Data Quality of Fleet Management Systems in Open Pit Mining:
Issues and Impacts on Key Performance Indicators for Haul Truck Fleets

by

Nick Hsu

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Queen’s University
Kingston, Ontario, Canada
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Open pit mining operations typically rely upon data from a Fleet Management Systems (FMS) in order to calculate Key Performance Indicators (KPI’s). For production and maintenance planning and reporting purposes, these KPI’s typically include Mechanical Availability, Physical Availability, Utilization, Production Utilization, Effective Utilization, and Capital Effectiveness, as well as Mean Time Between Failure (MTBF) and Mean Time To Repair (MTTR).

This thesis examined the datasets from FMS’s from two different software vendors. For each FMS, haul truck fleet data from a separate mine site was analyzed. Both mine sites had similar haul trucks, and similar fleet sizes. From a qualitative perspective, it was observed that inconsistent labelling (assignment) of activities to time categories is a major impediment to FMS data quality. From a quantitative perspective, it was observed that the datasets from both FMS vendors contained a surprisingly high proportion of very short duration states, which are indicative of either data corruption (software / hardware issues) or human error (operator input issues) – which further compromised data quality.

In addition, the datasets exhibited a mismatch (i.e. lack of one-to-one correspondence) between Repair events and Unscheduled Maintenance Down Time states, as well between Functional-Failure events and Production states. A technique for processing FMS data, to yield valid Functional Failure events and valid Repair events was developed, to enable accurate calculation of MTBF and MTTR.

A concept for identifying data quality issues in FMS data, based upon an examination of feasible durations for Production states (TBF’s) and Unscheduled Maintenance states (TTR’s), was developed and implemented through the duration-based filtering of both these categories of state. The sensitivity of the KPI’s in question to duration based filtering was thoroughly investigated, for both TBF and TTR filtering, and the consistent trends in the behavior of these KPI’s in response to the filtering were demonstrated. These results have direct relevance to continuous improvement processes applied to haul truck fleets.
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Chapter 1  
Introduction 

1.1 Raw Data and Analysis of Data Quality 
Like many industries centered around cyclical processes, the open pit mining sector seeks to maximize the bottom line through process optimization. Given that the net earnings (bottom-line) is dictated by countless factors, it is practical for a mine site to focus on controllable aspects within its operation: for example reducing operating costs and increasing throughput of materials handled. Analysis of historical data on equipment activity that is collected by a mine site's Fleet Management System (FMS) is fundamental for production planning, as well as maintenance planning – optimization of both of which is essential for competing in today's mining industry. 
Large open pit mines utilize fleets of haul trucks to transport ore and waste from the pit; but in order to manage and track the allocation of these complex and costly machines, the majority of today's open pit mines employ some form of FMS – which consists of both software and hardware components. In general, analysis on sequential data queried from historical databases (collected by the FMS) is the primary means of measuring and assessing the reliability, maintenance effectiveness, and production efficiency of mining haul trucks. These measures and assessments are then factored into operations and production planning. For example, the dispatch coordination team can increase the overall production time through decreasing man hours lost to logistical inefficiencies through better planning or improving equipment life through quantitatively measuring maintenance performance; these practices ultimately improve the bottom line. 
In addition, further analysis on FMS data streams can also provide the foundation for maintenance planning and investigating causes of failure. Using these data streams, Key Performance Indicators (KPI’s) can be calculated to provide quantifiable metrics used as a quick reference by mine managers as to the effectiveness of operations management, production management, the effectiveness of maintenance
policies and most importantly, where to focus improvement efforts. As shown in the diagram below, maintenance related costs typically account for approximately 41% of total costs for open pit mines.

![Typical Mining Costs Diagram](image)

**Figure 1: Typical break down of open pit mining costs [Daneshmend, 2009] (courtesy of Modular Mining).**

The most fundamental reliability and maintenance metrics used for gauging haul truck fleet performance are Mean Time Between Failure (MTBF), and Mean Time To Repair (MTTR). Furthermore, with increasing interest in automation by the mining industry, these data streams generated by FMS’s are becoming ever more important due to the use of predictive simulations.

KPI is a general term encompassing performance metrics used by many organizations for measuring the success of a specified activity. In general, industries such as the mining sector will use similar KPIs to evaluate common operating activities. Due to the cyclical nature of open pit mining truck haulage activities, continual improvements in the management of mining equipment will require the use of time-based quantitative KPIs.
1.2 Problem Definition and Thesis Objectives
The primary objective of this thesis is to examine the raw data acquired from an FMS, and determine if any data quality issues can be identified. Based on the identified quality issues, the next objective is to determine whether some form of processing or filtering of the raw data can improve the FMS data quality. Finally, the thesis aims to investigate what the impacts of FMS data quality might be on selected KPI’s.

This thesis focuses on the impacts of FMS data quality on the following KPI’s:

- Mean Time Between Failure (MTBF)
- Mean Time To Repair (MTTR)
- Availability: both Mechanical Availability and Physical Availability
- Utilization, Production Utilization, and Effective Utilization
- Capital Effectiveness

These are chosen because they are most frequently used for operations planning and maintenance planning in order to improve efficiency at mines.

1.3 Methodology
This thesis builds upon Barrick's time model [Barrick, 2006] which includes definitions for the KPI's of interest (except for Mechanical Availability), and event classification / categorization schemes.

The datasets collected from two different FMS’s, at two distinct mine sites are investigated (i.e. each dataset is obtained from a different FMS vendor, at a different mine site).

The first dataset is from an open pit gold mine located in the Site A mining district of central-east Chile – the Site A mine. This dataset was collected on 16 CAT 785 haul trucks and represents roughly 30,000 hours of operation (3 months of operation from October to the end of December in the year 2009). The second dataset was also from an open pit gold mine: the Site B mine, located in the Atacama Region of
northern Chile. This second dataset was for a fleet of 13 CAT 785 haul trucks, and represents roughly 10,000 hours of operation (one month of data, in the last month of 2009).

Analysis of the raw datasets focuses on durations of states, and whether state durations are “valid” – on the basis of either being too short to be feasible, or too long to have been correctly categorized.

1.4 Thesis Overview
Chapter 2 consists of a literature review, covering fleet management systems, data quality and management philosophies with focus on the application of six sigma philosophy on data analysis, as well as relevant KPIs, as well as haul truck automation. In Chapter 3 the data collection, classification, and representation process typically used by an FMS is discussed. A detailed review of how KPI's are calculated from a specific, commonly used, time model is provided in Chapter 4.

In Chapter 5, sensitivity analyses on KPI’s to the effects of applying filters on Unscheduled Maintenance Down Time states in the dataset are examined; these filters are based on Time To Repair (TTR) durations. Chapter 6 replicates the same analyses as in Chapter 5, but instead applies filters on Production states based on Time To Failure (TTF) durations.

Conclusions, primary contributions, and recommendations for future work are presented in Chapter 7.
Chapter 2
Literature Review

2.1 History of Data Collection

In 1979, when wireless data transfer was in the early stages of development, the highest rate of data transfer was only 1200 bits per second. Today, after more than thirty years of technological advancement, fleet management systems have the capability to transfer data exceeding rates of 10 megabits per second, approximately 10,000 times the rate compared to its beginning [Zoschke, 2001]. In addition, both data collection hardware and software have improved in the quantity of input parameters to provide more accurate simulations of mine operations. In turn, this allows for better management in all aspects of the equipment quantitatively rather than trial and error. Compared to having a foreman manually directing pieces of equipment to areas he feels is fit, current fleet management systems have the capability to monitor important aspects of a mine site in real time and utilize mathematical algorithms to optimizing equipment allocation. In addition, improvements in data storage capacities now allows for a greater range of mine site activities to be recorded into historical databases. Due to the large quantity of data collected on a day to day basis specified queries can also be performed by the dispatch software to extract specific portions from within the collected raw datasets. For the purpose of examining haul truck KPI's, a query on the raw database can be performed to extract data only concerning haul trucks, in sequential form, for further calculations.

2.2 Dispatch system providers

Currently Modular Mining Systems, Wenco International Mining Systems Limited, and Leica Geosystems are the leading providers for fleet management hardware and software. Modular Mining Systems offers the DISPATCH system which is customizable for both open pit and underground mines [Modular Mining Systems, 2012]. Leica Geosystems offer a package called Leica Jigsaw Fleet Management System (Jfleet) [Leica Geosystems, 2014]. And Wenco International Mining Systems Limited offers Wencomine fleet management system [Wenco International Mining Systems Limited,
Although each company offers unique solutions to managing equipment fleets, they all essentially provide the capability to track and monitor equipment location, production, maintenance, and safety through GPS and wireless radio networks. This chapter will focus primarily on Modular Mining System’s approach in collecting haul truck data.

### 2.3 Overview and History of Modular Dispatch™

Modular Mining Systems Inc.’s Dispatch™ is a fleet managing system containing a wide range of capabilities for managing a fleet of equipment such as in an open pit mine. The system contains multiple databases: the haulage model database portion of the software generates real-time models of an equipment fleet with the option for the user to manually modify the operating parameters while operations are live. Secondarily the software's reporting database records historical data on a shift by shift basis. From this historical database users can choose to display specified portions of the raw data for further analysis, such as in this thesis. In conjunction with each stored database are customizable directories in the form of enumerated tables which are built into the software for more efficient data storage. Databases used for the haulage model, reporting database, and enumerated tables are key elements within an FMS for collecting and quantifying daily equipment activities. Included with the software are operating manuals which were used as a starting point for understanding how truck fleet state transitions are generally recorded by a mine operation’s fleet management system. The diagram below shows a simplified representation of data flow.
2.4 Current Practice of Utilizing Data for KPI

Although numerous investigations have been focused on understanding the topic of using KPIs for improving production planning, sensitivity analysis of large datasets, and fleet management systems, little or no work has been done on performing data quality analysis on sequential data collected by a fleet management system for the purpose of calculating KPIs. Given that this paper focuses on the quality of these sequential datasets, it is appropriate to tie the different areas of research together to gain a picture of the current understanding with regards to the analysis implemented in this thesis.

KPI’s are the basis for measuring performance for most businesses, thus they are essential in all aspects of planning for cyclical processes. When planning any complex process, different KPIs will have increasing levels of uncertainty [Marz, 2012] as the scope and how far into the future the plan is from the present increases: i.e. short term planning will be much more accurate than long term planning. It is important to recognize that although each level of planning serves different levels of decision making in an organization, they all have mutual influence because they are based on an established set of KPIs. As indicated cycle times are often the limiting factor for assembly line type processes, which is similar to haul truck production cycles [Marz, 2012]. In other industries, it is common to use computers to simulate
cyclical processes through the use of KPIs. Since production planning is mainly based on KPIs derived from historical databases, it is of the utmost importance that these KPI’s are precise and accurate in order to generate effective plans and maximize productive hours of work [Modular Mining Systems, 2012]. A lot of research in the field of optimizing truck and shovel assignments has been done; much of the optimization process require expertise in order to factor in real life constraints [Ercelebi and Bascetin, 2009]. These constraints can be identified by historical databases, to be more specific, raw sequential data. Using models built upon identified constraints that are determined by historical databases, truck routes and allocations can then be simulated [Subtil, et al., 2011]. This is why fleet management systems have become so important in the process of planning, selecting fleet sizes and optimization of truck routes. Before the mid 1970’s trucks were assigned on a trip by trip basis and also by the intuition of a dispatcher; this resulted in inefficient processes when compared to today’s standards and ability to process large amounts of data though computers [Richards, 2000]. Even right up to the present day, it is standard practice for some mines to allocate a set of trucks to each operating loader at the start of a shift based on the production requirements for the day. It is clear that, due to the changing terrain for mining operations, this fixed allocation technique has many shortcomings compared to a system which reassigns each truck on a trip by trip basis and recalculates the base of changing states [Scheaffer and McClave, 1995].

Through the advent of fleet management systems along with the use of optimization algorithms, proper planning and reporting, the shortcomings of reactive decisions can be overcome [Dantzig and Ramser, 1959]. This type of research and application extends to other dispatching services such as delivery, courier and emergency response [Culley, et al., 1994]. Furthermore after the mid 1990’s the indoctrination of “context-aware maintenance support system” has become an integral part at all levels of planning in order to complete with the ever increasing competitive nature of industries such as mining. Metrics such as KPI’s allows a team to make decisions associated
with improving production planning such as the ratio of trucks to shovels [Kolonja and Mutmansky, 1993].

Due to the variability that exists from operation to operation, a broad range of different KPI’s are used to measure similar processes. However, a new problem has been identified: the subjective nature of how performance is measured; this leads to issues with inconsistency and inability to benchmark within the mining industry. In addition, due to the rapid turnover rate of employment in the mining industry, the inability to retain skill and expertise is also becoming a problem [Mathew, et al., 2011]. To elaborate, organizational boundaries in terms of expertise have broadened to resemble service networks; highly specialized understanding of complex processes are typically contracted out to avoid risk. Although this strategy is adaptive in today’s competitive market for the short term, the opportunity for knowledge retention and a deep understanding of each operation’s processes is lost. This leads to the issue of truly understanding and interpreting each company’s localized KPIs. It is widely mistaken that a short-term fix of this problem is resolved through the use of customized simulation models, data collection, calibration and validation software and hardware. Although customized simulation models are providing quantitative advice in terms of allocating resources, the opportunity to further optimize processes within the operation requires years of accumulated knowledge in order to be realized [Tywoniak, et al. 2008].

Among the academic community, it has also been recognized that an issue exists on the subject of data quality. Poor data quality leads to lost productivity, higher error rates for planning and the inability to accurately make high impact decisions. In addition, attempts to predict asset reliability and long term performance will be completely misguided by erroneous data. Many attempts have been made to define what data quality means. In general, it is understood that accuracy, relevance, fineness and timeliness are some of the requirements. This issue within the mining sector is one that most well established companies are aware of but avoid due to the expensive and time-consuming effort required. Regardless of how good the data collection mechanism is, if there is not enough expertise to calibrate the data collection process to meet the needs of further analysis, the investment is not able to generate optimal results. It is necessary to
invest in understanding the dynamics of overall equipment effectiveness as part of a system to enhance asset management practices [Zuashkiani, et al., 2011]. Strong evidence suggests that most organizations possess much more data than they need or actually utilize for further analysis. Above all, the surplus of data can make the portion of the dataset required for analysis harder to extract. As well, the lack of data visibility and interpretation reduces the accuracy and precision in the dataset. These factors ultimately lead to less effective planning decisions, and the inability to improve the process of concern [Lin, et al., 2006]. For the above reasons, this thesis focuses on the issue of data quality.

2.5 Six Sigma and Data Quality
In light of the desire to improve the bottom line through effective equipment management, as with other well established industries, much of the mining sector has adopted an overarching philosophy of continuous improvement processes centered on optimizing operational efficiency, effectiveness and flexibility of manageable aspects within the workplace. Consistent with that philosophy, this thesis is focused on a subset of the continuous improvement process known as Six Sigma. This section begins by addressing the first step of the DMAIC process (define, measure, analyze, improve and control) which is defining the end goal of improving KPIs performance used for measuring truck haulage performance. Only through establishing a precise definition of these performance metrics, can an accurate interpretation of the available datasets be achieved. Next, this paper addresses the second and third steps of the DMAIC process by investigating the data quality of the datasets used in calculating these key performance indicator metrics.

Like many continuous improvement theories, Six Sigma is also a philosophy for improving a process through continually reducing costs which ultimately translates to increased profits. Although Six Sigma is typically implemented on repetitive and well established processes, this method of continual improvement can also be applied to the management of open pit mining haulage operations. Specifically, the process of transporting the ore from the mining face to the dump location presents opportunities for implementing the Six Sigma philosophy thus improving truck fleet performance. Initially, Six Sigma methodologies were employed to reduce the average number of defects in the manufacturing industry; however, the less
well-known aspect of Six Sigma seeks to reduce deviations from specified levels of performance. This aspect of continuous improvement makes Six Sigma a very applicable method for reducing costs for the mining industry due to the cyclical nature of many of its processes and its tendency to deviate from optimal performance. As this paper is focused on improving the efficiency and effectiveness of data collected pertaining to truck haulage by fleet management systems, a continuous improvement process such as Six Sigma can be applied to help ensure data collected is indeed essential, and as well, further data analysis performed on the data collected is accurate, precise and necessary to improve the process of KPI analysis. Data quality is the key to accurate KPI calculations, which are essentially the representation of mine operations performance used for production planning.

To begin the integration of the Six Sigma philosophy into a process, it is helpful to utilize the abbreviation DMAIC. This abbreviation, as previously mentioned, is a roadmap defining the steps from beginning to end for achieving improvements in a process. DMAIC stands for Define, Measure, Analyze, Improve and Control [Desai and Shrivastava, 2008]. Although many continuous improvement processes inherently seeks to attain the same goal of improving the efficiency and effectiveness of a process, DMAIC provides a methodical framework for identifying which areas of a process requires attention. The DMAIC process will be applied in this section to the haul truck fleet management's data collection process to show how data quality can be improved and how it affects the resulting KPI calculations. Although it is well established that mining trucks constantly face changing environments, the required tasks for transporting ore generally remains a cyclical task. This cyclical nature allows the implementation of data collection regimes for the purpose of documentation, but more importantly the evaluation of a mine's performance. Because this collected data is measuring a very complex process, often the dataset collected includes too much information; some of which can be inaccurately included in KPI calculations, this mistake will often lead to an inaccurate representation of the process' performance. The means to accomplishing the six sigma goals is to identify the processes where no value is added, and to eliminate steps in the process where unnecessary rework exists [Hassan, 2013].
2.5.1 Define

The first step of the DMAIC is defining the scope, goal or objective of an improvement process. This initial step sets the boundaries of a process and allows focus to be directed on the identified problems through limiting the amount of variables. After setting boundaries, components within the process can then be separated as either controllable or uncontrollable. In accordance with the "Defining" step of the DMAIC process, the goal of improving the data quality of data collected by a fleet management system and the data analysis process, the boundaries must first be defined [Cordy and Coryea, 2006]. The scope of this paper specifically looks at data collected on haul trucks through a fleet management system with the end goal of generating a more accurate representation of haul truck performance pertaining to maintenance and allocation of resources.

