SCHOOL OF MINES AND ENGINEERING

OPTIMISATION OF SHOVEL-TRUCK HAULAGE SYSTEM IN AN OPEN-PIT USING QUEUING APPROACH

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DECLARATION

This thesis is my original work and has not been presented for a Degree in any other University.

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ABSTRACT

Equipment selection is key activity in mining operation because it accounts to more than 60% of total operation cost. When selection of equipment is not properly done it results into over-trucking or under-trucking. Under-trucking reduces loader utilisation which leads to waiting times for the loader while over-trucking reduces trucks utilisation which leads to trucks queue at the loader. The waiting times decreases the overall productivity of the haulage operations resulting into increased shovel-truck unit production cost, making the system more expensive.

This research study was carried out in a limestone open pit mine at Mombasa Cement Limited (Vipingo plant) Kenya using queuing theory technique to study and optimize the haulage system. A multichannel queuing model ($M_1/M_2/S/n$: FCFS) was developed to capture the activities and predict the behaviour of the haulage system from loading at the shovel to dumping at the crusher and back at the loading points.

The trucks inter-arrival time (min), service time (min), number of loaders, the truck capacities, and the current number of trucks in the system were recorded. This data was analysed based on the assumptions of a multichannel queuing approach with negative exponential inter-arrival time and negative exponential service time. The model was developed in Mat-lab software and used to calculate the inter-arrival rate and service rate for the different number of trucks subjected to the same queuing system. The current system gave an inter-arrival rate of 12 trucks/hour and service rate of 10 trucks/hour with 16 trucks and 2 servers in the system. Upon subjecting the data to the optimisation model, the results showed that when the number of trucks increased, the productivity of the shovel increased up to an optimal point after which, a

further increase in the number of trucks reduced the truck productivity hence increasing cost per tonne hauled. The result indicated that the optimal fleet size was 12 trucks with 2 servers in operation and thus the 4 trucks could be sold or parked only to be used upon breakdown.

DEDICATION

To Almighty God for been my provider, protector, and guider. To my dear family: my parents (Mr. Bernard K. Munyambu and my late mother Mrs Margret K. Kaungu), my wife (Alice Elijah), my daughter (Alicia Pendo) for being by my side in every step of my life. Lastly, to my sisters (Janet Kaungu, Angeline Kaungu, and Gladys Kaungu) and brother (Christopher Kaungu) who have been my motivator in my academic life.

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May God bless them abundantly!

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACRONYMS AND ABBREVIATIONS

CPU	Central processing unit
C_h	Haulage cost (Kshs/Tonne)
C_l	Loading cost (Kshs/Tonne)
C_t	Total Cost (Kshs/Tonne)
KShs	Kenya Shillings
MF	Matching Factor
MHS	Material Handling System.
M_1	Probability distribution for truck inter-arrival time
M_2	Probability distribution for shovel service time
n	Number of trucks
S	Number of loaders (shovels)
S-T	Shovel-Truck
Q_n	System daily production (Tonnes/day);
η_s	Shovel utilisation (%)
η_t	Truck utilisation (%)

1 INTRODUCTION

1.1 Background Information

Surface mining is the most practiced mining method carried out across the mining world (Meredith , 2013). In surface mining, there are mainly five stages which include prospecting, exploration, development, exploitation, and reclamation. Surface mining methods can either be open-pit mining, open cast mining, strip mining, dredging, and mountaintop-removal. The open-pit production operation accounts for more than 60% of all surface production (Hartman & Mutmansky, 2002). The production operation in open-pit mining involves a series of activities from loading, travelling loaded, manoeuvring at the dump, dumping, and travelling back to the loader. When and how to carry out these activities is subject to the decision made by the mining engineer or planer (Zeng, 2018). Figure 1.1 shows the share of mining technologies on the amount of mining production carried out around the world (Drebenstedt, 2018).

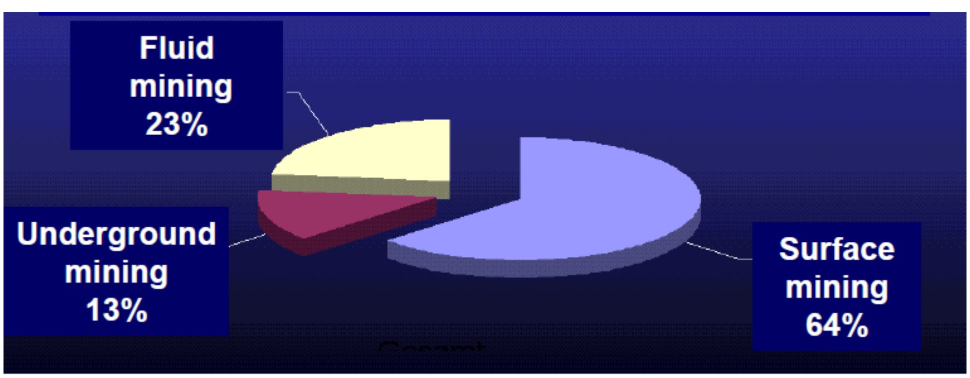

Figure 1.1*:* Share of mining technologies based on the world mining production

Loading and haulage are the major activities for mining transport scheme and they are commonly carried out using shovels and trucks system. The system is designed in line with the short and long -term production goals of the company. The design includes equipment selection to match the fleet size and loaders to get optimal equipment combination (Fisonga & Mutambo, 2017). The process of equipment selection is an optimisation procedure that involves determining the fleet size that has an overall minimum haulage cost and increased equipment utilisation (Nouri Qarahasanlou, Ataei, Khalokakaie, Fatoorachi, & Barabady, 2019).

Occasionally, waiting times are experienced at loading and dumping points. The waiting times at these stations reduce the capacity of operation and hence increases the unit cost per material hauled. It is evident that the waiting times occur when there is over-trucking or under-trucking. The system over-tucking increases loader utilisation but reduces truck utilisation; while under-trucking reduces shovel utilisation and thus reducing productivity. For example, over-trucking leads to a decrease in truck productivity while the production of the shovel will increase until the service rate is optimal (Hai, 2016). The estimation of these waiting times is fundamental since the goal of mining operations is to deliver material that meets the company's production target at a reduced cost. This estimation is aided by operation research like simulation or queuing technique. The implementation of these techniques, together with the performance calculators of trucks and shovels is an essential tool in the process of equipment selection and monitoring of daily production targets.

Queuing theory is an approach of providing service for random increasing demand while predicting the behaviour of the system. The approach gives a good method of estimating the waiting times in a haulage system because it is computationally fast, and quite simple to formulate as compared to simulation approaches (Meredith, 2013). In some cases, calculation using queuing approach can substitute simulation because it gives analysis in a short time and at a low cost. Taking into consideration the truck dispatching where the forward estimation of waiting times is vital information for the dispatcher, it provides the best and the only way quick enough to provide information (Elbrond, 1979). This research focuses on the queuing model that can be used during the calculation of shovel productivity as well as fleet production performance for open-pit mines.

1.2 Motivation of the Study

The demand for raw materials is quite high in the world. The fact is that high-grade ores are being depleted, and thus companies are going for low-grade ore deposits. This has led to large volumes of material being hauled to the processing plant for processing to get quantity of mineral that satisfies the market demand. The haulage of a big volume of the material to the processing plant has led to a big fleet size operation and thus proper equipment selection is necessary to reduce waiting times that increase unit production cost. This research focuses more on limestone quarry haulage systems in cement companies. The aim is to devise a model based on queuing theory technique to evaluate the behaviour of haulage systems to achieve optimal production targets at a reduced cost.

1.3 Study Justification

According to (Darling, 2011), haulage and loading costs contribute to 63% of the total production cost for any mine. This means that optimising haulage will lead into a cheaper and more efficient mining practice. Some companies have several loading points where they source the material. These loading points represent service points and for this case, more than one loader is needed. When the system involves more than one loader its complex and the fleet size needs to be defined well to reduce waiting times. To extract material from the surface entails several operations that yield significant cost implications. Among the activities, haulage has proved to be more costly, which takes a significant share of the operation cost as in Figure 1.2 (Darling, 2011).

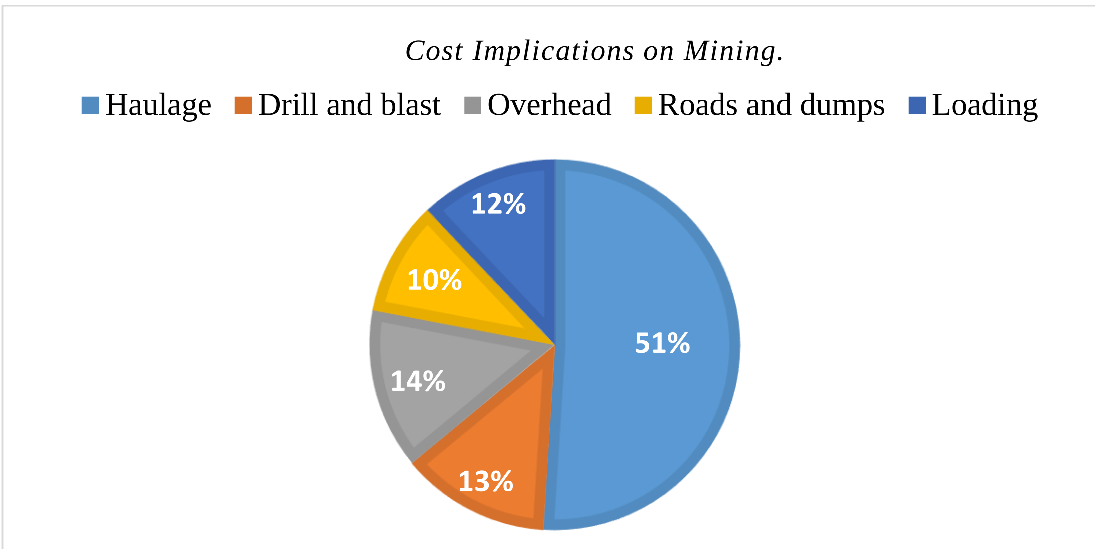

Figure 1.2: Cost Implications for Mining

1.4 Problem Statement

In open-pit mining, there are waiting times which are experienced at loading and dumping points due to poor equipment selection. Poor equipment selection results when there is over-trucking or under-trucking. This leads to reduction in the overall productivity of the haulage operations resulting in increased shovel-truck unit production cost hence making the system more expensive.

Previous studies have been carried out to address the challenge of increased unit production cost as a result of waiting times through various approaches such as bunching theory, matching factor, queuing theory, and simulation. However, bunching and matching approaches have several limitations as they only take into account the compatibility and number of the shovels/trucks while ignoring the production requirement (Hai, 2016). This has consequently limited the success of these approaches since their output does not guarantee optimal fleet size for the given production target. On the other hand, simulation is complex, costly, and time consuming where good decision-making is needed in a short time.

This research undertakes an investigative study to optimise shovel-truck production system using the queuing approach by developing a queuing model which is capable of reducing waiting times to increase equipment utilisation. The approach gives a better method of estimating the waiting times in a haulage system because of its calculation speed, low cost, and simplicity as compared to simulation.

Based on recent research done using queuing theory, this study develops a multichannel queuing model that is capable of carrying out backward and forward optimisation based on the existing system traffic congestion. Backward optimisation is optimisation of over-trucked system by removing truck by truck until an optimal fleet size is obtained. The forward optimisation is carried out in an under-trucked system by adding truck by truck until an optimal fleet size is obtained.

1.5 Objectives

The general objective of this study was to optimise shovel-truck (S-T) production in open pit mining operations using the queuing approach.

The study sought to achieve the following specific objectives:

1. To determine appropriate S-T haulage operation parameters;
2. To develop S-T operation model using queuing theory;
3. To determine optimal fleet size.

1.6 Overview of the Study

This research focuses on the application of the queuing theory to optimise shovel-truck haulage operation in open-pit mining. The system is analysed through a queuing model, which determines the utilisation and the fleet size. The optimal fleet size is a measure that can be used to determine the production capacity from the truck volume capacities.

2 LITERATURE REVIEW

2.1 Introduction

The mining companies are rapidly exploiting materials which are near the surface and also those within the suitable vicinity. This means that the future mines will be very deeper, and happening in extreme areas. This will leads to increased capital of operations due to large fleet size that will be required to load and haul the materials.

Intensive work carried out in loading and haulage operations incur high operation costs therefore, it is necessary to have a well-defined system that gives optimal material production. There are different ways of conducting material movement; but the commonly used one is the shovel-truck system due to its flexibility to changing dynamics of mining activities (Que, 2016). Loaders are of different types, including electric rope, hydraulic excavators, and front-end loaders (Erçelebi & Kirmanli, 2018). Figure 2.1 illustrates these types as they differ mostly in terms of availability of equipment, mode maintenance needed, and compatibility with different truck types (Caccetta, 2018), the loader volume capacity, and the cost per unit production (Mikhailov, 2017). These different characteristics affect the overall possible utilisation of the loading equipment and the utilisation of the trucking fleet (Burt & Caccetta, 2014).

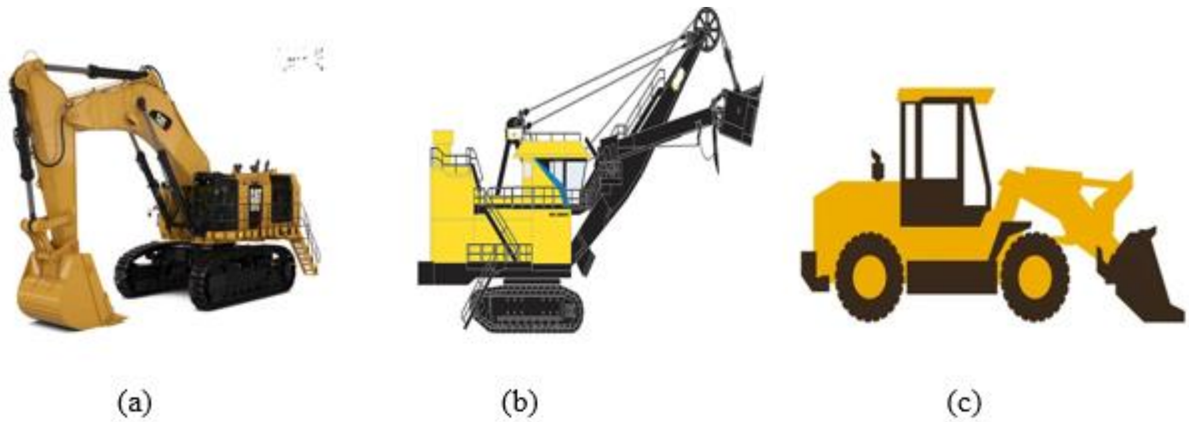

Figure 2.1: Excavating equipment (a) hydraulic shovel, (b) rope shovel and (c) front-end loader

2.2 Equipment Selection

The current hard economic situation reflects in all industries while the mining industry is growing towards cleaner and safer working environments, increased productivity, lower labour, and reduced energy costs. The cost incurred during these operations can be reduced by optimising the current system or by introducing a new one. The transition from an operational haulage system to a different one is complicated task that needs profound investigation (Mahieu, 2017). The investigation include real testing of new haulage systems in running mining operation which is time consuming with high cost impacts and more so affects the current production.

