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Methods for evaluating effect of operators on drag line energy efficiency

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METHODS FOR EVALUATING EFFECT OF OPERATORS ON DRAGLINE ENERGY EFFICIENCY

by

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ABSTRACT

Draglines are dominant machines and the most significant electricity consumers in surface coal mines. With the growing price of energy, environmental concerns, and the high sensitivity of mine profitability to dragline productivity, any improvement in efficiency of dragline will be beneficial for mines. Research has shown that operator practices have a significant impact on energy efficiency of mining loading tools. However, not enough work has been done to provide guidance on how to quantitatively assess the effect of operator practices on dragline energy efficiency.

The objectives of this work were to: (i) test the hypothesis that dragline operator's practices and skills significantly affect dragline energy efficiency; and (ii) develop a methodology to identify the critical parameters that explain the differences in operator energy efficiency. Statistical tests are suggested to study the effect of operator practice and skills on dragline energy efficiency to achieve the first research objective. The second objective was achieved with a novel methodology based on sound statistical principles. Both approaches were illustrated with a real-life dragline operation. The suggested methodology was used on the data collected from an 85yd^3 BE-1570w dragline to compare the energy efficiency of five operators during a one month period.

Valid methods have been formulated for testing operator effects on dragline energy efficiency and for identifying critical parameters that explain such differences. Using the developed approaches, the case study shows that operator practices can affect dragline energy efficiency. The tests show that there is a high probability that differences in energy efficiency are due to dumping height, vertical and horizontal drag distances, and spotting and dumping time among the surveyed operators.

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1. INTRODUCTION

1.1. BACKGROUND

Coal has been known as an important energy source for years. Today, coal is mostly used as a fuel for electric power generation, although, its significant historical role in industrial, transportation, and domestic heating cannot be denied. The United States (U. S.), Russia and China have the largest known coal reserves. 237 billion tonnes of proven recoverable coal reserves (27.6% of the global total) is located in U.S. The total coal consumption in the U.S. during 2011 was 909.9 million tonnes (U.S. Energy Information Administration (EIA), 2011a) and the total production was 992.8. In 2010, U.S. share of total global coal production was 13.5% (British Petroleum (BP), 2012). Table 1-1 shows the coal reserves, production and consumption of top five countries in the world.

Table 1-1 Coal reserves, production and consumption by countries (2011) (British Petroleum (BP), 2012),(U.S. Energy Information Administration (EIA), 2011a)

Country	Proven Reserves (Million tonnes)	Coal Production (Million tonnes)	Coal Consumption (Million tonnes)
U.S.	237,295	992.8	909.9
Russia	57,010	333.5	237.7
China	114,500	3520	3,676.8
Australia	76,400	415.5	129.3
India	60,600	588.5	714.9
Total World	860,938	7,695.4	7,252.9

Coal end uses in the U.S. can be classified into three groups; steam coal, metallurgical coal (coke), and industrial coal. Steam coal is used to produce heat or steam for industrial processes in power plants and counts for about 90% of total coal consumption. This share varies depending on natural gas price, which is a substitute fuel for coal in power plants. Metallurgical coal or coke is used in blast furnaces in standard iron smelting to produce steel. Industrial coal provides the heat for industrial processes in manufacturing plants, papers mills, food processors, and cement and limestone plants (World Energy Council, 2010). The recorded coal consumption in each group is displayed in Table 1-2.

Table 1-2 U.S. coal consumption by end use sector (2011 and 2010) (U.S. Energy Information Administration (EIA), 2011b)

End use sector	Electric Power	Metallurgical Coal (coke)	Industrial Coal
Coal consumption (thousand short tons)- 2011	932,484	21,434	49,031
Coal consumption (thousand short tons)- 2010	975,052	21,092	52,370

The coal mining method is chosen based on the depth, thickness and dip of coal seams, economic studies, and environmental concerns. Coal mining methods generally fall into two groups: surface and underground mining. In 1973, surface and underground coal mines both had equal share in total U.S. coal production. Large scale mining technology enabled coal mines to increase their production, especially in surface coal mines. In 2011, 68% of total coal was extracted using surface coal mines (U.S. Energy Information Administration (EIA), 2011b). Increasing mine productivity helps the mining industry to satisfy the growing demand for coal. Larger surface coal mines, utilizing larger and more efficient equipment with advanced control systems are known factors that improve mine productivity (Bonskowski, Watson, & Freme, 2006). The efficiency and environmental impacts of surface coal mining is, therefore, very important for the continued significance of coal.

1.2. STATEMENT OF PROBLEM

In 2007, the energy consumed in the U.S. mining industry is estimated to be 365 billion kWh (U.S. Department of Energy(DOE), 2007). Table 1-3 shows the estimated annual energy consumption by commodity group. Energy consumption in coal mines is estimated as 142 billion kWh per year. Electric equipment used for materials handling in coal mines consumes 13.3 billion kWh, annually (U.S. Department of Energy(DOE), 2007). Considering the average price of electricity for industry (6.65 cents/kwh in 2011 (U.S. Energy Infromation Administration, 2012)), the cost of electricity for materials handling in coal mines is $884 million each year. This accounts for 28% of total annual energy cost in the U.S. mining industry.

Draglines are dominant machines and the most critical units in mines, with capital cost of $50-100 million (Demirel & Frimpong, 2009; Kizil, 2010). The advantages of dragline mining systems include low mining cost, high production rate, and compatibility with wide range of overburden depth and material characteristics (Humphrey, 1990). Draglines are the most significant electricity consumers in surface coal mines. With the high capital investment, growing price of energy, and the high sensitivity of mine profitability to dragline productivity any improvement in efficiency and productivity of draglines will be beneficial for mines. In the Australian coal mining industry, one percent increase in dragline productivity is valued at $50,000 to $2,300,000, annually (G. Lumley, 2005).

Table 1-3 Annual energy consumption by commodity type (U.S. Department of Energy(DOE), 2007)

Commodity Type	Energy consumption (Trillion Btu/yr)	Energy consumption (Million kWh/yr)
Coal	485.3	142.2
Metals	553.1	162.1
Minerals	208.9	61.2
Total	1246.3	365.2

U.S. Department of Energy (DOE) carried out studies to show the total energy saving opportunities in energy-intensive industries, which can be achieved by improving current processes by implementing energy efficient practices. Their studies show that 70 billion kWh (49% of total energy consumption in coal mining) or $3.7 billion can be saved annually in the U.S. coal mining industry by improving energy efficiency and implementing best practices (Bonskowski et al., 2006; Humphrey, 1990). Due to the increasing cost of energy and growing concerns about energy availability and supply, managing energy efficiency has become a serious issue in surface coal mines (K. Awuah-

Offei, Osei, & Askari-Nasab, 2011). Bogenovic (2008) indicated that reduction in energy consumption and energy cost can be achieved by effective energy management systems in the way of measuring that measure energy consumption to identify energy saving opportunities and high-energy consumption units, and determining the relation between production and energy consumption (Bogunovic, 2008).

Generally, energy efficiency is described as the ratio of useful work done (energy output) to the input energy (Zhu & Yin, 2008). In cases where either energy output or input cannot be measured easily, proxy parameters are used in their place. Dragline energy efficiency is defined as the ratio of total weight of removed material (payload) to total energy consumed to remove this amount of material. Dragline energy efficiency depends on the equipment, operating conditions, and the operator (Figure 1-1).

For a given mine with a selected dragline, optimizing the dragline drive mechanism for energy efficiency can be very expensive. Mine planning can be used to reduce the effect of operating conditions on energy efficiency. However, due to the effect of geology, which cannot be changed for a mine, operating conditions can only yield so much energy efficiency. Research has shown that operator practices have a significant impact on energy efficiency of mining loading tools (Bogunovic, Kecojevic, Lund, Heger, & Mongeon, 2009; G. Lumley, 2005; Patnayak, Tannant, Parsons, Del Valle, & Wong, 2007). For instance, Bogunovic (2008) and Komljenovic et al. (2010) showed that dragline productivity can be significantly different for different operators under the same operation conditions (Bogunovic, 2008; Komljenovic, Bogunovic, & Kecojevic, 2010). Hence, a better understanding of the relationship between operator practices and energy efficiency can easily yield significant improvements in energy efficiency and costs. However, not enough work has been done to quantitatively assess the effect of operator practices on dragline energy efficiency and the reasons for such variations. Previous work has demonstrated the significant effect of operator's skills and practice on dragline productivity. In this study the relation between operators' practice and dragline energy efficiency is investigated using statistical tools. The goal is to develop a methodology to evaluate the effect of operator practice on dragline energy efficiency.

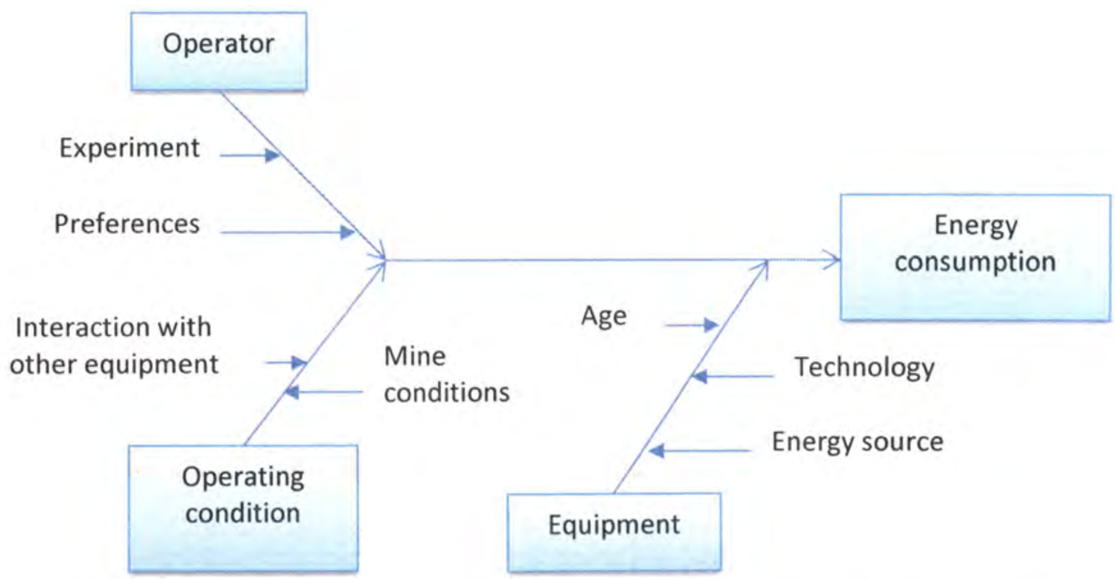

Figure 1-1 Factors affecting energy efficiency (adapted from (K. Awuah-Offei et al., 2011))

1.3. OBJECTIVES AND SCOPE OF THIS RESEARCH

The primary objective of this study was to describe the impact of operator practices on dragline energy efficiency. The specific objectives of this project were to:

1. Test the hypothesis that dragline operator's practices and skills significantly affect dragline energy efficiency; and
2. Develop a methodology to identify the critical parameters that explain the differences in operator energy efficiency.

All the tests and studies in this work were carried out on a dataset obtained from a specific dragline. The monitoring system of the dragline was limited in the number of recording parameters. For this reason the results of the second objective is limited to the recorded parameters in dragline's database.

1.4. RESEARCH METHODOLOGY

Figure 1-2 presents the research framework adopted in this work. Statistical tests are suggested as a tool to study the effect of operator practice and skills on dragline energy efficiency to achieve the first research objective. The second objective was achieved with a novel methodology based on sound statistical principles. Both approaches were illustrated with a real-life dragline operation. The data used as a case study was collected from a Bucyrus-Erie 1570w (85 yd^3 bucket) dragline operating in a coal mine in Wyoming during one month. The suggested methodology was used on this data to compare the energy efficiency of five operators during the one month period of data collection. SAS® (SAS Institute inc., 2011) and MATLAB (The MathWorks Inc., 2011) were used to apply the methodology on the given data.

The methods proposed to evaluate operator effects on dragline energy efficiency (objective one) make use of parametric and non-parametric statistical test for comparing means of groups of data. The challenges for using such tests on field obtained dragline energy efficiency data include data preparation, normality of data, and equality of variances. The approach suggested in this work systematically checks all these assumptions and minimizes their effect on the inferences drawn.

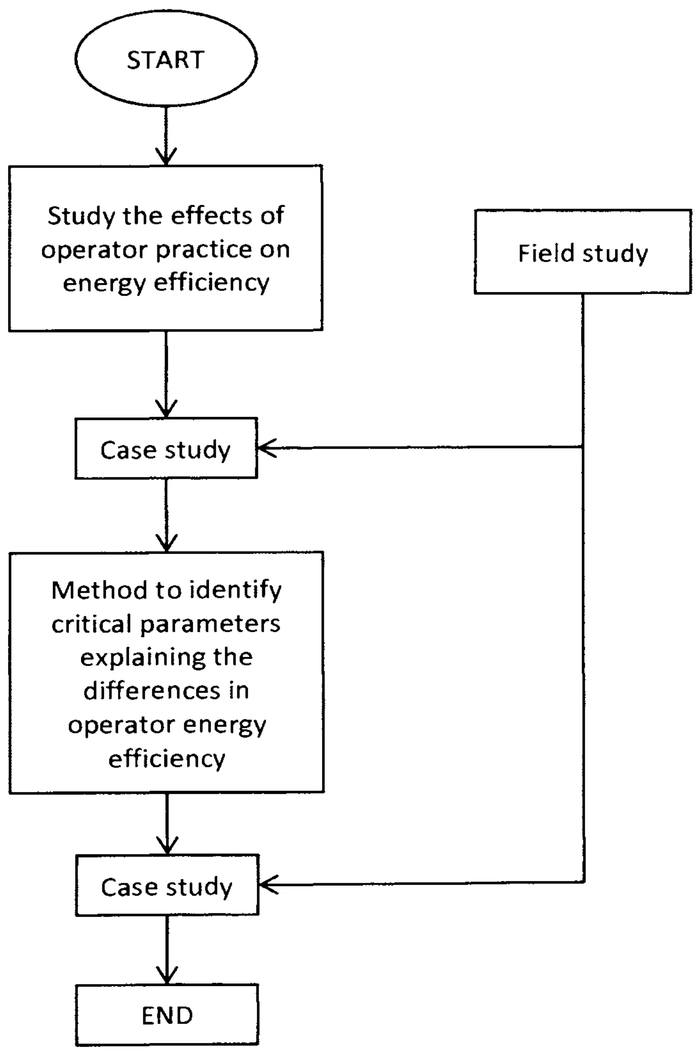

Figure 1-2 Activities/task in this research

The methods proposed to identify key parameters that lead to differences in operator performance make use of regression analysis of difference data to predict causes of under- or over-performance. The main challenge in using this approach for field obtained dragline energy efficiency data is the prevalence of missing data (Schafer & Graham, 2002) when preparing the difference data. Theoretically sound techniques are used to hypothesize the pattern or distribution of *missingness*, which is validated with the case study data. Random sampling techniques are used to generate equal number of samples for each pair of operators to generate the difference data for investigation. The proposed methods are illustrated with the case study data.

1.5. STRUCTURE OF THE THESIS

This thesis contains seven sections. Section 2, literature review, covers a review of relevant previous work. Information about the mine, the dragline and the dragline monitoring system used for the case studies in this work is provided in Section 3. In Section 4 the preliminary statistical analysis of the data used in the case studies, such as analyzing the structure of the dataset, and detecting and removing outliers, is presented. Section 5 discusses the effects of operator's skills on dragline energy efficiency (objective one). The section presents a methodology and a case study to illustrate it. Section 6 presents a methodology (and a case study) for examining which of the recorded parameters is responsible for observed differences in operator energy efficiencies (objective two). Section 7 provides the conclusions of this study and recommendations for future work.

2. LITERATURE REVIEW

2.1. DRAGLINE OPERATION

Draglines are the most dominant and critical machines in strip mines, commonly used for clearing the overburden to expose coal seams for extraction. Some properties of dragline operation include simple and low cost operation, high production rate, simple mine planning, and high capital and maintenance cost. Figure 2-1 shows a schematic view of a dragline. The drag and hoist machinery enable the bucket to move horizontally and vertically using electrical motors, gear reductions, wire ropes, and wire rope drums. Swing units (each consists of vertically mounted DC motors, gear reductions, and a main swing shaft) in swing machinery are mounted to a rotating frame. These units assist in swinging the dragline in order to position the bucket properly for loading or dumping (Humphrey, 1990).

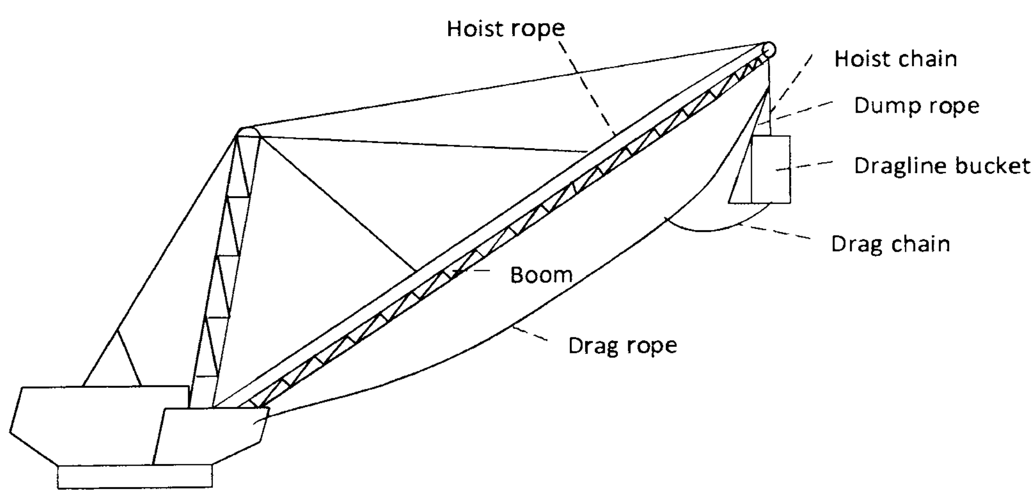

Figure 2-1 Schematic view of dragline

Dragline operation, not including the walking process, is a cyclic process. A cycle of a dragline operation consist of filling the empty bucket by dragging it on the (blasted) material, hoisting the bucket, swinging out to the dumping pile, dumping, returning (swinging in) to the digging spot, positioning the bucket to start the next cycle (Figure 2-2). Bucket size of walking dragline varies from 10 to 220 yd^3 (7 to 168 m^3) with boom lengths of 120 to 420 ft. (37 to 128 m) (Humphrey, 1990). The size of this machine, and its high production rate, makes it the main energy consumer in mines.

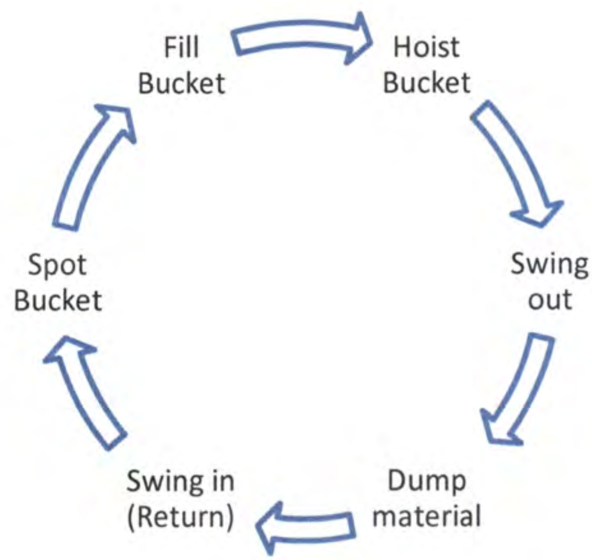

Figure 2-2 Dragline cycle

Simple side casting method is a common basic dragline mining method. In this method the dragline removes the overburden above the coal seam and dumps it into the space created by previous cuts (Figure 2-3).