Fundamentally, the sole purpose of this data collection process is to allow management to perform mine planning and quantitatively assess how operations are performing. This then allows management to identify which areas of the mining operation can be targeted for improvement. Thus, it is important that this step of the "Defining" process accurately represents what is happening in the data collection process. Just as important is that this step accurately defines the process of calculating KPI's to ensure the calculations are performed using relevant portions of the dataset and the resulting metrics are not skewed due to misinterpretations of the raw data. In accordance with the Six Sigma philosophy, every step within the process outlined above should have value added, whereby each step is necessary for the defined goal; each step has an impact on the process and each step is done right the first time. By ensuring these three guidelines, the Six Sigma philosophy will provide more efficient use of resources such as capital, labor and time. Essentially, the defined process of data collection is effectively meeting the needs and requirements of the objective, which is to quantify the level of performance of a haulage process.

2.5.2 Measure

As previously mentioned, in order to gauge the performance of each individual haul truck or the entire fleet, the process begins with an operator's input of what is happening in the field. This information is
collected in the form of raw data through a fleet management system, from which the sequential data can then be extracted. The dataset used for further analysis encompasses the documentation of every event change, the durations of each event, and a time stamp of each truck in the fleet. Secondly, a time model unique to each mine is used as a guide for categorizing each event into its corresponding time category. Once the time categories for each documented event have been added on to the dataset, further analysis such as KPI calculations can be performed.

As mentioned, to quantify the performance of a haul truck fleet, key performance indicators are used. These KPI's typically include MTTR, MTBF, Mechanical Availability, Physical Availability, Utilization, Production Utilization, Effective Utilization, and Capital Effectiveness. These performance indicators essentially examine the total duration that the truck fleet spends in each time category in the form of ratios made up of conglomerates of each time category in order to reveal the performance of controllable aspects associated with the truck fleet's performance. The key to this step in the DMAIC process is to compare truck fleet performance from period to period; this reveals unacceptable deviations from a specified level of performance. In essence, these KPI's reflect how efficient and effective the defined process is.

2.5.3 Analyze

The “Analyze” step in the DMAIC process is where expertise and experience in a defined process can help generate the most improvements. Of this entire data collection and analysis process for fleet management, it is important to identify controllable or manageable factors which are:

**Operator and software interface**

How accurately and precisely the operator is inputting what is actually happening with the haul truck during its defined nominal time.

**Software and hardware**

How much detail is documented by the data collection process and the accuracy and precision of data collected.
Analyze the accuracy and precision of the data and, just as importantly, the suitability of the data collected which is to be used for key performance indicator calculations.

These controllable factors are areas of intervention where management can significantly improve the accuracy of the resulting measurements of haul truck performance. Furthermore, this improvement in the accuracy of performance metrics allows supervision to better identify areas within the production side of operations to target for improvements.

**2.5.4 Improve**

The “Improve” phase requires profound knowledge with respect to the process and is the step where improvements are conceptualized and tested. For the fleet management data collection and analysis process previously defined, the “Improve” phase seeks to remove erroneous, irrelevant or unnecessary data. In order to identify which data points are relevant to the later steps, sensitivity analysis can be employed to improve overall data quality. After identifying which data points are not required for the purpose of calculating key performance indicators accurately, the data collection process can be improved again by using filters on the sequential dataset or even better, modifying the fleet management software or hardware. Secondarily, because erroneous data is also caused by operator input, better training can ensure precise and accurate operator input, thus reducing inaccuracy for KPI calculations later in the process chain. In applying these improvements, fewer data points will be collected which results in less costs for the process, less cost for data storage, less time spent for data analysis, increased accuracy in key performance indicators and ultimately more effective mine planning.

**2.5.5 Control**

The “Control” step is the last step in the Six Sigma DMAIC process and is often the most difficult to maintain. Once improvements have been realized from the previous steps, the control phase seeks to maintain the new level of performance. The main objective is to ensure previous defects do not reoccur, and the improvements in the process become the new standard. The reason this phase is the most difficult
to achieve for any mine site is because of the high turnover rates in expertise in the mining industry. Often the experience and expertise initially required to implement and maintain the new found improvements are lost due the inadequacy by the mining industry in capturing the new found knowledge.

2.6 Other Literature Review

2.6.1 Comparative Values for MTBF, MTTR, and Mechanical Availability

<table>
<thead>
<tr>
<th>OVERALL AVAILABILITY</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MTBF (s)</strong></td>
<td><strong>MTTR (s)</strong></td>
</tr>
<tr>
<td>793</td>
<td>66606</td>
</tr>
<tr>
<td><strong>OLD 797</strong></td>
<td>62578</td>
</tr>
<tr>
<td><strong>NEW 797</strong></td>
<td>100049</td>
</tr>
<tr>
<td>930E</td>
<td>61284</td>
</tr>
</tbody>
</table>

Table 1. Reference MTBF, MTTR, and availability [Lewis, 2007].

The data above are values of MTBF, MTTR and Availability for 16 old Caterpillar 793s, 30 new Komatsu 930Es, and 10 new and 14 old Caterpillar 797s at Suncor Energy Inc. oil sands operation in the Athabasca region of Northern Alberta. One year's worth of data which consisted of roughly 637,000 lines of data was used to calculate the KPI's above, these values act as a guideline as to typical MTBF, MTTR, and availability values. Taking the average of all the haul trucks and converting the values to hours, the entire fleet has a MTBF of 20.1 hours, MTTR of 2.7 hours, and Mechanical Availability of 87.75%.
In comparison, Figure 3 shows the distribution of MTBF of a large open pit mine in North America with seventy 190 ton Komatsu 685E haul trucks, and represents 2 years of operating data. Within two standard deviations above and below the mean, the MTBF is in the range of 17 to 31 hours. A value of 23 is used as the MTBF.
In addition, for this same 70-truck fleet of 685E’s, using the data collected on Down Time over the first eight months of operation in 1997, the MTTR is approximately 2 hours. Then using these MTTR and MTBF values, the mechanical availability is calculated to be 92%.

2.6.2 Autonomous Haul Trucks

On a related note, recently there has been a big push towards automating mining equipment due to a shortage of haul truck operators and increased labor costs in some countries, notably Australia [Bellamy, 2011]. In light of this opportunity, major haul truck manufacturers have developed technologies to fully automate haul trucks to potentially increase availability and utilization through more consistent driving [Zoschke, 2001]. However, assuming automated driving does provide benefits in the aforementioned KPIs, one potential disadvantage to be considered is the loss of "front line maintenance"; typically the operator provides valuable information in to the failure modes through observation of irregularities in the equipment’s operation. This absence of the observer can potentially result in longer MTTR due to the extended time it takes to diagnose the failure mode and find the solution for repair.

Furthermore, in order to achieve fully automate mining equipment such as haul trucks, additional systems would need to be installed. This then increases the complexity of the haul trucks which potentially results in additional failure modes. In short, more failure modes can lead to a lower MTBF unless the consistency...
of driverless technology significantly outweighs the resulting failure rates added from autonomous system components.

Many studies have been conducted to assess the economic benefits of autonomous haul truck operation. This effort is grounded on the assumption that reliability and maintainability metrics are accurate and a good representation of the wide range of operating conditions from mine to mine. This assumption however, may be false. Furthermore, the studies disregard the potential increase in MTTR and decrease in MTBF due to reasons previously mentioned.

### 2.6.3 Dispatch Algorithms

![Diagram of algorithms used for dispatch optimization](image)

**Figure 5: Model of algorithms used for dispatch optimization [Chapman, 2012].**

In the structure of algorithms used for optimizing fleet dispatch, it can be seen that equipment breakdowns is a parameter that triggers re-computation of the model [White, et al., 1982].
It is important to re-evaluate what the purpose and use of the data in order to properly define the parameters of the algorithm. Similar to the idea of the computation model it is also important to specify the purpose of the dataset in order to further process the data. More specifically, cut-off ranges for data must be defined in order to perform accurate KPI calculations.

Using this form of algorithm model for optimizing haul fleets, which is essentially a model that tries to meet the highest possible predetermined KPI's by varying parameters such as dump locations, the importance of separating parameter definition from data gathering and data processing (what is used for KPI calculations) can be realized [Carter, 2010]. As explained in this chapter, the process of collecting data contains innumerable steps where errors by the software or hardware and mistakes by the operator can occur.
Chapter 3
Data Collection and Interpretation

3.1 Data Collection Process Overview

The quality of raw data often poses an issue in the precision and accuracy of results from further analysis. Multiple causes can account for deviation in data measurements from actual behavior in the field. First, because mining operations exist all around the world, and data is collected in different languages, information can be altered or lost during the translation process. In addition, due to the unique nature of every mine's management approach and the subjective nature of the collection process, inconsistencies exists in the definitions of mining terminology, categorization of events, structure of time models and other minor details from mine to mine. This lack of precision within the mining industry makes benchmarking of operations performance problematic. Additionally, causes for poor quality of raw data collected can also be influenced by each operator's interpretation of input parameters. It is rare that every equipment operator has an accuracy of one hundred percent in his or her reporting practice. And secondary causes can also be attributed to the effectiveness of the dispatch offices oversight. Both the quality in which status changes are documented, as well as data on failure causes has significant implications for further analysis.

As mentioned, an equipment operator plays an important role in the performance of the equipment. Specifically for haul trucks on a mine site, each operator may drive the hauls trucks in a different manner. In short, the operator’s operating practices have massive implications on the reliability of the truck and just as important, the equipment status reporting process.
The field computer system is the interface that operators interact with. Generally, operators will input status and status changes by selecting the input from a range of options. Simultaneously, a time stamp will be entered each time the status has been changed. In addition, more information is usually provided such as the classification of the status, the reason code for the status change, and comments. The diagram below shows the typical arrangement of the field computer monitor.

The central computer is where the information collected on haul truck activity is stored. From the central computer, dispatch managers can monitor a truck’s weight, tire condition, drive system, engine, and location. The FMS monitors and records every piece of mining equipment status and event in real time.
This data stream comprises equipment ID, when the equipment changed status, what the new status is, the reason code and reason for the status change, additional dispatcher comments and the length of time in each time category. The dispatching office provides oversight for day to day equipment operations. A truck's location and movement can be seen on the dispatch offices computer monitor, whereby if a piece of equipment is operating irregularly, the dispatcher will radio in and investigate the reason for the deviation. A database is also created and stored in a central computer in chronological order. In addition, this database can be manually entered or edited.

Figure 8: Format of data gathered by a typical fleet management system [Modular Mining Systems, 2012].

Specified portions of data can be displayed or extracted by querying for a specific time frame, and for specific pieces of equipment or fleets of equipment can be selected from the raw database.

From the raw dataset, the status records can be extracted in the form of sequential data for further analysis.
It is imperative that every possible equipment status in the mine site is clearly defined in order to maintain consistency. By having a standardized time model, a mining company is able to reduce variability from the start of the data analysis process. The Barrick Time Model [Barrick, 2006] provides the basis for analysis of FMS data in this thesis. As will be defined in section 3.3, each status must be interpreted correctly in order to accurately calculate KPIs. Secondarily, because each documented status falls within a time category classification, the time categories must be precisely defined in order to maintain consistency later in the analysis process.

### 3.2 Database for Reporting and Database for Haulage Model

#### 3.2.1 Database for Reporting

Typically a tool is provided in a FMS for displaying, finding, creating, changing, and deleting data collected in the database. Within this database, records on normal operations are stored on a shift by shift basis. The records are segmented into load records, dump records, status records, fuel records, tram records, grade records, equipment records, auxiliary equipment records, location records, operator records and root information records. This tool also allows the user to output raw data in a specified summarized form. Shown in Figure 8 is the format in which the different datasets are collected.

#### 3.2.2 Database for Haulage Model

The Database used for modeling haulage allocation is used for management of equipment fleets when operations are live. This dynamic model within a FMS is the basis on which algorithms for optimizing equipment task assignment operate. Stored within this database are the coordinates of all active locations, the orientation and availability of haulage roads, travel distances, travel times between haulage routes, real time haul truck status, mining constraints and operator information. Production data constantly flows...
from the field to update the central database. This working model of haul truck activity allows the dispatcher to monitor and manage operations from the dispatch office.

### 3.2.3 Status, Reason, and Comment Field

The Status Records within the Reporting Database displays the time of each status change (Ready, Delay, Available, or Down), a reason code (what the reason was), comments, hours spent in each time category (operating hours, delay hours, availability/no operator hours (standby), or repairs/down hours). The table in Figure 9 shows the typical format in which this data is recorded.

Truck states are defined as either Ready, Delay, Available, or Down. Each data point under the “Hours in Time Category” is the duration of each status since the time stamp (under the “Time” column) of each status began. To elaborate, a status of “Delay” is the initial time stamp for when Operator Delay hours begins.

### 3.2.4 Reason

The Reason column records preprogrammed options selected by the equipment operator from the Field Computer System. Each Reason is mapped to a Code (integer) in an enumerated table. Using this method of data storage allows for improved efficiency in the volume of data stored. This column of the Status Records provides details on why each transition occurred for planning and maintenance purposes.

### 3.2.5 Comments

The Comment column of the Status Records collects information which is manually inputted by the operator. This data provides details on state transitions that deviate from normal mine operation. The information collected in this section can help in failure mode identification. For example, the comment section can provide the operator’s input concerning the context of a failure event.

### 3.3 Event Time Categories

#### 3.3.1 Inconsistency Issues

Time categories can vary from mine site to mine site. In order to improve the accuracy of industry equipment performance benchmarking, it is logical to make the time categories used in the KPI's
standardized as well. Currently, the definition of time categories and classifications of events into time categories remain inconsistent in the industry. As well, terminology can be inconsistent due to language and translation discrepancies. An example is differences in time models between Site B and Site A. Major differences include time categories where Site A has unscheduled delay time and programmed delay time, whereas Site B only has delay time. In addition, due to the subjective nature of interpreting which time category each event falls into, there are many differences in the classification of events in to similar time categories; most notably Operating Delay and Operating Standby. For example, where Site A classifies shift change time as programmed delays (Delay time); Site B classifies shift change time into operating standby.

3.3.2 Nominal Time

Nominal time is the period of time that is being evaluated. This period of time in a mining operation is the sum of every possible time category. Nominal time is the sum of operating delay time, operating standby time, scheduled maintenance time, unscheduled maintenance time, primary production time and secondary production time.

3.3.3 Delay Time

As defined by Barrick, operating delay time is, "Delays during an operating shift that are not necessarily related to a typical production cycle." To elaborate delay time represents the durations for haul trucks to get into production and is largely influenced by operator and effectiveness in truck allocation.

\[
\text{Delay Time} = \text{Nominal Time} - \text{Production Time} - \text{Standby Time} - \text{Scheduled Maintenance Down Time} - \text{Unscheduled Maintenance Down Time}
\]

Equation 3-1

Generally, this portion of the nominal time is an area for optimization, and although this time category does not provide value generation it is necessary for overcoming unexpected delays. Typical examples of haul trucks in the “delay time” time category include and are not limited to:

- Accident
• Emergency (manned)
• At weight scales
• Change operator
• Delayed for blast
• Fuelling
• GPS unavailable
• Incident event (manned)
• No access/ road closed (short duration)
• On board training(outside of regular production cycle)
• Operator inspection
• Personal break
• Site power failure (operator on equipment)
• Stuck in mud
• Truck cooling tires
• Waiting on auxiliary equipment
• Waiting on crusher (not queuing)
• Waiting on face/clean up
• Waiting for instruction
• Waiting on shovel (trucks manned and shovel not working)
• Waiting for tech support, survey, geo, etc.
• Wash out truck box (clean carry back)
• Weather/ delay due to environment/ act of god (manned)

3.3.4 Standby Time

As defined by Barrick, operating standby time is, "Time equipment may be operating but is not due to
management decision, equipment need, or operator availability to staff or operate machine." Standby time
represents the durations that cause disturbances to the production cycle and is typically outside the control of the production cycle.  

\[ Standby Time = Nominal Time - Production Time - Delay Time \]

- Total Maintenance Down Time

Equation 3-2

In generally, this portion of the nominal time concerns the logistics of allocating operators and employees. To specify, this time category represents events that are outside the scope of the regular production cycle. Examples of the “standby time” time category for haul trucks include and are not limited to:

- Emergency (unmanned)
- Equipment not needed
- Lunch/break
- Meeting
- No operator/labor
- Not enough shovels for trucks
- Opportune maintenance
- Shift change time
- Shovel out of muck
- Site power failure (long duration)
- Statutory holiday
- Strike
- Weather/Delay due to environment/act of god

A specific area of subjectivity is the distinction between standby time and delay time. From the Barrick Time Model, the main difference lies in the duration of the event and relevance to an operating cycle. For operating delay, events are transient, are within short term plans, and are generally intrinsic to the normal
operating cycle. Alternatively, operating standby events generally have longer durations, can be planned for and are not routine events in an operating cycle.

3.3.5 Scheduled Maintenance Down Time

As defined by Barrick, operating standby time is, "Any maintenance Work Orders that have been identified, planned and included on an approved Maintenance Schedule prior to commencement of the schedule time frame." Schedule maintenance down time represents durations of maintenance that is planned with consideration of every other time category. This portion of nominal time is required for maintaining the long term functionality of the haul truck and is typically limited by production time, delay time, and standby time.

