# Reliability Assessment and Energy Modeling for Alberta's Oil Sands Surface Mining Equipment

by

Azadeh Seif

A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in
Engineering Management

Department of Mechanical Engineering
University of Alberta

# Abstract

Alberta's surface mining sector is one of the largest energy-consuming industries in Canada, and so oil sands mining equipment performance has a significant impact on the economy. To achieve more sustainable oil sands mining production in Alberta, one of the influential factors is the improvement of the reliability of mining equipment. Through these reliability improvements, costs, energy consumption, and greenhouse gas (GHG) emissions can be mitigated. Energy consumption and equipment reliability have considerable risk associated with some main subsystems, and this risk must be determined in order to calculate the effect on expected operating cost. When mining equipment reliability improves, not only can costs associated with maintenance be reduced, but also energy consumption. As well, emissions quality can be improved through better maintenance, which in turn mitigates GHG emissions.

The objective of this research is to develop a demand tree, the reliability modeling for oil sands mining equipment, and make a link between energy consumption and reliability. To determine how much energy, cost, and GHG emissions can be reduced through improving equipment reliability, techniques of equipment risk assessment and reliability were studied. In addition, "reference scenarios" for improving the reliability in mining equipment were identified and developed. A probabilistic Bayesian belief network (BBN) method was used for the reliability analysis. The integrated energy-reliability (E-R) model developed for oil sands mining equipment provides a detailed reliability-energy analysis. This model helps to understand the relationship between energy and reliability, and clarifies the amount of energy consumption and energy saving possible through improving the reliability of equipment.

The E-R model was developed for four discrete states of reliability: State 1, the mining equipment is fully operational (reliability equals 1); State 2, the equipment operates under expected reliability (as defined by manufacturer); State 3, the equipment operates under low or limited reliability (also known as partial reliability); and State 4, the equipment fails.

Partial reliability was calculated for the major subsystems of the mining equipment used in surface mining of bituminous sands, and their associated energy consumption, based on the Markov degraded multi-state model under three states, which are described as: State 1, the system operates under expected reliability; State 2, the system operates under low or limited reliability; this is also known as partial reliability; and State 3, the system fails. LEAP software was used to calculate final energy consumption by each main subsystem for the study period of forty years. It was assumed that the emissions changed only due to change in energy consumption, although partially reliable equipment may have higher specific emissions as well.

The E-R model outcomes suggest that energy demand for equipment at current production rates will be reduced by an average of 603.5 million GJ, 1,151.40 million GJ , 1,125.53 million GJ , and 1,732.73 million GJ by year 2050 for states 1, 2, 3, and 4, respectively. Average annual as-spent cost savings of 60 Billion Canadian Dollars, 78 Billion Canadian Dollars, 99 Billion Canadian Dollars, and 158 Billion Canadian Dollars were obtained by year 2050 for operating in states 1, 2, 3, and 4. In addition, GHG emissions will be mitigated by an average of 27 million Metric Tons $CO_2$ equivalent, 77 million Metric Tons $CO_2$ equivalent, 75 million Metric Tons $CO_2$ equivalent, and 105 million Metric Tons $CO_2$ equivalent by year 2050 for states 1, 2, 3 and 4.

# Preface

This thesis is an original work by Azadeh Seif under the supervision of Professor Michael G Lipsett and Professor Amit Kumar. Parts of Chapter 4 have been published/presented as “Reliability and Energy Intensity Development of Critical Sub-system Equipment for Oil Sands Mining” in ASTR Conference (Accelerated Stress Testing and Reliability) in September 2015, and also as “Assessment of Reliability and Energy Intensity Development for Oil Sands Haul Truck of Surface Mining in Alberta” in ASQ Quality Conference in November 2015.

*I would like to dedicate this thesis with my deepest love and gratitude:*

*To my beloved parents, Mohammadreza and Farideh,*
*for all the sacrifices they have made on my behalf,*

*To my sister, Aramesh,*
*without whom my life would have been different,*

*And to my lovely husband, Hamed,*
*for all his patience and support,*

## Acknowledgment

I would like to acknowledge and thank my supervisors, Professor Michael G Lipsett and Professor Amit Kumar, for their continuous advice, endless support, patience throughout my course work and research, and their precious lessons not only in professional and technical fields but also in personal life. It has always been a great pleasure to conduct research under their supervision. The kind advice and support of Professor Robert Hall in the development of chapter 3 is appreciated.

I would like to thank Professor Ming J. Zuo and Hadi Moosavi for helping me with reliability concepts, Astrid Blodgett for her kind revisions, and Saeid Radpour and Veena Subramanyam for technical advice. I would like to gratefully acknowledge reliability mangers and maintenance engineers at Syncrude Canada Ltd., Husky Energy Inc., and Suncor Energy for their kind support.

I am also thankful to my good friends (too many to list here) for providing their support and friendship.

# Table of Contents

# List of Tables

# List of Figures

# List of Abbreviations

E-R model Energy-Reliability model

PDFs Probability Density Functions

LEAP The Long-range Energy Alternatives Planning System software

BBN Bayesian Belief Network

UGF Universal Generating Function

FMECA Failure Modes, Effects and Criticality Analysis

LHD Load Haul Dump

RCM Reliability Center Maintenance

GHG Greenhouse Gas

NLP Non-Linear Programming

TED Technology and Environment Database

NMS Network Management System

MSE Mean Square Errors

DTC Distributed Transaction Coordinator

KPIs Key Performance Indicators

K-R Kamat-Riley Algorithm

FSK Frequency-Shift Keying

WSNs Wireless Sensor Networks

REER Reliable Energy-Efficient Routing

ADAPT Adaptive Access Parameters Tuning

CDF Cumulative Distribution Function

MMT Million Metric Tons

RBD Reliability Block Diagram

# List of Nomenclature

| | |
|---|---|
| AB | Abuse |
| AC | The apron pan and conveyor chain |
| ACT | Actuators |
| APF | Apron feeder |
| B | Bearings |
| BC | Cracked body |
| BCH | Broken chain between the drive motor and drive roll |
| BF | Bolt fracture |
| BFA | Bucket fails |
| BR | Brake |
| C | Clutch |
| CA | Casting fails |
| CB | Cracked body |
| C-B | Connections and bearing |
| CBS | Boom and stick |
| CC | Coating corrosion |
| CF | Cab/control |
| COL | Cooling |
| CFT | Cables fail to transmit electricity |
| CON | Contamination |
| COR | Corrosion |
| CP | Cooling pump failure |
| CS | Control system |
| CU | Cut |
| CW | Casting wears out over time |
| DIS | Failure to report to assigned dispatcher |
| DM | Defecting material |
| DMA | Driving machine |
| DSF | Drive system |
| EB | Engine block |
| EC | Electricity cable |
| EF | Electric drive motor fails |
| EH | Excessive heat generation |
| EP | Electrical power |
| F | False |
| FIL | Filter assembly |
| FF | Fractures |
| FH | Frozen hoist |
| FHS | Frame, hopper, skirt, chute crack |

| | |
|---|---|
| FIR | Friction |
| FL | Deteriorated friction linings |
| FM | Foreign materials enter pump through suction |
| FP | Fan and pulley |
| FR | Hit by falling rocks |
| FRO | Feed roller |
| FS | Fuel system fails |
| G | Good |
| G | Gearbox |
| GS | Gearbox subsystem |
| H | Hardware |
| HE | Human error |
| HO | Housings |
| HL | High load |
| HOL | Hydraulic oil leaks |
| HP | Hydraulic pump |
| INS | Inspection |
| I | Impact |
| IC | Inappropriate care during assembly |
| IDM | Impact damages the rolls |
| IF | Internal motor fault |
| II | Internal leakage |
| IIR | Inappropriate rope installation |
| IL | Improper lubrication |
| IM | Impellers fails |
| IMOV | Improper mechanical operation of valve |
| IN | Erroneous information |
| INSHO | Insufficient supply of hydraulic oil |
| IS | Intake and exhaust system |
| IAS | Inappropriate assembly |
| ISD | Injector seat damage |
| ISM | Screen damage from impact |
| L | Lubrication |
| LA | Low air warning |
| LC | Loss of cylinder compression |
| LQ | Low quality fuel |
| LS | Lubrication system |
| LFS | Leaf spring |
| LST | Low strength |
| LT | Leaking cross feed tubes |
| M | Material falls from height |

| | |
|---|---|
| MA | Mechanical abuse |
| MF | Motor failure |
| MI | Material inflexibility |
| MOI | Motor internal fault |
| N | Stuck nozzle needle |
| NI | No injection indicators |
| NL | Lubrication |
| NP | Incorrect nozzle pressure |
| OD | Overload |
| OE | Operator errors |
| O-L | Insufficient oil for lubrication |
| OL | Oil and lubrication not provided |
| OP | Oil pressure drop |
| OR | O-rings |
| OS | Overload safety device |
| P | Probability |
| PL | Blown internal high-pressure seal |
| PC | Pitting corrosion |
| PD | Pressure drop |
| PQ | Poor weld quality |
| PR | Poor road conditions |
| PRL | Piston ring leakage |
| PUC | Pulley cleaner |
| RI | Rust in the injector |
| R | Radiator |
| RB | Rubber fraction |
| RF | Rolls fails |
| RG | Failure to register in check station |
| RS | Idler removal from the screen |
| S | Speed |
| SOF | Soft bench |
| SB | Springs brake |
| SBA | Solid beam axle |
| SC | Site condition |
| SD | Structure Damage |
| SF | Screening mesh fails |
| SH | Shroud damage |
| SHLA | Short and long arm |
| SHS | Shocks and struts |
| SO | Link stress during operation |
| SOF | Software |

| | |
|---|---|
| SR | Slew ring bolts fail |
| SR | Slew ring bolts |
| ST | Steering |
| SU | Surface fails |
| SW | Screening mesh wears out |
| t | Time |
| T | True |
| TAS | Trailing arm suspension |
| TBD | Timing belt drive |
| TF | Teeth fail |
| TH | Thermostat |
| TM | Tramp metal |
| TU | Turbocharger |
| TW | Twist |
| TWO | Teeth wear out over time |
| UJ | Universal joint |
| UM | Unusual mechanical load |
| VL | Valve leaking |
| SHV | Shutdown valve |
| VW | Vane wears out |
| W | Weather |
| WH | Wheels |
| WO | Wear out |
| WR | Wheel defect or rust |
| WOR | Wear off roller over time |
| WW | Wheel wear |
| ZR | ZAKO rings |
| $ | Cost |

**Chapter 1:**

# Introduction

# Chapter 1: Introduction

## 1.1 Overview

Alberta's oil reserves are an important part of Canada's economy. The oil sands are a naturally occurring mixture of quartz sand, clay, water, and bitumen. Bitumen is a heavy and extremely viscous oil that has to be upgraded before it can be used to produce usable fuels (i.e., gasoline and diesel). Bitumen can be extracted through surface mining when oil sands ore is close to the surface, with a stripping ratio of approximately 1:1 over the lifetime of the mining plant. New technologies are being developed to enhance bitumen recovery efficiency and treatment methods. There are other countries in the world that have large resources of oil sands deposits, such as the United States, Venezuela and Russia; however, the Athabasca region in Canada has the largest oil sands resources.

Even without new pipelines, it is anticipated that oil production from Canada's oil sands will increase by 4-5% annually over the next 15 years. Energy consumption intensity and equipment reliability play an important role in the costs associated with oil production in surface mining oil sands operations (1)

The effects of reliability on costs and emissions can be simulated through modeling the relationship between a change in equipment reliability due to a minor fault and a change in equipment emissions, which is the main focus of this research.

Oil sands deposits are located far from urban areas, and this makes access to mining equipment more complex, particularly with respect to maintaining efficiency and controlling costs. It is costly to provide service, repair, and maintenance for unscheduled equipment shutdowns during oil sands mining operations. A reliability study, an equipment and system failure assessment, and an analysis of energy consumption related to machine condition are the main objectives in this research.

Reliability is the probability that a system or component will work over a specific period of time (2). Statistical methods are used to analyze and determine the reliability from observed failure data; furthermore, a suitable model of the reliability assessment can be applied to create a relationship between equipment performance and improvement.

Reliability and availability of equipment are two appropriate metrics for quantitative evaluation and analysis of a system. Availability is a parameter that defines the probability of a component operating at a specific time (2).

The current work aimed to estimate reliability related to mining equipment (i.e., hydraulic and electrical shovels, haul trucks, crushers, conveyer belts, and slurry pumps) using a Bayesian Belief Network. A Bayesian Belief Network analyzes the reliability and availability of equipment components based on nodes and related links, even with uncertainty of parameters and lack of sufficient data.

The results from this research can be used by operating companies to understand how to mitigate unpredictable mining equipment failures and allow industries to formulate a quantitative approach to probabilistic modeling (as opposed to qualitative assessment of reliability), improve equipment reliability, determine optimal energy use over the lifetime of a piece of equipment, and reduce energy costs. In this work, artificial failure data are used to estimate unexpected failures, and energy consumption data are used to calculate emission and energy demand rates, which are input into the maintenance program.

## 1.2 Statement of the problem and gap in knowledge

Unpredictability in energy demand, its associated costs, and the importance of mitigating greenhouse gas emissions are increasing; therefore, an understanding of how to save energy through life cycle assessment of specific equipment is an important approach for more sustainable development in industry. Energy saving can be partially achieved by improving equipment reliability. Oil sands mining equipment has a vital role in energy consumption and surface mining costs, and a comprehensive reliability assessment can lead to considerable reductions in cost and energy consumption.

## 1.3 Research Objective

The main objective of this thesis is to combine a reliability analysis of equipment in an oil sands surface mining process and energy modeling to understand how to reduce energy demand emissions and costs via reliability improvement. The outcomes from this research allow the oil sands industry to understand how to improve the reliability of the components in mining equipment, will affect the energy efficiency of an oil sands mining operation. As historical data from actual mining operations were not available for this study, a Bayesian Belief Network (BBN) is used to model component failure for each piece of mining equipment for an Energy-Reliability (E-R) model.

This project focuses on the impact of equipment reliability, operation costs, and energy demands on mining equipment. Equipment failure probability, which leads to low-reliability or unreliability condition, depends on a number of variables such as local weather, environmental circumstances, human error, uncertain degree of equipment deterioration, and uncertainty in material and equipment.

In addition, this study assesses a reliability model for the main subsystem of oil sands mining equipment to determine value of energy demand over the remaining service life of equipment. The objectives of this research are as follows:

- To identify the variables and components that most affect oil sands mining equipment productivity;
- To calculate reliability of oil sands surface mining equipment;
- To identify the final energy demand for the selected oil sands mining equipment;
- To develop the base year energy demand for oil sands mining equipment based on reliability;
- To identify probability density functions (PDFs) for failure data of the selected oil sands mining equipment, which allow us to determine the final reliability function;
- To identify risk associated with equipment used in oil sands surface mining operations;
- To develop the base year energy demand and supply scenario in The Long-range Energy Alternatives Planning System (LEAP) software for oil sands surface mining equipment;
- To develop a scenario for improving reliability of mining equipment;

- To estimate the total possible energy demand and emissions for oil sands surface mining equipment in Alberta over the study period through the development of reliability scenarios using LEAP software; and
- To create relationships between reliability, emissions and energy demand to calculate the amount of energy that can be saved in Alberta on oil sands surface mining equipment.

## 1.4 Research Assumptions

The assumptions of this research are:

- Oil sands mining operation condition is at steady state;
- Expert evaluation of the data collected is required for the reliability of the main components based on true and false states (true is the scenario in which the failure mode is occurring, and false is the scenario in which the failure mode is not occurring); and
- Reliability modeling is a benchmark study.

## 1.5 Scope of the Current Study

The scope of this research includes the following:

- Reliability modeling of oil sands surface mining equipment in Alberta, Canada including hydraulic and electrical shovels, haul trucks, crushers, conveyer belts, and slurry pumps, along with calculation of their probability of failure based on a Bayesian Belief Network (BBN);
- Calculation of energy demand rates in oil sands mining equipment based on selected components that impact emissions using LEAP software;
- Development of a surface mining framework in the industrial demand modules using LEAP software;
- Performance of sensitivity analysis for slurry pumps and haul truck engines and tires in terms of total energy consumption through E-R modeling;
- Use of the E-R model to conduct an analysis of oil sands surface mining equipment over the course of 40 years starting nominally from 2010 to 2050. The E-R model

is used to forecast how much energy and cost can be saved by improving equipment reliability.

## 1.6 Limitations of the study

Data collection on reliability modeling

Reliability assessment was performed based on a Bayesian belief network for each main component (of equipment) based on a true/false state for each failure mode. The total reliability value and probability density function were calculated for each equipment using BBN model. Synthetic data were created based on qualitative input by industry benchmarking and expert judgment.

Data collection on financial impact

Financial data are collected and analyzed using the E-R model to determine the cost of each main component for the selected equipment. Costs were estimated based on expert opinion.

Data collection on energy demand and supply

Fuel and electricity consumption data are collected and interpreted to calculate the energy demand of each component for the selected equipment.

Baseline data for a period of 40 years were developed using outlook data found in various published reports and from Natural Resources Canada.

## 1.7 Methodology

In this research, multi-state reliability formulations are used to study the reliability of oil sands mining haul truck, which influences production capacity and operation costs. In addition, parallel and series reliability assessments are used to calculate total productivity probability in a specific productive time (one year). Production reliability of critical oil sands mining equipment was assessed by considering equipment failure modes of each main component. The developed reliability model provides a novel way to address system reliability challenges in terms of cost and energy demand.

After calculating the failure probability for each mechanical subsystem of each piece of mining equipment, based on the Bayesian Belief Network (BBN), risk associated with each main component was assessed

Strategies and methodologies used in this research are as follows:

- Identification of the list of failure modes related to the main components of the selected oil sands mining equipment;
- Calculation of the probability of failure for each component based on the Bayesian Belief Network (BBN);
- Calculation of the reliability of each component of the selected oil sands mining equipment;
- Calculation of the failure rate of selected oil sands mining equipment;
- Calculation of the consequence for each failure mode based on cost according to research reviews and reports;
- Calculation of the risk associated with each component of the selected oil sands mining equipment;
- Development of a base year energy demand and supply scenario in LEAP for the oil sands surface mining equipment in Alberta;
- Estimation of final energy demand of each component that directly influence energy efficiency;
- Development of an E-R model based on the reliability assessment and energy demand of surface mining equipment using LEAP over the study period.

## 1.8 Thesis Organization

This thesis is organized in the form of five chapters with a table of contents, a list of tables, a list of figures, a list of abbreviations, references, and an appendix.

Chapter 1 (this chapter) includes the overview of this study, research objectives, research hypothesis, scope of the current structure, limitation of the study, methodology, and an outline of the thesis' organization.

Chapter 2 provides a literature review on reliability, reliability of mining equipment, the Bayesian Belief Network and its application in industry, the Monte Carlo simulation, energy modeling approach, and the concept of energy-reliability intensity.

Chapter 3 concentrates on failure, cost, risk, and details of the developed reliability model for oil sands mining equipment (hydraulic and electrical shovels, haul trucks, crushers, conveyer belts, and slurry pumps) using the Bayesian Belief Network.

In Chapter 4 develops the Energy-Reliability (E-R) model in detail and provides a sensitivity analysis along with information of the system energy. Using LEAP software, the energy demand of each component was determined and developed.

Chapter 5 discusses the conclusions, engineering significance, and recommendations for future work based on this research.

**Chapter 2:**

# Literature Review

# Chapter 2: Literature Review

This chapter presents a review of the literature on reliability and its application in mining equipment, the Bayesian belief network method and its application in industry, and reliability and energy intensity. Reliability studies and energy intensity modelling in various industries including oil sands mining industry are discussed.

## 2.1 Reliability

Reliability is defined as a probability of the components working in a system under specific conditions for a period of time. Reliability studies allow us to predict, prevent, and reduce the likelihood or frequency of equipment failures (3). One of the popular methods to evaluate reliability of the system is k out of n system reliability. However, in the real world, most of the systems have more than two states to perform their function, which is called multi states. The multi-state *k*-out-of-*n*: G system model, is defined as the system working under different *k* values with respect to different states. In this section, multi-states k-out-of-n and Markov structures, two kinds of multi-state reliability modelling, are discussed (4).

Zhigang et al. 2007, used multi-state k-out-of-n systems to evaluate the oil supply system. They proposed a model of multi-state k-out-of-n system, which allocates various conditions on the number of components for different state levels. , and, very importantly, more practical engineering systems can fit into this model. ”Multi-state” in this model stands for multiple capacity level. To calculate the reliability of multi-state k-out-of-n systems, a recursive algorithm was used. The results show that this algorithm is an efficient way to assess reliability of a system (4).

Tian et al. 2009, offered a method for the joint reliability–redundancy optimization of multi-state series–parallel systems. The best redundancy level for each parallel subsystem was obtained by considering their states’ influence of component on every subsystem. This includes the technical and organization performance of a multi-state component and the accessibility of the system. Their model find out the numbers of components as well as the best technical and organizational actions for each subsystem of a multi-state series–parallel system, to minimize the cost of system through availability of the system (5).

Yi Ding et al. 2010, also developed a model for reliability estimation of multi-state weighted k-out-of-n systems. They developed fuzzy recursive and fuzzy universal generating function (UGF) algorithms to assess the multi-state *k*-out-of-*n* system. In addition, they calculated fuzzy weights based on the clustering technique and the curve fitting method. They developed a framework to estimate the reliability of multi-state weighted k-out-of n systems as well as improve the fuzzy recursive methods and fuzzy UGF techniques to evaluate the k-out-of n systems. To find the weights of fuzzy numbers of recursive algorithm, UGF techniques, and probabilities of states in this model, clustering technique, and curve fitting method were used. Their model allows the user to make timely calculations and generate accurate outcomes (6).

Lipsett et al, used the Markov method to estimate the reliability of a system under multi-state conditions. In their model, the probabilities and costs associated with a risk function were assessed, when the related component operates in a particular state. The Markov formulations used in their study show a range of functioning, fault, and repair states. Risk calculations were determined in terms of a sum of cost estimates for a product working under different states (7).

Yang Dongpeng et al, 2008, implemented reliability studies in industry for various devices and equipment. For example, reliability has been used for ventilation networks, used in coal mining to provide fresh air underground. They studied the reliability of ventilation networks using Boolean calculations and the Shannon formula. The results indicate that if this model is used to calculate reliability in coal mining ventilation networks, the highest efficiency for the ventilation network as well as of the entire operational system can be achieved (8).

Some network systems can operate with partial damage in the transmission, which known as a partial reliability. Lien et al, 2015 conducted research on computer network systems. They proposed a partial reliability model on Transmission Control Protocol (TCP) that describes the part of system works with partial reliability (9).

Donckers et al, made a link between energy intensity to partial reliability. They studied the effect of partial reliability and energy intensity in a mobile system. Their model controls the loss of capacity and delays, which leads to use lower energy intensity. They model can save about 0.57% of the energy consumption (10).

## 2.2 Reliability in mining equipment

Equipment reliability is a key factor in mining operations performance. Many kinds of equipment are used in oil sands mining operations, and down time are costly. Shovels, mining haul trucks, crushers, conveyor belts, and slurry pumps are widely used in oil sands mining in Alberta. Various methods and reliability distributions are used to find the best distribution function to fit the failure data. Some techniques are used in industry to assess reliability, including Pareto analysis, Failure Modes, Effects and Criticality Analysis (FMECA), and the Bayesian belief network (BBN). These techniques are used both to estimate the best reliability distribution to meet industry requirements and to improve reliability. The outcomes from these assessments generate clear operational and maintenance strategies to reduce cost while maintaining high performance. Reliability assessments found in the literature can be categorized into two distinct groups: assessments done on the entire operational mining system and those done on particular equipment.

***Mining Systems***

Nuzialea et al, 2007, used a reliability analysis to predict mining equipment failure rate using RelSoft software in order to expedite the maintenance assessment and reliability analysis of mining equipment. The authors used two approaches. They first calculated mining equipment failure trends using a maintenance analysis and then predicted failure trends using statistical reliability models. The authors concluded that using software and having a basic knowledge of statistics were key to efficiently maintaining mining equipment (11). Another mining equipment reliability assessment was conducted by Barabady and Kumar. They used a Weibull distribution for their parameter analysis. The conveyer subsystem and secondary screen subsystem were found to be the most important equipment in terms of reliability and regular maintenance (12).

Peng et al, 2014, analyzed underground mining equipment by using a genetic algorithm along with several statistical methods. They studied load haul dump (LHD) trucks over three- and six-month periods at an underground mine in Ontario. A statistical test was performed to validate the data collected with the actual data in the certain time. The objectives of this case study were to analyze the impacts of the amount of data and of sequential data on prediction outcomes. The results indicated that genetic algorithms are successful tools to calculate the maintenance elements of an LHD vehicle over the course of three and six months with a level of confidence of 5%. Moreover, to estimate an unexpected failure rate, the timeline of events is not important (13).

For surface mining equipment evaluation and selection, Hall and Daneshmend, 2003 analyzed reliability using data collected from sensors attached to mobile equipment. The reliability and maintainability model for surface mining equipment were combined with discrete models. A Pareto analysis was used to find reliability center maintenance (RCM) regarding “failure time" and "repair time" The Pareto analysis divides equipment according to their main parts, or sub-systems, to determine which parts need urgent maintenance and repair. The distribution of the equipment life cycle can be categorized as stationary and non-stationary. Stationary means that the probability of the distribution remains the same over the lifetime of the equipment. When insufficient data are available for a reliability assessment, then a Failure Modes, Effects and Criticality Analysis (FMECA) can be used to identify the failure. An FMECA uses expert opinion as a required data input, which is time consuming. The reliability growth rate obtained by this method is between 0.23 and 0.53 (14).

These reliability methods can help increase equipment availability in mining operations, decrease operation and maintenance costs, elevate design and maintenance performance, and improve mining business challenges. This simulation method can be used to manage equipment selection and maintenance as well.

***Mining Equipment***

Mining haul trucks have become larger over time and their technology and design have become more complex. Therefore, it is important to assess the reliability of these machines for maintenance planning schedules and scenarios. Hall et al, 2003 studied reliability and maintainability of mobile underground haulage equipment. They used the reliability model to help make decisions on maintenance planning using production-planning scenarios.

Pareto, Statistical, and FMECA analyses were used to model reliability. The data was collected to calculate reliability. The study showed that with data from the mine, a user can analyze reliability and thereby improve mining equipment design, increase of mining equipment accessibility, and decrease maintenance costs (14).

The mining shovel, an important piece of equipment in mining operations, digs ore from underground and makes it accessible for further extraction procedures. Having access to mining shovel reliability modelling is one the main challenges in mining operations and has been considered and investigated by many researchers (15-17). Samantha et al, 2003 applied a reliability analysis on shovels in coalmines and concluded that the Weibull distribution was the best fit for the failure characteristics of the shovel. The fault-tree analysis was used to evaluate reliability for the hydraulic shovel, and an algorithm was developed to find the lowest cut sets and the lowest path sets from the fault tree. Over the course of 240 operational hours, hydraulic shovel reliability was found to be lower than expected; however, the reliability of buckets and tracks was very high (15).

Moghaddam et al, 2008 used fault monitoring and reliability modeling for hydraulic shovels were collected and analyzed by. A test was conducted to identify variable failure rates and to calculate shovel reliability. Reliability was analyzed using the classical approach. Numerical results showed that fault observations in the system are achievable when energy inputs are varied, allowing us to maintain hydraulic shovel performance of at an acceptable level (17).

Imran Khan 2013, used an overview of reliability and maintenance management for oil sands mining mobile equipment. In his research, Khan identified some main parts of mining haul truck and shovels that significantly influenced the reliability of the equipment as a whole(16). In addition, Chung et al, 2013 used the linear model for surface mining haul trucks and shovels to determine the minimum number of trucks needed for a set of shovels. They quantified and drew the relationship between a shovel's idle probability and the number of trucks(18). Vaghar et al, 2012 applied reliability modeling to identify faults on off-road haul truck tires. Road quality and time of year were the two main factors in the root cause failure analysis for the tires. It was found that road quality (including conditions) has a major effect on tire reliability (19).

Barabady 2005, applied reliability and maintainability analyses of two crushing plants (I & II) and their subsystems. They empolyed Weibull, exponential, and lognormal distributions to assess reliability using ReliaSoft's Weibull++6 software. The distribution outcomes fit the downtime data well. Within 10 hours of operation, the reliability of crushing plants I and II decreased to 64% and 35%, respectively. These results confirm that the reliability and maintainability assessments are valuable and essential to identify maintenance gaps and to schedule and arrange maintenance (20).

## 2.3 Energy modelling

An energy model is a simulation tool used to analyze an energy system. An energy model can help us predict energy demand and current and future energy consumption. The Long-range Energy Alternative Planning Systems (LEAP) model is one kind of computer simulation software used to model energy systems. LEAP can simulate energy efficiency and greenhouse gas (GHG) emissions for several Canadian provinces using various models and techniques. In this section, MARKEL, the Bayesian belief network, and a LEAP model for Alberta's industrial energy demand are discussed.

One of the models to assess the energy intensity in a system is the MARKAL model. Seebregts et al, 2010 simulated energy-environmental planning using MARKAL. The MARKAL (short form for MARKet Allocation) model uses energy and environmental planning as a linear programming model (LP), focusing on the calculation of energy systems. Then energy system was calculated by a non-linear programming (NLP) technique, which merged the "bottom-up" with a "top-down" model. The MARKAL family of models can predict energy planning by MARKAL family related environmental impacts. It is a powerful tool, the results of which can be used to mitigate GHG emissions for specific actions and projects (21).

Subramanyam 2010, conducted research on predicting energy usage in mining. LEAP software is one of the most accurate and commonly used tools for simulating energy intensity based on different scenarios for various regions and countries. LEAP can predict energy supply and demand over a specific time. LEAP uses energy supply and demand data to simulate different energy demand scenarios. LEAP is also a powerful tool for policy- and decision-makers. It is made up of four modules: demand, transformation, resources, and the Technology and Environment Database (TED) (22).

LEAP has been broadly used by different researchers and organizations. Subramanyam et al, 2010 developed an energy model for Alberta's mining sector using LEAP. Different types of mining equipment were categorized based on their function, and LEAP was used to find the energy consumption and GHG emissions of the equipment for scenarios during the period 2005 to 2030. Results show a 35% growth in energy demand over 25 years in Alberta's mining sector. However, this growth rate in energy demand can be influenced by global oil price, and future energy production rate through renewable resources.

Alberta's mining sector has the highest energy demand and GHG emissions of all the industrial sectors in Canada. Tejas Shah et al. 2013, conducted a study using LEAP on energy intensity development for mining related industries in Alberta. Different subsectors and their related processes for mining equipment were identified and consolidated (23). The final energy demands based on the energy consumption of each piece of equipment were calculated using LEAP for the year 2005. In-situ mining and bitumen upgrading were found to be the most demanding areas of energy intensity. Energy efficient furnaces, boilers, and pumps were found to have highest potential to reduce GHG emissions (24).

LEAP has also been used to simulate energy intensity for different industries and technologies. Phdungsilp and Wuttipornpun conducted a simulation model of energy development for an industrial sector in Thailand between the years 2005 and 2030 using LEAP. Five scenarios were created to assess energy intensity, and they were compared with a reference case. Industry policy was evaluated though LEAP's multi-criteria decision-making model. The outcome from this model clarified how an energy system can switch from a highly carbonized to a decarbonized energy system. The development of energy efficiency was the main energy saving scenarios and can also lead to mitigation in $CO_2$ emissions (25).

The next generation of network operating systems requires large amounts of electricity, and this would have a direct impact on global energy consumption and global warming. Approximately 2-10% of global energy is consumed in the Information and Communication Technology (ICT) sector. Local area networks, data centres, servers, and fixed and mobile phones are some of the main sources of ICT energy consumption. Data centres alone account for 23% of overall power consumption. To come up with ways to reduce power consumption, cost, and $CO_2$ emissions, Santosh Kumar et al. 2011, carried out research using a Bayesian belief network to formulate a network management system (NMS). An energy alert network management system was simulated using a Bayesian belief network-based centralized decision management system. Total power savings in a local area network were calculated by adding more energy consumption of 0.48 watt. The outcome of this research showed a 2.5-6.5% saving in power consumption by having a 20-33% sleeping port (26).

## 2.4 Bayesian belief network

A Bayesian belief network is a model made up of nodes and arcs. Nodes represent variables; they show the area of interest and influence the reliability of a system or equipment. Arcs describe the relationships of those variables.

Bayesian belief networks are also called belief networks, influence diagrams, and causal diagrams. These diagrams were developed at Stanford University in the 1970s and were widely used in the 1980s and 1990s. Bayesian belief networks are powerful tools generally used to illustrate dependence between random variables and to calculate the probabilities of the failure of random variables as evidence related to their value accumulates over time (27, 28).

Bayesian belief networks have been considered a form of artificial intelligence that incorporates uncertainty through the probability theory and conditional dependency. In belief networks, nodes represent variables and arrows show conditional dependence relationships between variables in the graph. To develop a belief network, variables in a domain and their relationships are defined. To evaluate an entire network, for each node (variable), probability of failure in positive and negative states (evidence) can act as an input or output to each node. Eventually, for the remaining nodes with unknown states, the probability for each state is determined. (27, 29)

Bayesian belief networks make it possible to solve complex problems; although the outcomes from BBNs may not be logical, they may be rational. A complex set of problems can only be analyzed by using a Bayesian network method, which increase the complexity of the model. The main disadvantage of a Bayesian network is the time required to conduct an evaluation. It is predicted that the BBN method will be modified in order to extend its application in various areas (27, 30).

Huang et al. 2006, used the BBN technique to determine the reliability of a system when data are fuzzy. In many applications, it is not easy to calculate the exact related probability; therefore, many studies were performed to find out the related probability under certain types of distribution. Statistical methods and specific computational simulations were used to estimate the related parameters of distribution (31).

A fuzzy BBN method was used to find the reliability for a non-repairable multi-state series-parallel system. Bamrungsetthapong et al. 2014, used the Markov process to find the reliability for a non-repairable multi-state (32). They used exponential fuzzy numbers to simulate the model and the mean square to evaluate the model. Error was calculated from the fuzzy BBN of an NMSS (non-repairable multi-state series-parallel system) to determine the reliability of a fuzzy system. Upper and lower fuzzy BBNs were estimated. They gave better evaluations of mean square errors (MSE) when a α-cut was raised until it reached the value of 1 (32).

## 2.5 The Bayesian belief network in industry

The Bayesian belief network has been widely used in industry as an expert method to calculate the probability of failure. The related failure modes (variable) are determined and labeled as nodes, which influence reliability. A given variable is either positive or negative. The relationship of the nodes to the network is determined based on expert decision and data collection reports from mining sites. The conditional probability rate through the Bayesian belief network method is calculated based on the BBN formula. The results from a BBN method will allow those in industry to determine and identify the maintenance problems.

Another application for a BBN is in construction-related sectors (30). McCab et al. 1998, used a BBN for a concert hall construction project. The simulation outcomes provided an analytical solution to improve and elevate the construction operations. In addition, the BBN has been used to diagnose automotive electronic systems. The probabilistic methodology in a BBN uses a multiple- Distributed Transaction Coordinator (DTC)-orientated troubleshooting strategy and optimizes the procedure to troubleshoot failure cases (33). McCab et al. 2001, used the BBN to validate changes in an analytical investigation of construction projects. The Bayesian belief network has also been used to develop a mathematical model to calculate potential risks in software development projects. Results showed that only 61% of software development projects are completed on schedule. To keep the projects under control in terms of time and budget, the effective factors are needed to be defined as inputs to the model. The BBN was used to determine the dependencies between different risks and their impacts. Kwok et al. 2004, proposed a mathematical method to predict the project's success and risks. Their model predicted risks at early stages of the project to mitigate the related risks (34).

Barker 2004, employed the BBN to determine the reliability of a food safety system by calculating the probability of failure. Their model was subjected to uncertainty through BBN techniques. The Bayesian belief network was found to be a powerful and practical tool for both business assessment (35).

Smith 2006, presented a model using the Bayesian belief network to compare the geotechnical, hydrological and structural aspects of dam risk by considering dam risk broadly, The lifting mechanism, gantry crane, electrical winch, and manual winch were used as the fault tree's variables. The BBN was found to be an efficient method to assess equipment or system risks. The BBN method can deal with the problems associated with assessing actual risk (36).

Jeon et al. 2008, applied the BBN to analyze reliability in image processing. They studied de-connected weight measuring processes. The results showed that the proposed BBN model could solve many kinds of image processing problems (37).

Yuriy 2005, modeled event simulation and reliability for mining equipment based on genetic algorithms. Genetic algorithms are used in reliability assessment as input for a discrete-event simulation model. The study was aimed to show the impact of equipment failure on production in mining. The outcome of the study illustrated that if load-haul dump (LHD) machines encountered any failures, the loss in the mining operation would be 28.7% (38).

Gerbec et al, 2014, used key performance indicators (KPIs) to control risk in safety procedures. Equipment failures, human errors, and external causes were their KPIs. The Bayesian Belief Network was used to connect safety to KPIs. The case study performed for a tanker ship methanol un-loading operation at a liquid cargo terminal was used to validate their model. The outcome of Marko Gerbec and Kontic's experiment showed that their approach could be used to control risk (39).

## 2.6 Monte Carlo simulation

The Monte Carlo method uses random variables to determine the reliability of a piece of equipment or a system. The Monte Carlo simulation is one the methods that demonstrates the possible effects of a decision-making. Mular et al. 2002, used Monte Carlo simulation assesses the impact of risk and it can also be used to validate the outcome of risk. Specific software and mathematical methods are used to conduct a Monte Carlo simulation (40).

Gabriele et al. 2012 developed the Monte Carlo and fault tree analyses to calculate reliability in industry. The advantages of this model is high level modeling interface based on the fault tree method (41).

Hoseinie et al. 2013, used the Kamat-Riley (K-R) algorithm in Matlab software to conduct a reliability assessment of a longwall shearer machine based on the Monte Carlo simulation technique. The reliability results were used to improve short- and long-term of oil sands extraction from the mine (42).

Billinton et al. 2004, used non-sequential Monte Carlo model and likelihood calculation for reliability analysis in power system. These two models have their prone and cons. likelihood calculations are very easy to solve and generally needs little computational calculations. Although, Monte Carlo simulation is difficult and it requires more complex computational calculations, it is very flexible to model random performance of components. By combing these two methods, they get a valuable tool for short-term development purposes (43).

## 2.7 Reliability and energy intensity

Energy intensity and the potential to save energy are popular subjects in many industries. One of the major causes of energy waste is through leaks. Thus, it is critical to know whether equipment requires maintenance or is in good working order. This can be determined by making connections between increasing the reliability of equipment and energy demand. If equipment or process reliability is linked to energy intensity, energy intensity and GHG emissions can be decreased by improving the reliability of the entire system or equipment. It is important to find out where energy is being lost and how to stop the loss. There is limited published research in this area; however, there are some reports and articles related to sensor systems, the food industry, and wireless biomedical systems.

Herbert et al. 2009, made a link between efficiency and reliability in a milk powder processing factory. They found that energy consumption can be reduced by 15 when reliability of the plant is improved in the factory. The model results showed a significant connection between reliability, energy savings and cost (44).

Abouei et al. 2011, connected energy efficiency to reliability in wireless biomedical implant systems. Frequency-shift keying (FSK) was used to model reliability and cost in small implantable sensors. An FSK scheme has been widely utilized in energy-constrained wireless applications, as a simple and low power structure method. There are several methods to prevent an increase in the transmit power, and the most applicable method is employing channel coding schemes. Channel coding is a fundamental approach used to improve the link reliability using redundant information bits along with the transmitter energy saving due to the providing of coding gain. An FSK method was very easy and low power framework that is broadly used in energy-restricted wireless applications. By implementing channel coding schemes to FSK, the transmit power does not increase. Channel coding is a basic approach employed to develop the link between reliability and energy intensity in Wireless Biomedical Implant Systems by eliminating the unnecessary information bits in conjunction with the energy source saving because of the adding code.

The results showed that coded FSK were to be more energy efficient than uncoded FSK. The proposed model showed an energy savings of about 80% compared to the material layer standard with similar structure used for wireless sensor networks (45).

Francesco et al. 2011, presented a model for reliability and energy efficiency for a data set on wireless sensor networks for IEEE 802.15.4/ ZigBee standards. Their model contained an energy-alert variation element that completed the purpose of reliability assessment in order to decrease the power consumption. They presented algorithm called ADaptive Access Parameters Tuning (ADAPT), which can successfully satisfy the reliability assessment under a large range of working conditions, for both single-hop and multi-hop networking scenarios. They combined their result from the algorithm into wireless sensor networks (WSNs) based on IEEE 802.15.4/ZigBee standard with no change to the standard (46).

Min Chen et al. 2013, used a reliable energy-efficient routing (REER) protocol for the wireless sensor system in order to attain a more energy efficient wireless with a more reliable system. They combined the reliability assessment and energy efficiency in their model. The outputs of this model are as follows: with extending the failure rate, distance between the two nodes needs to adjust smaller to achieve the proper reliability. However, the distance value should not be very small; because it leads the system to consume more energy and it cause the delay. In addition, REER cannot operates in small interchange density situations. Moreover, if GPSR and REER are in the reliable situation, reliability will increase if distance between two nodes raise. Finally, REER displays more stable with having bigger reliability and smaller energy consumption value comparing to GPSR when the situation is unreliable.(47).

Chapter 3:

# Reliability Assessment of Oil Sands Mining Equipment

# Chapter 3: Reliability Assessment of Oil Sands Mining Equipment

## 3.1 Introduction

In this chapter, failure rate probabilities were calculated and a reliability assessment was done using Bayesian belief network (BBN) methodology applied to oil sands mining equipment. Some possible risks associated with critical components of selected mining equipment were enumerated from the literature review, benchmark studies, and expert opinion or related data received from industry sources. Risk was then calculated based on the failure rates and the consequence of each failure mode, which was mostly repair costs, but may also include rental of replacement equipment, or opportunity cost of lost production if there is no redundant processing capability available.

## 3.2 Reliability Analysis

As previously discussed, reliability is the probability of equipment running under specific conditions for a specified period of time within specified range of performance (48). If equipment has low reliability, then some of its components may face partial failure (defined as partial failure rate) and may use more energy and incur higher repair costs. In this section, different types of equipment used in oil sands surface mining were analyzed using the BBN method. Due to insufficient historical data on failure rates, probabilities of failures were used with expert input (23). The process flowchart of the reliability analysis for the oil sands mining sector is shown in Figure 3-1.

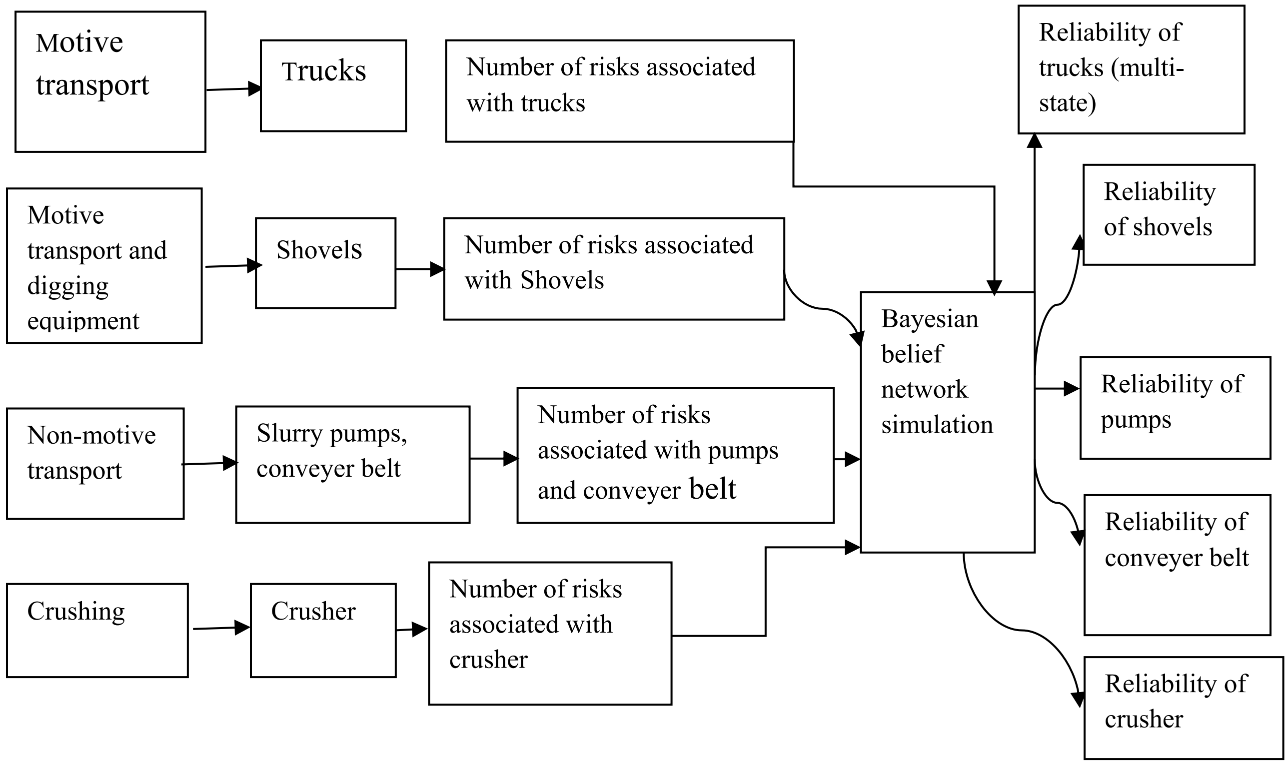



Figure 3-1: Reliability diagram for the oil sands mining sector

### 3.2.1 Bayesian Belief Networks

The Bayesian belief network method employs an acyclic directed graph or network diagram with a series of variables expressed as areas of interest. The BBN method consists of nodes, which represent variables, and states that are either true or false. Variables are defined by two states, which are either an event's failure (or true (T)), or lack of failure (or false (F)). If failure occurs, then the probability of this failure is shown by the state true (T), and false (F) is the probability of the failure not occurring In addition, arcs are used to show correlations between the variables (49).

### 3.2.2 Cost

Oil sands mining equipment costs include capital (initial and salvage), ongoing operating costs of production consumables, labor, maintenance, facility rental, infrastructure of equipment parts, and energy. Cost values are needed to calculate total cost to determine financial impact in the risk model (50). Unless activity-based accounting is used, it may be difficult for an organization to track accurate costs of each type of activity. In this study, costs associated with the components of equipment are considered as maintenance, capital and fuel cost (51).

### 3.2.3 Estimating a Failure Rate

Since it assumed that this model is steady state, therefore the reliability function and failure rate are time independent variables. Failure rate for the selected main part of equipment can be calculated directly based on failure probability over reliability (52).

Figure 3-2 illustrates the process of reliability modeling for oil sands mining equipment.

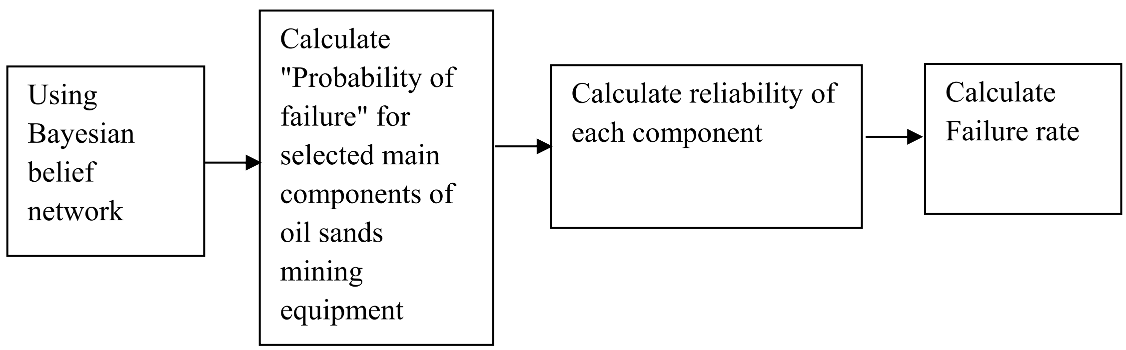



Figure 3-2: Reliability modeling approach for oil sands mining equipment

### 3.2.4 Reliability Modeling for Oil Sands Mining Equipment

Reliability modeling estimates the reliability of a system or equipment based on lifetime distribution. In this research, the system refers to all the main components of oil sands mining equipment. The failure probability was calculated based on the BBN methodology with respect to the useful lifetime of components in the system (49).. The failure probability for equipment was calculated using the BBN methodology by identifying the most common equipment failures. The BBN method determined failure probabilities by considering different states of variables in the network. Then, reliability was calculated based on the failure probability.

### 3.2.5 Equipment Reliability Model

An equipment reliability model can provide great quantitative information in mining management in terms of equipment selection and maintenance decision-making (53). The equipment reliability model in this research was focused on equipment used in oil sands surface mining operations, with the following main goals:

- Determining a list of the failure modes of the main components from the selected equipment;
- Calculating the failure probability for each component based on the BBN method;
- Calculating the reliability of each component;
- Calculating a failure rate for each sub-system of selected mining equipment;
- Calculating consequences based on cost ($) for each failure according to research reviews and reports (54);
- Calculating risk associated with each component; and
- Calculating the partial reliability for each main component to link reliability to energy consumption and cost.

## 3.3 Risk Attitude and Expert Opinion

To model uncertainty and risk analysis, personal opinions of experts were used in this study. Uncertainties of the variables could not be determined without expert opinions because (55)

- There are no historical data that were made available by operating companies due to information security concerns;
- New data gathering would be expensive and time-consuming;

### 3.3.1 Risk Analysis

An evaluation and risk analysis of the main components in the equipment helps to prioritize the level of risk against a set of standards according to target risk levels or other criteria (56). Risk is a direct function of probability of failure and cost. In other words, the risk associated with each component is directly linked to the energy demand and cost of that component. Therefore, it can be concluded that energy demand and cost will have a similar decreasing trend when reliability increases and vice versa.

To convert a qualitative approach to a quantitative approach, data can come from a company's maintenance records, operational records, previous research reports, or expert discussion. In this study, data from expert opinions were used for the risk analysis. The following steps for risk assessment were considered for the proposed model:

After calculating failure probabilities using a Bayesian belief network methodology along with estimating the severity of consequences, risk was determined. This analysis predicts the probability of failure based on the component failure modes and calculates related reliability. The risk analysis anticipates at what time and to what extent equipment may fail. This result will help decide if early replacement of a component is required to prevent extra cost, or if it is more affordable, in terms of energy and cost, to continue operating equipment under partial failure.

### 3.3.2 Risk Calculation

Risk can be calculated based on equations 1-1 and 1-2.

Risk ($/yr) = Consequence of event (cost) × Rate of occurrence (/yr) (1-1)

Risk (J/yr) = Consequence of event (energy demand) × Rate of occurrence (/yr) (1-2)

It can be interpreted from above formulas that risk is the rate of occurring events multiplied by the event's cost or energy demand. Rate is the frequency with which an event happens during a specific period.

In this study, reliability is calculated for one-year. Risk can also be defined according to the probability of failure [2]. This is illustrated in equations 1-3 and 1-4s:

Risk ($/yr) = Consequence ($) × (Number of chances to fail [/yr] × probability of failure) (1-3)

Risk (J/yr) = Consequence (J) × (Number of chances to fail [/yr] × probability of failure) (1-4)

The number of chances to fail is the number of failure chances that may happen to a component (in equipment) in a one-year time interval; and the probability of failure is the probability that the event of failure may happen. Risk values range between 0 and 1, indicating minimum and maximum possibility of component failure. The risk, which applies to equipment, can be calculated based on equations 1-5 and 1-6:

Risk ($/yr) = Consequence of failure ($) × (Number of chances to fail [/yr] × [1 – Reliability])

(1-5)

Risk (J/yr) = Consequence of failure (J) × (Number of chances to fail [/yr] × [1 – Reliability])

(1-6)

Probability of failure = 1 – Reliability

### 3.3.3 Risk Identification Goals

In this research, the prediction of risk is done with the following in mind:

- It provides early knowledge of a component's potential failure rate;
- It predicts life cycle costs for a component, a piece of equipment, and the whole system;
- It helps users decide whether it is worth continuing to use equipment to prevent extra cost;
- It helps users decide which components have the most impact on unreliability and failure;
- It helps users decide which components have the most impact on emissions and energy efficiency;
- It helps users decide if it is worth consuming more energy and money to use partially failing components or not; and
- It provides a link between probability of failures and cost.

### 3.3.4 Risk Analysis through the Bayesian Belief Networks Method

Risks associated with equipment and probabilities of their occurrence were determined. Then they were calculated based on their probability and consequence, and finally risks were ranked as per their value. Getting appropriate data to perform risk analysis was one of the challenges in this research. To overcome this problem, a Bayesian belief network

(BBN) methodology was used to perform risk assessment for oil sands mining equipment reliability (39).

## 3.4 Equipment Selection

In this section, oil sands mining haul trucks, shovels, crushers, conveyor belts, and slurry pumps used in Alberta's surface mining sector were studied. Table 3-1 show the types and number of this mining equipment, which are not necessarily accurately representative of actual equipment used in a given operation.

Table 3-1: Oil sands mining equipment used in the model

| Machinery | Capacity of each equipment (tons per hour) | Number of mining equipment |
|---|---|---|
| Shovels | 70 | 2 |
| Trucks | 500 | 10 |
| Crushers | 450 | 1 |
| Conveyer belts | 10,000 | 1 |
| Slurry pumps | 10,000 | 1 |

## 3.5 Oil Sands Mining Haul Trucks

Oil sands mining haul trucks transport oil sands ore from the mining site to bitumen extraction facilities. Haul trucks are divided into two categories: electric-drive and mechanical-drive. The mining haul truck studied in this research was the Caterpillar 797. (16). It was assumed that ten haul trucks were operating in two groups of five, in which each group works under multi-state system reliability. The fleet of five trucks operate in a series with a shovel (two shovels operate in parallel and five trucks operate in a series with one shovel). Trucking capacity on a short haul was assumed to be 500 tons per hour and if two trucks (k) out of five trucks (n) work, then the system can operate (G: Good operation). Truck reliability can be calculated with equation 3-4 (57):

$$\text{k out of n: G: 2 out of 5: G} = \binom{2}{5} \qquad (3\text{-}4)$$

### 3.5.1 Identification of Potential Risks Associated With Haul Trucks

This process identifies risks associated with oil sands mining haul trucks (58). Brainstorming and interviewing experts (mining engineers, reliability engineers, risk analysts, project managers) and reviewing the literatures helped to determine failure modes and rates (refer to chapter 2). Based on expert opinions, the reliability for trucks was assumed to be 0.85 over a year; therefore, truck failure is 0.15 over a year.

### 3.5.2 Main Mechanical Parts of Oil Sands Mining Haul Trucks

The main components of oil sands mining haul trucks, whose failures can lead to the loss of the truck, are:

- Cab/control, fuel system, engine, transmission, brakes, suspension, tires, dispatch system/GPS/radio, pneumatics/hydraulics, structure, and final drives (wheel sets).

In this chapter, major possible failure modes for each component were investigated and their failure probabilities were calculated based on the BBN method.

#### 3.5.2.1 Cab/Control

The weather in Alberta sometimes drops below -30$^o$C, which may induce cracks in the cab. If a level gauge shows a low air warning because of the cold, the truck cannot be properly controlled from the cab. This may cause excess airflow through the intake system, which may lead to the failure of the air filter and the loss of the control system. Oil and air gauges monitor air and oil pressure in the control system and are required to confirm the truck's condition. When the ambient temperature is so low that the oil pressure drops below its normal level the control system fails. Besides cold, human error can cause cab failure (11, 16, 59).

Assumptions:

- The parameters of weather (W), human error (HE), and site condition (SC) are independent.
- Cab/control cracks (CC), low air warning (LA), oil pressure drop (OP), and human error (HE) are independent.

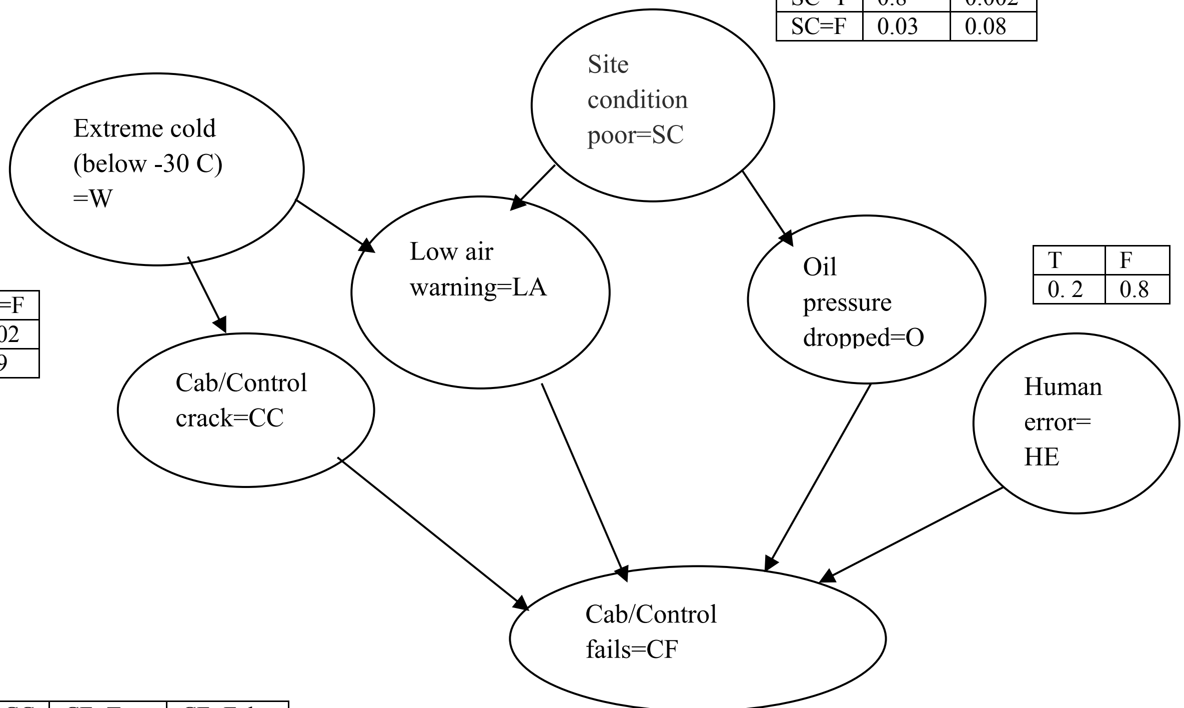
| T | F |
|---|---|
| 0.5 | 0.5 |

| T | F |
|---|---|
| 0.2 | 0.8 |

| | OP=T | OP=F |
|---|---|---|
| SC=T | 0.8 | 0.002 |
| SC=F | 0.03 | 0.08 |

| T | F |
|---|---|
| 0. 2 | 0.8 |

| | CC=T | CC=F |
|---|---|---|
| W=T | 0.9 | 0.002 |
| W=F | 0.01 | 0.09 |




| HE | LA | OP | CC | CF=True | CF=False |
|---|---|---|---|---|---|
| T | T | T | T | 0.085 | 0.002 |
| T | T | T | F | 0.001 | 0.03 |
| T | T | F | T | 0.0025 | 0.075 |
| T | F | T | T | 0.002 | 0.035 |
| F | T | T | T | 0.001 | 0.005 |
| T | F | T | F | 0.02 | 0.0025 |
| T | T | F | F | 0.005 | 0.0035 |
| F | T | F | T | 0.002 | 0.001 |
| F | F | F | T | 0.001 | 0.002 |
| F | F | T | T | 0.002 | 0.001 |
| F | T | F | F | 0.035 | 0.015 |
| F | F | T | F | 0.005 | 0.005 |
| T | F | F | F | 0.02 | 0.03 |
| F | F | F | F | 0.06 | 0.006 |

Figure 3-3: BBN model for haul truck cab/control failures

| W | SC | LA=T | LA=F |
|---|---|---|---|
| T | T | 0.7 | 0.002 |
| T | F | 0.01 | 0.09 |
| F | T | 0.02 | 0.08 |
| F | F | 0.04 | 0.001 |

The probability of failure and the reliability for cab/controls were calculated based on Figure 3-4 and from the formulas below:

$$P\,(CF) = \sum_{CC,OP,LA,HE} P\,(CF \mid CC, OP, LA, HE)\; P\,(CC, OP, LA, HE) \qquad (1)$$

$$P\,(CF) = \sum_{CC,OP,LA,HE} P\,(CF \mid CC, OP, LA, HE)\; P\,(CC)*P\,(OP)*P\,(LA)*P\,(HE) \qquad (2)$$

$$P\ (CC) = \sum_{W} P\ (CC \mid W)\ P\ (W) \qquad (3)$$

$$P\ (OP) = \sum_{SC} P\ (OP \mid SC)\ P\ (SC) \qquad (4)$$

$$P\ (LA) = \sum_{SC} P\ (LA \mid SC)\ P\ (LA) \qquad (5)$$

$$P\ (HE) = P\ (HE/T)*P\ (T) + P\ (HE/\ \text{Not True})\ P\ (\text{Not True}) \qquad (6)$$

$$P\ (SC) = P\ (SC/T)*P\ (T) + P\ (SC/\ \text{Not True})\ P\ (\text{Not True}) \qquad (7)$$

$$P\ (W) = P\ (W/T)*P\ (T) + P\ (W/\ \text{Not True})\ P\ (\text{Not True}) \qquad (8)$$

The probability of cab control failure was calculated as follows using equations 1 to 8 and Excel MS software as:

**P (CF) = 0.05**, Probability of failure for cab controls

**R (CF) = 0.95**, Reliability for cab controls

### 3.5.2.1.1 Cab/Control Cost

The parameter "$C_{Cab}$ ($)" was used for the cab/control cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.5.2.2 Fuel System

The fuel system in a diesel engine injects fuel into an engine cylinder. The fuel system is one of main components of an oil sands mining haul truck and has some subcomponents in its motor that send fuel to an engine (60, 61). The major components of a fuel system that help a fuel system to be reliable are the fuel tank, fuel transfer pump, fuel filters, injection pump, and injection nozzles. Regular problems related to a fuel system are leakage, pressure loss because of a broken fuel pump, wrong valve timing, and injector faults. They can cause power loss and increase exhaust gas emissions (16). Some of failure modes associated with a fuel system were identified as internal leakage and lack of fuel injection indicator. Some causes of internal leakage are:

- Damaged injector ball seat, leaking feed tubes, blown internal high-pressure seal, incorrect nozzle needle clearance, and cracked nozzle body or injector body.

Some causes of injection indicator fault are:

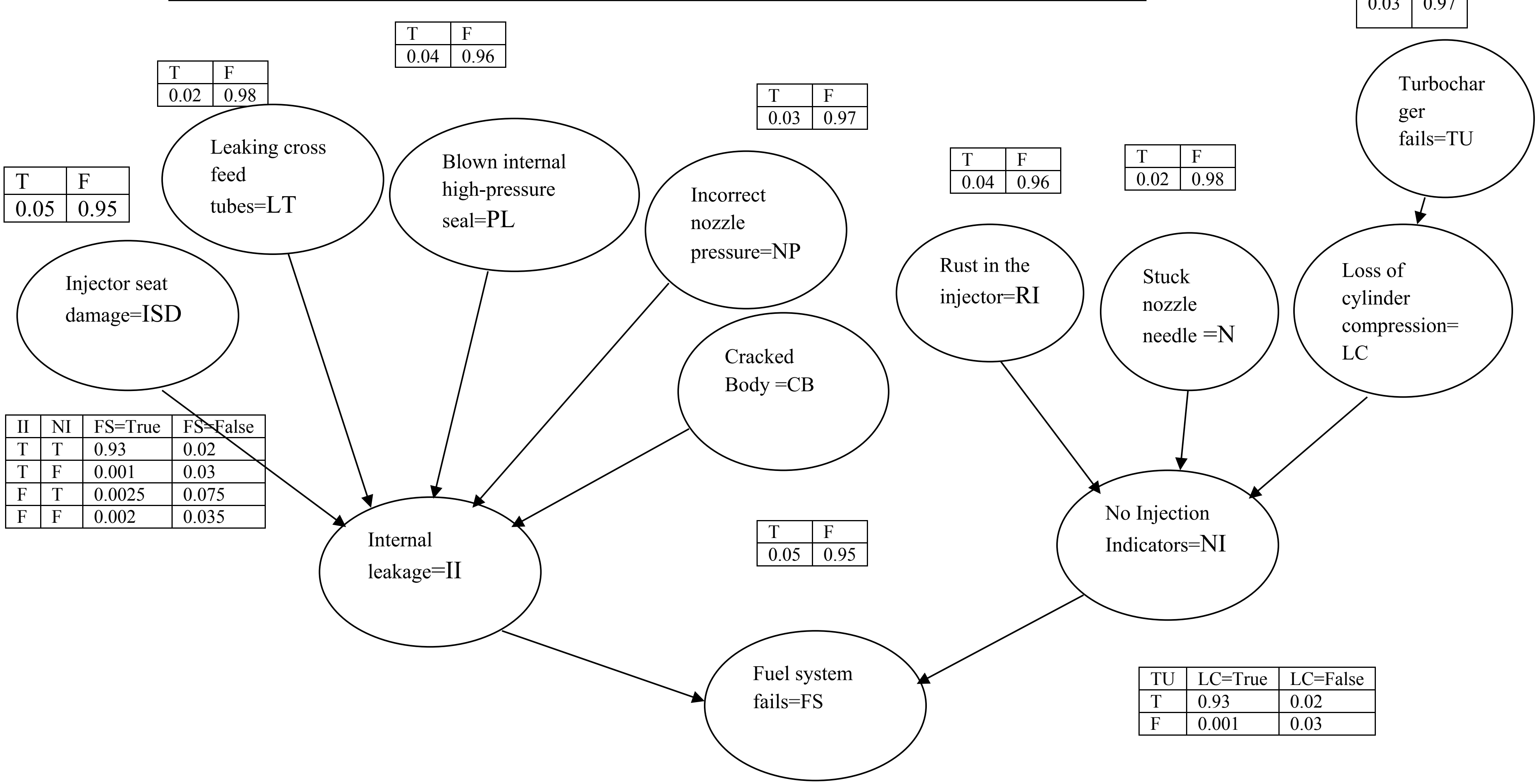
- A loss of cylinder compression (allowing fuel wash), and injector failure are also possible failure modes in the injection indicator of fuel system (61, 62).

The turbocharger is a turbine that increases engine efficiency and power by giving extra air into a combustion chamber. Turbochargers can raise an engine's output results by forcing more air, and proportionately more fuel, into a combustion chamber (63).

Assumptions for fuel system failure mode:

- No injection indicators (NI), turbocharger (TU), and internal leakage (II) are independent.
- Injector seat damage (ISD), leaking cross feed tubes (LT), blown internal high-pressure seal (PL), incorrect nozzle pressure (NP), and cracked body (BC) are independent.

  Rust in the injector (RI), stuck injector (N), and loss of cylinder compression (LC) are independent.




| T | F |
|---|---|
| 0.05 | 0.95 |

| T | F |
|---|---|
| 0.02 | 0.98 |

| T | F |
|---|---|
| 0.04 | 0.96 |

| T | F |
|---|---|
| 0.03 | 0.97 |

| T | F |
|---|---|
| 0.04 | 0.96 |

| T | F |
|---|---|
| 0.02 | 0.98 |

| T | F |
|---|---|
| 0.03 | 0.97 |

| II | NI | FS=True | FS=False |
|---|---|---|---|
| T | T | 0.93 | 0.02 |
| T | F | 0.001 | 0.03 |
| F | T | 0.0025 | 0.075 |
| F | F | 0.002 | 0.035 |

| T | F |
|---|---|
| 0.05 | 0.95 |

| TU | LC=True | LC=False |
|---|---|---|
| T | 0.93 | 0.02 |
| F | 0.001 | 0.03 |

Figure 3-4: BBN model for haul truck fuel system failures

| ISD | LT | PL | NP | BC | II=True | II =False |
|---|---|---|---|---|---|---|
| T | T | T | T | T | 0. 8 | 0.02 |
| T | T | T | T | F | 0.001 | 0.03 |
| T | T | T | F | T | 0.0025 | 0.075 |
| T | T | F | T | T | 0.002 | 0.035 |
| T | F | T | T | T | 0.001 | 0.005 |
| T | T | T | F | F | 0.003 | 0.01 |
| T | T | F | F | F | 0.004 | 0.004 |
| T | F | F | F | F | 0.0035 | 0.0015 |
| F | T | T | T | T | 0.002 | 0.025 |
| F | F | T | T | T | 0.005 | 0.035 |
| F | F | F | T | T | 0.002 | 0.1 |
| F | F | F | F | T | 0.01 | 0.2 |
| F | F | T | F | F | 0.03 | 0.006 |
| F | T | F | T | F | 0.04 | 0.009 |
| F | F | T | T | F | 0.007 | 0.02 |
| F | F | F | F | F | 0.0025 | 0.003 |

| RI | N | LC | NI=True | DS=False |
|---|---|---|---|---|
| T | T | T | 0.90 | 0.02 |
| T | T | F | 0.001 | 0.05 |
| T | F | T | 0.06 | 0.008 |
| T | F | F | 0.01 | 0.009 |
| F | F | T | 0.0001 | 0.025 |
| F | T | F | 0.02 | 0.0013 |
| F | T | T | 0.002 | 0.02 |
| F | F | F | 0.00015 | 0.3 |

The probability of failure and the reliability for the haul truck's fuel system were calculated based on Figure 3-5 and from the formulas below:

$$P\ (FS) = \sum_{II,NI} P\ (FS \mid II, NI)\ P\ (II, NI) \tag{9}$$

$$P\ (FS) = \sum_{II,NI} P\ (FS \mid II, NI)\ P\ (II)\ P\ (NI) \tag{10}$$

$$P\ (II) = \sum_{CB,NP,PL,LT,ISD} P\ (II \mid CB, NP, PL, LT, ISD)\ P\ (CB)\ P\ (NP)\ P\ (PL)\ P\ (LT)\ P\ (ISD) \tag{11}$$

$$P\ (NI) = \sum_{R,N,LC} P\ (NI \mid R, N, LC)\ P\ (R)\ P\ (N)\ P\ (LC) \tag{12}$$

P (CB) = P (CB)*P (T) +P (CB/ Not True) P (Not True) (13)

P (NP) = P (NP)*P (T) +P (NP / Not True) P (Not True) (14)

P (PL) = P (PL)*P (T) +P (PL/ Not True) P (Not True) (15)

P (LT) = P (LT)*P (T) +P (LT/ Not True) P (Not True) (16)

P (ISD) = P (ISD)*P (T) +P (ISD/ Not True) P (Not True) (17)

P (RI) = P (RI)*P (T) +P (RI/ Not True) P (Not True) (14)

P (N) = P (N)*P (T) +P (N/ Not True) P (Not True) (18)

$$P\ (LC) = \sum_{TU} P\ (LC \mid TU)\ P\ (TU) \tag{19}$$

P (TU) = P (TU)*P (T) +P (TU/ Not True) P (Not True) (20)

P (II) = 0.015

P (LC) = 0.059

P (NI) =0.268

The failure probability for fuel systems was calculated using equation 9 to 20 and Excel as:

**P (FS) = 0.05**, Probability of failure for fuel systems

**R (FS) = 0.95**, Reliability for fuel systems

### 3.5.2.2.1 Fuel System Cost

It was assumed that the fuel system cost around CAN $79,000 (64).

### 3.5.2.3 Engine

A diesel engine was considered in this research. The main causes of failure in an engine are shown in Figure 3-6.

Leakage of piston and low quality of fuel are some of the failure mode of engine. In addition, if cooling and lubrication system, intake and exhaust system and engine block system fails then engine will fail.