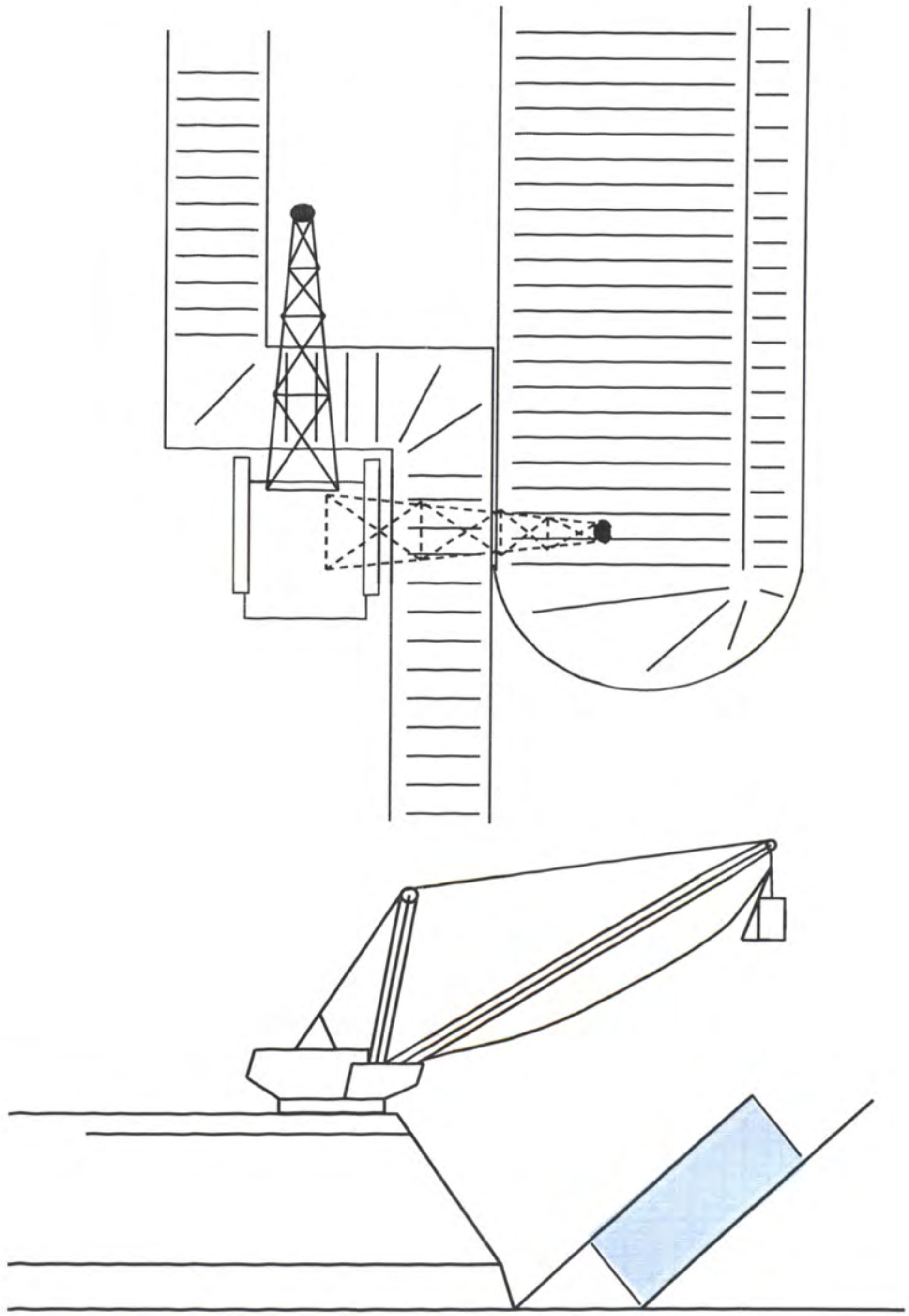

Figure 2-3 Simple side casting method

Some of the other common stripping mining methods are; extended bench method; split bench method; bench on spoil side method; and multi-pass methods (Baafi, Mirabediny, & Whitchurch, 1995).

2.2. SIGNIFICANCE OF ENERGY EFFICIENCY

It is anticipated that from 2010 to 2040 the world population will rise by more than 25% and the global economy will grow at an annual average rate of 2.8% (Exxon Mobil, 2013). If no change occurs in current practice, the world energy demand in 2020 will be 50-80% higher than the 1990 level (Omer, 2008). Given that the effects of improving energy efficiency should take into consideration to reduce the rise of energy demand. The share of the total energy production during 2011 provided by fossil fuels was 77.60% (Figure 2-4) (U.S. Energy Information Administration (EIA), 2011c). Combustion of fossil fuels emits greenhouse gases and also produces air pollutants such as nitrogen oxides, sulfur dioxide, volatile organic compounds and heavy metals. Growth in energy demand can potentially damage the environment and global health through emission of pollutants such as CO, CO_2, SO_2, and NO_x as well as contribute towards global warming (Exxon Mobil, 2013; Omer, 2008).

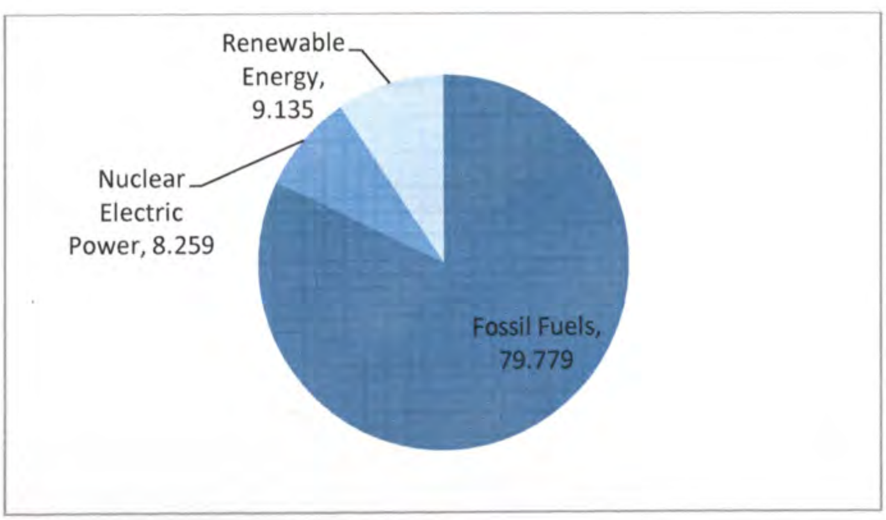

Figure 2-4 Energy Consumption 2011(Quadrillion Btu) (U.S. Energy Information Administration (EIA), 2011c)

Improving energy efficiency is a recognized and cost-effective approach to cut carbon dioxide emission and reduce environmental impacts of energy generation while keeping up with the world's growing energy demand. Major energy consuming countries such as China, U.S., European Union (EU), and Japan have new policies for reducing their energy consumption by improving energy efficiency(International Energy Agency (IEA), 2012; Omer, 2008). Improving energy efficiency will decrease the amount of energy used to produce a unit of GDP (Gross Domestic Product) output so the global energy demand will not rise as dramatically as economic growth. Improving energy efficiency with the existing technology can save 20% of the global energy demand (Ristic & Jefteni, 2012). Figure 2-5 demonstrates the effects of energy efficiency on global energy demand.

Coal mining industry plays an important role in the U.S. economy. In 2010, coal mining accounted for 40% of the total value of U.S. mining output and contributed $90 billion to GDP (National Mining Association (NMA), 2012). In 2007, the U.S. mining industry consumed about 365 billion kWh (1,246 trillion Btu) and coal mining accounted for about 39% of this.

Generally, mining processes can be divided into three main stages; extraction, material transportation and handling, and beneficiation and processing. Figure 2-6 shows the share of energy requirement for each of these stages in coal mining, estimated by the U.S. Department of Energy (DOE). Annual energy consumption of digging equipment including hydraulic shovels, cable shovels, continuous mining machines, long-wall mining machines, and draglines in coal mining industry is estimated as 7.7 billion kWh. However, based on the DOE study, practical minimum energy required for digging equipment in coal mines is 5.16 billion kWh. The DOE bandwidth analysis shows that there is a potential of reducing the annual energy consumption to 169 billion kWh (579 Trillion Btu) which is about 46% of current annul energy consumption (U.S. Department of Energy(DOE), 2007). The high potential for energy savings in mining has motivated mining companies to identify opportunities for improving energy efficiency.

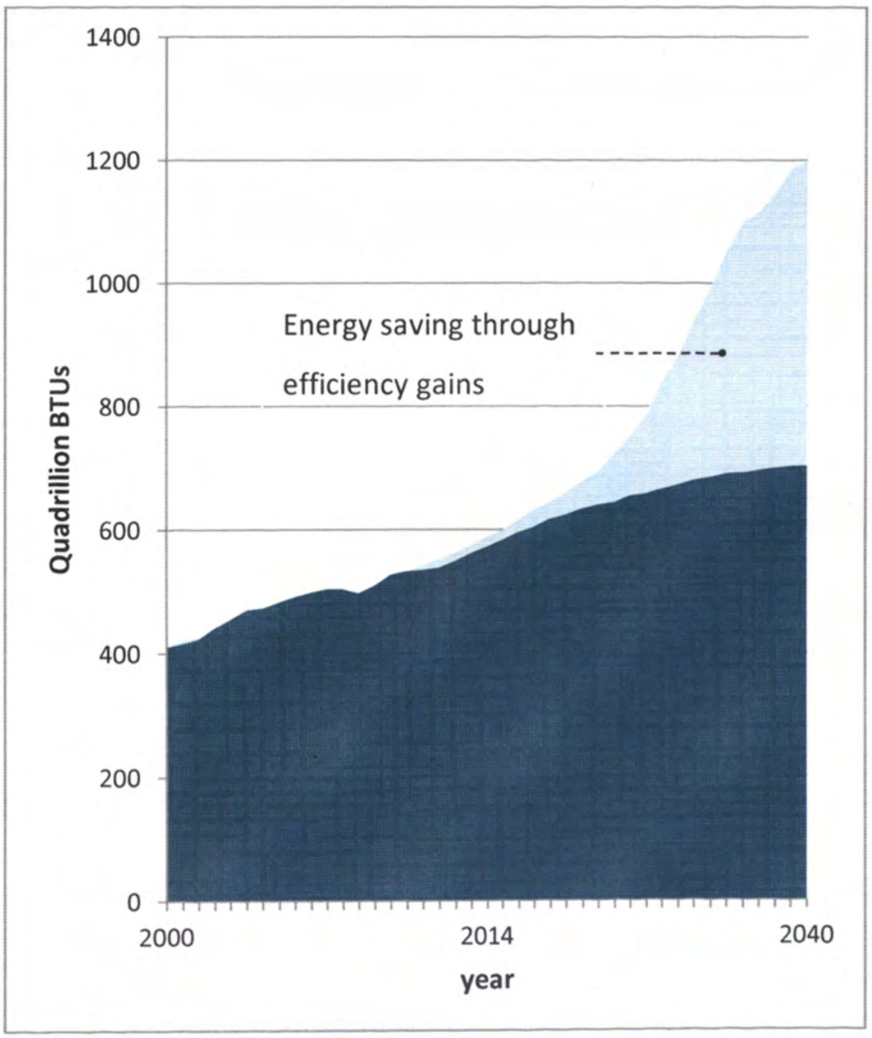

Figure 2-5 World energy demand, adapted from (Exxon Mobil, 2013)

Energy costs account for 20 to 40 percent of typical mining operational costs (Mielli & Wallace, 2012). Energy consumption is a key contributor to a business' greenhouse gas emissions profile, which is currently voluntarily reported in the US (U.S. Energy Information Administration (EIA), 2013), but may become compulsory in the future. Improving energy efficiency in mining operations can reduce costs for energy, increase profits and reduce emissions to meet government reporting requirements. Efficient operations consume fewer resources for the same services or products (Dincer & Rosen, 1999; Mielli, 2011; Steele & Sterling, 2011; World Energy Council, 2010).

An effective energy management system, that measures energy consumption to identify energy saving opportunities and determines the relation between production and energy consumption, is an important step to increase energy efficiency. Accurate measurement of energy consumption is an important requirement for a successful energy efficiency program. Limited information on energy consumption in mining operations is one of the major challenges in identifying the best strategies to improve energy efficiency (Bogunovic, 2008; Bush, Killingsworth, & Ruffel, 2002; Dessureault, 2007; Harney, 2007; Mielli, 2011).

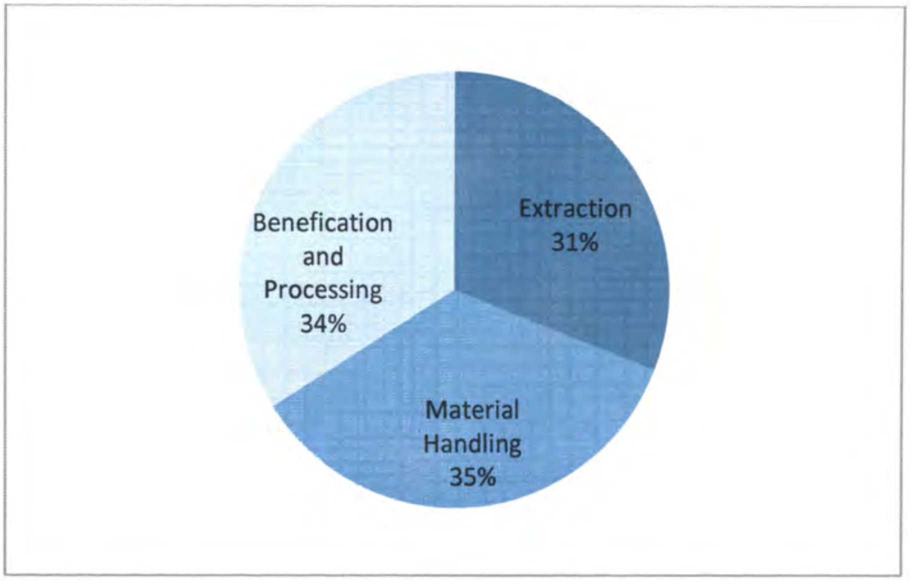

Figure 2-6 Energy requirement for coal mining (TBtu/ton of coal) (U.S. Department of Energy(DOE), 2007)

2.3. DRAGLINE ENERGY EFFICIENCY

Draglines, as one of the main energy consumers in surface coal mines, consume about 15-30% of total mine energy (Orica Mining Services, 2010). Because of the high rate of energy consumption and production, energy efficiency of draglines can significantly affect the profitability of mines (Williams, 2005). So it is essential to investigate dragline energy efficiency to identify approaches to reduce energy consumption while increasing production. Thanks to dragline monitoring systems, energy consumption and production of this machine can be monitored in real time. This information is essential in building energy efficiency strategies in mining operations.

Drag, hoist, and swing motors in the dragline provide the desired force to dig the material and move it to the dump position in each cycle. By investigating the duty cycle of the dragline the useful work (output energy) of each set of motors can be estimated from engineering principles. Drag and hoist motors are mainly engaged in the digging phase and elevating the material (Morley, Trutt, & Buchan, 1982). Eq. 2-1 describes the work done by drag motors in each cycle.

$$E_{out\_drag} = W_{drag\_bucket} + W_{drag\_material} + W_{resistance} + W_{friction} \qquad 2\text{-}1$$

Where E_{out_drag} is the output energy of drag motors; W_{drag_bucket} is the work done to drag the bucket; $W_{drag\_material}$ is the work done to drag the material; $W_{resistance}$ is the work done to overcome the resistance of the material to the cutting action; and $W_{friction}$ is the work done to overcome the friction between material and the bucket.

The main duty of hoist motors is to raise the material to the desired dumping height. The useful work done by these motors can be written as in Eq. 2-2.

$$E_{out\_hoist} = W_{hoist\_material} + W_{hoist\_bucket} + W_{hoist\_chains} \qquad 2\text{-}2$$

Where E_{out_hoist} is the output energy of hoist motors; $W_{hoist\_material}$ is the work done to overcome the weight of the material; W_{hoist_bucket} is the work done to overcome the weight of the bucket; and W_{hoist_chains} is the work done to overcome the weight of the chains

Swing motors provide rotation of the machine from the digging to the dumping position and return. The output energy of the swing motors can be calculated using Eq. 2-3.

$$E_{out\_swing} = \tau_{swing} \times \theta_{swing} \quad \text{2-3}$$

Where E_{out_swing} is the output energy of swing motors; τ_{swing} is swing torque; and θ_{swing} is the angular displacement of the machine during the swing out and swing in.

Generally, energy efficiency is defined as the ratio of useful work done (energy output) to the input energy (Zhu & Yin, 2008). In cases where either energy output or input cannot be measured easily, proxy parameters are used in their place. Several examples of this approach exist in the literature (Acaroglu, Ozdemir, & Asbury, 2008; K. Awuah-Offei, Frimpong, & Askari-Nasab, 2005; K. Awuah-Offei et al., 2011; Cooley, 1955; Dupriest & Koederitz, 2005; Iai & Gertsch, 2013; Karpuz, C., Ceylanoğlu & Paşamehmetoğlu, 1992; Matuszak, 1982; Muro, Tsuchiya, & Kohno, 2002; Teale, 1965; Torrance & Baldwin, 1990; Vynne, 2008). Vasilescu et al. (2010) used work done in carrying the payload from depth, d, for time, t, as a proxy for useful work done in their work to design and control algorithms of an autonomous underwater vehicle capable of missions of marine survey and monitoring (Vasilescu et al., 2010). Specific energy (energy required to produce unit volume/mass of rock/soil) is widely used in excavation, tunnel boring and soil cutting to measure efficiency of the excavation, boring, or cutting process (Acaroglu et al., 2008; Muro et al., 2002). For instance, Muro et al. (2002) in designing an experiment to estimate the steady state cutting performance, for varying cutting depth for a disc cutter bit, used specific energy as the measure of performance (Muro et al., 2002). Acaroglu et al. (2008) also used specific energy of a disc cutter for predicting the performance of TBM (Acaroglu et al., 2008). Specific energy has also been used in drilling (Dupriest & Koederitz, 2005; Teale, 1965), shovel excavation (K.

Awuah-Offei et al., 2005; Karpuz, C., Ceylanoğlu & Paşamehmetoğlu, 1992), and ripping (Iai & Gertsch, 2013). Specific energy is the inverse of energy efficiency, where material produced (payload) is used as a proxy for energy output. Hence, higher specific energy (or lower energy efficiency) is undesirable.

To find energy efficiency for loading and hauling operations, the amount of material handled and fuel consumption are used as proxies for energy output and energy input, respectively (Kwame Awuah-Offei, Osei, & Askari-Nasab, 2012). Dragline energy efficiency can be defined as the ratio of total weight of removed material to total energy consumed to remove this amount of material (Eq.2-4).

$$Energy\ Efficiency = \eta = \frac{P}{E_t}\left(\frac{tonnnes}{kWh}\right) \qquad 2\text{-}4$$

Where P is the payload and E_t is the energy consumption

2.4. DRAGLINE ENERGY MONITORING

A real-time monitoring system is an essential tool to reduce dragline energy consumption. These monitoring systems can improve dragline performance and productivity by displaying key performance indicators (KPIs) such as payload, swing angle, drag energy, cycle time, and its components. They also notify the operator when the dragline is overloaded (payload exceeds recommended weight) or when certain alarm conditions occur to reduce the maintenance cost. Providing operators with real-time information helps them improve their performance and operate more efficiently (Vynne, 2008).

Prior to the 1980s, the mining industry was not motivated to conduct accurate monitoring of dragline productivity because of the relatively smaller dragline sizes. At that time, swing charts were used for collecting data manually. Tons of ore or coal or overburden moved was used to describe dragline performance. However, these parameters included the productivity of trucks, shovels and other material handling systems as well as blasting performance into dragline performance (Cooley, 1955; Matuszak, 1982).

In the 1980s, several different data loggers were developed; but it took time for mining companies to realize the significant role these monitoring systems could play in dragline monitoring. Data loggers are capable of reporting; total operating time, productive operating time, machine motion performance, average swing angle, vertical hoist to dump, average and maximum drag force, average bucket load, average maximum lowering and payout speeds, etc. (Matuszak, 1982).

Tritronics 9000 Monitor is one of the oldest and most popular monitoring systems and was first developed in 1983. Several technical challenges, such as proper detection of all the different facets of dragline operation, strong computational power to convert all the measured values to meaningful metrics and the ability to be left unattended while collecting and storing data for later analysis, were solved to build this monitoring system. It had an onboard computer for monitoring dragline operation and radio telemetry to transfer the data to an off board computer for storing and analyzing. The onboard computer logs armature voltage and current of drag, hoist, and swing motors; swing angle; hoist and drag rope length; position of drag and hoist master switches; indication of propel mode; and number of steps in the walking process. This data is necessary for quantitative measurements of production in each cycles and real-time analysis of bucket position. Operators logged in the digging modes and delay codes into system manually. Parameters such as total number of swings since the shift began and the running total of material moved were displayed for the operator via a digital readout. These inputs were then converted into a record for each cycle, stored, and transferred into to the mine office computer (Hawkes, Spathis, & Sengstock, 1995; Torrance & Baldwin, 1990).

These days several manufacturers produce different real-time monitoring systems. Each uses a different method to evaluate the key parameters and operator performance. AccuWiegh™ by Drives & Controls Services (DCS) and Virtual Information Management System (VIMS) by Caterpillar® are other monitoring systems that use raw data from the dragline and convert it into meaningful information with supplied software. The data is then stored in different databases, using software such as; MS Access, MS SQL, MySQL, and Oracle, for further analysis (Bogunovic et al., 2009; Drives & Controls Services, 2003; Komljenovic et al., 2010).

A dragline monitoring system collects and stores different sets of parameters in each cycle depending on the system set up and metrics. Monitoring dragline operation for even a short period will result in a big data set. This data can be a great source for assessing useful metrics such as productivity, dragline performance for different operating conditions or tasks, and operator performance, as well as help identify the best strategies to improve energy efficiency. However, only a small portion of the collected information contributes to useful results, because of data overload and absence of post processing software (Morrison & Scott, 2002). Despite the high potential of monitoring systems to contribute in these analyses, not enough attention has been paid to analyzing the data collected and post processing analyses by dragline monitoring systems (Hettinger & Lumley, 1999; Morrison & Scott, 2002).