Scheduled Maintenance Down Time

\[
\text{Scheduled Maintenance Down Time} = \text{Nominal Time} - \text{Production Time} - \text{Delay Time} - \text{Standby Time} - \text{ Unscheduled Maintenance Down Time} \quad \text{Equation 3-3}
\]

Equation 3-3 can also be expressed as equation 3-4.

Scheduled Maintenance Down Time

\[
\text{Scheduled Maintenance Down Time} = \text{Total Maintenance Down Time} - \text{ Unscheduled Maintenance Down Time} \quad \text{Equation 3-4}
\]

Examples of events that fall in the category of scheduled maintenance down time include:

- Maintenance inspection
- Oil/ Lube
- Tire change
- Truck travelling to shop/ at ready line
- Wash bay

3.3.6 Unscheduled Maintenance Down Time
As defined by Barrick, an unscheduled maintenance down event occurs when, "Unit is unavailable due to an unplanned maintenance failure". Unscheduled maintenance down time represents the duration of time when equipment is unable to operate due to a functional breakdown.

\[
\text{Unscheduled Maintenance Down Time} = \text{Nominal Time} - \text{Production Time} - \text{Delay Time} - \text{Standby Time} - \text{Scheduled Maintenance Down Time}
\]

Equation 3-5

Equation 3-5 can also be expressed as equation 3-6

\[
\text{Unscheduled Maintenance Time} = \text{Total Maintenance Down Time} - \text{Scheduled Maintenance Time}
\]

Equation 3-6

The “unscheduled maintenance down time” time category can be attributed to durations of time when the haul truck has broken down due to stress induced by production and is required to get equipment back to functionality. Common contributors to these stresses experienced by the haul truck are the operator’s skill, environment, nature of work, and the natural decay of the equipment. Examples of events that are classified as an unscheduled maintenance down time event include:

- Accident-Repair
- Dispatch system down
- Flat tire
- Maintenance inspection
- Truck travelling to shop/ at ready line
- Unscheduled maintenance breakdown
- Waiting for maintenance personnel
- Waiting for parts
3.3.7 Primary Production Time
As defined by Barrick, primary production time is, "the time spent in an efficient production cycle". Primary production represents a portion of production time when ore or waste is being produced and is generating value for the operation.

\[
\text{Primary Production Time} = \text{Production Time} - \text{Secondary Production Time} \quad \text{Equation 3-7}
\]

Production time can also be expressed as equation 3-8.

\[
\text{Primary Production Time} = \text{Nominal Time} - \text{Down Time} - \text{Standby Time} - \text{Delay Time} - \text{Secondary Production Time} \quad \text{Equation 3-8}
\]

Furthermore, equation 3-8 can be expanded to equation 3-9.

\[
\text{Primary Production Time} = \text{Nominal Time} - \text{Unscheduled Maintenance Time} - \text{Scheduled Maintenance Time} - \text{Standby Time} - \text{Delay Time} - \text{Secondary Production Time} \quad \text{Equation 3-9}
\]

3.3.8 Secondary Production Time
As defined by Barrick, secondary production time is, "Extra time required to complete a production cycle due to external interactions, rework due to ground conditions, etc." This subcategory of production time is necessary for preparing the environment for primary production.

\[
\text{Secondary Production Time} = \text{Production Time} - \text{Primary Production Time} \quad \text{Equation 3-10}
\]
3.3.9 Production Time

As defined by Barrick, production time is "Operating Time minus delays that occur during the operating shift." This is the total time when ore or waste mining is occurring during a typical production cycle. Production time represents the durations when a haul truck operator is being effective in a regular production cycle and generating value for the operation. This time category is the summation of primary production time and secondary production time.

\[ \text{Production Time} \]

\[ = \text{Nominal Time} - \text{Total Maintenance Down Time} \]

\[ - \text{Standby Time} - \text{Delay Time} \]

Equation 3-11

Equation 3-11 can be expanded to equation 3-12.

\[ \text{Production Time} \]

\[ = \text{Nominal Time} \]

\[ - \text{Unscheduled Maintenance Time} \]

\[ - \text{Scheduled Maintenance Time} - \text{Standby Time} \]

\[ - \text{Delay Time} \]

Equation 3-12

Furthermore, equation 3-11 and equation 3-12 can be expressed as Equation 3-13.

\[ \text{Production Time} \]

\[ = \text{Primary Production Time} \]

\[ + \text{Secondary Production Time} \]

Equation 3-13

Typical events in the “production time” time category include:

- Dumping
- Hauling
- Travelling empty
- Queued at dump
3.4 Aggregated Time Categories

3.4.1 Maintenance Down Time
As defined by Barrick, maintenance down time is, "Total Time the equipment is down for mechanical reasons and must be repair before returning to work." Maintenance Down is an aggregated time category and is the summation of unscheduled maintenance down time and scheduled maintenance down time. In general terms, maintenance down time is when equipment is unable to be directed towards generating value due to maintaining functionality for the short term and as well over long term. Total maintenance down time is expressed as in Equation 3-14.

\[
T_{NP} = T_{NP} + U_{NP}
\]

\[\text{Equation 3-14}\]

Figure 10 “Maintenance Down” time category in the time model.

3.4.2 Up Time
As defined by Barrick, up time is the, "Total time that equipment is mechanically capable of production."

Up time is made up of standby time and operating time, where operating time is made up of production
time, and delay time. Generally speaking, up time comprises the entire duration when equipment is functionally able to (standby time), in progress of (delay time), or actually (production time) generating value. Up time can be expressed as Equations 3-15 to 3-18.

\[
Up Time = Nominal Time - Total Maintenance Down Time \quad \text{Equation 3-15}
\]

\[
Up Time = Nominal Time - Unscheduled Maintenance Time - Scheduled Maintenance Time \quad \text{Equation 3-16}
\]

\[
Up Time = Operating Time + Standby Time \quad \text{Equation 3-17}
\]

\[
Up Time = Production Time + Delay Time + Standby Time \quad \text{Equation 3-18}
\]

Figure 11 “Up Time” time category in the time model.

3.4.3 Operating Time
As defined by Barrick, operating time is “Up Time minus the time that there is no operator intending to run the machine (no operator, on break, etc.)”. Operating time is the summation of production time and delay time and represents the total time directed at generating value, and time required for overcoming
inherent factors within a regular production cycle. Operating time can be expressed as Equations 3-19 to 3-22.

\[
\text{Operating Time} = \text{Nominal Time} - \text{Total Maintenance Down Time} - \text{Standby Time}
\]

Equation 3-19

\[
\text{Operating Time} = \text{Nominal Time} - \text{Unscheduled Maintenance Time} - \text{Scheduled Maintenance Time} - \text{Standby Time}
\]

Equation 3-20

\[
\text{Operating Time} = \text{Production Time} + \text{Delay Time}
\]

Equation 3-21

\[
\text{Operating Time} = \text{Primary Production Time} + \text{Secondary Production Time} + \text{Delay Time}
\]

Equation 3-22

3.5 State Transitions

The transition of a haul truck’s state is an indicator of data quality. Through logical deduction and taking a close look of the dataset, it was found that there are feasible and unfeasible transitions between time categories. Furthermore when looking at the dataset, there are transitions that point towards hardware or software errors due to the short duration and back and forth transitions between two states.

From the Site B dataset which contained approximately 15,000 individual single transitions, it was found that the most frequent transition occurred as operating to operating delay (31.6%), and operating delay back to operating (30.8%).
Table 2. Transition frequencies of the Site B dataset.

The least common transition occurred as operating delay to scheduled maintenance (3 instances) and unscheduled maintenance to scheduled maintenance (2 instances). From this analysis it was found that scheduled maintenance never transitions into operating delay or unscheduled maintenance, which adds validity to the dataset. In addition, unscheduled maintenance never transitions into operating delay. These identified "rules" are just a starting point for state transition analysis. This analysis can be taken a step further by calculating the rate of individual transitions from one state to another as a function of frequency and the duration of the initial state, which in essence can give you the number of time each state transitions to another state per period measured.

<table>
<thead>
<tr>
<th>Initial State</th>
<th>Operating</th>
<th>Operating Delay</th>
<th>Operating Standby</th>
<th>Unscheduled Maintenance</th>
<th>Scheduled Maintenance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operating</td>
<td>4820</td>
<td>2388</td>
<td>92</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>31.6%</td>
<td>15.7%</td>
<td>0.6%</td>
<td>0.2%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Initial State</th>
<th>Operating Delay</th>
<th>Operating Delay</th>
<th>Operating Standby</th>
<th>Unscheduled Maintenance</th>
<th>Scheduled Maintenance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operating Delay</td>
<td>4654</td>
<td>252</td>
<td>6</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>30.8%</td>
<td>15.5%</td>
<td>0.6%</td>
<td>0.0%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Initial State</th>
<th>Operating Standby</th>
<th>Operating Standby</th>
<th>Operating Delay</th>
<th>Unscheduled Maintenance</th>
<th>Scheduled Maintenance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operating Standby</td>
<td>2677</td>
<td>50</td>
<td>45</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>17.6%</td>
<td>0.5%</td>
<td>0.3%</td>
<td>0.1%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Initial State</th>
<th>Unscheduled Maintenance</th>
<th>Unscheduled Maintenance</th>
<th>Unscheduled Maintenance</th>
<th>Unscheduled Maintenance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operating</td>
<td>73</td>
<td>54</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Frequency</td>
<td>0.5%</td>
<td>0.4%</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Initial State</th>
<th>Scheduled Maintenance</th>
<th>Scheduled Maintenance</th>
<th>Scheduled Maintenance</th>
<th>Unscheduled Maintenance</th>
</tr>
</thead>
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<td>16</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Frequency</td>
<td>0.2%</td>
<td>0.2%</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

Total 15237
Chapter 4
Time Model Elements and Key Performance Indicator Definitions

4.1 Time Model

As shown above time categories are organized into a time model to define how they relate to each time category; each category is used in KPI calculations. It is important to recognize that time models can vary from mine site to mine site. More importantly, classifications of activities in to each time category is the foundation for any time model. Thus differences in the time model can vary dramatically due to the subjective nature of interpreting and classifying each activity in a mining operation.

Figure 12. Typical time model.

Figure 13. Re-imagined time model.
The re-imagined time model above uses time categories that are elements for standard KPI calculations. Each color represents different levels of elements in each time category; white is the most basic element and light blue contains all the time categories.

4.2 Key Performance Indicators (KPIs)

The way each time category is placed in the time model determines how they are used in KPI calculations. For haul trucks the most common KPI's measured are availability and utilization. To be more precise, availability can be further specified as physical availability or mechanical availability, and utilization can be utilization, production utilization or effective utilization. Even if definitions and formulas for these common KPI's are similar across the mining industry, inconsistencies can still exist in the categorization of activities into time categories; which is essentially defined in each mine's specific time model. In Chapter 4, the time categories used for the analysis in this thesis were identified. This section presents equations for calculating the KPI's based on those time categories.

4.2.1 Mean Time Between Failure (MTBF)

\[
MTBF = \frac{(Total\ Production\ Time)}{(Total\ Number\ of\ Functional\ Failure\ Events)} \quad \text{Equation 4-1}
\]

Note that the Total Number of Functional Failure Events may not be accurately reflected in a raw dataset obtained from a real information source. A Functional Failure Event is defined as the transition from a Production State to an Unscheduled Maintenance Down State – this can either be a direct transition between the two states, or an indirect transition via one more other states (such as Delay).

It is important not to confuse the count of Functional Failure Events with the number of instances of Production States which may be present in an actual dataset. For example, in the data analyzed in Chapters 5 and 6 of this thesis, which is obtained from mine haul truck Fleet Management Systems, there are typically far more instances of Production States than there are of actual Functional Failure Events. This arises because these datasets typically contain multiple instances of Production States between any two instances of Unscheduled Maintenance Down Time States.
4.2.2 Mean Time to Repair (MTTR)

\[ MTTR = \frac{\text{(Total Unscheduled Maintenance Down Time)}}{\text{(Total Number of Repair Events)}} \]

Equation 4-2

From the definition of a Functional Failure, it follows that for each Functional Failure Event there can only be one Repair Event. There the number of Repair Events must always be equal to the number of Functional Failure Events.

Note that, as was the case for Functional Failure Events versus Production States, in the data analyzed in Chapters 5 and 6 of this thesis, which is obtained from mine haul truck Fleet Management Systems, there are typically far more instances of Unscheduled Maintenance States than there are of actual Repair Events.

4.2.3 Mechanical Availability

Mechanical availability is a subcategory of availability. In the reliability engineering literature, it is defined as [Salvendy, 2001]:

\[ Mechanical \ Availability = \frac{MTBF}{MTBF + MTTR} \]

Equation 4-3

Figure 14. How mechanical availability can be visualized in the time model.

MTBF is a measurement of average production time, or time that equipment is experiencing degradation-inducing stresses, and MTTR is a measurement of average unscheduled maintenance time, or average time that equipment requires before it is repaired from a Functional Failures.

Due to the simple nature of this metric, which only considers two possible time categories (production time and unscheduled maintenance down time) mechanical availability represents the percentage of time
that a physical asset is in a Production state rather than in an Unscheduled Maintenance state. From this simplified model of mechanical availability, inefficiencies ("Delay" time, "Standby" time and, "Scheduled Maintenance Down" time) in the operation can be excluded from the representation of equipment reliability.

Alternatively, mechanical availability can also be defined as follows, from a maintenance engineer’s point of view:

\[
Mechanical\ Availability = \frac{Production\ Time}{Production\ Time + Unscheduled\ Maintenance\ Down\ Time}
\]

Equation 4-4

This calculation should yield the same result, if the MTBF and MTTR are calculated consistently and correctly.

This alternate form of the equation for mechanical availability makes it explicit that it excludes scheduled maintenance, standby time and delay time; hence it reveals what percentage of time the equipment or equipment fleet is actually experiencing degradation or failure causing stress versus when it is not. In essence, this metric reflects a balance between how reliable this equipment is and how maintainable it is.

4.2.4 Physical Availability

Physical availability is typically defined as “The percentage of Nominal Time that the equipment is physically available for production”. In the most basic form, physical availability is calculated as follows (reference to Barrick Standard):

\[
Physical\ Availability = \frac{Up\ Time}{Nominal\ Time}
\]

Equation 4-5

As shown in Figure 12, Up time is defined as nominal time minus down time, therefore physical availability can also be expanded as follows:

\[
Physical\ Availability = \frac{Nominal\ Time - Total\ Maintenance\ Down\ Time}{Nominal\ Time}
\]

Equation 4-6
Furthermore, because down time is the sum of scheduled maintenance and unscheduled maintenance, physical availability can be expanded to:

\[
\text{Physical Availability} = \frac{(\text{Nominal Time} - \text{Scheduled Maintenance Down Time} - \text{Unscheduled Maintenance Down Time})}{(\text{Nominal Time})}
\]

Equation 4-7

By subtracting down time from nominal time, the remaining segments of activity times within the period being examined are operating time and standby time. Thus, physical availability can also be defined as follows:

\[
\text{Physical Availability} = \frac{(\text{Operating Time} + \text{Standby Time})}{(\text{Production Time} + \text{Delay Time} + \text{Total Maintenance Down Time})}
\]

Equation 4-8

Finally, because operating time is equal to production time plus delay time, the most expanded and definitive form of physical availability is defined as follows:

\[
\text{Physical Availability} = \frac{(\text{Production Time} + \text{Delay Time} + \text{Standby Time})}{(\text{Production Time} + \text{Delay Time} + \text{Standby Time} + \text{Scheduled Maintenance Down Time} + \text{Unscheduled Maintenance Down Time})}
\]

Equation 4-9

To be more precise, physical availability represents the percentage of time that equipment is able to operate but may (production time) or may not (standby time, delay time) be "operating" due to reasons other than mechanical limitations. Because the summation of the numerator for physical availability
includes standby time and delay time along with production time, it gives a higher value of availability when compared to mechanical availability. Due to this reason, operations planners will often prefer to use physical availability over mechanical availability. Mechanical availability can be used to be more precise in reporting actual equipment availability without influence from aspects of planning and dispatch. Physical Availability is the duration of time when equipment is in use for purposes other than maintenance requirements and calculated as a percentage of total calendar time (nominal time).

In conclusion, physical availability and mechanical availability represent different perspectives on interpreting the operating efficiency of equipment. In a theoretical scenario where duration of total standby time is zero and duration of total delay time is zero, mechanical availability will be equal to physical availability.

In general, dispatch management will prefer to use physical availability over mechanical availability because standby time, delay time and scheduled maintenance time are included in the calculation; this effectively overestimates the duration of when a piece of equipment is doing work. In reality, from a reliability and maintenance standpoint, mechanical availability reflects equipment availability more precisely, from a physical degradation point of view.

4.2.5 Utilization

Three forms of utilization are used to quantify performance in different areas of operations planning on the production side. Barrick Gold Corporation defines utilization as, "The percentage of Up Time that the..."
equipment has an operator capable of utilizing the equipment." The equation for calculating utilization is defined as follows [Barrick Gold Corporation, 2006]:

\[
Utilization = \frac{Operating \ Time}{Up \ Time}
\]

Equation 4-10

As shown in Figure 12, operating time is the nominal time minus both standby and maintenance, while up time represents the total time equipment is mechanically able to produce and hence includes standby time. The equation for calculating utilization can be expanded to the following form:

\[
Utilization = \frac{(Nominal \ Time - Standby \ Time - Unscheduled \ Maintenance \ Down \ Time - Scheduled \ Maintenance \ Down \ Time)}{(Nominal \ Time - Scheduled \ Maintenance \ Down \ Time - Unscheduled \ Maintenance \ Down \ Time)}
\]

Equation 4-11

Alternatively because operating time is defined as production time plus delay time and up time is defined as production time plus delay time and standby time, utilization can also be represented as the following equation:

\[
Utilization = \frac{Production \ Time + Delay \ Time}{Production \ Time + Delay \ Time + Standby \ Time}
\]

Equation 4-12

In essence, utilization is a metric for gauging the efficiency of the mining cycle during the total period of time that the equipment is operating as planned; which is the sum of production time, delay time and standby time.