Equipment selection in open-pit mining is critical in mine planning, and it has a great impact on the economic viability of operations. The purpose of equipment selection is to come up with optimum equipment with minimum cost while maximising production (Burt & Caccetta, 2014). There are several techniques used in equipment selection and the basic flow of each technique follows the simple procedure illustrated in the flow chart Figure 2.2 (Burt, 2008).

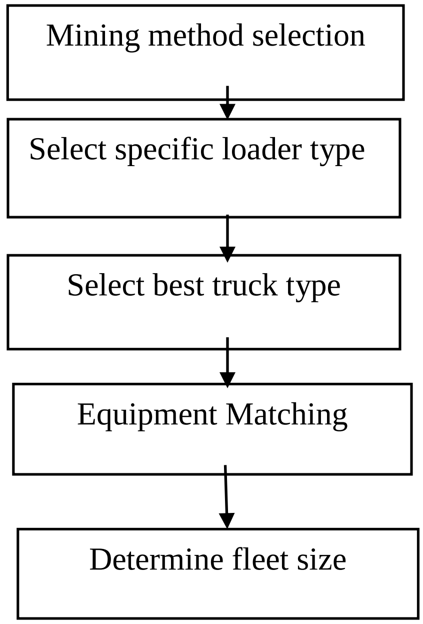

Figure 2.2: Basic Heuristic Equipment Selection Technique

The methods of equipment selection differ on the assumptions and type of constraints that are included in the model resulting in different success rates. The methods with high accuracy are expensive and this results in one of the biggest challenges to small companies with low income to purchase the expensive software. These methods include heuristic, statistical, artificial intelligence, and optimisation techniques.

Heuristic methods are primarily used for learning or discovery and don't guarantee optimal solution but are sufficient for immediate goals. Mostly, they are employed where the process of obtaining an optimal solution is impossible or impractical. An example of the heuristic method is the match factor which can give the number of trucks, but it does not guarantee the optimal number of trucks that can meet the production target. The match factor has been used as a means of determining the appropriate fleet size (Burt & Caccetta, 2014); however, selecting the best equipment types must be performed by an expert before applying the formula.

Statistical methods summarise data from a sample using indexes such as mean, standard deviation and, inferential statistics to draw conclusion from data that is subject to random variation. A multiple linear regression model was developed at around 1999 to estimate the important equipment selection parameters that display great variation, such as truck cycle time, tyre consumption, fuel consumption, and truck operating hours. The model argued that these parameters are usually estimated via simulation with questionable results due to variations in truck power and load carried. These parameters can then be used to determine an appropriate fleet of trucks and loaders using the simple match factor heuristic approach. This method relies on the existence of large data sets for the appropriate parameters for the mine in question (Hai, 2016).

Artificial intelligence is among the commonly used approaches in shovel-truck operations due to its ability to get feasible solutions within the shortest time possible. There are three common approaches to artificial intelligence, which includes expert system, decision support system, and genetic algorithms. The most common methods in the literature are the expert system and decision support system methods (Soofastaei, Aminossadati, Kizil & Knights, 2016).

Samanta, Bandopadhyay, and Ganguli studied equipment selection based on the expert system. In their research, they determined key factors in the equipment selection model and concluded that the parameter to include in the model would depend on the soil and mining conditions. They also found that the analytical hierarchy process is a decision support system, and it puts into consideration all aspects of equipment selection including geological condition and equipment matching. Naoum and Haidar developed a model of equipment selection problems using a genetic algorithm. The model only worked for homogenous fleet type, and the loader was to be selected before the optimization process is started. The key assumption of the model was that equipment were to be used from purchase until they were completely worn out (Hai, 2016).

Simulation has proven to be the most powerful tool for the mining industry and commonly stochastic simulation (Mauti, 2016). Some of the known simulation tools for mining are Talpac, Arena, Fleet production cost, Monte Carlo simulator, and others. When using stochastic simulation techniques like Monte Carlo simulation for equipment selection, the simulated model creates probability distributions from stochastic variables based on the cycle time data collected. Shi used simulation to predict production for earth movement and also the interaction of particular equipment (Meredith , 2013).

Optimisation techniques are widely applied in mining operations. Integer programs have been used to create mining schedules and for pit optimisation (Mai, Topal, & Erten, 2016). However, for equipment selection, much of the focus is on project completion and dispatching or allocation (Erçelebi & Kirmanli, 2018).

Temeng, Otuonye, and Frendewey developed a real-time dispatching process through a transportation algorithm integrated with a goal programming model. The model considered both the production rate and the ore grade in the objective function to optimise the total production. Considering different haul routes between a source and a destination, the routes that have the shortest cycle time was selected, to maximize production at each haul route. Then, shovels were assigned to haul routes to minimize each route's cumulative deviation of production from the optimal target production. In the last stage, using the transportation model, trucks are assigned to the shovels to minimise the total waiting time for both (Hai, 2016).

Some optimisation methods look at optimising productivity and equipment matching (Caccetta, 2018). Queuing approach is one of those methods used in optimisation by evaluating the current system behaviour and giving the basis for decision making on the efficiency of the system. The approach determines the number of trucks in the fleet that can be operated to meet production targets and at a minimal cost. To determine the number of trucks, the specific throughput of the loaders has to be known first before applying queuing technique. The queuing approach has been used in haulage operation in mining with success by different research as discussed in section 2.4.4.

2.3 Shovel- Truck Productivity Study

In surface mining operations there is always a set production target for the processing plant in a specific period. Time is an important parameter when determining the productivity of the shovel-truck system. The set target has to equal production from the haulage system to ensure that the downstream operations are not affected. The shovel-truck productivity study for this research is more focusing on the application of queuing theory in haulage operation as an optimisation technique.

It is quite important to distinguish between production and productivity in their nature because there is a difference in achieving the set production target and operating efficiently. Production in mining is termed as the total tonnes of material loaded and hauled while productivity in mining is the rate at which production is carried, usually given in per unit time, per unit of capacity, per unit of expense, per machine (Hardy, 2007). The key parameter in shovel-truck productivity is the number of trips the truck can make per shift. The trips are determined by the cycle time because several parameters of haulage can be incorporated in cycle time.

The truck cycle time comprises of the load time, travel when loaded, dump time at the dumpsites, return when empty, queuing, and spotting times. The cycle begins at the loader when the truck is loaded. The dumpsites include the crusher, stockpile, or even waste dumps with the act of manoeuvring at the loader or the dumpsite termed as spotting (Morley, Joseph, & Lu, 2013). The cycle time is crucial parameter in truck production analysis as it can incorporate many parameters related to it. If the need to include the intimate details of the mine arises, such as topography and rolling resistance in the modelling process, these parameters are estimated in form of time before modelling and incorporated in the truck cycle time.

Also, truck cycle time can be used to estimate other parameters such as rim-pull, haul grade, and haul distance into it. Furthermore, the level of truck queuing at the loader depends on the fleet size, and this makes it difficult to accurately determine the truck cycle time before fleet size determination (Burt & Caccetta, 2014). Figure 2.3 simply illustrates the basic haulage cycle but the parameters indicated are not the only influencing factors for truck cycle time (Soofastaei, Aminossadati, Kizil & Knights, 2016).

Figure 2.3: S-T Unit Operation Cycle

It is difficult to predict the cycle time of a fleet with different types of trucks (a heterogeneous fleet) or loaders. This is because the actual cycle time of trucks and loaders can vary significantly with the accompanying fleet without any changes to the fleet type. For the heterogeneous fleet type, the individual truck cycle time is measured in the field and the mean cycle time is calculated (Burt, 2008).

2.4 Determination of Shovel-truck productivity

The shovel-truck productivity research focuses mainly on estimating and optimising the productivity of the loader and truck fleet based on the notion that improving productivity will lead to cost reduction. This approach of optimising productivity can be developed to act as an equipment selection technique with the key target being to determine the fleet size needed to achieve a certain material production target at minimal cost (Burt, 2008). The simplest method of determining the number of trucks in a fleet, N based on productivity is given in the Equation 2.1 (Burt, 2008) as:

$$\mathrm{N} = \frac{Hourly\ production\ requirement}{Hourly\ production\ per\ truck} \tag{2.1}$$

In production optimisation, there are several methods that have proven to be critical as seen in previous research conducted. They include matching, bunching, and queuing approaches.

2.4.1 Matching Factor Approach

Matching factor (MF) is a vital productivity index in the mining industry. This is because the factor gives the measure of the productivity of the fleet, with the ratio been used to match the truck arrival rate to loader service rate. This ratio isolates itself from equipment capacities, and potential productivity, by including only the loading times in the truck cycle times. Equation 2.2 gives a mathematical expression of the match factor and its parameters.

$$\mathrm{MF} = \frac{number\ of\ trucks \times loader\ cycle\ time}{number\ of\ loaders \times truck\ cycle\ time} = \frac{truck\ arrival\ rate}{loader\ service\ rate} \tag{2.2}$$

The cycle time in the equation above does not include waiting times at the loading area. Ideally, the best match of equipment selection is 1 as shown in Figure 2.4. The MF below 1.0 shows under-trucking while the MF above 1.0 shows over-trucking and therefore, MF controls the shovel utilisation and minimises differences in productivity (Burt & Caccetta, 2014) . Hence assigning the correct number of trucks to the shovel results in optimised productivity and performances of the S-T system. Optimisation is done by improving truck cycle time while the loader idle time is eradicated or minimised.

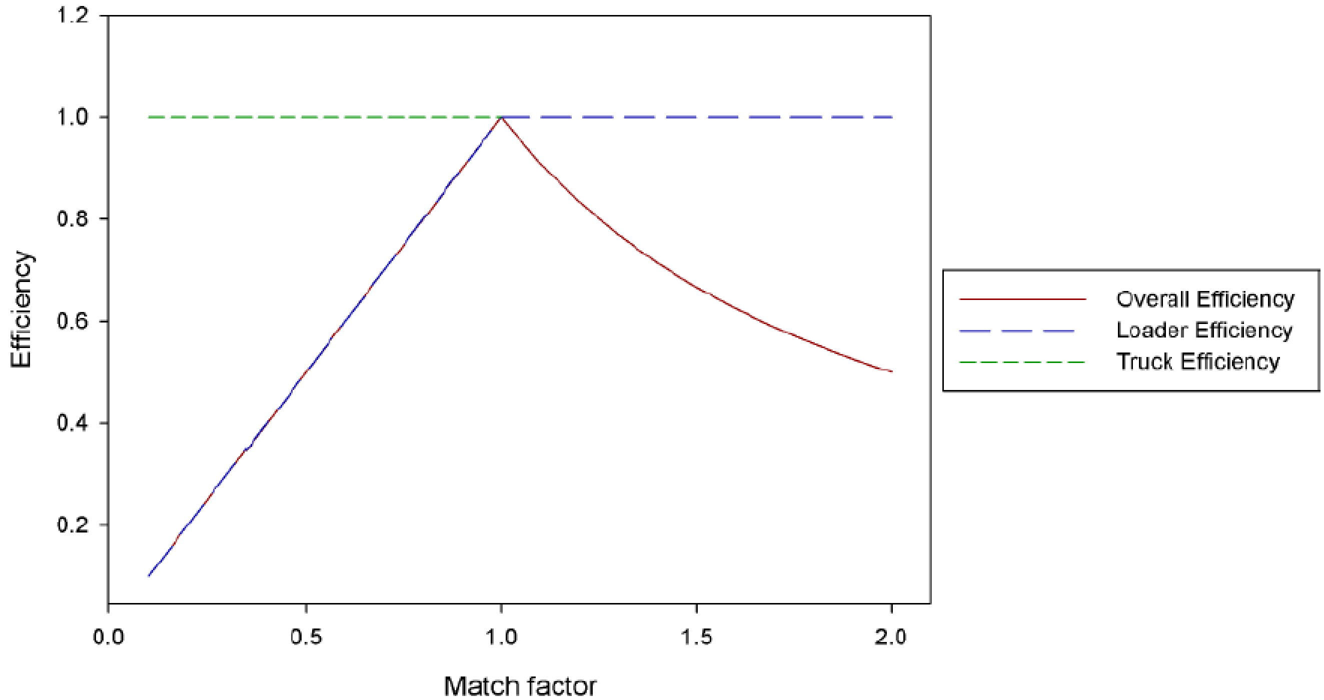

Figure 2.4: Combination of Relative Efficiencies of Truck and Loader

Though, claims that the system operation with low MF is inefficient such claims must be interpreted carefully. These claims meant that fleets with a low MF can be cheap and cannot meet the production target of the operation. The use of the word efficient is usually used strictly in showing the ability of the trucks and loaders to work to their optimal capacity. When the MF is used to determine the suitability of the selected fleet, one ought to understand that the minimum cost fleet may not be considered ideal for a mining operation, as this corresponds to optimal production capacity. This means that, loader at 50% capacity may be significantly cheaper to run than that loader operating at 100% capacity in the same conditions. Finally, this approach should not be used as a sole measure of the efficiency for the S-T system, and thus its result should be counter-checked with other known methods to evaluate its validity (Choudhary, 2015).

2.4.2 Bunching Theory

Bunching mostly occurs when the system does not allow overtaking and the fastest trucks in a fleet catch up with the slowest truck along the haul route and in such a way that all will be forced to move with the speed of the slowest truck. Bunching is known to reduce optimal fleet operation by reducing equipment utilisation. The relationship of bunching effect in loaders and its fleet size is not complicated as that in buses and passengers (Al-Zwainy, & Hadhal, 2016). When trucks have bunched behind the slower truck, the time shifts towards the slower truck. Literature reviews show that when there is a perfect match between a loader and trucks, the bunching effect is 20 to 30 % less (Burt, 2008). According to (Lashgari, Yazdani, & Sayadi, 2010) replacing the old fleet with a new fleet instead of adding a new truck to the existing system minimises the bunching effect since there is always available truck to be loaded with inter-arrival times being slightly constant.

