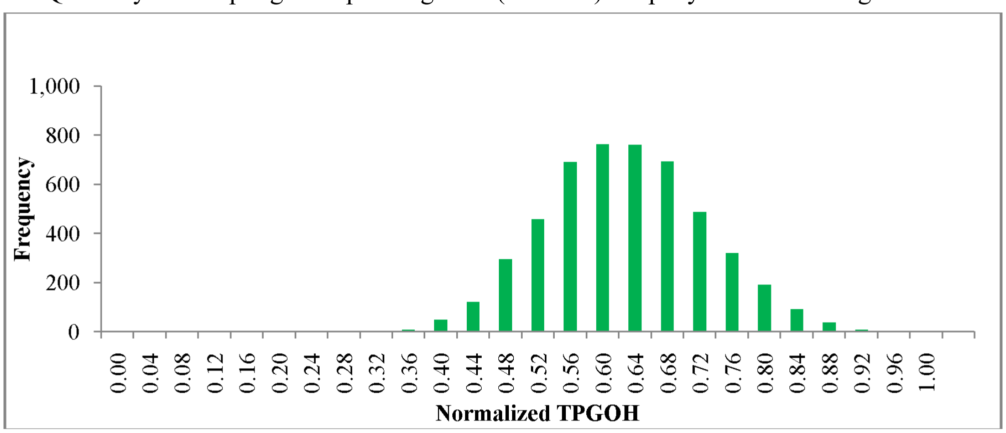

Fig. 13. Quarterly tonnes per gross operating hour (TPGOH) Method 1 output – scenario 1

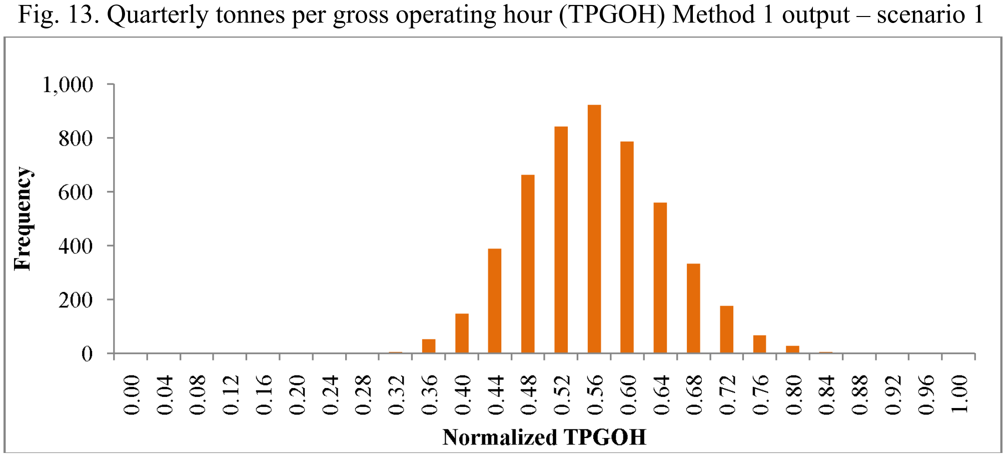

Fig. 14. Quarterly tonnes per gross operating hour (TPGOH) Method 2 output – scenario 1

3.2. Scenario 2 (return trip included)

Fig. 15, 16 and 17 present the histograms of TPGOH values for scenario 2 derived from historical recorded data and the predictions from Method 1 and Method 2, respectively. A statistical comparison of the results is presented in Table 6.This scenario shows more precise estimations of TPGOH compared to scenario 1. Again, Method 2 outperforms method 1 in predicting the mean value of TPGOH with a difference of only 0.09% from recorded data in comparison to 8% for Method 1. Similar to scenario 1, standard deviation of the estimates remain very small in comparison to recorded data for the same reasons outlined above.