Assumptions:

- Low quality fuel (LQ), cooling (COL), lubrication system (LS), intake and exhaust system (IS), fuel system (FS), engine block (EB), and piston ring leakage (PRL) are independent.
- Fan and pulley (FP), radiator (R), thermostat (TH), and cooling pump failure (CP) are independent.

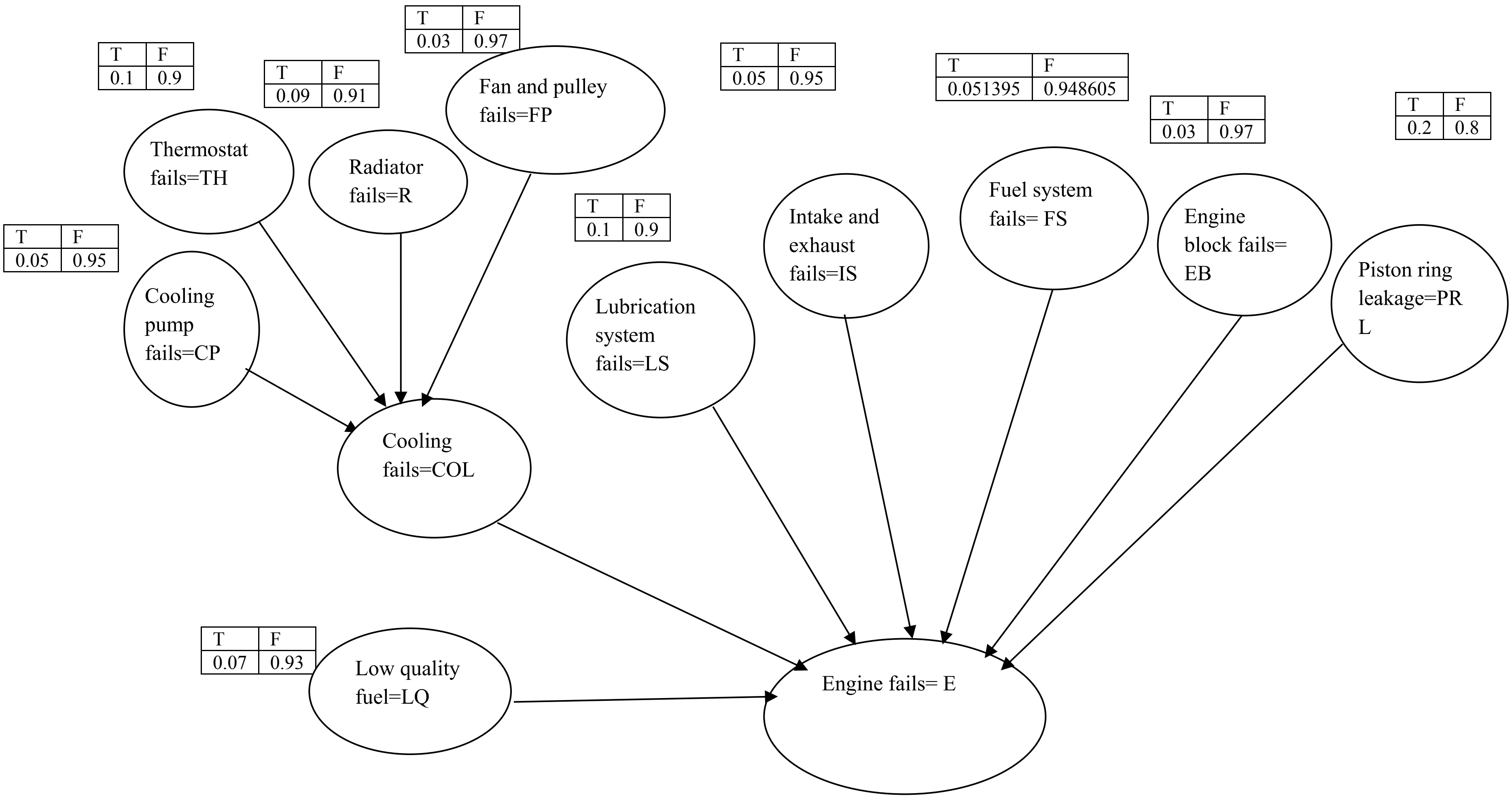



Figure 3-5: BBN model for haul truck engine failures

| CP | FP | TH | R | COL=True | COL=False |
|---|---|---|---|---|---|
| T | T | T | T | 0.93 | 0.02 |
| T | T | T | F | 0.001 | 0.03 |
| T | T | F | T | 0.0025 | 0.075 |
| T | F | T | T | 0.002 | 0.035 |
| F | T | T | T | 0.21 | 0.004 |
| T | T | F | F | 0.06 | 0.02 |
| T | F | F | F | 0.0005 | 0.006 |
| T | F | T | F | 0.0035 | 0.002 |
| F | T | F | T | 0.005 | 0.035 |
| F | F | T | T | 0.002 | 0.1 |
| F | F | F | T | 0.01 | 0.2 |
| F | F | F | F | 0.0025 | 0.003 |

| LQ | COL | LS | IS | FS | EB | PRL | E=True | E =False |
|---|---|---|---|---|---|---|---|---|
| T | T | T | T | T | T | T | 0.8 | 0.02 |
| T | T | T | T | T | T | F | 0.001 | 0.006 |
| T | T | T | T | T | F | T | 0.001 | 0.03 |
| T | T | T | T | F | T | T | 0.0025 | 0.075 |
| T | T | T | F | T | T | T | 0.7 | 0.003 |
| T | T | F | T | T | T | T | 0.004 | 0.02865 |
| T | F | T | T | T | T | T | 0.002 | 0.4822 |
| F | T | T | T | T | T | T | 0.007 | 0.8411 |
| T | T | T | T | T | F | F | 0.001 | 0.7491 |
| T | T | T | T | F | F | F | 0.002 | 0.4552 |
| T | T | F | F | F | F | F | 0. 09 | 0.004 |
| T | F | F | F | F | F | F | 0.03 | 0.06 |
| T | T | T | T | F | F | T | 0.0030 | 0.01 |
| F | T | T | T | F | F | F | 0.084 | 0.0740 |
| F | T | T | F | F | F | T | 0.004 | 0.004 |
| F | T | T | F | F | F | F | 0.048 | 0.003 |
| F | T | F | T | F | T | F | 0.0035 | 0.0015 |
| F | F | T | T | T | T | T | 0.0176 | 0.008 |
| F | F | F | T | T | T | T | 0.002 | 0.025 |
| F | F | F | F | T | T | F | 0.093 | 0.002 |
| F | F | F | F | F | T | T | 0.0050 | 0.014 |
| F | F | F | F | F | F | T | 0.074 | 0.0094 |
| F | F | T | T | F | F | T | 0.004 | 0.009 |
| T | F | F | T | F | F | F | 0.002 | 0.0086 |
| T | F | F | T | T | T | T | 0.005 | 0.035 |
| T | F | F | T | T | T | F | 0.821 | 0.07 |
| T | F | F | F | T | T | T | 0.1766 | 0.05 |
| T | F | F | F | F | T | T | 0.1338 | 0.0332 |
| F | F | F | F | F | F | F | 0.0025 | 0.003 |

The probability of failure and the reliability for haul truck engines were calculated based on Figure 3-6 and from the formulas below:

$$P(E) = \sum_{LQ,COL,LS,IS,FS,EB,PRL} P(E|\ LQ, COL, LS, IS, FS, EB, PRL)\ P(LQ)\ P(COL)\ P(LS)\ P(IS)\ P(FS)\ P(EB)\ P(PRL) \quad (21)$$

$$P(COL) = \sum_{CP,FP,TH,R} P(COL\ |\ CP, FP, TH, R)\ P(CP)\ P(FP)\ P(TH)\ P(R) \quad (22)$$

P (CP) = P (CP)*P (T) +P (CP/ Not True) P (Not True) (23)

P (FP) = P (FP)*P (T) +P (FP/ Not True) P (Not True) (24)

P (TH) = P (TH)*P (T) +P (TH/ Not True) P (Not True) (25)

P (R) = P (R)*P (T) +P (R / Not True) P (Not True) (26)

P (LQ) = P (LQ)*P (T) +P (LQ/ Not True) P (Not True) (27)

P (LS) = P (LS)*P (T) +P (LS/ Not True) P (Not True) (28)

P (IS) = P (IS)*P (T) +P (IS/ Not True) P (Not True) (29)

P (FS) = P (FS)*P (T) +P (FS/ Not True) P (Not True) (30)

P (EB) = P (EB)*P (T) +P (EB/ Not True) P (Not True) (31)

P (PRL) = P (EB)*P (T) +P (EB/ Not True) P (Not True) (32)

Engine failure probability was calculated using equations 21 to 32 and Excel as:

P (COL) = 0.01

**P (E) = 0.01**, Probability of failure for engine

**R (E) =0.99**, Reliability for engine

### 3.5.2.3.1 Engine Cost

It was assumed that the engine cost CAN $18,242 (65).

### 3.5.2.4 Transmission

The transmission transfers power from the engine to the wheels. It usually has an efficiency of over 90% for the full transmission capacity of the haul truck. The transmission consists of the gearbox, connections, bearing, clutch, universal joint, and wheels. Inefficiencies occur through losses from the clutch, universal joint, and wheels from transmission oil in gears and twisting force converters, as well as dissipation of energy by sliding friction in the gearbox and bearings (5, 61). The major possible failure modes for the transmission with their failure probability rates based on positive and negative modes in the BBN method for this study are shown below.

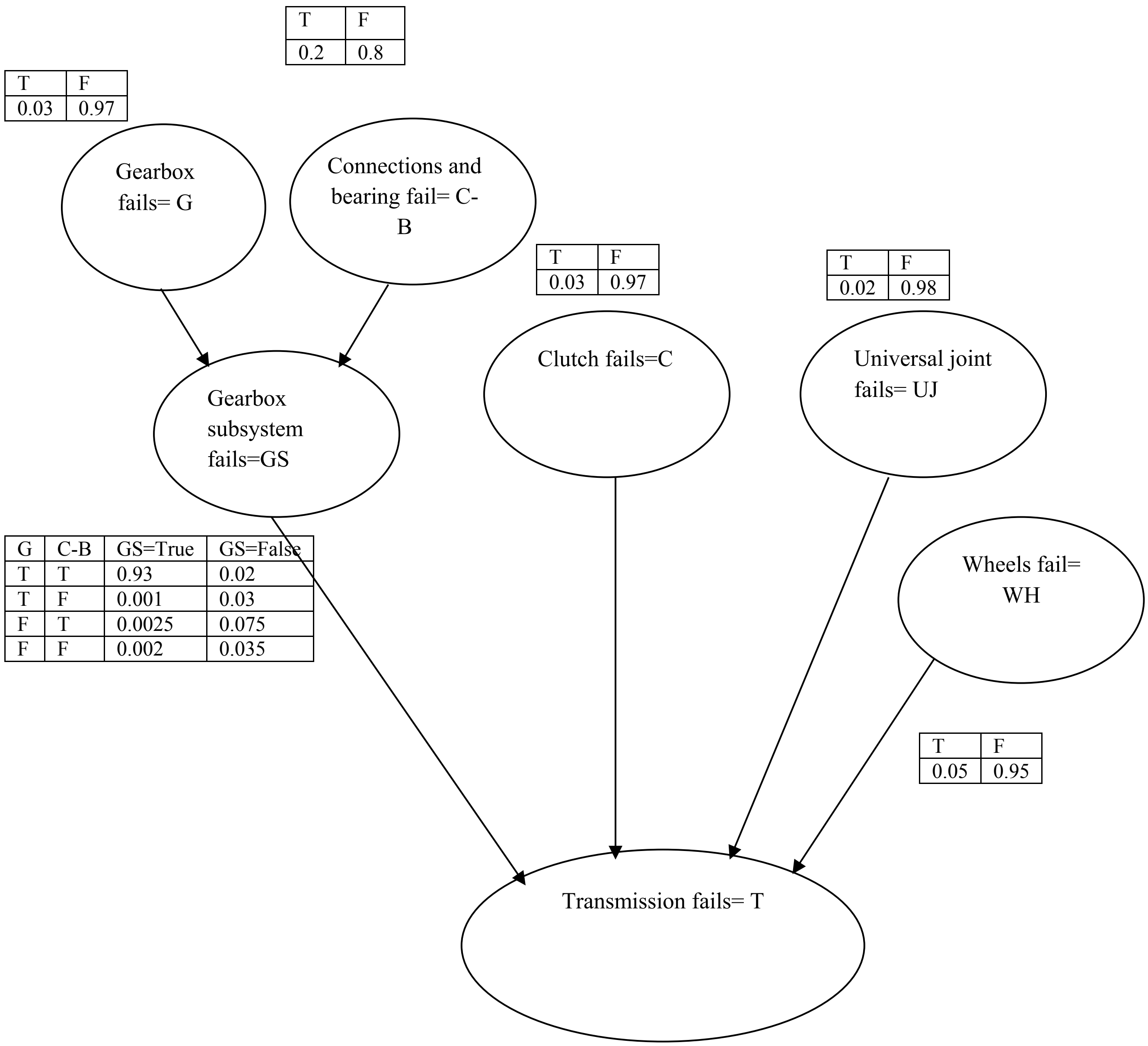



Figure 3-6: BBN model for haul truck transmission failure

| GS | C | UJ | WH | T=True | T =False |
|---|---|---|---|---|---|
| T | T | T | T | 0. 8 | 0.02 |
| T | T | T | F | 0.001 | 0.03 |
| T | T | F | T | 0.0025 | 0.075 |
| T | F | T | T | 0.002 | 0.035 |
| F | T | T | T | 0.001 | 0.005 |
| T | T | F | F | 0.003 | 0.01 |
| T | F | F | F | 0.004 | 0.004 |
| T | F | T | F | 0.0098 | 0.078 |
| F | T | F | T | 0.004 | 0.0002 |
| F | F | T | T | 0.002 | 0.1 |
| F | F | F | T | 0.01 | 0.2 |
| F | F | F | F | 0.0025 | 0.003 |

The probability of failure and the reliability for haul truck transmissions were calculated based on Figure 3-7 and from the formulas below:

Assumptions:

- Gearbox subsystem (GS), clutch (C), universal joint (UJ), and wheels (WH) are independent.
- Gearbox (G), and connections and bearing (C-B) are independent.

$$P(T) = \sum_{GS,C,UJ,WH} P(T|\ GS, C, UJ, WH)\ P(GS)\ P(C)\ P(UJ)\ P(WH) \tag{33}$$

$$P(GS) = \sum_{G,C-B} P(GS \mid G, C\text{-}B)\ P(G)\ P(C\text{-}B) \tag{34}$$

$$P(G) = P(G)*P(T) + P(G/\ \text{Not True})\ P(\text{Not True}) \tag{35}$$

$$P(C\text{-}B) = P(C\text{-}B)*P(T) + P(C\text{-}B\ /\ \text{Not True})\ P(\text{Not True}) \tag{36}$$

$$P(C) = P(C)*P(T) + P(C/\ \text{Not True})\ P(\text{Not True}) \tag{37}$$

$$P(UJ) = P(UJ)*P(T) + P(UJ\ /\ \text{Not True})\ P(\text{Not True}) \tag{38}$$

$$P(WH) = P(WH)*P(T) + P(WH\ /\ \text{Not True})\ P(\text{Not True}) \tag{39}$$

Transmission failure probability was calculated from equations 33 to 39 and Excel as:

P (GS) = 0.05

**P (T) =0.1**, Probability of failure for transmissions

**R (T) =0.9**, Reliability for transmissions

### 3.5.2.4.1 Transmission Cost

The parameter "$C_{Transmission}$" was used for the capital cost of transmissions as a cause of transmission failure, in modeling risk. The presumed cost can be substituted in Table 3-2 to calculate risk.

### 3.5.2.5 Brakes

Brakes convert kinetic energy to thermal energy and make a vehicle stop. A brake system includes actuators, bearings, housings, seals, friction linings, and springs. Some of problems associated with brakes failures are (6, 16, 61):

- Improper loading, which may cause brakes to overheat and break down;
- Missing or broken mechanical components;
- Air leakage in a brake chamber;
- A defective brake.

For this study, some possible failure modes related to brakes with their failure probability rates based on positive and negative modes in the BBN method are shown below.

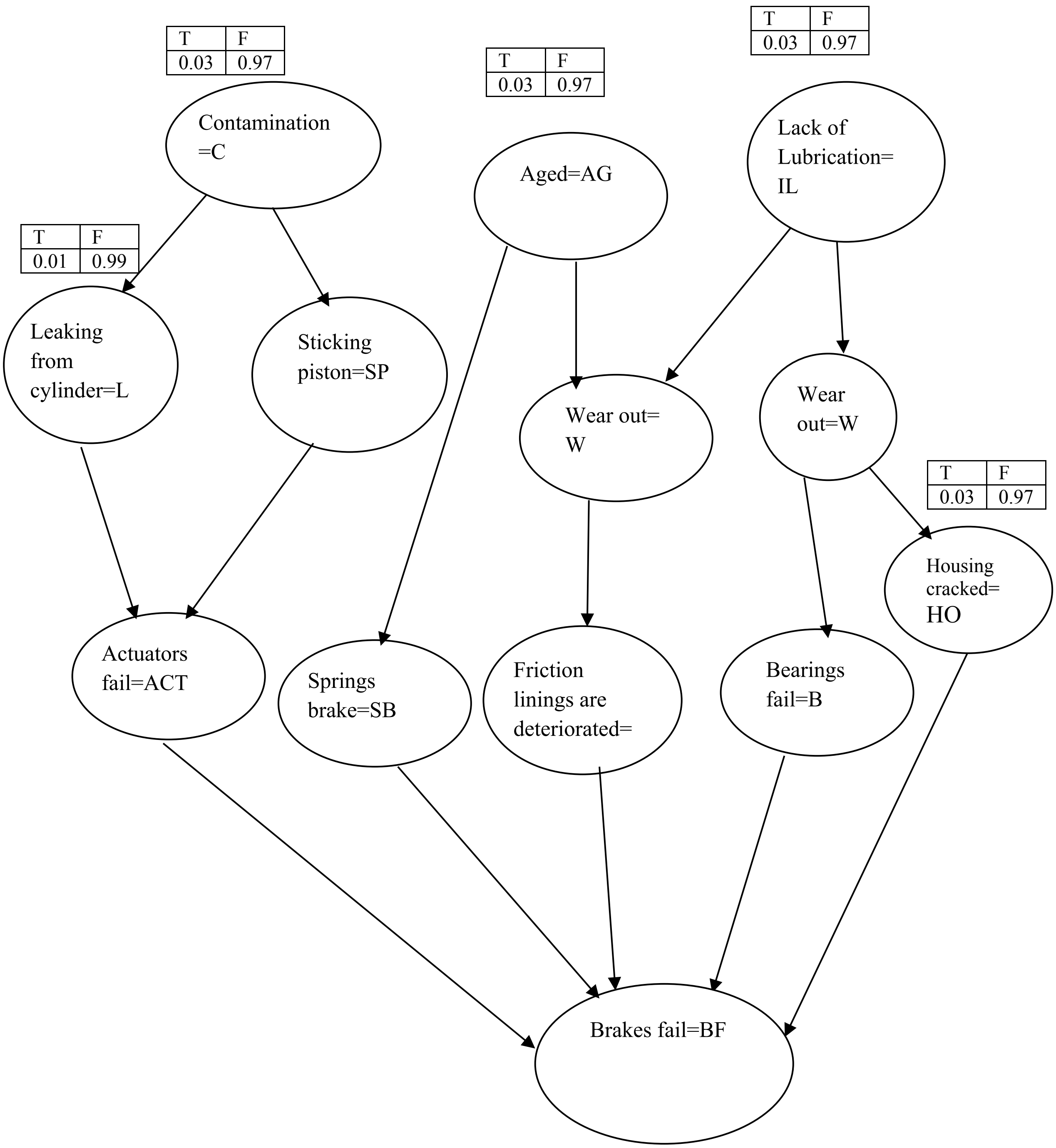



Figure 3-7: BBN model for haul truck brake failures

| ACT | SB | FL | B | HO | BF=True | BF =False |
|---|---|---|---|---|---|---|
| T | T | T | T | T | 0.97 | 0.02 |
| T | T | T | T | F | 0.01 | 0.03 |
| T | T | T | F | T | 0.025 | 0.075 |
| T | T | F | T | T | 0.02 | 0.035 |
| T | F | T | T | T | 0.001 | 0.005 |
| T | T | T | F | F | 0.03 | 0.01 |
| T | T | F | F | F | 0.04 | 0.004 |
| T | F | F | F | F | 0.035 | 0.0015 |
| F | T | T | T | T | 0.002 | 0.025 |
| F | F | T | T | T | 0.05 | 0.035 |
| F | F | F | T | T | 0.002 | 0.1 |
| F | F | F | F | T | 0.01 | 0.02 |
| F | F | T | F | F | 0.03 | 0.006 |
| F | T | F | T | F | 0.04 | 0.009 |
| F | F | T | T | F | 0.07 | 0.02 |
| F | F | F | F | F | 0.025 | 0.003 |

The probability of failure and the reliability for haul truck brakes were calculated based on Figure 3-8 and from the formulas below:

Assumptions:

- Actuators (ACT), springs brake (SB), deteriorated friction linings (FL), bearings (B), and housings (HO) are independent.

$$P\ (BF) = \sum_{ACT,SB,FL,B,HO} P\ (BF \mid ACT, SB, FL, B, HO)\ P\ (ACT, SB, FL, B, HO) \quad (40)$$

$$P\ (BF) = \sum_{ACT,SB,FL,B,HO} P\ (BF \mid ACT, SB, FL, B, HO)\ P\ (ACT)\ P\ (SB)\ P\ (FL)\ P\ (B)\ P\ (HO) \quad (41)$$

$$P\ (ACT) = \sum_{L,SP} P\ (ACT \mid L, SP)\ P\ (L)\ P\ (SP) \quad (42)$$

$$P\ (L) = \sum_{C} P\ (L \mid C)\ P\ (C) \quad (43)$$

$$P\ (SP) = \sum_{C} P\ (SP \mid C)\ P\ (C) \quad (44)$$

$$P\ (SB) = \sum_{AG} P\ (SB \mid AG)\ P\ (AG) \quad (45)$$

$$P\ (FL) = \sum_{W} P\ (FL \mid W)\ P\ (W) \quad (46)$$

$$P\ (W) = \sum_{AG,HO} P\ (W \mid AG, HO)\ P\ (AG)\ P\ (HO) \quad (47)$$

P (AG) = P (AG/T)*P (T) +P (AG/ Not True) P (Not True) (48)

P (HO) = P (HO/T)*P (T) +P (HO/ Not True) P (Not True) (49)

$$P(C) = P(C/T)*P(T) + P(C/\text{Not True})\,P(\text{Not True}) \tag{50}$$

$$P(B) = \sum_{W} P(B \mid W)\,P(W) \tag{51}$$

$$P(HO) = \sum_{W} P(HO \mid W)\,P(W) \tag{52}$$

$$P(W) = \sum_{IL} P(W \mid IL)\,P(IL) \tag{53}$$

$$P(IL) = P(IL/T)*P(T) + P(IL/\text{Not True})\,P(\text{Not True}) \tag{54}$$

Brake failure probability is calculated from equations 40 to 54 and Excel as:

**P (BF) =0.12**, Probability of failure for brakes

**R (BF) =0.88**, Reliability for brakes

### 3.5.2.5.1 Brake Cost

The parameter "$C_{Brakes}$ ($)" was used for the cost of brakes as a cause of brake failure in modeling risk. The actual cost can be substituted in Table 3-2 to calculate risk.

### 3.5.2.6 Suspension

The suspension is the system that attaches a truck to its wheels and makes appropriate movements between the tire and the wheels (7). The main mechanical components of the suspension are (8, 9, 61):

- Solid beam axle;
- Trailing link;
- Shocks and struts;
- Short and long arm.

The major possible failure modes related to suspensions with their failure probability rates based on positive and negative modes shown in the BBN method for this study are shown below.

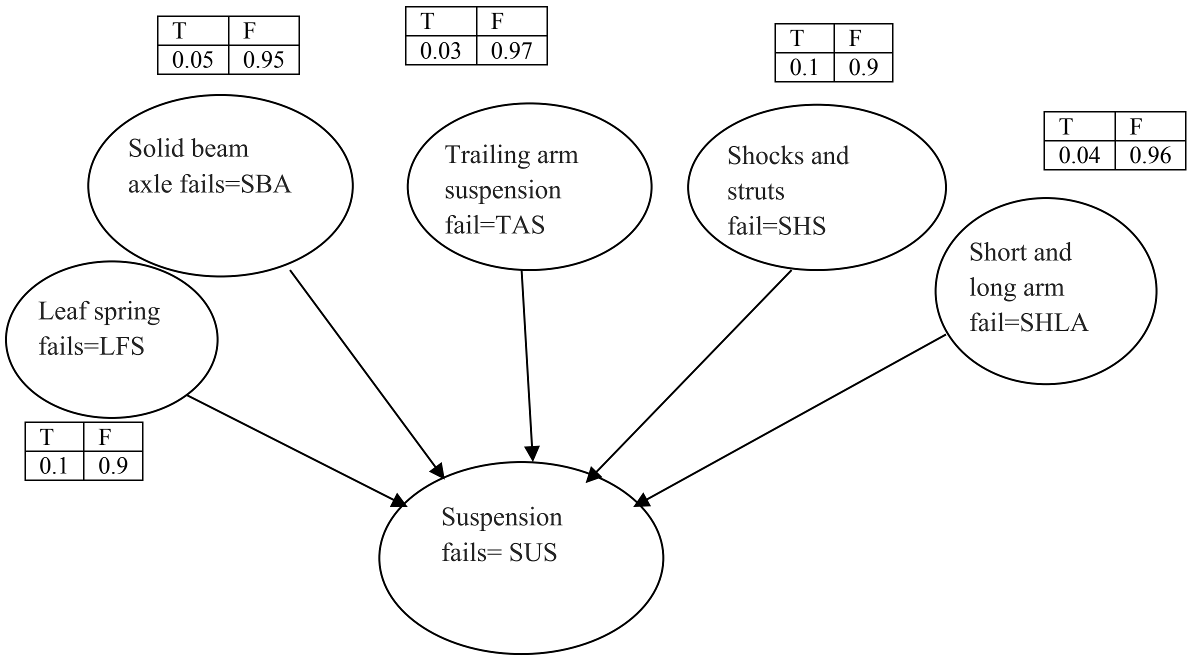



Figure 3-8: BBN graphical model for haul truck suspension failures

| LFS | SBA | TAS | SHS | SHLS | SUS=True | SUS =False |
|---|---|---|---|---|---|---|
| T | T | T | T | T | 0.8 | 0.02 |
| T | T | T | T | F | 0.1 | 0.03 |
| T | T | T | F | T | 0.25 | 0.075 |
| T | T | F | T | T | 0.02 | 0.035 |
| T | F | T | T | T | 0.1 | 0.005 |
| F | T | T | T | T | 0.2 | 0.006 |
| T | T | T | F | F | 0.3 | 0.01 |
| T | T | F | F | F | 0.004 | 0.004 |
| T | F | F | F | F | 0.7 | 0.001 |
| T | F | F | T | T | 0.002 | 0.1 |
| T | F | T | F | T | 0.08 | 0.004 |
| F | F | T | T | T | 0.09 | 0.08 |
| F | F | F | F | T | 0.01 | 0.2 |
| F | F | F | F | F | 0.025 | 0.003 |

The probability of failure and the reliability for haul truck suspensions were calculated based on Figure 3-9 and from the formulas below:

Assumptions:

- Leaf spring (LFS), solid beam axle (SBA), trailing arm suspension (TAS), shocks and struts (SHS) and short and long arm (SHLA) are independent.

P (SUS) = $\sum_{LFS,SBA,TAS,SHS,SHLA}$ P (SUS | LFS, SBA, TAS, SHS, SHLA) P (LFS, SBA, TAS, SHS, SHLA) (55)

P (SUS) = $\sum_{LFS,SBA,TAS,SHS,SHLA}$ P (SUS | LFS, SBA, TAS, SHS, SHLA) P (LFS) P (SBA) P (TAS) P (SHS) P (SHLA) (56)

P (LFS) = P (LFS/T)*P (T) +P (LFS/ Not True) P (Not True) (57)

P (SBA) = P (M/T)*P (T) +P (M/ Not True) P (Not True) (58)

P (TAS) = P (TAS /T)*P (T) +P (TAS / Not True) P (Not True) (59)

P (SHS) = P (SHS /T)*P (T) +P (SHS / Not True) P (Not True) (60)

P (SHLA) = P (SHLA /T)*P (T) +P (SHLA / Not True) P (Not True) (61)

Suspension failure probability was calculated from equations 55 to 61 and Excel as:

**P (SUS) =0.08**, Probability of failure for the suspension

**R (SUS) =0.92**, Reliability for the suspension

### 3.5.2.6.1 Suspension Cost

The parameter "$C_{Suspension}$ (\$)" was used for the suspension cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.5.2.7 Dispatch system/GPS/Radio

The dispatch system is another important haul truck component, since costs associated with material transportation are about 60% of operating costs in settings (66). A dispatch system can optimize a transportation model for a given unload design of truck hauling. A dispatch system allows truck drivers to track the location of truck and enter the location and other information into field control units (67).

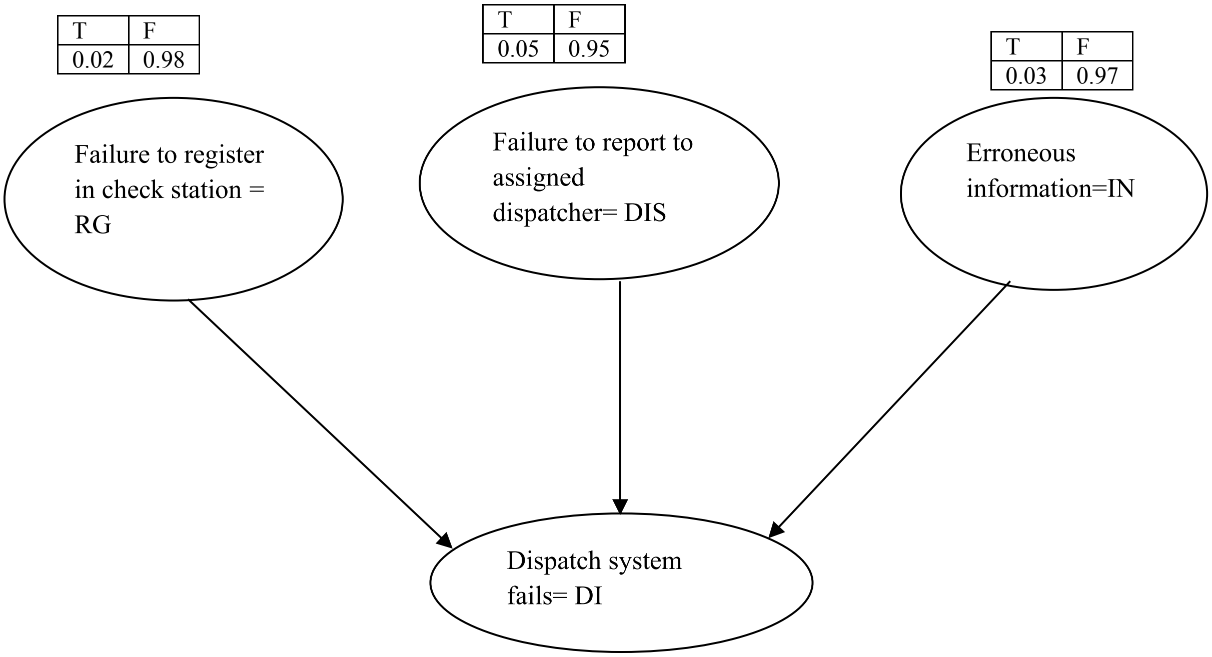



Figure 3-9: BBN graphical model for haul truck dispatch system failures

| RG | DIS | IN | DI=True | DI =False |
|---|---|---|---|---|
| T | T | T | 0.95 | 0.02 |
| T | T | F | 0.5 | 0.03 |
| T | F | T | 0. 25 | 0.075 |
| F | T | T | 0.02 | 0.035 |
| T | F | F | 0. 3 | 0.01 |
| F | F | T | 0. 1 | 0.2 |
| F | T | F | 0.01 | 0.05 |
| F | F | F | 0. 025 | 0.03 |

Some of the failure modes associated with haul truck dispatch systems are (11):

- Failure to register in and out of check stations.
- Failure to report to an assigned dispatcher at a specific time when the driver needs to do so; and
- Display of incorrect information from a dispatcher.

Some possible failure modes related to a dispatch system with their failure probability rates based on positive and negative modes in the BBN method are shown in Figure 3-10.

Assumptions:

- Erroneous information (IN), failure to report to assigned dispatcher (DIS) and failure to register in check station (RG) are independent.

$$P\ (DI) = \sum_{RG,DIS,IN} P\ (DI \mid RG, DIS, IN)\ P\ (RG, DIS, IN) \quad (62)$$

$$P\ (DI) = \sum_{RG,DIS,IN} P\ (DI \mid RG, DIS, IN)\ P\ (IN)\ P\ (DIS)\ P\ (RG) \quad (63)$$

$$P\ (IN) = P\ (IN/T)*P\ (T) + P\ (IN/\ Not\ True)\ P\ (Not\ True) \quad (64)$$

$$P\ (DIS) = P\ (DIS/T)*P\ (T) + P\ (DIS/\ Not\ True)\ P\ (Not\ True) \quad (65)$$

$$P\ (RG) = P\ (RG/T)*P\ (T) + P\ (RG/\ Not\ True)\ P\ (Not\ True) \quad (66)$$

Dispatch system failure probability was calculated using equations 62 to 66 and Excel as:

**P (DI) =0.15**, Probability of failure for dispatch systems

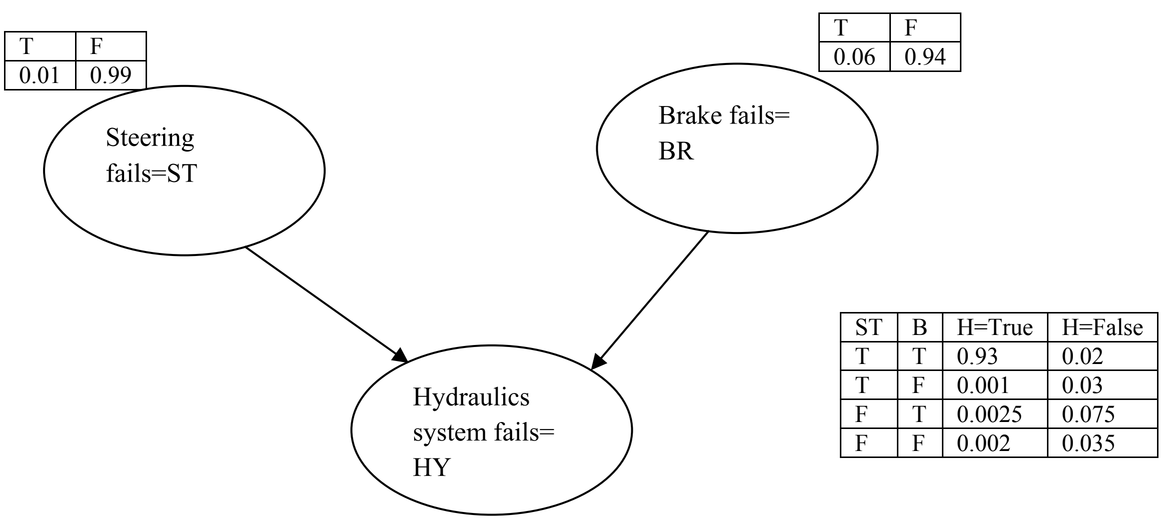
**R (DI) =0.85**, Reliability for dispatch systems

### 3.5.2.7.1 Dispatch System/GPS/Radio Cost

The parameter "$C_{\text{Dispatch system}}$ (\$)" was used for the dispatch system cost as a cause of dispatch system failure in modeling risk. The actual cost can be substituted in the Table 3-2 to calculate risk.

### 3.5.2.8 Pneumatics/Hydraulics

A pneumatics/hydraulic system consists of steering, brakes, and hydraulics. If any of these parts fails, the pneumatics/hydraulic system will fail (16). All possible failure modes related to hydraulics with the failure probability rate based on positive and negative modes from the BBN method for this study are shown below.




| T | F |
|---|---|
| 0.01 | 0.99 |

| T | F |
|---|---|
| 0.06 | 0.94 |

| ST | B | H=True | H=False |
|---|---|---|---|
| T | T | 0.93 | 0.02 |
| T | F | 0.001 | 0.03 |
| F | T | 0.0025 | 0.075 |
| F | F | 0.002 | 0.035 |

Figure 3-10: BBN graphical model for haul truck hydraulic system failures

The probability of failure and the reliability for haul truck hydraulic systems were calculated based on Figure 3-11 and from the formulas below:

Assumptions:

- Steering (ST) and brake (BR) are independent.

$$P\ (HY) = \sum_{ST,B} P\ (HY \mid ST, B)\ P\ (ST, BR) \quad (67)$$

$$P\ (HY) = \sum_{ST,B} P\ (HY \mid ST, BR)\ P\ (ST)\ P\ (BR) \quad (68)$$

$$P\ (ST) = P\ (ST/T)*P\ (T) + P\ (ST/\ Not\ True)\ P\ (Not\ True) \quad (69)$$

$$P\ (BR) = P\ (BR\ /T)*P\ (T) + P\ (BR\ /\ Not\ True)\ P\ (Not\ True) \quad (70)$$

Hydraulic system failure probability was calculated from equations 67 to 70 and Excel as:

**P (HY) =0.1**, Probability of failure for hydraulic systems

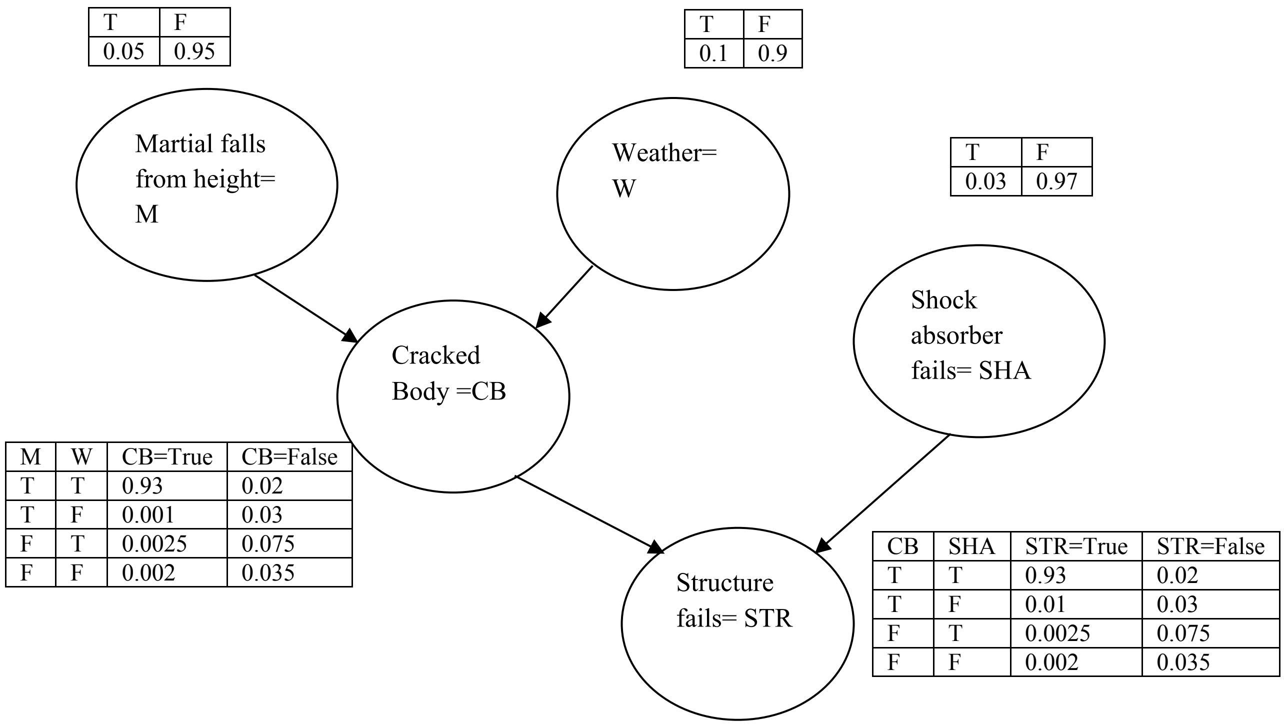
**R (HY) =0.9**, Reliability for hydraulic systems

### 3.5.2.8.1 Pneumatics/Hydraulics Cost

The parameter "$C_{Hydraulic}$ (\$)" was used for the pneumatic/hydraulic system cost as a cause of pneumatic/hydraulic failure in modeling risk. The presumed cost can be substituted in Table 3-2 to calculate risk.

### 3.5.2.9 Structure

Structure refers to the physical framework of an oil sands mining haul truck. One of the major causes of haul truck failure is frame cracking. Alberta’s freeze-thaw cycle damages roads, which in turn causes considerable damage to truck structure. Repairs can take several days and often require the removal of other components to perform the work. Effective identification, planning, scheduling, and execution can significantly decrease the impact of structural damage. Eliminating damage from happening in the first place, as well as having a true predictive maintenance procedure, would have the largest positive impact on a mine operation’s outcome. The root cause of structure failure is the combination of truck speed, load, and bad road conditions. Since stopping production is not a desirable option, the main focus of risk elimination is road conditions. Real-time strut pressure data were received from a mobile monitor along with GPS coordinates, which provide list of the sections of roads that are in operations to maintenance crews (13). All possible failure modes related to truck structure with their probability failure rates based on positive and negative modes in the BBN method are shown below.




| T | F |
|---|---|
| 0.05 | 0.95 |

| T | F |
|---|---|
| 0.1 | 0.9 |

| T | F |
|---|---|
| 0.03 | 0.97 |

| M | W | CB=True | CB=False |
|---|---|---|---|
| T | T | 0.93 | 0.02 |
| T | F | 0.001 | 0.03 |
| F | T | 0.0025 | 0.075 |
| F | F | 0.002 | 0.035 |

| CB | SHA | STR=True | STR=False |
|---|---|---|---|
| T | T | 0.93 | 0.02 |
| T | F | 0.01 | 0.03 |
| F | T | 0.0025 | 0.075 |
| F | F | 0.002 | 0.035 |

Figure 3-11: BBN graphical model for haul truck structure failures

Assumptions:

- Cracked Body (CB) and shock absorber (SHA) are independent.
- Material falls from height (M), weather (W) and shock absorber (SHA) are independent.

The probability of failure and the reliability for haul truck structures were calculated based on Figure 3-12 and from the formulas below:

$$P\ (STR) = \sum_{CB,SHA} P\ (STR \mid CB, SHA)\ P\ (CB, SHA) \quad (71)$$

$$P\ (STR) = \sum_{CB,SHA} P\ (STR \mid CB, SHA)\ P\ (CB)\ P\ (SHA) \quad (72)$$

$$P\ (CB) = \sum_{W,M} P\ (CB \mid W, M)\ P\ (W, M) \quad (73)$$

$$P\ (CB) = \sum_{W,M} P\ (CB \mid W, M)\ P\ (W)\ P\ (M) \quad (74)$$

$$P\ (W) = P\ (W/T)*P\ (T) + P\ (W/\ Not\ True)\ P\ (Not\ True) \quad (75)$$

P (M) = P (M/T)*P (T) +P (M/ Not True) P (Not True) (76)

P (SHA) = P (SHA/T)*P (T) +P (SHA/ Not True) P (Not True) (77)

Structure failure probability was calculated from equations 71 to 77 and Excel as:

**P (STR) =0.04**, Probability of failure for structure

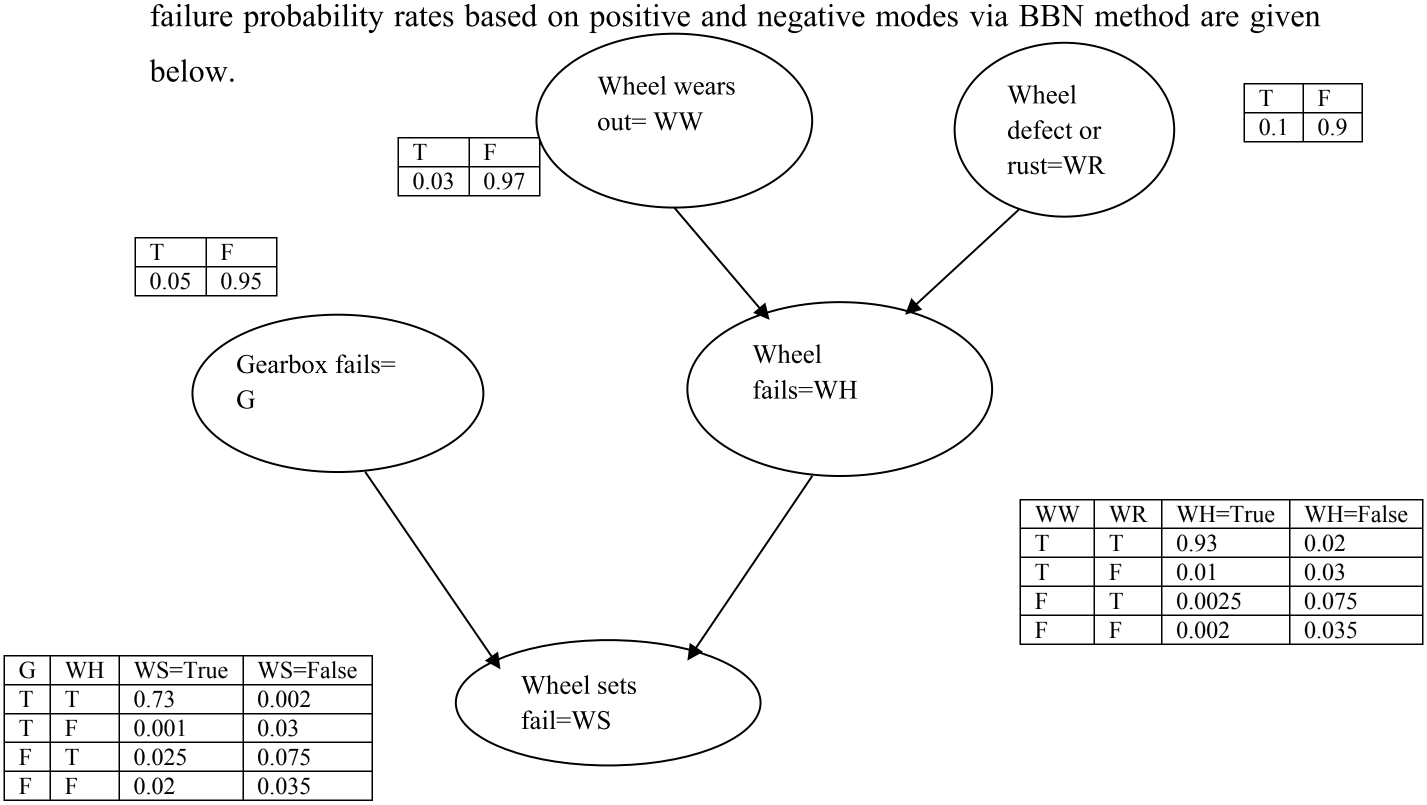
**R (STR) =0.96**, Reliability for structure

### 3.5.2.9.1 Structure Cost

The parameter "$C_{Structure}$ ($)" was used for structure cost in modeling equations as a cause of structure failure in modeling risk. The actual cost can be substituted in Table 3-2 to calculate risk.

### 3.5.2.10 Final Drives (Wheel Sets)

Truck final drives consist of the wheels and gearbox, and drive failure can have a significant impact on the wheel set. If the wheels wear out, either through defects or rust, they will fail. All possible failure modes related to the final drive (wheel set) with their failure probability rates based on positive and negative modes via BBN method are given below.




| T | F |
|---|---|
| 0.03 | 0.97 |

| T | F |
|---|---|
| 0.1 | 0.9 |

| T | F |
|---|---|
| 0.05 | 0.95 |

| WW | WR | WH=True | WH=False |
|---|---|---|---|
| T | T | 0.93 | 0.02 |
| T | F | 0.01 | 0.03 |
| F | T | 0.0025 | 0.075 |
| F | F | 0.002 | 0.035 |

| G | WH | WS=True | WS=False |
|---|---|---|---|
| T | T | 0.73 | 0.002 |
| T | F | 0.001 | 0.03 |
| F | T | 0.025 | 0.075 |
| F | F | 0.02 | 0.035 |

Figure 3-12: BBN graphical model for haul truck wheel sets failure

Assumptions:

- The wheels (WH) and gearbox (G) are independent.
- Wheel wear (WW), wheel defect or rust (WR) and gearbox (G) are independent.

The probability of failure and the reliability for haul truck wheel sets were calculated based on Figure 3-13 and from the formulas below:

$$P\,(WS) = \sum_{G,WH} P\,(WS \mid G, WH)\, P\,(G, WH) \quad (78)$$

$$P\,(WS) = \sum_{G,WH} P\,(WS \mid G, WH)\, P\,(G)\, P\,(WH) \quad (79)$$

$$P\,(WH) = \sum_{WW,WR} P\,(W \mid WW, WR)\, P\,(WW, WR) \quad (80)$$

$$P\,(WH) = \sum_{WW,WR} P\,(WH \mid WW, WR)\, P\,(WW)\, P\,(WR) \quad (81)$$

$$P\,(WW) = P\,(WW/T)*P\,(T) + P\,(WW/\text{ Not True})\, P\,(\text{Not True}) \quad (82)$$

$$P\,(WR) = P\,(WR/T)*P\,(T) + P\,(WR/\text{ Not True})\, P\,(\text{Not True}) \quad (83)$$

$$P\,(G) = P\,(G/T)*P\,(T) + P\,(G/\text{ Not True})\, P\,(\text{Not True}) \quad (84)$$

Wheel set failure probability was calculated from equations 78 to 84 and Excel as:

P (WH) = 0.045

**P (WS) =0.05**, Probability of failure for final drive (wheel sets)

**R (WS) =0.95**, Reliability for final drive (wheel sets)

### 3.5.2.10.1 Final Drives (Wheel Sets) Cost

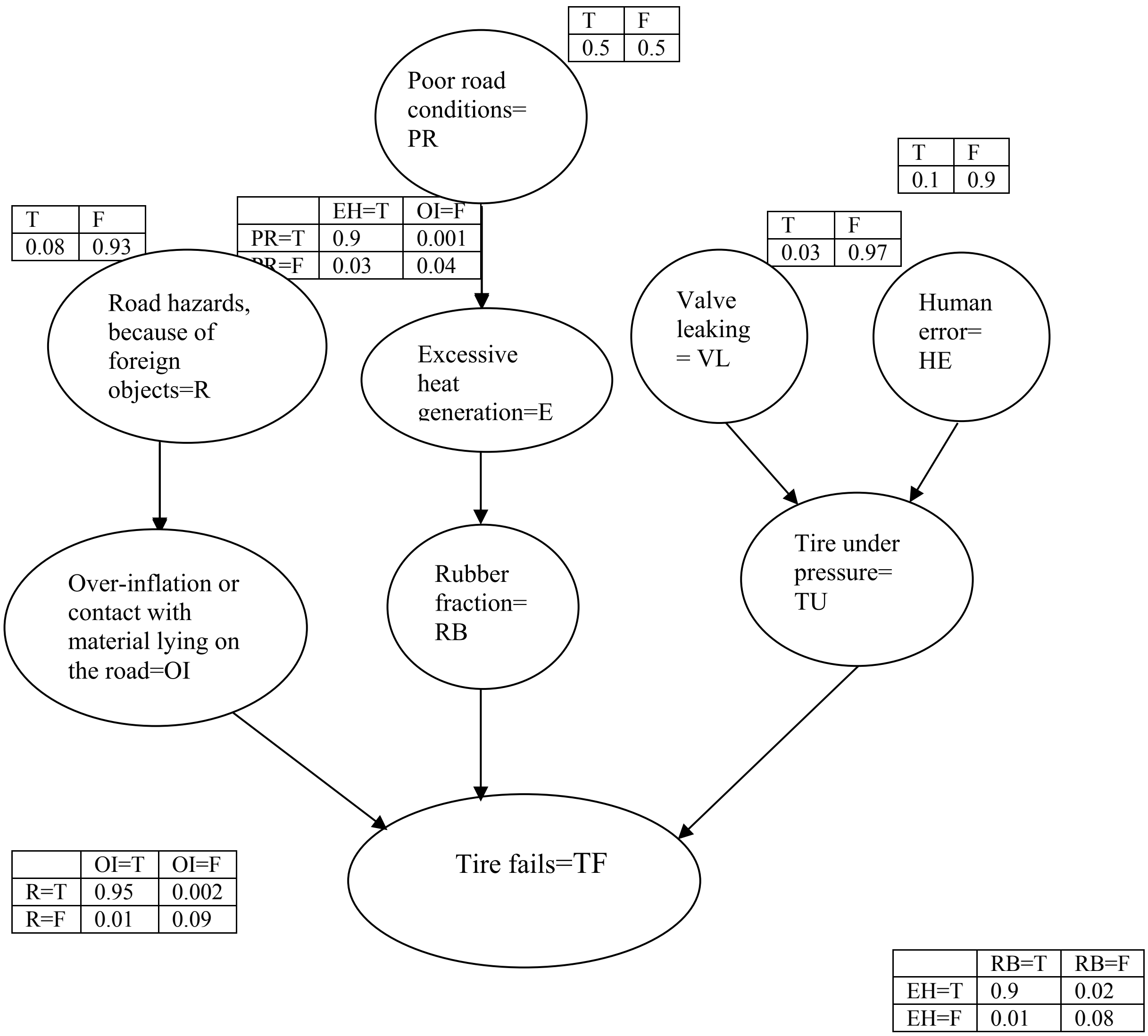
The parameter "$C_{\text{final drive}}$ (\$)" was used for the final drive cost as a cause of final drive failure in modeling risk. The actual cost can be substituted in Table 3-2 to calculate risk. .

### 3.5.2.11 Tires

Tires can work with partial damage. When tire pressure is low or the tire is partially flat, the truck can still operate, but it consumes more energy than under normal operation. Road hazards, foreign objects, over-inflation, and high-speed operation can damage tires. Below are some failure modes (16):

- Heat generation exceeded due to poor road conditions.
- Tire breakdowns will increase when tires contact material lying on a road.
- Foreign objects on roads and high speed may cause tire breakdown.

Some possible failure modes related to tires with their failure probability rates based on positive and negative modes via BBN method are shown below.




| T | F |
|---|---|
| 0.5 | 0.5 |

| T | F |
|---|---|
| 0.1 | 0.9 |

| T | F |
|---|---|
| 0.08 | 0.93 |

| | EH=T | OI=F |
|---|---|---|
| PR=T | 0.9 | 0.001 |
| PR=F | 0.03 | 0.04 |

| T | F |
|---|---|
| 0.03 | 0.97 |

| | OI=T | OI=F |
|---|---|---|
| R=T | 0.95 | 0.002 |
| R=F | 0.01 | 0.09 |

| | RB=T | RB=F |
|---|---|---|
| EH=T | 0.9 | 0.02 |
| EH=F | 0.01 | 0.08 |

Figure3-13: BBN graphical model for haul truck tire failures

| OI | RB | TU | TF=True | TF =False |
|---|---|---|---|---|
| T | T | T | 0.95 | 0.02 |
| T | T | F | 0.5 | 0.03 |
| T | F | T | 0. 25 | 0.075 |
| F | T | T | 0.02 | 0.035 |
| T | F | F | 0. 3 | 0.01 |
| F | F | T | 0. 1 | 0.2 |
| F | T | F | 0.01 | 0.05 |
| F | F | F | 0. 025 | 0.03 |

| VL | HE | TU=True | TU=False |
|---|---|---|---|
| T | T | 0.9 | 0.02 |
| T | F | 0.01 | 0.03 |
| F | T | 0.022 | 0.005 |
| F | F | 0.002 | 0.005 |

The probability of failure and the reliability for haul truck tires were calculated based on Figure 3-14 and from the formulas below:

$$P\ (TF) = \sum_{OI,RB,TU} P\ (TF \mid OI, RB, TU)\ P\ (OI)\ P\ (RB)\ P\ (TU) \quad (85)$$

$$P\ (OI) = \sum_{R} P\ (OI \mid R)\ P\ (R) \quad (86)$$

$$P\ (RB) = \sum_{EH} P\ (RB \mid EH)\ P\ (EH) \quad (87)$$

$$P\ (EH) = \sum_{PR} P\ (EH \mid PR)\ P\ (PR) \quad (88)$$

$$P\ (TU) = \sum_{VL,HE} P\ (TU \mid VL, HE)\ P\ (VL)\ P\ (HE) \quad (89)$$

P (R) = P (R/T)*P (T) +P (R/ Not True) P (Not True) (90)

P (PR) = P (PR/T)*P (T) +P (PR/ Not True) P (Not True) (91)

P (VL) = P (VL/T)*P (T) +P (VL/ Not True) P (Not True) (92)

P (HE) = P (HE/T)*P (T) +P (HE/ Not True) P (Not True) (93)

Tire failure probability was calculated from equations 85 to 93 and Excel as:

**P (TF) = 0.17,** Probability of failure for tires

**R (TF) =0.83,** Reliability for tires

### 3.5.2.11.1 Tire Cost

The cost of each Caterpillar CAT 797 tire was assumed to be $75,000. Six tires will therefore cost $450,000 (68).

## 3.5.3 Calculation of Risk for Oil Sands Haul Trucks

Haul truck component failure modes, rates, and related consequences discussed in the previous sections are summarized in Table 3-2. The highest probability of failure was observed for tires, followed by the dispatch system/GPS/radio and brakes. The lowest probability of failure was observed in cab/control, followed by the engine and structure.

Table 3-2: Risk associated with haul truck for a year 2010

| No | Description | Probability of failure | Consequence | Risk (CAN$) |
|---|---|---|---|---|
| 1 | Cab/control | 0.01 | $C_{Cab}$ | $0.01 * C_{Cab}$ |
| 2 | Fuel system | 0.1 | 79,000 | 0.1*79,000 |
| 3 | Engine | 0.01 | 18,242 | 0.01*18,242 |
| 4 | Transmission | 0.1 | $C_{Transmission}$ | $0.1 * C_{Transmission}$ |
| 5 | Brakes | 0.12 | $C_{Brakes}$ | $0.12 * C_{Brakes}$ |
| 6 | Suspension | 0.08 | $C_{Suspension}$ | $0.08 * C_{Suspension}$ |
| 7 | Tires | 0.17 | 450,000 | 0.17*450,000 |
| 8 | Dispatch system/GPS/radio | 0.15 | $C_{Dispatch\ system}$ | $0.15 * C_{Dispatch\ system}$ |
| 9 | Pneumatics/hydraulics | 0.1 | $C_{Hydraulic}$ | $0.1 * C_{Hydraulic}$ |
| 10 | Structure | 0.04 | $C_{Structure}$ | $0.04 * C_{Structure}$ |
| 11 | Final drives (wheel sets) | 0.05 | $C_{final\ drive}$ | $0.05 * C_{final\ drive}$ |

### 3.5.4 Mining Haul Truck Failure Rate

The reliability model is estimated to be steady state; therefore, the failure rate is a time independent variable. Table 3-3 shows the failure rate for the selected main parts in a mining haul truck.

Table 3-3: failure rate value for some main sub system of mining haul truck

| No | Description | Probability of failure | Reliability | Failure rate |
|---|---|---|---|---|
| 1 | Cab/control | 0.01 | 0.99 | 0.01 |
| 2 | Fuel system | 0.1 | 0.9 | 0.11 |
| 3 | Engine | 0.01 | 0.99 | 0.01 |
| 4 | Transmission | 0.1 | 0.9 | 0.11 |
| 5 | Brakes | 0.12 | 0.88 | 0.14 |
| 6 | Suspension | 0.08 | 0.92 | 0.09 |
| 7 | Tires | 0.17 | 0.83 | 0.20 |
| 8 | Dispatch system/GPS/radio | 0.15 | 0.85 | 0.18 |
| 9 | Pneumatics/hydraulics | 0.1 | 0.9 | 0.11 |
| 10 | Structure | 0.04 | 0.96 | 0.04 |
| 11 | Final drives (wheel sets) | 0.05 | 0.95 | 0.05 |

### 3.5.4.2 Discussion: Analysis of Root Causes of Failure

Based on the calculated reliability modeling results, tires are identified as one of the major causes of mining haul truck failure that significantly affect energy consumption and GHG emission. Haul truck tires can operate under partial failure; however, partial failure leads to more energy consumption and more GHG emissions.

## 3.6 Oil Sands Mining Shovels

Shovels play a key role in the mining industry. Shovels dig oil sands ore from the ground and transfer it to trucks. Lack of regular maintenance and repair may cause shovels to fail and suspend mining processes, eventually leading to increases in cost, energy intensity, and GHG emissions. Unscheduled shutdowns and repairs may occur. Simulating realistic scenarios can predict and model shovel failure and maintenance schedules. This section is an attempt to describe how to approach the shovel modeling and unexpected shovel failures in oil sands mining operations. Two types of shovels are used in surface mining industries, hydraulic and electric. Cost was calculated based on the rate of the Canadian dollar in May 2015.

Shovels have three main parts (16):

- The car body, made up of the engine, fuel, hydraulic pumps, supporting composition for the attachment of a diesel hydraulic shovel, and operator cab.
- The attachment, made up of the boom, stick, and bucket.

### 3.6.1 Hydraulic Shovels

A hydraulic shovel excavates the ground to find oil sands ore, coal, and other natural resources. Its engine consumes diesel fuel. The shovel is controlled by a driver who manages and controls the shovels in the mining area. The hydraulic shovel studied in this research was a Hitachi 8000, which has a capacity of approximately 80-100 tons and a capital cost of approximately $12 million (69). In this section, the following assumptions were made on the model hydraulic oil sands mining shovel failure probability (70):

- Shifts and breaks are not considered;
- Ore blending is not required;
- The shovel capacity is 80 tons; and
- The average time to fill a 500-tons truck is 10 minutes.

All critical

parts that impose a high hazard risk were identified and, using a BBN method, the failure probabilities of each critical part were calculated. Finally, with the failure probabilities and the consequence of each (i.e., cost), associated risks were calculated.

### 3.6.1.1 Main Mechanical Parts of Mining Hydraulic Shovels

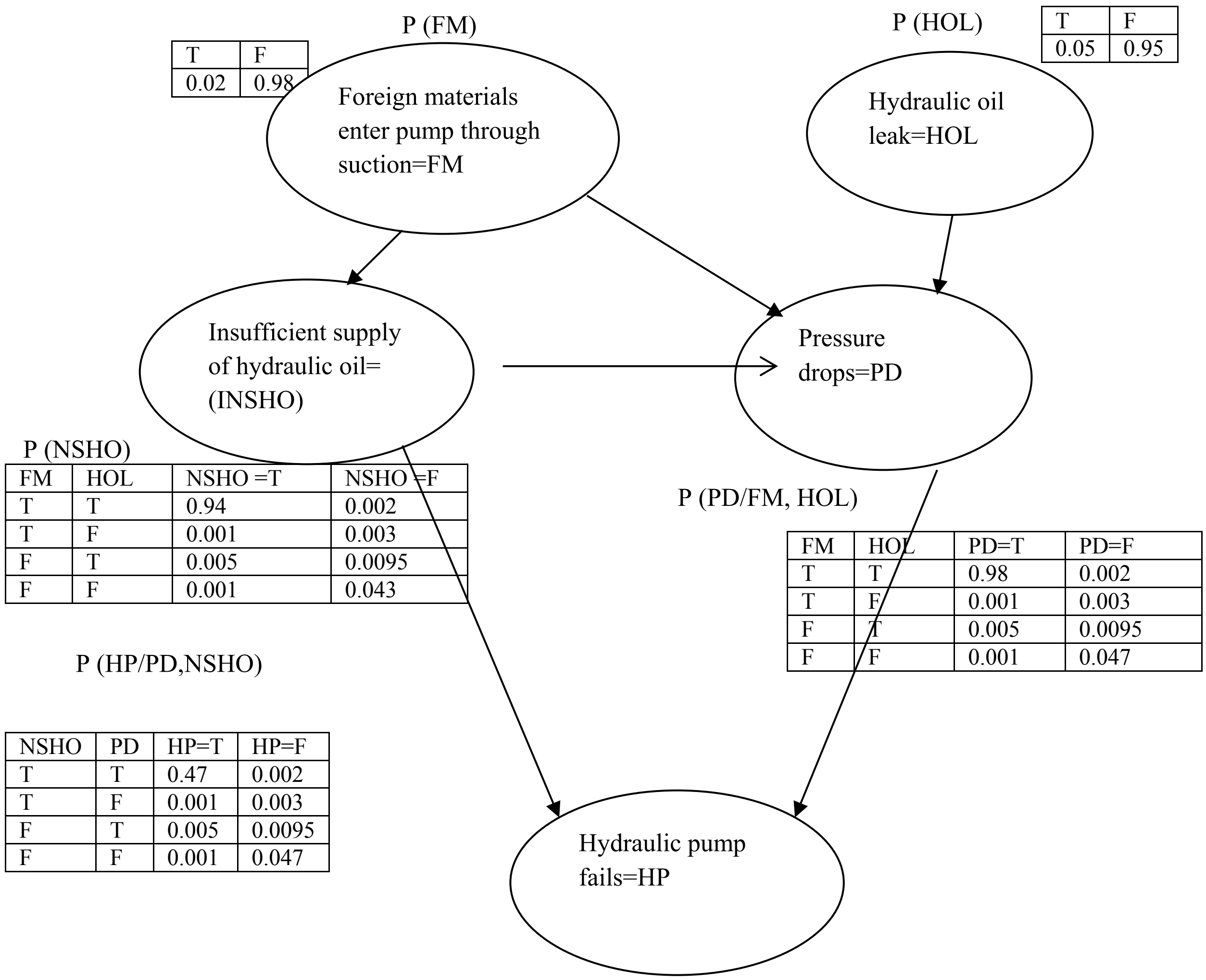
The main components of an oil sands hydraulic shovel whose failures can results in the loss of the shovel are the hydraulic pump, shutdown valve, filter assembly, ZAKO-rings, O-rings, boom and stick, slew ring bolts, cab/control, engine, and brakes (16). In this section, major possible failure modes for each component were investigated and their failure probabilities were calculated through the BBN method.

### 3.6.1.1.1 Hydraulic Pumps

A hydraulic pump transports oil to a hydraulic system. Foreign material sucked into the pump will cause pump pressure to decrease (that is, the materials can prevent the supply of sufficient oil to the pump). An oil leak will reduce the oil supply to the pump, and the pump will not be able to operate (16).

Assumptions:

- Foreign materials enter pump through suction (FM) and hydraulic oil leaks (HOL) are independent variables;




P (FM)

| T | F |
|---|---|
| 0.02 | 0.98 |

P (HOL)

| T | F |
|---|---|
| 0.05 | 0.95 |

P (NSHO)

| FM | HOL | NSHO =T | NSHO =F |
|---|---|---|---|
| T | T | 0.94 | 0.002 |
| T | F | 0.001 | 0.003 |
| F | T | 0.005 | 0.0095 |
| F | F | 0.001 | 0.043 |

P (PD/FM, HOL)

| FM | HOL | PD=T | PD=F |
|---|---|---|---|
| T | T | 0.98 | 0.002 |
| T | F | 0.001 | 0.003 |
| F | T | 0.005 | 0.0095 |
| F | F | 0.001 | 0.047 |

P (HP/PD,NSHO)

| NSHO | PD | HP=T | HP=F |
|---|---|---|---|
| T | T | 0.47 | 0.002 |
| T | F | 0.001 | 0.003 |
| F | T | 0.005 | 0.0095 |
| F | F | 0.001 | 0.047 |

Figure 3-14: BBN graphical model for the shovel's hydraulic pump failures

The probability of failure and the reliability for the shovel's hydraulic pump were calculated based on Figure 3-23 and from the formulas below:

P (HP|PD, NSHO) = P (PD|NSHO) (1)

Conditional independence: Naïve Bayes formula for hydraulic oil:

P (HO, NHO, NSHO, PD, HP) = P (HO)* P (NHO)*P (NSHO)*P (PD)*P (HP|PD, NSHO)*P (NSHO |HO, NHO) P (PD|HO, NHO) (2)

P (HP) = $\sum_{NSHO,PD}$ P (HP | NSHO, PD) P (NSHO, PD) (3)

P (HP) = $\sum_{NSHO,PD}$ P (HP | NSHO, PD) P (NSHO)* P (PD) (4)

P (PD) = $\sum_{FM,HOL}$ P (PD | FM, HOL) P (FM) P (HOL) (5)

P (FM) = P (FM/T)*P (T) +P (FM/ Not True) P (Not True) (6)

P (HOL) = P (HOL/T)*P (T) +P (HOL/ Not True) P (Not True) (7)

P (NSHO) = $\sum_{FM,HOL}$ P (NSHO | FM, HOL) P (FM) P (HOL) (8)

The hydraulic pump failure probability was calculated with formulas 1 to 8 and Excel as:

P (PD) =0.05

P (NSHO) = 0.04

P (HP) = 0.05, Probability of failure for hydraulic pumps

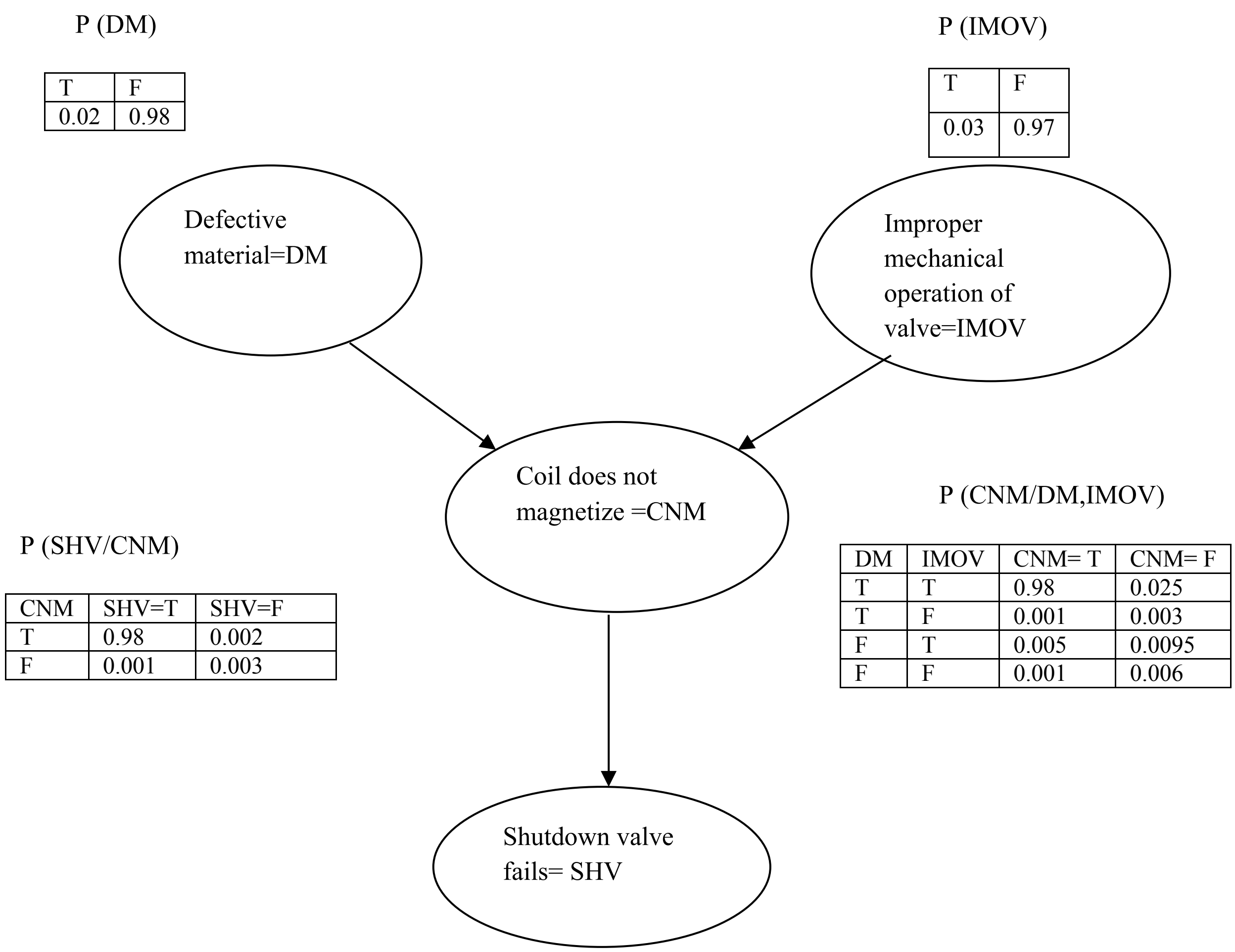
R (HP) = 0.95, Reliability for hydraulic pumps

### 3.6.1.1.1.1 Hydraulic Pump Cost

The parameter "$C_{\text{hydraulic pump}}$ (\$)" was used for the cost of the hydraulic pump in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.6.1.1.2 Shutdown Valve

The shutdown valve closes the valve to prevent fuel from entering into an injector. There are some root causes of failure in a shutdown valve. The shutdown valve has a coil. The shutdown valve locks as soon as its coil is energized by a pulsation from a shutdown system. If suspended materials (defecting materials) in the fuel flow reach the shutdown valve or if the valve has some mechanical faults, then the coil cannot be magnetized and the shutdown valve will fail (16).




