Open Pit Mine Loading and Haulage Simulation

by

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ABSTRACT

The objective of this research is to estimate the main KPI's of an open pit mining truck and shovel operations, while quantifying uncertainty about the KPI's with high statistical confidence. Short-term production scheduling base their estimations on deterministic approaches, but the nature of mining operation is variable, so when execution of the plan comes, it faces a reality different to what it forecasts. The main contribution of this thesis is to quantify uncertainty in truck and shovel KPI's due to operational uncertainties, planned and un-planned maintenance, and weather events with a 95% confidence interval.

To achieve the research objectives, a discrete event simulation model for truck and shovel operations is built, verified, and validated against historical dispatch data. The following tasks are completed: a) statistical data analysis of historical dispatch data, b) fitting probability density functions on historical operational data, c) building a truck and shovel simulation model in Arena software, d) adding the preventive maintenance, failures, and weather events into the simulation model for trucks and shovels, e) validation of equipment performances against historical data, f) four different major scenarios are assessed with changing the number of ore and waste trucks and the throughput rate of the crusher to find the near optimal size of the fleet, g) the detail short-term expected production of ore and waste under monthly and weekly time frames are reported along with KPI's for tonnage, time charts, availably, and efficiency.

The main contribution of this research is a discrete event simulation model for truck and shovel operations that predicts the major KPIs of a mining operation with 95% statistical confidence about the statistics of interest while quantifying the uncertainty around the estimation.

PREFACE

This thesis research is an original work by Luisa Fernanda Montes Higuita. It was a product of an investigation in the area of open pit mine haulage simulation based on the shortfalls revealed in the current literature. As a result; a conceptual model was built to simulate truck and shovel activities, a simulation model was built and case studies were carried out to study the impact of number of trucks and crusher throughput rates on the main KPI's. During research process my supervisor H. Askari-Nasab was guiding and giving feedbacks.

This Thesis is Proudly Dedicated:

To my family, Flor Maria Higuita, Carlos Jesus Montes, Julian Jose Montes y Angelica Beatriz Tuiran

The community of Mckernan Baptist Church

&

The Holy Spirit who gave me wisdom and company during the years of my masters

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LIST OF ABBREVIATIONS

AGVS	Autonomous guided vehicle system
CRN	Common random number
GOH	Gross operating hours
GPSS	General purpose simulation system
KPI	Key performance indicative
LP	Linear programming
MCB	Comparisons with the best
LOM	Life of mine
MILG	Mixed integer linear goal programming
MILGP	Mixed integer linear goal programming
MILP	Mixed integer linear programming
MOOT	Mine operational optimization tool
NOH	Net operating hours
NPV	Net present value
PM	Preventive maintenance
QQ PLOT	Quantile-quantile plot
ROM	Run of Mine
STOPPS	Short-term Optimum pit production
WOH	Work operating hours

1. Chapter 1

1.1. Background

It is well known in mining industry that volatility has always characterized the price of metals. However, revenues have to be maintained according to how the mine plan has projected the NPV for the life of mine. In order to achieve the corporate goals, the mining operations must continuously improve productivity so as to mitigate the variability of commodity prices. This involves reducing operational costs so as to preserve the profit that is expected. A study analyzing historic data has also recommended that the gap between planned and actual should be closed by integrating operations across mining and processing in order to improve productivity and assure optimal asset utilization (Wachman 2016).

Haulage represents more than 50% of the mining operations' costs, therefore a tool which can predict the performance of a truck-shovel system in the presence of operational uncertainty with high statistical confidence would be a valuable asset for mining companies. Discrete event simulation has evolved as a robust tool over the years for predicting the impact of any operational changes on the desired outputs of interest and capturing operational uncertainties. Discrete event simulation has been proven to be a reliable tool to close the gap between the planned and actual key performance indicators in different industries. The focus of this thesis is on simulation of open pit mine haulage systems using discrete event simulation.

1.2. Statement of the Problem

Currently, the main approach of long-term to short-term mine planning in the industry is based on deterministic models using expected values for all the input variables. As the result, the outputs of such models are deterministic values failing to capture the stochastic nature of mining operations and the uncertainty around predicted outcomes. The deterministic approach lacks the measurement of deviations from the targets due to variability in the availability, uptime and downtime for preventive maintenance and failures of the mining equipment. Also, all the haulage cycles main components such as loading time, spotting time, dumping time, and truck velocities on the road are modeled as expected values. The deterministic approach to calculate the key performance indicators (KPI's) of the truck and shovel stochastic system results in predictions that do not materialize in the real world mining operations and therefore, introduces a considerable error in the planned versus actuals of mining operations.

This thesis aims at answering the following research question:

> *How can the uncertainty about the truck and shovel operations' key performance indicators be quantified considering stochastic input variables based on historical operational data and time events including haulage; spotting; loading; backing; dumping; uptime and downtime of preventative maintenance; unscheduled maintenance and failures; and standby/ delays for weather events?*

1.3. Summary of Literature Review

A literature review in the area of truck and shovel allocation and simulation is carried out and presented in chapter 2. Here is a highlight of that review and a list of short-comings found in the current literature.

The open pit mining activity often linked with truck and shovel operation as resources for haulage and loading has been studied with the goal of improving the productivity of the mining operations in the past. The early work of Koenigsberg (1958) is an approximation to simulate the process with the interest of focusing on queuing at the shovels and dump locations. Since then many more approaches are studied in the area of truck and shovel allocation such as Ataeepour and Baafi (1999), Awuah-Offei et al.(2003) , Bonates (1996), Ercelebi and Bascetin (2009), Li (1990), Newman et al.(2010) and Awuah-Offei et al.(2011).

An introduction to microscopic simulation to account for the congestion and its consequences on the mining operations is studied by Jaoua et al.(2009) and Krause (2007), which studied in parallel for the machine repair theory with the loading processing time to perform the simulation. A similar approximation is done Bauer and Calder (1973), who used Monte Carlo simulation, while established a relationship between loading time, quality of the blast and the arrangement of truck and shovel operation. Blouin et al. (2001), widely explains the grounds of discrete event and vector simulation and how to proceed to perform a work under this framework. The detailed modeling of the mine road network can be found in Awuah-Offei et al.(2003), Bonates (1996), Lizotte and Bonates (1987), Soofastaei et al.(2016) and Chanda and Wilke (1992).

Other research shows integration of mathematical programming and discrete event simulation in order to improve shovel allocation while minimizing costs and maximizing the utilization of the mining fleet. Notifiable research in this area include Upadhyay and Askari-Nasab(2016), Subtil et al.(2011), Ercelebi and Bascetin (2009), Li (1990), Upadhyay and Askari-Nasab (2013), Torkamani and Askari-Nasab (2012), Soofastaei et al.,(2016) and Matamoros and Dimitrakopoulos (2016).

The review of literature in chapter two revealed the following limitations in the current state of discrete event simulation of mining operations:

- Mostly, the truck and shovels are considered to be identical in terms of model and size. In reality mining operations consist of mixed fleet with a mixture of newer and older equipment,
- Traffic congestion on the mine road network is not measured and modeled,
- Complete interaction between the trucks on the road network and at the intersections with stop signs are not modeled,
- Most of the simulation studies did not present validation of the simulation models against historical dispatch and processing plant data,
- Many simulation models do not consider queue length and time in the assessment of their results,
- There is not a link between the simulation model to the mine polygons/production schedule and consequently the estimated grades of main, by products, and deleterious elements in the block model are not traced at the crusher, and
- Lack of accounting for uncertainty in production and availability of equipment.

1.4. Objectives of the Study

Given the research question presented in the thesis and the list of the shortcomings established through the literature review, the main objective of the research is to estimate the main KPI's of an open pit mining truck and shovel operations while quantifying the uncertainty about the KPI's with high statistical confidence. To achieve this goal in this research a discrete event truck and shovel simulation model for open pit mining is developed, verified, and validated with stochastic input variables and a link to the short-term mine plan. The developed discrete event simulation model honors the simulation process theory and is capable to simulate the mine operation process delays, mechanical planned and unplanned events of truck-and-shovel, and weather events.

A simulation case-study of truck and shovel operations is presented. The model reports the major KPI's, such as ore and waste tonnage, average queue and cycle time, availability, and operating efficiency of truck and shovel systems. A number of scenarios are ran using the simulation model to assess the impact of change in the number of ore and waste trucks, and the throughput rates at the crusher. The model is used to determine the optimal fleet size, number of ore and waste trucks, and the throughput rate at the crushers which will meet the short-term production schedule targets.

1.5. Scope of the work

The scope of this research is mainly centered around assessing the validity of a mine short-term production schedule with a monthly resolution using discrete event simulation. The model captures mine haulage systems, interaction between shovels and trucks, failures, preventive maintenance, stand by due to weather, dumps, crushers following a short-term schedule. However, other mine activities like blasting and drilling are not counted as constraint in this simulation.

1.6. Research methodology

To achieve the research objectives, the following tasks are completed:

1. A database from a mine dispatching software was provided, including; tonnage, material type, spotting, loading, dumping, backing, loaded and empty velocities of trucks, shovel and truck matching information, dump locations, crusher locations, hauling times, and cycle times. With this information, the number of passes that

loaded every truck are calculated knowing the equipment specification, density of the material, and the truck load.

2. Data is cleaned up of outliers, histograms are made so as to make visible ranges in which the time falls more frequently for the spotting, loading, velocities emptied and full, dumping, loading, bucket load tonnage and number of passes. MATLAB code with a link to a SQL Server database is used to carry out this stage of the study.
3. The relevant data ranges from the last step are taken to Arena Input analyzer software to fit probability distributions on data. For every truck and shovel type matching, that for this case is a matrix of 6 shovel types and 4 truck types.
4. A short-term schedule is provided from an iron ore deposit. The production schedule includes tonnage, grade and the road network detailed information with the shovel and dump positions. The trucks are modeled as Guided Path Transporters in Arena (Rockwell Atomization Inc.)
5. Another input into the simulation model is the short-term production schedule provided as sequenced mining polygons with their respective tonnages and grades of interest. The mining polygons information includes coordinates, tonnage, grade, dump id, period, shovel id and sequence, that honor the precedence of mining.
6. The truck and shovel mining operation is simulated in Arena where the mining polygons and each truck load is an entity that will be matched with a truck in accordance with the truck type and the material type. Trucks will be will be allocated to a shovel that holds this polygon.

7. The failures, preventive maintenance, and weather events are modeled. If failures or a preventive maintenance code occurs trucks are sent to a failure location, while stand by weather events affecting trucks will send them to the failure just if they are queuing at the shovel, otherwise they will remain at their current position.
8. Shovels are also taken down for preventive maintenance and unplanned failures. If a shovel fails, the truck will keep on waiting in the queue but if there is a weather event and the truck is already waiting to be allocated it is hold as weather event and taken out of the queue.
9. The simulation will be run for the time proposed initially. The simulation will go for the number of replications calculated, which is 10, so as to work inside the half width demanded by the project which is around 95%, this for the ore tonnage as it is at the end of the day the target goal to achieve.
10. The next step will be to verify the simulation against the historical data, time durations and bucket loads will be analyzed with the use of QQ plots, to account for objective representation of the reality.
11. Once the verification is done, the next stage is to run scenarios with different number of trucks, while mine production targets, KPI's, are evaluated.

1.7. Contribution of thesis

A discrete event simulation model for truck and shovel operations that predicts the major KPI's of the mining operations with 95% statistical confidence about the statistics of interest while quantifying the uncertainty around the estimation.

1.8. Organization of thesis

Chapter 1 presents the background, statement of the problem, research objectives, and methodology. Chapter 2 covers a literature review on simulation in mine operations while highlighting the branches of dispatching and non-dispatching, and stochastic and deterministic modeling approaches. Chapter 3 shows the procedures for simulation modeling applied to this specific case. Descriptive steps are provided together with flow chart to conceptualize the simulation interaction building and testing. Chapter 4 presents the verification and validation of the simulation. Also, it presents the case study and different scenarios ran in order to find the proper number of ore trucks and waste trucks. Chapter 5 is the discussion and conclusions.

2. Chapter 2

Literature Review

2.1. Open pit mining

The open pit mining process extracts ore minerals out of the earth's surface at depth of less than 150 m, due to the geological ore disposition and the technical requirements involved in extraction. "Ore is a metalliferous mineral, or an aggregate of metalliferous minerals, more or less mixed with gangue which from the stand point of the miner can be mined at a profit or, from the stand point of a metallurgist can be treated at a profit " (Hustrulid and Kuchta, 2013). In general, open pit mining involves the movement of a huge amount of gangue, sterile, waste or overburden material which covers the material ore of interest. However, the cost ~~o~~f the waste movement is paid from the ore selling price for the mining business to maintain profitability. The revenues must balance the cost that the system involves.

$$\mathrm{Pr}\,ofits = \mathrm{Re}\,venues - Costs \quad (1)$$

The revenue portion of the equation can be written as:

$$Revenues \;=\; Material\ sold\ \left(units\right)\ x\ Price\,/\,unit \quad (2)$$

The costs can be similarly expressed as:

$$Costs \;=\; Material\ sold\ \left(units\right)\ x\ Cost\,/\,unit \quad (3)$$

Combining the equations yields:

$$Profits \;=\; Material\ sold\ \left(units\right)\ x\ \left(Price\,/\,unit \;—\; Cost\,/\,unit\right) \quad (4)$$

It can be seen that as long as the profit equation yields positive values, the business maintains stability.

2.2. Mining development phases

The planning phase of the project emerges from the need to evaluate potential areas of interest due to increasing demand or advances in technology. This evaluation is made in terms of economic attractiveness. Following this phase, the feasibility report provides basis to decide about construction of a mining and concentration plant. It also provides more details on the implementation, investment or design of the construction phase to finally reach the operation and production phase. As the production phase starts, material is delivered to the plant to be transformed to a final product. During the planning phase, there is a window of opportunity to minimize the capital and operating cost of the ultimate project, while maximizing the operability and profitability of the venture. However, the opposite can also happen. Therefore, as Hustrulid and Kuchta (2013) note, these phases provide the opportunity to minimize costs. To elaborate on this, in the planning stage the production planning runs for the LOM. Long-term yearly plan has a duration from 10 years up to the LOM, and the planning period has a duration of a year or two. The mine planning period evaluates the economic viability of mining and provides the bases for short-term plan, focusing on maximizing economic profit, and consequently NPV, which is defined as the summation of the discounted cash flows over the LOM. On the other hand, the short-term plan has a duration of one year and is schedule over periods of one month, taking the long-term plan as a basis. Its main objective is to meet the production target and minimize the cost (Torkamani, 2013).

2.3. Short-term planning and truck and shovel

After selecting an appropriate time frame for planning, which may range from one year to daily production, a short-term plan is established. The main goal is to deliver tonnage and grade within the long-range plan specified. Many approaches to this issue have been developed to respect ore body configuration, consider uncertainty and computer techniques in a more individual format. All of this aims to facilitate the process in elaboration and execution of short-term plan. Also, optimization techniques have been carried out using LP and deterministic methodologies. Chanda and Wilke (1992) developed an optimization short-term plan study focused on the format of a specific operation, using LP for the selection of shovel, maintain low deviations of tonnage and grade.

Many authors point out the importance of short-term planning in cash flow of the project especially with this economy. Chanda and Wilke (1992), argued that poor schedule can trash cash flow and, as a result short-term planning has an important role as there is more certainty in ore body at this point. Chanda and Wilke (1992), refer also to the short-term planning as time frame of monthly planning, knowing that its objectives are different from the long-term plan. Their work also suggests that short-term plans should be modeled separated so as to consider all the variables in detail.

Finally, Chanda and Wilke (1992) suggested seven milestones that the short-term plan should include: 1. Next month's ore quality from the faces and reliability, 2. Fluctuation of daily grade, 3. Maintain long-term plan ore and waste locations, where in the schedule they should be mined, rate, composition of the ROM, stripping ratio and optimum sequence, 4. Deviations from the ROM, since it will affect the blend composition and the mill recovery, 5. Location in detail of the mining equipment and allocation to blocks, 6.Efficient utilization of the open pit equipment, and 7.Ensure a flexible plan and operability. Newman et al.(2010), also emphasize the short-term plan's goal is to increase the truck and shovel productivity, while meeting the demand requirements. The planners are first to determine the location of the shovel, then use the network model to establish an optimal production plan that includes times and routes, so decisions are made in real time for truck and shovel.

2.4. Mining simulation procedure

To begin with, simulation is a modeling technique that attempts to predict changes in performance of a complex operating system, without actually changing the system, as Newman et al.(2010) explained. Maintaining the main objective of the long-term planning, the short-term planning seeks to keep the production under the statement proposed. Many researchers have been trying to maintain this boundary. Mathematical approximations have been developed to come up with outcomes of the exact target of mining ore and waste tonnage, grade, stripping ratio, costs, etc. Other research in short-term planning has the goal to simulate the short-term plan. The simulation procedure emerged from the necessity to mimic the reality to be consistent with the system in a time structure. The principal objectives are to understand procedures, develop training in a safely environment, and perform modifications on the process in a short time without any harm to the operation.

In simulation, the short-term plan is input with all features as tonnage, grade, period, precedence, dump destination, polygon number, material type, coordinate, etc. The simulation is run to analyze inputs and outputs. Simulation suits very well in the mining operation because it is a compound of activities that happen one at the time and the discrete event simulation methodology represents this reality. The concept of discrete event simulation is introduced in as a process in which during a small increment of time, the stated variables change a countable number of times, like a truck being loaded, a shovel breaking down, ore passes, and a ship arriving in a port. It can be seen that the mining operation is understood as a summation of events, for a mine discrete event simulation.

Every time a truck finishes a cycle, the question arises "Where the truck should be sent next?” in accordance with the schedule and in order to maximize resources. This is a dispatching problem. This problem has been individualistically studied with customized approaches like the AGVS, Automated guided vehicle systems are developed. Alarie and Gamache (2002) explain dispatching problem as a demand in an exact point destination that can be related as the loading and dumping points, where the vehicle is sent with options of routing or being sent to a parking area. However, the AGVS will pick up only one item at a time.

Two main approaches in truck dispatch simulation have been developed based on either one general criteria or a multistage approach. Therefore, the problem is addressed by two techniques. The first technique focuses on the demand variability of resources; when the complexity of the problem increases, it is difficult to solve it by exact methods. The alternative is due to practicability heuristic solutions, Ronen (1988) depicts on this point in his research. This heuristic methodology has been widely used in truck dispatching due to the simplicity of real time execution and computation time to make decisions. However, the solution found is not exact and there is no mathematical evidence of the goodness of solution. However, the problem is addressed on logical and practical procedures. This has been discussed by Alarie and Gamache (2002).

The second technique divides the system into main components, upper stage that contains production targets for every shovel and lower stage that assigns trucks to shovel to minimize the deviation from production targets suggested by the upper stage. Linear and non-linear programming is the mathematical tool employed. It is used for upper stage targets while heuristics methods are used in the lower stage, as described by Alarie and Gamache (2002).

2.4.1. Chronological background

Historically, the discrete event simulation has been recognized, for truck and shovel allocation. The earliest approximation was done by Koenigsberg (1958) which in his paper Cyclic queues, provided a deterministic production schedule for a set number of crews working in faces at a underground mine. The first computer simulation work was recorded by K.Rist (1961), in a molybdenum mine that focused on optimizing the number of trains that line up at a portal and wait until the single track was clear and until the crusher is free (Sturgul, 2000). Later, the same approach was replicated, and modified to be presented at a APCOM conference by Harvey (2007).

Moreover, a belt for conveyor underground coal mine usage, with Fortran language programming by Sanford (1965), was investigated. Furthermore, belts were added to the system to reach 25 and 12 loading points by Juckett (1969). In 1977, a program named GASPV was developed with similar features of GPSS. In the next year, a Fortran program simulator which worked with room pillar mining operation was develop by Suboleski and Lucas, 1969 (1969).The handling materials simulated by 1967 ,while truck and shovel open pit mining was also simulated by Bauer and Calder (1973).

In addition, in 1969 an outstanding simulation was conducted by Cross and Williamson (1969),using the data from an open pit mine in the southwest of the United States. This study examined truck and shovel loading, with a deterministic methodology, and with dispatching techniques through the whole simulation, to decrease waiting time. However, it ends up in using 1000 lines of computer coding.

All the last chronological background was supported by Sturgul (2000) , in the section review of simulation in mining.

2.4.2. Dispatching Vs Non-Dispatching

The mining operation process follows the mining schedule, where tonnage of ore and waste are set as a target. To accomplish this task, trucks are sent to shovels where they are loaded with ore or waste and then travel full of material to their material destination, which will correspond to the crusher if it is ore, waste if it is gangue and stockpile if the material is lean ore. They dump the material at their respective location and they are again reassigned to a shovel location. When the trucks are allocated always to the same shovel, then the system is called to be locked and it is a non-dispatching technique. On the other hand, when trucks are allocated to a shovel by using a technique so as to improve utilizations or maximize production, the system is under dispatching.

Subtil et al.(2011) suggested two dispatching strategies: "1 truck-for-n-shovel and m-trucks-for-1-shovel". For the first strategy, the truck can be sent to a shovel without considering the next truck. One of the dispatching techniques is minimizing truck waiting time. Trucks are assigned to the shovel focusing on the least waiting time for the truck being dispatched, as a result circuits are created amongst the closer shovels. Trucks utilization is maximized by encouraging trucks to be dispatched to a closer shovel which will unbalance the shovel production. Shovel minimization of waiting time is achieved by assigning trucks to a shovel that has been waiting longest. Trucks maximization of momentary production work with the ratio between truck capacity and cycle time of truck tones/minutes. To minimize shovel saturation assignation to the lowest degree of saturation is performed. A ratio that is equal to the number trucks that have been assigned and the desired number of trucks that should have been assigned.

The second strategy is described by Alarie and Gamache (2002) , "m-trucks-for-1-shovel", take into account the m trucks that will request dispatch, but considering 1 shovel at a time. Shovels are sorted according to a measure that indicates how they are delayed in their production. The strategy is to assign to the current shovel the truck that reduces this measure as Subtil et al. (2011) explained. Finally, Alarie and Gamache (2002), presents the concept of the strategy "m-trucks-for-n-Shovels".

Ataeepour and Baafi (1999), built a simulation system for a mine with an specific number of shovel, working faces, and dumps locations. The same truck type and two-way traffic road were assumed. A sub-optimization and an optimization technique are employed and distributions were assigned for timing activities. The simulation is run for a non-dispatching system, considering a mine with 1 shovel, 5 faces are interpreted as 5 mines. The sub-optimization varies the number of trucks served in steps of one unit at the time, while the others shovels serve three trucks. The optimal is the sub-optimal for the shovel face with unique destination. On the other hand, the dispatching model aims to minimize the queue time to maximize the utilization of the trucks and productivity. The research concluded that in small fleets the system is under-truck and in a big fleet the system is over-truck. Moreover, in the model could be seen an improvement in the productivity when the system is in dispatching conditions.

Comparing dispatching techniques, Subtil et al.(2011) proved the successful use of multi-objective optimization techniques united with simulation techniques in a multistage strategy. A simulation dispatching optimization is run with LP. As a result, 12.38 % and 47.92% more in the total material hauled at the mine from two shifts was observed. Moreover, operation delays were reduced by 53%.

A latter approach by Eskandari et al.(2013), formulate a stochastic mine discrete event simulation, with a flow orientated FIFO queue. All shovels and trucks are the same, and dispatching and non-dispatching techniques are simulated. They are run with OptQuest, application of Arena (Rockwell Automatization Inc.) that works with an objective function and constraints in decision variables. The highlight advantages of using Arena (Rockwell Automatization Inc.) were debugging, animation, and improvements in resources utilization and production due to the dispatching technique achieved by the OptQuest.

Hashemi and Sattarvand (2015) studied the link of the dispatching of truck and shovel, with their performance to minimize the waiting time of truck due to use of an end front loader. Stochastic times were captured with distributions and the system is structured by loading stations, and dumps. Dispatching and non-dispatching techniques are addressed with the concept of over-truck and under-truck so an increase in the production of 40%. Data from simulation was compared with the real data, which validated the outcomes but not spotting, and failing on shovel, trucks or crusher were considered.

Finally, after many years of comparisons and improvements, industry and researches had conclude that the dispatching techniques attempts to give better outcomes in terms of usage and indeed production rather than leaving equipment’s lock to a shovel.

2.4.3. Deterministic and Stochastic approach

The discrete event simulation allows the inclusion of time event delay process to entities. In the case of mining operation, the process activities are velocity empty, travelling empty, spotting time, loading time, velocity loaded, backing time, and dumping time. Deterministic approach will assume expected values for delay process but stochastic procedure will fit distribution and assume uncertainty to model the delays mentioned. Sturgul (1992), explains the difference between a deterministic and stochastic simulation by using simple queuing theorem mean time vs statistical distributions, by a GPSS language programming.

For the deterministic discrete even simulation run, the average exact time was used for the delays, for a horizon of 10 days. Uniform distributions fit for delays on the process were for 50 days. Finally, an exponential distribution which better described the behavior of the queuing mean time delay is run for 100 days due to the skewed to the right tendency of this distribution. The findings shown that for the simulation exact time the optimal number of trucks will be 4 trucks with a profit of $3213; however, when simulation with uniform distributions is analyzed, the number of optimal trucks is 5 and the corresponding profit is $3069. Finally, fitting the most likely distribution to adjust to the reality, exponential distribution, the optimal number of trucks is 6 and profit is $2633.

As the expectations are less as more randomness is added to the process, which is the main tendency of mining operation. The last statement will lead to the practice of sampling from a distribution to include variability by using stochastic statistics. As a result, language as GPSS and SIMAN are used to input these stochastic variables in a simulation software. Other studies have been done under the same structure of comparing deterministic and stochastic approximation, like Dindarloo et al. (2015), where the deterministic assumption is taken as case base and then improvements are done from that point. Researches with different cases that will input stochastic time frame have been carried out are Sturgul (1992), Soofastaei et al.(2016), Upadhyay and Askari-Nasab (2016), Matamoros and Dimitrakopoulos (2016), Awuah-Offei et al. (2003), Newman et al.(2010), Awuah-Offei et al., (2011), Hashemi and Sattarvand (2015), Subtil et al.(2011) and Ataeepour and Baafi(1999)

2.5. Simulation and Truck and Shovel operation. Heuristic approaches

Complex systems interactions with simulation have been widely studied, as organizational and environmental changes can be simulated and the effect of these alterations on the system can be studied. Knowledge gained in designing a simulation can be used to improve the system. The model can be useful to identify the variables of importance to the system and how they interact. Simulation models designed for training allow learning without the cost and disruption on the job. Animation is shown in simulated operation so that the plan can be visualized so modern complex systems are best studied using simulation. When time-varying (non-stationary) behavior must be examined, simulation can be used to experiment with new designs prior to implementation (Tabesh et al., 2016).Standard simulation offers a representation of the system parameters, mathematical equations, speeds, times, rolling resistance to predict performance, etc.

Bonates (1996), provided detail about heuristic grounds in dispatching. With the idea of stochastic modeling distribution for delays, as an aim to optimize truck and shovel productivity, the research proposed an advanced clock approach that check at various points of the haulage network the dispatching rules. The dispatching rules are: minimizing shovel idle time, maximizing immediate truck use, assigning truck to shovels to meet production targets, and validation of a match factor to balance the flow in the shift. Heuristic dispatching is implemented to suggest the operator the optimal assignment. Semi-. automated, where the human intervention is necessary to display the information to the operator. Finally, the fully automated dispatching, where machine can receive and send direct information to the operators. The research corresponded to an experiment at a mine Quebec, Lac d'Amiante. The main findings were that production will increase as number of truck will. Production will increase until average truck waiting time triples the ranges of the fleet size tested. Therefore, average waiting time will decrease 25% and the loading time rise in same proportion.

A further development found in the area of heuristic truck dispatching by Arelovich et al.(2010), implemented discrete simulation using peer to peer communication to estimate the optimal travel plan, focusing in two main objectives: 1.Configurate probabilistic distributions for the resources velocity, and 2.Alternate real dispatching system that makes global decisions working towards the global. For the first one, the fundaments are based on properties of the vehicle and the empirical model of the road to model vehicle movement by making histograms of velocity for each section. Probability distributions are tested by a mine simulation. The second one, is addressed by rules, which assigns to shovels with less trucks, distance to travel and number in queue. This study assumes the truck assigned to the shovel until it reaches the point, allowing the operator to make another choice. It came out with the idea that sometimes the longest path will be selected due to the ability to travel faster, which will be traduced into more number of loads.

Additionally, dispatching heuristic techniques that minimize tonnage, grade, and waiting time deviations are the studied in the research of Temeng et al.(1997). Under the frame of multistage, linear or non-linear, and heuristic mathematical programming to establish short-term plan sequence, tonnage, grade and constrain capacities, and develop real time dispatching, with quickly responses. The principles of dispatching suggested are: minimizing waiting time by adding the shortest path to the simulation, determine the current needy shovels, path to connect to needy shovels, shovel demand, tonnage required to meet the target in the path and number of trucks needed with the last information. The case accounts for shovels break downs with 2 scenarios. Considering one shovel brakes the whole shift, while the other work and partial breaks downs. It assesses the grade supply hourly in every shift and analyzes the variation when the failure happens.

Jaoua et al.(2009) based on inability of the macroscopic modeling to capture detail interaction between vehicles, decided to implement microscopic modeling. Interaction between trucks is important due to congestion that happens in the road affects the production and oil consumption, which leads also problems upstream in dispatching process. As a result, this research developed a realist microscopic simulator, which has an objective to develop more efficient roads and provide updated real times allocations. The core of this work, as it was mentioned, is based on microscopic simulation approaches to ensure robust traffic and congestion control, at the highest level of detail. The validation technique used is tested against the macroscopic simulation, which will hold the road in a lower level detail, and another technique used is a sensitivity analysis with use of variance. Using the concept of heterogeneity in truck fleet for traffic congestion, as differences of truck speed will cause bunching. Also the research investigated different alternatives to reduce bouncing by adding alternatives roads, while analyzes the travel time, production and oil consumption.

Krause (2007) generated a project, where they could apply the machine repair model in the simulation truck and shovel, called a virtual minute. Using software Arena(Rockwell Automatization Inc.) to simulate variability of multiple distributions to fit for every component of the cycle. Modeling inter-arrival rate and service rate under model repair and queues, ramps and rolling resistance. The repair will emulate the loading and so on. Moreover, this study compares the simulation outcome with real performance of a coal mine operation, and another software outcome for validation of the simulation of the loading by shift. Because in the model loading times are exponential distributions and in another software, they are lognormal.

Probabilistic Monte Carlo simulation is used by Bauer and Calder (2010), for study of cyclical queues, which also allows random event time selection, like the loading time. The study classifies quality of the blast product in terms of good, fair, and poor fragmentation in digging rate. It established a relationship between the blast outcome, loading time, and truck and shovel arrangement. The research finds out the saturation size for every fleet according to the fragmentation material. In terms of statistic validation and verification for simulation models, Kolonja et al.(1993), researched on multiple comparisons with the best (MCB) and the combination of MCB with reduction technique known as common random number (CRN). The work aims to develop techniques to reduce variance up to 29%, number of replications by 48% and narrow the confidence interval by 18%. These goals are achieved by designing simulation experiment to take advantage of components of the variance. Using the same random numbers within pairs of replications as to introduce positive covariance among the responses within a paired set of replications. As a result; random number must be synchronized in the simulation. Dispatching heuristic techniques are tested like minimizing shovel waiting time, truck cycle time, waiting time, and shovel saturation.

Blouin et al.(2001), addressed the dispatching issue by making decision task, using discrete event simulation and vector discrete event system comparison. The work explains characteristics that should include solutions of the problem, given fleets of trucks and shovels subject to some specification. If there exists some dispatching solution, quantity, location, configuration and capacity should be included, while specifications like safety, maintenance, and operation are satisfied. In detail, the paper informs how is the process of discrete event simulation. However, it does not consider break downs and assumes continuity in the production.

Fioroni et al.(2008), worked on short-term planning schedule simulation and optimization. The ideas are based on modeling correctly to represent the real system, with the detail just enough to accomplish the goals studied. Leaning on discrete simulation, there is a concern about losing details on modeling, and level of precision trying to simplify procedure to model. Also, the study refers to the necessity of verifying the model, because it is mean to be used as prediction tool for mine planning so the reliability should be guarantee. The research highlighted the ability of discrete event simulation to account for randomness. Vasquez (2014), developed scenarios and set alarms so as to use the discrete event simulation as controlling tool. The simulation advantages were studied, not also in the capability of assessing new scenarios of increasing roads but also monitoring and controlling in detail up to the level of alerting when KPI's are off the limits previously established.

A study to improve truck and shovel utilization was done by Torkamani and Askari-Nasab (2013), referencing discrete event simulation that adds uncertainty in the short-term planning with the use of fitting density function for all the truck and shovel activities. The research in an iron ore mine in Iran, with three dump destinations, two of them ore attached to a two stock-piles. Same truck and shovel fleet, Cat 785C and Cat 7295M, nominal capacities of 120 and 40 tons respectively. The methodology was to tackle the operation problem in two stages. First, finding the right size represented in this case by number of trucks and shovels, using the production as a main requirement. Secondly, searching into deeply detail for the KPI's of the feasible scenario found on the first stage. It wraps up with the waiting times sensitivity analysis as cycle and queue times improvements for shorter periods of times as night and day shift.

Another earlier development in the same area of truck and shovel utilization optimizations is conducted by Torkamani and Askari-Nasab (2012).Using the fundamentals of discrete event simulation presented a verification of short-term mine planning , as a necessity to link uncertainty and analyzing truck an shovel in detail. The study presented a schedule given and then a simulation of different scenarios increasing the number of trucks, with a sensitivity analysis on the truck and shovel utilization and the production rose, while assessing when it is proper to include in the panorama another shovel.

Recently, Tabesh et al.(2016),developed a conceptual procedure for discrete event simulation truck and shovel operation, that outlines the requirements to validate a simulation model with historical data. Historical data, capturing and modeling interactions of truck and shovel are explained using flow chart with the Arena (Rockwell Automatization Inc.) interface format. This approach is conducted with failures, maintenance, coffee breaks, and events failures for shovel, truck and plant. Explanation on the technique used to fit distributions for all these events and the truck and shovel interactions as dumping, loading, spotting, etc., is also denoted. A format validation is suggested for single replication and real historical data for the same schedule given with an assessment of percentage difference. Moreover, a multiple replication validated with 20 runs, is carried out under half width of 95% confidence with same schedule scenario, obtaining also satisfactory results in terms of the difference real and simulation outcomes.

Interested in forecasting the fleet size demanded by a 3 years plan, Awuah-Offei et al (2003) used a SIMAN computer simulation package, sampling from a distribution to assign times and taking into account the failure of the equipment , as an input from a mine in Africa. An objective oriented simulation system entity, which can be attach to an attribute. The model watch after average queue length of trucks, average shovel utilization, and number of trucks loaded by shift.

Using microscopic simulation in mining, areas and activities in the operation that could have been improved are widely studied by Bonates(1996), with a DETSIM program. This program calculates truck haul and return cycle time, while assess the effect of rolling resistance on the productivity of the system. The research includes deterministic simulation to account for performance of a mine haulage truck along a specific road profile. It is mainly focused on estimation of haulage time, description of input components with language Fortran programming. It will take all information related to available rim pull, gross or net vehicle weight, engine output, weight to power radio, speed factors, and haulage profile characteristics. Based on heuristic dispatching techniques Ahangaran et al. (2012), focused on decreasing waiting time so as to increase production. The algorithm is centered in finding the shortest path and allocate using integer programming. Concluding that the dispatching system is an important stage in the profitability of the operation costs.

A latest approach was conducted in terms of the payload truck by Soofastaei et al.(2016). The highly payload variance decreased the accuracy of maintenance program, as wear and tear usage were less predictable. Moreover, average cycle time increases dramatically as does variance of the payload. It takes stochastic inputs, while it has as an objective of fuel consumption reduction by a LP simulation. Another approach is pointed in this case, in the area of emissions earth moving, Kaboli and Carmichael (2014), achieved savings through the appropriate allocation of truck and dump sited, which will lead to fuel reduction and positive impact in cost and indeed emissions, as over truck levels are kept as less.

A more holist approach is introduced by Kuhl et al.(2013), where a mine coal operation is simulated together with dumps locations, hopers and trains. In a shift time frame. Establishing a relationship between the amount of trucks and the number of events with the production. The half width will vary with the tons and indeed the number trucks, making it more predictable when the amount of trucks is higher. Distribution are fitted by the tonnage and the revenue is maximizing with more variance.

Under this same area of simulation and LP, Chanda and Wilke (1992) established a new concept of short-term planning named STOPPS, short-term optimum pit production that aim to maximize the metal in ROM and minimize deviations on grade and tonnage, with the use of LP to keep last constrains mentioned out of deviations and shovel rates. Replicating the dispatching with a heuristic methodology. As an intent to promote mine simulation, this research showed advantages in the area of finances and computing time. Finally, Castillo and Cochran (1987), exposed statistical analysis to ensure validation and verification, while experiment in a real case. The study points out the importance of simulation over the prediction of the dispatching algorithm performance, which ever coding technique used.

2.5.1. Multistage dispatching system highlights

To excel the outcome of the simulation, many researches have been done in mixing simulation and LP so as to promote mine optimization in the area of allocation. A multi-criteria optimization is built using LP with a schedule input plan, where the maximum capacity is the current scenario and an optimized version size will also meet these criteria. The 12.38% and 47.92% of the total material hauled at the mine in the daily and night shift is increased, while reducing the level of operation delay by 53% , this study is carry out by Subtil et al. (2011). Moreover, Li (1990), worked with the maximum inter-truck type deviation rule. The least square deviation is used to count how much ore and waste to be transported in the haul road for the transporter and how the trucks should be assigned. The main topics threaded are haulage planning, truck dispatching and equipment matching. Basing the LP in a minimization problem to solve the optimal truck flow, not outcomes were displayed with a data run, just the formulation.

A hierarchical link was proposed by Eivazy and Askari-Nasab (2012)between strategic open pit mine plan with the optimal medium-term production schedule. It developed, implemented, and verified a mathematical programming framework for the optimal medium-term plan using integer LP. Under the statement of minimizing the operating cost. To achieve this goal multiple destination as stockpiles, dumps and processing plants were taken into account, as well as decision making to deterministic extraction sequence of ore and waste and modeling the stockpile. Moreover, aggregate blocks into a practical scheduling units, named hierarchical clustering, are created based on similarity index between blocks. The principal aim of the clustering is mine selectivity and reduce the number of binary variables, for more information search on Eivazy and Askari-Nasab (2010).

Eivazy and Askari-Nasab (2012) in their paper explained how to build connection between medium-term planning and short-term planning. As Eivazy and Askari-Nasab (2012), defined a hierarchical open pit mine production scheduling methodology that link the optimal strategic open pit mine plan to optimal medium-term production schedule by a MILP approximation to minimize the operating cost, as waste rehabilitation, processing, mining, haulage, and re-handling cost.

Among the years, many studies have been done to measure the cost involve in mining activities through mine planning since the early plan. To begin with the queuing theory in the field of optimization of shovel-truck system but the shovel assignment to mine faces have not received sufficient attention (Upadhyay and Askari-Nasab, 2013). Upadhyay and Askari-Nasab (2013), proposed a MILP into an upper stage. This approach was leaded by the variability caused by the unavailability of trucks and shovel. As a result, this formulation works with the deviation from the short-term plan and the long-term plan. Optimizing the usage so as to meet strategic production schedule by the shovel assignment to faces over shift-shift horizon. It takes as an input cuts (faces Ids), coordinates of faces, tonnage of material, fraction to be mined in a given period, mine haul road distance from the working face, precedence cuts ids and average grade.

A similar work was proposed by Upadhyay and Askari-Nasab (2016), based on necessity of introducing a better decision making environment in short-term planning, which could lead to better predictions. A discrete event simulation short-term planning framework is combined with decision making MILP. With an Iron ore schedule, two scenarios are simulated, using the very similar procedure than the one suggested in the previous work with Arena (Rockwell Automatization Inc.) and VBA interaction. C1, one truck fleet Cat 785C, and C2 Cat785C for ore and CAT 793C for waste non dispatching. Different trials are run increasing the number of trucks. For C1 no improvement in ore production is observed due to the way the optimization MOOT works achieving processing and production targets. On the other hand, scenario C2, shows improvements in ore and waste production as the number of trucks increase. Another scenario is set to evaluate sensibility on the crusher throughput capacity and feeding rate to the plant. It could corroborate relationships, widely described in this literature review, between shovel utilization, queues at the shovel, rates on the plant, queues at the dumps and utilization in long distance shovel destinations.

L'Heureux et al. (2013)defined a model that established the sequence of mine for a period ranging from days to several months, determined order of blocks to be mined and shovel movement to meet the production capacity equipment. The research gave the detail of the drilling and blasting areas with the purpose to show the sequence of this activities. In this order, the objective function is set with the minimization of cost concept, and the constraints defined as equality and inequalities so as to save computation time. In this stage, every single cost can be measured.

To improve the grade blending, scheduling and decision making. Non-preemptive programming was developed by Soofastaei et al.(2016), under the adversity of shovel inefficient plans. The paper is focused on preserving in acceptable ranges the deviation of quantity and quality of processing plant and stockpile feed with respect to desired feed and also an operational escalation.

Fioroni et al.(2008), describes how variability on the availability equipment can affect the productivity. The center of this study is to allocate trucks according to their operation performance. Introduces the importance of the RAM, reliability, availability and maintainability to the optimization. A formulation with a multiple integer Knapsack problem is described so as to perform optimization based on expected productivity of each equipment based on its operating performance. The equipment's are considered as identical without accounting for these characteristics. The works is composed of three main stages. The simulation in Arena (Rockwell Automatization Inc.) has been employed, which gives the option as it has been mention before to the reproduce the probabilistic and random behavior of such events like maintenance and breakdowns, reading an setting basic information, specification, schedule in Excel throughout VBA and the optimizer that uses Lingo.

Other attempts have been done to model merely using mathematical programming the short-term plan, falling into tedious techniques that are long in running time and tedious to build and their outcomes do not allow different scenarios evolutions (Matamoros and Dimitrakopoulos, 2016)

2.6. Limitations findings

- In most of the studies all the trucks are considered identical in terms brand and size, the same problem exists around the shovel.
- Cost measurement saving and emissions to the atmosphere are not often account.
- Accountability for the most congested path so as to improve mobility are not reviewed in most the bibliography.
- Delays due to stops signs are not simulated.
- Most of the simulation studies do not consider validation against historical data by statistical techniques procedure.

- Most of the simulation studies do not consider queue length and time in the assessment and configuration.
- There is not a clear linkage between discrete and continuous simulation.
- Models do not consider block by block excavations.
- Models do not consider truck's interactions on the road.
- Difficulties in satisfying variability on the demand of trucks in the dispatching concepts.
- Difficulties to deal with event change.
- Lack of accounting for uncertainty in production and availability.
- Processing plant capacity is considered fixed.

3. Chapter 3

Theoretical framework

3.1. Introduction

Complexity of the mining process has been widely studied in order to overcome productivity issues. Considering unappealing deterministic predictions, mining production reconciliation is very poor. An explanation can be found in the magnitude of sub-activities and variables that the mining business includes.

Long-term planning usually aims at maximizing cash flow as it provides a broad vision of the profit over the LOM. It is presented as a depletion strategy of the ore body over time, and shows the sequential nature of exploitation to determine the order of block extraction during the mine life as Askari-Nasab and Awuah-Offei (2009) describe. The principal outputs are ultimate pit limits and mine schedule, which are related to each other making the process complex to handle. Due to the fact that finding the optimal pit limits that maximize the profit needs a schedule that also honors that profit, the problem becomes computationally intractable. As a results, many techniques have been developed to facilitate this study. For example, Lerchs and Grossman, 2D and 3D counts for strategic ultimate pit limits, and linear, mixed integer, and binary programming, which all provide values for tactical block sequencing that meet the relationship previously established. Another mathematical model that helps to handle the complexity of time and computation as branch bound, is described by Awuah-Offei and Askari-Nasab (2008) in terms of mining cuts and precedence. Granular detail of the long-term mine planning is often defined for ore reserves, stripping ratio, and major yearly investment plans, in 20 years to increasing NPV, it is a statement proposed by Eivazy and Askari-Nasab (2012).

Medium-term planning has a main goal of honoring the long-term plan, while minimizing mining cost and increasing operational details. Indeed, the long-term plan within the schedule output is translated into an input of mining, processing, slope-precedence, and equipment availability, all constraints that plan has to follow. Sequencing the block removal extraction from the mine respecting a variety of physical and economic constraints is also advisable as Eivazy and Askari-Nasab (2012), refer. To sum up, medium-term plan should make the plan operational within the framework of the year's plan, and still consider some aspects of mining production such as haulage roads, mining sequence of ore and waste, and equipment investment Hesameddin and Askari-Nasab (2011).

Short-term planning, described by, Chanda and Wilke (1992) as, a production schedule that minimizes mining costs, while meeting the goals of the medium-term plan, all within a monthly time frame, a high level of operational details available at this stage. Suggested below are objectives that this stage should meet:

1. Prediction of the next month's ore quality and reliability of that prediction,
2. Determination of the anticipated fluctuations in the daily grade around the estimated monthly grade,
3. Indications of exact locations of the ore, and waste zones to be mined in a determinate period, and at which rates, in order to satisfy demands on tonnage, composition of the ROM, ore and waste/ore ratios,
4. Absolute deviations from the stipulated quality requirements in ROM ore must be minimized since the variations in compositions of blended ore can affect mill recovery,
5. Detailed allocation of mining equipment,

6. Efficient utilization of open pit equipment and
7. Assurance that the plan is flexible and practically executable.

Fytas et al.(1993) propose that short-term mine planning procedure has downsides regarding designed production, due to discrepancies between planning expectations and actual production. Due to this weakness at upper stages being translated into lower stages, bias is increased increasing the biased and it compromises profitably of the business. However, research sustains that issues like technical constraints, which are imposed in the long-term range that does not ensure the fulfillment of the medium-term and short-term plan, and can also be the root of the problem. In order to depict the information given about hierarchical level of mine planning, Figure 1, is introduced with the simulation role inside.

After broadly viewing the difficulties of the hierarchical mine planning stages that affect short-term mine planning, this chapter will introduce evidence of these issues focusing truck and shovel simulation. The inputs will be described, as well as the short-term plan, with each of the headers and constraints. The truck and shovel historical background variables will be modeled, as well as the software's used to connect these variables. Making possible the interaction and simulation. The theory underlying each truck and shovel interaction, will be modeled, using flow charts. The importance of the reliability of the simulation will be discussed; and the KPI's that should follow every scenario so as to achieve feasibility.

3.2. Short-term plan input

3.2.1. Clustering algorithm

A mine schedule for a period of 12 months of an iron ore mine is given. Instead of a block sequence for the mine schedule, polygons structure is followed. The reason for using polygons to achieve more realistic mining cuts that improve operability coming straight from the short-term plan. Therefore, a clustering algorithm is used as a powerful tool that groups similar objects together, while satisfying other mutually exclusive and inclusive objects, maintaining maximum cluster sizes, and also keeping constrains on the cluster size. Within the clustering techniques, the hierarchical procedure has shown to have better outcomes (Tabesh and Askari-Nasab, 2012).

As it was mentioned before, the clustering algorithm is looking for mining shapes to be used as mining units, which should be homogenous in grade and rock type to maintain quality and dilution constraints. Moreover, so as to preserve the approximation of the material sent to the processing plant between rational ranges previously established. Another variable tracked, due to the influence on the mining shape, is the direction (Tabesh and Askari-Nasab, 2012).This procedure takes care of these variables by penalties and ranges inputted. Major element index (number of elements to control), distance weight (distance and direction of search), grade weight (on the major element), cluster, rock type, and destination penalty values as not to mix different categories in one cluster, average, maximum and minimum blocks per cut, number of precedence arcs and blocks from different regions cannot be mixed together (Tabesh and Askari-Nasab, 2012).

Then, it is known that this mining cut aggregation is effective for the short-term plan. It is useful for the short-term planner as it will in another case have to be digitalized manually for the excavation guideline of shovel and geologist. It is useful for the operation, as it decreases bias and prevents dilution, while it outputs are more accurate for tonnage and grade to the ROM. Finally, it not also summarizes the size of the production schedule in the short range but also can be able from the early stage of long-term range to achieving improvements in terms of computing time costs.

3.2.2. Results and definitions

The clustering schedule given is in the form of a data-base with the following headers:

- Polygon number: numerates all the polygons in the schedule from 1 to 166.
- Coordinates: gives the position x, y and z for each polygon number to conform a closed mining cluster.
- Tonnage: each polygon has a specific weight given in tonnage.
- P gram: grade of phosphor in each polygon, considered contaminant.
- S gram: grade of sulfide in each polygon, considered contaminant.
- MWT: grade of magnetic recovery in each polygon considered as material of interest.
- Dump ID: Indicates the waste disposal facility of destination.1 and 2 for ore and 3 for waste.
- Period: each polygon has a period assigned to as to guarantee the feed to the plant monthly. It will take values from 1 to 12 in this case.
- Dig-logs: it is composed for six columns, four of them belong to the shovel station, one for starting point, another for queue and the rest part of the polygon.

- Shovel: each polygon has their own shovel that is supposed to dig into that polygon and feed the respective truck match with. It will take values from 1 to 2 for ore and from 3 to 5 for waste.
- Sequence: as the polygons as labeled with the polygon number, they are numerated in sequence of extraction.
- Cluster ID: as it was mentioned previously mentioned, this polygon is modeled based on the clustering methodology so as to keep track the clustering origin it is also labeled.
- Precedence, cluster ID: likewise, as the information is coming from the scheduling clustering format, the clustered demanded to be mined before than this are enumerated in this item of 11 columns, allowing this much of restriction of 11 clusters.
- Distance Mill 1: distance in meters from the polygon to Mill 1, corresponding to dump 1 for ore.
- Distance Mill 2: distance in meters from the polygon to Mill 1, corresponding to dump 2 for ore.
- Distance W dump: distance in meters from the polygon to dump 3 for waste.

It can be seen explained the dump and shovel relationship with the ore and waste in Figure 2.

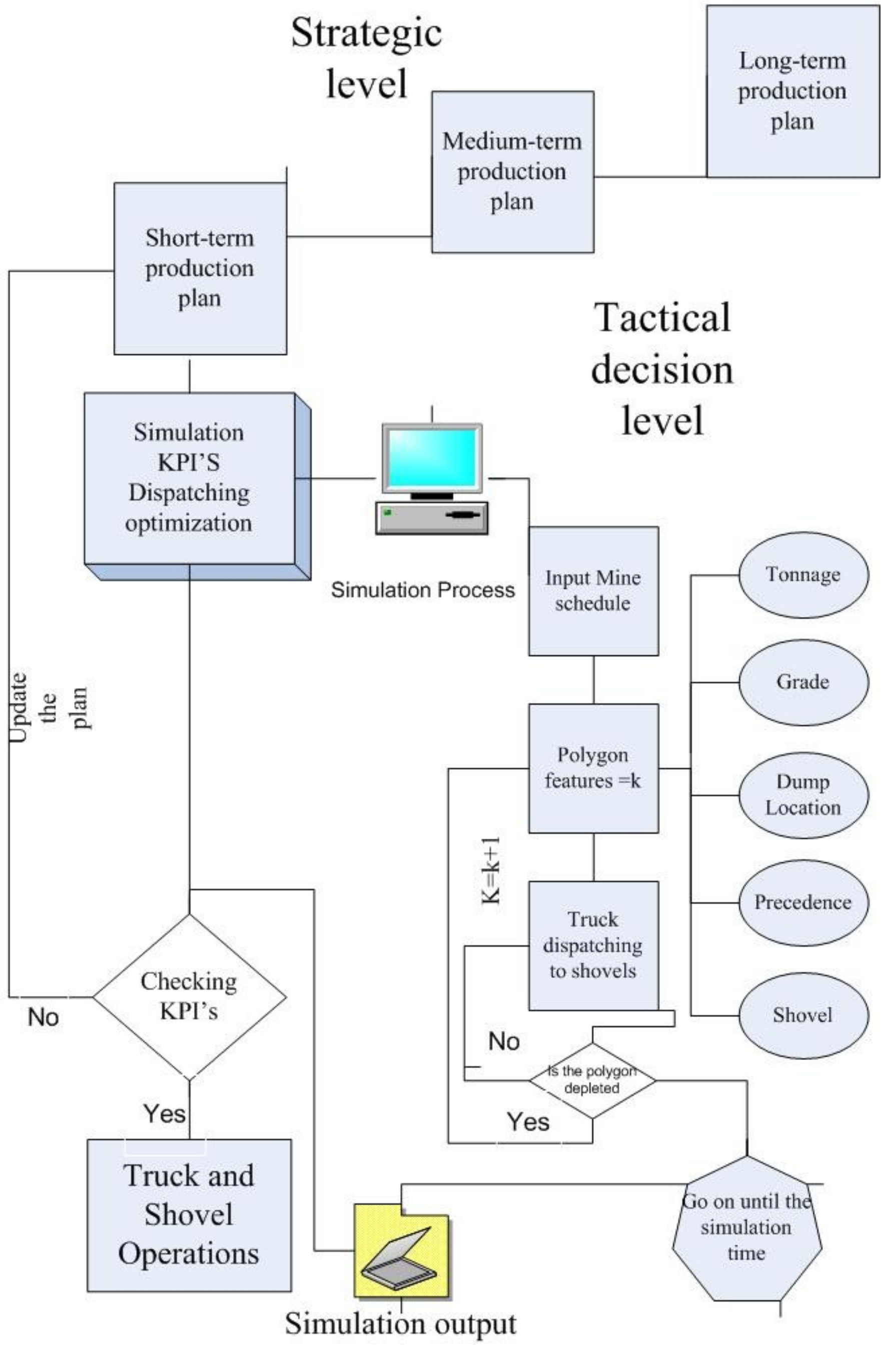

Figure 1. Flow of the mine planning process level

3.3. Historical data

The Jigsaw data-base given has dispatching information that is stored under the next headers, (Header that will be described obey just to the ones used for the simulation proposes):

- Spot time: it is the time in seconds that the shovel spent waiting for the truck to positioned under itself.
- Load time: it is the time in seconds that the shovel spent loading the truck.
- Backing time: it is the time in seconds that the truck spent reversing to dump in the disposal facility or mill.
- Dump time: it is the time in seconds that the truck spends disposing the material out of the truck into the waste disposal facility or mill.
- Truck ID: unique identifier for every truck.
- Shovel ID: unique identifier for every shovel.
- Fleet truck: the type of truck under the brand name, specification sequence initials.
- Fleet shovel: the type of shovel under the brand name, specification sequence initials.
- Tonnage: the weight that every truck carries on, in tonnage units.
- Type of material: the initials of the material type used as to identify whether if it is ore or waste to estipulate density.
- Speed loaded: the velocity at which a full truck travels km/h.
- Speed empty: the velocity at which an empty truck travels km/h.

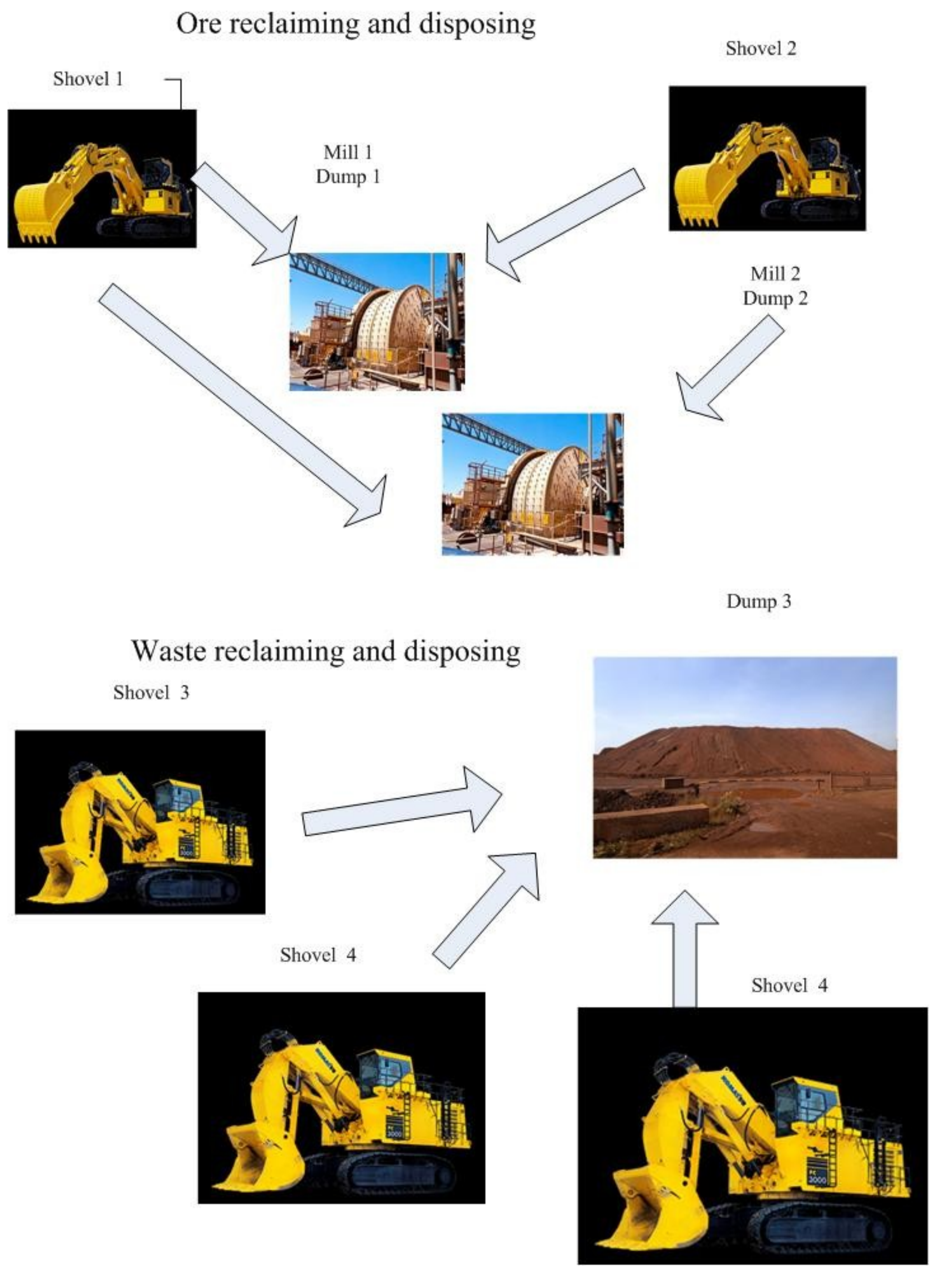

Figure 2. Reclaiming and disposing logic

- Nominal bucket size: the volume in cubic meters that the manufactory indicates for the shovel.

- Density: the mass by volume that the mine uses to account for ore and waste, which is 2.7 for ore and 1.9 for waste.

With this information a bucket weight is calculated, then with the tonnage of every cycle a number of passes can be estimated by every truck arrangement as all of them match perfectly with the tonnage capable to carry on a truck indicated by the manufacturer.

3.4. Road network

Elaborating a short-term plan is a process that faces many problems. One of them is the time the trucks spent traveling on the road to the destinations. One of the reasons is the issues with the roads due to over trucking, poor dispatching, poor conditions and indeed velocities. Therefore, it is important to include this parameter in the simulation so as to assess for these bottlenecks. In this project guided transport system feature in Arena (Rockwell Automatization Inc.) is used.

The idea of honoring the rule of not overtaking trucks is modeled in the system using Guided path transporters, which correspond to trucks in this case. As a result, the segments mentioned earlier are created as network links that include zones. Establishing the zone control rule, Arena (Rockwell Automatization Inc.) allows any truck to seize the next zone only when it has to being released by the previous truck. Consequently, zone lengths are set as summation average truck length and the safety distance. Figure 2 explains how the main points on the road are established, shovels to dump facilities.

3.4.1. Processing information

A historical Jigsaw dispatching data-base a gold mine is used for the simulation purposes. Information about every truck load is captured during 2008 for all the trucks and shovels fleet. In order to perform a valid statistical analysis, frequency histograms to visualize outliers are plotted in Matlab. As the size of the data base is large, it is impossible to handle it in Excel so SQL is used. Matlab then retrieve the information by matrix construction using looping. First the number of passes is assessed for every truck and shovel match. The objective is to have three valid values to make it reasonable to perform. This will be the basis from where the loading cycle time, the weight of the load and the match matrix for truck and shovel.

Once the number of passes is established, the loading cycle time, and the load weight are plotted by frequency histograms, based on number of passes and truck and shovel match. All of these are performed in order to establish valid ranges. Moreover, dumping, backing, and spotting time, and velocities of emptied and loaded trips are plotted in frequency histogram with the same goal. Finally, all these ranges are structured to fit distribution.

Distributions are fitted in Arena (Rockwell Automatization Inc.) input analyzer. It uses chi square goodness fit to pick the distribution that best fitted the data under the range established in the previous step, this is the one with less error. A matrix is built for number of passes, dumping, backing and spotting time, and velocities for each truck and shovel match. Another type of matrix is the loading cycle time and the load weight by number of passes within the truck and shovel. The information is imported to Arena (Rockwell Automatization Inc.) using VBA coding that reads each distribution inside these matrices as expressions in Arena (Rockwell Automatization Inc.) that will then be used as attributes or variables. This information is detailed described in Figure 3.

Table 1. Truck and shovel types

Shovel	Cat 992GHL	Cat 994A	Cat 994F	CAT 994 D	Hi 2500	Hi 5500EX
Truck	Cat 785C	Cat 793B	Cat 793C	Cat 793D		

According to Table 1. Truck and shovel types, six different types of shovels are retrieved from the data base and four truck types as well.

3.5. Simulation process

An input schedule is given, that has the information of 5 types of shovel, the information sorted by shovel so as to have a final of five data sets, which are represented in the simulation by five entities that receive at first the information of the shovels' first polygon. Then as the truck is loaded with the shovel that it is matched with, a verification of the tonnage remaining in polygon is done until it is depleted and another polygon is released by adding to the first five entities one by one as presented in Figure 4. Another sub-model is designed to control the crusher, Figure 5 explains the process, capacities of the mills' throughput rates. Failures, preventive maintenance, and weather events for the trucks and shovel are also sub models created.

3.5.1. Dispatching

The methodology selected in this case study is in order to improve the utilization of the equipment and to minimize the shovel's idle times. Trucks are assigned to shovels with the least number of trucks allocated. Using a math function in Arena called min over a variable that contains all the number of truck assigned at the moment to every truck. To control that no truck is assigned to a shovel that is due to failure, shovel out variable is added to the equation with a big number so it is not selected under the "Min function". Moreover, the match is based on the truck type defined by historical data-base and the production schedule.

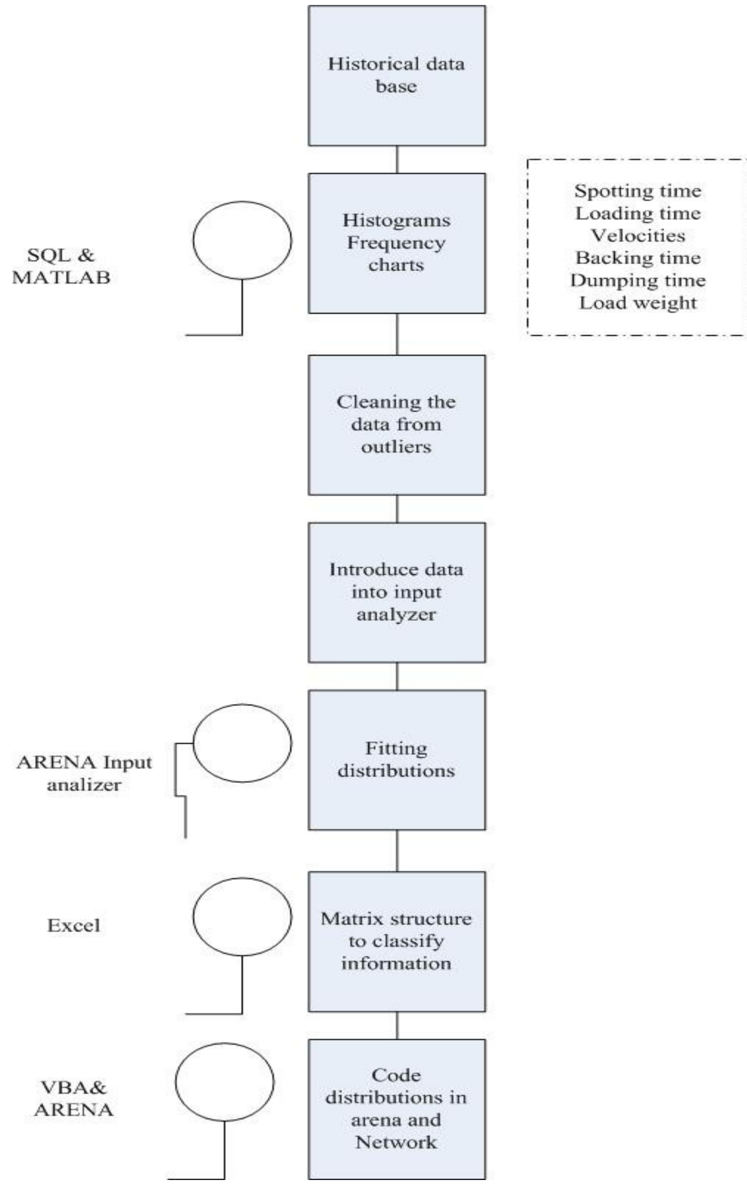

Figure 3. Flow chart for input information and processing

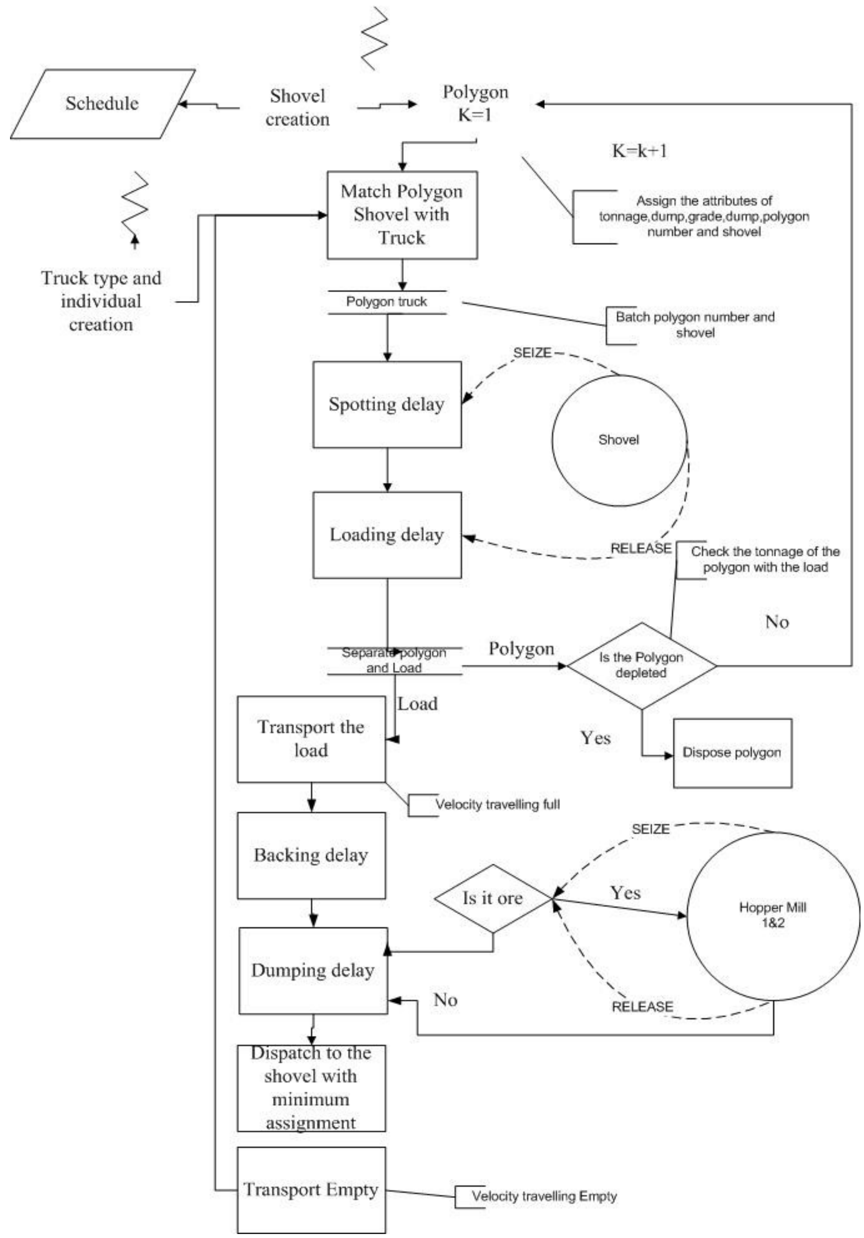

Figure 4. Flow chart main module

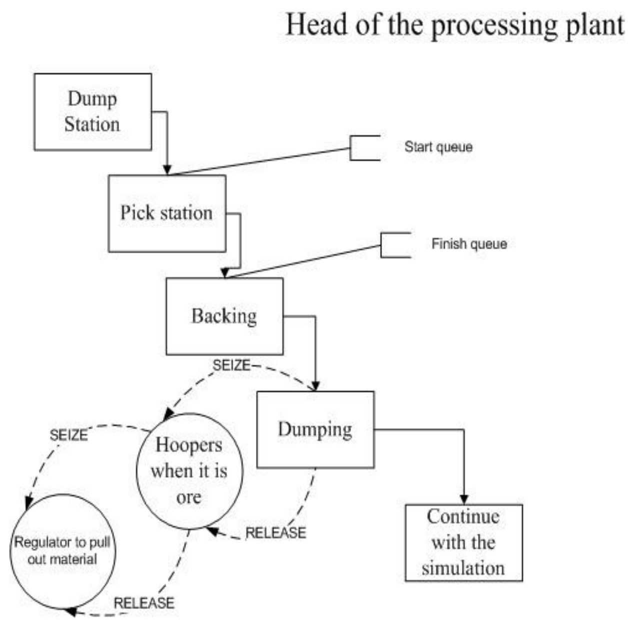

Figure 5. Flow chart dumping and regulator sub model

3.5.2. Shovel failure and PM

To take down shovels for failures and PM, an independent sub-model is created, called Shovel sub-model failure, that samples from the distributions for failures and PM for the respective shovel given as attributes to Arena (Rockwell Automatization Inc.). It includes up time and downtime, for each PM and failure. Before the down time start a variable status = 1 for each specific shovel (one-dimension variable 1 column and 5 rows for each shovel). This variable is checked after a shovel finishes to load and is ready to load, if the variable status = 1 the shovel is taken out of the system and a variable called shovel out takes the value of 1. When variable shovel out =1, the entity in the independent sub-model is allowed to be delayed for the time the distribution has been sampled. Once the delay finished and variable shovel status in the sub-model changes to 0 so in the main model the shovel is read as ready and the variable shovel out = 0. Then shovel is ready to be assigned to a truck. Explanation on the process interaction sub-model and main model is in Figure 6.