Utilization is a measure of when equipment is directed at generating value (Operating time = Production time + Delay Time) but also includes consideration of logistical planning factors (Standby time).
4.2.6 Production Utilization

As defined by Barrick, production utilization is, "The percentage of Operating Time the equipment is in a production cycle and not delayed for an operating related reason." Production utilization is defined as the following equation:

\[
P_{\text{PU}} = \frac{N_{\text{NT}} - S_{\text{DM}} - D_{\text{MT}} - D_{\text{DM}}}{N_{\text{NT}} - S_{\text{DM}} - D_{\text{MT}} - D_{\text{DM}} + U_{\text{DM}} + U_{\text{ST}}}
\]

Equation 4-13

As stated, because down time is equal to scheduled maintenance and unscheduled maintenance time, production utilization can be expanded to the following equation:

\[
P_{\text{PU}} = \frac{(N_{\text{NT}} - S_{\text{ST}} - D_{\text{DM}} - D_{\text{MT}} - S_{\text{ST}} - U_{\text{DM}} - U_{\text{ST}})}{N_{\text{NT}} - S_{\text{ST}} - D_{\text{DM}} - D_{\text{MT}} - S_{\text{ST}} - U_{\text{DM}} - U_{\text{ST}}}
\]

Equation 4-14
Alternatively, production Utilization can also be called Utilization of Availability because it is a measure of how much of the production time which was used as a percentage of operating time and is represented in the equation below:

\[
\text{Production Utilization} = \frac{\text{Production Time}}{\text{Operating Time}} \quad \text{Equation 4-15}
\]

Because operating time is production time plus delay time, production utilization can be expanded as follows:

\[
\text{Production Utilization} = \frac{\text{Production Time}}{\text{Production Time} + \text{Delay Time}} \quad \text{Equation 4-16}
\]

Given that production utilization is the percentage of production time out of the sum of production time and operating delay time, it effectively measures the efficiency of dispatch planning or the interaction between production equipment, specifically trucks and shovels.

Production Utilization can be thought of as when equipment is actually generating value (Production time) as a percentage of when equipment is directed at generating value (Operating Time).

![Figure 17. How production utilization can be visualized in the time model.](image)

### 4.2.7 Effective Utilization

As defined by Barrick, effective utilization is, "The percentage of Up Time that the equipment spends in a production cycle." Effective utilization can be defined as follows:

\[
\text{Effective Utilization} = \frac{\text{Production Time}}{\text{Up Time}} \quad \text{Equation 4-17}
\]
Because up time is the sum of operating time and standby time, effective utilization can also be calculated as follows:

\[
\text{Effective Utilization} = \frac{(Production \ Time)}{(Production \ Time + Delay \ Time + Standby \ Time)}
\]

Equation 4-18

Another alternative form of the equation for effective utilization can also be calculated as follows:

\[
\text{Effective Utilization} = \frac{(Nominal \ Time - Delay \ Time - Standby \ Time - Total Maintenance \ Down \ Time)}{(Nominal \ Time - Total Maintenance \ Down \ Time)}
\]

Equation 4-19

Or further expanded as follows:

\[
\text{Effective Utilization} = \frac{(Nominal \ Time - Delay \ Time - Standby \ Time - Total Maintenance \ Down \ Time - Scheduled Maintenance \ Down \ Time - Unscheduled Maintenance \ Down \ Time)}{(Nominal \ Time - Scheduled Maintenance \ Down \ Time - Unscheduled Maintenance \ Down \ Time)}
\]

Equation 4-20

Alternatively, because utilization comprises operating time in the numerator and up time in the denominator, and production utilization comprises production time in the numerator and operating time in the denominator, effective utilization can be calculated as the product of utilization and production utilization because operating times cancel out. Hence, the equation of effective utilization is also:

\[
\text{Effective Utilization} = \text{Utilization} \times \text{Production Utilization}
\]

Equation 4-21

Essentially, effective utilization represents the percentage of time when equipment is producing ore or waste out relative to the duration when the equipment is running or "up". This metric effectively reflects equipment performance under degradation inducing stress (Production Time) as a portion of when the
equipment is mechanically capable of doing work (the sum of Production Time, Operating Delay Time, and Standby Time).

Effective Utilization is a measure of when equipment is actually generating value (Production Time) out of when equipment is physically (Delay Time), logistically (Standby Time), and mechanically capable (not constrained by equipment repair or long term maintenance requirements) of generating value.

Figure 18. How effective utilization can be visualized in the time model.

4.2.8 Capital Effectiveness

As defined by Barrick, capital effectiveness is, "A measure of the effective use of the capital asset."

Capital effectiveness is defined as the following equation:

\[
\text{Capital Effectiveness} = \frac{\text{Primary Production Time}}{\text{Nominal Time}}
\]

Equation 4-22

Capital effectiveness can also be calculated as follows:
Capital Effectiveness

\[
= \frac{(Nominal\ Time - Delay\ Time - Standby\ Time - Secondary\ Production\ Time - Scheduled\ Maintenance\ Down\ Time - Unscheduled\ Maintenance\ Down\ Time)}{(Primary\ Production\ Time + Secondary\ Production\ Time + Delay\ Time + Standby\ Time + Schedule\ Maintenance\ Down\ Time + Unscheduled\ Maintenance\ Down\ Time)}
\]

Equation 4-23

Capital effectiveness is the percentage of the entire period when equipment is producing ore or waste. This metric essentially reflects the equipment’s ability to generate value without the impact of dispatch, planning and maintenance.
This chapter investigates the impact on KPI’s of filtering Unscheduled Maintenance Down Time states, which occur in the raw dataset generated by a Fleet Management System. The filtering technique is based on the duration of those states. Duration based filtering is applied using two approaches: either the minimum (lower limit cut-off) or maximum (upper limit cut-off) durations of Times-To-Repair (TTR’s). In addition, the combination of minimum and maximum durations is also investigated. A range of cut-offs are chosen to enable sensitivity analysis of the KPI’s with respect to the filtering. This analysis provides insight into the impacts of data quality issues related to Unscheduled Maintenance Down Time states.

A significant number of data points within the dataset showed time to Unscheduled Maintenance Down Time duration in fractions of a second. Although a down time of any duration might be labeled in the dataset as Unscheduled Maintenance Down Time, in order to be accurate any such down time must correspond to a Functional Failure. For any real Functional Failure, the time to repair must be physically feasible. In reality, actual Functional Failure on a haul truck is not repairable within the span of a few seconds (or in many cases even within the span of a few minutes), and any such “unfeasible” repair times can only be due to poor data quality, and as such they have the potential to compromise the accuracy of the KPI’s which depend on the Unscheduled Maintenance Down Time category.

The first part of the analysis in this chapter focuses on the need for processing for purposes of accurately calculating the number of Functional Failure Events and Repair Events in the dataset. The next part of this chapter examines MTTR as a function of TTR, in order to identify where significant trends exist in the distribution of TTR, in order to help select values of the duration filters to be used in the sensitivity analysis.
The filters are applied to each dataset: first to the Site A, and then to the Site B data. For each dataset:

- First, short duration filtering is applied, with the filtered states simply being excluded
- Second, short duration filtering is applied, but with the duration of a filtered state being added back to whatever state precedes it in the raw dataset (and hence being added to the time category of the preceding state)
- Thirdly, long duration filtering is applied, with the filtered states simply being excluded
- Fourthly, long duration filtering is applied, but with the duration of a filtered state being split into two: the duration corresponding to the long duration filter value is retained as Unscheduled Maintenance Down Time, while any amount in excess of the long duration filter value is added to the Scheduled Maintenance Down Time category
- Finally, the combination of both short duration and long duration filtering is applied.

For each of the above cases of filtering, the resulting KPI’s are recalculated based on the filtered dataset and then analyzed. The diagram below shows the flow of the TTR duration sensitivity analysis carried out in this chapter.

![Diagram showing the flow of analysis for investigation of TTR sensitivities.](image)

**Figure 19: Flow of analysis for investigation of TTR sensitivities.**
5.1 Processing for Purposes of Calculating Number of Functional Failure Events and Repair Events

In order to achieve accurate and consistent calculation of MTBF and MTTR, it is necessary to extract the number of actual Functional Failure Events (which equals the number of Repair Events) in any chronologically sequential dataset obtained from a Fleet Management System. This applies to the raw (unfiltered) dataset, as well as to any processed (filtered) datasets which are subsequently generated.

The processing used for this purposes consists of the following sequence of steps:

1. Consecutive repetitions of time category states were merged into one state and had their durations combined. This resulted in the conversion of a larger number of Unscheduled Maintenance States into a smaller number.

2. The resulting intermediate dataset was then stripped of all states except for Production States and Unscheduled Maintenance States.

3. The stripped dataset was then again subjected to the merging process of Step 1 (above), which further reduced the number of Production States and Unscheduled Maintenance States – yielding a dataset for which:
   - The number of Production States equals the number of Functional Failure Events
   - The number of Unscheduled Maintenance States equals the number of Repair Events
   - The number of Functional Failure Events is identical to the number of Repair Events

5.2 Behaviour of MTTR with respect to TTR Cut-off for the Site A Dataset

This analysis uses the raw (unprocessed), chronologically sequential, dataset for the entire truck fleet at Site A.

5.2.1 Critical Short TTR durations

The purpose of this initial analysis was to investigate whether any trends could be identified in how MTTR changed as the value of the TTR-duration-based filter was varied. This was achieved by extracting all the Unscheduled Maintenance Down Time States (TTR’s) from the raw sequential dataset, and
rearranging them in increasing order of duration. The first MTTR was calculated using all the TTR data points except the first TTR. The second MTTR was calculated using all the TTR data points while excluding the first and second TTR data points and so on. Once all the MTTR’s had been calculated, they were plotted against the corresponding TTR durations.

As shown in Figure 20, the sensitivity of MTTR as a function of filtering by duration of TTR cut-off is represented by the slope of the graph: as expected the TTR data points cluster at shorter durations.

![Figure 20: Initial analysis plotting TTR durations versus MTTR (Site A dataset).](image)

From Figure 20, points where the slope changed significantly were identified at approximately 12 hours, 30 hours, 35 hours, and 64 hours of TTR cut-off duration.
In addition, by zooming in on the left hand portion of Figure 20, it can be seen that significant slope changes also occurs at 0.0025 hours (9 seconds) – as shown in Figure 21.

The most likely reason for the slope change at this very short duration is software error (mislabeling of state or data corruption), though hardware errors and human (operator input) error may also play a role.

5.2.2 Critical Long TTR durations

From Figure 22, points where the slope changed significantly at longer durations were identified at approximately 30 hours, 35 hours, 40 hours, 50 hours, 65 hours, 75 hours, and 100 hours.

The slope changes at longer TTR durations can likely be attributed to the mislabeling of scheduled maintenance events.
5.3 Filtering of Unscheduled Maintenance Down Time States with short durations for the Site A Dataset

This section, as well as the subsequent sections in this Chapter, utilize the raw, chronologically sequential, dataset.

5.3.1 Filtering of Short TTR Durations while Excluding Filtered Segments

The first step of the analysis focused on filtering of short TTR durations, while excluding the filtered segments from the dataset. This was implemented by removing segments from the dataset that had smaller durations than the specified TTR cut-off.

As shown in subsection 5.2.1, significant slope changes occurs at around 9 seconds (0.0025 hours). This is further detailed in Figure 23. In order to investigate the sensitivity of KPI’s to this lower limit, TTR cut-off durations of 3 seconds, 5 seconds, 10 seconds, and 15 seconds were chosen. This analysis identifies and removes TTR’s with durations less than that deemed plausible for time to repair (unscheduled maintenance).
The selected cut-off durations were then used as bins to generate a histogram of the number of Unscheduled Maintenance States within each range in the raw dataset, which yields the distribution shown in Table 3 and Figure 24. Note that the processing for purposes of calculating the number of Functional Failure Events and Repair Events (see section 5.1) results in the number of Unscheduled Maintenance States being reduced from a total of 1576 to 1209 Repair Events (see row 9 in Table 4), i.e. a reduction of 23%.

<table>
<thead>
<tr>
<th>Bin</th>
<th>Bin (hours)</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
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<td>77</td>
</tr>
<tr>
<td>5 sec</td>
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</tr>
<tr>
<td>10 sec</td>
<td>0.00278</td>
<td>79</td>
</tr>
<tr>
<td>15 sec</td>
<td>0.00417</td>
<td>29</td>
</tr>
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<td>0.01667</td>
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</tr>
<tr>
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</tr>
<tr>
<td>10 min</td>
<td>0.16667</td>
<td>153</td>
</tr>
<tr>
<td>30 min</td>
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<td>271</td>
</tr>
<tr>
<td>1 hr</td>
<td>1.00000</td>
<td>126</td>
</tr>
<tr>
<td>More</td>
<td></td>
<td>491</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>1576</td>
</tr>
</tbody>
</table>

Table 3: Distribution of Unscheduled Maintenance States, with bins corresponding to cut-off durations used in filtering analysis (Site A dataset)
In addition, 1 minute, 5 minutes, 10 minutes, 30 minutes, and 1 hour TTR cut-offs were introduced to further investigate the sensitivity of KPI calculations. For each of the selected TTR cut-off durations, the data segments excluded by the filter were also removed from the dataset (i.e. they were not reassigned to a different event category). The modified datasets resulting from filtering were used to re-calculate the KPI’s, which are presented in Table 4 below.
Table 4: Filtering of Unscheduled Maintenance States with short durations while excluding filtered segments for Site A dataset.

As Table 4 shows, this MTTR lower-limit cut-off filter analysis, where the filtered segments were excluded from the calculation of the KPI’s, only affects:

- the number of repair events (which equals the number of functional failure events)
- MTTR
- MTBF
- mechanical availability
- physical availability
- capital effectiveness

This is consistent with expectations, since the above KPI’s are all affected by the duration of unscheduled maintenance. However the first three KPI’s in the above list are affected significantly, while the last three above listed KPI’s are only slightly affected – as shown below.
Figure 25: Number of functional failure events versus short TTR filter durations (while excluding filtered segments - Site A dataset).

As illustrated in Figure 25, as the duration of the minimum TTR cut-off filter increases, the number of repair events decreases exponentially. Using a 3 second filter cut-off, 42 TTR events were removed from a total of 1209 events (i.e. 3.5%), whereas using a filter with 1 hour duration, 919 TTR events were removed (i.e. 76%).

Figure 26: MTTR versus TTR filter durations (while excluding filtered segments - Site A dataset).

As expected, Figure 26 shows that MTTR increases significantly as the duration of the minimum TTR cut-off filter increases. Using a 3 second filter cut-off, MTTR changes from 3.13 to 3.24 – an increase of 3.5% increase relative to the unfiltered data. In contrast, a 1 hour filter cut-off increases MTTR to 12.44 hours: an increase of 297%.
Figure 27: MTBF versus TTR filter durations (while excluding filtered segments - Site A dataset)

Figure 27 shows MTBF also changed significantly as the filter duration was increased. Using a filter of 3 seconds, the MTBF increased by 3.6% compared to the original MTBF, whereas using a filter of 1 hour, the MTBF increased by 317%.

Figure 28: Mechanical availability versus TTR filter durations (while excluding filtered segments - Site A dataset)

In contrast to the significant sensitivity of the three previous KPI’s, Figure 28 shows that changes in Mechanical Availability were negligible: Mechanical Availability changed by less than 1% as the filter cut-off was varied from 3 seconds to 1 hour. This is due to the ratio of MTTR to MTBF remaining almost constant.
Figure 29: Physical availability versus TTR filter durations (while excluding filtered segments - Site A dataset).

Figure 29 shows that Physical Availability is also relatively insensitive to variation of the TTR filter cut-off – again varying by less than 1%. This is to be expected since unscheduled maintenance down time accounts for only a small contribution to the value of the denominator (nominal time) in the equation for this KPI.

Figure 30: Capital Effectiveness versus TTR filter durations (while excluding filtered segments - Site A dataset).

From Figure 30 it can be seen that Capital Effectiveness exhibits the same level of insensitivity as Physical Availability, because of the similarity in their equations, where only the denominator (unscheduled maintenance down time, and indirectly nominal time) is affected.
5.3.2 Filtering of Short TTR Durations with addition of Filtered Segments back into preceding state

This subsection repeats the analysis of the previous subsection, however in this case, the filtered unscheduled maintenance states are merged into the preceding state (i.e. relabeled and added). The same filter cut-off durations were used as in the previous subsection: 3 seconds, 5 seconds, 10 seconds, 15 seconds, 1 minute, 10 minutes, 5 minutes, 10 minutes, 30 minutes, and 1 hour.

As shown in Table 5 below, the number of functional failure events and all the time categories (other than Nominal) were affected by employing this filtering technique. This is because the filtered events can occur subsequent to all of the other time categories throughout the dataset. As a result, all the KPI’s are affected by this filtering.