2.5 Queuing Theory

The theory of queuing started early 19th century when it was first used to model telephone calls traffic. In the telephone traffic, randomly arising calls would arrive and be handled by the switchboard with a finite maximum capacity (Torkamani, & Askari-Nasab, 2015). There is a frequent waiting queue in most service locations, either bank, hospitals, government agencies, or even post offices. Variable arrival and service rates in the systems lead to regular waiting queues, and models have to be developed to predict these queues length for better service decision making. This thesis study investigates the optimization of the truck-shovel system, and in the study, customers are trucks, and servers are the shovels.

2.5.1 **Queuing Model Element and Characteristics**

Major components when modelling a cyclic waiting-line system are, calling population, arrival, waiting line, processing order, service, and leaving the system as illustrated in Figure 2.5 (Lin, Wang & Sadek , 2014).

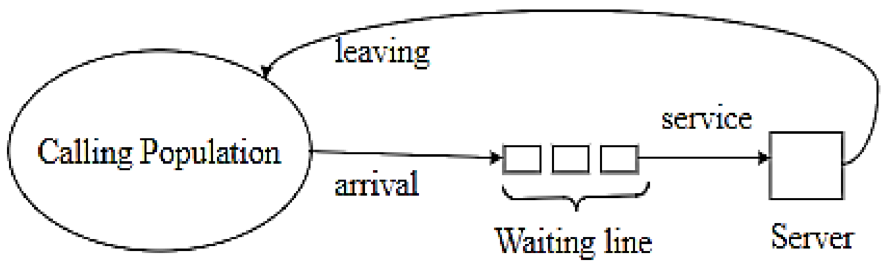

Figure 2.5: Major Components of a Waiting-Line System

2.5.1.1 Calling Truck Population

In queuing a calling population is termed as set of customers likely to arrival in to the system for the service. The population can be finite or infinite. The calling population is termed as infinite when the source is big enough. In this case, the probability of arrival cannot be changed mainly by the fact that there is other customers waiting for the service. In a case, where a system has limited access to service, and there is a limited number of customers to be served this population is termed finite. In this situation the number of customers waiting for services influence the probability of another arrival to decrease as a result of percentage decrease in population. In this study, the truck's population is said to be finite because the number of trucks expected in the system is known.

2.5.1.2 Truck Inter-arrival

The truck's inter-arrival in the queuing system is stochastic because the inter-arrival time is not constant. The inter-arrival time keep of changing with changing dynamic including breakdown, driver efficiency, truck age (Meredith , 2013). The assumption made here is that once the trucks enter the queue they wait until and when served to leave the system. Another assumption that is related to truck inter-arrival is the inter-arrival rate variability, which follows a negative exponential distribution, as shown in Figure 2.6 (Lin, Wang & Sadek , 2014).

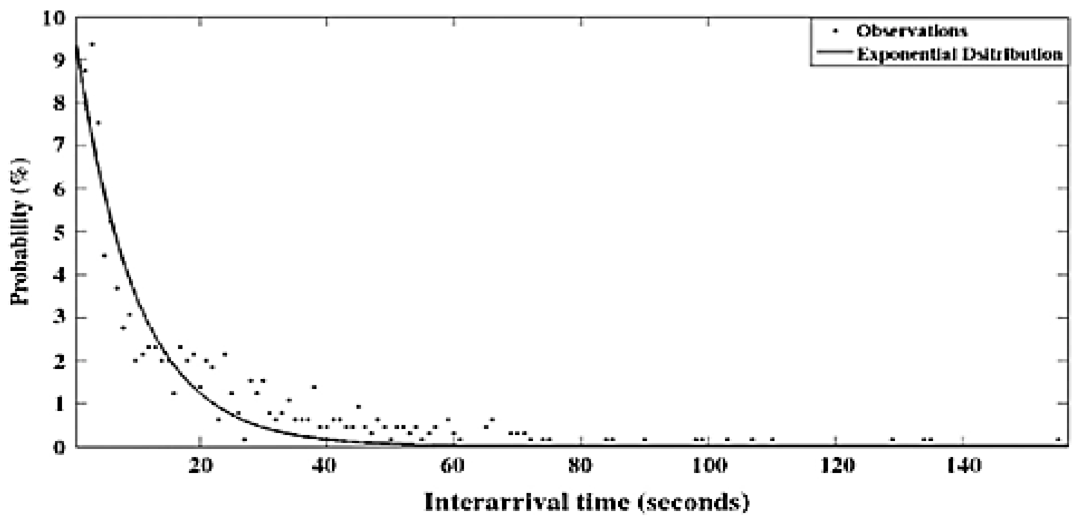

Figure 2.6: Inter-Arrival Time Distribution Curve

2.5.1.3 Waiting Line

The waiting line is also called the service distribution. This step consists of trucks that have already signed into the system and waiting for service. When modelling, the assumption made is that once the truck has been booked into the system, it can only leave once it has been served.

2.5.1.4 Processing Order

The processing order is also referred to as the discipline of service to the trucks. The discipline of service in the queuing model to be developed is First Come First Served (FCFS).

2.5.1.5 Service Stations

The critical aspect is the number of shovels present and their service capacity because this is what is used to determine system fleet size. The service can have one shovel (single channel) or even multiple channels, and the service can have one or a few steps that are handled together referred to as a single phase. The most common assumption made is that the service time can also be denoted by an Erlang distribution, as seen in Figure 2.7 (Lin, Wang & Sadek , 2014).

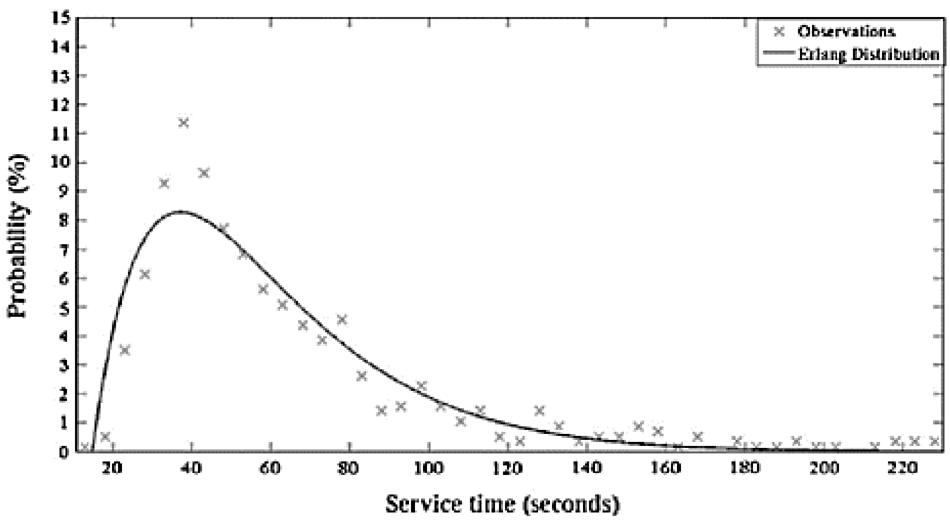

Figure 2.7: System Service Time Distribution

2.5.1.6 Leaving the System

Leaving the system is the last activity a truck does when served. In this research, the truck can only leave if it has been served.

2.5.2 **Queuing Model Classification in Mining**

Mining operations experience queue mostly in the haulage, dumping, and loading when trucks are poised to wait in the line for their turn to get served. Figure 2.8 represents the typical mining operation in the queuing system (Meredith , 2013).

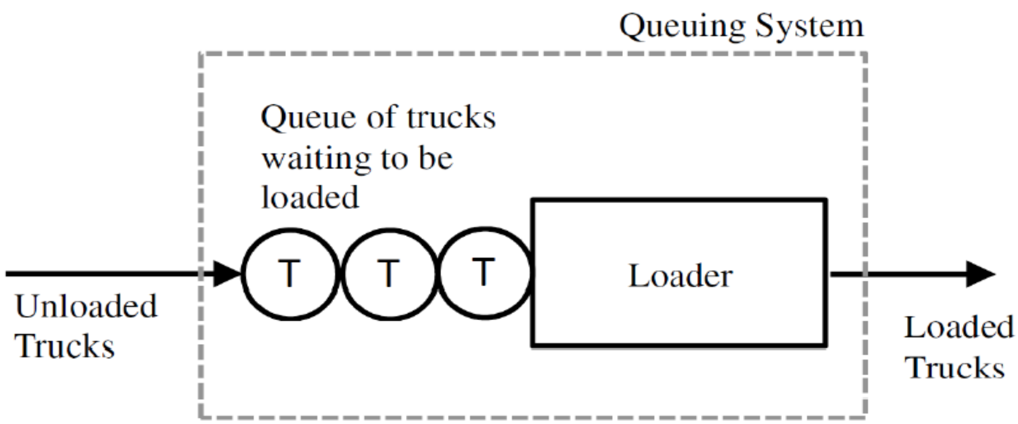

Figure 2.8: Shovel-Truck queuing system

The queuing model can be classified mainly into two: single-channel model and multiple-channel model as shown in the Figure 2.9. The single-channel model is where we have one loader while multiple channel model is where we have more than one loader.

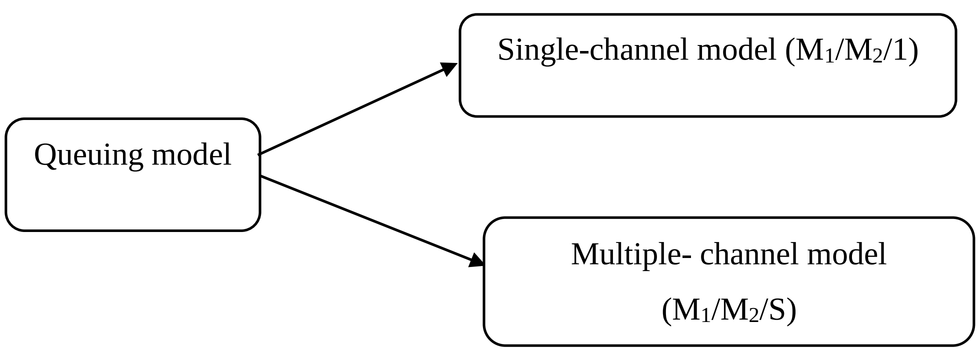

Figure 2.9: Queuing model classification

In cyclic queuing where there is a continuous repetition of similar events in the system the operations can be represented as in Figure 2.10. The haulage route can be subdivided into four main parts: the loader, haul route when loaded, crusher, and haul route when unloaded. Figure 2.11 also represents a single-channel queuing system with only loader or shovel (Meredith , 2013).

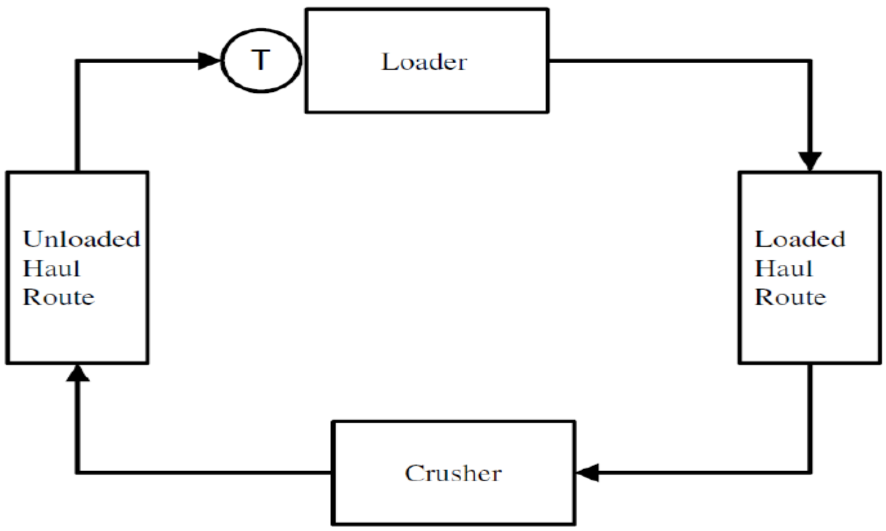

Figure 2.10: Shovel-Truck cyclic queuing system

In some mine operations, the high demand for the materials lead to multi-server being used, and hence the cyclic system can be twisted to fit queuing system with multiple servers. The queuing system here with multiple servers is hereby assumed that the loaders are arranged in parallel as shown in Figure 2.11 (Meredith , 2013). This arrangement can also be called a multiple-channel system.

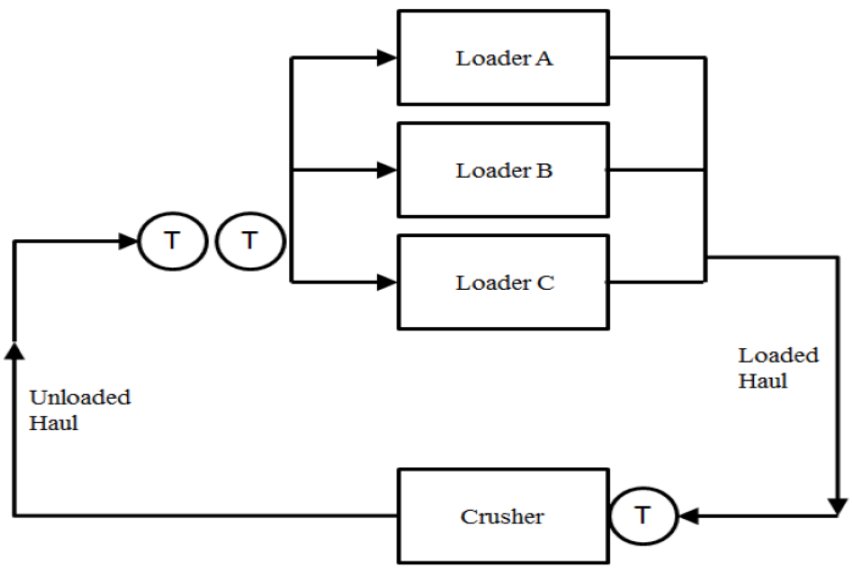

Figure 2.11: Shovel-Truck cyclic queuing system with parallel servers

2.6 Queuing Approach in Mining

The queuing theory was first applied in a mining operation by Koenigsberg. The study modelled conventional, mechanised room and pillar mining operations for closed-loop queuing systems. It considering a finite number of customers based on the assumption of exponential service time distributions. The mining system was deemed to have a set of specialised machines that were working in succession on a series of active mine faces. The entities involved in the cycle were a cutting machine, drilling jumbo, blasting crew, loading machine group, and a roof bolting machine. Each machine was made to proceed to the next face when done with its task. The study also explained that queuing theory notation of the equipment operation cycle has a closed queue with N customers being served in order of arrival from P machines. After the P^{th} stage, the customer (mine face) is in contention for service for the next machine operation. Figure 2.12 illustrate the basic sequence of operation of equipment where the faces serve as customers and the equipment status is shown by 1, 2, 3, 4, and 5 (Torkamani, & Askari-Nasab, 2015).