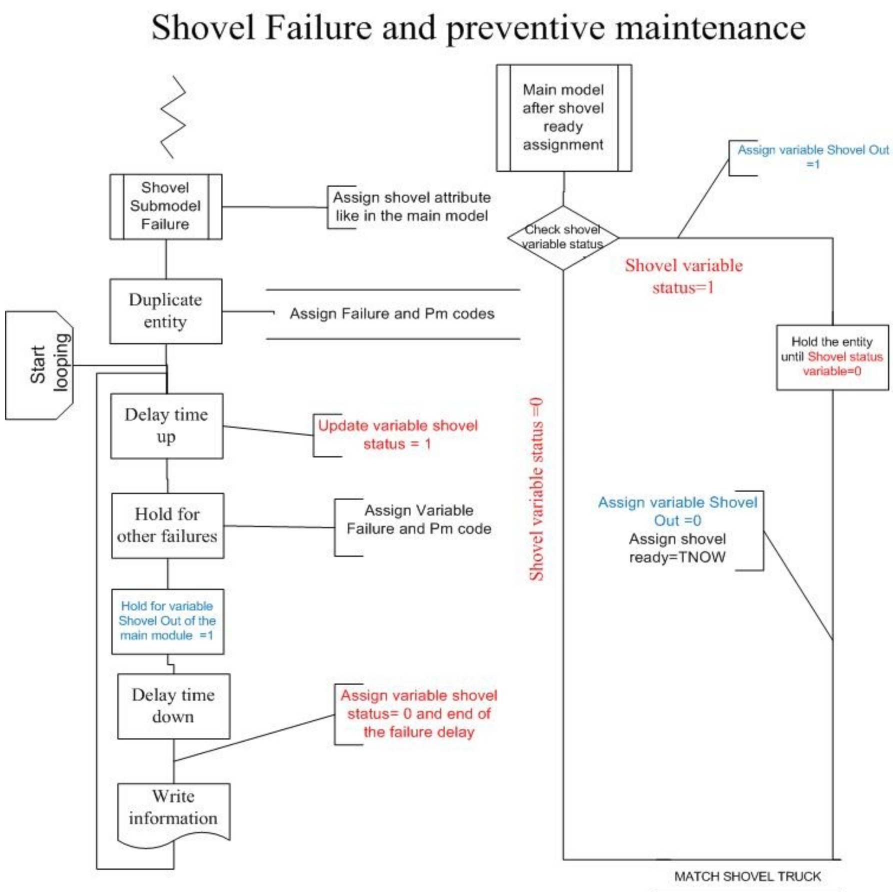

Figure 6.Failure and preventive maintenance sub-model shovel and main model interaction

3.5.3. Truck failure and PM

For failures in trucks, also an independent sub-model similar to shovels is formulated. It has two variables to connect with the main model truck status and truck out, they are also one dimension variables, one column and number of row with the number of trucks. Variable truck status is checked in every truck, when they are at the road network. If the truck has a variable status = 1, updated in the sub-model, it will be sent to the failure station and from there is taken out of the system by switching the variable truck out = 1. Figure 7, explains in detail the process of failure and PM for trucks.

Truck Failure and preventive maintenance

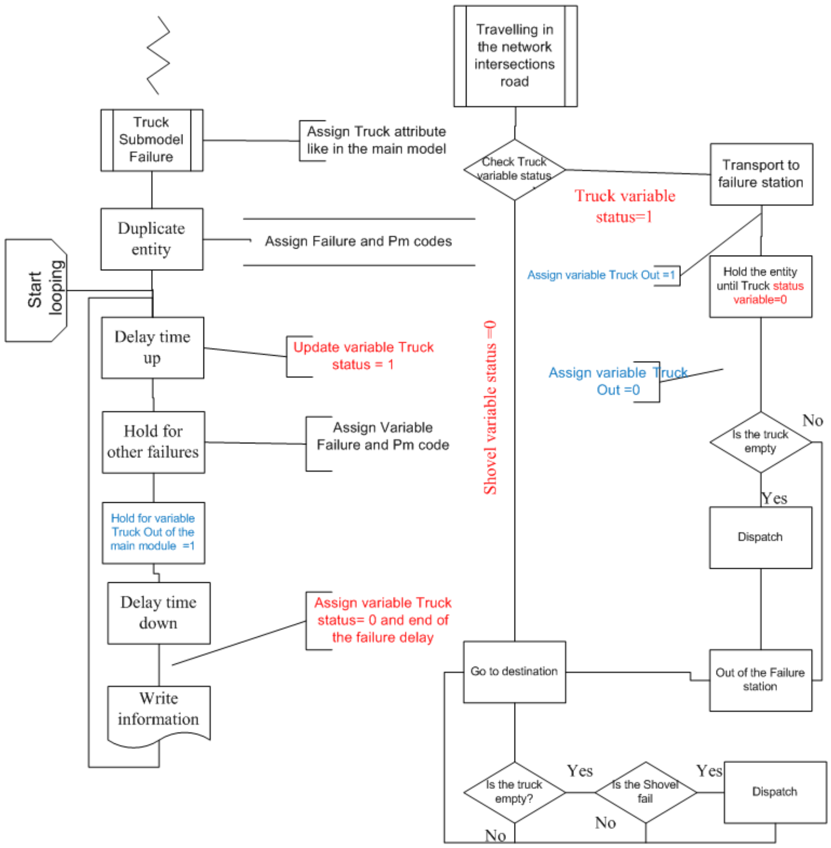

Figure 7. Failure and preventive maintenance sub-model Truck and main model interaction

3.5.4. Shovel and Weather stand by process

As the failure shovel sub-model that connects with a variable with the main model, stand by weather sub-model connects with the shovel with the variable weather. Also, if a shovel is already in the queue to be matched, there is another independent sub-model that will pick up the shovel from the queue and hold it until the delay. Figure 8, explains how the process of stand by for shovels works.

3.5.5. Truck and Weather stand by process

Variable weather also is connected with the trucks in the road network, queue at the dump, after dumping and loading; therefore, trucks may fall in standby in these exact locations. Moreover, if the truck is waiting in the shovel queue same variable will be checked and in case of standby weather delay, it will be sent to the failure module. Figure 9,outlines that information.

3.6. Simulation cycle

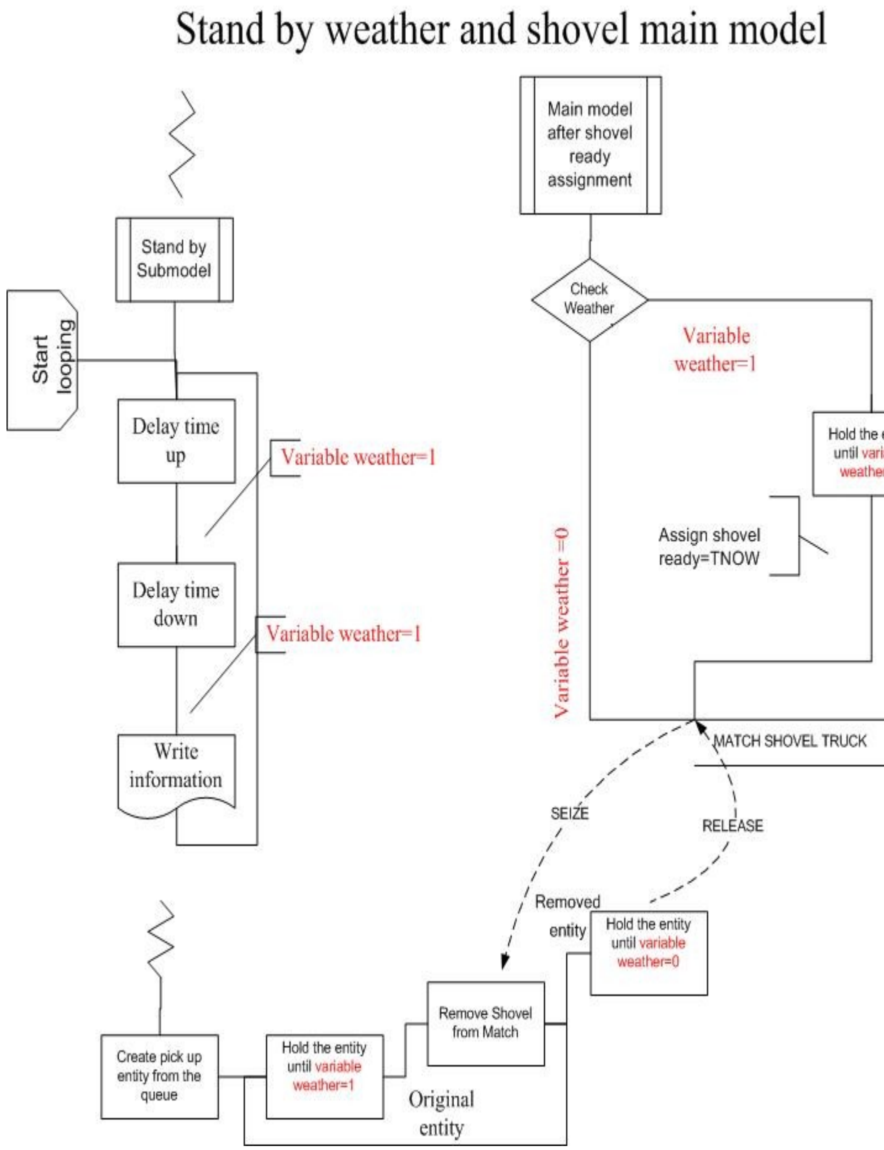

Figure 8.Stand by weather sub-model and shovel main model interaction

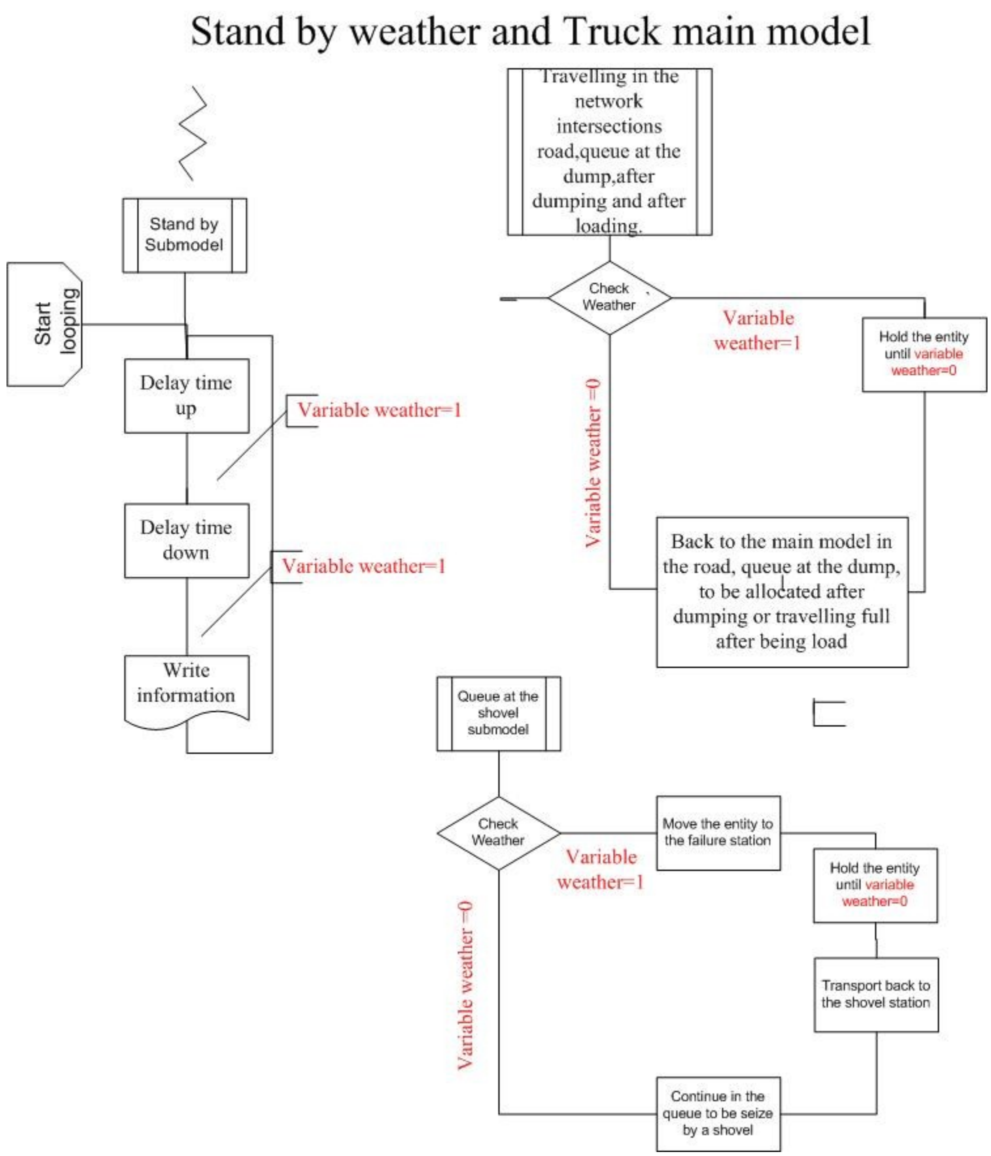

Figure 9. Stand by weather sub-model and truck main model interaction

After this requirement are met, the processing scenarios can continue. Figure 10, Describes how the validation and verification are part of the simulation process and they interact with each other.

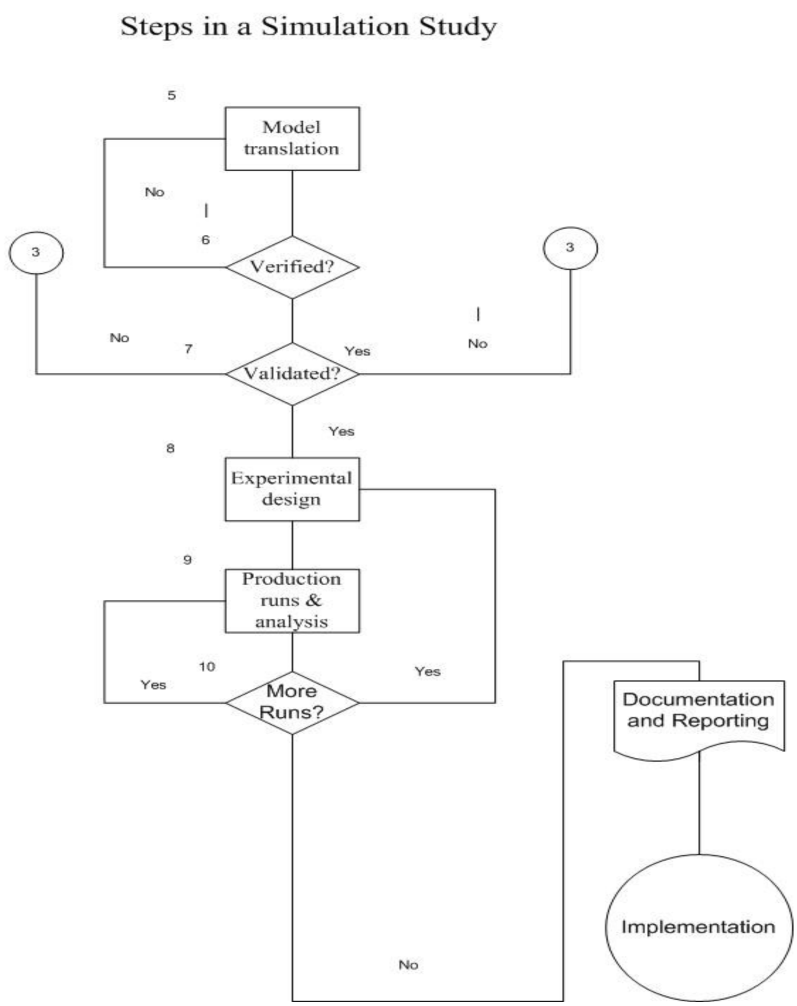

Figure 10.Flow chart simulation process.

3.7. Key performance indicators

Key performance indicators in mine operation, are projected in the plans. They are known as a tool of reconciliation against the reality so as to assess the quality of the plan. They are also a measurement to evaluate the performance of the operation. In this study KPI's are classified by the process and equipment. They are defined as:

- Tonnage: Ore tonnage, waste tonnage and total production of the simulation against the schedule projection.

- Average time: Average queues times at the dump and shovel, average cycle time, and average time travelling empty and loaded.
- Metrics definitions of time categories by equipment (Shovel and truck)
  - ✓ Time categories: Delay % (hanging for shovel and queue for trucks), down PM and failures), GOH (available hours-standby) %, Standby (stand by weather) %, NOH (GOH-delays), and Tonnage per GOG (Tonnage/GOH).
  - ✓ Availability categories: Mechanical availability% (GOH/GOH+ Down), physical availability% (Schedule-down/Schedule, Use of availability), and use of availability% (GOH/GOH+ Standby).
  - ✓ Efficiency categories: Capital efficiency % NOH/schedule hours) and Operating efficiency % (WOH/GOH).

3.7.1. Case studies

Four cases are analyzed. First the influence of decreasing number of waste trucks, then for ore and then increasing waste trucks to achieve production KPI with the best balance of efficiency categories and average time KPI's. The last scenario evaluated the influence of the crushers' rates over the same KPI's. The best scenario is taken from every case to the next as case base. All the KPI's are calculated in every scenario to have a better understanding of the outcomes. Finally, a short-term plan is given for a monthly and weekly period with uncertainty in the KPI's.

3.8. Summary and conclusion

In this chapter all the fundamental knowledge needed to understand the simulation procedure carried out and the research study are explained. Starting from the mine planning definitions to short-term planning specific problematic and pitfalls. Detail description of the inputs as short-term plan initial characteristics and road network, and data-base time delays, velocities and tonnage. Process information before fitting distributions and procedure to read road network and distributions to Arena (Rockwell Automatization Inc.). How the main characteristics of the mine operation are modeled including, dispatching, dumping, failures, PM and stand by weather.

4. Chapter 4

Case and discussion of results

4.1. Case study

The simulation procedure is performed using a pit design and a historic Jigsaw data-base given. With a pit layout given, mainly conformed with four main ramps to access to five working faces and one exit point in pit to head to the waste dump and two mill locations. Ore and waste polygons are spread over the pit, but schematically shovel 3 and 4, feed the waste dump with sterile material, located in the west side working faces. While the shovels 1 and 2 in the East side, working faces feed the mill locations. Shovel 5 also in the East location feed the waste dump. Three dump facilities two mills and one waste dump have two dumping capacities, so as to have the option of having two trucks dumping at the same time from different points. Figure 11outlines this information.

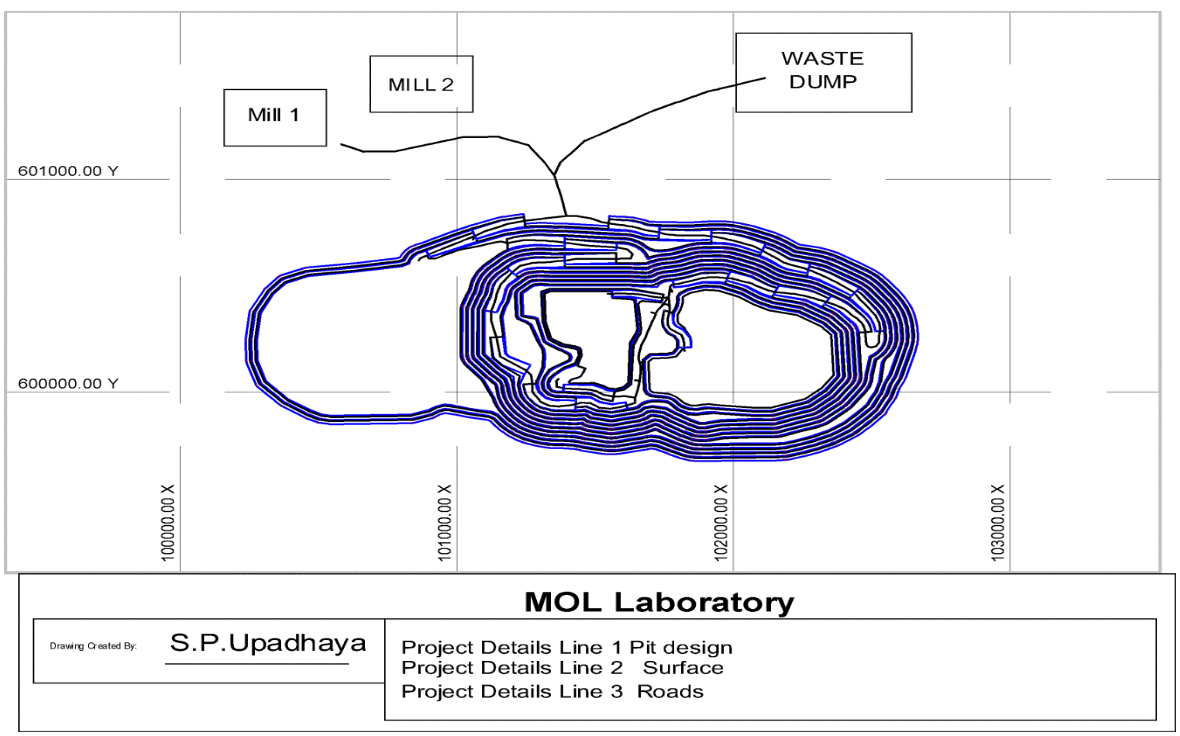

Figure 11. Plant view of the pit year pit design S.P. Upadahay. Courtesy

As it is mentioned before, the methodology used to address simulation of the truck and shovel is done through Arena (Rockwell Automatization Inc.) transporters Guided path, where the transporters are trucks traveling with entities in this case loaded with ore or waste. This specific type of transporter is called AGV, autonomous guided vehicle, programmed to move between locations along the paths. Transporters competes with each other for space in the paths. For this reason, transporter size should be specified and the dimensions of the paths. In guided transporter the path is divided in network of links and intersections. A link goes from intersection to intersection and it is formed by zones, each zone has the same length in the specific link, and specific distance that divide transporter to transporter while they are travelling; as a result, the zone length should be at least the length of the AGV.

Consequently, all the mine routes and handling roads are modeled under the structure of network links, intersections and zones. In order to use the AGV and the Guided path feature, which apart from account for every distance as the five shovel-working faces and the 6 points dumping locations given by the three dumping facilities, gives also the ability to use the shortest path when it comes to travel. Since there may be multiple paths through the network, Arena (Rockwell Automatization Inc.) uses standard algorithms to find the shortest path,(Rossetti, 2009). Moreover, the vehicle speed could be manipulated as it travels empty or full.

The yearly schedule comes from and Iron ore mine, that feeds two mills with the aim of processing certain grades of magnetic weight recovery MWT, with main contaminants as phosphor and sulfur, is provided by S.P. Upadhyay & H. Askari (2016), which provide a detailed information of shovel location and polygon, tonnage, grades, destination and location coordinates. Table 2, provides information about monthly tonnage movement of ore and waste by shovel. Ore requirement and the waste that need to be removed monthly, total of 14.124.180 tons of ore and 38.558.561 tons of waste, during the whole year.

Table 2. Monthly Shovel Production ore and waste

Month\Shovel	1	2	3	4	5
1	636,600	737,400	1,199,644	1,029,390	1,181,070
2	553,500	655,950	1,067,092	1,110,000	1,168,350
3	651,420	616,800	1,193,473	1,062,600	1,060,290
4	553,500	494,700	964,258	1,064,700	1,179,300
5	520,050	716,700	1,057,174	1,049,850	793,800
6	594,450	607,800	1,138,500	1,191,900	1,078,800
7	763,440	632,550	1,110,000	1,206,300	1,202,850
8	570,600	534,750	1,054,500	1,065,600	817,920
9	631,800	616,500	954,600	1,164,230	1,117,950
10	634,920	615,000	954,600	1,199,320	1,097,100
11	376,350	718,500	1,132,200	1,065,600	891,450
12	690,900	-	477,300	1,076,700	1,380,150
Total	7,177,530	6,946,650	12,303,341	13,286,190	12,969,030

Hitachi 2500 shovel for ore with 18 seconds loading cycle time and bucket capacity of 16 m^3 and Hitachi 5500Ex shovel for waste with 18 seconds loading cycle time and 30 m^3 bucket capacity were utilized at the operations. In terms of trucks, Cat 785C for ore, capacity of 136 tons and Cat 793C for waste, capacity of 223 tons. A density of 2.7 tonnage per cubic meter is assumed for ore and 1.9 tonnage per cubic meter for waste. Number of passes where calculated from the historical data-base knowing the tonnage of every pass and the truck load, bucket count probabilities were estimated base on 3, 4, and 5 number of passes for both fleets ore and waste, using histograms so as to account for the bucket count that will fill the truck. Table 4 informs about it.

Starting from shovel spotting time, related to the match equipment shovel and truck, Table 3, outlines the functions, followed by the number of buckets with which the shovel will fill the truck. In Table 4,the information is detailed. Bucket size tonnage it is also fitted according to shovel and truck type, Table 5 outlines this information. Next, the shovel loading cycle time not always will depend on the number of buckets previously mentioned, but also depends on the season, in this case raining from January, February, March, April, October, November and December, and summer May, June, July, August and September, and once again the matching matrix established by the equipment type. Table 6 and Table 7 show that information.

Trucks are loaded and sent to the proper destination mill 1, mill 2 or waste dump based on the polygon's destination label and the matrix velocity full, Table 8. Dumping and backing time are also calculated similarly in Table 9 and Table 10.Finally, trucks will travel empty with a distribution from Table 11.

Table 3. Probability density functions Spotting time

Spotting time				
	Cat 785C	Cat 793B	Cat 793C	Cat 793D
Cat 992GHL	3 + LOGN(35.6, 34.4)	0	0	0
Cat 994A	3 + LOGN(27.4, 22.8)	3 + LOGN(32.7, 28.6)	3 + LOGN(31.7, 28)	3 + LOGN(27.6, 24.8)
Cat 994F	3 + LOGN(29.6, 22.6)	3 + LOGN(39.4, 37.5)	3 + LOGN(35.2, 27.3)	3 + LOGN(35.4, 32.7)
CAT 994 D	3 + LOGN(26.7, 20.9)	3 + LOGN(32.9, 26.6)	3 + LOGN(32.2, 27.1)	0
Hi 2500	3 + LOGN(26.4, 23.6)	3 + LOGN(31.9, 27.2)	3 + LOGN(35.7, 39)	3 + LOGN(27.4, 21.2)
Hit 5500EX	3 + LOGN(29.5, 29.3)	3 + LOGN(37, 51.8)	3 + LOGN(31.2, 32.8)	3 + LOGN(29.3, 32)

Table 4. Probability density functions Bucket count

Bucket Count				
	Cat 785C	Cat 793B	Cat 793C	Cat 793D
Cat 992GHL	DISC(0.006411,2,0.194763,3,1,4)	1*0	1*0	1*0
Cat 994A	DISC(0.000206,1,0.206161,2,1,3)	DISC(0.106866,3,0.998806,4,1,5)	DISC(0.002436,2,0.140654,3,1,4)	DISC(0.000998004,2,0.124251497,3,1,4)
Cat 994F	DISC(0.107567,2,0.99991,3,1,4)	DISC(0.063465,3,0.788303,4,1,5)	DISC(0.084076,3,0.699805,4,1,5)	DISC(0.075371,3,0.731039,4,1,5)
CAT 994 D	DISC(0.000998,2,0.124251,3,1,4)	DISC(0.0025,2,0.129583,3,1,4)	DISC(0.003125,2,0.16243,3,1,4)	DISC(0.001025,2,0.161580161,3,1,4)
Hi 2500	DISC(0.532056,2,0.971344,3,1,4)	DISC(0.041875,3,0.649147,4,1,5)	DISC(0.027236,3,0.513742,4,1,5)	DISC(0.023178,3,0.722746168,4,1,5)
Hit 5500EX	DISC(0.551456,2,1,3)	DISC(0.277409,3,0.564442,4,1,5)	DISC(0.274387,3,0.507932,4,1,5)	DISC(0.334853071,3,0.56018806,4,1,5)

Table 5. Probability density functions Bucket size tonne

Bucket size				
	Cat 785C	Cat 793B	Cat 793C	Cat 793D
Cat 992GHL	26 + 7 * BETA(1.29, 2.26)	1*0	1*0	1*0
	26 + 7 * BETA(1.7, 3.03)	1*0	1*0	1*0
	19 + 4 * BETA(1.89, 1.87)	1*0	1*0	1*0
Cat 994A	65 + 16 * BETA(1.51, 1.86)	69 + 12 * BETA(2.76, 1.56)	74 + 7 * BETA(1.94, 1.16)	77 + 4 * BETA(1.22, 1.27)
	42 + 13 * BETA(2.27, 2.6)	74 + 7 * BETA(1.7, 1.76)	1*0	1*0
	1*0	46 + 8 * BETA(1.16, 3.18)	45 + 7 * BETA(2.21, 2.58)	78 + 3 * BETA(0.501, 0.75)
Cat 994F	62 + 7 * BETA(1.85, 1.07)	72 + 17 * BETA(2.29, 3.51)	75 + 13 * BETA(1.83, 2.7)	75 + 13 * BETA(1.85, 2.93)
	45 + 12 * BETA(1.28, 3.11)	57 + 3 * BETA(0.433, 0.679)	58 + 9 * BETA(1.02, 2.81)	56 + 10 * BETA(2.33, 3.84)
	1*0	1*0	1*0	1*0
CAT 994 D	32 + 6 * BETA(1.97, 1.78)	32 + 6 * BETA(1.1, 1.66)	24 + 2 * BETA(2.51, 1.34)	32 + 6 * BETA(1.85, 2.22)
	21 + 6 * BETA(2.59, 0.977)	24 + 2 * BETA(2.51, 1.34)	24 + 3 * BETA(3.95, 2.49)	23 + 2 * BETA(4.1, 1.12)
	1*0	24 + 2 * BETA(2.51, 1.34)	26 + 0.901 * BETA(1.73, 3.43)	23.4 + 3.51 * BETA(1.95, 1.77)
Hi 2500	41 + 3 * BETA(1.95, 2.65)	36 + 7 * BETA(1.82, 2.04)	36 + 7 * BETA(2.37, 2.07)	36 + 8 * BETA(2.86, 3.37)
	35 + 5 * BETA(0.991, 1.67)	27 + 3 * BETA(2.43, 1.59)	27 + 3 * BETA(2.9, 1.3)	27 + 3 * BETA(3.2, 1.44)
	24 + 5 * BETA(2.81, 1.26)	27 + 3 * BETA(0.816, 0.919)	27 + 5 * BETA(1.27, 2.8)	29 + 1.74 * BETA(1.82, 2.58)
Hi 5500EX	61 + 20 * BETA(2.32, 2.34)	45 + 16 * BETA(1.17, 1.11)	77 + 4 * BETA(1.06, 1.25)	76 + 5 * BETA(1.68, 1.62)
	40 + 41 * BETA(1.04, 1.3)	62 + 19 * BETA(0.603, 0.628)	61 + 4 * BETA(0.912, 1.31)	61 + 20 * BETA(0.578, 0.616)
	1*0	47 + 10 * BETA(0.647, 1.26)	46 + 7 * BETA(1.24, 2.07)	45 + 8 * BETA(2.15, 2.7)

Table 6. Probability density functions Summer loading cycle time seconds

Summer Loading cycle time				
	Cat 785C	Cat 793B	Cat 793C	Cat 793D
Cat 992GHL	8 + 7 * BETA(0.7, 0.7)	1*0	1*0	1*0
	15.5 + 8.5 * BETA(1.08, 1.17)	1*0	1*0	1*0
	24 + 7 * BETA(0.645, 0.496)	1*0	1*0	1*0
Cat 994A	8.5 + 25 * BETA(1.02, 1.3)	30.5 + 30 * BETA(0.322, 0.398)	12.5 + 24 * BETA(0.229, 0.445)	16.5 + 31 * BETA(0.423, 0.403)
	16.5 + 58 * BETA(0.964, 0.73)	38.5 + 53 * BETA(0.497, 0.478)	24.5 + 49 * BETA(0.439, 0.654)	24.5 + 3 * BETA(0.578, 0.809)
	32.5 + 16.5 * BETA(0.916, 0.417)	49.5 + 64 * BETA(0.74, 0.56)	39.5 + 52 * BETA(0.677, 0.576)	39.5 + 52 * BETA(0.198, 0.245)
Cat 994F	12.5 + 13.5 * BETA(1.21, 0.823)	17.5 + 10.5 * BETA(1, 0.833)	15.5 + 13.5 * BETA(1.77, 1.22)	16.5 + 42 * BETA(0.71, 1.12)
	25.5 + 14.5 * BETA(2.14, 1.18)	17.5 + 10.5 * BETA(1, 0.833)	23.5 + 16.5 * BETA(1.66, 1.11)	23.5 + 48 * BETA(0.799, 0.99)
	39.5 + 14.5 * BETA(1.25, 1.43)	36 + 13 * BETA(1.7, 0.886)	31.5 + 17.5 * BETA(1.18, 0.622)	31.5 + 16.5 * BETA(1.51, 0.783)
CAT 994 D	12.5 + 55.5 * BETA(0.989, 1.58)	9.5 + 7.5 * BETA(0.874, 0.676)	9.5 + 10.5 * BETA(1.03, 1.26)	9.5 + 10.5 * BETA(1.08, 1.21)
	25.5 + 61.5 * BETA(0.95, 1.45)	19.5 + 9.5 * BETA(0.837, 1.1)	21 + 9 * BETA(0.742, 0.92)	19.5 + 9.5 * BETA(0.624, 0.559)
	40 + 13 * BETA(1.14, 1.02)	29.5 + 12.5 * BETA(1.1, 1.63)	29.5 + 7.5 * BETA(0.527, 0.643)	29.5 + 6.5 * BETA(0.535, 0.754)
Hi 2500	11 + 42.5 * BETA(1.15, 0.739)	13.5 + 43 * BETA(1.41, 2.4)	29 + 10 * BETA(0.62, 0.722)	25 + 14 * BETA(1.52, 1.11)
	48 + 32.5 * BETA(2.3, 1.95)	39 + 9 * BETA(1.03, 0.589)	36 + 13 * BETA(1.46, 0.827)	37 + 12 * BETA(1.17, 0.727)
	35 + 14 * BETA(2.88, 1.65)	51 + 12 * BETA(1.17, 1.28)	49 + 12 * BETA(1.11, 0.934)	48 + 14 * BETA(1.4, 1.1)
Hi 5500EX	8.5 + 17.5 * BETA(1.05, 0.753)	12 + 41.5 * BETA(0.951, 0.838)	12 + 41.5 * BETA(1.03, 0.933)	12 + 41.5 * BETA(1.07, 0.878)
	11.5 + 42.5 * BETA(3.04, 1.77)	24 + 56.5 * BETA(1.33, 1.22)	24 + 56.5 * BETA(1.33, 1.28)	24 + 56.5 * BETA(1.42, 1.2)
	35 + 42 * BETA(1.43, 2.67)	36 + 62.5 * BETA(0.916, 1.1)	36 + 62.5 * BETA(0.926, 1.25)	1*0

Table 7. Probability density function raining loading cycle time seconds

Raining Loading Cycle time				
	Cat 785C	Cat 793B	Cat 793C	Cat 793D
Cat 992GHL	10 + 90 * BETA(2.16, 2.39)	1*0	1*0	1*0
	10 + 90 * BETA(3.21, 5.49)	1*0	1*0	1*0
	10 + 90 * BETA(2.57, 1.62)	1*0	1*0	1*0
Cat 994A	10 + 90 * BETA(2.57, 1.62)	30 + 120 * BETA(2.86, 2.62)	20 + 130 * BETA(2.65, 2.22)	10 + 180 * BETA(5.03, 6.58)
	10 + 90 * BETA(2.83, 3.71)	42 + 58 * BETA(1.83, 1.96)	1*0	1*0
	1*0	20 + 80 * BETA(3.7, 4.34)	1*0	10 + 118 * BETA(5.24, 8.58)
Cat 994F	10 + 90 * BETA(2.48, 1.73)	40 + 60 * BETA(2.07, 1.56)	10 + 90 * BETA(2.51, 1.19)	10 + 90 * BETA(1.97, 1.06)
	10 + 90 * BETA(2.99, 4.45)	10 + 90 * BETA(2.55, 1.74)	10 + 90 * BETA(3.6, 2.52)	10 + 90 * BETA(3.47, 2.41)
	1*0	1*0	1*0	1*0
CAT 994 D	10 + 90 * BETA(3.31, 5.83)	10 + 90 * BETA(4.38, 6.85)	10 + 90 * BETA(3.83, 6.32)	10 + 90 * BETA(5.29, 9.03)
	10 + 90 * BETA(5.31, 14.9)	10 + 90 * BETA(6.85, 15.8)	10 + 90 * BETA(4.03, 9.54)	10 + 90 * BETA(5.35, 12.5)
	10 + 90 * BETA(4.63, 17.1)	10 + 90 * BETA(8.16, 23.8)	10 + 90 * BETA(7.47, 21.8)	10 + 90 * BETA(8.36, 24.3)
Hi 2500	10 + 90 * BETA(2.85, 5.08)	10 + 90 * BETA(5.36, 9.62)	10 + 90 * BETA(5.33, 9.68)	10 + 90 * BETA(5.17, 9.35)
	10 + 80 * BETA(2.94, 4.8)	10 + 72.5 * BETA(5.42, 11.9)	10 + 90 * BETA(5.32, 15.7)	10 + 90 * BETA(4.97, 15.8)
	10 + 40 * BETA(2.83, 2.55)	10 + 50 * BETA(3.43, 4.55)	10 + 63.5 * BETA(6.1, 13.1)	10 + 50 * BETA(3.43, 4.55)
Hi 5500EX	10 + 90 * BETA(1.78, 4.96)	10 + 90 * BETA(4.56, 10.4)	10 + 90 * BETA(2.85, 6.88)	10 + 90 * BETA(3.78, 8.92)
	10 + 90 * BETA(2.32, 9.22)	10 + 90 * BETA(4.5, 12.4)	10 + 50 * BETA(3, 2.99)	10 + 50 * BETA(3.1, 2.96)
	1*0	10 + 90 * BETA(4.64, 14.7)	10 + 40 * BETA(3.07, 3.19)	10 + 40 * BETA(2.48, 2.56)

Table 8. Probability density functions travelling full velocity km/h

Velocity Full				
	Cat 785C	Cat 793B	Cat 793C	Cat 793D
Cat 992GHL	NORM(18.1, 6.63)	1*0	1*0	1*0
Cat 994A	NORM(19.2, 6.46)	NORM(18.2, 3.52)	NORM(17.8, 3.37)	NORM(18.7, 3.45)
Cat 994F	NORM(20.3, 5.14)	NORM(19.5, 4.19)	NORM(19.6, 4.23)	NORM(19.3, 4.05)
CAT 994 D	NORM(19.7, 4.54)	NORM(19.6, 4.83)	NORM(19.3, 4.4)	NORM(21, 4.94)
Hi 2500	NORM(16, 4.68)	NORM(18, 5.05)	NORM(16.2, 4.12)	NORM(16.8, 4.38)
Hit 5500EX	NORM(16.1, 4.09)	NORM(18.1, 4.8)	NORM(17.9, 4.85)	NORM(18, 5.12)

Table 9. Probability density function Dumping time km/h

Dumping time				
	Cat 785C	Cat 793B	Cat 793C	Cat 793D
Cat 992GHL	10 + 118 * BETA(4.16, 7.95)	1*0	1*0	1*0
Cat 994A	NORM(50.3, 17.1)	NORM(56.7, 17.9)	NORM(55.6, 16.8)	NORM(47.5, 16.7)
Cat 994F	NORM(52.1, 16.5)	NORM(60.2, 17.4)	NORM(50.9, 12.5)	NORM(51.4, 20.5)
CAT 994 D	NORM(49.6, 18)	NORM(60.8, 18.2)	NORM(55.6, 19.9)	NORM(52.4, 17.6)
Hi 2500	NORM(52.5, 17.5)	NORM(60.4, 19.4)	NORM(61.6, 17.2)	NORM(54.7, 16.1)
Hit 5500EX	NORM(46.4, 18.3)	NORM(68.5, 5.72)	NORM(54.3, 17.7)	NORM(43, 16.7)

Table 10. Probability density function backing time seconds

Backing time				
	Cat 785C	Cat 793B	Cat 793C	Cat 793D
Cat 992GHL	3 + WEIB(15.2, 1.64)	1*0	1*0	1*0
Cat 994A	3 + WEIB(10.8, 1.73)	3 + WEIB(11, 1.57)	3 + WEIB(10.5, 1.68)	3 + WEIB(10.6, 1.52)
Cat 994F	6 + WEIB(5.58, 1.26)	3 + WEIB(14.2, 1.88)	3 + WEIB(11.1, 1.77)	3 + WEIB(10.8, 2.09)
CAT 994 D	3 + WEIB(13.6, 1.55)	3 + WEIB(15.3, 1.23)	3 + WEIB(16, 1.68)	3 + WEIB(15.5, 1.87)
Hi 2500	3 + WEIB(14.4, 1.51)	3 + WEIB(12.5, 2.4)	3 + WEIB(16.1, 2.28)	3 + WEIB(14.7, 1.83)
Hit 5500EX	3 + WEIB(12.6, 1.86)	3 + WEIB(12.5, 2.4)	3 + WEIB(15.3, 1.77)	3 + WEIB(16.9, 1.68)

Table 11. Probability density function travelling empty velocity km/h

Velocity Empty				
	Cat 785C	Cat 793B	Cat 793C	Cat 793D
Cat 992GHL	NORM(27.2, 12)	1*0	1*0	1*0
Cat 994A	NORM(31.7, 10.7)	NORM(32.5, 9.93)	NORM(33.8, 9.89)	NORM(35.9, 9.73)
Cat 994F	NORM(30.6, 11)	NORM(30.8, 11.9)	NORM(31.4, 11)	NORM(35.9, 9.73)
CAT 994 D	NORM(30.4, 11.3)	1*0	NORM(31.5, 11.1)	NORM(33, 11.1)
Hi 2500	NORM(29.6, 11.2)	NORM(29.1, 11.6)	NORM(30.7, 11)	NORM(32, 11.2)
Hit 5500EX	NORM(31.4, 10.3)	NORM(31.7, 10.4)	NORM(32.5, 10.2)	NORM(33.8, 10.2)

4.2. Base Case deterministic calculation number of trucks

The number of trucks are calculated with a deterministic method for every shovel, using the formula and the historical Jigsaw data-base, together with the knowledge of the distance from the five shovels working faces to their destination, dump location and two different crushers.:

$$\#Trucks = \frac{TruckCycleTime}{ShovelCycleTime}$$

Details follows:

$$\#\text{Trucks} = \frac{Emptytraveltime + Fulltraveltime + Spottingtime + Loadingtime + Backingtime + Dumpingtime}{Spottingtime + Loadtime}$$

As a result Table 12,Table 13, Table 14, Table 15, and Table 16 show the required number of trucks for each shovel, knowing the distances from every shovel to their destination, It can be seen that the number of trucks needed to run this mine is 56 trucks, under a raining season.

Table 12. Number of trucks for Shovel 1, cycle time in hours

Shovel 1	Empty Travel Time	Full Travel Time	Spotting Time	Loading Time	Backing Time	Dumping Time	Total
Cycle time trucks hours	0.134766667	0.224611111	0.009277778	0.021805556	0.00430556	0.014583333	0.40935
Cycle time shovel 1 hours			0.009277778	0.021805556			0.031083
Numer of trucks	14						

Table 13. Number of trucks for Shovel 2, cycle time in hours

Shovel 2	Empty Travel Time	Full Travel Time	Spotting Time	Loading Time	Backing Time	Dumping Time	Total
Cycle time trucks	0.124666667	0.207777778	0.009277778	0.021805556	0.00430556	0.014583333	0.382417
Cycle time shovel 2			0.009277778	0.021805556			0.031083
Numer of trucks	13						

Table 14. Number of trucks for Shovel 3, cycle time in hours

Shovel 3	Empty Travel Time	Full Travel Time	Spotting Time	Loading Time	Backing Time	Dumping Time	Total
Cycle time trucks	0.079484848	0.145722222	0.016666667	0.021944444	0.00438889	0.014833333	0.28304
Cycle time shovel 3			0.016666667	0.021944444			0.038611
Numer of trucks	8						

Table 15. Number of trucks for Shovel 4, cycle time in hours

Shovel 4	Empty Travel Time	Full Travel Time	Spotting Time	Loading Time	Backing Time	Dumping Time	Total
Cycle time trucks	0.091	0.166833333	0.016666667	0.021944444	0.00438889	0.014833333	0.315667
Cycle time shovel 4			0.016666667	0.021944444			0.038611
Numer of trucks	9						

Table 16. Number of trucks for Shovel 5, cycle time in hours

Shovel 5	Empty Travel Time	Full Travel Time	Spotting Time	Loading Time	Backing Time	Dumping Time	Total
Cycle time trucks	0.131060606	0.240277778	0.016666667	0.021944444	0.00438889	0.014833333	0.429172
Cycle time shovel5			0.016666667	0.021944444			0.038611
Numer of trucks	12						

In this order the simulation is run for 365 days adding 10.000.000 tonnages to the last polygon the last month for every shovel so as to ensure that the shovel is not set idle due to the lack of material to mine.

4.3. Verification

Following the standard stages of the simulation process, the next step is to verify the simulation. Verification answers the question "did I build the model right?". Simulation is run and the outputs are saved, measurements of the time duration are outlined by equipment type. Distribution of the total simulation time is sorted by loading, spotting, preventive maintenance, failure, weather standby and hanging time. Total simulation time is 4.380 hours, corresponding to 12 hours shift per day and 365 days of a year.

Figure 12, outlines how all the cycles of each shovel in each scenario, from 1 to 16, is adding up 4.380 hours. In addition, information in the graph relates with alteration in number of trucks by scenario, which will be explained in detail later in this chapter. At the beginning more trucks are inputted in the model so more loading and less hanging time is observed; on the other hand, later scenarios include less number of trucks so less loading and more hanging time is obtained.

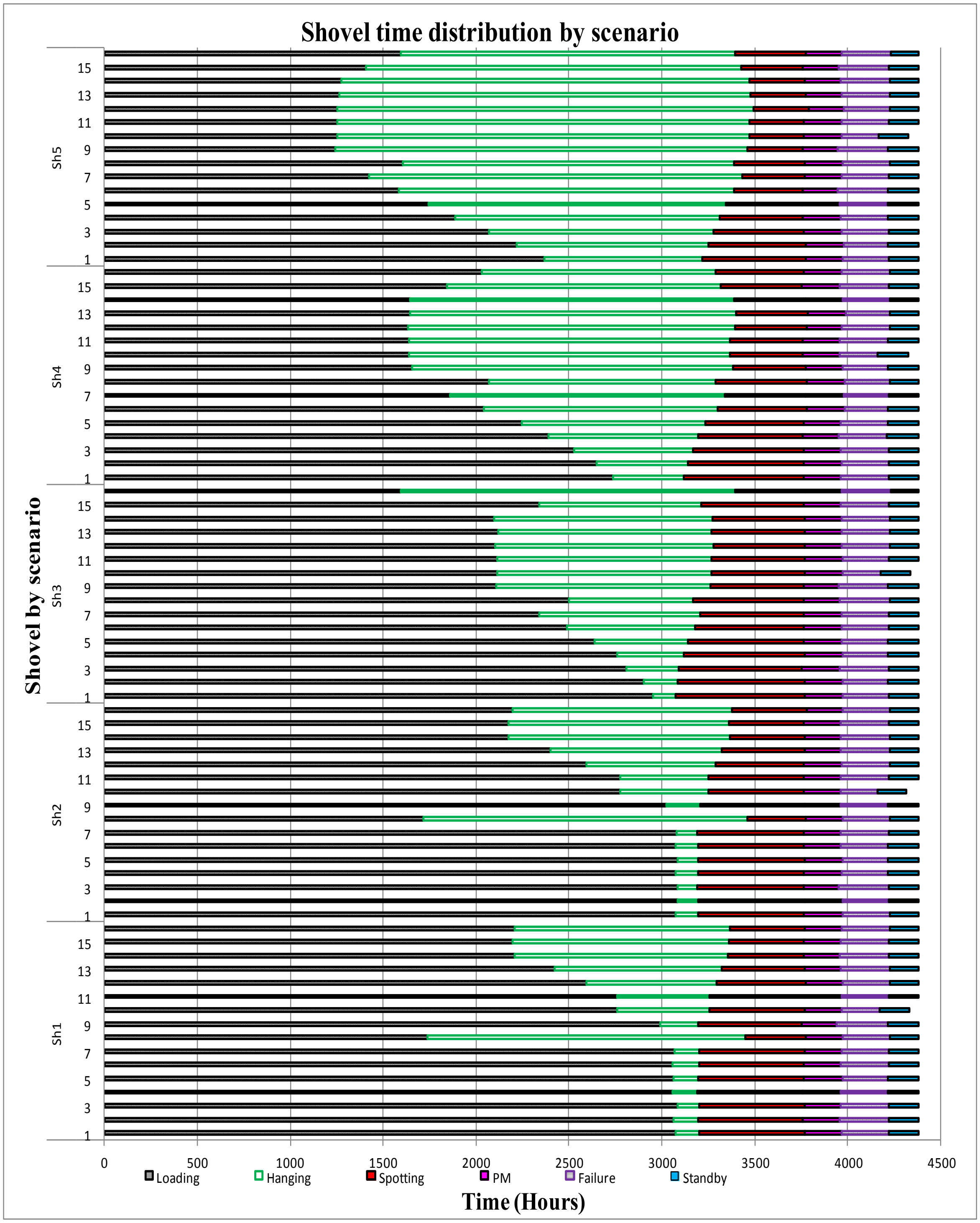

Figure 12. Total time distribution shovel by scenarios

4.4. Validation

The next step is concern with answering the question "Did I build the right model?", If the model is built correctly, it is an accurate representation of the reality, it is indeed a process comparing the model with the historical performance of the system. QQ-plots are used to measure similarity of the model outputs with the real system historical performance. Based on the study of a historical jigsaw data-base distributions have been fitted on the historical data and chi-square tests were carried out for the goodness test. The simulation output is compared with the historical data using Q-Q plots with a non-parametrical approach to compare the underlying distributions.

4.5. Number of replications

In this case the process is analyzed in a window of 365 days so the replications have finite horizons. Standard statistical techniques based on having random sample are the fundamental of analysis; as a result, variables are assumed to be independent so as to relate to a random sample. With the aim of guarantee the independency of these variables the half width of the statistic is used to calculate the number of replications. The reason of that assumption is that the half width demands the samples to be normally distributed. Its obtained with more than 320 sample mostly that correspond to data non-correlated with independent samples as it is mentioned previously. With a desired half width of 100000 in the ore tonnage, so as to keep the uncertainty within 5% for this potential KPI, 5 replications are need using the formula:

$$n = n_0 \frac{h_0^2}{h^2}$$

Where:

n = number of replications

h = half width

Using a Half width from a pilot run, the optimal number is replication is found

and it is the value of n= 10 replications that offers a value of half width of less than 5% in

the ore production.

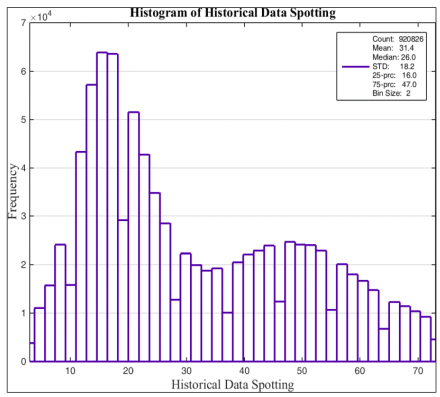

Figure 13. Histogram historical data spotting time

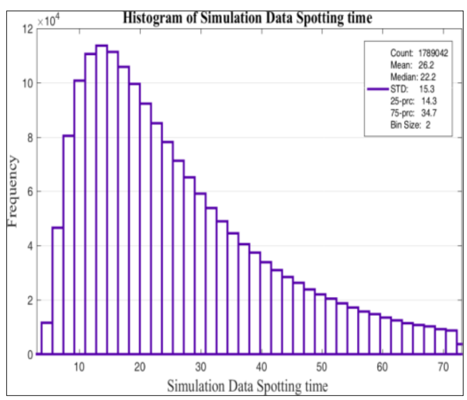

Figure 14. Histogram Simulation data spotting time

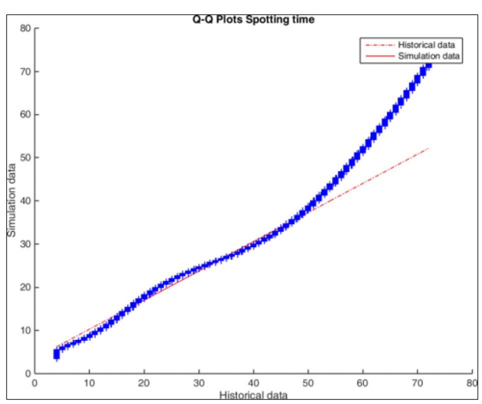

Figure 15. Spotting time Q-Q Plot

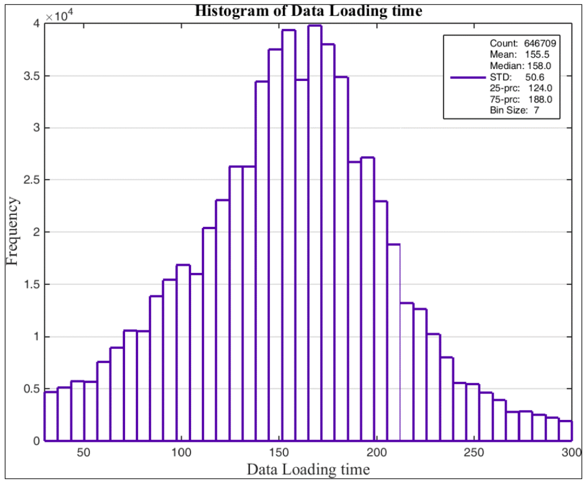

Figure 16. Histogram historical data Loading time

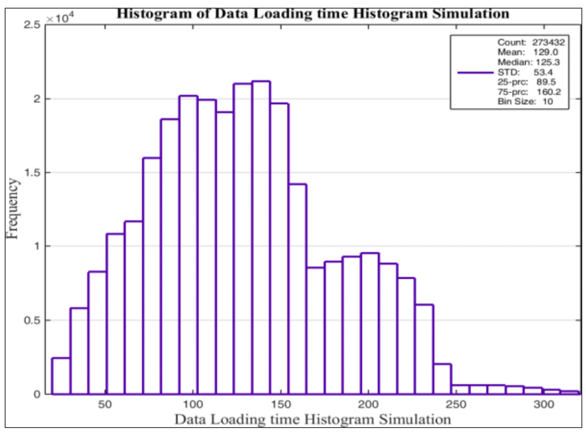

Figure 17. Histogram Simulation data spotting time

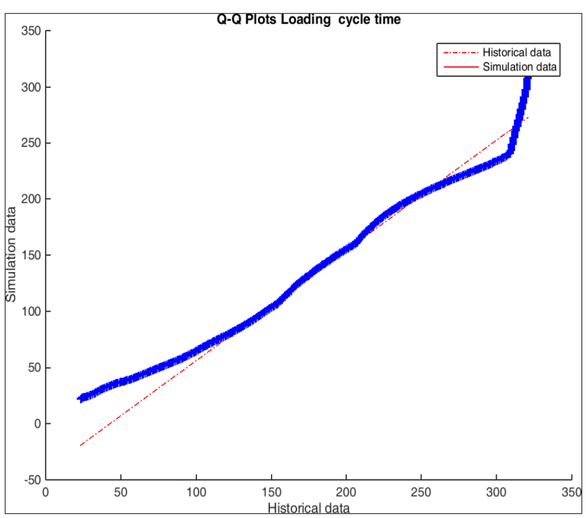

Figure 18. Loading cycle time Q-Q Plot

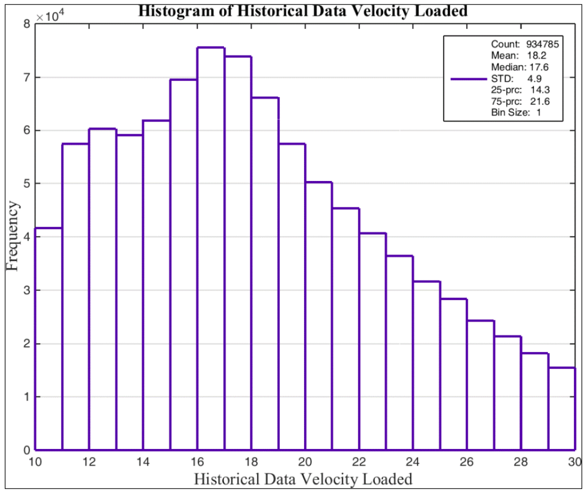

Figure 19. Histogram historical data Velocity Loaded

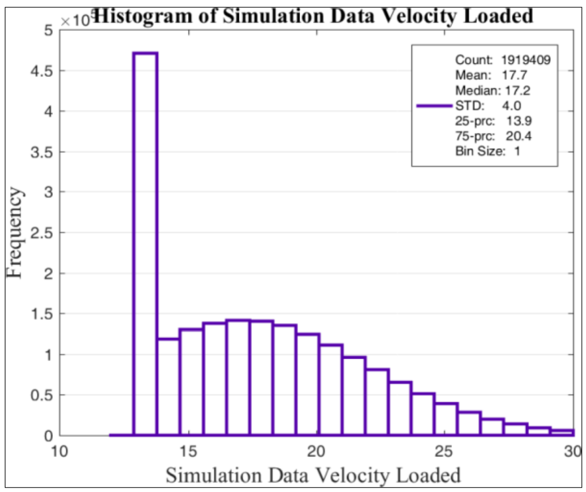

Figure 20. Histogram Simulation Data Velocity Loaded

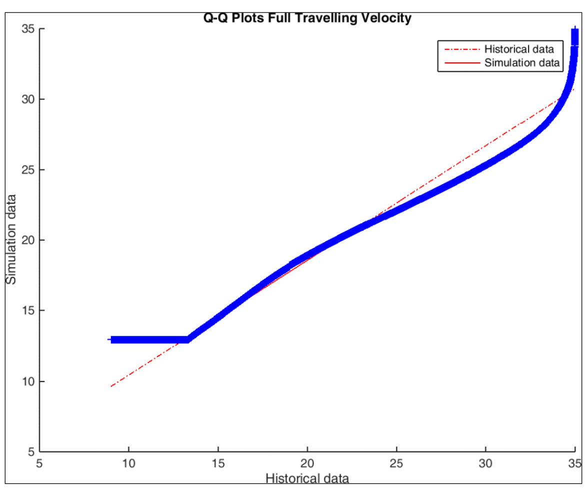

Figure 21. Full Travelling Velocity Q-Q Plot

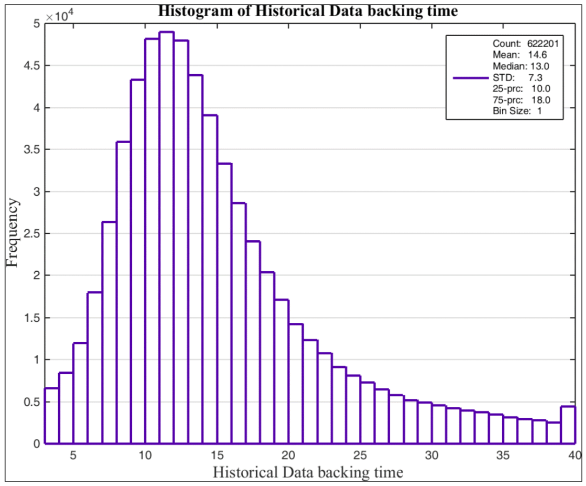

Figure 22. Histogram Historical data backing time

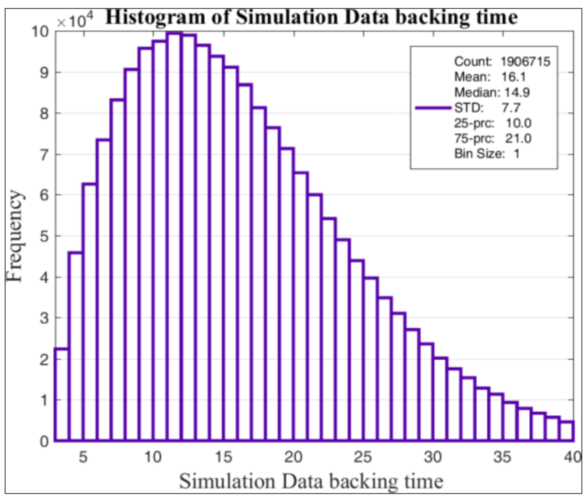

Figure 23. Histogram Simulation data backing time

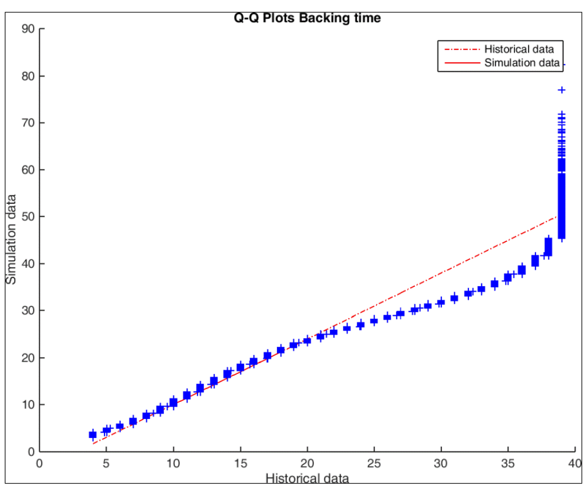

Figure 24. Backing time Q-Q Plot

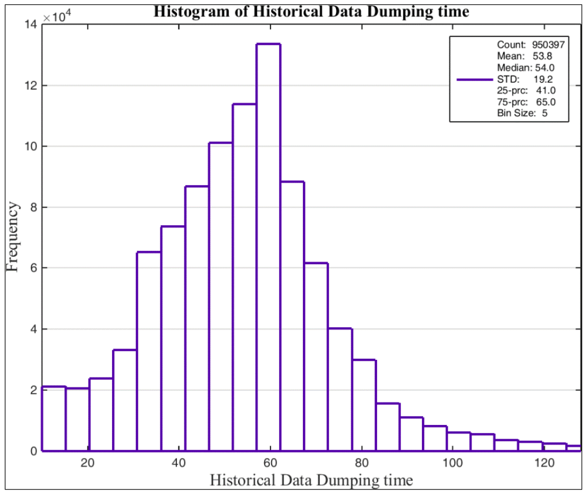

Figure 25. Histogram Historical data dumping time

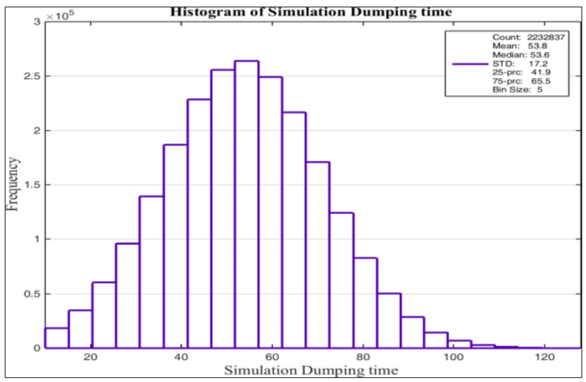

Figure 26. Histogram Simulation data dumping time

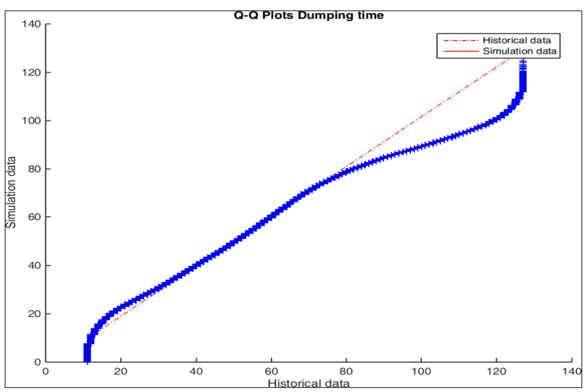

Figure 27. Dumping time Q-Q Plot

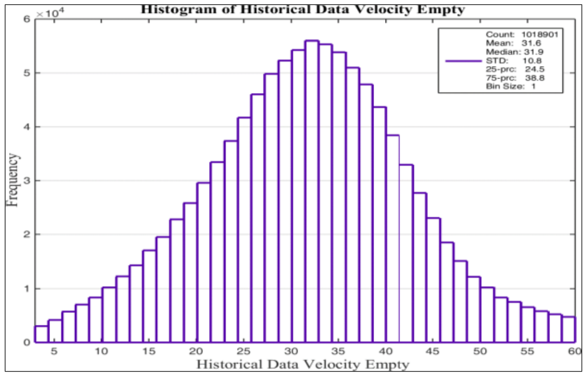

Figure 28. Histogram Historical Data Velocity Empty

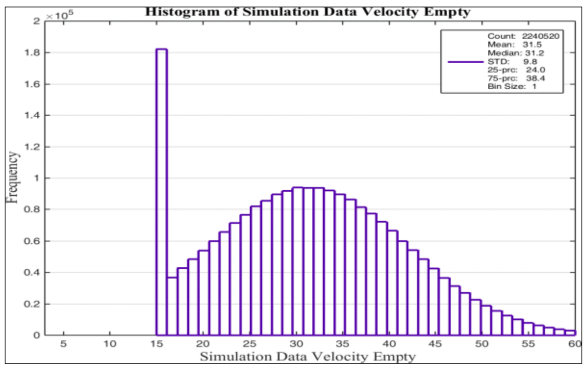

Figure 29. Histogram Simulation Data Velocity Empty

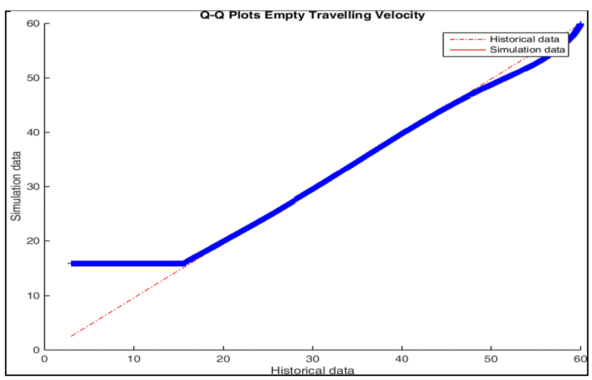

Figure 30. Empty travelling velocity Q-Q Plot

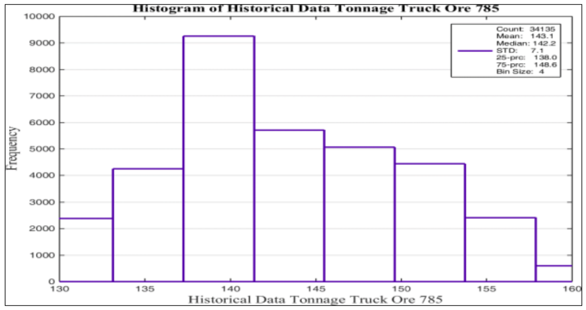

Figure 31. Histogram Historical Data Tonnage Cat 785C ore

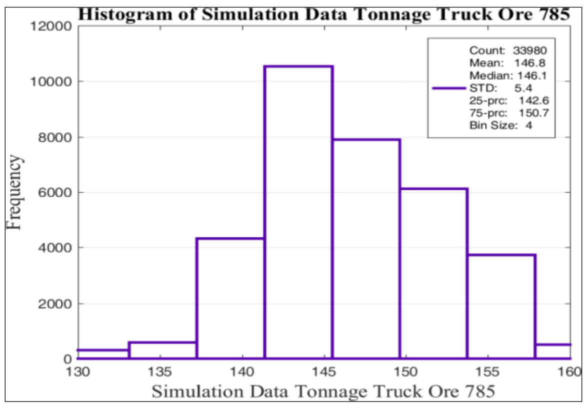

Figure 32. Histogram Simulation Data Tonnage Cat 785C ore

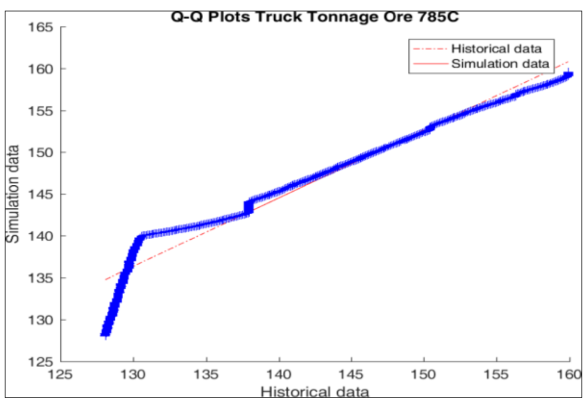

Figure 33. Ore Tonnage Cat 785C Q-Q Plot

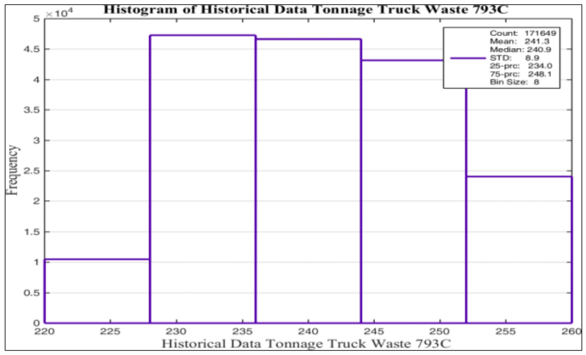

Figure 34. Histogram Historical Data Tonnage Cat 793C Waste

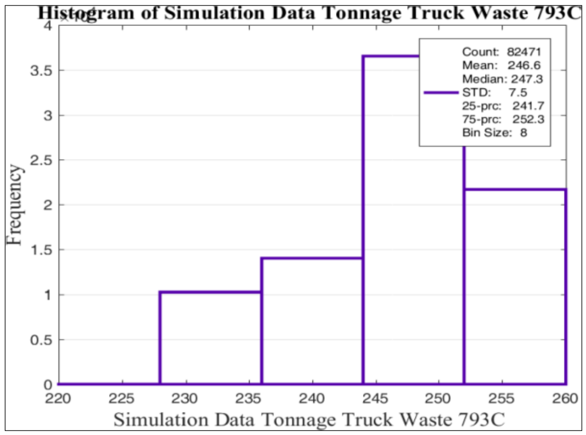

Figure 35. Histogram Simulation Data Tonnage Cat 793C Waste

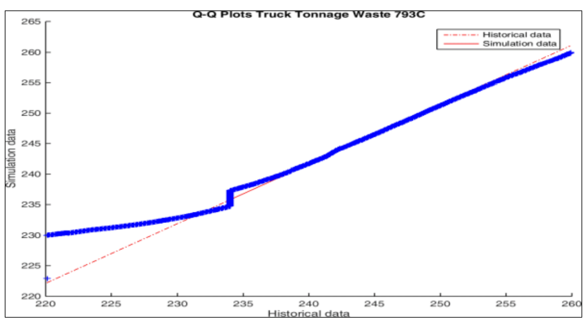

Figure 36.Waste Tonnage Cat 793C Q-Q Plots

4.6. Case O. Decreasing number of waste trucks CAT 793C in an interval of 2. 8400 ton/h rate at both crushers and 8400 tons' capacity at both crushers

At this point the number required trucks was already calculated deterministically for each shovel. This fleet will be the base case scenario for Case 0. Different scenarios with variation of the fleet size for waste trucks, Cat 793C, will be studied. In order to come up with an appropriate number of trucks that meets the waste production with a good balance of KPI’s previously mentioned. After analyzing the outcomes, the best case scenario will be taken from Case 0, as input to Case 1, and it will be called base case.

4.6.1. Tonnage KPI's Case 0

Base case is 56 trucks, 27 ore trucks, Cat 785C, and 29 waste trucks, Cat 793C. From base case to scenario 8, the number of trucks for the waste fleet will be decreased from 29 to 15 trucks. Figure 37,shows production distribution through scenarios 1 to 8. Starting from base case with 29 waste trucks to scenario 8 with 15 waste trucks. The desired production is almost met at the last scenario, but before that happened there was slight growth in production that will be studied in detail later on. In general, as the number of waste trucks decreased so did the production of waste.