<table>
<thead>
<tr>
<th>Time Categories</th>
<th>Nominal (hours)</th>
<th>Production (hours)</th>
<th>Down (Unscheduled) (hours)</th>
<th>Standby (hours)</th>
<th>Delay (hours)</th>
<th>Scheduled Maintenance (hours)</th>
<th># of Functional Failure Events (= # of Repair Events)</th>
<th>MTTR (hours)</th>
<th>MTBF (hours)</th>
<th>Mechanical Availability</th>
<th>Physical Availability</th>
<th>Utilization</th>
<th>Production Utilization</th>
<th>Effective Utilization</th>
<th>Capital Effectiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower limit duration filter no cut-off</td>
<td>30.864.00</td>
<td>18.027.75</td>
<td>3.782.74</td>
<td>3.081.60</td>
<td>4.692.78</td>
<td>1.279.14</td>
<td>1209</td>
<td>3.13</td>
<td>14.91</td>
<td>82.66%</td>
<td>83.60%</td>
<td>88.06%</td>
<td>79.35%</td>
<td>69.87%</td>
<td>58.41%</td>
</tr>
<tr>
<td>Lower limit duration filter (hours)</td>
<td>0.000833</td>
<td>0.001389</td>
<td>0.002278</td>
<td>0.004167</td>
<td>0.016667</td>
<td>0.083333</td>
<td>0.166667</td>
<td>0.16667</td>
<td>0.500000</td>
<td>82.68%</td>
<td>83.60%</td>
<td>88.06%</td>
<td>79.35%</td>
<td>69.87%</td>
<td>58.42%</td>
</tr>
</tbody>
</table>

Table 5: Filtering of short Unscheduled Maintenance State durations with addition of filtered segments back in to the preceding state for Site A dataset.

Figure 31 and Figure 32 show that this filtering technique yields the same results as the previous filtering technique (where the filtered segments were simply excluded) both for the number of TTR events and the MTTR.
Figure 31: Number of functional failure events versus TTR filter durations (while adding filtered segments to preceding state - Site A dataset).

Figure 32: Mean time to repair versus TTR filter durations (while adding filtered segments to preceding state - Site A dataset).
Figure 33: Mean time between failure versus TTR filter durations (while adding filtered segments to preceding state - Site A dataset).

Figure 34: Mechanical Availability versus TTR filter durations (while adding filtered segments to preceding state - Site A dataset).

Mechanical Availability exhibits a sensitivity of less than 1% over the range of filter cut-offs (see Figure 34).
As shown in Figure 35 and Figure 36, Physical Availability varied by less than 0.6%, and Capital Effectiveness varied by less than 0.4%. Utilization, Production Utilization and Effective Utilization (see Figure 37, Figure 38, and Figure 39) all varied by less than 0.2%. Hence these five KPI’s can all be assessed as being relatively insensitive to this filtering technique.
Figure 37 Utilization versus TTR filter durations (while adding filtered segments to preceding state - Site A dataset).

Figure 38: Production Utilization versus TTR filter durations (while adding filtered segments to preceding state - Site A dataset).
5.4 Filtering of Long Unscheduled Maintenance States durations for the Site A Dataset

In contrast to the previous section, this section focuses on filtering TTR durations that are much longer than a typical unscheduled maintenance down time event, by removing the identified data points from the dataset. Based on the analysis in subsection 5.2.2, filters that excluded TTR durations of over 30 hours, 35 hours, 40 hours, 50 hours, 65 hours, 75 hours, and 100 hours were used to investigate the sensitivity of the calculated KPI’s.

The data in this section is preprocessed in the same manner as in the previous section, and the number of functional failure events is calculated in the same way.

5.4.1 Filtering of Long TTR Durations while Excluding Filtered Segments

As was the case for the filtering of short TTR durations, the filtering of long TTR durations is first performed for the case where the data segments excluded by the filter are simply removed from the dataset (i.e. they are not reassigned to a different event category). The modified datasets resulting from filtering were used to re-calculate the KPI’s, which are presented in Table 6 below.
Table 6: Filtering of long Unscheduled Maintenance States durations while excluding filtered segments from the dataset for Site A.

As Table 6 shows, this MTTR upper-limit cut-off filter analysis, where the filtered segments were excluded from the calculation of the KPI’s, only affects:

- the number of functional failure events (which equals the number of repair events)
- MTTR
- MTBF
- mechanical availability
- physical availability
- capital effectiveness

These are the same KPI’s which were affected by the short duration TTR filter with filtered data segments excluded. In summary, the number of functional failure events, MTBF, and MTTR are all less sensitive to long duration TTR filtering than to short duration TTR filtering, while the Mechanical Availability, Physical Availability, and Capital Effectiveness are all more sensitive. This can be attributed to the fact
that there are far fewer functional failure events with long durations, hence far fewer data point being filtered. However, because the durations that were filtered are much longer when compared to the filtered short durations, each excluded event carries more weight, and there is still a measurable effect.

![Upper limit filter duration vs # Functional Failure Events](image1)

**Figure 40:** Number of functional failure events versus long TTR filter durations (while excluding filtered segments - Site A dataset).

Using a 30 hour TTR duration filter, 19 out of 1209 functional failure events were removed compared to not having a filter. Whereas using a 100 hour filter 8 functional failure events were removed from the dataset.

![Upper limit filter duration vs MTTR](image2)

**Figure 41:** MTTR versus long TTR filter durations (while excluding filtered segments - Site A dataset).
As shown in Figure 41 the duration of the filter has a noticeable effect on the MTTR. The MTTR of the filtered dataset using a 30 hour filter is only 31% of the unfiltered value, whereas when using a filter with a duration of 100 hours the MTTR is 45% of the unfiltered value.

![Upper limit filter duration vs MTBF](image)

**Figure 42: MTBF versus long TTR filter durations (while excluding filtered segments - Site A dataset).**

Figure 42 shows that the MTBF increases by 1.6% relative to the unfiltered value when the 30 hour long-duration filter is applied. However, increasing the filter cut-off beyond 30 hours has negligible additional effect.

![Upper limit filter duration vs Mechanical Availability](image)

**Figure 43: Mechanical Availability versus long TTR filter durations (while excluding filtered segments - Site A dataset).**
As shown in Figure 43, when employing a long TTR duration filter with a range of 30 hours to 100 hours, the mechanical availability is significantly affected, increasing by 13.66% from the original mechanical availability when using a 30 hour filter: an effect which attenuates as the filter duration is increased – so that a 100 hour cut-off results in an increase of only 10.52% relative to the unfiltered value.

Figure 44: Physical availability versus long TTR filter durations (while excluding filtered segments - Site A dataset).

The sensitivity of Physical Availability shown in Figure 44 is slightly less than the sensitivity of Mechanical Availability. Using a filter with duration of 30 hours, the Physical Availability changes by 7.76% when compared to not having a filter, whereas using a filter of 100 hours, the physical availability changes by 6.03%.

Figure 45: Capital Effectiveness versus long TTR filter durations (while excluding filtered segments - Site A dataset).
Figure 45 shows that Capital Effectiveness decreased significantly as the duration of the filter was increased. Using a 30 hour TTR duration filter, capital effectiveness increased from 58.41% to 63.83%, representing an increase of 5.42% relative to the unfiltered value. However using a TTR duration filter of 100 hours, capital effectiveness increased by only 4.21% relative to the unfiltered value. Capital effectiveness is impacted because the long duration filter modifies the total duration of the unscheduled maintenance down time category: which is impacts the nominal time in the denominator of the calculation of capital effectiveness.

5.4.2 Filtering of Long TTR Durations with addition of Filtered Segments back into Scheduled Maintenance Down Time Categories

In this part of the analysis, the following logic is applied to add the filtered segments back into the maintenance down time categories:

\[
\text{If } T_{\text{segment}} > T_{\text{cutoff}} \text{ then} \\
\quad \text{add } T_{\text{cutoff}} \text{ to } \text{Unscheduled\_Maintenance\_Category} \\
\quad \text{add } (T_{\text{segment}} - T_{\text{cutoff}}) \text{ to } \text{Scheduled\_Maintenance\_Category};
\]

as shown in the table below, only MTTR and mechanical availability were affected. This is because unscheduled down time event durations that are filtered are added into the total scheduled maintenance down durations and all other KPI equations separate unscheduled maintenance down event durations versus scheduled maintenance down event durations. It can be seen that the number of functional failure events was not affected by employing a long TTR duration filter and reintroducing the durations of filtered data points back into the dataset because the number of instances of unscheduled maintenance down time category events were not removed but simply reduced to equal the specified long duration filter. Unscheduled maintenance down events that are filtered by the long duration filter were added in to the total scheduled maintenance down time, thus a range of durations was used to examine the effect of choosing when an event is classified as a unscheduled maintenance down event rather than a scheduled maintenance down event. This portion of sensitivity analysis is much more realistic than just removing
data points that are identified by the filter because the durations identified are reintegrated back into the dataset.

<table>
<thead>
<tr>
<th>Time To Repair Cut off (TTR)</th>
<th>Upper limit filter duration (hours)</th>
<th>0</th>
<th>30</th>
<th>35</th>
<th>40</th>
<th>50</th>
<th>65</th>
<th>75</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nominal (hours)</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
</tr>
<tr>
<td>Production (hours)</td>
<td>18,027.75</td>
<td>18,027.75</td>
<td>18,027.75</td>
<td>18,027.75</td>
<td>18,027.75</td>
<td>18,027.75</td>
<td>18,027.75</td>
<td>18,027.75</td>
<td>18,027.75</td>
</tr>
<tr>
<td>Down (Unscheduled) (hours)</td>
<td>3,782.74</td>
<td>1,790.99</td>
<td>1,882.87</td>
<td>1,956.97</td>
<td>2,096.28</td>
<td>2,284.05</td>
<td>2,381.25</td>
<td>2,606.25</td>
<td></td>
</tr>
<tr>
<td>Standby (hours)</td>
<td>3,081.60</td>
<td>3,081.60</td>
<td>3,081.60</td>
<td>3,081.60</td>
<td>3,081.60</td>
<td>3,081.60</td>
<td>3,081.60</td>
<td>3,081.60</td>
<td>3,081.60</td>
</tr>
<tr>
<td>Delay (hours)</td>
<td>4,692.78</td>
<td>4,692.78</td>
<td>4,692.78</td>
<td>4,692.78</td>
<td>4,692.78</td>
<td>4,692.78</td>
<td>4,692.78</td>
<td>4,692.78</td>
<td>4,692.78</td>
</tr>
<tr>
<td>Scheduled Maintenance (hours)</td>
<td>1,279.14</td>
<td>3,270.89</td>
<td>3,175.00</td>
<td>3,104.90</td>
<td>2,965.59</td>
<td>2,777.82</td>
<td>2,680.63</td>
<td>2,455.63</td>
<td></td>
</tr>
<tr>
<td># of Functional Failure Events (= # of Repair Events)</td>
<td>1209</td>
<td>1209</td>
<td>1209</td>
<td>1209</td>
<td>1209</td>
<td>1209</td>
<td>1209</td>
<td>1209</td>
<td></td>
</tr>
</tbody>
</table>

Table 7: Filtering of long Unscheduled Maintenance State durations with addition of filtered segments back into total scheduled maintenance down time for Site A

Figure 46: MTTR versus long TTR filter durations (with addition of filtered segments back into total scheduled maintenance down - Site A dataset).
A significant change is evident in the MTTR's when the filtered unscheduled down time event’s durations are merged back into the dataset, when compared to just removing those data points. This is because as mentioned above, the number of instances of functional failures remain unchanged in this part of the analysis whereas in the previous long duration filtering analysis identified data points were removed; a large portion of the number of unscheduled down time category instances was deleted from the dataset.

Figure 47: Mechanical Availability versus long TTR filter durations (with addition of filtered segments back into total scheduled maintenance down - Site A dataset).

As can be seen in the two figures above, MTTR and mechanical availability exhibit an opposite relationship because MTTR is only on the denominator for the equation for mechanical availability.

In addition it is important to note the number of functional failure events remain the same as with the original dataset because the number of unique unscheduled maintenance events remains the same because that entry is either added back into the duration of scheduled maintenance down or remains unchanged.

5.5 Combined Filtering of Both Short and Long Unscheduled Maintenance State durations for the Site A Dataset (with addition of filtered segments back into the dataset)

The final part of the analysis for time to repair filtering on KPI sensitivity was to combine the previously developed long and short duration filters and apply them to the dataset. This is implemented in a consecutive manner – first, the short duration TTR filter (with addition of filtered segments back into the
preceding state), followed by the long duration TTR filter (with addition of filtered segments back into maintenance time categories).

Two combinations were investigated. For each combination, a single value of the short duration filter was chosen, while the long duration filter was varied.

For the first combination a 3 second short duration TTR filter was used while varying the long duration filter. For the second combination, a 30 minute short duration TTR filter was used while varying the long duration filter. The decision to choose a 30 minute duration filter over a 1 hour duration filter is attributed to the assumption that every TTR data point with duration less than 30 minutes is highly unlikely to represent an actual repair of a functional failure on a haul truck, whereas TTR durations greater than 30 minutes but less than an hour may be plausible.

This part of the analysis revealed that when filtered unscheduled maintenance down events was reintroduced back into the dataset, all KPI's were affected relative to the KPI’s from the unfiltered dataset (without even the 3 second short duration filter). When compared to the KPI’s resulting from applying only the short duration filter, the long duration filter only affected MTTR and Mechanical Availability.

5.5.1 Maintaining the Short Duration Filter at 3 Seconds While Varying the Long Duration Filter

This first part of the analysis uses a 3 Seconds duration filter whilst varying the long duration filter.
Table 8: Maintaining the short duration filter at 3 seconds while varying the long duration filter.

As seen in Table 8, MTTR and mechanical availability were the only KPI's affected. The number of functional failure events remained constant at 1167 as result of the 3 second filter. This remained unchanged as the long duration filter was varied because as previously mentioned, the unscheduled maintenance down time category instances were not removed, but reduced to the specified long duration filter's duration.

![Figure 48: MTTR versus long TTR filter durations (with constant 3 second short duration filter and addition of filtered segments back into total scheduled maintenance down - Site A dataset).](image)

### Table 8:

<table>
<thead>
<tr>
<th>Time Categories</th>
<th>Nominal (hours)</th>
<th>Production (hours)</th>
<th>Down (Unscheduled) (hours)</th>
<th>Standby (hours)</th>
<th>Delay (hours)</th>
<th>Scheduled Maintenance (hours)</th>
<th># of Functional Failure Events (= # of Repair Events)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
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<td>30,864.00</td>
<td>30,864.00</td>
</tr>
<tr>
<td></td>
<td>30,864.00</td>
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<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
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<tr>
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<td>30,864.00</td>
<td>30,864.00</td>
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<tr>
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<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
<td>30,864.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Key Performance Indicators (KPI's)</th>
<th>MTTR (hours)</th>
<th>MTBF (hours)</th>
<th>Mechanical Availability</th>
<th>Physical Availability</th>
<th>Utilization</th>
<th>Production Utilization</th>
<th>Effective Utilization</th>
<th>Capital Effectiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3.2%</td>
<td>1.53%</td>
<td>82.66%</td>
<td>83.60%</td>
<td>88.06%</td>
<td>79.35%</td>
<td>69.87%</td>
<td>58.41%</td>
</tr>
<tr>
<td></td>
<td>1.81%</td>
<td>1.68%</td>
<td>90.56%</td>
<td>83.60%</td>
<td>88.06%</td>
<td>79.35%</td>
<td>69.87%</td>
<td>58.41%</td>
</tr>
<tr>
<td></td>
<td>1.80%</td>
<td>1.53%</td>
<td>90.21%</td>
<td>83.60%</td>
<td>88.06%</td>
<td>79.35%</td>
<td>69.87%</td>
<td>58.41%</td>
</tr>
<tr>
<td></td>
<td>1.95%</td>
<td>1.53%</td>
<td>89.58%</td>
<td>83.60%</td>
<td>88.06%</td>
<td>79.35%</td>
<td>69.87%</td>
<td>58.41%</td>
</tr>
<tr>
<td></td>
<td>2.04%</td>
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<td>88.80%</td>
<td>83.60%</td>
<td>88.06%</td>
<td>79.35%</td>
<td>69.87%</td>
<td>58.41%</td>
</tr>
<tr>
<td></td>
<td>2.23%</td>
<td>1.53%</td>
<td>87.37%</td>
<td>83.60%</td>
<td>88.06%</td>
<td>79.35%</td>
<td>69.87%</td>
<td>58.41%</td>
</tr>
</tbody>
</table>
Figure 48 shows that filtering unscheduled maintenance down event durations less than 3 seconds and in addition, instances of unscheduled maintenance down time categories greater the each specified long duration filter, results in MTTR increasing as the long duration filter’s duration increases. While employing a 3 second short TTR duration filter with a 30 hour long TTR duration filter, the MTTR is 1.53, whereas a 3 second short duration filter with a 100 hour long duration filter yields an MTTR of 2.23; this represents a 46% increase.

In Figure 49 Mechanical Availability can be seen to decrease steadily as the duration of the long cut-off filter increases, resulting in a variation of 3.59% as the long duration filter varies from 30 hours to 100 hours.

![Filter duration vs Mechanical Availability](image)

**Figure 49:** Mechanical Availability versus long TTR filter durations (with constant 3 second short duration filter and addition of filtered segments back into total scheduled maintenance down - Site A dataset).

### 5.5.2 Maintaining the Short Duration Filter at 30 Minutes While Varying the Long Duration Filter

The second part of the analysis uses a 30 minutes TTR duration filter whilst varying the long TTR duration filter.
Table 9: Maintaining the short duration filter at 30 minutes while varying the long duration filter.

By employing a filter with duration of 30 minutes while varying the long duration filter, there is a less significant impact on MTTR and Mechanical Availability, as compared to using a 3 second short duration filter while varying the long duration filter.

![Filter duration vs MTTR](image)

Figure 50: MTTR versus long TTR filter durations (with constant 30 minute short duration filter and addition of filtered segments back into total scheduled maintenance down - Site A dataset).
As shown in Figure 50, the MTTR for using the 100 hours long duration filter is 6.91 hours, whereas for the 30 hour long duration filter the MTTR is 8.22; this represents a 16% variance.