2.5. FACTORS AFFECTING DRAGLINE ENERGY EFFICIENCY

Eq. 2-4 implies payload or productivity and energy consumption are key parameters that control dragline energy efficiency. In order to manage dragline energy efficiency, it is essential to identify factors that affect dragline productivity and energy consumption. This section provides a summary of previous work done to recognize factors that affect energy consumption and productivity.

Payload, cycle time, digging time and energy, fill factor, engagement and disengagement position are important KPIs, which are closely linked to dragline productivity and energy consumption (Figure 2-7). These parameters are controlled by four main governing factors; operating condition, mine design and planning, equipment characteristics, and operator's practice (K. Awuah-Offei et al., 2011; Bogunovic & Kecojevic, 2011; Hettinger & Lumley, 1999; Kizil, 2010; G. Lumley, 2005).

2.5.1. Important KPIs. Important KPIs significantly affect dragline productivity, energy consumption, and, consequently, dragline energy efficiency. These parameters have been used in previous studies to assess dragline performance metrics such as productivity and operators' performance.

2.5.1.1 Payload. The results of the correlation analysis between dragline KPIs and productivity shows that payload has a strong relation with dragline productivity. Factors such as bucket design, material properties or geology, operators' skill, motor characteristics, blast performance affect the payload in each cycle (G. Lumley, 2005; Williams, 2005).

2.5.1.2 Cycle time. Cycle time is a critical parameter that is closely related to production. Studies show that a small reduction in cycle time can result in a significant increase in productivity (Bogunovic, 2008; Erdem & Düzgün, 2005). The components of dragline cycle can be found in Figure 2-2.With the considerable difference between dragline tasks in a cycle of operation, it is reasonable to analyze cycle time components, separately.

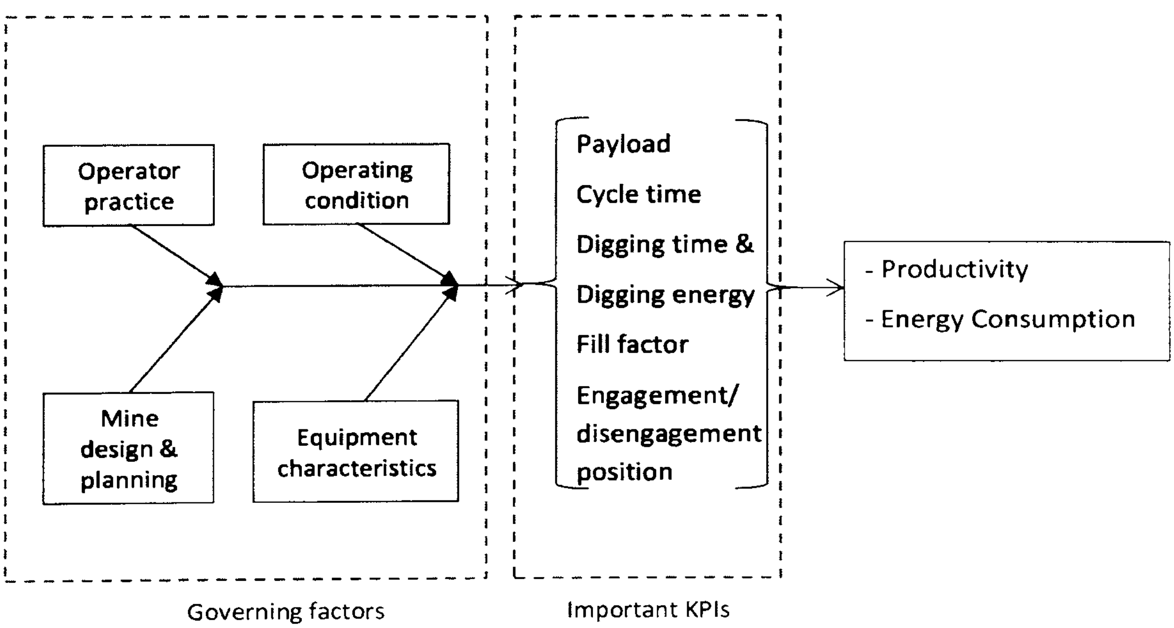

Figure 2-7 Factors affecting dragline productivity and energy consumption

2.5.1.3 Digging time and digging energy. Many authors have found the digging phase the most critical component in dragline cycle with the highest impact on energy consumption and production rate. Different digging conditions such as digging near cut walls, cut bottom or key cutting can significantly increase dig time. Dig time can be reduced by proper bench blasting and proper angle of attack between the bucket teeth and the ground, which is controlled by operator (Bogunovic & Kecojevic, 2011; Erdem & Düzgün, 2005; Rai, Ratnesh, & Nath, 2000; Rai, 2004; Torrance & Baldwin, 1990; Williams, 2005). Bogunovic (2008) used the energy consumption of just digging phase to evaluate operator performance (Bogunovic, 2008). Bogunovic (2011) concluded that dig time is the only cycle time component that is influenced by operator performance (Bogunovic & Kecojevic, 2011). The weakness of these assumptions and conclusions is that they are made without considering other phases in the dragline operation cycle.

2.5.1.4 Fill factor. Bucket fill factor is found as a parameter that influences production rate and energy consumption. Eq. 2-5 shows the definition of bucket fill factor

$$FF = \frac{P \times SF}{BV \times MD} \qquad \text{2-5}$$

Where; FF is fill factor, W is payload, SF is swell factor, BV is volume of bucket, and MD is material density.

The best fill factor for a given dragline should maximize payload and minimize dig energy consumption. This factor is controlled by operator skill and performance. Blast performance and material properties can also affect the dig energy consumption. A study done on a Marion 8200 dragline, with the bucket capacity of 82 yd^3, indicated that the optimal bucket fill factor (78%) reduces electricity used in digging phase by 36% and improve production rate by 1.4% (Bogunovic & Kecojevic, 2011; Bogunovic, 2008).

2.5.1.5 Engagement/disengagement position. Specific functional analysis done by Hettinger and Lumley (1999) shows that bucket engagement position, which is influenced by mine plan and operator habit, affects dragline productivity. For each bucket and rigging system there is a particular disengagement position at which payload is maximized. Disengage positions away from this optimum point result in payload spillage, increased cycle time and loss of productivity (Hettinger & Lumley, 1999).

2.5.2. Governing Parameters. Governing parameters are parameters that control important KPIs and consequently dragline production, energy consumption and energy efficiency.

2.5.2.1 Operating conditions. Operating conditions, such as geology, material properties, groundwater level, and weather condition, are known to be controlling parameters. Each mine has its own operating condition, which makes the size of the mine, mine plans and equipment selection unique for that specific mine. Based on the operating conditions of a mine, dragline performance can vary, significantly (Bogunovic & Kecojevic, 2011), (Rai et al., 2000), (Bogunovic, 2008). Operating conditions are not changeable so mine designs should be compatible with these conditions to get the maximum efficiency.

2.5.2.2 Mine design and planning. Digging method, mine strips and dumping position affect swing angle, swing time, and, consequently, cycle time. An optimum mine design should assign tasks to the dragline in proper timing to maximize mine productivity and keep energy consumption, maintenance cost, and wasted time minimum. Assigning inappropriate tasks, such as deep cuts, to dragline can increase energy consumption and make the operation inefficient (Erdem & Düzgün, 2005; Rai et al., 2000). For example, Pippenger (1995) showed that changing dragline shift from seven-day, three-shift, eight-hour to two 12-hour shifts per day reduces lost operational times and increases productivity (Pippenger, 1995).

2.5.2.3 Equipment characteristics. An appropriate bucket size, sufficient motor power, and proper gear ratios can increase dragline productivity and reduce energy consumption (Pippenger, 1995), (Rowlands & Just, 1992).

In cases where a mine purchases used draglines, the bucket size and drive system may not be completely compatible with the operating condition. Thus, some modifications may need to be done on draglines. However, modifying dragline drive system or bucket is costly. In Australia, during 2003 and 2004, about $30 million was spent on UDD (Universal-Dig-Dump) conservation: more than $20 million on new buckets, boom upgrades, and electrical upgrades, etc. (G. Lumley, 2005).

2.5.2.4 Operators practice. Operators' skills and habits have been observed to be important factors affecting dragline KPIs, productivity, and energy consumption. An operator's practice and skills are mostly measured by his/her performance and productivity. Due to the important role of draglines in mine profitability, assessing operator performance is an important issue. Australian coal mines became more profitable and efficient after the structural changes in their hiring policy in 1997. As a major part of this, mines now have the ability to select operators and employees based on their performance rather than seniority. Lumley (2004) detected the average difference of 35% between productivity of the best and the worst operator in GBI database (G. I. Lumley, 2004; G. Lumley, 2005). Dragline productivity varies greatly between operators, even in the same operating condition (K. Awuah-Offei et al., 2011; Bogunovic et al., 2009; Bogunovic, 2008; Komljenovic et al., 2010; Norman, 2011; Patnayak et al., 2007). Dragline production has always overshadowed dragline energy efficiency. The objective function of most of the studies described in this section is to maximize dragline productivity. However, with the growing concerns about reducing energy consumption and improving energy efficiency more investigations need to be carried out on dragline energy consumption and efficiency to help mining companies increase their productivity whilst keeping their energy consumption and energy cost reasonable.

Of all the factors that affect dragline productivity and energy efficiency, operator skill and performance is, probably, the most inexpensive factor to change. Operating condition, mine design and planning, equipment characteristics and operators' skill are factors that control dragline productivity, energy consumption and efficiency. In a given mine, maximizing energy efficiency by changing operating condition is not possible. Also optimizing dragline drive mechanism can be costly. Mine design should not assign tasks to dragline in which its efficiency is low. But some of these circumstances are unavoidable, for instance digging near cut walls, cut bottom or a key cutting. Operators can be trained to improve their performance and increase productivity. Training operators is a relatively cheap improvement and valid approach in comparison to other modifications. To train operators, it is critical to understand the effect of operators practice on dragline productivity, energy consumption and energy efficiency and quantify this relationship.

2.6. ASSESSING THE EFFECT OF OPERATOR'S PRACTICE

The importance of operator performance for profitability highlights the significance of an operator performance assessment system. Multiple criteria have been used to assess operator performance for different equipment in different industries. Parameters such as course, altitude, speed, timing, and handling are used to assess the performance of pilots in a flight simulator test in each flight task. These single dimension values are then combined for evaluating the final score of each pilot (Johannes et al., 2007). For haul trucks, operator training and performance evaluation focuses on improving productivity, reducing maintenance cost, and improving safety (Vista, 2013).

Patnayak (2007) suggested using hoist energy consumption per tonne of material excavated and number of required cycles to load a truck to assess operator performance and productivity. He also used the one-way analysis of variance (ANOVA) to test the hypothesis that the mean of hoist and crowd power between operators are equal in electric shovels. The results of these tests indicated that hoist power is significantly different between operators at a significance level of 0.01 (Patnayak et al., 2007). Although, the ANOVA test is a common and valid approach to compare the mean between more than two groups, comparing the hoist power alone without considering the productivity, is limited as a measurement of performance of different operators. In cases where crowd and swing energy are significantly different, the inferences may be misleading.

Bogunovic (2008) introduced a dragline operator performance indicator (PI) using electricity consumption and productivity. PI is calculated by first normalizing production and energy consumption of an operator in a given time period and then finding the difference between normalized values of production and energy consumption (Eq. 2-6). Bogunovic (2008) used only digging energy as energy consumption and assumed that energy consumption of other cycle components are constant for all operators. A positive value of PI represents an efficient operation and the performance of operators with positive PI was evaluated further in the study. Unit production, unit energy, loading time, cycle time, angle, and working hours were used to evaluate dragline operators' performance score (Bogunovic, 2008). Since Bogunovic's PI assume constant energy consumption for other cycle components, where there are significant differences in energy consumption of the other cycle components, this metric will result in inaccurate conclusions.

$$PI(i) = \frac{P(i)}{\sum_{i=1}^{nop} P(i)} - \frac{E_t(i)}{\sum_{i=1}^{nop} E_t(i)} \qquad 2\text{-}6$$

Where PI(i) is Performance Indicator of operator i, P(i) is production of operator i over a given time, E(i) is energy consumption of operator i over a given time, and nop is the number of operators.

Komljenovic et al. (2010) presented an operator performance indicator (OPI) that specifically evaluates dragline productivity and energy consumption. OPI was defined as the dragline production over the dragline energy consumption in a given period of time (Eq. 2-7). Different confidence intervals were used to create a classification system to evaluate operators' performance based on OPI. Assuming that OPI follows t-distribution (when number of operators are less than 30), Eq. 2-8 was used to define the boundaries of the classification system (Komljenovic et al., 2010).

$$OPI(i) = \frac{P(i)}{E(i)} \tag{2-7}$$

Where OPI(i) is the Operator Performance Indicator of operator i

$$OPI_{upper;lower} = OPIs \pm t_{\frac{\alpha}{2};nop-1} \frac{S_s}{\sqrt{nop}} \tag{2-8}$$

Where $OPI_{upper;lower}$ is OPI boundaries, OPIs is sample mean, S_s sample standard deviation, $t_{\alpha/2;nop-1}$ is the $100\alpha/2$ percentage point of the Student distribution with (nop-1).

Bogunovic (2008) and Komljenovic et al. (2010) used single performance criteria over a period. This prevents analysts from tracking the effect of variations in control variables over the period of evaluation. In cases where such control variables vary significantly over the evaluation period and between operators, wrong conclusions can be made about operator performance. It is important to monitor variables that significantly affect operator practice during performance assessment. Knowing which of these variables are significantly different between operators with different performance metrics, can help us to improve training systems. Intuitively, this approach is the basis for crew coaching in many mines. For example at the Coal Creek Mine, a leader operator (expert operator) spends time watching and evaluating oiler/groundman (operator with less experience) and provides him/her with feedback to increase his/her performance, based on observed sub-optimal practices (Norman, 2011).

2.7. SUMMARY

Improving energy efficiency is a cost-effective approach to meet the increasing demand of energy whilst reducing environmental impacts of energy consumption. Productivity and energy efficiency of the dragline, as a dominant machine in surface mines, have a great impact on mine profitability. The real-time monitoring systems on draglines provide us essential information to build energy efficiency strategies in mining operations. Energy efficiency of dragline can be defined by using payload and total energy consumption as proxy parameters for useful work and input energy, respectively.

Identifying factors that affect dragline productivity and energy consumption is essential to manage dragline energy efficiency. Key performance indicators, which are closely linked to dragline productivity and energy consumption, include payload, cycle time, digging time and energy, fill factor, engagement and disengagement position. Four governing factors; operator practice, operating conditions, mine design and planning, and equipment characteristics control these KPIs. Among these governing factors operator performance is the most inexpensive factor to modify in order to maximize energy efficiency. In a given mine changing operating condition is not always possible, optimizing dragline drive mechanism can be costly, and sometimes it is unavoidable to assign inefficient tasks to dragline. Training operators to improve their performance can be a relatively cheap improvement and a valid approach to improve energy efficiency.

It is critical to understand the effect of operator practice on dragline energy efficiency and quantify this relationship. Identifying variables that are significantly different between operators with different performance can help us to improve training systems.

3. FIELD DATA ACQUISITION FOR CASE STUDIES

3.1. STUDY SITE

The methods presented in this work are illustrated with data from a real mine. The data was collected from a mine[1] located in the Powder River Basin (PRB) in Wyoming. PRB covers 20,000 mile square in north-central Wyoming and south-east Montana. It is recognized as a valuable source of coal bed methane, coal, petroleum, conventional natural gas and uranium oxide (United States Environmental Protection Agency (EPA), 2004).

3.1.1. Geology. PRB is a thick sequence of sedimentary rock ranged from Paleozoic through Mesozoic and Tertiary. Paleocene Fort Union and Eocene Wasatch are two formations in PRB containing coal beds (Wyoming State Geological Survey, 2010).

Wasatch formation covers 1/3 of PRB and contains mostly continuous and thin (6 feet or less) coal beds with high heat values and agglomeration characteristics (United States Environmental Protection Agency (EPA), 2004; Wyoming State Geological Survey, 2010). Coal deposits in Fort Union formation are identified as the thickest and most extensive deposits of low-sulfur subbituminous coal in the world and are mostly formed in the upper Tongue River Member (United States Environmental Protection Agency (EPA), 2004). They range from subbituminous C to A in apparent rank, in the shallow part of the basin (surface to 1,000 ft. of depth) low rank coal (subbituminous C) can be found. Middle rank coal (subbituminous B) and high rank coal (subbituminous A)

[1] To protect the mine's identity no name will be used in this thesis.

are placed in intermediate depth (1,000 to 1,400 ft.) and deeper part of the basin (more than 1,400 ft.), relatively (Stricker et al., 2007).

The average energy content in the PRB coal is 8,500 Btu/lb with low sulfur content. Considering that the average energy content of coal produced in the U.S. in 2011 was nearly 9,800 Btu/lb., PRB coal has a low energy content (U.S. Energy Information Administration (EIA), 2012). However, the low sulfur content enables power plants to burn the PRB coal with no need for expensive emissions control equipment, which makes PRB coal economic to extract ("PRB Coal Properties," 2013). The share of the coal production from PRB was 37% of total coal production in the U.S. in 2011 (United States Environmental Protection Agency (EPA), 2004).

US Geological Survey (USGS) (2008) divided PRB into three regional areas. Gillette coalfield is the most significant area (covers about 2,000 mile squared); known as the most prolific coalfield in the U.S. In 2006, nine out of ten largest coal mines were in this coalfield. Tongue River member supply the 13 active mines operating in Gillette coalfield, including the understudied mine (USGS, 2008). Figure 3-1 displays the stratigraphy of coal in this coalfield. The Ronald coal bed, with the average thickness of 10ft, is the boundary between Wasatch and Fort Union formation. The maximum thickness of this coal bed and maximum overburden are 52 ft. and 1,175 ft, respectively. The mine extracts coal from this coal bed. The two main seams in this mine are Roland 1 and Ronald 3 with the average energy content of 8,226 Btu and 5.67% of ash (USGS, 2008).

3.1.2. Mine Operations. Construction in the mine started in spring 1979 and the first coal was shipped in May 1982. As at December 2011, the recoverable reserve is estimated at 175.4 million tons (Arch Coal Inc., 2012).

Formation	Bed name	Average thickness (ft)
Wasatch	Felix Rider	7.0
	Felix	14.0
Fort union (Tongue river member)	Roland	10.0
	Smith	25.0
	Anderson Rider	8.0
	Anderson	45.0
	Dietz	8.0
	Canyon	26.0
	Werner	9.0
	Gates	13.0
	Pawnee	14.0

Figure 3-1 Coal stratigraphy in the Gillette coalfield (adapted from (USGS, 2008))

The total coal production of the mine in 2011 was about 11.4 million tons. Average thickness of coal seams Roland 1 and 3 are 26 feet and 13 feet. The two seams are separated by a thin interburden. Mining is done by strip mining with truck and shovel pre-stripping. The average thickness of overburden is 90 feet. In places where the thickness of overburden exceeds 100 feet shovels and trucks are used to clear the overburden until an overburden thickness of 100 feet. The remaining 100-foot overburden is removed with a Bucyrus-Erie 1570W dragline with a bucket capacity of 85 yd^3.

The dragline is equipped with Accuweigh™ monitoring system (by Drives & Control Services [2]) that collects raw machine signals, converts them to meaningful parameters in each cycle and stores them in a database (Drives & Controls Services, 2003). The relevant parameters in the database were retrieved from the database for this study. Table 3-1 shows the operating specifications of the dragline. Figure 3-2 displays a typical mining sequence at the mine. Figure 3-3 shows the configuration of the dragline drive mechanism and the list of the dragline's electrical drive components (motors and generators) is displayed in Table 3-2.

3.2. FIELD EXPERIMENT

The field experiment involved a site visit, monitoring the dragline for one month during which different operators run the machine under similar conditions, and data retrieval for research. The mine visit (which was on June 19th and 20th, 2012) involved visiting the mine site, and surrounding area, and observing the dragline operation under study and two other draglines in another mine in the area. The author observed working draglines with different operators, operator habits, different operating conditions, and dragline drive components, which helped to better understand the collected data.