Table 17. Scenarios Case 0

	Scenario1	Scenario2	Scenario3	Scenario4	Scenario5	Scenario6	Scenario7	Scenario8
Cat785C	27	27	27	27	27	27	27	27
Cat793C	29	27	25	23	21	19	17	15
Total fleet	56	54	52	50	48	46	44	42

4.6.2. Queues KPI's average times Case 0

Truck cycle time for Cat 793C decreases proportional to the number of trucks in the waste fleet trucks, Cat 793C,Figure 38 describes that information. In addition, the average cycle time for ore trucks also goes down during scenario 6 and 7 .The same pattern is observed in Figure 39,where the queue time at shovel goes down as the number of Cat 793C fleet becomes smaller, while the queue time at shovel, where the Cat 785C fleet is being loaded, remains around 11-13 minutes as the fleet size remains the same.

In terms of average queuing at the dump, Figure 40, shows that for waste trucks ,once again, there is a decrease in the average time in queue at the dump, whereas for the queue at the dump for the ore trucks there is no meaningful change observed . It also has to be highlighted that for scenarios 4 and 5, there is no change at the average queue time. Empty and loaded average velocities, are uniform through all scenarios, Figure 41 and Figure 42, outline these information. Ore trucks travel 30 km/h empty and 16.5 km/h loaded, while waste trucks 32.5 km/h and 18 km/h empty and loaded. Figure 43 and Figure 44,show that Cat 785C fleet, ore trucks, in average travels the same time empty and loaded, 9 and 13.5 minutes; however empty and full travelling time average for Cat 793C fleet slightly goes down around a one minute as the number of truck changes. Figure 45 and Figure 46, validate the past information and they both keep the general tendency of Figure 39 and Figure 40, while detail is added.

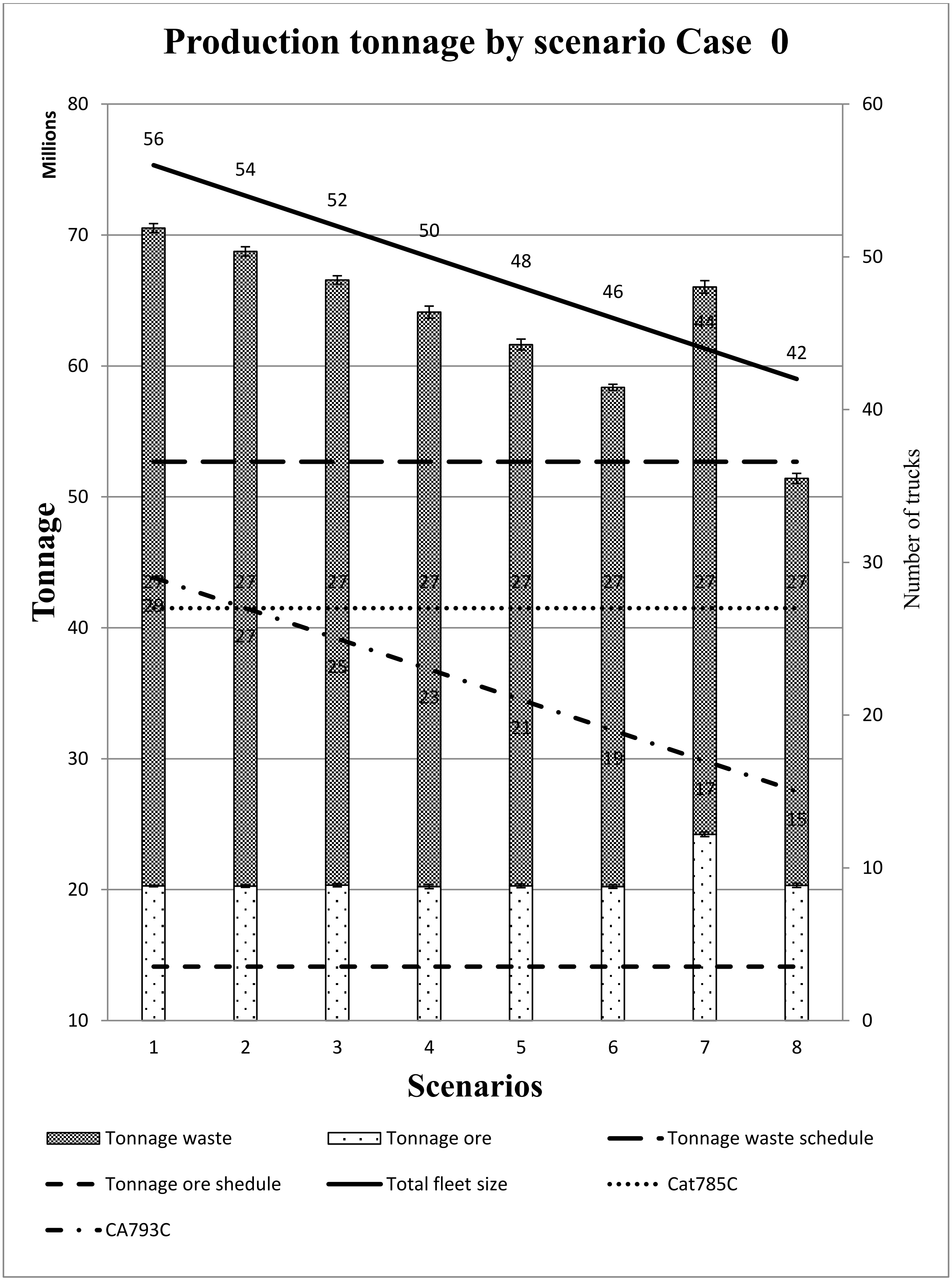

Figure 37. Production tonnage Case 0

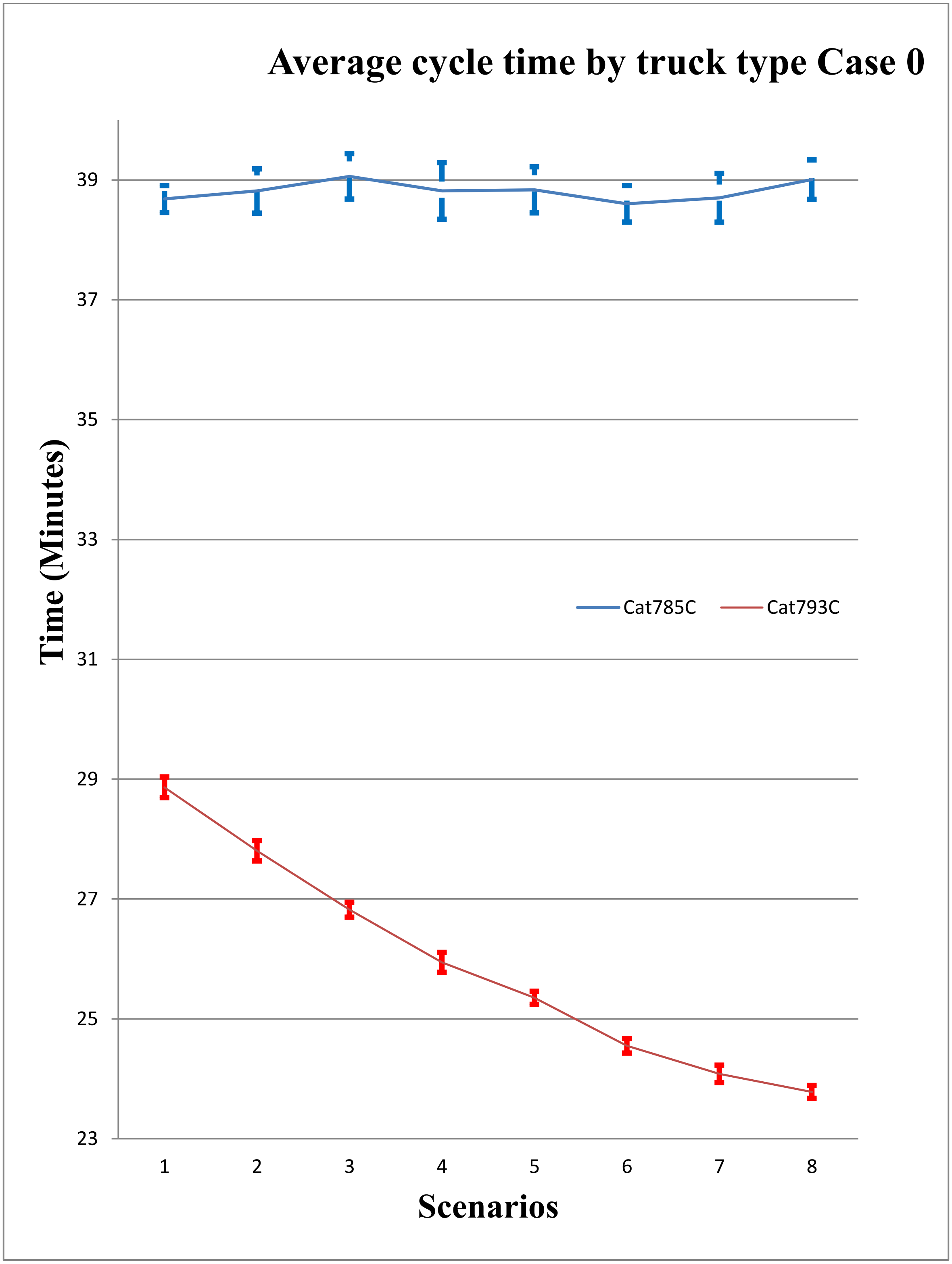

Figure 38. Average cycle time by truck type minutes Case 0

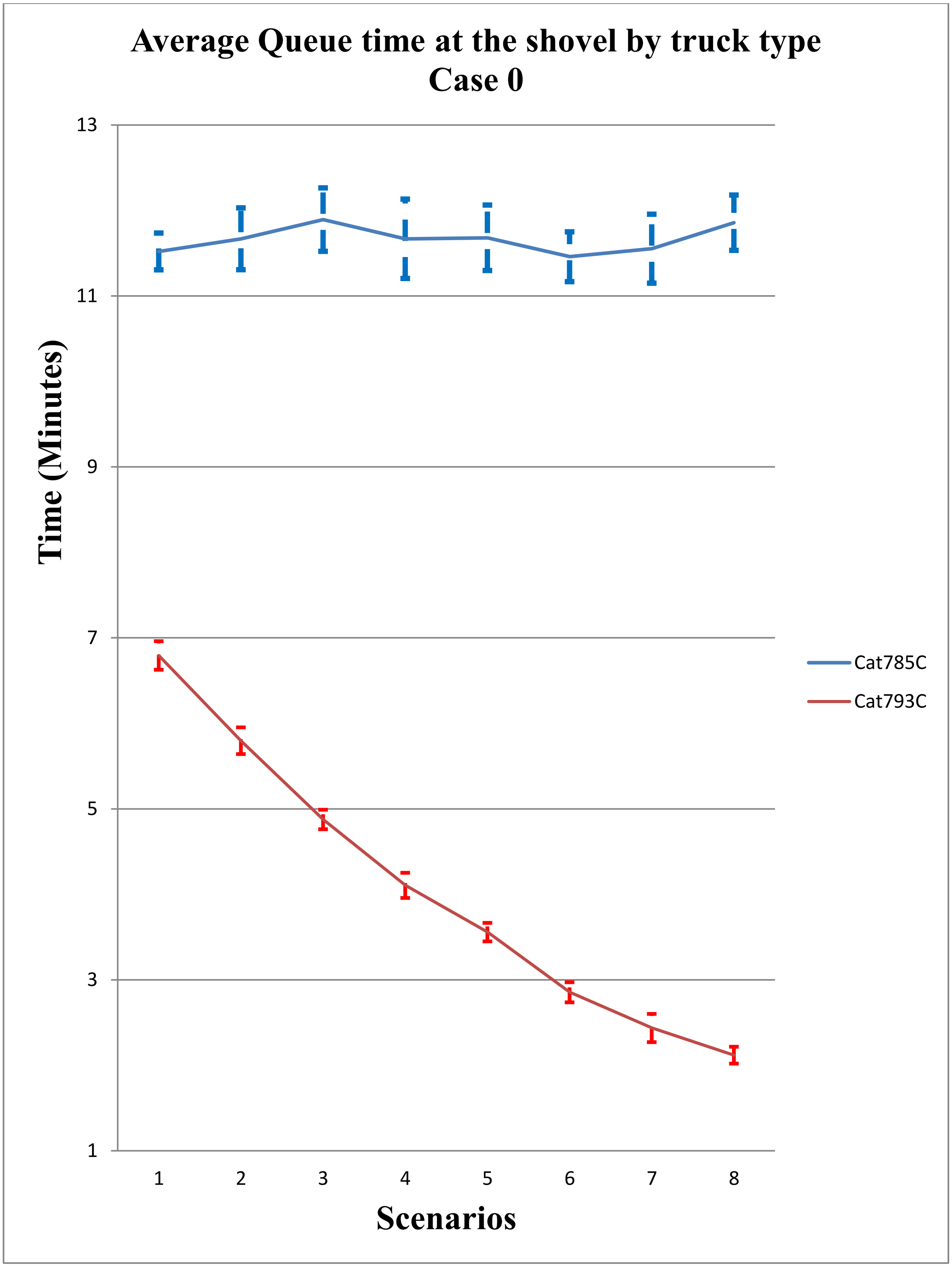

Figure 39. Average queue time at shovel by truck type minutes Case 0

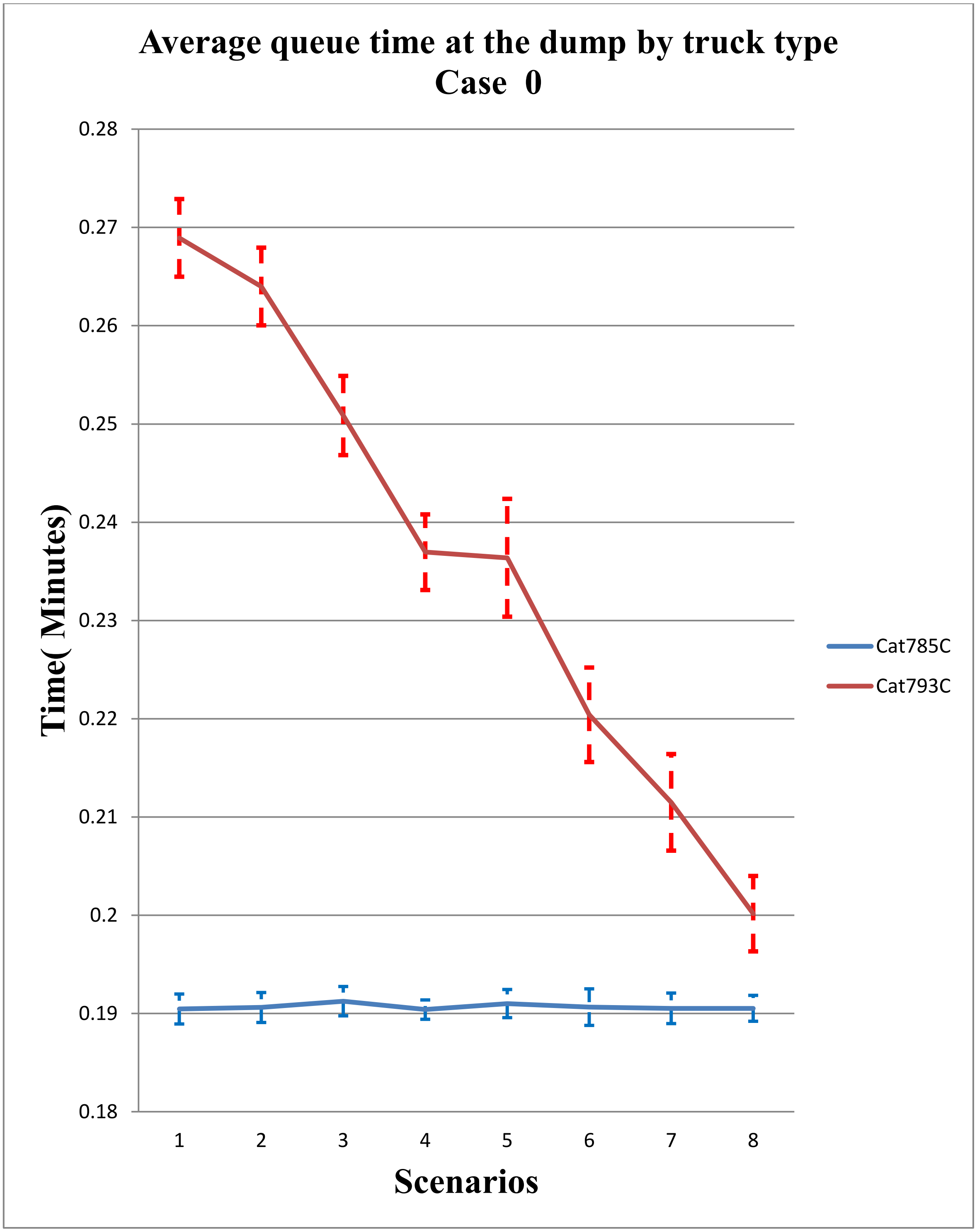

Figure 40. Average queue time at dump by truck type Case 0

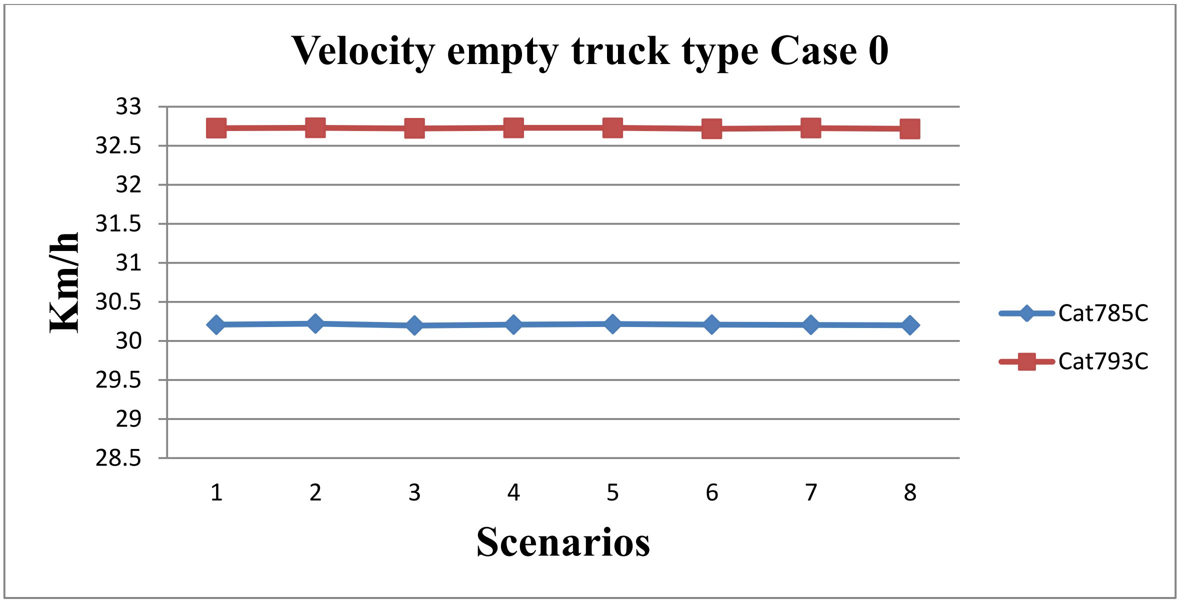

Figure 41. Average empty velocity km/h by truck type Case 0

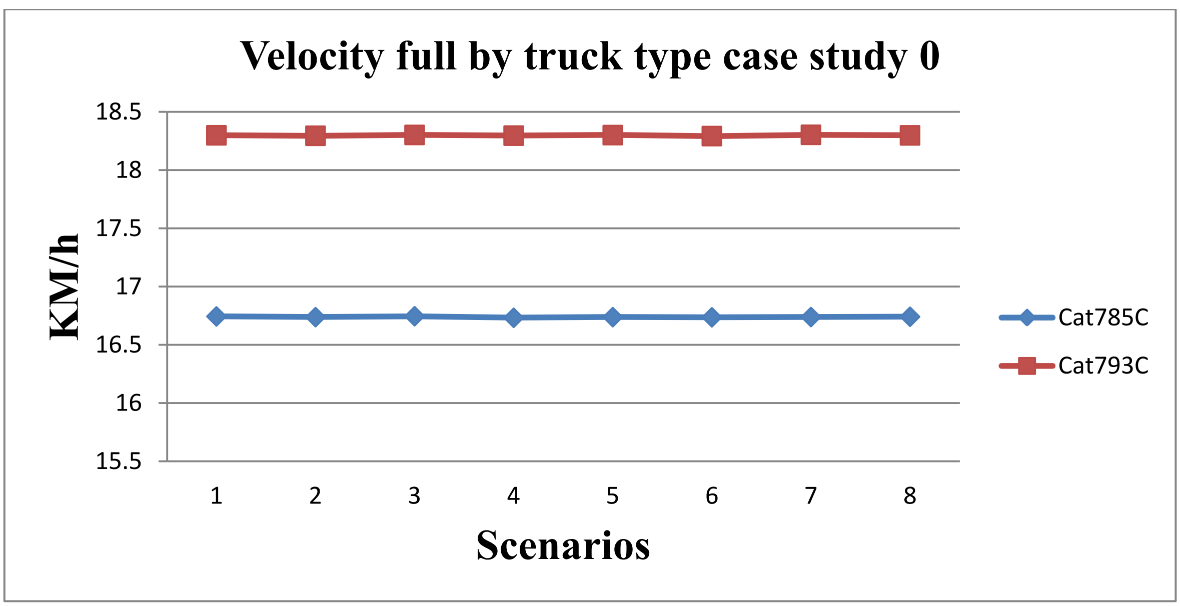

Figure 42. Average full velocity km/h by truck type Case 0

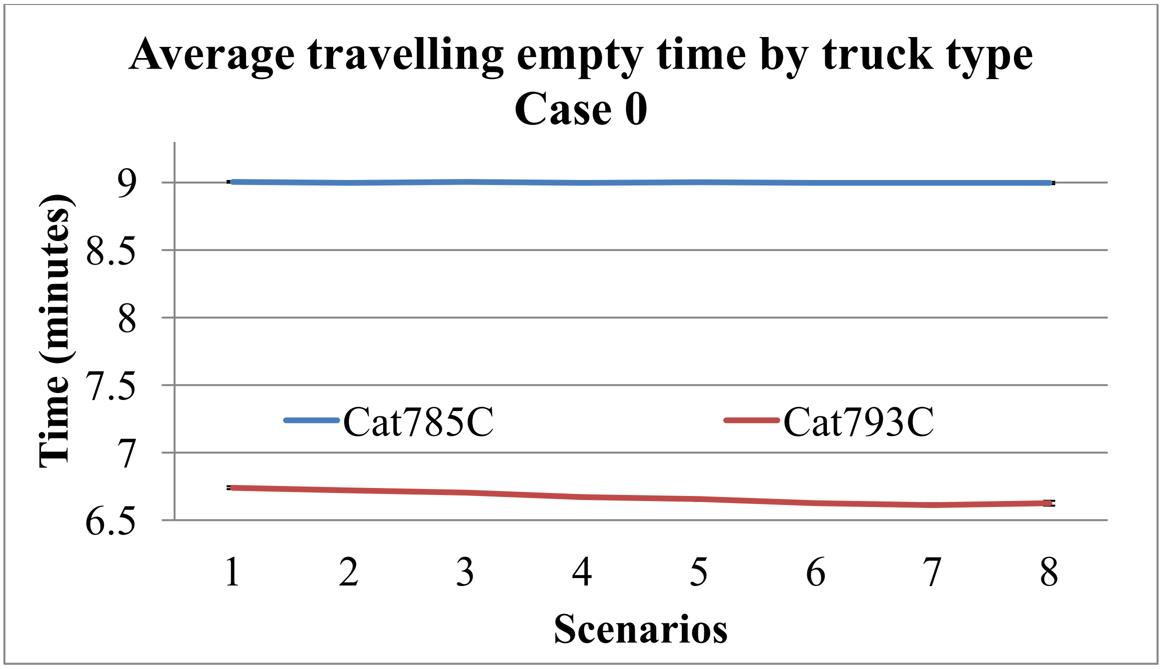

Figure 43.Average travelling empty time by truck type in minutes Case 0

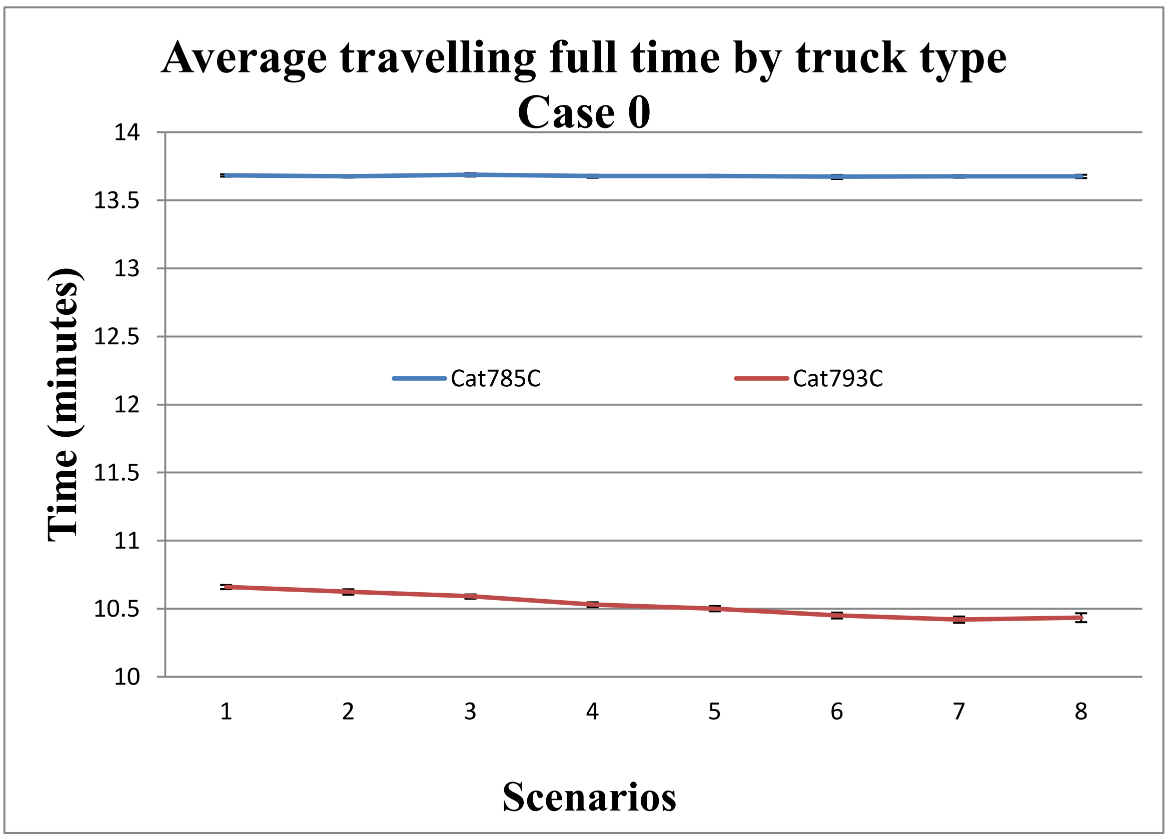

Figure 44. Average travelling full time by truck type in minutes Case 0

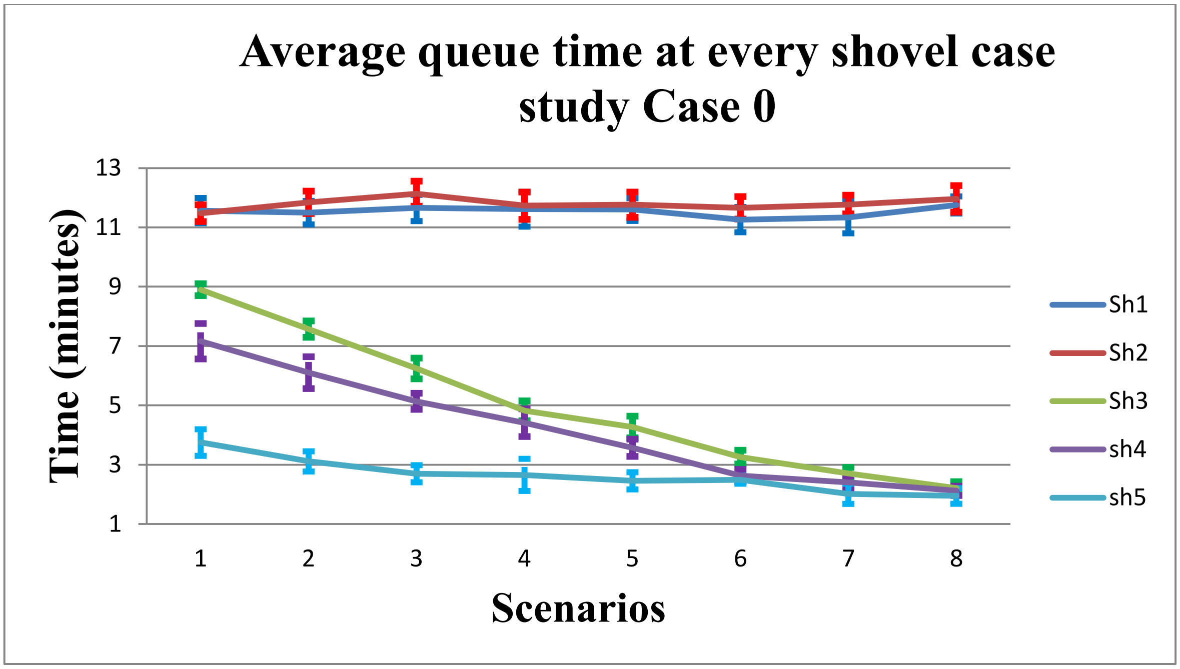

Figure 45.Average queue time at every Shovel Case 0

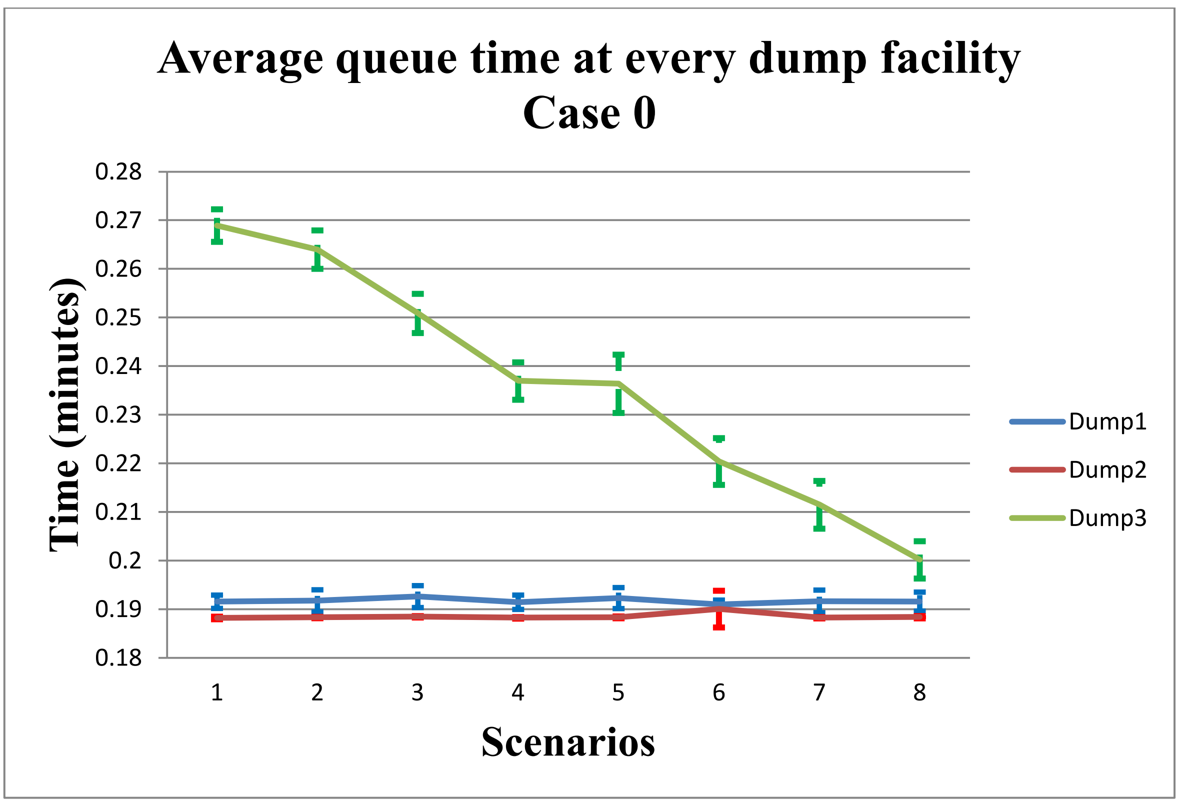

Figure 46. Average queue time at every Dump Case 0

4.6.3. Shovel Time category KPI

As it was mentioned previously, Hitachi 2500 is the ore shovel type, shovels 1 and 2, and Hitachi 5500EX is the waste shovel type, shovels 1, 2 and 3. Standards KPI's will be analyzed by shovel in every scenario to specify a best performance.

A measurement of the percentage of hours spent in operation in relationship to the total hours (in this case 4380 hours) is outlined in Figure 47, shovel type Hitachi5500Ex, waste shovels is always less than ore shovels in gross operating hours (GOH) percentage.

It can clearly be seen, Figure 48,how net operating hours decreases through scenarios from 3200 hours to 2200 hours for waste shovels, while net operating hours for ore shovels remains the same. Shovel delays, Figure 49,in this case represented by hanging time, increases for waste shovel type, as truck fleet size is diminished in every scenario, to balance hours lost in NOH for net operating hours in waste shovels, while again for ore shovels there is not a variation in delays. In terms of down-time Figure 50.Shovel down time by shovel type Case 0. (PM AND FAILURE) indicates that through all the scenarios, both shovel types spent between 10.20 and 10.50% of their time in PM and failure.

Regarding Tonnage by GOH, Figure 51 waste shovel fleet, Hitachi 5500Ex ton/GOH decays from 14000 to 8000 which corresponds to the desired waste. Ore shovels, Hitachi 2500 fleet, tonnage/GOH remains at the same value in all the scenarios which is 5800. Although ore shovels are more for GOH%, Ton/GOH is less than waste trucks due to the bucket size of this fleet, which is in fact smaller.

Figure 50 gives a clear explanation to Figure 47. The fluctuation always below of the trend in GOH% for Hi 5500EX, it is related to the changes in its respective down-time. When down-time rises for waste shovels, GOH% decreases as it obeys to a relationship of working time through the year. If the waste shovels are down, it means they are not working. Same relationship it is applied to ore shovels. Mechanical availability for shovels, outlined in Figure 52,is the ratio of time in operation to time in operation plus down, it is also inversely proportional to the down time. It can be visualized that availability of shovel constrained by the hours it must spend in planned and unplanned repair. Moreover, Physical availability as the ratio of scheduled hours' minus down time to scheduled hours, also known as gross operating hours plus standby. Measures the machine ability to fulfill requirements in exploitation process, it is represented in this Case 0 by Figure 53. In what degree the shovel is used to work taking into account its ability to work. The behavior in this case is equal to mechanical availability in the line tendency but slightly less in 2% value.

The effective utilization of the shovel, Figure 55,shows how the use of availability decreases for both ore and waste equipment significantly, in every scenario but it can be noticed that for the last, scenario 8, the use of availability comes back to the starting point. The tendency obeys to stand by variability in Figure 54,ore and waste shovel type standby weather % rise in scenario 4 to decline again in scenario 7;According to Figure 55, Use of availability for both shovel, behaves the opposite during those scenarios, as an overall they both dropped 1%.

Figure 56,ratios of WOH (in this case same as NOH) to actual operating hours. This is also function of NOH, Figure 48, in the sense that operating efficiency is directly proportional to NOH. Shovel operational efficiency remains in more than 96% through scenarios in ore shovel, while for waste there is a drop to 61%. It also relates to the shovel delays, that are increasing for Hi 5500Ex, as less trucks are involved in further scenarios. Finally, capital efficiency, gives a ratio of net operating hours to schedule hours in a year, follows also a parallel tendency with operating efficiency. Figure 57,corroborates this information but in a smaller scale, ore shovels remaining around 84% and waste shovels dropping to 48%.

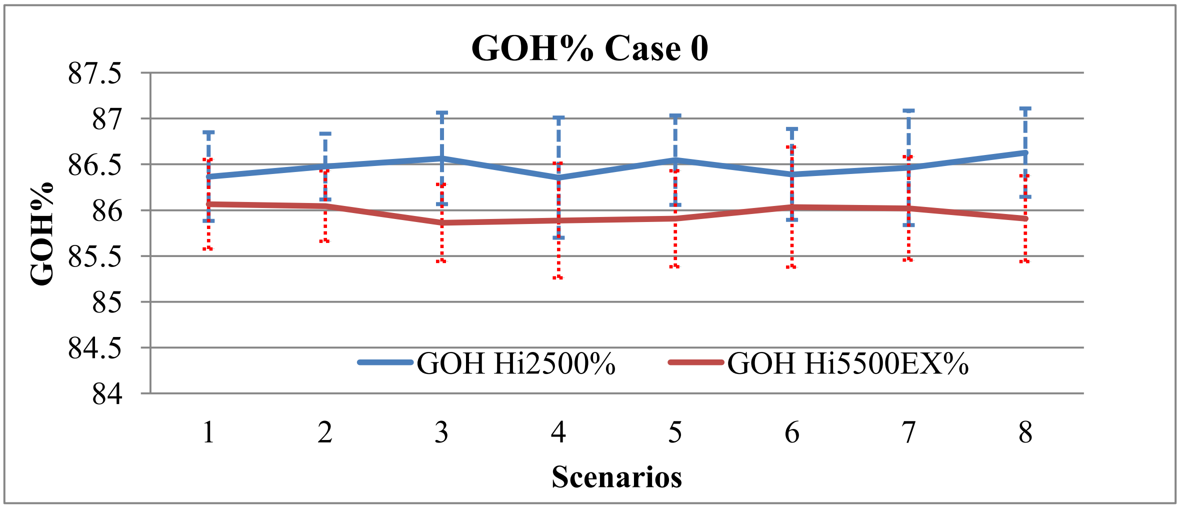

Figure 47.Shovel Gross Operating hours GOH % Case 0

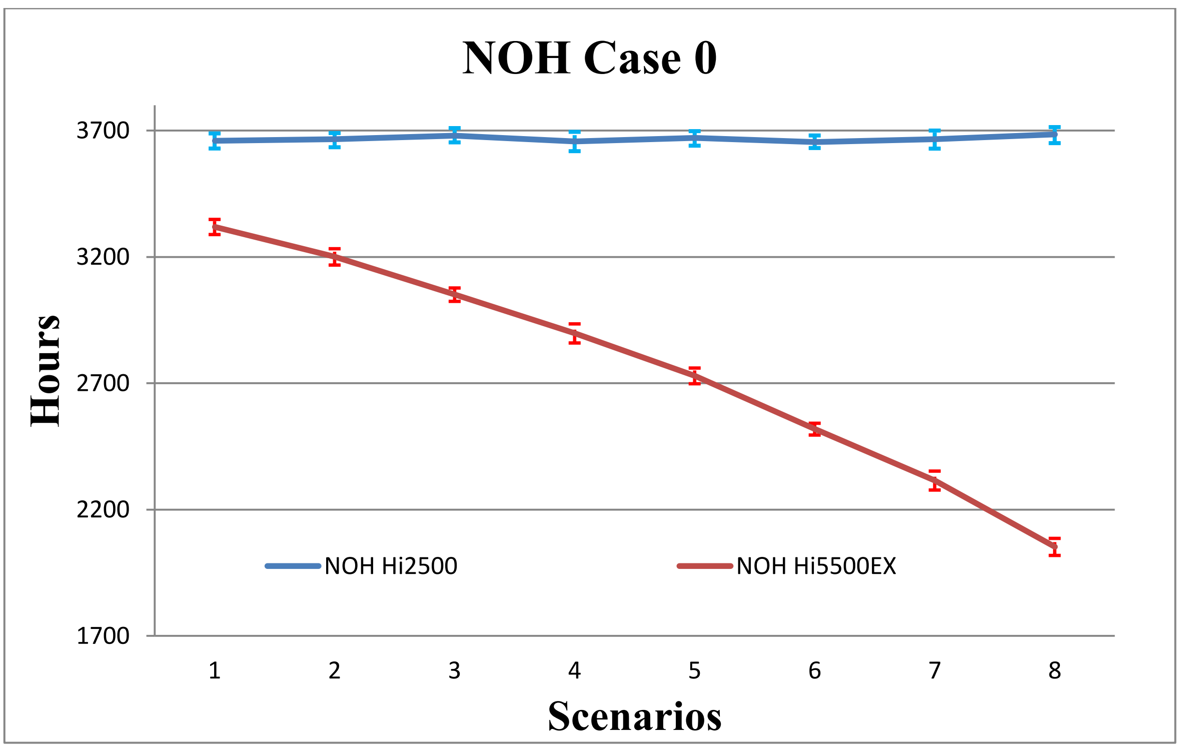

Figure 48.Shovel Net Operating hours Case 0

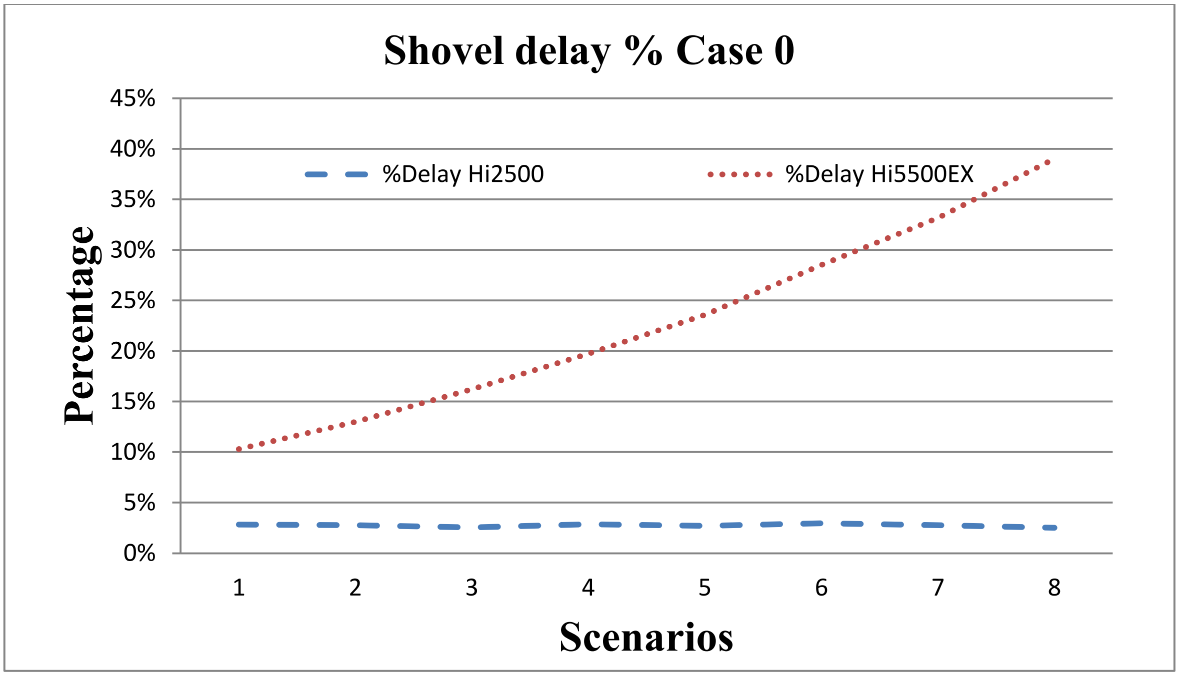

Figure 49.Shovel delays% by shovel type Case 0

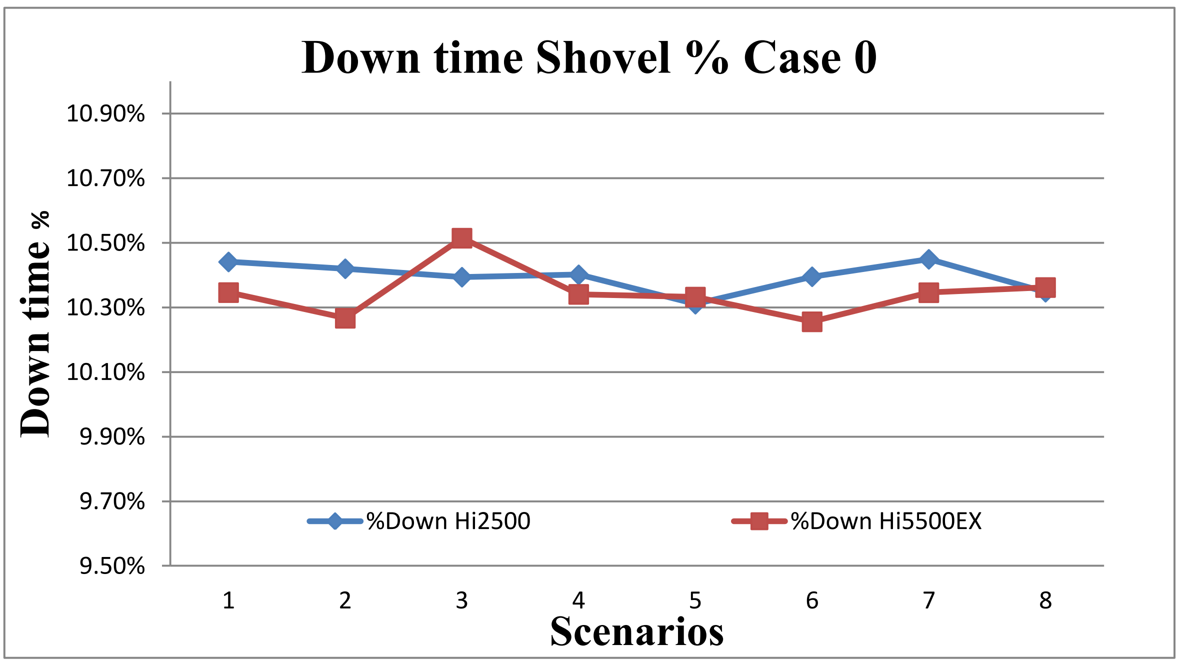

Figure 50.Shovel down time by shovel type Case 0. (PM AND FAILURE)

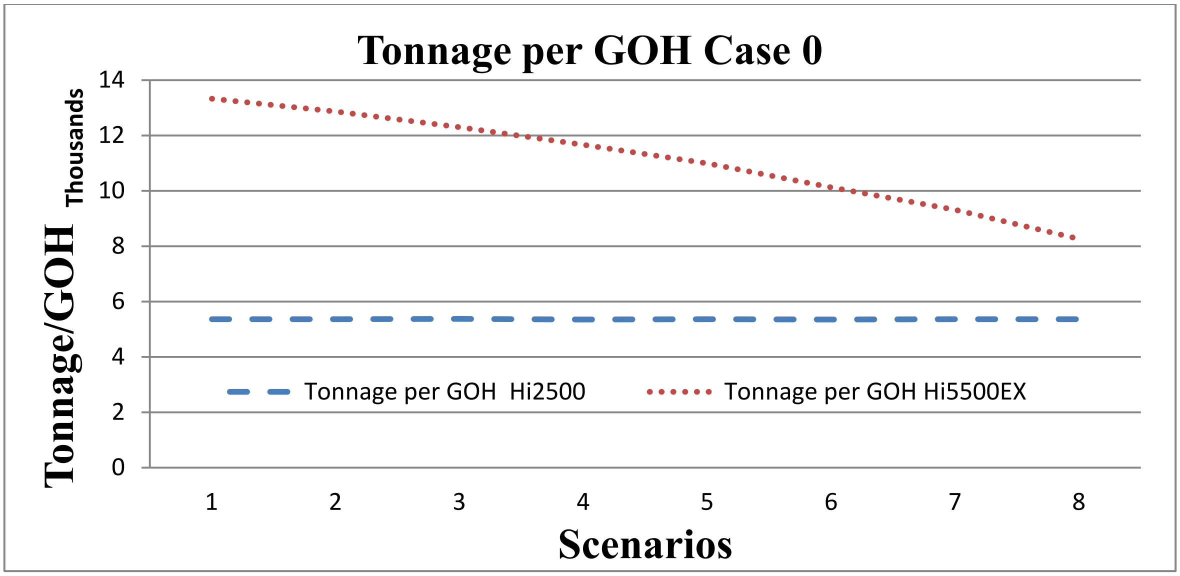

Figure 51.Shovel Tonnage per gross operating hours Case 0

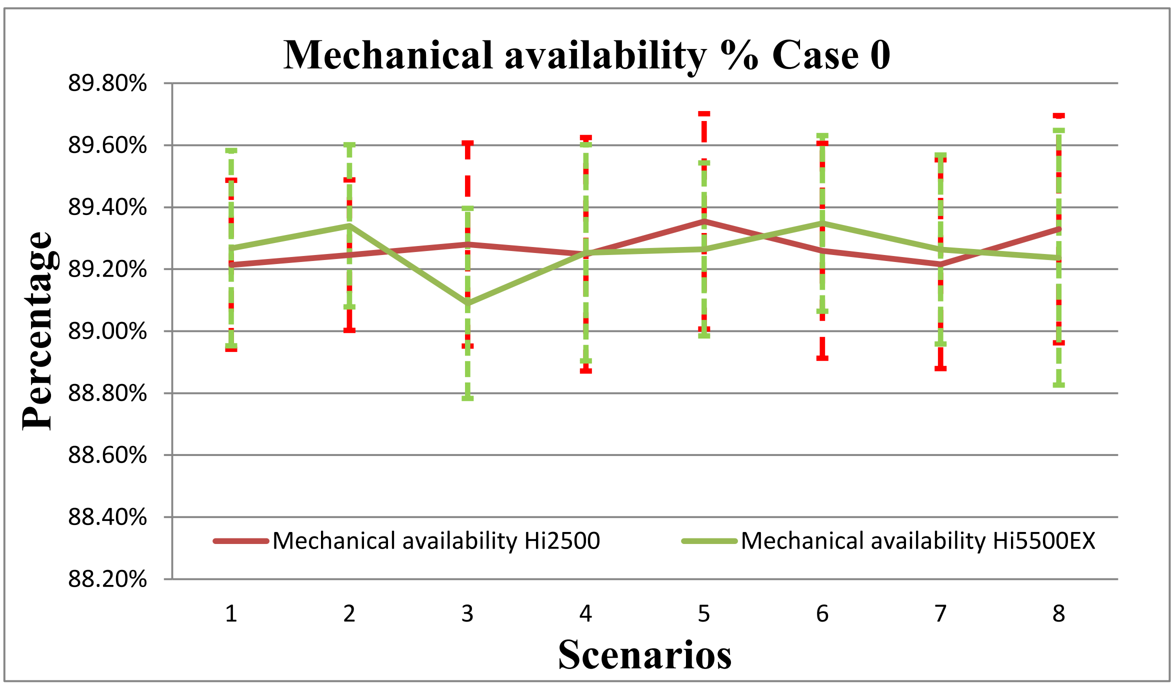

Figure 52.Shovel Mechanical availability Case 0

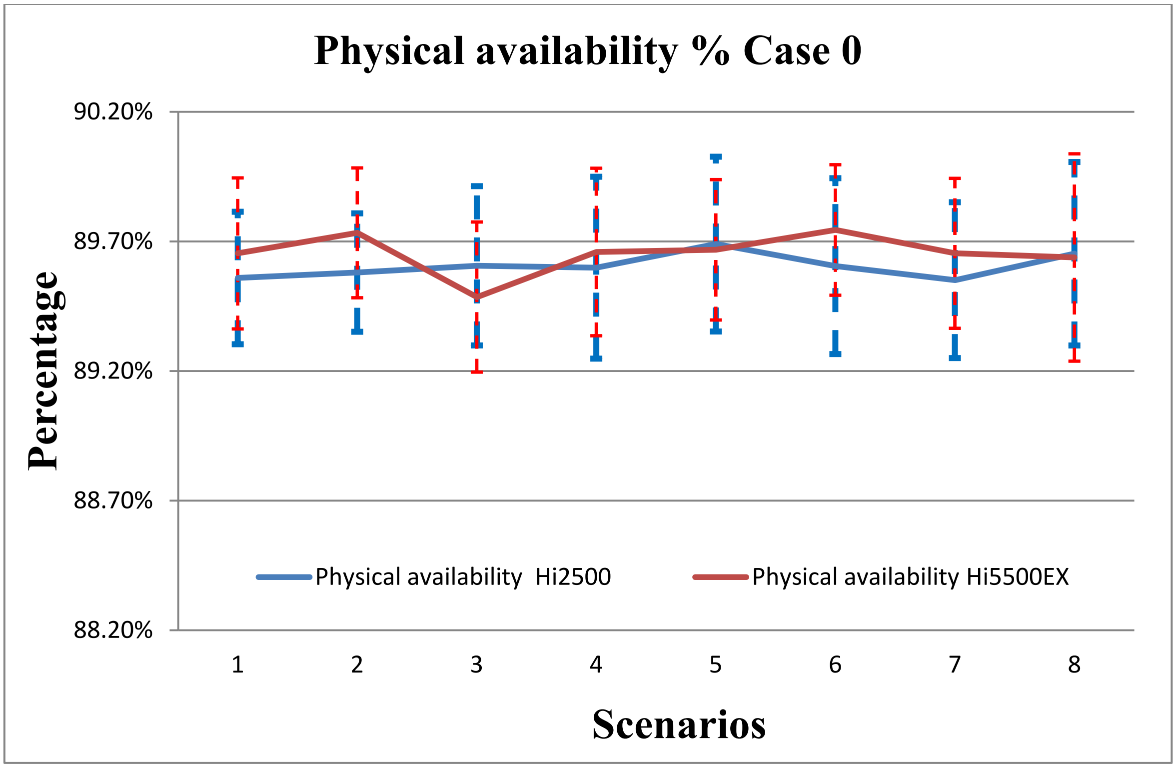

Figure 53.Shovel Physical availability Case0

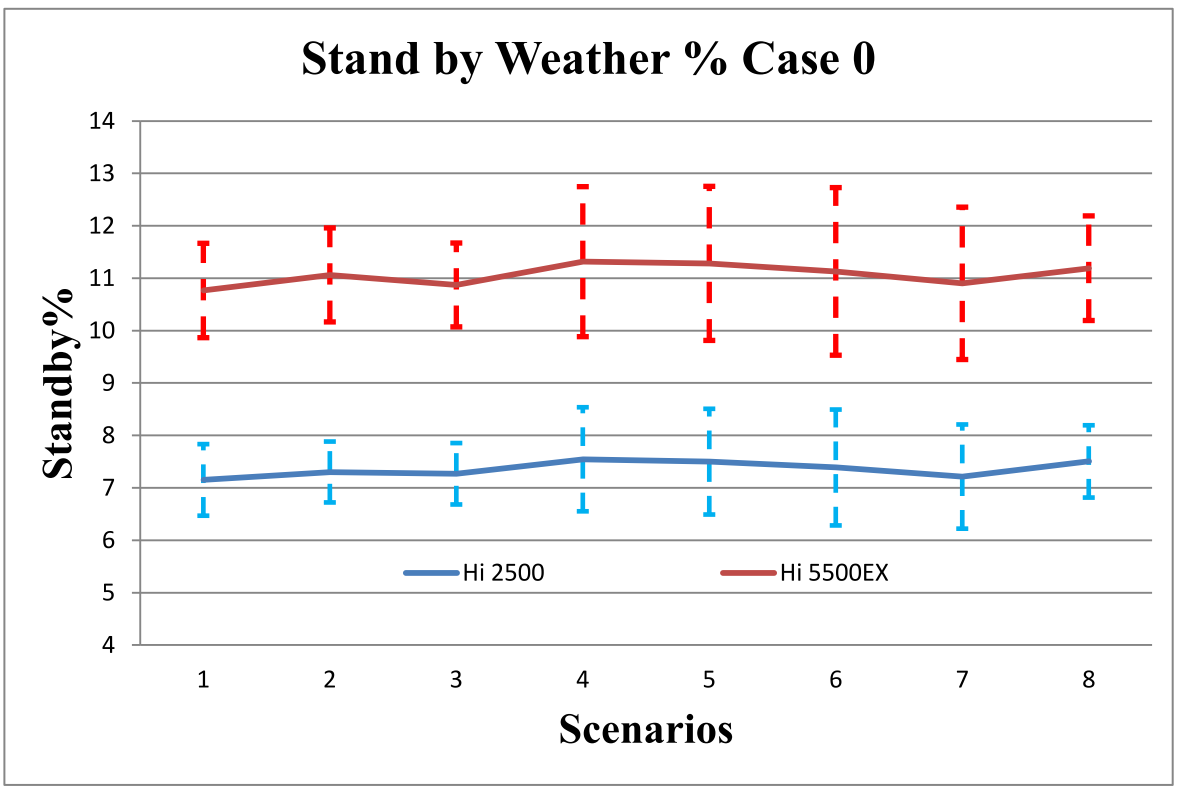

Figure 54.Shovel Stand by weather Case 0

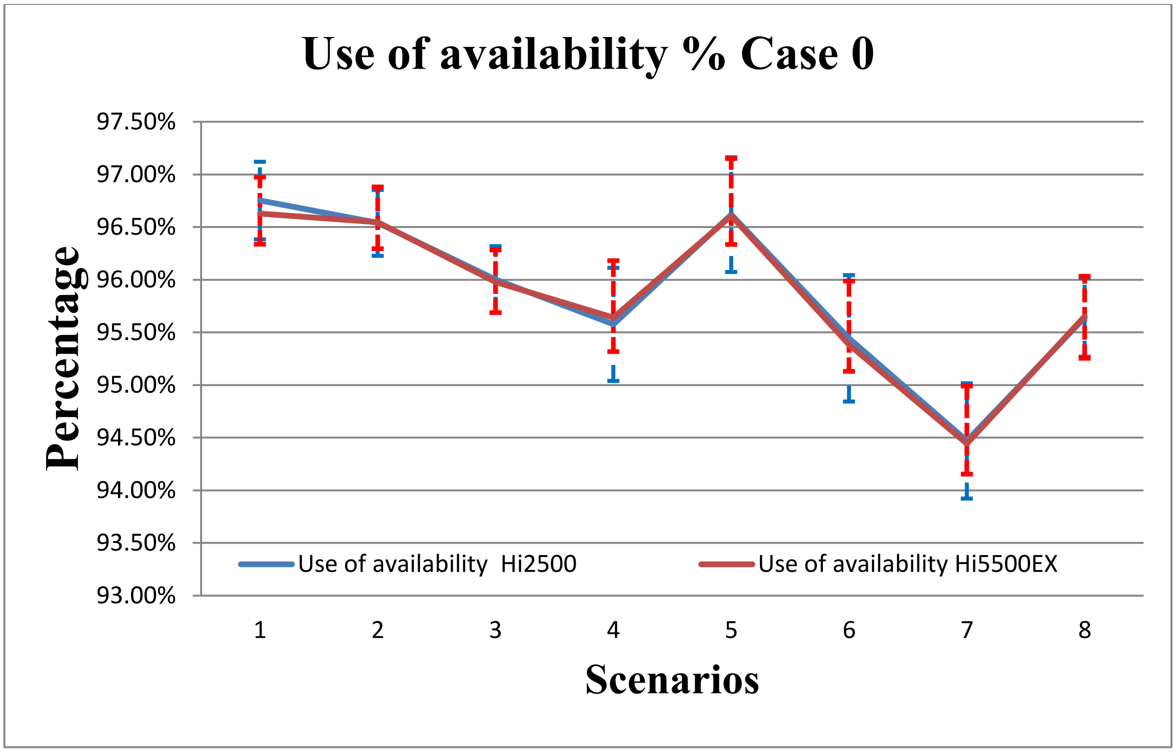

Figure 55.Shovel Use of availability Case 0

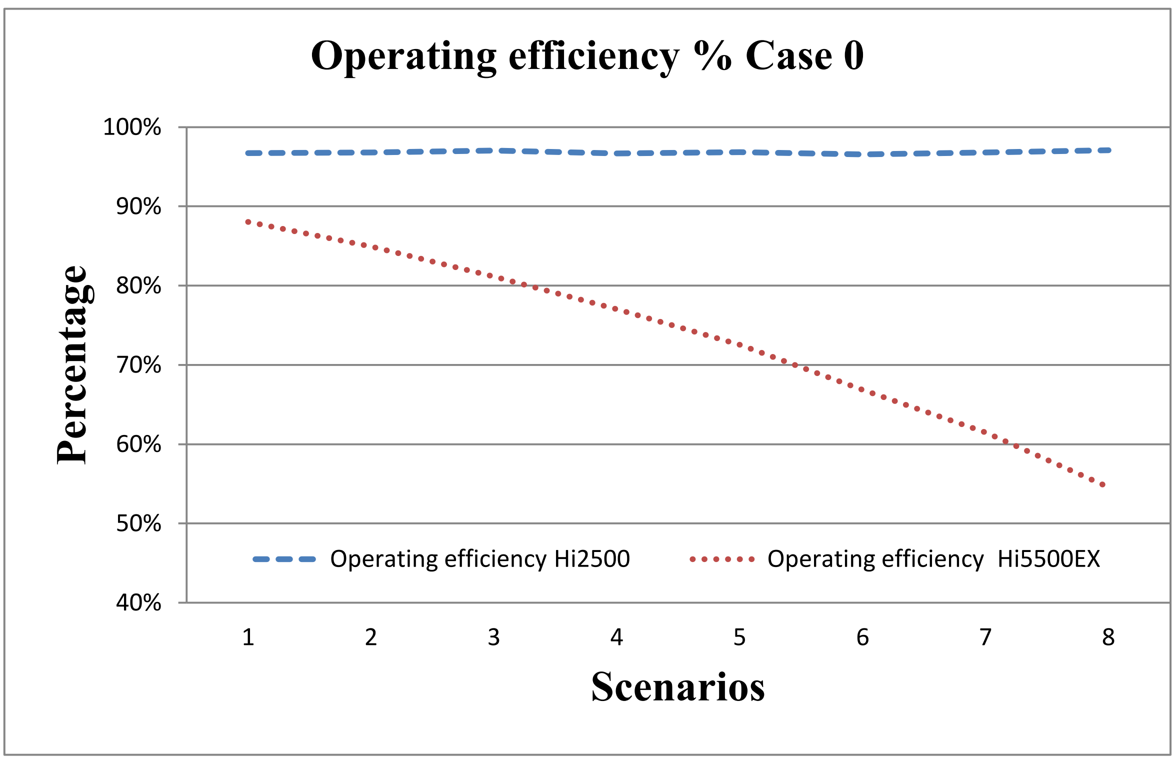

Figure 56.Shovel Operating efficiency Case 0

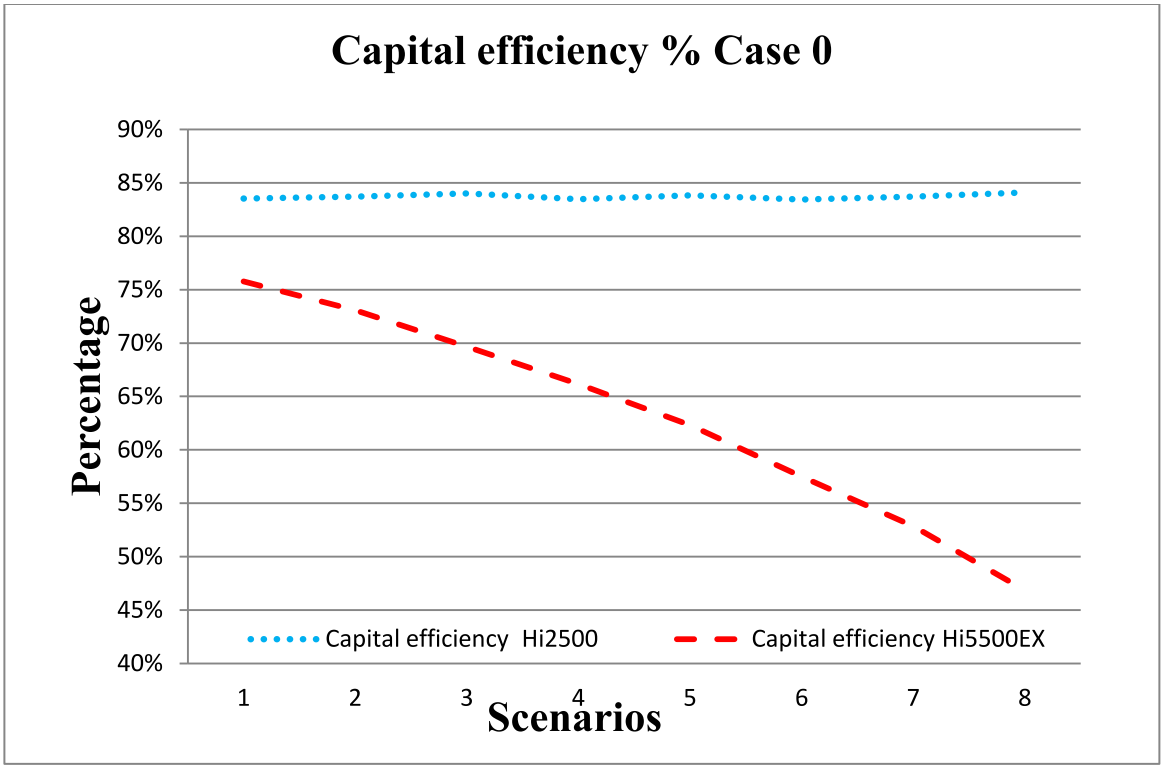

Figure 57.Shovel Capital efficiency Case 0

4.6.4. Truck Time category KPI's

The same process carried out for shovel performance analysis is done for the trucks. Ore trucks correspond to Cat785C and waste trucks Cat793C. As an overall, from Figure 58, it can be seen that in ore trucks, the percentage of yearly hours spent in operation is higher for ore trucks than for waste trucks. NOH in Cat 785C trucks remains constant in 2300 hours, while the Cat 793C truck increases from 2500h to 2900h, through different scenarios, information can be found in Figure 59.Truck delay, in this case represented by queue at the shovel and dump location, is shown in Figure 60. Truck delay for CAT 785C, ore fleet remains on the same values, around 24%, whereas waste fleet drops from 19% to 8% as the scenarios varies, decreasing the number of trucks. Figure 62, once again allow to visualize how the tonnage hauled remains the same for ore trucks as the number of trucks is constant; however, for waste fleet tonnage per gross operating hours increases as trucks are less in the system, due to more NOH and less delays.

In terms of truck availability, Figure 63,provides an idea on how the availability constraint by failures will behave in each scenario.