![Filter duration vs Mechanical Availability](image)

**Figure 51: Mechanical availability versus Mean time to repair versus long TTR filter durations (with constant 30 minute short duration filter and addition of filtered segments back into total scheduled maintenance down - Site A dataset).**

Mechanical Availability was affected by variation of the long duration filter, decreasing from 89.01% to 87.2%.

### 5.6 Behaviour of MTTR with respect to TTR Cut-off for the Site B Dataset

#### 5.6.1 Critical Short TTR durations

As was done for the Site A dataset, an initial analysis of short TTR duration filtering versus MTTR was performed in order to any trends in the dataset. The Figure 52 plots the entire Site B dataset’s TTR data points versus MTTR.
Figure 52: Initial analysis plotting TTR durations versus MTTR (Site B dataset).

Figure 53: Initial analysis plotting very short TTR durations versus MTTR.

By focusing in on the short durations in Figure 53 it can be seen that changes of slope exist in the dataset exist around 0.03, 0.04, 0.14, and 0.16 hours (i.e. 1.8, 2.4, 8.4, 9.6 minutes). Similarly to what was previously postulated for the Site A dataset, the most likely reason for the slope change at these short durations include human (operator input) errors, though software error (mislabling of state or data corruption) and hardware errors may also play a role.
The selected cut-off durations were then used as bins to generate a histogram of the number of Unscheduled Maintenance States within each range in the raw dataset, which yields the distribution shown in Table 10 and Figure 54. Note that the processing for purposes of calculating the number of Functional Failure Events and Repair Events (see section 5.1) results in the number of Unscheduled Maintenance States being reduced from a total of 131 to 127 Repair Events (see row Table 11), i.e. a reduction of 3%.

<table>
<thead>
<tr>
<th>Bin (minutes)</th>
<th>Bin (hours)</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.8</td>
<td>0.03</td>
<td>4</td>
</tr>
<tr>
<td>2.4</td>
<td>0.04</td>
<td>2</td>
</tr>
<tr>
<td>8.4</td>
<td>0.14</td>
<td>4</td>
</tr>
<tr>
<td>9.6</td>
<td>0.16</td>
<td>6</td>
</tr>
<tr>
<td>More</td>
<td></td>
<td>115</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>131</td>
</tr>
</tbody>
</table>

Table 10: Distribution of Unscheduled Maintenance States, with bins corresponding to cut-off durations used in filtering analysis (Site B dataset)

Figure 54: Histogram of Unscheduled Maintenance States, with bins corresponding to cut-off durations used in filtering analysis (Site B dataset)
5.6.2 Critical Long TTR durations

![TTR Cut-off vs MTTR](image)

**Figure 55: Initial analysis plotting TTR durations versus MTTR.**

As shown in and Figure 52, regions of significant change in slope exist for long durations of TTR filtering at around 10, 14, 18, 24, and 28 hours.

5.7 Filtering of short Unscheduled Maintenance State durations for Site B Dataset

5.7.1 Filtering of Short duration while excluding filtered segments from the Site B Dataset

This portion of the analysis examines the effect of applying a short duration filter while excluding filtered segments from the Site B dataset. Based on the initial analysis above, short duration TTR filter cut-offs of 0.03, 0.04, 0.14, and 0.16 hours (i.e. 1.8, 2.4, 8.4, 9.6 minutes) were investigated.
As shown in Table 11, only the number of functional failure events (which equals the number of repair events), the MTTR, the MTBF, and the Mechanical Availability were affected by this short TTR duration filter. In fact, Physical Availability and Capital Effectiveness were also affected – but by a very small amount (to less than two decimal places).

Table 11: Filtering of short duration while excluding filtered segments from the Site B dataset.
Figure 56: Number of functional failure events versus each TTR filter’s durations.

As shown in Figure 56, the number of functional failure events (which equals the number of repair events) by a total of 16, or 13%, as the cut-off of the short duration TTR filter is increased from no filter up to 0.16 hours.

Figure 57: MTTR versus each TTR filter’s durations.

Figure 57 shows that MTTR increases by approximately 3% with the introduction of a 1.80 minute (0.03 hour) filter when compared to the unfiltered data, but when a 9.60 minute (0.16 hour) filter is used, the MTTR increased by approximately 14%.
Similarly (see Figure 58) MTBF was increased by between 3% and 14% when compared to the unfiltered dataset.

Mechanical availability was only affected very minimally. As Figure 59 shows, the MTBF only increased by less than 0.02%. (The variation is more apparent in the figure than in the table, because of the representation to only two decimal places in the table.)
5.7.2 Filtering of Short Durations with addition of filtered segments back in to the preceding State for Site B

This portion of the analysis was performed in the same manner as in the analysis for the Site A dataset: filtered TTR segments were added back into the dataset.

<table>
<thead>
<tr>
<th>Time To Repair Cut off (TTR)</th>
<th>1.80</th>
<th>2.40</th>
<th>8.40</th>
<th>9.60</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower limit filter duration</td>
<td>No Cut-off</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower limit filter duration (hours)</td>
<td>No Cut-off</td>
<td>0.03</td>
<td>0.04</td>
<td>0.14</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time Categories</th>
<th>9,669.53</th>
<th>9,669.53</th>
<th>9,669.53</th>
<th>9,669.53</th>
<th>9,669.53</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nominal (hours)</td>
<td>4,326.86</td>
<td>4,326.89</td>
<td>4,326.95</td>
<td>4,327.28</td>
<td>4,328.01</td>
</tr>
<tr>
<td>Production (hours)</td>
<td>1,151.86</td>
<td>1,151.82</td>
<td>1,151.75</td>
<td>1,151.43</td>
<td>1,150.40</td>
</tr>
<tr>
<td>Standby (hours)</td>
<td>3,028.63</td>
<td>3,028.64</td>
<td>3,028.64</td>
<td>3,028.64</td>
<td>3,028.94</td>
</tr>
<tr>
<td>Delay (hours)</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
</tr>
<tr>
<td>Scheduled Maintenance (hours)</td>
<td>581.12</td>
<td>581.12</td>
<td>581.12</td>
<td>581.12</td>
<td>581.12</td>
</tr>
<tr>
<td># of Functional Failure Events</td>
<td>127</td>
<td>123</td>
<td>121</td>
<td>118</td>
<td>111</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Key Performance Indicators (KPI's)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MTTR (hours)</td>
</tr>
<tr>
<td>MTBF (hours)</td>
</tr>
<tr>
<td>Mechanical Availability</td>
</tr>
<tr>
<td>Physical Availability</td>
</tr>
<tr>
<td>Utilization</td>
</tr>
<tr>
<td>Production Utilization</td>
</tr>
<tr>
<td>Effective Utilization</td>
</tr>
<tr>
<td>Capital Effectiveness</td>
</tr>
</tbody>
</table>

Table 12: Filtering of short durations with addition of filtered segments back in to the preceding state for Site B

Relative to the analysis in the previous subsection, where the filtered segments were not added back, the results for adding the filtered segments back yield almost identical KPI’s. This is due to the fact that only a small number of unscheduled maintenance down events are captured by the filtering, and each of the filtered events is of a small duration: hence adding them back into the preceding event category has a minimal impact on any particular event category.
5.8 Filtering of long Unscheduled Maintenance States durations for Site B Dataset

5.8.1 Filtering of Long TTR Durations while excluding the filtered segments from the dataset for Site B

As shown in Table 13, the number of TTR events, MTTR, MTBF, Mechanical Availability, Physical Availability and Capital Effectiveness were affected when a long duration TTR filter was applied to the Site B dataset. This is consistent with the behavior seen for the same filtering analysis on the Site A dataset.

<table>
<thead>
<tr>
<th>Time To Repair Cut off (TTR)</th>
<th>Upper limit duration filter</th>
<th>No Cut-off</th>
<th>10 hrs</th>
<th>14 hrs</th>
<th>18 hrs</th>
<th>24 hrs</th>
<th>28 hrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper limit duration filter (hours)</td>
<td>10.00</td>
<td>14.00</td>
<td>18.00</td>
<td>24.00</td>
<td>28.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Categories</td>
<td>Nominal (hours)</td>
<td>9,669.53</td>
<td>8,769.94</td>
<td>8,827.85</td>
<td>8,857.15</td>
<td>8,896.43</td>
<td>8,974.02</td>
</tr>
<tr>
<td></td>
<td>Production (hours)</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Down (Unscheduled) (hours)</td>
<td>1,151.86</td>
<td>252.27</td>
<td>310.18</td>
<td>339.48</td>
<td>378.77</td>
<td>456.36</td>
</tr>
<tr>
<td></td>
<td>Standby (hours)</td>
<td>3,028.63</td>
<td>3,028.63</td>
<td>3,028.63</td>
<td>3,028.63</td>
<td>3,028.63</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Delay (hours)</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Scheduled Maintenance (hours)</td>
<td>581.12</td>
<td>581.12</td>
<td>581.12</td>
<td>581.12</td>
<td>581.12</td>
<td></td>
</tr>
<tr>
<td></td>
<td># of Functional Failure Events (= # of Repair Events)</td>
<td>127</td>
<td>112</td>
<td>117</td>
<td>118</td>
<td>120</td>
<td>123</td>
</tr>
<tr>
<td></td>
<td>Key Performance Indicators (KPI's)</td>
<td>MTTR (hours)</td>
<td>9.07</td>
<td>2.25</td>
<td>2.65</td>
<td>2.88</td>
<td>3.16</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MTBF (hours)</td>
<td>34.07</td>
<td>38.63</td>
<td>36.98</td>
<td>36.67</td>
<td>36.06</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mechanical Availability</td>
<td>78.98%</td>
<td>94.49%</td>
<td>93.31%</td>
<td>92.72%</td>
<td>91.95%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Physical Availability</td>
<td>82.08%</td>
<td>90.50%</td>
<td>89.90%</td>
<td>89.61%</td>
<td>89.21%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Utilization</td>
<td>61.84%</td>
<td>61.84%</td>
<td>61.84%</td>
<td>61.84%</td>
<td>61.84%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Production Utilization</td>
<td>88.16%</td>
<td>88.16%</td>
<td>88.16%</td>
<td>88.16%</td>
<td>88.16%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Effective Utilization</td>
<td>54.52%</td>
<td>54.52%</td>
<td>54.52%</td>
<td>54.52%</td>
<td>54.52%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Capital Effectiveness</td>
<td>44.75%</td>
<td>49.34%</td>
<td>49.01%</td>
<td>48.85%</td>
<td>48.64%</td>
</tr>
</tbody>
</table>

Table 13: Filtering of Long Repair Durations While Excluding the Filtered Segments from the Dataset for Site B.
Figure 60: Number of functional failure events versus long TTR filter durations (while excluding filtered segments - Site B dataset).

Figure 61: MTTR versus long TTR filter durations (while excluding filtered segments - Site B dataset).
Figure 62: MTBF versus long TTR filter durations (while excluding filtered segments - Site B dataset).

Figure 63: Mechanical Availability versus long TTR filter durations (while excluding filtered segments - Site B dataset)
Figure 64: Physical availability versus long TTR filter durations (while excluding filtered segments - Site B dataset).

Figure 65: Capital effectiveness versus long TTR filter durations (while excluding filtered segments - Site B dataset).
5.8.2 Filtering of Long Repair durations with addition of filtered segments back in to total Scheduled Maintenance Down Time for Site B

The results shown in Table 14 are consistent with the behavior seen for the same filtering analysis on the Site A dataset.

<table>
<thead>
<tr>
<th>Time To Repair Cut off (TTR)</th>
<th>No Cut-off</th>
<th>10 hrs</th>
<th>14 hrs</th>
<th>18 hrs</th>
<th>24 hrs</th>
<th>28 hrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper limit filter duration</td>
<td>No Cut-off</td>
<td>10.00</td>
<td>14.00</td>
<td>18.00</td>
<td>24.00</td>
<td>28.00</td>
</tr>
<tr>
<td>Nominal (hours)</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
</tr>
<tr>
<td>Production (hours)</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td>4,326.86</td>
</tr>
<tr>
<td>Down (Unscheduled) (hours)</td>
<td>1,151.86</td>
<td>422.27</td>
<td>478.18</td>
<td>519.48</td>
<td>570.77</td>
<td>596.36</td>
</tr>
<tr>
<td>Standby (hours)</td>
<td>3,028.83</td>
<td>3,028.83</td>
<td>3,028.83</td>
<td>3,028.83</td>
<td>3,028.83</td>
<td>3,028.83</td>
</tr>
<tr>
<td>Delay (hours)</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
</tr>
<tr>
<td>Scheduled Maintenance (hours)</td>
<td>581.12</td>
<td>1,310.71</td>
<td>1,254.80</td>
<td>1,213.51</td>
<td>1,162.22</td>
<td>1,136.63</td>
</tr>
<tr>
<td># of Functional Failure Events (= # of Repair Events)</td>
<td>127</td>
<td>127</td>
<td>127</td>
<td>127</td>
<td>127</td>
<td>127</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Key Performance Indicators (KPI's)</th>
<th>MTTR (hours)</th>
<th>MTBF (hours)</th>
<th>Mechanical Availability</th>
<th>Physical Availability</th>
<th>Utilization</th>
<th>Production Utilization</th>
<th>Effective Utilization</th>
<th>Capital Effectiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>9.07</td>
<td>3.32</td>
<td>3.77</td>
<td>4.09</td>
<td>4.49</td>
<td>4.70</td>
<td>54.52</td>
<td>44.75%</td>
</tr>
<tr>
<td></td>
<td>34.07</td>
<td>34.07</td>
<td>34.07</td>
<td>34.07</td>
<td>34.07</td>
<td>34.07</td>
<td>54.52</td>
<td>44.75%</td>
</tr>
<tr>
<td>Mechanical Availability</td>
<td>78.99%</td>
<td>91.11%</td>
<td>90.05%</td>
<td>89.28%</td>
<td>88.35%</td>
<td>87.89%</td>
<td>54.52%</td>
<td>44.75%</td>
</tr>
<tr>
<td>Physical Availability</td>
<td>82.08%</td>
<td>82.08%</td>
<td>82.08%</td>
<td>82.08%</td>
<td>82.08%</td>
<td>82.08%</td>
<td>54.52%</td>
<td>44.75%</td>
</tr>
<tr>
<td>Utilization</td>
<td>61.84%</td>
<td>61.84%</td>
<td>61.84%</td>
<td>61.84%</td>
<td>61.84%</td>
<td>61.84%</td>
<td>54.52%</td>
<td>44.75%</td>
</tr>
<tr>
<td>Production Utilization</td>
<td>88.16%</td>
<td>88.16%</td>
<td>88.16%</td>
<td>88.16%</td>
<td>88.16%</td>
<td>88.16%</td>
<td>54.52%</td>
<td>44.75%</td>
</tr>
<tr>
<td>Effective Utilization</td>
<td>54.52%</td>
<td>54.52%</td>
<td>54.52%</td>
<td>54.52%</td>
<td>54.52%</td>
<td>54.52%</td>
<td>54.52%</td>
<td>44.75%</td>
</tr>
<tr>
<td>Capital Effectiveness</td>
<td>44.75%</td>
<td>44.75%</td>
<td>44.75%</td>
<td>44.75%</td>
<td>44.75%</td>
<td>44.75%</td>
<td>44.75%</td>
<td>44.75%</td>
</tr>
</tbody>
</table>

Table 14: Filtering of long repair durations with addition of filtered segments back in to total scheduled maintenance down time for Site B
Figure 66: MTTR versus long TTR filter durations (with addition of filtered segments back into total scheduled maintenance down – Site B dataset).

Figure 67: Mechanical Availability versus long TTR filter durations (with addition of filtered segments back into total scheduled maintenance down – Site B dataset).
5.9 Combined filtering of both Short and Long Unscheduled Maintenance State Durations for Site B Dataset

For the Site B dataset, the same analysis was applied as in the Site A dataset where a fixed short duration TTR filter was applied in combination with a range of long duration TTR filters. Initially, a short duration TTR filter with a cut-off of 0.03 hours was used, in combination with long duration TTR filters having cut-offs of 10 hours, 14 hours, 18 hours, 24 hours and 28 hours. Next a 0.16 hour cut-off short duration TTR filter was applied with the same long duration TTR filters.

5.9.1 Maintaining the Short Duration Filter at 1.8 Minutes While Varying the Long Duration Filter

As stated above, the first part of the analysis was done with a 1.8 minutes (0.03 hour) short duration filter. The Table 15 shows the impact on the KPI's with the application of combining a short TTR duration filter and long TTR duration filters. As in the analysis for the Site A dataset, all filter data points from both the filters were added back into the appropriate time categories. These results are consistent with the behavior seen for the same filtering analysis on the Site A dataset.
Table 15: Maintaining the short duration filter at 1.8 minutes while varying the long duration filter.