Table 6. Quarterly tonnes per gross operating hour simulation output summary (normalized) – scenario 2

	Database	Method 2	Difference (%)	Method 1	Difference (%)
Mean	0.3654	0.3651	–0.09	0.3951	8.1
95% confidence interval	0.0009	0.0014	58.6	0.0015	76.3
Median	0.3739	0.3629	–2.9	0.3929	5.1
Standard deviation	0.1139	0.0491	–56.8	0.0547	–52

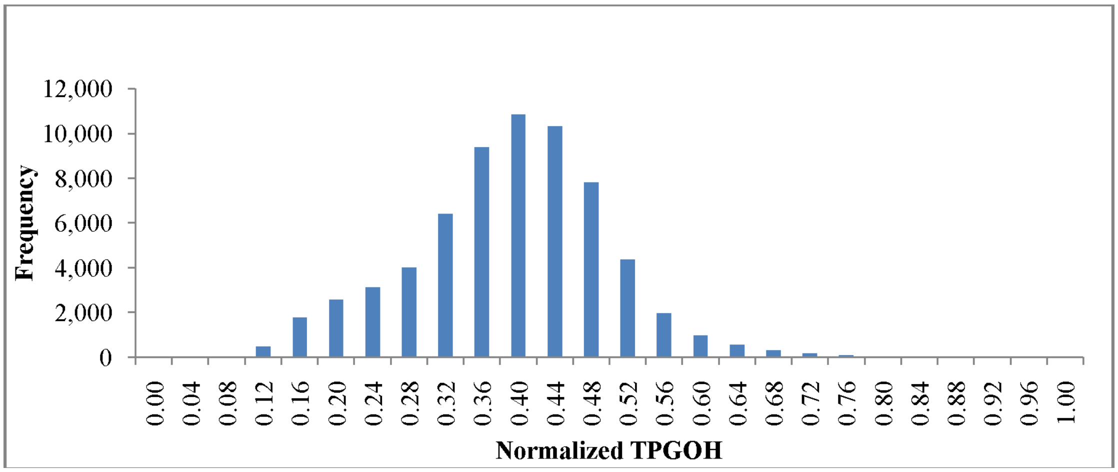

Fig. 15. Quarterly tonnes per gross operating hour (TPGOH) database histogram – scenario 2

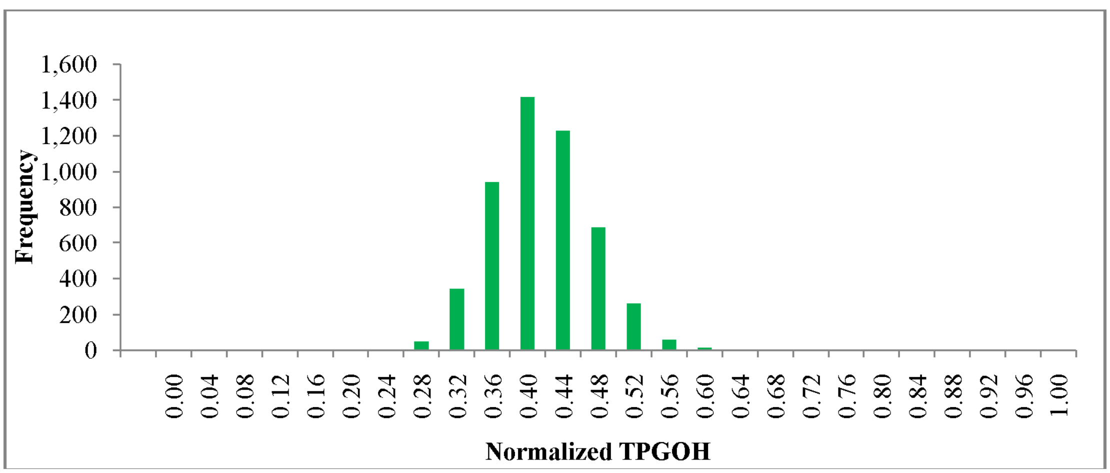

Fig. 16. Quarterly tonnes per gross operating hour (TPGOH) Method 1 averaged output – scenario 2