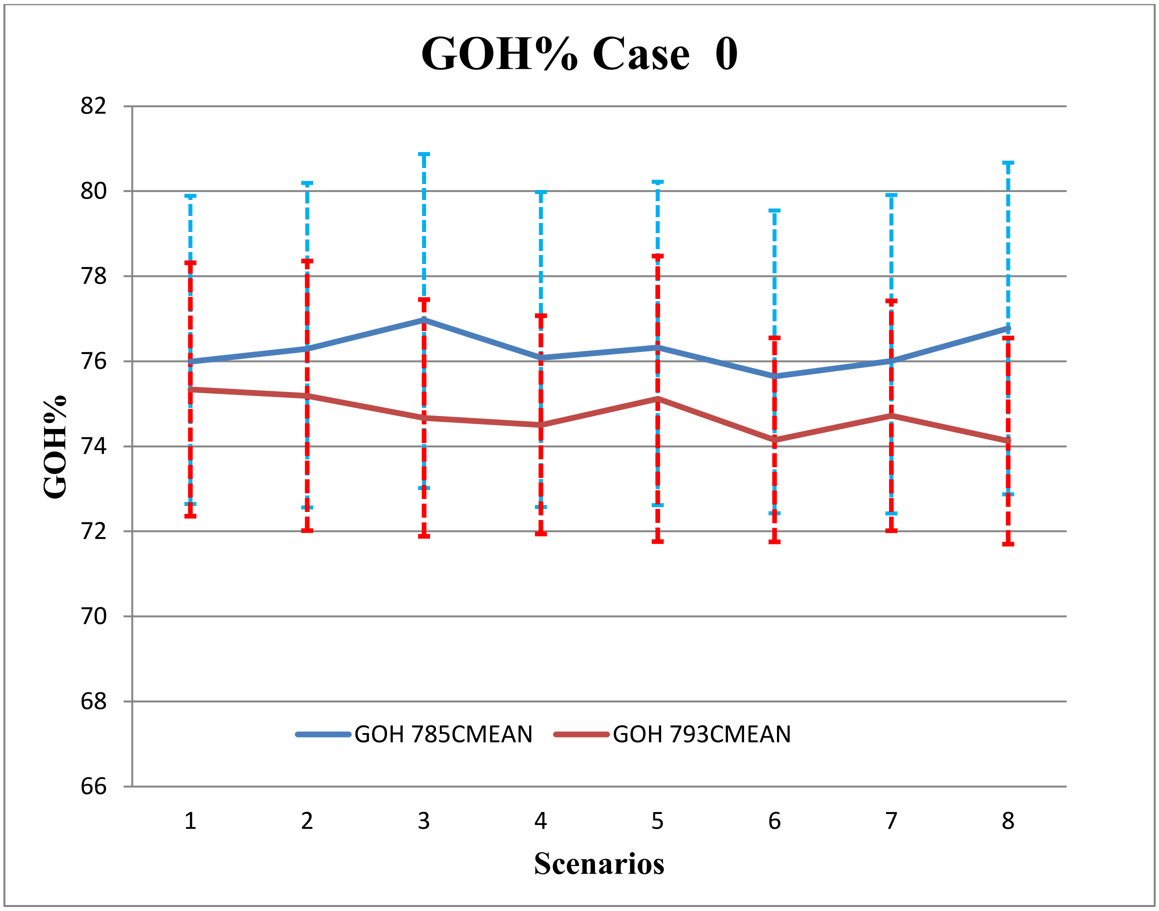

Figure 58.Truck Gross Operating hours GOH % Case 0

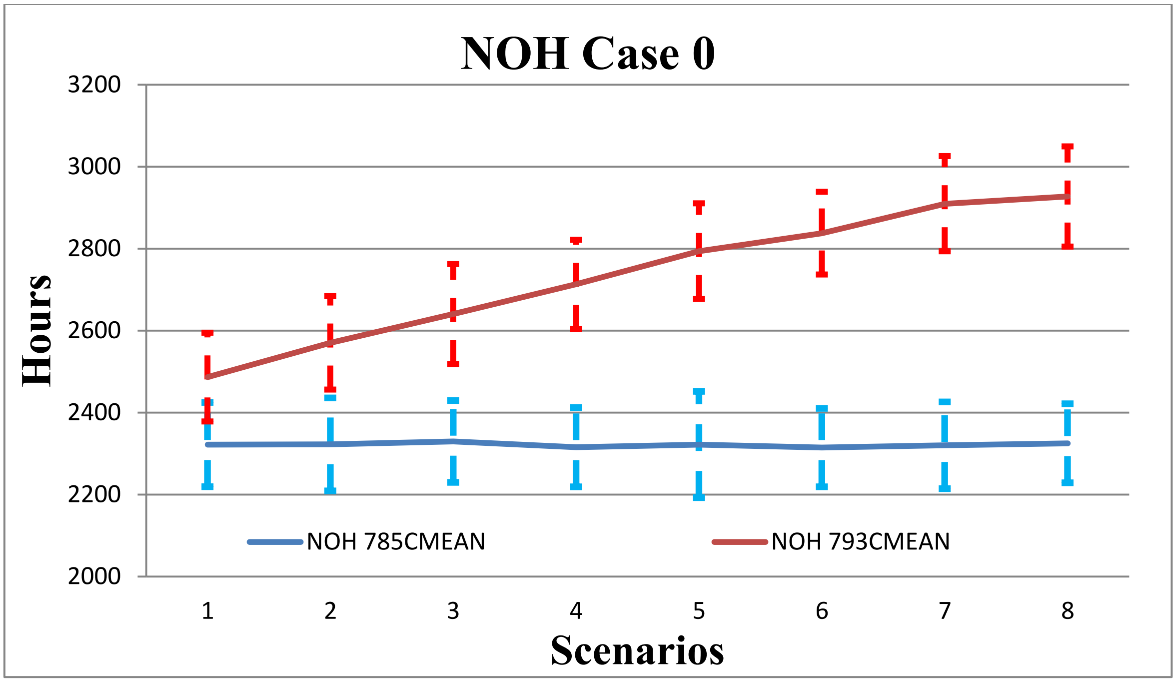

Figure 59.Truck Net Operating hours NOH Case 0

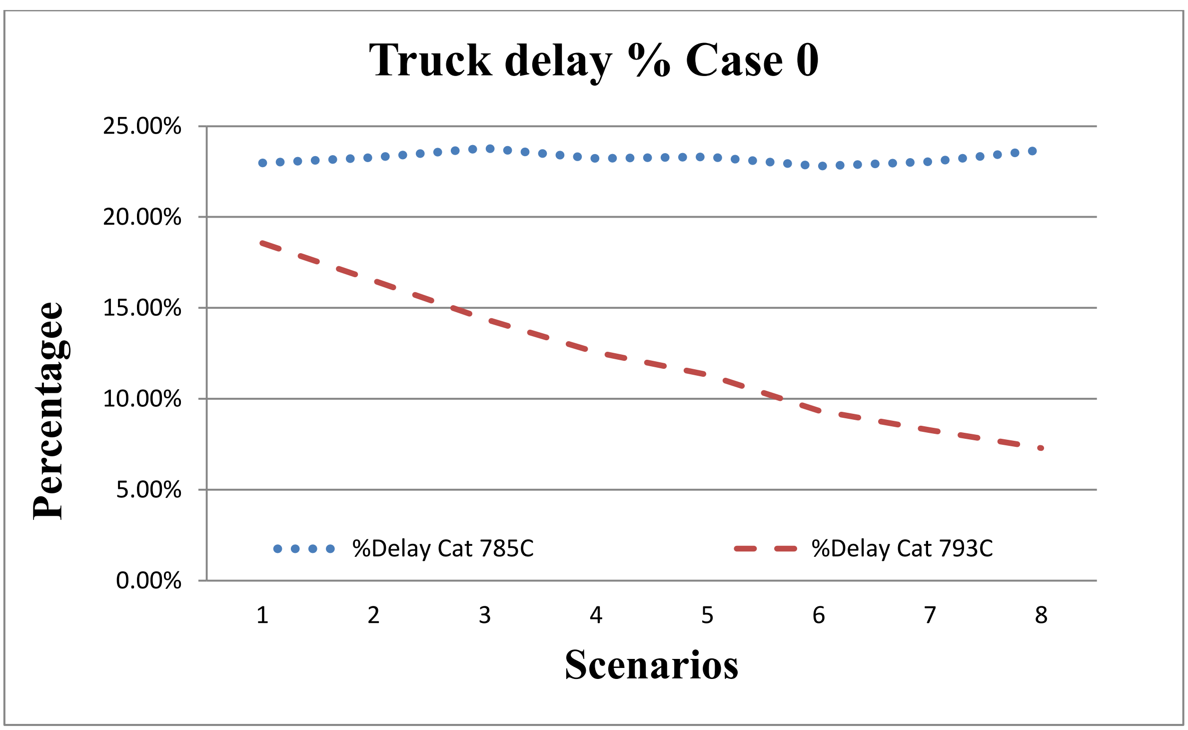

Figure 60.Truck delay% by truck type Case 0

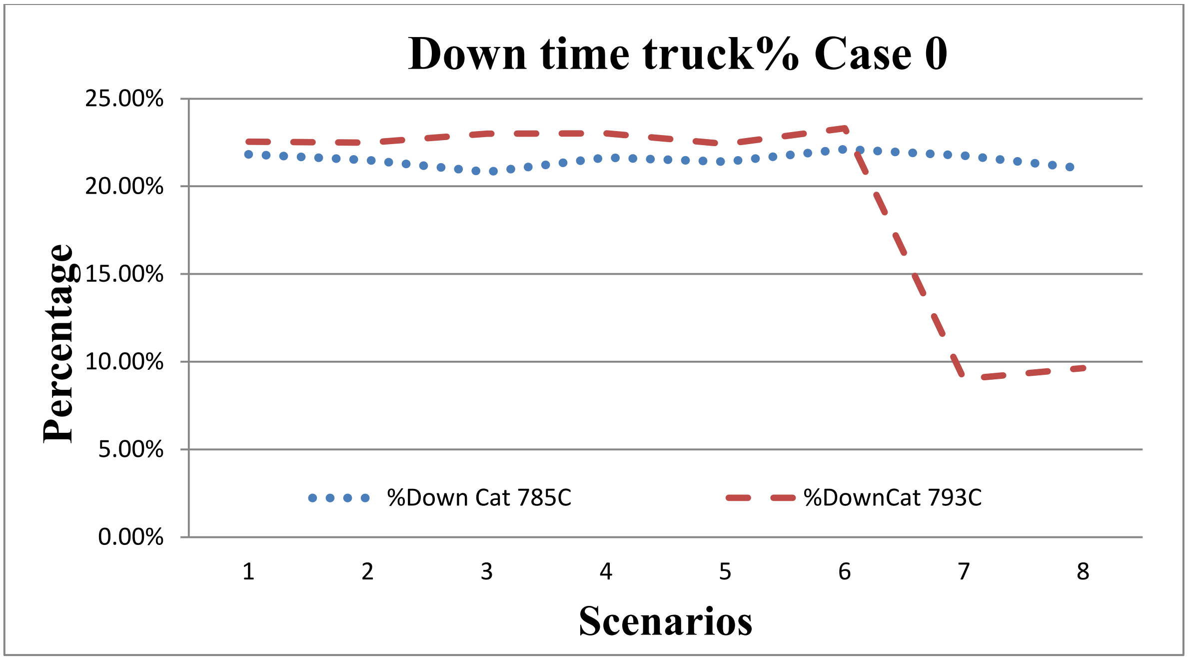

Figure 61.Truck down time % by truck type Case 0 (DOWN AND FAILURE

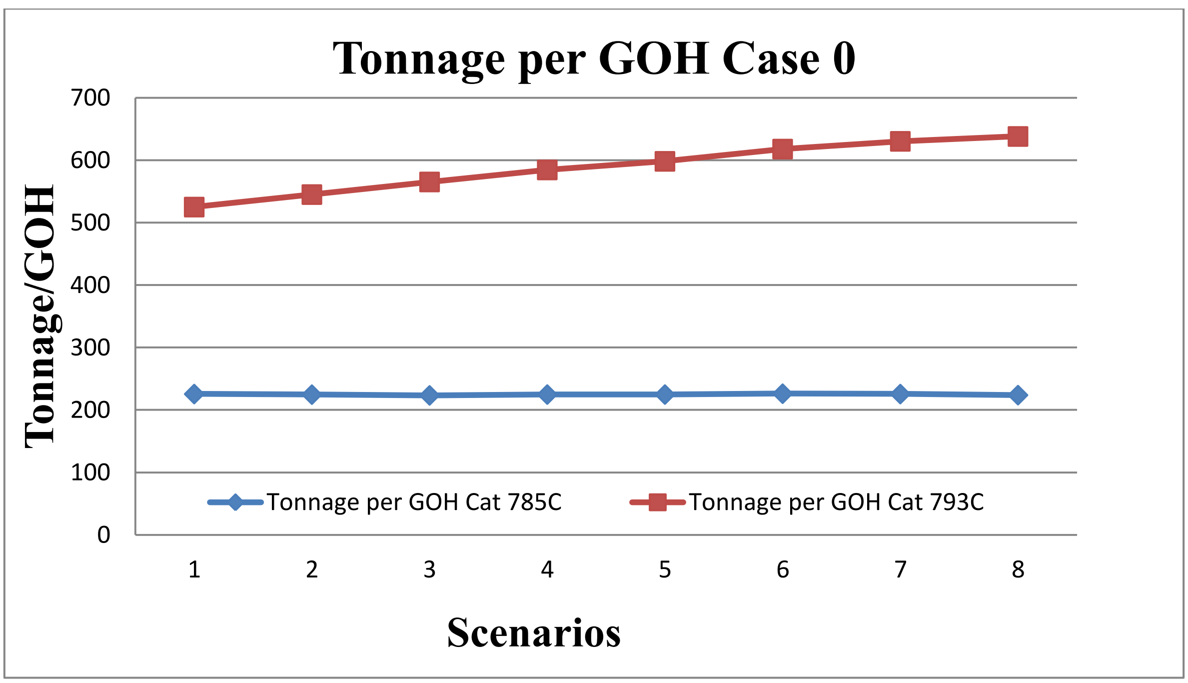

Figure 62 Truck Tonnage per gross operating hours Case 0

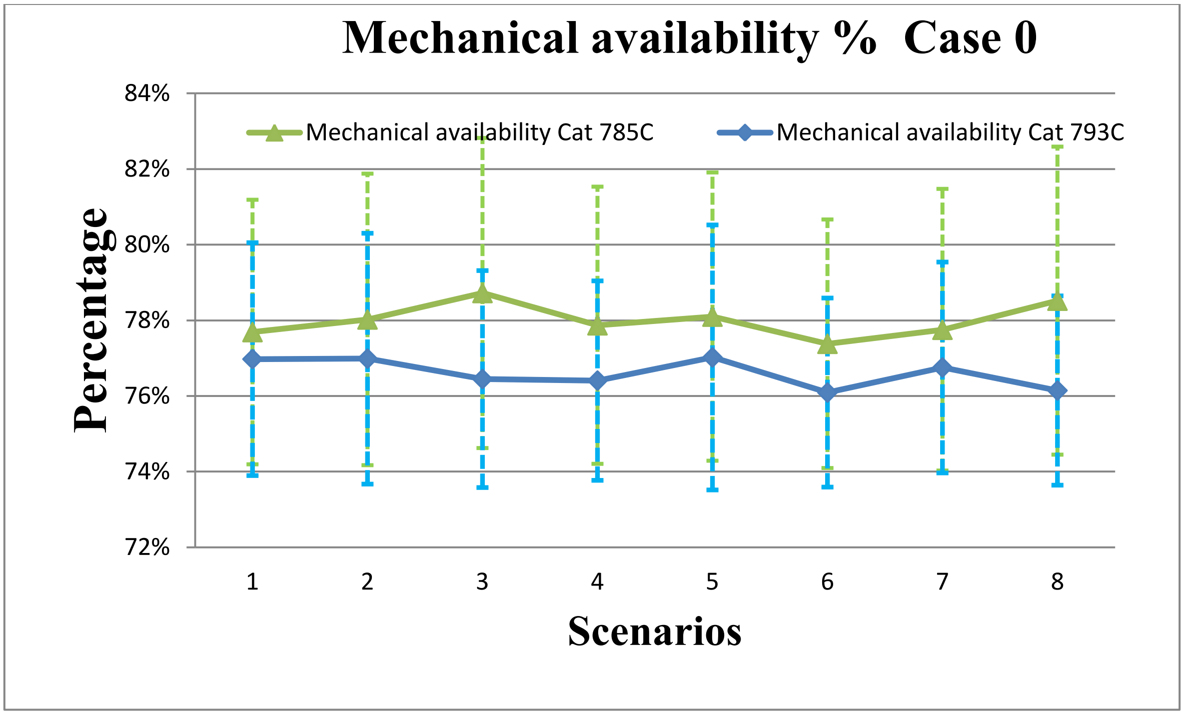

Figure 63.Truck Mechanical availability Case 0

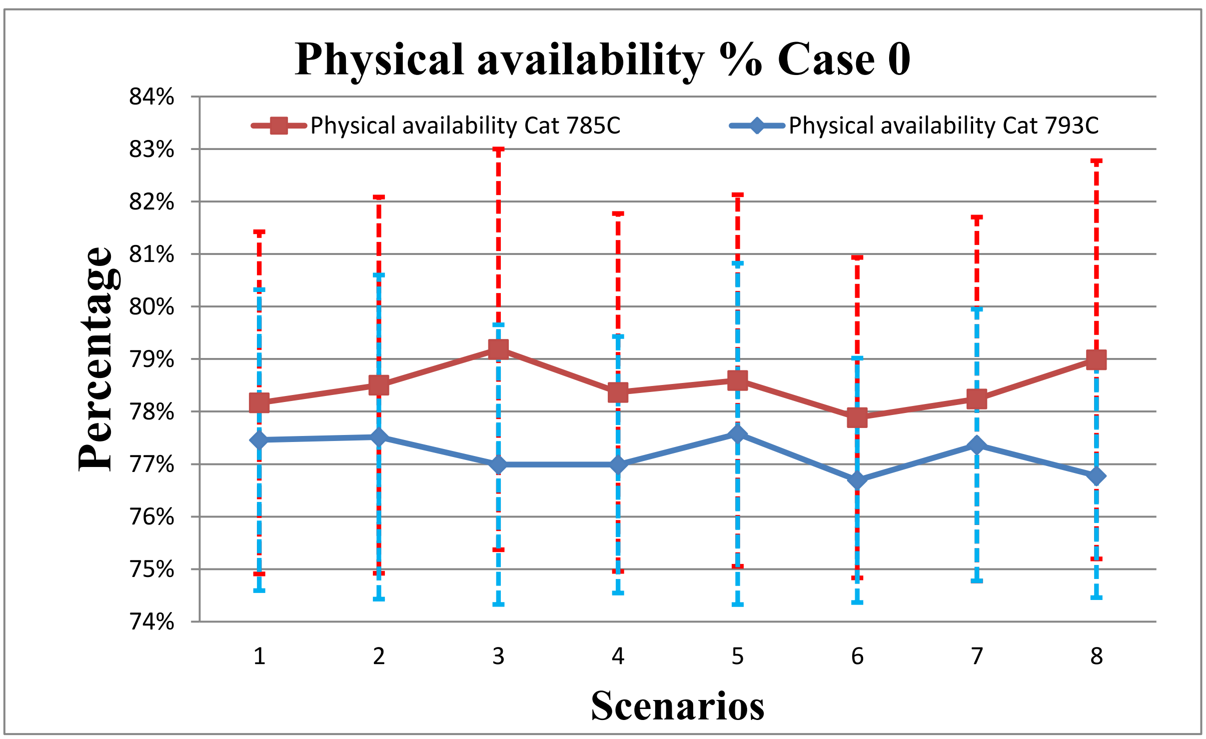

Figure 64.Truck Physical availability Case 0

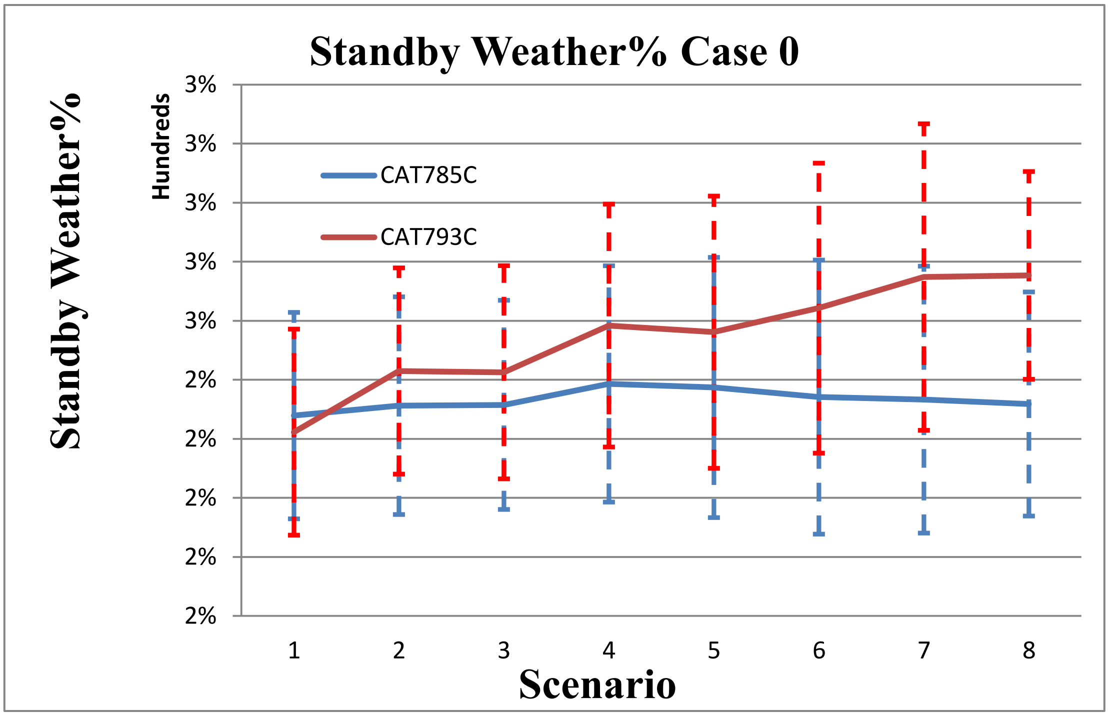

Figure 65.Truck Standby Weather Case 0

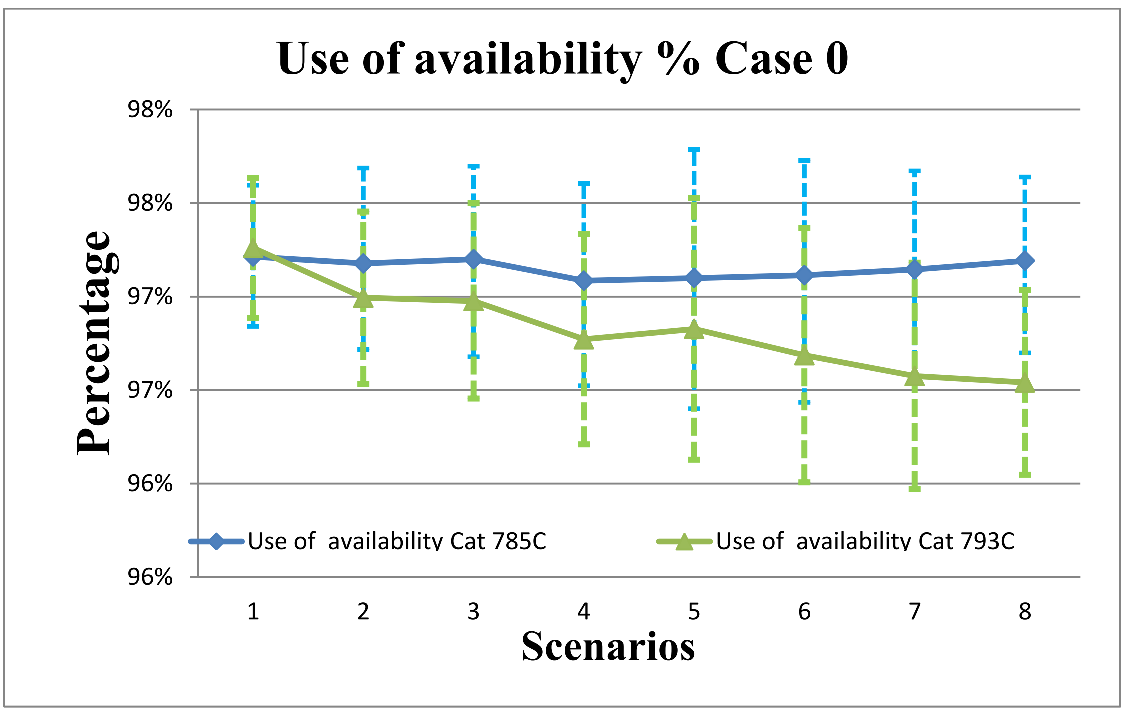

Figure 66.Truck Use of availability Case 0

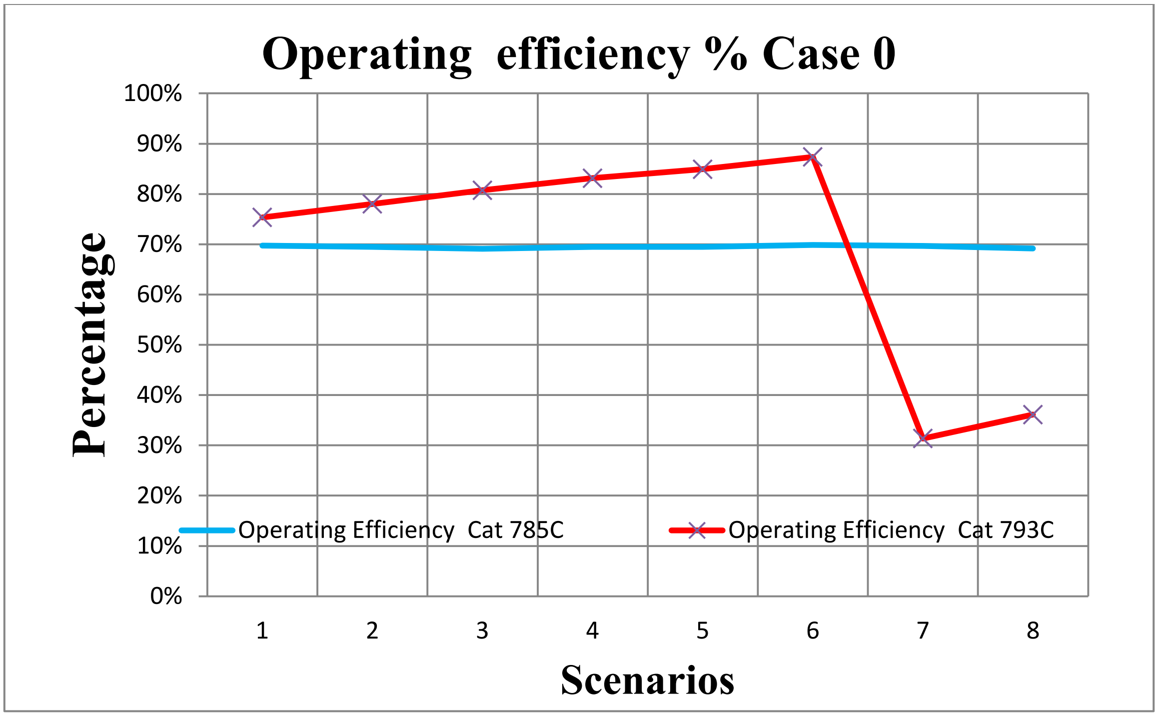

Figure 67.Truck Operating efficiency Case 0

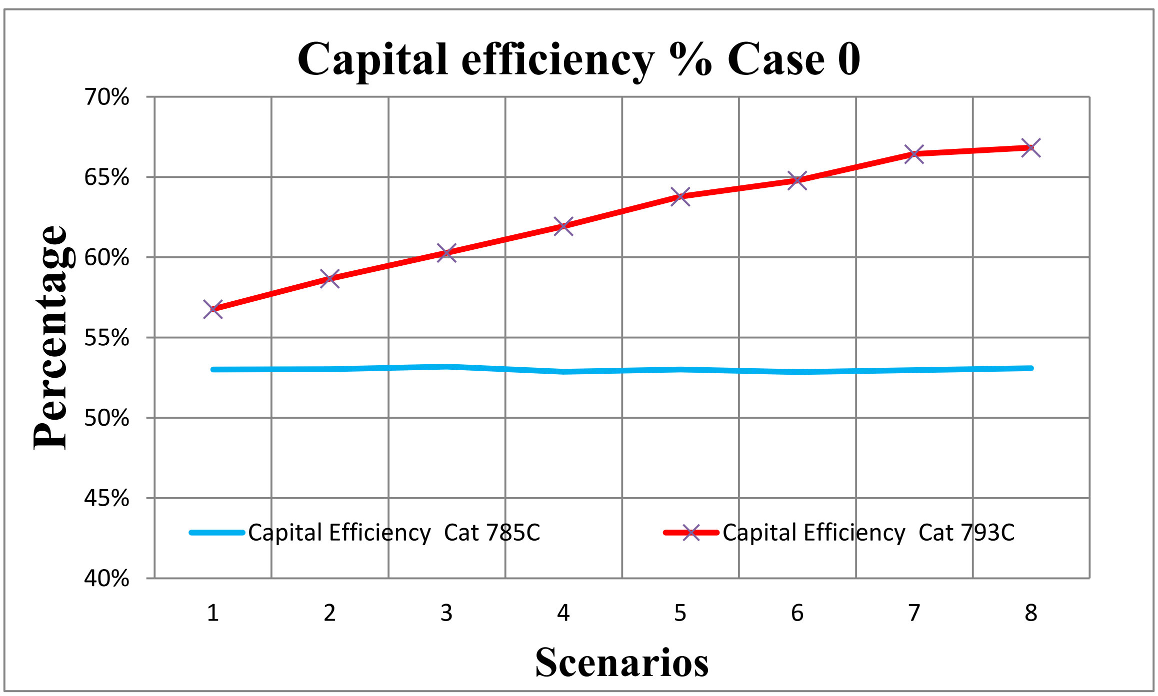

Figure 68.Truck Capital efficiency Case 0

4.6.5. Best case scenario Case 0.

Finding the right set of trucks for the schedule given, is not only limited to meet the target tonnage. It also requires acceptable KPI's of time, efficiency and availability categories for every equipment. The last categories, as it has been mentioned, are assumed in this research as KPI's to meet between an adequate range. KPI's has been calculated by shovel and truck type in order to account for both of them when it comes to make a decision. In Figure 69, ore and waste production can be seen along with capital efficiency for both truck and shovel. Main highlights are: scenario 8 meets the waste production satisfactory, however the ore production is higher than what it is required, capital efficiency for ore shovel and trucks remains the same 85 and 55%, capital efficiency for waste trucks increase to almost 70%, while for shovel decrease to 45%, through scenarios. Figure 70, shows under the same format tonnage with operating efficiency of shovel and trucks. Ore fleet operating efficiency shovel and truck also remains constant 99% and 70%,but shovel waste decreases up to 50% and trucks waste increases almost to 70%.Finally, more explanation is found studying the delays of both equipment's, Figure 71, shows the information of the hanging time for shovel, and the queue time for truck , also along with the ore and waste tonnage. Following the same trend that characterized the behavior of operating and capital efficiency, delay for ore shovel and truck remains constant in all the scenarios, as no change in the number of trucks is observed. In addition, shovel delay for Hi 5500Ex, changes from 10 to 40%, while trucks waiting time decreases from 20 to 8%. Although Ore tonnage schedule is to reached yet and Kip's still can be improved, the best scenario is number 8, which meet the waste movement with descent capital and operating efficiency.

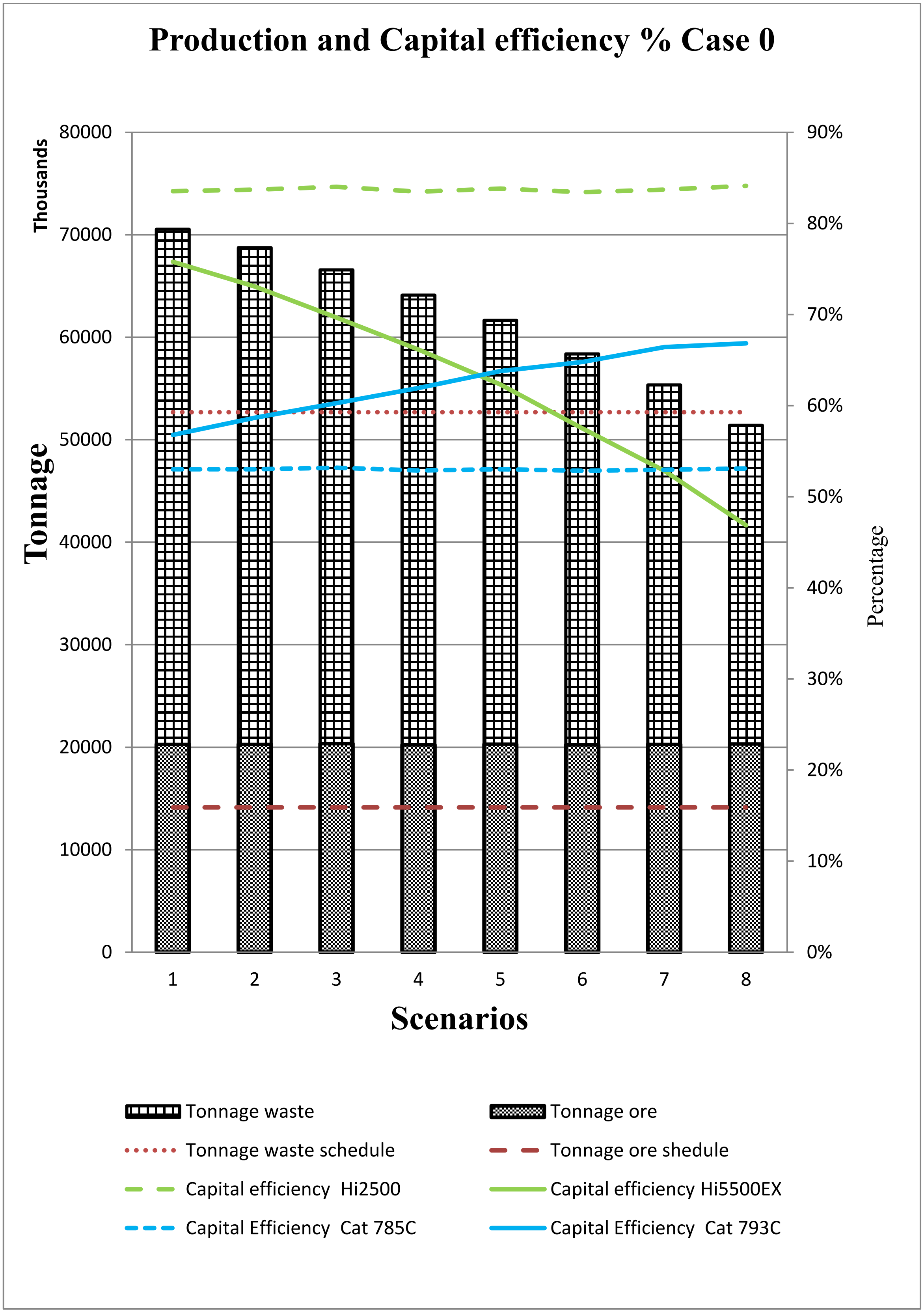

Figure 69.Production and equipment capital efficiency Case 0

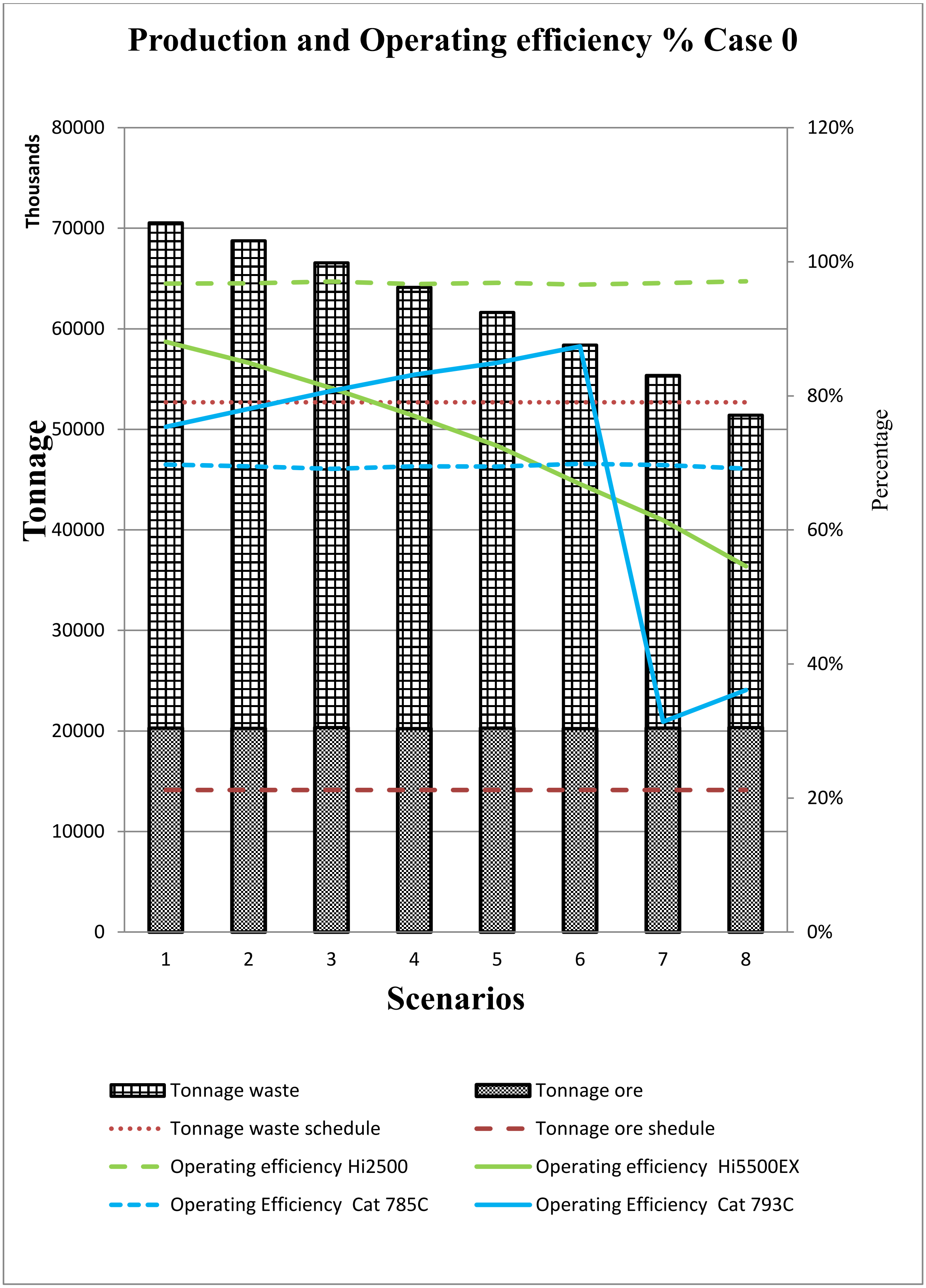

Figure 70.Production and Operating efficiency Case 0

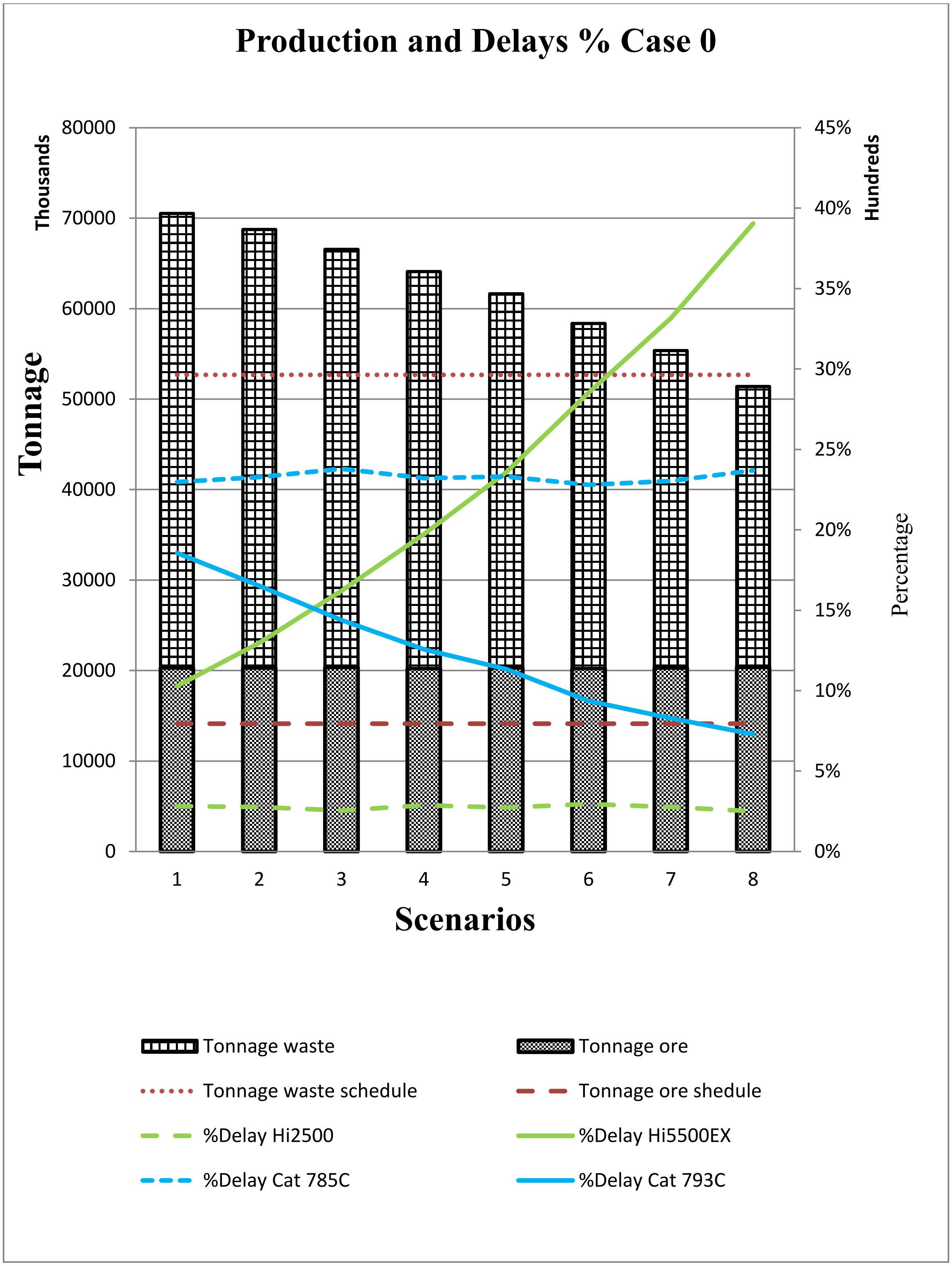

Figure 71.Production and delays Case 0

4.7. Case 1. Decreasing number of ore trucks CAT 785C in an interval of 2, 8400 ton/h rate at both crushers and 8400-ton capacity at both crushers

Different scenarios with variation of the size of ore trucks fleet, Cat 785C, are studied. In order to end with an appropriate number of trucks that meets the ore production with a good balance of KPI’s previously mentioned. Cat 785C fleet will be decreased in intervals of 2. After analyzing the outcomes, the best case scenario will be taken from Case 1, as input to Case 2, and it will be called base case. Base case in this Case 1, is the last from Case 0, scenario 8, 27 ore trucks and 15 waste trucks.

4.7.1. Tonnage KPI's Case 1

As number of trucks decreases for Cat785C fleet so does the ore tonnage. Figure 72 shows that information scenario by scenario. Desired ore tonnage is found in scenario 7; however, waste tonnage is not met. Waste fleet remains the same at 15 truck.

Table 18. Scenarios Case 1

	Scenario1	Scenario2	Scenario3	Scenario4	Scenario5	Scenario6	Scenario7
Cat785C	27	25	23	21	19	17	15
Cat793C	15	15	15	15	15	15	15
Total fleet	42	40	38	36	34	32	30

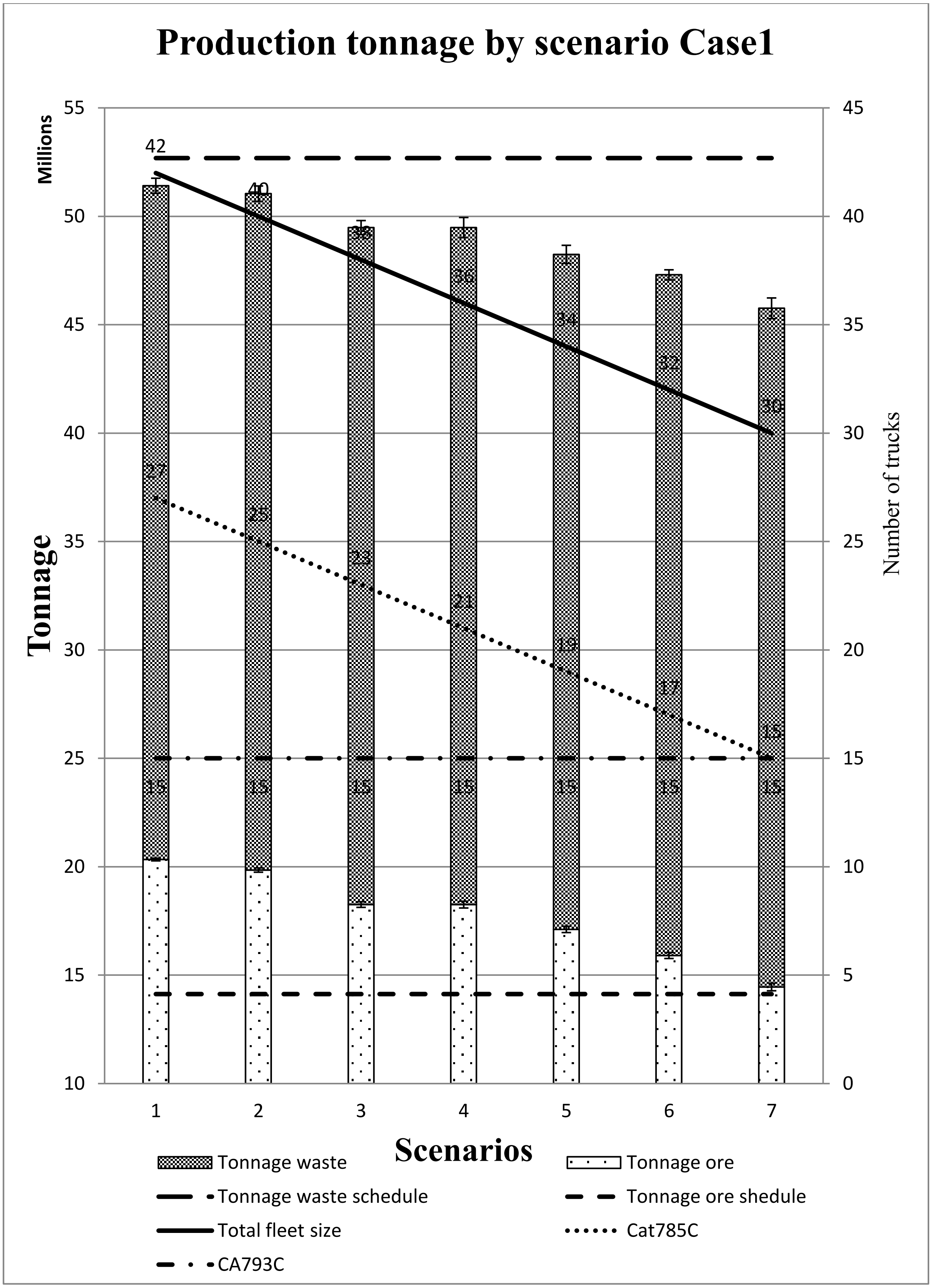

Figure 72.Production tonnage Case 1.

4.7.2. Queues and averages KPI's times

As less ore trucks are in the system average cycle time for Cat 785C, also is less than from 12 minutes to around 3 minutes. Waste fleet average cycle time remains around 2 minutes. This information is found in Figure 73.Considering the waiting time in queue at their respective shovel, Figure 74, the average waiting time decreases by 10 minutes for Cat 785C, as scenarios with less ore truck are included. Average waiting time for Cat 793C fleet remains the same. Although average waiting queue time at the dump, Figure 75,presents very negligible time variation for both truck type, it can be noticed a slight drop in the average waiting time for ore trucks at the dumps, correspondent to the fact that less trucks are involved as scenarios are included for this fleet. Additional information about each shovel and dump waiting time Figure 78 and Figure 79.

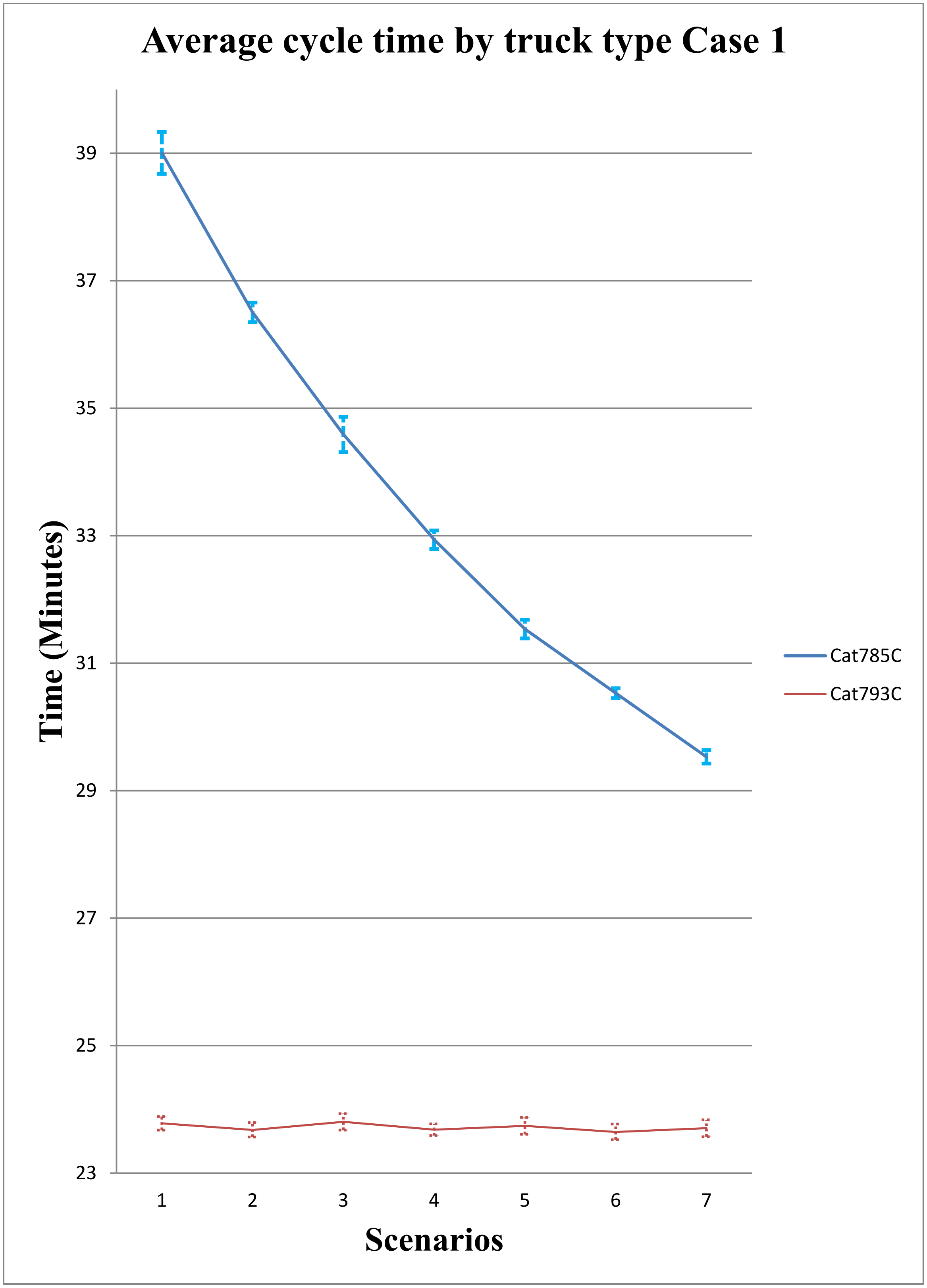

Figure 73.Average cycle time at the shovel by truck type minutes Case 1

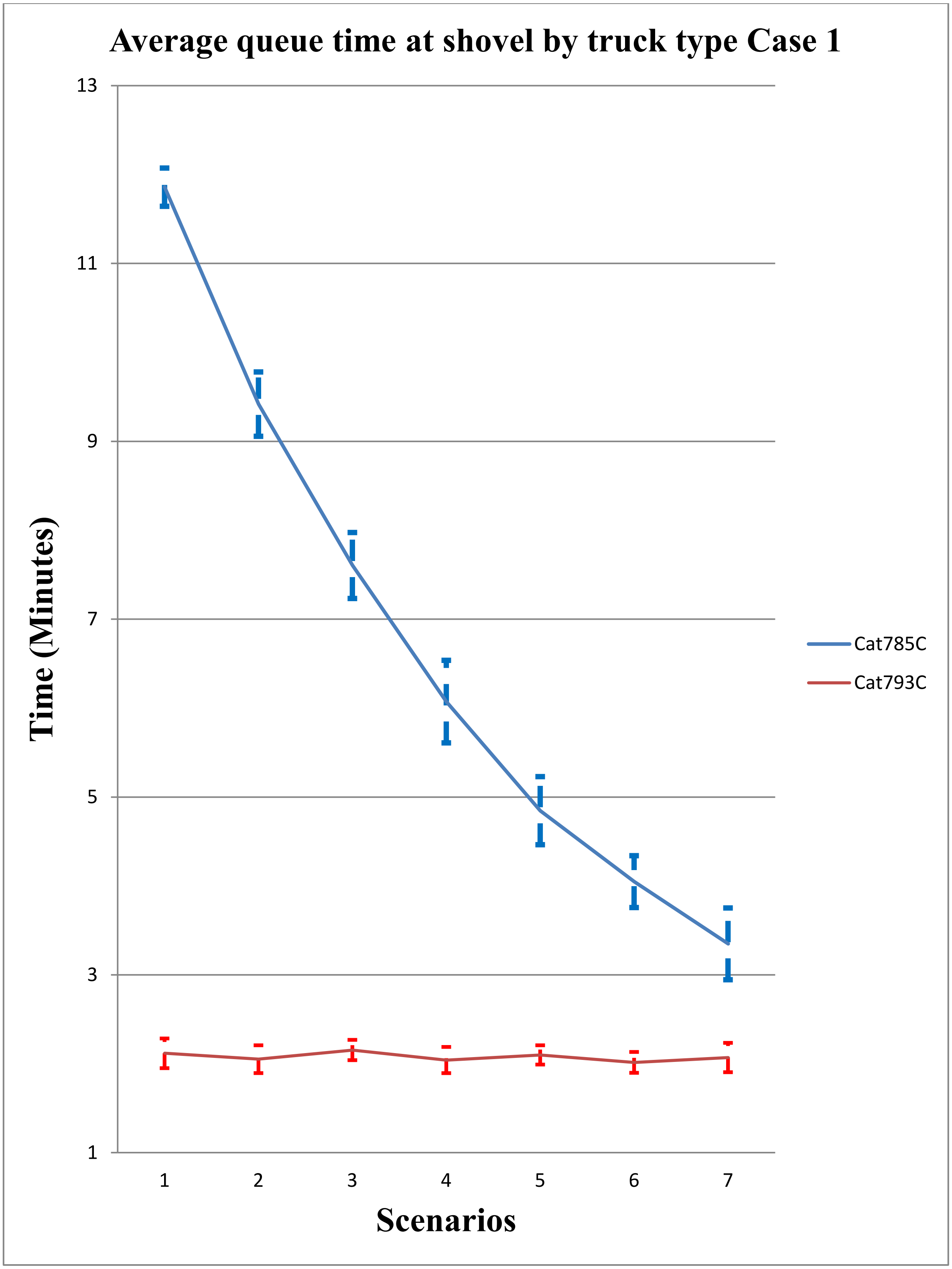

Figure 74.Average queue time at shovel by truck type minutes Case 1

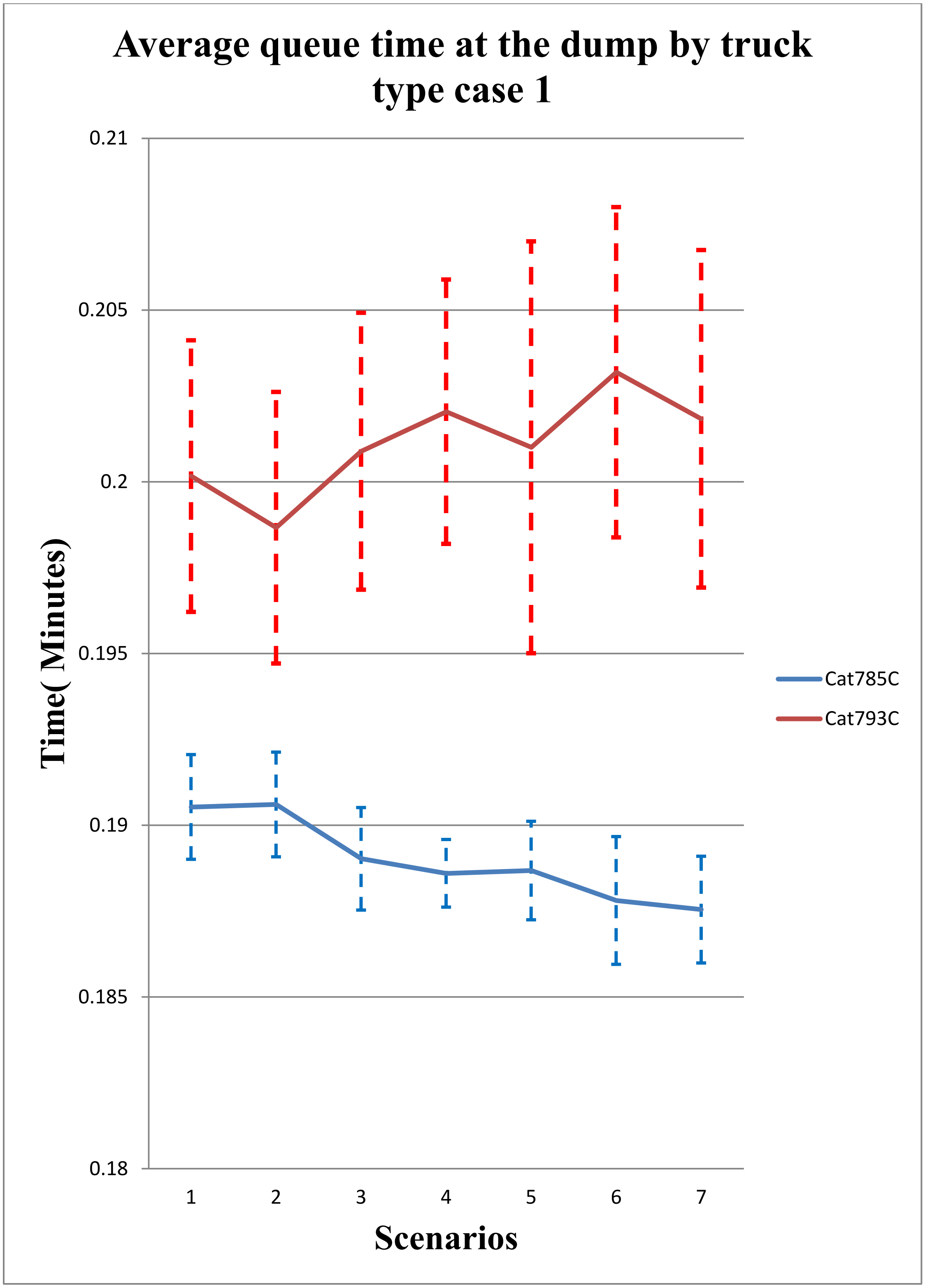

Figure 75.Average queue time at dump facility by truck type minutes Case 1

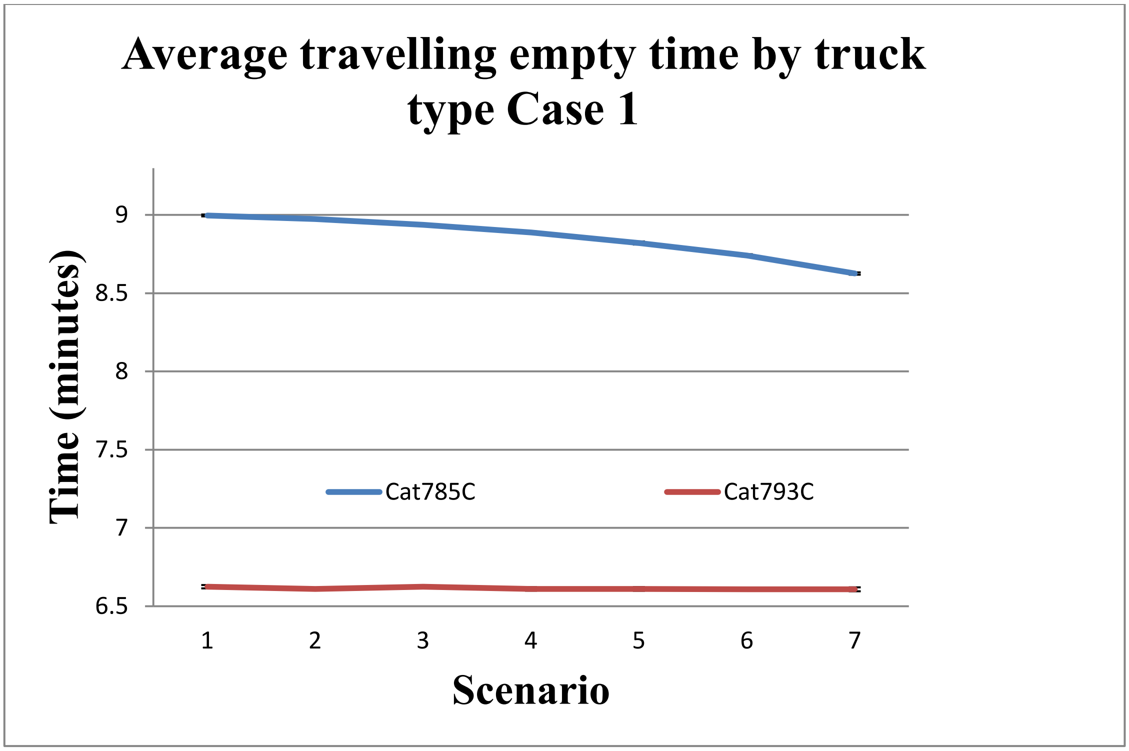

Figure 76.Average travelling empty time by truck type in minutes Case 1

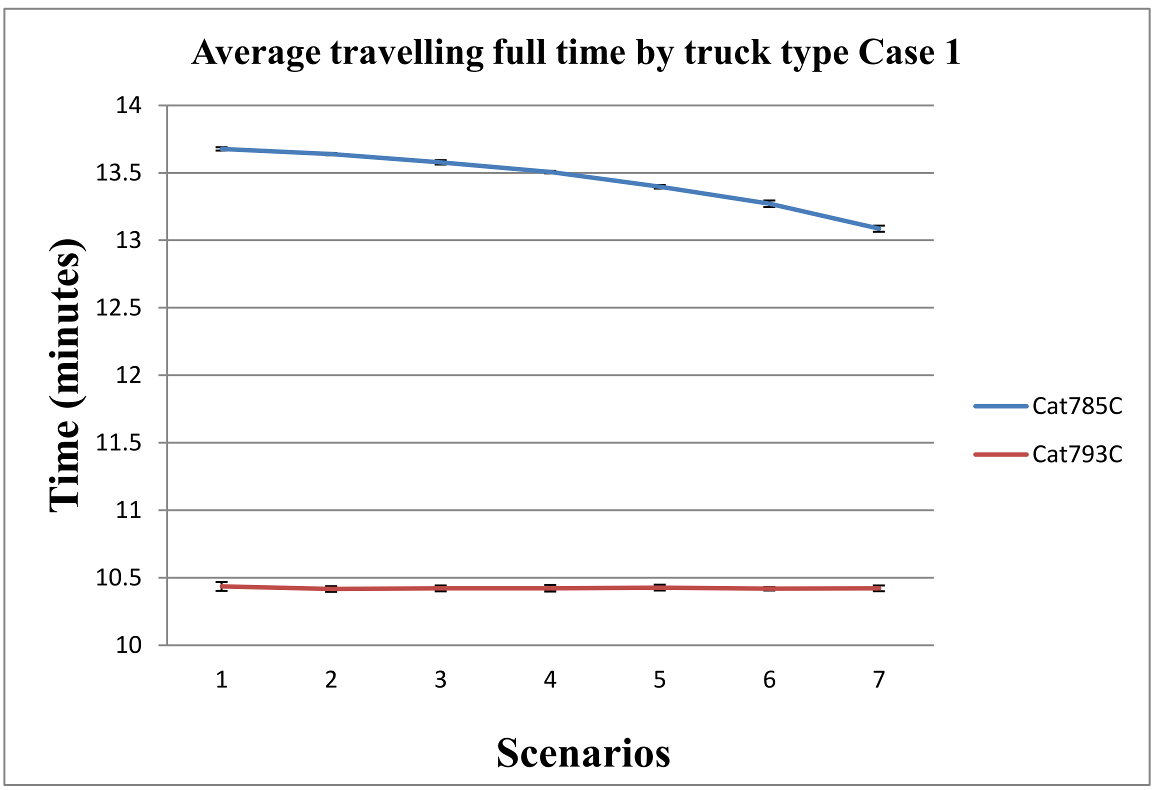

Figure 77. Average travelling full time by truck type in minutes Case 1

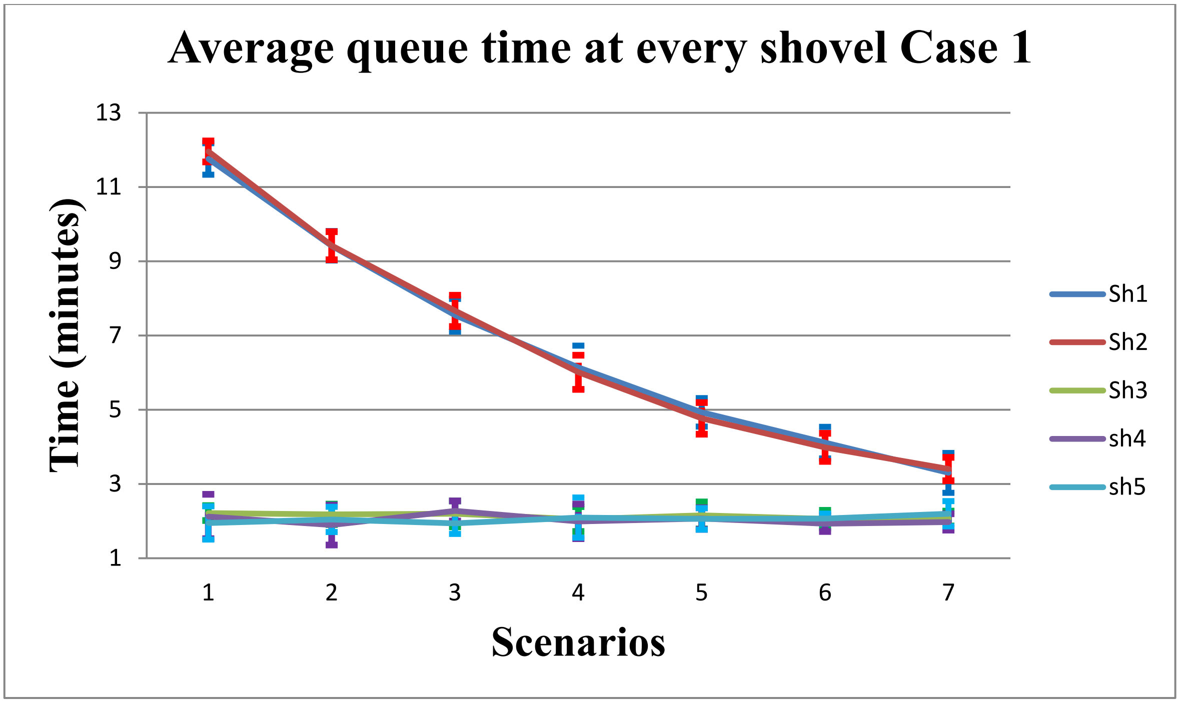

Figure 78.Average queue time at every Shovel Case 1

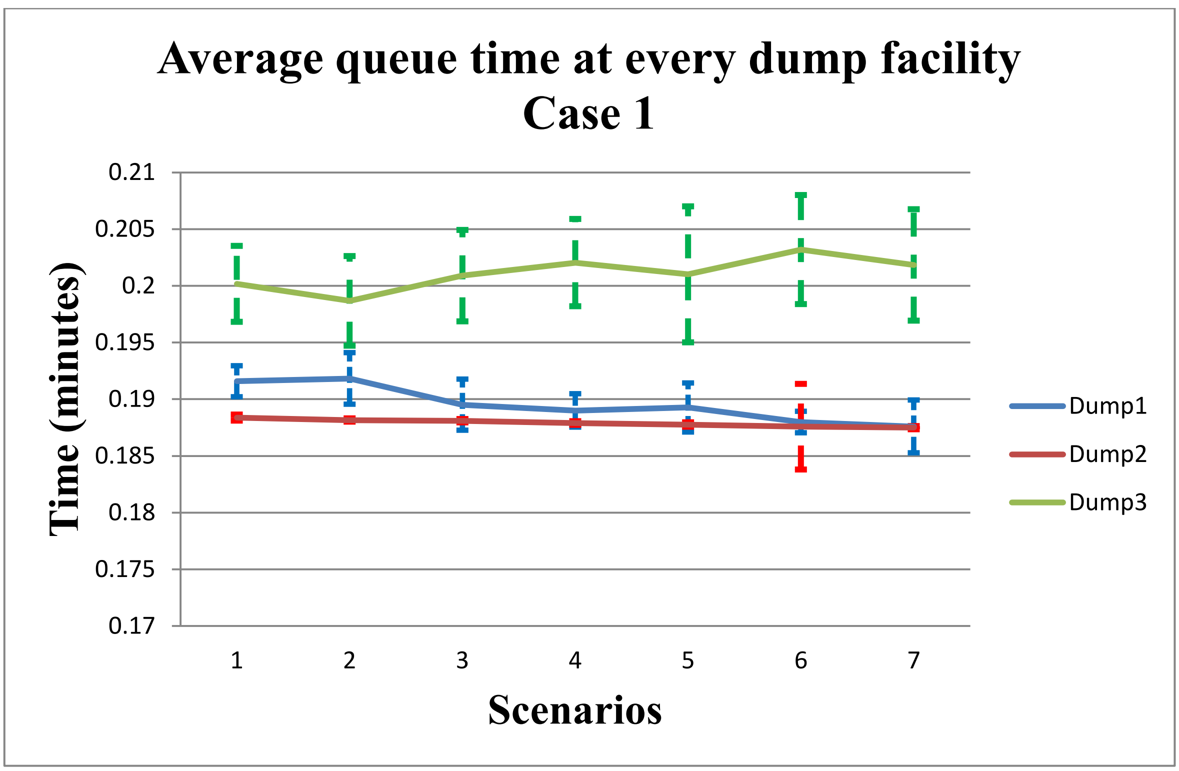

Figure 79. Average queue time at every Dump Facility Case 1

4.7.3. Shovel time category KPI's

Percentage of yearly work hours, remains constant for waste fleet, while it drops from 86% to 74% for the ore fleet as in Figure 80. Also NOH for ore shovels goes down as the number of trucks is reduced until 2000hr. NOH for waste remains also at 2000 hr., Figure 81 outlines that information. Shovel hang time, described as delays, is explained in Figure 82.Accordinly, waste shovel waiting time remains around 40%, while for ore shovels increases to 25% due to less ore trucks in the system.

The material hauled by gross operating hours, Figure 83, from each shovel, is always more from waste shovels because the bucket size of waste shovels is larger. However, for both ore and waste shovels the general pattern is remaining constant. In down-time % topic, described in Figure 84,also an erratic pattern is described ore shovel down-time% is always above waste shovel down-time%. The use of availability for ore shovels is more than 6% for waste trucks. The tendency of use of availability % can be explained by Figure 88.It can be observed a relationship when the stand by line is not less than 10.5%, the use of availability% remains , but when standby weather% goes beyond this value it decreases for Hi 2500 but slightly rises for Hi5500EX.

Operating efficiency and capital efficiency, in Figure 85 and Figure 86, also share the same behavior , decreasing for ore shovels and remaining constant for waste shovel , throughout the scenarios as number of ore trucks is lesser.