P (DM)

| T | F |
|---|---|
| 0.02 | 0.98 |

P (IMOV)

| T | F |
|---|---|
| 0.03 | 0.97 |

P (CNM/DM,IMOV)

| DM | IMOV | CNM= T | CNM= F |
|---|---|---|---|
| T | T | 0.98 | 0.025 |
| T | F | 0.001 | 0.003 |
| F | T | 0.005 | 0.0095 |
| F | F | 0.001 | 0.006 |

P (SHV/CNM)

| CNM | SHV=T | SHV=F |
|---|---|---|
| T | 0.98 | 0.002 |
| F | 0.001 | 0.003 |

Figure 3-15: BBN graphical model for hydraulic shovel shutdown valve failures

Assumptions:

- Defecting material (DM) and improper mechanical operation of valve (IMOV) are independent.

The probability of failure and the reliability for shovel shut down valves were calculated based on Figure 3-24 and from the formulas below:

P (CNM) = $\sum_{DM,IMOV}$ P (CNM | DM, IMOV) P (DM, IMOV) (9)

P (CNM) = $\sum_{DM,IMOV}$ P (CNM | DM, IMOV) P (DM) P (IMOV) (10)

P (DM) = P (DM/T)*P (T) +P (DM/ Not True) P (Not True) (11)

P (IMOV) = P (IMOV/T)*P (T) +P (IMOV/ Not True) P (Not True) (12)

P (CVM) was calculated using equations 11 to 14 as:

P (CNM) = 0.008

$$P(SHV) = \sum_{CNM} P(SHV \mid CNM)\, P(CNM) \qquad (13)$$

From formulas 9 to 13 and Excel, the shutdown valve failure probability was calculated as:

P (SHV) = 0.01, Probability of failure of the shutdown valve

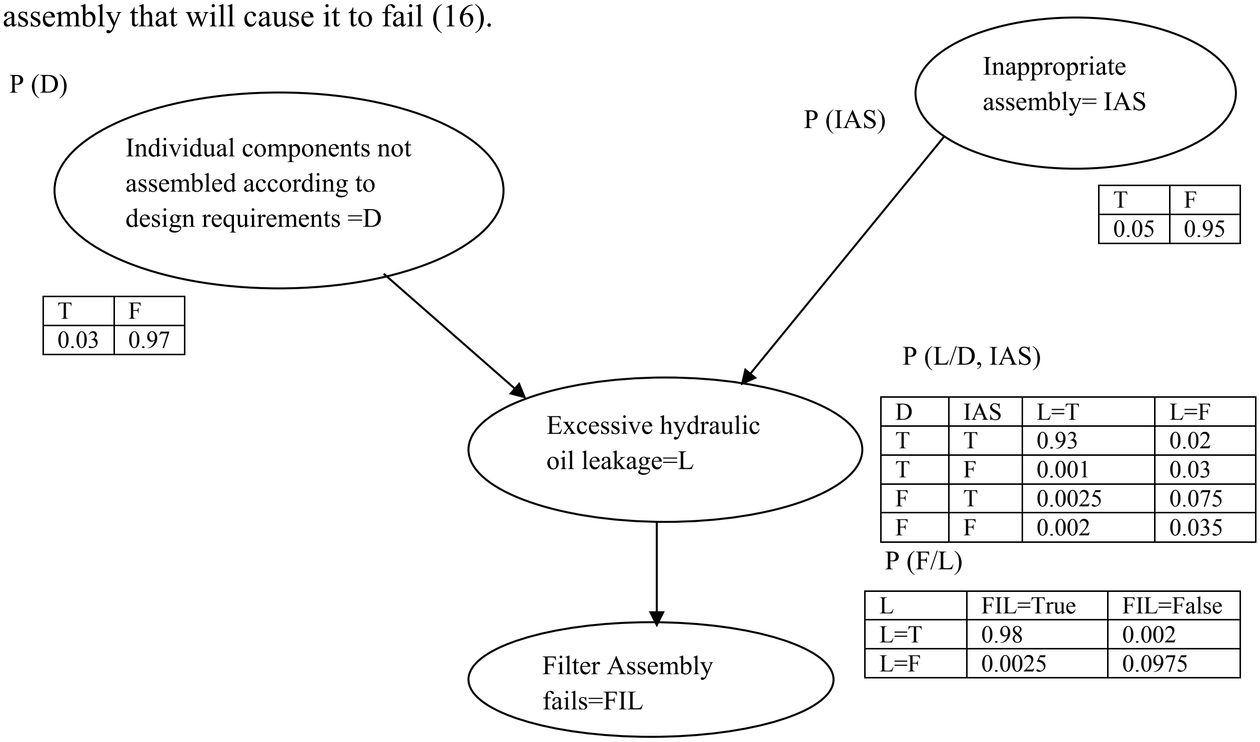
R (SHV) = 0.99, Reliability of the shutdown valve

### 3.6.1.1.2.1 Shutdown Valve Cost

It was assumed that this valve was a 2.5", pressure-reducing check valve with a class 150 flange operating pressure and the cost $1,793 (25).

### 3.6.1.1.2 Filter Assembly

The filter assembly separates suspended materials from the oil coming from the transportation pump. Some root causes of failure associated with the filter assembly were studied. For instance, when individual components are not assembled according to design requirements or were inappropriately assembled, there will be excessive oil leakage in the assembly that will cause it to fail (16).




P (D)

| T | F |
|---|---|
| 0.03 | 0.97 |

P (IAS)

| T | F |
|---|---|
| 0.05 | 0.95 |

P (L/D, IAS)

| D | IAS | L=T | L=F |
|---|---|---|---|
| T | T | 0.93 | 0.02 |
| T | F | 0.001 | 0.03 |
| F | T | 0.0025 | 0.075 |
| F | F | 0.002 | 0.035 |

P (F/L)

| L | FIL=True | FIL=False |
|---|---|---|
| L=T | 0.98 | 0.002 |
| L=F | 0.0025 | 0.0975 |

Figure 3-16: BBN graphical model hydraulic shovel filter failures

Assumptions:

- Individual components are not assembled according to design requirements (D) and inappropriate assembly (IAS) are independent.

The probability of failure and the reliability for hydraulic shovel filters were calculated based on Figure 3-25 and from the formulas below:

P (L) = $\sum_{D,IAS}$ *P (L | D, IS) P (D, IAS)* (14)

P (FIL) = $\sum_{L}$ P (FIL | L) P (L) (15)

P (D) = P (D/T)*P (T) +P (D/ Not True) P (Not True) (16)

P (IAS) = P (IAS/T)*P (T) +P (IAS/ Not True) P (Not True) (17)

From formulas 14 to 17 and Excel, the filter assembly failure probability was calculated as:

P (L) = 0.04

P (FIL) =0.14, Probability of failure of filter assembly

R (FIL) = 0.86, Reliability of filter assembly

### 3.6.1.1.2.1 Filter Assembly Cost

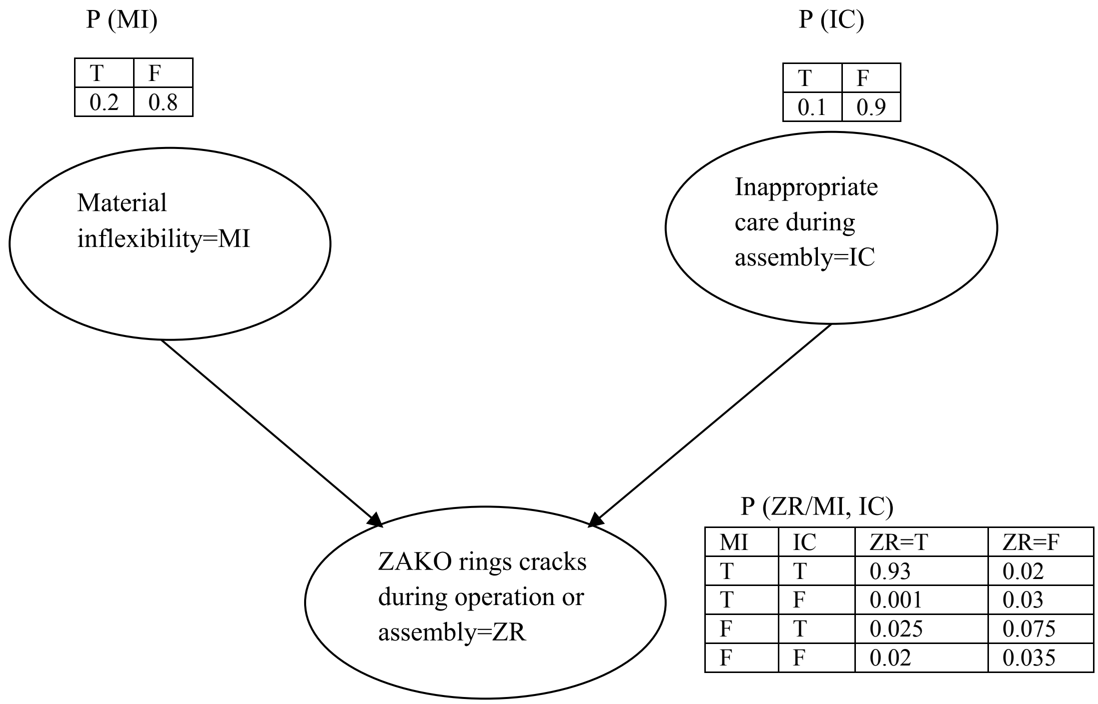
The parameter "$C_{\text{filter assembly}}$ ($)" was used for the filter assembly cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.6.1.1.3 ZAKO Rings

ZAKO rings connect a pipe joint to a hydraulic shovel. ZAKO rings can crack during operation or assembly if inappropriate care is taken or if they are made of inflexible materials (16).

Assumptions:

- Material inflexibility (MI) and inappropriate care during assembly (IC) are independent;
- Probabilities describe random variables of the model; and
- Calculations were made in the model using benchmark data




P (MI)

| T | F |
|---|---|
| 0.2 | 0.8 |

P (IC)

| T | F |
|---|---|
| 0.1 | 0.9 |

P (ZR/MI, IC)

| MI | IC | ZR=T | ZR=F |
|---|---|---|---|
| T | T | 0.93 | 0.02 |
| T | F | 0.001 | 0.03 |
| F | T | 0.025 | 0.075 |
| F | F | 0.02 | 0.035 |

Figure 3-17: BBN graphical model for hydraulic shovel Zako ring cracks

The probability of failure and the reliability for hydraulic shovel Zako rings were calculated based on Figure 3-26 and from the formulas below:

$$P\ (ZR) = \sum_{MI,IC} P\ (ZR \mid MI, IC)\ P\ (MI, IC) \tag{18}$$

$$P\ (MI) = P\ (MI/T)*P\ (T) + P\ (MI/\ \text{Not True})\ P\ (\text{Not True}) \tag{19}$$

$$P\ (IC) = P\ (IC/T)*P\ (T) + P\ (IC/\ \text{Not True})\ P\ (\text{Not True}) \tag{20}$$

From formulas 18 to 20 and Excel, the failure probability for ZAKO rings was calculated as:

P (ZR) = 0.07, Probability of failure for ZAKO rings

R (ZR) = 0.93, Probability of failure for ZAKO rings

### 3.6.1.1.3.1 Cost of ZAKO Rings

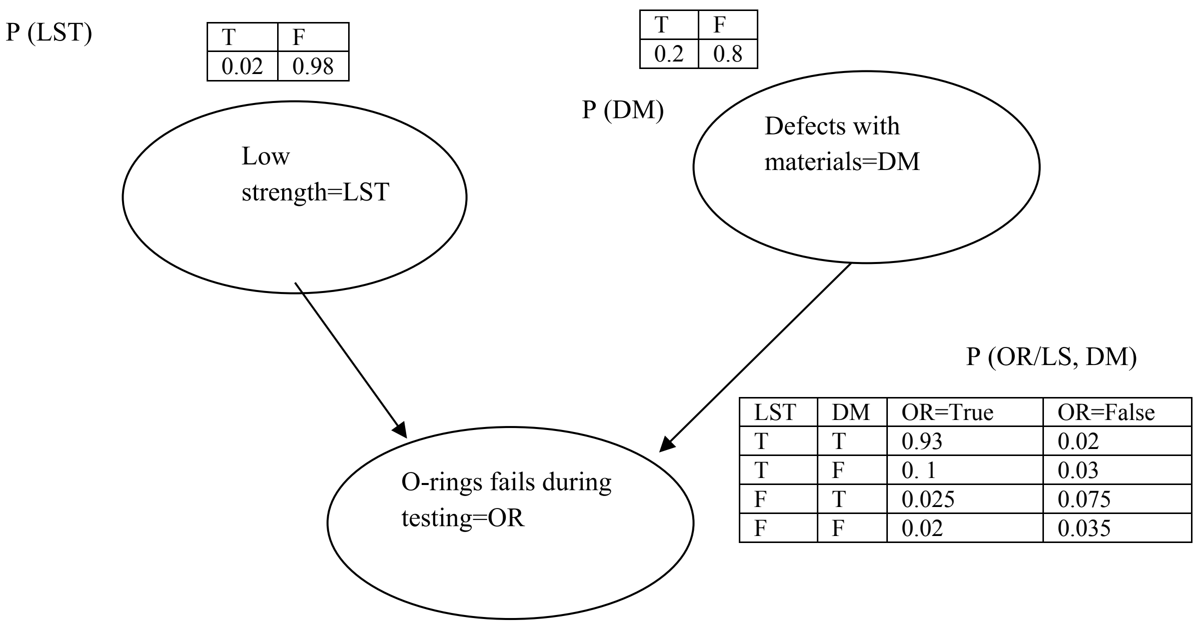
ZAKO rings cost £161.62 (CAN$ 309.27).

### 3.6.1.1.4 O-rings

O-rings provide leak-proof joints for a hydraulic shovel. Some root causes of failure for O-rings, including defective materials and low strength, were found during tests (16).

Assumptions:

- Low strength (LST) and defect with materials (DM) are independent.




P (LST)

| T | F |
|---|---|
| 0.02 | 0.98 |

P (DM)

| T | F |
|---|---|
| 0.2 | 0.8 |

P (OR/LS, DM)

| LST | DM | OR=True | OR=False |
|---|---|---|---|
| T | T | 0.93 | 0.02 |
| T | F | 0. 1 | 0.03 |
| F | T | 0.025 | 0.075 |
| F | F | 0.02 | 0.035 |

Figure 3-18: BBN graphical model for hydraulic shovel O-rings failure

The probability of failure and the reliability for hydraulic shovel O-rings were calculated based on Figure 3-27 and from the formulas below:

$$P\ (OR) = \sum_{LST,DM} P\ (OR \mid LST, DM)\ P\ (LST, DM) \quad (21)$$

$$P\ (LST) = P\ (LST/T)*P\ (T) + P\ (LST/\ Not\ True)\ P\ (Not\ True) \quad (22)$$

$$P\ (DM) = P\ (DM/T)*P\ (T) + P\ (DM/\ Not\ True)\ P\ (Not\ True) \quad (23)$$

From formulas 21 to 23 and Excel, the O-ring failure probability was calculated as:

P (OR) = 0.07, Probability of failure for O-rings

R (OP) = 0.93, Reliability for O-rings

### 3.6.1.1.4.1 Cost of O-rings

The parameter "$C_{O\text{-rings}}$ ($)" was used for the cost of O-rings in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.6.1.1.5 Boom and Stick

A boom and stick lifts a bucket and extends a shovel arm horizontally. A boom and stick can fail through cracking caused by corrosion or from being struck by falling materials (16).

Assumptions:

- Link stress during operation (SO), hit by falling rocks (FR) and corrosion (COR) are independent.

P (FR)

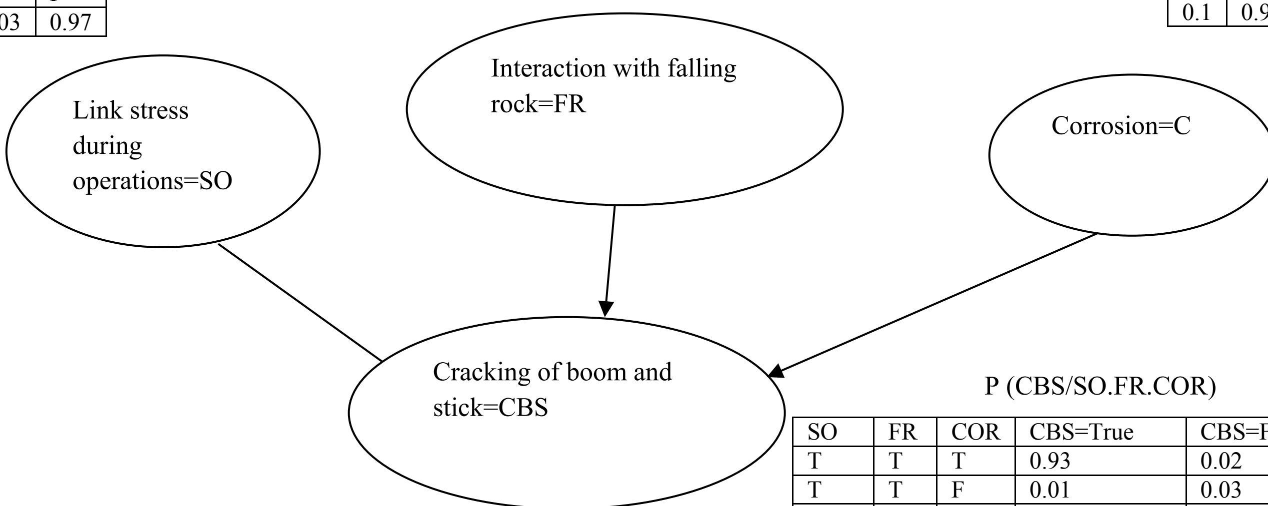
| T | F |
|---|---|
| 0.2 | 0.8 |

P (COR)

| T | F |
|---|---|
| 0.1 | 0.9 |

P (SO)

| T | F |
|---|---|
| 0.03 | 0.97 |




P (CBS/SO.FR.COR)

| SO | FR | COR | CBS=True | CBS=False |
|---|---|---|---|---|
| T | T | T | 0.93 | 0.02 |
| T | T | F | 0.01 | 0.03 |
| T | F | T | 0.025 | 0.075 |
| F | T | T | 0.002 | 0.035 |
| F | F | T | 0.001 | 0.005 |
| T | F | F | 0.02 | 0.0025 |
| T | F | T | 0.05 | 0.0035 |
| F | F | F | 0.002 | 0.01 |

Figure 3-19: BBN graphical model for hydraulic shovel boom and stick cracking

The probability of failure and the reliability for the hydraulic shovel boom and stick were calculated based on Figure 3-28 and from the formulas below:

$$P\,(CBS) = \sum_{SO,FR,COR} P\,(CBS \mid SO, FR, COR)\, P\,(SO, FR, COR) \quad (24)$$

$$P\,(SO) = P\,(SO/T)*P\,(T) + P\,(SO/\text{ Not True})\, P\,(\text{Not True}) \quad (25)$$

$$P\,(FR) = P\,(FR/T)*P\,(T) + P\,(FR/\text{ Not True})\, P\,(\text{Not True}) \quad (26)$$

$$P\,(COR) = P\,(COR/T)*P\,(T) + P\,(COR/\text{ Not True})\, P\,(\text{Not True}) \quad (27)$$

With equations 24 to 27 and Excel, the boom and stick failure probability was calculated as:

P (CBS) = 0.01, Probability of failure for the boom and stick

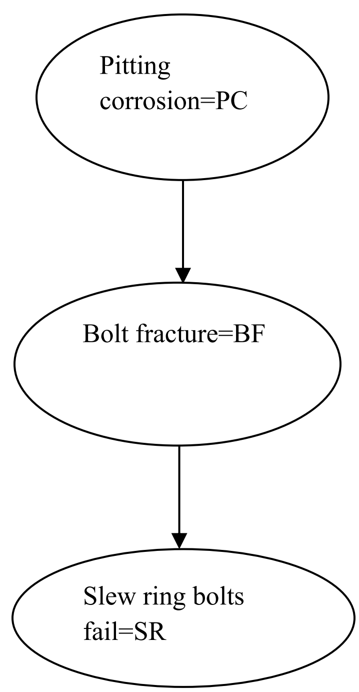
R (CBS) = 0.99, Reliability for the boom and stick

## 3.6.1.1.5.1 Boom and Stick Cost

The parameter "$C_{\text{Boom and Stick}}$ (\$)" was used for the boom and stick cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

## 3.6.1.1.6 Slew Ring Bolts

Slew ring bolts hold a machine house at the boom of shovel, which is moved by crawler tracks. Bolt fracturing through pitting corrosion (local corrosion) will cause slew ring bolt to fail (16).




P (PC)

| T | F |
|---|---|
| 0.02 | 0.98 |

P (BF/PC)

| | BF=True | BF=False |
|---|---|---|
| PC=T | 0.8 | 0.002 |
| PC=F | 0.03 | 0.08 |

P (SR/BF)

| | SR=True | SR=False |
|---|---|---|
| BF=T | 0.98 | 0.002 |
| BF=F | 0.025 | 0.09 |

Figure 3-20: BBN graphical model for hydraulic shovel slew ring bolt failures

The probability of failure and the reliability for the hydraulic shovel's slew ring bolts were calculated based on Figure 3-29 and from the formulas below:

$$P(SR) = \sum_{BF} P(SR \mid BF)\, P(BF) \tag{28}$$

$$P(BF) = \sum_{PC} P(BF \mid PC)\, P(PC) \tag{29}$$

$$P(PC) = P(PC/T)*P(T) + P(PC/\ Not\ True)\ P(Not\ True) \tag{30}$$

Slew ring bolt failure probability was calculated using equations 28 to 30 and Excel as:

P (BF) = 0.12

**P (SR) = 0.22**, Probability of failure for slew ring bolts

**R (SR) = 0.78**, Reliability for slew ring bolts

### 3.6.1.1.6.1 Slew Ring Bolt Cost

The cost of slew ring bolt was calculated based on following assumptions in Table 3-4 (26).

Table 3-4: Slew ringbolt specifications

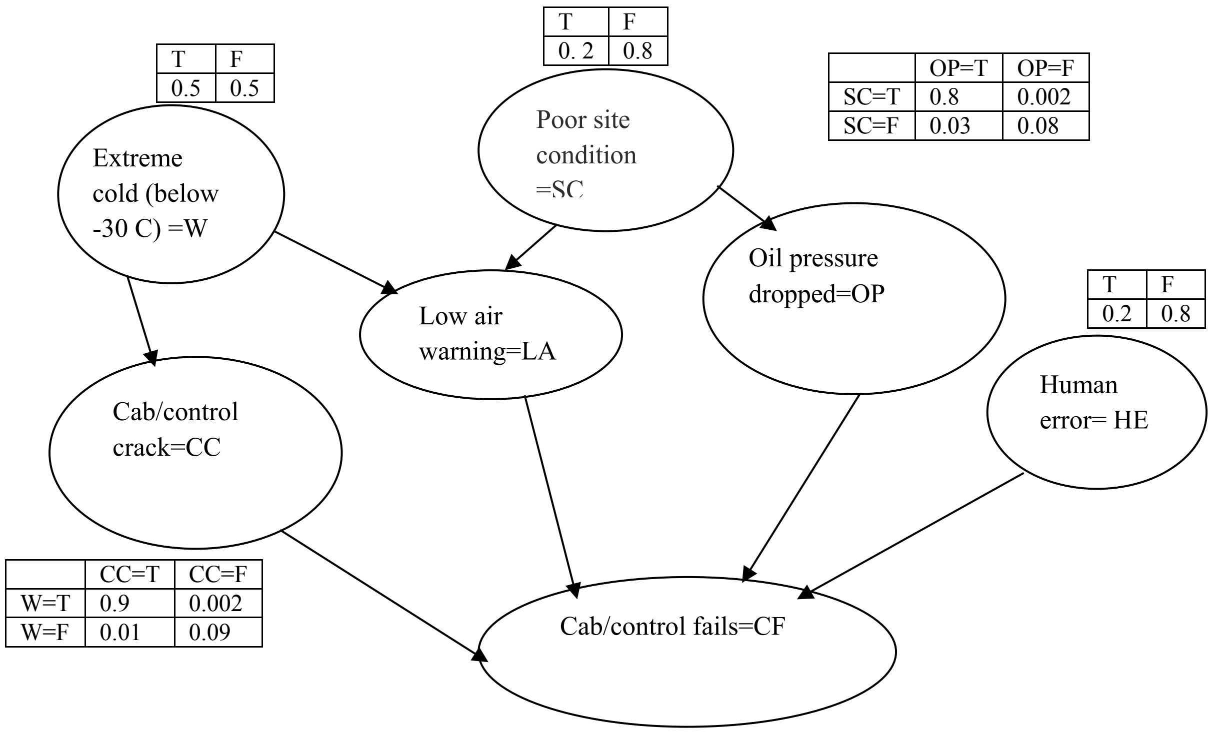
| Maximum permitted static overturning torque | Maximum permitted static load rating radial | Maximum permitted dynamic load rating radial | Maximum application temperature | Weight | Price |
|---|---|---|---|---|---|
| Nm | N | N | °C | kg | CAN$ |
| 120 | 4000 | 1000 | 60 | 0.45 | 124.28 |

### 3.6.1.1.7 Shovel Cab/Control

The weather in Alberta sometimes drops below -30$^{o}$C, which may induce cracks in the cab. If a level gauge shows a low air warning because of the cold, the shovel cannot be properly controlled from the cab. This may cause excess airflow through the intake system, which may lead to the failure of the air cleaner and the loss of the control system. Oil and air gauges monitor air and oil pressure in the control system and are required to confirm the shovel's condition. When the ambient temperature is so low that the oil pressure drops below its normal level, the control system fails. Besides cold, human error can cause cab/control failure (11, 59).

Assumptions:

- Weather (W), human error (HE), and site conditions (SC) are independent;
- Cab/control cracks (CC), low air warning (LA), oil pressure (OP), and human error (HE) are independent.




| T | F |
|---|---|
| 0.5 | 0.5 |

| T | F |
|---|---|
| 0. 2 | 0.8 |

| | OP=T | OP=F |
|---|---|---|
| SC=T | 0.8 | 0.002 |
| SC=F | 0.03 | 0.08 |

| T | F |
|---|---|
| 0.2 | 0.8 |

| | CC=T | CC=F |
|---|---|---|
| W=T | 0.9 | 0.002 |
| W=F | 0.01 | 0.09 |

Figure 3-21: BBN graphical model for hydraulic shovel cab/control failure

| W | SC | LA=T | LA=F |
|---|---|---|---|
| T | T | 0.7 | 0.002 |
| T | F | 0.01 | 0.09 |
| F | T | 0.02 | 0.08 |
| F | F | 0.04 | 0.001 |

| HE | LA | OP | CC | CF=True | CF=False |
|---|---|---|---|---|---|
| T | T | T | T | 0.085 | 0.002 |
| T | T | T | F | 0.001 | 0.03 |
| T | T | F | T | 0.0025 | 0.075 |
| T | F | T | T | 0.002 | 0.035 |
| F | T | T | T | 0.001 | 0.005 |
| T | F | T | F | 0.02 | 0.0025 |
| T | T | F | F | 0.005 | 0.0035 |
| F | T | F | T | 0.002 | 0.001 |
| F | F | F | T | 0.001 | 0.002 |
| F | F | T | T | 0.002 | 0.001 |
| F | T | F | F | 0.035 | 0.015 |
| F | F | T | F | 0.005 | 0.005 |
| T | F | F | F | 0.02 | 0.03 |
| F | F | F | F | 0.06 | 0.006 |

The probability of failure and the reliability for the hydraulic shovel's cab/control were calculated based on Figure 3-30 and from the formulas below:

$$P\ (CF) = \sum_{CC,OP,LA,HE} P\ (CF \mid CC, OP, LA, HE)\ P\ (CC, OP, LA, HE) \quad (31)$$

$$P\ (CF) = \sum_{CC,OP,LA,HE} P\ (CF \mid CC, OP, LA, HE)\ P\ (CC)*P\ (OP)*P\ (LA)*P\ (HE) \quad (32)$$

$$P\ (CC) = \sum_{W} P\ (CC \mid W)\ P\ (W) \quad (33)$$

$$P\ (OP) = \sum_{SC} P\ (OP \mid SC)\ P\ (SC) \quad (34)$$

$$P\ (LA) = \sum_{SC} P\ (LA \mid SC)\ P\ (LA) \quad (35)$$

P (HE) = P (HE/T)*P (T) +P (HE/ Not True) P (Not True) (36)

P (SC) = P (SC/T)*P (T) +P (SC/ Not True) P (Not True) (37)

P (W) = P (W/T)*P (T) +P (W/ Not True) P (Not True) (38)

The cab control failure probability was calculated using equations 31 to 38 and Excel as:

**P (CF) = 0.01**, Probability of failure for cab/controls

**R (CF) = 0.99**, Reliability for cab/controls

### 3.6.1.1.7.1 Shovel Cab/Control Cost

The parameter "$C_{cab\ /control}$ ($)" was used for the shovel cab/control cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.6.1.1.8 Engine

An engine can fail when any one of the following fails (71):

- Lubrication system, engine block, or intake and exhaust;

Assumptions:

- The lubrication system (LS), engine block (EB), and intake and exhaust systems (IS) are independent.

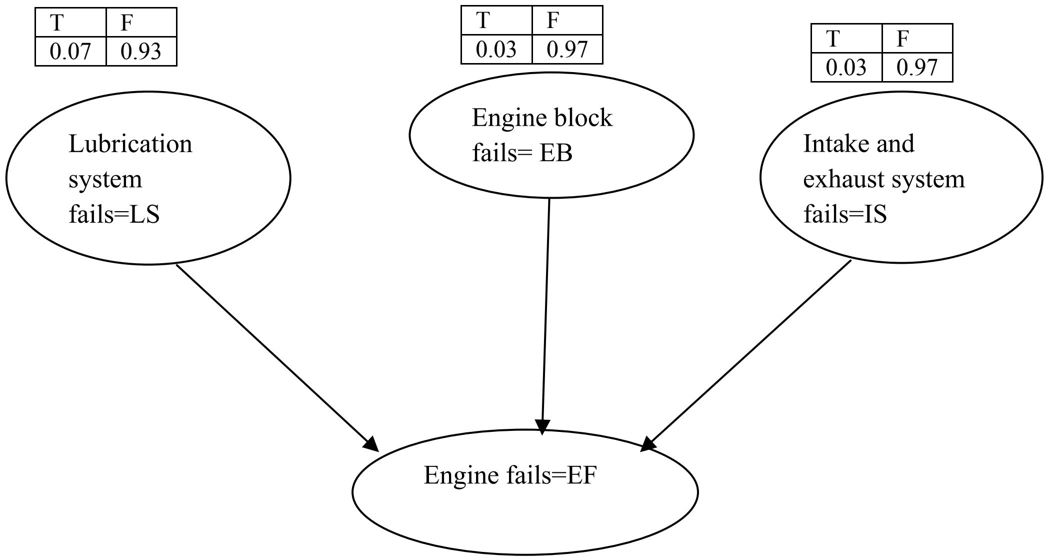



Figure 3-22: BBN graphical model for hydraulic shovel engine failure

| LS | EB | IS | EF=True | EF=False |
|---|---|---|---|---|
| T | T | T | 0.93 | 0.02 |
| T | T | F | 0.001 | 0.03 |
| T | F | T | 0.0025 | 0.075 |
| F | T | T | 0.002 | 0.035 |
| F | F | T | 0.001 | 0.005 |
| T | F | F | 0.02 | 0.0025 |
| T | F | T | 0.005 | 0.0035 |
| F | F | F | 0.002 | 0.1 |

The probability of failure and the reliability for the hydraulic shovel engine were calculated based on Figure 3-31 and from the formulas below:

$$P\ (EF) = \sum_{LS,EB,IS} P\ (EF \mid LS, EB, IS)\ P\ (LS, EB, IS) \tag{39}$$

$$P\ (EF) = \sum_{LS,EB,IS} P\ (EF \mid LS, EB, IS)\ P\ (LS)*P\ (EB)*P\ (IS) \tag{40}$$

$$P\ (LS) = P\ (LS/T)*P\ (T) + P\ (LS/\ \text{Not True})\ P\ (\text{Not True}) \tag{41}$$

$$P\ (EB) = P\ (EB/T)*P\ (T) + P\ (EB/\ \text{Not True})\ P\ (\text{Not True}) \tag{42}$$

$$P\ (IS) = P\ (IS/T)*P\ (T) + P\ (IS/\ \text{Not True})\ P\ (\text{Not True}) \tag{43}$$

Engine failure probability was calculated using equations 39 to 43 and Excel as:

**P (EF) =0.09**, Probability of failure for the engine

**R (EF) = 0.91**, Reliability for the engine

### 3.6.1.1.8.1 Engine Cost

Engine price was calculated based on the specifications given in Table 3-5. An S&S cycle 93″ shovelhead engine with a cast gear cover costs CAN$ 8,569.20.

Table 3-5: Engine specifications (27)

| |
|---|
| Alternator or generator: alternator |
| Compression ratio:8.5:1 |
| Displacement size CC: 1524 |
| Displacement size CI: 93 |
| Finish: natural |
| Ignition: yes |
| Single or dual plugs: single |
| Stroke: 4 1/2″ |

### 3.6.1.1.9 Brakes

The brakes are another important shovel component. Brakes can fail in many circumstances and be costly. In this chapter, only three possible causes are considered: weather (W), speed (S), and improper inspection (INS).

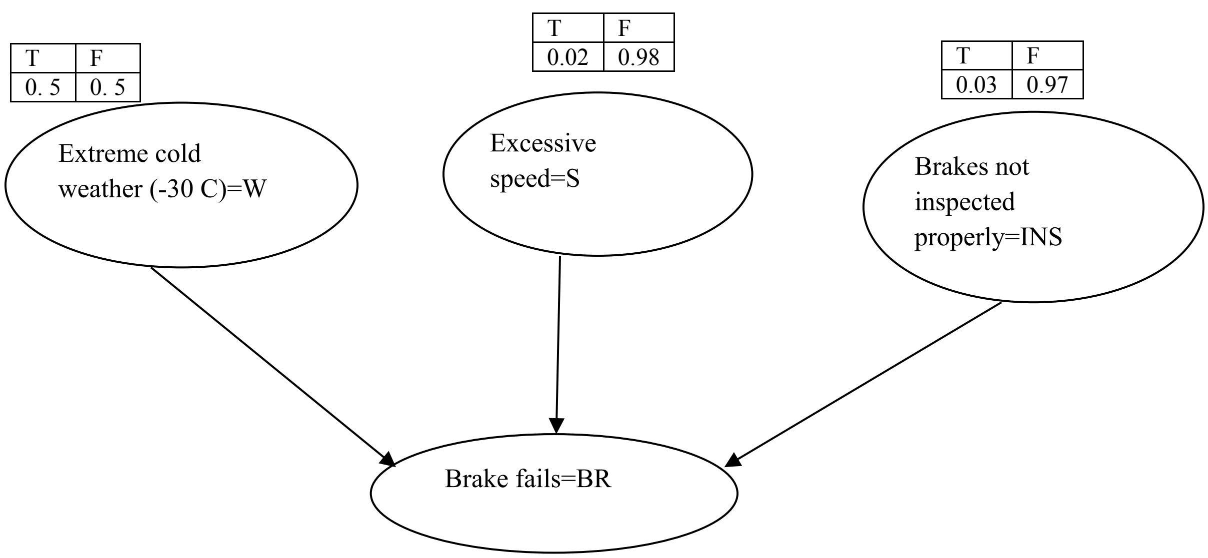



Figure 3-23: BBN graphical model for hydraulic shovel brake failure

| W | S | INS | BR=True | BR=False |
|---|---|---|---|---|
| T | T | T | 0.93 | 0.02 |
| T | T | F | 0.001 | 0.03 |
| T | F | T | 0.0025 | 0.075 |
| F | T | T | 0.002 | 0.035 |
| F | F | T | 0.001 | 0.005 |
| T | F | F | 0.02 | 0.0025 |
| T | F | T | 0.005 | 0.0035 |
| F | F | F | 0.002 | 0.1 |

Assumptions:

- Weather (W), speed (S), and inspection (INS) are independent.

The probability of failure and the reliability for the hydraulic shovel brake were calculated based on Figure 3-32 and from the formulas below:

$$P\ (BR) = \sum_{W,S,INS} P\ (BR \mid W, S, INS)\ P\ (W)*P\ (S)*P\ (INS) \qquad (44)$$

$$P\ (W) = P\ (W/T)*P\ (T) + P\ (W/\ \text{Not True})\ P\ (\text{Not True}) \qquad (45)$$

$$P\ (S) = P\ (S/T)*P\ (T) + P\ (S/\ \text{Not True})\ P\ (\text{Not True}) \qquad (46)$$

$$P\ (INS) = P\ (INS/T)*P\ (T) + P\ (INS/\ \text{Not True})\ P\ (\text{Not True}) \qquad (47)$$

Brake probability failure was calculated with equations 44 to 47 and Excel as:

**P (BR) =0.06,** Probability of failure for brake

**R (BR) = 0.94**, Reliability for brake

### 3.6.1.1.9.1 Brake Cost

The parameter "$C_{brake}$ ($)" was used for the brake cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.6.1.1.10 Risk Calculations for Hydraulic Shovels

Risks are generally measured in terms of likelihood and consequence. Table 3-6 summarizes common probabilities of failure modes and their causes in hydraulic shovels. The highest probability of failure was observed for slew ring bolts, followed by filter assemblies and engines. The lowest probability of failure was observed in the boom and stick, followed by the shutdown valve and cab/control.

Table 3-6: Risk associated with hydraulic shovels

| No | Description | Probability of Failure | Consequence (CAN$) | Risk (CAN $) |
|---|---|---|---|---|
| 1 | Cab/control | 0.01 | 700,000 | 7,000 |
| 2 | Hydraulic pump | 0.05 | 130,886 | 6,544.30 |
| 3 | Brakes | 0.06 | 78,532 | 4,711.92 |
| 4 | Boom and stick | 0.01 | 104,709 | 1,047.1 |
| 5 | Engine | 0.09 | 8,569 | 771.21 |
| 6 | Slew ring bolts | 0.22 | 124 | 27.3 |
| 7 | ZAKO rings | 0.07 | 309 | 21.63 |
| 8 | Shutdown valve | 0.01 | 1,793 | 17.93 |
| 9 | Filter assembly | 0.14 | 70 | 9.8 |
| 10 | O-rings | 0.07 | 7 | 0.49 |

### 3.6.1.2 Hydraulic Shovel Failure Rate

As the reliability function in this research assumed to be steady state for hydraulic shovel; therefore, the failure rate in time independent. Table 3-7 shows the failure rate for the selected main parts of the hydraulic shovel.

Table 3-7: failure rate value for some main sub system of hydraulic shovel

| No | Description | Probability of Failure | Reliability | Failure Rate |
|---|---|---|---|---|
| 1 | Cab/control | 0.01 | 0.99 | 0.01 |
| 2 | Hydraulic pump | 0.05 | 0.95 | 0.05 |
| 3 | Brakes | 0.06 | 0.94 | 0.06 |
| 4 | Boom and stick | 0.01 | 0.99 | 0.01 |
| 5 | Engine | 0.09 | 0.91 | 0.10 |
| 6 | Slew ring bolts | 0.22 | 0.78 | 0.28 |
| 7 | ZAKO rings | 0.07 | 0.93 | 0.08 |
| 8 | Shutdown valve | 0.01 | 0.99 | 0.01 |
| 9 | Filter assembly | 0.14 | 0.86 | 0.16 |
| 10 | O-rings | 0.07 | 0.93 | 0.08 |

### 3.6.2 Electric Shovels

Electric shovels use electricity as an energy source. An electric shovel with the same capacity as a hydraulic shovel is usually larger than its hydraulic counterpart. The capacity of the electric shovel is approximately 100 to 115 tons and the capital cost is $15 million (16, 72).

#### 3.6.2.1 Reliability

The reliability block diagram (RBD) for an electric shovel is shown in Figure 3-39. This RBD shows that electro motors, hoist ropes, buckets, teeth, and crawlers operate in a series from the electric shovel and if any of these components fail, the electric shovel will fail.

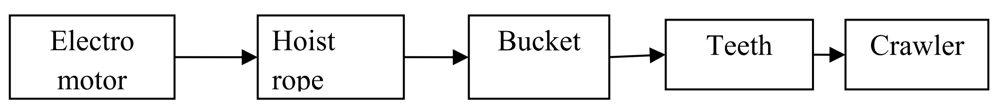



Figure 3-24: Reliability block diagram for the electric shovel

#### 3.6.2.2 Possible Failure Modes for the Electric Shovel

The main components of the oil sands electric shovel, whose failures can cause the loss of the shovel, are the hoist rope, bucket, teeth, crawler, and electro motor, which were shown in figure 3-39. All possible failure modes for each component were investigated and their failure probabilities were calculated based on the BBN.

##### 3.6.2.2.1 Hoist Ropes

Some of causes of hoist rope failure are:

- Parts may wear out when they touch hoist sheaves and taps.
- Corrosion due to insufficient lubricant as well as exposure to moisture or heat (i.e., when the temperature exceeds 120°C.
- Repeated curving over the time.
- Mechanical abuse, through crushing, cutting, or dragging the rope.

- Twisting due to inappropriate installation.
- Inappropriate rope installation.

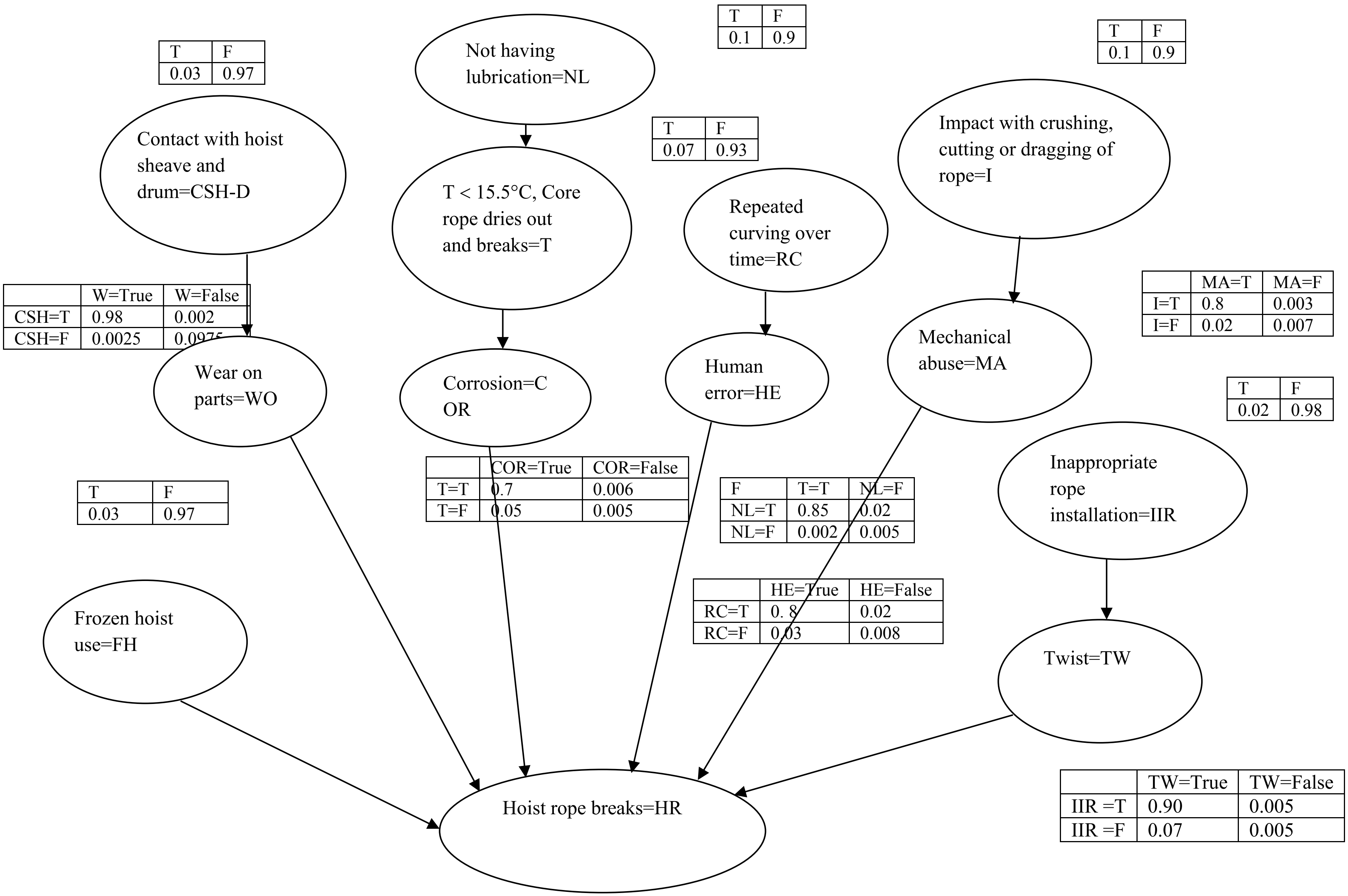



Figure 3-25: BBN graphical model for electric shovel hoist rope failures

| FH | WO | COR | HE | MA | TW | HR=True | HR =False |
|---|---|---|---|---|---|---|---|
| T | T | T | T | T | T | 0.8 | 0.02 |
| T | T | T | T | T | F | 0.001 | 0.03 |
| T | T | T | T | F | T | 0.0025 | 0.075 |
| T | T | T | F | T | T | 0.002 | 0.035 |
| T | T | F | T | T | T | 0.001 | 0.005 |
| T | F | T | T | T | T | 0.02 | 0.006 |
| F | T | T | T | T | T | 0.01 | 0.007 |
| T | T | T | T | F | F | 0.003 | 0.01 |
| T | F | T | F | T | F | 0.006 | 0.01 |
| T | T | T | F | F | F | 0.004 | 0.004 |
| T | T | F | F | F | F | 0.0035 | 0.0015 |
| F | F | T | T | T | T | 0.002 | 0.025 |
| F | F | F | T | T | T | 0.005 | 0.035 |
| F | F | F | F | T | T | 0.002 | 0.1 |
| F | F | F | F | F | T | 0.01 | 0.2 |
| T | F | F | T | F | F | 0.03 | 0.006 |
| F | T | F | T | F | T | 0.04 | 0.009 |
| F | F | F | T | T | F | 0.007 | 0.02 |
| F | T | T | F | F | F | 0.008 | 0.001 |
| F | F | F | F | F | F | 0.0025 | 0.003 |

Assumptions:

- Frozen hoist (FH), wear out (WO), human error (HE), mechanical abuse (MA), inappropriate rope installation (IIR), and twist (TW) are independent.

The probability of failure and the reliability for electric shovel hoist ropes were calculated based on Figure 3-40 and from the formulas below:

P (HR) = $\sum_{FH,WO,COR,HE,MA,IIR,TW}$ P (HR | FH, WO, COR, HE, MA, IIR, TW) P (FH, WO, COR, HE, MA, IIR, TW) (1)

P (HR) = $\sum_{FH,WO,COR,HE,MA,IIR,TW}$ P (HR | FH, WO, COR, HE, MA, IIR, TW) P (FH)*P (WO)*P (COR)*P (HE)*P (MA)*P (IIR) *P (TW) (2)

P (FH) = P (FH/T)*P (T) +P (FH/ Not True) P (Not True) (3)

P (WO) = $\sum_{CSH-D}$ P (WO | CSH-D) P (CSH-D) (4)

P (CSH-D) = P (CSH-D /T)*P (T) +P (CSH-D / Not True) P (Not True) (5)

P (COR) = $\sum_{T}$ P (COR | T) P (T) (6)

P (T) = $\sum_{NL}$ P (T | NL) P (NL) (7)

P (NL) = P (NL/T)*P (T) +P (NL/ Not True) P (Not True) (8)

P (T) = $\sum_{COR}$ P (T | COR) P (COR) (9)

P (COR) = P (COR/T)*P (T) +P (COR/ Not True) P (Not True) (10)

P (MA) = $\sum_{I}$ P (MA | I) P (I) (11)

P (MA) = P (MA/T)*P (T) +P (MA/ Not True) P (Not True) (12)

P (TW) = $\sum_{IIR}$ P (TW | IIR) P (IIR) (13)

P (IIR) = P (IIR/T)*P (T) +P (IIR/ Not True) P (Not True) (14)

P (HE) = $\sum_{RC}$ P (HE | RC) P (RC)

P (RC) = P (RC/T)*P (T) +P (RC/ Not True) P (Not True)

Hoist rope break failure probability was calculated using equations 1 to 14 and Excel as:

**P (HR) = 0.02**, Probability of failure for hoist rope breaks

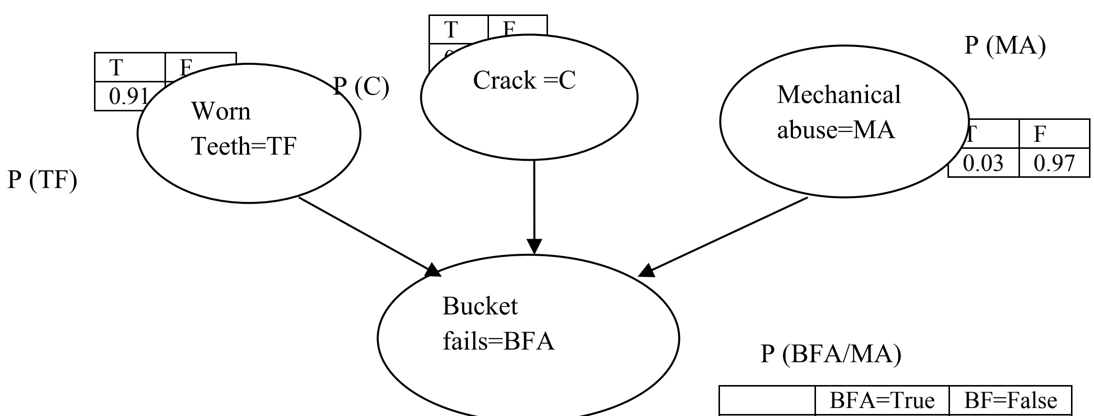
**R (HR) = 0.98**, Reliability for hoist rope breaks

#### 3.6.2.2.1.1 Hoist Ropes Break Cost

The parameter "C $_{\text{hoist rope}}$ (\$)" was used for the hoist ropes break cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.6.2.2.2 Buckets

Bucket are one of the main compnents of electric shovel to fail when oil sands ore is so hard to excavate or other materials are mixed with the ore and it can easily crack. Teeth wear predictably, but teeth and adapters can be lost. In addition, if the bucket is not used properly (i.e., if there is mechanical abuse), it can suffer sudden structural failure.




P (BFA/MA)

| | BFA=True | BF=False |
|---|---|---|
| MA=T | 0.9 | 0.02 |
| MA=F | 0.03 | 0.001 |

Figure 3-26: BBN graphical model for electric shovel bucket failures

The probability of failure and the reliability for electric shovel buckets were calculated based on Figure 3-41 and from the formulas below:

$$P\ (BFA) = \sum_{MA} P\ (BFA \mid MA, C, TF)\ P\ (MA) \quad (15)$$

$$P\ (MA) = P\ (MA/T)*P\ (T) + P\ (MA/\ Not\ True)\ P\ (Not\ True) \quad (16)$$

Bucket failure probabilities were calculated using equations 15 and 16 and Excel as:

**P (BF) =0.06**, Probability of failure for buckets

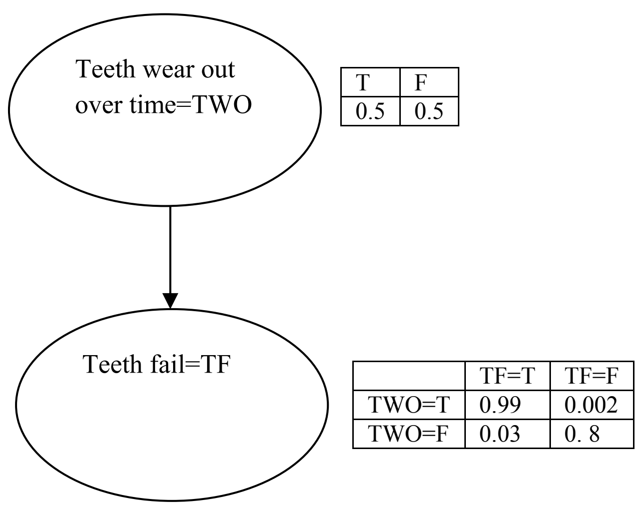
**R (BF) = 0.94**, Reliability for buckets

## 3.6.2.2.2.1 Bucket Cost

Price was assumed to be US $37,460 (CAN$ 46,555.85) (30).

## 3.6.2.2.3 Teeth

Teeth are important components of electric shovels and can wear out over time. Teeth reliability is low and teeth need to be replaced regularly; therefore, the costs associated with teeth maintenance are considerable.




| T | F |
|---|---|
| 0.5 | 0.5 |

| | TF=T | TF=F |
|---|---|---|
| TWO=T | 0.99 | 0.002 |
| TWO=F | 0.03 | 0. 8 |

Figure 3-27: BBN graphical model for electric shovel teeth failures

The probability of failure and the reliability for electric shovel teeth were calculated based on Figure 3-42 and from the formulas below:

$$P\ (TF) = \sum_{TWO} P\ (TF \mid TWO)\ P\ (TWO) \quad (17)$$

$$P\ (TWO) = P\ (TWO/T)*P\ (T) + P\ (TWO/\ Not\ True)\ P\ (Not\ True) \quad (18)$$

Teeth failure probability was calculated using equations 17 to 18 and Excel:

**P (TF) = 0.91**, Probability of failure for teeth

**R (TF) = 0.09**, Reliability teeth

### 3.6.2.2.3.1 Teeth Cost

Price was assumed to be US $5,468 (CAN$ 6,795.71). (30)

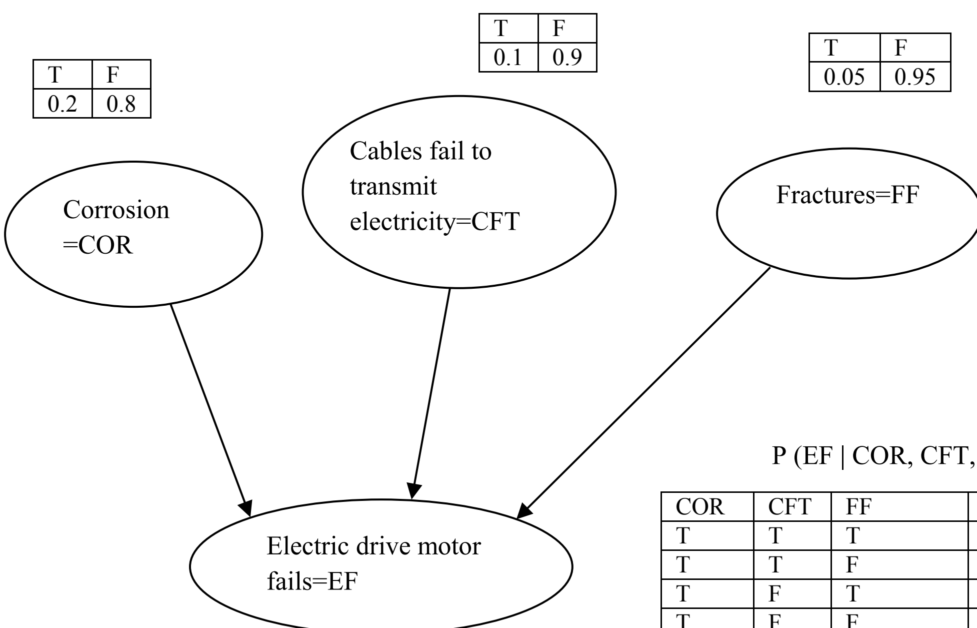
### 3.6.2.2.4 Electric Drive Motor

An electric drive motor will fail if the following happens (73):

- The motor is corroded;
- The motor has fractures;
- A cable cannot transmit electricity.

Assumptions:

- Corrosion (COR), cables fail to transmit electricity (CF), and fractures (FF) are independent.




P (EF | COR, CFT, FF)

| COR | CFT | FF | EF=True | EF=False |
|---|---|---|---|---|
| T | T | T | 0.90 | 0.02 |
| T | T | F | 0.001 | 0.05 |
| T | F | T | 0.06 | 0.008 |
| T | F | F | 0.01 | 0.009 |
| F | F | T | 0.0001 | 0.025 |
| F | T | F | 0.02 | 0.0013 |
| F | T | T | 0.002 | 0.02 |
| F | F | F | 0.00015 | 0.3 |

Figure 3-28: BBN graphical model for electric shovel electric drive motor failures

The probability of failure and the reliability for electric shovel drive motor were calculated based on Figure 3-43 and from the formulas below:

$$P(EF) = \sum_{COR,CFT,FF} P(EF \mid COR, CFT, FF)\, P(COR, CFT, FF) \qquad (19)$$

$$P(EF) = \sum_{COR,CFT,FF} P(EF \mid COR, CFT, FF)\, P(COR)\, P(CFT)\, P(FF) \qquad (20)$$

$$P(COR) = P(COR/T)*P(T) + P(COR/\text{Not True})\, P(\text{Not True}) \qquad (21)$$

$$P(CFT) = P(CFT/T)*P(T) + P(CFT/\text{Not True})\, P(\text{Not True}) \qquad (22)$$

$$P(FF) = P(FF/T)*P(T) + P(FF/\text{Not True})\, P(\text{Not True}) \qquad (23)$$

Electric drive motor failure probability was calculated using equations 19 to 23 and Excel as:

**P (EF) = 0.21**, Probability of failure for electric drive motors

**R (EF) = 0.79**, Reliability for electric drive motors

### 3.6.2.2.4.1 Electric Drive Motor Cost

The price of the electric drive motor is US $345,000 (CAN$ 428,771) (31).

### 3.6.2.2.5 Crawler

If a crawler bench becomes soft or there is insufficient supply of hydraulic oil insufficient lubrication available, the crawler will fail. Furthermore, if the structure is damaged, the crawler will fail.

Assumptions:

- Soft bench (SOF), lubrication (L), and structure (SD) are independent;
- Abuse (AB) and poor quality (PQ) are independent.

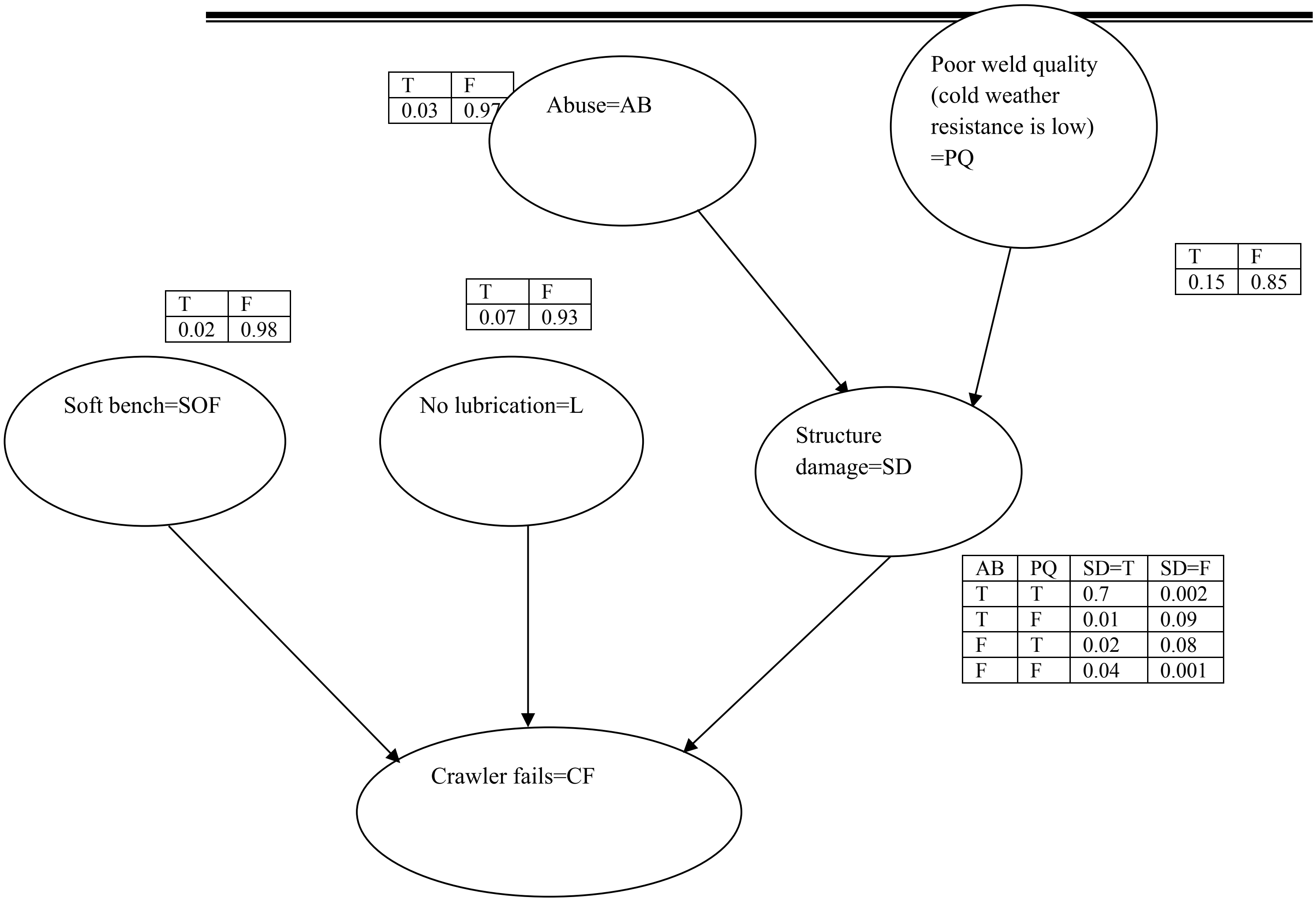



Figure 3-29: BBN graphical model for electric shovel crawler failures

| SOF | L | SD | CF=True | CF=False |
|---|---|---|---|---|
| T | T | T | 0.90 | 0.02 |
| T | T | F | 0.001 | 0.05 |
| T | F | T | 0.06 | 0.008 |
| T | F | F | 0.01 | 0.009 |
| F | F | T | 0.0001 | 0.025 |
| F | T | F | 0.02 | 0.0013 |
| F | T | T | 0.002 | 0.02 |
| F | F | F | 0.015 | 0.3 |

The probability of failure and the reliability for electric shovel crawlers were calculated based on Figure 3-44 and from the formulas below:

$$P\,(CF) = \sum_{SOF,L,SD} P\,(CF \mid SOF, L, SD)\, P\,(SOF, L, SD) \qquad (24)$$

$$P\,(CF) = \sum_{SOF,L,SD} P\,(CF \mid SOF, L, SD)\, P\,(SOF)\, P\,(L)\, P\,(SD) \qquad (25)$$

$$P\,(SD) = \sum_{PO,AB} P\,(SD \mid PQ, AB)\, P\,(PQ)\, P\,(AB) \qquad (26)$$

P (AB) = P (AB/T)*P (T) +P (AB/ Not True) P (Not True) (27)

P (PQ) = P (PQ/T)*P (T) +P (PQ/ Not True) P (Not True) (28)

P (SD) = 0.06

P (L) = P (L/T)*P (T) +P (L/ Not True) P (Not True) (29)

P (SOF) = P (SOF/T)*P (T) +P (SOF/ Not True) P (Not True) (30)

Crawler failure probability was calculated using equations 19 to 23 and Excel as:

**P (CF) = 0.02**, Probability of failure for crawlers

**R (CF) = 0.98**, Reliability for crawlers

### 3.6.2.2.5.1 Crawler Cost

The parameter "$C_{crawler}$ ($)" was used as the crawler cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.6.2.2.6 Calculation of Risks for the Electric Shovel

Table 3-8 summarizes risk associated with each failure mode and its related consequence in terms of financial impact for each of the main parts of an electric shovel. As the table shows, teeth have the highest probability of failure followed by the electric drive motor. The crawler and the hoist rope have the lowest probability of failure.

Table 3-8: Risk associated with electric shovels

| No | Description | Probability of Failure | Consequence (CAN$) | Risk(CAN$) |
|---|---|---|---|---|
| 1 | Electric drive motor | 0.21 | 428,771 | 90,042 |
| 2 | Teeth | 0.91 | 6,796 | 6,184 |
| 5 | Crawler | 0.01 | 190,000 | 1,900 |
| 3 | Bucket | 0.06 | 46,556 | 2,793 |
| 4 | Hoist rope | 0.02 | 95,000 | 1,900 |

### 3.6.2.3 Electric Shovel Failure Rate

As the reliability function in this research assumed to be steady state for electric shovel, therefore, the failure rate is a time independent variable. Table 3-9 shows the failure rate for the selected main parts of the hydraulic shovel.

Table 3-9: failure rate value for some main sub system of electric shovel

| No | Description | Probability of Failure | Reliability | Failure Rate |
|---|---|---|---|---|
| 1 | Electric drive motor | 0.21 | 0.79 | 0.27 |
| 2 | Teeth | 0.91 | 0.09 | 10.11 |
| 5 | Crawler | 0.01 | 0.99 | 0.01 |
| 3 | Bucket | 0.06 | 0.94 | 0.06 |
| 4 | Hoist rope | 0.02 | 0.98 | 0.02 |

## 3.7 Oil Sands Mining Crushers

An oil sands mining crusher reduces large pieces of ore to smaller pieces by applying pressure on the ore with a metal surface. Crusher failure leads to unscheduled shutdowns for repair and suspends mining procedures, thereby increasing cost and energy demand. Therefore, the modeling of crusher failure scenarios is crucial to predict a crusher's failure rate and to prevent extra financial impacts. This section is an attempt to describe how to approach the modeling of crushers and unexpected failures in oil sands mining operations. In this chapter, a double roll crusher (fixed crusher) and a sizer were considered. Both crushers (double roll crusher and mineral sizer) have rolls with horizontal axes (74). The advantages of a double roll crusher (fixed crusher) are its high capability to size ore with a simple structure and its ability to crush the ore to the desired size.

### 3.7.1 Mineral Sizer Crusher

A mineral sizer has several sets of meshing rotors with large teeth that drive at a low speed on a relatively small shaft. A mineral sizer crusher has three major components along with interacting features: breaking action, revolving screen effect, and deep scroll tooth design. The deep scroll tooth transports the bigger ore to the end of the machine and helps to reject the large ore. When the crusher is in operation, the leading faces of the opposite rotor teeth contact the ore. With various points loading, pressure is applied to the ore to develop natural faults. Next, the ore is broken because of the tightness of the three-point loading applied by the front tooth on one rotor and the rear tooth faces on the other rotor. Large pieces of ore are broken because the rotors cut ore from side to side with fixed teeth. A toothed rotor is designed to allow free-flowing undersized ore to pass through continuously shifting gaps created by relatively slow-moving shafts. The primary roll passes bigger pieces of ore to the end of the machine and extends a feed across the full length of the rotors to reject oversized ore (75).

### 3.7.2 Double Roller Crusher

A double roller crusher is used to crush ore of medium or lower stiffness. In a double roller crusher, ore drops between two rollers and the final ore is obtained. Some material cannot be crushed into small pieces. To deal with such material, a roller will allow a spring and a hydraulic actuator to change the gap between two rollers to allow solid ore to be crushed. The adjustable roll gap between two rollers of a double roller crusher can be changed to make the final ore size. To crush ore to less than 6”, roller crushers that are unlikely to be affected by sticky oil sands ore are used. The main disadvantage of roller crushers is their inability to crush hard ore efficiently. The double roller crusher has roller bodies equipped with crushing rings and segments. The rollers are locked with fixed bolts and disks or with screws (76). The drive consists of electric motors with couplings and gear motors. The drive allows reverse operation in case of overload to increase system availability. Figure 3-52 shows the location of the crusher in the oil sands extraction process train.

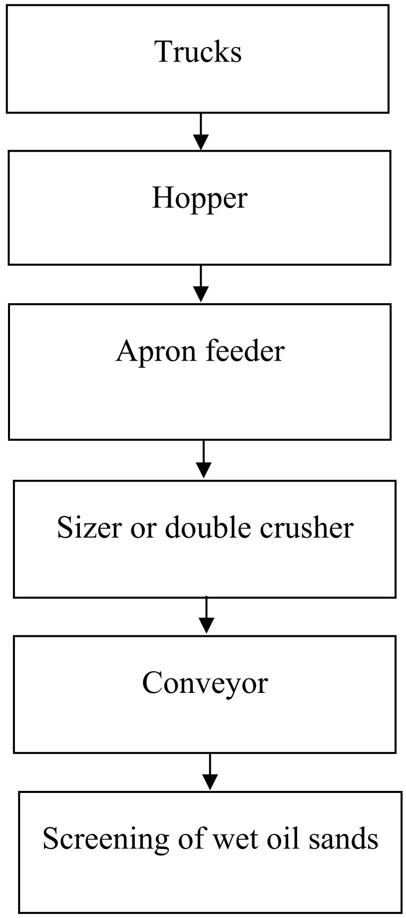



Figure 3-30: Crusher position in oil sands mining operations

### 3.7.3 Description of Each Failure Mode

In this study, the key failure modes and causes for an oil sands crusher were identified. Then, based on a BBN, their failure probabilities were calculated. With the related probability and consequence of each failure, the risk associated with each failure mode was calculated. The main advantage of using a Bayesian belief network is its flexibility, which allows new nodes to be added. In addition, because benchmark data were not the actual data, a BBN was used to deal with the uncertainty and raise the confidence of the results. The Bayesian belief network estimates the probability derived from the dependencies (77).

### 3.7.4 Identification of Potential Risks for Crusher

Risks associated with crusher failure were investigated based on benchmark data and interviews with experts. The structure, teeth, rolls, drive system, apron feeder, and control system are the mechanical parts of a crusher that will cause a crusher to fail if they stop working.