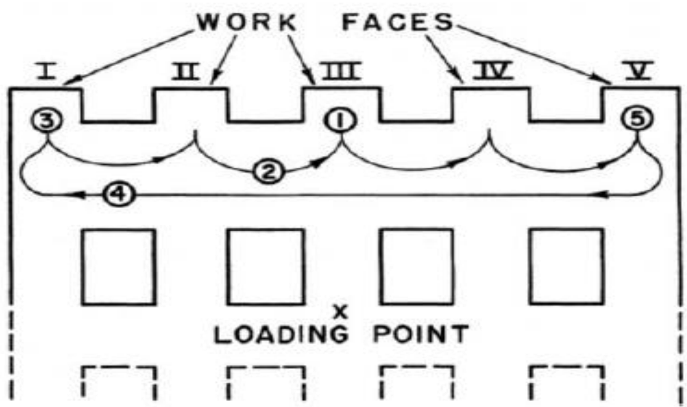

Figure 2.12: Typical mine layout with 1-2-3-4-5 showing equipment operation sequence

The research came with formulas that were used to determine the probability of the equipment system in a specific state, the mean of the equipment waiting for service at a particular stage. It also calculated the delays experienced at that stage, mean cycle time, the probability that stage can be idle and daily output. These equations can be modified for different numbers of servers and customers to compare different machine configurations. The outcome of the study found that output increase as the number of working location were increased while the overall output was limited by the service rate of the slowest machine (Hai, 2016).

Although simulation was common around the 1960s, the queuing approach grew in demand since computer simulation by then needed a computer memory and CPU time, which by then were costly and time-consuming. Analytical modelling approaches like queuing theory with little or no computing requirement become a viable alternative to computer simulation models

(Meredith , 2013). Using queuing theory, it also predicted the production loss as a result of the queue of the trucks at the loader as well as the productivity of different truck fleets (Hai, 2016).

Queuing techniques can be adopted in both civil engineering earth-moving projects and open-pit mining in haulage operations as the haulage operations follow similar technique. Maher and Cabrera applied the closed-loop queuing approach in finding the optimum number of trucks that were capable of minimizing the cost per unit volume of material moved. In their research, the haulage system was analysed to consider loading and transit time as constant or variable, fitting a negative exponential distribution. After data analysis, the model came with graphical charts for choosing the best cost-effective number of trucks based on the ratio of loading time and haulage time and the ratio of the loader and the truck operating costs (Hai, 2016).

Jorgen Elbrond, developed a more direct calculation technique based on queuing theory. His model acted as an alternative to computer simulation for assessing open-pit transport operation capacity, and the approach was based on the queuing theory formula for waiting time in a closed operation where the research also added correcting factors due to the varying times of loading, travels, and dumping. Waiting times were calculated as a function of the number of trucks in operation by averaging the results found through simulations for three different cases: (a) constant travel time and constant service time, (b) exponentially distributed travel time and exponentially distributed service time, and (c) exponentially distributed travel time and constant service time. The correction factors combining theoretical and simulated cases were calculated using an interpolation procedure while other essential data to the truck haul cycle like dumping time and shift data was found using time studies. After developing the model, time measurement made at *Hamersley Iron* indicated a correlation coefficient of 0.865 between the observed and calculated wait time at the loader. This proved that the model developed was accurate for haulage systems (Meredith , 2013)

Karshenas modified the queuing approach, where he made several improvements that were incorporated into equipment selection criteria. The model used interval time in one truck and not interval in the whole truck fleet but, due to the nature of the model, it was restricted to homogenous fleets because the model required the times between the arrivals (Meredith , 2013). However, the work continued in the attempt to a develop model for selecting the truck fleet size by using a better accurate productivity estimate to minimise the cost of the idle equipment. The fleet model was $M_1/M_2/S/FIFO/t_1/t_2$, where M_1 and M_2 showed the customer arrival rate and service rate exponential distribution. S indicated the number of servers that were termed to be parallel, and the discipline of service was *First-In-First-Out* with the upper bound of customer allowed to be t_1, while the t_2 been the maximum number of potential customers. The model showed that a selection of fleet sizes that match the maximum efficiency for both loading points and haulage equipment should be adopted. Although it was questionable whether such a method would improve the economic result, the results proved to be useful considering the degree of variability of some of the parameters of the equipment selection process like truck cycle time and queue length (Hai, 2016).

A queuing computer model was developed that captured values like server utilisation that was used in the calculation of haulage system production. The model was called FLSELECTOR, and it was used in choosing the best fleet size. FLSELECTOR was coded in VBA (Visual Basic for Application) and Microsoft Excel. It allowed the optimum fleet to be selected based on the least cost and maximum production (Salem, Salah, Ibrahim, & Moselhi, 2017).

FLSELECTOR compared outputs achieved using different haul routes but loading and dumping material at a common point (Lashgari, Yazdani, & Sayadi, 2010). The charts from the best ten fleets can be printed and viewed in the process for a given set of data with each fleet size arrival rate, utilisation, cycle time, service rate, production, cost per unit been calculated.

Although FLSELECTOR is limited to the fact that it can only handle a maximum of three loaders, and it assumes that there were no queues at the dumping point when compared to deterministic models it gave a small production value than the deterministic model. This was inconsistent with other studies that have found that deterministic models tend to overestimate the total production values. FLSELECTOR gave results that were closer to that of simulation system SIMEARTH and comparing the two systems; it showed an average difference of 14% (Salem, Salah, Ibrahim, & Moselhi, 2017).

Later, queuing approach that tackled mine scheduling problems was developed by Najor and Hagan, and it incorporated a heuristic model based on the queuing method. This model aimed at ensuring fleet size matches the target production to reduce the final expenditure in the mine haulage system through efficient fleet management, maximising the use of the equipment, and minimising resources that are used to support the fleet operation. The model applied the queuing approach to develop a capacity-constrained model based on the truck capacity (Meredith , 2013).

Najor and Hagan queuing model was developed for calculating production values and estimation for cost per tonne of hauled material used parameters such as expected wait time and the expected number of trucks to be serviced. The model when compared to the capacity-constrained model, and the conventional model showed that the capacity-constrained model offers more conservative production than the conventional approach, which leads to an overestimation of mining capacity. The conventional approach underestimated the mine life by 8% as compared to the mine life of a capacity-constrained method (Meredith , 2013).

Machine Repair Model, which is an example of a finite source queuing model could also be applied in the estimation of fleet size and yielded accurate results. Based on model modified by Kruse and Musingwini, a dump truck is sent for loading (repair) in every cycle completed, and there are several loading points (repair bays). In this case, both inter-arrival time and service time are taken to be exponentially distributed, and the state of the system is determinant of arrival pattern because trucks are drawn from a finite population. The equations of the Machine Repair Model were adjusted to fit loading and hauling situations whereby the average time of the trucks on the waiting for repair becomes the average amount of time a truck can queue at either dumpsite or loading site (Hai, 2016).

A closed queuing network model developed which only used one type of truck by Ercelebi and Bascetin. The goal of the study of the truck-shovel system was to minimise cost per material hauled, with a balance between the cost of the idle time of the loader (shovel) and the cost associated with providing new trucks with loading, hauling, and dumping times assuming exponential distributions. The cost prediction was done using queuing and the results were compared to the results obtained using linear programming. The two results indicated that queuing theory gave minimum loading and hauling cost for the system and also the optimal number of trucks assigned to the shovel (Meredith , 2013).

The truck and shovel behaviour in oil sands capture the nonlinear relationship between the average mine output and the number of dump trucks used and then developed an optimal model out of the relationship (Meredith , 2013). The model has two options: (1) for only a single truck size and (2) multiple truck sizes. The individual trucks are assigned a readiness parameter so that the model can display both the number of necessary truck and the truck individual which should be used. The truck cycle times and shovel service times were represented with an Erlang distribution, and the probability that the shovel is idle was linearized so that the shovel output is expressed as a linear function. Information about truck utilization and idle time was not calculated in this model but when compared to simulation results, it is shown that the optimal model correctly predicted shovel utilization. It also calculated the idle time as it provided good worthy information on the number of trucks to be used to achieve production targets (Yadav, 2019).

A (M/M/1) was applied by Hai to determine the relationship between the number of trucks in the fleet and shovel utilisation, production, and the queue length at Cao Son coal. The model could be used in any haulage system if data on the arrival times of the trucks and service times of the shovel fit to the exponential distribution. The case study data used, which was Cao Son coal gave optimized fleet size with the minimum cost of operation. The results showed that when the number of trucks increases more trucks have to queue at the loading point leading to more shovel efficiency and utilisation but idle times on the trucks. However, it was realised that there was a limit to the number of trucks at which shovel utilisation reaches a limit, and adding an extra truck, a queue is evidenced. To get the optimised fleet size, the model compared the operating costs for the different fleet sizes in the system (Hai, 2016).

The fact that Hai used single channel model which involves one loader doesn't reflect real situation in the current mining set-up. Most mines have more than one loader and hence multi-channel queuing approach is required to capture the real mining reflection. Another key limitation of the existing queuing model is that, they only do forward optimisation. Forward optimisation involves starting with lowest number of truck that can be found in a practical haulage system. The lowest number of trucks can be equal to number of shovels present. If the trucks are less than the loading shovel, this system will not be practical. Then there is backward optimisation in queuing which is carried out if the number of trucks in the system exceed the loader(s) capacity. In this kind of situation the value assigned to the model is the number of trucks in the existing system. The model does backward calculation by eliminating truck by truck until optimal fleet size is achieved. In this study, the model developed can do both forward and backward optimisation.

2.7 Summary

Material handling and haulage system of ore and waste in open-pit mining has captured the interest of many researchers for many decades. This is because it has a significant impact on the operating cost of mine which is nearly half of the total cost implication. As mining goes deep it results in inconstant fleet size because haul road distance increases and more trucks are needed to meet the production target. The flexibility of the truck and shovel is critical in adapting to the change of depth and pit design, but the feasibility of the system needs to be evaluated each time to understand when and at what exact time to field extra truck(s).

The queuing process is a multi-step operation that starts from a population, arrival for the designated service, waiting for the service, then receiving the service and finally leaving. These processes are the typical steps that any queue can follow. The queue can be cyclic or open. The cyclic queue is where the customer after receiving service does not leave the queue but re-joins. This a typical example of haulage system in mining where the truck after dumping it goes back to the loading point. In the open queue, the customer leaves the queue and does not come back. This is typical example of a banking service system where a customer after visiting the teller they will leave the bank.

The queuing process is applied based on the task at hand. For example, haulage system in mining follow queuing modification whereby, the loaders are the servers, and the trucks are the customers. This research applies multichannel cyclic queuing system with parallel servers to develop an optimisation model as discussed in the next chapter (Chapter 3).

3 MODEL DESIGN AND METHODOLOGY

3.1 Introduction

This chapter considers model design, data collection, and data analysis. The model design captures the algorithm formulation of the model, the platform, and the optimisation model. The data collection comprises the study area, the relevant data collected, and the input parameters that are calculated from the data collected. The data analysis involves the clean-up of the data collected. The clean-up means removing the outliers and carrying out a statistical calculation to determine the mean value for the bulk data such as loading time and inter-arrival time.

3.2 Model Design

The system analysis being applied adopts the queuing approach ($M_1/M_2/S/n$) to develop a model; where M_1/M_2 represents the probability distribution of truck cycle time and probability distribution of service time, respectively. In the research the following assumption were made as in (Hai, 2016):

- A negative exponential inter-arrival rate for the trucks;
- A negative exponential service time for the loaders;
- Discipline order of first come, first served (FCFS);
- Mean service rate for all loaders (homogenous loaders);
- Homogenous fleet type for all the servers.

3.3 Model Parameters

These are the key input parameters of the model that represent the characteristic behaviour of the system. When executing queuing theory, the following parameters are crucial to be studied in order to capture the correct representative behaviour of the system, as shown in Table 3.1

Table 3.1: Queuing Model Input Parameters

Parameter Symbol	**Units**	**Parameters Definition**
λ	Trucks per hour	The average arrival rate of trucks
μ	Trucks per hour	Average service rate per loader
S	Real number	Number of loaders operating in parallel
N_x	Real number	Number of trucks in the system
N_c	Real number	Truck capacity
H_w	Real number	Working hours per day
C_h	Kenya shilling	Haulage cost
C_l	Kenya shilling	Loading cost

3.3.1 Model Equations

The haulage system comprises of loaders and trucks used in the material handling in the mine. The data collected in the mine is truck inter-arrival time and loader service time in a stable working shift. This data is used to calculate truck inter-arrival rate, λ, and loader service rate, μ. These parameters are used to define system utilisation, ρ which is the measure of traffic congestion for several loaders, r which is the system utilisation for a single loader (Meredith , 2013) given in Equation 3.1.

$$r = \frac{\lambda}{\mu} \tag{3.1}$$

Thus, the service rate factor ρ, which is the measure of traffic congestion is expressed in Equation 3.2 as:

$$\rho = \frac{r}{s} = \frac{\lambda}{s\mu} \tag{3.2}$$

where, s is the number of shovels,

When $\rho > 1$ it means that the average truck arrivals into the system exceed the average shovel service rate ($\lambda > s\mu$). When $\rho < 1$ it means the shovel service rate exceeds average trucks arrival rates. In conditions where the 1< ρ, the probability of having zero trucks in the queuing system, P_o is expressed in Equation 3.3 (Hai, 2016) as:

$$P_o = \left\{\sum_{n=0}^{s-1} \frac{K!}{(K-n)!} r^n + \sum_{n-s}^{K} \frac{K!}{(K-s)!s!s^{n-s}} r^n\right\}^{-1} \tag{3.3}$$

Alternatively, the possibility of having n trucks in the system, P_n is given by probability expression in Equation 3.4 (Hai, 2016) as:

$$P_n = \begin{cases} \binom{K}{n} r^n P_o & n = 0,1 \ldots s-1 \\ \frac{K!}{(K-n)!s!s^{n-s}} r^n P_o & n = s, s+1 \ldots K \end{cases} \tag{3.4}$$

K, is the fleet size and n, the number of trucks already in the haulage system.