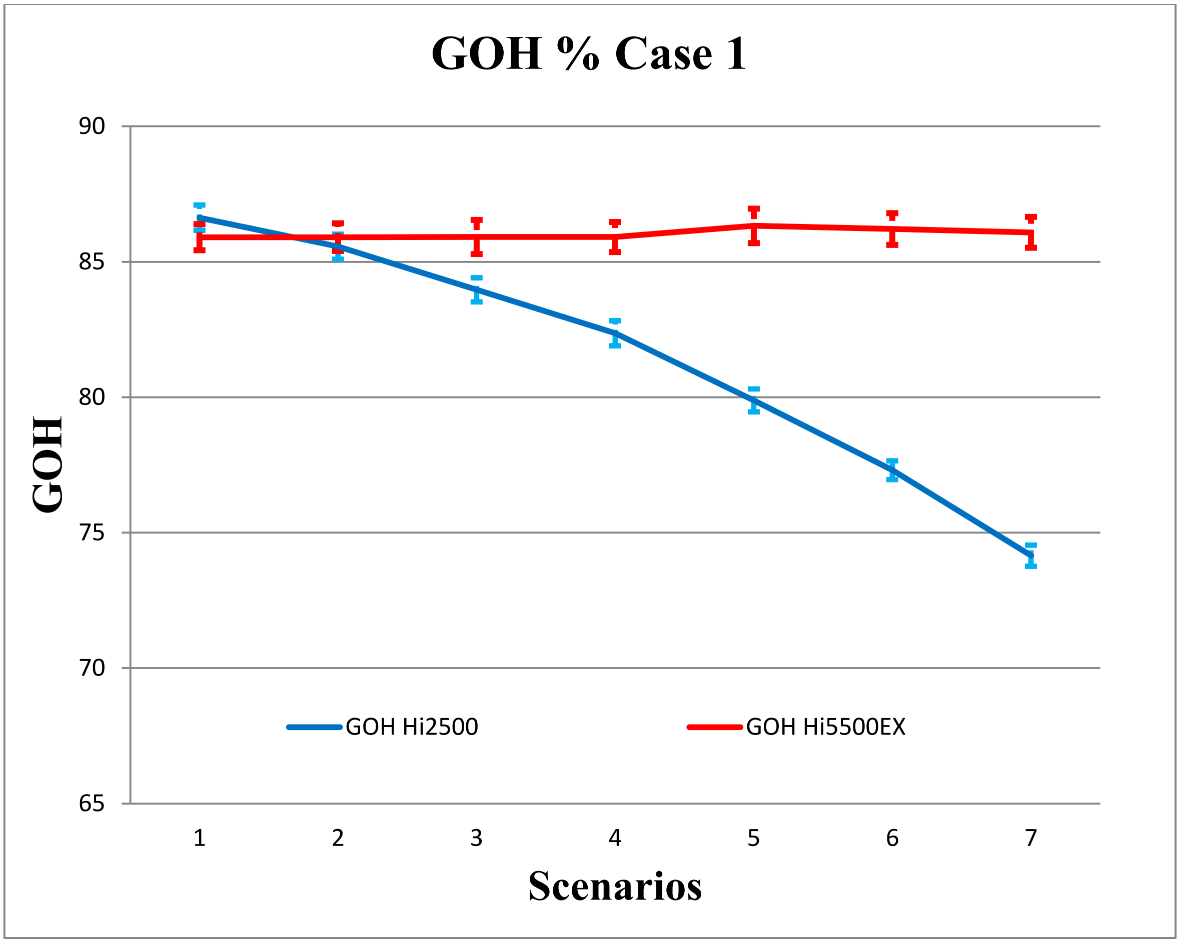

Figure 80.Shovel Gross Operating hours GOH% Case 1

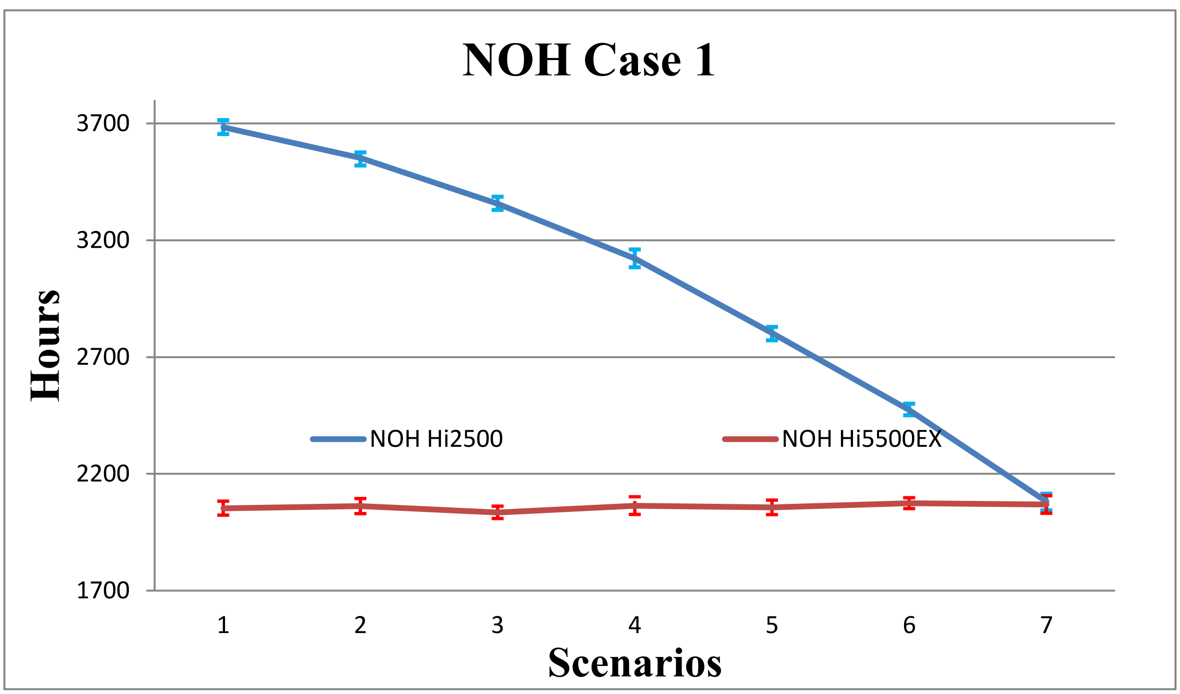

Figure 81.Shovel Net Operating hours Case 1

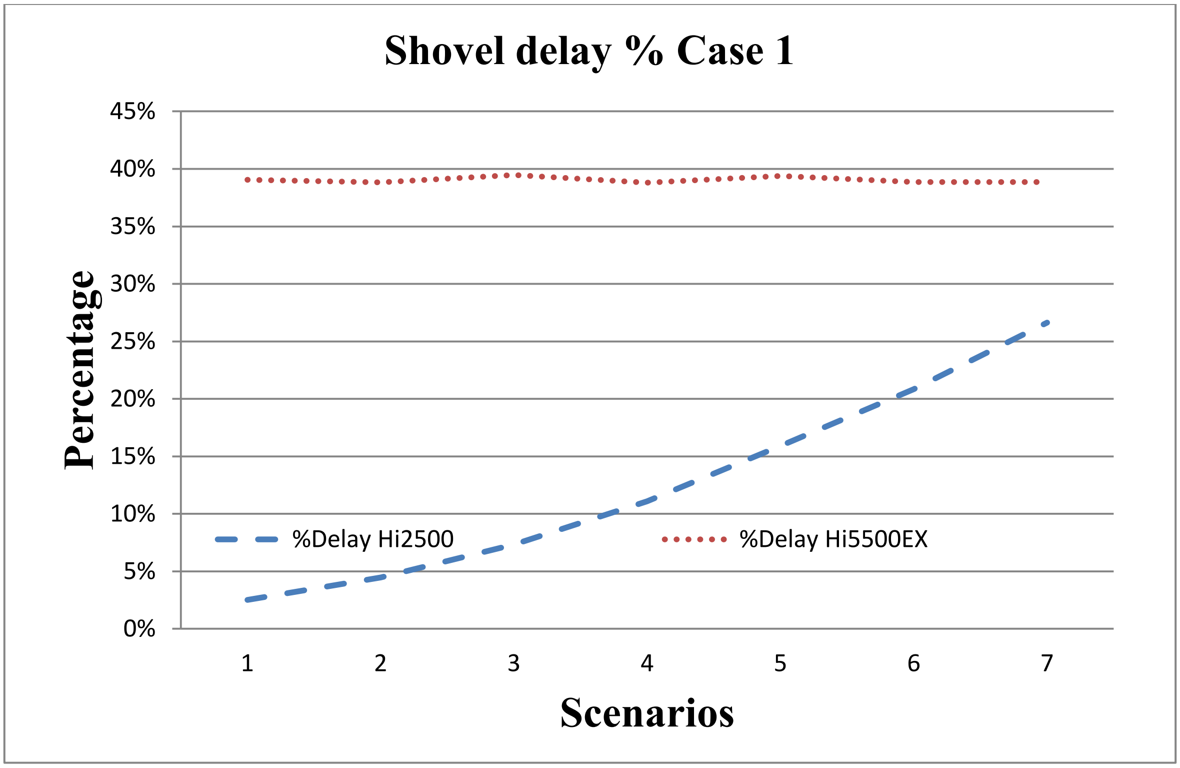

Figure 82.Shovel delays% by shovel type Case 1

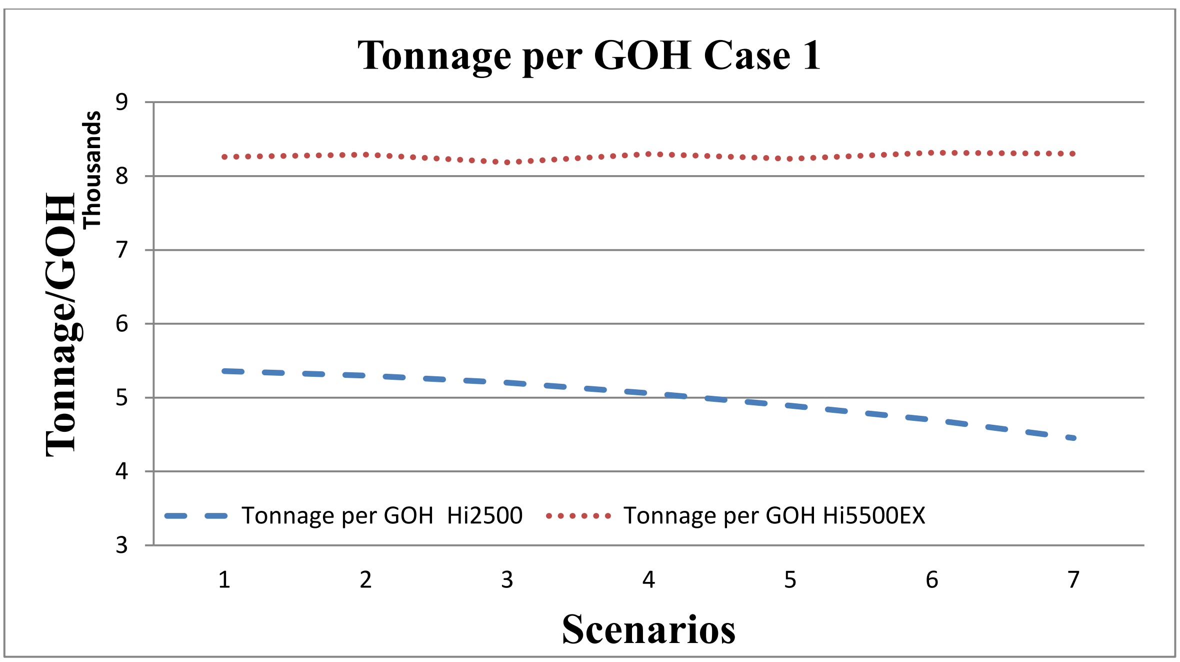

Figure 83.Shovel Tonnage per gross operating hours Case 1

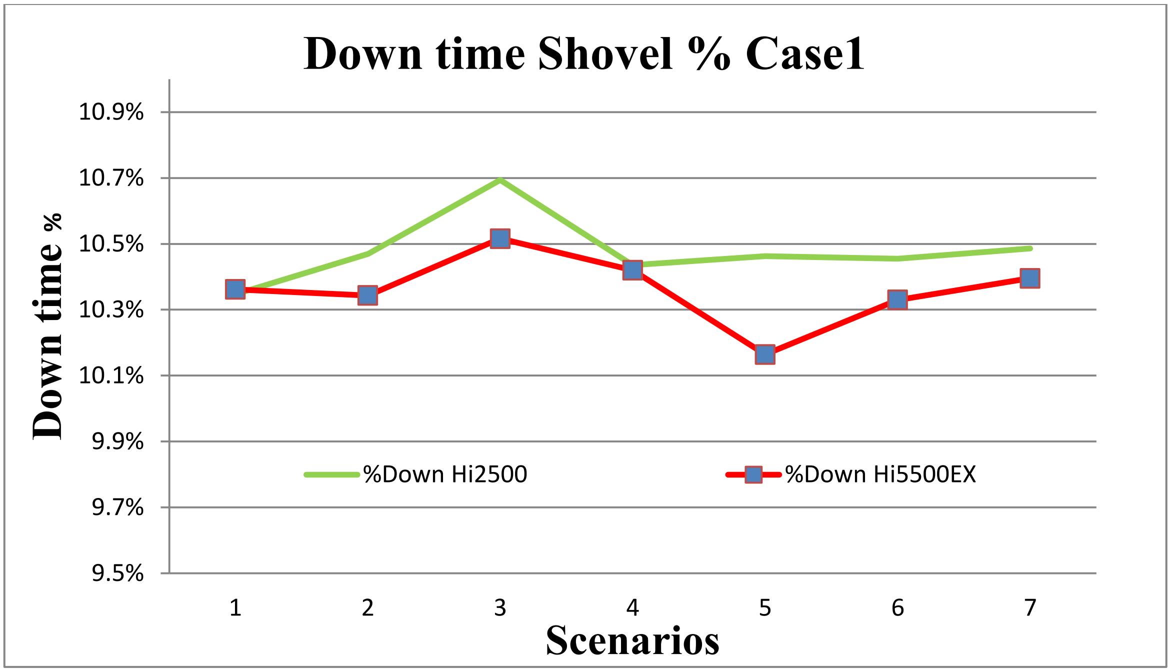

Figure 84.Shovel down time by shovel type Case 1. (PM AND FAILURE).

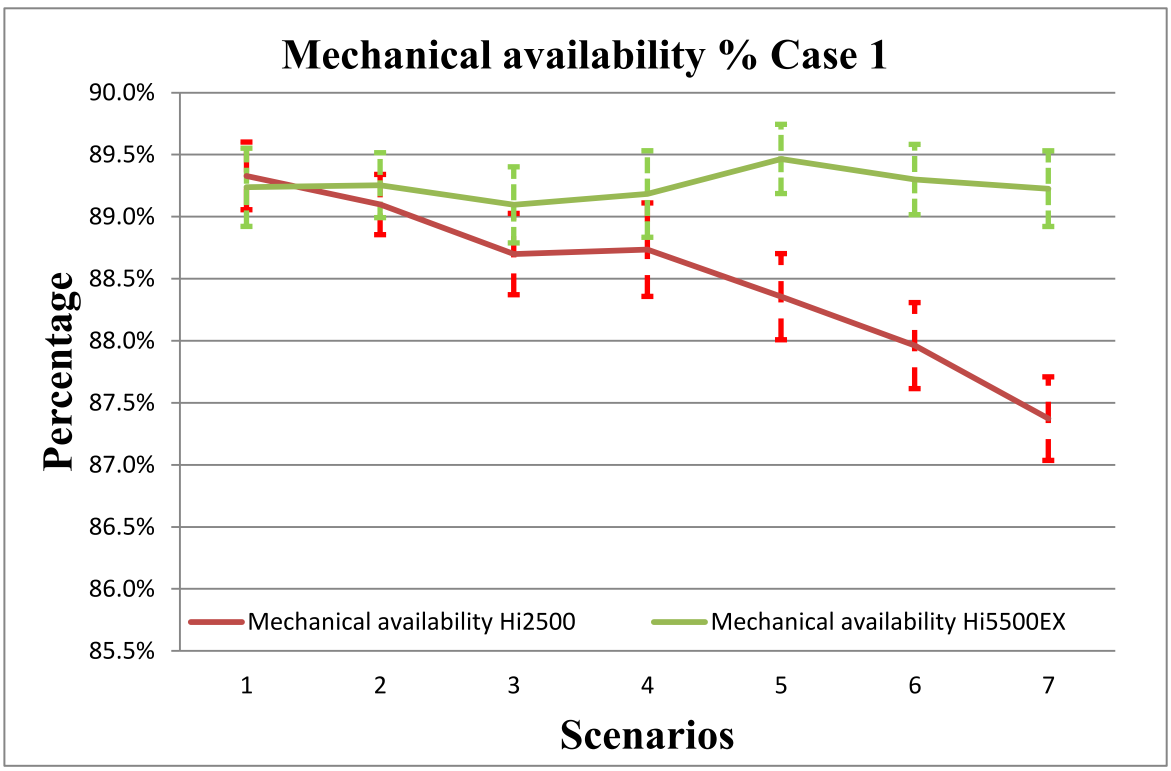

Figure 85.Shovel Mechanical availability Case 1

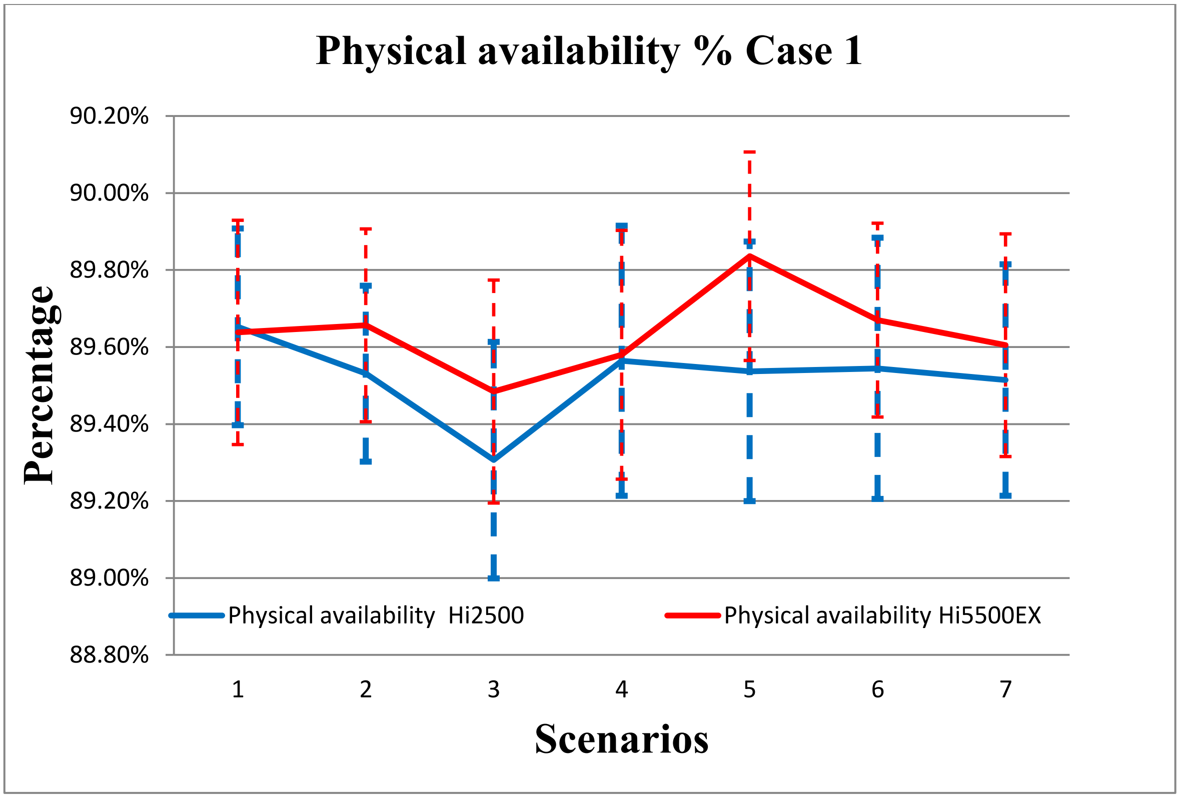

Figure 86.Shovel Physical availability Case 1

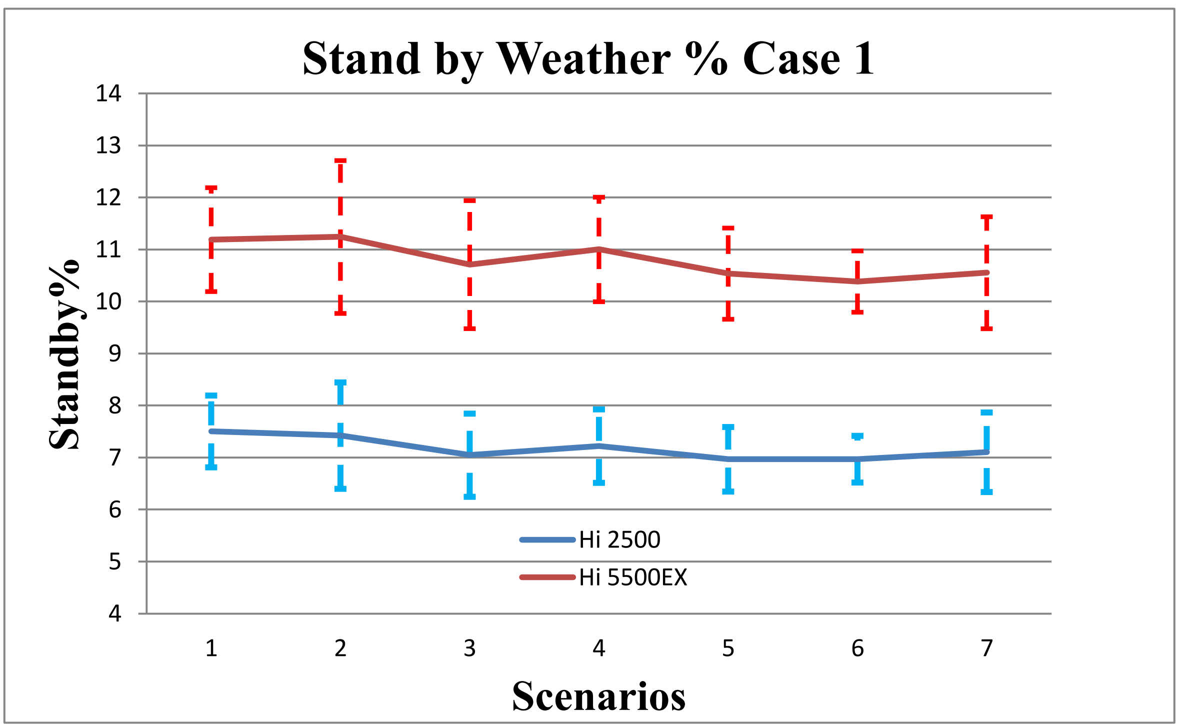

Figure 87.Shovel Stand by Weather Case 1

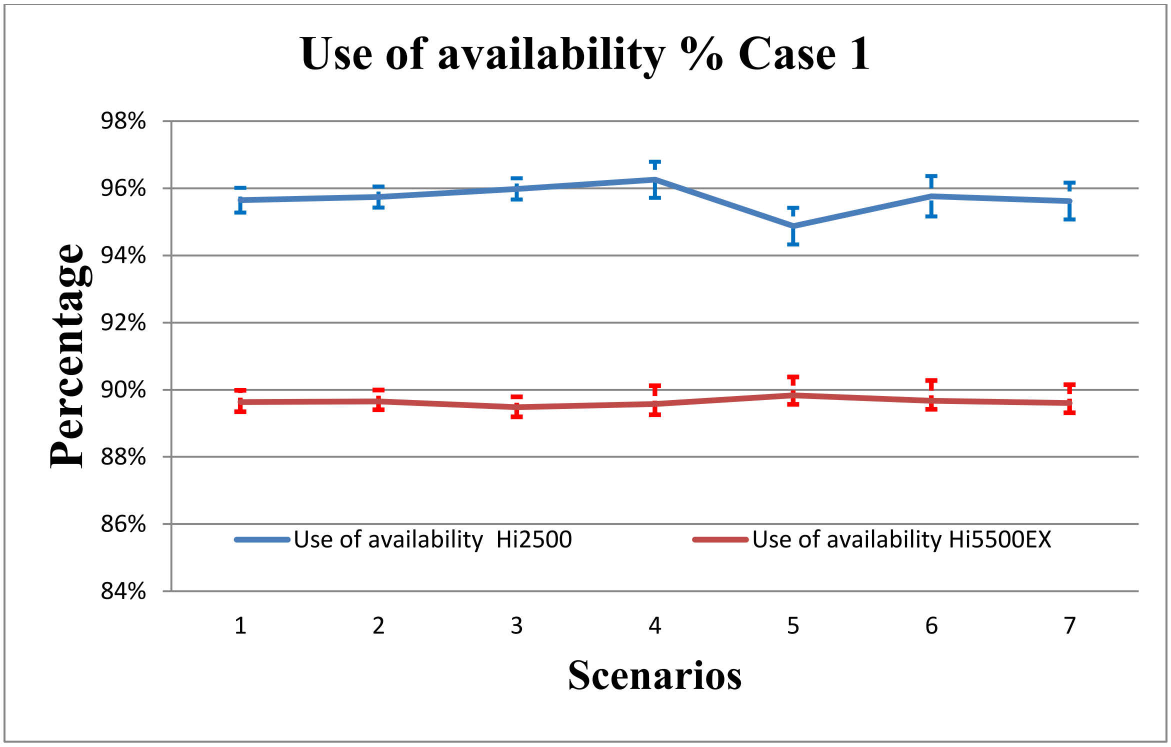

Figure 88.Shovel Use of availability Case 1

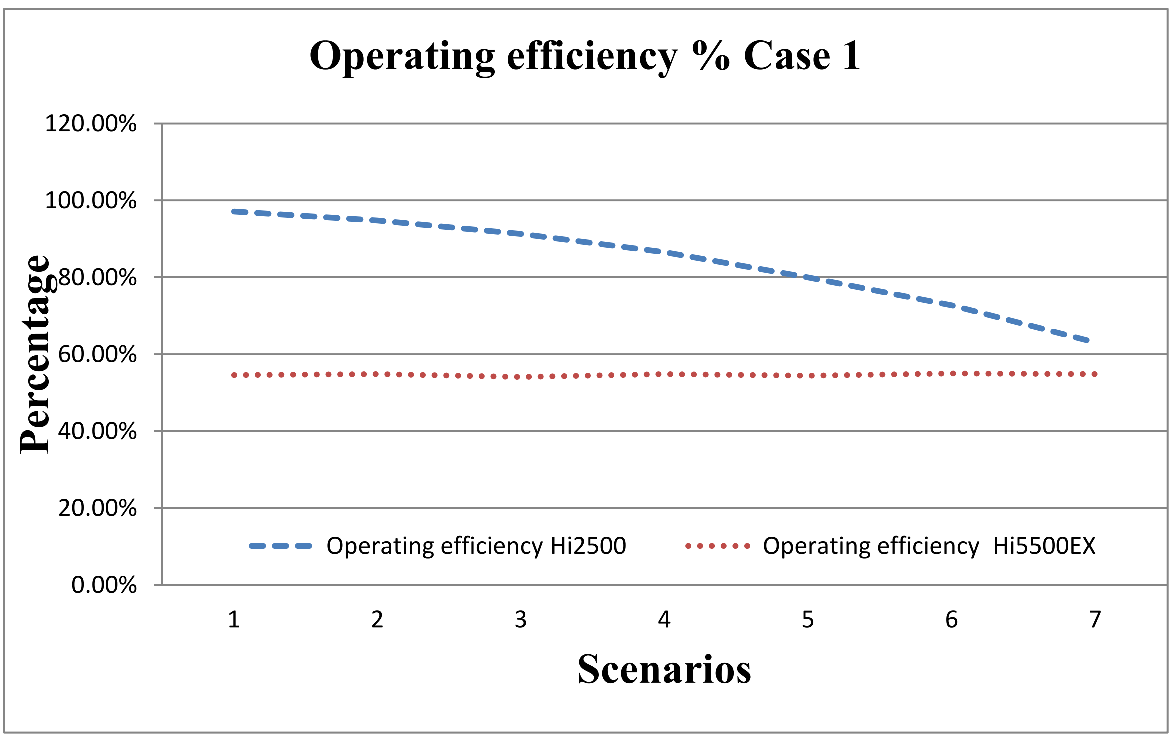

Figure 89.Shovel Operating efficiency Case 1

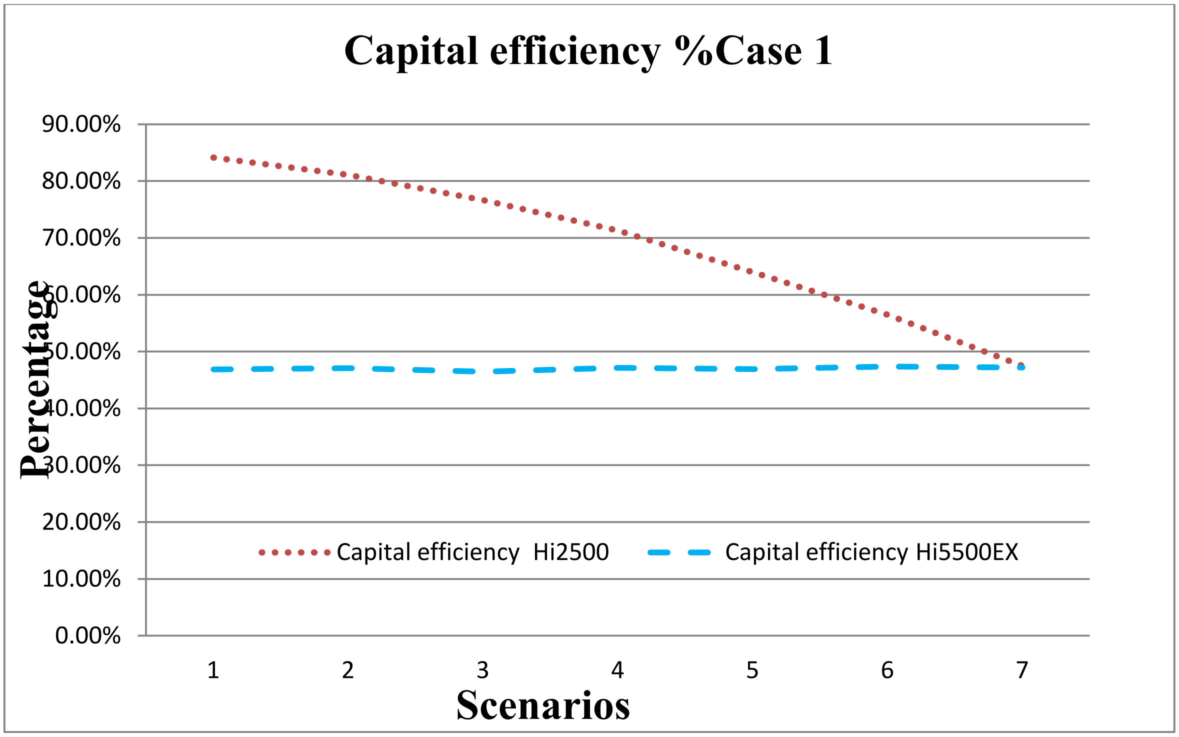

Figure 90.Shovel Capital efficiency Case 1

4.7.4. Truck Time category KPI's

Regarding of truck efficiency, KPI's are analyzed. Figure 91, informs that the percentage of GOH for Cat 785C, ore trucks goes down in about 2%,while waste trucks GOH% remains at 74% through all scenarios. Figure 92, shows that NOH for Cat785C levels up from 2300 to 2900 hr, with the less number of truck and waste trucks NOH is always 2900hr.The last trends are explained with the truck delays in Figure 93, where also for waste trucks is constant at 7% delays and ore trucks delays decrees from 24 to 8% which allows NOH also level up. Haulage tonnage by gross operating hours is also more for waste truck than for ore, again due to bucket size and also less GOH for Cat 793C, shown in Figure 94.Down time %, which is calculated with PM and failures, in Figure 95 is about 23% for Cat785C in all the scenarios for case 1 but for waste truck down time% increases from 8 to 23% in scenario 5, from where the value remains the same. Mechanical availability and physical availability, one more time have inversely proportional behaviour with down time, information is shown in Figure 96 and Figure 97.In general, use of availability is related to stand by weather %,Figure 98.Therefore,as stand by weather % goes down for Cat 785C fleet ,it will be reflected in use of availably % as an increase, Figure 99.Likewise for waste fleet.

Capital efficiency and operating efficiency, for waste trucks have grown with the decreasing of ore trucks, Figure 100 and Figure 101.outlines these information.

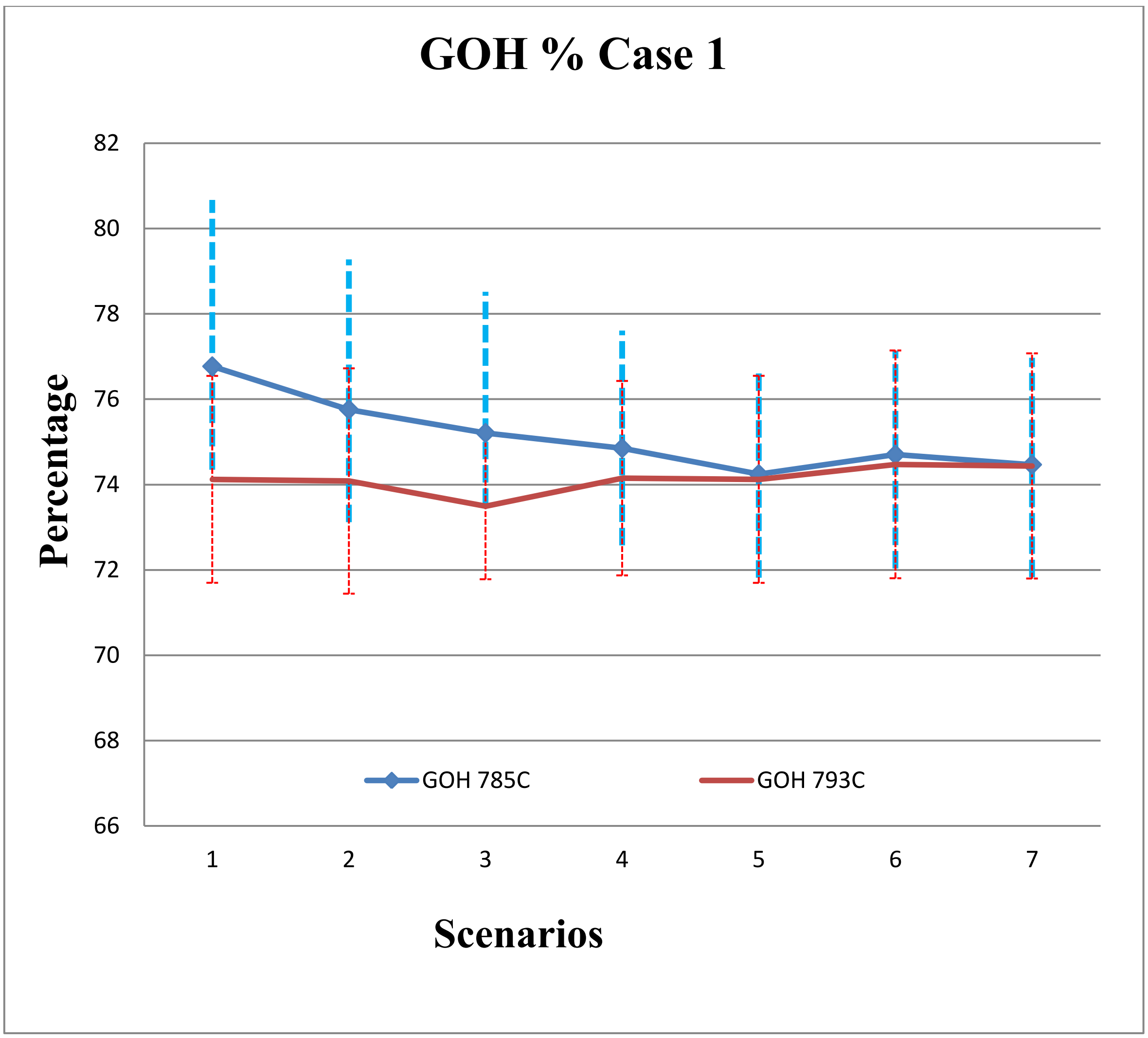

Figure 91.Truck Gross Operating hours GOH % Case 1

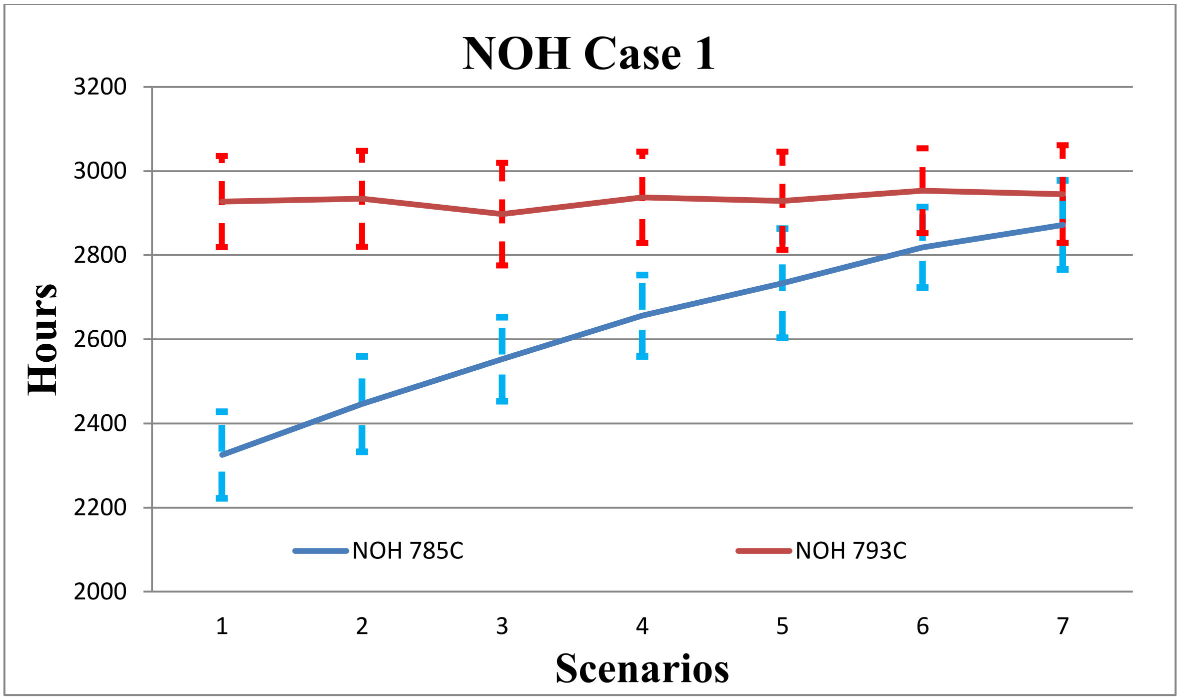

Figure 92.Truck Net Operating hours NOH Case 1

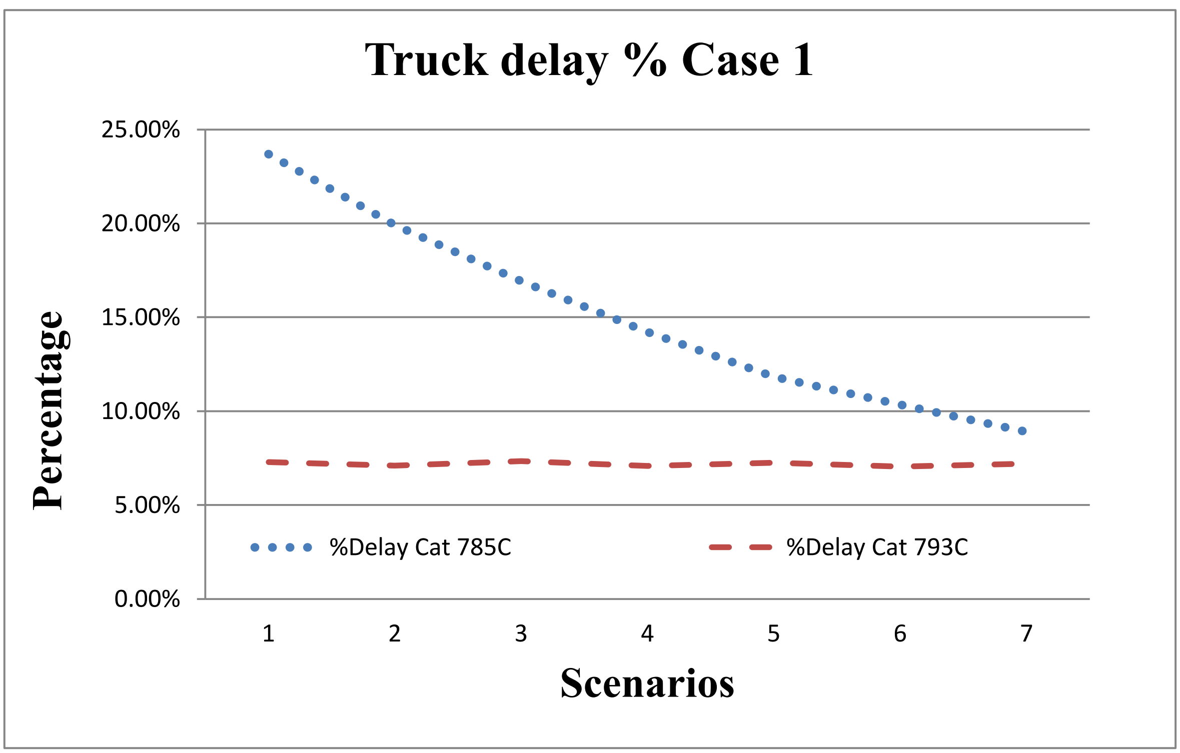

Figure 93.Truck delay% by truck type Case 1

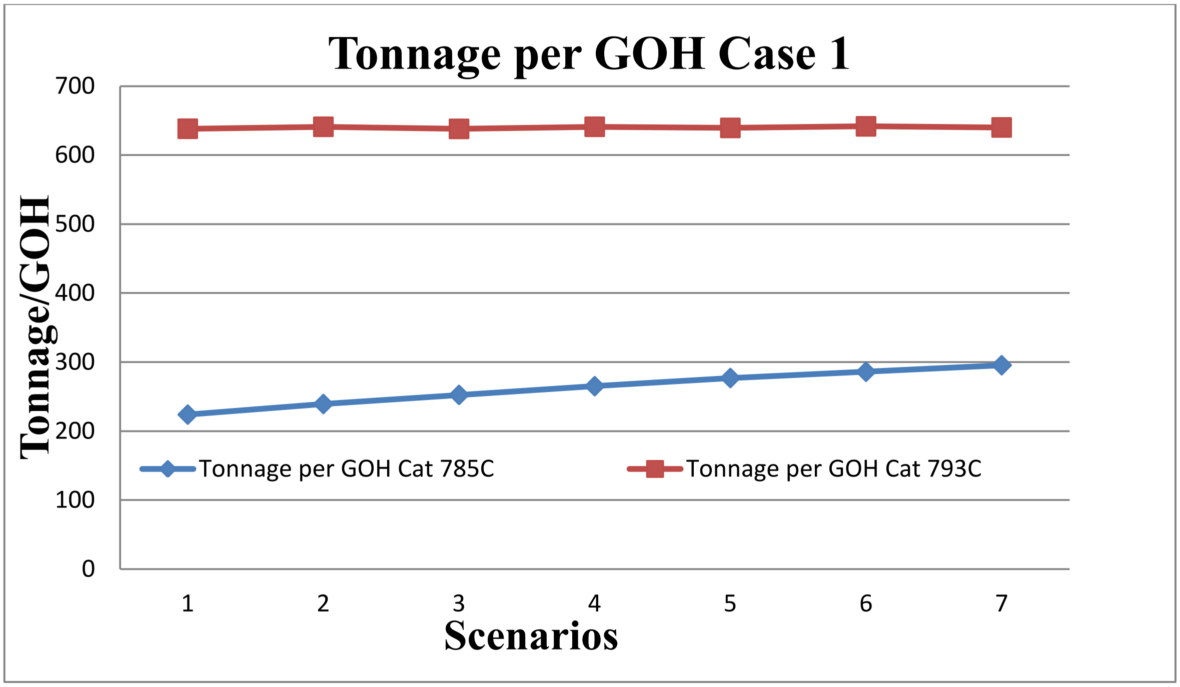

Figure 94 Truck Tonnage per gross operating hours Case 1

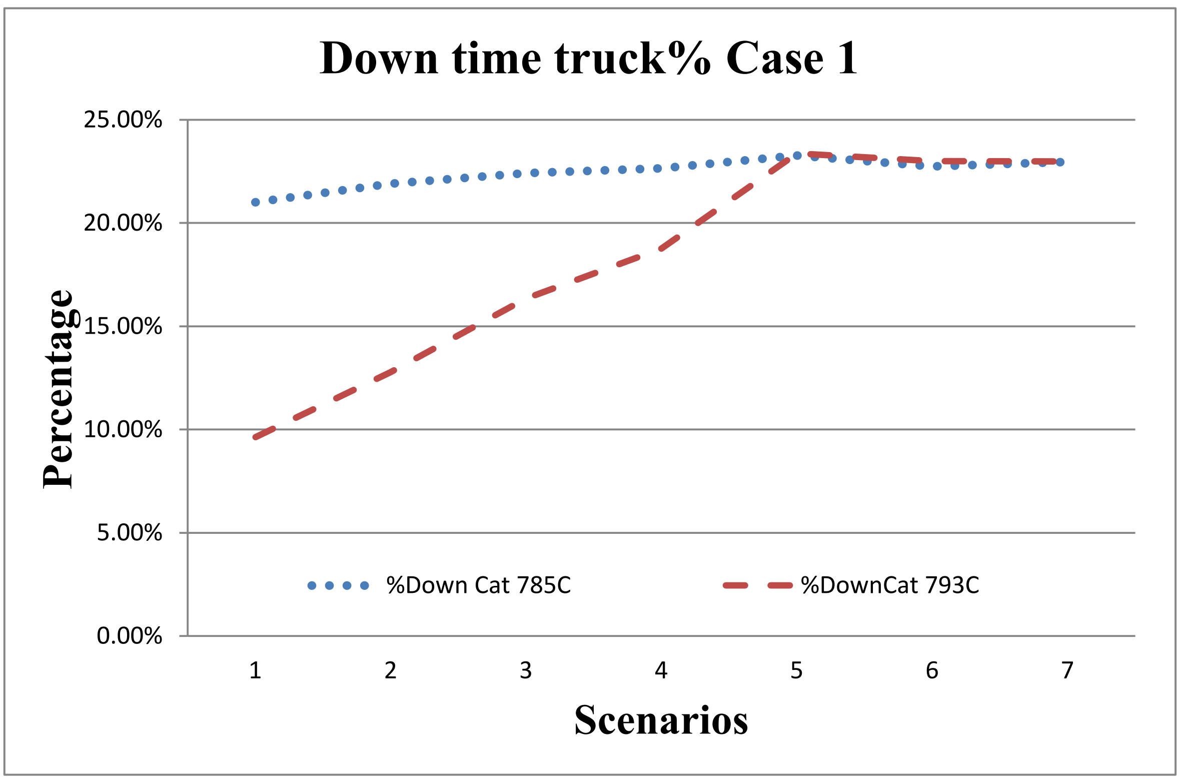

Figure 95.Truck down time % by truck type Case 1 (DOWN AND FAILURE)

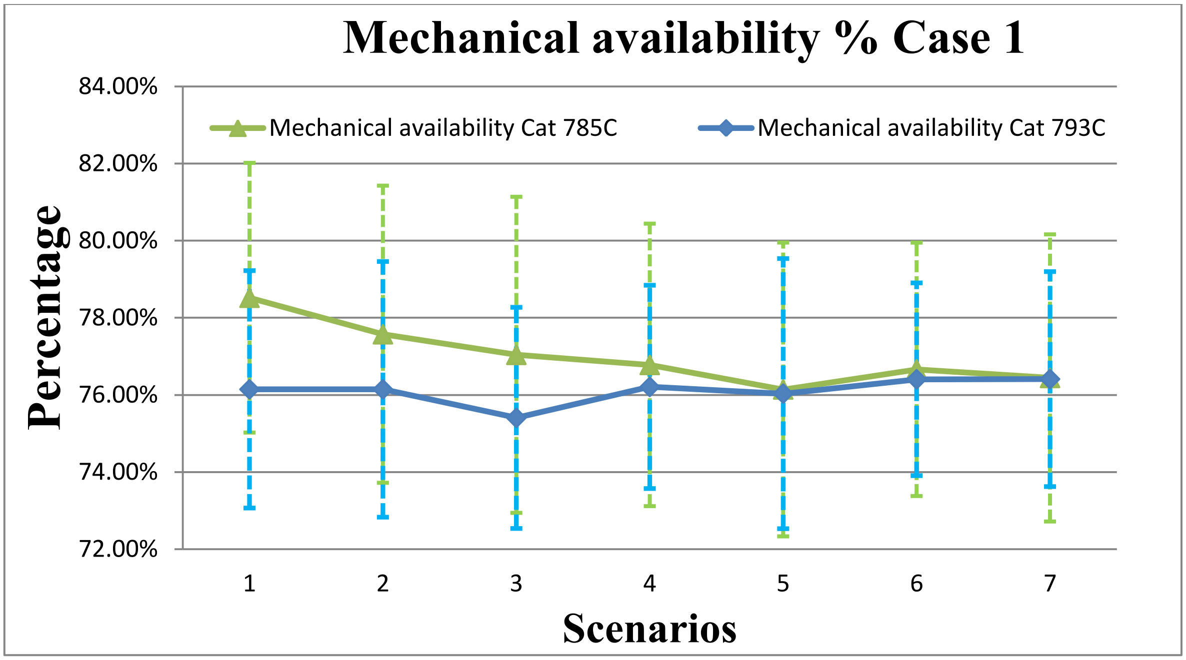

Figure 96.Truck Mechanical availability Case 1

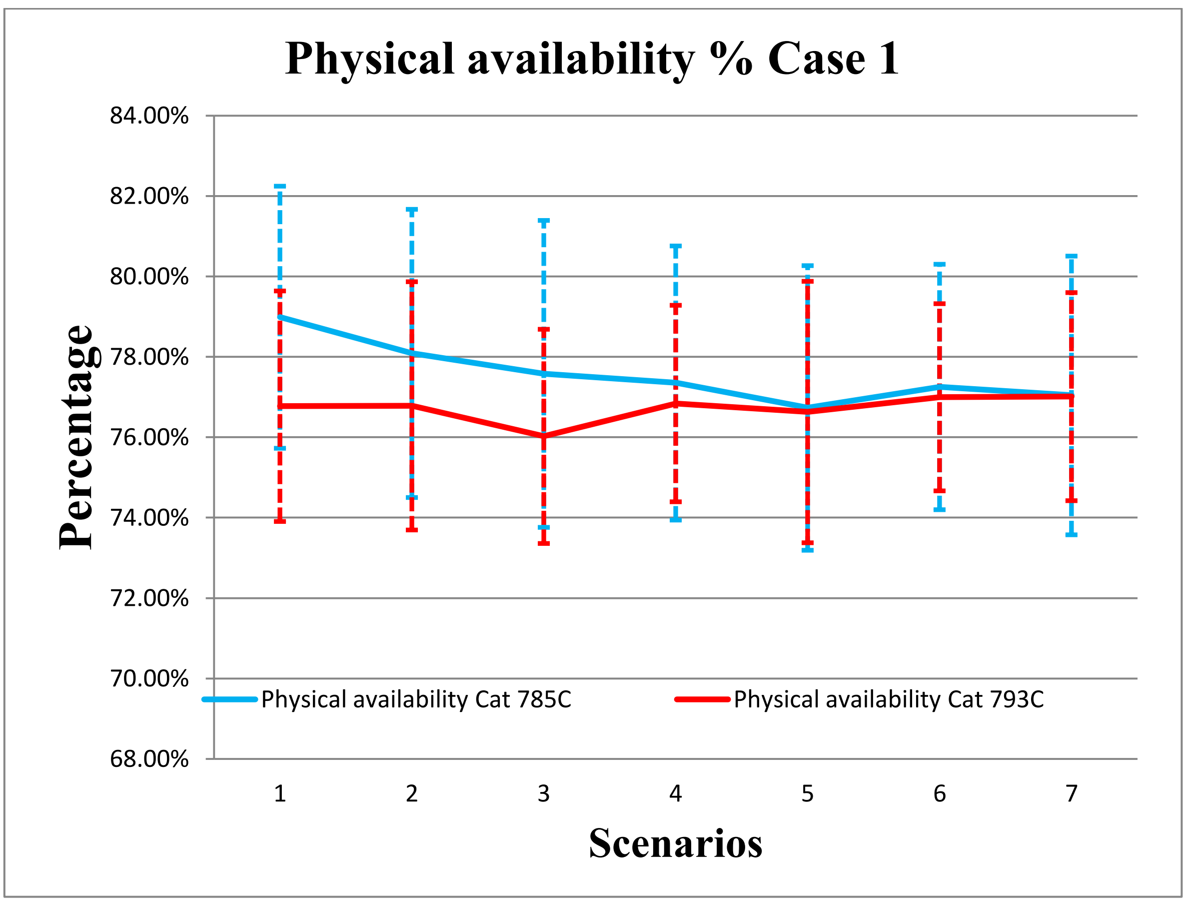

Figure 97.Truck Physical availability Case 1

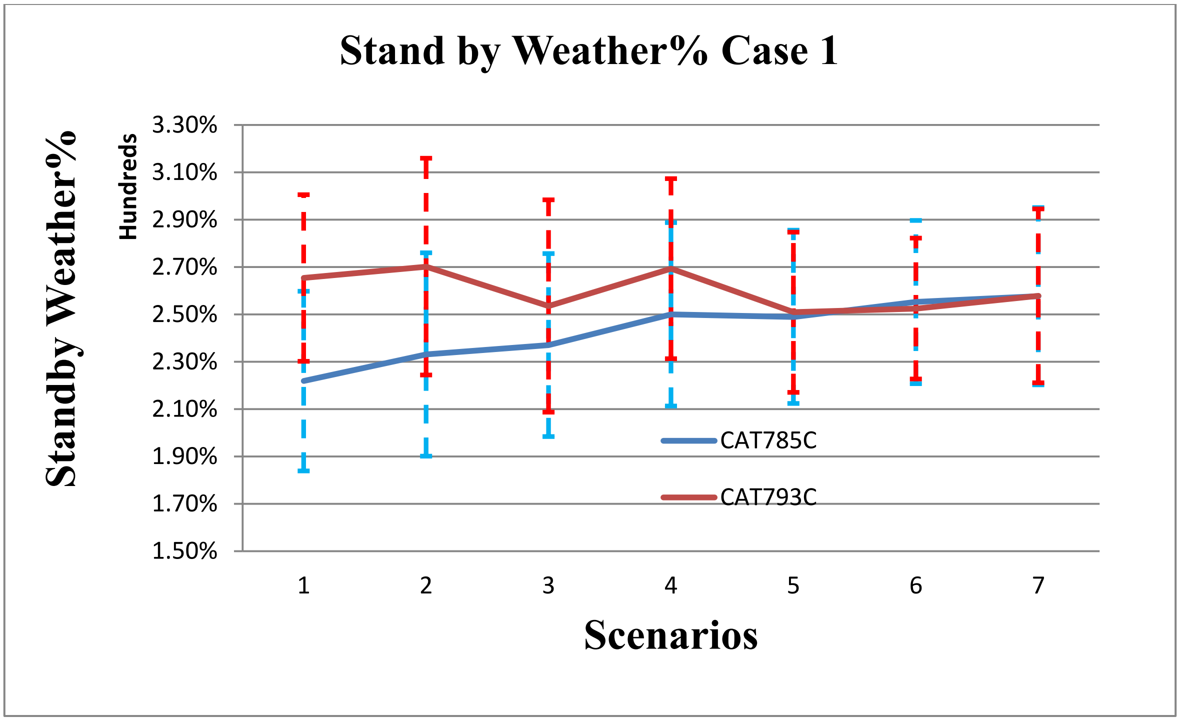

Figure 98.Shovel Stand by Weather Case 1

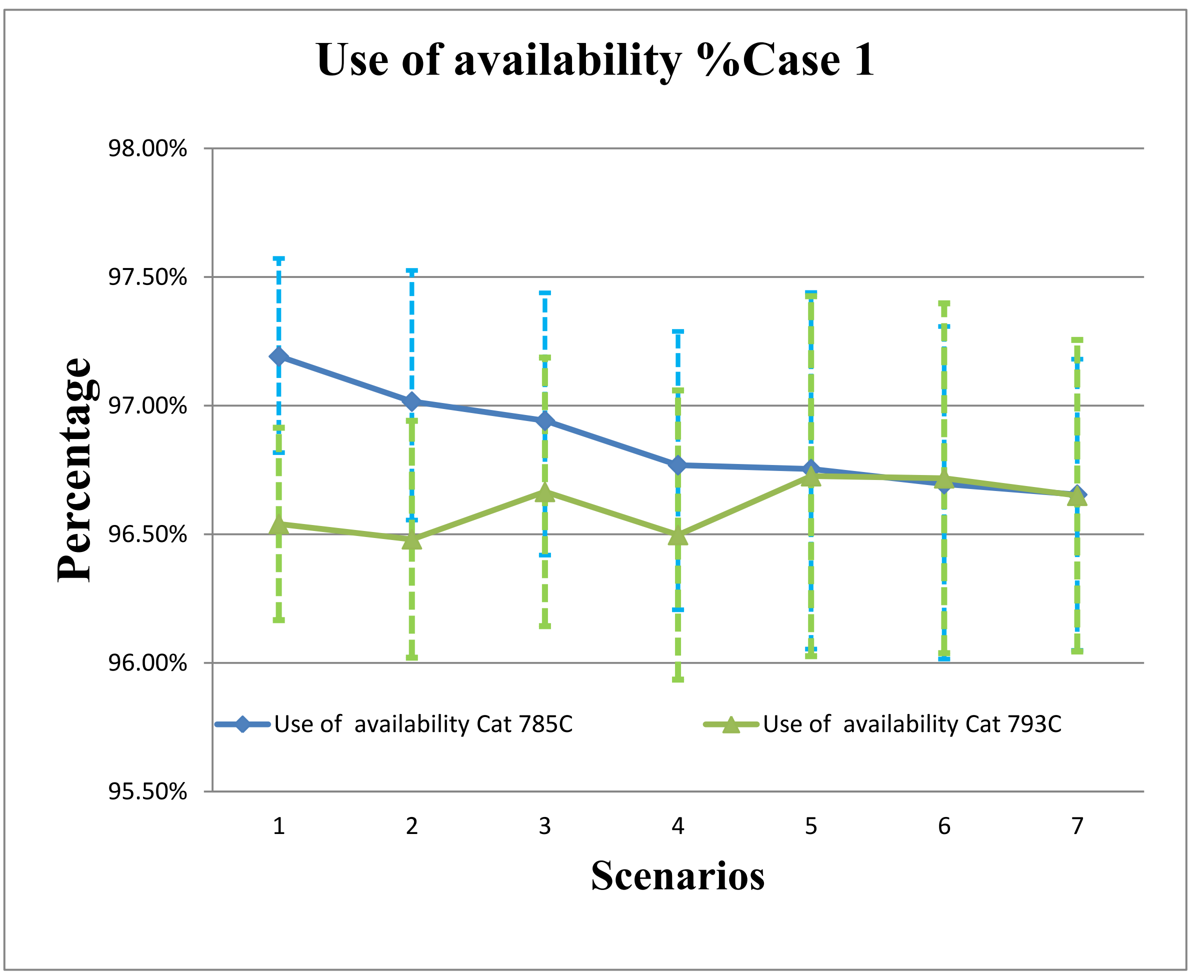

Figure 99.Truck Use of availability Case 1

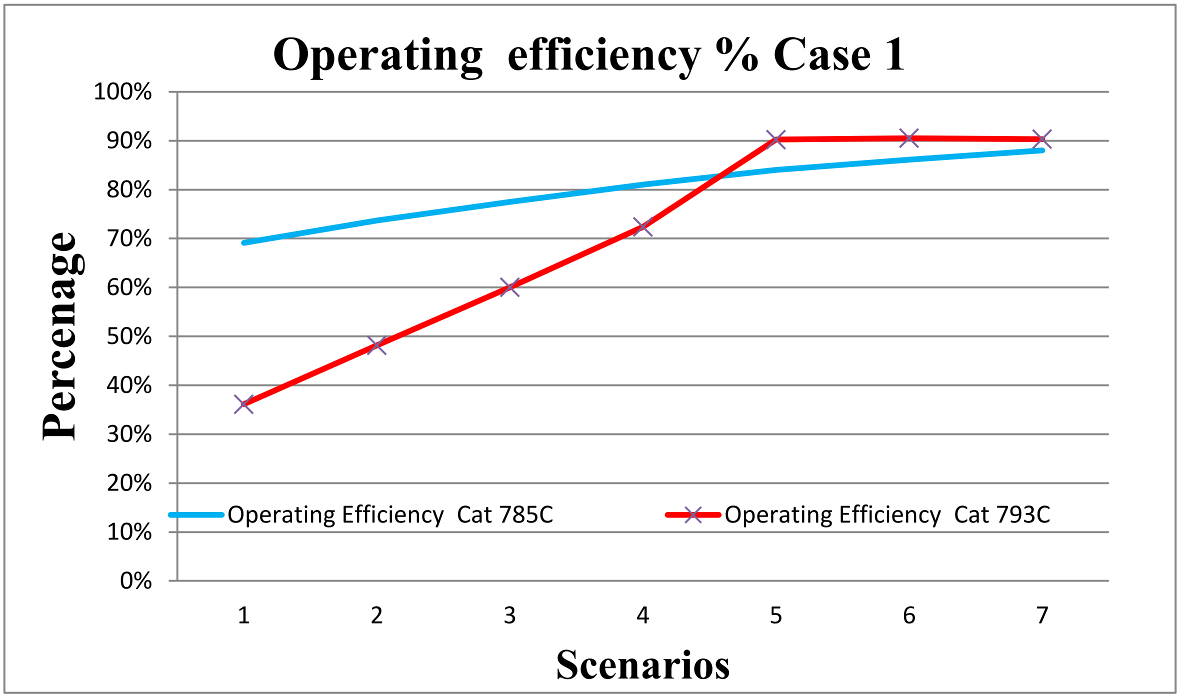

Figure 100.Truck Operating efficiency Case 1

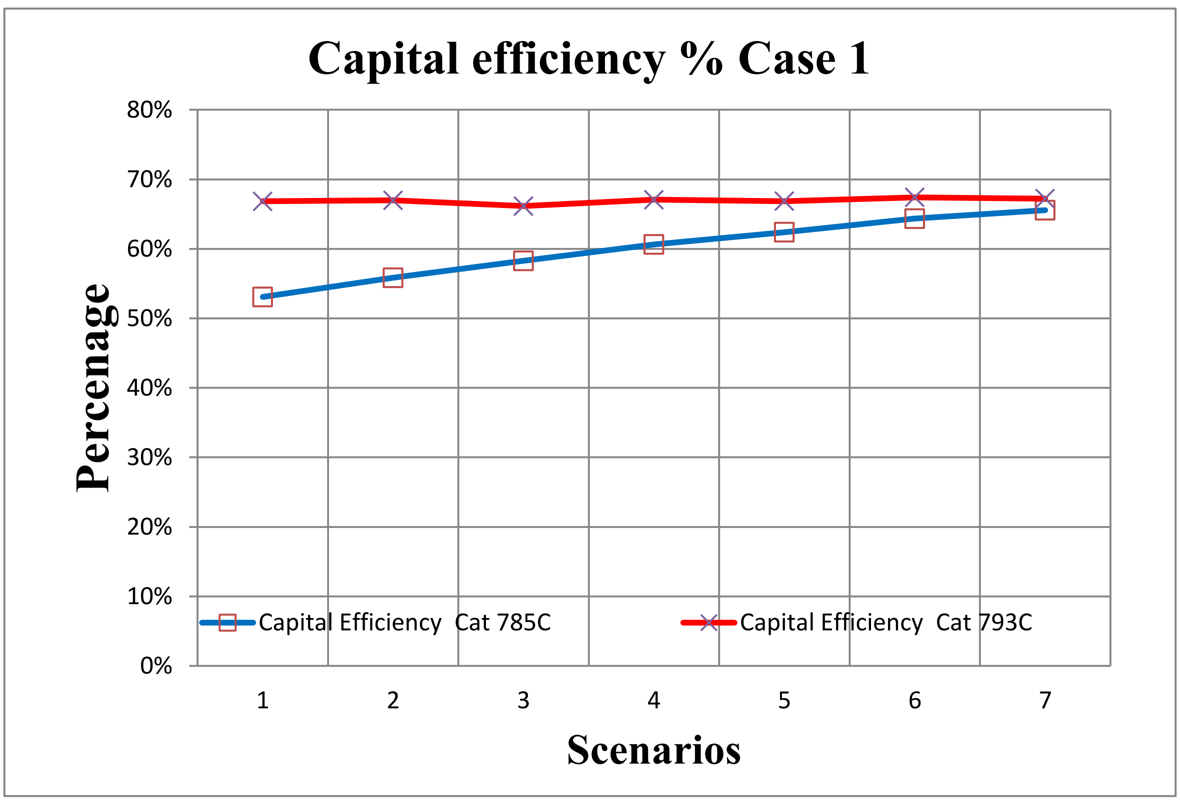

Figure 101.Truck Capital efficiency Case 1

4.7.5. Best case scenario Case 1.

Evaluating the performance equipment efficiency of the Case 1, among all the equipment shovels and trucks. In terms of operating efficiency, in Figure 102, for waste shovel it remains at 58%,while for ore shovels decays from 98 to 60%.On the other hand operating efficiency of ore and waste trucks grow to 90%.Capital efficiency, in Figure 103, the same pattern of operating efficiency can be seen but capital efficiency for waste trucks instead of increasing remains at 68%.Delays, in Figure 104,for waste trucks is 8%,whereas for ore trucks delays decreases from 24% to 9%; Consequently, shovel delays for ore type increases and for waste type decreases.

As it can be seen, production is not met for waste despite ore production being met. To do so and improvement of performance in time and efficiency Kip's is execute two more scenarios. They are run increasing the number of waste truck in steps of 2 to balance production and delays in this shovel type.

4.8. Case 2 increasing waste trucks

As an improvement from case 1, where ore trucks where diminished to reach the production, Case 2 is developed. Case 2, has an objective of rise up capital efficiency, operating efficiency and balance in truck and delays, while increasing waste and production targets as close as possible to the schedule. Case 1 achieved ore tonnage target but it flawed into reach the waste movement and also the KPI's capital efficiency and delays performance were poor. Waste tonnage, fell short as the ore movement decreased. As a result, two new scenarios are executing to meet these shortfalls and see their effectiveness in performance, they consist in increasing the number of truck Cat 793C.

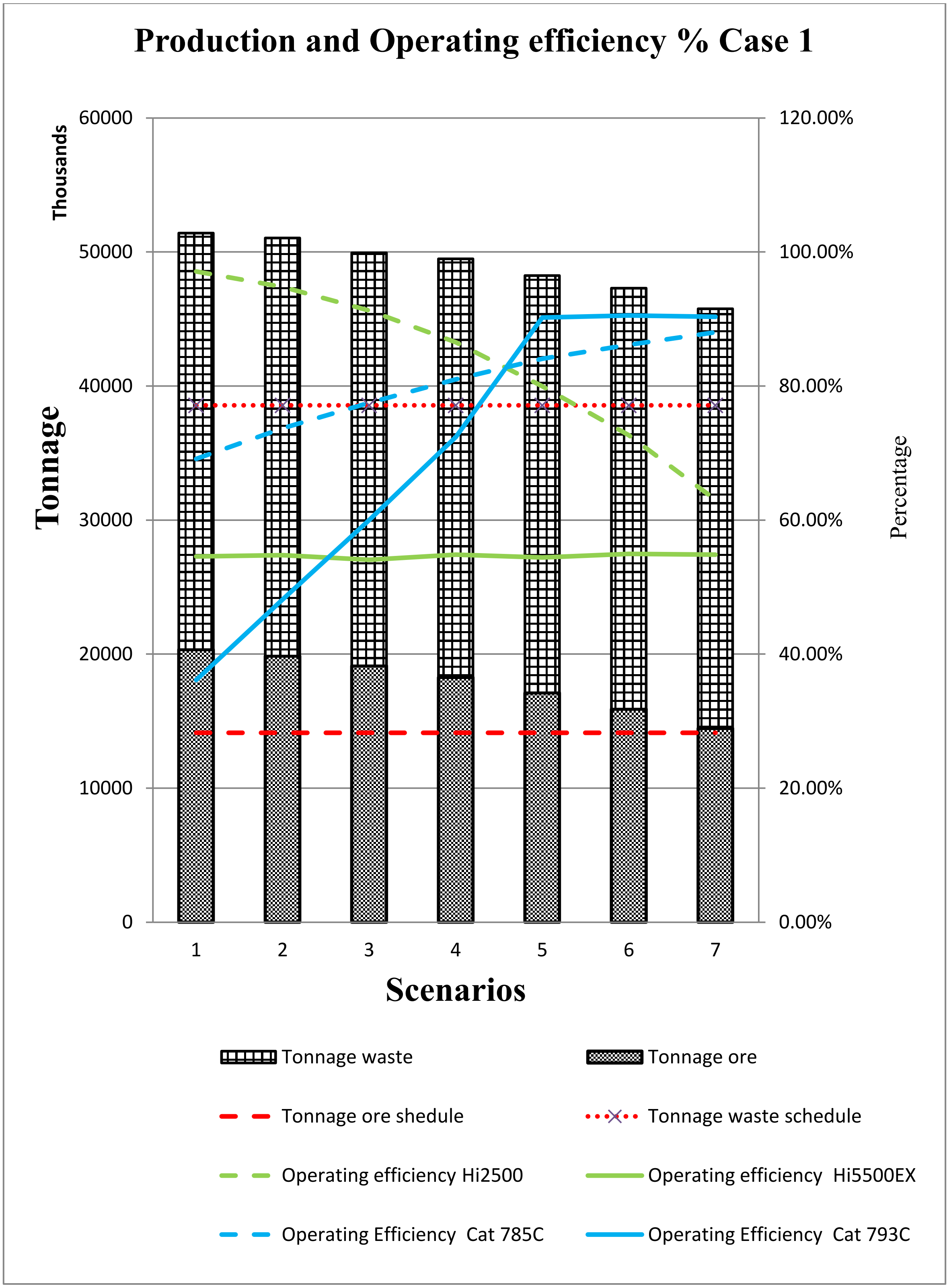

Figure 102.Production and Operating efficiency Case 1For

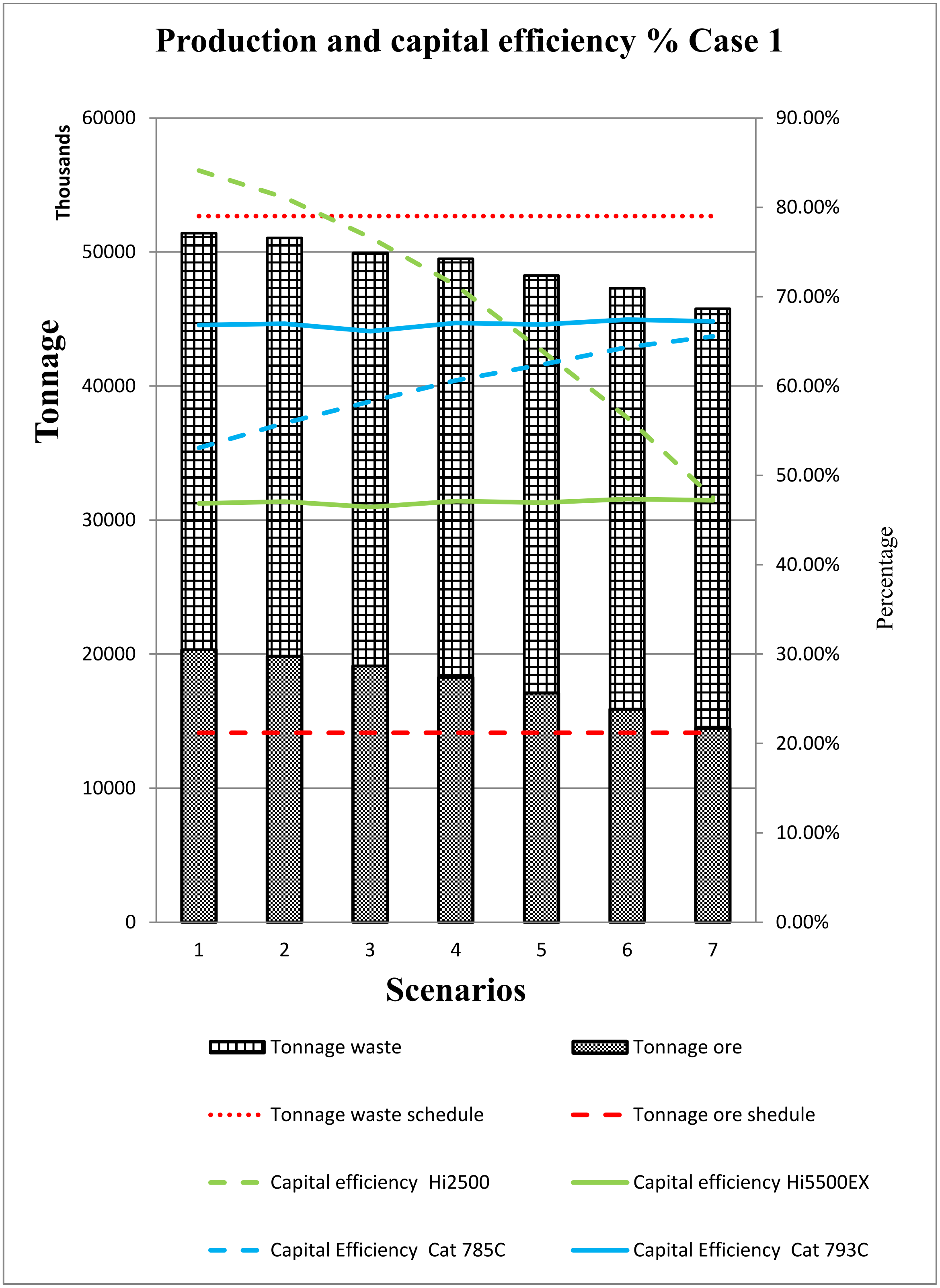

Figure 103.Production and capital efficiency Case 1

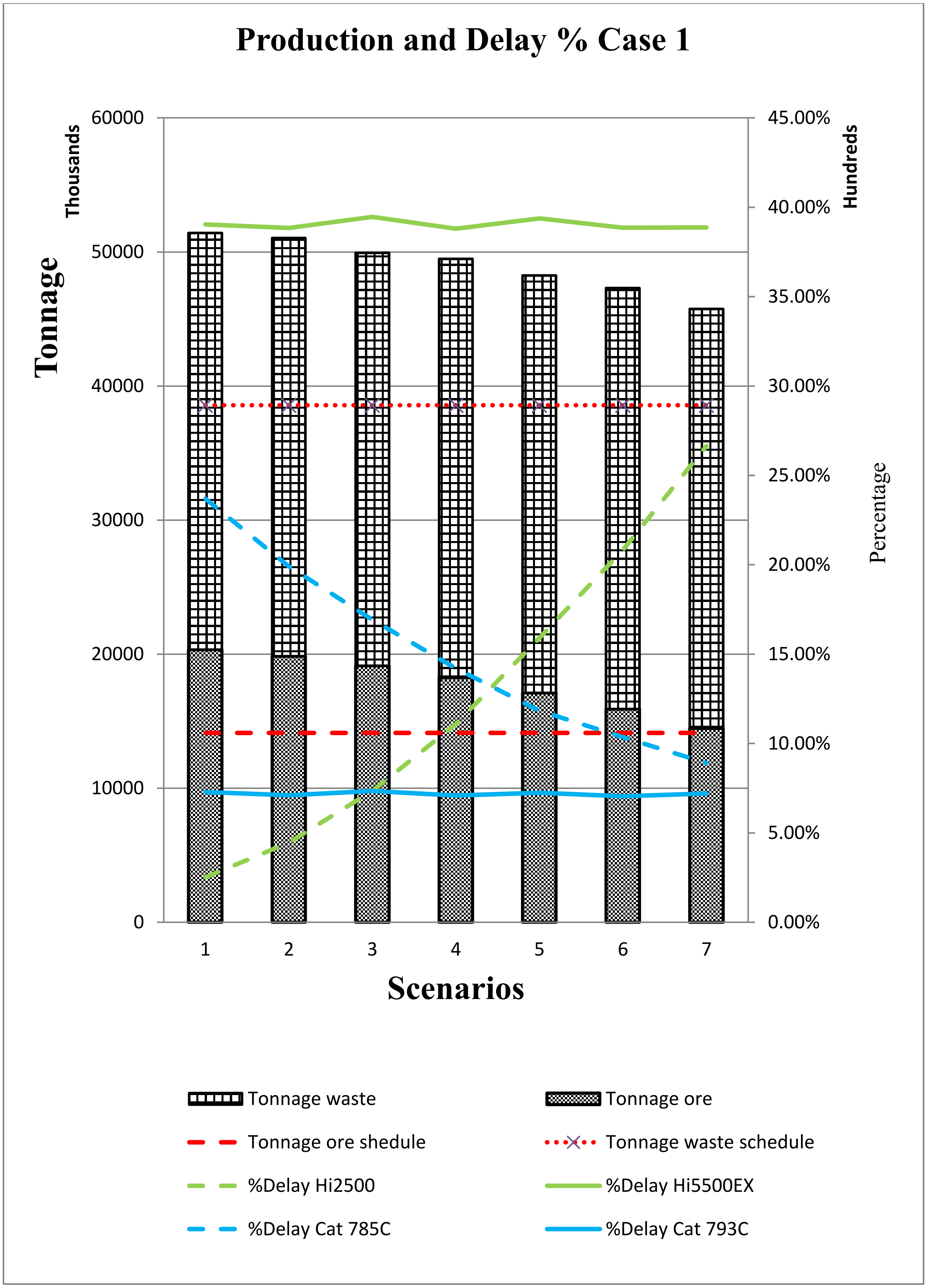

Figure 104.Production and delay% Case 1

An insight of operating efficiency is given in Figure 105.Although number of trucks on the waste fleet has been risen , operating efficiency for both ore and waste fleet still around in about 90%, waste truck operating efficiency very negligible went down. Shovel operating efficiency remains the same for Hi2500. A rise in operating efficiency for Hi5500Ex and Hi2500 at 70%, for the last scenario 9, in which also the waste and ore production is met.