### 3.7.4.1 Structure

The structure is the frame of the crusher. The structure's parts wear out due to insufficient lubrication oil, which will cause the structure to fail.

| T | F |
|---|---|
| 0.03 | 0.97 |

| O-L | WO=T | WO=F |
|---|---|---|
| T | 0. 95 | 0.003 |
| F | 0.075 | 0.0095 |

| CL-C | WO | S-D=True | S-D=False |
|---|---|---|---|
| T | T | 0.90 | 0.02 |
| T | F | 0.001 | 0.05 |
| F | T | 0.003 | 0.008 |
| F | F | 0.0001 | 0.025 |

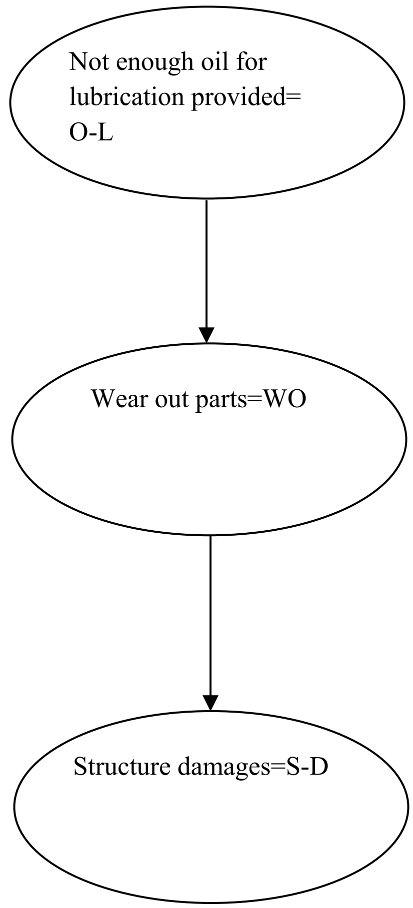



Figure 3-31: BBN graphical model for crusher structure damage

The probability of failure and the reliability for the crusher structure were calculated based on Figure 3-53 and from the formulas below:

P (S-D) = $\sum_{WO}$ P (S-D | WO) P (WO) (1)

P (WO) = $\sum_{O-L}$ P (WO | O-L) P (O-L) (2)

P (O-L) = P (O-L/T)*P (T) +P (O-L/ Not True) P (Not True) (3)

Crusher structure failure probability was calculated using formulas 2 and 3 and Excel as:

**P (S-D) = 0.05,** Probability of failure for the crusher's structure

**R (S-D) = 0.95**, Reliability for the crusher's structure

#### 3.7.4.1.1 Structure Cost

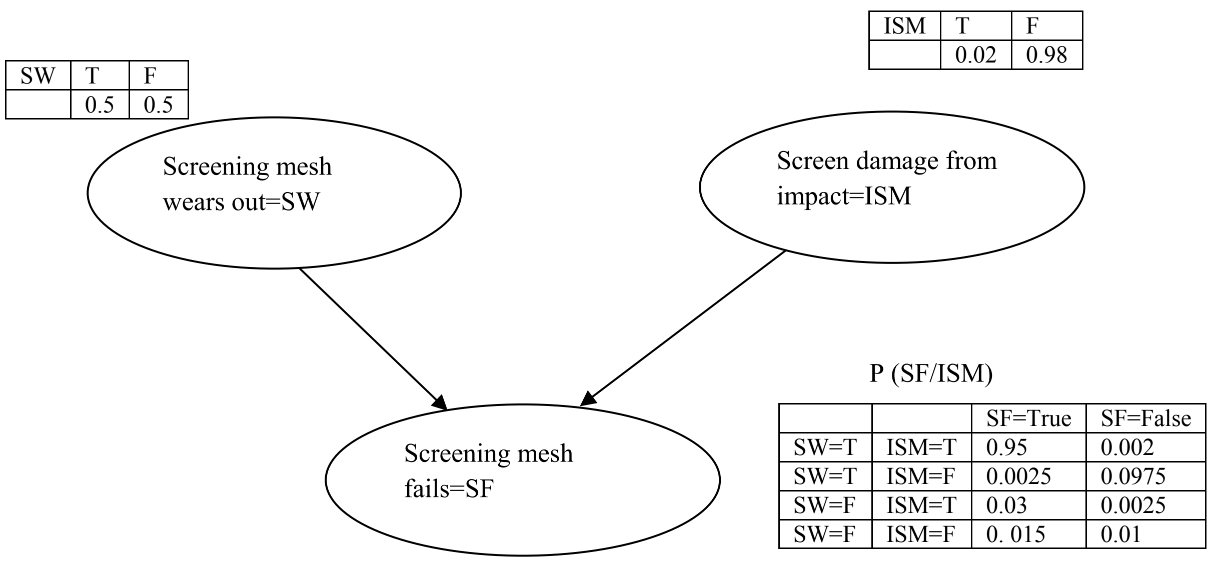
The parameter "$C_{structure}$ ($)" was used for structure cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.7.4.2 Screen Mesh

Screen meshes are used to reduce the size of crushed ore. Different mesh sizes can be used depending on the size requested by a company (78). The mesh will fail if its parts wear out or the screen is damaged.

Assumption:

- Screen mesh wear out (SW) and screen damage from impact (ISM) are independent.




| SW | T | F |
|---|---|---|
| | 0.5 | 0.5 |

| ISM | T | F |
|---|---|---|
| | 0.02 | 0.98 |

P (SF/ISM)

| | | SF=True | SF=False |
|---|---|---|---|
| SW=T | ISM=T | 0.95 | 0.002 |
| SW=T | ISM=F | 0.0025 | 0.0975 |
| SW=F | ISM=T | 0.03 | 0.0025 |
| SW=F | ISM=F | 0. 015 | 0.01 |

Figure 3-32: BBN graphical model for crusher screen mesh failures

The probability of failure and the reliability for crusher screen mesh were calculated based on Figure 3-54 and from the formulas below:

$$P(SF) = \sum_{ISM,SW} P(SF \mid ISM, SW)\, P(ISM)\, P(SW) \qquad (4)$$

$$P(ISM) = P(ISM/T)*P(T) + P(ISM/\text{ Not True})\, P(\text{Not True}) \qquad (5)$$

P (SW) = P (SW /T)*P (T) +P (ISM/ Not True) P (Not True) (6)

The probability for screen mesh failure was calculated using formulas 4 to 6 and Excel as:

**P (SF) =0.07,** Probability of failure for a screen mesh

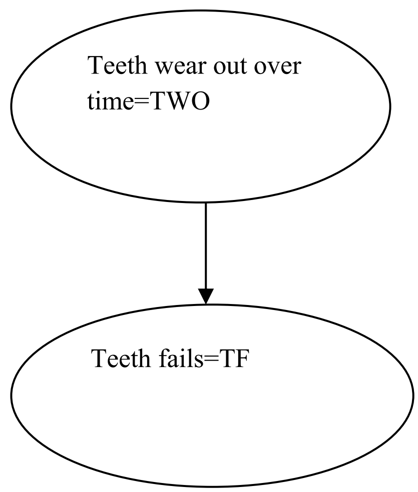
**R (SF) =0.93**, Reliability for a screen mesh

#### 3.7.4.2.1 Screen Mesh Cost

The screen mesh cost about CAN $3,500 (79).

### 3.7.4.3 Teeth

Teeth are important parts of a crusher that wear out over time and need to be replaced frequently.




| TWO | T | F |
|---|---|---|
| | 0.90 | 0.10 |

P (TF/TW)

| | TF=True | TF=False |
|---|---|---|
| TW=T | 0.99 | 0.002 |
| TW=F | 0.0025 | 0.0975 |

Figure 3-33: BBN graphical model for crusher teeth failures

The probability of failure and the reliability for crusher teeth were calculated based on Figure 3-55 and from the formulas below:

P (TF) = $\sum_{TWO}$ P (TF | TWO) P (TWO) (7)

P (TWO) = P (TWO/T)*P (T) +P (TWO/ Not True) P (Not True) (8)

Screen mesh failure probability was calculated using formulas 7 and 8 and Excel as:

**P (TF) = 0.9,** Probability of failure for teeth

**R (TF) = 0.1**, Reliability for teeth

#### 3.7.4.3.1 Teeth Cost

The parameter "$C_{teeth}$ ($)" was used for teeth cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

## 3.7.4.4 Rolls

Cylindrical rolls are formed by twisting material around a cylinder or by twisting material repeatedly on itself with no folding. Rolls will fail if impact damages the rolls due to tramp metal or if the roller wears out over time.

Assumptions:

- Tramp metal (TM) and the wearing out of rollers over time (WR) are independent;
- Impact damage of rolls (IDM) and wear off roller (WOR) are independent.

| TM | T | F |
|---|---|---|
| | 0.03 | 0.97 |

| | TM=T | TM=F |
|---|---|---|
| IDM =T | 0.95 | 0.03 |
| IDM =F | 0.0015 | 0.085 |

| WOR | T | F |
|---|---|---|
| | 0.05 | 0.95 |

| IDM | PM | WOR | RF=True | RF=False |
|---|---|---|---|---|
| T | T | T | 0.93 | 0.02 |
| T | T | F | 0.001 | 0.03 |
| T | F | T | 0.0025 | 0.075 |
| F | T | T | 0.09 | 0.87 |
| F | F | T | 0.68 | 0.003 |
| T | F | F | 0.004 | 0.002 |
| F | T | F | 0.02 | 0.005 |
| F | F | F | 0.002 | 0.035 |

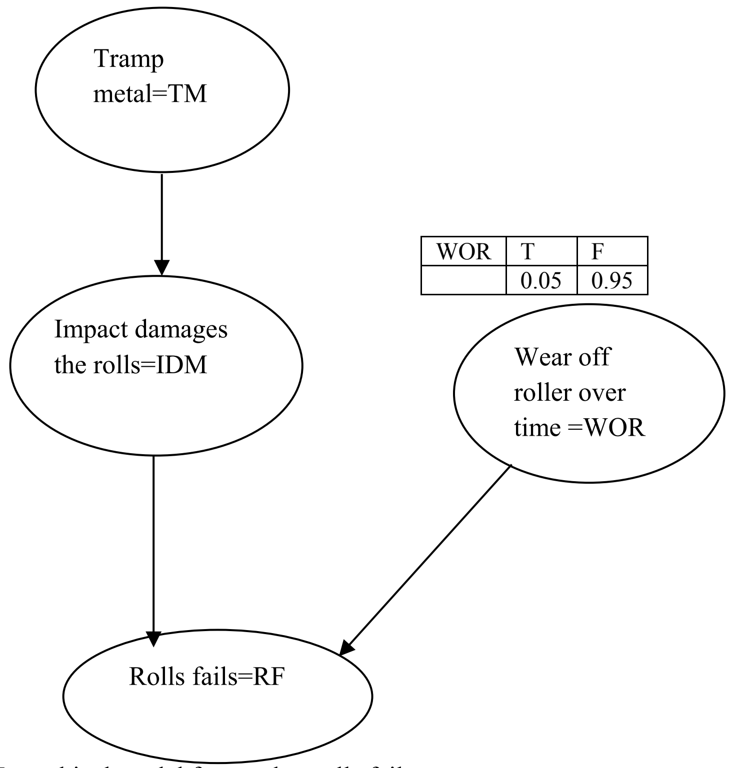



Figure 3-34: BBN graphical model for crusher rolls failure

The probability of failure and the reliability for crusher rolls were calculated based on Figure 3-56 and from the formulas below:

$$P\ (RF) = \sum_{WOR,IDM} P\ (RF \mid WOR, IDM)\ P\ (WOR, IDM) \quad (9)$$

$$P\ (RF) = \sum_{WOR,IDM} P\ (RF \mid WOR, IDM)\ P\ (WOR)\ P\ (IDM) \quad (10)$$

$$P\ (WOR) = P\ (WOR)*P\ (T) + P\ (WOR/\ Not\ True)\ P\ (Not\ True) \quad (11)$$

$$P\ (IDM) = \sum_{TM} P\ (IDM \mid TM)\ P\ (TM) \quad (12)$$

P (TM) = P (TM)*P (T) +P (TM/ Not True) P (Not True) (13)

Roll failure probability was calculated using formulas 9 to 13 and Excel as:

**P (RF) = 0.12,** Probability of failure for rolls

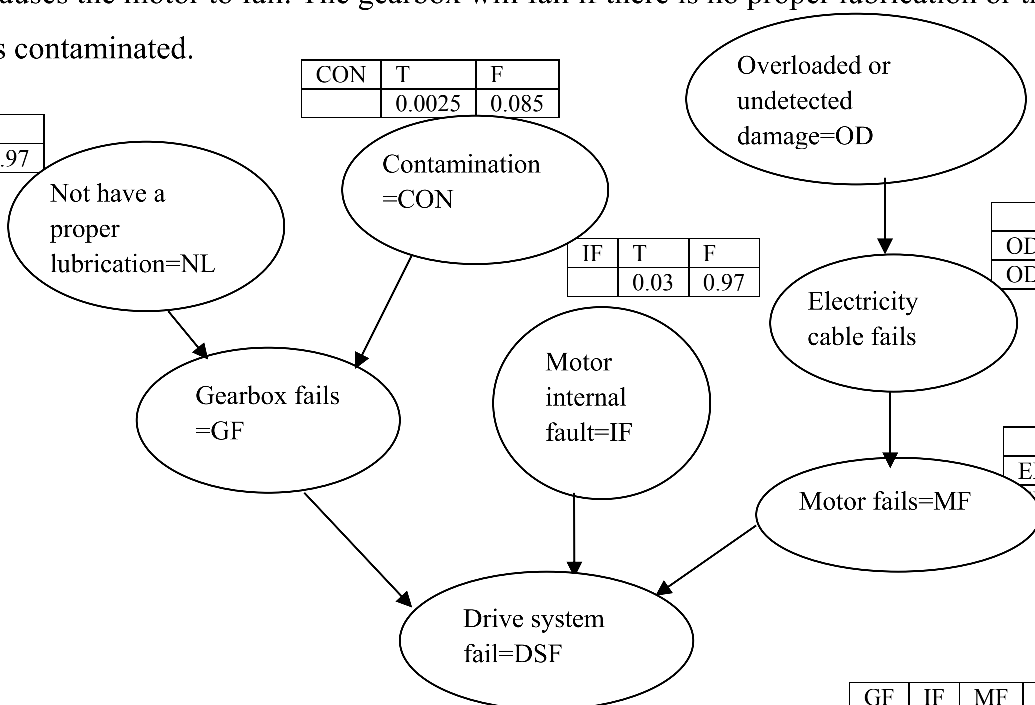
**R (RF) = 0.88**, Reliability for rolls

### 3.7.4.4.1 Roll Cost

A roll crusher can cost between CAN $ 17, 636.00, and 215, 377.00, depending on the capacity. Capacity is given in kg per second with a typical minimum capacity of 1 kg per second up to a maximum of 100 kg per second.

### 3.7.4.5 Drive System

The drive system makes a motor operate. The drive system consists of electric motors with coupling and gear motors and is designed to operate in reverse in case of overload to increase system availability. The drive system can fail if the motor or internal motor fails or if the gearbox fails. If the drive system overloaded, then the electricity cable fails and causes the motor to fail. The gearbox will fail if there is no proper lubrication or the system is contaminated.




| NL | T | F |
|---|---|---|
| | 0.03 | 0.97 |

| CON | T | F |
|---|---|---|
| | 0.0025 | 0.085 |

| OD | T | F |
|---|---|---|
| | 0.05 | 0.95 |

| | EF=T | EF=F |
|---|---|---|
| OD=T | 0.89 | 0.002 |
| OD=F | 0.0025 | 0.0975 |

| IF | T | F |
|---|---|---|
| | 0.03 | 0.97 |

| | OD=T | OD=F |
|---|---|---|
| EF=T | 0.89 | 0.002 |
| EF=F | 0.0025 | 0.0975 |

Figure 3-35: BBN graphical model for crusher drive system failures

| GF | IF | MF | DSF=True | DSF=False |
|---|---|---|---|---|
| T | T | T | 0.93 | 0.02 |
| T | T | F | 0.001 | 0.03 |
| T | F | T | 0.0025 | 0.075 |
| F | T | T | 0.09 | 0.87 |
| F | F | T | 0.68 | 0.003 |
| T | F | F | 0.004 | 0.002 |
| F | T | F | 0.02 | 0.005 |
| F | F | F | 0.002 | 0.035 |

| | | GF=True | GF=False |
|---|---|---|---|
| NL=T | C=T | 0.95 | 0.002 |
| NL=T | C=F | 0.0025 | 0.0975 |
| NL=F | C=T | 0.03 | 0.0025 |
| NL=F | C=F | 0. 015 | 0.01 |

Assumptions:

- Lubrication (NL), contamination (CON), electricity cable (EC), internal motor fault (IF), and overload (OD) are independent.
- Gearbox (GF), internal motor fault (IF), and motor failure (MF) are independent.

The probability of failure and the reliability for crusher drive systems were calculated based on Figure 3-57 and from the formulas below:

$$P\ (DSF) = \sum_{GF,IF,MF} P\ (DSF \mid GF, IF, MF)\ P\ (GF)\ P\ (IF)\ P\ (MF) \quad (14)$$

$$P\ (MF) = \sum_{EC} P\ (MF \mid EC)\ P\ (EC) \quad (15)$$

$$P\ (EC) = \sum_{OD} P\ (EC \mid OD)\ P\ (OD) \quad (16)$$

$$P\ (OD) = P\ (OD/T)*P\ (T) + P\ (OD/\ Not\ True)\ P\ (Not\ True) \quad (17)$$

$$P\ (GF) = \sum_{NL,CON} P\ (GF \mid NL, CON)\ P\ (NL).\ P\ (CON) \quad (18)$$

$$P\ (NL) = P\ (NL/T)*P\ (T) + P\ (NL/\ Not\ True)\ P\ (Not\ True) \quad (19)$$

$$P\ (CON) = P\ (CON/T)*P\ (T) + P\ (CON/\ Not\ True)\ P\ (Not\ True) \quad (20)$$

$$P\ (IF) = P\ (IF/T)*P\ (T) + P\ (IF/\ Not\ True)\ P\ (Not\ True) \quad (21)$$

P (EC) = 0.09

The probability of failure for drive system was calculated using formulas 14 to 21 and Excel as:

**P (DSF) = 0.17,** Probability of failure for drive systems

**R (DSF) =0.83**, Reliability for drive systems

### 3.7.4.5.1 Drive System Cost

The parameter "$C_{drive\ system}$ ($)" was used for the drive system cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.7.4.6 Apron Feeder

The feeder considered in this research is an apron feeder. The feeder is one of the main mechanical parts of the crusher and its performance affects crusher efficiency. To avoid wearing out the feeder, it is better to operate it at its lowest possible rate. Some of the hazards that damage a crusher are shown as nodes in the BBN diagram (80).

Assumptions:

- The apron pan conveyor chain (AC), driving machine (DMA), frame, hopper, skirt, chute crack (FHS), overload safety device (OS), and feed roller (FRO) are independent.

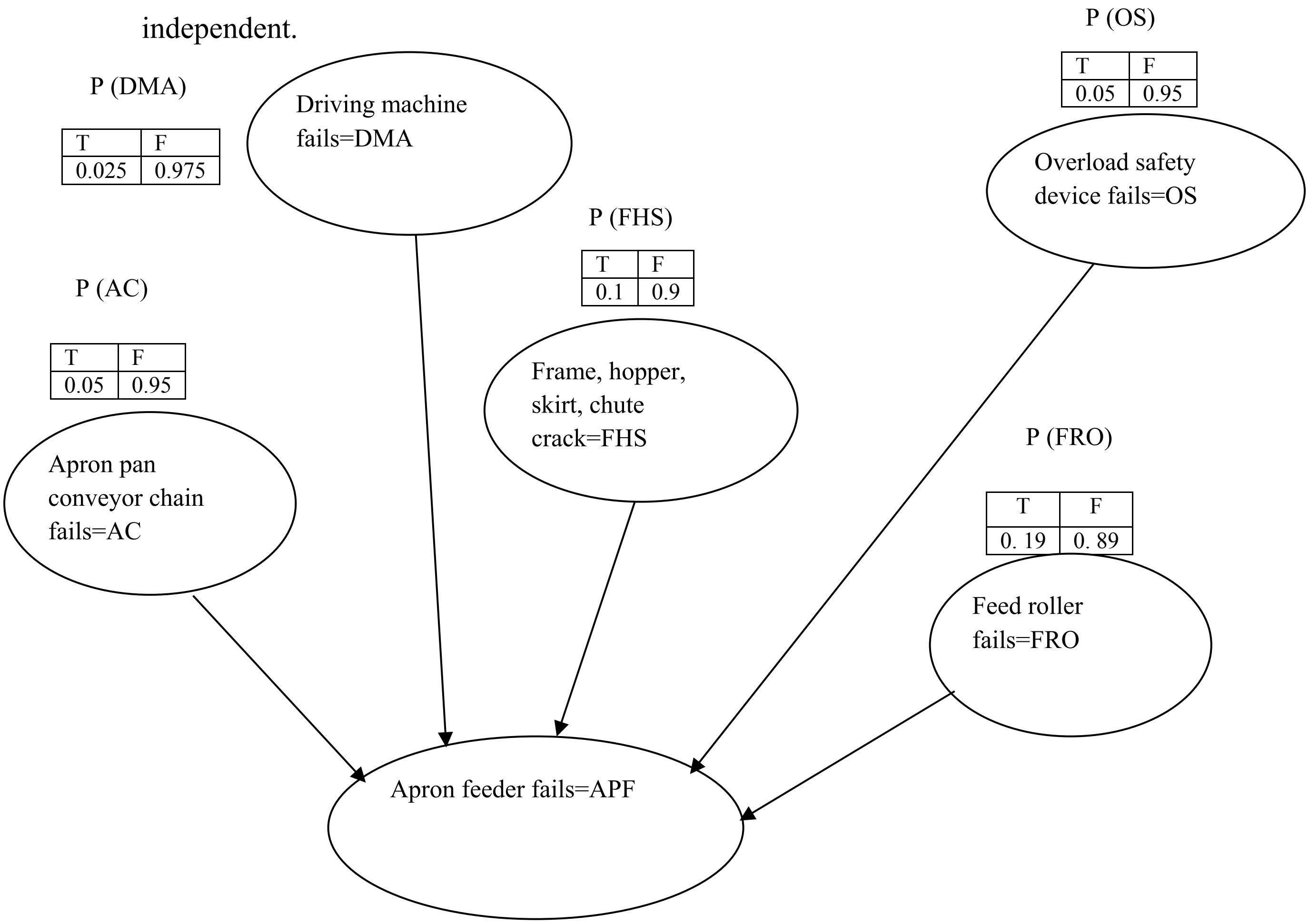



Figure 3-36: BBN graphical model for crusher apron feeder failures

P (APF | AC, DMA, FHS, OS, FRO)

| AC | DMA | FHS | OS | FRO | APF=True | APF =False |
|---|---|---|---|---|---|---|
| T | T | T | T | T | 0. 8 | 0.02 |
| T | T | T | T | F | 0.001 | 0.03 |
| T | T | T | F | T | 0.0025 | 0.075 |
| T | T | F | T | T | 0.002 | 0.035 |
| T | F | T | T | T | 0.001 | 0.005 |
| F | T | T | T | T | 0.002 | 0.025 |
| F | F | T | T | T | 0.005 | 0.035 |
| F | F | F | T | T | 0.002 | 0.1 |
| F | F | F | F | T | 0.01 | 0.2 |
| F | F | F | F | F | 0.0025 | 0.003 |

The probability of failure and the reliability for the crusher's apron feeder were calculated based on Figure 3-58 and from the formulas below:

P (APF) = $\sum_{AC,DMA,FHS,OS,FRO}$ P (APF | AC, DMA, FHS, OS, FRO) P (AC, DMA, FHS, OS, FRO) (22)

P (APF) = $\sum_{AC,DMA,FHS,OS,FRO}$ P (APF | AC, DMA, FHS, OS, FRO) P (AC) P (DMA) P (FHS) P (OS) P(FRO) (23)

P (AC) = P (AC/T)*P (T) +P (AC/ Not True) P (Not True) (24)

P (DMA) = P (DMA/T)*P (T) +P (DMA/ Not True) P (Not True) (25)

P (FHS) = P (FHS/T)*P (T) +P (FHS/ Not True) P (Not True) (26)

P (OS) = P (OS/T)*P (T) +P (OS/ Not True) P (Not True) (27)

P (FRO) = P (FRO/T)*P (T) +P (FRO/ Not True) P (Not True) (28)

Apron feeder failure probability was calculated using formulas 22 to 28 and Excel as:

**P (APF) = 0.04**, Probability of failure for apron feeders

**R (APF) =0.96,** Reliability for apron feeders

### 3.7.4.6.1 Apron Feeder Cost

An apron feeder costs about CAN$ 58,000 (81).

### 3.7.4.7 Control System

The control system can fail through hardware, software, and operator errors.
Assumptions:

- Hardware (H), software (SOF), and operator errors (OE) are independent.

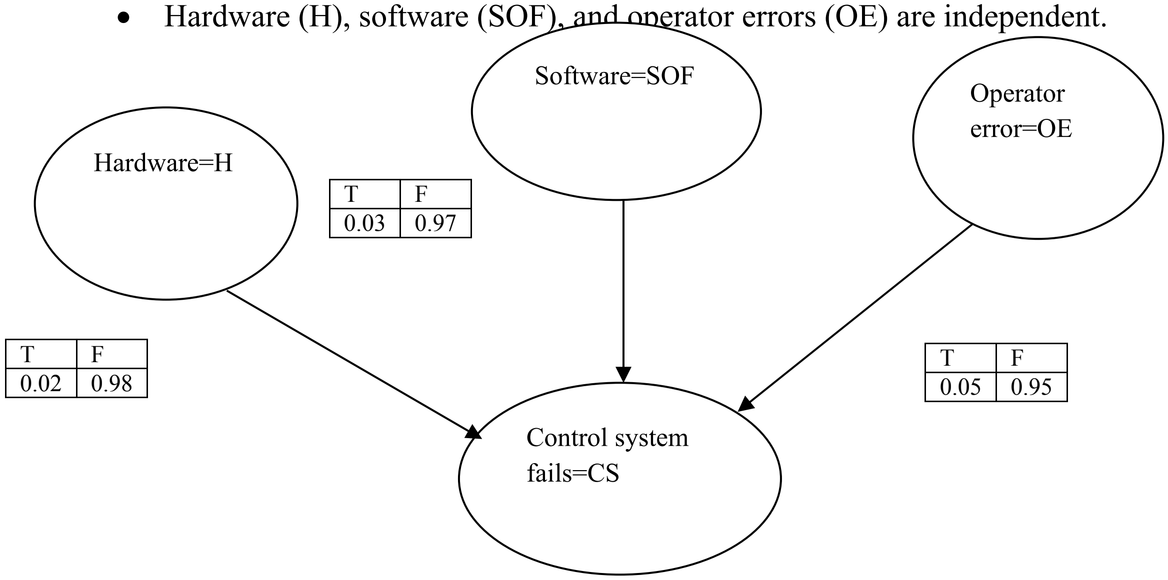



Figure 3-37: BBN graphical model for crusher control system failure

| H | SOF | OE | CS=True | CS=False |
|---|---|---|---|---|
| T | T | T | 0.9 | 0.02 |
| T | T | F | 0.06 | 0.008 |
| T | F | T | 0.01 | 0.009 |
| F | T | T | 0.0001 | 0.025 |
| F | F | T | 0.02 | 0.0013 |
| T | F | F | 0.015 | 0.002 |
| T | F | F | 0.06 | 0.015 |
| F | T | F | 0.01 | 0.015 |
| F | F | F | 0.00015 | 0.1 |

The probability of failure and the reliability for the crusher's control system were calculated based on Figure 3-59 and from the formulas below:

$$P(CS) = \sum_{H,SOF,OE} P(CS \mid H, SOF, OE)\, P(H, SOF, OE) \qquad (29)$$

$$P(CS) = \sum_{H,SOF,OE} P(CS \mid H, SOF, OE)\, P(H)\, P(SOF)\, P(OE) \qquad (30)$$

$$P(H) = P(H/T)*P(T) + P(H/\text{Not True})\, P(\text{Not True}) \qquad (31)$$

$$P(SOF) = P(FC/T)*P(T) + P(SOF/\text{Not True})\, P(\text{Not True}) \qquad (32)$$

$$P(OE) = P(A/T)*P(T) + P(OE/\text{Not True})\, P(\text{Not True}) \qquad (33)$$

The control system failure was calculated using formulas 29 to 33 and Excel as:

**P (CS) = 0.01,** Probability of failure for control systems

**R (CS) =0.9**, Reliability for control systems

### 3.7.4.7.1 Control System Cost

The parameter "$C_{\text{control system}}$ ($)" was used for the control system cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

## 3.7.5 Calculation of Failure Probability Based On Associated Risks

Crusher reliability was determined to be 90% based on expert opinion. The consequences of an occurrence refer to the financial impact of the event. The annual rate and consequence of an event in financial terms (CAN $) were calculated to find the annual cost of risk. The reliability and probability of failure of a crusher were calculated to be 0.90 and 0.1, respectively (82). Table 3-10 illustrates failure modes and failure probability rates obtained through the BBN method for selected crushers for the oil sands industry.

Table 3-10: Risks and corrective action for crusher

| No | Description | Probability of Failure | Consequence ($) | Risk | Corrective Action |
|---|---|---|---|---|---|
| 1 | Structure | 0.05 | C1 | $0.05*C_1$ | Maintenance, regular inspection |
| 2 | Screen mesh | 0.07 | C2 | $0.07*C_2$ | Continuous monitoring, maintenance, regular inspection |
| 3 | Teeth | 0.90 | C3 | $0.90*C_3$ | Continuous monitoring, maintenance, regular inspection |
| 4 | Rolls | 0.12 | C4 | $0.12*C_4$ | Continuous monitoring, maintenance, regular inspection |
| 5 | Drive system | 0.17 | C5 | $0.17*C_5$ | Training, proper supervision, regular inspection |
| 6 | Apron feeder | 0.04 | C6 | $0.04*C_6$ | Continuous monitoring, maintenance, regular inspection |
| 7 | Control system | 0.10 | C7 | $0.10*C_7$ | Safety, employee training, appropriate supervision, regular inspection |

### 3.7.6 Crusher Failure Rate

As the reliability function in this research assumed to be steady state for crusher, therefore, the failure rate did not change by the time. Table 3-11 shows the failure rate for the selected main parts of crusher. As shown in Table 3-11, teeth have the highest failure rate in crusher. The screen mesh was found to be the most reliable component of the crusher.

Table 3-11: failure rate value for some main sub system of crusher

| No | Description | Probability of Failure | Reliability | Failure Rate |
|---|---|---|---|---|
| 1 | Structure | 0.05 | 0.95 | 0.05 |
| 2 | Screen mesh | 0.07 | 0.93 | 0.08 |
| 3 | Teeth | 0.90 | 0.1 | 9.00 |
| 4 | Rolls | 0.12 | 0.88 | 0.14 |
| 5 | Drive system | 0.17 | 0.83 | 0.20 |
| 6 | Apron feeder | 0.04 | 0.96 | 0.04 |
| 7 | Control system | 0.10 | 0.9 | 0.11 |

## 3.8 Conveyor Belt

The conveyor belt is a piece of mining equipment that transfers bulk mine products from the crusher to the slurry pump. It is essential to have a reliable conveyor because of the continuous transfer of bulk materials; therefore, conveyor belt reliability is vital. A lack of regular maintenance and repair can cause conveyor belt failure and suspend mining processes. A simulation of reliability for conveyor belts is done to predict failures. This section describes conveyor belt reliability and unexpected failures in oil sands mining operations.

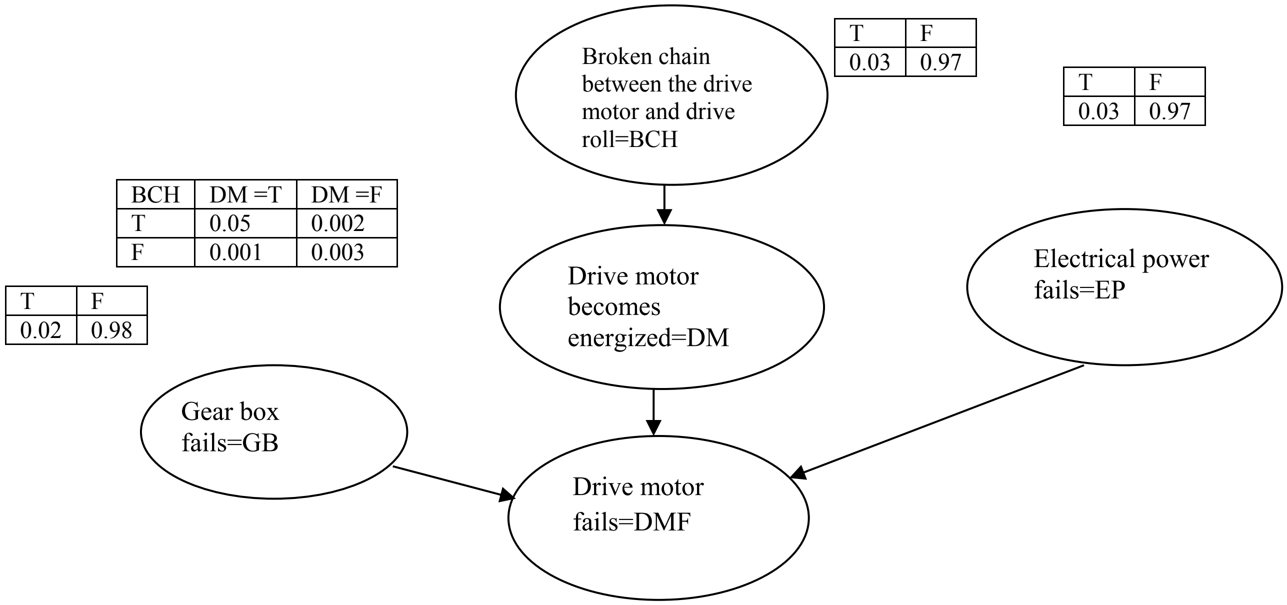
### 3.8.1 Identification of Potential Conveyor Belt Risks

A conveyor belt has some main parts whose failures will cause conveyor belt failure. The main parts of the conveyor belt that were studied are:

- Drive motor, power rollers, head pulley, tail pulley, return idler, pulley cleaner, and belt.

### 3.8.2 Drive Motor

The drive unit consists of the electric motor, the coupling (which attaches the output shaft to the pulley), and the gearbox. If the gearbox does not work, the drive motor can fail. However, there are some circumstances in which the gearbox does not work properly but the drive motor continues to run, albeit with greater energy consumption. In addition, when the electrical power (the source that produces electricity) completely fails, the drive motor will fail, too. However, if the electrical power does not work properly, as with a poorly functioning gearbox, more energy is consumed to operate the drive motor.




| T | F |
|---|---|
| 0.03 | 0.97 |

| T | F |
|---|---|
| 0.03 | 0.97 |

| BCH | DM =T | DM =F |
|---|---|---|
| T | 0.05 | 0.002 |
| F | 0.001 | 0.003 |

| T | F |
|---|---|
| 0.02 | 0.98 |

Figure 3-38: BBN graphical model for conveyor belt drive motor failure

| EP | GB | DM | DMF =T | DMF =F |
|---|---|---|---|---|
| T | T | T | 0. 97 | 0.002 |
| F | T | T | 0.085 | 0.0095 |
| T | F | T | 0.001 | 0.00252 |
| T | T | F | 0.0045 | 0.0014 |
| F | F | T | .002 | 0.0021 |
| T | F | F | 0.003 | 0.0015 |
| F | T | F | 0.0058 | 0.003 |
| F | F | F | 0.00001 | 0.01 |

Assumptions:

- Gear box (GB), broken chain between the drive motor and drive roll (BCH), and electrical power (EP) are independent;
- Probabilities describe random variable of the model.

The probability of failure and the reliability for the conveyor belt's drive motor were calculated based on Figure 3-68 and from the formulas below:

$$P\ (DMF) = \sum_{GB,DM,EP} P\ (GB \mid GB, DM, EP)\ P\ (CM)\ P\ (DM)\ P\ (EP) \quad (1)$$

$$P\ (DM) = \sum_{BCH} P\ (DM \mid BCH)\ P\ (BCH) \quad (2)$$

$$P\ (BCH) = P\ (BCH/T)*P\ (T) + P\ (BCH/\ Not\ True)\ P\ (Not\ True) \quad (3)$$

$$P\ (GB) = P\ (GB/T)*P\ (T) + P\ (GB/\ Not\ True)\ P\ (Not\ True) \quad (4)$$

$$P\ (EP) = P\ (EP/T)*P\ (T) + P\ (EP/\ Not\ True)\ P\ (Not\ True) \quad (5)$$

From equation 1 to 5 and Excel, probability of failure for drive motor was as:

P (DM) = 0.005

**P (DMF) = 0.01,** Probability of failure for drive motors

R=1-0.009737= 0.99,

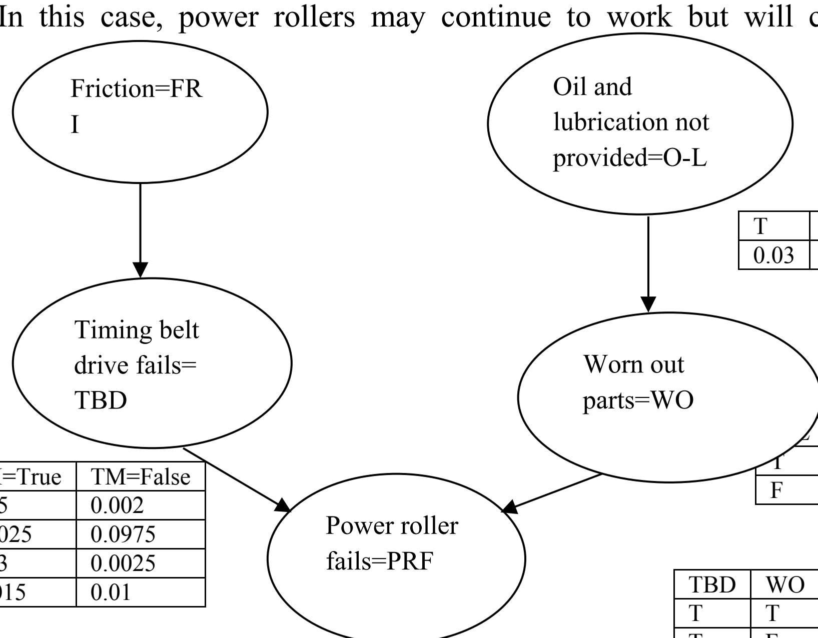
**R (DMF) =0.99,** Reliability for drive motors

### 3.8.2.1 Drive Motor Cost

The estimated cost for a 0.075 meter long, 0.5 m wide drive motor with a 6.4 m conveying distance is CAN $843.

## 3.8.3 Power Roller

A power roller is used to spread mechanical power along conveyors. The timing belt is one of the important parts of a power roller. If there is any friction or parts are worn out due to insufficient lubrication, the power roller may fail. Like the drive motor, power rollers were analyzed in an E-R model. Sometimes the timing belt has some friction but is not worn out completely. In this case, power rollers may continue to work but will consume more energy.




| T | F |
|---|---|
| 0.02 | 0.98 |

| T | F |
|---|---|
| 0.03 | 0.97 |

| L | WO=T | WO=F |
|---|---|---|
| T | 0. 95 | 0.003 |
| F | 0.075 | 0.0095 |

| FRI | WO | TM=True | TM=False |
|---|---|---|---|
| T | T | 0.95 | 0.002 |
| T | F | 0.0025 | 0.0975 |
| F | T | 0.03 | 0.0025 |
| F | F | 0. 015 | 0.01 |

| TBD | WO | PRF=True | PRF=False |
|---|---|---|---|
| T | T | 0.90 | 0.02 |
| T | F | 0.001 | 0.05 |
| F | T | 0.003 | 0.008 |
| F | F | 0.0001 | 0.025 |

Figure 3-39: BBN graphical model for conveyor belt power roller failure

Assumptions:

- Timing belt drive failure (TBD) and worn-out parts (WO) are independent;

- Friction (FRI) and insufficient oil and lubrication (O-L) are independent;

The probability of failure and the reliability for conveyor belt power rollers were calculated based on Figure 3-69 and from the formulas below:

$$P\ (PRF) = \sum_{TBD,WO} P\ (PRF \mid TBD, WO)\ P\ (TBD, WO) \quad (6)$$

$$P\ (PRF) = \sum_{WO,FRI} P\ (PRF \mid WO, FRI)\ P\ (WO)\ P\ (FRI) \quad (7)$$

$$P\ (WO) = \sum_{O-L} P\ (WO \mid O\text{-}L)\ P\ (O\text{-}L) \quad (8)$$

P (FRI) = P (FRI /T)*P (T) +P (FRI / Not True) P (Not True) (9)

P (O-L) = P (O-L/T)*P (T) +P (O-L/ Not True) P (Not True) (10)

Power roller failure probability was calculated using equations 6 to 10 and Excel as:

P (WO) = 0.11

P (TBD) = 0.03

**P (PRF) =** 0.03, Probability of failure for power rollers

**R (PRF)** = 0.97, Reliability for power rollers

#### 3.8.3.1 Power Roller Cost

There are two types of power roller, those with a 0.075 m center and those with a 0.1 m center. Rollers vary in width from 0.3 to 0.5 m. In this research, a power roller with a 0.1 m centre, 0.5 m wide, and a conveying distance of 7 m was considered. The capital cost of such a power roller was estimated to be $586 (56).

### 3.8.4 Head and Tail Pulley

The head and tail pulley consists of two bearings, a shaft, shell, and coating (special material that improves the belt-pulley contact). The pulley supplies dynamic power to the conveyor. The head and tail pulley will fail if the bearings fail, if the coating face corrodes, or if parts wear out (through insufficient oil and lubrication).

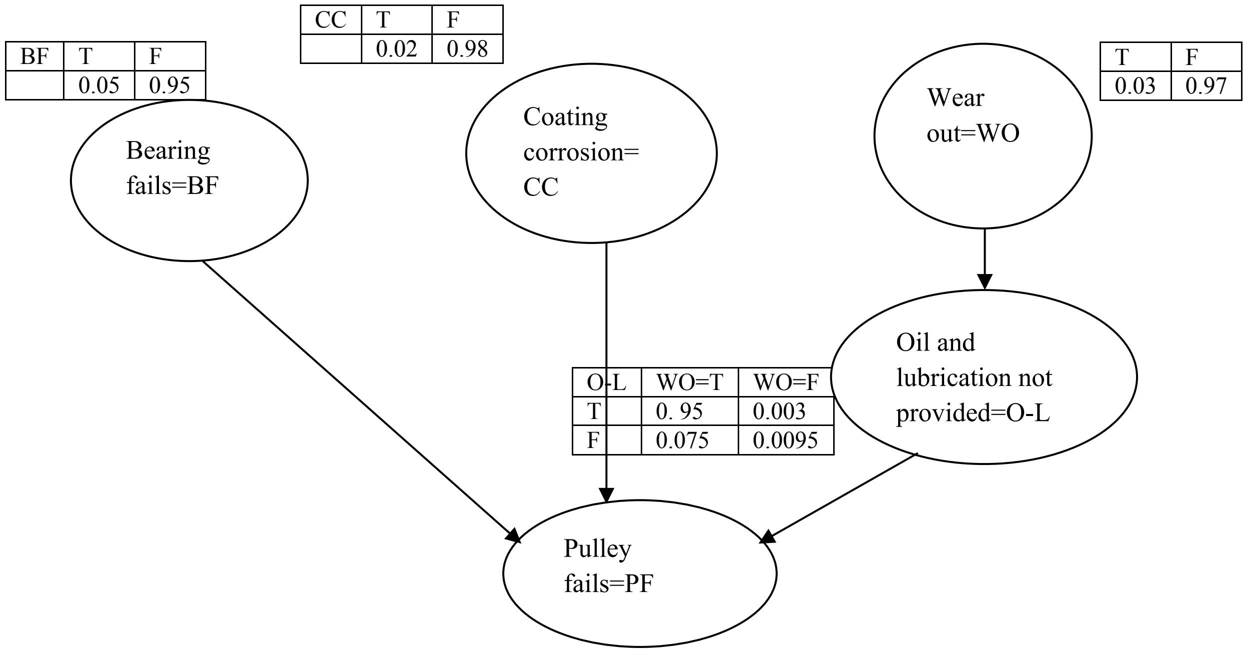



Figure 3-40: BBN graphical model for conveyor belt pulley failure

| BF | CC | WO | HF =T | HF =F |
|---|---|---|---|---|
| T | T | T | 0. 97 | 0.002 |
| F | T | T | 0.085 | 0.0095 |
| T | F | T | 0.001 | 0.00252 |
| T | T | F | 0.0045 | 0.0014 |
| F | F | T | .002 | 0.0021 |
| T | F | F | 0.003 | 0.0015 |
| F | T | F | 0.0058 | 0.003 |
| F | F | F | 0.00001 | 0.01 |

Assumptions:

- Bearing failure (B), coating corrosion (CC), and wear out (WO) are independent;
- Bearing failure (B), coating corrosion (CC), and insufficient lubrication (O-L) are independent.

The probability of failure and the reliability for the conveyor belt pulley were calculated based on Figure 3-70 and from the formulas below:

$$P\ (PF) = \sum_{B,CC,WO} P\ (PF \mid B, CC, WO)\ P\ (B)\ P\ (CC)\ P(WO) \qquad (11)$$

$$P\ (WO) = \sum_{O-L} P\ (WO \mid O\text{-}L)\ P\ (O\text{-}L) \qquad (12)$$

$$P\ (B) = P\ (B/T)*P\ (T) + P\ (B/\ \text{Not True})\ P\ (\text{Not True}) \qquad (13)$$

$$P\ (CC) = P\ (CC\ /T)*P\ (T) + P\ (CC/\ \text{Not True})\ P\ (\text{Not True}) \qquad (14)$$

Pulley failure probability has been calculated using equations 11 to 14 and Excel as:

P (WO) = 0.11

**P (PF) =0.01**, Probability of failure for head and tail pulleys

**R (PF) =0.99**, Reliability for head and tail pulleys

### 3.8.4.1 Head and Tail Pulley Cost

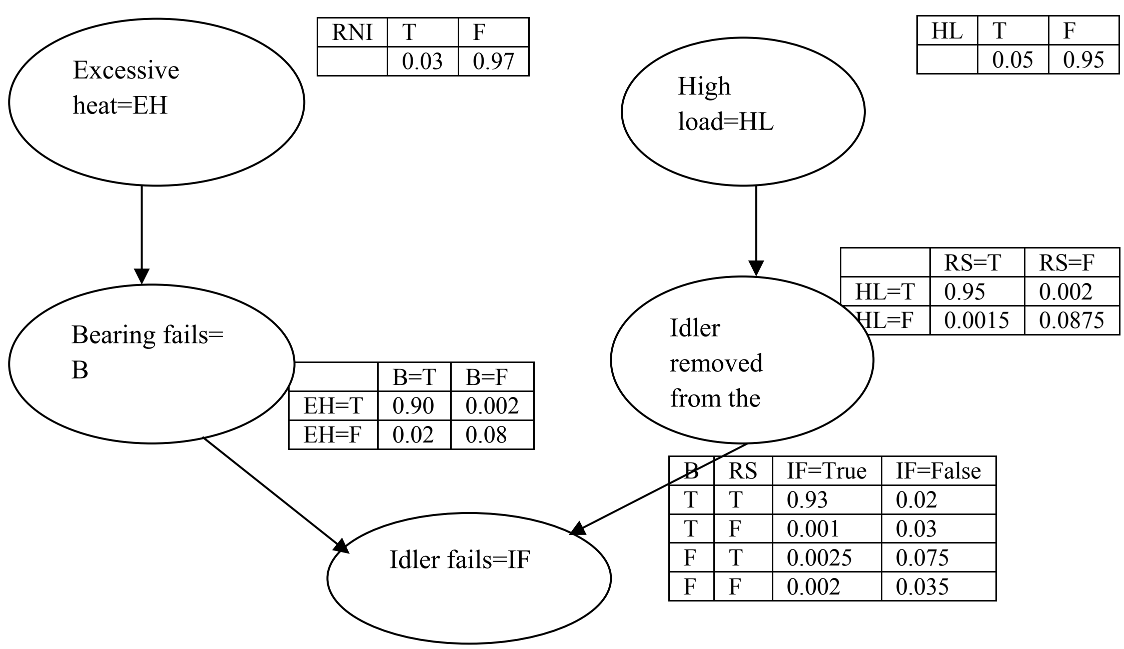
The parameter "$C_{\text{Head and Tail pulley}}$ (\$)" was used as the head and tail pulley cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.8.5 Idler

The idler supports a conveyor belt and reduces tension in the belt (83). If a bearing fails due to excessive heat or the idler is removed from a pulley because of a high load, the idler will fail.

Assumptions:

- Excessive heat (EH) and high load (HL) are independent.
- Bearing failure (B) and idler removal from the screen (RS) are independent.




| RNI | T | F |
|---|---|---|
| | 0.03 | 0.97 |

| HL | T | F |
|---|---|---|
| | 0.05 | 0.95 |

| | RS=T | RS=F |
|---|---|---|
| HL=T | 0.95 | 0.002 |
| HL=F | 0.0015 | 0.0875 |

| | B=T | B=F |
|---|---|---|
| EH=T | 0.90 | 0.002 |
| EH=F | 0.02 | 0.08 |

| B | RS | IF=True | IF=False |
|---|---|---|---|
| T | T | 0.93 | 0.02 |
| T | F | 0.001 | 0.03 |
| F | T | 0.0025 | 0.075 |
| F | F | 0.002 | 0.035 |

Figure 3-41: BBN graphical model for conveyor belt idler failure

The probability of failure and the reliability for the conveyor belt idler were calculated based on Figure 3-71 and from the formulas below:

$$P\,(IF) = \sum_{B,RS} P\,(IF \mid B, RS)\, P\,(B)\, P\,(RS) \qquad (15)$$

$P(B) = \sum_{EH} P(B \mid EH)\, P(EH)$ (16)

P (EH) = P (EH/T)*P (T) +P (EH/ Not True) P (Not True) (17)

$P(RS) = \sum_{HL} P(RS \mid HL)\, P(HL)$ (18)

P (HL) = P (HL/T)*P (T) +P (HL/ Not True) P (Not True) (19)

P (B) = 0.12

P (RS) = 0.13

Idler failure probability has been calculated using equations 15 to 19 and Excel as:

**P (IF) = 0.06**, Probability of failure for idlers

**R (IF) = 0.94**, Reliability for idlers

#### 3.8.5.1 Idler Cost

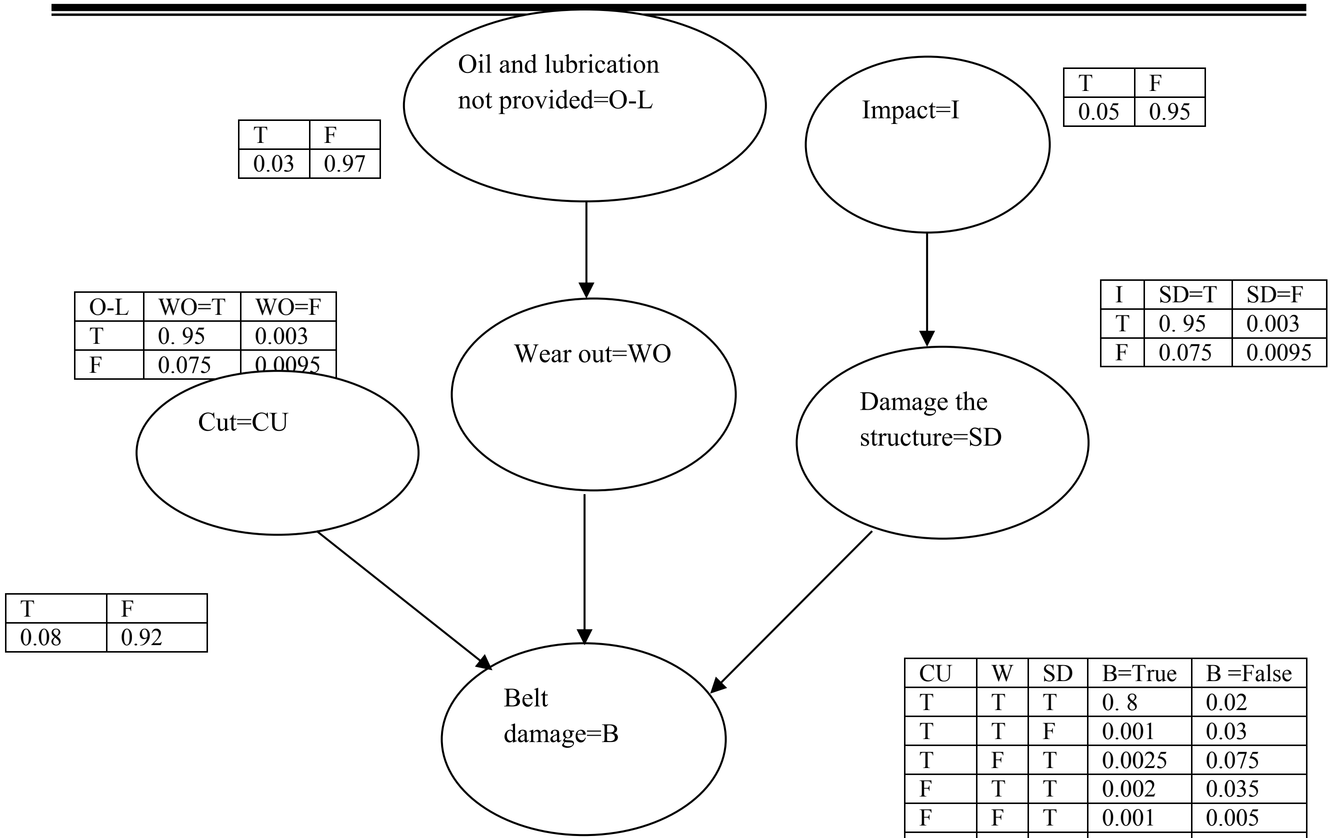
The parameter "$C_{Idler}$ ($)" was used for the idler cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.8.6 Belt

The belt is another important part of a conveyor system. A belt can be damaged or wear out over the time due to insufficient lubrication.

Assumptions:

- Cut (CU), oil and lubrication not provided (OL), and impact (I) are independent;
- Cut (CU), wear out (WO), and structure (SD) are independent.




| T | F |
|---|---|
| 0.03 | 0.97 |

| T | F |
|---|---|
| 0.05 | 0.95 |

| O-L | WO=T | WO=F |
|---|---|---|
| T | 0. 95 | 0.003 |
| F | 0.075 | 0.0095 |

| I | SD=T | SD=F |
|---|---|---|
| T | 0. 95 | 0.003 |
| F | 0.075 | 0.0095 |

| T | F |
|---|---|
| 0.08 | 0.92 |

| CU | W | SD | B=True | B =False |
|---|---|---|---|---|
| T | T | T | 0. 8 | 0.02 |
| T | T | F | 0.001 | 0.03 |
| T | F | T | 0.0025 | 0.075 |
| F | T | T | 0.002 | 0.035 |
| F | F | T | 0.001 | 0.005 |
| T | F | F | 0.002 | 0.025 |
| F | T | F | 0.005 | 0.035 |
| F | F | F | 0.002 | 0.1 |

Figure 3-42: BBN graphical model for conveyor belt failures

The probability of failure and the reliability for the conveyor belt idler were calculated based on Figure 3-72 and from the formulas below:

$$P(B) = \sum_{CU,WO,SD} P(B \mid CU, WO, SD)\, P(CU, WO, SD) \qquad (20)$$

$$P(B) = \sum_{CU,WO,SD} P(B \mid CU, WO, SD)\, P(CU)\, P(WO)\, P(SD) \qquad (21)$$

$$P(SD) = \sum_{I} P(SD \mid I)\, P(I) \qquad (22)$$

$$P(WO) = \sum_{O-L} P(WO \mid O\text{-}L)\, P(O\text{-}L) \qquad (23)$$

$$P(O\text{-}L) = P(O\text{-}L/T)*P(T) + P(O\text{-}L/\text{ Not True})\, P(\text{Not True}) \qquad (24)$$

$$P(CU) = P(CU/T)*P(T) + P(CU/\text{ Not True})\, P(\text{Not True}) \qquad (25)$$

$$P(I) = P(I/T)*P(T) + P(I/\text{ Not True})\, P(\text{Not True}) \qquad (26)$$

Belt failure probability was calculated using equation 20 to 26 and Excel as:

P (WO) = 0.11, P (SD) = 0.13

**P (B) = 0.85,** Probability of failure for belts

**R (B) =0.15,** Reliability for belts

### 3.8.6.1 Belt Cost

Belts have three width options (0.75, 0.6, and 0.4 m) that influence cost. In this study, a 0.75 m wide belt with a conveying distance of 5 m was considered with a capital cost of CAN $ 14,605 (52). Types of belts available and their related costs are shown in the appendix.

## 3.8.7 Pulley Cleaner

A pulley cleaner is installed at the back of a conveyor pulley to prevent bitumen, sand, and clay from entering and damaging the pulley. Without the cleaner, bitumen builds up on the pulley surface and quickly destroys the belt (52). A pulley cleaner may fail from repeated contact of the oil sands materials with the pulley cleaner surface. In addition, when related parts wear out because of insufficient oil and lubrication, the pulley cleaner can fail

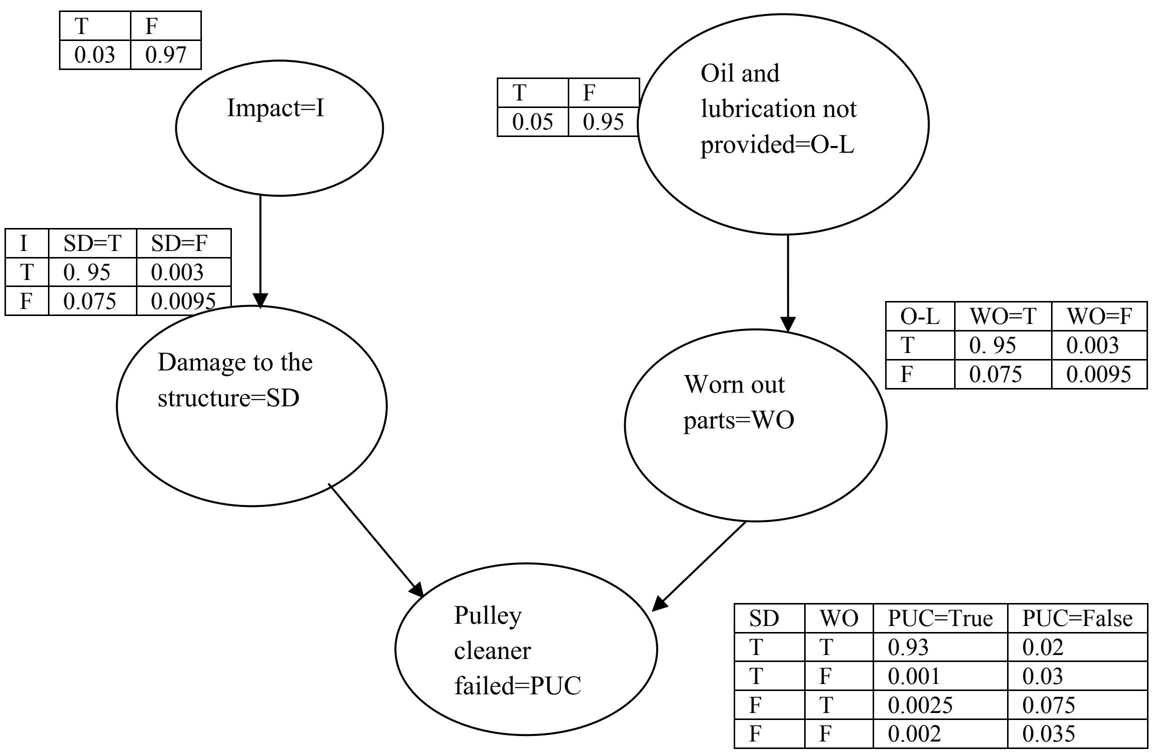



Figure 3-43: BBN graphical model for conveyor belt pulley cleaner failure

Assumptions:

- Impact (I) and insufficient lubrication not provided (OL) are independent;
- Damage to the structure (SD) and worn out parts (WO) are independent.

The probability of failure and the reliability for the conveyor belt pulley cleaner were calculated based on Figure 3-73 and from the formulas below:

P (PUC) = $\sum_{WO,SD}$ P (PUC | WO, SD) P (WO, SD) (27)

P (PUC) = $\sum_{WO,SD}$ P (PUC | WO, SD) P (WO) P (SD) (28)

P (SD) = $\sum_{I}$ P (SD | I) P (I) (29)

P (WO) = $\sum_{O-L}$ P (WO | O-L) P (O-L) (30)

P (O-L) = P (O-L/T)*P (T) +P (O-L/ Not True) P (Not True) (31)

P (I) = P (I/T)*P (T) +P (I/ Not True) P (Not True) (32)

Pulley cleaner failure probability was calculated using equations 27 to 32 and Excel as:

P (WO) = 0.11

P (SD) = 0.13

**P (PUC) = 0.05,** Probability of failure for pulley cleaners

**R (PUC) = 0.95,** Reliability for pulley cleaners

### 3.8.7.1 Pulley cleaner cost

The parameter "$C_{\text{Pulley cleaner}}$ ($)" was used for the pulley cleaner cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

## 3.8.8 Conveyor Belt Risk Calculation

Table 3-12 illustrates common conveyor belt failure mode probabilities along with their cause and effects on belt reliability. As seen in the table, the idler and pulley cleaner have the highest probability of failure of the conveyor belt parts, and the pulley cleaner and idler show the highest risks.

Table 3-12: Risks and corrective actions for conveyor belt

| No | Description | Probability of Failure | Consequence ($) | Risk | Corrective Action |
|---|---|---|---|---|---|
| 1 | Drive motor | 0.01 | $C_1$ | $0.01 * C_1$ | Maintenance, regular inspection |
| 2 | Power Roller | 0.03 | $C_2$ | $0.03 * C_2$ | maintenance, Regular inspection |
| 3 | Head and tail Pulley | 0.01 | $C_3$ | $0.01 * C_3$ | Continuous monitoring, maintenance, Regular inspection |
| 4 | Idler | 0.06 | $C_4$ | $0.06 * C_4$ | Continuous monitoring, maintenance, Regular inspection |
| 5 | Belt | 0.85 | $C_5$ | $0.85 * C_5$ | Continuous monitoring, maintenance, Regular inspection |
| 6 | Pulley cleaner | 0.05 | $C_6$ | $0.05 * C_6$ | Fire extinguisher, remove the potential ignition cause |

### 3.8.8.1 Conveyor Belt Failure Rate

As the reliability function in this research assumed steady state for conveyor belt, therefore, the failure rate is a time independent variable. Table 3-13 shows the failure rate for the selected main parts of conveyor belt.

Table 3-13: Failure rate for conveyor belts main part

| No | Description | Probability of Failure | Reliability | Failure Rate |
|---|---|---|---|---|
| 1 | Drive motor | 0.01 | 0.99 | 0.01 |
| 2 | Power Roller | 0.03 | 0.97 | 0.03 |
| 3 | Head and tail Pulley | 0.01 | 0.99 | 0.01 |
| 4 | Idler | 0.06 | 0.94 | 0.06 |
| 5 | Belt | 0.85 | 0.15 | 5.67 |
| 6 | Pulley cleaner | 0.05 | 0.95 | 0.05 |

### 3.8.8.8 Discussion-Analysis of Root Causes of Failure of Conveyor Belts

Based on the computed reliability modeling results, the pulley cleaner and idler were identified as major causes of conveyor belt failures that critically influence energy consumption and GHG emissions. A preventative action can be frequent pulley cleaner lubrication, which can reduce the rate at which the cleaner wears out. In addition, the pulley cleaner structure must be inspected regularly for tracking. The preventative action for the pulley cleaner and idler includes monitoring and inspection for excessive heat and high loads.

## 3.9 Slurry Pump

A slurry pump is specifically designed to transport a liquid containing a significant amount of suspended solids. A mixture of water with oil sands ore creates a slurry mixture, which requires a slurry pump for transportation. Slurry pump reliability is one of the main ongoing challenges in oil sands mining operations, due to unexpected and frequent slurry pump failures. This study investigates risk associated with a pump's components. A BBN was used to determine failure probabilities. Different types of pumps are used in the oil sands industry to pump slurries. One of the most common ones is the centrifugal pump, which uses centrifugal force generated by a rotating impeller to convey kinetic energy to the slurry. The size and design of the impeller as well as appropriate material for the shaft seal are important considerations when selecting a centrifugal slurry pump (84).

### 3.9.1 Identification of Potential Slurry Pump Risks

There are some risks associated with slurry pump operation. The following are critical mechanical parts of the slurry pump, without which it cannot operate:

- Surface,
- Motors,
- Impellers,
- Structure, and
- Casings.

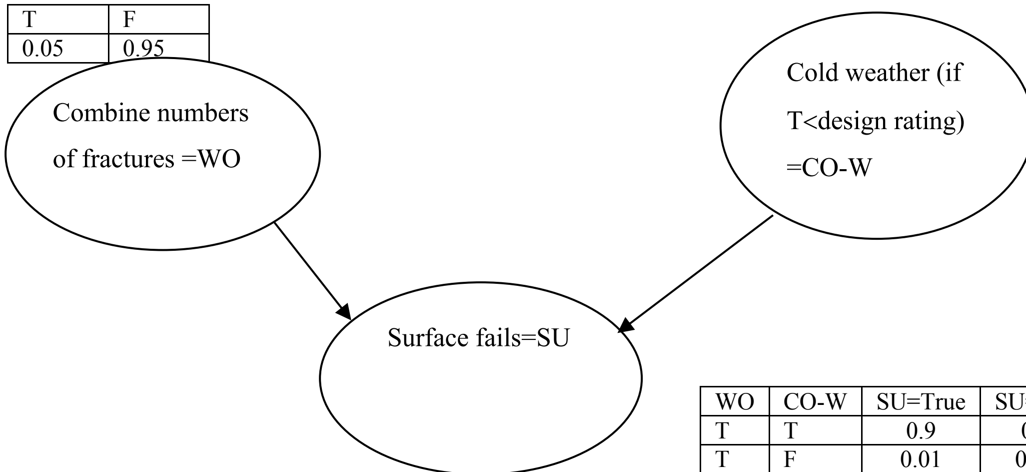
It is necessary to determine risks associated with slurry pumps to prevent unpredictable failure (82). These risks are discussed and calculated in the following sections.

### 3.9.1.1 Surface

The outside part of a slurry pump is called the surface, and it must be monitored regularly to track failure modes. The cold weather in Alberta may damage the pump's surface and reduce its lifetime. Therefore, the surface should be inspected and monitored regularly for effects of weather (cold temperature) and whether there are fractures that need to be replaced or repaired

| T | F |
|---|---|
| 0.03 | 0.97 |

| T | F |
|---|---|
| 0.05 | 0.95 |




| WO | CO-W | SU=True | SU=False |
|---|---|---|---|
| T | T | 0.9 | 0.02 |
| T | F | 0.01 | 0.009 |
| F | T | 0.0001 | 0.025 |
| F | F | 0.02 | 0.0013 |

Figure 3-44: BBN graphical model for slurry pump surface failure

Assumptions:

- Worn out parts (WO) and cold weather (CO-W) are independent.

The probability of failure and the reliability for the slurry pump surface were calculated based on Figure 3-82 and from the formulas below:

$$P\ (SU) = \sum_{WO,CO-W} P\ (SU \mid WO,\ CO\text{-}W)\ P\ (WO,\ CO\text{-}W) \quad (1)$$

$$P\ (SU) = \sum_{WO,CO-W} P\ (SU \mid WO,\ CO\text{-}W)\ P\ (WO)\ P\ (CO\text{-}W) \quad (2)$$

P (WO) = P (WO/T)*P (T) +P (WO/ Not True) P (Not True) (3)

P (CO-W) = P (CO-W /T)*P (T) +P (CO-W / Not True) P (Not True) (4)

Slurry pump surface failure probability was calculated using equations 1 to 4 and Excel as:

**P (SU) = 0.10,** Probability of failure for the slurry pump's surface

**R(SU) =0.90**, Reliability for the slurry pump's surface

## 3.9.1.1.1 Surface Cost

The parameter "$C_{surface}$ (\$)" was used for the cost of the pump surface in modeling equations. The actual cost can be substituted in the equation to calculate risk.

## 3.9.1.2 Motor

The drive motor consists of electric motors with coupling as well as gear motors. It is designed to operate in reverse in case of overloading and blockage in order to increase availability and functionality of the pump's system. The motor is one of the main components of the slurry pump, and its failure may lead to the failure of the pump. If the motor does not work properly for any reason, the slurry pump will use more energy to operate and consequently emit more GHGs. In addition, insufficient lubrication and contamination in the internal parts of motor can result in motor failure. Finally, a motor may fail if it has an internal fault or if there are unusual mechanical loading conditions (85).

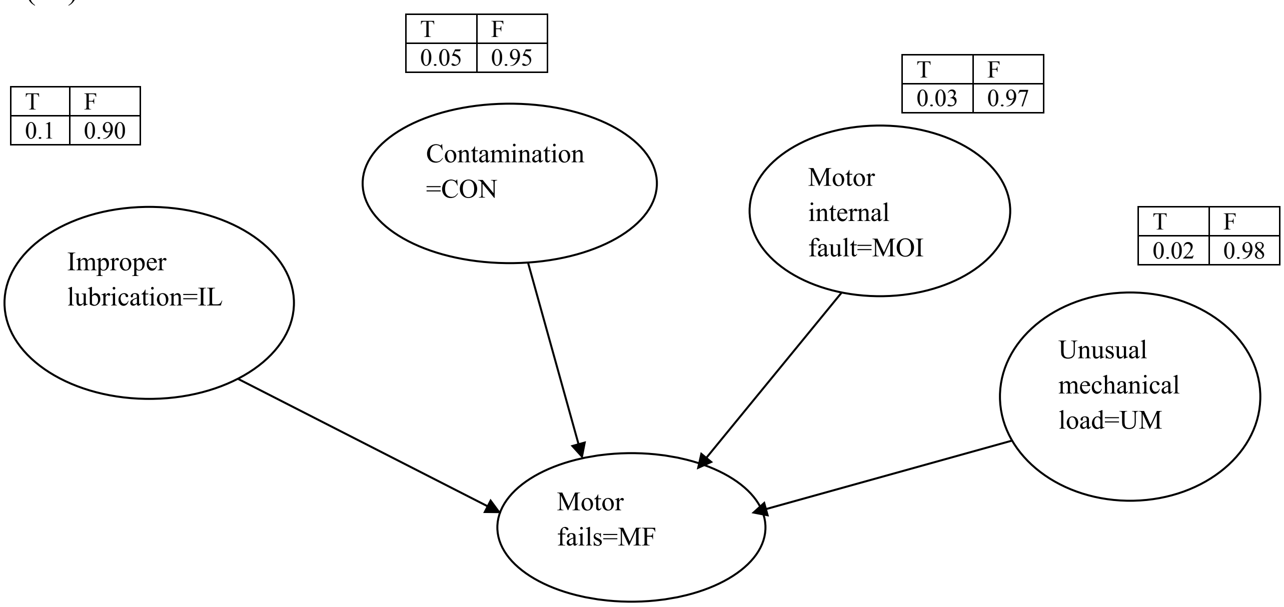



Figure 3-45: BBN graphical model for slurry pump motor failure

| IL | CON | MOI | UM | M=True | MF=False |
|---|---|---|---|---|---|
| T | T | T | T | 0. 8 | 0.02 |
| T | T | T | F | 0.001 | 0.03 |
| T | T | F | T | 0.0025 | 0.075 |
| T | F | T | T | 0.002 | 0.035 |
| F | T | T | T | 0.001 | 0.005 |
| T | T | T | T | 0.002 | 0.025 |
| F | F | T | T | 0.002 | 0.1 |
| F | F | F | T | 0.01 | 0.2 |
| F | F | F | F | 0.0025 | 0.003 |

Assumptions:

- Improper lubrication (IL), contamination (CON) , motor internal fault (MOI), and unusual mechanical load (UM) are independent.