[2] http://www.drivesandcontrols.com/

Table 3-1 Operating specifications of a Bucyrus-Erie 1570W dragline

Parameter	Value
Clearance radius (Rear end)	21.4 m
Operating radius	87.5m
Boom length	99.1 m
Boom angle	38°
Clearance height (under frame)	2.4 m
Tub Diameter	20.1 m
Dumping Clearance	45.7 m
Boom point height	65.2 m
Maximum digging depth	53.3 m
Width (shoe-shoe)	28.0 m
Rated suspended load	176 tonnes
Step length (approx.)	2.6 m

Table 3-2 Electrical configuration of dragline motors/generators

Quantity	Motors/ Generators
2	2000 HP- 4 unit MG sets (Motor generator sets)
2	3000 HP- 5 unit MG sets (Motor generator sets)
6	1300 HP hoist motors
4	1300 HP drag motors
4	1045 HP swing motors
4	500 HP propel motors

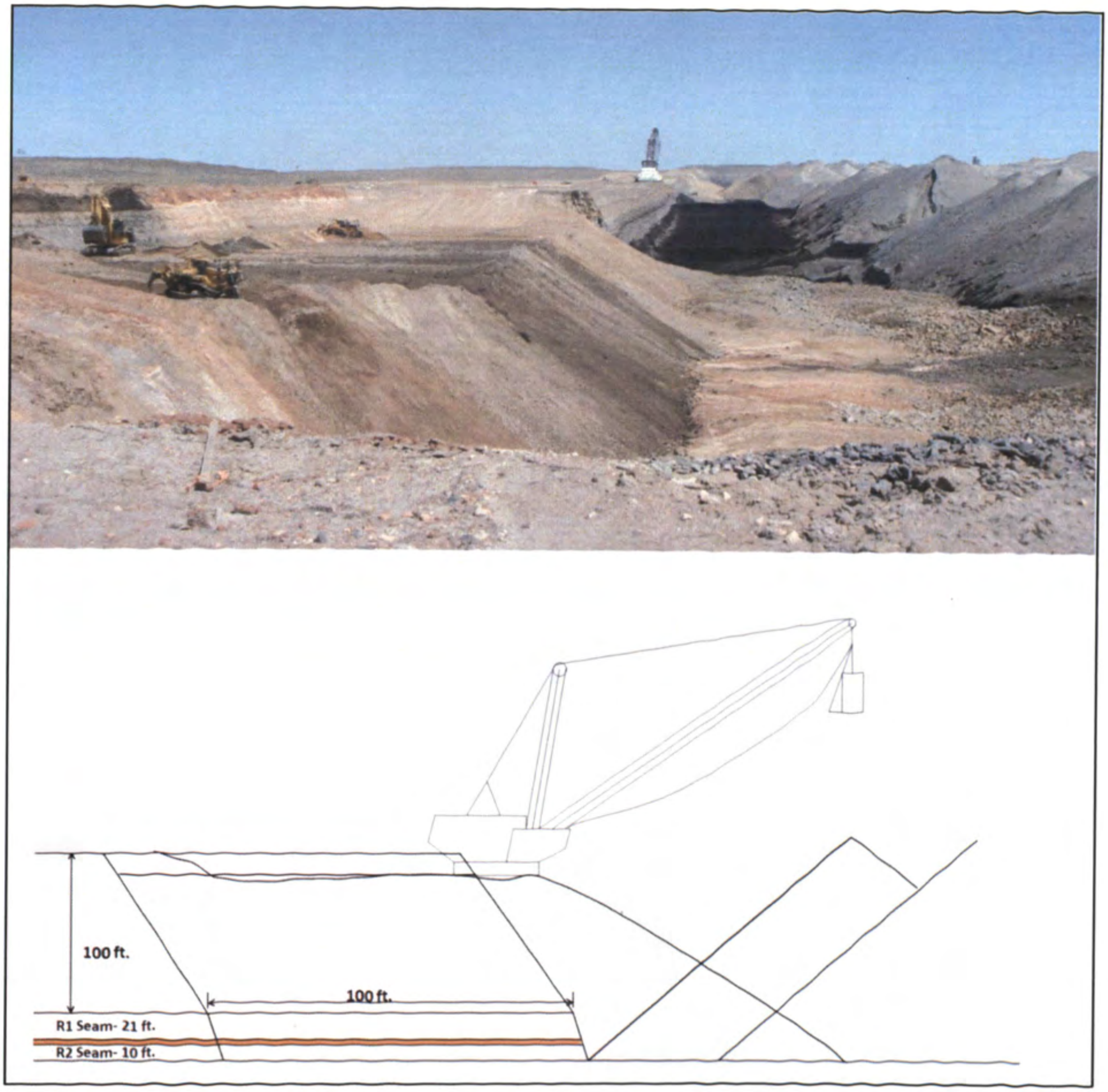

Figure 3-2 Mining sequence in the mine

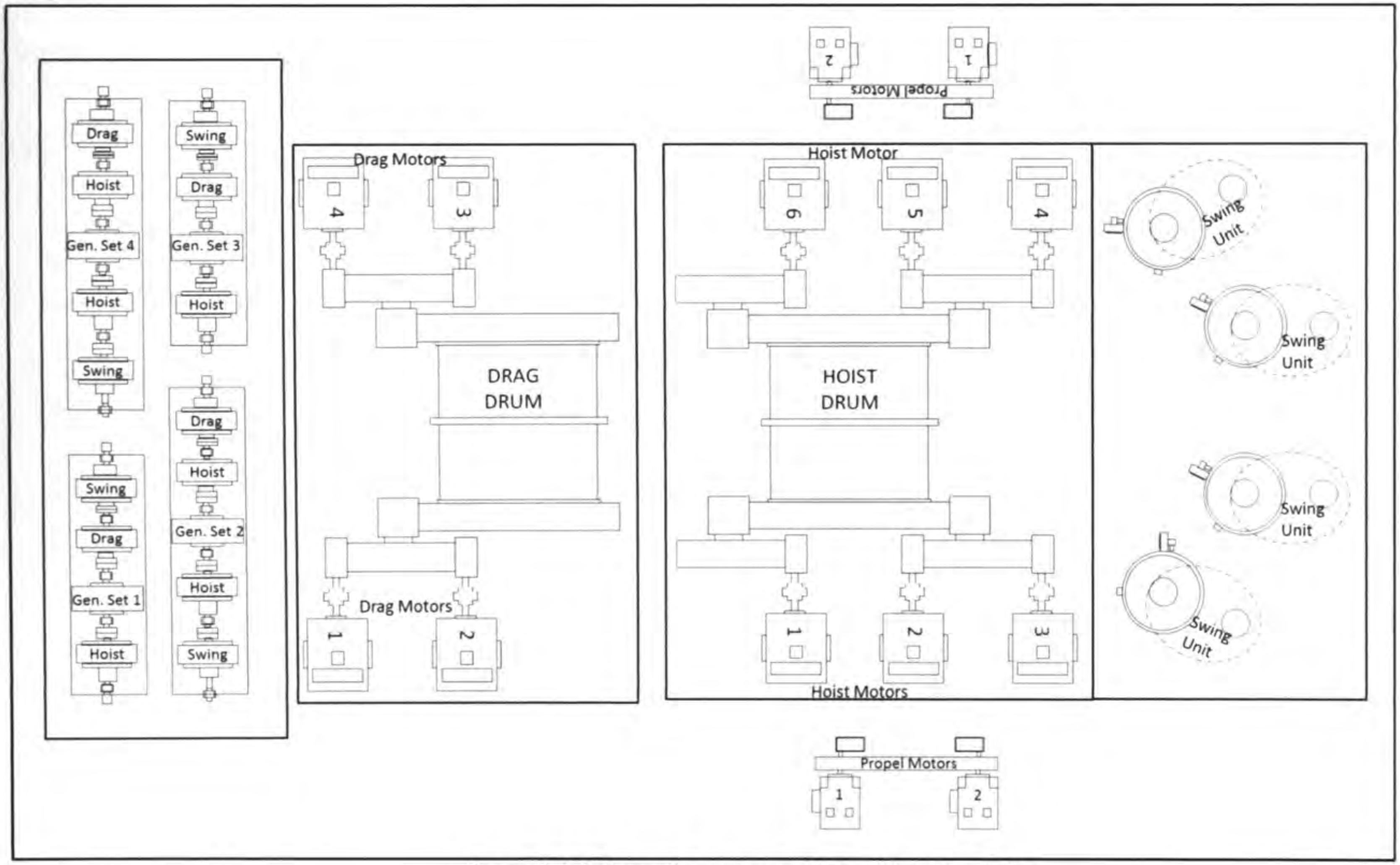

Figure 3-3 Schematic representation of dragline drive

The data used in this work was collected during one month (June 18th to July 18th, 2013). Accuweigh™ monitoring system was used as a remote observation tool. Such micro-processor based data acquisition is cheaper (no labor costs), comprehensive (data capture is continuous throughout the experimental period), and more accurate as human errors are removed or minimized in the data collection. Accuweigh™ monitoring system provides the operator with information such as position of the bucket on a map on the digital screen, payload, swing angle, etc. in a real time. The monitoring system also keeps track of over loading the machine and warns the operator. Not all the recorded parameters are displayed to the operators, but they are all stored in the main data base. In order to fully capture energy efficiency, there is a need to monitor the components of energy consumption during a dragline cycle – drag, hoist, and drag energy. Since Accuweigh™ does not store this data in the database, this work involved modifying the program to store this data in the extra database fields of the database. The main data base also contains information from shovels, trucks, draglines, etc. in separated tables. Information such as operator's ID number, dragline activity code, operating shift and pit are recorded in separate tables. By matching records in this table with records in the dragline table, the author was able to verify that during the period of data collection the dragline worked in the West Pit with thirteen different operators. The dragline activity during this time included digging below grade (84.7 %), rehandling (15%), and other activities (0.3%). The average recorded temperature during this time was 74°F.

3.3. SUMMARY

Data collected from a real mine was used in this work to illustrate the presented methods. Data was collected from BE-1570w dragline with bucket capacity of 85 yd^3 equipped with Accuweigh™ monitoring system during one month. Some modification to the program was necessary to store drag, hoist and swing energy in the database. The main duty of the dragline in this mine is to remove the overburden (with average thickness of 90 ft.) from the coal seams. It is assumed that during the data collection the material type remained constant as the dragline was operating in one pit. During this time dragline spent 84.7% of its time for digging below grade, 15% rehandeling, and 0.3% for other activities.

4. PRELIMINARY DATA ANALYSIS OF FIELD DATA

This section contains preliminary data analysis of the field data, which is used to illustrate the methods formulated in this research. The preliminary data analysis is helpful for studying the structure and behavior of the field data prior to analysis. In this section the data collected from a Bucyrus-Erie 1570w (85 yd^3 bucket) using Accuweigh™ monitoring system is studied graphically and quantitatively using SQL server management studio (Microsoft, 2008), MATLAB, and SAS.

4.1. STRUCTURE OF DATASET

The dataset used in this study was retrieved from the main dragline monitoring database of the mine. In one month 34,326 cycles were recorded. Each cycle contains 44 parameters regarding the working positions, time spent on the cycles and portions of cycles, swinging angles, dumping heights, and energy consumed by drag, hoist and swing motors (a list of all 44 parameters and their definitions are included in APPENDIX A). The Accuweight™ monitoring system is designed to collect the total time spent on each cycle and the tasks carried out in each cycle, separately. A cycle is defined to start when the last load was dumped and end when the current load is dumped. Components of a cycle are swinging out, dumping, swinging in, spotting and loading (Figure 4-1). Swinging out time is measured as the time elapsed from the moment the bucket is detected to be full to the time it is detected to be empty. Dumping time is the time between when the bucket is in the dump zone to when the bucket is detected as empty. Swinging in time is the time between when the bucket is dumped and when a dig detect is triggered. Spotting time is measured from the moment the swing velocity is less than a given value to the moment when the dig detect is activated. The time between when the bucket fill is detected and full hoist is detected is defined as loading time.

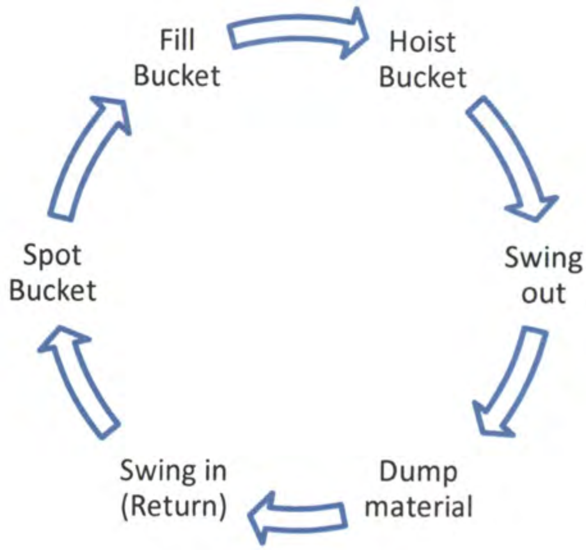

Figure 4-1 Dragline cycle components

Not all the 44 parameters recorded in the dataset were relevant to this work. Fourteen parameters adjudged to be useful for studying dragline energy efficiency were retrieved from the main database for further analysis. Table 4-1 shows a brief summary of these parameters.

Table 4-1 Relevant Parameters

Parameters	Swing out time	Swing in time	Load bucket time	Dump time	Cycle time	Spot time	Payload
Units	Milliseconds	Milliseconds	Milliseconds	Milliseconds	Milliseconds	Milliseconds	Pounds
Minimum	1500	13000	6000	6000	41000	1000	337833
Maximum	2500	34000	16000	13000	70000	16000	501283
Mean	2.05e+4	2.15e+4	1.08e+4	9.11e+3	5.40e+4	8.28e+3	4.29e+5
Variance	5.17e+6	1.97e+7	6.16e+6	1.74e+6	4.29e+7	6.98e+6	1.12e+9

Parameters	Angle swing out	Drag distance (horizontal)	Drag distance (vertical)	Dump height	Drag energy	Hoist energy	Swing energy
Units	Degree	Inch	Inch	Inch	Kw-s	Kw-s	Kw-s
Minimum	1	0	-466	235	-7491	14299	1570
Maximum	384	837	980	2299	20971	54859	21065
Mean	61.73	138.94	138.43	1.02e+3	3.25e+3	3.23e+4	6.6e+3
Variance	838.83	12267.66	18372.49	1.54e+5	3.44e+7	8.63e+7	7.43e+6

The data was first classified based on the number of attempts operators made to fill the bucket. In the majority (about 98%) of cycles, the operator successfully filled the bucket on the first attempt (Table 4-2). All the cycles which took more than one attempt were ignored in this study (some of these could be highwall chopping operations) because they did not represent "normal" loading operations. APPENDIX B contains raw data used in this work.

Table 4-2 Classification of the data based on number of bucket reloads

Bucket Reload	Count	Proportion (%)
0	33,492	97.56
1	738	2.15
2	53	0.15
3 or more	43	0.13

4.2. DETECTING AND REMOVING OUTLIERS

Outliers must be removed prior to any analysis in order to prevent inaccurate inferences. In this research, outliers arise from errors (values recorded during periods when the dragline is not operating etc.) and anomalous operating cycles. The fourteen parameters were examined for outliers. A common approach to detect outliers is to determine the first (Q_1) and third quartiles (Q_3) and calculate the interquartile range using Eq.4-1.

$$IQR = Q_3 - Q_1 \qquad \text{4-1}$$

The points that are outside the quartiles by one and a half IQR (lower and upper Whisker) are labeled as mild outliers. Boxplots are commonly used to display the outliers graphically. In Figure 4-2 red crosses represent the outliers.

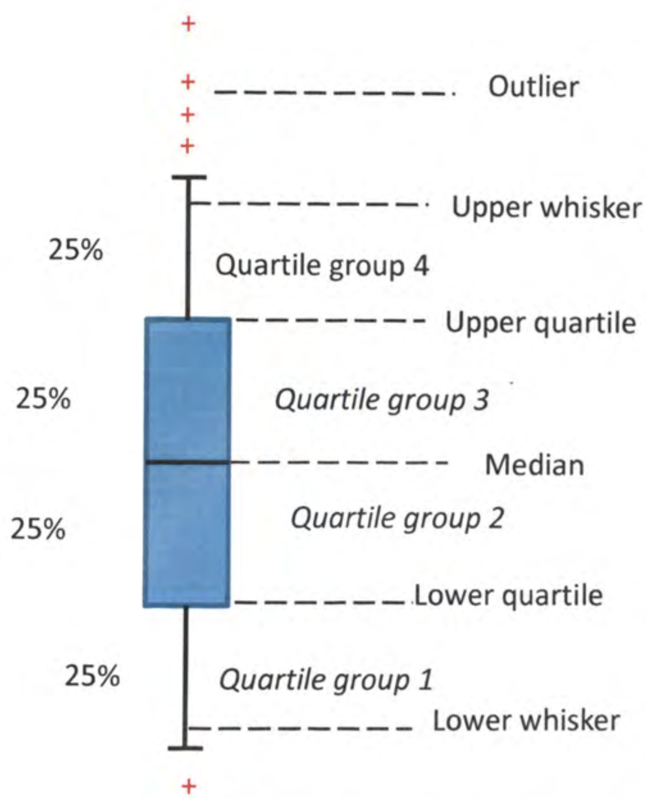

Figure 4-2 Boxplot definition in this work

MATLAB was used to plot the boxplots of the fourteen parameters in the database (Figure 4-3). Figure 4-4 shows the boxplots after removing mild outliers. Note that new "outliers" are identified because the statistics (Q_1, Q_2, and IQR) have changed with the new data set (i.e. data without the original outliers).

4.3. DRAGLINE OPERATORS

During the one month of data collection, thirteen different operators operated the dragline. Table 4-3 shows the operating time and number of cycles for each operator. It is essential to have equal support from all operators in the analysis to make reasonable inferences. Not all operators worked sufficient amount of hours to be considered in the statistical analysis.

Table 4-3 Operator activity

Operator	# of cycles	Total operating time (hr)
	3,897	56.91
B	3,611	54.62
C	3,350	49.60
D	3,058	45.64
E	2,211	32.77
F	1,529	23.55
G	1,023	15.70
H	761	12.39
I	271	4.36
J	129	2.04
K	88	1.09
L	29	0.49
M	24	0.35