Capital efficiency is outlined in Figure 106. Also for both truck fleet still almost unchanged at about 65%. Moreover, as it was expected shovel capital efficiency grow until 68% for waste shovel, while ore shovels remain reporting constant efficiency of 65%, after coming from a decreasing trend.

An explanation to this improvement in terms of capital and operating efficiency can be found in the new delays trend, in Figure 107, the information is outlined. From the last cases study and also honoring the theory, as number of trucks increase the hanging time in shovel is less. This is verified in from scenario 7 to 9, where the delays stop rising for the waste shovel to 28%, where it meets with the ore shovel delay, making the system be more balanced. At the same time that the waste shovel delay is lesser, capital and operating efficiency for this shovel type is better. On the other hand, this achievement is accomplishing without compromising truck delays for this fleet (waste), the increasing of truck is up to a point that no queue delay is increased drastically that can deeply affect capital and operating efficiency.

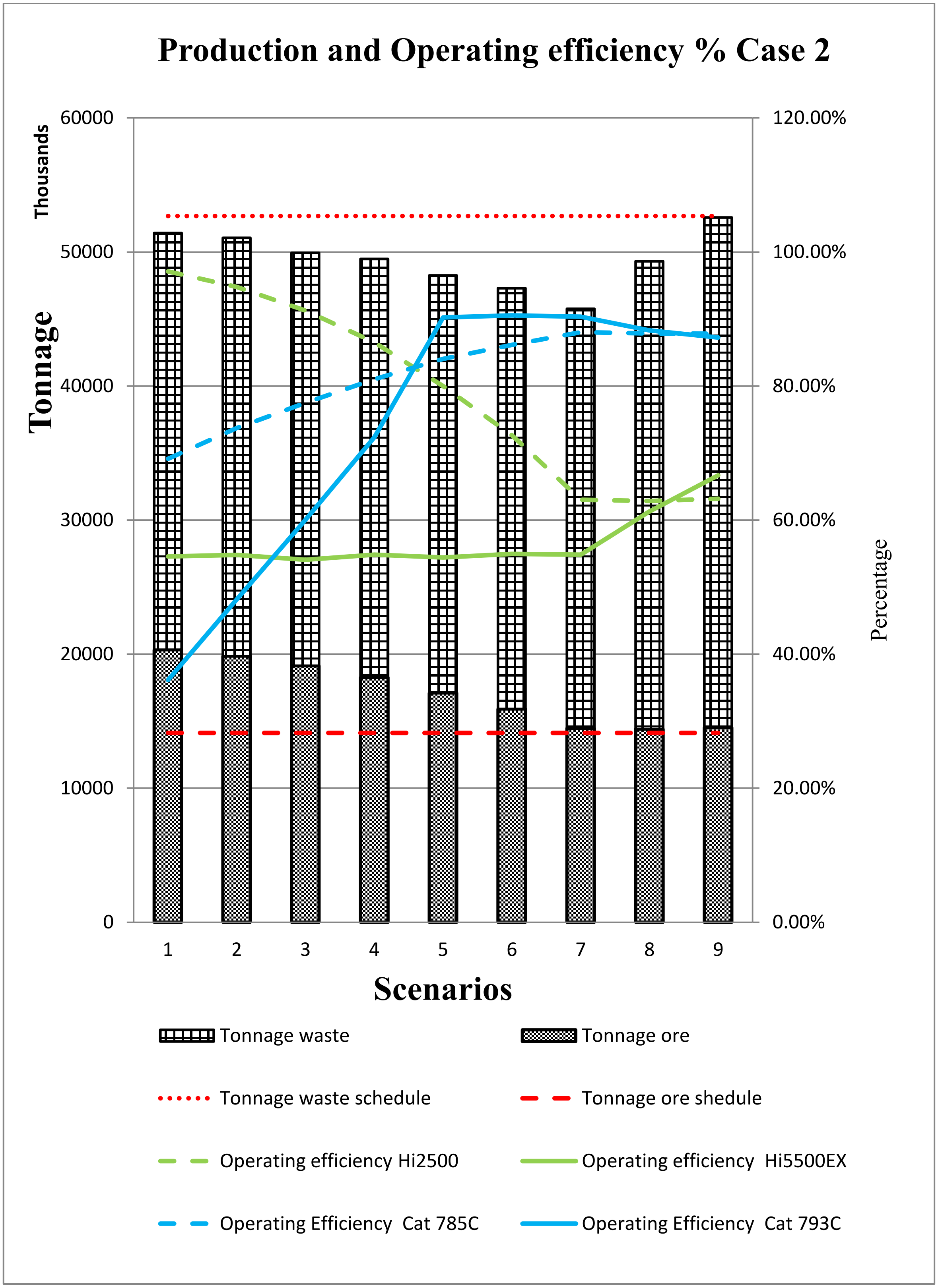

Figure 105.Production and Operating efficiency Case 2

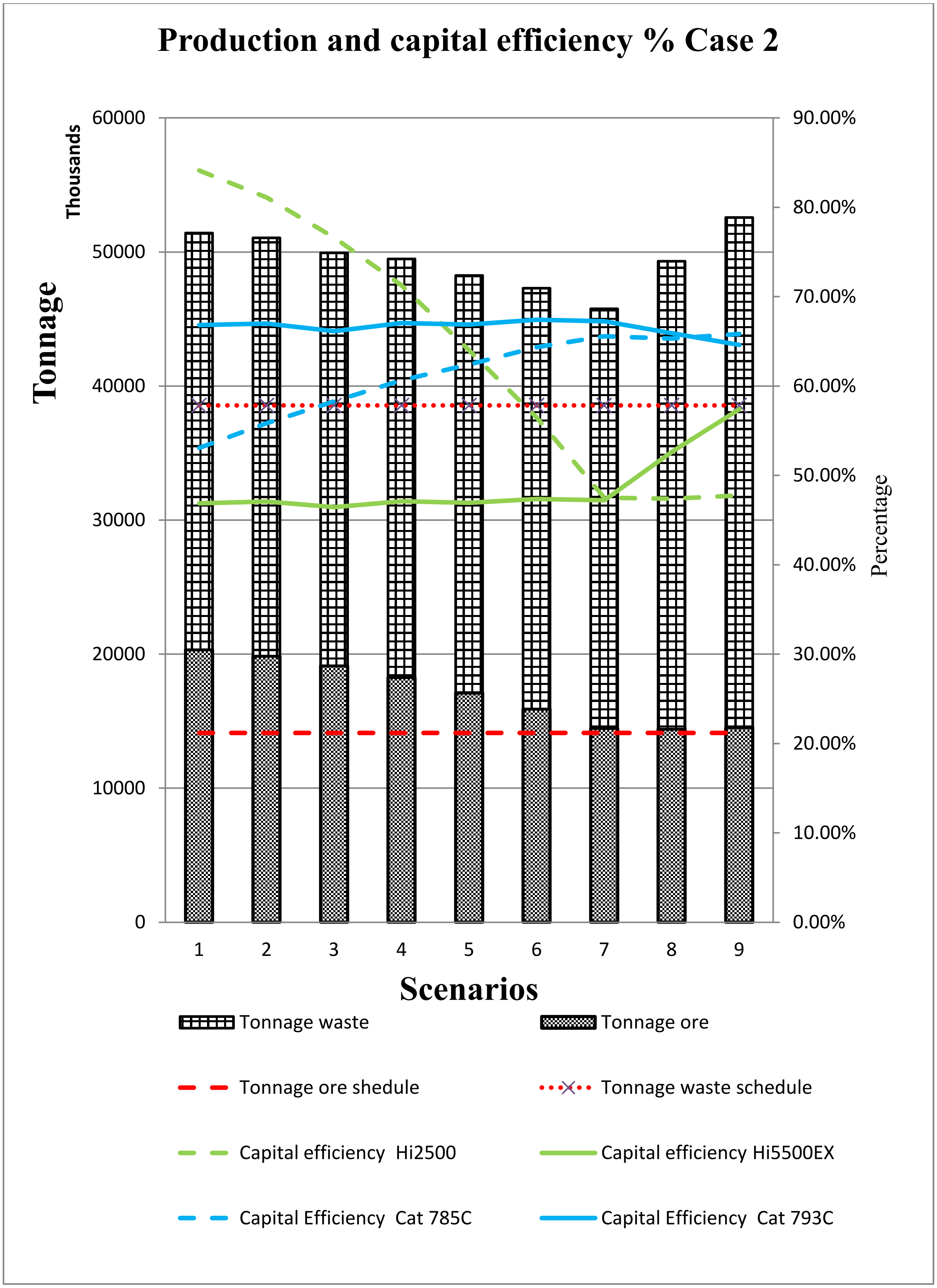

Figure 106.Production and capital efficiency Case 2

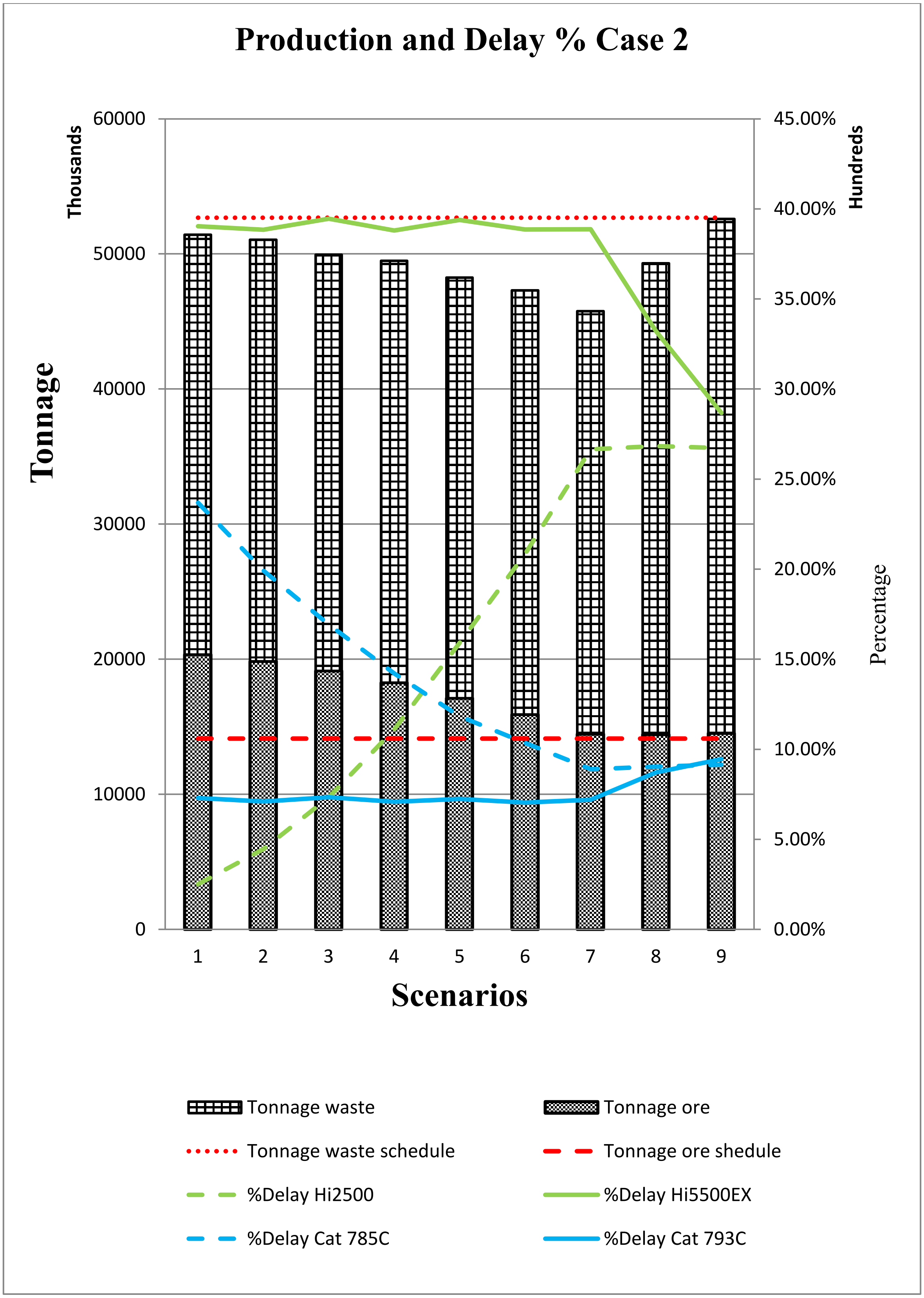

Figure 107.Production and delays Case 2

4.9. Case 3. Different rates.15 Ore trucks, Cat 785C and 19 Waste trucks, Cat 793C.

After finding the right number of trucks in Case 2, in order to make the study more realistic, new rates at the crushers that feed mills 1 and 2 are investigated. Also, one of the objectives of this research is to develop understanding of operation's milestones with simulation, assessing the sensibility of variables in the kip's established, without any arm to the environment, health or production itself.

Case 0,1 and 2 have crushers in dump 1 and 2 (mill 1 and 2) with a very high rate so as to model scenarios with no constraint on the crusher throughput and capture the variability impact of number of trucks in the KPI's clearly, without bias. It is also estimated that keeping a throughput rate at the crusher very higher than the dump; as a result, to calculate dumping rate, weight of dumped load, dumping and backing time are needed, (145.7/ (0.015+0.004) = 7668), for facilities 1 and 2 was 7668 ton/h and the crusher rate 8400 ton/hr. Any significant increase in average dumping process will be observed that could be related to waiting for the crusher to free material from the dump facility.

Case 3 will be focused in evaluating the performance of the KPI's with different sets of crushers' throughput rates to build a best case scenario in the sense that will honor KPI's while an optimal throughput rate in the crusher is used. Six more scenarios are included in this study number of trucks for ore and waste will be the same but the rate in the crushers will change.

4.9.1. Tonnage KPI's Case 3

As the crusher throughput rate decreases so does the ore tonnage, Table 19, shows that information scenario by scenario.

Table 19. Crushers rates Case 3 Scenarios

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Hopper-D1 rate ton/h	8400	1700	2600	2600	2800	3000	3400
Hopper-D2 rate ton/h	8400	1700	1800	2600	2800	3000	3400

To analyze the sensibility of KPI's to different crusher rates, Scenario 1 is a case base with no constraint in crusher rate at all. Scenario 2 is the result of calculating the desired rate according to ore schedule and the schedule hours or simulation time, which is a year with 12 daily operation hours. Ore schedule is 14.124.180 ton and schedule hours (365*12 = 4380), rate desired will be 3224 ton/h of ore. The operation Case as it is mentioned before has two crushers at each mill so expected rate at each mill will be 1612 ton/h to meet an of 3224 ton/h ore; however, to work with a round number 1700 ton/h are assigned to each crusher. Scenario 3, is configured based on the dumping process time that includes dumping and waiting for crusher to free dump facility. For mill 1, crusher rate is 145.7/0.057 = 2556 ton/h (Dump1). Mill 2, crusher rate is 145.7/0.084 = 1735 ton/h (Dump2). Once again values where round to 2600 for crusher-D1 rate and 1800 for crusher-D2 rate. To assess the sensibility of different rates scenarios 4, 5, 6 and 7 are studied.

To evaluate Case 3 and its scenarios Figure 108 outlines ore and waste movement along with the rate in each crusher being used, as it was mentioned before number of trucks for ore and waste are maintained through all the scenarios. Ore production drops to 11.388.121 ton and waste production rise more than 500.000 with a crusher rate of 1700 ton/h in booth mills locations, for scenario 2. Same waste and ore movement is observed for scenario 3, which has crusher-D1 2600 ton/h and crusher-D2 1800 ton/h. Increasing rates at booths crushers to 2600 ton/h shows a significant increase in ore production in scenario 4, with 13.326.4293 ton. The rise in ore tonnage continues until scenario 7, when it reaches the ore movement without affecting waste tonnage, at a crusher rate of 3400 ton/h each crusher. It can be seen how the rate in the crushers affects production as dumping process is influenced by the pace at which the material is released from the dumps facilities. Comparing scenario 1 with scenario 7, production is met in both scenarios but in scenario 7 with less rate at the crushers. This information can be useful in the future for expansion projects, studying bottlenecks problems or as a saving opportunity.

4.9.2. Queues and averages KPI's times Case 3

In terms of the average time spent in the operation system, it can be seen that average cycle time for waste fleet is not affected by rates changes in mill's crushers; however, average cycle time for ore fleet is inversely proportional to the rate. In detail a cycle time of an average 29 minutes for Cat 785C, rise up to 37 minutes when the rate for both crushers at the mill is 1700 ton/h and as the rate keeps on increasing in the crusher, average cycle time drops. A steep drop is seen from scenario 2 to 4 in average cycle time for Cat 785C from where it starts to decrease slowly, as rate increments in 200 ton/h steps. Figure 109, outlines that information.

Average queue time at the shovel is shown in Figure 110.Cat 785C fleet truck queues at the shovel went back to their value of 3.3 average queue time at the shovel as the rate increases. More information in detail in Figure 113.

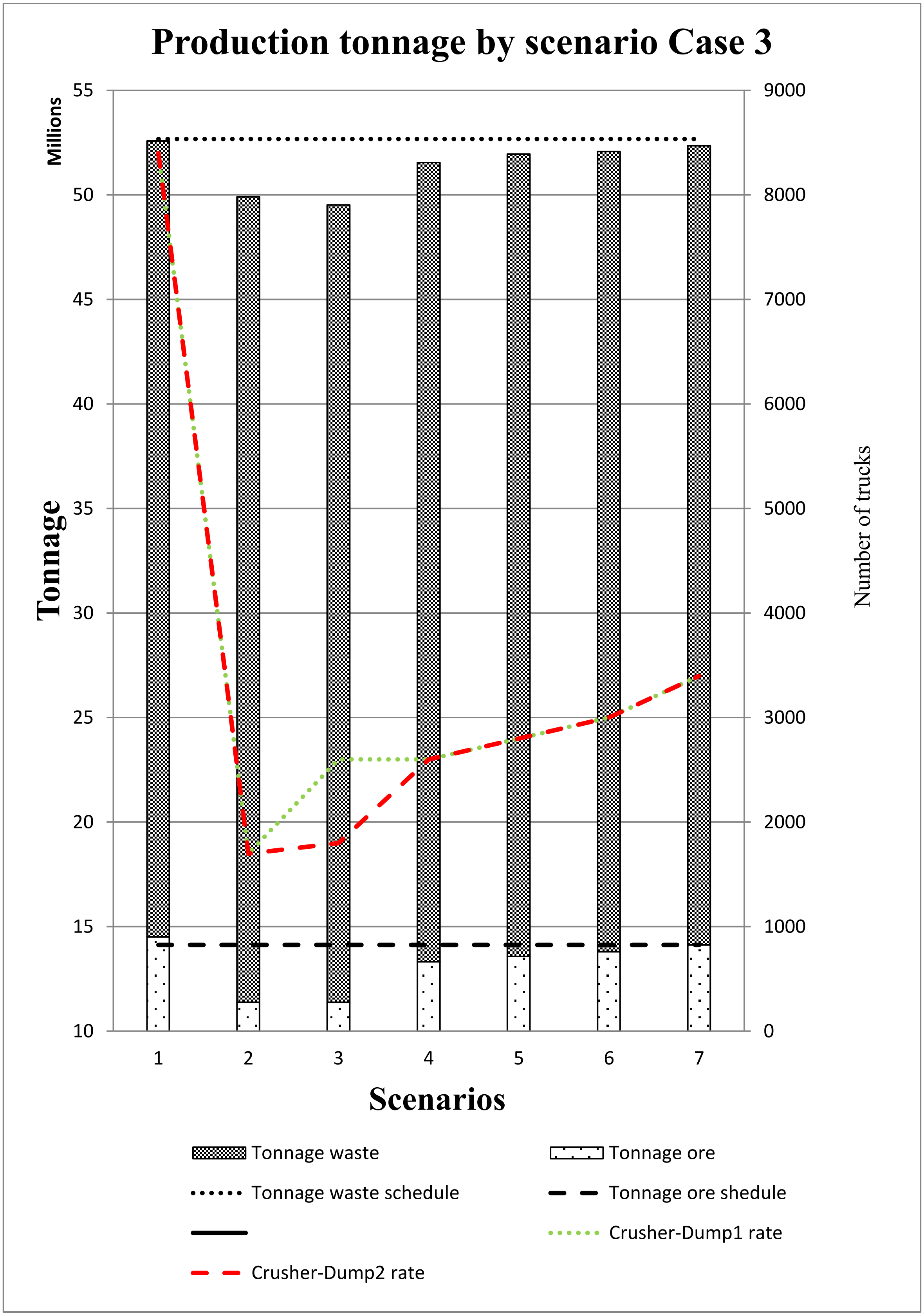

Figure 108.Production tonnage Case 3.

A correlation with average cycle time is the average dumping queue time in Figure 111 and Figure 114 ,which again remains constant for Cat793C fleet trucks but as the cycle time for Cat 785C trucks levels up for scenario 2 so does the average queue time at the dumps but with a more sharper trend from around 0.5 to 6 minutes. To detail more information about how the rate affect the dumping time process itself, Figure 112 is outlining ups and downs in the dumping process time as the rate change which also goes parallel to the average queue time at the dump by truck type. Average processing dumping time for case base scenario is around 0.5 minutes with rate change it goes up to 4.3 minutes to end up at the last scenario with 1.3 minutes' average processing time

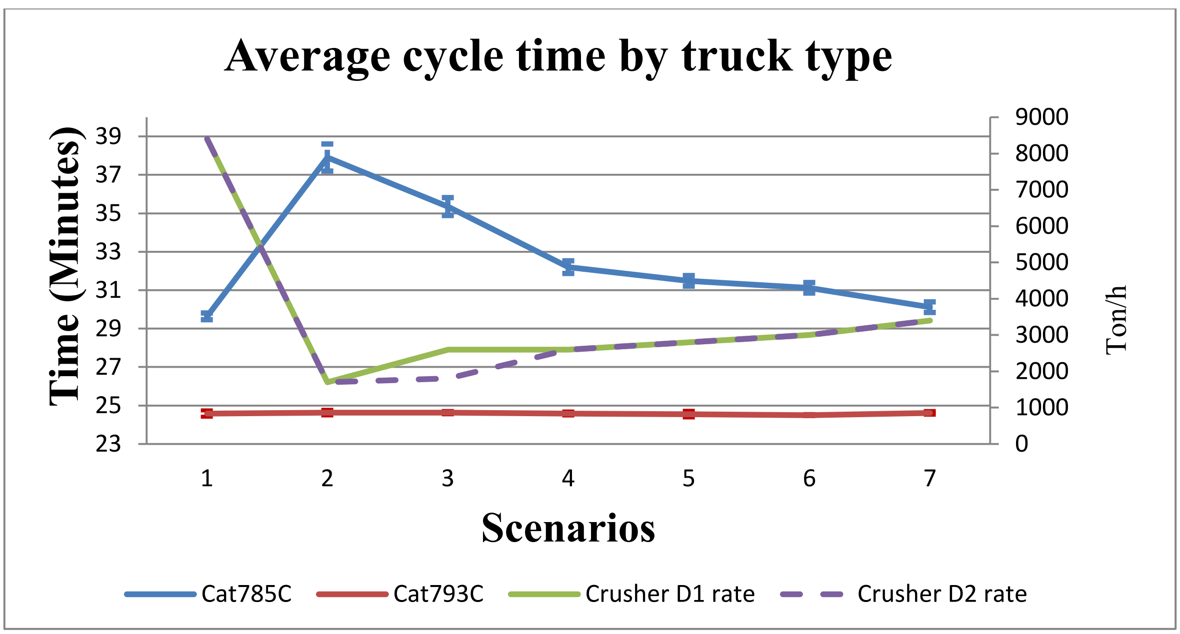

Figure 109.Average cycle time at the shovel by truck type minutes Case 3

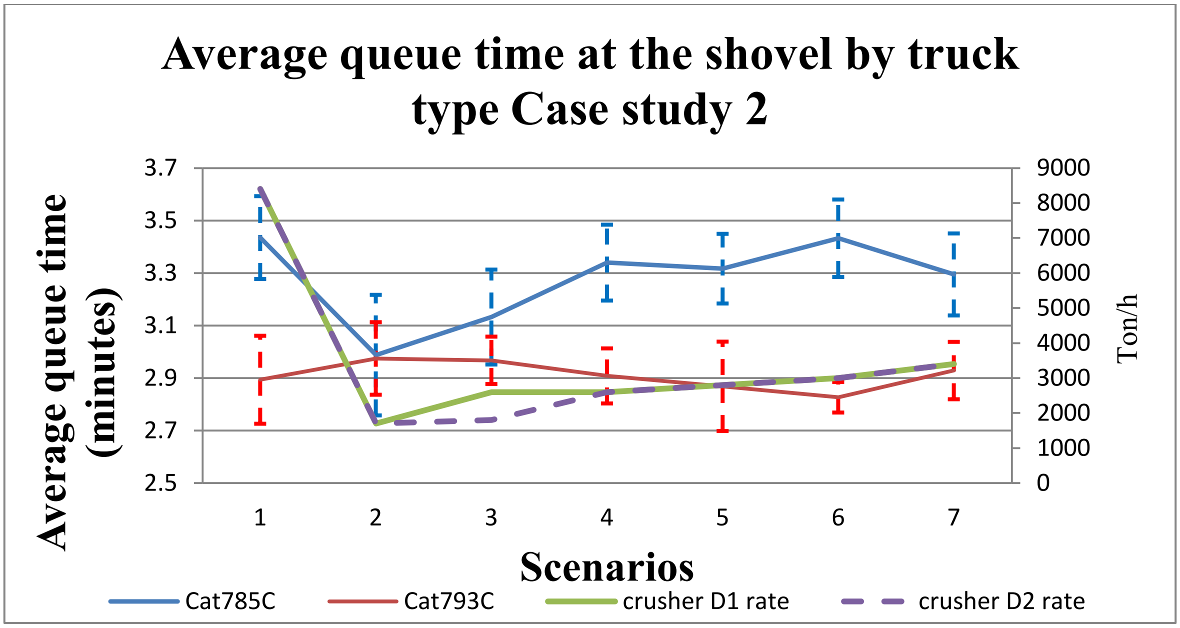

Figure 110.Average queue time at shovel by truck type minutes Case 3

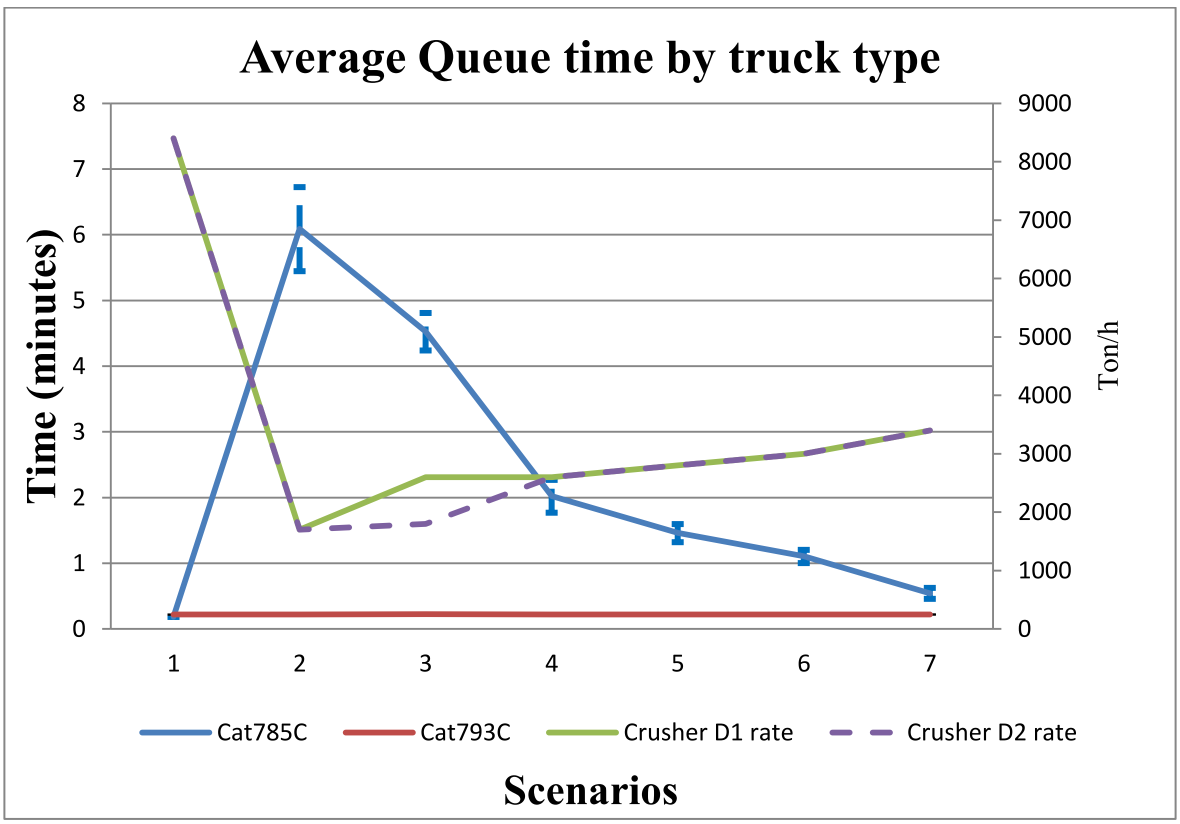

Figure 111.Average queue time at dump facility by truck type minutes Case 3

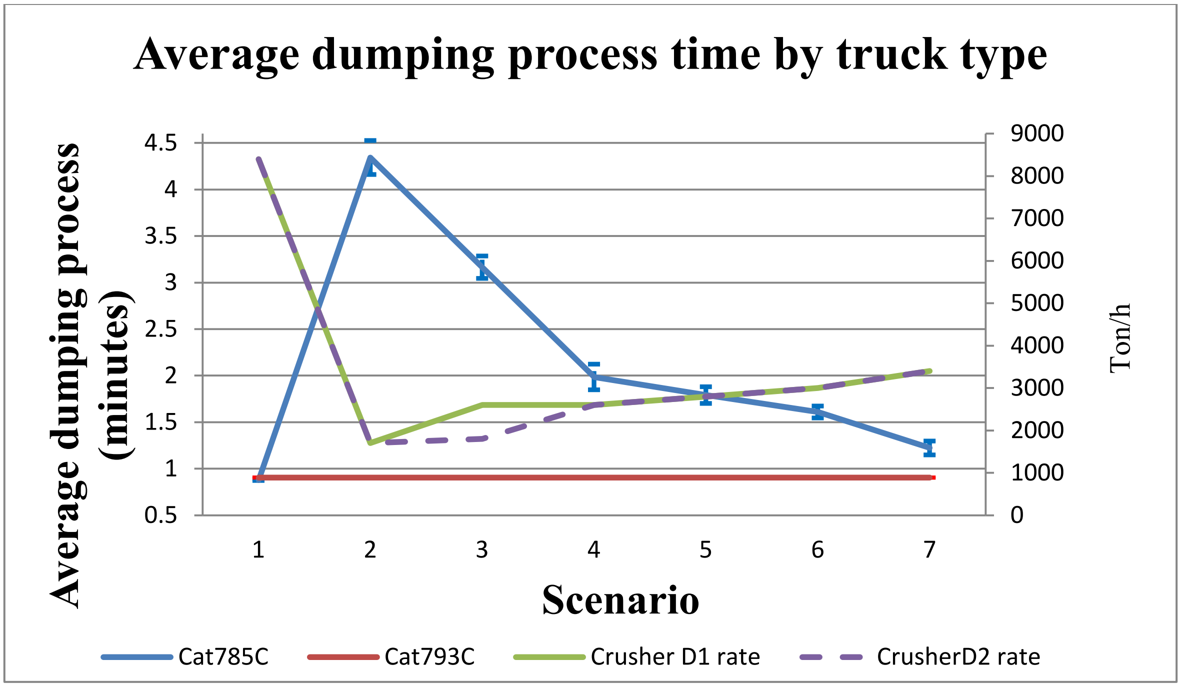

Figure 112.Average dumping process time by truck type Case 3

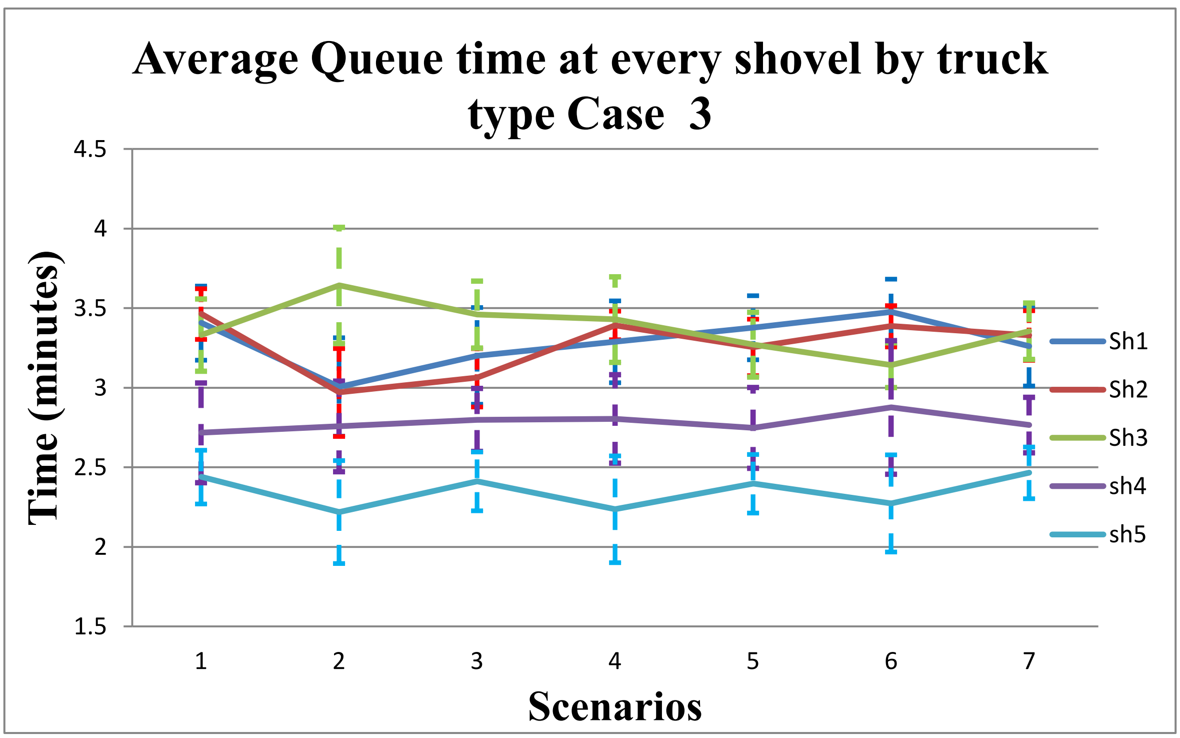

Figure 113.Average queue time at every Shovel Case 3

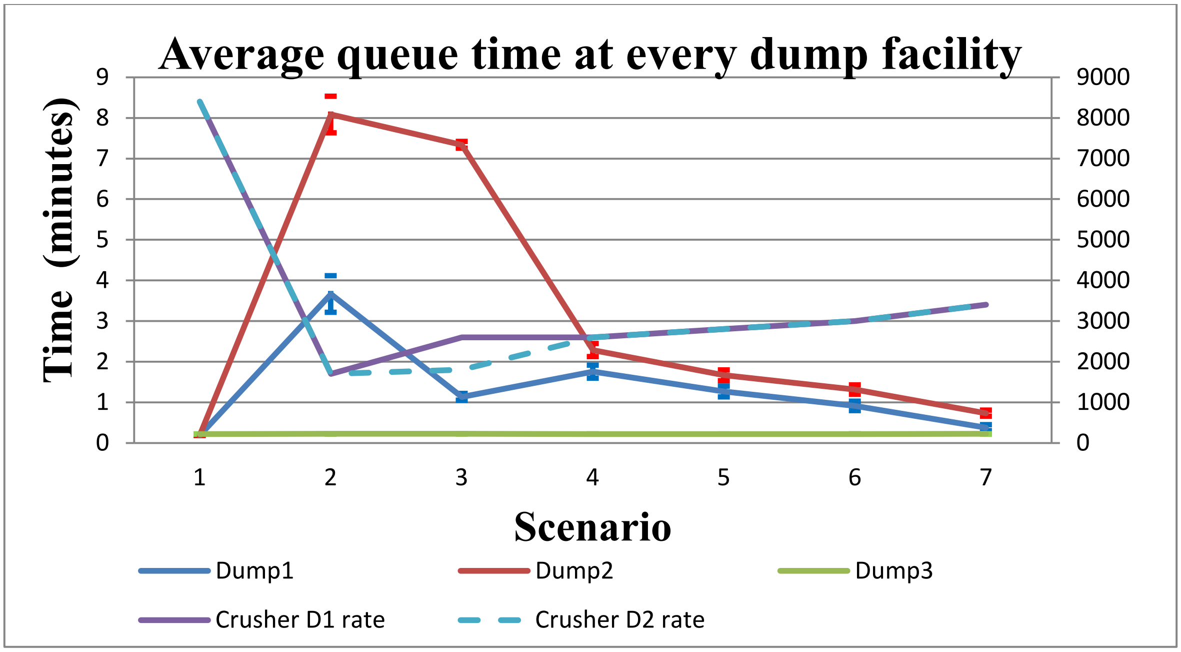

Figure 114. Average queue time at every Dump Facility Case 3

4.9.3. Shovel Time category KPI's

Evaluating time KPI's in Figure 115, is describing the percentage of hours of the schedule spent in operation of a shovel type. GOH% for shovel type Hi2500, remains constant at 86% but ore shovel plunge from 75% down to 68% as rate in the crushers does for scenario 2 to start increasing to almost 75% GOH in the last scenario 7. Parallel shape is observed in Figure 116 which describes shovel fleet type and hours spent working without delays. Shovel type Hi 5500 Ex total hours spent working without hanging (NOH) does not show any alteration through scenarios, it remains constant at 2500 hr. However, like GOH% shovel type Hi 2500 NOH hours went down to 1200 hr from 2000 hr as the crusher rate did, after that NOH leveled back to 2000hr for scenario 7. An insight about this trend can be found in Figure 117.Shovel type Hi5500ex delay% is 28% in all the scenarios but Hi 2500 shovel delays% rises up for scenario 2 which means shovel hangs while the rate is low in crusher. Delay at ore shovel improves as the rate in the crushers increase to the point it was at the case base 28%.

On the other hand down time % for both shovel types fluctuates in different rates but parallel until scenario 5, when they behave inversely proportional, Figure 118 shows that information. Figure 119, show how ton/GOH for waste shovel type is 10000 ton/GOH and 4000 for ore shovel type , with a slight drop due to crusher rate.

Figure 120, explains mechanical availability. As an overall for Shovel Hi5500Ex mechanical availability is almost same 89% but with slight growth from scenario 3 due to a decrease in down time %. Similar trend down time% and mechanical availability is seen in Hi2500 shovel type, where is fluctuates abruptly due to the influence of both down% and GOH variability. Physical availability, in Figure 121 for shovel type Hi2500 fluctuates around 89.7% and for shovel type Hi 5500Ex around 89.50%. To evaluate how well the shovel is used when it is available, use of availability is described in Figure 123. Shovel type Hi 2500 and Hi 5500EX, have same behave in terms of use of availably but waste shovel type reaches always higher levels. It can be notices use of availability is higher for the last scenario 7 than for the case base it can observe an improvement when they reached 96 and 97% respectively. These behavior is also product of stand by weather% in Figure 122 .

Capital efficiency and operating efficiency, which measure NOH against GOH and schedule respectively, Figure 124 and Figure 125 relate to that information. The trends in both categories is same but in smaller dimensions for capital efficiency as it is expected. Shovel Hi5500 has capital efficiency of 59% and Operating efficiency of 59% and Shovel

Hi 2500 capital and operating efficiency fluctuates parallel to crusher rates changes but they go back to their original value in case base of 45% and 60% respectively.

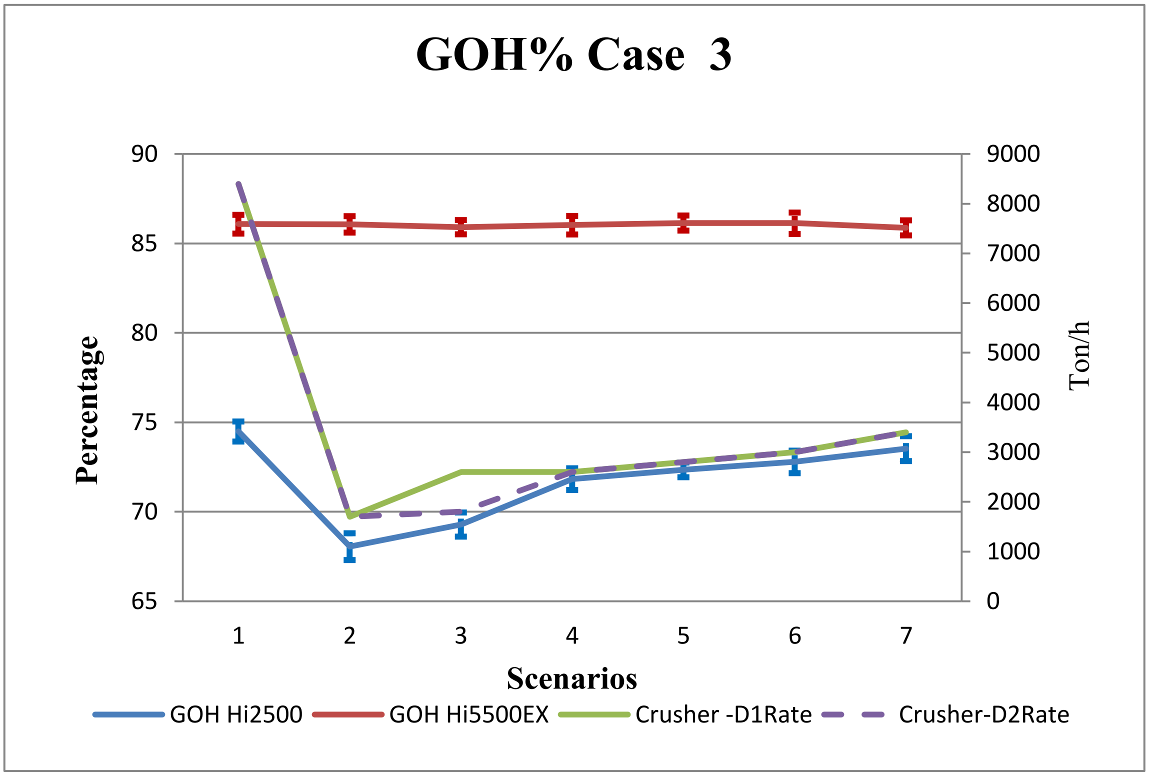

Figure 115.Shovel Gross Operating hours GOH% Case 3

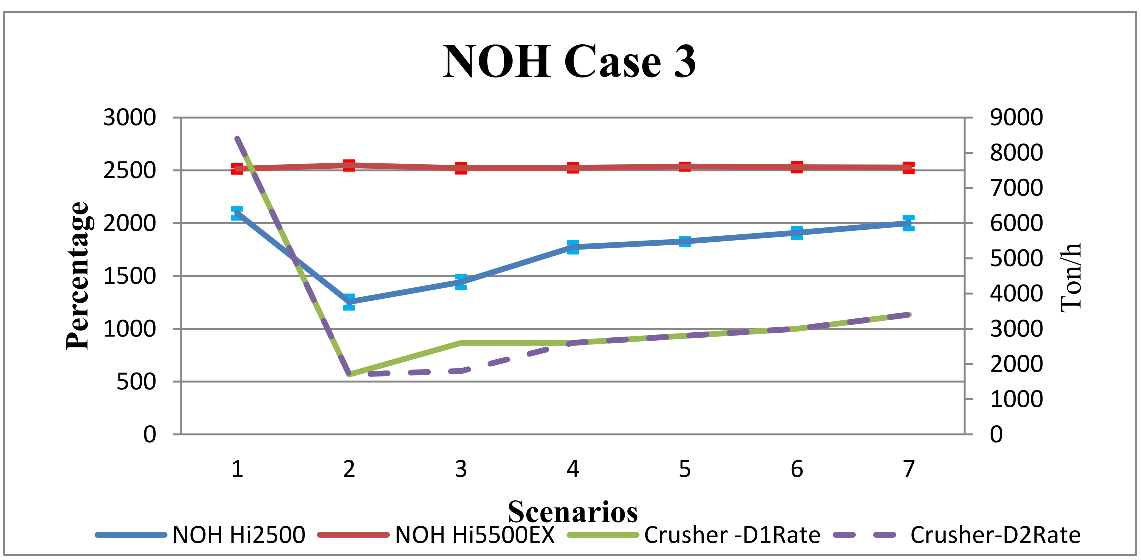

Figure 116.Shovel Net Operating hours Case 3

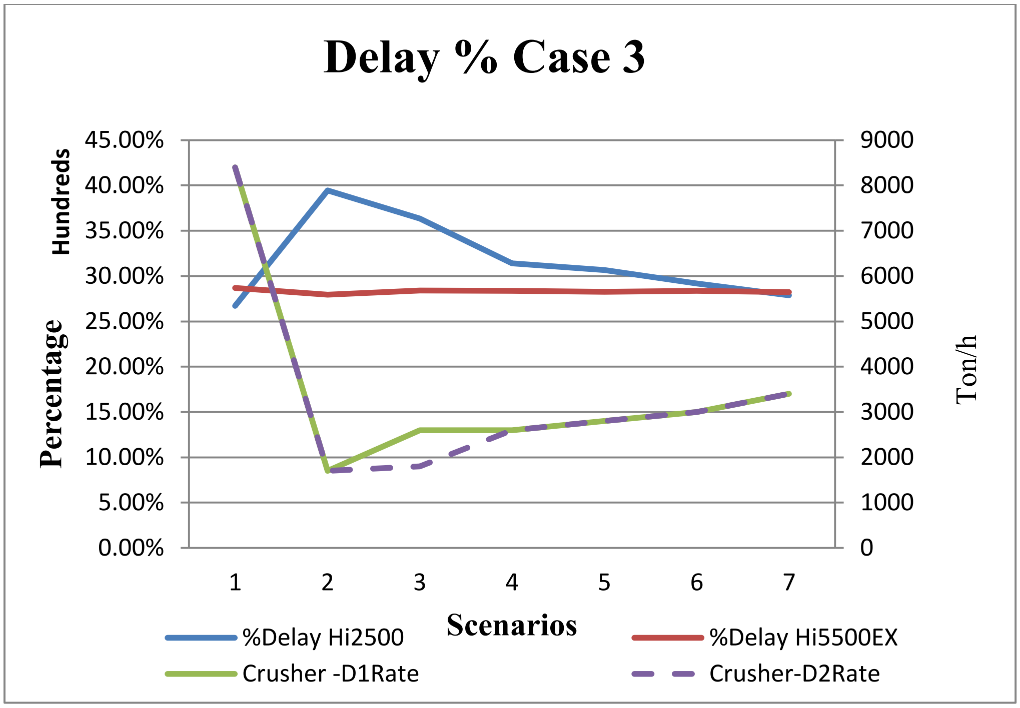

Figure 117.Shovel delays% by shovel type Case 3

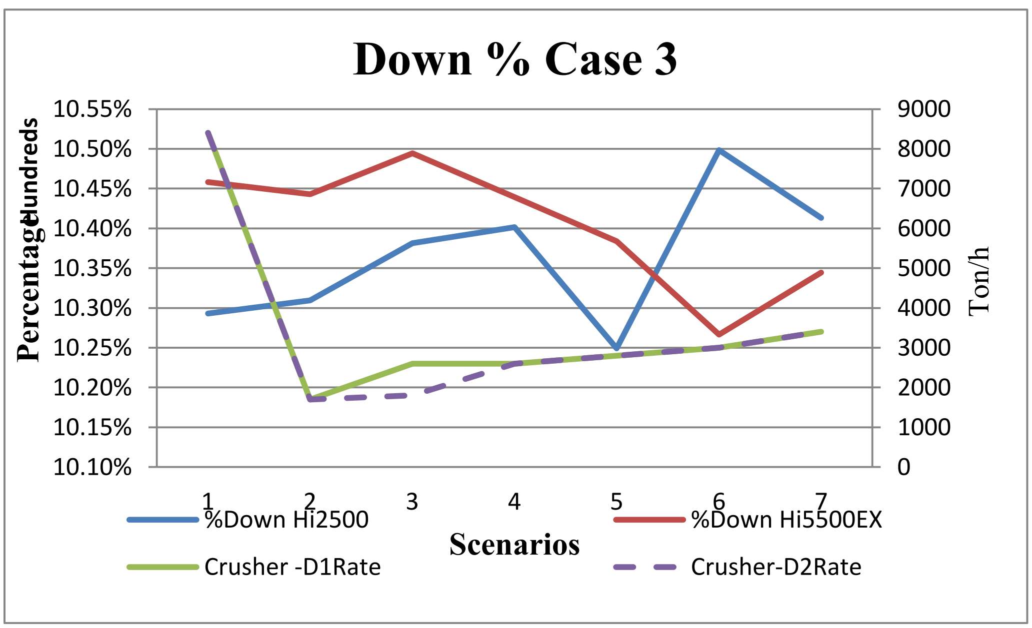

Figure 118.Shovel down time by shovel type Case 3. (PM AND FAILURE).

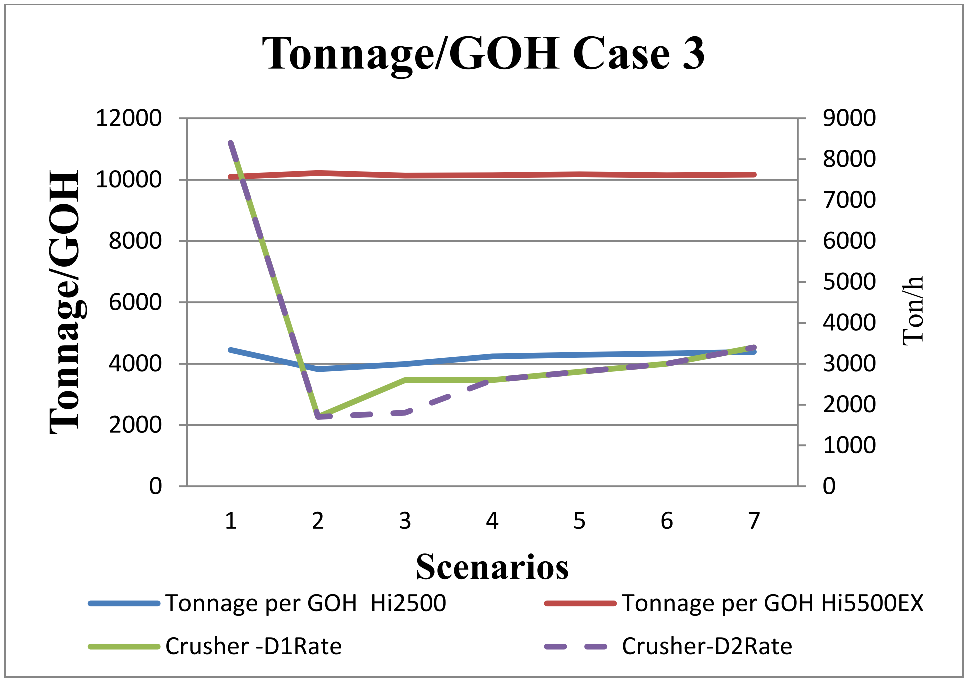

Figure 119.Shovel Tonnage per gross operating hours Case 3

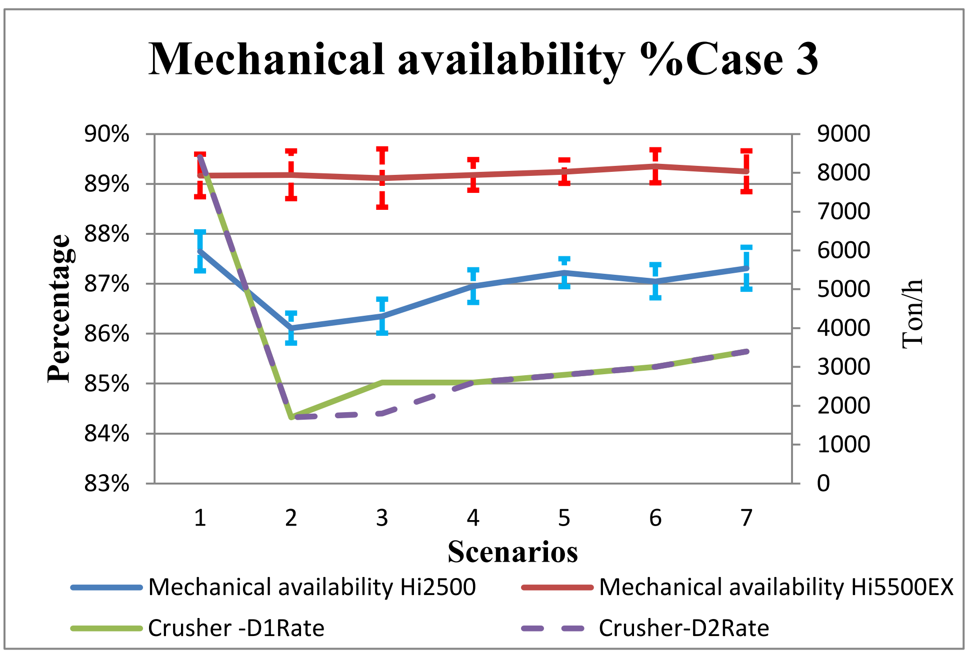

Figure 120.Shovel Mechanical availability Case 3

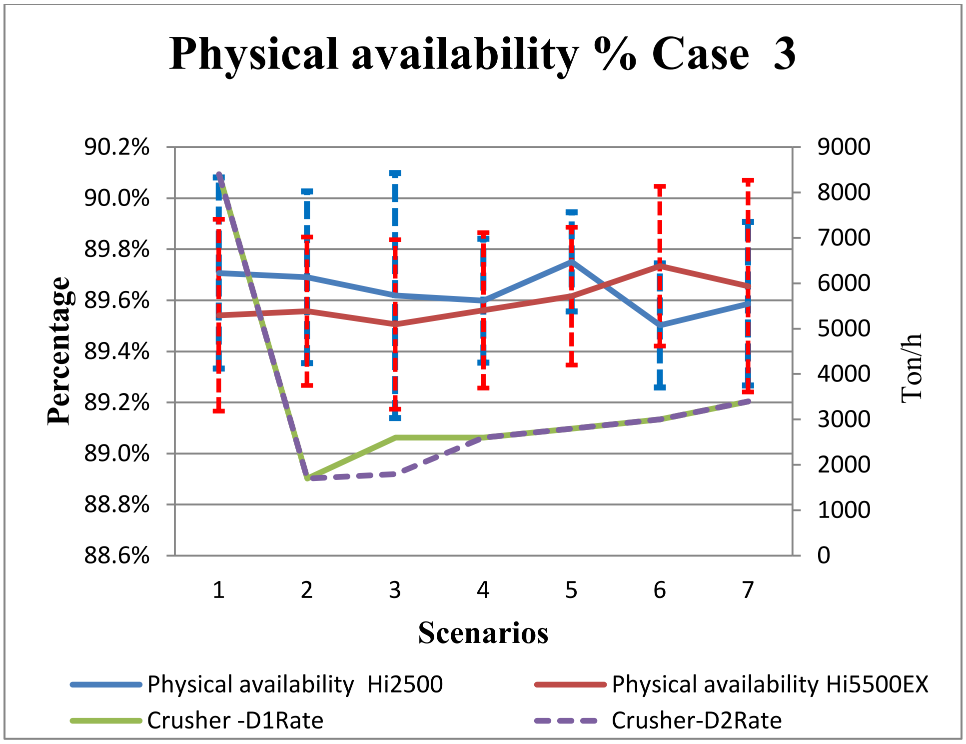

Figure 121.Shovel Physical availability Case 3

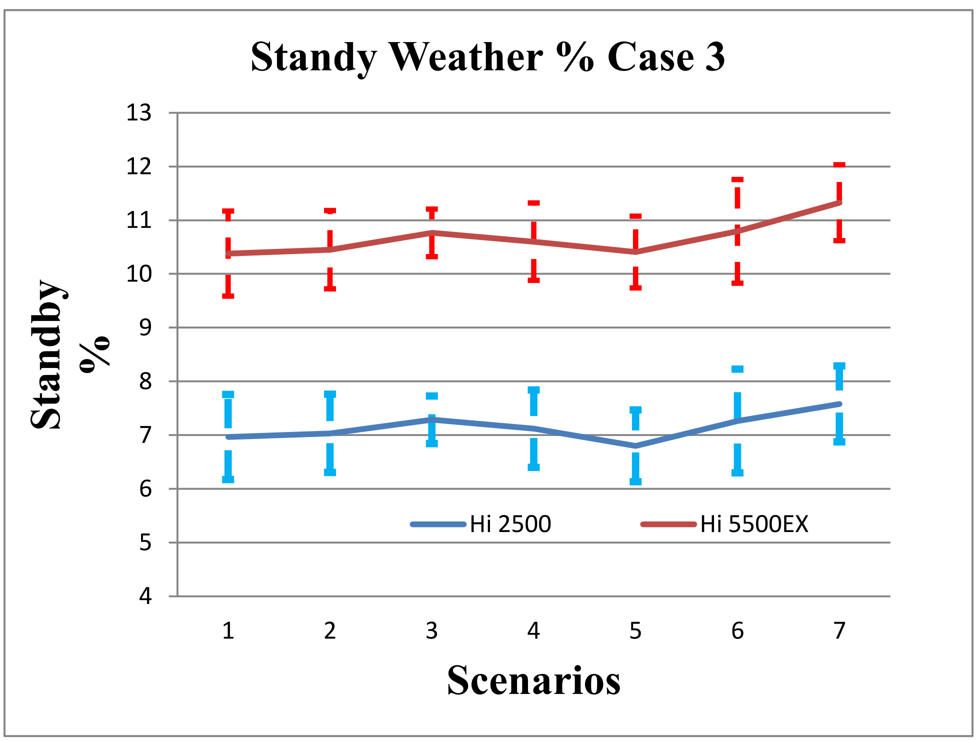

Figure 122.Shovel Stand by weather Case 3

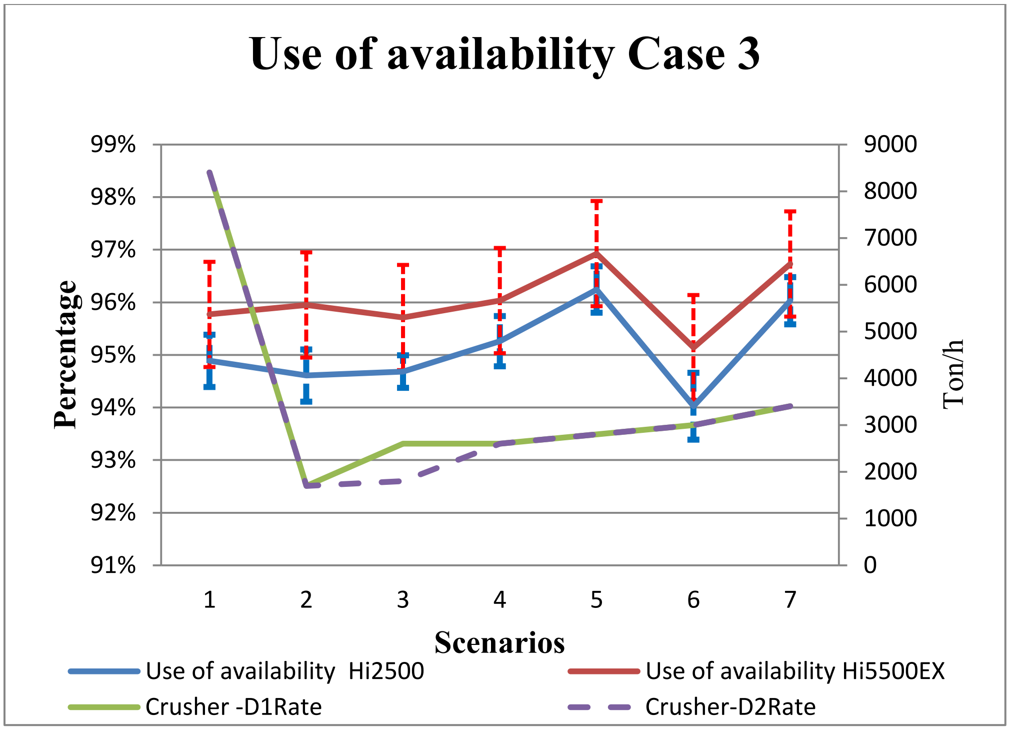

Figure 123.Shovel Use of availability Case 3

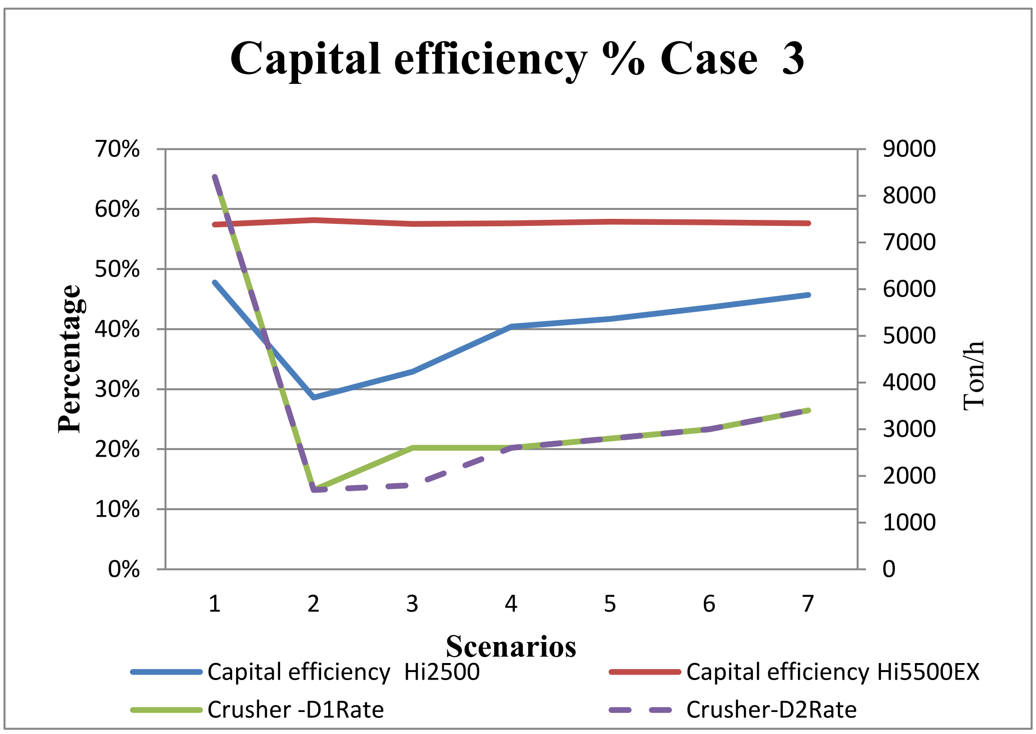

Figure 124.Shovel Capital efficiency Case 3

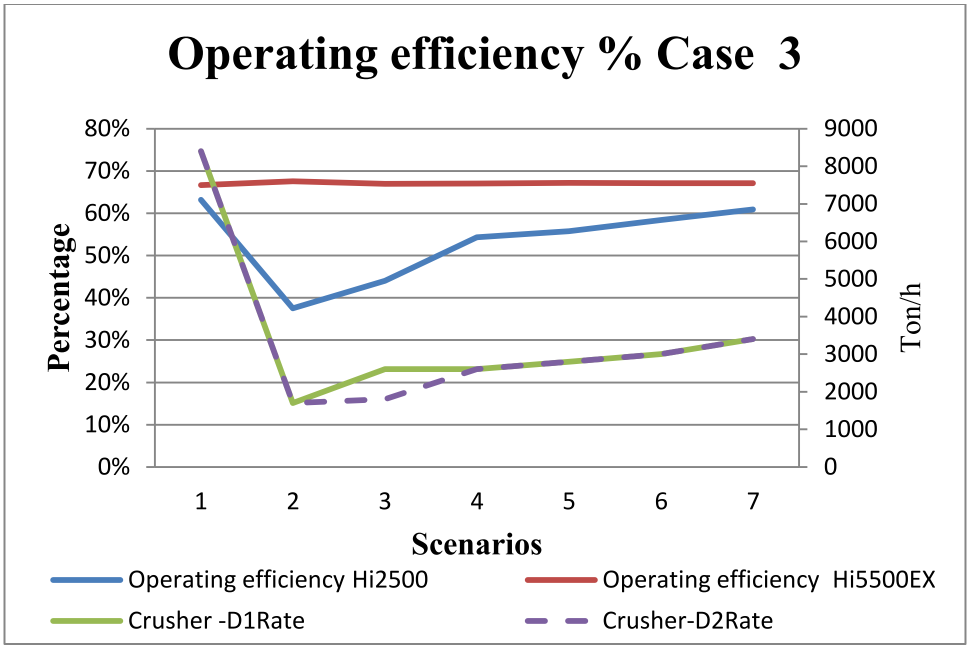

Figure 125.Shovel Operating efficiency Case 3

4.9.4. Truck Time category KPI's

GOH% is almost the same for both truck fleets with not so much fluctuation, 74 to 75%, Figure 126 shows the values. In more detail, without describing delays NOH by truck type, shown in Figure 127, number of NOH hours truck type Cat793C is more stable than Cat785C,it remains about 2850hr, while ore fleet changes as the scenarios goes by in different rates. NOH for ore trucks drops as rates at the crushers do but at the end, for scenario 7, it goes back to the original number of hours of more than 2800hr. This relationship is explained with the trucks delay %, which are a summation of queue at shovel and dump facility, Figure 128 has this information. The growth in delay% for truck fleet Cat785C, is opposite to rate decrease in crusher rate by scenarios, for scenario 3, delay went up to 18% from 10%. At the end for scenario 7, delay% goes back to 10%.

Material hauled in truck type Cat 793C is also very stable and always higher than Cat785C as average cycle time is lesser and bucket tonnage more. Figure 129, depicts this information. regarding to down time % it is very erratic for both but with higher values for Cat793C than for Cat785C, information is in Figure 130. Mechanical availability is shown in Figure 131. It is also smooth as GOH% with some variability related to down time. For both ore and waste trucks it fluctuates around 76-77%. Physical availability in Figure 132, also relates to availability of the truck to operate including the fact that standby weather events can happen and still truck being available, no down time is considered inside physical availability. For both these value is constant around 77.5 and 76.5%.

Finally, inside the topic of availability use of availability that is how much the trucks works inside the available time, varies from 96 to 97% for both fleets, in Figure 134, this information is shown. Capital and operating efficiency, in Figure 136 and Figure 135 are showing how the time not relating to delays is invested in schedule and in gross operating hours. For Cat785C its dependent of the rate of the crusher.