The probability of failure and the reliability for the slurry pump motor were calculated based on Figure 3-83 and from the formulas below:

$$P\ (MF) = \sum_{IL,CON,MOI,UM} P\ (M \mid IL, CON, MOI, UM)\ P\ (IL).\ P\ (CON)\ P\ (MOI)\ P\ (UM) \quad (5)$$

$$P\ (IL) = P\ (IL/T)*P\ (T) + P\ (IL/\ Not\ True)\ P\ (Not\ True) \quad (6)$$

$$P\ (CON) = P\ (CON/T)*P\ (T) + P\ (CON/\ Not\ True)\ P\ (Not\ True) \quad (7)$$

$$P\ (MOI) = P\ (MOI\ /T)*P\ (T) + P\ (MOI\ /\ Not\ True)\ P\ (Not\ True) \quad (8)$$

$$P\ (UM) = P\ (UM\ /T)*P\ (T) + P\ (UM\ /\ Not\ True)\ P\ (Not\ True) \quad (9)$$

Motor failure probability was calculated using equations 5 to 9 and Excel as:

**P (MF) = 0.17,** Probability of failure for the slurry pump's motor

**R (MF) =0.83,** Reliability for the slurry pump's motor

### 3.9.1.2.1 Motor Cost

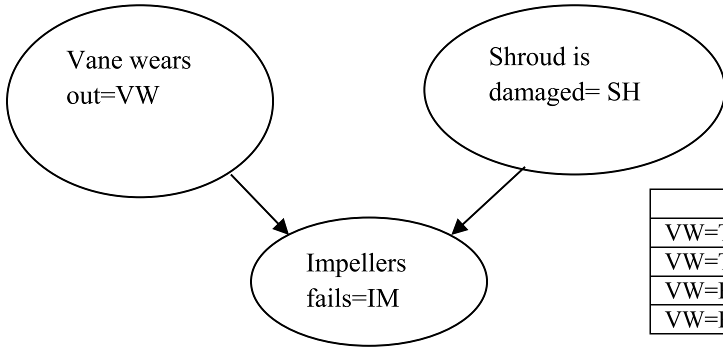
The parameter "$C_{motor}$ ($)" was used for motor cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.9.1.3 Impellers

The impeller, one of the key parts of a slurry pump, has front lines to send centrifugal energy to liquid. Closed impellers are usually more efficient. Semi-open impellers are common in smaller pumps, where the shear supplied by an open impeller is a support for pumping. An additional characteristic of slurry pump impellers is the pump out or ejecting vanes on the back and front shrouds, which decrease pressure and keep solids out of the gaps between the casing and the impeller by centrifugal action. The design of the impeller is important because it can influence flow, and ultimately the reliability of the impeller depends on its design. If the design is not appropriate, more stress and vibration will result and can damage the pump. The impellers will fail if a vane wears out or a shroud is damaged (84).

| VW | T | F |
|---|---|---|
| | 0.5 | 0.5 |

| SH | T | F |
|---|---|---|
| | 0.02 | 0.98 |




| | | IM=True | IM=False |
|---|---|---|---|
| VW=T | SH=T | 0.95 | 0.002 |
| VW=T | SH=F | 0.0025 | 0.0975 |
| VW=F | SH=T | 0.03 | 0.0025 |
| VW=F | SH=F | 0. 015 | 0.01 |

Figure 3-46: BBN graphical model for slurry pump impeller failure

Assumptions:

- Vane wears out (VW) and shroud damage (SH) are independent.

The probability of failure and the reliability for the slurry pump impeller was calculated based on Figure 3-84 and from the formulas below:

$$P\ (IM) = \sum_{SH,VW} P\ (IM \mid SH, VW)\ P\ (SH)\ P\ (VW) \qquad (10)$$

$$P\ (SH) = P\ (SH/T)*P\ (T) + P\ (SH/\ Not\ True)\ P\ (Not\ True) \qquad (11)$$

$$P\ (VW) = P\ (VW\ /T)*P\ (T) + P\ (VW/\ Not\ True)\ P\ (Not\ True) \qquad (12)$$

Slurry pump impeller failure probability was calculated using equations 10 to 12 and Excel as:

**P (I) =0.07,** Probability of failure for slurry pump impellers

**R (I) =0.93,** Reliability for slurry pump impellers

### 3.9.1.3.1 Impellers Cost

The parameter "$C_{impellers}$ ($)" was used for the impeller's cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

### 3.9.1.4 Structure

The pump structure acts as a shell to protect the pump. Therefore, it is important to assess reliability for slurry pump structure. If the structure wears out, through insufficient oil and lubrication in the internal parts, the structure may fail.

| T | F |
|---|---|
| 0.03 | 0.97 |

| O-L | WO=T | WO=F |
|---|---|---|
| T | 0. 95 | 0.003 |
| F | 0.075 | 0.0095 |

| WO | WO | S-D=True | S-D=False |
|---|---|---|---|
| | | | |
| T | T | 0.90 | 0.02 |
| T | F | 0.001 | 0.05 |
| F | T | 0.003 | 0.008 |
| F | F | 0.0001 | 0.025 |

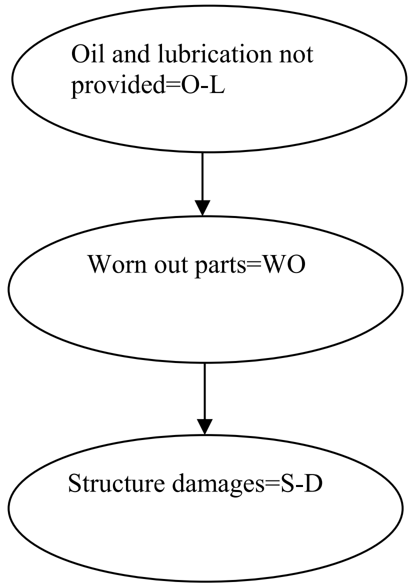



Figure 3-47: BBN graphical model for slurry pump structure failures

The probability of failure and the reliability for the slurry pump structure were calculated based on Figure 3-85 and from the formulas below:

$$P\ (S\text{-}D) = \sum_{WO} P\ (S\text{-}D \mid WO)\ P\ (WO) \qquad (13)$$

$$P\ (WO) = \sum_{O-L} P\ (WO \mid O\text{-}L)\ P\ (O\text{-}L) \qquad (14)$$

$$P\ (O\text{-}L) = P\ (O\text{-}L/T)*P\ (T) + P\ (O\text{-}L/\ \text{Not True})\ P\ (\text{Not True}) \qquad (15)$$

Slurry pump structure failure probability was calculated using equations 13 to 15 and Excel as:

**P (S-D) = 0.05,** Probability of failure for slurry pump structure

**R(S-D) = 0.95**, Reliability for slurry pump structure

### 3.9.1.4.1 Structure Cost

The parameter "$C_{Structure}$ ($)" was used for the structure cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

## 3.9.1.5 Casings

A casing is a curved funnel that receives the fluid being pumped by the impeller and leads the flow to the discharge port. The casing's shape is generally a geometric curve, with large clearance at the cutwater area, which is shown in Figure 3-86. A cutwater has a V shape, which acts as a flow splinter between cone and eject in a casing. The clearance at the cutwater raises the effectiveness of slurry pump by reducing the moving fluid flow at the efficiency point (86). Open casings are less efficient, volute-style casings; however, they wear better. Casings wear out over time, and it is necessary to find out their failure probability (87).

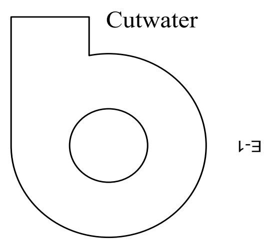



Figure 3-48: Casing shape (87)

| CW | T | F |
|---|---|---|
| | 0.90 | 0.10 |

| | CA=True | CA=False |
|---|---|---|
| CW=T | 0.99 | 0.002 |
| CW=F | 0.0025 | 0.0975 |

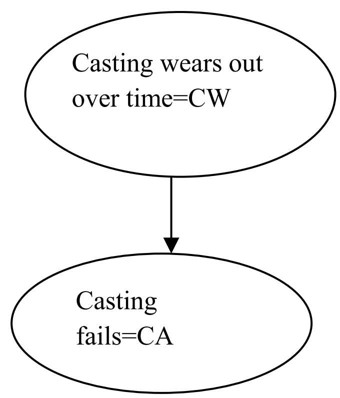



Figure 3-49: BBN graphical model for slurry pump casting failures

Assumptions:

- Probabilities describe random variable of the model; and
- The model was computed from benchmark data.

The probability of failure and the reliability for the slurry pump casting were calculated based on Figure 3-87 and from the formulas below:

$P(CA) = \sum_{CW} P(CA \mid CW)\, P(CW)$ (16)

P (CA) = P (CA/T)*P (T) +P (CA/ Not True) P (Not True) (17)

Slurry pump casing failure probability was calculated using equations 13 to 15 and Excel as:

**P (CA) = 0.90,** Probability of failure for slurry pump casing

**R (CA) = 0.10**, Reliability for slurry pump casing

### 3.9.1.5.1 Casing Cost

The parameter " $C_{casing}$ ($)" was used for casing cost in modeling equations. The actual cost can be substituted in the equation to calculate risk.

## 3.9.2 Slurry Pump Risk Calculation

Table 3-32 shows common failure mode probabilities and consequence in slurry pumps. As shown in Table 3-14, impellers have the highest probability of failure among slurry pump parts and the surface has the lowest probability of failure, followed by the motor.

Table 3-14: Risks Associated with Slurry Pumps

| No | Description | Probability of Failure | Consequence ($) | Risk | Corrective Action |
|---|---|---|---|---|---|
| 1 | Surface=SU | 0.10 | $C_1$ | 0.10*$C_1$ | Maintenance, regular inspection |
| 2 | Motors=MF | 0.17 | $C_2$ | 0.17*$C_2$ | Continuous monitoring, maintenance, regular inspection, proper lubrication |
| 3 | Impellers=IM | 0.07 | $C_3$ | 0.07*$C_3$ | Continuous monitoring, maintenance, regular inspection |
| 4 | Structure=SD | 0.05 | $C_4$ | 0.05*$C_4$ | Continuous monitoring, maintenance, regular inspection |
| 5 | Casing=CA | 0.90 | $C_5$ | 0.90*$C_5$* | Continuous monitoring, maintenance, regular inspection |

## 3.9.3 Slurry Pump Failure Rate

As the reliability function in this research assumed steady state for slurry pump; therefore, the failure rate is a time independent variable. Table 3-15 shows the failure rate for the selected main parts of slurry pump.

Table 3-15: Failure rate for slurry pump main parts

| No | Description | Probability of Failure | Reliability | Failure Rate |
|---|---|---|---|---|
| 1 | Surface=SU | 0.10 | 0.90 | 0.11 |
| 2 | Motors=MF | 0.17 | 0.83 | 0.20 |
| 3 | Impellers=IM | 0.07 | 0.93 | 0.08 |
| 4 | Structure=SD | 0.05 | 0.95 | 0.05 |
| 5 | Casing=CA | 0.90 | 0.10 | 9.00 |

### 3.9.3.1 Slurry Pump Reliability Analysis

The reliability block diagram (RBD) for a slurry pump is shown in Figure 3-88. The RBD shows that the surface, motors, impellers, structure, and casing of the slurry pump work together. Therefore, if any of these components fail, the slurry pump will likely fail.

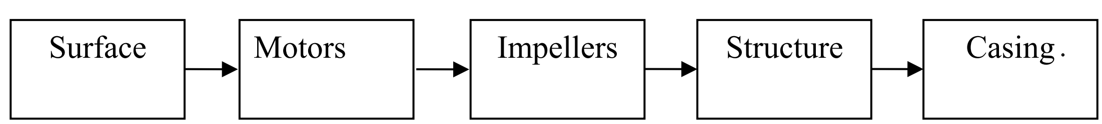



Figure 3-50: Slurry pump reliability block diagram

### 3.9.3.5 Discussion-Analysis of root causes of slurry pump failure

Based on the reliability modeling results and table 3-15, casing had the greatest failure rate. Therefore, motor needs to be tested frequently for wear out and damage.

**Chapter 4:**

# An Energy-Reliability (E-R) Model for Oil Sands Mining Equipment

# Chapter 4: An Energy-Reliability (E-R) Model for Oil Sands Mining Equipment

## 4.1 Energy-Reliability (E-R) Model Introduction

An energy-reliability (E-R) mathematical model calculates energy savings based on improvements in equipment reliability. In this research, the relationship between a change in equipment reliability due to a minor fault and a change in equipment emissions was modeled, and the effects on energy demand with respect to partial reliability for mobile and fixed equipment were presented in an E-R model. Partial reliability may be beneficial for mining operations because it allows equipment to continue to operate, albeit under more energy-consuming conditions. An E-R model allows industries to evaluate these benefits of postponing the maintenance and continue to operate under partial reliability. These benefits can be determined through providing a link between reliability and energy demand using E-R model.

In this study, the amount of energy wasted during idle operation of engines and equipment was not taken into account in E-R model, because this wasted energy (fuel) is independent of mining operation activities. The results obtained in the E-R model were based on a Markov discrete multi-state model with four states. The ability to understand how and why equipment fails is essential for the development of energy-efficient strategies and operation and maintenance of mining equipment. There are many models for analysing energy demand in different scenarios and conditions. Some of the models are designed to simulate the energy demand of different equipment or systems in energy-environment and energy-economy interactions, as well as energy systems. There are also various models that simulate system reliability (88). However, to the best of my knowledge, there has not been a study on reducing energy, cost, and greenhouse gas (GHG) emissions by improving the reliability of oil sands mining equipment. This chapter is an attempt to bridge gaps in knowledge in energy demand and reliability challenges in oil sands operations and to determine available opportunities and capacities for saving energy and reducing GHG emissions. The main objective in this chapter is to develop a model based on energy consumption and reliability of mining equipment. The E-R model calculates extra energy consumption when the equipment operates under multi-states of reliability, that is, states in which the reliability of a component is influenced by the potential failure modes of the component or how the system or component works (89). The Long-range Energy Alternatives Planning (LEAP) System software was used to determine final energy demand over the course of 40 years (2010 to 2050) for selected components.

## 4.2 Energy-Reliability (E-R) Model Purpose

The E-R model does not consider the opportunity cost of lost production. In other words, the model does not consider a scenario in which loss capacity is replaced, but rather a system operating at low production rates. The E-R model links equipment energy efficiency, GHG emissions, and reliability to long-term saved energy and reduced emissions by developing several scenarios based on multi-state reliability models. Failure probability and reliability for each equipment component were taken from chapter 3. In E-R modeling, the reliability of critical mining equipment (CME) in different states is needed to link the impacts of the equipment's emissions and energy demand. Hence, component failure probabilities and failure consequences were calculated for CME. An improved reliability strategy will elevate the performance and availability of CME. An analysis of the relationship between reliability, energy demand, demand cost, and GHG emissions in multi-state reliability for the CME discussed in this thesis can benefit the oil sands industry, in terms of both reduction of expenditures and increased sustainability.

### 4.2.1 Energy Model

An energy model is a simulation and mathematical approach used in this research to calculate the amount of energy needed by a piece of equipment. Energy model can be used in oil sands surface mining operations to provide the results in terms of energy and GHG emission through reference scenario and improving equipment reliability scenario. Generally, outputs from the energy model are energy fuel flows required investments and costs, $CO_2$ emissions, and end-user pricing (90). The model developed for this thesis covers energy development scenarios from 2010 to 2050 for selected mining equipment in Alberta and takes into account reliability improvement with respect to mining operations, GHG emissions, energy consumption, and demand costs. It was observed from the reports and expert opinion that if reliability of equipment improve, then the costs, energy consumption and GHG emissions will decrease. The amounts by which they decrease can be calculated by LEAP and through the E-R model (91).

#### 4.2.1.1 Energy Efficiency

Oil sands mining equipment can be more made energy efficient by improving the equipment's reliability.

#### 4.2.1.2 Demand Sector - Reference Case

The reference case represents energy demand data and consumption for the year 2010, and energy demand was simulated using the E-R model up to the year 2050. The assumptions considered for this research are as follows:

Slurry pumps and conveyor belts are in the sub-category “non-motive equipment”. They use electricity at a rate of 4.488 kWh/barrel and 0.107 kWh/barrel, respectively (based on the Delphi technique). Haul trucks are in the sub-category “motive equipment” and use diesel fuel at an average rate of 1.9 liters/barrel. Hydraulic shovels and crushers are in the sub-category “digging and crushing equipment” and use electricity at the rate of 7.2 and 0.48 kWh/barrel, respectively (24). Alberta's mining sector industrial growth rate is expected to remain at 3% each year to 2050, based on the past trend (60).

### 4.2.2 Partial Reliability in the E-R model

Partial reliability refers to the ability of equipment or components to operate under certain conditions. Even though the equipment or components are no longer fully reliable, they can still operate, usually at lower capacity, lower efficiency, and higher GHG emission rates. Partial reliability provides a way for equipment to continue to operate under the minimum desired reliability and maximum tolerance of component failure (9). To determine partial reliability in the E-R model, all the components of CME (Critical Mining Equipment) that can operate under partial reliability conditions need to be identified. When a component loses some of its ability to operate, its new reliability level is calculated, and if the component is still above the limit at which the equipment is deemed operational, the equipment may continue to operate.

Loss capacity, also called fraction of loss, can be obtained from equation 4-1:

$$\mathrm{E\,L}\,(t) = \sum_{i=1}^{n} L_i(t) \times p_i(t) \qquad [4\text{-}1]$$

Where:

$L_i(t)$=fraction loss of capacity from state i at time t (fraction of possible available time that equipment is not available for use)

$p_i(t)$=probability of failure equipment i at time t

Partial reliability was calculated based on a Markov degraded system, which has three states, given below and in Figure 4-1 (2):

State 1: the system is working under normal duty (with its actual reliability value).

State 2: the system operates under partial failure mode. (Each component may work under a specific reliability, albeit at higher energy use, cost and GHG emissions)

State 3: the system fails.

..

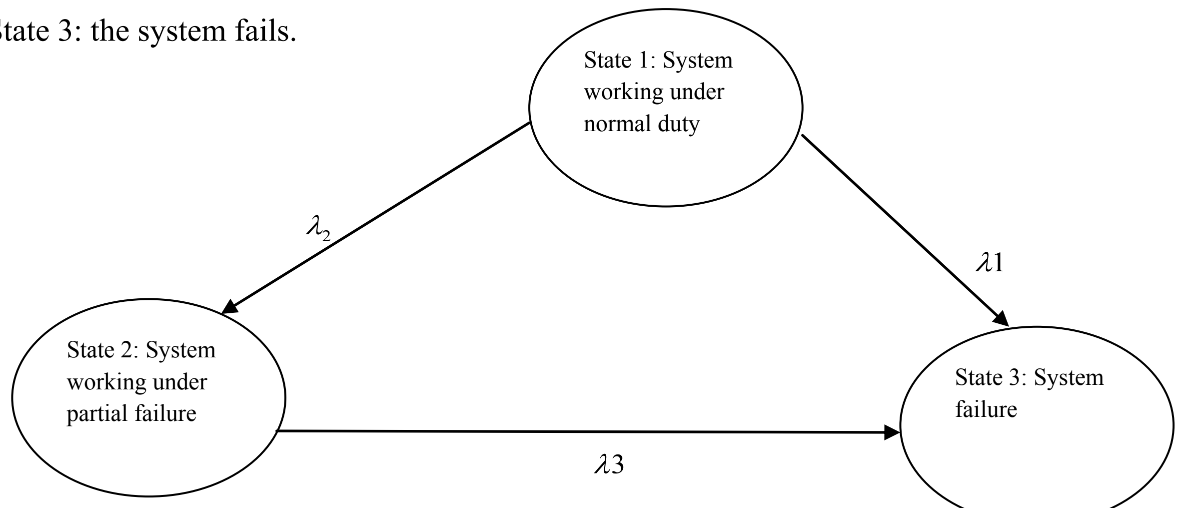



Figure 4-1: Degraded reliability model for mining equipment with three states

Based on the calculated probability density function obtained from chapter 3, the failure rate of selected components can be calculated; then, with the reliability and probability density functions for each component from chapter 3, the failure rate of each selected component is calculated based on its probability density functions (as described below).

$\lambda$ is a failure rate obtained from the calculated probability density function from chapter 3 of this thesis.

Based on R (t) and distribution function, find t

It was assumed that the failure rate relationship between working under normal conditions and partial failure is to the same as partial failure to full failure ($\lambda_2 = \lambda_3$).



$\lambda_2$

The probability of failure under normal working conditions is calculated from Equation 4-2:

$$P_1 = e^{-(\lambda_1+\lambda_2)t} \quad [4\text{-}2]$$

The probability of failure when the equipment is operating under partial failure is calculated from Equation 4-3:

$$P_2\,(t) = \frac{\lambda_2}{\lambda_1+\lambda_2-\lambda_3}[e^{-\lambda_3} - e^{-(\lambda_1+\lambda_2)*t}] \quad [4\text{-}3]$$

## 4.3 Simulation

An E-R model was used to simulate equipment performance and energy demand in four states based on the discrete Markov multi-state model. The E-R model simulates energy, GHG emissions, and cost based on reference scenarios in each state and compared these to situations in which, in each state, the reliability of mining equipment was improved. These comparisons show the actual energy, cost, and GHG emission that could be saved. The results from these simulations can be validated through sensitivity analyses. Simulation through an E-R model includes calculating the failure rate of main components of mining equipment and finding out if it is better to continue running equipment with partial failure under more energy consumption than to stop running the equipment. The components' energy consumption is obtained from LEAP (the Long-range Energy Alternatives Planning System).

In this research, LEAP, and Excel software were used to develop the E-R model. First, Excel was used to calculate the probability of failure based on the Bayesian belief network (BBN) method and failure rate, respectively. Then, for each of the four states, the reference case and improving equipment reliability scenarios were defined. In this thesis, only four states were reviewed. Depending on the state, energy demand and operational cost are added to the reference scenario and need to be calculated. Once this calculation is made, further calculations are made for equipment based on improved reliability. LEAP software calculated the energy and cost demand for each scenario through the E-R model for every mining equipment state in order to find savings in energy demand, cost, and GHG emissions. The surface mining reference scenario was developed based on that previously identified by Subramanyam et al, 2015. (22).

## 4.4 Energy-Reliability (E-R) Model Analysis

E-R modeling simulation was done using LEAP software. LEAP was used to evaluate data over medium- to long-term user-defined planning horizons (for 40 years in this study) (92). The model consists of following:

**-Reference Scenario:** This base case scenario was based on Subramanyam et al.'s model. Then it was developed in each state regarding the E-R model for the period 2010 to 2050.

**-Environmental Impact of Energy Use:** The reference and improving mining equipment reliability scenarios assess $CO_2$ emissions based on fuel consumption (diesel and electricity). The diesel (used for haul trucks) and the electricity (used for shovels, crushers, conveyer belts, and slurry pumps) were assessed in terms of GHG emissions and energy consumption.

**-Investment in the Energy Sector:** The E-R model helps assess whether it is worth investing in improving equipment reliability.

**-Reliability Model:** The reliability value of each component from the selected mining equipment was calculated using the BBN method. Then, the probability density function for each piece of mining equipment was found, and from this, a failure rate was determined. Finally, partial reliability for each state in the E-R model was calculated.

## 4.5 Goals to Be Achieved by Implementing an Energy-Reliability Model

Generally, equipment asset managers, policy decision makers, and reliability engineers encounter challenges in balancing the need to reduce costs with the need to increase reliability and availability of a system. A reliability and energy (E-R) model is an analytical tool that effectively assesses the extra energy consumption, cost and GHG emissions from mining equipment when it operates under partial reliability. Oil sands mining equipment is expensive, and periodic and unpredictable shutdowns have a large and adverse financial impact on mining operators. Therefore, it is crucial to find a way to deal with equipment failures. The main goals in implementing an E-R model are:

- To identify the most influential variables affecting productivity in oil sands mining equipment;

- To create relationships between a piece of equipment's reliability, energy efficiency, and GHG emissions, and to calculate the amount of energy savings in equipment used for loading when its reliability is improved;
- To determine operational reliability of oil sands surface mining equipment; and
- To calculate financial impact of mining equipment operating under partial reliability.

With this model, I developed scenarios in which mining equipment reliability was improved in order to find the amount of saved energy, cost, and GHG emissions over a 40-year period.

## 4.6 Energy Model Structure

Energy demand was developed in LEAP based on electricity and diesel consumption fuel. Final energy demand obtained from model was linked to energy consumption (diesel and electric) by equipment.

## 4.7 Technical Aspects and Key Assumptions

Here are the technical aspects and key assumptions used in developing the E-R model:

1- *Area:* Alberta's oil sands are 142,200 $km^2$. Surface mining covers 4,800 $km^2$ (63).

2- *Economic growth:* economic growth was assumed to be 3% in the year 2010 (22).

3- *Energy demand and type:* In this research, two types of energy (electricity and diesel) were studied.

4- *Reliability model and equipment operation:* Several types of oil sands mining equipment were considered in the E-R model. The reliability model used in this thesis was the Markov multi-state discrete model under 4 states. Four states of each identified component were studied in this research based on the component's reliability: fully reliable, expected reliability, partial reliability, and complete failure. Additional costs and energy demand related to each state were calculated.

## 4.8 GHG Emissions

Greenhouse gas (GHG) emissions threaten the environment. GHG emissions include carbon dioxide, carbon monoxide, methane, nitrous oxide, nitrogen oxide, sulfur dioxide, and non-methane volatile organic components. There is considerable capacity for GHG abatement by improving mining equipment reliability.

## 4.9 Cost Assumptions

LEAP software analyses cost benefits from a common perspective by adding up all the costs in the system, including all of the costs associated with subsequent components (93). Costs are defined as capital and operating expenditures and may include the following:

- Capital costs.
- Variable operating and maintenance costs.
- Costs of original resources.
- Fuel costs.

In this study operating costs, which include fuel (diesel or electricity) costs, labour costs, and fixed costs (the cost of buying equipment, in this case based on the equipment's present value with a discount rate of 12% (94), were considered. As LEAP calculates the cost based on oil production, the cost was calculated in this thesis based on CAN$/barrel of oil production in one year.

## 4.10 E-R Model for Oil Sands Mining Equipment

In this chapter, selected mining equipment (haul trucks, hydraulic and electric shovels, crushers, conveyor belts, and slurry pumps) was analyzed through the E-R model. Energy and cost saving opportunities were calculated and plotted through the E-R model over the 40 years between 2010 and 2050.

### 4.10.1 Oil Sands Mining Haul Truck - Introduction

In this section, a suitable approach to link reliability and energy demand of the oil sands mining haul truck was designed and developed. The main objectives were to identify the failure mode, calculate the probability of failures based on the BBN method, calculate the failure rate based on the reliability function, and find a relationship between haul truck energy demand and reliability.

#### 4.10.1.1 The E-R Model for the Oil Sands Mining Haul Truck

The scope of the model developed for this analysis encompasses all the processes of the specific components or sub-components of haul trucks that influence energy demand. The E-R model was developed with the following assumptions:

- Only the fuel system, tires, engine, transmission, and suspension were studied (based on Delphi method). The Delphi method is a communication process, which is in a form of gathering response from the expert in the related subject through questions in a structured questionnaire. Finding the best agreed feedback is the objective of Delphi method (95).If these components partially fail, then haul trucks may continue to operate. However, under partial failure, more energy is consumed and more GHGs are emitted, and energy demand and cost will increase.
- The scope of this research was limited to haul trucks with diesel engines.

#### 4.10.1.2 Calculating Partial Reliability for Critical Parts of a Haul Truck

In this research, partial reliability is described as a mode in which a component does not work under its normal duty, therefore a component suffers partial damage. Operating under partial reliability can damage the haul truck; however, a haul truck still may operate under a fraction of its original capacity. In order to determine the extra cost and energy, the probability of failure in each state need to calculate for every part of a mining haul truck that has an impact on energy demand. Experts using the Delphi method selected these components. Therefore, partial reliability can be calculated using Equation 4-1 and Figure 4-1 (9, 96). In this research, mining equipment component failure probability was modeled through the Markov degraded process. The resulting model is a discrete multi-state reliability model that makes some assumptions based on three states (shown in Figure 4-2) (57). Partial reliability for fuel system is calculated as follow:

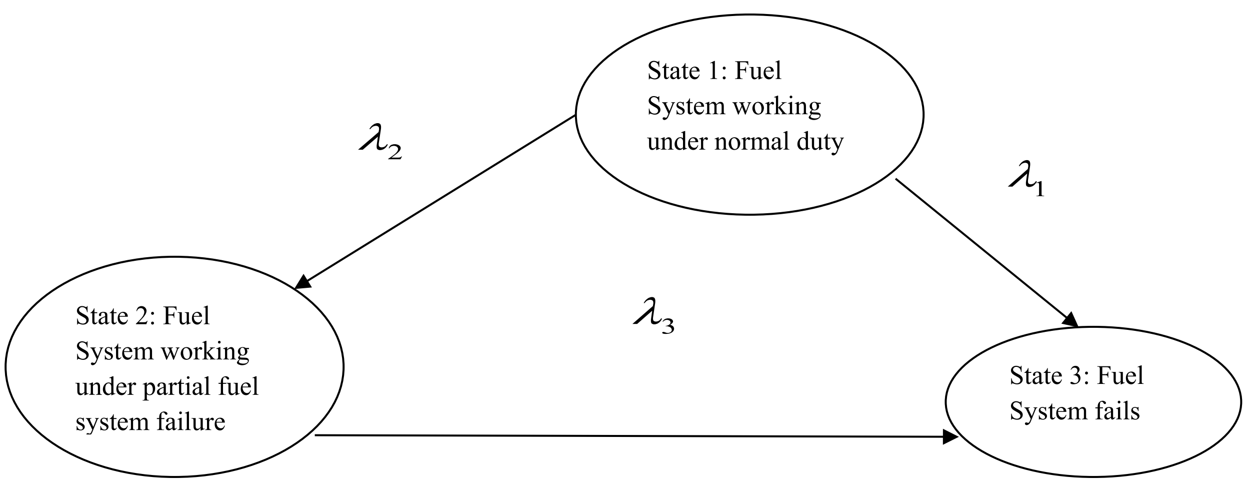



Figure 4-2: Degraded reliability model for a haul truck fuel system with three states (2)

When the fuel system is in partial failure, it can still operate but it needs to consume more energy and emits more GHG. For instance, if there is a little leakage in fuel system because of the incorrect nozzle pressure, the reliability of fuel system is decreased. However, if this leakage is small, the fuel system still can operate but it needs more energy and GHG emission is going to be increased. The quality of emissions is not assumed to change when the equipment changes reliability state; however, it is possible for some faults that emission severity can change between states.

Under State 1, the fuel system is working under normal conditions with a failure probability of 0.11 (calculated in chapter 3). State 2 is the situation in which there is partial failure of the fuel system; however, a fuel system (system) still can operate. State 3 is the condition in which a fuel system (system) fails and cannot work anymore. The failure rate for the fuel system when it works under normal duty (fuel system reliability is equal 0.9) is 0.11 (failure rate ( $\lambda_1$ ) is equal to0.11 (reliability and probability of failure rate were taken from chapter 3).

A fuel system's partial failure and partial reliability are calculated based on the formulas below.

The probability of failure for State 1 is calculated from Equation 4-2 (62):

$$P_1=e^{-(\lambda_1+\lambda_2)t} \tag{4-2}$$

R=fuel system reliability under normal duty=0.9 (from chapter 3)

$P_1$=fuel system probability of failure under normal duty=1-0.9=0.1

It was assumed in this research that in Alberta a haul truck works for 9 months under normal duty and 3 months under partial failure. Therefore, the actual time for a fuel system working under a reliability of 0.95 is 0.75 and the actual working time under partial failure is 0.25.

Based on Equation 4-2, $\lambda_2$ is calculated as:

$0.1=e^{-(0.11+\lambda_2)*0.75}$

$\text{Ln } 0.05=-(0.11+\lambda_2)*0.75$

$\lambda_2=2.96$

The probability of a fuel system's partial failure (i.e., State 2) is calculated from Equation 4-3 (2):

$$P_2(t) = \frac{\lambda_2}{\lambda_1 + \lambda_2 - \lambda_3}[e^{-\lambda_3 * t} - e^{-(\lambda_1+\lambda_2)*t}]$$

In this state t=0.25.

$$P_2(t) = \frac{2.96}{0.11}[e^{-2.96*0.25} - e^{-(2.96+0.11)*0.25}]$$

The truck's fuel system partial failure probability and partial reliability were:

$P_2$ (t) = 0.35 (partial probability of failure)

R 2(t) =0.65 (partial reliability)

Similar calculations were performed for the engine, transmission, suspension, and tires and the results are presented in Table 4-1. In this research, $P_{new}$ and $R_{new}$ are partial probability of failure and partial reliability.

Table 4-1: Calculated partial reliability for critical parts of a haul truck

| No. | Haul truck part | P (Probability of failure*) | R (Reliability*) | $\lambda_1$ | $\lambda_2$ | $P_{new}$ (Probability of partial failure**) | $R_{new}$ (Partial reliability**) |
|---|---|---|---|---|---|---|---|
| 1 | Fuel system | 0.05 | 0.95 | 0.11 | 2.96 | 0.35 | 0.65 |
| 2 | Engine | 0.01 | 0.99 | 0.01 | 6.13 | 0.33 | 0.67 |
| 3 | Transmission | 0.1 | 0.9 | 0.11 | 2.96 | 0.35 | 0.65 |
| 4 | Suspension | 0.08 | 0.92 | 0.09 | 3.28 | 0.36 | 0.64 |
| 5 | Tire | 0.03 | 0.97 | 0.2 | 2.16 | 0.31 | 0.69 |

*from chapter 3

**Partial probability of failure and Partial reliability

#### 4.10.1.3 Energy Modeling for Haul Trucks Using LEAP

The energy demand for a haul truck was simulated in LEAP software. In this section motive transport in Alberta's oil sands mining sector was modeled. The following assumptions were made to facilitate energy modeling:

- A haul truck is sub-system of motive transport.
- Most diesel fuel, which goes to the fuel system, is burned through the engine.
- Energy demand for the fuel system was assumed to be 1.9 liter per barrel, and only 1.7 liter per barrel went to the engine (91).
- The haul truck is a Caterpillar 797, with a capital cost of CAN $ 5,000,000 (68)

The surface mining sector demand tree was developed for oil sands mining haul trucks using an end-use approach (see Figure 4-3).

To calculate energy demand through the E-R model, some scenarios based on each component state need to be defined.

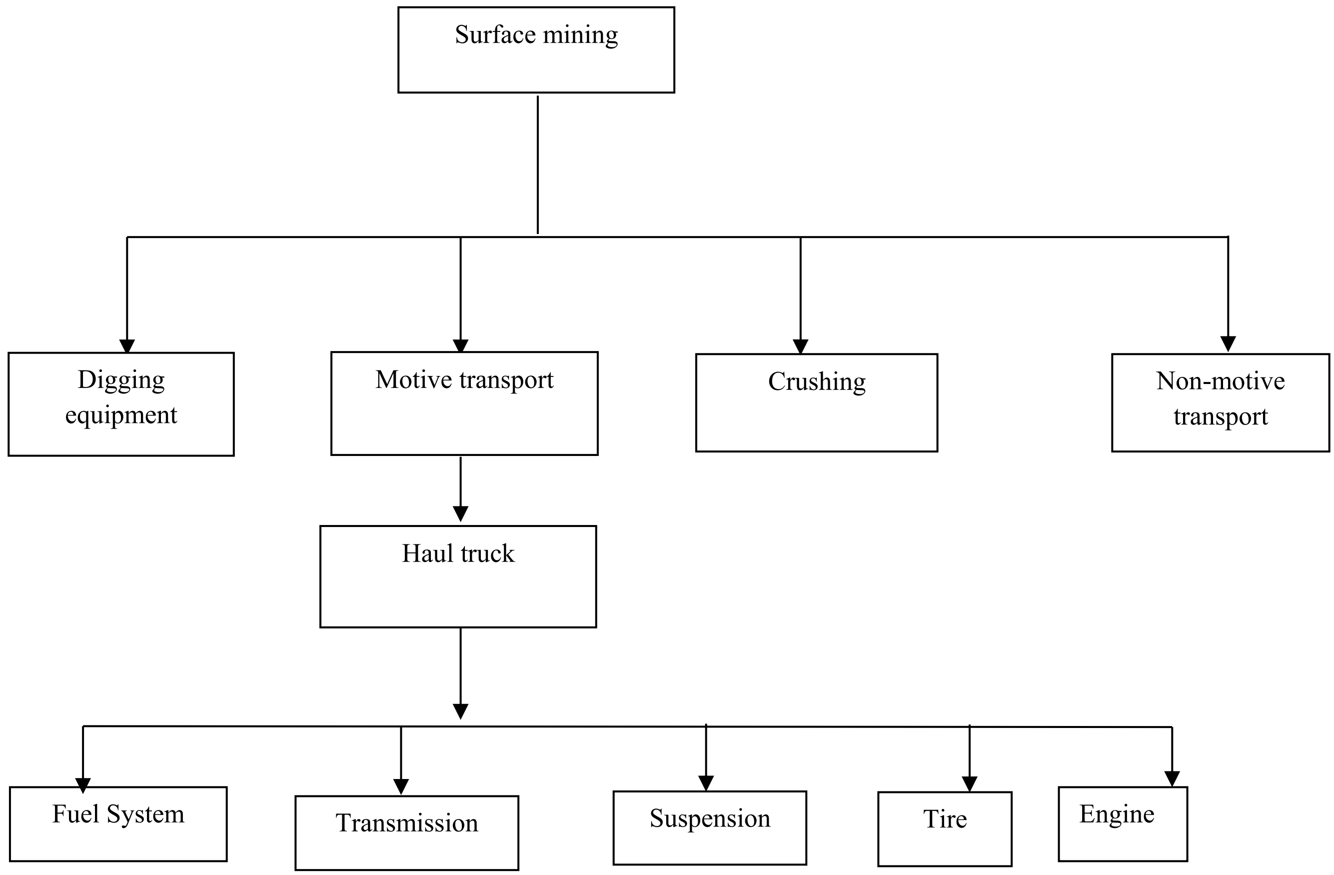



Figure 4-3: Haul truck energy demand tree

### 4.10.1.4 The E-R Model Results for a Haul Truck

By using equation 4-1 to 4-3, failure loss for each state of haul truck was calculated:

State 1: the mining haul truck was fully operational; in other words, its reliability was equal to 1 (it does not encounter any failure; this is the ideal state)

State 2: haul truck was working under expected reliability. Every piece of equipment had its own reliability value based on its probability density function and their local situation; this is known as expected reliability. In this research, expected reliability was calculated based on the probability of failure (it was taken from chapter 3).

State 3: haul truck was working under partial reliability. If some parts of equipment were damaged but the haul truck still can operate perhaps under lower reliability, this is known as partial reliability. Partial reliability was calculated in section 4.2.2.

State 4: haul truck failed. Therefore, haul truck needs the extra cost and energy to be fixed and to be able to operate a gain. The fraction of loss is defined as the fraction of energy or cost which is lost during operation due its probability of failure value.

The loss of capacity and its consequences (based on energy and cost) for a mining haul truck for each state was calculated as:

Failure loss for state 1=0, Failure loss for state 2=0.05*0.1=0.005

Failure loss for state 3 =0.5*0.35=0.175, Failure loss for state 4=0

The costs, including capital, maintenance, fuel and labor, for the truck were calculated to be 0.323 CAN$/barrel of oil production in one year. Similar calculations were done for engine, transmission, suspension and tire faults. Then, this cost was added to the extra cost of each state to find the total cost of haul truck. Tables 4-2 to 4-7 show the fraction of loss of capacity and the consequence of each loss based on cost and energy for each state.

In E-R model, based on the fraction of lost in each state, the extra energy, which was needed to run the equipment, was defined. The total cost of haul truck when it operates under state 1, was calculated based on the type of truck ( truck capacity, working hour per day, life of tire and oil sands production). Maintenance, material, fuel and labor costs (operating cost) along with the fixed cost were calculated to find the total cost for a mining haul truck. Consequence of loss of capacity was determined as fraction of loss times the operating cost. E-R model calculates the extra energy to run equipment in each state.

Table 4-2: Fraction of loss of and extra cost of fuel system under E-R model for haul truck-States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%)* | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra cost of fuel system (CAN$/bbl) | Total cost haul truck (CAN$/bbl) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operation | 1 | 0 | 100 | 0 | 0 | 0.045 | 0.325 |
| 2 | Expected working | 0.95 | 10 | 90 | 0.01 | 0 | 0.0452 | 0.325 |
| 3 | Partial reliability | 0.65 | 50 | 50 | 0.025 | 0.005 | 0.050 | 0.330 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.045 | 0.090 | 0.370 |

- The capacity percentage values are obtained from (97)

Table 4-3: Fraction of loss of and extra cost of engine under E-R model for haul truck-States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra cost of engine (CAN$/bbl) | Total cost haul truck (CAN$/bbl) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operation | 1 | 0 | 100 | 0 | 0 | 0.042 | 0.322 |
| 2 | Expected working | 0.99 | 10 | 90 | 0.01 | 0 | 0.042 | 0.322 |
| 3 | Partial reliability | 0.67 | 50 | 50 | 0.025 | 0.006 | 0.048 | 0.328 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.042 | 0.084 | 0.364 |

Table 4-4: Fraction of loss of and extra cost of transmission under E-R model for haul truck-States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra cost of transmission(CAN$/bbl) | Total cost (CAN$/bbl) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operation | 1 | 0 | 100 | 0 | 0 | 0.020 | 0.3 |
| 2 | Expected working | 0.9 | 10 | 90 | 0.01 | 0.000 | 0.0202 | 0.3 |
| 3 | Partial reliability | 0.65 | 50 | 50 | 0.025 | 0.001 | 0.021 | 0.301 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.020 | 0.040 | 0.320 |

Table 4-5: Fraction of loss of and extra cost of suspension under E-R model for haul truck-States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra cost of suspension (CAN$/bbl) | Total cost truck (CAN$/bbl) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operation | 1 | 0 | 100 | 0 | 0 | 0.01 | 0.290 |
| 2 | Expected working | 0.92 | 10 | 90 | 0.01 | 0 | 0.0101 | 0.290 |
| 3 | Partial reliability | 0.64 | 50 | 50 | 0.025 | 0.001 | 0.011 | 0.291 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.010 | 0.020 | 0.300 |

Table 4-6: Fraction of loss of and extra cost of tires under E-R model for haul truck-States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra cost (CAN$/bbl) | Total cost (CAN$/bbl) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operation | 1 | 0 | 100 | 0 | 0 | 0.04 | 0.32 |
| 2 | Expected working | 0.97 | 10 | 90 | 0.01 | 0 | 0.0401 | 0.32 |
| 3 | Partial reliability | 0.69 | 50 | 50 | 0.025 | 0.003 | 0.043 | 0.323 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.04 | 0.08 | 0.36 |

Table 4-7: E-R model for the mining haul truck based on States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy-diesel lit/bbl) | Fuel intensity (diesel, lit/bbl) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 3 |
| 2 | Expected working | 0.95 | 10 | 90 | 0.01 | 0.015 | 3.015 |
| 3 | Partial reliability | 0.80 | 50 | 50 | 0.025 | 0.3 | 3.3 |
| 4 | Failed | 0 | 100 | 0 | 1 | 3 | 6 |

Because the E-R model is a discrete Markov multi-state model, to assess the energy and cost saving with the model, four scenarios (one for each state) were developed and are defined below.

#### 4.10.1.5 Surface Mining Haul Truck Scenarios 1 to 4–States 1 to 4

These scenarios calculate the energy demand, total cost from mining haul truck in Alberta's surface mining sector when a haul truck operates under State 1 (fully operational), State 2 (expected operating), State 3 (partial reliability), and 4 (complete failure). The input data and assumption are given below.

##### 4.10.1.5.1 Input Data and Assumptions for Reference Scenario of a Haul Truck Operating Under States 1 to 4

State 1: When haul truck is working with 100% reliability, it is considered to be fully operational and no failure occurs. The details of this scenario were developed by Subramanyam et al. 2015 (91). In the base case, diesel needed for a haul truck is 3 L/ barrel in the year 2010 and the cost is 0.323 CAN$/ barrel of oil production in one year.

State 2: When the haul truck is working with its actual reliability, it is considered to be operating under "expected working conditions." Therefore, there is some failure associated with components and haul truck. The E-R model shows that in State 2 the haul truck requires an extra 0.015 lit/ barrel of oil production energy (Diesel) and 0.044 (CAN$/ barrel of oil production) cost. Therefore, the total energy and cost required for this state are

3.015 lit/ barrel of oil production and 0.324 CAN$/ barrel of oil production of total oil production.

State 3: An extra 0.3 Lit / barrel of oil production energy (Diesel) and 0.047 (CAN$/ barrel of oil production) are required. Therefore, the total energy and cost required for this state is 3.3 lit/ barrel of oil production and 0.327 CAN$/ barrel of oil production of total oil production.

State 4: In State 4, 3 lit/ barrel of oil production extra energy (Diesel) and 0.086 CAN$/ barrel of oil production are added to the simulation in LEAP. Therefore, the total energy and cost required for this state are 6 lit/ barrel of oil production and 0.366 CAN$/ barrel of oil production of total oil production.

#### 4.10.1.5.2 Scenario: Improving the Reliability of Mining Haul Truck for States 1 to 4

In this scenario, energy consumption, total cost, and GHG emissions in the Alberta's mining haul truck were assessed when crusher reliability is improved and it operates under State 1, 2, 3 and 4.

#### 4.10.1.5.2.1 Input Data and Assumptions for Improving Mining Haul Truck Reliability, Scenarios 1 to 4

Improving oil sands haul truck reliability can save up to 14% of total primary and secondary energy consumption over 20 years. Maintenance costs will increase by 8% in years 1, 2, and 3 and from year 4 will decrease by 40% until year 10. Moreover, there will be a 14.3% increase in labour costs in year 1 and a 6% increase in years 2 and 3. From year 4 to year 10, labour costs will go down by 14.3% (98). These are the result of improving reliability of mining haul truck, which are used as input for the scenario of improving mining equipment including haul truck in states 1 to 4 and plotted in LEAP. Data was calculated based on energy and cost saving data for each scenario for years 2010 to 2050 in Excel.

### 4.10.1.5.3 Results - Energy Profile for States 1 to 4-Haul Truck

The reference case scenario for reliability improvement in a mining haul truck when operating under State 1 (fully operational), State 2 (expected working), State 3 (partial reliability), and State 4 (complete failure) were simulated in LEAP (see Table 4-8).

State 1: LEAP estimated the energy demand of the haul truck (Diesel) to be 1,605.45 MM Gigajoule for the year 2050. By improving the haul truck reliability, the expected energy demand will decrease by 1,236.79 of MM Gigajoule /year by 2050.

State 2 LEAP estimated an energy demand in the haul truck to be 1605.54 MM Gigajoule/year. By improving the haul truck reliability, the expected energy demand will decrease by 690.80 of MM Gigajoule /year by 2050.

State 3: LEAP estimates energy demand of 1,607.20 MM Gigajoule/year by 2015 when the haul truck is working under partial reliability. When the reliability is improved, energy demand is expected to decrease by 756.92 MM Gigajoule/year.

State 4: LEAP estimated an energy demand to be 1,622.90 MM Gigajoule/year. By improving the haul truck's reliability, the expected energy demand will decrease by 360.12 of MM Gigajoule /year by 2050.

Table 4-8: Mining haul truck energy demand (million Gigajoule)- State 1 to 4-year 2050

| Energy | Diesel | | | |
|---|---|---|---|---|
| Scenario | 1 | 2 | 3 | 4 |
| Reference | 1,605.45 | 1,605.54 | 1,607.20 | 1,622.90 |
| Reliability improvement | 1,236.79 | 690.80 | 756.92 | 360.12 |
| Total | 2,842.24 | 2,296.34 | 2,364.12 | 1,983.02 |

### 4.10.1.5.4 Energy Saving Results from the E-R Model for an Oil Sands Mining Haul Truck Operating Under States 1 to 4

State 1: Energy demand for the mining haul truck was plotted in LEAP over 40 years for both the reference case and Scenario 1 and is shown in Figure 4-4. Plotted energy demand over a specific period (from 2010 to 2050) indicates that there will be on average 0.45% energy saving per year through when the reliability of a haul truck under state 1 is improved.

Scenario 2 (State 2): There is on average 0.57% energy saving annually when the reliability of a mining haul truck operating state2 reliability is improved (see Figure 4-5).
Scenario 3 (State 3): There is on average 0.45% energy saving per year when the reliability of a mining haul truck operating under state 3 is improved (see Figure 4-6).
Scenario 4 (State 4): There is on average 0.16% energy saving annually when the reliability of a mining haul truck operating under state 4 is improved (see Figure 4-7).

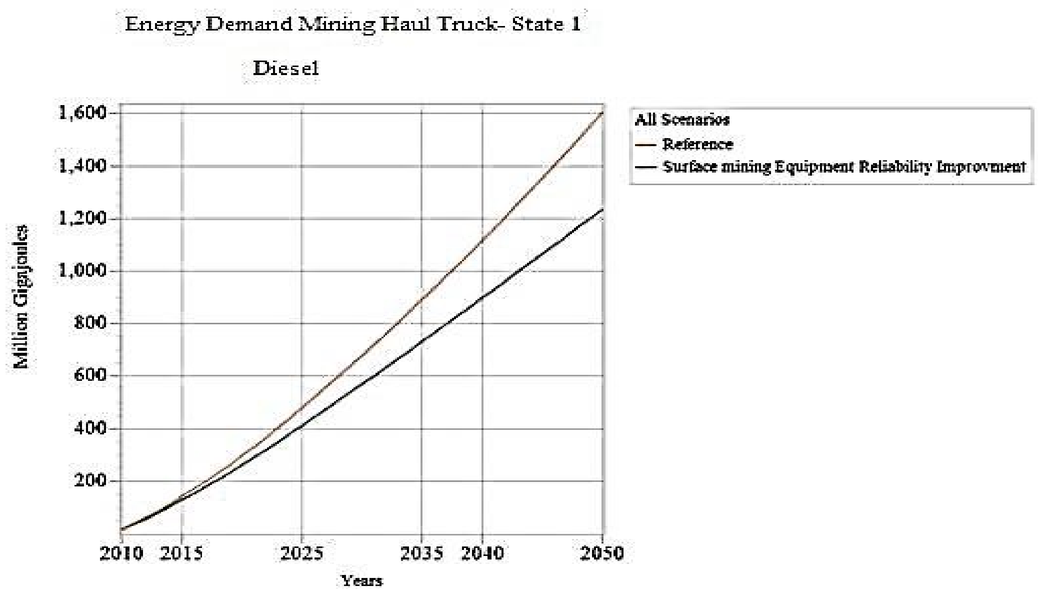



Figure 4-4: Energy saving for the mining haul truck, 2010–2050: Scenario 1 vs reference scenario

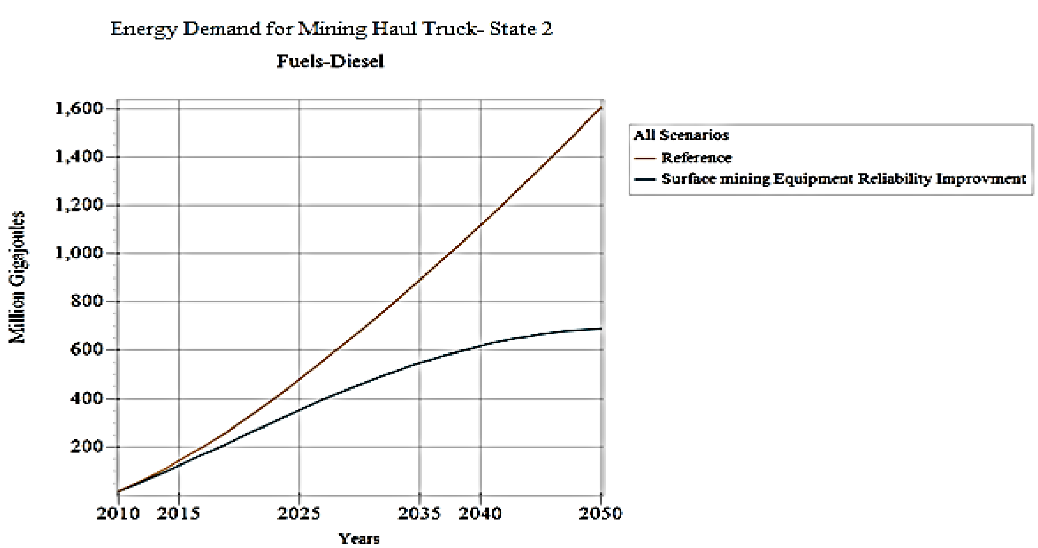



Figure 4-5: Energy saving for the mining haul truck, 2010–2050: Scenario 2 vs reference scenario 2

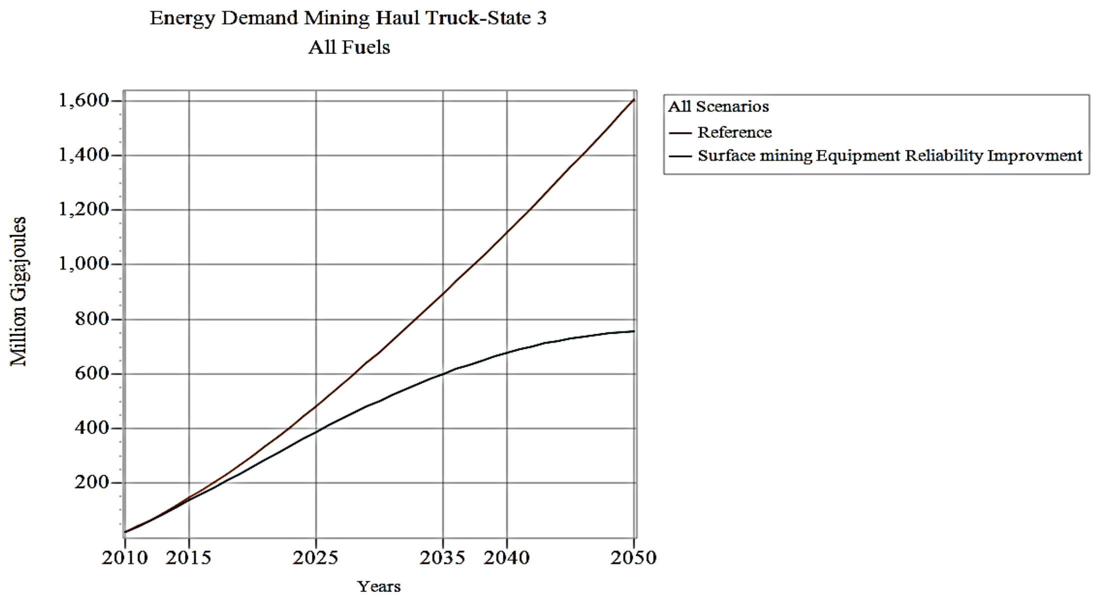



Figure 4-6: Energy saving for the mining haul truck, 2010–2050: Scenario 3 vs reference scenario 3

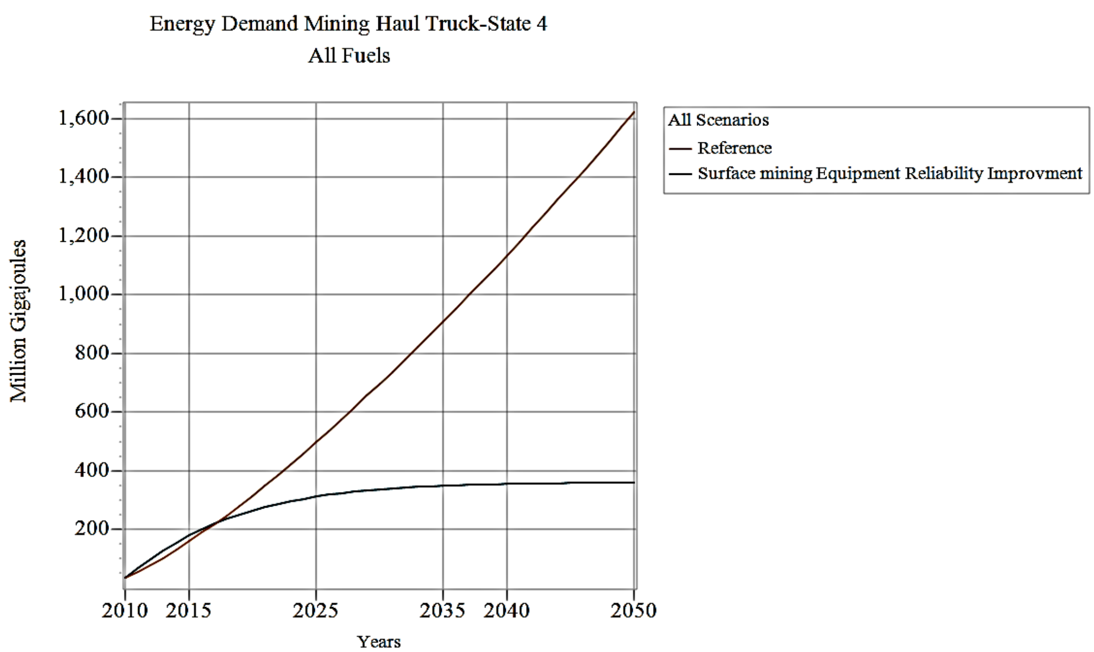



Figure 4-7: Energy saving for the mining haul truck, 2010–2050: Scenario 4 vs reference scenario 4

### 4.10.1.5.5 Cost Saving Results from the E-R Model for the Mining Haul Truck Operating Under States 1 to 4

State 1: Operating costs for the haul truck were plotted over 40 years (from 2010 to 2050) (see Figure 4-8). By improving haul truck reliability, on average 0.69 % operational cost savings can be made.

State 2 (Scenario 2): There is on average 0.61% operational cost saving annually through improving the reliability of a mining haul truck operating under expected working conditions (see Figure 4-9).

State 3 (Scenario 3), there is on average 0.6% operational cost saving annually through improving the reliability of a mining crusher operating under partial reliability (see Figure 4-10).

State 4 (Scenario 4), there is on average 0.52% operational cost saving annually through improving the reliability of a mining haul truck that has completely failed (see Figure 4-11).

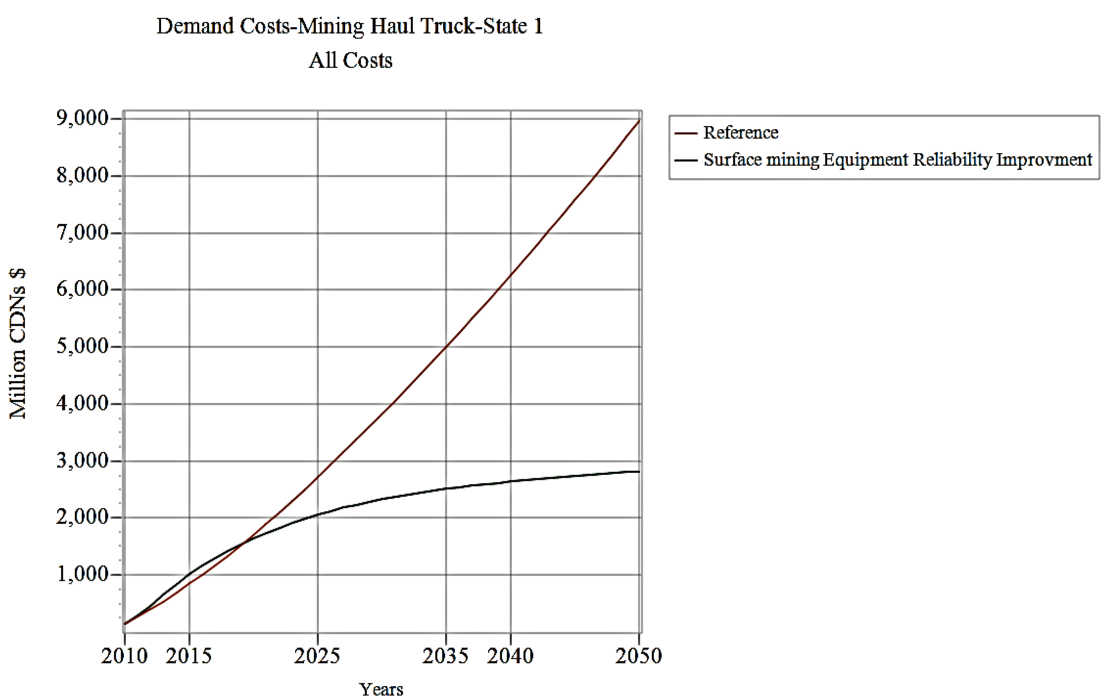



Figure 4-8: Cost saving for the mining haul truck, 2010–2050: Scenario 1 vs reference scenario 1

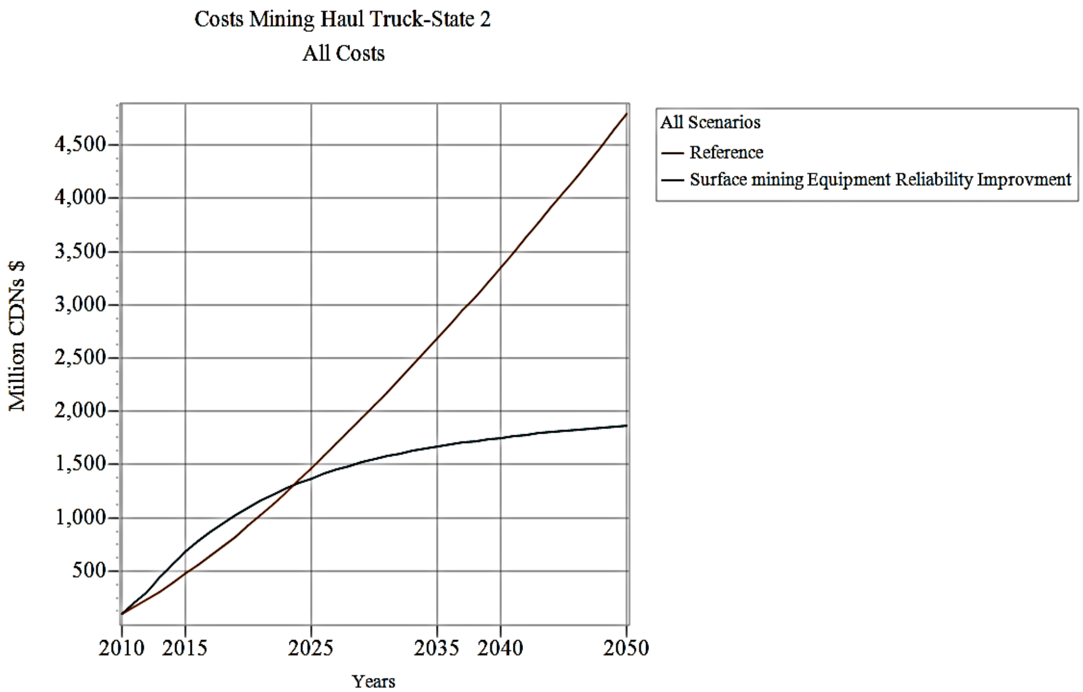



Figure 4-9: Cost saving for the mining haul truck, 2010–2050: Scenario 2 vs reference scenario 2

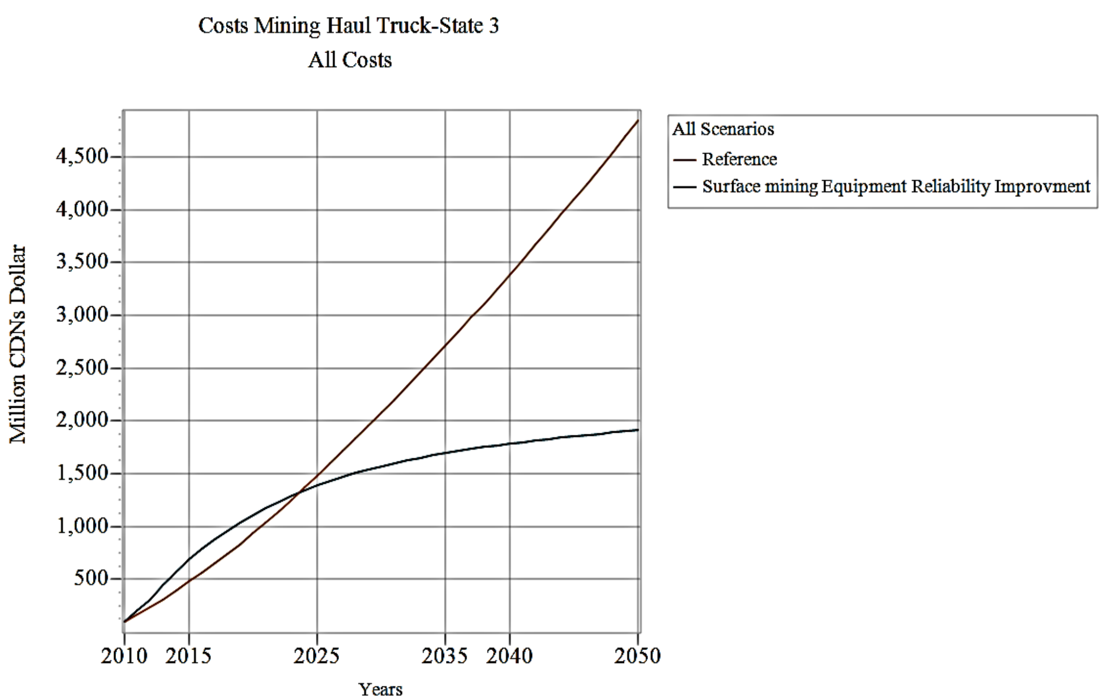



Figure 4-10: Cost saving for the mining haul truck, 2010–2050: Scenario 3 vs reference scenario 3

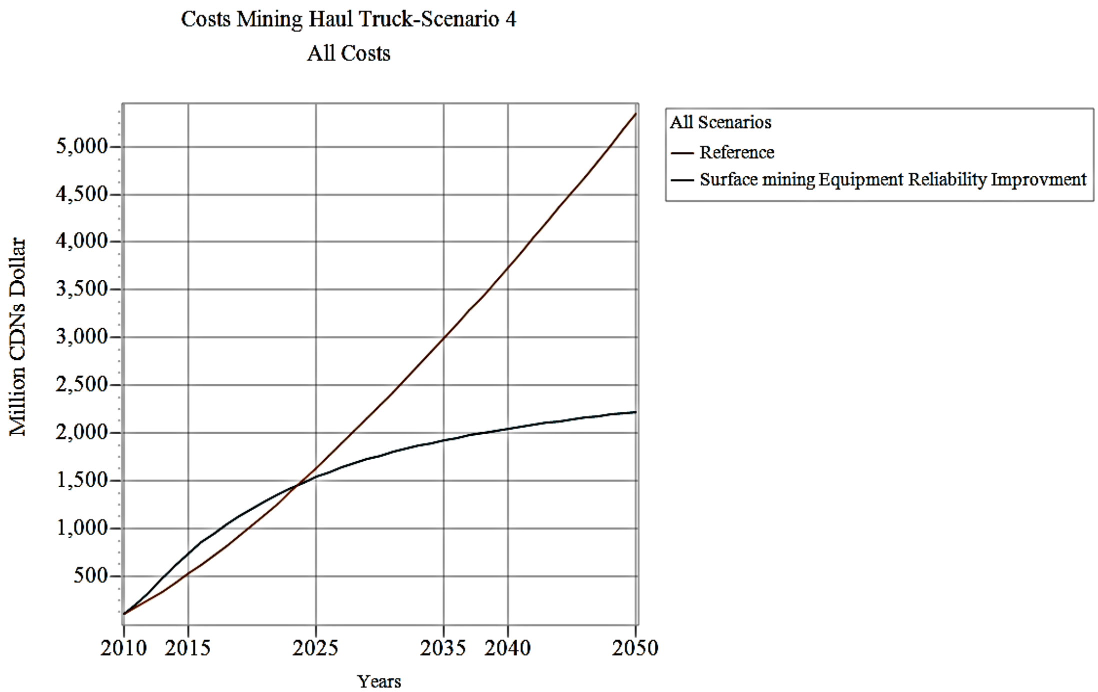



Figure 4-11: Cost saving for the mining haul truck, 2010–2050: Scenario 4 vs reference scenario 4

### 4.10.1.5.6 GHG Emission Results from the E-R Model for an Oil Sands Mining Haul Truck Operating Under States 1 to 4

Oil sands mining haul truck GHG emissions were plotted over 40 years (2010-2050) for the reference case and Scenarios 1 to 4 (see Figures 4-12 to 4-15 and Tables 4-9 to 4-12).

**For Scenario 1 (State 1):** The results show that when the reliability of the mining haul truck when it works under state 1 is improved, GHG emissions can be reduced on average 0.33% in a year. The GHG emissions for a mining haul truck operating under state 1 were 116.84 million metric tonnes of $CO_2$ in 2050. After improving the reliability of the engine or the tires, GHG emissions are expected to be 90.01 million metric tonnes of $CO_2$ by 2050 (see Figure 4-12 and Table 4-9).

**For Scenario 2 (State 2):** For the reference scenario and Scenario 2, GHG emissions for the oil sands mining haul truck was plotted over 40 years (2010 to 2050).. The graph in Figure 4-13 suggests that by improving the reliability of a mining haul truck operating under state 2, GHG emissions can be reduced by an average of 0.94 % yearly. GHG emissions for a mining haul truck operating under state 2 were 3,723.57 million metric tonnes of $CO_2$ in 2050. When the reliability of the truck improves, GHG emissions will decline to 203.10 MMT of $CO_2$ in 2050 (see Table 4-10).

**For Scenario 3 (State 3):** The reference scenario and Scenario 3 GHG emissions for the oil sands mining haul truck were plotted over a 40 year period (2010 to 2050) As shown in the graph in Figure 4-14, by improving the reliability of a haul truck operating under state 3, GHG emissions can be reduced on average 0.53% yearly. The GHG emissions for a mining haul truck operating under partial reliability (state 3) will be 116.97 million metric tonnes of $CO_2$ in 2050. After improving the reliability of the engine or the tires, GHG emissions are expected to decline to 55.09 million metric tonnes of $CO_2$ by 2050 (see Table 4-11).

**For Scenario 4 (State 4):** By improving the reliability of the mining haul truck in State 4, GHG emissions can be reduced on average 0.78 % per year. The GHG emissions for a mining haul truck operating under state 4 will be 3723.80 million metric tonnes of $CO_2$ in 2050. After improving the reliability of the haul truck, GHG emissions are expected to decline to 15.80 million metric tonnes of $CO_2$ by 2050 (see Table 4-12 ).