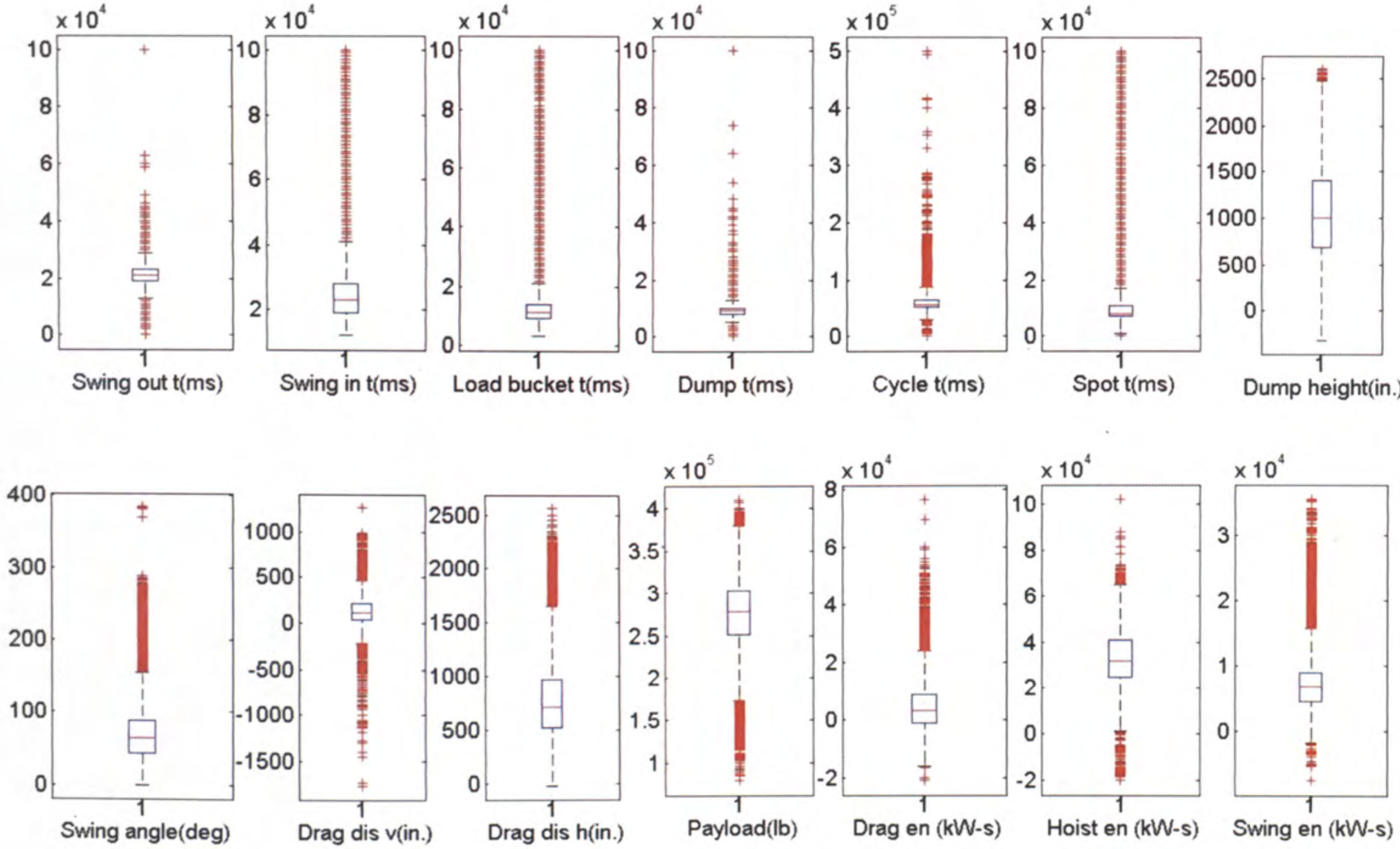

Figure 4-3 Boxplots of relevant parameters before removing any outlier

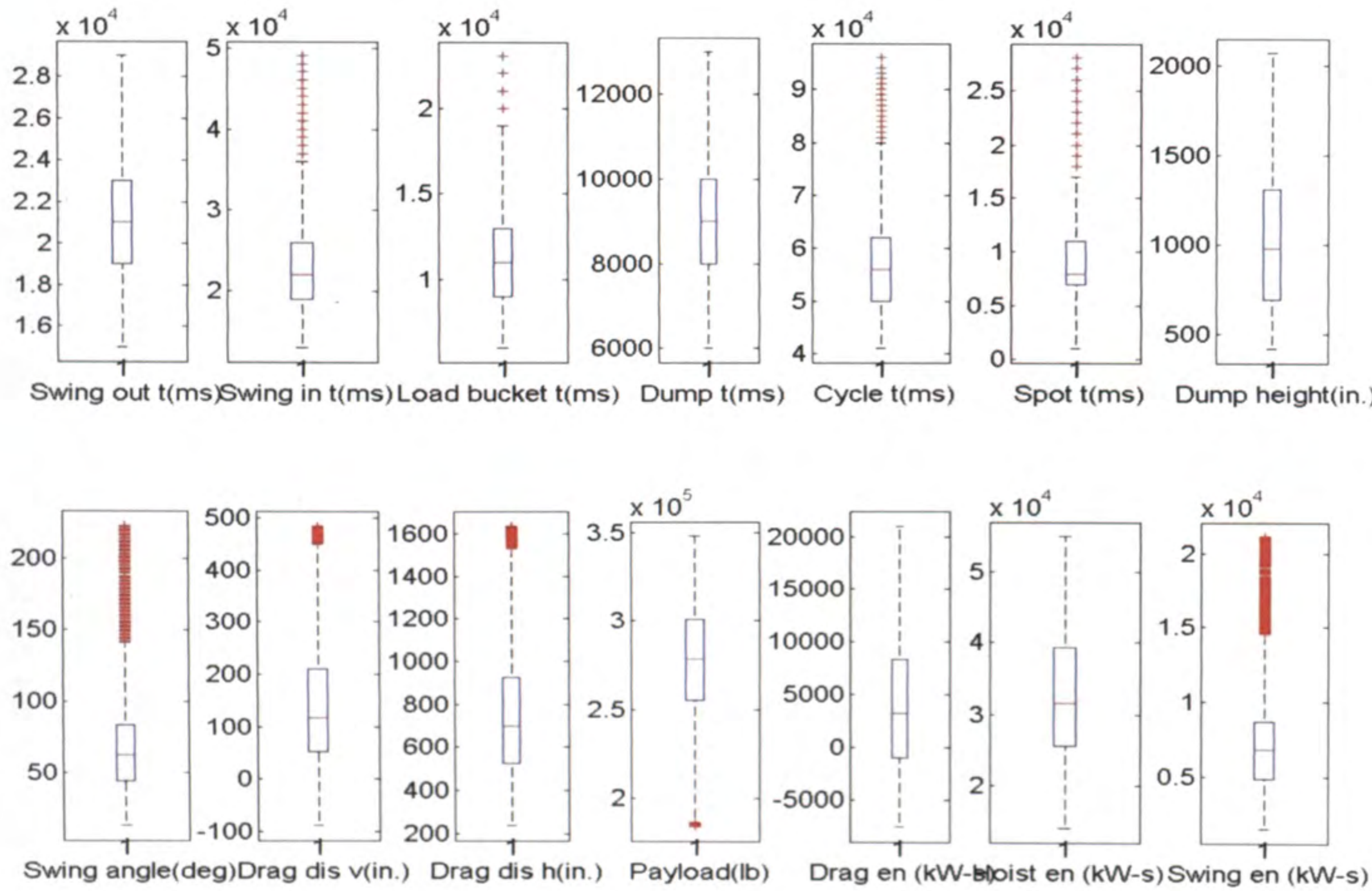

Figure 4-4 Boxplots of relevant parameters after removing outliers

The mean standard error of energy efficiency of each operator was calculated using Eq. 4-2 (Biau, 2011). The gradient of the standard error increased after operator H (Figure 4-5). Operators with mean standard error greater than 0.06 were removed from the database. Figure 4-6 displays the mean standard error and the number of cycles of eight operators. The increase in gradient of the standard error after operator D shows a change in the mean standard error. Because of the sudden change the mean standard error of operator D can be used as a cut-off value. Operator E was also included in the analysis, based on the author's engineering judgment, to increase the number of operators in the analysis while maintaining reasonable confidence in estimates of the mean energy efficiency. Thus, 0.04 was chosen as the cut-off value to find the minimum required number of cycles.

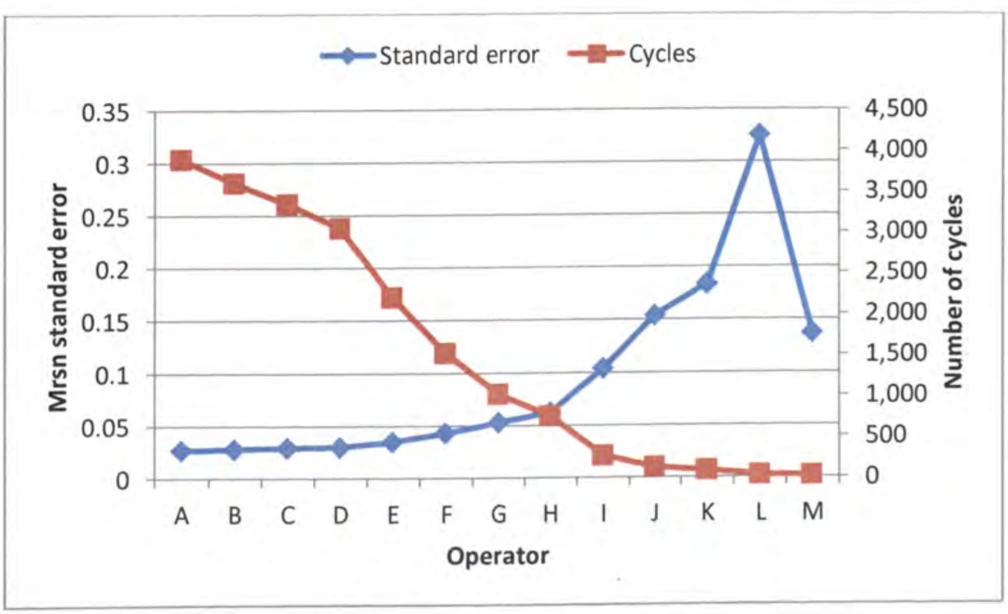

Figure 4-5 Mean standard error and number of cycles of all operators

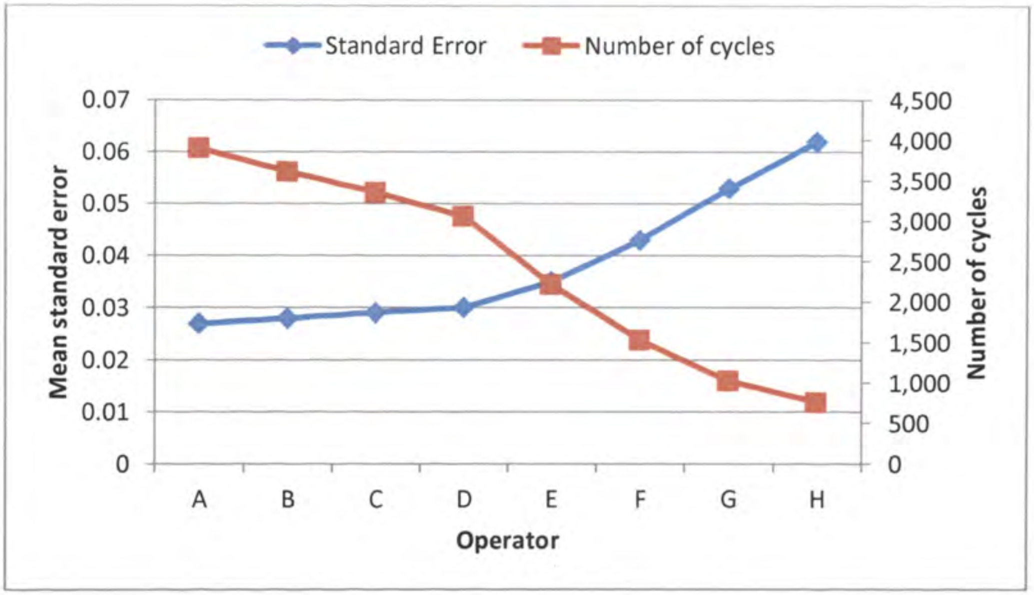

Figure 4-6 Mean standard error and number of cycles of eight operators

It can be concluded from Table 4-4 that operators with number of cycles less than 2000 have the relatively high standard error (greater than 0.04). Operators A, B, C, D, and E with standard error less than 0.04 were included in the analysis.

$$SE_i = \frac{\sigma_i}{nOc_i} \tag{4-2}$$

Where SE_i is the mean standard error of operator *i* energy efficiency; σ_i is standard deviation of operator *i* energy efficiency; nOc_i is number of cycles of operator *i*.

4.4. SUMMARY

Preliminary data analysis in this work included; investigating the structure of the data; removing the outliers; and identifying operators with sufficient working hours to be considered in further analysis. Cycles in which the bucket was not filled successfully in the first attempt were removed from the data since they did not represent normal loading operation. Mild outliers were removed to reduce the chance of drawing wrong inferences. Five operators with standard error of mean of energy efficiency less than 0.04 were used for further analysis.

Table 4-4 Standard error

Operator	# of cycles	Time (hours)	Mean energy efficiency	Standard deviation energy efficiency	Standard error
A	3,897	56.91	5.31	1.680	**0.027**
B	3,611	54.62	6.06	1.712	**0.028**
C	3,350	49.60	6.26	1.707	**0.029**
D	3,058	45.64	6.34	1.680	**0.030**
E	2,211	32.77	6.41	1.686	**0.035**
F	1,529	23.55	6.47	1.700	0.043
G	1,023	15.70	6.49	1.707	0.053
H	761	12.39	6.55	1.712	0.062
I	271	4.36	6.82	1.712	0.104
J	129	2.04	6.88	1.755	0.154
K	88	1.09	7.19	1.733	0.184
L	29	0.49	7.24	1.756	0.326
M	24	0.35	7.29	0.671	0.137

5. EFFECTS OF OPEARTOR PRACTICE ON DRAGLINE ENERGY EFFICIENCY

5.1. DRAGLINE ENERGY EFFICIENCY

For mines to reduce their energy consumption while increasing their productivity at the same time, they need to assess dragline operator performance measures that consider both energy consumption and productivity. For example, the operator performance indicator (OPI) presented by Komljenovic (2010) that specifically evaluates both dragline productivity and energy consumption is a good metric. This OPI was defined as the dragline production over dragline energy consumption in a given period of time (Eq. 5-1). The limitations of such a metric have been discussed in Section 2 of this thesis.

$$OPI(i) = \frac{P(i)}{E(i)} \tag{5-1}$$

In this study, dragline energy efficiency is introduced as an indicator of an operator's performance. Energy efficiency is the inverse of OPI; but is defined for each cycle (5-2).

$$\eta = \frac{P}{E_t} \tag{5-2}$$

For the data used in this study payload, energy consumption of swing, drag, and hoist motors were recorded by dragline monitoring system. The energy efficiency of the five operators under review was calculated for each cycle using Eq. 5-3. Table 5-1 shows the summary of operator performance during the data collection period.

$$\eta(i) = \frac{P(i)}{E_t(i)} = \frac{P(i)}{E_s(i) + E_d(i) + E_h(i)} \qquad 5\text{-}3$$

Where $\eta(i)$ is energy efficiency in cycle i; P(i) is payload in cycle i; $E_s(i)$ is swing energy in cycle i; $E_d(i)$ is drag energy in cycle i; $E_h(i)$ is hoist energy in cycle i.

Table 5-1 Summary of operators performance

Opr	No. of cycles	Time (h)	Material weight (tonnes)	Energy consumption (kw-h)	Production (tonnes/h)	Energy Efficiency (tonnes/ KWh)
A	3,897	56.91	496,177	44,850	8,719	11.063
B	3,611	54.62	450,217	43,894	8,243	10.257
C	3,350	49.60	427,226	39,827	8,613	10.727
D	3,058	45.64	383,552	36,879	8,404	10.400
E	2,211	32.77	277,554	23,395	8,469	11.864

To achieve the first objective of this research (to test the hypothesis that dragline operator's practices significantly affect dragline energy efficiency), statistical tests were used to compare the energy efficiency of different operators. In the following sections the methodology and the results of the approach when applied to the case study are described.

5.2. EVALUATING THE EFFECT OF OPERATOR PRACTICE ON DRAGLINE ENERGY EFFICIENCY

Any approach to study the effect of operator practice on dragline energy efficiency should be able to handle the high variability in the measured data on the performance metric (as can be seen from the preliminary data analysis of the case study data – Table 4-1). For example, a simple comparison of the means of the metric is invalid because it does not address whether the difference in the means of the metric for the operators is by chance (due to the sample) or is significant. To study the effect of operator practice on dragline energy efficiency, in this work, hypothesis tests were performed to test whether energy efficiency of different operators are significantly different. Analysis of Variance (ANOVA) and t-tests are commonly used to compare the means of different groups. It is important to choose a statistical test which is compatible with the nature of the data set. Each statistical test has specific assumptions and violating these assumptions can lead into misapplication of the test (Herberich, Sikorski, & Hothorn, 2010). Figure 5-1 shows the approach developed in this research.

Preliminary data analysis can help to better understand the data and check for the assumptions of the tests. In the case of comparing the means between groups, preliminary data analysis includes estimating summary statistics, testing for normality, and testing for equality of variances. The best statistical test is chosen based on the result of the preliminary data analysis. Rejecting the null hypothesis of the best test at a given significant level (α) shows that the means are not equal at significant level of α.

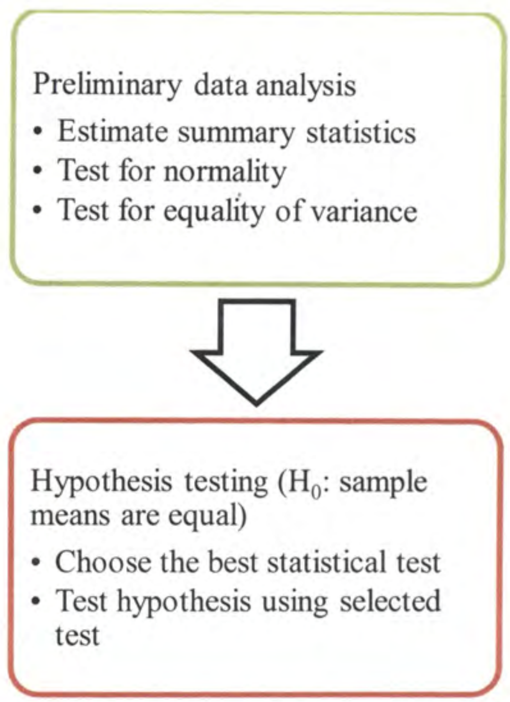

Figure 5-1 Process for evaluating operator effects on dragline energy efficiency

5.2.1. Preliminary Data Analysis. Both Analysis of Variance (ANOVA) and t-test require three assumptions. First, the observations should be independent. This assumption seems reasonable as we assume energy efficiency of one operator does not affect the energy efficiency of other operators.

Second, the observations should follow a normal distribution. Graphical methods and numerical methods can be used to test the normality of the data. In graphical methods plots, such as histograms, Q-Q plots, etc., can be used to compare an empirical distribution and a theoretical normal distribution. Numerical methods look at skewness and kurtosis of data and also the result of statistical tests of normality (such as goodness-of-fit tests) to check the normality of the data (Park, 2008). In this work both numerical methods and graphical methods were used to check the normality of energy efficiency of each operator.

Shapiro-Wilk (W) test (S. S. Shapiro & Wilk, 1965), Kolmogorov-Smirnov (KS) test, Anderson-Darling (AD) test (Anderson & Darling, 1952), and Cramer-vol Mises (CM) test (Anderson, 1961), are some of the common tests that are used to test the normality of a data. Shapiro-Wilk (W) test is the most powerful test; however, it is limited in the sample size. The sample size should be greater than or equal to 7 and less than or equal to 2,000 (S S Shapiro, Wilk, & Chen, 1968; Stephens, 1974) . In this case, even for short periods of observation, the sample sizes are likely to exceed the range of support of the Shapiro-Wilk test. KS, AD, and CM tests are recommended for the large data. These tests are based on the empirical cumulative distribution (Park, 2008; Schlotzhauer, 2009). When the KS test is rejected it can be concluded that the data does not follow normal distribution with the sample mean and sample variance; however it can be normal at other values of the mean and variance. AD and CM tests also share this weakness (Drezner, Turel, & Zerom, 2010; Stephens, 1974). Given the weakness of these statistical tests, it is helpful to consider the results of the both numerical methods and graphical methods when testing for the normality.

Third, the variances of the samples should be equal. Several statistical tests, including F-test, Bartlett's test and Levene's test, examine the differences in variation among two or more samples. The F-test and the related Bartlett's test are too sensitive to normality of data (Schultz, 1983). Levene's test, introduced by Levene (1960), was modified by Van Valen (1978) and suggested as an alternative to the F-test. This test is robust even when the data is not normally distributed (Levene, 1960; Van Valen, 1978). Hence, Levene's test was used to test for equality of variances in this research.

Figure 5-2 describes the suggested algorithm of choosing the statistical test compatible with the data set, when there are more than two operators to compare. In cases when there is just one pair of operators to compare, the different tests are recommended as in Figure 5-3.

5.2.2. Test for Equality of Means. Analysis of variance (ANOVA) and t-test are the two most common tests for comparing the means of different samples. ANOVA is a parametric analysis which tests the hypothesis of equality of means between two or more groups.

The null hypothesis is that the mean values of the groups are the same. The alternative hypothesis is that at least two groups have different means. T-test is used to compare the means of two groups. This test is easy to conduct but can cause a type 1 error[3] (Zhou, Gao, & Hui, 1997). Since the t-test is for pairwise comparison, when there are more than two operators in the data set multiple pairwise tests are necessary. At each run of the t-test, there is 5% chance of type 1 error. For *nOp* operators, the probability of Type 1 error is given by Eq. 5-4, where α is the significant level of the t-test. ANOVA test can replace t-test in cases when there are more than two operators to reduce the chance of type 1 error.

[3] Type 1 error is when a true null hypothesis is rejected (Sheskin, 2004)

$$\text{Chance of Type I error} = 1-(1-\alpha)^{\binom{n()p}{2}} \qquad \text{5-4}$$

It is probable for the energy efficiency data to violate the assumption of normality and equality of variances. One approach to handle the violation of the normality assumption is to transform the data (typically using a natural log transformation). Performing tests for comparing the means of different groups on log-transformed data can cause its own problems.

The null hypothesis based on the log-transformed outcomes is not equivalent to the null hypothesis based on the original outcomes, especially when the variances are not equal. Zhou et al. (1997) showed that if the variances of two groups are not equal the null hypothesis of t-test (equality of means) performed on log-transformed data is not equivalent to the original null hypothesis. Hence, it is possible to reject the equality of means in the original data even after not rejecting the null hypothesis of log-transformed data(Zhou et al., 1997). Therefore, data transformation should be used carefully, when the normality assumption cannot be justified for the dragline energy efficiency data.

Welch ANOVA and Welch t-test, in which the third assumption (equality of variances) is relaxed (Welch, 1947), can be used to address the problem caused by violating the third assumption. Welch's test is a practical, simple and accurate test. It is based on Student's distribution with degree of freedom depending on both sample size and sample variance. In some cases, Welch's test is recommended as a replacement of t-test even when the variances are equal (Krishnamoorthy, Lu, & Mathew, 2007; Rodgers & Nicewander, 1988).