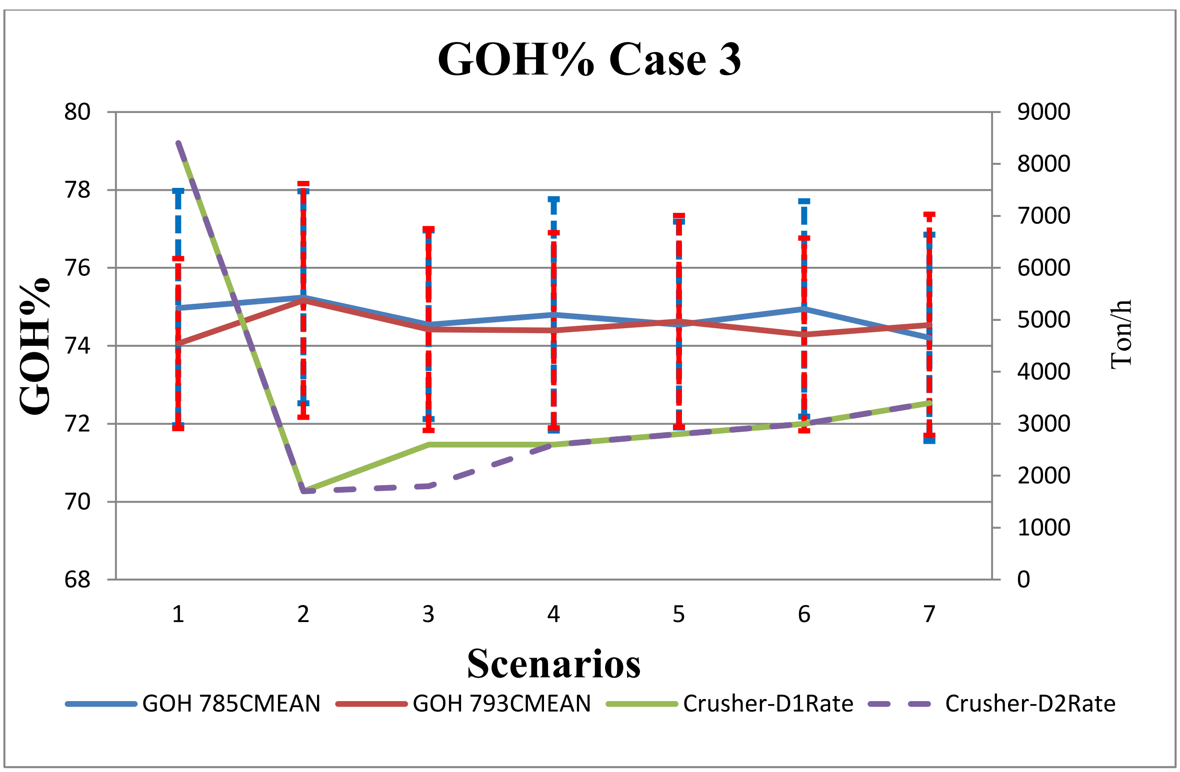

Figure 126.Truck Gross Operating hours GOH % Case 3

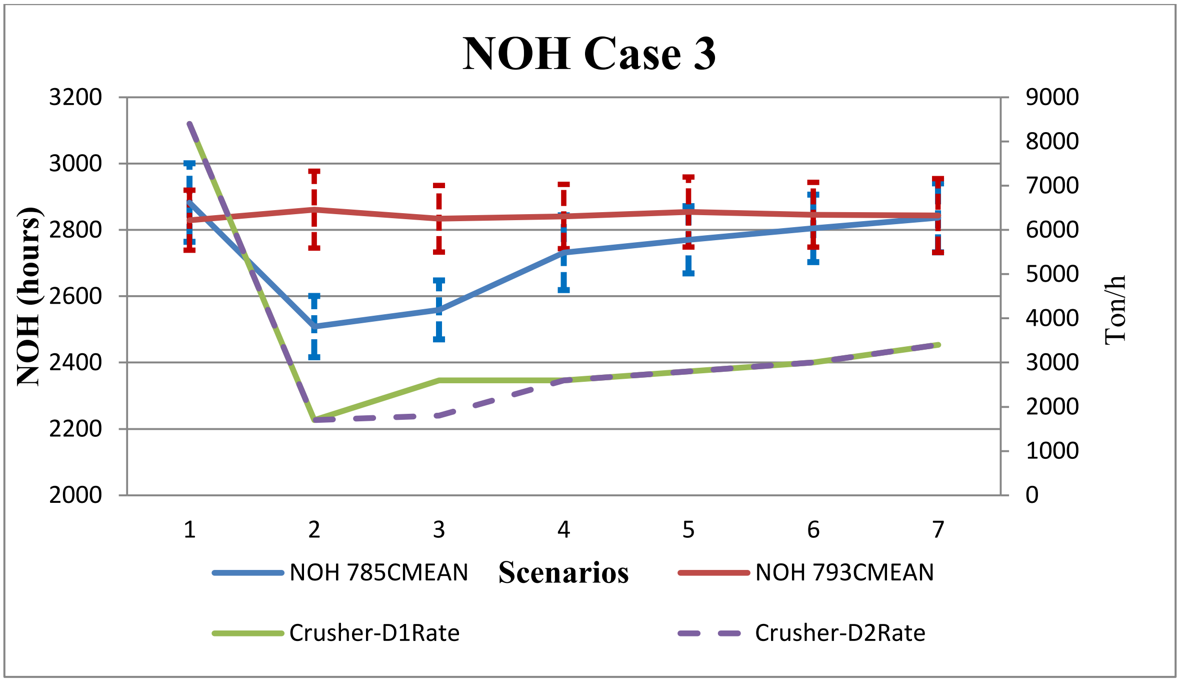

Figure 127.Truck Net Operating hours NOH Case 3

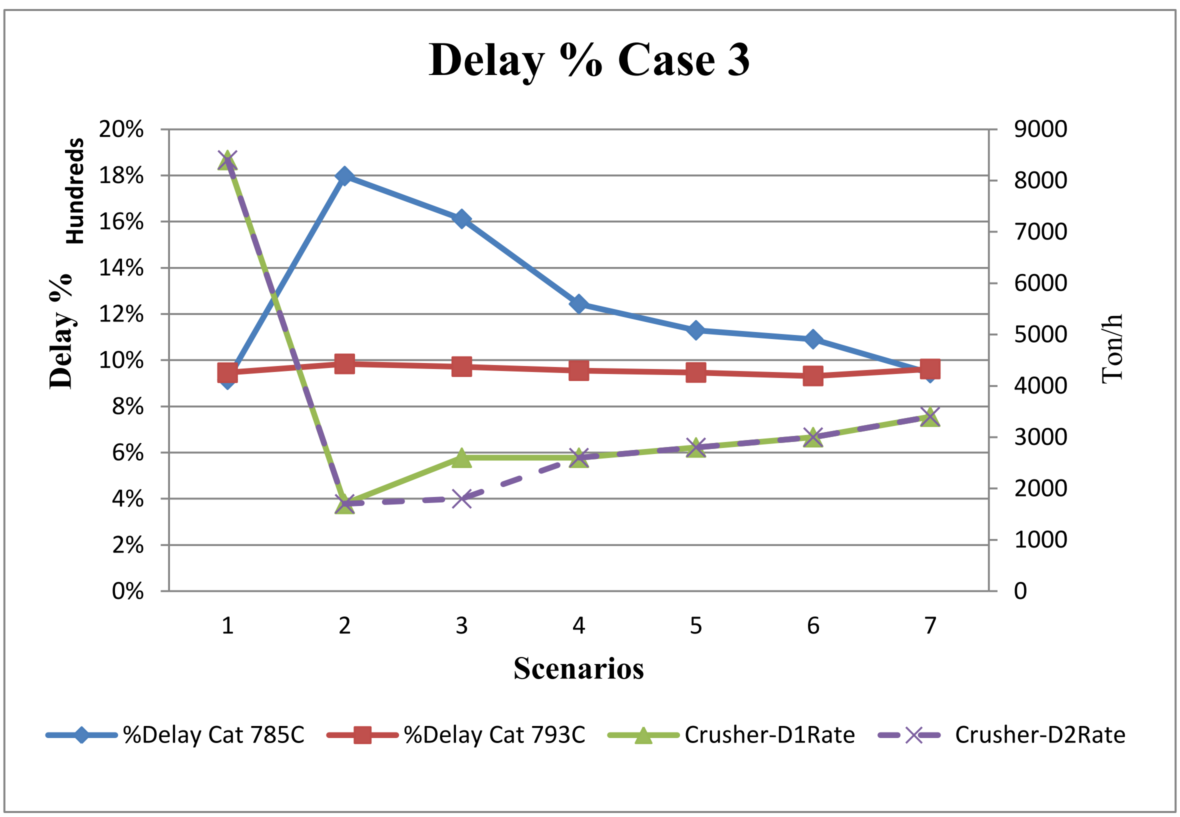

Figure 128.Truck delay% by truck type Case 3

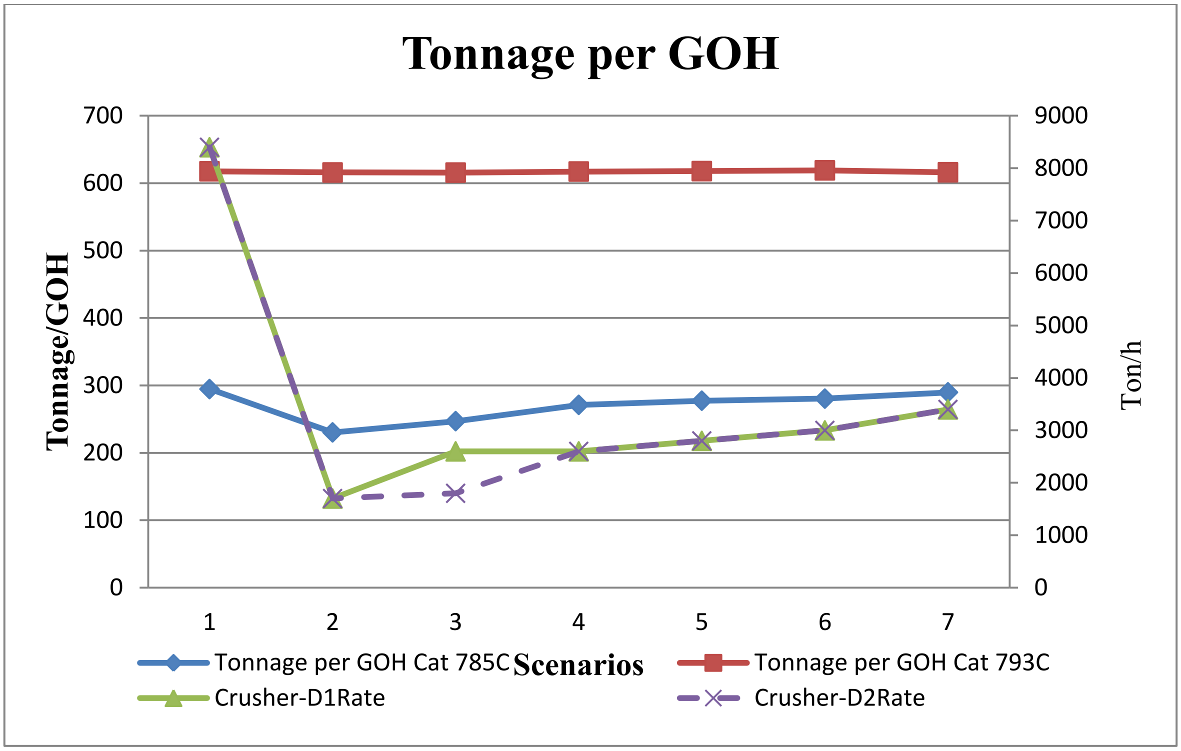

Figure 129 Truck Tonnage per gross operating hours Case 3

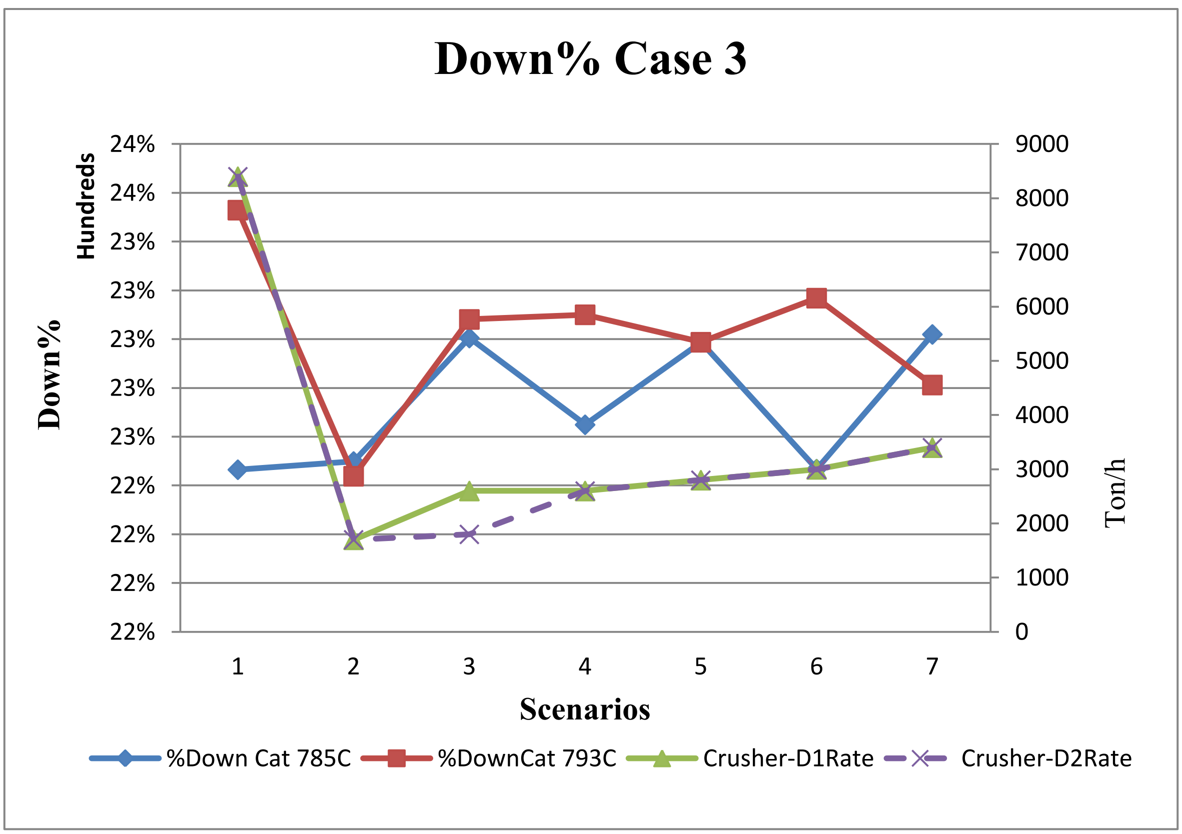

Figure 130.Truck down time % by truck type Case 3 (DOWN AND FAILURE)

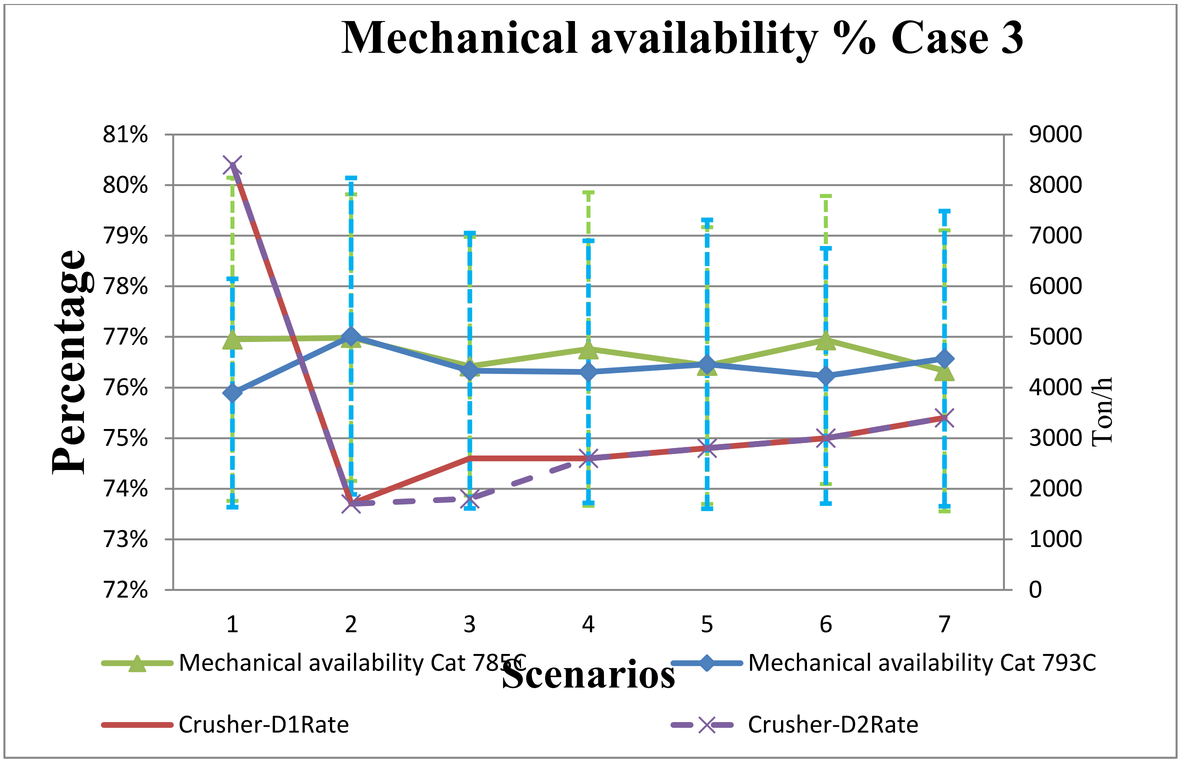

Figure 131.Truck Mechanical availability Case 3

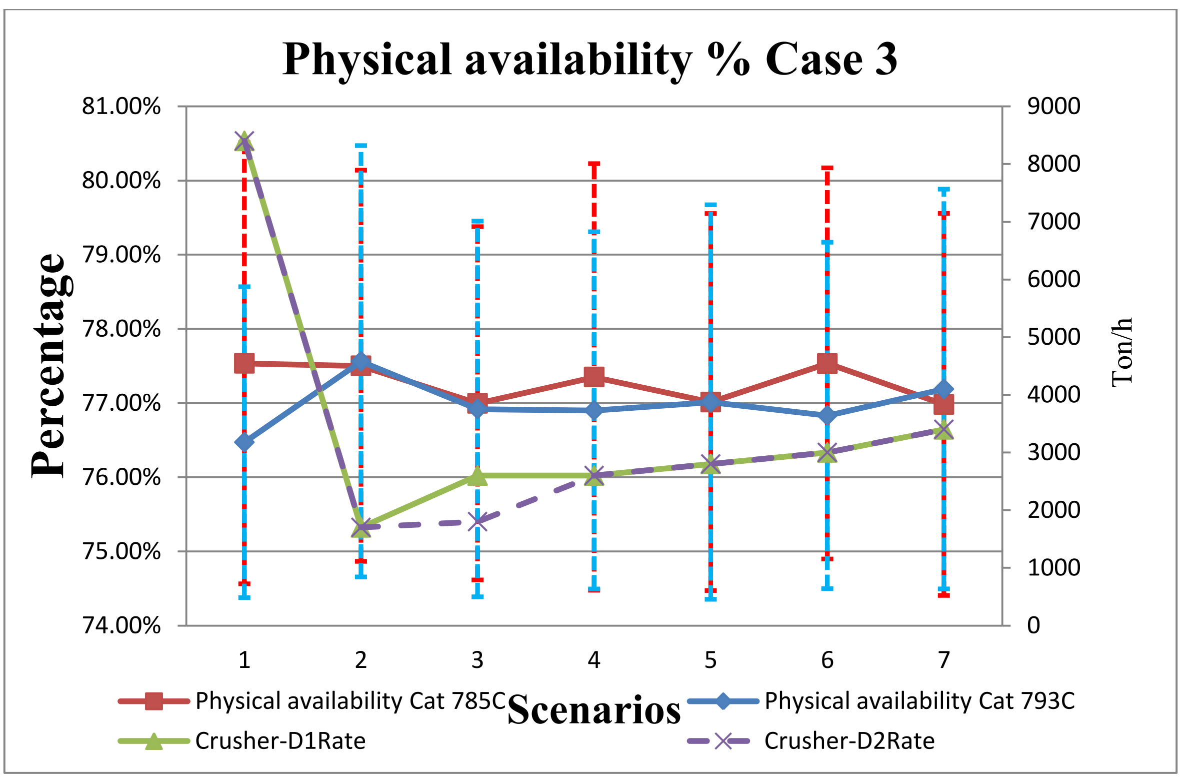

Figure 132.Truck Physical availability Case 3

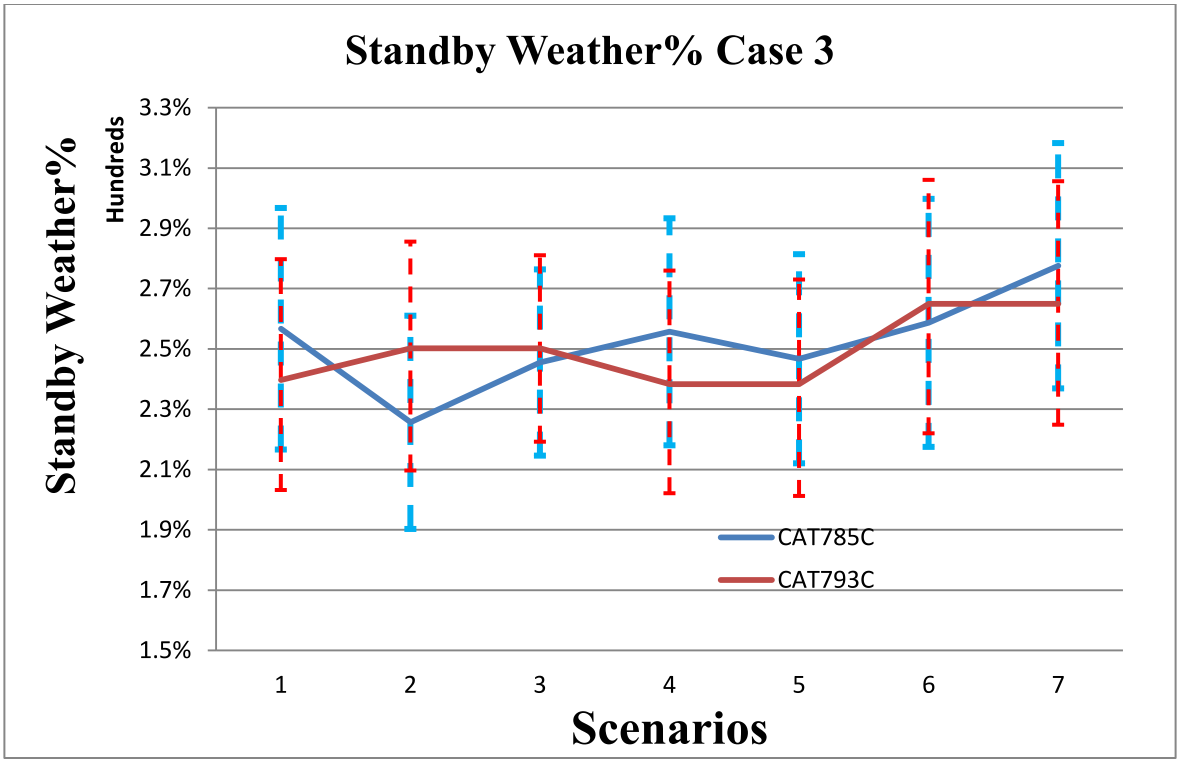

Figure 133.Truck Stand by weather % Case 3

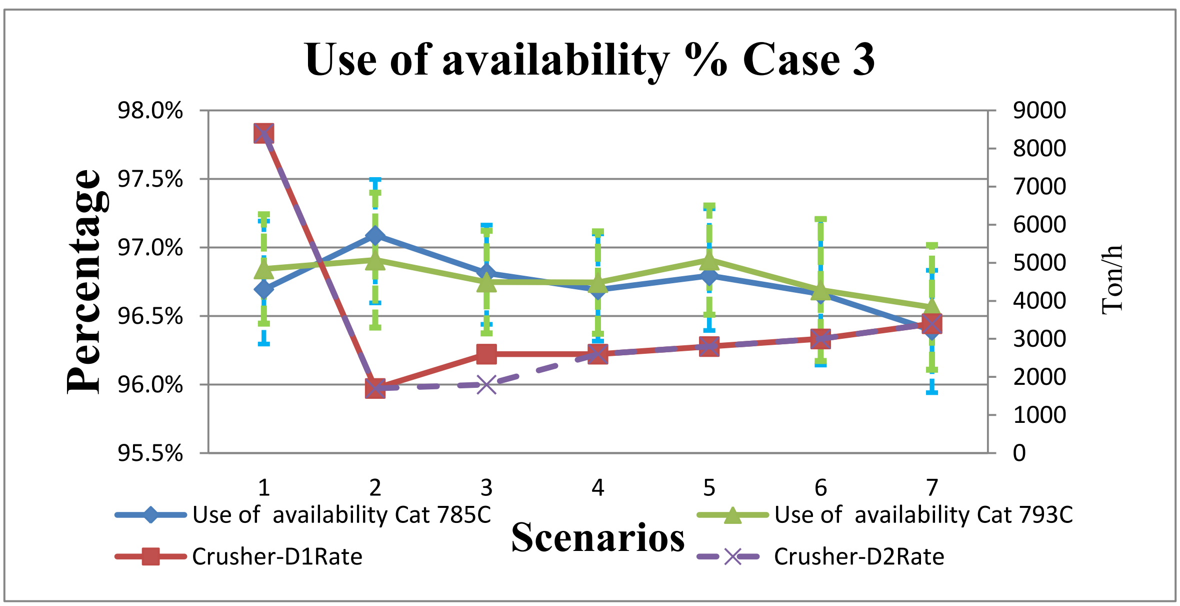

Figure 134.Truck Use of availability Case 3

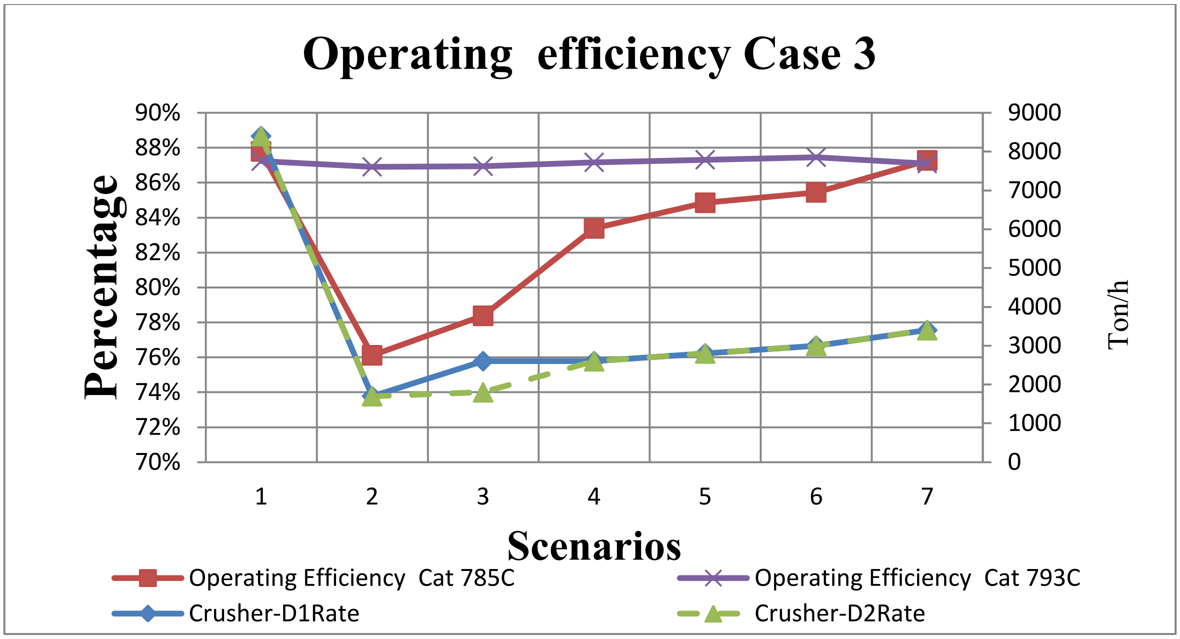

Figure 135.Truck Operating efficiency Case 3

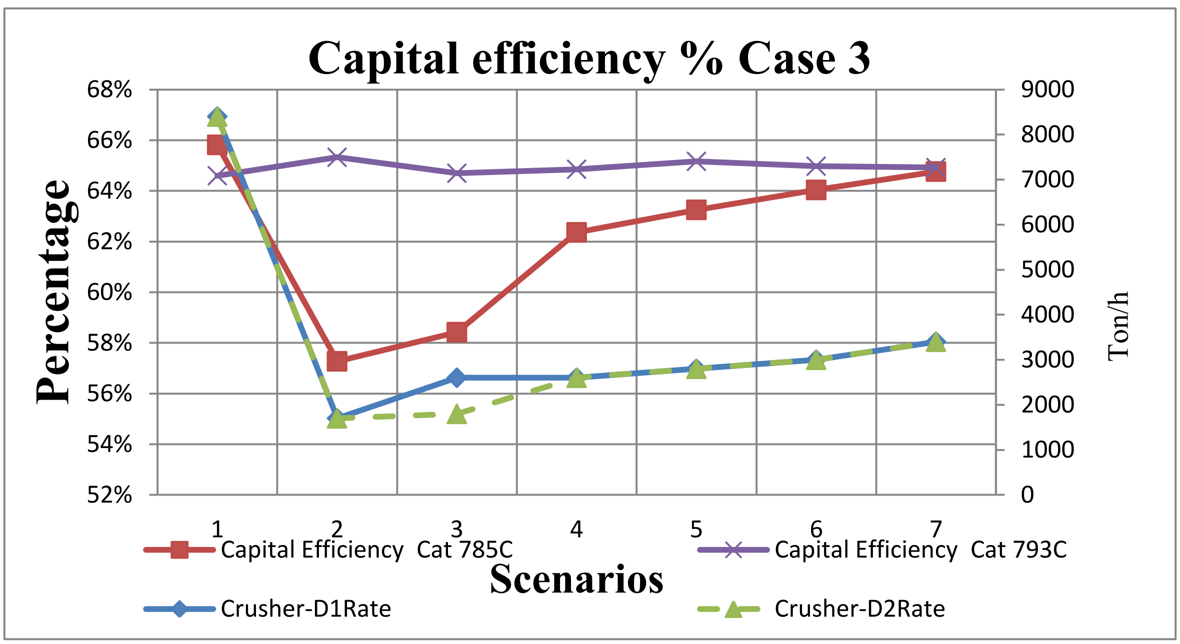

Figure 136.Truck Capital efficiency Case 3

4.10. Best case scenario Case 3

Case 3 is implemented for academic purposes to investigate in improvements of the system. Relationship between truck and shovel effectiveness and time could be established with crusher rates. Sensibility analysis was performed in capital, operational effectiveness and production a better performance than the initial case is achieved with a less rate. Information valuable for future projects. Figure 137, Figure 138 and Figure 139 outline that information. As a result, Best case scenario in Case 3 is number 7.

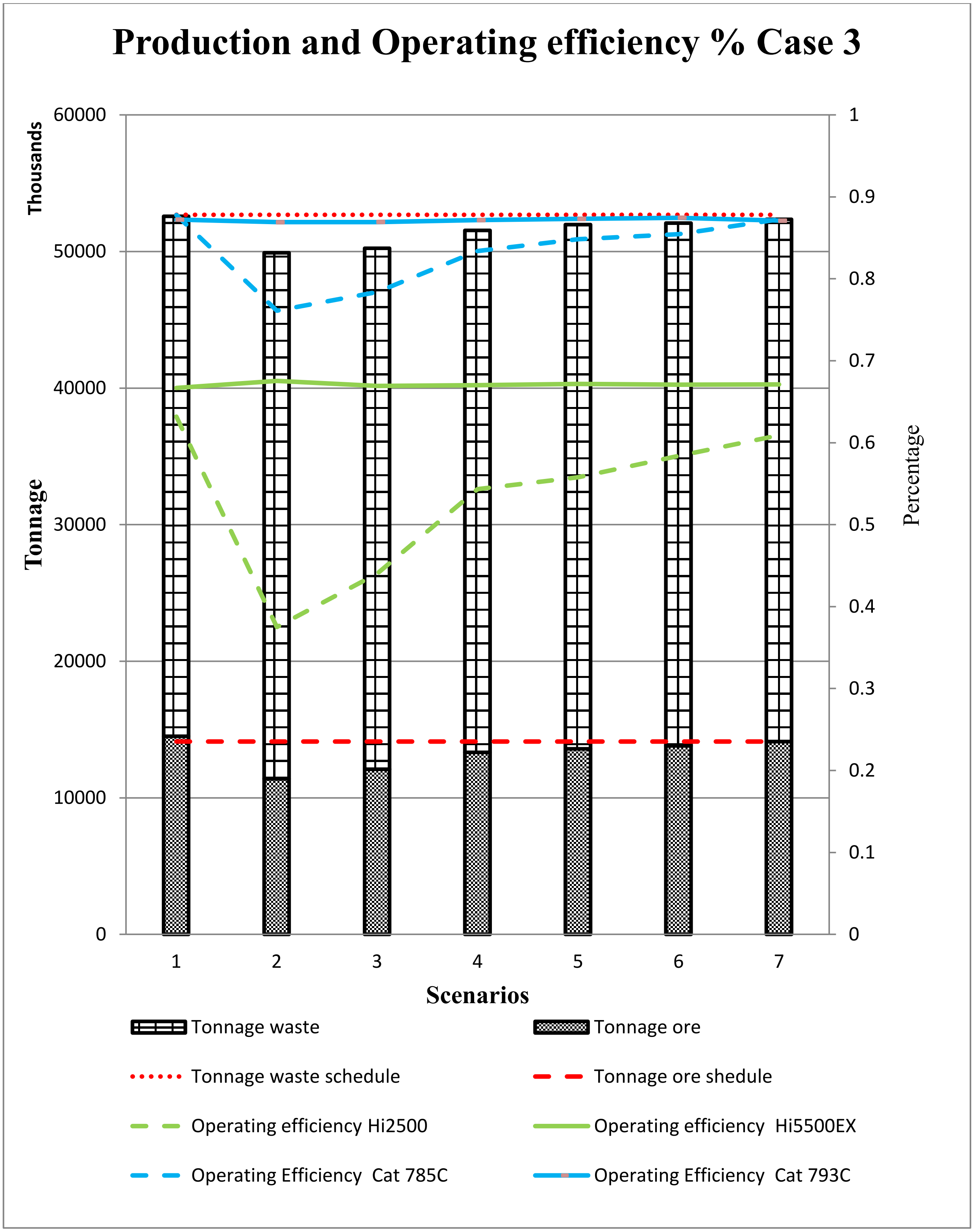

Figure 137. Production and operating efficiency case 3

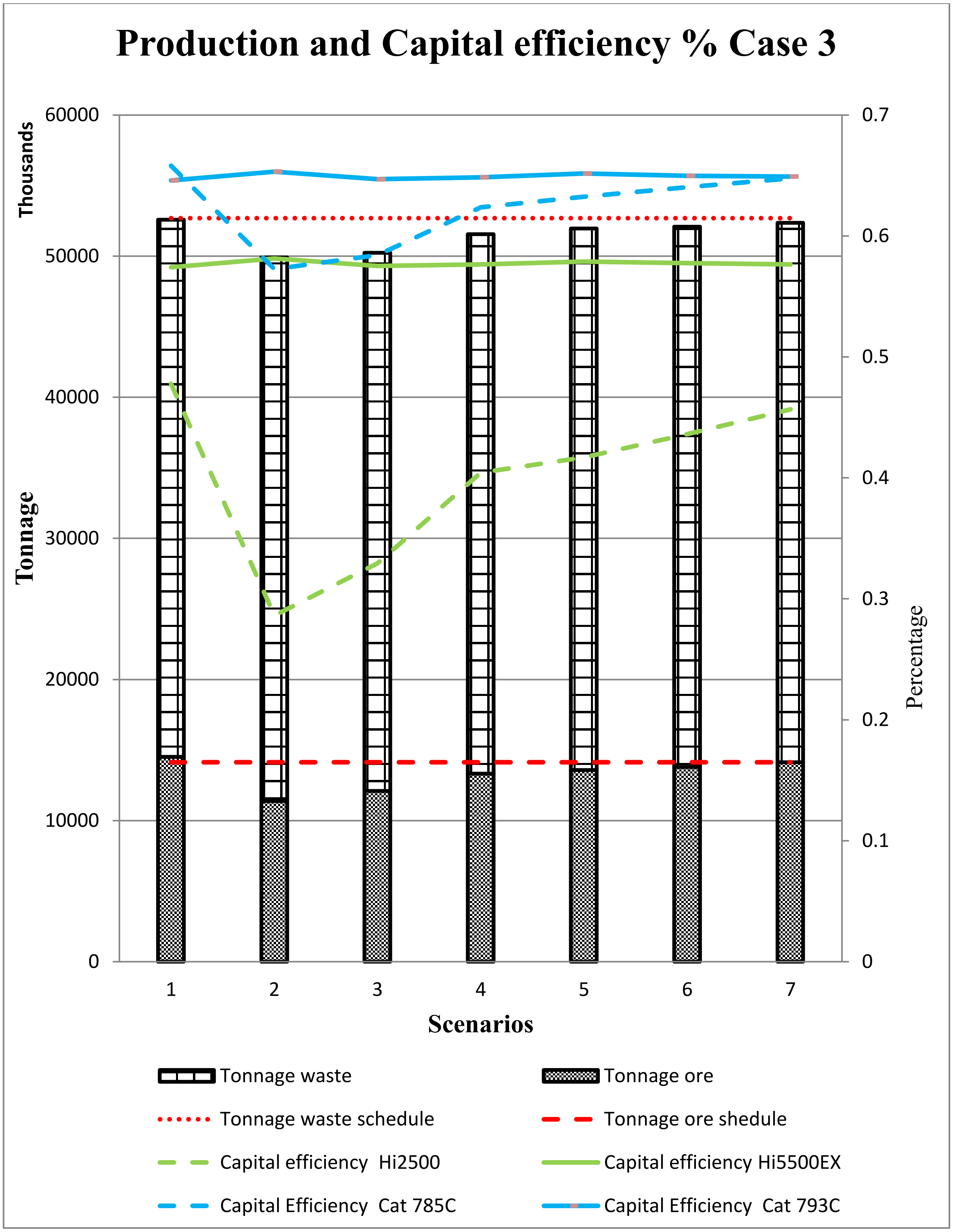

Figure 138.Production and Capital efficiency case 3

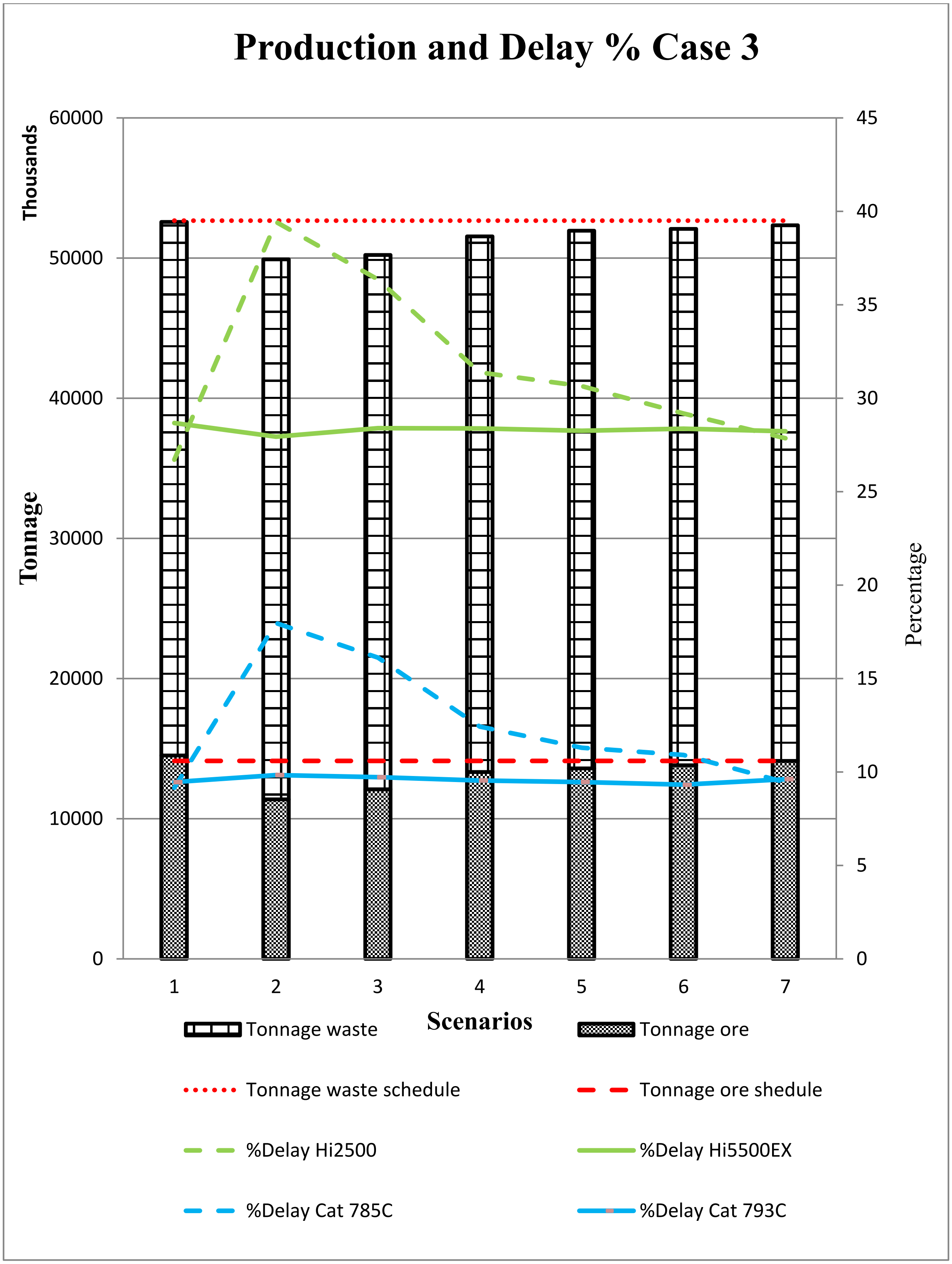

Figure 139.Production and delay case 3

4.11. Short-term plan

The best case scenario 34 trucks,15 Cat 785C, and 19 Cat 793C, and crusher rate of 3400 ton/h in both mill locations is elected to develop short-term plan with. As one of the objectives was to build short-term plan with uncertainty at KPI's, monthly and weekly schedule are presented with box plots which feature variability in the outcomes and allow window of operation for the mine planner strategies creation.