<table>
<thead>
<tr>
<th>Time Categories</th>
<th>Nominal (hours)</th>
<th>Production (hours)</th>
<th>Down (Unscheduled) (hours)</th>
<th>Standby (hours)</th>
<th>Delay (hours)</th>
<th>Scheduled Maintenance (hours)</th>
<th># of Functional Failure Events (= # of Repair Events)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time To Repair Cut off (TTR)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upper limit cut-off</td>
<td>Upper limit cut-off (hours)</td>
<td>short filter only</td>
<td>10.00</td>
<td>14.00</td>
<td>18.00</td>
<td>24.00</td>
<td>28.00</td>
</tr>
<tr>
<td>Time Categories</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal (hours)</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td></td>
</tr>
<tr>
<td>Production (hours)</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td>4,326.86</td>
<td></td>
</tr>
<tr>
<td>Down (Unscheduled) (hours)</td>
<td>1,151.86</td>
<td>422.27</td>
<td>479.16</td>
<td>519.45</td>
<td>570.73</td>
<td>596.31</td>
<td></td>
</tr>
<tr>
<td>Standby (hours)</td>
<td>3,028.63</td>
<td>3,028.63</td>
<td>3,028.63</td>
<td>3,028.63</td>
<td>3,028.63</td>
<td>3,028.63</td>
<td></td>
</tr>
<tr>
<td>Delay (hours)</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td></td>
</tr>
<tr>
<td>Scheduled Maintenance (hours)</td>
<td>581.12</td>
<td>1,310.71</td>
<td>1,254.82</td>
<td>1,213.54</td>
<td>1,162.26</td>
<td>1,136.68</td>
<td></td>
</tr>
<tr>
<td># of Functional Failure Events (= # of Repair Events)</td>
<td>123</td>
<td>123</td>
<td>123</td>
<td>123</td>
<td>123</td>
<td>123</td>
<td></td>
</tr>
</tbody>
</table>

Key Performance Indicators (KPI’s)

<table>
<thead>
<tr>
<th>MTTR (hours)</th>
<th>MTBF (hours)</th>
<th>Mechanical Availability</th>
<th>Physical Availability</th>
<th>Utilization</th>
<th>Production Utilization</th>
<th>Effective Utilization</th>
<th>Capital Effectiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td>9.36</td>
<td>35.18</td>
<td>78.98%</td>
<td>82.08%</td>
<td>61.84%</td>
<td>88.16%</td>
<td>54.52%</td>
<td>44.75%</td>
</tr>
<tr>
<td>3.43</td>
<td>35.18</td>
<td>91.11%</td>
<td>82.08%</td>
<td>61.84%</td>
<td>88.16%</td>
<td>54.52%</td>
<td>44.75%</td>
</tr>
<tr>
<td>3.89</td>
<td>35.18</td>
<td>90.05%</td>
<td>82.08%</td>
<td>61.84%</td>
<td>88.16%</td>
<td>54.52%</td>
<td>44.75%</td>
</tr>
<tr>
<td>4.22</td>
<td>35.18</td>
<td>89.28%</td>
<td>82.08%</td>
<td>61.84%</td>
<td>88.16%</td>
<td>54.52%</td>
<td>44.75%</td>
</tr>
<tr>
<td>4.64</td>
<td>35.18</td>
<td>88.35%</td>
<td>82.08%</td>
<td>61.84%</td>
<td>88.16%</td>
<td>54.52%</td>
<td>44.75%</td>
</tr>
<tr>
<td>4.85</td>
<td>35.18</td>
<td>87.89%</td>
<td>82.08%</td>
<td>61.84%</td>
<td>88.16%</td>
<td>54.52%</td>
<td>44.75%</td>
</tr>
</tbody>
</table>

Figure 68: MTTR versus long TTR filter durations (with constant 1.8 minutes short duration filter and addition of filtered segments back into total scheduled maintenance down – Site B dataset).
5.9.2 Maintaining the Short Duration Filter at 9.6 Minutes While Varying the Long Duration Filter

The second part of this analysis was done with a 9.6 minutes (0.16 hours) short TTR duration filter. Table 16 shows the impact on the KPI’s with the application of this longer duration short filter combined with different long duration filters. These results are consistent with the behavior seen for the same filtering analysis on the Site A dataset.
Table 16: Maintaining the short duration filter at 9.6 minutes while varying the long duration filter.

<table>
<thead>
<tr>
<th>Upper limit filter duration</th>
<th>short filter only</th>
<th>10 hrs</th>
<th>14 hrs</th>
<th>18 hrs</th>
<th>24 hrs</th>
<th>28 hrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Categories</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal (hours)</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
<td>9,669.53</td>
</tr>
<tr>
<td>Production (hours)</td>
<td>4,328.01</td>
<td>4,328.01</td>
<td>4,328.01</td>
<td>4,328.01</td>
<td>4,328.01</td>
<td>4,328.01</td>
</tr>
<tr>
<td>Down (Unscheduled) (hours)</td>
<td>1,150.40</td>
<td>420.80</td>
<td>476.72</td>
<td>518.00</td>
<td>569.29</td>
<td>594.82</td>
</tr>
<tr>
<td>Standby (hours)</td>
<td>3,028.94</td>
<td>3,028.94</td>
<td>3,028.94</td>
<td>3,028.94</td>
<td>3,028.94</td>
<td>3,028.94</td>
</tr>
<tr>
<td>Delay (hours)</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
<td>581.06</td>
</tr>
<tr>
<td>Scheduled Maintenance (hours)</td>
<td>581.12</td>
<td>1,310.72</td>
<td>1,254.80</td>
<td>1,213.52</td>
<td>1,162.23</td>
<td>1,136.70</td>
</tr>
<tr>
<td># of Functional Failure Events (= # of Repair Events)</td>
<td>111</td>
<td>111</td>
<td>111</td>
<td>111</td>
<td>111</td>
<td>111</td>
</tr>
</tbody>
</table>

Key Performance Indicators (KPI’s)

| MTTR (hours) | 9.07 | 3.79 | 4.29 | 4.67 | 5.13 | 5.36 |
| MTBF (hours) | 38.99| 38.99| 38.99| 38.99| 38.99| 38.99|
| Mechanical Availability | 81.13% | 91.14% | 90.08% | 89.31% | 88.38% | 87.92% |
| Physical Availability     | 82.09% | 82.09% | 82.09% | 82.09% | 82.09% | 82.09% |
| Utilization                | 61.84% | 61.84% | 61.84% | 61.84% | 61.84% | 61.84% |
| Production Utilization     | 88.16% | 88.16% | 88.16% | 88.16% | 88.16% | 88.16% |
| Effective Utilization      | 54.52% | 54.52% | 54.52% | 54.52% | 54.52% | 54.52% |
| Capital Effectiveness      | 44.76% | 44.76% | 44.76% | 44.76% | 44.76% | 44.76% |

Figure 70: MTTR versus long TTR filter durations (with constant 9.6 minute short duration filter and addition of filtered segments back into total scheduled maintenance down – Site B dataset).
Figure 71: Mechanical Availability versus long TTR filter durations (with constant 9.6 minute short duration filter and addition of filtered segments back into total scheduled maintenance down – Site B dataset).
Chapter 6

Sensitivity of KPI’s to Filtering of Production States based on Duration of Time-Between-Failure (TBF)

This part of the analysis investigates the effect of applying time between failure (TBF) duration filters on the dataset and its impact on the resulting key performance indicator.

The filters are applied to each dataset: first to the Site A, and then to the Site B data. For each dataset:

- First, short duration filtering is applied, with the filtered states simply being excluded
- Second, short duration filtering is applied, but with the duration of a filtered state being added back to whatever state precedes it in the raw dataset (and hence being added to the time category of the preceding state)

For each of the above cases of filtering, the resulting KPI’s are recalculated based on the filtered dataset and then analyzed. The diagram below shows the process flow of the TBF duration sensitivity analysis carried out in this chapter.

![Diagram](image.png)

Figure 72: Flow of analysis for investigation of TBF sensitivities.
6.1 Behaviour of MTBF with respect to TBF Cut-off for Site A Dataset

Similarly to the analysis that was performed for detecting significant changes in the behavior of the MTTR with respect to change in TTR filter cut-off durations (see section 5.2), a graphical approach was adopted to investigating the behavior of MTBF with respect to TBF durations. Initially, the time between failure (TBF) durations versus Mean Time Between Failure (MTBF) was plotted – see Figure 73. At first glance, the data shows a fairly linear relationship between the two variables.

Figure 73: Initial analysis plotting TBF durations versus MTBF (Site A dataset).
However, once the plot is zoomed into the region below 0.2 hours, Figure 74 it reveals changes in the sensitivity of MTBF as a function of TBF centered around TBF durations at 0.02 hours (72 seconds), 0.05 hours (3 minutes), 0.09 hours (5.4 minutes) and 0.185 hours (11.1 minutes).

The selected cut-off durations were then used as bins to generate a histogram of the number of Production States within each range in the raw dataset, which yields the distribution shown in Table 17 and Figure 75. Note that the processing for purposes of calculating the number of Functional Failure Events and Repair Events (see section 5.1) results in the number of Production States being reduced from a total of 347,196 to 1209 Production Events (see row 9 in Table 18), i.e. a reduction of 99.7%.

Figure 74: Initial analysis – further zoomed on very short TBF durations.
Table 17: Distribution of Production States, with bins corresponding to cut-off durations used in filtering analysis (Site A dataset)

<table>
<thead>
<tr>
<th>Bin</th>
<th>Bin (hours)</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>72 secs</td>
<td>0.02</td>
<td>156,181</td>
</tr>
<tr>
<td>3 minute</td>
<td>0.05</td>
<td>42,050</td>
</tr>
<tr>
<td>5.4 minutes</td>
<td>0.09</td>
<td>83,931</td>
</tr>
<tr>
<td>11.1 minutes</td>
<td>0.185</td>
<td>49,050</td>
</tr>
<tr>
<td>More</td>
<td></td>
<td>13,984</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>347,196</td>
</tr>
</tbody>
</table>

Figure 75: Histogram of Production States, with bins corresponding to cut-off durations used in filtering analysis (Site A dataset)
6.2 Filtering of Production States with short durations for the Site A dataset

6.2.1 Filtering of Short TBF Durations for the Site A Dataset (while excluding filtered segments)

<table>
<thead>
<tr>
<th>Time Between Failure Cut off (TBF)</th>
<th>no cut-off</th>
<th>72 secs</th>
<th>3 mins</th>
<th>5.4 mins</th>
<th>11.1 mins</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower limit filter duration</td>
<td>0</td>
<td>0.02</td>
<td>0.05</td>
<td>0.09</td>
<td>0.185</td>
</tr>
<tr>
<td>Lower limit filter duration (hours)</td>
<td>30864.00</td>
<td>30830.31</td>
<td>30691.60</td>
<td>30266.79</td>
<td>28379.28</td>
</tr>
<tr>
<td>Nominal (hours)</td>
<td>18027.75</td>
<td>17994.05</td>
<td>17855.35</td>
<td>17430.54</td>
<td>15543.02</td>
</tr>
<tr>
<td>Production (hours)</td>
<td>3782.74</td>
<td>3782.74</td>
<td>3782.74</td>
<td>3782.74</td>
<td>3782.74</td>
</tr>
<tr>
<td>Down (Unscheduled) (hours)</td>
<td>3081.60</td>
<td>3081.60</td>
<td>3081.60</td>
<td>3081.60</td>
<td>3081.60</td>
</tr>
<tr>
<td>Standby (hours)</td>
<td>4692.78</td>
<td>4692.78</td>
<td>4692.78</td>
<td>4692.78</td>
<td>4692.78</td>
</tr>
<tr>
<td>Delay (hours)</td>
<td>1279.14</td>
<td>1279.14</td>
<td>1279.14</td>
<td>1279.14</td>
<td>1279.14</td>
</tr>
<tr>
<td>Scheduled Maintenance (hours)</td>
<td>1209</td>
<td>1171</td>
<td>1163</td>
<td>1158</td>
<td>1147</td>
</tr>
<tr>
<td># of Functional Failure Events (= # of Repair Events)</td>
<td>3.13</td>
<td>3.23</td>
<td>3.25</td>
<td>3.27</td>
<td>3.30</td>
</tr>
<tr>
<td>Key Performance Indicators (KPI's)</td>
<td>14.91</td>
<td>15.37</td>
<td>15.35</td>
<td>15.05</td>
<td>13.55</td>
</tr>
<tr>
<td>MTTR (hours)</td>
<td>82.66%</td>
<td>82.63%</td>
<td>82.52%</td>
<td>82.17%</td>
<td>80.43%</td>
</tr>
<tr>
<td>MTBF (hours)</td>
<td>83.60%</td>
<td>83.58%</td>
<td>83.51%</td>
<td>83.28%</td>
<td>82.16%</td>
</tr>
<tr>
<td>Mechanical Availability</td>
<td>88.06%</td>
<td>88.04%</td>
<td>87.98%</td>
<td>87.77%</td>
<td>86.78%</td>
</tr>
<tr>
<td>Physical Availability</td>
<td>79.35%</td>
<td>79.31%</td>
<td>79.19%</td>
<td>78.79%</td>
<td>76.81%</td>
</tr>
<tr>
<td>Utilization</td>
<td>69.87%</td>
<td>69.83%</td>
<td>69.67%</td>
<td>69.16%</td>
<td>66.66%</td>
</tr>
<tr>
<td>Production Utilization</td>
<td>58.41%</td>
<td>58.36%</td>
<td>58.18%</td>
<td>57.59%</td>
<td>54.77%</td>
</tr>
</tbody>
</table>

Table 18: Filtering of short TBF durations while excluding filtered segments for Site A dataset.

From the results in Table 18, it can be seen that by varying the short duration TBF filter the number of functional failure events (which equals the number of repair events), MTTR, and MTBF, are all noticeably affected. In contrast, the other KPI’s are only negligibly impacted.
From Figure 76, it can be seen that the number of functional failure events drops from 1209 without a filter to 1147 using an 11.1 minute filter. This represents a change of approximately 5%.

In Figure 77, it can be seen that MTTR is also only affected by 0.17 hours as the short duration TBF filter is varied: a range of slightly over 5%.
Similarly, in Figure 78, it can be seen that MTBF is also only affected by 0.81 hours as the short duration TBF filter is varied: a range of slightly over 5%.

Since both MTBF and MTTR vary by similar ratios (due to the fact that only a very small portion of production time is being filtered for these ranges of TBF filter cut-off), the calculation of Mechanical Availability (which is based on those two metrics) remains effectively constant (change of less than 0.01%). This is illustrated in Figure 79. The same minimal changes apply to the rest of the KPI’s.

Figure 79: Mechanical Availability versus short TBF filter durations (while excluding filtered segments - Site A dataset).
6.2.2 Filtering of short TBF Durations for Site A Dataset (with addition of filtered segments back into the dataset)

<table>
<thead>
<tr>
<th>Time Between Failure Cut off (TBF)</th>
<th>Lower limit filter duration</th>
<th>no cut-off</th>
<th>72 secs</th>
<th>3 mins</th>
<th>5.4 mins</th>
<th>11.1 mins</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower limit filter duration (hours)</td>
<td>0</td>
<td>0.02</td>
<td>0.05</td>
<td>0.09</td>
<td>0.185</td>
<td></td>
</tr>
</tbody>
</table>

**Time Categories**

| Nominal (hours)    | 30864.00 | 30864.00 | 30864.00 | 30864.00 | 30864.00 |
| Production (hours) | 18027.75 | 17994.05 | 17855.35 | 17430.54 | 15543.02 |
| Down (Unscheduled) (hours) | 3782.74 | 3,783.70 | 3,785.74 | 3,792.49 | 3,806.42 |
| Standby (hours)     | 3081.60  | 3,085.50 | 3,096.19 | 3,125.91 | 3,251.96 |
| Delay (hours)       | 4692.78  | 4,721.60 | 4,847.58 | 5,235.86 | 6,983.18 |
| Scheduled Maintenance (hours) | 1279.14 | 1,279.14 | 1,279.14 | 1,279.21 | 1,279.42 |
| # of Functional Failure Events (= # of Repair Events) | 1209 | 1171 | 1163 | 1158 | 1147 |

**Key Performance Indicators (KPI's)**

| MTTR (hours)     | 3.13 | 3.23 | 3.26 | 3.28 | 3.32 |
| MTBF (hours)     | 14.91 | 15.37 | 15.35 | 15.05 | 13.55 |
| Mechanical Availability | 82.66% | 82.63% | 82.51% | 82.13% | 80.33% |
| Physical Availability | 83.60% | 83.60% | 83.59% | 83.57% | 83.52% |
| Utilization      | 88.06% | 88.04% | 88.00% | 87.88% | 87.38% |
| Production Utilization | 79.35% | 79.21% | 78.65% | 76.90% | 69.00% |
| Effective Utilization | 69.87% | 69.74% | 69.21% | 67.58% | 60.30% |
| Capital Effectiveness | 58.41% | 58.30% | 57.85% | 56.48% | 50.36% |

Table 19: Filtering of short TBF durations with addition of filtered segments back in to the preceding state for Site A dataset.

![Lower limit filter duration vs # Functional Failure Events](image)

Figure 80: Number of functional failure events versus TBF filter durations (while adding filtered segments to preceding state - Site A dataset).
As shown in Table 19 and Figure 80, the number of functional failure events which equals the number of repair events) ranges from 1171 for the 72 second (0.02 hour) to 1147 for 11.1 minutes (0.185 hours), a maximum deviation of 5% relative to 1209 events for the unfiltered dataset.

Figure 81: MTTR versus TBF filter durations (while adding filtered segments to preceding state - Site A dataset).

Figure 81 shows that MTTR varies by 0.19 hours, or 6% relative to the unfiltered dataset.

Figure 82: MTBF versus TBF filter durations (while adding filtered segments to preceding state - Site A dataset).

MTBF is more sensitive to the short duration TBF filter cut-off: as Figure 82 shows, MTBF ranges from +3.1% to -10%, relative to the value for the unfiltered dataset of 14.91 hours.
Figure 83: Mechanical Availability versus TBF filter durations (while adding filtered segments to preceding state - Site A dataset).

Physical Availability was negligibly affected by short duration TBF filtering (less than 0.1%). However Utilization, Production Utilization, Effective Utilization and Capital Effectiveness were all significantly affected by the short duration TBF filtering – as shown in figures Figure 84, Figure 85, Figure 86, and Figure 87.