It should be noted that queuing line have no definitive pattern where arrival and service rate are not deterministic, and therefore the probability distribution of queue length is calculated out of the arrival rate and the loading rate (Shortle, Thompson, Gross, & Harris, 2018). Hence the expected number of trucks, L_q waiting to be served based on the probability, P_n is expressed in Equation 3.5 (Trivedi, Rai & Nath, 1999) as:

$$L_q = \sum_{n=s}^{K}(n-s)P_n \tag{3.5}$$

The average number of trucks, $\mathrm{L_s}$ and the average time truck spends in the queue,$\mathrm{W_q}$ is calculated by applying Little's formula. Hence the expected number of trucks in the system is given in Equation 3.6 (Shortle *et al.*, 2018).

$$L_s = \sum_{n=0}^{K} n \times P_n \tag{3.6}$$

The long-term average number of units in a stable system, $\mathrm{L_s}$ is equal to the product of long-term average effective arrival rate($\bar{\lambda}$)and the average time a truck spends in the system,$\mathrm{W_s}$. The effective arrival $\bar{\lambda}$ is given by Equation 3.7 (Hai, 2016).

$$\bar{\lambda} = \sum_{n=0}^{K} \lambda(K-n)P_n \tag{3.7}$$

The expected time a truck will spend in the queue is given by Equation 3.8 (Hai, 2016):

$$W_q = \frac{L_q}{\bar{\lambda}} \tag{3.8}$$

Likewise, the average time a truck spends in the queuing system, W_s can be expressed as in Equation 3.9 (Hai, 2016).

$$W_s = \frac{L_s}{\bar{\lambda}} \tag{3.9}$$

The utilisation of the shovel, η_s and the utilisation of the trucks, η_t is given in Equation 3.10 and 3.11 respectively (Hai, 2016).

$$\eta_s = 1 - Po \tag{3.10}$$

$$\eta_t = 1 - \frac{W_q}{W_q + cycle\ time} \tag{3.11}$$

Cycle time referred in this equation is the loading time, travelling time when loaded, dumping time, travelling time when empty and manoeuvring time.

3.3.2 System Cost Model

System production is the parameter of prime importance to a mining company. This is because the more the material delivered in the processing plant the higher the profit generated at a given time (Hai, 2016). The hourly system production is given as shown in Equation 3.12:

$$Production = Time\ period\ of\ interest \times shovel\ service\ rate \times shovel\ utilisation \times truck\ capacity \tag{3.12}$$

The main focus of shovel-truck operation in mining is to minimise the cost of operation while meeting the production goals. When reducing the cost of operation, basically the decision has to be made in between trading-off cost of shovel idle time and the cost of adding an extra truck. The total hourly operation cost of the system is given by, $C_l S + C_h N$ (Hai, 2016); where C_l is the cost per unit time of the shovel, and C_h is the cost per unit time of the truck. S represents the number of shovels, and n, represents the number of trucks. The total cost of unit production can be expressed as Equation 3.13 (Hai, 2016):

$$Total\ Unit\ Cost = \frac{(C_l \times S) + (C_h \times n)}{System\ Production} \tag{3.13}$$

After deriving the cost model to determine unit production cost for a different number of trucks, the total cost is plotted against the number of trucks, and the optimum fleet size is interpolated from the minimum cost in the plotted graph (Meredith , 2013).

3.4 Optimisation Steps

The flow chart in Figure 3.1 describes the conceptual model for the algorithm code. The code was executed in MATLAB software with an excel spreadsheet linked to the code which acts as an interface for input data.

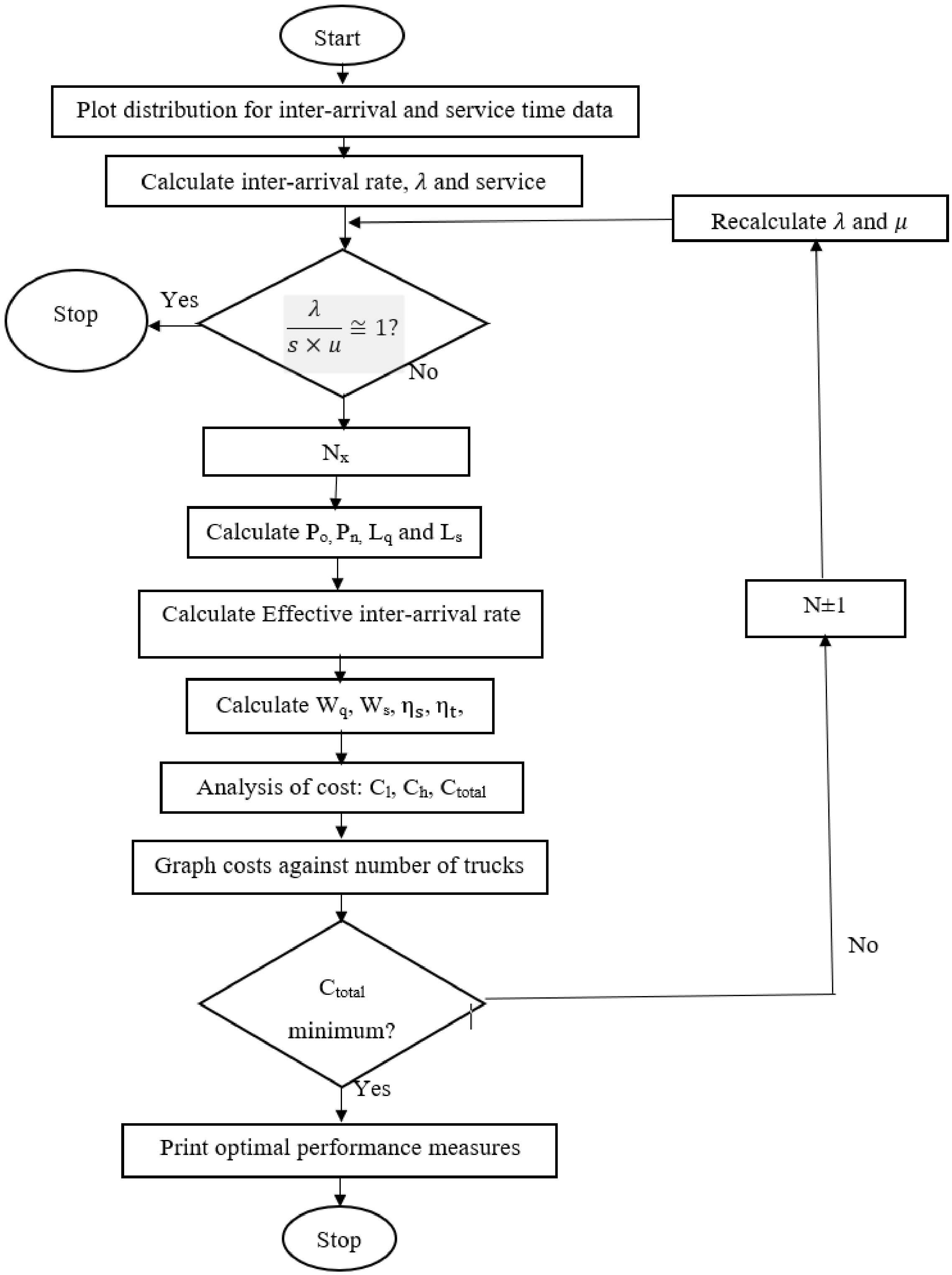

Figure 3.1: S-T Queuing Conceptual Model

The model is constituted of two main part which captures the scenario which can be found in S-T haulage system. The first part of the model is optimization when the truck arrival rate is less than the service rate. In this case, the code keeps on adding truck by truck while displaying the results until the optimal number of trucks is reached. The second part is the optimization of the system when the truck arrival rate is higher than the service rate. In this case, the model reduces truck by truck displaying the results until the optimal number is reached.

It is important to note that every running model has to be bound. This enables the model to run for designated times and then, display results otherwise the model can run without stopping. The S-T haulage model designed has lower and upper limits which should be defined in excel input interface. The lower limit is defined by the number of loaders, while the upper limit is any number slightly above the fleet size present. The lower limit and upper limit can be readjusted based on the nature of the graph of total unit cost against the number of trucks.

3.5 Summary

The shovel-truck haulage operation is cyclic in nature: whereby, the truck is loaded, travel when loaded to the dump site, dump the material, and travel back to the loading point. These activities can be modified in the queuing theory to set up a shovel-truck haulage model. Queuing model gives results of the current system and from these results the site engineer can readjust the system accordingly to reduce time wastage in the operation. The key parameters in queuing are service rate (loading rate) of the shovels and inter-arrival rate of the trucks. The model is developed based on the sequence of activities as outlined in Figure 3.1. The results of the model give the technical description of the system whether there is under trucking or over trucking in the system. A case study is the used to give data that was used in the research as explained in the next chapter (Chapter 4).

4 APPLYING QUEUING APPROACH IN SHOVEL-TRUCK HAULAGE SYSTEM

4.1 Introduction

The mining industry in Kenya is more prominent in limestone mining because of the growing demand for cement across the country. The growth of the cement manufacturing industry is as a result of faster growth of the economy hence more infrastructure is being built. There are six cement companies in Kenya as shown in Table 4.1.

Table 4.1: Table of Cement Manufacturing Companies in Kenya and their Location

Company	**Location**	**Brand**
Mombasa Cement Limited	Vipingo, Kilifi County and Athi-River Machakos County	Nyumba
Athi River Mining	Kaloleni- Kilifi County and Athi River Machakos County	Rhino Cement
Bamburi Cement	Bamburi Mombasa County, Athi River Machakos County	Bamburi Cement
East Africa Portland Cement	Athi-River Machakos County	Blue Triangle
National Cement	Athi-River-Lukenya Machakos County	Simba Cement
Savannah Cement	Kitengela, Kajiado County	Savannah Cement
Ndovu Cement	Athi-River Machakos County	Ndovu Cement

4.2 Case Study Area

This research was conducted at Mombasa Cement Limited (MCL) in Vipingo- Kilifi County. MCL is among the leading cement producers in Kenya. The Mombasa Cement Limited is set to increase the current clinker production capacity from 3,000 tons of clinker per day to 9,000 tons of clinker per day and thus increasing cement production by the same ratio. As a result, the company is growing rapidly and thus the haulage system. This research is devising a structured model that can be used for equipment selection as a way of optimising the current shovel-truck haulage system to reduce unnecessary operation costs from the haulage delays which consequently will improve the profit.

Several data values were recorded which were used to generate input parameters for the shovel-truck model. The recording was done between the dates 24th February 2020 to 30th February 2020.

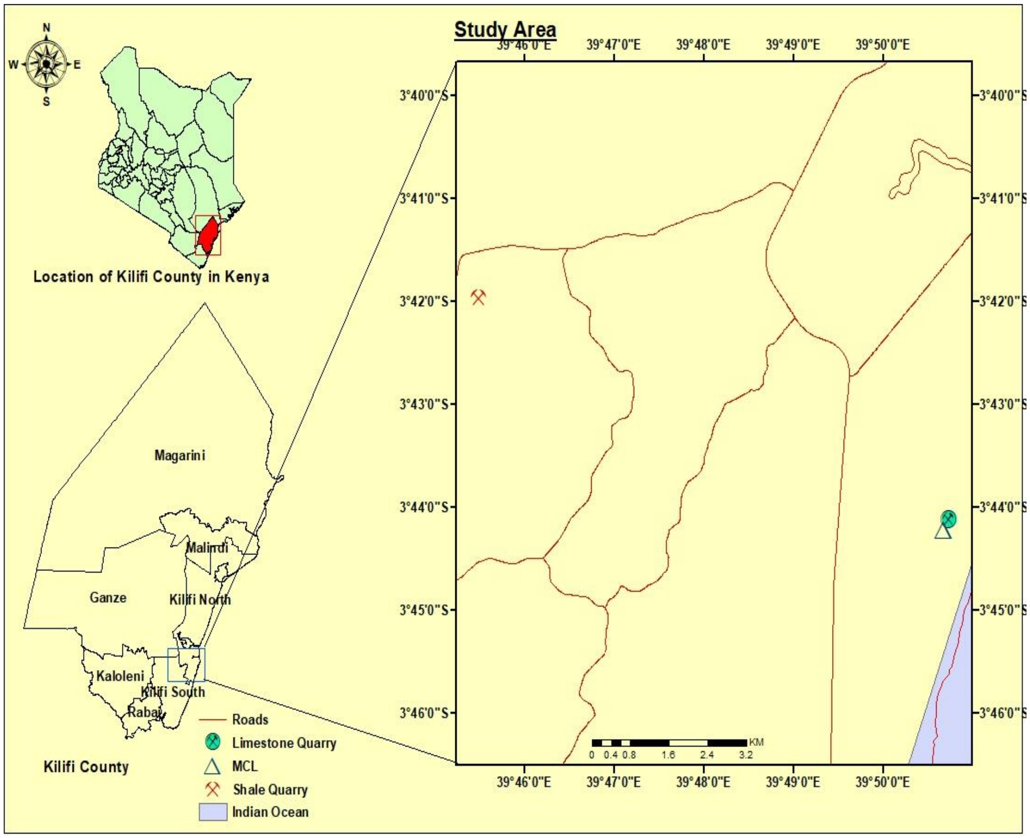

Figure 4.1: Location of Study Area (Source: ArcMap)

The quarry had four shovels with one fitted to a breaker for breaking hard limestone material. The second shovel was used for reaping limestone which that is mainly weak in the coast region. The other two shovels used to load trucks as shown in Figure 4.2. The shovels were made by DOOSAN manufacturing company with a bucket capacity of 3 cubic meters.

Figure 4.2: 3 m^3 Bucket Capacity Shovels Loading into 25 tonnes Capacity Trucks at the Quarry

There were 16 trucks in operation during the period of data collection and the haulage operation in the company was contracted to a haulage company. The truck type was SX3255DR384 from SHACMAN manufacturing company. The loading (shovels) and haulage (trucks) system create the queuing system which is cyclic because the loaded trucks follow the same route travelling when loaded and when empty.

4.3 Model Inputs

The two variables bulk data recorded were inter-arrival time and service time which is used to calculate inter-arrival rate, λ and service rate, μ respectively. The inter-arrival rate is the number of trucks arriving per hour (trucks/hour) while service is the number of trucks served per hour (trucks/hour). The data obtained for both inter-arrival time and service time is first cleaned up to remove the outliers. Outliers majorly occur when there is a breakdown of one of the trucks or bulking during operation. The outliers are determined using the following steps:

- Step 1: Arrange data in ascending order and divide it into four quarters.
- Step 2: Get mean for the first quarter (Q_1) and third quarter (Q_3).
- Step 3: Get interquartile range (Q_3-Q_1).
- Step 4: The data value is an outlier if it's greater than Q_3 + 1.5(interquartile range) or lower than Q_1- 1.5(interquartile range).