4.11.1. Monthly schedule

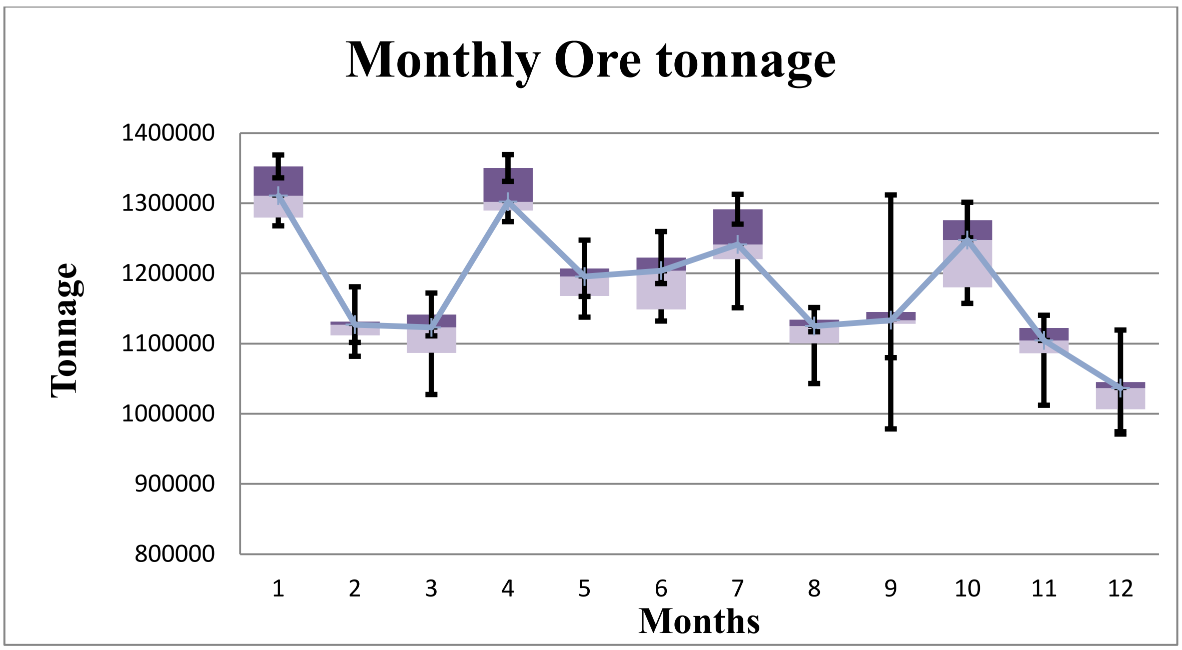

Figure 140.Monthly ore tonnage

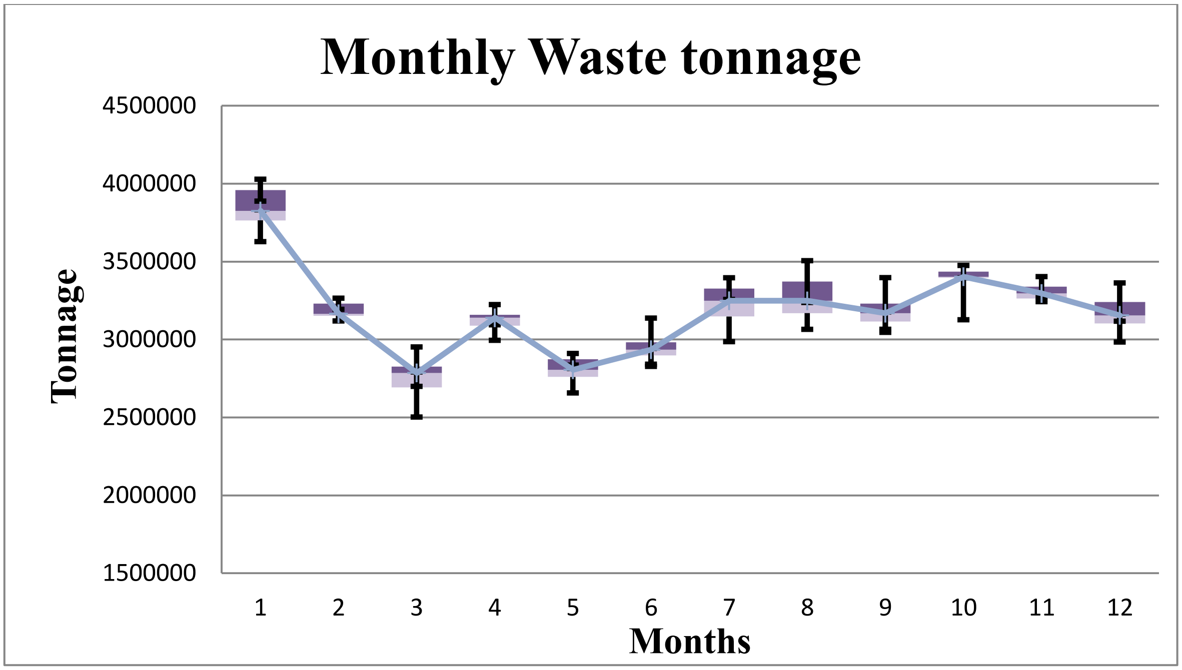

Figure 141.Montlhy waste tonnage

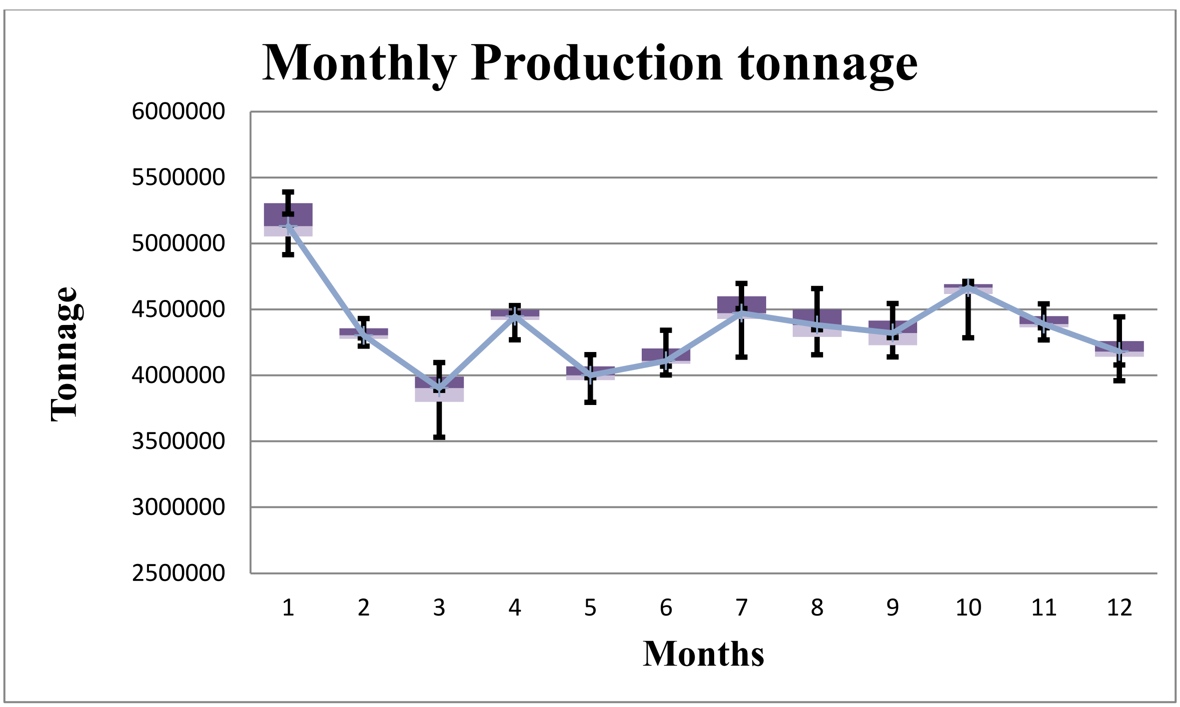

Figure 142.Monthly tonnage production ROM

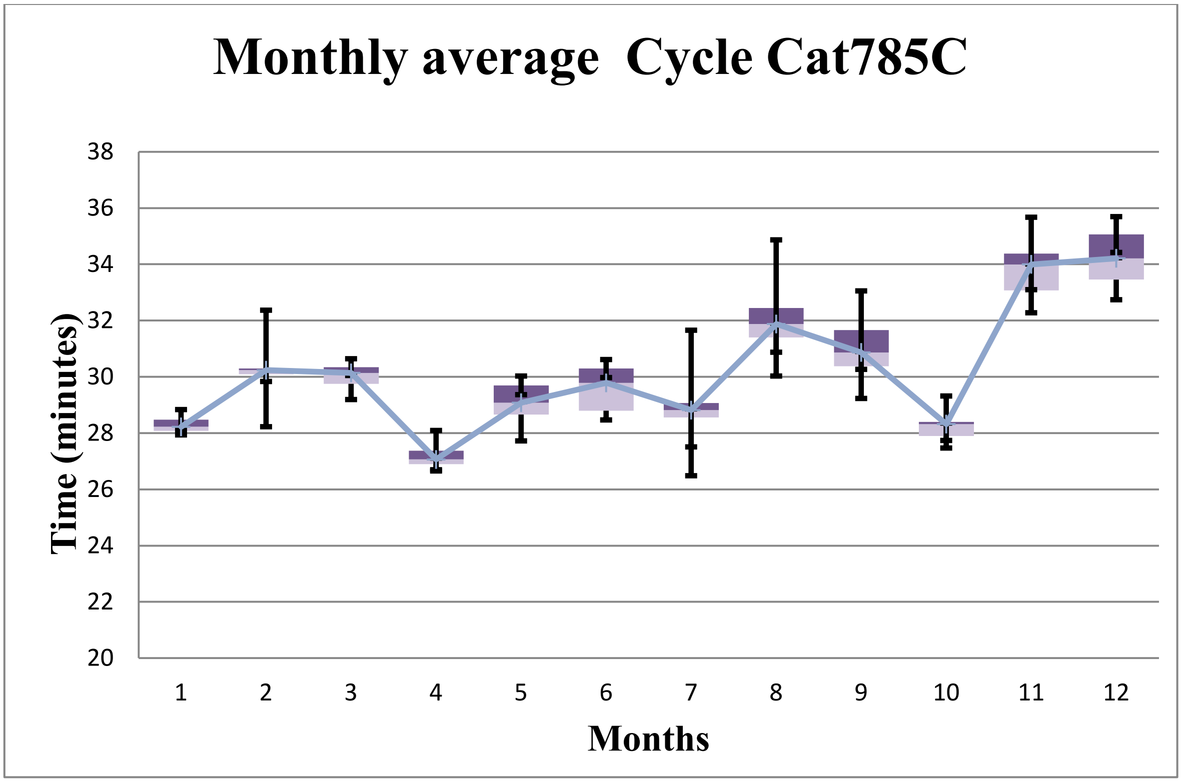

Figure 143.Monthly average cycle time Cat785C, Ore fleet

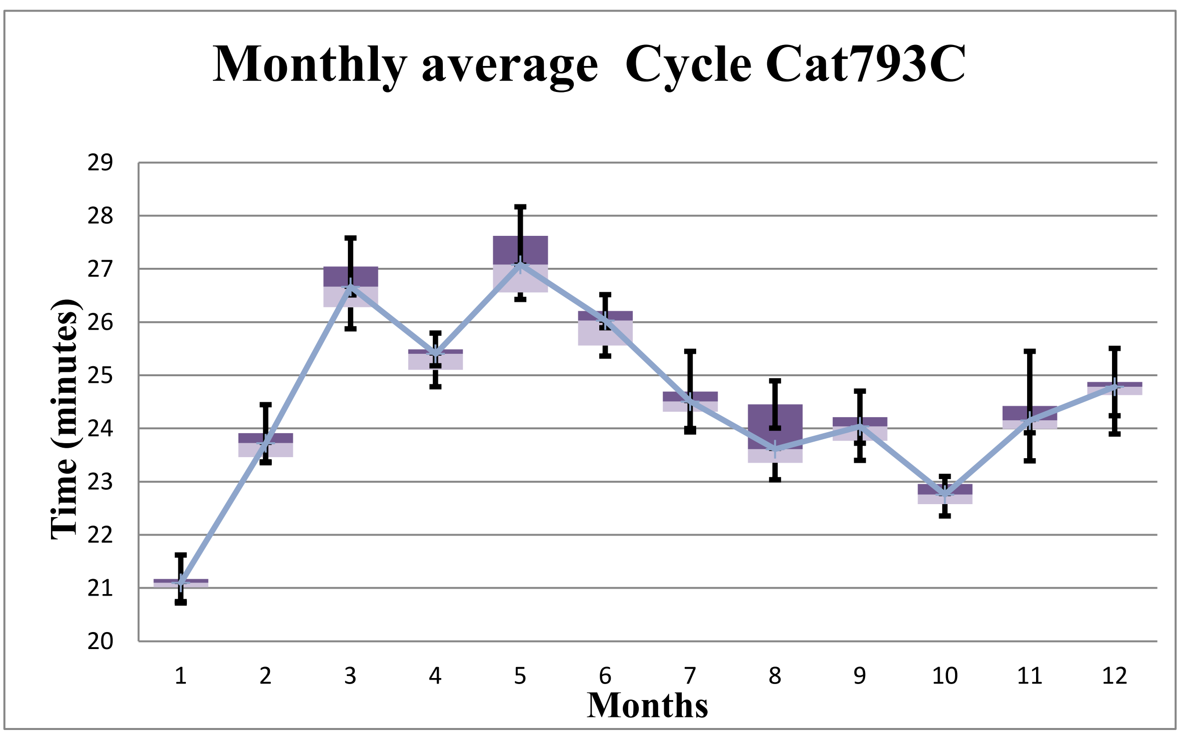

Figure 144. Monthly average cycle time Cat793C, Waste fleet

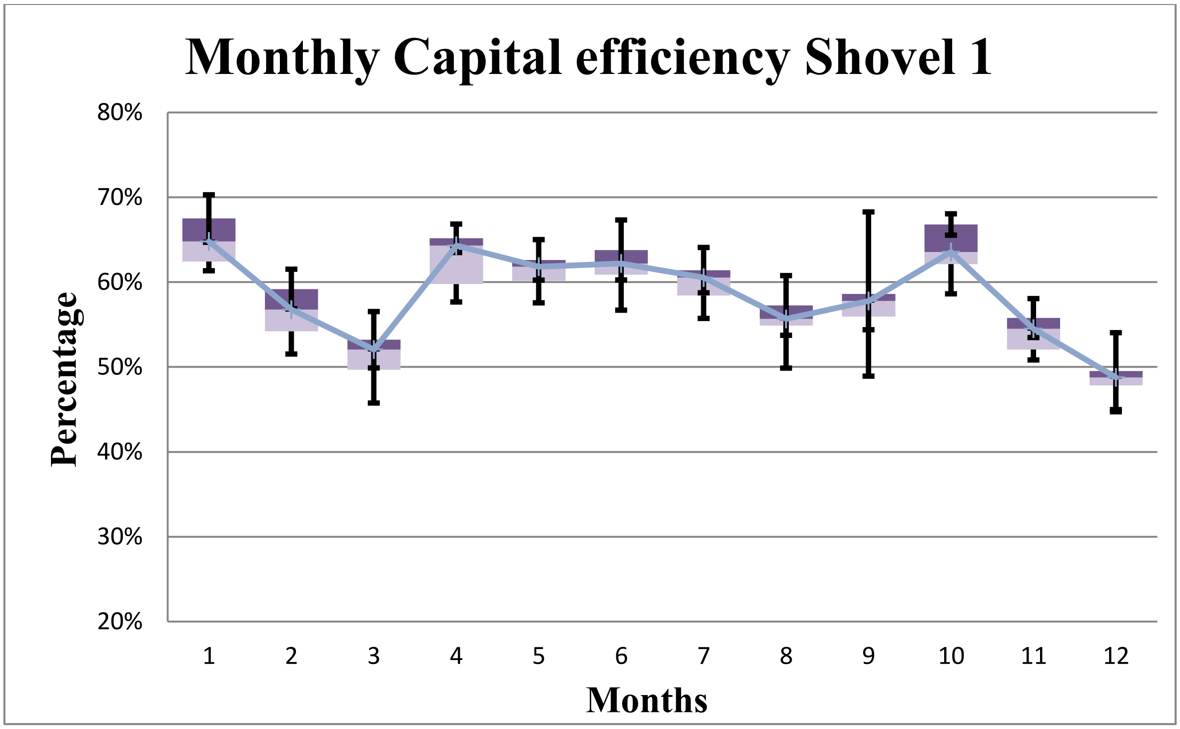

Figure 145.Monthly Capital efficiency shovel 1

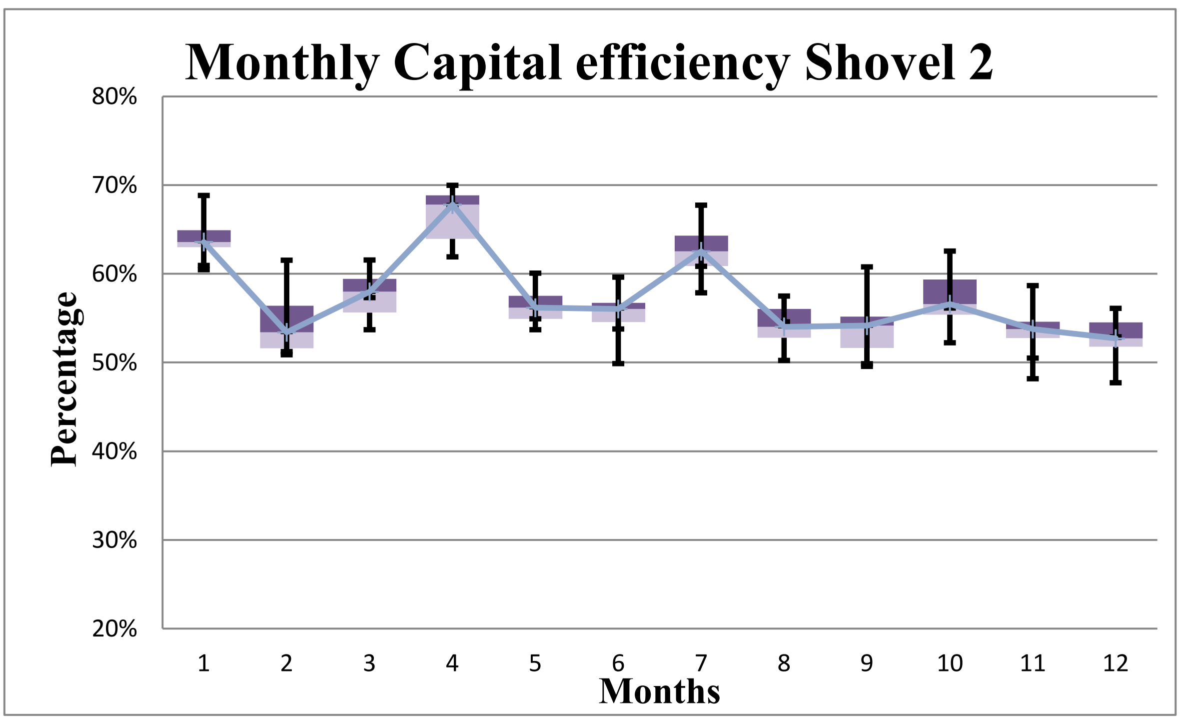

Figure 146. Monthly Capital efficiency shovel 2

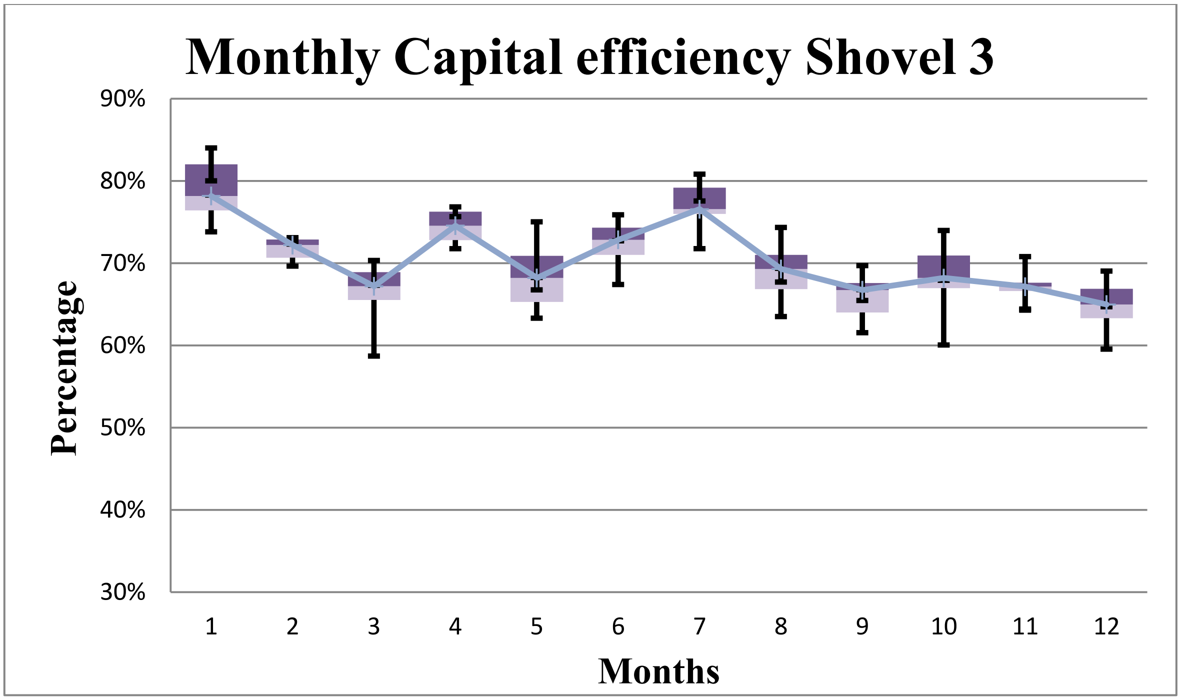

Figure 147. Monthly Capital efficiency shovel 3

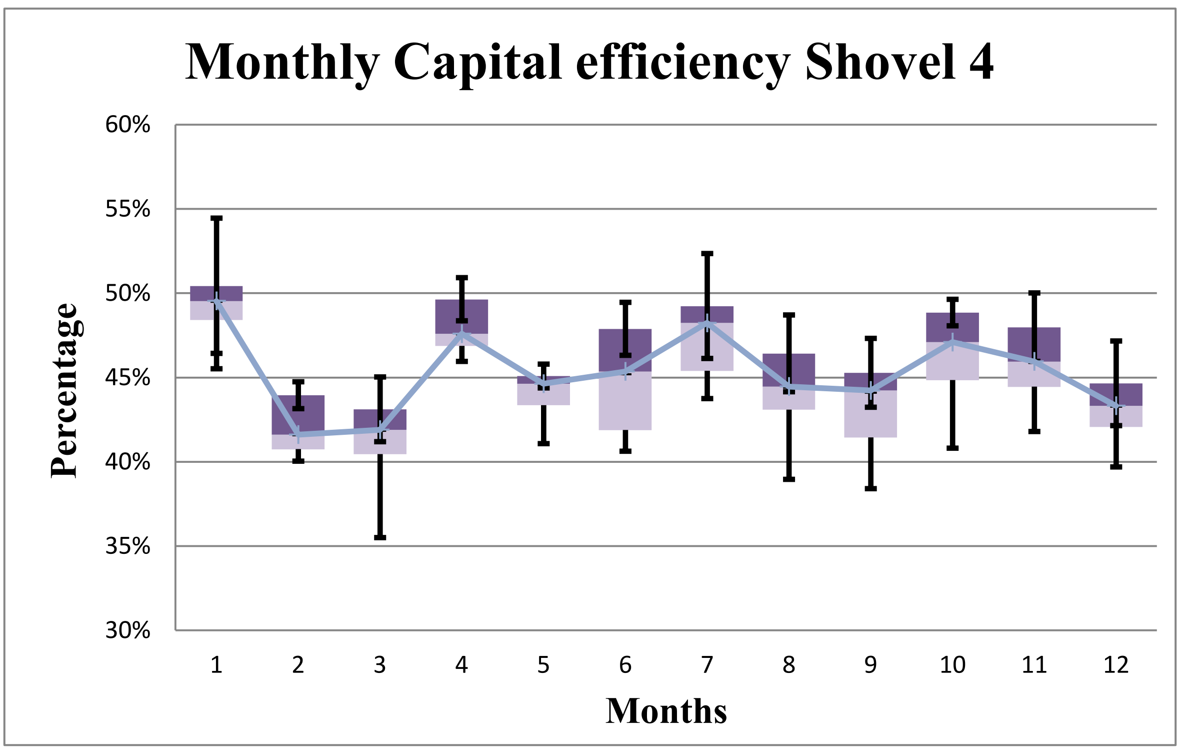

Figure 148. Monthly Capital efficiency shovel 4

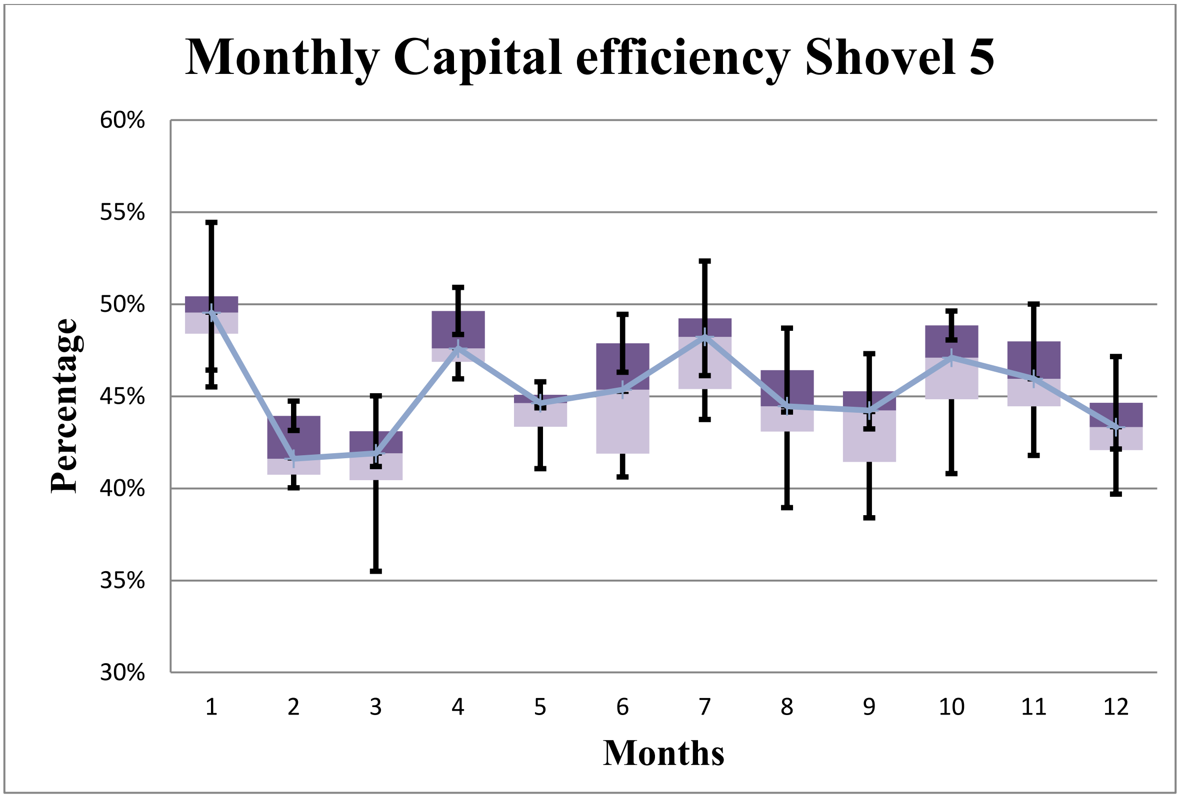

Figure 149. Monthly Capital efficiency shovel 5

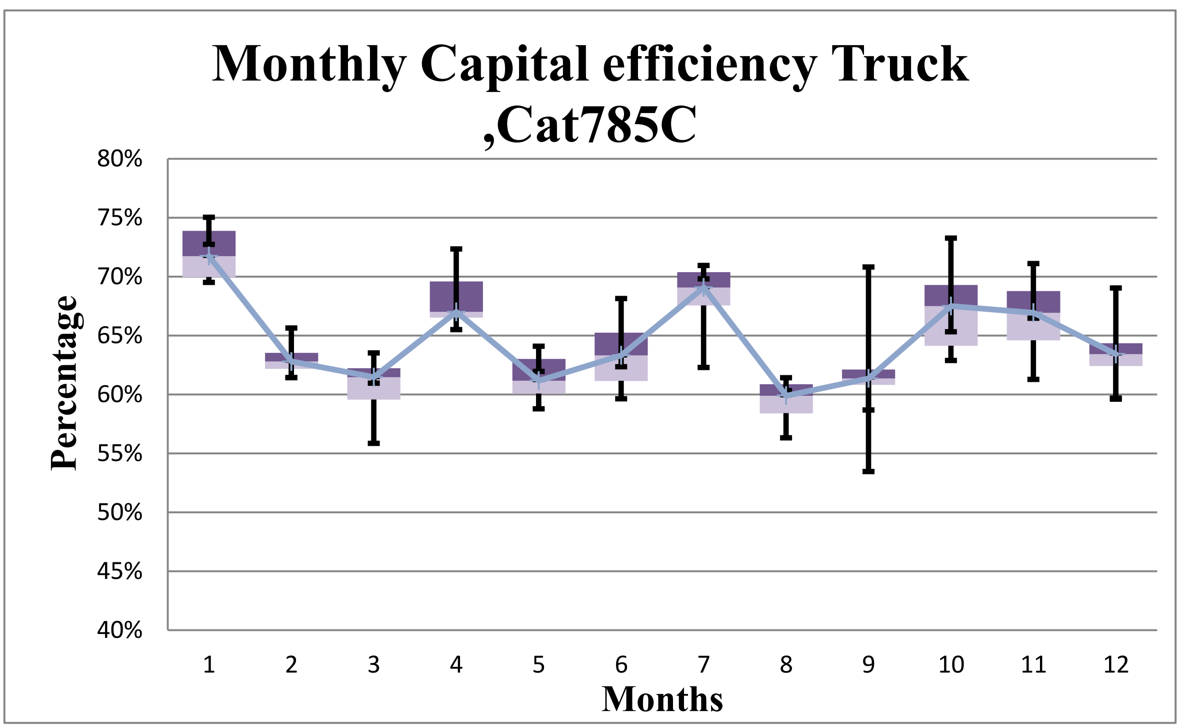

Figure 150. Monthly Capital efficiency Truck 785C

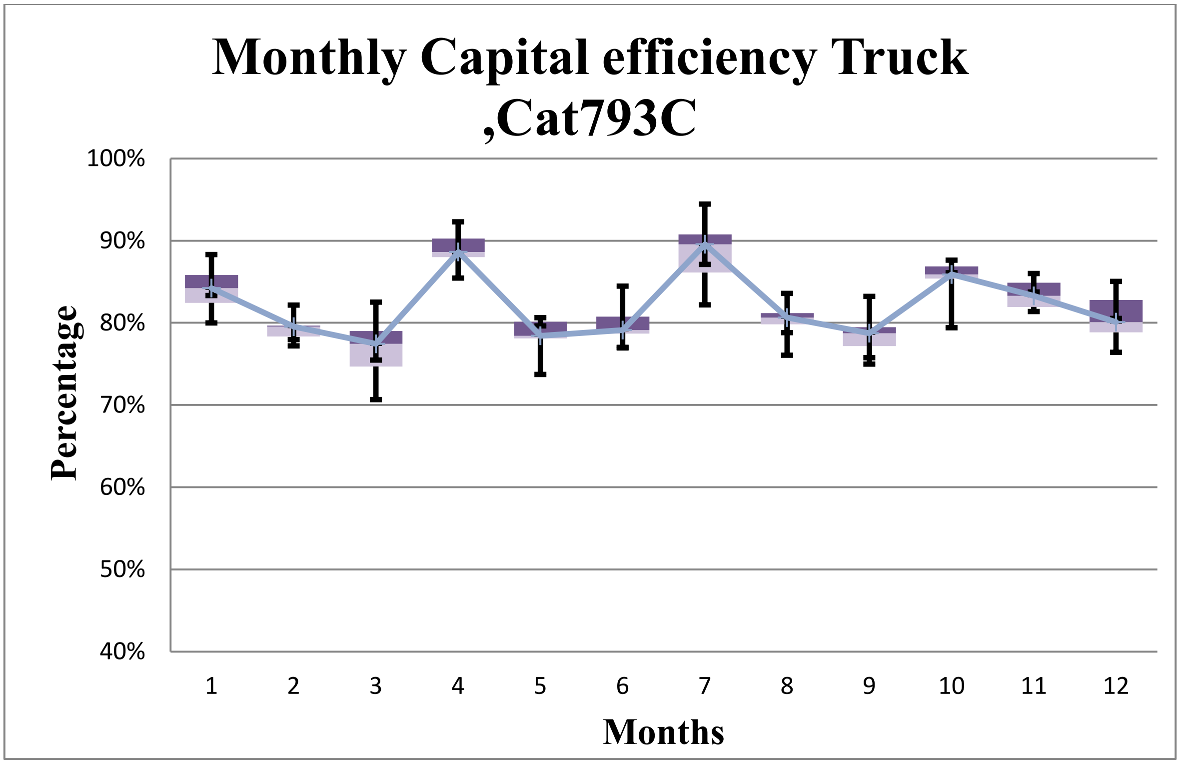

Figure 151. Monthly Capital efficiency Truck 793C

4.11.2. Weekly schedule

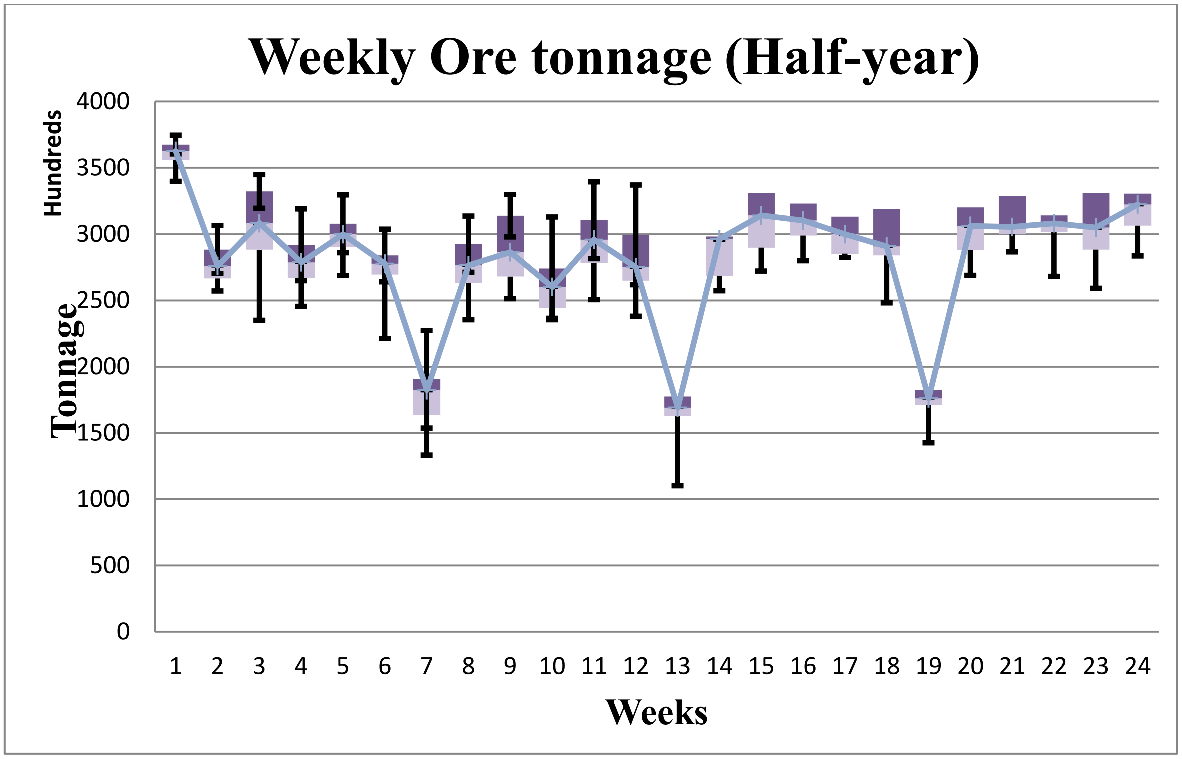

Figure 152.Weekly Ore tonnage

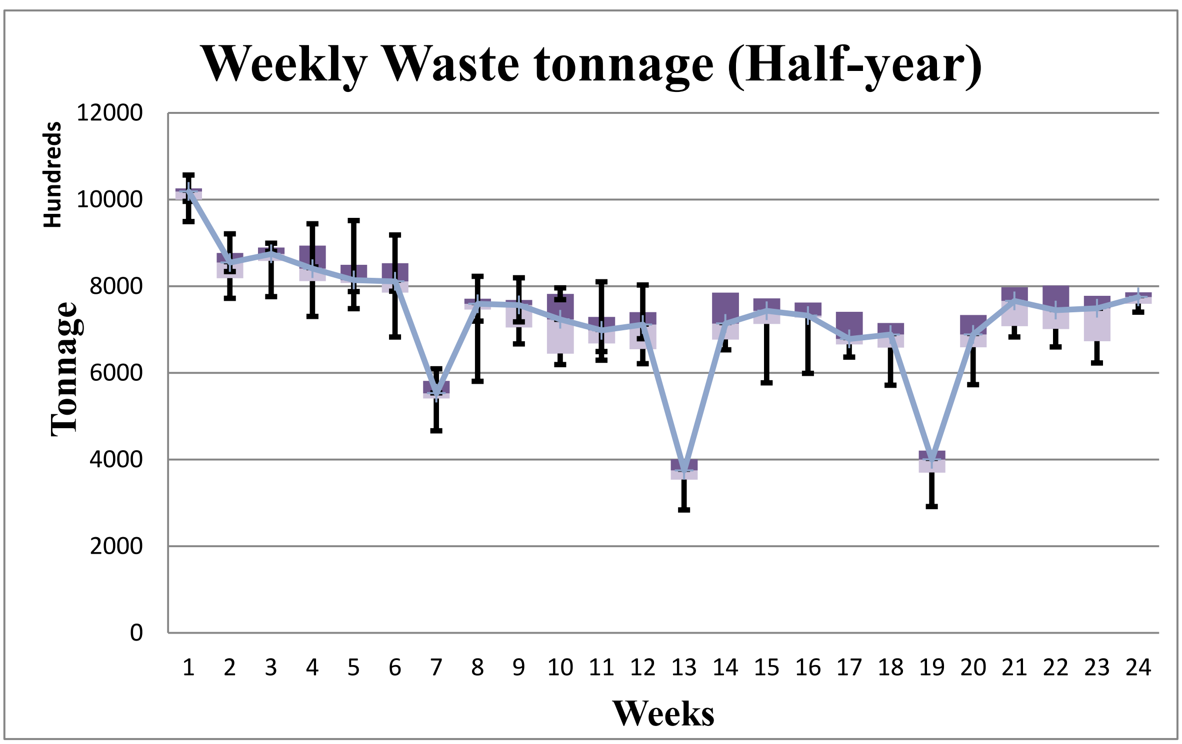

Figure 153.Weekly Waste tonnage

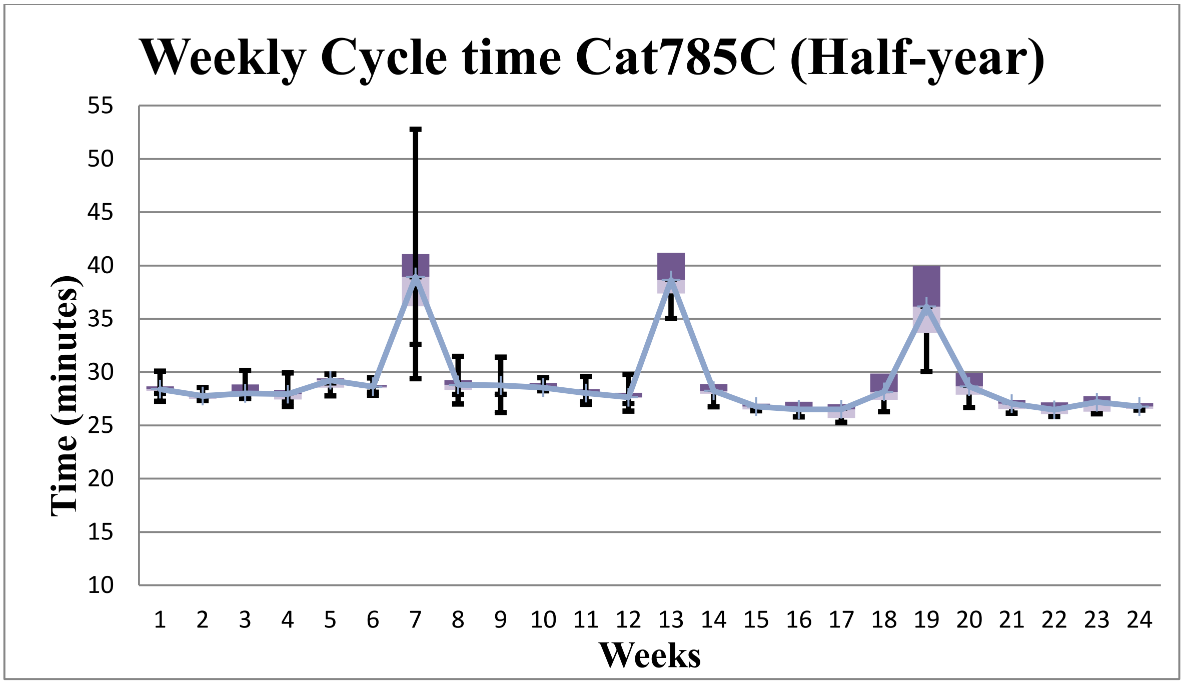

Figure 154.Weekly Cycle time Cat 785C,Ore fleet

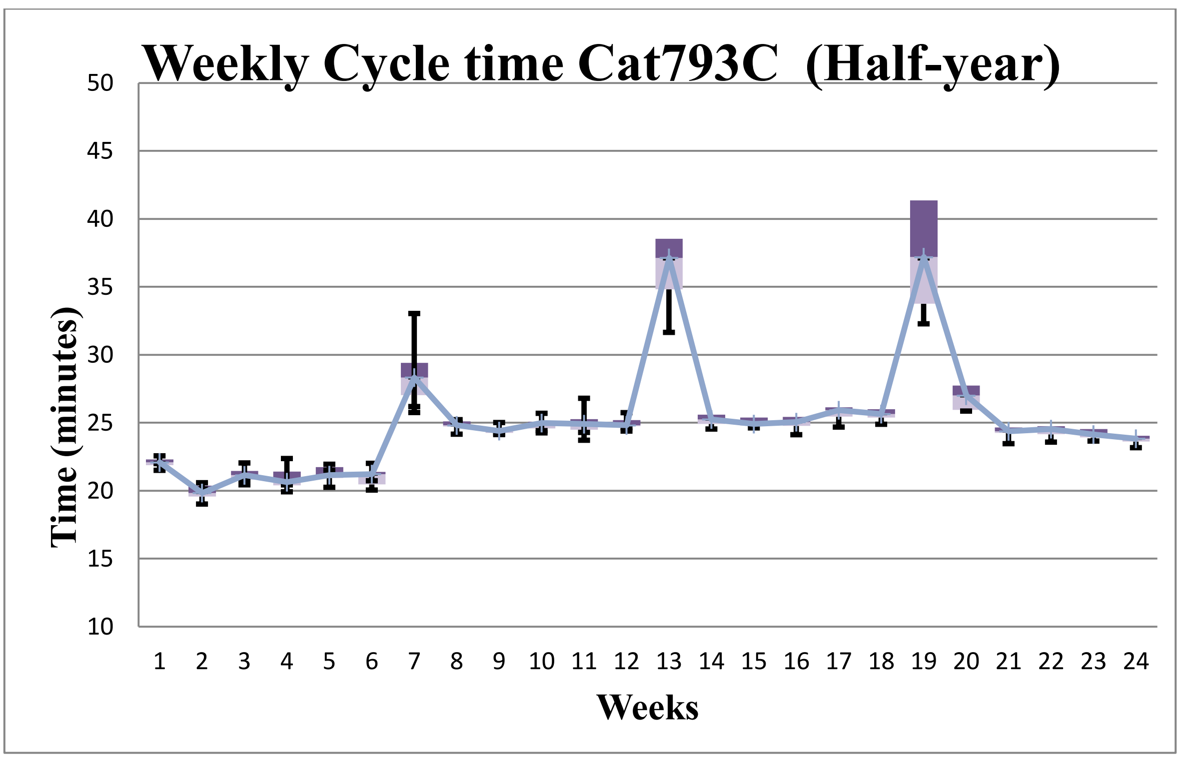

Figure 155.Weekly Cycle time Cat 793C.Waste fleet

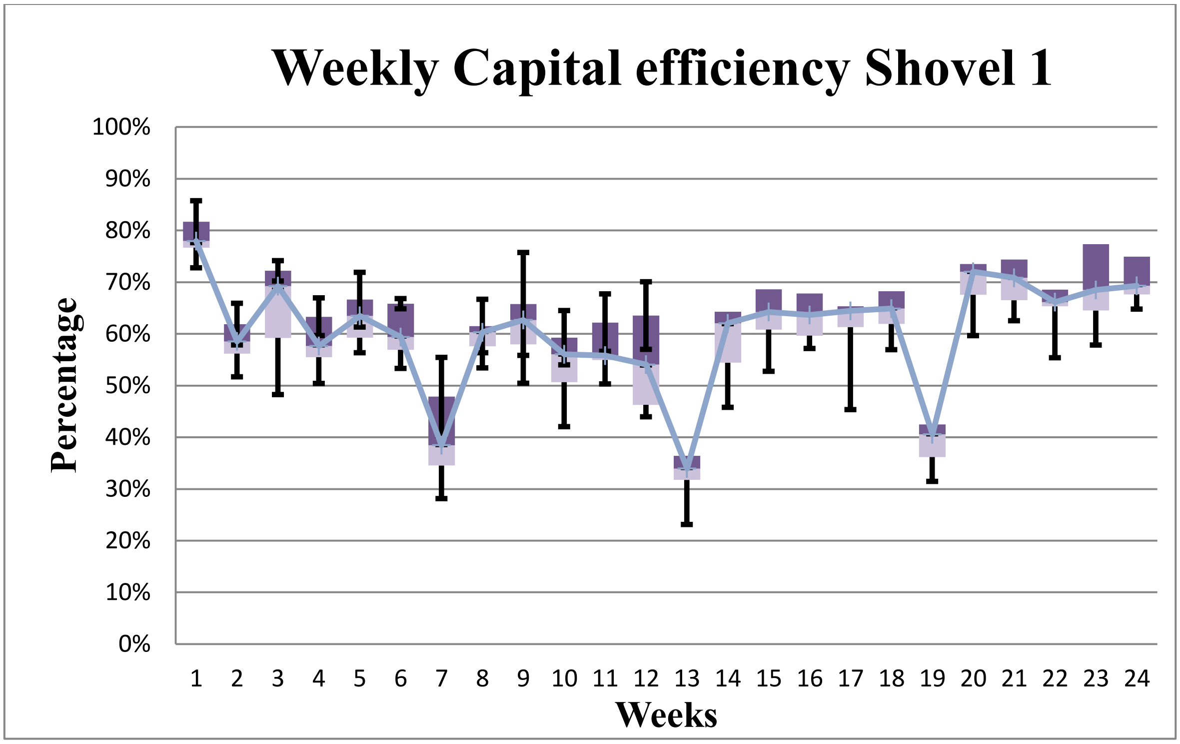

Figure 156.Weekly Capital efficiency Shovel 1

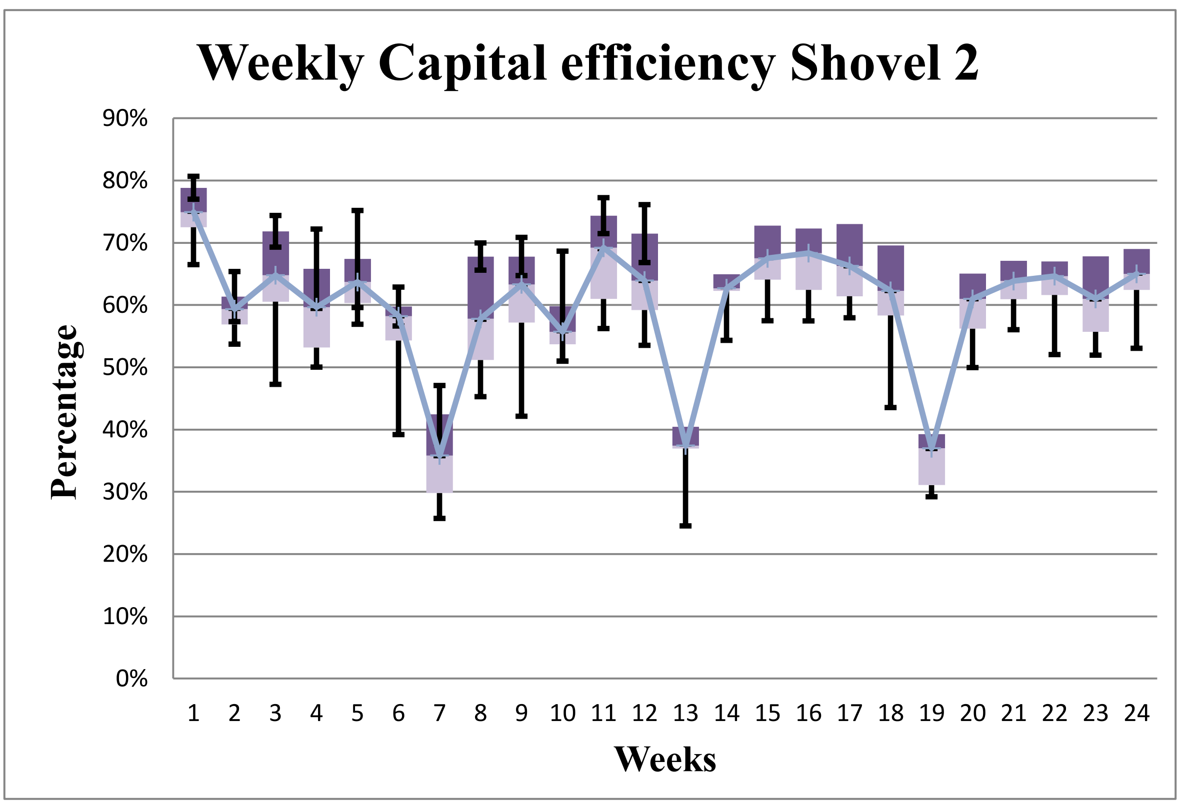

Figure 157. Weekly Capital efficiency Shovel 2

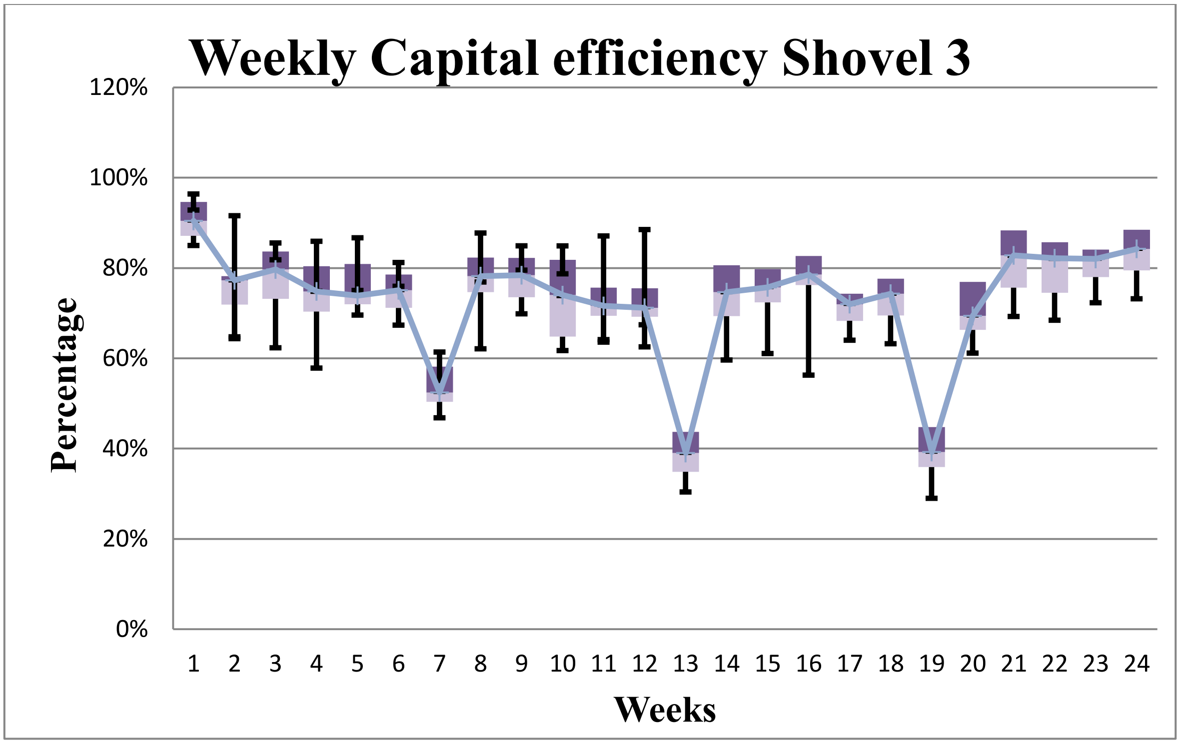

Figure 158. Weekly Capital efficiency Shovel 3

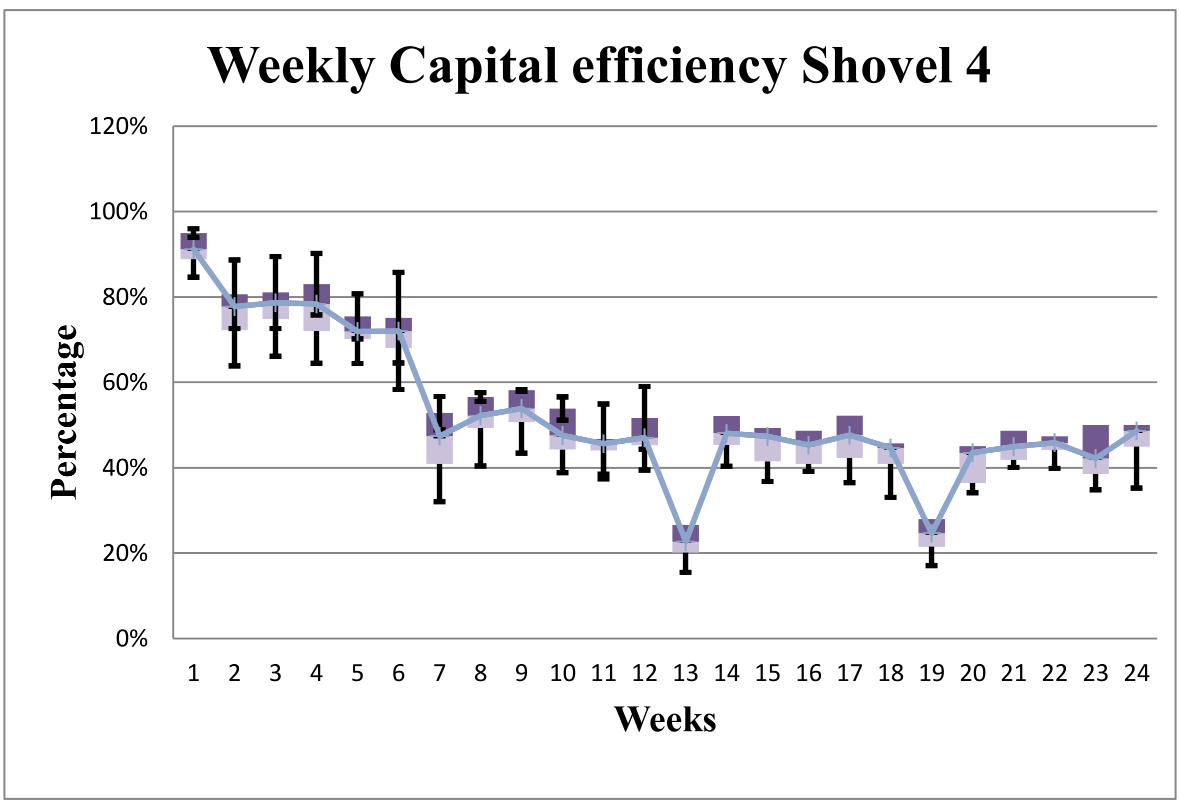

Figure 159. Weekly Capital efficiency Shovel 4

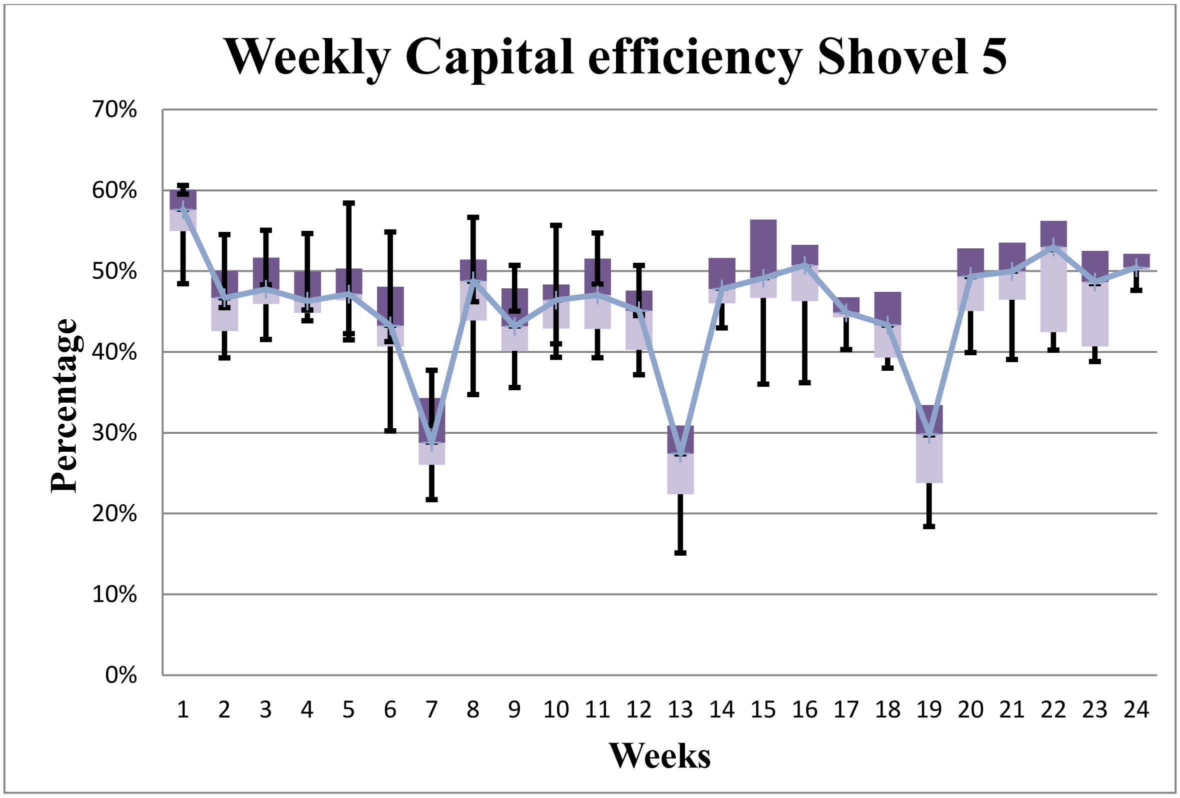

Figure 160.Weekly Capital efficiency Shovel 5

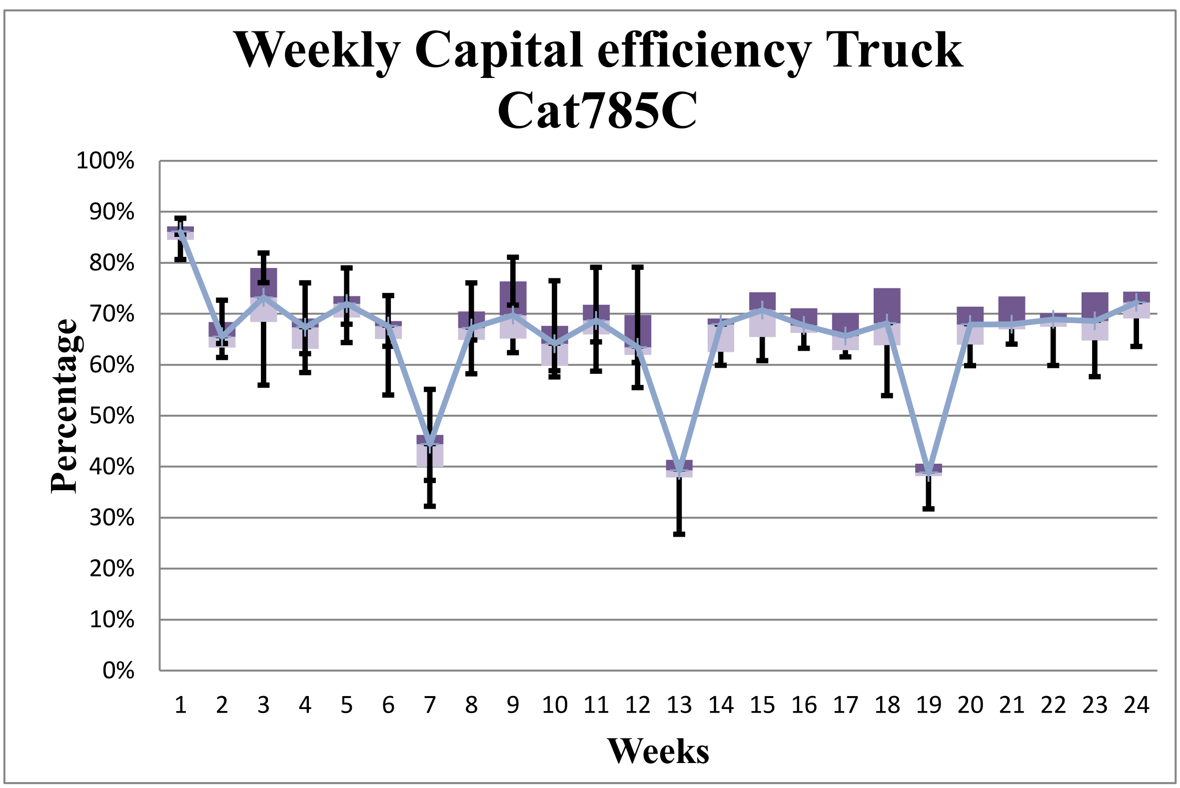

Figure 161.Weekly Capital efficiency Cat 785C

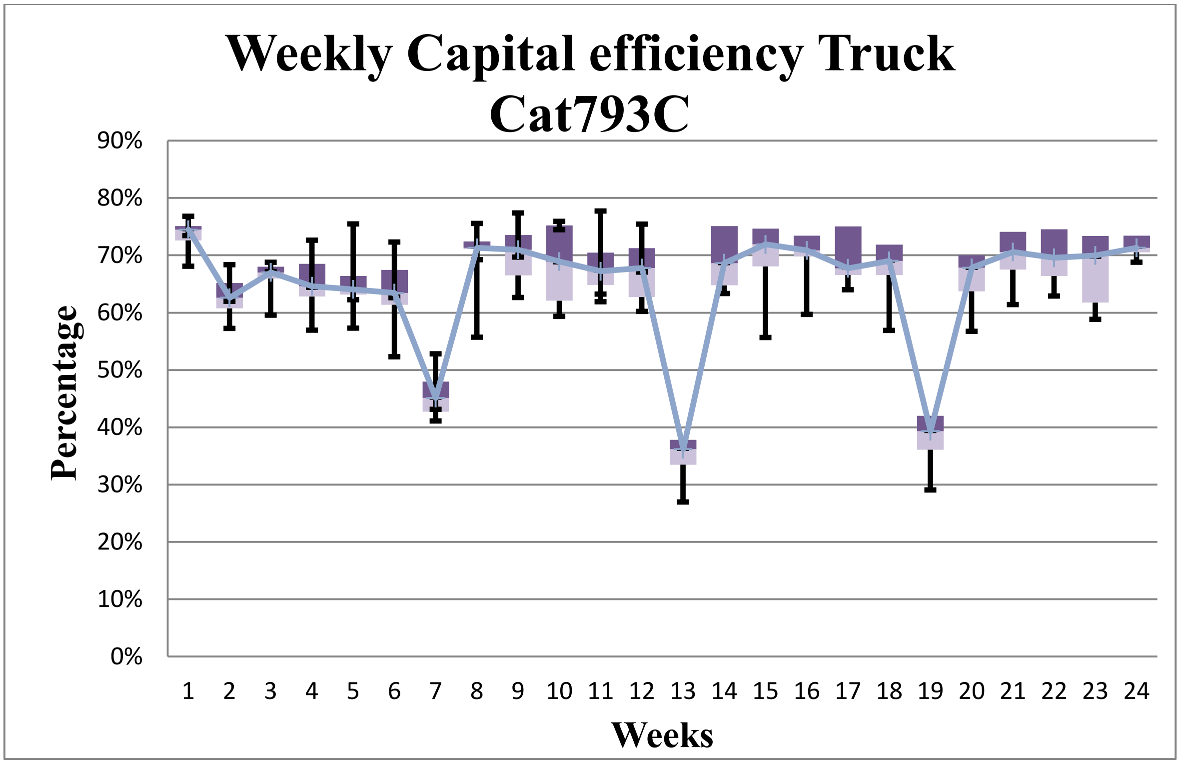

Figure 162.Weekly Capital efficiency Cat 793C

4.11.3. Improvement opportunity

Figure 152.Weekly Ore tonnage and Figure 153.Weekly Waste tonnage reflect a deficiency in ore and waste production during the weeks 7, 13 and 19. This information is valuable to know as corrections down and upstream can be execute and is available for the planner due to failures, preventive maintenance and standby weather are modeled. In deterministic schedule this outcome could not have been assessed .Figure 163, Figure 164, Figure 165, Figure 166, and Figure 167 explain the reason of the tonnage movement deficiency during these specific weeks as averages time in queue level out also. In more detail queues increase due to overlapping in down time (failure and preventive maintenance) for the complete ore and shovel fleet during the last mentioned weeks. Information is in Figure 168,Figure 169,Figure 170, and Figure 172.

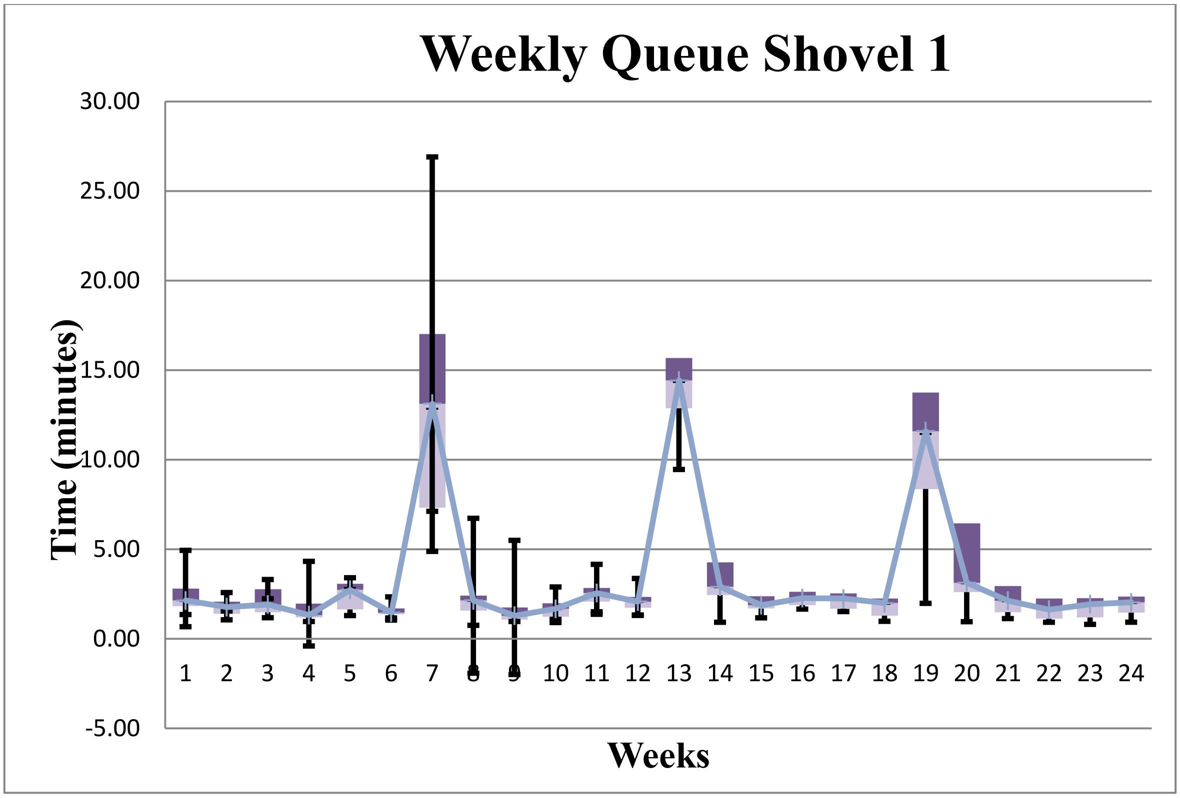

Figure 163.Weekly queue at shovel 1

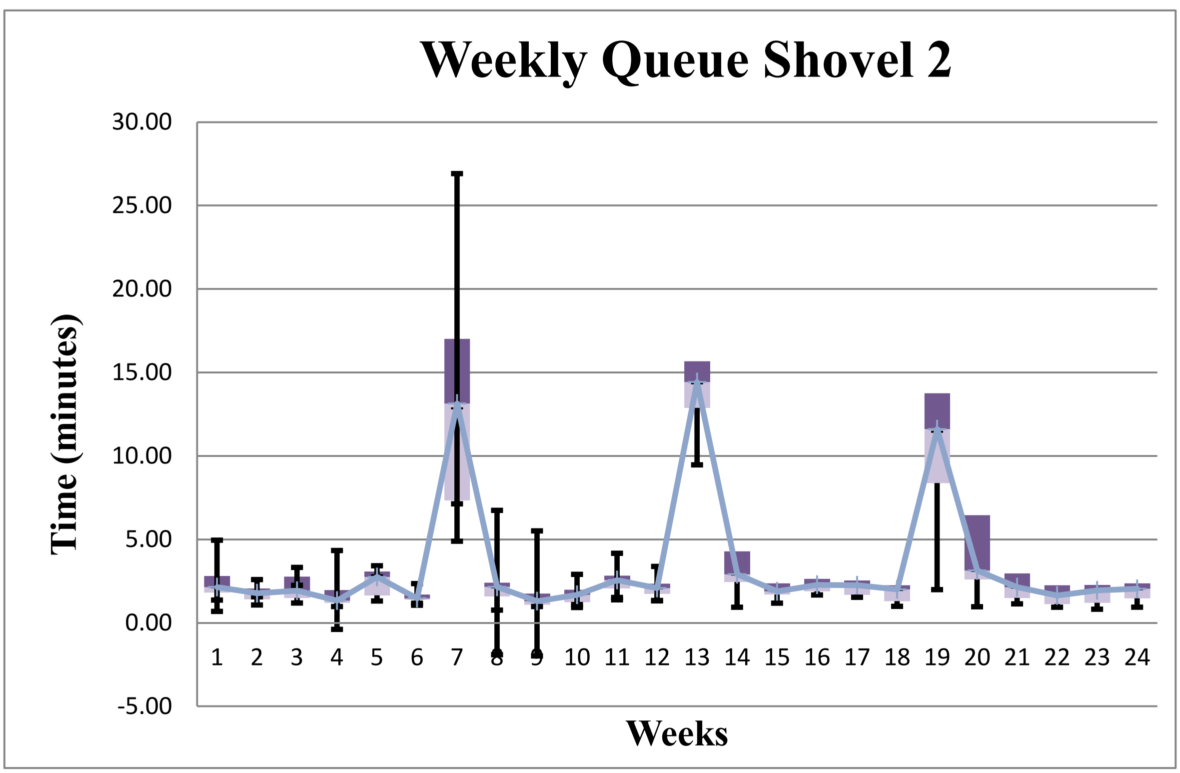

Figure 164.Weekly queue at shovel 2

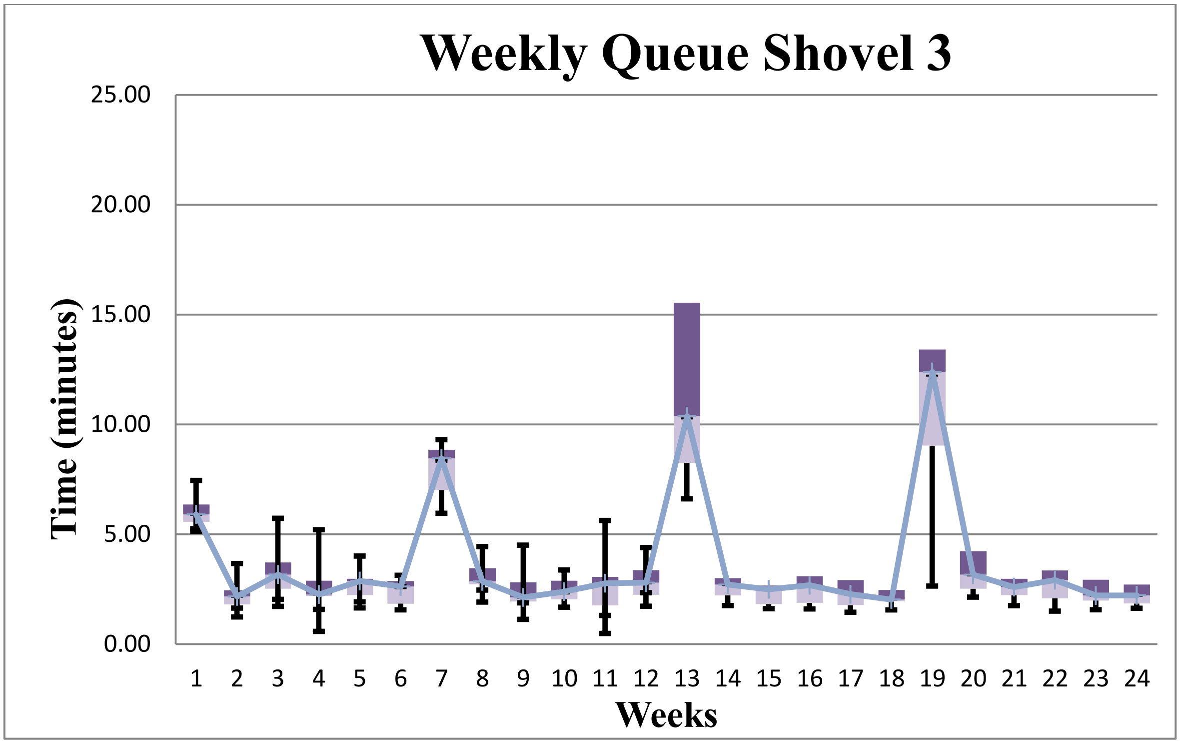

Figure 165.Weekly queue at shovel 3

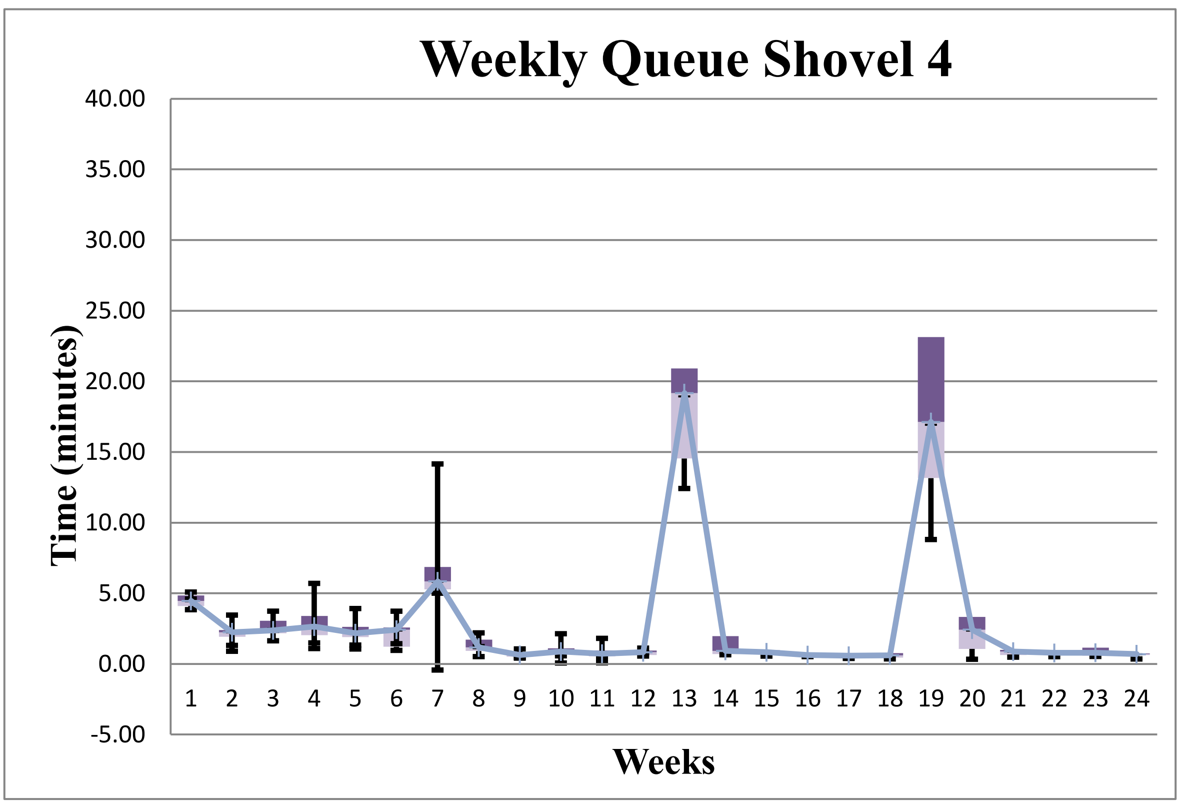

Figure 166. Weekly queue at shovel 4

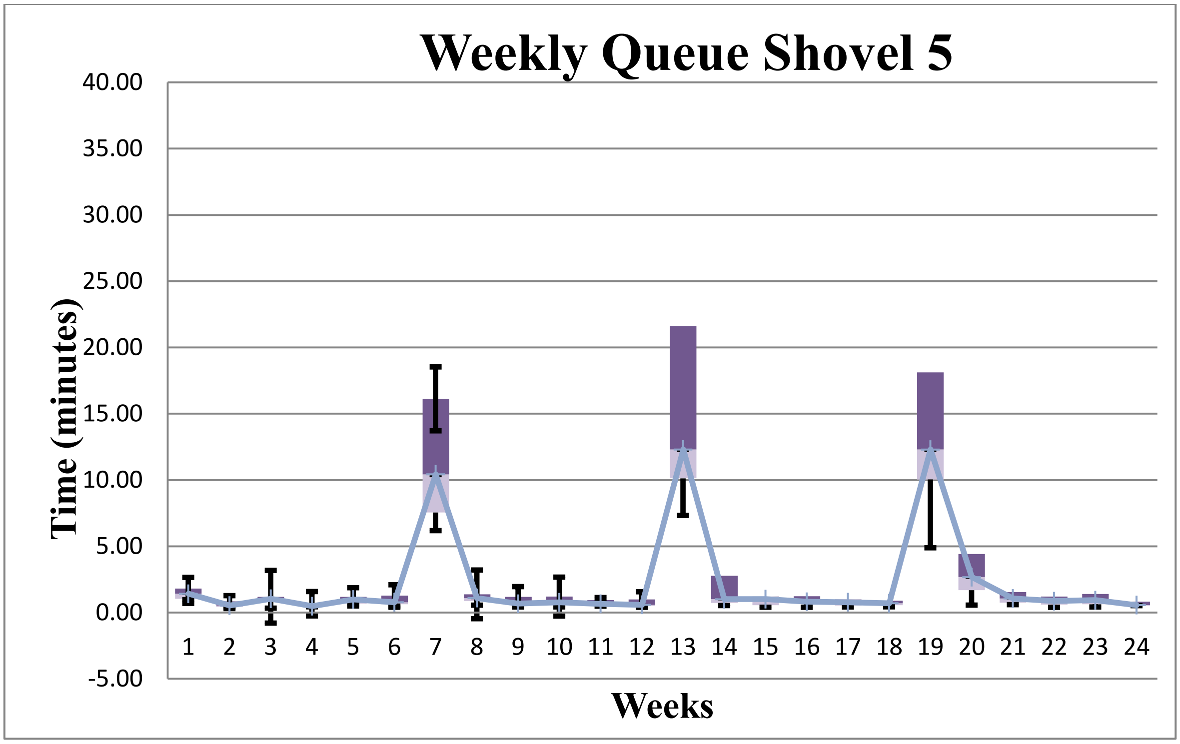

Figure 167. Weekly queue at shovel 5

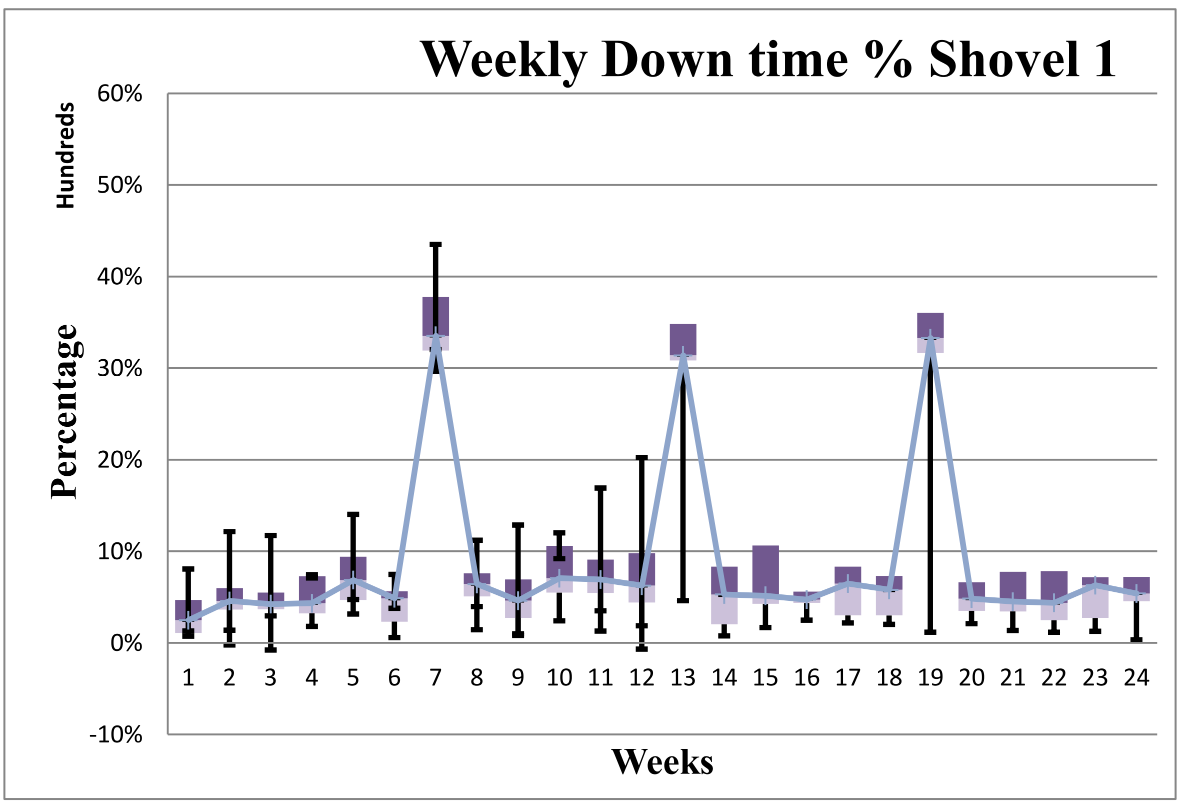

Figure 168.Weekly down% Shovel 1

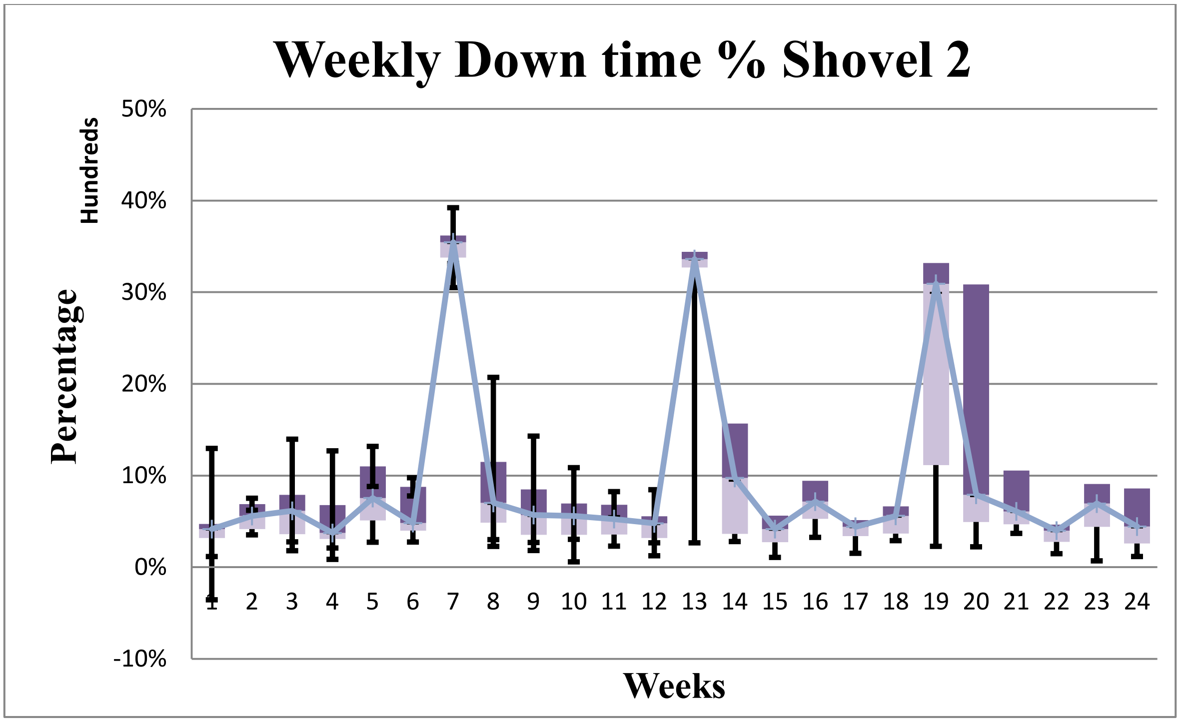

Figure 169.Weekly down% Shovel 2

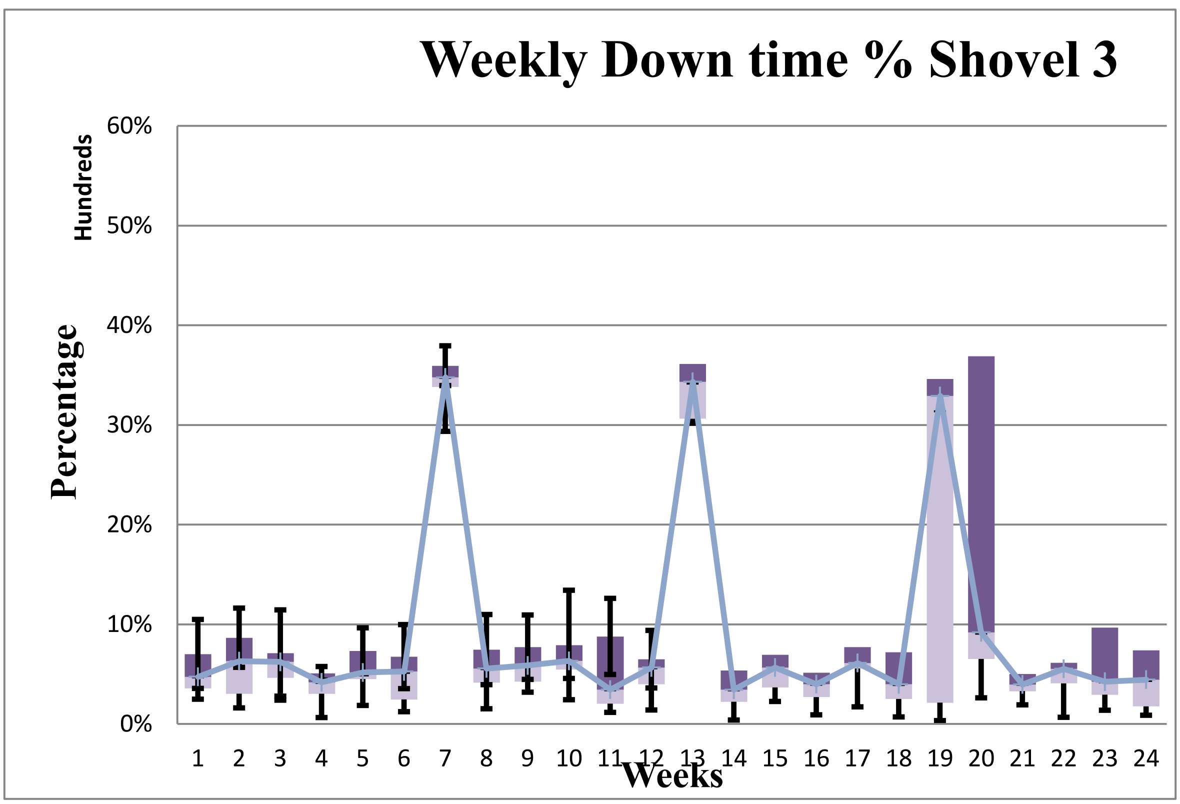

Figure 170. Weekly down% Shovel 3

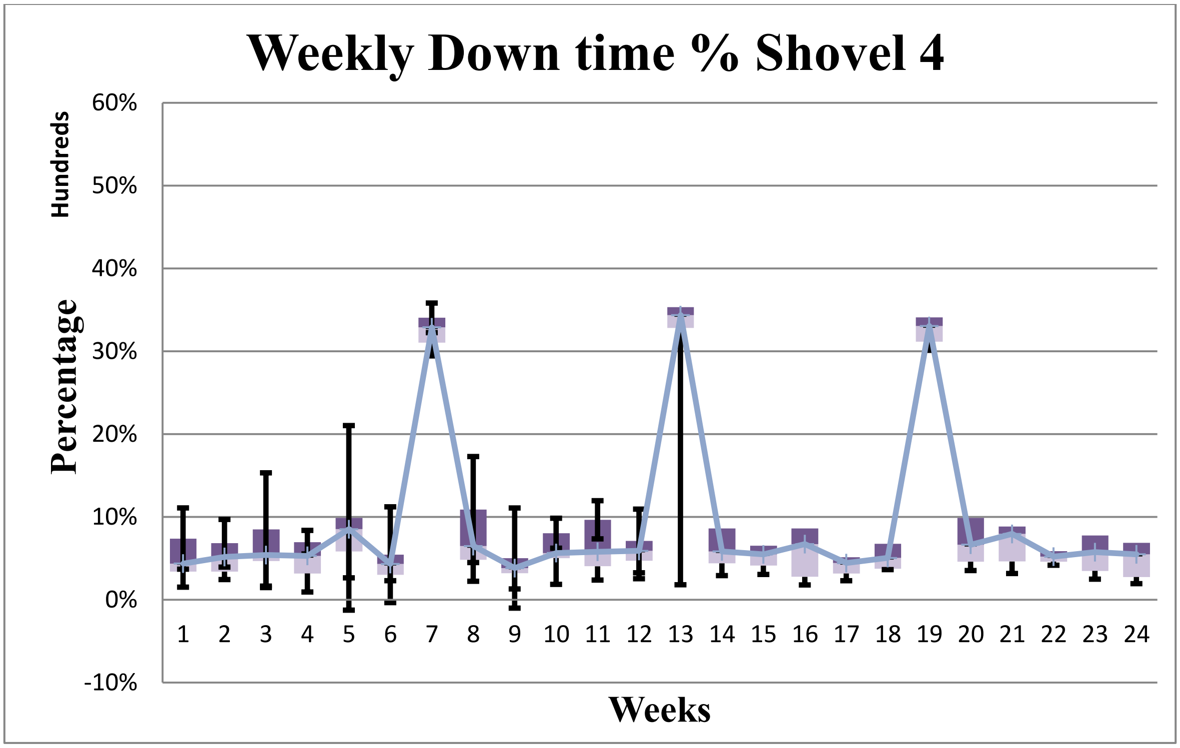

Figure 171. Weekly down% Shovel 4

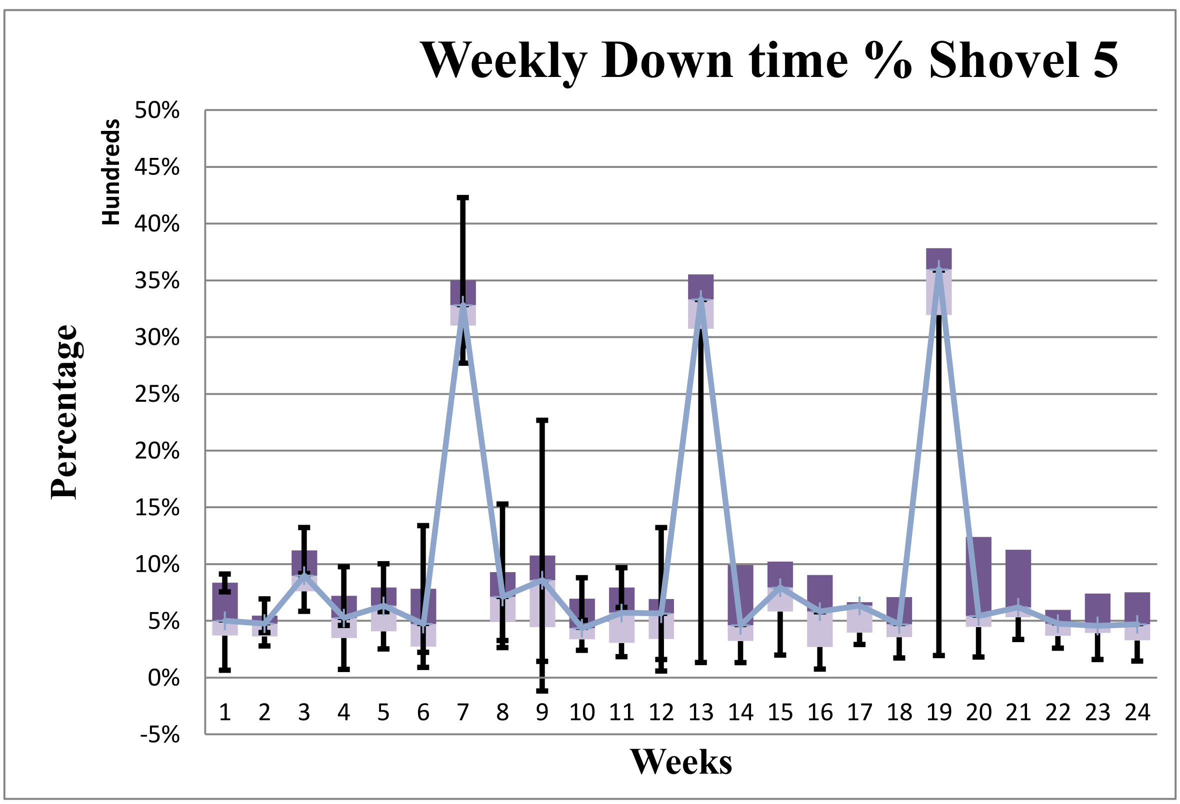

Figure 172.Weekly down% Shovel 5

4.12. Summary and Conclusions

This chapter is explaining how the simulation tool is verified, validated and used to conform the objectives of this study previously described in Chapter 1. Case study is presented of an iron ore mine, with 5 shovels, 2 ore and 3 waste,2 truck different truck types for ore and waste,1 waste disposal facility and 2 ore dumps which feed 2 mills and regulated by crusher rates. A schedule is developed and a mine road, schedule tonnage, clusters, precedence, grade, destinations and periods are given as input. On the other hand, historical data base is given to model processing time delays of an operation mine, including preventive maintenance, failure and stand by weather. Finally, deterministic number of truck calculation is estimated.

Following the simulation procedure, the verification stage cares for the action of building the model right. Shovel time distribution during the whole simulation 4380 hours, for every scenario is tested, as time delays spent spotting, loading, hanging, preventive maintenance, failure and stand by weather events should behave according to a logic pattern in the number of trucks and should add all together 4380. Whereas validation process is concerned about whether the built model is right or not, Q-Q plots are used to compare the trend of the historical data and the outcome of the simulation. Loading, spotting, dumping, backing, travelling empty and full velocities, and tonnages validation are evaluated as they should follow their original trend (historical).

Once the simulation testing requirements are met, number of replications are conforming to meet half width required to honor the variability range that it is desired to cover.10 replications are run in every simulation to be within a 5% error for ore production. Case 0,study tonnage, average queue and cycle times, time ,availability and efficiency categories' kip's within variation of waste fleet trucks by decreasing in intervals of 2.As a result, waste production decreased meeting waste tonnage kip but also an improvement was noticed with less number of waste truck on the road in terms of average cycle time for Cat793C and so on the hanging time of waste shovel type did not decay so time and efficiency categories' KPI's also experiment an improvement. Case 1, dealt with meeting ore tonnage KPI's decreasing the number of ore trucks, similar tendency was also observed for the ore cycle time. Finally, two separate scenarios are created under case 2, as ore tonnage kips is met but waste tonnage decreased. Each case study had best case which will be input to the next case as base case.

To evaluate crusher rates, case 3 has scenarios varying rates, while comparing outcomes in KPI's. Best case scenario from case 2 is taken and the same waste and ore tonnage KPI's is obtain as well as better time and efficiency categories' with lesser crusher rates. This fact can lead to future projects for efficiency and saving costs.

To end with a short-term plan able to quantify uncertainty in KPI's to improve reliability, reconciliation and plan compliance.

5. Chapter 5

Conclusions

5.1. Summary of research

In this research, a mine discrete event simulation has been developed and tested against the theoretical procedure for simulation, which includes verification and validation of the outcome in order to prove reliability of the results. Moreover, studies of the system performance have been executed by varying the number of trucks, shovels and crusher throughput rates, which are structured in case studies. In every case study KPI's are calculated to evaluate the optimal number of trucks and crusher throughput rate. Recognizing and understanding these relationships is critical to the mining operation process as resources can be optimized. Therefore, operation costs could be reduced. Chapter 2, provides an overview of the current state of the literature in the area of truck and shovel simulation. Accordingly, this research focuses on addressing the deficiencies that exist in the current literature. The following short-comings were tackled in this thesis:

- In most of the research trucks and shovels are considered identical in terms of model and size. The simulation model in this study was built as a real mining operation that accounted for two types of trucks and shovels for waste and ore. In addition, different number of trucks were assessed.
- Traffic congestion and interaction between trucks on the road network are not modeled. As every truck type has a different velocity and the road is a structure that holds segments, segment is made out of zones, every truck has their own velocity and it can occupy one zone at the time which make the system realistic avoiding trucks over passing or driving too close to each other.

- Most of the simulations studies did not present validation of the simulation models against historical dispatch and processing plant data. As part of the simulation process the model has to be verified and validated. The model is verified with the accountability of the number of hours spent in shovel cycle time for all the scenarios. The model is validated with historical data using Q-Q plots which offer an evaluation of the simulated outcome vs. the historical input data.

- Many simulation studies do not consider queue length and time in the assessments of their results. As it was mentioned before, time chart KPI's are calculated for every case study, which includes average time and number in queue at the shovel and dump facility.

- In most studies, there is no link between the simulation model and mine polygons/production schedule, and consequently, the estimated grades of metal, by products, and deleterious elements in the block model are not traced at the crusher. In this study one of the inputs is the mine schedule, which is read in the simulation polygon by polygon as entities with attributes as grade, tonnage, destination, shovel, deleterious elements, etc.

- To quantify uncertainty, as it can be seen in chapter 4, the short-term expected production KPI's are presented as boxplots that reports the KPI’s with a confidence interval around the mean.

5.2. Conclusions

Following the objectives established in chapter 1, the main highlights were:

- A mine discrete event simulation model is built, verified and validated for a particular operation. This model includes uncertainty in haulage time events, for un-planned and planned mechanical events, and standby weather events.
- Simulation model output with 95% confidence guaranteed in the ore tonnage.
- Stochastic short-term plan calculations for time, availability and efficiency KPI's. Level of detail for month and weekly time frame expressing KPI's values with box plots that allow visualization of window of uncertainty.
- Simulation model agrees with theoretical concepts of queuing theory. When the number of trucks is changed in the model so does the queue time for shovel and dumping positions.
- Interactions on the road are noticed with the variation of average empty and full travel time for a specific truck fleet when the number of truck is being changed.
- The required number of trucks was established, under uncertain availability of trucks and shovels. As a result, 15 Cat 785C, ore trucks and 19 Cat 793C, waste trucks were the optimal number of trucks that will meet the target production with minimum queuing time at the shovel’s and the crusher.
- Required optimal rate for the crushers to work under expected KPI's. Changing the throughput rate of the crusher affects ore production. The best performance was found at a rate of 3200 ton/h.
- Short fall in the weekly production is identified due to lack of shovel availability for weeks 7, 13 and 19. The mechanical down time overlaps for ore and waste shovels during this week. This allow to visualize events like this for specific time

frames and make action plans to tackle this deficit in production. Modifications can be done for Shovel PM so as to guarantee ore production targets.

5.3. Contribution of the Research

A few efforts have been done to link short-term and tactical operational mine operations. Mine operation is well known for the level of detail activities to account and the stochastic nature of this process. In this research, a mine discrete event simulation model is built as a tool to study and optimize with high level of details a mine operation with changes in the number of trucks and the crusher throughput rate. Expected productions are reported with uncertainty in KPI's due to variability in the availability.

5.4. Recommendations for Further Research

Simulation of truck and shovel accounting uncertainty in KPI's is developed in this thesis. Standby weather events are being input with planned and un-planned mechanical events in shovels and trucks. However, to maintain a reliable short-term plan uncertainty should be included in the grade estimation. Although studies have been done in the area of grade uncertainty, studies should be done including uncertainty in grade and equipment availability. Moreover, drilling and blasting process should be included as constraint to the process. Equipment needed for blasting and drilling is limited by their availably so process activities also are linked with uncertainty. Finally, in addition to the interactions being modeled the next step will be to study the effects of the road signals, like stop and yield signs with the cycle time and production.

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