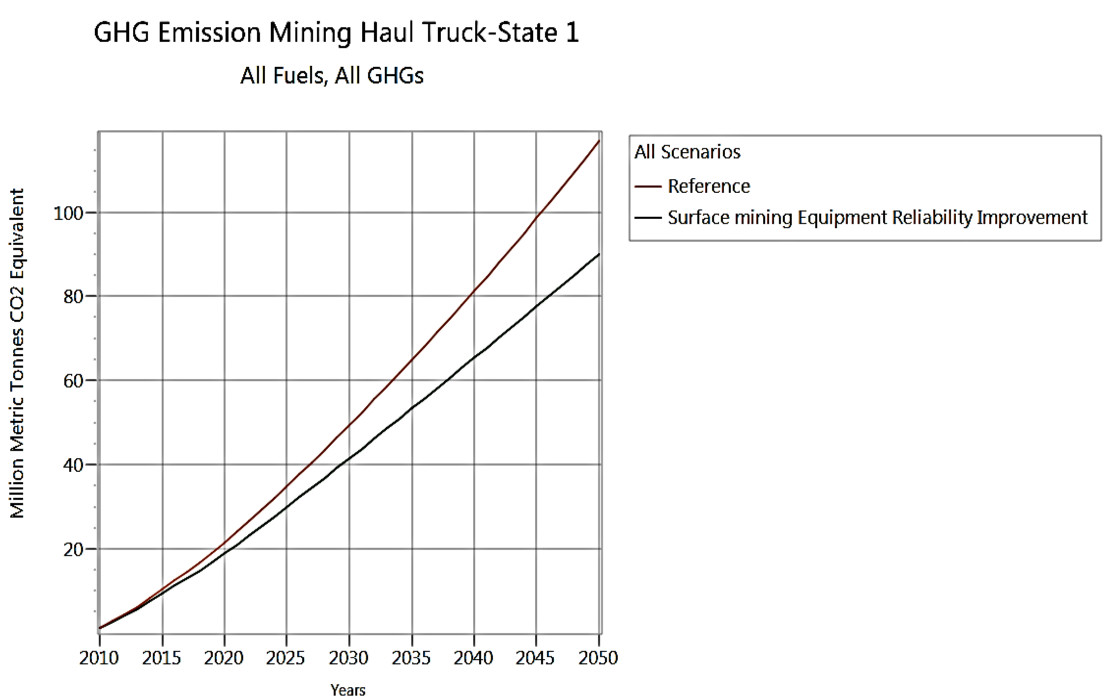



Figure 4-12: GHG emissions saving for the mining haul truck, 2010–2050: Scenario 1 vs reference scenario 1

Table 4-9: Haul truck GHGs, Year 2050 (million metric tonnes $CO_2$ equivalent)-State 1

| **Scenarios** | **Nitrous oxide** | **Methane** | **Carbon dioxide non biogenic** | **Total** |
|---|---|---|---|---|
| Reference | 0.30 | 0.07 | 116.48 | 116.84 |
| Mining Haul truck reliability improvement | 0.23 | 0.05 | 89.73 | 90.01 |
| Total | 0.53 | 0.12 | 206.20 | 206.85 |

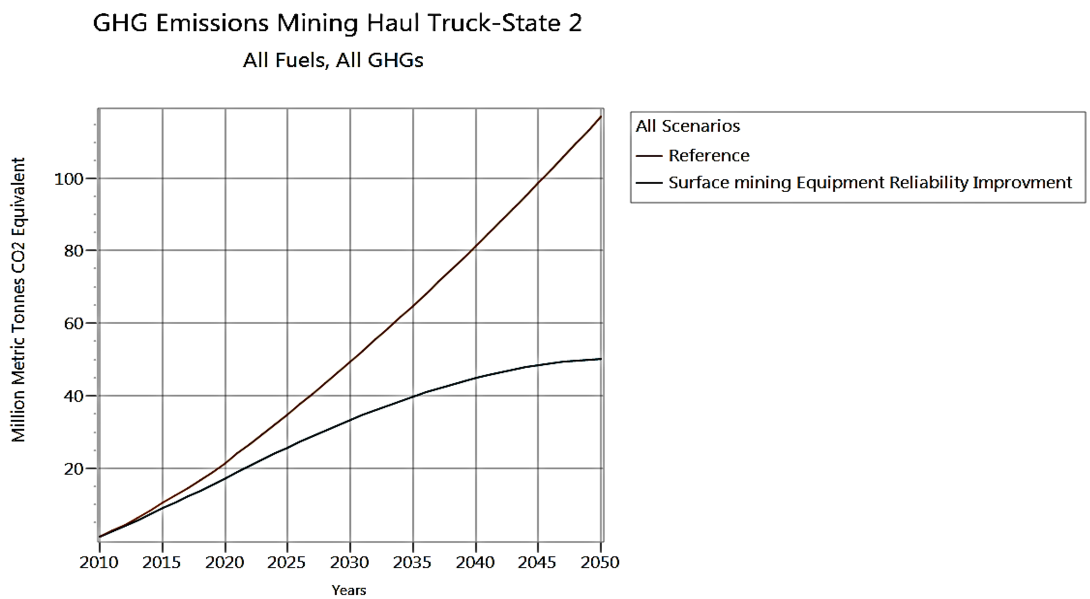



Figure 4-13: GHG emissions saving for the mining haul truck, 2010–2050: Scenario 2 vs reference scenario 2

Table 4-10: Haul truck GHGs, Year 2050 (million metric tonnes $CO_2$ equivalent) - State 2

| **Scenarios** | **Nitrous Oxide** | **Methane** | **Carbon dioxide non biogenic** | **Total** |
|---|---|---|---|---|
| Reference | 9.52 | 2.15 | 3,711.91 | 3,723.57 |
| Mining Haul truck reliability improvement | 0.52 | 0.12 | 202.47 | 203.10 |
| Total | 10.04 | 2.27 | 3,914.37 | 3,926.67 |

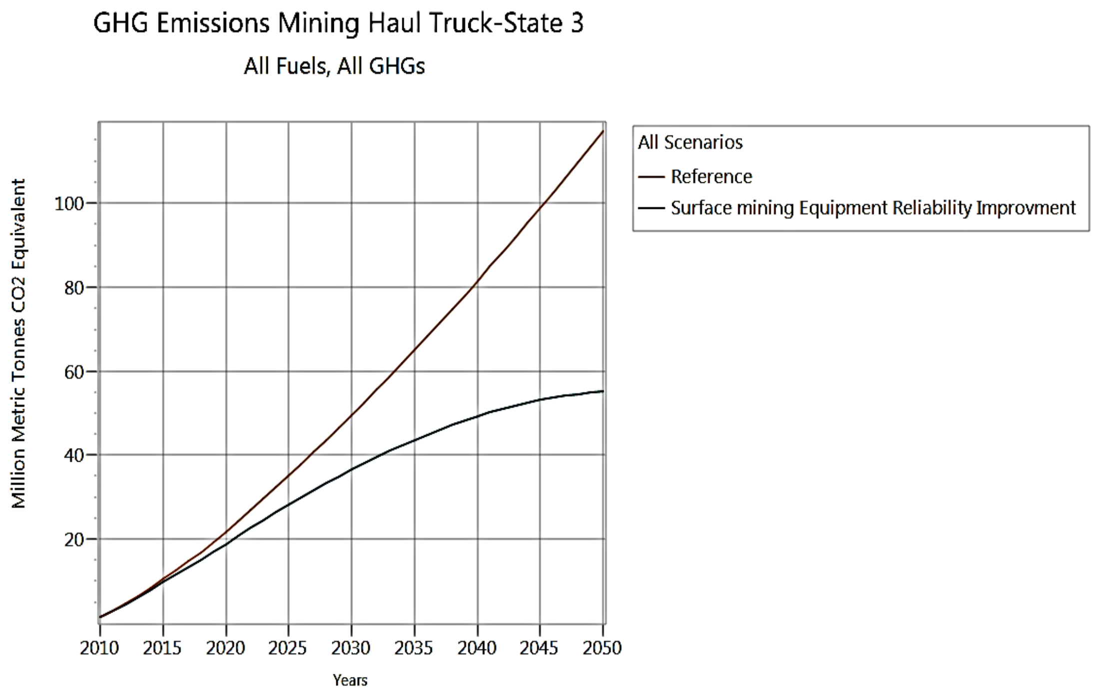



Figure 4-14: GHG emissions saving for the mining haul truck, 2010–2050: Scenario 3 vs reference scenario 3

Table 4-11: Haul truck GHGs, Year 2050 (million metric tonnes $CO_2$ equivalent)-State 3

| **Scenario** | **Nitrous Oxide** | **Methane** | **Carbon Dioxide Non Biogenic** | **Total** |
|---|---|---|---|---|
| Reference | 9.52 | 2.15 | 3,711.91 | 3,723.57 |
| Mining haul truck reliability improvement | 0.58 | 0.13 | 224.96 | 225.67 |
| Total | 10.09 | 2.28 | 3,936.87 | 3,949.24 |

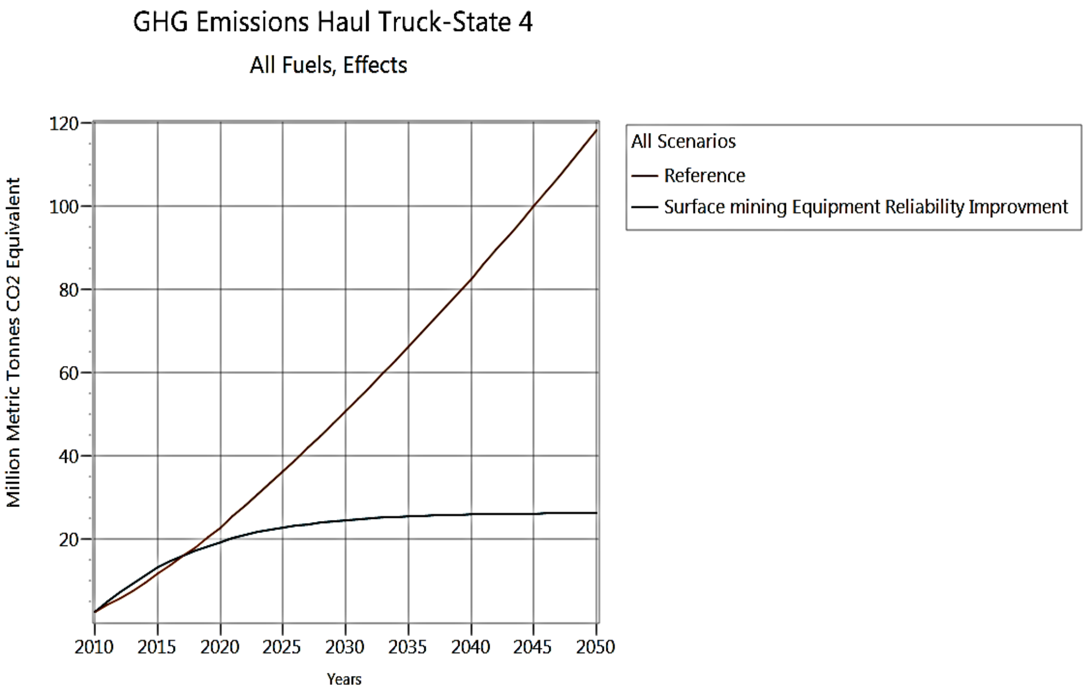



Figure 4-15: GHG emissions saving for the mining haul truck, 2010–2050: Scenario 4 vs reference scenario 4

Table 4-12: Haul truck GHGs, Year 2050 (million metric tonnes $CO_2$ equivalent) -State 4

| **Scenario** | **Nitrous oxide** | **Methane** | **Carbon dioxide non biogenic** | **Total** |
|---|---|---|---|---|
| Reference | 9.52 | 2.15 | 3,711.91 | 3,723.57 |
| Mining haul truck reliability improvement | 0.04 | 0.01 | 15.75 | 15.80 |
| Total | 9.56 | 2.16 | 3,727.65 | 3,739.37 |

## 4.10.2 Oil Sands Hydraulic and Electric Shovels - Introduction

In this section, a method to link reliability and energy demand for the oil sands mining hydraulic and electric shovels were developed. The scope of this model encompasses all the processes of specific components or sub-components of shovel (hydraulic and electric) that have an impact on energy consumption. It was assumed that only the engine from the hydraulic shovel and the drive motor from the electric shovel have a direct impact on energy consumption. If the hydraulic shovel's engine or the electric shovel's drive motor partially fails, the shovel can operate, but the shovel consumes more energy consumption and emits more GHGs than otherwise.

### 4.10.2.1 E-R Model Assumptions for Hydraulic and Electric Shovels

Energy consumption in hydraulic and electric shovels was simulated under the sub-category of “digging equipment” in LEAP. Some assumptions were made when modeling digging equipment:

- Only the drive motors from electric shovels and engines from hydraulic shovels were considered to have an energy impact.
- Energy demands for the drive motor (which consumes electricity) and the engine (which consumes diesel fuel) were considered to be equal in the reference scenario.
- All input data were for the province of Alberta and 2010 was used as the base year.
- Hydraulic and electric shovels were assumed to have the following specifications : a hydraulic shovel is a Hitachi ZX670LC-5, with a bucket force of 72,838 lb and dig depth of 30 ft (9.5 m) and weight of 131,000 lb (99). The engine power was assumed to be 347 HP. Capital cost was calculated to be $1,025,000. The electric shovel is Hitachi 8000 with Bucket Capacity (heaped) 40.0 m3 with the voltage AC 6 000 - 6 600 V / 50 Hz. The capital cost for the electric shovel was assumed to be $3,400,000.

#### 4.10.2.1.1 Calculating Partial Reliability for the Engine (Hydraulic Shovel) and the Electric Drive Motor (Electric Shovel)

With Equations 4-1 and 4-2 and similar calculations from section 4.2.2, partial reliability for hydraulic and electric shovels is presented in Table 4-13.

A similar calculation from section 4.10.1.2 was used to find the failure rate for an engine of hydraulic shovel and electric shovel’s electric drive motor.

Table 4-13: Calculated partial reliability for critical parts of hydraulic and electric shovels

| No. | Critical part of shovels | P (Probability of failure*) | R (Reliability*) | $\lambda_1$ | $\lambda_2$ | $P_{new}$ (Probability of partial failure**) | $R_{new}$ (Partial reliability**) |
|---|---|---|---|---|---|---|---|
| 1 | Engine in hydraulic shovel (E) | 0.09 | 0.91 | 0.1 | 3.11 | 0.35 | 0.65 |
| 2 | Electric drive motor in electric shovel (EF) | 0.21 | 0.79 | 0.27 | 1.82 | 0.28 | 0.72 |

*from chapter 3

**Partial probability of failure and Partial reliability

### 4.10.2.1.2 Energy Modeling of Hydraulic and Electric Shovels

Energy consumption for hydraulic and electric shovels was simulated in LEAP software in order to analyze energy demand for digging equipment in Alberta's oil sands surface mining sector. Figure 4-16 displays the energy demand tree for digging equipment.

### 4.10.2.2 E-R Model for Hydraulic and Electric Shovels

The loss of capacity and its consequences for the hydraulic shovel in four states based on Equation 4-3 and 4-4were calculated as

Failure loss for State 1= 0

Failure loss for state 2=0.05*0.09=0.0045

Failure loss for state 3 (Partial failure) =0.5*0.35 =0.18

Failure loss for state 4=0

The operational costs for a hydraulic shovel's engine, including, capital, maintenance, fuel, and labor, were calculated to be CANS \$0.08/ barrel of oil production by the hydraulic shovel engine. Tables 4-14 and 4-15 indicate the fraction of loss of capacity and the consequences of each loss based on cost and energy for each state.

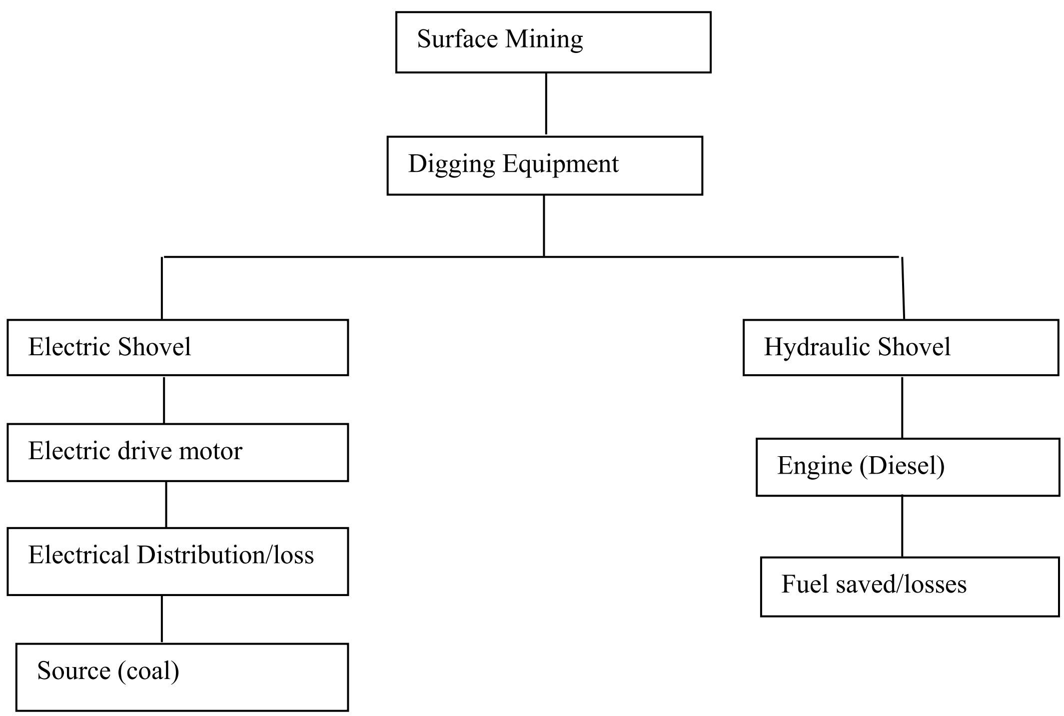



Figure 4-16: Energy demand tree for digging equipment

Table 4-14: Fraction of loss of capacity for the hydraulic shovel for States i=1 to 4-Extra cost

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$/bbl) | Final cost (CAN$/bbl) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.08 |
| 2 | Expected working | 0.91 | 10 | 90 | 0.01 | 0.0004 | 0.081 |
| 3 | Partial reliability | 0.65 | 50 | 50 | 0.025 | 0.015 | 0.1 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.08 | 0.16 |

Table 4-15: E-R model for hydraulic shovel for States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy-Diesel liters/bbl) | Fuel Intensity (Diesel, lit/bbl) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 2 |
| 2 | Expected working | 0.91 | 10 | 90 | 0.01 | 0 | 2 |
| 3 | Partial reliability | 0.65 | 50 | 50 | 0.025 | 0.36 | 2.36 |
| 4 | Failed | 0 | 100 | 0 | 1 | 2 | 4 |

The loss of capacity and its consequences for the electric shovel:

Failure loss for State 1= 0

Failure loss for state 2=0.05*0.21 =0.01

Failure loss for state 3 (Partial failure) =0.5*0.28 =0.14

Failure loss for State 4four=0

The operational cost for electric shovel's drive motor, including, capital cost, maintenance, fuel and labor, was calculated to be CANS $0.0415/bbl of oil production by electric shovel. Tables 4-16 and 4-17 indicate the fraction of loss of capacity and the consequences of each loss based on cost for each state for the electric shovel.

Table 4-16: Fraction of loss of capacity with the cost consequence for the electric shovel based on states i=1 to 4-Extra cost

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Final cost (CAN$/bbl) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.0415 |
| 2 | Expected working | 0.79 | 10 | 90 | 0.01 | 0.0042 | 0.045 |
| 3 | Partial reliability | 0.72 | 50 | 50 | 0.025 | 0.006 | 0.05 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.0415 | 0.08 |

Table 4-17: E-R model for electric shovel for states i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy-Diesel lit/bbl) | Fuel intensity (Electricity, Kwh/bbl) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 8 |
| 2 | Expected working | 0.79 | 10 | 90 | 0.01 | 0.08 | 8.08 |
| 3 | Partial reliability | 0.72 | 50 | 50 | 0.025 | 1.12 | 9.12 |
| 4 | Failed | 0 | 100 | 0 | 1 | 8 | 16 |

To assess the energy and cost savaging with the E-R model, four scenarios were developed.

#### 4.10.2.2.1 Surface Mining Hydraulic and Electric Shovels Scenarios 1 to 4 –States 1 to 4

##### 4.10.2.2.1.1 Input Data and Assumptions for the Reference Scenario under States 1 to 4

**State 1 (Fully Operational):** This scenario was developed by Subramanyam et al.2012 earlier. The base case energy (diesel) and cost requirement for the hydraulic shovel is 2 liters/bbl and 0.08 CAN$/ barrel of oil production, respectively. The base case energy (electricity) and cost requirement for the electrical shovel was 8 Kwh/bbl 0.042 CAN$/ barrel of oil production, respectively.

**State 2 (Expected working):** When equipment is working with its actual reliability, it is considered to be operating under "expected working conditions The E-R model for hydraulic shovels calculates energy consumption (diesel) to be 2.009 liters/bbl and additional cost to be 0.081 CAN$/ barrel of oil production. The base case energy (electricity) and cost requirement for the electrical shovel was 8.08 Kwh/bbl. The base case cost is 0.045 CAN$/ barrel of oil production.

**State 3 (Partial reliability):** When equipment is working under partial reliability, the loss of energy and cost will add approximately 50% to the total energy and cost compared to equipment working under 100% reliability. For this states, the base case energy (diesel) and cost requirement for the hydraulic shovel is 2.36 liters/ barrel and 0.1 CAN$/ barrel of oil production , respectively. The base case energy (electricity) and cost requirement for the electrical shovel was 9.24 Kwh/ barrel 0.05 CAN$/ barrel of oil production, respectively.

**State 4 (Complete failure):** When equipment fails, there is a 100% loss of energy and cost capacity. Therefore, an additional 100% energy and cost are imposed on the business operation. In this state, the base case energy (diesel) and cost requirement for the hydraulic shovel was 4 liters/ barrel and 0.16 CAN$/ barrel of oil production, respectively. The base case energy (electricity) and cost requirement for the electrical shovel is 16 Kwh/ barrel 0.08 CAN$/ barrel of oil production, respectively.

### 4.10.2.2.1.2 Input Data and Assumptions for Improving the Reliability of Mining Hydraulic and Electric Shovels for Scenarios 1 to 4

This is similar to section 4.10.5.2.1 (98).

### 4.10.2.2.1.3 Results - Energy Profile for States 1 to 4 – Hydraulic Shovel

The reference case scenario for reliability improvement for a hydraulic shovel when operating under States 1 through 4 was simulated in LEAP (see Table 4-18).

**State 1**: LEAP estimates an energy demand of hydraulic shovels (diesel) as 974.06 million Gigajoule/year. By improving the reliability of the hydraulic shovel engine, the energy (diesel) will decrease to 826.56 of MM Gigajoule/year by the year 2050.

**State 2**: LEAP estimates an energy demand (diesel) in hydraulic shovels of 978.44 MM Gigajoule/year when the hydraulic shovel operates under state 2. By improving the reliability of the hydraulic shovel engine, the energy (diesel) will decrease to 829.88 of MM Gigajoule/year by the year 2050.

**State 3**: LEAP estimates an energy demand in the hydraulic shovel (diesel) of 1607.20 MM Gigajoule in year 2050. When the reliability is improved, energy demand will decrease to 756.92 MM Gigajoule/year.

**State 4:** An energy demand in the hydraulic shovel (diesel) of 1,984.12 MM Gigajoule/year 2050 was calculated. When the reliability is improved, energy demand will decrease to 1,651.59 MM Gigajoule/year.

Table 4-18: Hydraulic shovel energy demand (million Gigajoule)-State 1 to 4

| Energy | Electricity | | | |
|---|---|---|---|---|
| Scenario | 1 | 2 | 3 | 4 |
| Reference | 974.06 | 978.44 | 1607.20 | 1,984.12 |
| Reliability improvement | 826.56 | 829.88 | 756.92 | 1,651.92 |
| Total | 1,800.62 | 1,808.26 | 2,364.12 | 3,599.71 |

### 4.10.2.2.1.4 Results - Energy Profile for States 1 to 4 – Electric Shovel

The reference case scenario for reliability improvement in an electric shovel when operating under States 1 through 4 were simulated in LEAP (see Table 4-19).

**State 1**: LEAP estimates energy demand of electric shovels (electricity) to be 372.08 million Gigajoule/year for the year 2050. When reliability is improved, energy demand will decrease to 315.74 million Gigajoule/year

**State 2**: LEAP estimates energy demand in the electric shovel (electricity) to be 978.44 million Gigajoule/year. When reliability is improved, energy (electricity) will decrease by 829.88 million Gigajoule/year by the year 2050.

**State 3:** LEAP estimates (electricity) energy demand of 375.80 million Gigajoule/year by the year 2050 for the electric shovel. When reliability is improved, energy demand will decrease to 318.79 million Gigajoule/year.

**State 4**: Energy demand (electricity) of 13,746.94 million Gigajoule/year 2050 was calculated for the shovel in under State 4. When reliability is improved, energy demand will decrease to 26,041.09 million Gigajoule/year.

Table 4-19: Electric shovel energy demand (million Gigajoule)-State 1 to 4

| Energy | Electricity | | | |
|---|---|---|---|---|
| Scenario | 1 | 2 | 3 | 4 |
| Reference1 to 4 | 372.08 | 375.80 | 429.76 | 13,746.94 |
| Reliability improvement1 to 4 | 315.74 | 318.79 | 364.22 | 12,294.15 |
| Total | 687.82 | 694.59 | 793.97 | 26,041.09 |

### 4.10.2.2.1.5 Energy Saving Results from the E-R Model for Oil Sands Hydraulic Shovels Operating Under State 1 to 4

Energy demands for a hydraulic shovel were plotted in LEAP over 40 years for both the reference case and Scenarios 1 to 4 and are shown in Figure 4-17 to 4-20.

For Scenario 1 (State 1), plotted energy demand for the hydraulic shovel for the years 2010 to 2050 indicates an average energy savings of 0.12 % per year through improving the reliability of the hydraulic shovel engine in a fully operational shovel (see Figure 4-17).

For Scenario 2 (State 2), there is 0.15% energy saving per year on average through improving the reliability of the hydraulic shovel (see Figure 4-18).

For Scenario 3 (State 3), there is on average 0.11% energy saving per year through improving the reliability of the hydraulic shovel (see Figure 4-19).

For Scenario 4 (Sate 4), there is on average 0.15% energy saving per year through improving the reliability of the hydraulic shovel engine (see Figure 4-20).

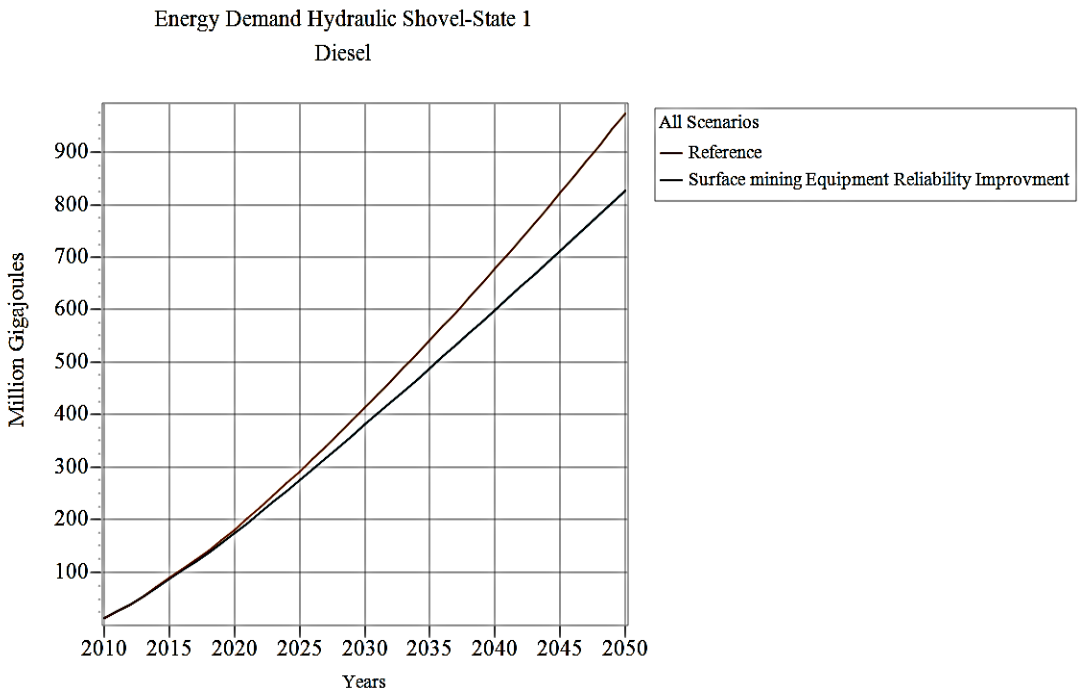



Figure 4-17: Hydraulic shovel energy saving from 2010–2050: Scenario 1 vs reference scenario 1

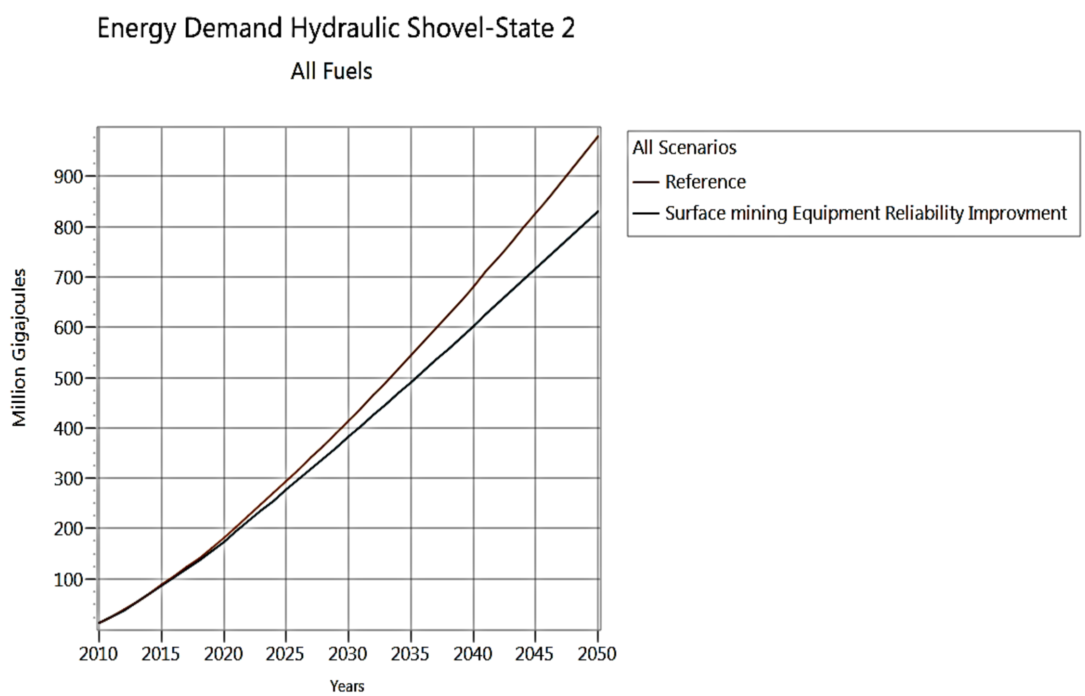



Figure 4-18: Hydraulic shovel energy saving from 2010–2050: Scenario 2 vs reference scenario 2

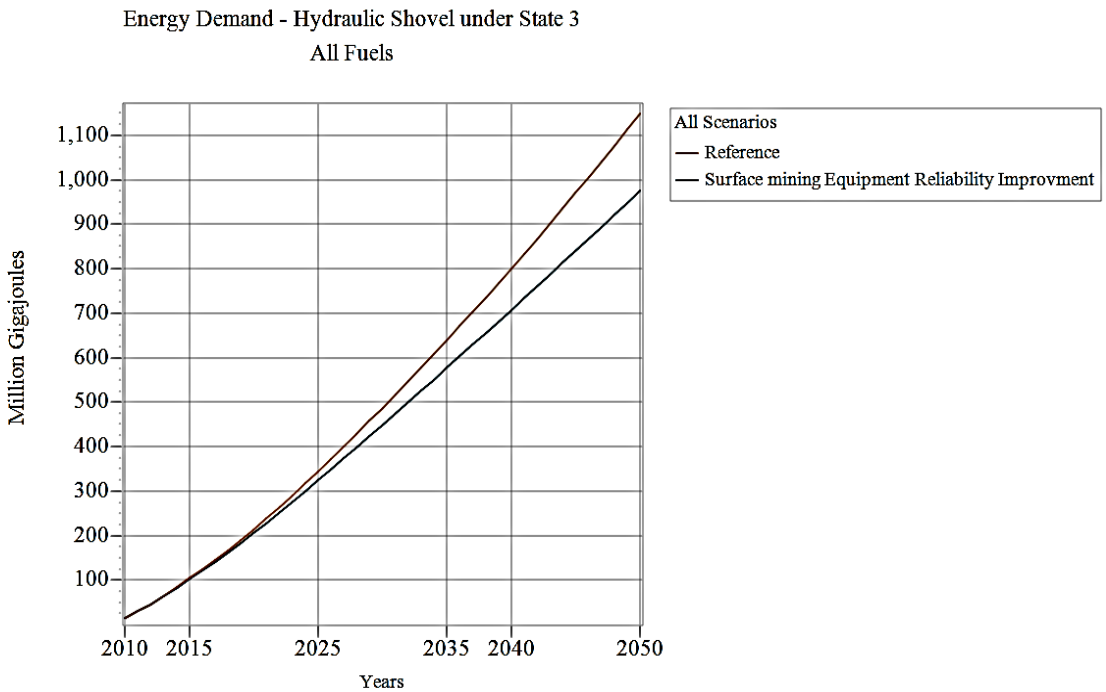



Figure 4-19: Hydraulic shovel energy saving from 2010–2050: Scenario 3 vs reference scenario 3

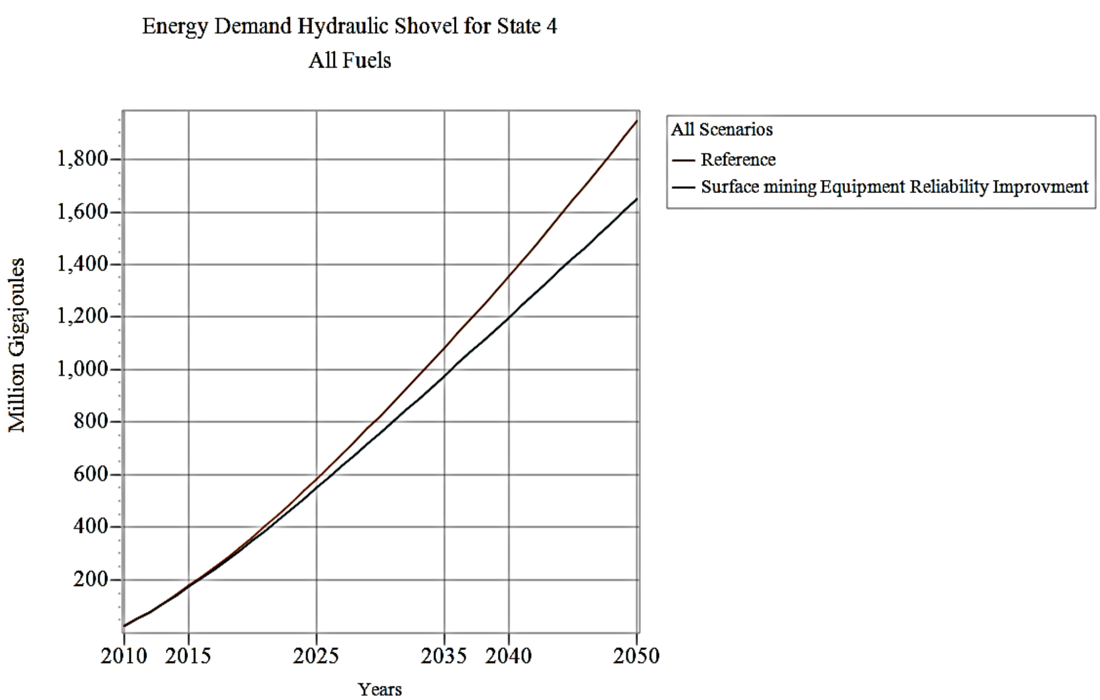



Figure 4-20: Hydraulic shovel energy saving from 2010–2050: Scenario 4 vs reference scenario 4

### 4.10.2.2.1.6 Energy Saving Results from the E-R Model for Electric Shovels Operating Under States 1 to 4

Energy demand for an electric shovel was plotted in LEAP over 40 years for both the reference case and Scenarios 1 to 4 and is shown in Figure 4-4.

For Scenario 1 (State 1), plotted energy demand over the years 2010 to 2050 shows an average energy saving of 0.11 % per year through improving the reliability of the electric shovel (see Figure 4-21).

For Scenario 2 (State 2), there is an average energy saving of 0.151 % per year when the reliability of an electric shovel is improved (see Figure 4-22).

For Scenario 3 (State 3), there is an average energy saving of 0.152% per year when the reliability of an electric shovel is improved (see Figure 4-23).

For Scenario 4 (State 4), there is an average energy saving of 0.11 % per year when the reliability of an electric shovel is improved (see Figure 4-24).

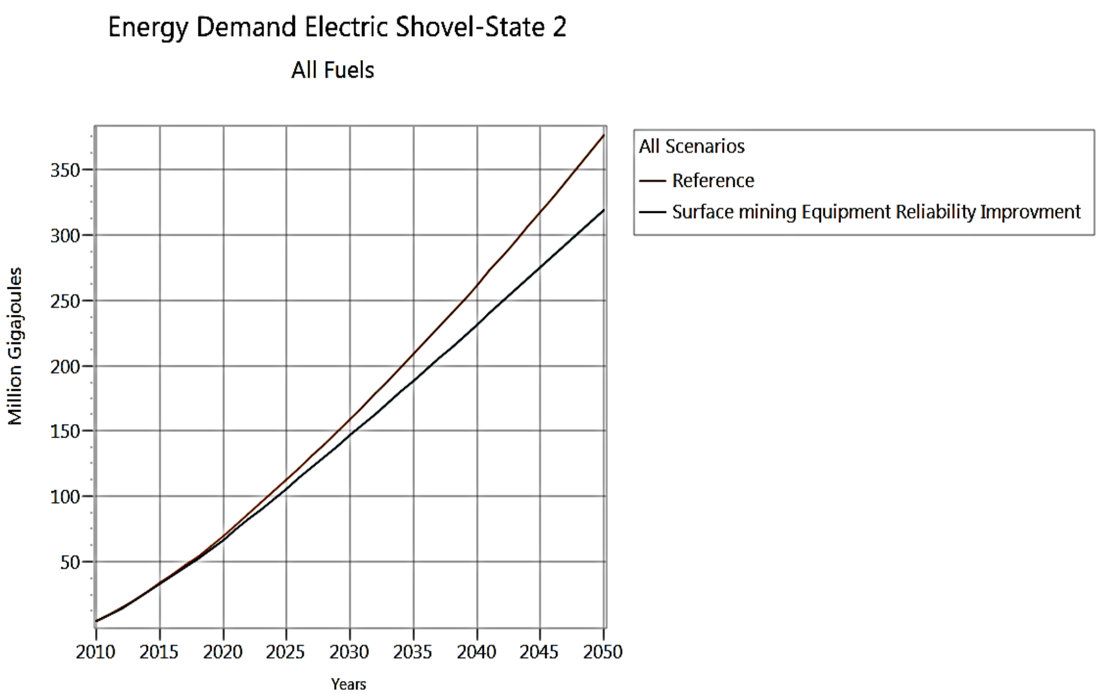



Figure 4-21: Electric shovel energy saving from 2010–2050: Scenario 2 vs reference scenario-State 2

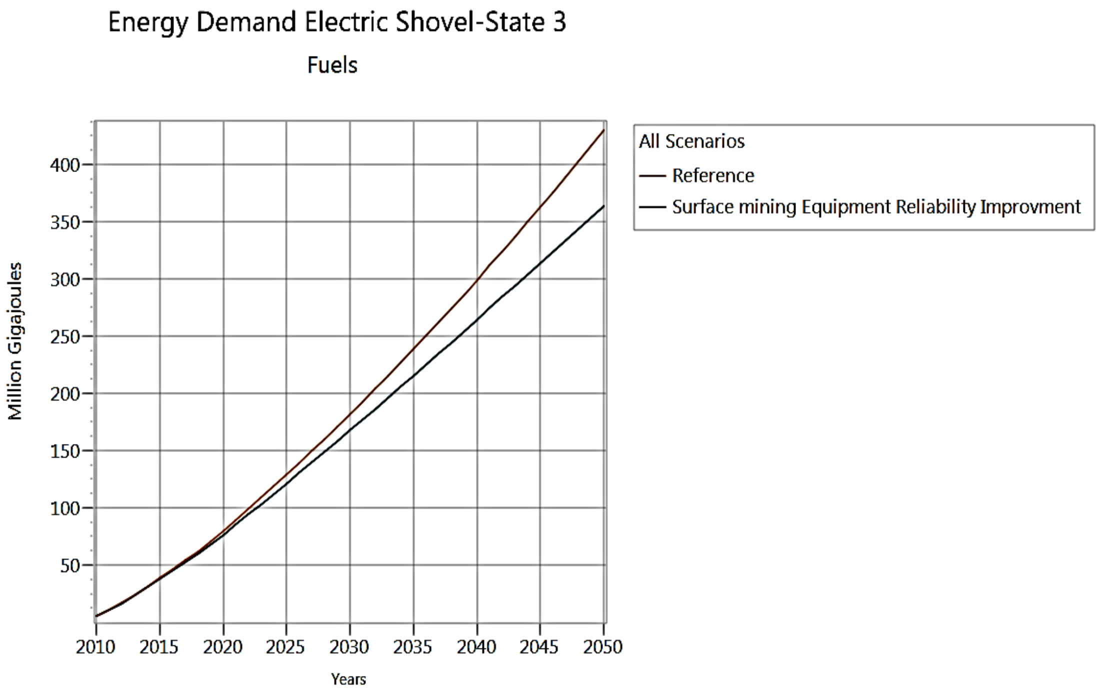



Figure 4-22: Electric shovel energy saving from 2010–2050: Scenario 3 vs reference scenario-State 3

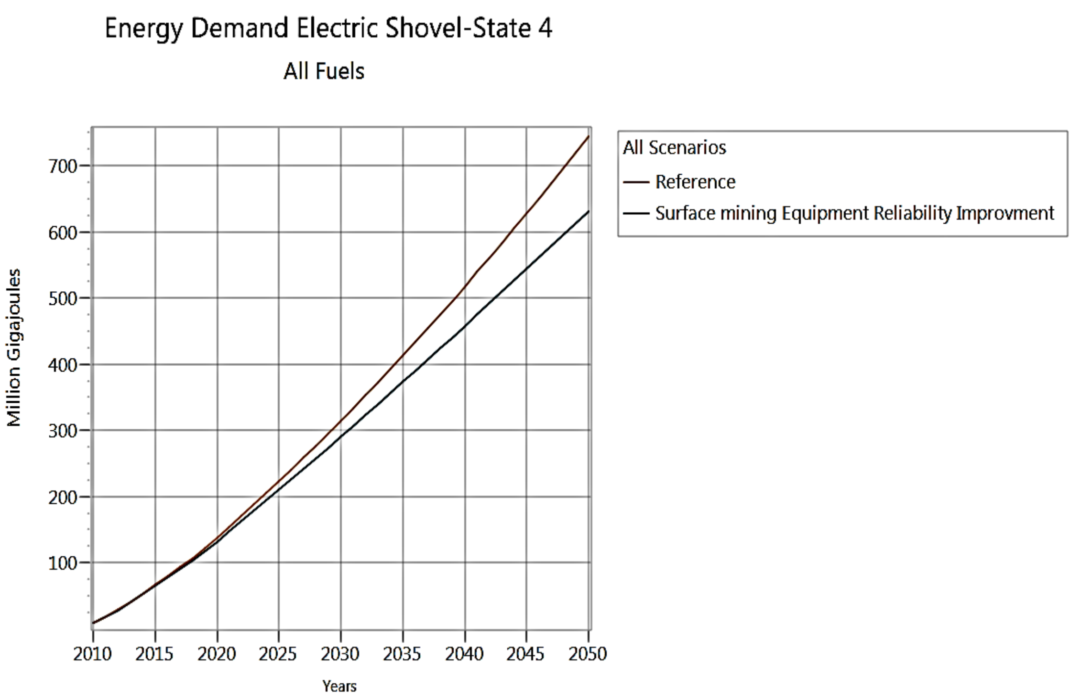



Figure 4-23: Electric shovel energy saving from 2010–2050: Scenario 4 vs reference scenario-State 4

### 4.10.2.2.1.7 Cost Saving Results from the E-R Model for Oil Sands Hydraulic Shovels Operating Under State 1

Oil sands mining hydraulic shovel operational costs were plotted over 40 years (2010-2050) for the reference case and Scenarios 1 to 4 (see Figures 4-25 to 4-28).

For Scenario 1, as the graph in Figure 4-25 shows, an average cost saving of 0.94% per year can be reduced through improving the reliability of a hydraulic shovel.

For Scenario 2 (State 2), there is an average cost saving of 0.73% per year through improving the reliability of a hydraulic shovel (see Figure 4-26).

For Scenario 3, there is an average cost saving of 0.71% per year through improving the reliability of a hydraulic shovel. Although the cost of improving reliability will increase until the year 2025 due to maintenance costs, the operating cost will decrease from 4,909.43 MM CAN$ to 1,407.31 MM CAN$ in 2050 (see Figure 4-27).

For Scenario 4 (State 4), there is an average cost saving of 0.67% per year annually through improving the reliability of a shovel. Although maintenance costs will increase the costs of improving reliability until 2025, the operating cost will decrease from 5,684.06 MM CAN$ to 1,893.49 MM CAN$ in 2050 (see Figure 4-28).

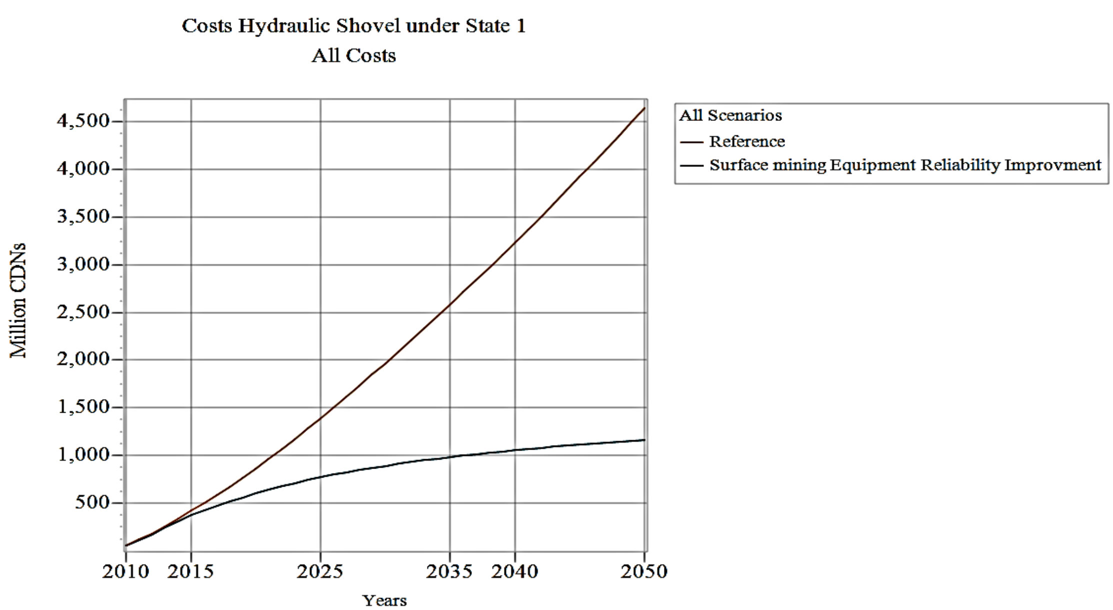



Figure 4-24: Hydraulic shovel costs saving–Scenario 1 vs reference scenario 1

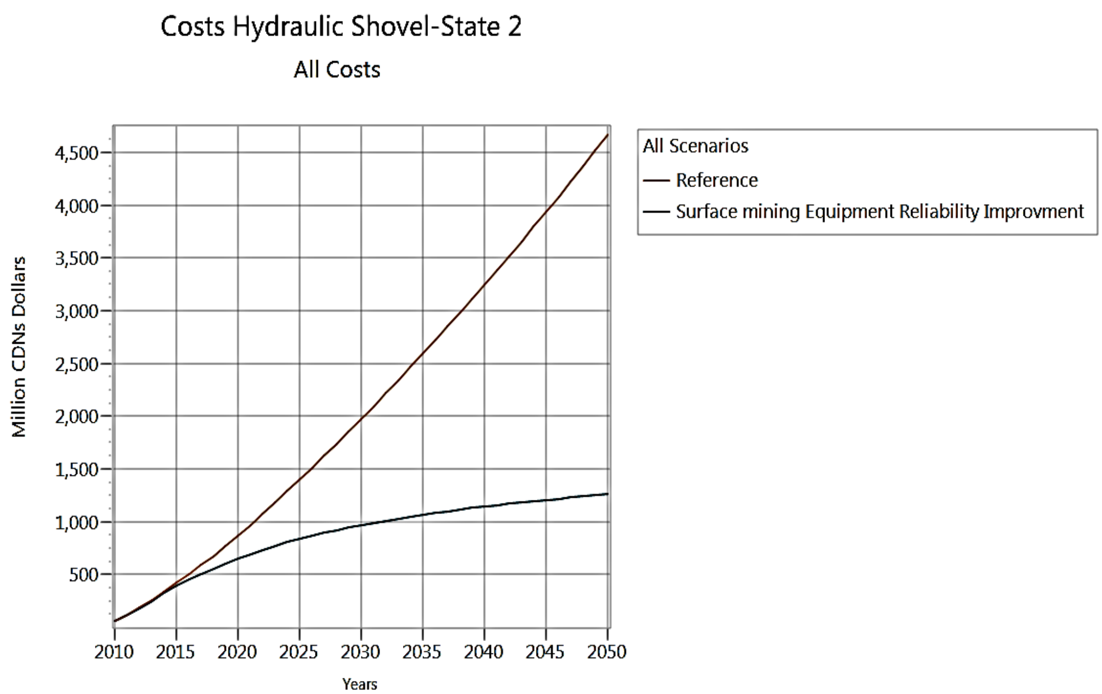



Figure 4-25: Hydraulic shovel costs saving –Scenario 2 vs reference scenario 2

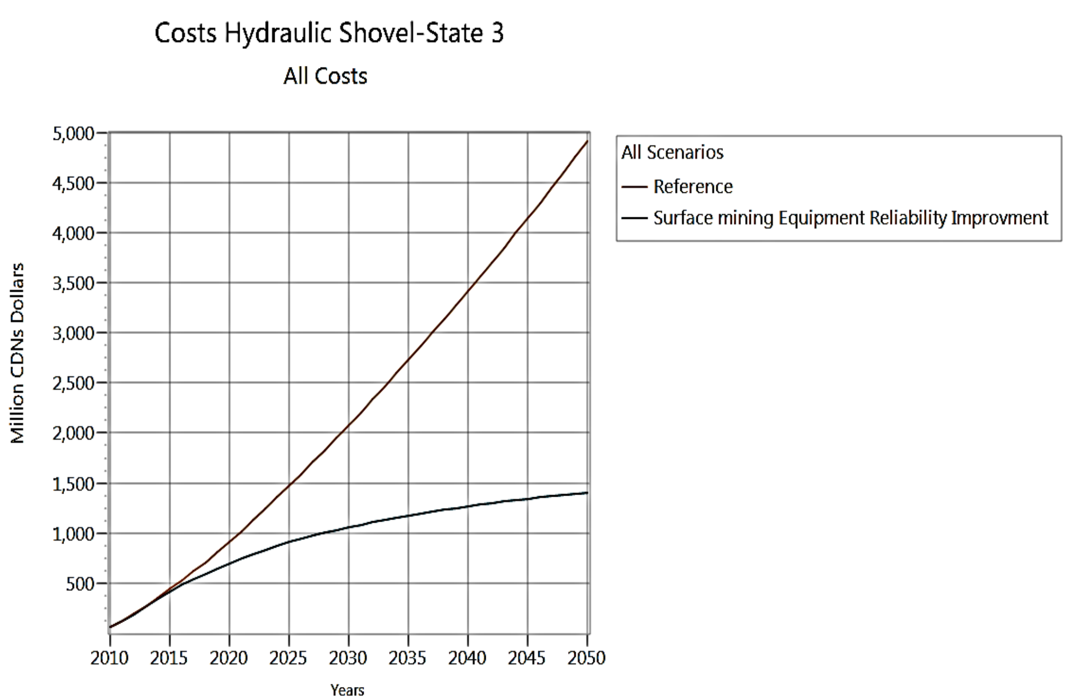



Figure 4-26: Hydraulic shovel costs saving –Scenario 3 vs reference scenario 3

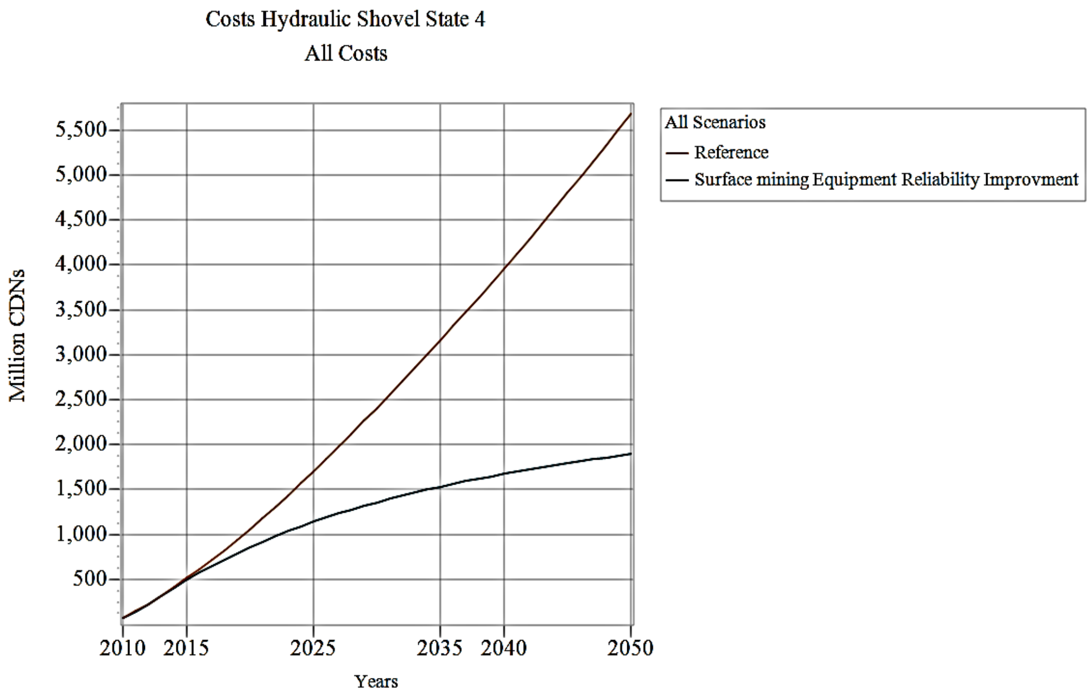



Figure 4-27: Hydraulic shovel costs saving –Scenario 4 vs reference scenario 4

## 4.10.2.2.1.7 Cost Saving Results from the E-R Model for Oil Sands Electric Shovels Operating Under States 1 to 4

Oil sands mining electric shovels operational costs were plotted over 40 years (2010-2050) for the reference case and Scenarios 1 to 4 (see Figures 4-29 to 4-32).

For Scenario 1, as the graph in Figure 4-29 shows, on average 0.78% of annual costs can be reduced through improving reliability of an electric shovel.

For Scenario 2 (State 2), there is on average 0.77% cost saving annually through improving reliability of an electric shovel (see Figure 4-30).

For Scenario 3, there is on average 0.76% cost saving annually through improving reliability of an electric shovel (see Figure 4-31).

For Scenario 4 (State 4), there is on average 0.73 % cost saving annually through improving reliability of an electric shovel. The costs of improving reliability will decrease from 4,702.71 MM CAN$ to 1,270.86 MM CAN$ in 2050 (see Figure 4-32).

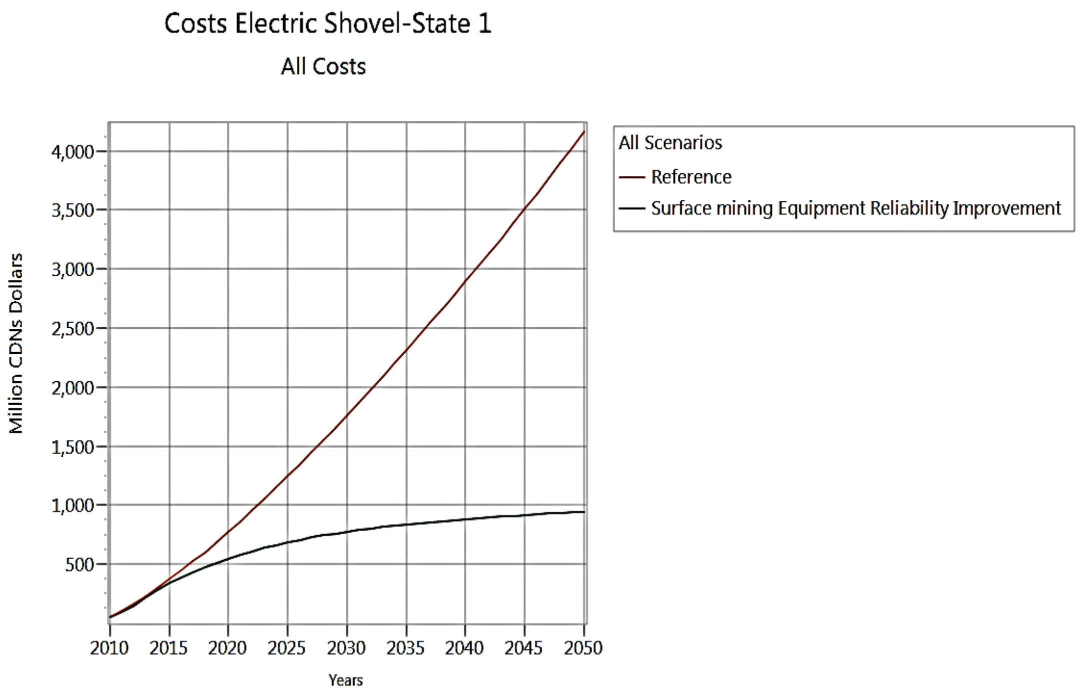



Figure 4-28: Electric shovel costs saving –Scenario 1 vs reference scenario 1-State 1

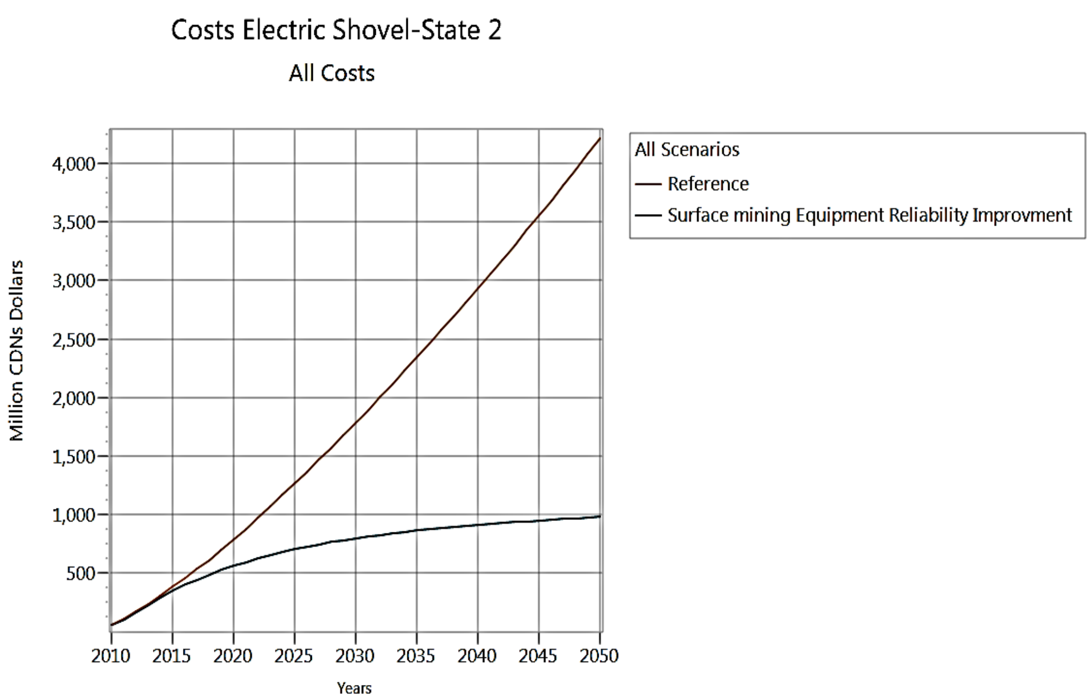



Figure 4-29: Electric shovel costs saving –Scenario 2 vs reference scenario 2-State 2

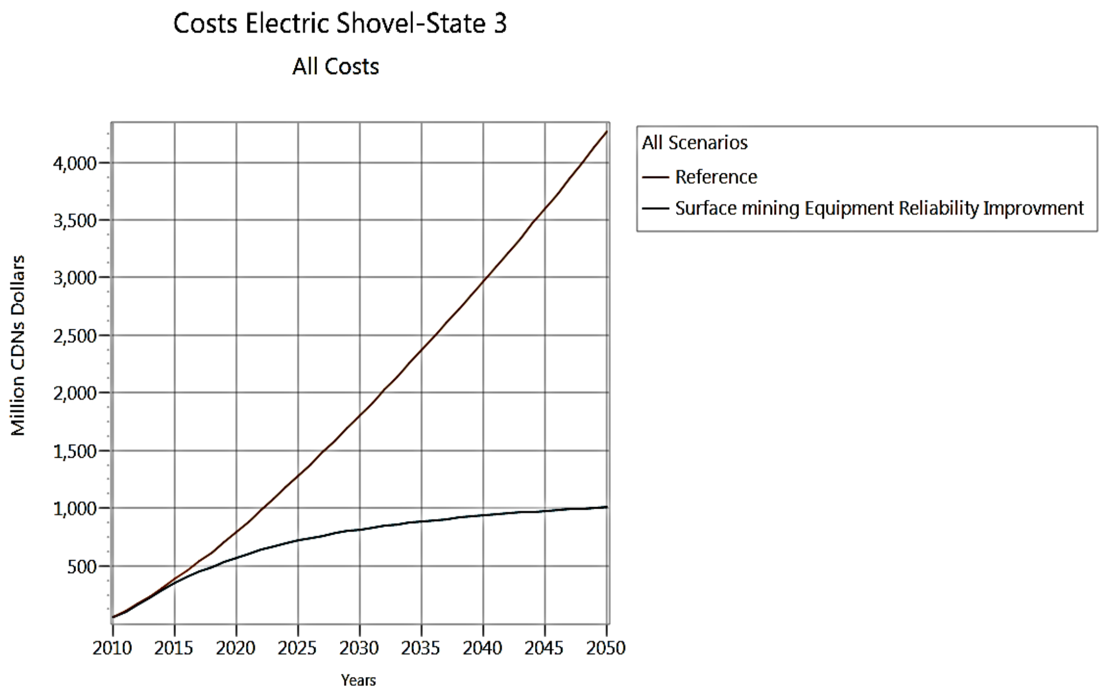



Figure 4-30: Electric shovel costs saving –Scenario 3 vs reference scenario 3-State 3

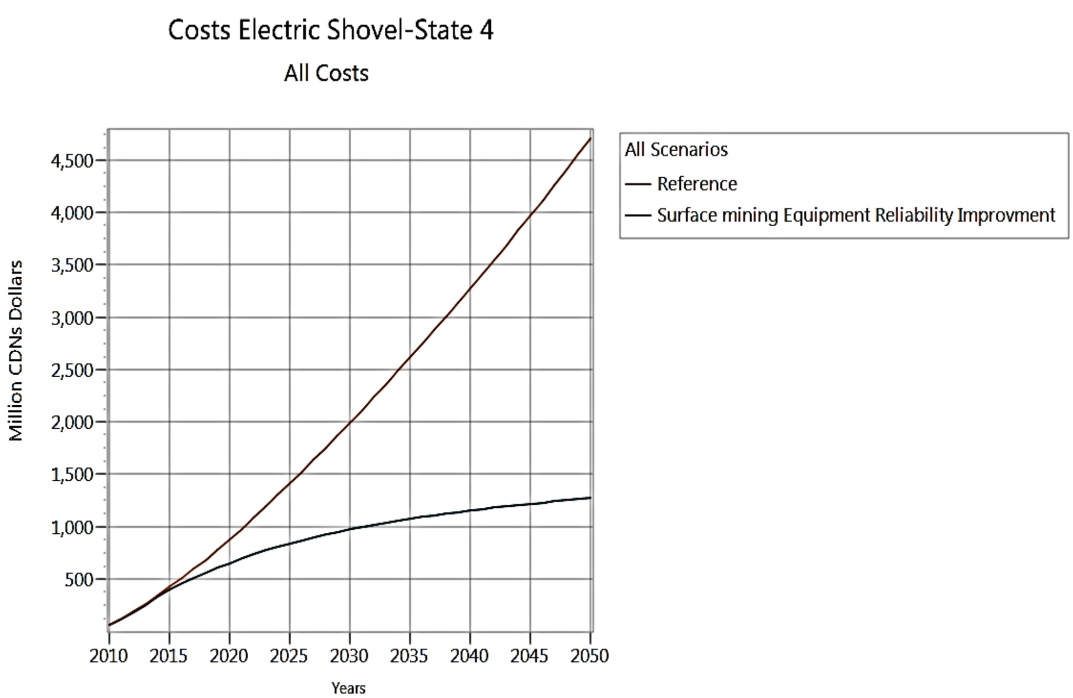



Figure 4-31: Electric shovel costs saving –Scenario 4 vs reference scenario 4-State 4

#### 4.10.2.2.1.8 GHG Emission Results from the E-R Model for an Oil Sands Hydraulic Shovel Operating Under States 1 to 4

Oil sands mining hydraulic shovel GHG emissions were plotted over 40 years (2010-2050) for the reference case and Scenarios 1 to 4 (see Figures 4-33 to 4-36).

**For Scenario 1 (State 1):** The results show that when the reliability of (State 1) mining hydraulic shovel is improved, GHG emissions can be reduced on average 0.15 % per year (see Figure 4-33 and Table 4-20)

**For Scenario 2 (State 2):** By improving reliability of a hydraulic shovel, an average GHG emissions saving of 0.16 % in a year. The GHG emission for a mining hydraulic shovel when operating under expected working conditions will be 30.18 and 71.21 million metric tonnes of $CO_2$ in year 2030 and 2050, respectively. After improving the reliability of hydraulic shovel, GHG emissions will decline to 27.83 MT/year by 2030 and 60.39 MT/year by 2050 (see Figure 4-34 and Table 4-21).

**For Scenario 3 (State 3):** By improving the reliability of hydraulic shovels, GHG emissions can be reduced on average 0.15% yearly(see Figure 4-35 and Table 4-22).

**For Scenario 4 (State 4):** By improving the reliability of the hydraulic shovel, GHG emissions can be reduced on average 0.16 % per year(see Figure 4-36 and Table 4-23).