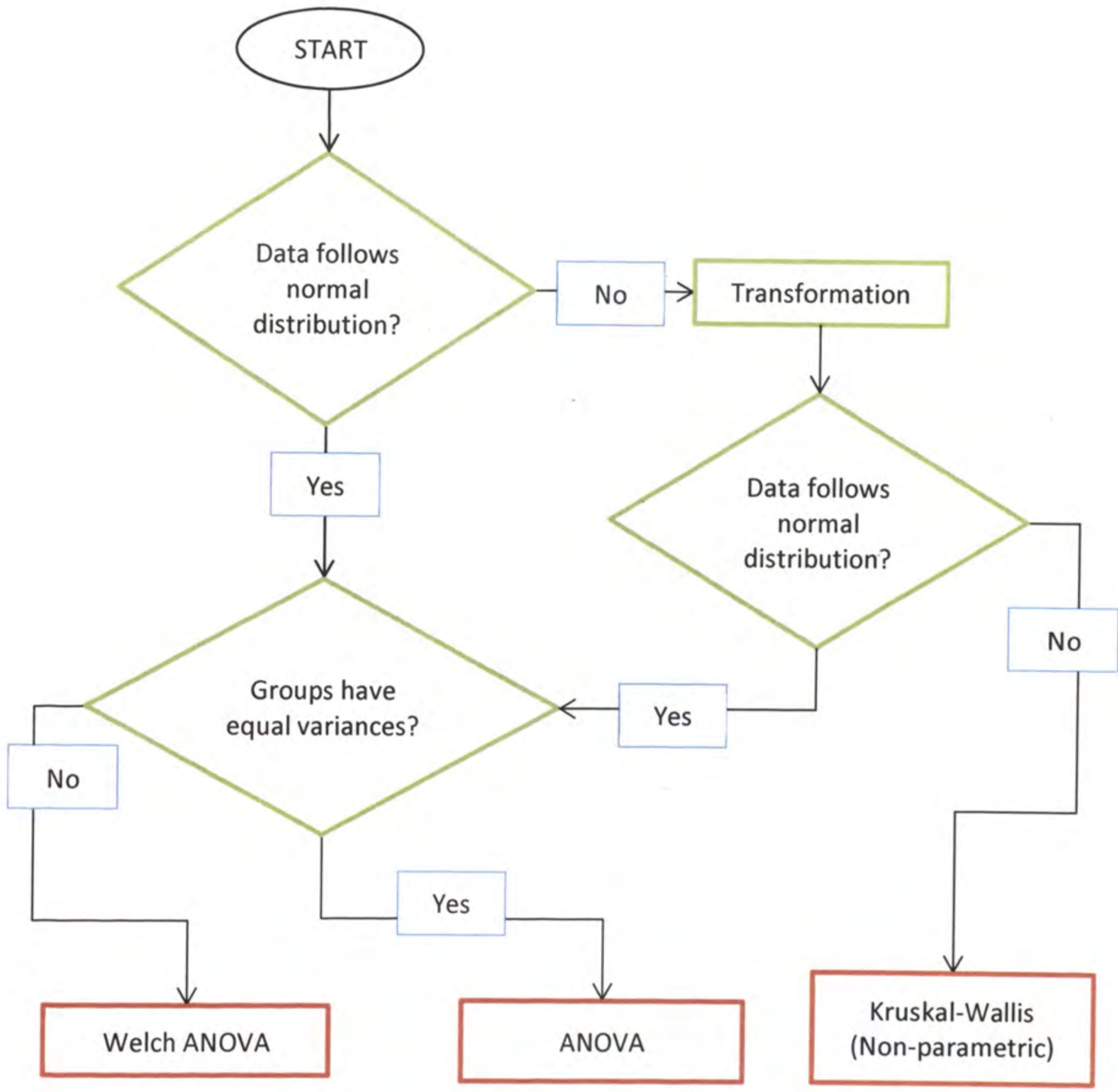

Figure 5-2 Algorithm of choosing an appropriate test of comparing the means (more than two groups)

To reduce the chance of misusing statistical tests, non-parametric tests can be used alongside of parametric tests. Non-parametric tests have fewer assumptions in comparison to parametric tests; however they are less powerful in detecting differences (Schlotzhauer, 2009). The Kruskal-Wallis test, which is a non-parametric equivalent test for ANOVA (Wilcoxon-Mann-Whitney a replacement for t-test), can be used instead of

ANOVA (t-test) (Cody, 2011). The null hypothesis of this test is that all groups (more than two groups) have identical cumulative distribution function and the alternative hypothesis is that at least two of the groups differ only with respect to location (median). In this test the assumption of normality is relaxed. When performed on log-transformed data the results may be invalid when the data is extremely skewed (McElduff, Cortina-Borja, Chan, & Wade, 2010).

To sum up, it is critical to check the assumptions of statistical tests prior to using them. T-test and ANOVA are two common tests for comparing the means between two or more than two groups, respectively. Data should follow a normal distribution for valid results of ANOVA and t-test. Numerical and graphical methods can test the normality of data. Non-parametric tests such as Kruskal-Wallis and Wilcoxon-Mann-Whitney can replace ANOVA and t-test when the data is not normal. Equal variance between groups is another assumption of ANOVA and t-test. Welch ANOVA and Welch t-tests are not sensitive to equality of variances and can be used as replacement for ANOVA and t-test when the assumption of homogeneity (equality of variances) is violated. The result of valid statistical tests can be used to investigate the effect of operator practice on dragline energy efficiency.

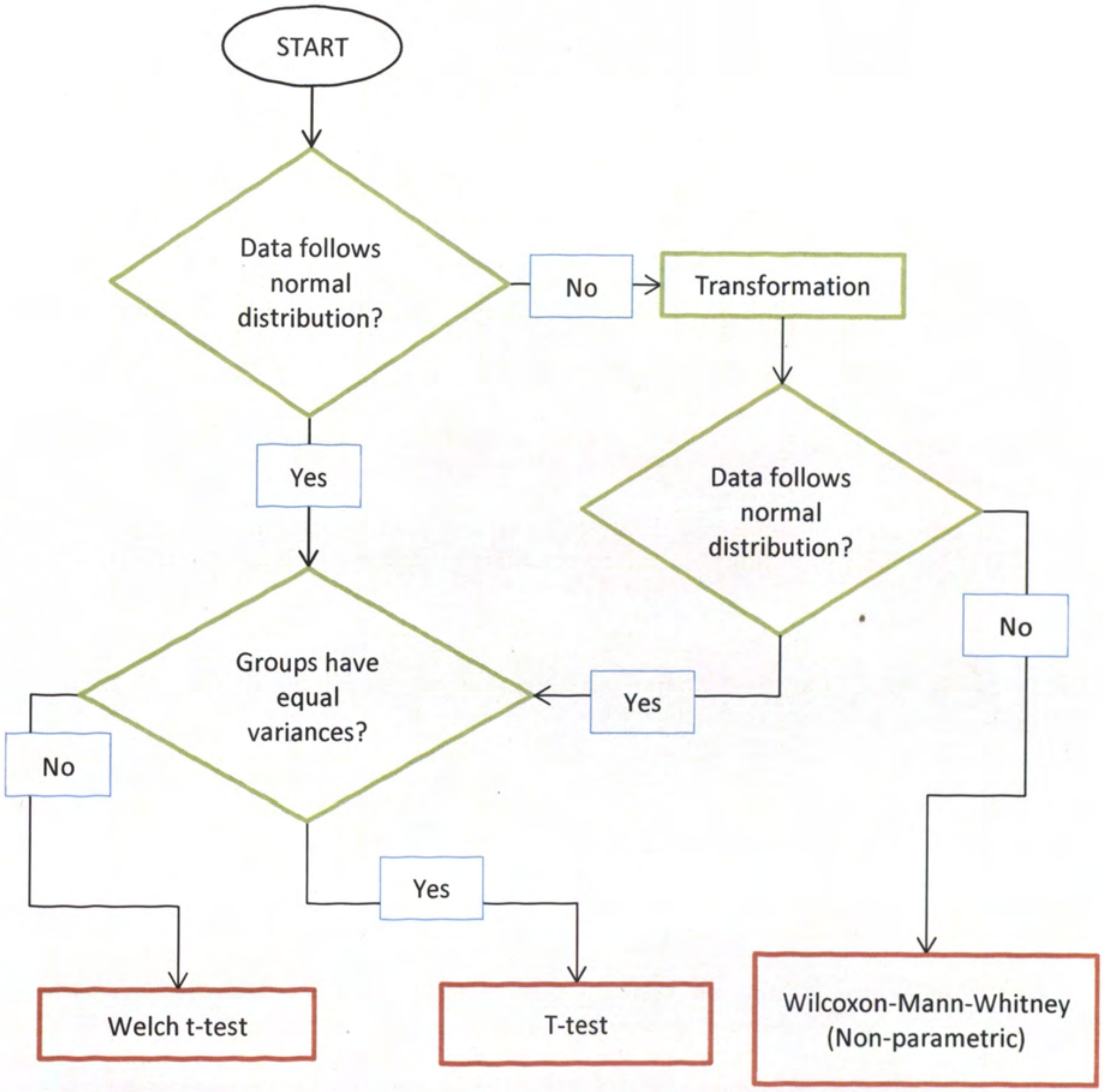

Figure 5-3 Algorithm of choosing an appropriate test of comparing the means (two groups)

5.3. CASE STUDY

5.3.1. Preliminary Data Analysis. Summarizing data from five operators can provide a better understanding of the data and help to choose an appropriate test to compare energy efficiency of operators. Descriptive statistics for energy efficiency of each operator can be found in Table 5-2.

Table 5-2 Descriptive statistics of energy efficiency of operators

Statistical measures	Opr A	Opr B	Opr C	Opr D	Opr E
N	3985	4550	4253	3427	2649
Mean	11.23	10.37	11.14	10.60	11.91
Median	10.78	9.96	10.64	10.17	11.60
Standard deviation	2.80	2.62	2.74	2.71	2.98
Skewness	0.49	0.72	0.69	0.98	0.33
Variation	7.84	6.83	7.55	7.32	8.90
Kurtosis	-0.46	0.37	0.13	1.21	-0.37
Coefficient of correlation	24.9%	25.2%	24.7%	25.5%	25.0%

SAS® 9.3 was used to perform these tests on the data and the results can be found in Table 5-3 .The results of the tests show that the null hypothesis in all tests (data follows normal distribution) is rejected and energy efficiency of none of the operators follows normal distribution (all p-values are less than 0.005). Given the weakness of these statistical tests it is important to also use graphical methods to gain a better understanding of the nature of the data. Histogram plots in **Error! Reference source not found.** show right skewness in the data. The positive values of skewness in Table 5-2 also confirm this conclusion.

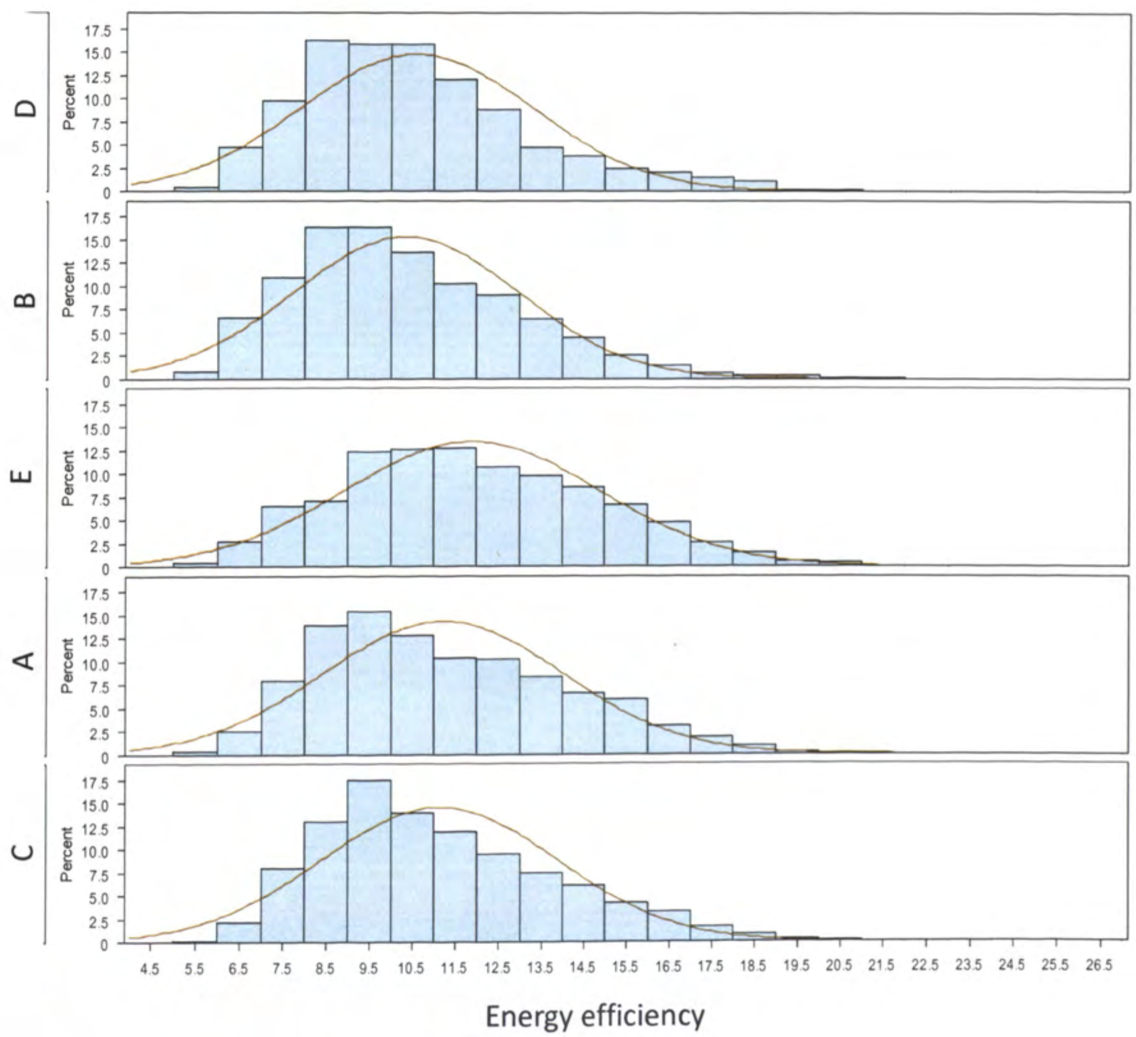

Figure 5-4 Histograms of energy efficiency of different operators

Log-transformation is commonly used to reduce the skewness of the data (Zhou et al., 1997). Statistical test were performed on the log transformed data and the Table 5-3 shows the results of these tests. Again the results show that the log-transformed data is not following the normal distribution. Because of the deficiencies of statistical tests graphical methods were also used to study the effects of log-transformation. Figure 5-5 shows the histograms of log-transformed data and it can be concluded from the histograms that the data is closer to normal distribution after log-transformation.

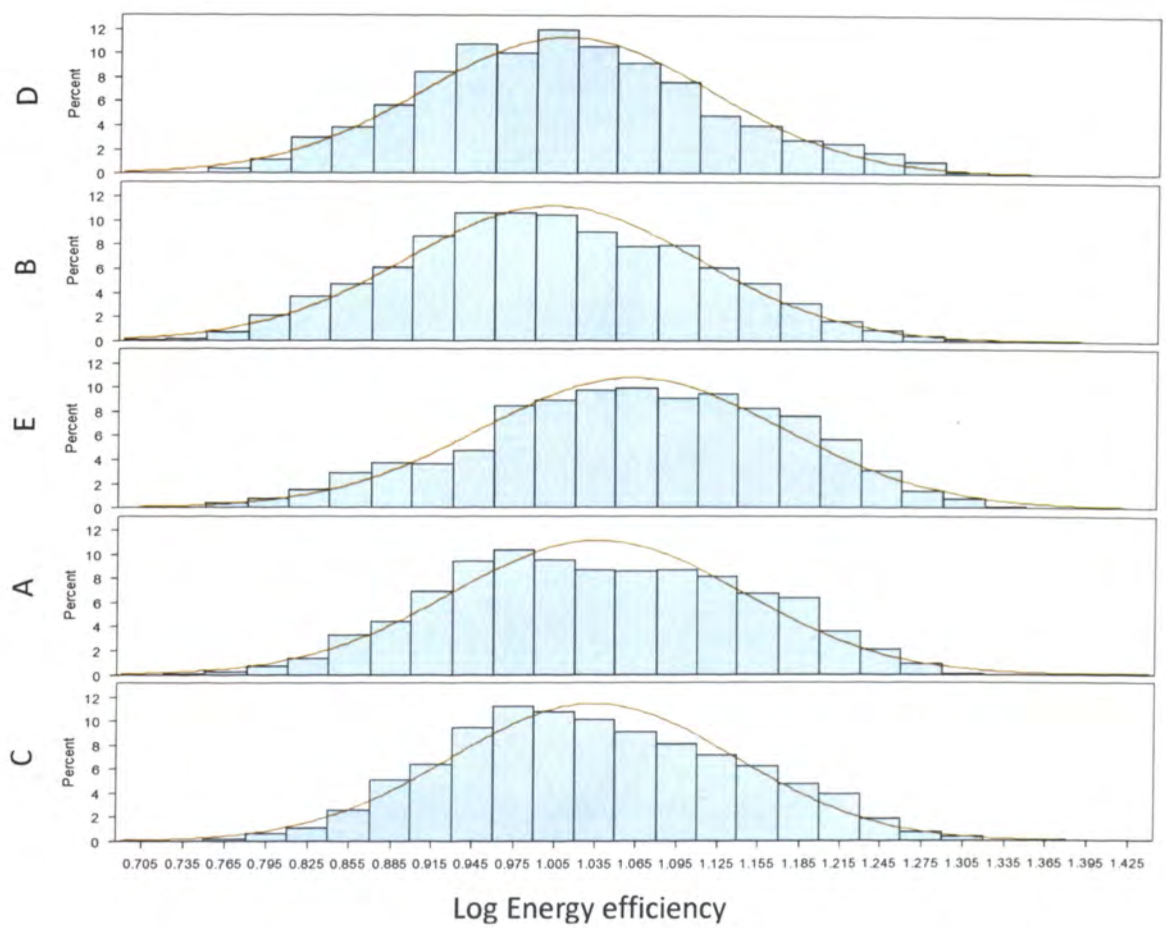

Figure 5-5 Histograms of log-transformed energy efficiency of different operators

Table 5-3 Results of the statistical tests on original data and log-transfomed data

Energy efficiency	Opr A		Opr B		Opr C		Opr D		Opr E	
	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value
Kolmogorov-Smirnov (D)	0.07166	<0.010	0.06621	<0.010	0.07527	<0.010	0.07718	<0.010	0.0426	<0.010
Cramer-von Mises (W^2)	6.02058	<0.005	6.34709	<0.005	7.68707	<0.005	7.18008	<0.005	1.2886	<0.005
Anderson-Darling (A^2)	35.9658	<0.005	37.9851	<0.005	45.2889	<0.005	45.5553	<0.005	7.7490	<0.005

Log-energy efficiency	Opr A		Opr B		Opr C		Opr D		Opr E	
	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value
Kolmogorov-Smirnov (D)	0.04082	<0.010	0.02514	<0.010	0.03724	<0.010	0.02766	<0.010	0.03113	<0.010
Cramer-von Mises (W^2)	1.97118	<0.005	0.75778	<0.005	1.56015	<0.005	0.79087	<0.005	0.66522	<0.005
Anderson-Darling (A^2)	11.7729	<0.005	4.53897	<0.005	9.07657	<0.005	5.66382	<0.005	5.03061	<0.005

Quantile-quantile plots (Q-Q) were also used to study the effect of log-transformation of the data. These plots compare ordered value of a variable with quantiles of a normal distribution. The closer the data is to the normal distribution, the closer the points will be to the linear pattern passing through the origin with the unit origin (Johnson & Wichern, 2007). Figure 5-6 displays these Q-Q plots of the original data. Q-Q plots of the log-transformed data can be found in Figure 5-7 . The Comparison between the Q-Q plots and also histograms indicates that log-transformation helped the data to get closer to normal distribution.

The results of the statistical tests show that neither the original data nor the log-transformed data follows normal distribution. These statistical tests cannot always be trusted. Graphical methods were utilized to confirm the results of the statistical tests. Histograms and Q-Q plots indicate that the assumption of log-transformed data following normal distribution may be valid.

SAS® 9.3 was used to perform Levene's test to examine the equality of variances between log-transformed data from different operators. The p-value of 0.0008 was calculated. It can be concluded that at significance level of 0.05 the null hypothesis of equal variances was rejected. The result of the Levene's test showed that the third assumption will be violated with the given data set. Performing the Levene's test on the original data also indicated that the variances between energy efficiency of operators are significantly different (p-value was less than 0.0001).