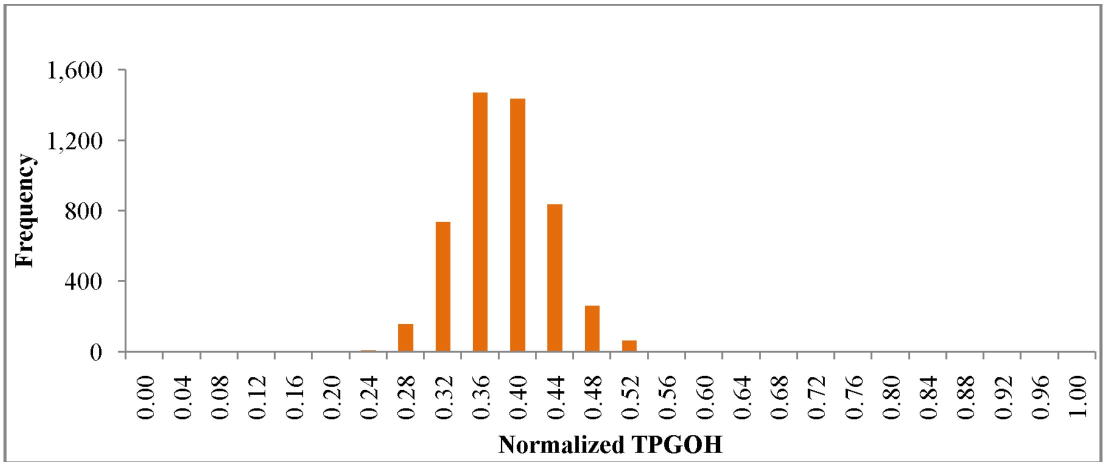

Fig. 17. Quarterly tonnes per gross operating hour (TPGOH) Method 2 averaged output – scenario 2

As expected, the outputs from Method 1 overestimate productivity by underestimating truck cycle times. However, Method 2 provides very close predictions of cycle times and productivity. This analysis proves the validity of the model and Method 2 in estimating the mean value of productivity/TPGOH and that the model is well calibrated and correct.

To improve the current company 'in-house' method, it was compared to Method 2, as proposed in this paper. Using the 'in-house' method, three productivity curves are generated using two years of data, one year of data, and a dataset from the quarter to predict TPGOH for the quarter studied above. A comparison of predictions from the three curves against recorded TPGOH at the mine showed an under-prediction of TPGOH by 12.3,10.3, and 18.2%, respectively. In comparison, Method 2 was applied to replace the full haul distance with EFH while fitting the productivity curves. The resultant curve overestimated the quarterly TPGOH by 4% as compared to recorded data. Although, it is not an exact prediction, this represents a significant improvement in the 'in-house' method. Moreover, an analysis of data used for fitting the productivity curves in both categorizations, i.e. EFH and full haul, showed a reduction in standard deviation by 25% for EFH, which can be regarded as a significant improvement in data variability for fitting amore representative productivity curve.

4. Conclusion

This paper presented a framework for improving the travel time predictions of loaded haul trucks in open pit mines with a focus on large scale oil sands operations, and an improvement to the industrial in-house method of productivity curve estimation for efficient prediction of truck requirements and budgeting. The framework presented here is the result of a thorough investigation of the production data for the mine site used in the case study. The proposed framework was developed to be flexible and easy to implement. During the development of this framework, the main data sources were identified and limited to those that are typically available from mine dispatch systems. Very tight half widths and high confidence intervals were achieved in short computation times for the validation/verification of the case study, adding to the positive features of this framework. The method also shows definite improvement over existing methods which rely solely on rimpull and manufacturer provided data. This improvement is rooted in the fact that the proposed framework is driven by historical data and thus incorporates the characteristics of the specific mine site.