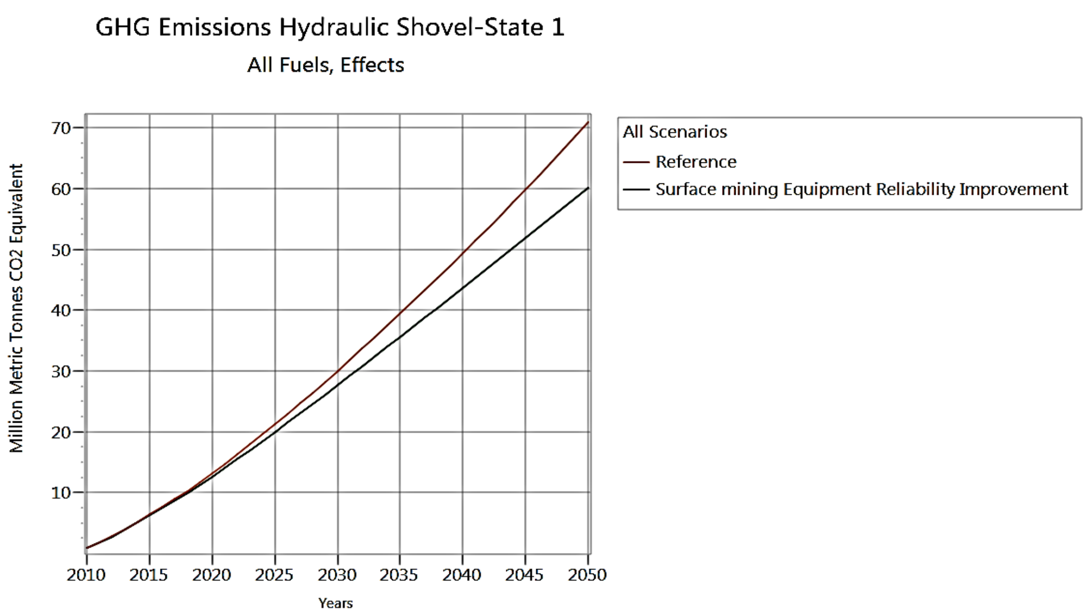



Figure 4-32: GHG emissions for oil sands mining hydraulic shovel: Scenario 1 vs reference scenario

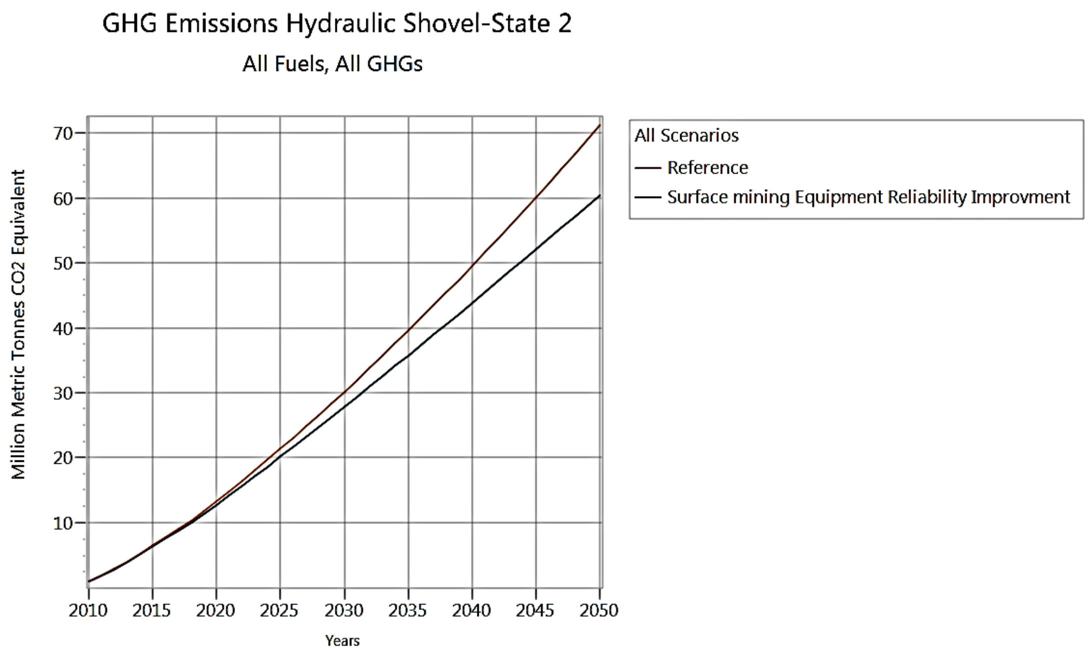



Figure 4-33: GHG emissions saving for hydraulic shovel: Scenario 2 vs reference scenario

Table 4-20: Hydraulic shovels, GHGs Emissions – Year 2050 (million metric tonnes $CO_2$ equivalent)-State 1

| Scenarios | Nitrous Oxide | Methane | Carbon Dioxide Non Biogenic | Total |
|---|---|---|---|---|
| Reference | 5.77 | 1.30 | 2,249.64 | 2,256.71 |
| Reliability Improvement | 4.27 | 0.96 | 1,664.73 | 1,669.96 |
| Total | 10.04 | 2.27 | 3,914.37 | 3,926.67 |

Table 4-21: Hydraulic shovels, GHGs Emissions – Year 2050 (million metric tonnes $CO_2$ equivalent) –State 2

| Scenarios | Nitrous oxid | Methane | Carbon dioxide non biogenic | Total |
|---|---|---|---|---|
| Reference | 5.79 | 1.31 | 2,259.76 | 2,266.86 |
| Reliability Improvement | 4.27 | 0.96 | 1,664.73 | 1,669.96 |
| Total | 10.06 | 2.27 | 3,924.50 | 3,936.83 |

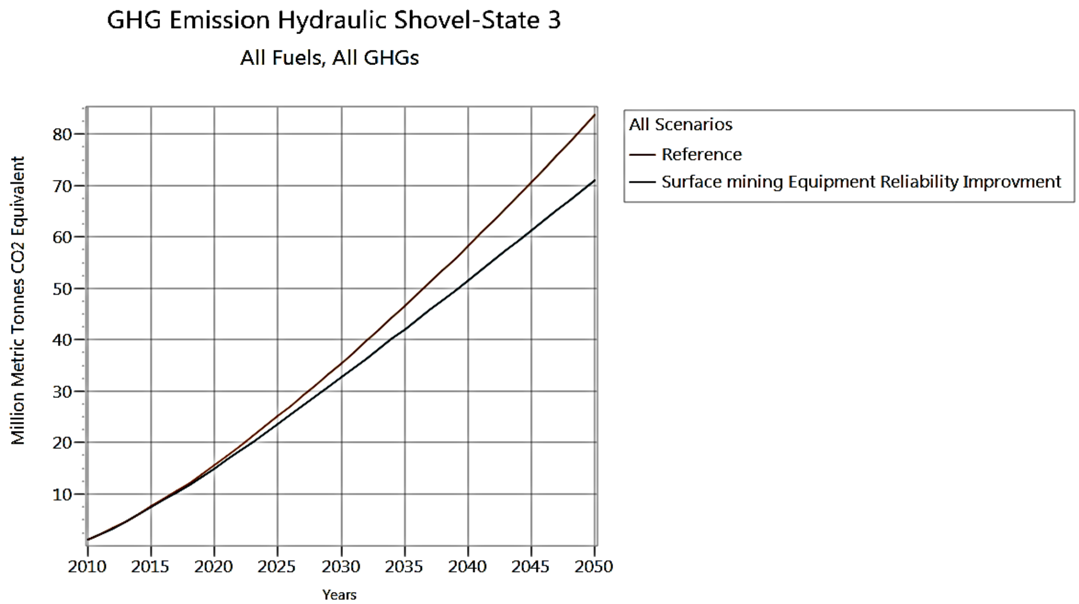



Figure 4-34: GHG emissions saving for hydraulic shovel – Scenario 3 vs reference scenario 3-State 3

Table 4-22: Hydraulic shovels, GHGs Emissions – Year 2050 (million metric tonnes $CO_2$ equivalent) – State 3

| Scenarios | Nitrous oxide | Methane | Carbon dioxide non biogenic | Total |
|---|---|---|---|---|
| Reference | 6.81 | 1.54 | 2,654.57 | 2,662.92 |
| Reliability Improvement | 5.05 | 1.14 | 1,968.43 | 1,974.62 |
| Total | 11.85 | 2.68 | 4,623.01 | 4,637.54 |

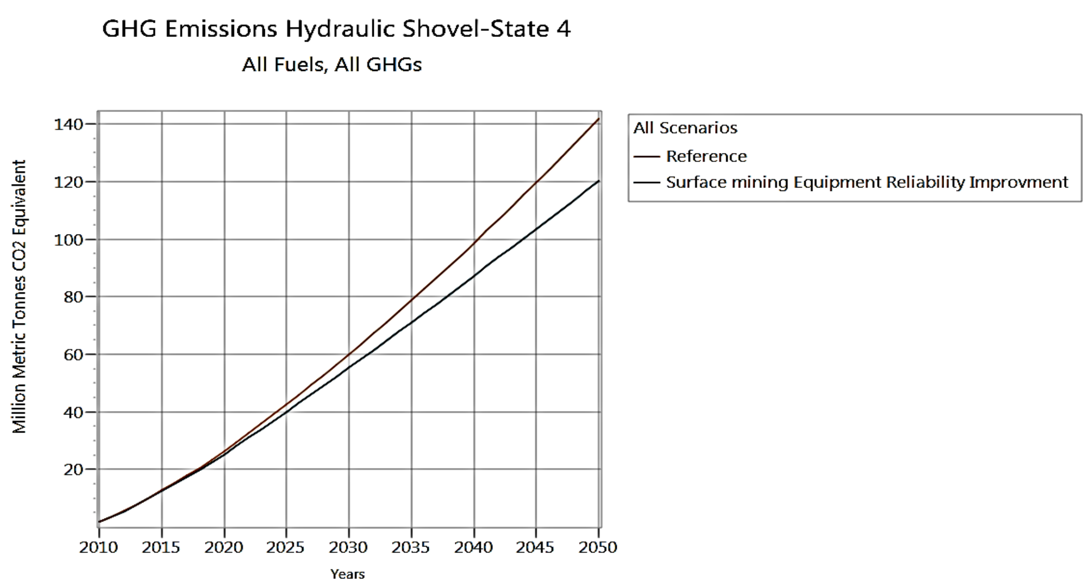



Figure 4-35: GHG emissions saving for hydraulic shovel – Scenario 4 vs reference scenario-State 4

Table 4-23: Hydraulic shovels, GHGs Emissions-Year 2050 (million metric tonnes $CO_2$ equivalent) – State 4

| Scenarios | Nitrous oxide | Methane | Carbon dioxide non biogenic | Total |
|---|---|---|---|---|
| Reference | 11.54 | 2.60 | 4,499.28 | 4,513.42 |
| Reliability Improvement | 8.51 | 1.92 | 3,318.22 | 3,328.65 |
| Total | 20.04 | 4.53 | 7,817.50 | 7,842.06 |

## 4.10.3 Oil Sands Mining Crusher - Introduction

In this section, a method to link reliability and energy demand for the oil sands mining crusher was developed. The scope of this model encompasses all the processes of specific components or sub-components of a crusher that impact on energy consumption. It was assumed that only the drive system and apron feeder has a direct impact on energy consumption. If either of these components partially fails, the crusher can operate, but the crusher consumes more energy consumption and emits more GHGs than otherwise.

### 4.10.3.1 E-R Model for the Crusher

The LEAP software models the crushing process based on energy use and supply to simulate various scenarios of energy demand. The following assumptions were made in modeling:

- Only the drive system and apron feeder are considered to have an energy impact under partial reliability (91).
- The crusher drive system and apron feeder are considered in this research to have the same energy demand.
- Crusher capital cost was $24,000,000 (100).

An apron feeder is a mechanical feeder used to remove raw material from the dump hopper, bins, and stockpiles. The electric drive system has several benefits, i.e., it makes the particle size consistent through speed control (101, 102).

The scope of this section includes the development of the energy demand model for oil sands surface mining crushers using LEAP. The drive system and apron feeder are part of the crusher subsystem and a demand tree was developed in LEAP for them.

#### 4.10.3.1.1 Calculating Partial Reliability for the Critical Parts of a Crusher

Using Equations 4-1 to 4-4 and similar calculations from section 4.2.2, partial reliability for the crusher's apron feeder and drive system reliability were calculated and are shown in Table 4-24.

Table 4-24: Calculated partial reliability for critical parts in a crusher

| No. | Critical part of crusher | P (Probability of failure*) | R (Reliability*) | $\lambda_1$ | $\lambda_2$ | $P_{new}$ (Probability of partial failure**) | $R_{new}$ (Partial reliability**) |
|---|---|---|---|---|---|---|---|
| 1 | Apron feeder (APF) | 0.04 | 0.96 | 0.04 | 4.25 | 0.37 | 0.63 |
| 2 | Drive system (DSF) | 0.17 | 0.83 | 0.2 | 2.16 | 0.31 | 0.69 |

*taken from chapter 3

**Partial probability of failure and Partial reliability

### 4.10.3.2 Energy Modeling for the Crusher Using LEAP

To determine energy efficiency, an E-R model was developed through LEAP for all four operational states based on the discrete Markov model for repairable systems for the base year 2010 of crusher. The model was then used to find the total GHG emissions. The "improving mining equipment reliability" scenario and the reference scenario for each equipment state were built and run in this model to determine total energy and GHG emissions saved. There is good potential to save energy, reduce GHG emissions, and improve reliability through the use of energy efficient crushers. The contribution from the reference scenario and each "improving reliability" scenario in each state is important, and the amount of energy savings will increase when production levels increase. Figure 4-37 shows the energy demand tree for a crusher. Some assumptions were made to model energy intensity in LEAP, i.e., final energy consumption for the drive system and apron feeder are 0.25 kilowatt-hour/barrel and 0.25 kilowatt-hour/barrel, respectively (91).

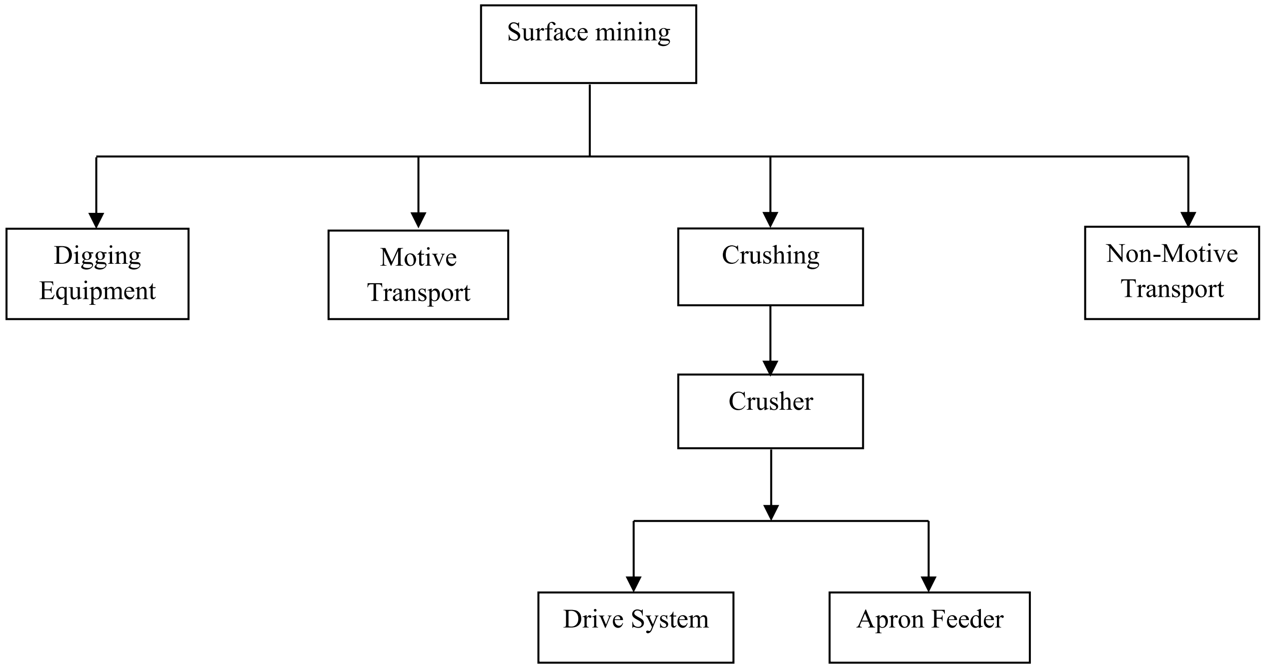



Figure 4-36: Crusher energy demand tree

### 4.10.3.3 The E-R Model Results for a Crusher

A suitable approach to link reliability and energy consumption for a crusher was developed. With Equations 4-1 to 4-4 and similar calculations from section 4.10.1.4, the crusher's apron E-R model's output for the drive system and apron feeder are shown in Table 4-25 to Table 4-28.

Table 4-25: E-R model for the oil sands mining crusher on Apron feeder energy in terms of cost (apron feeder)

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra cost (CAN$/bbl) | Total cost (CAN$/bbl) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0 | 0.298 |
| 2 | Expected working | 0.96 | 10 | 90 | 0.01 | 0.004 | 0.001 | 0.300 |
| 3 | Partial reliability | 0.63 | 50 | 50 | 0.025 | 0.18 | 0.054 | 0.352 |
| 4 | Failed | 0 | 100 | 0 | 1 | 1 | 0.289 | 0.587 |

Table 4-26: E-R model for the mining crusher based on Apron feeder for States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy-diesel lit/bbl) | Fuel intensity (electricity, Kwh/bbl) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.250 |
| 2 | Expected working | 0.96 | 10 | 90 | 0.01 | 0.001 | 0.251 |
| 3 | Partial reliability | 0.63 | 50 | 50 | 0.025 | 0.045 | 0.3 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.25 | 0.5 |

Table 4-27: E-R model for the oil sands mining crusher in terms of cost (drive system)

| Number | States | Reliability | failure | Loss of capacity (%) | Capacity (%) | Fraction of Loss of Capacity= E L | Consequence of E L (CAN$/bbl) | Total Cost (CAN$/bbl ) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operated | 1 | 0 | 0 | 100 | 0 | 0 | 0.34 |
| 2 | Expected working | 0.96 | 0.17 | 10 | 90 | 0.01 | 0.002 | 0.35 |
| 3 | Partial reliability | 0.63 | 0.2 | 50 | 50 | 0.025 | 0.034 | 0.38 |
| 4 | Failed | 0 | 1 | 100 | 0 | 1 | 0.345 | 0.69 |

Table 4-28: E-R model for the mining crusher based on drive system for States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy-diesel lit/bbl) | Fuel intensity (electricity, Kwh/bbl) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.250 |
| 2 | Expected working | 0.83 | 10 | 90 | 0.01 | 0.001 | 0.251 |
| 3 | Partial reliability | 0.69 | 50 | 50 | 0.025 | 0.025 | 0.275 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.250 | 0.500 |

### 4.10.3.3 Mining Crusher Scenarios 1 to 4–States 1 to 4

These scenarios calculate the energy demand, total cost from mining crusher in Alberta's surface mining sector when a crusher operates under State 1 (fully operational), State 2 (expected operating), State 3 (partial reliability), and 4 (complete failure). The input data and assumption are given below.

#### 4.10.3.3.1 Input Data and Assumptions for Reference Scenario of a Crusher Operating Under States 1 to 4

State 1: Subramanyam et al. developed this scenario (page 7 of (91)) earlier . In the base case, electricity needed for a crusher is 0.5 Kwh/ barrel and the cost is 0.298 CAN$/ barrel of oil production for Apron feeder and 0.345 CAN$/ barrel of oil production for drive system. State 2: The E-R model shows that in State 2 the crusher requires extra 0.001 Kwh /bbl energy (electricity) for Apron feeder and drive system. The extra cost was calculated as 0.001 (CAN$/ barrel) for Apron feeder and 0.002 (CAN$/ barrel of oil production) for drive system. Therefore, the total energy for Apron feeder and drive system are similar as 0.250 Kwh / barrel and cost required for this state are 0.3 CAN$/ barrel of oil production for Apron feeder and 0.346 CAN$/ barrel of oil production for drive system.

State 3: The extra cost was calculated as 0.054 (CAN$/ barrel of oil production) for Apron feeder and 0.034 (CAN$/ barrel of oil production) for drive system. Therefore, the total energy for Apron feeder and drive system are similar as 0.295 Kwh / barrel and cost required for this state are 0.352 CAN$/ barrel of oil production for Apron feeder and 0.379 CAN$/ barrel of oil production for drive system.

State 4: In State 4, 0.25 Kwh/ barrel extra energy (in the form of electricity) for each Apron feeder and drive system is required. The extra cost was calculated as 0.054 (CAN$/ barrel of oil production) for Apron feeder and 0.034 (CAN$/ barrel of oil production) for drive system. Therefore, the total energy for Apron feeder and drive system are similar as 0.5 Kwh / barrel and cost required for this state are 0.587 CAN$/ barrel for Apron feeder and 0.689 CAN$/ barrel of oil production for drive system.

#### 4.10.3.3.2 Scenario: Improving the Reliability of Crusher for States 1 to 4

This is similar to section 4.10.1.5.2.

#### 4.10.3.3.3 Results - Energy Profile for States 1 to 4-Crusher

The reference case scenario for reliability improvement in a crusher when operating under State 1 (fully operational), State 2 (expected working), State 3 (partial reliability), and State 4 (complete failure) were simulated in LEAP.

State 1: LEAP estimated the energy demand of the crusher (electricity) to be 11.63 MM Gigajoule for the year 2050 (see Table 4-29).

State 2 LEAP estimated an energy demand in the crusher to be 11.67 MM Gigajoule/year. By improving the crusher reliability, the expected energy demand will decrease by 9.91 of MM Gigajoule /year by 2050 (see Table 4-29).

State 3: LEAP estimates energy demand of 1,607.20 MM Gigajoule/year by 2015 when the crusher is working under partial reliability. When the reliability is improved, energy demand is expected to decrease by 756.92 MM Gigajoule/year (see Table 4-29).

State 4: LEAP estimated an energy demand to be 11.67 MM Gigajoule/year. By improving the crusher's reliability, the expected energy demand will decrease by 9.91 of MM Gigajoule /year by 2050 (see Table 4-29).

Table 4-29: Mining crusher energy demand (million Gigajoule)-State 1 to 4-year 2050

| Electricity | | | | |
|---|---|---|---|---|
| Scenario | 1 | 2 | 3 | 4 |
| Reference | 11.63 | 11.67 | 421.97 | 23.26 |
| Reliability improvement | 9.87 | 9.91 | 307.23 | 19.73 |
| Total | 21.49 | 21.59 | 729.20 | 42.99 |

#### 4.10.3.3.4 Energy Saving Results from the E-R Model for an Oil Sands Crusher Operating Under States 1 to 4

State 1: Energy demand for the crusher was plotted in LEAP over 40 years for both the reference case and Scenario 1 and is shown in Figure 4-38. Plotted energy demand over a specific period (from 2010 to 2050) indicates that an average energy saving of 0.148% per year will be achieved through the reliability improvement of crusher when crusher working under state 1.

Scenario 2 (State 2): An average energy saving of 0.15% per year will be achieved through the reliability improvement of crusher when crusher working under state 2 (see Figure 4-39).

Scenario 3 (State 3): An average energy saving of 0.11% per year will be achieved through the reliability improvement of crusher when crusher working under state 3 (see Figure 4-40).

Scenario 4 (State 4): An average energy saving of 0.16% per year will be achieved through the reliability improvement of crusher when crusher working under state 4 (see Figure 4-41).

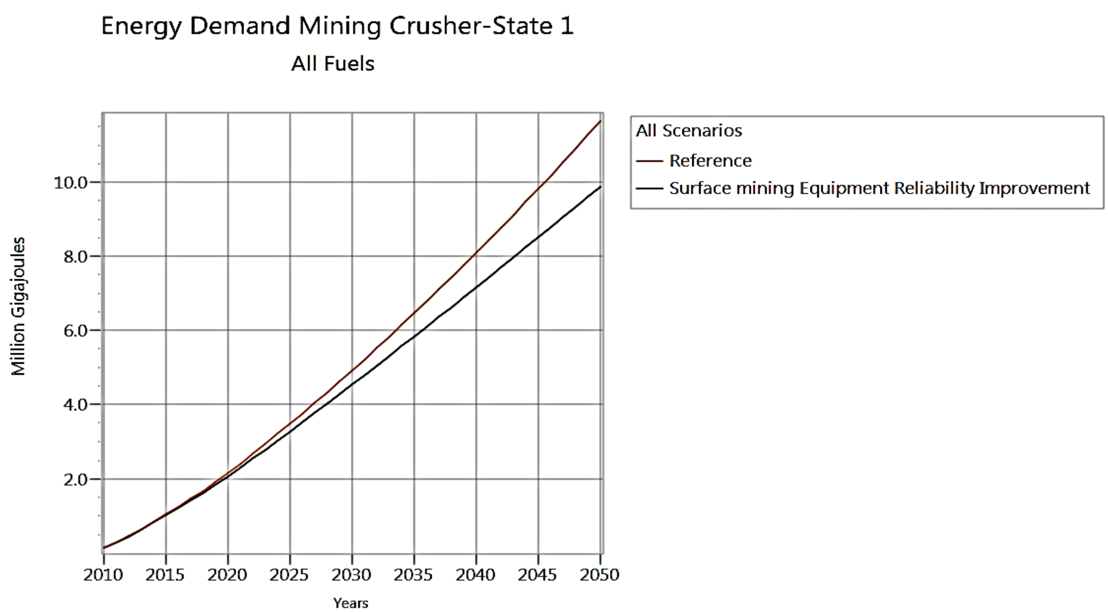



Figure 4-37: Energy saving for the mining crusher, 2010–2050: Scenario 1 vs reference scenario 1

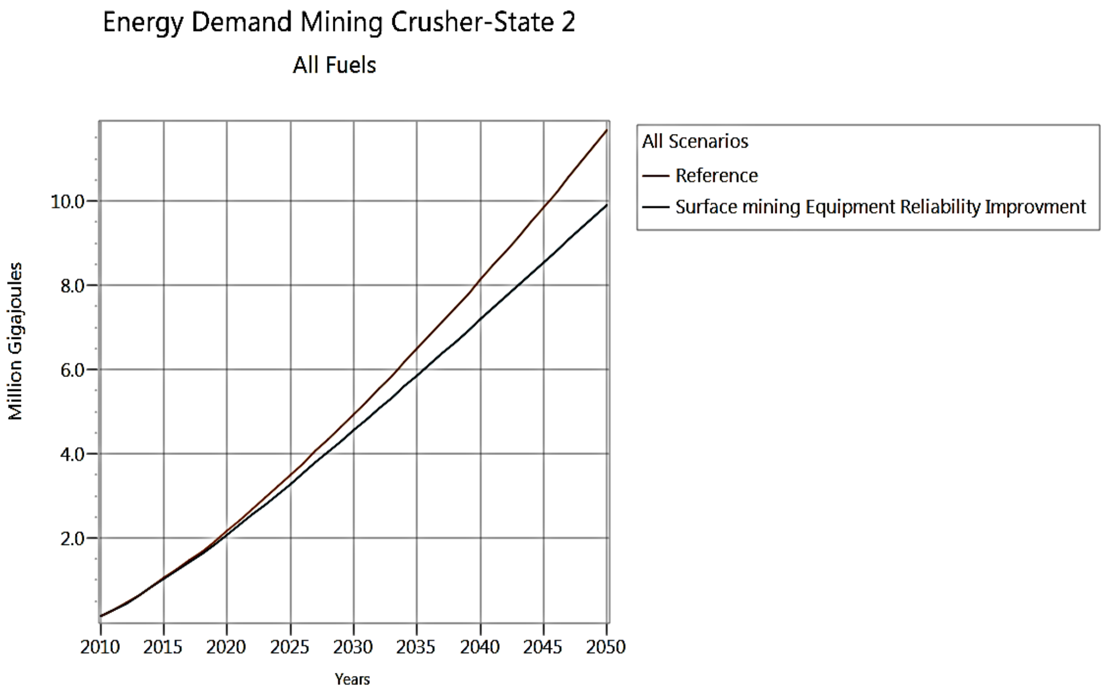



Figure 4-38: Energy saving for the mining crusher, 2010–2050: Scenario 2 vs reference scenario 2

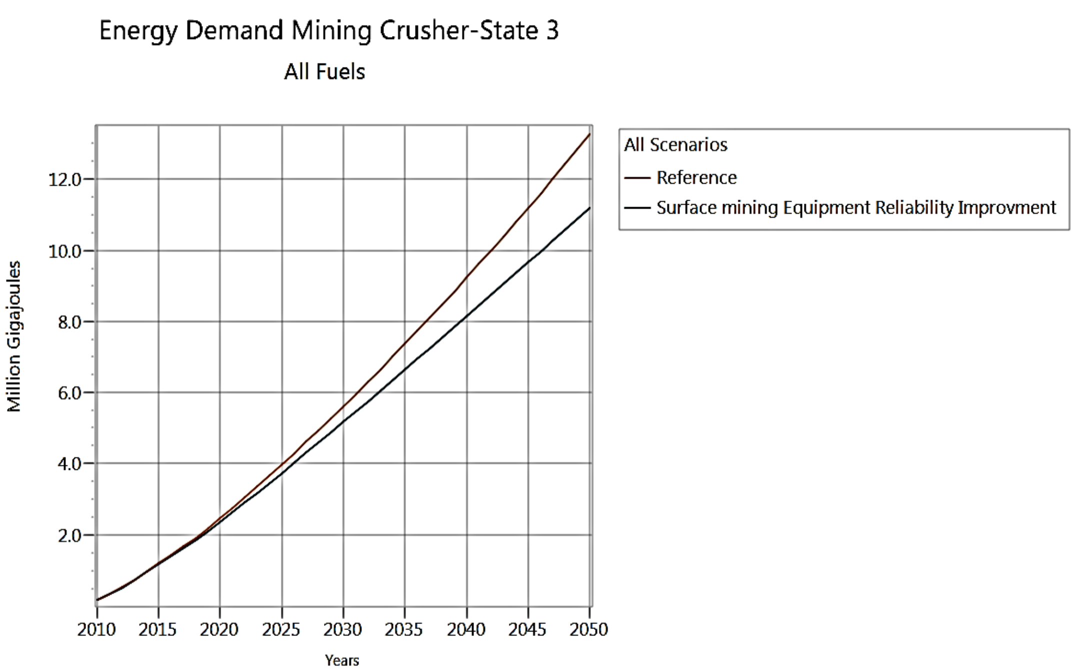



Figure 4-39: Energy saving for the mining crusher, 2010–2050: Scenario 3 vs reference scenario 3

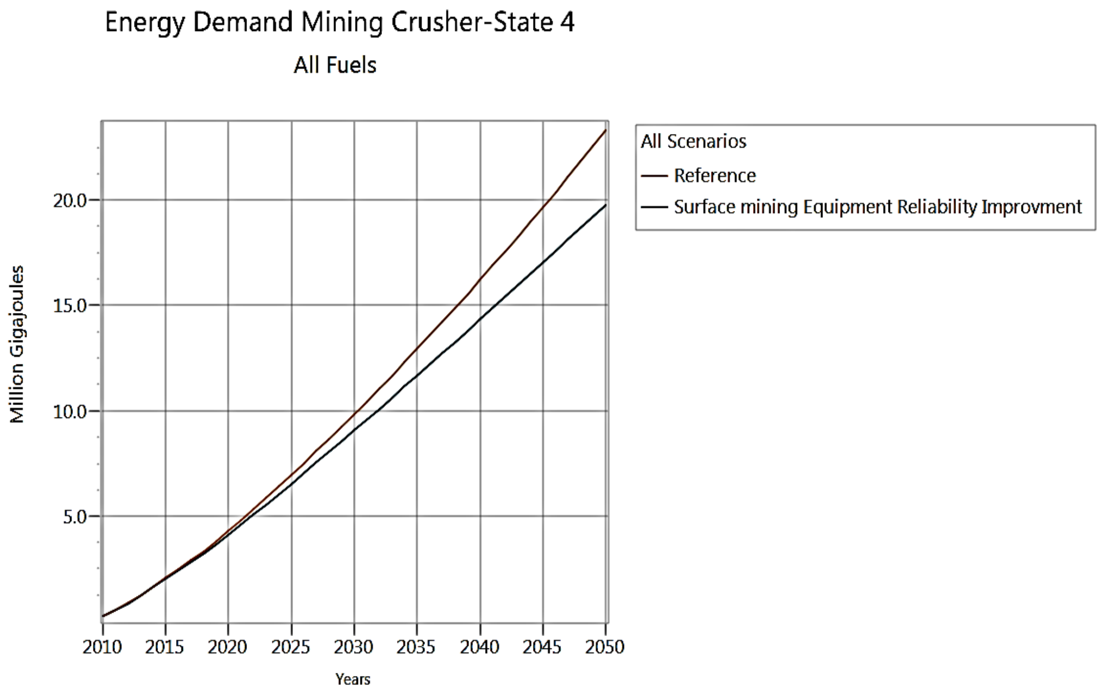



Figure 4-40: Energy saving for the mining crusher, 2010–2050: Scenario 4 vs reference scenario 4

#### 4.10.3.3.5 Cost Saving Results from the E-R Model for the Crusher Operating Under States 1 to 4

State 1: Operating costs for the crusher were plotted over 40 years (from 2010 to 2050) (see Figure 4-42). By improving crusher reliability, on average 0.77 % cost savings can be made.

State 2 (Scenario 2): An average cost saving of 0.77% per year will be achieved through the reliability improvement of crusher when crusher working under state 2 (see Figure 4-43).

State 3 (Scenario 3), there is on average 0.73% cost saving annually through improving the reliability of a mining crusher operating under state 3 (see Figure 4-44).

State 4 (Scenario 4), An average cost saving of 0.52% per year will be achieved through the reliability improvement of crusher when crusher working under state 4 (see Figure 4-45).

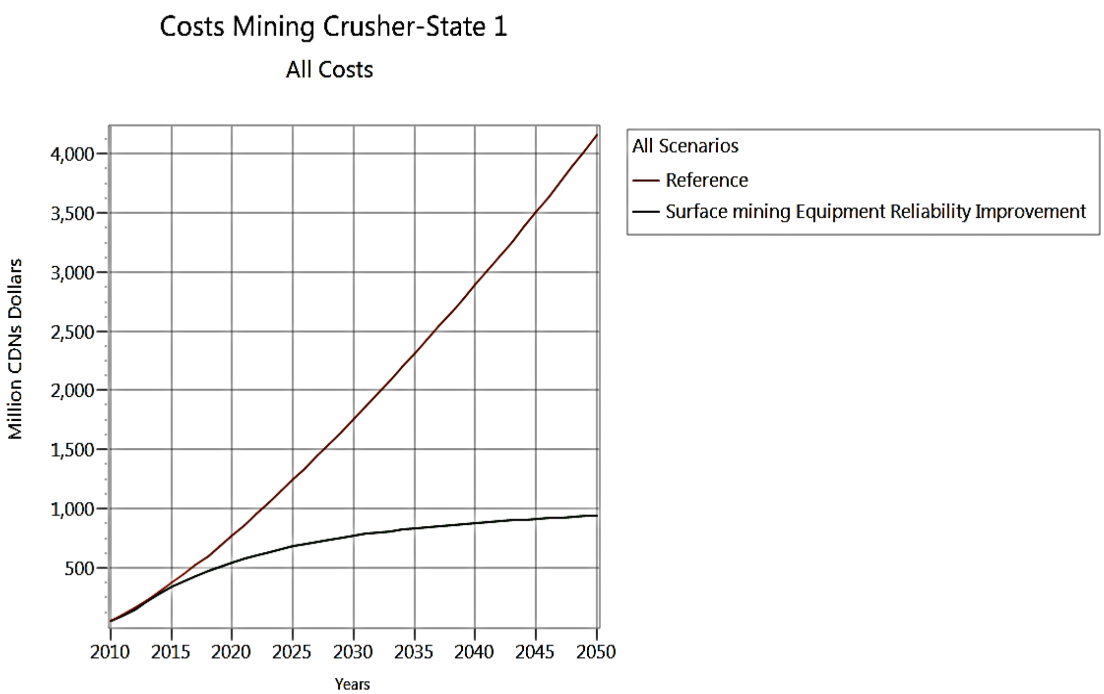



Figure 4-41: Oil sands crusher demand costs - improving reliability vs reference scenarios-State 1

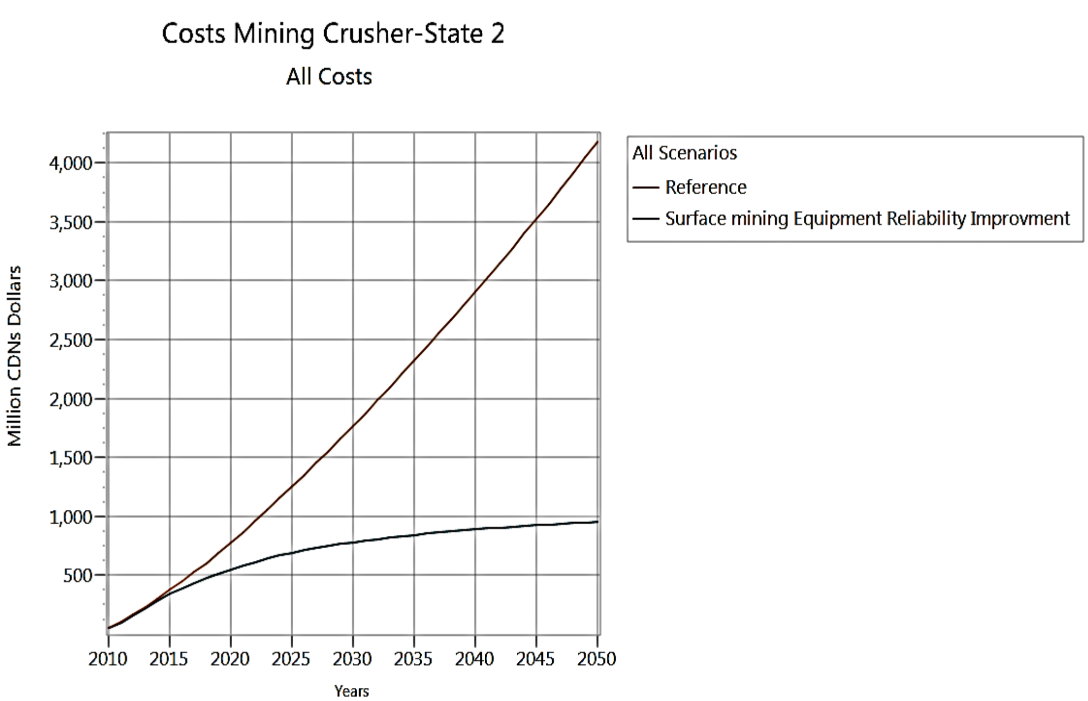



Figure 4-42: Oil sands crusher demand costs - improving reliability vs reference scenarios-State 2

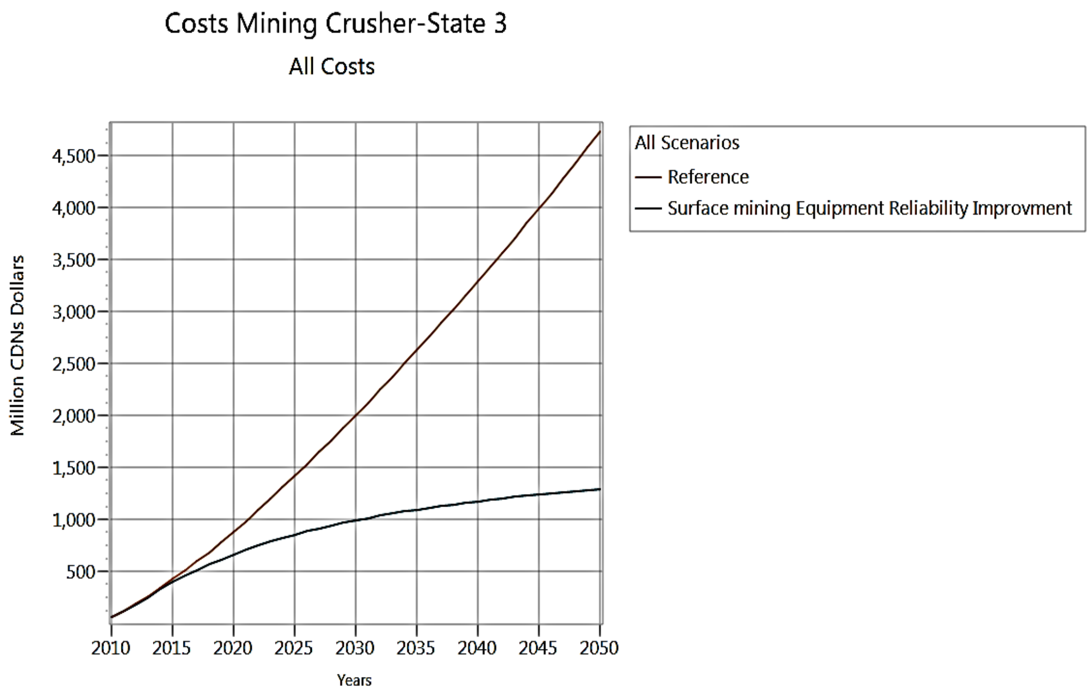



Figure 4-43: Oil sands crusher demand costs - improving reliability vs reference scenarios-State 3

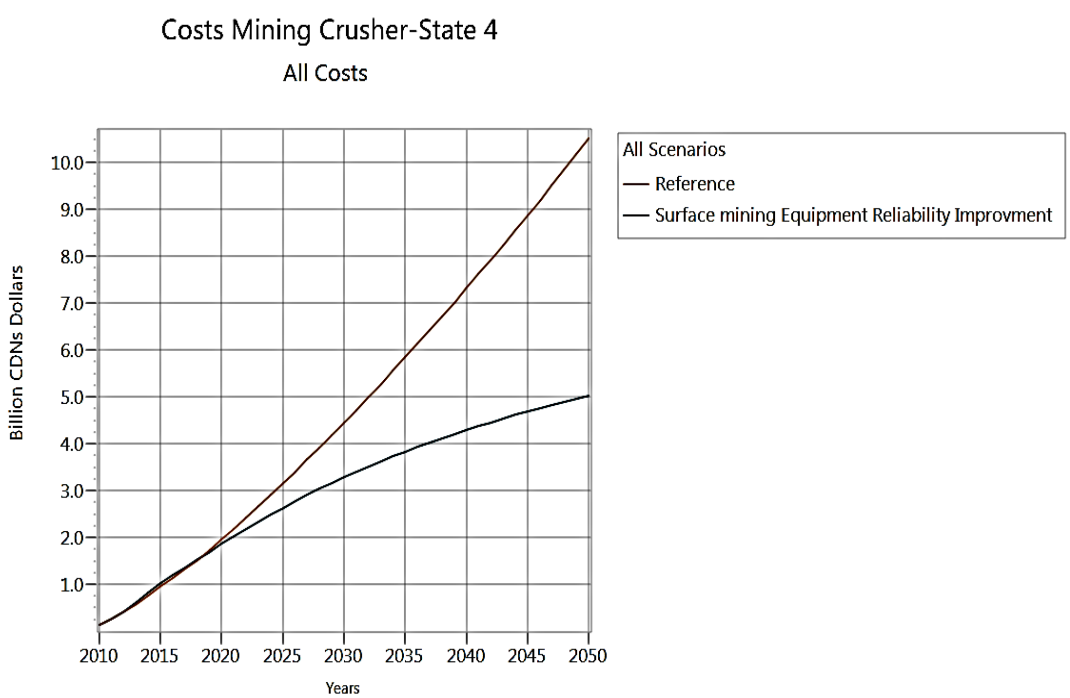



Figure 4-44: Oil sands crusher demand costs - improving reliability vs reference scenarios-State 4

## 4.10.4 Oil Sands Mining Conveyor Belt

In this section a suitable approach to link conveyor belt reliability and energy consumption was developed. The main objective was to analyze the causes of failures, calculate the probability of failures and partial reliability based on BBN method, and find a relationship between energy consumption and partial reliability for conveyor belts. The following assumption was made:

- Only the conveyor belt drive motor and power rollers are selected for the E-R model. According to expert opinion (Delphi method), only these parts have a direct impact on energy consumption.

### 4.10.4.1 The E-R Model for an Oil Sands Conveyor Belt

The E-R model simulated the energy demand and cost of an oil sands mining conveyor belt using LEAP software. The model calculated the amount of energy demand and use for the motor and power rollers; these are discussed in detail in this chapter.

#### 4.10.4.1.1 Calculating Partial Reliability for Critical Parts of the Conveyor Belt

Equations and calculations similar to those used in section 4.10.1.2 were performed for the conveyor belts motor and power rollers. The results are presented in Table 4-30.

Table 4-30: Calculated partial reliability for critical parts of the conveyor belt

| No. | Critical part of conveyor belt | P (Probability of failure*) | R (Reliability*) | $\lambda_1$ | $\lambda_2$ | $P_{new}$ (Probability of partial failure**) | $R_{new}$ (Partial reliability**) |
|---|---|---|---|---|---|---|---|
| 1 | Motor | 0.01 | 0.99 | 0.01 | 6.13 | 0.33 | 0.67 |
| 2 | Power roller | 0.03 | 0.97 | 0.03 | 4.64 | 0.36 | 0.64 |

*from chapter 3

**Partial probability of failure and Partial reliability

#### 4.10.4.1.2 Energy Modeling for the Conveyor Belt Using LEAP

LEAP models non-motive transport equipment based on energy consumption and supply data and simulates various energy demand scenarios. Some assumptions were made to model a conveyor belt in LEAP.

- The conveyor belt is a sub-system of non-motive transport equipment.
- Energy consumption for the drive motor and power roller were assumed to be 0.10 and 0.07 kilowatt-hour per barrel, respectively (91).
- A conveyor belt 0.75 m wide with a conveying distance of 5 m and a capital cost of CAN $ 18161.17 was selected (103).

The scope of this section included non-motive transport equipment for Alberta's oil sands mining sector and used the LEAP model to analyze energy demand. The scope is illustrated in the energy demand tree in Figure 4-46.

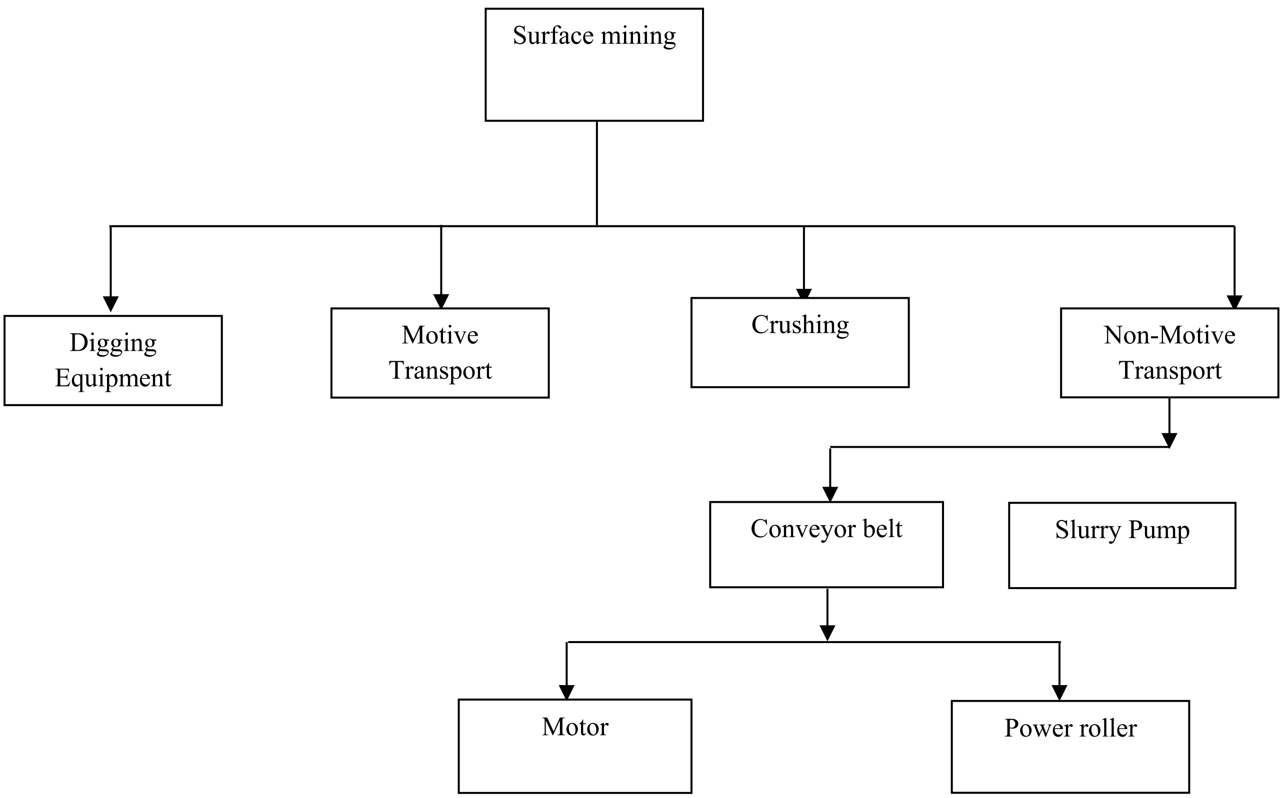



Figure 4-45: Energy demand tree for the conveyor belt

Referring to Subramanyam et al, 2012 final energy consumption for the conveyor belt to be 0.17 kilowatt-hour/barrel (Page 7 (91)). Energy consumption for the motor and power roller is assumed to be 0.10 kilowatt-hour/barrel and 0.07 kilowatt-hour/barrel, respectively (based on expert).

#### 4.10.4.1.3 The E-R Model Results for a Conveyor Belt

The calculations from section 4.10.1.4 were used to find the extra energy and cost data for a conveyor belt in every state for the year 2010. The loss of capacity and its consequence for conveyor belt's drive motor for each state was calculated as:

Failure loss for State 1=0

Failure loss for State 2=0.1 * 0.01=0.001

Failure loss for State 3 =0.5*0.33=0.17

Failure loss for State 4=1

The loss of capacity and its consequence for the conveyor belt power roller for each state was calculated as

Failure loss for State 1=0

Failure loss for State 2=0.1 * 0. 03=0. 003

Failure loss for State 3 =0.5*0.36 =0.18

Failure loss for State 4=1

The costs, including capital, maintenance, fuel and labor, for the conveyor belt motor and power roller were calculated to be 0.47 CANS $/ barrel and 0.046 CANS $/ barrel, respectively. Tables 4-31 to 4-34 show the fraction of loss of capacity and the consequence of each loss based on cost and energy for each state.

Table 4-31: Fraction of loss of for States i=1 to 4 – Extra cost – mining conveyor belt motor

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra Cost (CAN$/bbl) | Total Cost (CAN$/bbl) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.47 | 0.75 |
| 2 | Expected working | 0.99 | 10 | 90 | 0.001 | 0.00047 | 0.471 | 0.751 |
| 3 | Partial reliability | 0.67 | 50 | 50 | 0.17 | 0.08 | 0.55 | 0.83 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.47 | 0.94 | 1.22 |

Table 4-32: E-R model for the mining conveyor belt motor for States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy-Electricity-kWh/barrel) | Fuel demand (Electricity-kWh/barrel) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.1 |
| 2 | Expected working | 0.99 | 10 | 90 | 0.001 | 0.0001 | 0.1 |
| 3 | Partial reliability | 0.67 | 50 | 50 | 0.17 | 0.017 | 0.12 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.1 | 0.2 |

Table 4-33: Fraction of loss of for States i=1 to 4 – Extra cost –mining conveyor belt power roller

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra Cost (CAN$/bbl) | Total Cost (CAN$/bbl) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.046 | 0.326 |
| 2 | Expected working | 0.97 | 10 | 90 | 0.003 | 0.0001 | 0.047 | 0.327 |
| 3 | Partial reliability | 0.64 | 50 | 50 | 0.18 | 0.0644 | 0.053 | 0.33 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.046 | 0.092 | 0.37 |

Table 4-34: E-R model for mining conveyor belt power roller for States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy-Electricity-kWh/barrel) | Fuel demand (Electricity-kWh/barrel) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.07 |
| 2 | Expected working | 0.97 | 10 | 90 | 0.003 | 0 | 0.07 |
| 3 | Partial reliability | 0.64 | 50 | 50 | 0.18 | 0.0126 | 0.08 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.07 | 0.14 |

### 4.10.4.1.4 Surface Mining Conveyor Belt Scenario 1 to 4 – States 1 to 4

**State 1:** Subramanyam et al.2012, developed this scenario (page 7 of (91)) earlier . In the base case, electricity needed for a conveyor belt motor and power roller are 0.1 Kwh/

barrel and 0.07 Kwh/ barrel respectively. The total cost is 0.75 CAN$/ barrel for conveyor belt motor and 0.326 CAN$/barrel of oil production for conveyor belt power roller.

**State 2:** The E-R model shows that in State 2 the conveyor belt requires 0.07 Kwh / barrel energy (electricity) for power rollers and 0.1 Kwh / barrel energy (electricity) for drive system. The extra cost was calculated as 0.047 (CAN$/ barrel of oil production) for power rollers and 0.471 (CAN$/ barrel) for motor. Therefore, the total cost required for this state are 0.327 CAN$/ barrel of oil production for power rollers and 0.751 CAN$/ barrel of oil production for motor.

**State 3:** The E-R model shows that in State 3 the conveyor belt requires 0.08 Kwh / barrel energy (electricity) for power rollers and 0.12 Kwh / barrel energy (electricity) for drive system. The extra cost was calculated as 0.05 (CAN$/ barrel of oil production) for power rollers and 0.55 (CAN$/ barrel of oil production) for motor. Therefore, the total cost required for this state are 0.33 CAN$/ barrel for power rollers and 0.83CAN$/ barrel of oil production for motor.

**State 4:** In State 4, The E-R model shows that in State 4, the conveyor belt requires 0.14 Kwh / barrel energy (electricity) for power rollers and 0.2 Kwh / barrel energy (electricity) for drive system. The extra cost was calculated as 0.092 (CAN$/ barrel of oil production ) for power rollers and 0.94 (CAN$/ barrel of oil production) for motor. Therefore, the total cost required for this state are 0.7 CAN$/ barrel of oil production for power rollers and 1.22 CAN$/ barrel for motor.

### 4.10.4.1.5: Input Data and Assumptions for Improving Conveyor Belt Reliability, Scenarios 1 to 4

This is similar to section 4.10.5.2.1 (98).

### 4.10.4.1.6 Results – Energy Profile for Scenarios 1 to 4 – Conveyor Belt

The reference case scenario for reliability improvement for a conveyor belt when operating under States 1 through 4 were simulated in LEAP (see Table 4-35).

**State 1**: LEAP estimates an energy demand of conveyor belt (electricity) as 3,953.38thousand Gigajoule/year. By improving the reliability of the conveyor belt, the energy (diesel) will decrease to 3,339.30 of thousand Gigajoule/year by the year 2050.

**State 2**: LEAP estimates an energy demand (electricity) in conveyor belt of 3,953.38thousand Gigajoule/year when the hydraulic shovel operates under state 2. By improving the reliability of the conveyor belt, the energy (electricity) will decrease to 3,339.30 of thousand Gigajoule/year by the year 2050.

**State 3**: LEAP estimates an energy demand in the conveyor belt (electricity) of 4,185.93 thousand Gigajoule in year 2050. When the reliability is improved, energy demand will decrease to 3,552.94thousand Gigajoule/year.

**State 4:** An energy demand in the conveyor belt (electricity) of 7,906.76 thousand Gigajoule/year 2050 was calculated. When the reliability is improved, energy demand will decrease to 6,669.89 thousand Gigajoule/year.

Table 4-35: Conveyor belt energy demand (thousand Gigajoule)-State 1 to 4-year 2050

| Electricity | | | | |
|---|---|---|---|---|
| Scenario | 1 | 2 | 3 | 4 |
| Reference | 3,953.38 | 3,953.38 | 4,185.93 | 7,906.76 |
| Reliability improvementc c | 3,339.30 | 3,339.30 | 3,552.94 | 6,669.89 |
| Total | 7,292.68 | 7,292.68 | 7,738.87 | 14,576.66 |

## 4.10.4.1.7 Energy Saving Results from the E-R Model for an Oil Sands Mining Conveyor Belt Operating Under States 1 to 4

Energy demand for a conveyor belt was plotted in LEAP over 40 years for both the reference case and Scenario 1 and is shown in Figure 4-47. Plotted energy demand over a specific period (from 2010 to 2050) indicates that there will be on average 0.16% energy saving per year through improving the reliability of a fully operational conveyor belt.

For Scenario 2 (State 2), there will be on average 0.158% energy saving through improving the reliability of a conveyor belt operating under state 2 (see Figure 4-48).

For Scenario 3 (State 3), there will be on average 0.155% energy saving through improving the reliability of a conveyor belt operating under state 3 (see Figure 4-49).

For Scenario 4 (State 4), there will be on average 0.156% energy saving through improving the reliability of a conveyor belt under state 4 (see Figure 4-50).

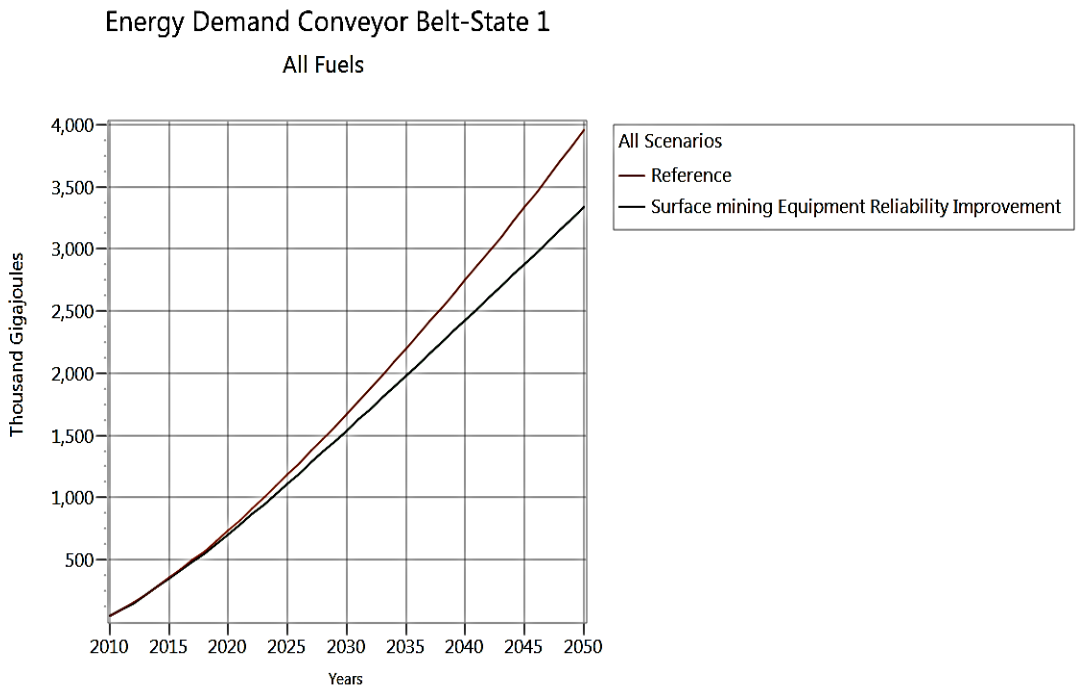



Figure 4-46: Energy saving for the conveyor belt, 2010–2050: Scenario 1 vs reference scenario

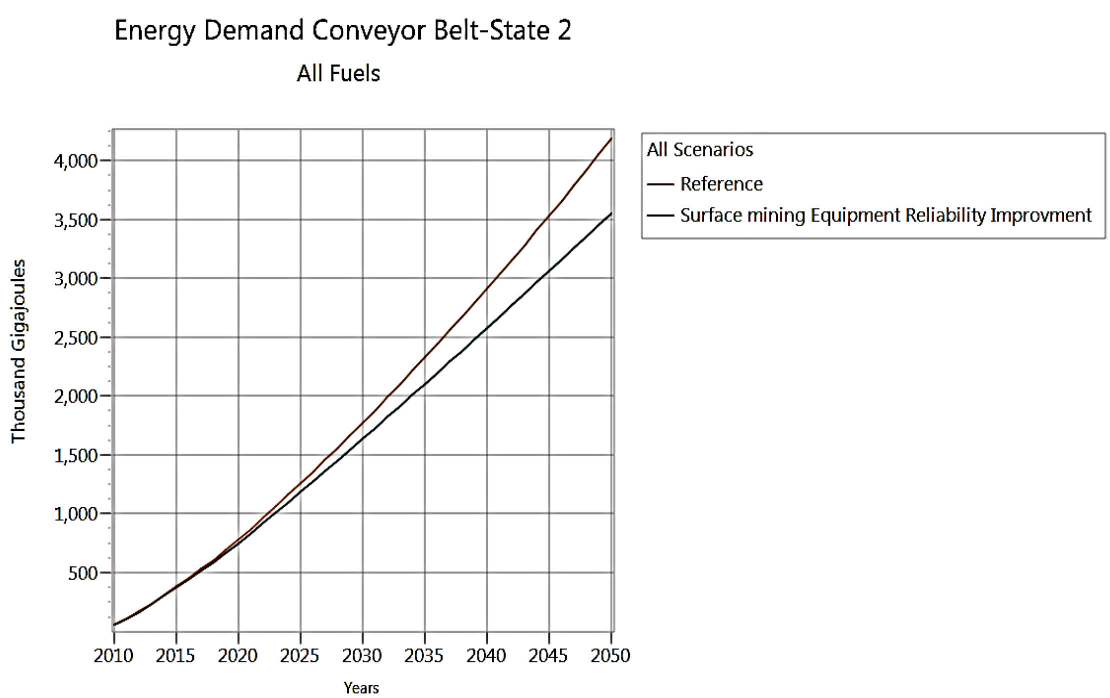



Figure 4-47: Energy saving for the conveyor belt, 2010–2050: Scenario 2 vs reference scenario 2

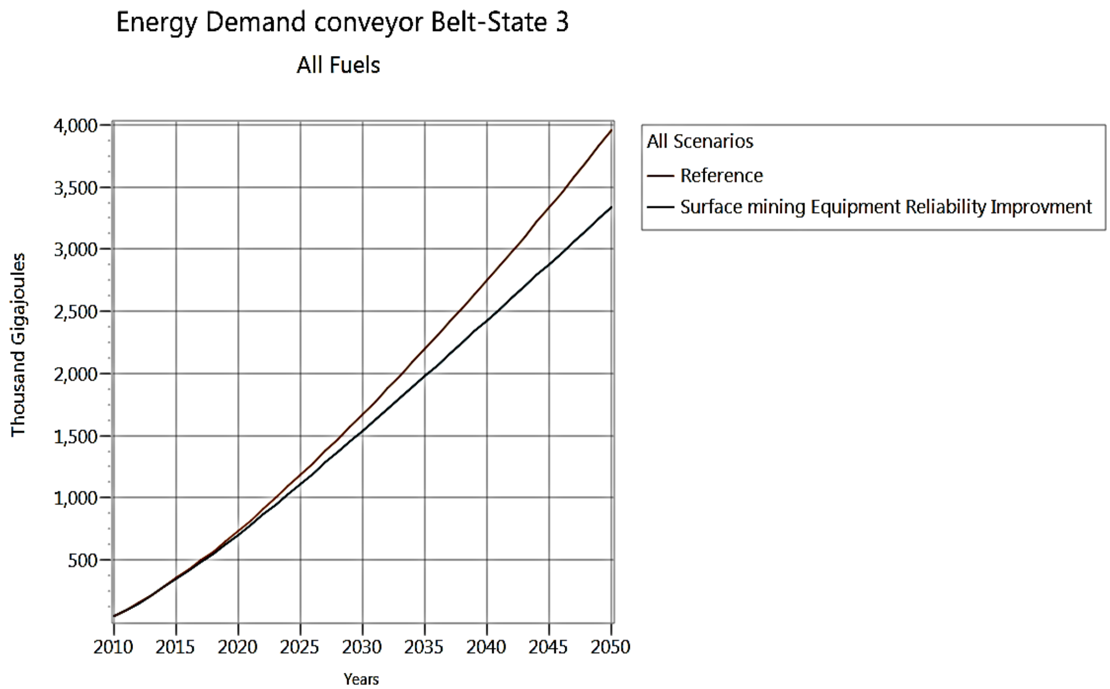



Figure 4-48: Energy saving for the conveyor belt, 2010–2050: Scenario 3 vs reference scenario 3

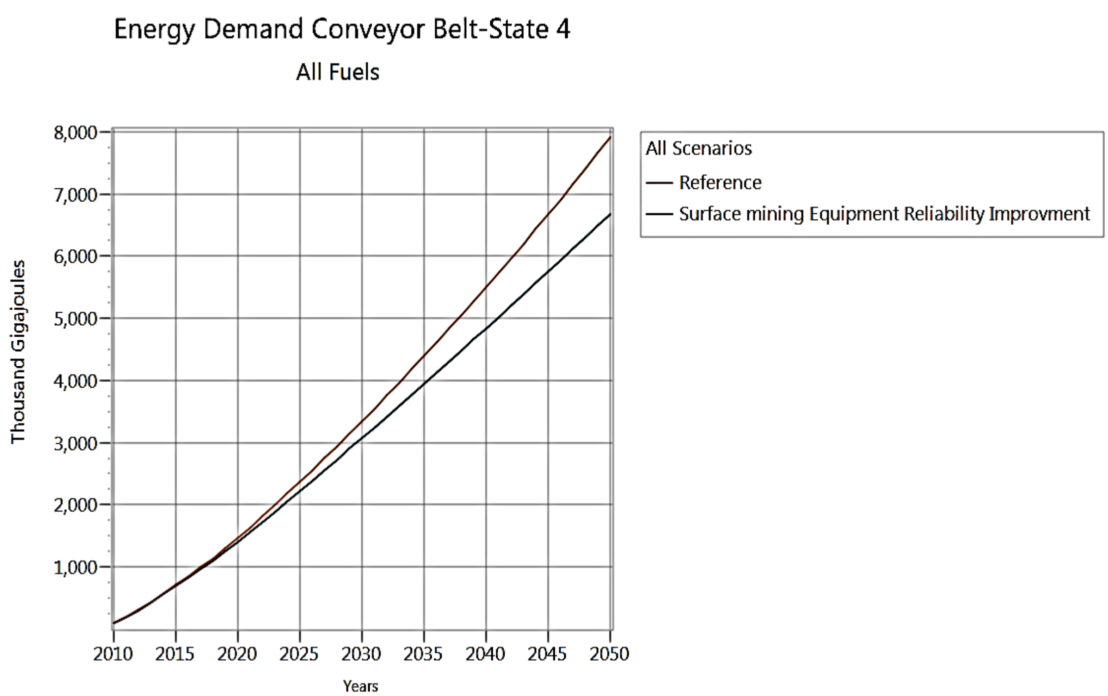



Figure 4-49: Energy saving for the conveyor belt, 2010–2050: Scenario 4 vs reference scenario 4

#### 4.10.4.1.8 Cost Saving Results from the E-R Model for an Oil Sands Mining Conveyor Belt Operating Under States 1 to 4

Oil sands mining conveyor belt operational costs were plotted over 40 years (2010-2050) for the reference case and Scenarios 1 to 4 (see Figures 4-51 to 4-54).

For Scenarios 1 and 2, as the graph shows, annual costs can be reduced on by an average of 0.61 % per year when the reliability of conveyor belt is improved (see Figures 4-51 and 4-52).

For Scenario 3, there will be an average of 0.59% cost saving annually through improving the reliability of a conveyor belt operating under state 3 (see Figure 4-53).

For Scenario 4 (State 4), there will be on average 0.49% cost saving per year through improving the reliability of a conveyor belt under state 4 (see Figure 4-54).

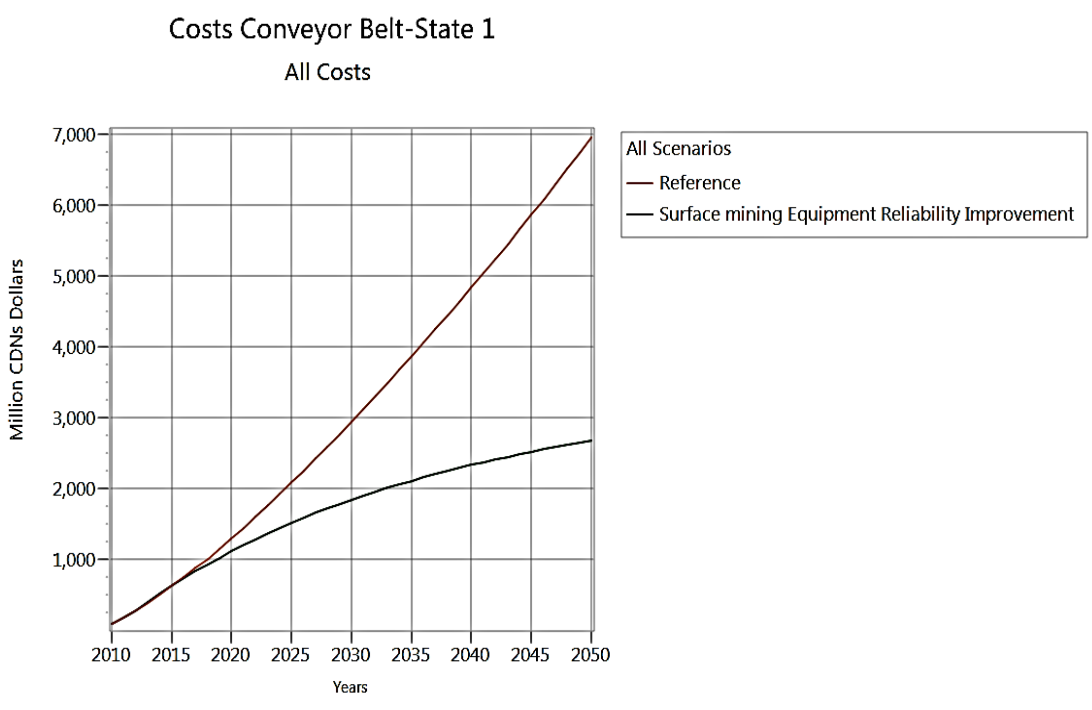



Figure 4-50: Cost saving for conveyor belt, 2010–2050: Scenario 1 vs reference scenario 1

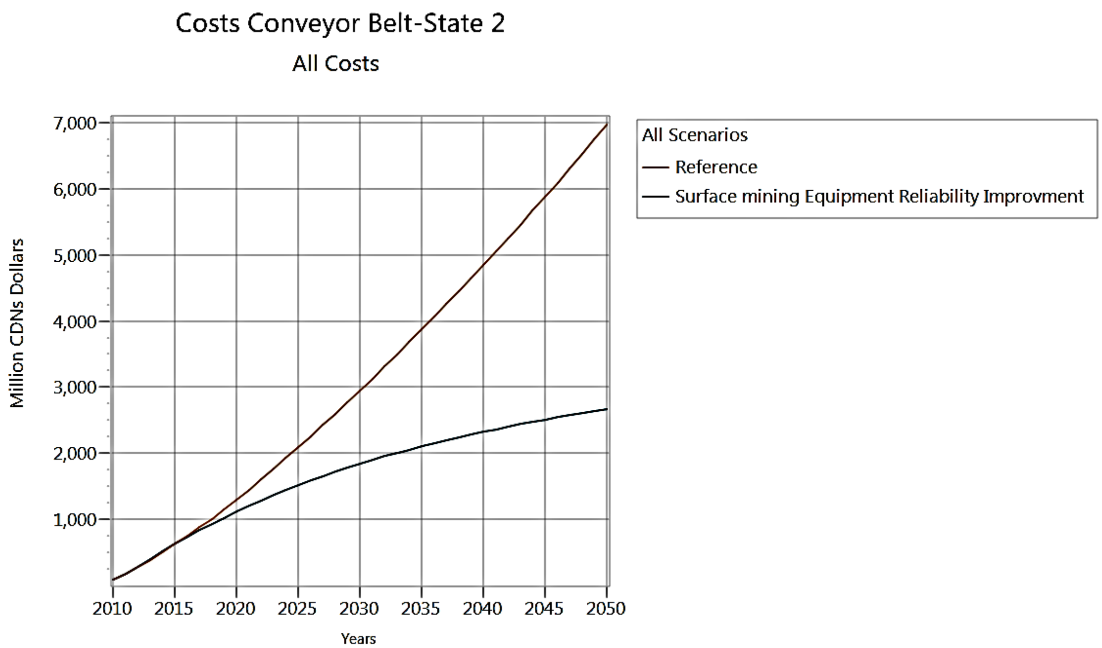



Figure 4-51: Cost saving for conveyor belt, 2010–2050: Scenario 2 vs reference scenario 2

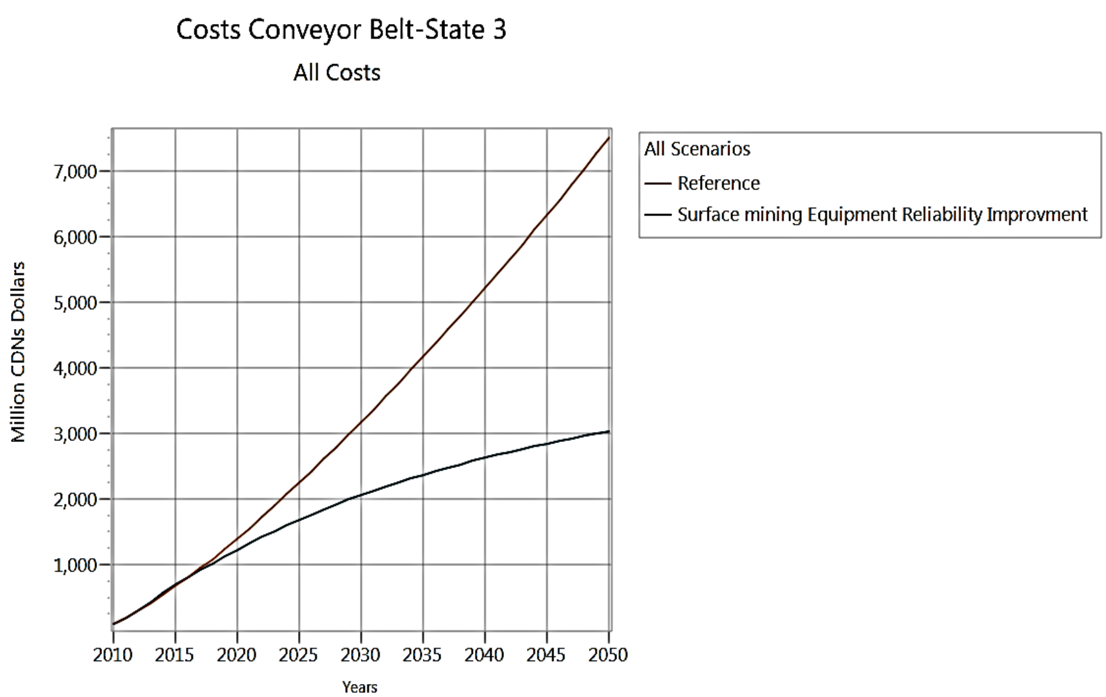



Figure 4-52: Cost saving for conveyor belt, 2010–2050: Scenario 3 vs reference scenario 3

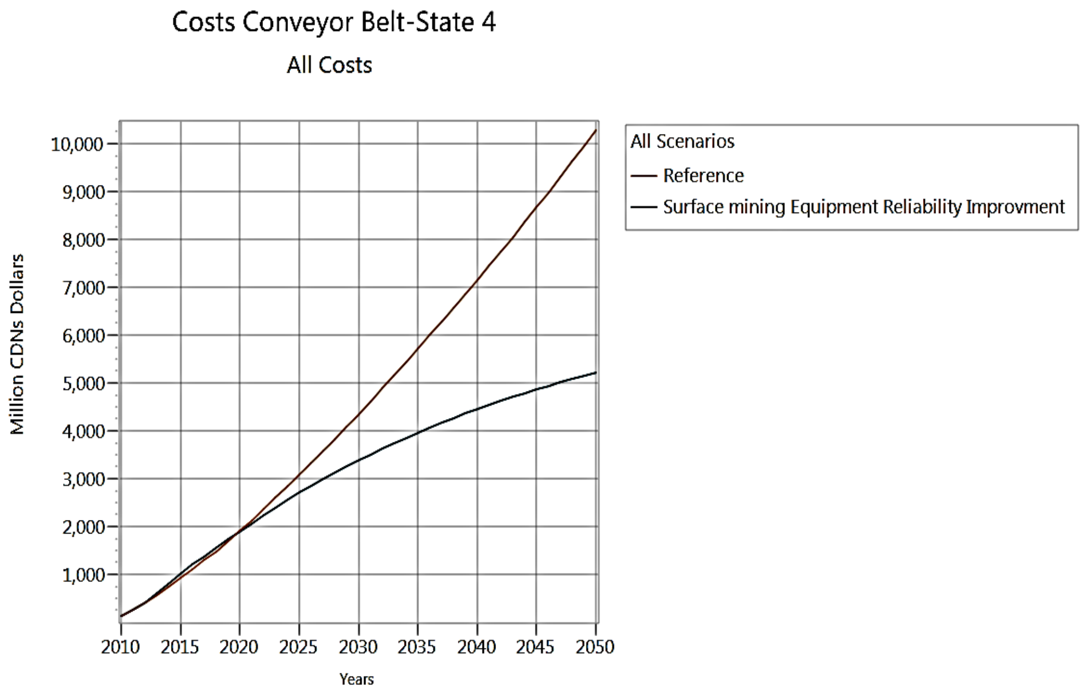



Figure 4-53: Cost saving for conveyor belt, 2010–2050: Scenario 4 vs reference scenario 4

### 4.10.5 Oil Sands Mining Slurry Pump

This section considers the mechanical components or sub-components of the slurry pump that have an impact on energy consumption. Given that only the motor has a direct impact on energy consumption, only the motor was considered in modeling. The slurry pump can operate with partial motor failure, though it consumes more energy and emits more GHGs. Energy demand and cost will consequently increase.