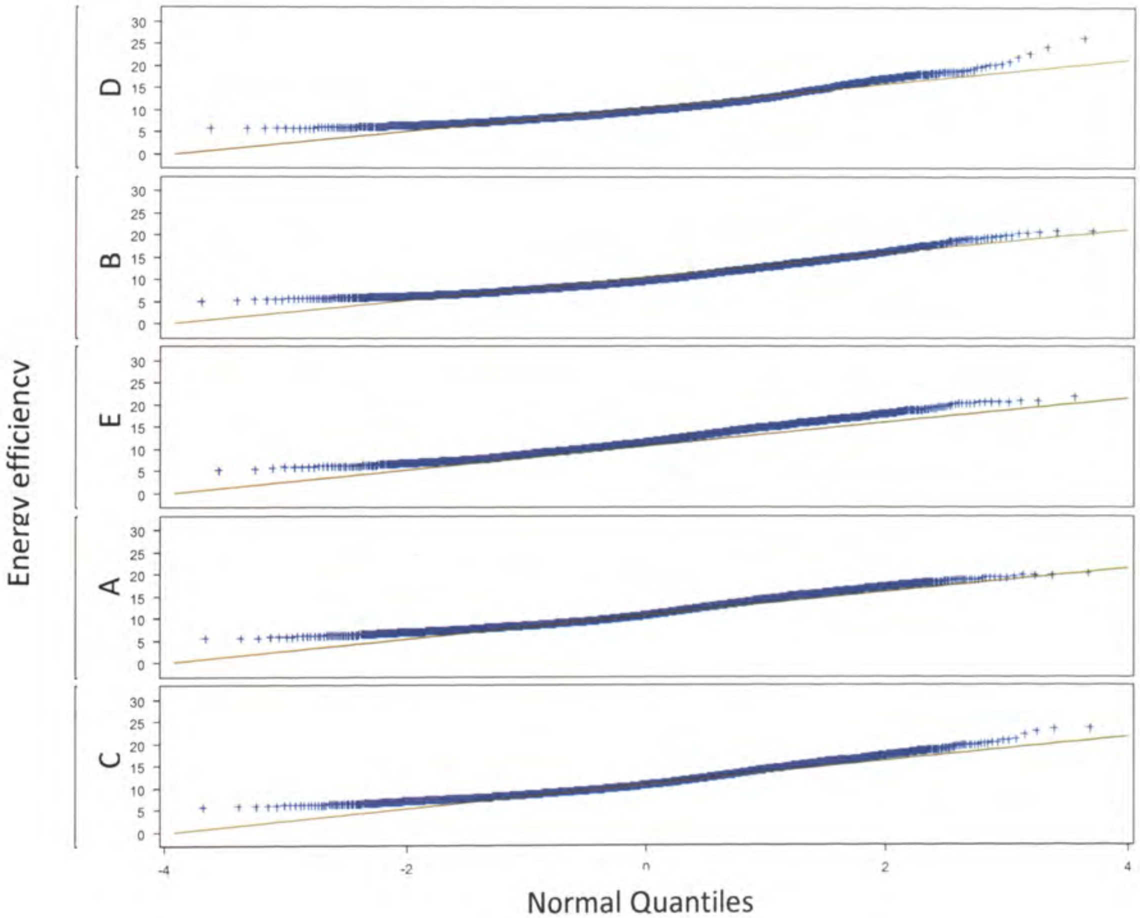

Figure 5-6 Q-Q plot of energy efficiency

5.3.1. Test for Equality of Means. The results of the Welch ANOVA test at significance level of 0.05 showed that energy efficiency is significantly different between operators (p-values <0.0001). Kruskal-Wallis also confirmed the results of Welch ANOVA test and indicated that energy efficiency of operators is significantly different between operators (Table 5-4).

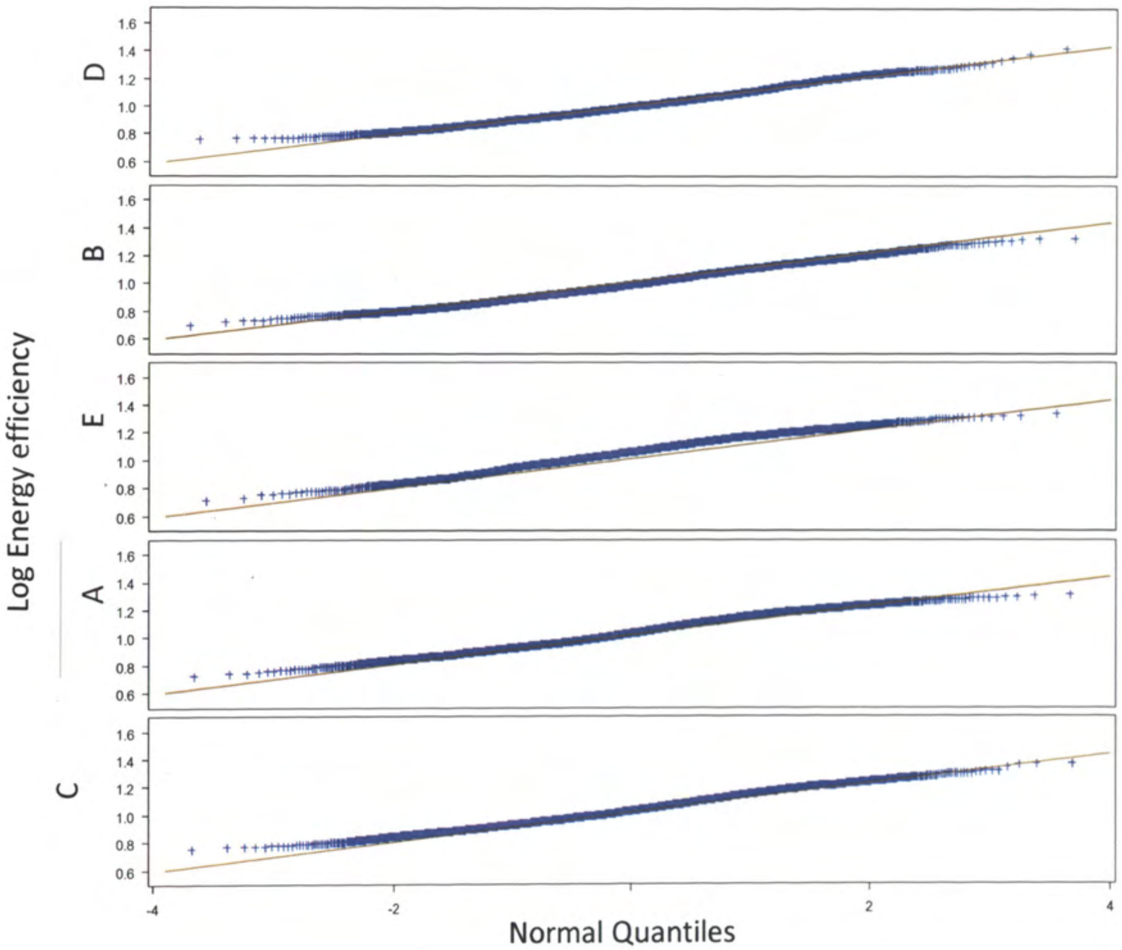

Figure 5-7 Q-Q plot of log-transformed data

Table 5-4 Result of the statistical test

Test	Degree of freedom	Statistics	P-value
Welch-ANOVA	4	F value 154.63	<0.0001
Kruskal-Wallis test	4	Chi-square 614.38	<0.0001

In this study there were five operators for comparison. Considering that t-test can handle a pair-wise comparison at each run, 10 runs were needed to compare all the operators. Therefore the chance of committing type 1 error was 40%. It was concluded that the results of the t-test cannot be trusted because of the high risk of committing type 1 error and also the fact that the assumption of homogeneity (equality of variances) between energy efficiency of operators (original and log-transformed data) was violated. The final conclusion was drawn based on the result of the Welch ANOVA and Kruskal-Wallis test which indicates that the energy efficiency is significantly different between different operators (at significance level of 0.05) (Table 5-4).

5.4. SUMMARY

This research proposes a two stage process to evaluate the effect of operators on dragline energy efficiency, given a dataset. The first stage involves evaluating the validity of three basic assumptions – independence, normality, and equality of variances. It is assumed that energy efficiency data for dragline cycles are independent since the energy efficiency of cycles by one operator does not depend on another operator. Graphical and numerical tests are suggested for testing whether the energy efficiency data, for each operator, is normal or not. Levene's test is suggested for testing for equality of variances due to low sensitivity to the normality of the data set. The second stage of the suggested process involves tests for equality of means. Depending on the number of pairs of operators to be compared, this work recommends two different processes for determining the appropriate tests. Both parametric and non-parametric tests are considered, based on the stage one analysis (test for independence, normality, and equality of variances). The goal is to draw the right inference about the effect of operators on energy efficiency, given the data properties and to reduce type 1 errors. The process is illustrated with a case study using the field data in this research.

Five operators operated with sufficient working hours during the data collection exercise. Due to the high chance of type 1 error, t-test was not used. The results of the numerical and graphical analysis showed that the assumption of log-transformed data following normal distribution was valid. Levene's test rejected the hypothesis of equality of variances. Therefore, Welch ANOVA was used to compare the means of energy efficiency between five operators. The null hypothesis of Welch's test was rejected at significant level of 0.05. The result of Kruskal-Wallis test confirmed the result of the Welch's test (Table 5-4). It can be concluded form the results of the statistical tests that energy efficiency is significantly (significant level of 0.05) different between the five operators.

6. IDENTIFYING PARAMETERS THAT CAUSE DIFFERENCES BETWEEN ENERGY EFFICIENCY OF OPERATORS

6.1. INTRODUCTION

The results of Section 5 indicate that operator practices significantly affect dragline energy efficiency. This section addresses the second objective of this study by proposing a method to identify key parameters that lead to differences in operator energy efficiency (responsible parameters). In this method, first, correlation analysis is used to detect the parameters in the dataset that are correlated with energy efficiency. It is assumed that this relationship is linear and Pearson correlation analysis is suggested as a tool to measure the linear dependence between parameters and energy efficiency. Difference matrices are then built for each pair of operators. Linear regression is then used to determine the responsible parameters. This method is then illustrated with the case study data. Figure 6-1 shows the flow chart of the proposed method.

6.2. CORRELATION ANALYSIS

Correlation analysis can be used to detect the parameters that affect dragline energy efficiency. Correlation is a statistical tool to measure the dependence and relationship between two random variables. Pearson correlation analysis is the most popular method of measuring the linear relation between two variables (Rodgers & Nicewander, 1988). Pearson correlation can be defined as Eq. 6-1.

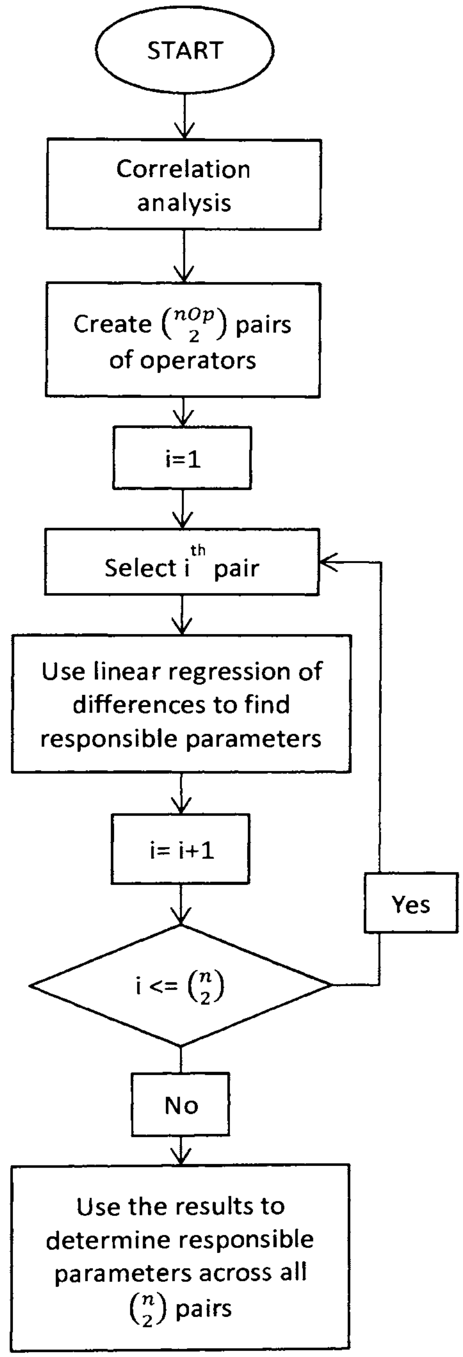

Figure 6-1 Flow chart of the main algorithm

$$\rho_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \times \sigma_Y} \tag{6-1}$$

The Pearson correlation coefficient can take a value between -1 and 1. Value of 1 indicates a perfect positive linear relationship and value of -1 indicates a perfect decreasing linear relationship. When the variables are independent then $\rho = 0$. The parameters that are correlated with energy efficiency can be identified (correlated parameters) based on the value of ρ and the desired confidence level. The p-value of the null hypothesis (H_0: $\rho = 0$) can be estimated using the Student's t-distribution (Gibbons & Chakraborti, 2010). This allows one to make the inference, at a particular confidence level, whether to accept or reject the null hypothesis of no correlation between the two random variables under consideration.

6.3. IDENTIFYING RESPONSIBLE PARAMETERS

The proposed method is based on pair-wise comparison of operators. Assuming *nOp* operators, there are $\binom{nOp}{2}$ pairs of operators. The data from these pairs are then used to create the difference matrix. Equal number of cycles for two operators is required in order to build the difference matrix for operator *i* and operator *j*. In reality, because of high variability in cycle time, the chance of getting equal number of cycles for two operators even in equal working hours is very low. This results in a situation where there is "missing data", an issue common in many scientific and engineering research (Schafer & Graham, 2002). Assuming that the number of cycles for operator i is greater than number cycles for operator j (ci > cj) the pattern of the data set and the missingness can be displayed as Table 6-1.

Table 6-1 Pattern of the data set

	Opr i	Opr j
Cycle 1	X_{i1}	X_{j1}
Cycle 2	X_{i2}	X_{j2}
	.	.
	.	.
	.	.
Cycle cj	$X_{i\,cj}$	$X_{j\,cj}$
.	.	
Cycle k	$X_{i\,k}$	
.	.	
Cycle ci	$X_{i\,ci}$	

When the response mechanism is missing at random (MAR) then the probability of X_{jk} missing for cycle k (probability of missingness) may depend on the observed data but not on the missing data. A special case of MAR is missing completely at random (MCAR), which describes a data set where the probability of missingness does not depend on the observed data either (Schafer & Graham, 2002). There are different approaches to handle missing data such as complete case analysis (CCA), multiple imputation (MI), and maximum likelihood (ML). MI and ML are modern missing data analysis methods. These methods estimate the value of missing data based on the values of available data. For large data sets, such as the ones in this research, these methods are computationally expensive and become ineffective (Graham, 2009).

In CCA, a case (in this work, cycle with all the recorded parameters) will be deleted if any of the parameters in that case are missing. CCA assumes that the missingness in the data is completely at random. Violating this assumption can result in incorrect inferences. CCA is a robust method and the parameters estimated are unbiased when the data is MCAR (Schafer & Graham, 2002; Truxillo, 2002). Little (1992) proved that estimates are still unbiased in this method if observations are MAR (Little, 1992). One disadvantage of CCA is the inefficiency of this approach due to the loss of information. Considering the large number of dragline cycles (samples) even for a short period of operation this flaw of CCA seems irrelevant to this work.

Considering the nature of the data (the missing cycles and the probability that those cycles are not captured do not depend on the observed or unobserved cycles), it is assumed that response mechanism is missing at random (MAR) and CCA is suggested to handle the incompleteness of data. To have equal number of cycles for operator i and operator j, ci – cj cycles need to be removed from operator i's data. With the assumption of MAR, ci – cj cycles are selected at random for deletion. The difference matrix can then be created using the *treated* data. Table 6-2 shows the difference matrix of operator i and operator j. This matrix is calculated by finding differences between energy efficiency ($\Delta\eta$) and correlated parameters in each cycle.

Linear regression analysis is used to fit a linear model to the difference matrix where $\Delta\eta$ is the dependent variable vector and Δpar matrix contains the independent variable (predictor variable) matrix. The significance of coefficient test with desired confidence level identifies parameters with the significant values of coefficients. These parameters are designated as parameters that are responsible for the differences in energy efficiency of operator *i* and operator *j* (responsible parameters).

Table 6-2 Difference matrix of operator i and j

$$
\begin{array}{l|c}
 & \Delta\eta \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad \Delta par \\
\begin{array}{l} \text{cycle 1} \\ \text{cycle 2} \\ \cdot \\ \cdot \\ \cdot \\ \text{cycle c} \end{array} &
\left[\begin{array}{c|ccccc}
\eta_{i1}-\eta_{j1} & par_{i11}-par_{j11} & par_{i12}-par_{j12} & \cdot & \cdot & par_{i1v}-par_{j1v} \\
\eta_{i2}-\eta_{j2} & par_{i21}-par_{j21} & par_{i22}-par_{j22} & \cdot & \cdot & par_{i2v}-par_{j2v} \\
\cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
\eta_{ic}-\eta_{jc} & par_{ic1}-par_{jc1} & par_{ic2}-par_{jc2} & \cdot & \cdot & par_{icv}-par_{jcv}
\end{array}\right]
\end{array}
$$

The output of the coefficient test is saved as a binary variable; the output is 1 if the coefficient is significant (the parameter is a responsible) and 0 if the coefficient is not significant (the parameter is not responsible). Table 6-3 shows the output of a coefficient test for one pair of operators.

Table 6-3 Output of coefficient test for one pair

$$
\begin{array}{ccccc}
\text{Par 1} & \text{Par 2} & . \;\; . \;\; . & \text{Par v} \\
\end{array}
$$
$$
\left[\begin{array}{ccccc}
0/1 & 0/1 & . \;\; . \;\; . & 0/1
\end{array}\right]
$$

To draw a correct conclusion it is critical to consider the effect of randomly selecting equal number of cycles from operators when building difference matrix. To reduce the effect of random sampling error, the process of selecting (ci-cj) cycles from operator i for deletion and regression analysis is repeated k times. A parameter is a responsible parameter, if in (1-α) % (at confidence level of α) of runs it is recognized as a responsible parameter (Table 6-4).

The algorithm of using linear regression of differences to find responsible parameters can be found in Figure 6-2. In the main algorithm, the process of determining responsible parameters using linear regression is repeated for each pair of operators (Figure 6-1). From the result of the $\binom{n}{2}$ pair-wise comparisons the probability for a parameter to be a responsible parameter (at confidence level of α) can be determined. The case study is used to illustrate the suggested approach in the next section.

Table 6-4 Output of coefficient test and final conclusion of k runs (one pair)

	Par 1	Par 2	. . .	Par v
Run 1	0/1	0/1	. . .	0/1
Run 2	0/1	0/1	. . .	0/1
.	.	.		.
.	.	.		.
.	.	.		.
Run k	0/1	0/1	. . .	0/1
Final conclusion	0/1 at confidence level of α	0/1 at confidence level of α	. . .	0/1 at confidence level of α

An example can help one to better understand the process of selecting equal number of cycles and testing for being a responsible parameter. Let us say the purpose of an experiment is to test whether the duration of warm up for a baseball player (a parameter) is a contributor to differences in their batting average (energy efficiency). In order to detect this relationship, k games of two players can be selected at random for observation and to test the relationship. If in more than $(1-\alpha)$ % (at confidence level of α) times the duration of warm up was a contributor to differences in the batting average then it can be concluded that duration of warm up is a contributor, otherwise it is not a contributor. The probability for duration of warm up to be a contributor can be calculated by repeating this process for other pairs of players and counting the number of pairs in which duration of warm up is recognized as a contributor. The case study is used to illustrate the suggested approach in the next section.

6.4. CASE STUDY

To illustrate the suggested method the given data was used. The Accuweigh™ monitoring system recorded 44 parameters for each cycle during the one month period of data collection. Fourteen parameters were extracted from the data base as relevant parameters for this work (see Section 4). MATLAB was used to perform Pearson correlation analysis to detect the parameters correlated with dragline energy efficiency.

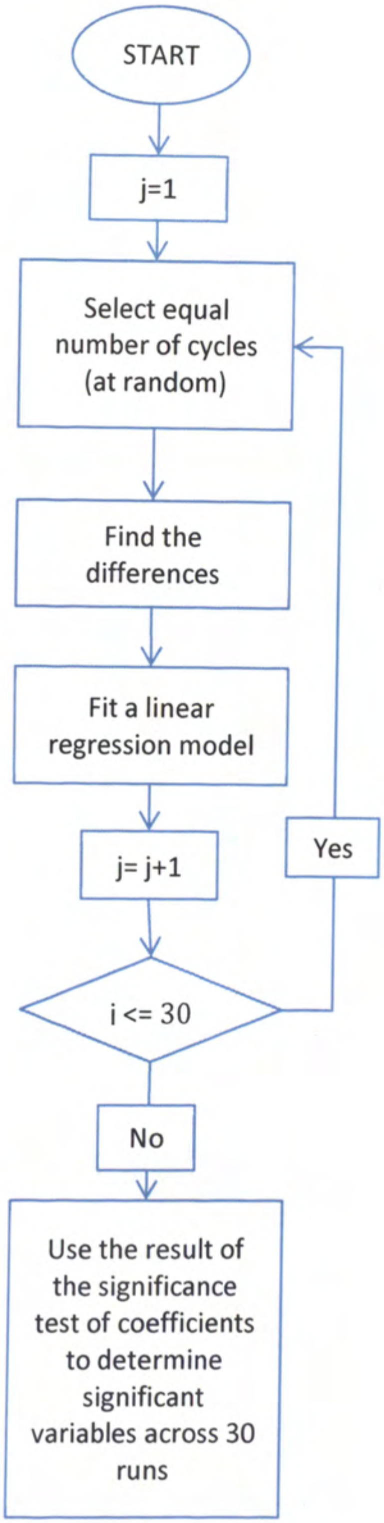

Figure 6-2 Algorithm of using linear regression of differences to find significant parameters

Table 6-5 shows the result of the Pearson correlation. The p-value indicates the result of testing the hypothesis of no correlation against the alternative hypothesis that there exists a non-zero correlation. At the significance level of 0.05 all tests were rejected except for swing out time. It can be concluded that all the parameters except swing out time are correlated with energy efficiency.