After data was cleaned up, the distribution fitting was done in Mat-lab software using a distribution fitting application. The distribution fitting application sorts' inter-arrival time and service time to create data density. Data density, also called probability density function (PDF), uses the logic of continuous random variables. The variable integral across an interval gives the probability of whether the value of the variables lies within the same interval. The graphical relationship in Figure 4.3 and Figure 4.4 shows that both inter-arrival time and service time follow negative exponential-distribution.

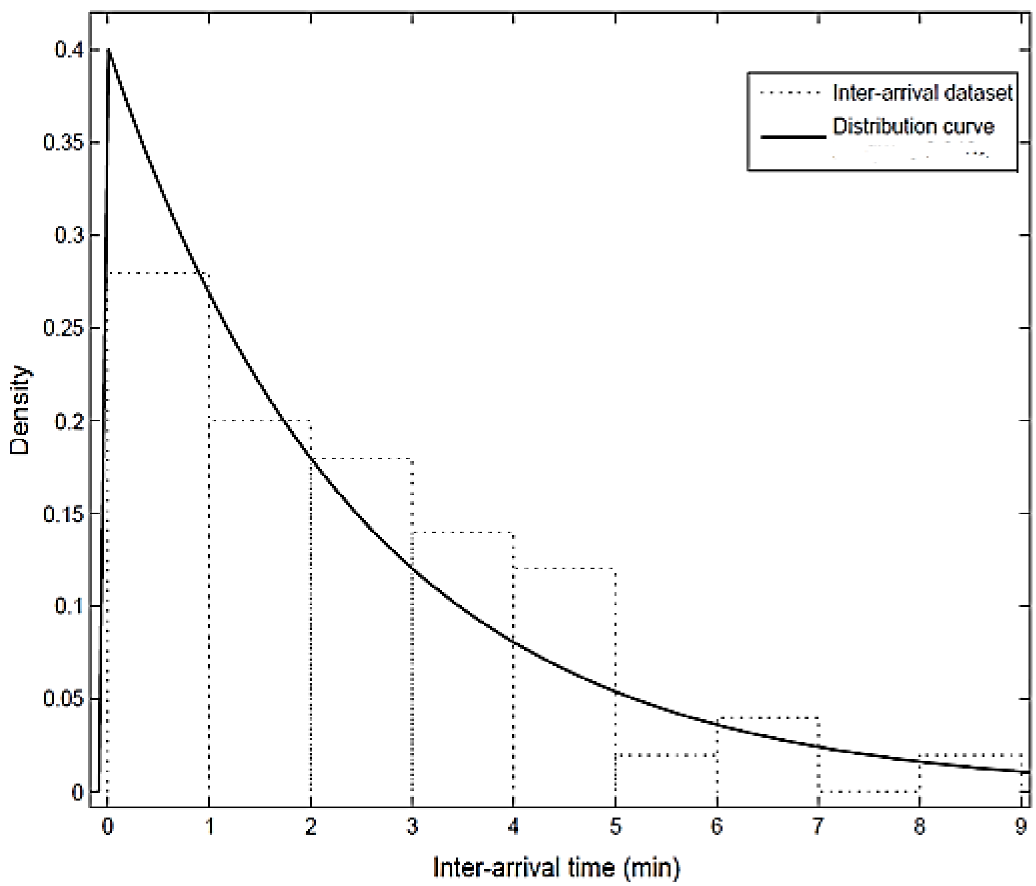

Figure 4.3: Inter-arrival Time Distribution

The service time in this research is the time when the shovel starts loading the truck until it fills the truck; plus the manoeuvring time while loading and the time the next truck manoeuvres to align for loading. The time between the filling of one truck until when the next one starts to load is not instant and therefore, there is a time frame that laps while the truck paves way for the previous one to leave so that it can manoeuvre and set for loading. This time frame in queuing is very vital, and once assumed it leads to over trucking. This leads to the underutilisation of the haulage system.

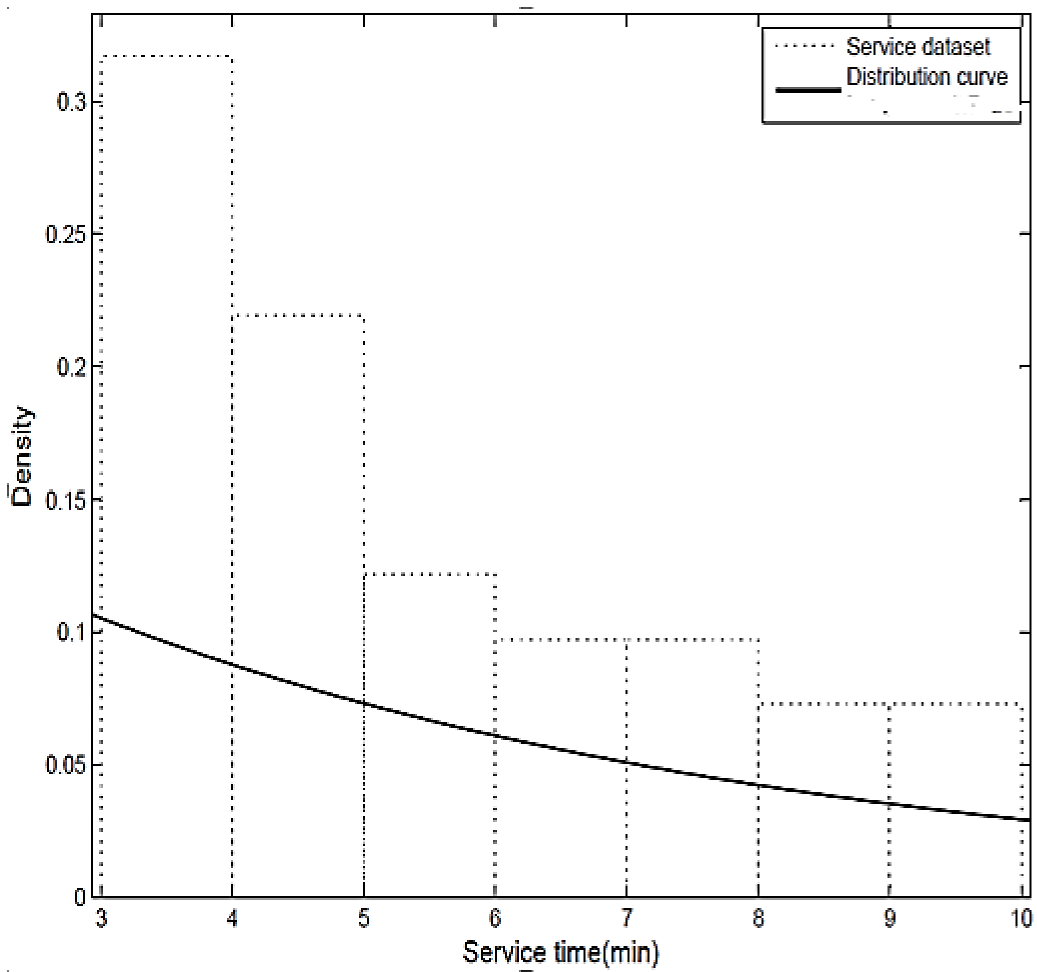

Figure 4.4: Service Time Distribution

4.4 Input Parameters Calculation Process

There are 8 parameters in the shovel-truck queuing model as shown in Table 4.2. The inter-arrival rate is calculated from the mean inter-arrival time data while the service rate is calculated from mean service time data (Hai, 2016) as in Equation 4.1 and 4.2. The data collected from the field is attached at appendix A.

Inter-arrival rate, $\lambda = \frac{60\ (minutes\ in\ an\ hour)}{Average\ inter-arrival\ time(min)}$ (4.1)

Service rate, $\mu = \frac{60\ (minutes\ in\ an\ hour)}{Average\ service\ time\ (min)}$ (4.2)

Table 4.2: Model Input Parameters

Inter-arrival rate, λ	24 trucks/hr
Service rate, μ	10 trucks/hr
Number shovels, S	2
Number of trucks in the system, N_x	16
Truck capacity, N_c	25 tonnes
Working hours per day, H_w	16 (2 shifts)
Loading cost per truck, C_l	KShs 24,200 ($242) per hour
Haulage cost per truck, C_h	KShs 17,500 ($175) per hour
* KShs (Kenya shillings)	

The input parameters are stored in an excel spreadsheet as shown in Table 4.3. The spreadsheet is linked to the code in MATLAB as shown in Figure 4.5. This Excel spreadsheet acts as a data input interface for the model. The interface takes the mean service time and inter-arrival time and then the model computes the service rate and inter-arrival rate.

Table 4.3: Excel Input Interface

Service time(min)	Inter-arrival time(min)	Haulage cost, Ct/hr	Loading cost, Cs/hr	Truck_start	Working hours/day	Number of shovels	Truck capacity(tonnes)	Lower limit	Upper limit
6.28	2.50	17500	24200	16	16	2	25	2	30

The code that extracts the input parameters in the excel spreadsheet reads the parameters in "Num" as shown in Figure 4.5. This code reads the row first and then a column in integer form i.e., Num (row, column).

```
% Optimazation problem.
% The aim is to find the optimal trucks scheduling in an open-pit mine.
% And determine the minimum cost.
clc;            % Clear the command window.
close all;      % Close all figures (except those of in tool).
clear;          % Erase all existing variables.
workspace;      % Make sure the workspace panel is showing.
%------------------------------------------------------------------------
[Num, raw, txt] = xlsread('ReadExcel',2);
Service_Time = Num(1,1);
Interarrival_Time = Num(1,2);
Truck_OpCost = Num(1,3);
Shovel_OpCost = Num(1,4);
Start_Trucks = Num(1,5);
Working_hours = Num(1,6);
Shovels_Number = Num(1,7);
Truck_Capacity = Num(1,8);
Lower_Limit = Num(1,9);
Upper_Limit = Num(1,10);
%------------------------------------------------------------------------
```

Figure 4.5: Model Code that Extracts Input Data from Excel Spreadsheet

4.5 Model Output

The model output can be termed as the performance measures of the system. These outputs are the probability of having zero trucks in the system, number of trucks in the queue, number of trucks in the system, waiting time in the queue, waiting in the system, shovel utilisation, and system production. The output is used by the engineer to predict the behaviour of the system and effect necessary changes. Table 4.4 shows the output parameters from the model starting from 2 trucks to 16 trucks. The model lower boundary condition should be the number of shovels in operation. This is because it is not logical to have two shovels loading into one truck.

Table 4.4: Model Output

K	λ	P_0	L_q	L_s	W_q	W_s	η_s	η_t	Q_n	C_l	C_h	C_t
2	3.00	0.74677	0.00	0.27	0.00	3.14	25.32329	100.00	1935.85	40.28	29.13	69.40
3	4.51	0.52802	0.01	0.58	0.06	3.20	47.19757	99.86	3608.03	26.85	29.13	55.98
4	6.01	0.32611	0.08	1.02	0.27	3.41	67.38856	99.33	5151.54	20.14	29.14	49.28
5	7.51	0.17100	0.31	1.64	0.75	3.89	82.89994	98.17	6337.31	16.13	29.16	45.28
6	9.01	0.07228	0.85	2.50	1.61	4.75	92.77190	96.12	7091.98	13.46	29.19	42.65
7	10.51	0.02321	1.75	3.61	2.94	6.08	97.67898	93.14	7467.10	11.56	29.25	40.80
8	12.02	0.00546	2.92	4.88	4.67	7.81	99.45419	89.53	7602.80	10.13	29.30	39.43
9	13.52	0.00094	4.19	6.18	6.61	9.75	99.90573	85.81	7637.32	9.02	29.35	38.37
10	15.02	0.00012	5.46	7.46	8.57	11.71	99.98769	82.33	7643.59	8.13	29.39	37.52
11	16.52	0.00001	6.69	8.69	10.50	13.64	99.99874	79.19	7644.43	7.40	29.42	36.82
12	18.03	0.00000	7.88	9.88	12.37	15.51	99.99990	76.36	7644.52	6.79	244	36.23
13	19.53	0.00000	9.04	11.04	14.19	17.33	99.99999	73.78	7644.53	6.79	31.92	38.71
14	21.03	0.00000	10.18	12.18	15.98	19.12	100.00000	71.42	7644.53	6.79	34.37	41.16
15	22.53	0.00000	11.30	13.30	17.74	20.88	100.00000	69.24	7644.53	6.79	36.83	43.62
16	24.03	0.00000	12.41	14.41	19.48	22.62	100.00000	67.22	7644.53	6.79	39.28	46.07

4.6 Summary

This chapter is broken down into 6 sections: the introduction, the case study, input parameters calculation process, and model output. The model output is the results of the model which are used to make decision on the adjustment to be made on the system. From Table 4.2, 6 of the 8 input parameters are read directly from the field while the remaining 2 are calculated from the data collected in the field. The 2 parameters are service rate, and inter-arrival rate which are calculated from service time and inter-arrival time, respectively.

The results generated from the mode are as shown in Table 4.4. This table shows that, the waiting time increase as the number of trucks increases. The increase in the number of trucks also leads to increased utilisation for both trucks and shovel. It can be evidently seen that when the trucks are 12, the shovel utilisation is optimal. The results in Table 4.4 are discussed in the next chapter (Chapter 5) where the effect of varying the number of trucks is graphically displayed.

5 DISCUSSION

5.1 Introduction

The main output parameters of the haulage system in mining are system production, shovel utilisation, truck utilisation, time trucks spend in the queue, and length of queue (Meredith, A., 2013). These performance measures can be integrated to determine the optimal numbers of trucks in the system. The optimality of the system is where the system utilisation and production are increased while the time trucks spend in the queue, and length of the queue is reduced. This leads to a minimum cost of operation while achieving the production target.

5.2 Results Discussion

The effects of increasing the number of trucks from (2-16) to the system production, shovel utilisation, truck utilisation, trucks waiting time in the queue, length of the queue, and costs are graphically represented in Figure 5.1 to 5.6. This helps to track the trend as changes occur.

The production of the shovel increases rapidly from 2 to 9 because the probability of forming a queue increases with number of trucks. As the trucks nears 12 from 9, the rate of change of the curve is small as compared to later. This shows high probability of the queue and also outmost utilisation being reached as shown in Figure 5.1. After 12, the curve becomes steady with the production remaining constant as seen in the table of results. Any addition of extra trucks leads the long queue, thus increasing the waiting time.