Figure 84: Physical Availability versus TBF filter durations (while adding filtered segments to preceding state - Site A dataset).
Figure 85: Production Utilization versus TBF filter durations (while adding filtered segments to preceding state - Site A dataset).

Figure 86: Effective Utilization versus TBF filter durations (while adding filtered segments to preceding state - Site A dataset).
6.3 Behaviour of MTBF with respect to TBF Cut-off for Site A Dataset

As for the Site A dataset, an analysis that was performed for detecting significant changes in the behavior of the MTTR with respect to change in TTR filter cut-off durations for the Site B dataset.

Figure 87: Capital Effectiveness versus TBF filter durations (while adding filtered segments to preceding state - Site A dataset).

Figure 88: Initial analysis plotting TBF durations versus MTBF.
Based on Figure 88 and Figure 89, the sensitivity of MTBF to TBF cut-off exists at 0.09 hours, 0.33 hours, 0.62 hours, 1.04 hours and 1.67 hours.

The selected cut-off durations were then used as bins to generate a histogram of the number of Production States within each range in the raw dataset, which yields the distribution shown in Table 20 and Figure 90. Note that the processing for purposes of calculating the number of Functional Failure Events and Repair Events (see section 5.1) results in the number of Production States being reduced from a total of 7,358 to 127 Production Events (see row 9 in Table 21), i.e. a reduction of 98.3%.

<table>
<thead>
<tr>
<th>Bin (minutes)</th>
<th>Bin (hours)</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.4</td>
<td>0.09</td>
<td>1,338</td>
</tr>
<tr>
<td>19.8</td>
<td>0.33</td>
<td>2,890</td>
</tr>
<tr>
<td>37.2</td>
<td>0.62</td>
<td>1,242</td>
</tr>
<tr>
<td>62.4</td>
<td>1.04</td>
<td>834</td>
</tr>
<tr>
<td>100.2</td>
<td>1.67</td>
<td>491</td>
</tr>
<tr>
<td>More</td>
<td></td>
<td>563</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>7,358</td>
</tr>
</tbody>
</table>

Table 20: Distribution of Production States, with bins corresponding to cut-off durations used in filtering analysis (Site B dataset)
Figure 90: Histogram of Production States, with bins corresponding to cut-off durations used in filtering analysis (Site B dataset)
6.4 Filtering of Production States with short durations for the Site B dataset

6.4.1 Filtering of Short TBF Durations for Site B Dataset while Excluding Filtered Segments

Table 21: Filtering of short TBF durations while excluding filtered segments for Site B dataset.

<table>
<thead>
<tr>
<th>Time To Failure Cut-off (TBF)</th>
<th>Nominal (hours)</th>
<th>Production (hours)</th>
<th>Down (Unscheduled) (hours)</th>
<th>Standby (hours)</th>
<th>Delay (hours)</th>
<th>Scheduled Maintenance (hours)</th>
<th># of Functional Failure Events (- # of Repair Events)</th>
<th>MTTR (hours)</th>
<th>MTBF (hours)</th>
<th>Mechanical Availability</th>
<th>Physical Availability</th>
<th>Utilization</th>
<th>Production Utilization</th>
<th>Effective Utilization</th>
<th>Capital Effectiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Cut-off</td>
<td>9,671.89</td>
<td>4,326.85</td>
<td>1,151.85</td>
<td>3,028.63</td>
<td>581.06</td>
<td>581.12</td>
<td>127</td>
<td>9.07</td>
<td>34.07</td>
<td>76.98%</td>
<td>87.93%</td>
<td>61.84%</td>
<td>88.16%</td>
<td>54.52%</td>
<td>44.74%</td>
</tr>
<tr>
<td>5.40</td>
<td>9,629.91</td>
<td>4,287.24</td>
<td>1,151.89</td>
<td>3,028.63</td>
<td>581.06</td>
<td>581.12</td>
<td>123</td>
<td>9.36</td>
<td>34.86</td>
<td>76.68%</td>
<td>87.03%</td>
<td>61.65%</td>
<td>88.06%</td>
<td>54.29%</td>
<td>44.52%</td>
</tr>
<tr>
<td>19.80</td>
<td>8,985.46</td>
<td>3,642.79</td>
<td>1,151.86</td>
<td>3,028.63</td>
<td>581.06</td>
<td>581.12</td>
<td>120</td>
<td>9.60</td>
<td>30.36</td>
<td>75.76%</td>
<td>86.07%</td>
<td>58.24%</td>
<td>86.24%</td>
<td>50.23%</td>
<td>40.54%</td>
</tr>
<tr>
<td>37.20</td>
<td>8,413.94</td>
<td>3,071.27</td>
<td>1,151.86</td>
<td>3,028.63</td>
<td>581.06</td>
<td>581.12</td>
<td>114</td>
<td>10.10</td>
<td>26.94</td>
<td>72.42%</td>
<td>86.19%</td>
<td>54.67%</td>
<td>84.09%</td>
<td>45.97%</td>
<td>36.50%</td>
</tr>
<tr>
<td>62.40</td>
<td>7,759.29</td>
<td>2,416.62</td>
<td>1,151.86</td>
<td>3,028.63</td>
<td>581.06</td>
<td>581.12</td>
<td>99</td>
<td>11.63</td>
<td>24.41</td>
<td>67.22%</td>
<td>85.02%</td>
<td>49.74%</td>
<td>80.62%</td>
<td>40.10%</td>
<td>31.14%</td>
</tr>
<tr>
<td>100.20</td>
<td>7,115.62</td>
<td>1,772.95</td>
<td>1,151.86</td>
<td>3,028.63</td>
<td>581.06</td>
<td>581.12</td>
<td>91</td>
<td>12.66</td>
<td>19.48</td>
<td>59.98%</td>
<td>83.67%</td>
<td>43.73%</td>
<td>75.32%</td>
<td>32.94%</td>
<td>24.92%</td>
</tr>
</tbody>
</table>

From the results in Table 21, above, it can be seen that all re-calculated KPI’s were significantly affected by the application of a short-duration TBF filter without adding the filtered data points back into the dataset. This is illustrated in Figure 91 through to Figure 99 below.
Figure 91: Number of functional failure events versus short TBF filter durations (while excluding filtered segments - Site B dataset).

Figure 92: MTBF versus short TBF filter durations (while excluding filtered segments - Site B dataset).
Figure 93: MTTR versus short TBF filter durations (while excluding filtered segments - Site B dataset).

Figure 94: Mechanical Availability versus short TBF filter durations (while excluding filtered segments - Site B dataset).
Figure 95: Physical Availability versus short TBF filter durations (while excluding filtered segments - Site B dataset).

Figure 96: Utilization versus short TBF filter durations (while excluding filtered segments - Site B dataset).
Figure 97: Production Utilization versus short TBF filter durations (while excluding filtered segments - Site B dataset).

Figure 98: Effective Utilization versus short TBF filter durations (while excluding filtered segments - Site B dataset).
Figure 99: Capital Effectiveness versus short TBF filter durations (while excluding filtered segments - Site B dataset).
6.4.2 Filtering of Short Time Between Failure Durations For Site B Dataset
With Addition of Filtered Segments Back Into the Dataset

Table 22: Filtering of short TBF durations with addition of filtered segments back in to the preceding state for Site B dataset.

As shown in the table above, merging the filtered segments back into the dataset had a relative large impact on each of the re-calculated KPIs when compared to not including the filtered segments back into the dataset.
The number of functional failure events remained the same as in the analysis without adding the filtered data points back into the dataset.

MTTR increased slightly when compared to not adding the filtered data points back into the dataset. This is because some of the filtered production events were added in to the total unscheduled maintenance down event time category duration.
MTBF and Mechanical Availability decreases as the duration of the TBF duration filter increases, same as the behaviour in the analysis of Site A dataset.
Figure 104: Physical Availability versus TBF filter durations (while adding filtered segments to preceding state - Site B dataset).

Figure 105: Utilization versus TBF filter durations (while adding filtered segments to preceding state - Site B dataset).
Figure 106: Production Utilization versus TBF filter durations (while adding filtered segments to preceding state - Site B dataset).

Figure 107: Effective Utilization versus TBF filter durations (while adding filtered segments to preceding state - Site B dataset).
When compared to not adding the filtered segments back into the dataset, physical availability, utilization, production utilization, effective utilization and capital effectiveness also had a less drastic change as the duration of the TBF filter increases. This is because each of these KPI’s are also functions of other time categories.
Chapter 7
Conclusions and Recommendations for Future Work

7.1 Conclusions

This thesis analyzed the datasets obtained from two different Fleet Management Systems, at two different open-pit mine sites, operated by the same mining corporation:

- The first dataset (Site A) consisted of a total of 30,000 hours of nominal time, from a fleet of sixteen 150-ton haul trucks
- The second dataset (Site B) consisted of a total of 10,000 hours of nominal time, from a fleet of thirteen 150-ton haul trucks

Based on this analysis, the following findings were arrived at:

I. A major impediment to obtaining good quality data from Fleet Management Systems is the inconsistency of labelling / assignment of activities to time categories – even between two mines operated by the same corporation (see section 3.1)

II. The raw datasets from both Fleet Management Systems contained a surprisingly high proportion of very short duration states, which are indicative of either data corruption (software / hardware issues) or human error (operator input issues) – and hence further compromise data quality:

   a. Unscheduled Maintenance Down Time states with durations of 10 minutes or less
      i. 34% at Site A
      ii. 12% at Site B

   b. Production states with durations of 5 minutes or less
      i. 82% at Site A
      ii. 18% at Site B

III. The raw datasets exhibit mismatch (i.e. lack of one-to-one correspondence) between:
a. The number of valid Repair events as a percentage of the number Unscheduled Maintenance Down Time states
   i. Only 77% at Site A
   ii. 97% at Site B
b. The number of valid Functional-Failure events as a percentage of the number of Production states
   i. Only 0.3% at Site A
   ii. 1.7% at Site B
IV. Based on the preceding finding (#3), a need was identified to improve the data quality for purposes of calculating two key KPI’s: MTBF and MTTR. This was achieved by determining valid instances of Repair events and Functional Failure events (see section 5.1)
V. Filtering based on the minimum duration of Unscheduled Maintenance Down states (TTR’s) was found to be necessary to improve KPI calculations.
   a. It was further concluded that these filtered states must be relabeled so that they are merged back into the preceding state, and hence the filtered duration is added to the total of the time category of the preceding state (see subsection 5.3.2).
VI. Filtering based on the maximum duration of Unscheduled Maintenance Down states (TTR’s) was also found to be necessary to improve KPI calculations.
   a. It was further concluded that these filtered states must be decomposed: the duration of the filtered state that exceeds the filter cut-off is assigned to the Scheduled Maintenance Down time category, while the duration that equals the filter cut-off is assigned to the Unscheduled Maintenance Down time category (see subsection 5.4.2).
VII. Filtering based on the minimum duration of Production states (TBF’s) was found to be necessary to improve KPI calculations.
a. It was further concluded that these filtered states must be relabeled so that they are merged back into the preceding state, and hence the filtered duration is added to the total of the time category of the preceding state (see Chapter 6).

VIII. The sensitivity of KPI’s to filtering of the duration of Unscheduled Maintenance Down states (TTR’s)

a. Short duration (lower limit cut-off) filter with merging (adding back) of filtered state, with cut-off set at 10 minutes, relative to the KPI’s calculated on the raw dataset

i. Site A (see Table 5),

1. Very significant decrease in number of Functional Failure events (which equals number of Production events) - by 59%
2. Very significant increase of both MTTR and MTBF – by 140%
3. Mechanical Availability and Physical Availability are relatively insensitive – both increase – but very slightly – by 0.1% or less
4. Utilization, Production Utilization, Effective Utilization, and Capital Effectiveness are also relatively insensitive – they all decrease – but very slightly – by 0.1% or less

ii. Site B (see Table 12)

1. Very significant decrease in number of Functional Failure events (which equals number of Production events) - by 13%
2. Significant increase of both MTTR and MTBF – by 14%
3. Mechanical Availability and Physical Availability are relatively insensitive – both increase – but very slightly – by 0.02% or less
4. Utilization, Production Utilization, Effective Utilization, and Capital Effective are also relatively insensitive – all decrease – but very slightly – by 0.02% or less
b. Long duration (upper limit cut-off) filter with merging (adding back) of filtered state, with cut-off set at around 30 hours, relative to the KPI’s calculated on the raw dataset
   
   i. Site A (Table 7)
      1. No change in number of Functional Failure events (which equals number of Production events)
      2. No change in MTBF
      3. Very significant decrease of MTTR – by 53%
      4. Mechanical Availability increases significantly – by 8%
      5. Physical Availability, Utilization, Production Utilization, Effective Utilization, and Capital Effective are all unchanged

   ii. Site B (Table 14)
      1. No change in number of Functional Failure events (which equals number of Production events)
      2. No change in MTBF
      3. Very significant decrease of MTTR – by 48%
      4. Mechanical Availability increases significantly – by almost 9%
      5. Physical Availability, Utilization, Production Utilization, Effective Utilization, and Capital Effective are all unchanged

   c. Combined filtering: using a short duration filter with a cut-off of 30 minutes for Site A (10 minutes for Site B), combined with a long duration filter with a cut-off of 30 hours for Site A (28 hours for Site B), with the following comparative results relative to the KPI’s calculated on with the short duration filter only
      
   i. Site A (Table 9)
      1. No change in number of Functional Failure events (which equals number of Production events)
      2. No change in MTBF
3. Very significant decrease of MTTR – by 40%
4. Mechanical Availability increases significantly – by almost 6%
5. Physical Availability, Utilization, Production Utilization, Effective
   Utilization, and Capital Effective are all unchanged

ii. Site B (Table 16)
   1. No change in number of Functional Failure events (which equals number of
      Production events)
   2. No change in MTBF
   3. Very significant decrease of MTTR – by 41%
   4. Mechanical Availability increases significantly – by almost 7%
   5. Physical Availability, Utilization, Production Utilization, Effective
      Utilization, and Capital Effective are all unchanged

IX. The sensitivity of KPI’s to filtering of the duration of Production states (TBF’s)
   a. Short duration (lower limit cut-off) filter with merging (adding back) of filtered state, with
      cut-off set at 5.4 minutes, relative to the KPI’s calculated on the raw dataset
      i. Site A (see Table 19),
         1. Decrease in number of Functional Failure events (which equals number of
            Production events) - by 4%
         2. Increase of both MTTR and MTBF – by almost 5%, and over 9%
            respectively
         3. Mechanical Availability is affected minimally – a decrease of 0.5%
         4. Physical Availability is very insensitive – a decrease of 0.03%
         5. Utilization is fairly insensitive – a decrease of 0.18%
         6. Production Utilization, Effective Utilization, and Capital Effectiveness are all
            significantly impacted – they all decrease in the range of 2% to 2.5%
ii. Site B (see Table 22)

1. Decrease in number of Functional Failure events (which equals number of Production events) – by 3%
2. Increase of both MTTR and MTBF – by almost 3.5%, and 2.5% respectively
3. Mechanical Availability, Physical Availability, Utilization, Production Utilization, Effective Utilization, and Capital Effectiveness are all minimally impacted – they all decrease in the range of 0.2% to 0.6%

7.2 Primary Contributions

- A framework for consistently comparing alternative Time Model definitions and their relationships to the calculation of KPI’s from Fleet Management System data was developed (Chapter 3 and Chapter 4).

- A technique for processing raw Fleet Management System data, to yield valid Functional Failure events and valid Repair events was developed (section 5.1) and applied (Chapters 5 and 6).

- The concept of identifying data quality issues in Fleet Management System data, based upon an examination of feasible durations for Production states (TBF’s) and Unscheduled Maintenance states (TTR’s), was developed and further expanded upon through the development of duration based filtering of states (Chapters 5 and 6).

- The sensitivity of KPI’s to duration based filtering was thoroughly investigated, for both TBF and TTR filtering, and the consistent trends in the behavior of these KPI’s in response to the filtering were demonstrated (Chapters 5 and 6).

7.3 Recommendations for Future Work

1. The root cause of duration related data quality issues that were seen in the two datasets is still unknown. While it is likely that software/hardware issues or human error sources are the primary contributing factors, the only effective means of determining the root cause would a be a field study. This could take the form of a researcher performing a “ride along” with a haul truck operator, and
essentially doing a “time and motion study” in which the actual operating state and operating context of the haul truck was noted. This would enable comparison of the states observed by the researcher with the states reported in the Fleet Management System dataset.

2. It is recommended that a survey is conducted on the awareness amongst Fleet Management System vendors, as well as amongst their customers (i.e. mine sites), on whether they are aware of such duration related data quality issues – and if they employ any measures to remedy them.

3. There is a compelling case for the formulation and adoption of a single, comprehensive, and consistent, Time Model across the open-pit mining industry. Furthermore, this standard Time Model should be the basis for all KPI calculations which are based on Fleet Management System data.

4. It should be noted that the Barrick Time Model [Barrick, 2006] which was extensively relied upon in this thesis, has recently been updated (in 2013). Therefore it would be worthwhile to examine whether the updated Barrick Time Model would result in any changes to the findings of this thesis.

5. The practical implication of the MTBF and MTTR variations could be investigated through examining the sensitivity of the results of reliability modelling and reliability simulation for a particular range of KPI’s derived from the filtering analysis – for example to calculate “mission reliability” for conventional (non-automated) haul trucks and to predict Mechanical Availability for various scenarios of automated haul truck behaviour.

6. The practical implications of these data quality issues in Fleet Management Systems could be further investigated through examining how resulting variations in KPI’s would impact production planning decisions.

7. The preliminary work done on state transition frequencies in the Site B dataset (section 3.5) should be expanded upon to encompass the Site A dataset. Models derived from state transition frequencies could potentially be used for constructing probabilistic simulations which do not assume a fixed underlying probability density function.
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