Table 6-5 Pearson correlation result

#	Parameter	rho	P-value
1	Dump height	-0.6560	<0.001
2	Hoist energy	-0.5857	<0.001
3	Drag distance (vertical)	-0.5089	<0.001
4	Drag energy	-0.4569	<0.001
5	Drag distance (horizontal)	-0.4807	<0.001
6	Load bucket time	-0.4548	<0.001
7	Dump time	-0.3050	<0.001
8	Cycle time	-0.3755	<0.001
9	Swing energy	-0.2724	<0.001
10	Swing in time	-0.3362	<0.001
11	Spot time	-0.1725	<0.001
12	Angle swing out	-0.1556	<0.001
13	Swing out time	0.0123	0.0913
14	Payload	0.2429	<0.001

Based on the result of the Pearson correlation, the linear model of energy efficiency difference ($\Delta\eta$) can be written as Eq.6-2. This model is a model of the relative performance of the two operators. Drag, hoist, and swing energy consumption were not included in the regression analysis, as energy efficiency is a representation of total energy consumption and it is not necessary to include these parameters in the model.

$$\begin{aligned}\Delta\eta = k_0 + k_1 \times \Delta D_h + k_2 \times \Delta DD_v + k_3 \times \Delta DD_h + k_4 \times \Delta lb_t + \\ k_5 \times \Delta D_t + k_6 \times \Delta C_t + k_7 \times \Delta Si_t + k_8 \times \Delta S_t + k_9 \times \Delta\theta_o + k_{10} \times \Delta P\end{aligned} \qquad \text{6-2}$$

Where D_h is dump height; DDv is drag distance (vertical); DD_h is drag distance (horizontal); lb_t is load bucket time; D_t is dump time; C_t is cycle time; Si_t is swing in time; S_t is Spot time; θ_o is angle swing out; and P is payload.

Equal numbers of samples were selected at random for each pair of operators to build the difference matrices (30 matrices per pair) of the pair. Linear regression was used to fit Eq. 6-2 to the difference matrix data. The dependent variable is the difference between energy efficiency and the differences between correlated parameters (10 parameters) were the independent variables. Testing for significance of coefficient was carried out at 95% confidence level.

The process of linear regression analysis is repeated 30 times for each pair to reduce the effect of random sampling. The result of the 30 runs for each pair can be found in Table 6-6. Numbers in this table show the number of times in 30 runs that a parameter in a pair-wise comparison is recognized as a parameter with significant coefficient or a responsible parameter (i.e. the coefficient was non-zero at 95% confidence).

Table 6-6 Results of the 30 times run of regression analysis. Numbers indicate the number of times that a parameter is recognized as a parameter with significant coefficient (responsible parameter)

	Correlated parameters	D,B	D,E	D,A	D,C	B,E
1	Dump height	30	30	30	30	30
2	Drag distance (vertical)	30	30	30	30	30
3	Drag distance (horizontal)	30	30	30	30	30
4	Load bucket time	4	30	26	30	0
5	Dump time	30	30	8	30	30
6	Cycle time	3	16	6	2	2
7	Swing in time	3	16	28	10	16
8	Spot time	30	30	30	30	30
9	Angle swing out	14	30	4	8	18
10	Payload	14	3	15	12	2
		B,A	B,C	E,A	E,C	A,C
1	Dump height	30	30	30	30	30
2	Drag distance (vertical)	30	30	30	30	30
3	Drag distance (horizontal)	30	30	30	30	30
4	Load bucket time	8	20	5	22	30
5	Dump time	8	30	30	30	30
6	Cycle time	26	0	10	5	27
7	Swing in time	29	30	3	6	7
8	Spot time	30	30	21	30	30
9	Angle swing out	30	30	22	30	2
10	Payload	13	1	6	8	30

A parameter is recognized as a responsible parameter in each pair-wise comparison if the number of having significant coefficient in 30 runs is more than 28 (confidence level of 95%). Table 6-7 and Figure 6-3 show the results using the cut-off value of 28. The value of 1 is assigned to responsible parameters in each pair. The probability column in Table 6-7and Figure 6-3 shows the estimated probability that a parameter is a responsible parameter. Dump height, drag distance (vertical), and drag distance (horizontal) have a 100% probability. It can be concluded that there is more than 95% chance of these parameters being responsible for differences in energy efficiency for all 10 pairs of operators in the given dataset.

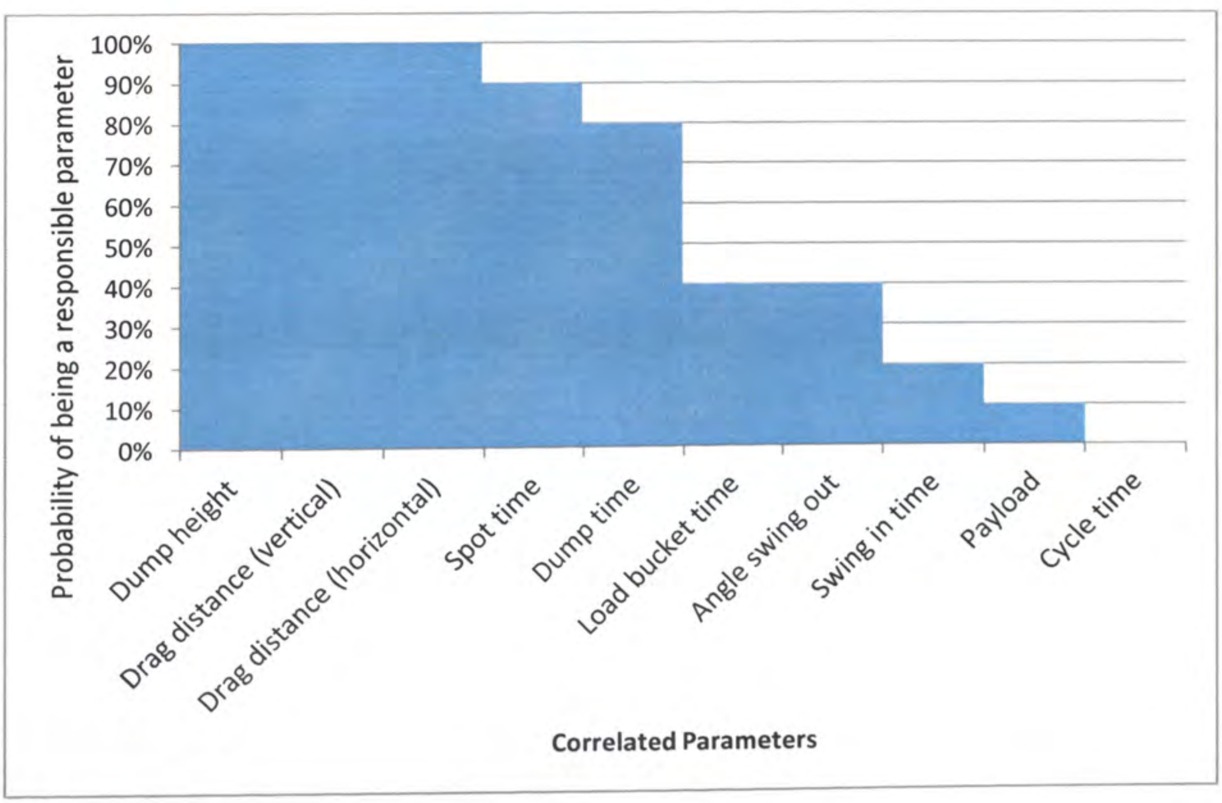

Figure 6-3 Estimated probability for correlated parameters to be responsible parameter

It can be concluded from Figure 6-3 and Table 6-7 that there is a high chance for dump height, drag distance (v), drag distance (h), spot time, and dump time to be a responsible parameter. On the other hand, for parameters such as cycle time, payload and, swing in time the probability of being a responsible parameter is relatively low.

Previous studies (Bogunovic & Kecojevic, 2011; Bogunovic, 2008; Erdem & Düzgün, 2005; Hettinger & Lumley, 1999; G. Lumley, 2005; Rai et al., 2000; Rai, 2004; Torrance & Baldwin, 1990; Williams, 2005) have shown that payload, cycle time, digging time and digging energy, fill factor, engagement and disengaeegement position affect dragline productivity and energy consumption and, consequently, energy efficiency. Also, Bogunovic and colleagues (Bogunovic & Kecojevic, 2011; Bogunovic, 2008) show that digging time (or loading bucket time in this work) was introduced as the most important component of dragline cycle. The case study confirms these parameters as important explanatory variables of dragline energy efficiency (Table 6-5). Dumping height is shown to be highly correlated to energy efficiency ($\rho = -0.6560$, $p < 0.001$). This has never been shown with experimental data, to the best of this author's knowledge. It must be noted, however, that the fact that these parameters are correlated to energy efficiency does not necessarily mean they are responsible for differences in operator performance. Any of the parameters, that energy efficiency is sensitive to, can cause differences in energy efficiency, if it varies significantly between operators.

Table 6-7 Final result based on assigning 0 and 1

	D,B	D,E	D,A	D,C	B,E	B,A	B,C	E,A	E,C	A,C	total	probability
Dump height	1	1	1	1	1	1	1	1	1	1	10	100%
Drag distance (vertical)	1	1	1	1	1	1	1	1	1	1	10	100%
Drag distance (horizontal)	1	1	1	1	1	1	1	1	1	1	10	100%
Spot time	1	1	1	1	1	1	1	0	1	1	9	90%
Dump time	1	1	0	1	1	0	1	1	1	1	8	80%
Load bucket time	0	1	1	1	0	0	0	0	0	1	4	40%
Angle swing out	0	1	0	0	0	1	1	0	1	0	4	40%
Swing in time	0	0	1	0	0	0	1	0	0	0	2	20%
Payload	0	0	0	0	0	0	0	0	0	1	1	10%
Cycle time	0	0	0	0	0	0	0	0	0	0	0	0%

In this case study, dumping height, vertical and horizontal drag distance, and spotting and dump time are shown to be the primary parameters driving differences in energy efficiency. Surprisingly, digging time, which has been identified by many researchers as a key discriminator between operators (Bogunovic & Kecojevic, 2011; Erdem & Düzgün, 2005; Rai et al., 2000; Torrance & Baldwin, 1990; Williams, 2005), was not found to be a significant factor between the five operators included in this study. The result of this work shows that there is only a 40% probability that energy efficiency of cycles from these operators is significantly different because of differences in digging time. This probability is less than other cycle time components such as spotting and dumping time. This shows that operator performance evaluation, which is based solely on digging time or other parameters of the digging cycle (e.g. digging energy) (Bogunovic, 2008; Komljenovic et al., 2010) can be misleading. On the other hand, drag distance (vertical and horizontal) has a high chance of being a responsible parameter. This confirms the point that engagement and disengagement parameters are important parameters and affect dragline performance (Hettinger & Lumley, 1999).

Payload and cycle time have been shown to affect productivity (Bogunovic, 2008; Erdem & Düzgün, 2005; G. Lumley, 2005; Williams, 2005). In the case study data set, the correlation coefficients between energy efficiency and payload and cycle time are low (0.2429 and -0.3755, respectively). However the results in Table 6-7 show that among the five operators payload and cycle time have a low chance of being a responsible parameter and are not likely to cause differences in energy efficiency. It can be concluded that, given a particular group of operators, not all parameters that are correlated with energy efficiency are necessarily correlated to the difference of energy efficiency between operators. That is, not all correlated parameters are the source of differences between energy efficiency of operators. Hence, the methods proposed in this work are necessary to find out which parameters are actually responsible for the differences in performance, so that operator training can focus on these responsible parameters.

As discussed in Section 2, it is important to consider both productivity and energy consumption in assessing dragline performance. Displaying energy efficiency, which captures both production and energy consumption, in real-time on the screens in the cabin can help operators to improve their performance. Identifying the parameters that affect energy efficiency can be used as a guideline to improve the performance through operator training and peer coaching.

6.5. SUMMARY

Identifying parameters that are responsible for the differences between energy efficiency of operators can be used in operator training programs along with the crew coaching method. The methodology proposed in this section is robust and can be used to find the probability for a parameter to be a responsible parameter. Correlation analysis between parameters and energy efficiency can identify the correlated parameters. The response mechanism, with respect to the missing data, is assumed to be missing at random, in the worst case, and missing completely at random, in the best case. Hence, complete case analysis can be used to handle the missing data issues associated with the fact that pairs of operators will not, most likely, have equal number of cycles during the observation period. Difference matrix of a pair of operators is built by subtracting correlated parameters and energy efficiency of two operators in each cycle. Equal number of cycles is selected at random, since having equal number of cycles in each pair is required in order to create the difference matrix. Fitting linear model to the difference matrix and testing the significance of coefficient can be used to identify responsible parameters (those parameters responsible for differences in energy efficiency).

The results achieved by applying the proposed method to the case study partially confirm established results discussed in the literature review. Spotting and dumping time were found to be more likely to be a responsible parameter than digging time (load bucket time), contrary to some previous work. Engagement and disengagement position of the bucket, as components of digging phase which have been found to be parameters that affect productivity, were found to be very likely to cause differences in operator energy efficiencies. No prior work (to the best of the author's knowledge) has discussed the effect of dumping height on productivity or energy consumption. This work has shown that dumping height is highly correlated to energy efficiency ($\rho = -0.6560$, $p < 0.001$) and also likely to be a responsible parameter (i.e. the source of differences in operator energy efficiency).

7. CONCLUSIONS AND RECOMMENDATIONS

7.1. SUMMARY

Draglines are dominant machines and the most significant electricity consumers in surface coal mines. With the growing price of energy and environmental concerns and the high sensitivity of mines' profitability to dragline production, any improvement in efficiency of dragline operations will be beneficial for mines. Training operators to improve their performance can be a relatively cheap improvement and valid approach to improve energy efficiency. The goals of this work were to: (i) test the hypothesis that dragline operator's practices and skills significantly affect dragline energy efficiency; (ii) develop a methodology to identify the critical parameters that explain the differences in operator energy efficiency (responsible parameters).

To achieve the first objective of this work a two stage process was proposed. The process is based on statistical tests to compare the mean of energy efficiency between operators. The first stage involves evaluating the validity of assumptions underlying the relevant statistical tests. This to ensure the analyst draws the right inferences about the effect of operators on dragline energy efficiency given the data properties and to reduce type 1 error. The second stage of the suggested process involved testing the equality of means between energy efficiency of operators. Depending on the number of the operators (two or more than two) two different processes for determining the appropriate test were recommended.

A methodology was proposed to achieve the second goal of this work and to identify key parameters that lead to differences in operator energy efficiency (responsible parameters). In this method, first, correlation analysis is used to detect the parameters in the dataset that are correlated with energy efficiency. Difference matrices are then built for each pair of operators. Linear regression is then used to determine the responsible parameters. Data collected from a real mine was used to illustrate the presented methods and tests. The data was recorded from a BE-1570w dragline with bucket capacity of 85 yd^3 during one month.

7.2. CONCLUSIONS

From the work it can be concluded that:

- Mean standard error of energy efficiency can be used to find the minimum working hours required for an operator to be considered in the analysis in order to have the same support from all operators. This approach is superior to the previous approach suggested by Komlejenovi et al. (2010) because it truly goes to the heart of the problem (equal support for the different data sets). Also, the approach suggested by Komlejenovi et al. (2010) fails (the lower limit becomes negative) with highly variable working hours of operators (Komljenovic et al., 2010)

- Due to the high variability of dragline energy efficiency data (coefficient of variation more than 25% in the case study) testing for normality can be challenging. Considering the result of both numerical and graphical methods can help to test the normality of the data or transformed data more precisely.

- Using t-test to compare the equality of means between more than two operators can increase the chance of getting type 1 error. Therefore, pair-wise t-tests are proposed in previous work increases the likelihood of type 1 error as the number of operators in the study increases. However, ANOVA can handle multiple (more than two) operators without increasing chance of getting type 1 error.

- A valid method is proposed in this work facilitate accurate inferences on the effect of operators on dragline energy efficiency in the presence of high variability and data skewness. This method recommends the right statistical test to draw the desired inferences based on observed data properties and addresses the short comings, related to type 1 errors, of some of the previous work. This novel method is illustrated successfully with real-life data.

- A novel and valid method is proposed in this work to evaluate the causes of differences in energy efficiency, once operator effects on energy efficiency have been established. The method is based on a linear model of the differences in energy performance. The difference matrix (a matrix of the differences in energy efficiency and explanatory variables) is calculated using sound missing data theory to overcome the challenges of using real field data in such analysis. This work is a novel attempt to combine statistical random sampling, complete case analysis (missing data theory), and linear models of relative energy efficiencies to establish causes of operator effects on energy efficiency.

- The methods developed in this research were illustrated with a case study. Several conclusions can be drawn based on this study of a single dragline. Although these conclusions cannot be said to be widely applicable, they are worth mentioning here:

    - It was concluded from the result of the statistical tests, histograms, and Q-Q plots that energy efficiency of operators is not normality distributed and the data has a right skewness. Log-transformation of data reduced the skewness and it was concluded that log transformed data follows normal distribution.

    - The Levene's test with the null hypothesis of equality of variances on the data was rejected. This result shows that using the ANOVA test could result in wrong inferences since a key underlying assumption of ANOVA tests is the equality of variances. This shows that in some cases the previous approaches presented in the literature (Patnayak et al., 2007) can lead to wrong inferences if no systematic approach, like the methodology developed in this research, is used to choose the right statistical test.

- The result of the Welch-ANOVA and Kruskal-Wallis tests on the data proved that dragline energy efficiency is different between operators at significant level of 0.05.

- The parameters that are correlated with energy efficiency may not necessarily be responsible for the differences between energy efficiency of operators. Cycle time and payload were found to be correlated ($p < 0.001$) with energy efficiency but not responsible for differences in operator energy efficiencies.

- The results of the proposed method shows that there is a high chance for dumping height, vertical and horizontal drag distances, spotting time, and dumping time to be a responsible parameter. On the other hand, cycle time, payload and, swing in time the probability of being a responsible parameter is relatively low.

- For the first time (to the best of this author's knowledge) the effect of dumping height on energy efficiency has been examined with field data and found to be significant. The case study shows that it is highly correlated to energy efficiency ($\rho = -0.6560$, $p < 0.001$) and also likely to be a responsible parameter (100% of the time among the five operators used in the case study).

- The case study shows that operator performance evaluation, based solely on digging time or other parameters of the digging cycle alone (e.g. digging energy) (Komljenovic et al., 2010) can be misleading. Digging time was not found to be a significant factor between the five operators included in this study (only a 40% probability that energy efficiency of cycles from the five operators are significantly different because of differences in digging time). This probability is less than other cycle time components such as spotting (90%) and dumping (80%) time.

7.3. RECOMMENDATIONS FOR FUTURE WORK

The following recommendations are made for future work:

- This work is limited because a linear model is used for the relative energy efficiency of operators. In the future, the non-linear model should be investigated to examine the effect of such a model on the inferences. The proposed methodology will still be valid with a non-linear model, so long as a test for the significance of the coefficients of the non-linear model can be formulated.

- A model for dragline energy efficiency can be built using additional information on the characteristics of dragline motors such as gear ratio, torque and etc. and more data on current and voltage signals. This model can help to predict dragline energy efficiency in different operating conditions. The model can be used to simulate different operator practices and their effect on energy efficiency.

- Although care was taken during the field experiment to ensure similar working conditions, parameters of the working conditions were not recorded due to budget constraints that forced remote data collection. Future experiments should endeavor to record working condition parameters such as material properties, bench height, and weather conditions to ensure operators are compared while working in the same conditions.

- The proposed methods should be tested with data from other draglines in other operations. This could include data collected from other draglines with different bucket sizes, boom lengths, and drive characteristics to observe the effect of data nuances that may not have been observed in the test data.

APPENDIX A

LIST OF 44 PARAMETERS IN THE DATABASE

1. INTRODUCTION

APPENDIX A contains the list of 44 parameters in the database. The document has been prepared as Microsoft Word 2010.

APPENDIX B

EXPERIMANTAL FIELD DATA

1. INTRODUCTION

APPENDIX B contains the experimental field data, collected from BE-1570w dragline. The documents have been prepared as a Microsoft Excel 2010.

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