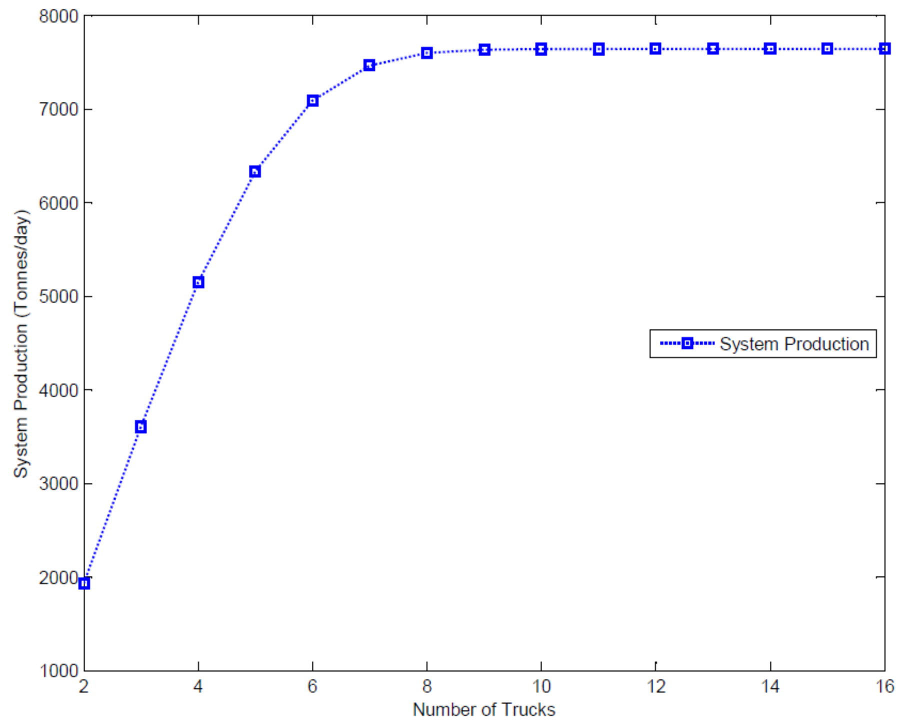

Figure 5.1: Shovel Production against the Number of Trucks

The utilisation of the shovel goes in hand with the production and it gives indication on how engaged the shovel is. As shown in Figure 5.2, the utilisation of the shovel increases rapidly up to 9. This change is where the probability of having a queue is probably less as compared at the maximum utilisation. Thereafter, the utilisation increases gently up to 12. The gentle increment is as a result high probability of queue being formed. Afterward, the curve remains constant since system optimality has been reached. The addition of extra trucks leads to queue being formed, thus increasing the waiting time.

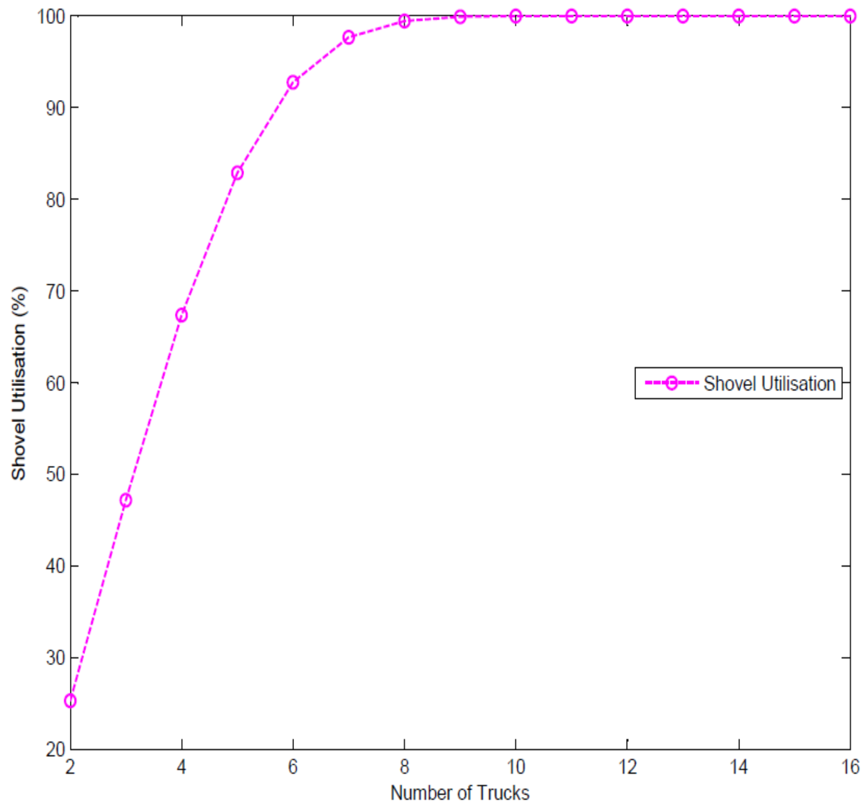

Figure 5.2: Shovel Utilisation against the Number of Trucks

Truck utilisation is a reverse of shovel utilisation. This is because any addition of a truck to the system it will increase the probability of forming a queue. The truck utilisation is at 100% for the two trucks. This is any indication that trucks will not queue for loading since the number of trucks are equal to the number of trucks. The general trend thereafter is that truck utilisation decreases with number of trucks, as seen in Figure 5.3 indicating the possibility of forming a queue. At 12, the utilisation keep on reducing. This shown that for the trucks the optimal utilisation is not 100% unlike the shovel. This is because for group of population each unit is dependent of one another and thus there is higher chances of forming a queue when the population is big than when it is small.

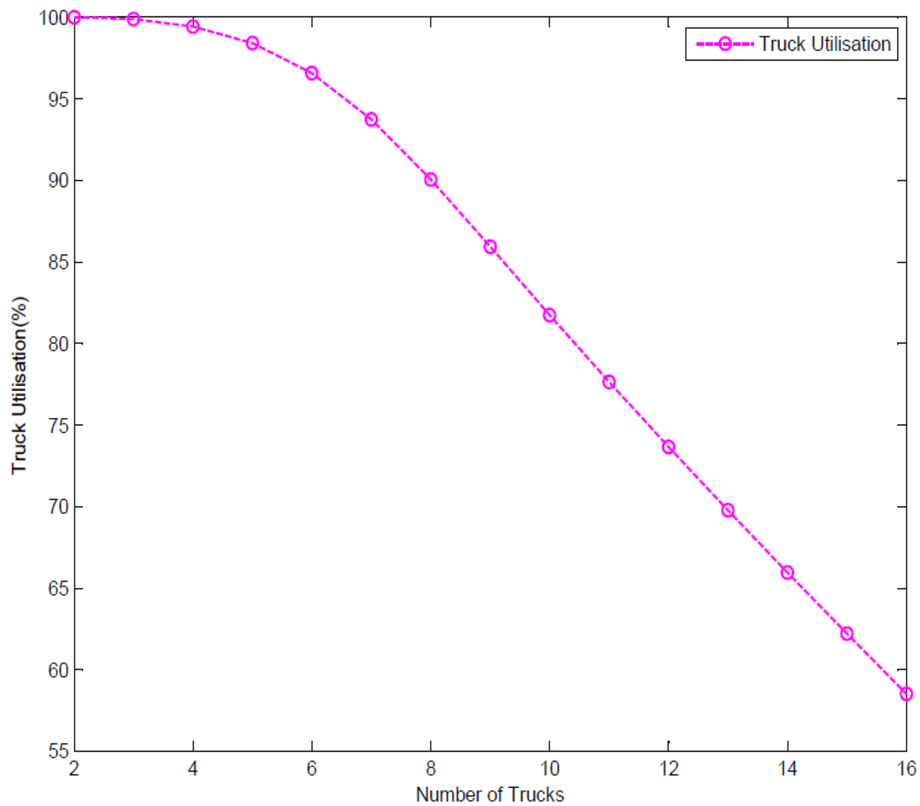

Figure 5.3: Truck Utilisation against Number of Trucks

The truck waiting time in the queue is much determined by the utilisation of the trucks. When the trucks are least utilised the probability the waiting time is higher while when trucks are utilised most the waiting time in the queue becomes less. As shown in Figures 5.4 the waiting time increases with the number of trucks because the probability of forming a queue increases. This means that when trucks are less a truck will wait for less time for the trucks ahead to be loaded as compared when trucks are more. The waiting time is the key parameters as it has cost implication on the system. This aspect will trigger an engineer to keep checking the system to minimise the waiting time.

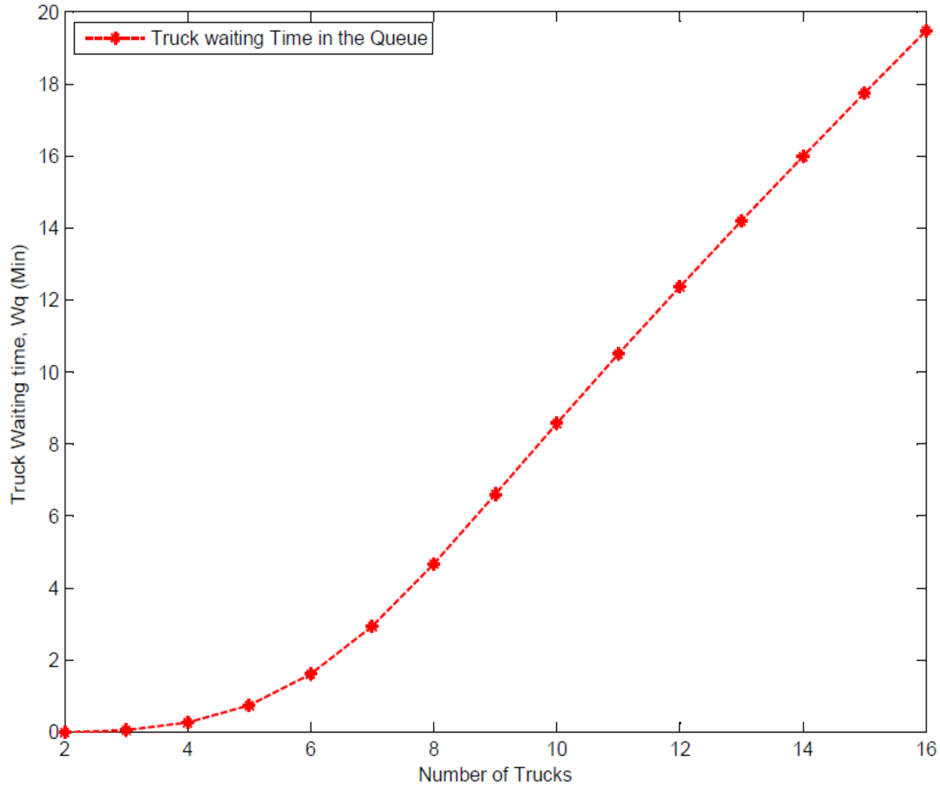

Figure 5.4: Trucks waiting time in the Queue against the Number of Trucks

The length of the queue is subject to the number of trucks in the system. Logically, the queue will be long if the number of trucks are more as compared when they are less. For this reason, the length of the queue increasing as the number of trucks increases as shown in Figures 5.5. This means that the probability of forming long queue increase with the number of trucks.

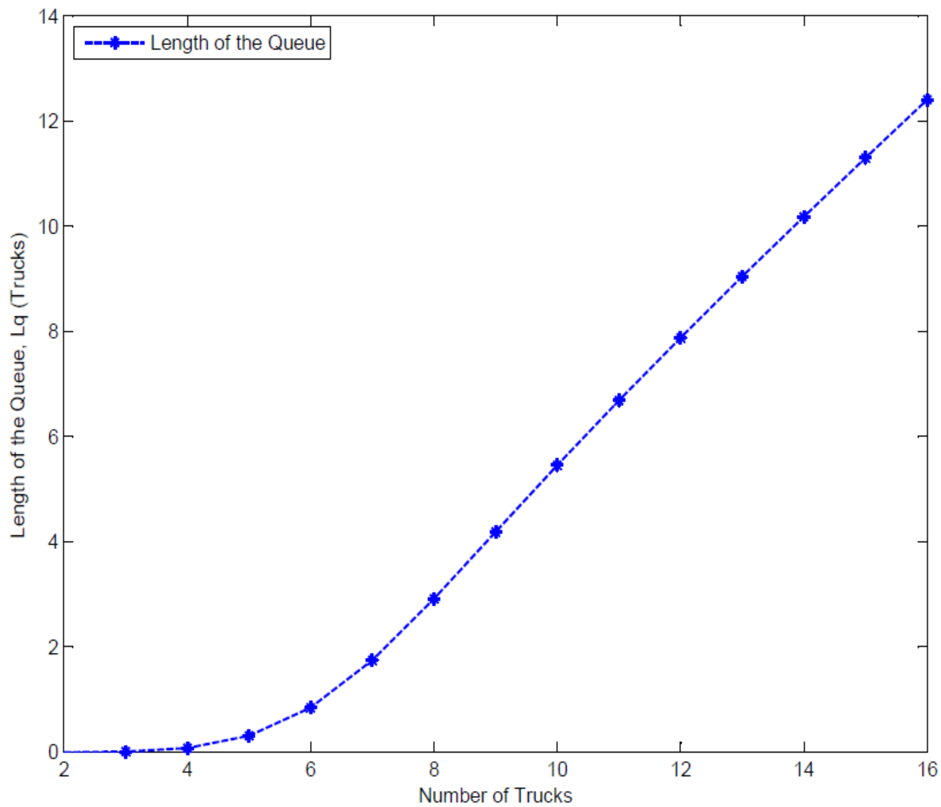

Figure 5.5: Length of the Queue against the Number of Trucks

The waiting time in the queue for any system cannot be eliminated, but it can be reduced to save the excessive cost of system operation (Caccetta, 2018). In Figure 5.6, the reduction of waiting time is achieved by optimising the system; through which the minimum unit cost of production is determined. The unit cost of the trucks remains constant from 2 up to 12 and then shifts upwards. This is because from 2 to 12 trucks the increase in the number of trucks is proportional to the increase in production. After 12, the production remained constant as the number of trucks increased.

The unit cost of the shovel decreased from 2 to 12 and then remained constant thereafter. This is because the cost of operation of the shovel remained constant as the production increased with an increasing number of trucks. After 12, the cost of operation and system production remained constant giving a steady curve. The optimisation curve (combined) is the sum of trucks and shovels unit cost. The total unit cost reduces as the number of trucks increases to 12, and then significantly shifts upwards. The minimum total unit cost of production is achieved with 12. 12 being the lowest point of the optimisation curve it is called the null point. This point represents the number of trucks that can operate optimally with the two designated shovels to meet the company's production target at minimum cost.