The proposition to replace loaded flat haul with EFH to derive productivity curves also showed reasonable improvements in its prediction. The proposed framework overestimates TPGOH by 4% in comparison to an underestimation of over 10% by the current in-house method used at the case-study mine. However, further improvements to the framework are proposed to improve prediction methods and to model truck travel times more accurately by capturing the actual spread in the travel times. In addition, as future work, the incorporation of methods to estimate empty truck travel times is also proposed. This would incorporate a realistic empty truck travel times to dig locations from various dump locations, similar to that provided by a dynamic dispatch system, in the proposed static simulation framework. Also, efforts will be made to more accurately characterize dig locations in order to model the variation in travel distances of trucks over the duration of mining at each location.

5. References

[1] Bozorgebrahimi, E., Hall, R. A., & Blackwell, G. H. (2003). Sizing equipment for open pit mining – a review of critical parameters. [doi: 10.1179/037178403225003591]. *Mining Technology, 112*(3), 171-179.

[2] Burt, Christina N., & Caccetta, Lou. (2014). Equipment Selection for Surface Mining: A Review. *Interfaces, 44*(2), 143-162.

[3] Burt, Christina Naomi. (2008). *An Optimisation Approach to Materials Handling in Surface Mines.* Curtin University of Technology.

[4] Campbell, S, & Hagan, P. (2012). *Selection of an optimum truck and shovel fleet based on effective flat haul and capacity constraint modelling*. Paper presented at the Eighth Open Pit Operators' Conference.

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

[6] Curi, Adilson, Felsch, Walter Schmidt, Rodovalho, E. Cunha, & Meireles, B. Prado. (2014). *Evaluation of Haul Trucks Performance in a CSN Mine*. Paper presented at the MPES Conference.

[7] Dotto, Magreth S. (2014). *Impact of hauler scale in mine planning.* Unpublished Thesis, University of Alberta, Edmonton.

[8] Hargroves, K., Gockowiak, K., McKeague, F., & Desha, C. (2014). *An Overview of Energy Efficiency Opportunities in Mining and Metallurgy Engineering*: The University of Adelaide and Queensland University of Technology (The Natural Edge Project), commissioned by the Australian Government Department of Industry, Canberra.

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

[10] Joseph, T. G., Curley, M., & Anand, A. (2017). Operational Methodologies for Rolling Resistance Evaluation. [journal article]. *Geotechnical and Geological Engineering, 35*(6), 2935-2946.

[11] Kuo, Yao-chen. (2004). *Highway earthwork and pavement production rates for construction time estimation.* The University of Texas at Austin, Austin, Texas.

[12] Manyele, Samwel Victor. (2017). Analysis of Waste-Rock Transportation Process Performance in an Open-Pit Mine Based on Statistical Analysis of Cycle Times Data. *Engineering, Vol.09No.07*, 649-679.

[13] Newmont. (2014). Full Potential Newmont Newsroom: http://www.newmont.com/newsroom/newsroom-details/2014/Full-Potential/default.aspx.

[14] RungePincockMinarco. (2015). Talpac (Version 10.1.4). Brisbane, Queensland, Australia.

[15] Sheremeta, Robin. (2015). Truck Shovel Productivity: The Historical and Future Strategic Advantage for Teck Coal (pp. 41): Simon Fraser University.

[16] Thompson, R. J., & Visser, A. T. (1997). An introduction to the integrated design of surface mine haul roads. [doi: 10.1080/09208119708944074]. *International Journal of Surface Mining, Reclamation and Environment, 11*(3), 115-120.

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

[18] Upadhyay, S. P., Suglo, R. S., Lin, Z., Sundararajan, S., & Szymanski, J. (2013). Simulation analysis model and equipment selection in continuous surface mining systems. *CIM Journal, 4*(2), 87-94.

[19] Upadhyay, Shiv Prakash, & Askari-Nasab, Hooman. (2018). Simulation and optimization approach for uncertainty-based short-term planning in open pit mines. *International Journal of Mining Science and Technology, 28*(2), 153-166.