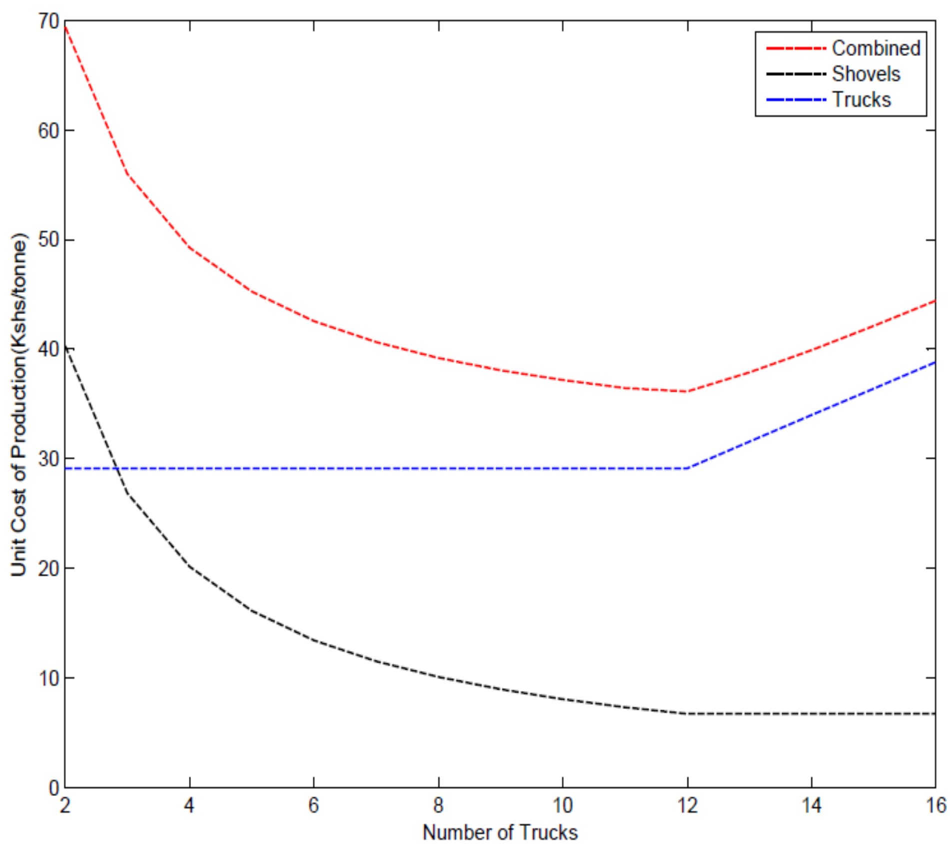

Figure 5.6: Unit cost of production against the number of trucks

In Figure 6.1, the system was not stable when the trucks were 2 to 11 because truck inter-arrival rate (λ) < shovels service rate ($s\mu$). When shovel service rate exceeds the average truck arrival rate, this indicates the system is being under trucked and thus the addition of trucks accelerates the utilisation factor of the shovel. In addition, the stability of the system is measured when none of the sides of operation either trucks or shovels is being strained by operation. Table 4.3 shows, the optimal system production is 7644.52 tonnes/day which was approximately in line with the expected 7600 tonnes production target per day.

The waiting time in the queue and length of the queues increasing as the number of trucks increases as Figures 5.4 and 5.5 shows. Table 4.3 and Figure 5.3, the truck utilisation when 16 trucks are in the system is 67.22% and upon optimisation, the utilisation improved to 76.36 %. This improvement coincides with waiting time in the queue as 19.48 minutes/truck when 16 trucks are in the system and 12.37 minutes/truck when 12 trucks were in the system. Overall, this translated to a 9.14% improvement in truck utilisation, and a 7.11 minutes/truck waiting time reduction after system optimisation.

5.3 Summary

In this chapter, the relationship between different parameters against number of trucks is discussed. The optimisation graph Figure 5.6 shows that on getting the optimal number of trucks, the cost value does not alter the truck number optimality (X-axis) rather it shifts the unit production cost along the Y-axis. Therefore, if the cost changes the system optimal number of trucks is not affected.

6 CONCLUSION, RECOMMEDATIONS AND SCOPE FOR FUTURE STUDY

6.1 Conclusion

This study focused on the application of the queuing approach to optimise shovel-truck haulage operations at a limestone quarry. In a mining operation, haulage costs accounts for more than 50% of the total operation cost. Every company work on reducing the cost of operation to increasing the profit generated. This process is done through optimisation whereby the right number of trucks and shovels are selected to reduce delays in operation while delivering the required production target. From the results, we can conclude the following:

1. With the system observed having 2 shovels and 16 trucks in operation, the model analyses indicate that the waiting times were long as a result of an excess number of trucks in the system. It was established that waiting time at the queue, Wq, and length of the queue, Lq, kept on increasing as the number of trucks increased. An attempt to optimise the haulage system necessitated the reduction of the waiting times, and consequently, reducing the length of the queues to obtain the production targets at the minimum costs.

2. The optimal number of trucks was found to be 12, and thus the 4 extra trucks could be parked only to be used upon breakdown or when a truck is under maintenance. Shovel utilisation was at its peak with 12. From Table 4.3, the waiting time a truck spends in the queue reduced by 7.11 minute/truck (difference between waiting time in the queue for 16 and 12 trucks) as seen in model output.

3. The multichannel queuing model $M_1/M_2/S/n$ proved to be a good approach to optimise the shovel-truck haulage system in mining. This approach gives a variety of performance measures that can be used to analyse and readjust the system to operate optimally. Of prime importance, the model gives the parameter to measure the performance of the system set. This interrelationship gives a clear vision of the adjustments that can be made in the system to achieve minimal operation costs.

6.2 Recommendations

Based on our finding, we recommend the following:

1. The shovels serving the haulage system at the CattaPut limestone quarry should be maintained because their daily production coincides with the company's daily production target. Their current maintenance operation state should also be maintained because lack of proper maintenance reduces equipment output and life.
2. The 4 extra trucks should be parked or sold because the system optimal truck fleet size that can be served by the two shovels in place is 12 trucks. In this case, parking the two trucks reduces the cost of operation as well as providing standby trucks when there is a mechanical breakdown of either of the trucks in operation.
3. The operations of the haulage system are very intense and thus random checks of the system performance characteristics should always be done to adjust the system accordingly. This helps in ensuring the final production target is achieved. Also, this enables monitoring the right time to replace equipment if it does not satisfy production requirements based on the operation performance measures. The application developed

in this study helps in evaluating and monitoring the truck and shovel system with ease, quickly and cheaply.

4. The mine layout can have several pits, and these pits call for different haulage route. Therefore, multichannel queuing model ($M_1/M_2/S$) should be modified to include all haulage routes in the mine layout not just haulage activities in one pit.

6.3 Scope for Future Study

The multichannel can be expounded to capture operation in the entire mining layout. This is because mining operation involves operation from different routes (mines) and every route has different inter-arrival time. This means that each route should be customized independently to reflect the activities in that route.

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APPENDICES

Appendix A: Data Collected

The tables A-1and A-2 show data of loading time (service time) and inter-arrival time respectively. The two sets of data are used to calculate service rate for the loaders and inter arrival rate for the trucks. These two parameters are the main input for the queuing.

Table A-1: Service Time Data

Service time (Min)	**Service time (Min)**
7.35	7.44
4.01	5.38
6.37	7.41
5.51	7.02
6.56	7.49
6.50	7.12
6.21	7.02
4.49	6.32
6.29	6.13
5.49	6.40
6.46	9.01
5.46	6.02
5.58	6.40
7.00	5.78
6.07	6.21
6.14	4.51
6.26	7.00
5.37	8.01
6.43	7.11
4.42	6.22
5.43	6.41
5.41	5.49
7.20	6.34
7.27	6.29
6.51	6.05

A- 2: Inter-arrival Time Data

Inter-arrival time (min)	**Inter-arrival time (min)**
0.78	4.08
2.13	0.78
3.53	0.74
3.65	2.63
1.80	1.15
1.78	3.14
3.88	0.55
2.49	0.76
8.67	2.03
2.47	1.45
2.81	0.88
4.00	1.54
4.28	0.41
4.74	0.59
6.07	0.75
4.18	2.32
1.32	2.25
3.63	0.04
6.70	2.78
4.85	0.28
1.99	1.10
3.20	0.81
5.37	1.92
3.80	0.89
0.97	1.86

Table A-3 and table A-4 show dumping time and travelling time (travelling empty and travelling loaded) data, respectively. This is a supportive data of the model developed. This data is used in finding trucks utilisation.

Table A-3: Dumping Time Data

Dumping Time (min)	**Dumping Time (min)**
0.88	0.55
0.65	0.50
0.45	0.52
0.47	0.48
0.53	0.52
0.60	0.75
0.48	0.52
0.58	0.67
0.55	0.47
0.63	0.45
0.57	0.43
0.50	0.55
0.45	0.52
0.70	0.47
0.47	0.80
0.47	1.24
0.53	0.42
0.55	0.58
0.35	0.57
0.62	0.50
0.52	1.58
0.45	0.47
0.33	0.51
0.48	0.52

Table A-4: Truck Travelling Loaded and Travelling Empty Time Data

Travelling Empty Time (min)	**Travelling loaded Time (min)**
15.78	18.26
13.98	19.48
11.21	17.17
16.35	28.32
12.40	23.25
11.71	20.95
16.07	26.50
12.30	21.05
21.89	23.58
14.53	19.17
12.86	20.38
11.29	22.83
18.22	23.90
12.70	20.67

Appendix B: Developed Code

This code was developed in mat-lab as per the algorithm in developed in chapter 3. The attached section of the code is the last part of result printing. The results include shovel production, shovel utilisation, trucks utilisation, truck waiting time in the queue, truck waiting time in the system, number of trucks in the queue, number of trucks in the system and graphical relationship between all the parameters and the different truck fleet.

```
Shovel_Production = Shovel_Production(lowerbound:Truck_Start);
Shovel_Utilization = Shovel_Utilization(lowerbound:Truck_Start);
Truck_Utilization = Truck_Utilization(lowerbound:Truck_Start);
Wq_Store = Wq_Store(lowerbound:Truck_Start);
Lq_Store = Lq_Store(lowerbound:Truck_Start);
Ws_Store = Ws_Store(lowerbound:Truck_Start);
Ls_Store = Ls_Store(lowerbound:Truck_Start);
P0_Store = P0_Store(lowerbound:Truck_Start);
Lambda_Bar_Store = Lambda_Bar_Store(lowerbound:Truck_Start);
Lambda_Store = Lambda_Store(lowerbound:Truck_Start);
Qn_Store = Qn_Store(lowerbound:Truck_Start);

figure(1) % Unit cost for shovel, truck, & combined
plot(Truck_Count,UNIT_Cost_Count,'-.r','LineWidth',1.2)
hold on
plot(Truck_Count,Unit_Shovel_COST,'-.k','LineWidth',1.2)
hold on
plot(Truck_Count,Unit_Truck_COST,'-.b','LineWidth',1.2)
xlabel('Number of Trucks')
ylabel('Unit Cost of Production(Kshs/tonne)')
xlim([Truck_Count(1) Truck_Count(end)])
legend({'Combined','Shovels','Trucks'},'Location','northeast')
% hold on
figure(2)
plot(Truck_Count,UNIT_Cost_Count,'-.r','LineWidth',1.2)
```

```
xlabel('Number of Trucks')
ylabel('Unit Cost of Production (Kshs/tonne)')  % Unit cost of production
xlim([Truck_Count(1) Truck_Count(end)])
legend('Total Unit Cost','Location','northeast')

figure(3)
plot(Truck_Count,Shovel_Production,':bs','LineWidth',1.2)
xlabel('Number of Trucks')
ylabel('System Production (Tonnes/day)')  % Shovel production
xlim([Truck_Count(1) Truck_Count(end)])
legend('System Production','Location','east')

figure(4)
plot(Truck_Count,Shovel_Utilization,'--mo','LineWidth',1.2)
xlabel('Number of Trucks')
ylabel('Shovel Utilisation (%)')  % Shovel utilization
xlim([Truck_Count(1) Truck_Count(end)])
legend('Shovel Utilisation','Location','east')

figure(5)
plot(Truck_Count,Truck_Utilization,'-.mo','LineWidth',1.2)
xlabel('Number of Trucks')
ylabel('Truck Utilisation(%)')
xlim([Truck_Count(1) Truck_Count(end)])
legend('Truck Utilisation','Location','northeast')

figure(6)
plot(Truck_Count,Wq_Store,'-.r*','LineWidth',1.2)
xlabel('Number of Trucks')
ylabel('Truck Waiting time, Wq (Min)')
xlim([Truck_Count(1) Truck_Count(end)])
legend('Truck waiting Time in the Queue','Location','northwest')

figure(7)
```

```
plot(Truck_Count,Lq_Store,'-.b*','LineWidth',1.2)
xlabel('Number of Trucks')
ylabel('Length of the Queue, Lq (Trucks)')
xlim([Truck_Count(1) Truck_Count(end)])
legend('Length of the Queue','Location','northwest')

figure(8)
plot(Truck_Count,Qn_Store,'-.b','LineWidth',1.2)
xlabel('Number of Trucks')
ylabel('System Production,Qn (Tonnes/day)')
xlim([Truck_Count(1) Truck_Count(end)])
legend('System Production','Location','northwest')
end

fprintf('\tTrucks\t Total Unit Cost\t Shovel Unit Cost\t Truck Unit Cost\t Truck Utilization\t Shovel Utilization\t
Production Qn\n')
 for i = 1:length(Truck_Count)
fprintf('%10.0f\t\t%10.5f\t\t%10.5f\t\t\t%10.5f\t\t\t%10.5f\t\t\t%10.5f\t\t\t%10.5f\n',Truck_Count(i),UNIT_Cost_
Count(i),Unit_Shovel_COST(i),Unit_Truck_COST(i),Truck_Utilization(i),Shovel_Utilization(i),Qn_Store(i))
 end
fprintf('\tTrucks\t\t Lambda\t\t Lambda_Bar \t\t P0 \t\t Lq \t\t Ls \t\t Wq \t\t Ws\t\t Shovel Production\n')
 for i = 1:length(Truck_Count)
fprintf('%10.0f\t\t%10.4f\t\t%10.4f\t%10.5f\t%10.4f\t%10.4f\t%10.4f\t%10.4f\t%10.5f\n',Truck_Count(i),Lambd
a_Store(i),Lambda_Bar_Store(i),...
   P0_Store(i),Lq_Store(i),Ls_Store(i),Wq_Store(i),Ws_Store(i),Shovel_Production(i))
 end
```

Appendix C: Publication

The following is a peer -reviewed publication that has emanated from this work:

1. Kaungu Elijah, Githiria J., Mutua Samuel, Dalmus Mauti, 2021. Optimisation of shovel-truck haulage system in an open pit using queuing approach. Arabian Journal of Geosciences 14(11), http://doi.org/10.1007/s12517-021-07365-z