#### 4.10.5.1 Calculating Partial Reliability for a Slurry Pump Motor

The equations and calculations used in section 4.10.1.2 were performed for the slurry pump motor. The results are presented in Table 4-36.

Table 4-36: Calculated partial reliability for critical part of a slurry pump

| No. | Slurry pump part | P (Probability of failure*) | R (Reliability*) | $\lambda_1$ * | $\lambda_2$ | $P_{new}$ (Probability of partial failure**) | $R_{new}$ (Partial reliability**) |
|---|---|---|---|---|---|---|---|
| 1 | Motor (M) | 0.17 | 0.83 | 0.2 | 2.16 | 0.31 | 0.69 |

*from chapter 3

**Partial probability of failure and Partial reliability

### 4.10.5.2 Energy Modeling for the Slurry Pump in LEAP

The slurry pump was modeled in the LEAP software based on energy consumption and supply, and the model simulated various energy demand scenarios. The following assumptions were made in the model:

- The slurry pump is categorized as a sub-system of non-motive transport equipment.
- The slurry pump capital cost is 4.5 million dollars (54).
- The slurry pump motor was assumed to deliver 4000 kW power with a capital cost of CAN $ 107,868 (104).

A surface mining sector demand tree, was developed for an oil sands mining slurry pump using an end-use approach (see Figure 4-55).

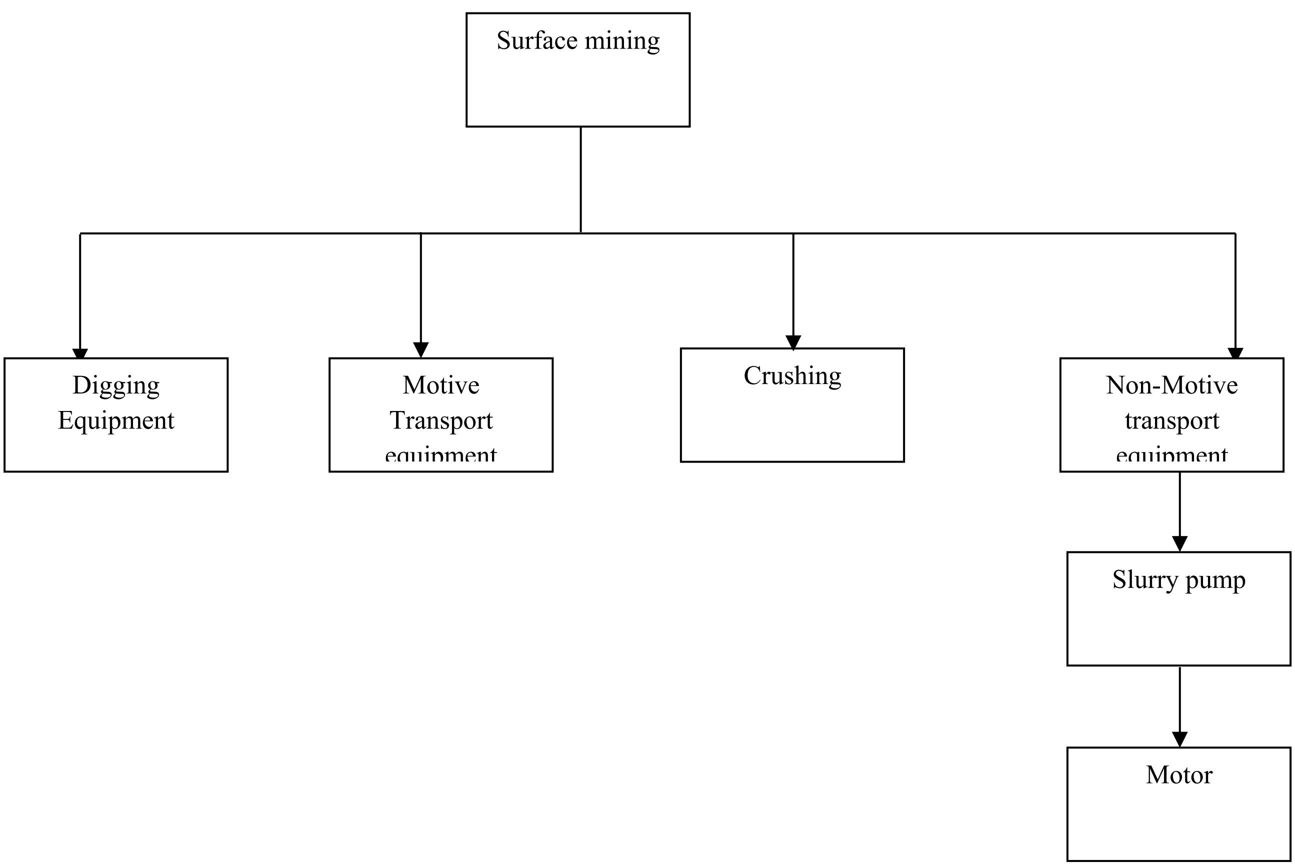



Figure 4-54: Energy demand tree for slurry pump

### 4.10.5.3 The E-R Model Results for a Slurry Pump

Similar calculations to those used in section 4.10.1.4 were used to find the extra energy and cost data for mining slurry pump in every state for the year 2010.

The loss of capacity and its consequences for the slurry pump for each state (as defined in 4.10.2.2) was calculated as:

Failure loss for State 1=0

Failure loss for State 2=0.1 * 0.17=0.017

Failure loss for State 3 =0.5*0.31=0.16

Failure loss for State 4=0

The total costs of the slurry pump's motor was 0.054 CANS $/barrel of oil production. Tables 4-37 and 4-38 show the fraction of loss of capacity and the consequence of each loss based on cost and energy for each state.

Table 4-37: Fraction of loss of for States i=1 to 4-Extra cost - mining slurry pump motor

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra cost (CAN$/bbl) | Total cost (CAN$/bbl) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.054 | 0.334 |
| 2 | Expected working | 0.83 | 10 | 90 | 0.017 | 00.001 | 0.055 | 0.335 |
| 3 | Partial reliability | 0.69 | 50 | 50 | 0.19 | 0.009 | 0.064 | 0.344 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.054 | 0.11 | 0.39 |

Table 4-38: E-R model for mining slurry pump for States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy-Electricity-kWh/barrel) | Fuel demand (Electricity-kWh/barrel) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 4 |
| 2 | Expected working | 0.95 | 10 | 90 | 0.017 | 0.068 | 4.068 |
| 3 | Partial reliability | 0.80 | 50 | 50 | 0.19 | 0.76 | 4.76 |
| 4 | Failed | 0 | 100 | 0 | 1 | 4 | 8 |

### 4.10.5.4 Surface Mining Slurry Pump Scenarios 1 to 4 – States 1 to 4

The assumptions data for the energy demand and cost for the slurry pump are presented in Table 4-39.

Table 4-39: Total energy and cost required by the slurry pump for the reference scenario for each state

| Reference Data | Energy (Kwh/bbl) | Cost (CAN$/bbl) |
|---|---|---|
| Scenario 1-State 1 | 4 | 0.334 |
| Scenario 2-State 2 | 4.068 | 0.335 |
| Scenario 3-State 3 | 4.76 | 0.344 |
| Scenario 4-State 4 | 8 | 0.39 |

#### 4.10.5.4.1 Input Data and Assumptions for Improving Slurry Pump Reliability – Scenarios 1 to 4

This is similar to section 4.10.1.5.2 (98).

### 4.10.5.5 Results – Energy Profile for Scenarios 1 to 4 – Slurry Pump

The reference case scenario for reliability improvement for a slurry pump when operating under States 1 through 4 were simulated in LEAP (see Table 4-40).

**State 1:** LEAP estimates an energy demand of slurry pump (electricity) as 186.04 million Gigajoule/year. By improving the reliability of the slurry pump, the energy (diesel) will decrease to 157.87 of million Gigajoule/year by the year 2050.

**State 2:** LEAP estimates an energy demand (electricity) in slurry pump of 189.20 million Gigajoule/year when the hydraulic shovel operates under state 2. By improving the reliability of the conveyor belt, the energy (electricity) will decrease to 160.58 of million Gigajoule/year by the year 2050.

**State 3:** LEAP estimates an energy demand in the conveyor belt (electricity) of 221.39 million Gigajoule in year 2050. When the reliability is improved, energy demand will decrease to 187.75 million Gigajoule/year.

**State 4:** An energy demand in the conveyor belt (electricity) of 372.08 million Gigajoule/year 2050 was calculated. When the reliability is improved, energy demand will decrease to 315.74 million Gigajoule/year.

Table 4-40: Slurry pump energy demand (million Gigajoule)-State 1 to 4-year 2050

| Electricity | | | | |
|---|---|---|---|---|
| Scenario | 1 | 2 | 3 | 4 |
| Reference | 186.04 | 189.20 | 221.39 | 372.08 |
| Reliability improvementc c | 157.87 | 160.58 | 187.75 | 315.74 |
| Total | 343.91 | 349.79 | 409.14 | 687.82 |

### 4.10.5.6 Energy Saving Results from the E-R Model for an Oil Sands Mining Slurry Pump Operating Under States 1 to 4

**Scenario 1** under State 1 (slurry pump is fully reliable): Energy demand for the slurry pump was calculated in LEAP over 40 years for both the reference case and Scenario 1 and is shown in Figure 4-56. Plotted energy demand over a specific period (from 2010 to 2050) indicates that there will be a 0.15% energy saving per year on average through improving reliability of a slurry pump.

**Scenario 2** under State 2 (slurry pump is working under expected working conditions): Plotted energy demand over the years 2010 to 2050 indicates an average annual energy savings of 0.151% when reliability of a slurry pump is improved (see Figure 4-57)

**Scenario 3** under State 3 (slurry pump is working under partial reliability): Plotted energy demand over the years 2010 to indicates an average annual energy savings of 0.152% when reliability of a slurry pump is improved (see Figure 4-58).

**Scenario 4** under State 4 (slurry pump fails): Plotted energy demand over the years 2010 to 2050 indicates an average annual energy (electricity) savings 0.15% when reliability of a slurry pump is improved (see Figure 4-59).

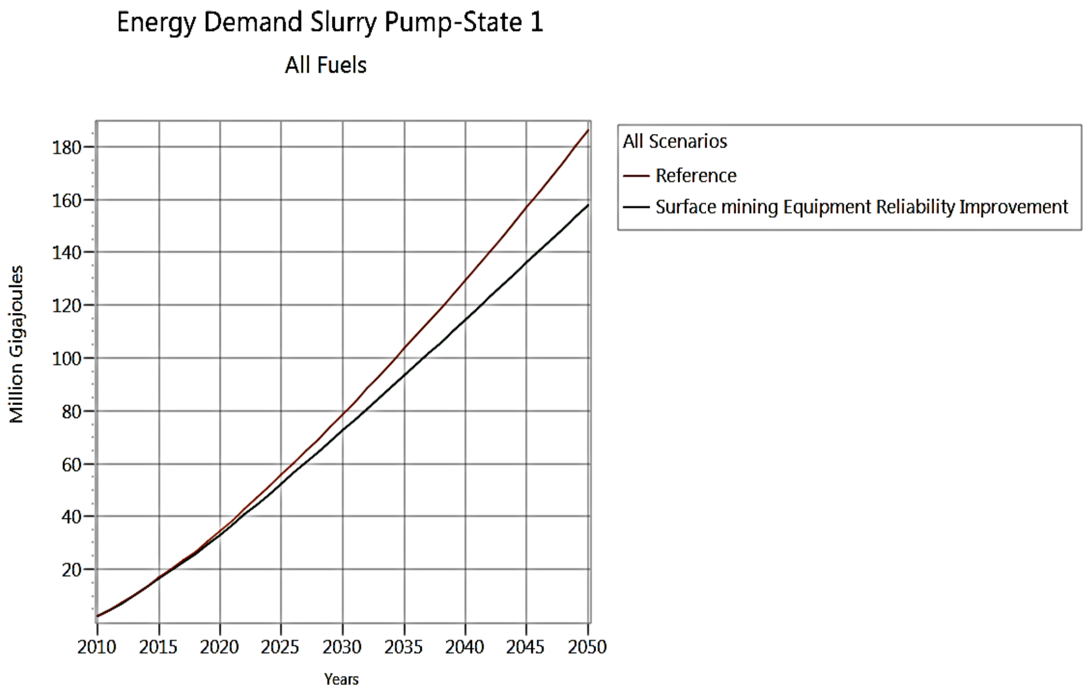



Figure 4-55: Energy saving for the slurry pump, 2010–2050: Scenario 1 vs reference scenario 1

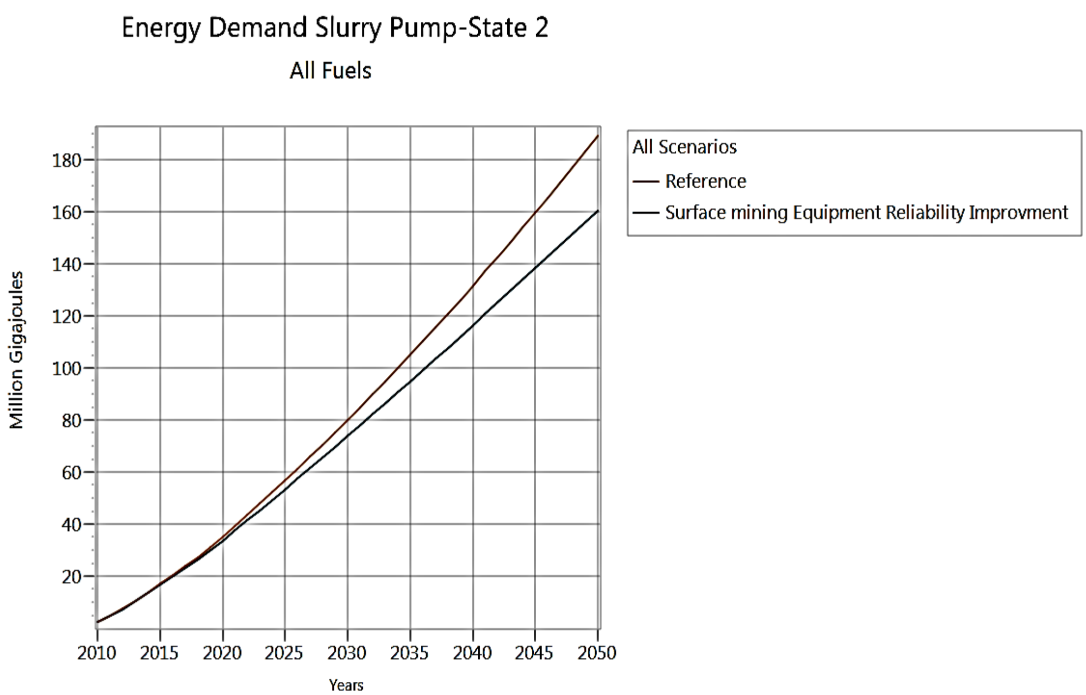



Figure 4-56: Energy saving for the slurry pump, 2010–2050: Scenario 2 vs reference scenario 2

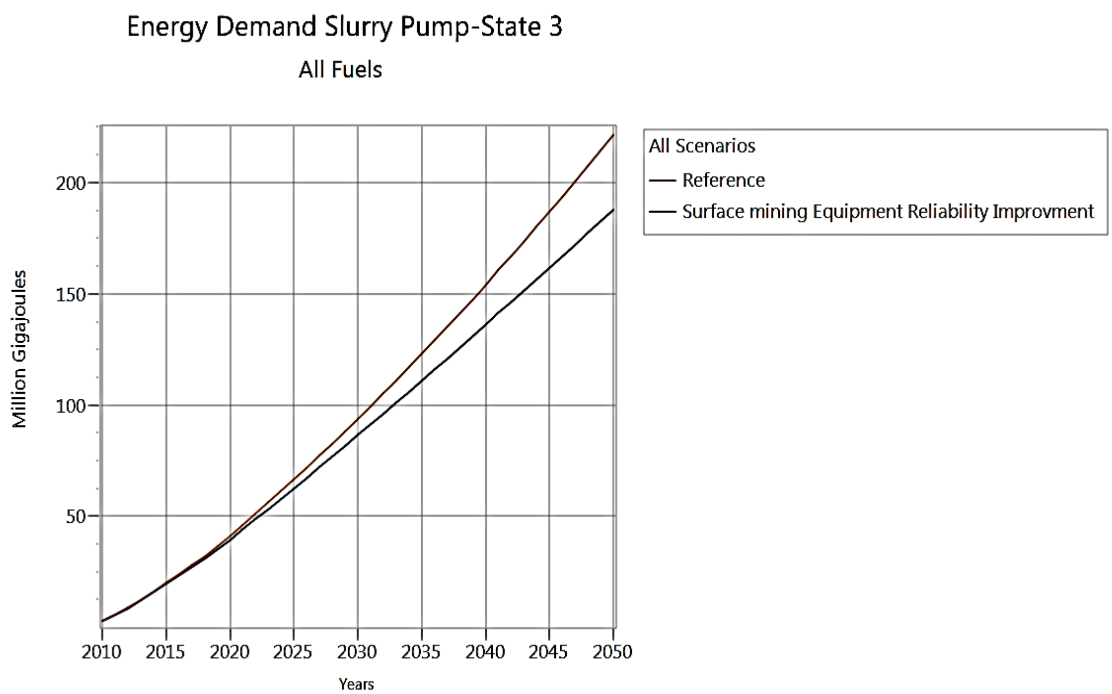



Figure 4-57: Energy saving for the slurry pump, 2010–2050: Scenario 3 vs reference scenario 3

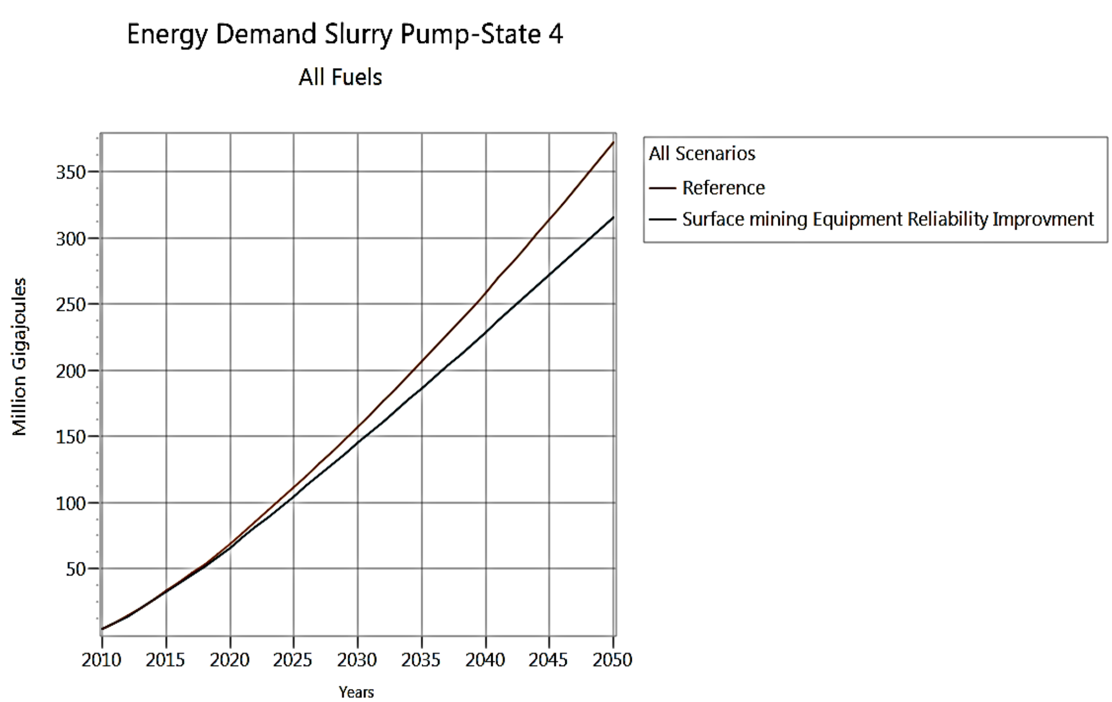



Figure 4-58: Energy saving for the slurry pump, 2010–2050: Scenario 4 vs reference scenario 4

## 4.10.5.7 Cost Saving Results from the E-R Model for an Oil Sands Mining Slurry Pump Operating Under States 1 to 4

Oil sands mining slurry pump operational costs were plotted over 40 years (2010-2050) for the reference case and Scenarios 1 through 4 (see Figures 4-60 through 4-63).

Scenario 1 under state 1 (slurry pump is fully reliable): As the graph in Figure 4-60 shows, costs can be reduced by an average of 0.76 % annually through improving the reliability of a slurry pump .

Scenario 2 under state 2 (slurry pump is working under expected working conditions): As the graph in Figure 4-61 shows, on average 0.75 % of annual costs can be reduced through improving the reliability of the slurry.

Scenario 3 under state 3 (slurry pump is working under partial reliability): As the graph in Figure 4-62 shows, on average 0.74 % of annual costs can be reduced through improving reliability of a slurry pump.

Scenario 4 under state 4, an average cost saving of 0.68 % per year can be achieved through improving reliability of a slurry pump (see Figure 4-63).

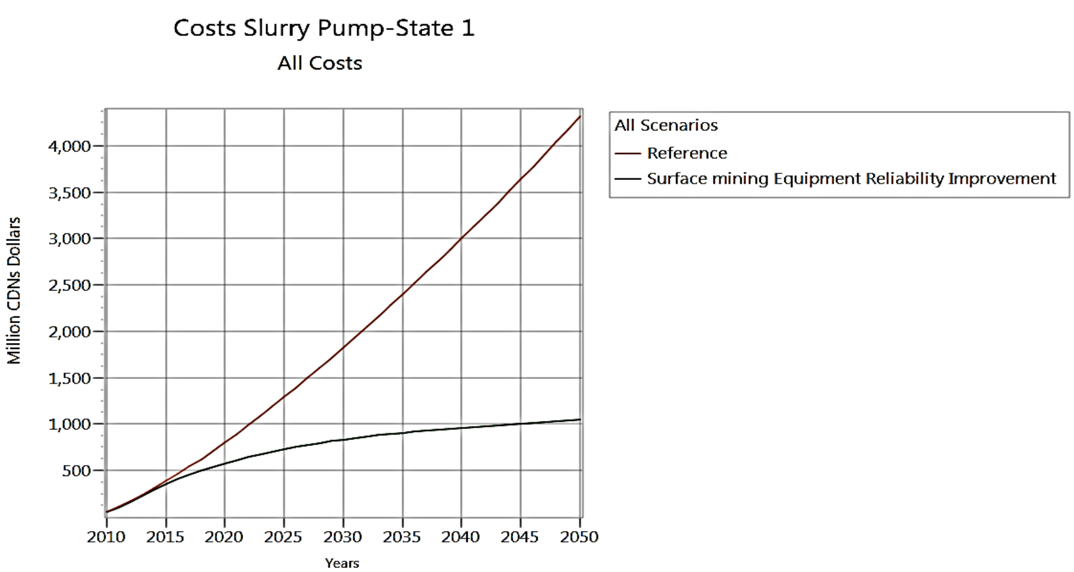



Figure 4-59: Cost saving for the oil sands slurry pump: Scenario 1 vs reference scenario – State 1

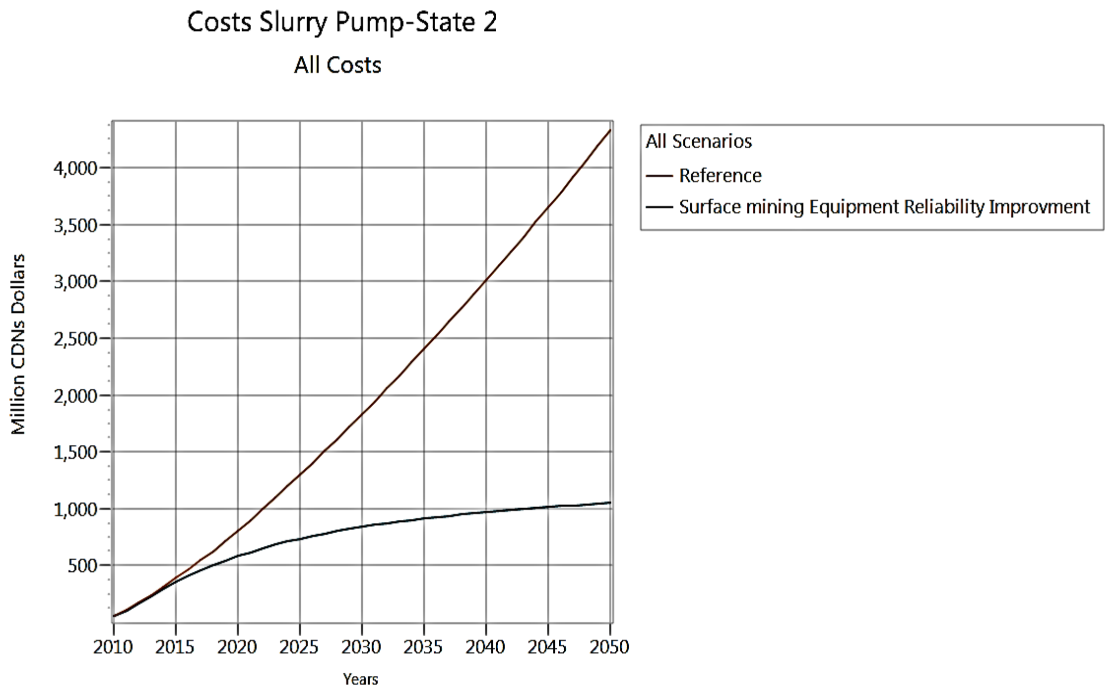



Figure 4-60: Cost saving for the oil sands slurry pump: Scenario 2 vs reference scenario - State 2

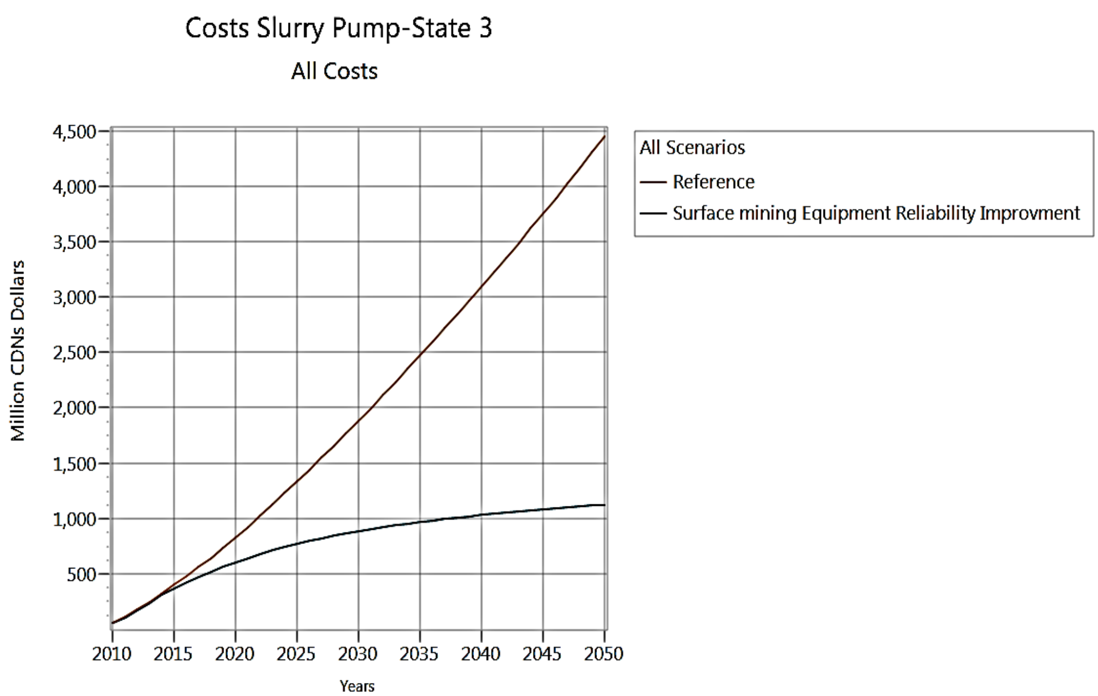



Figure 4-61: Cost saving for the oil sands slurry pump: Scenario 3 vs reference scenario - State 3

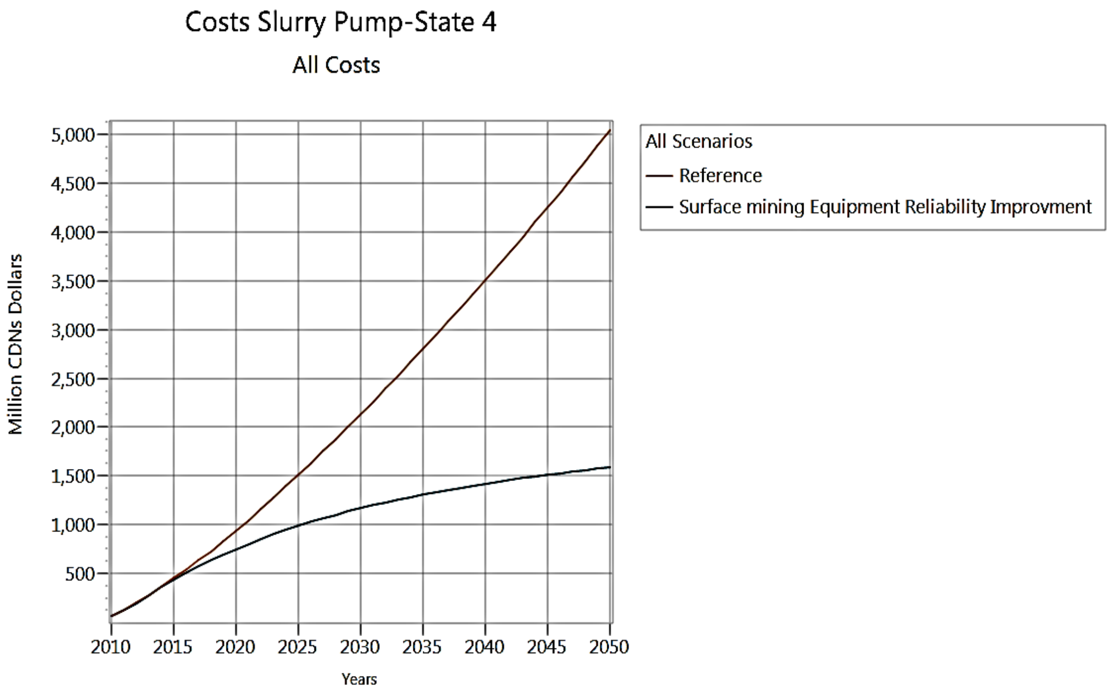



Figure 4-62: Cost saving for the oil sands slurry pump: Scenario 4 vs reference scenario - State 4

## 4.11 Energy-Reliability (E-R) Model Methodology for Mining Equipment

In this thesis, a reliability block diagram (RBD) was designed to display the reliability of surface mining equipment processes, which is shown in Figure 4-64. As shown in the RBD, two shovels in the system work in parallel. Each shovel works in a series to a fleet of five trucks. In surface mining operations, haul trucks operate in multi-states, because the industry usually uses several trucks in the mine in order to run the business if a truck fails. The fleet of five trucks work in a series with a crusher, conveyor belt, and slurry pumps.

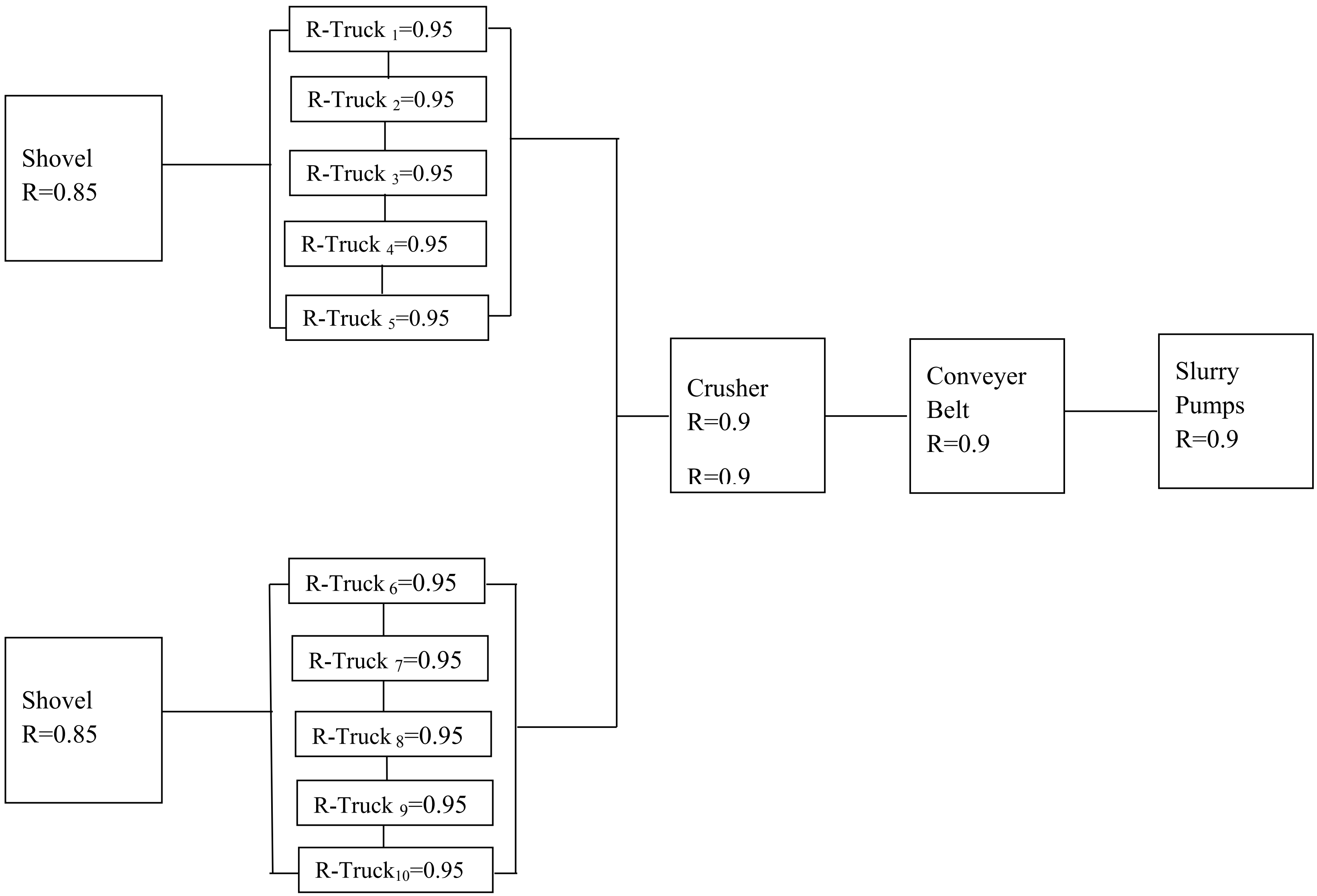



Figure 4-63: Reliability block diagram (RBD) for surface mining equipment

## 4.12 Energy Modeling Structure in LEAP

In this study, an energy model was developed to simulate some of Alberta's oil sands surface mining equipment with the aim of improving reliability. Considerations include energy supply, demand, and transformation. An energy demand tree based on fuel consumption for some oil sands mining operations is given in Figure 4-65. Table 4-41 shows fuel consumption data for diesel and electricity.

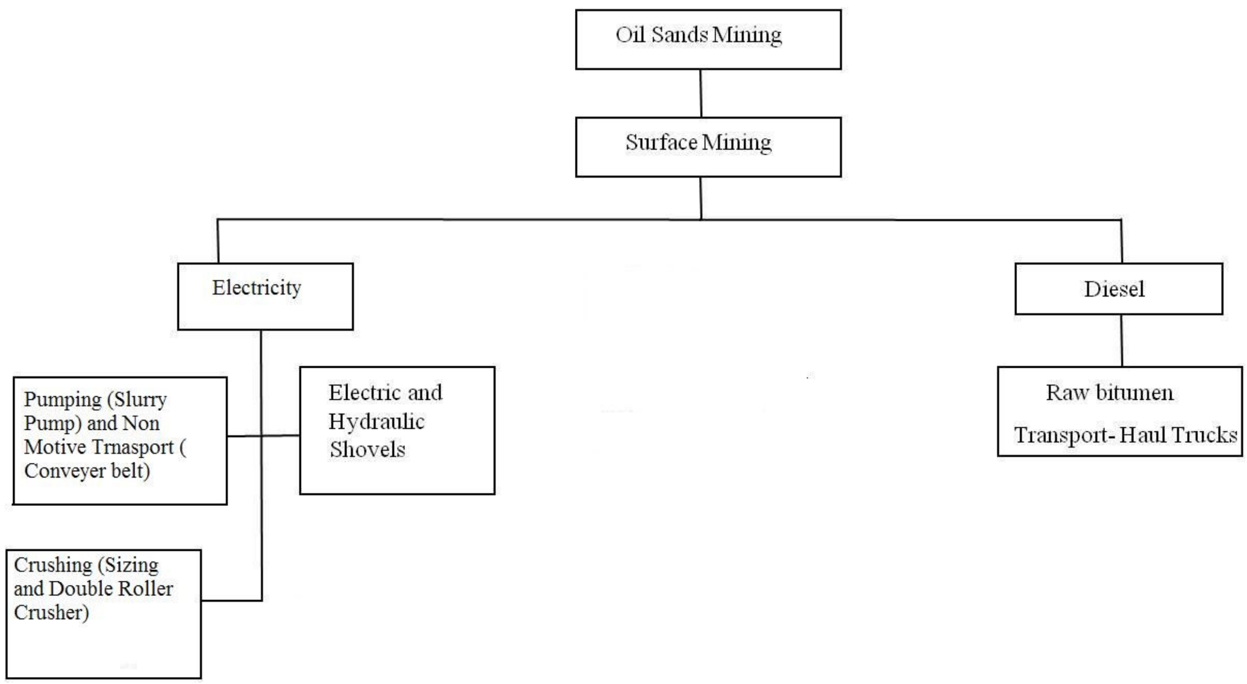



Figure 4-64: Energy demand tree for oil sands surface mining of Alberta based on fuel consumption

Table 4-41 Fuel used by oil sands surface mining equipment (105)

| **Oil Sands Mining** | **Equipment** | **Fuel (Intensity)** |
|---|---|---|
| Surface mining | Raw bitumen transport (trucks) | Diesel (1.9 litter/ barrel) |
| | Digging (shovels) | Electricity (7.2 kWh/ barrel) |
| | Pumping | Electricity (4.488 kWh/ barrel) |
| | Crushing, sizing and mixing (crusher) | Electricity (0.3 kWh/ barrel) |
| | Slurry transportation (conveyer belt) | Electricity (0.3 kWh/ barrel) |

## 4.13 Energy-Reliability (E-R) Model Chart

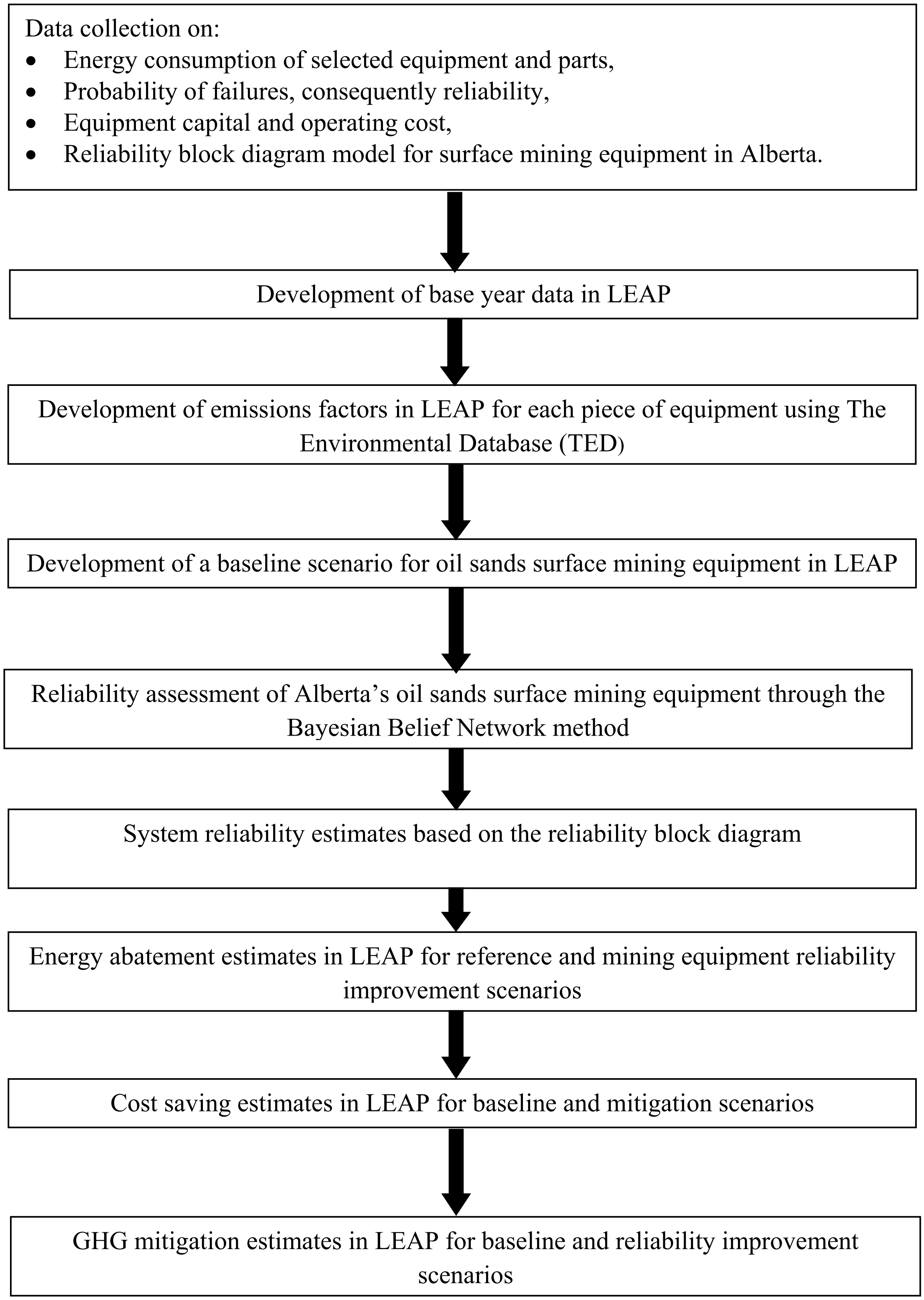



Figure 4-65: E-R model structure chart

Figure 4-66 shows the chart behind the energy-intensity scenario development, considering critical sub-system surface mining equipment reliability. This methodology facilitated model development in terms of calculating equipment energy, cost, and GHG emissions reduction.

### 4.13.1 Data Sources

Widely varying sources of data were used for this research. Data were taken from government resources, utility statistics, published research, relevant company reports, and expert opinion. The data were processed to meet the input requirements of the LEAP software to develop a base year dataset. Growth in GDP and in Alberta's surface mining sector were assumed to be the same in all scenarios. However, obtaining data was one of the major problems of this research.

### 4.13.2 Cost Analysis

All capital cost estimates are from mining equipment manufacturers in Alberta and are in Canadian dollars per barrel of oil production in year 2010. The capital costs were validated based on previous reports, mining equipment catalogues, and open sources.

## 4.14 Energy-Reliability (E-R) Model Process

The process of E-R modeling is summarized in Figure 4-67.

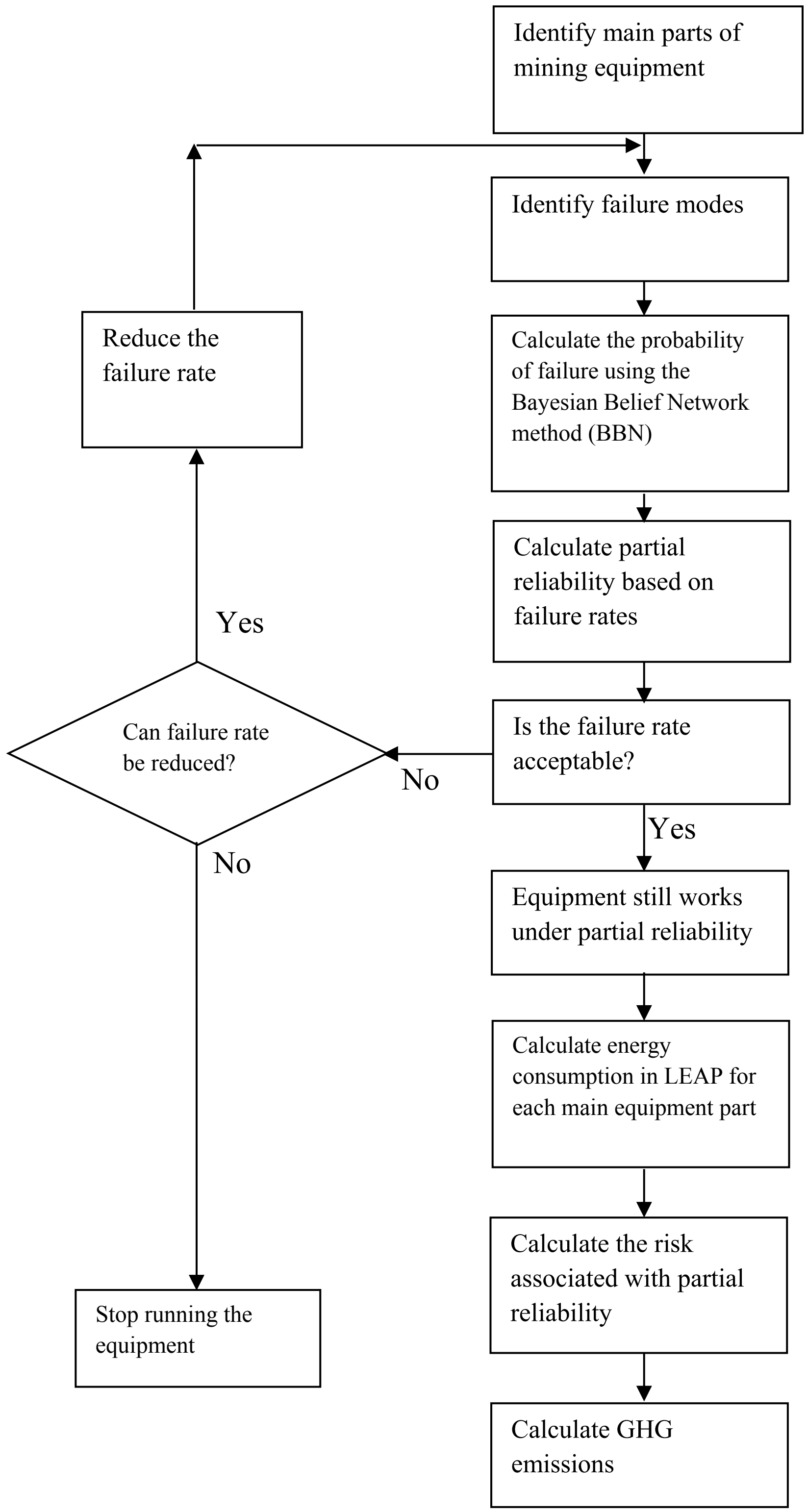



Figure 4-66: E-R model process

The above flowchart provides a brief description of the E-R model process for mining operations. Energy consumption includes all diesel and electricity consumption by the selected mining equipment. Electricity consumption was measured in Kilowatt hours/ barrel and diesel consumption was measured in gigajoules/bbl.

## 4.15 E-R Model Results for the Mining Equipment

The calculations from section 4.10.1.4 were used to find the extra energy and cost data for mining equipment in Alberta's surface mining operations in four states for the year 2010. The loss of capacity and its consequence for mining equipment for each state was calculated as shown in Table 4-42 and the results are given in Tables 4-43 to 4-50.

Table 4-42: Fraction of loss for mining equipment in surface mining of Alberta

| **Haul Truck:** | **Hydraulic Shovel:** |
|---|---|
| Failure loss for State 1=0 | Failure loss for State 1=0 |
| Failure loss for State 2=0.1 * 0.05=0.005 | Failure loss for State 2= 0.1 * 0. 1=0.01 |
| Failure loss for State 3 =0.5*0.16=0.08 | Failure loss for State 3 =0.5*0.36=0.18 |
| Failure loss for State 4=1 | Failure loss for State 4=1 |
| **Digging Equipment:** | **Crusher:** |
| Failure loss for State 1=0 | Failure loss for State 1=0 |
| Failure loss for State 2=0.1 * 0. 1=0.01 | Failure loss for State 2=0.1 * 0. 1=0.01 |
| Failure loss for State 3 = 0.15 | Failure loss for State 3 =0.5*0.28=0.14 |
| Failure loss for State 4=1 | Failure loss for State 4=1 |
| **Conveyor Belt:** | **Slurry Pump:** |
| Failure loss for State 1=0 | Loss of failure for State 1=0 |
| Failure loss for State 2=0.1 * 0. 1=0.01 | Failure loss for State 2=0.1 * 0. 1=0.01 |
| Failure loss for State 3 =0.5*0.31=0.16 | Failure loss for State 3 =0.5*0.37=0.19 |
| Failure loss for State 4=1 | Failure loss for State 4=1 |
| **Non Motive transport:** | |
| Failure loss for State 1=0 | |
| Failure loss for State 2=0.1 * 0. 1=0.01 | |
| Failure loss for State 3 =0.18 | |
| Failure loss for State 4=1 | |

Table 4-43: Fraction of loss of for States i=1 to 4-Extra cost- mining motive transport

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra Cost (CAN$/ barrel of oil production) | Total Cost (CAN$/ barrel of oil production) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.6 | 0.88 |
| 2 | Expected working | 0.83 | 10 | 90 | 0.01 | 0.006 | 0.606 | 0.89 |
| 3 | Partial reliability | 0.63 | 50 | 50 | 0.08 | 0.048 | 0.65 | 0.93 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.6 | 1.2 | 1.48 |

Table 4-44: E-R model for mining motive transport based on States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy- Electricity- kWh/barrel) | Fuel demand (Diesel- lit/barrel) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 3 |
| 2 | Expected working | 0.95 | 10 | 90 | 0.01 | 0.03 | 3.03 |
| 3 | Partial reliability | 0.80 | 50 | 50 | 0.08 | 0.24 | 3.24 |
| 4 | Failed | 0 | 100 | 0 | 1 | 3 | 6 |

Table 4-45: Fraction of loss of for States i=1 to 4-Extra cost- mining digging equipment

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra Cost (CAN$/ barrel of oil production) | Total Cost (CAN$/ barrel of oil production) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 5.6 | 5.88 |
| 2 | Expected working | 0.83 | 10 | 90 | 0.01 | 0.056 | 5.66 | 5.94 |
| 3 | Partial reliability | 0.63 | 50 | 50 | 0.15 | 0.84 | 5.7 | 6 |
| 4 | Failed | 0 | 100 | 0 | 1 | 5.6 | 11.2 | 11.48 |

Table 4-46: E-R model for mining digging equipment based on States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy-Electricity-kWh/barrel) | Fuel demand (Diesel-lit/barrel) Electricity (Kwh/ barrel of oil production) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 2<br>8 |
| 2 | Expected working | 0.95 | 10 | 90 | 0.01 | 0.02<br>0.08 | 2.02<br>8.08 |
| 3 | Partial reliability | 0.80 | 50 | 50 | 0.15 | 0.3<br>1.2 | 2.3<br>9.2 |
| 4 | Failed | 0 | 100 | 0 | 1 | 2<br>8 | 4<br>16 |

Table 4-47: Fraction of loss of for States i=1 to 4-Extra cost- mining crushing

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra Cost (CAN$/ barrel of oil production) | Total Cost (CAN$/ barrel of oil production) |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 5.82 | 6.1 |
| 2 | Expected working | 0.83 | 10 | 90 | 0.01 | 0.0582 | 5.88 | 6.2 |
| 3 | Partial reliability | 0.63 | 50 | 50 | 0.14 | 0.81 | 6.63 | 6.9 |
| 4 | Failed | 0 | 100 | 0 | 1 | 5.82 | 11.64 | 11.9 |

Table 4-48: E-R model for mining crushing equipment based on States i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy- Electricity-kWh/barrel) | Fuel demand Electricity (Kwh/ barrel) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.5 |
| 2 | Expected working | 0.95 | 10 | 90 | 0.01 | 0.005 | 0.51 |
| 3 | Partial reliability | 0.80 | 50 | 50 | 0.14 | 0.07 | 0.57 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.5 | 1 |

Table 4-49: Fraction of loss of for States i=1 to 4-Extra cost- non-motive transport

| Number | States | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (CAN$) | Extra Cost (CAN$/ barrel of oil production) | Total Cost (CAN$/ barrelbarrel of oil production |
|---|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 0.75 | 1.03 |
| 2 | Expected working | 0.83 | 10 | 90 | 0.01 | 0.0075 | 0.76 | 1.04 |
| 3 | Partial reliability | 0.63 | 50 | 50 | 0.34 | 0.255 | 1.01 | 1.29 |
| 4 | Failed | 0 | 100 | 0 | 1 | 0.75 | 1.50 | 1.78 |

Table 4-50: E-R model for non-motive transport based on states i=1 to 4

| Number | State | Reliability | Loss of capacity (%) | Capacity (%) | Fraction of loss of capacity (E L) | Consequence of E L (Energy- Electricity- kWh/barrel) | Fuel demand Electricity (Kwh/ barrel) |
|---|---|---|---|---|---|---|---|
| 1 | Fully operational | 1 | 0 | 100 | 0 | 0 | 4.17 |
| 2 | Expected working | 0.95 | 10 | 90 | 0.01 | 0.04 | 4.21 |
| 3 | Partial reliability | 0.80 | 50 | 50 | 0.34 | 1.42 | 5.59 |
| 4 | Failed | 0 | 100 | 0 | 1 | 4.17 | 8.34 |

### 4.15.1 Results – Energy Results of Surface Mining Equipment, Scenarios 1 to 4

The reference case scenario for reliability improvement for mining equipment in surface mining of Alberta when operating under States 1 through 4 were simulated in LEAP (see Table 4-51 ).

For State 1 (fully operational), LEAP estimated the energy demand of Alberta's surface mining equipment to be 2,579.51 million Gigajoule and 573.71 million Gigajoule for diesel and electricity, respectively, for the year 2050. By improving the reliability of mining equipment, diesel and electricity will be decreased to 2,063.35 and 486.82 million Gigajoule, respectively.

For State 2 (expected working conditions), energy demand was estimated to be 2,583.98 million Gigajoule and 580.87 million Gigajoule for diesel and electricity, respectively, for the year 2050. By improving the reliability of mining equipment, energy demand will decrease to 1,520.61 and 492.84 million Gigajoule for diesel and electricity, respectively.

For State 3 (partial reliability), energy demand as diesel was estimated to be 2,756.59 million Gigajoule and as electricity, 668.35 million Gigajoule for the year 2050. By improving the reliability of mining equipment diesel and electricity will be decreased to 1,732.91 and 566.50 million Gigajoule, respectively.

For State 4 (complete failure), the energy demand as diesel was estimated to be 3,571.01 million Gigajoule and as electricity, 1,147.41 million Gigajoule for the year 2050. By improving the reliability of mining equipment, energy demand as diesel and electricity may decrease to 2,011.72 and 973.97 million Gigajoule, respectively.

Table 4-51: Alberta mining equipment energy demand (million Gigajoule)-State 1 to 4-year 2050

| Scenario | 1 | | 2 | | 3 | | 4 | |
|---|---|---|---|---|---|---|---|---|
| Energy | Electricity | Diesel | Electricity | Diesel | Electricity | Diesel | Electricity | Diesel |
| Reference | 2,579.51 | 573.71 | 2,583.98 | 580.87 | 2,756.59 | 668.35 | 3,571.01 | 1,147.41 |
| Reliability improvementc c | 2,063.35 | 486.82 | 1,520.61 | 492.84 | 1,732.91 | 566.50 | 2,011.72 | 973.97 |
| Total | 4,642.86 | 1,060.52 | 4,104.60 | 1,073.71 | 4,489.49 | 1,234.85 | 5,582.73 | 2,121.38 |

### 4.15.2 Energy Saving Results from the E-R Model for Oil Sands Mining Equipment Operating Under State 1

For Scenario 1 (State 1), energy demand for Alberta's surface mining equipment was plotted in LEAP over 40 years for both the reference case and Scenario 1 and is shown in Figure 4-68. Plotted energy demand over a specific period (from 2010 to 2050) indicates that there will be on average 0.19% energy saving per year through improving the reliability of fully operational mining equipment.

For Scenario 2 (State 2), there will be on average 0.36% energy saving annually through improving the reliability of mining equipment (see Figure 4-69).

For Scenario 3 (State 3), there will be on average 0.33 % energy saving annually through improving the reliability of mining equipment (see Figure 4-70).

For Scenario 4 (State 4), there will be on average 0.37% energy saving annually through improving the reliability of mining equipment (see Figure 4-71).

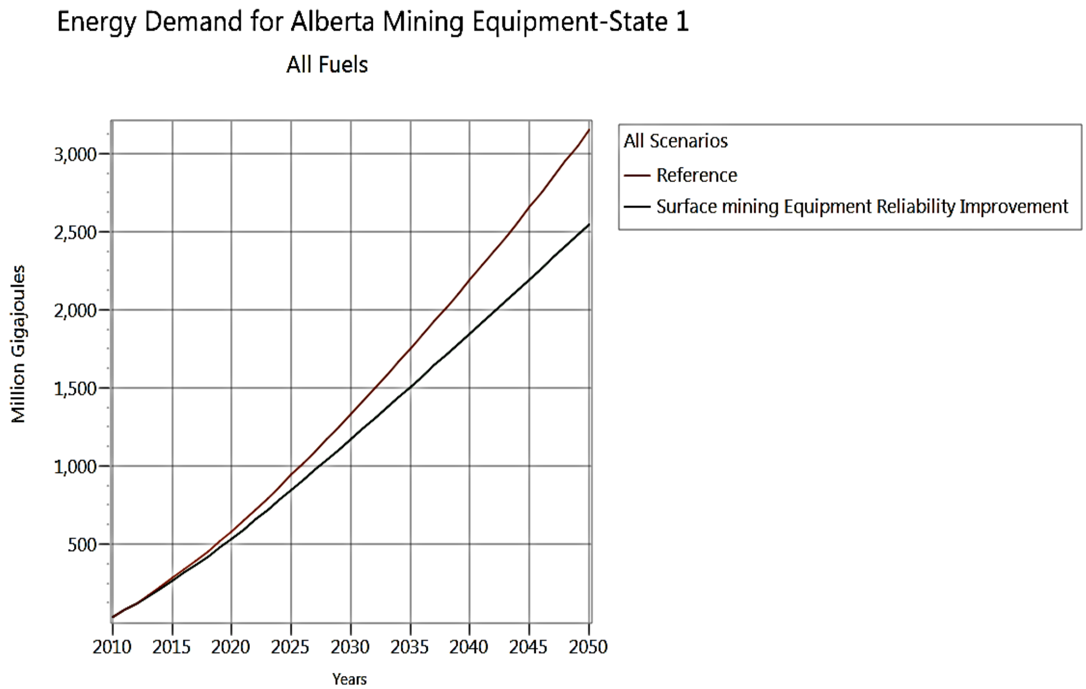



Figure 4-67: Energy saving for Alberta's surface mining equipment from 2010–2050: Scenario 1 vs reference scenario - State 1

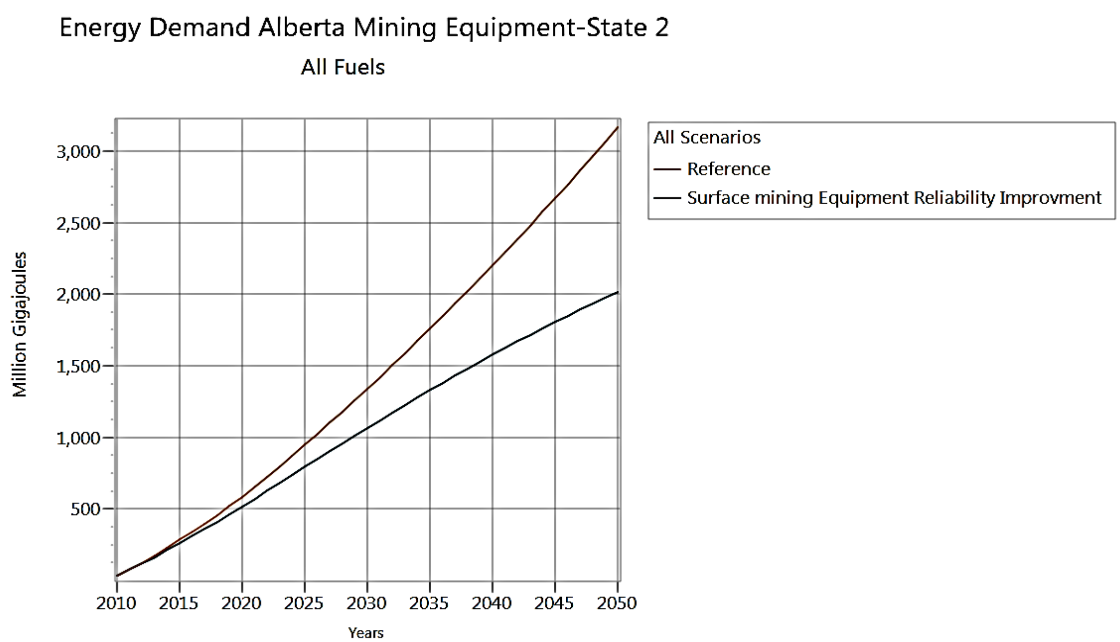



Figure 4-68: Energy saving for Alberta's surface mining equipment from 2010–2050: Scenario 1 vs reference scenario - State 2

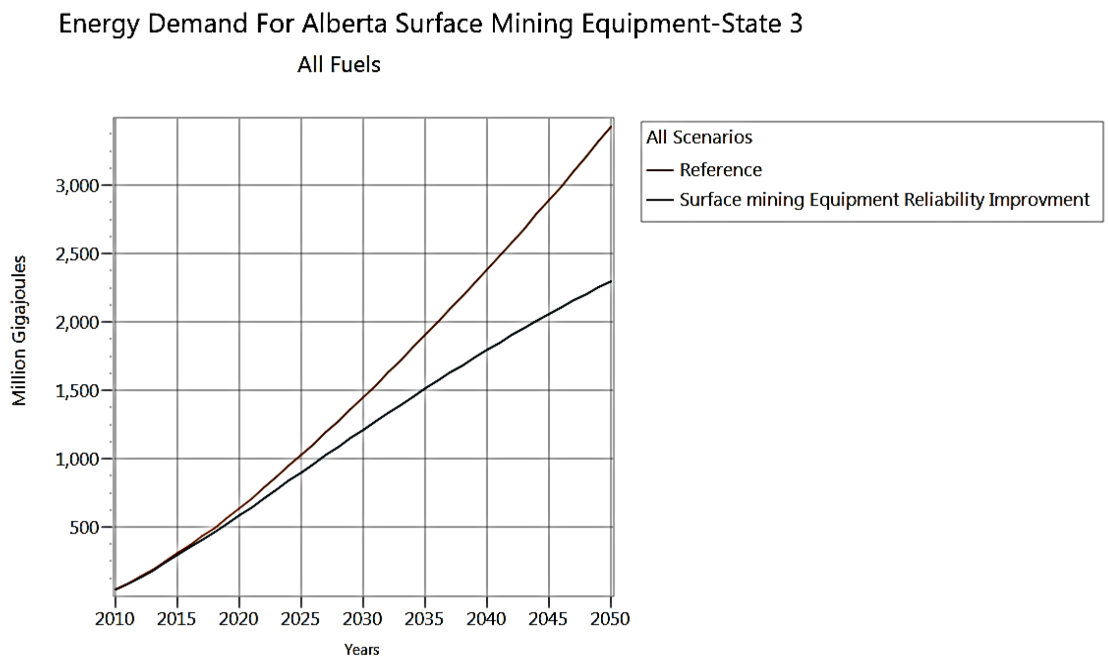



Figure 4-69: Energy saving for Alberta's surface mining equipment from 2010–2050: Scenario 1 vs reference scenario - State 3

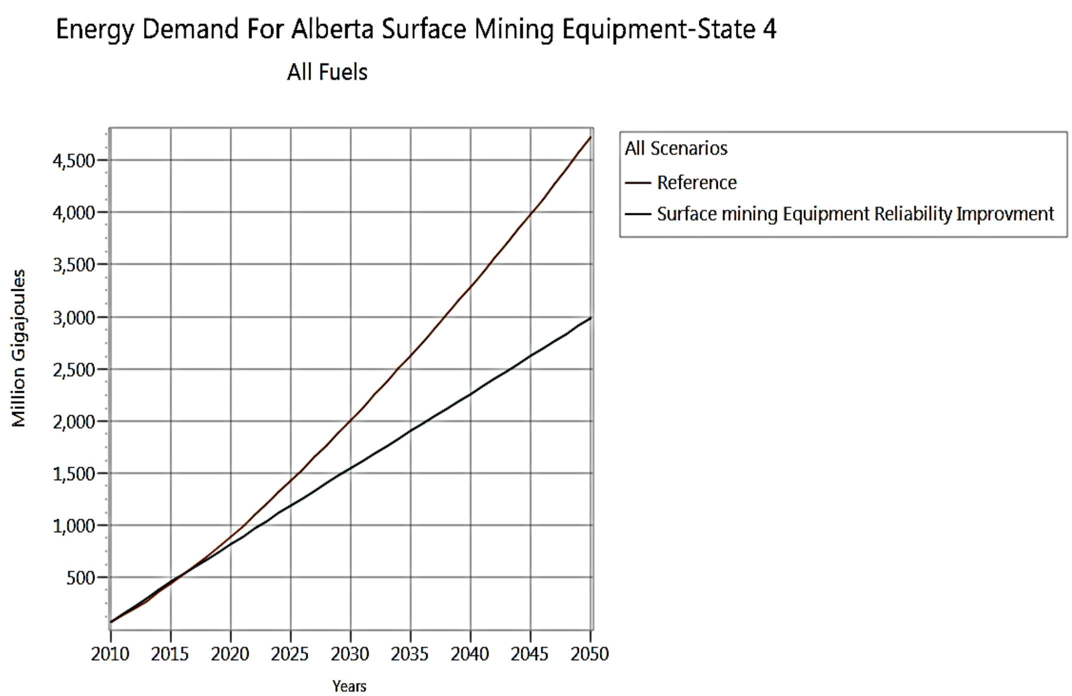



Figure 4-70: Energy saving for Alberta's surface mining equipment from 2010–2050: Scenario 4 vs reference scenario - State 4

### 4.15.3 Cost Saving Results from the E-R Model for Oil Sands Mining Equipment Operating Under States 1 to 4

Alberta oil sands mining equipment operational costs were plotted over 40 years (2010-2050) for the reference case and Scenarios 1 to 4 (see Figures 4-72 to 4-752).

For Scenario 1, as the graph shows, on average 0.77 % of annual costs can be reduced through improving the reliability of mining equipment (see Figure 4-72).

For Scenario 2, there will be on average 0.07% of annual cost saving through improving the reliability of mining equipment (see Figure 4-73).

For Scenario 3, there will be an average cost saving of 0.33 % per year through improving the reliability of mining equipment (see Figure 4-74).

For Scenario 4, there will be an average cost saving of 0.35 % per year through improving the reliability of mining equipment (see Figure 4-75).

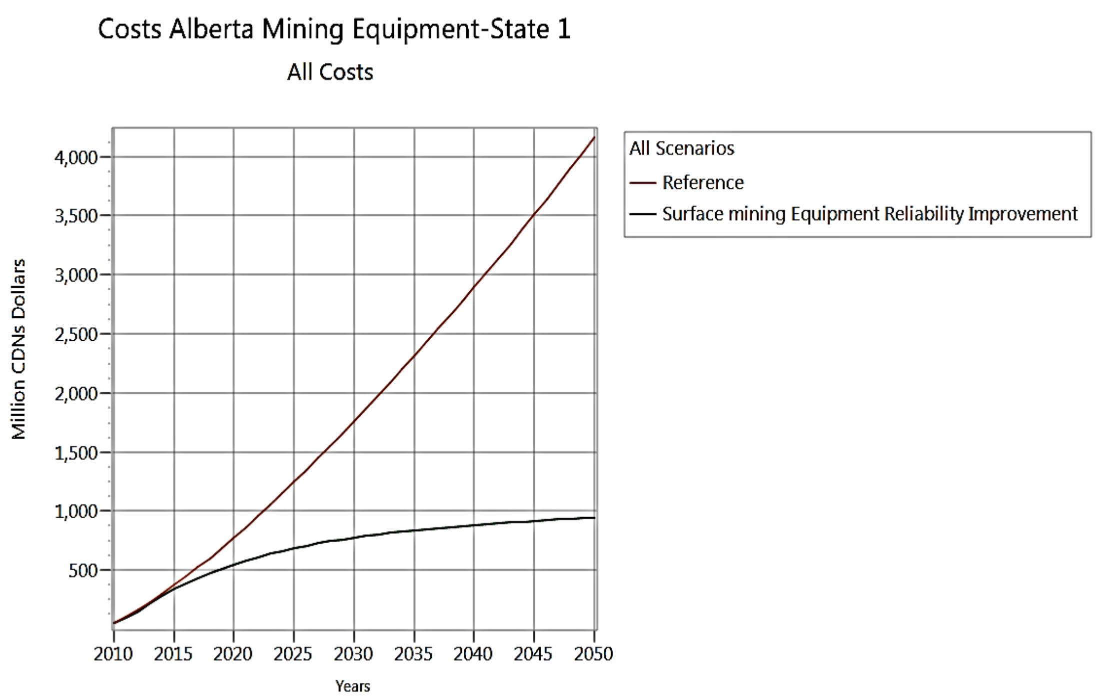



Figure 4-71: Cost saving for Alberta's surface mining equipment: Scenario 1 vs its reference scenario - State 1

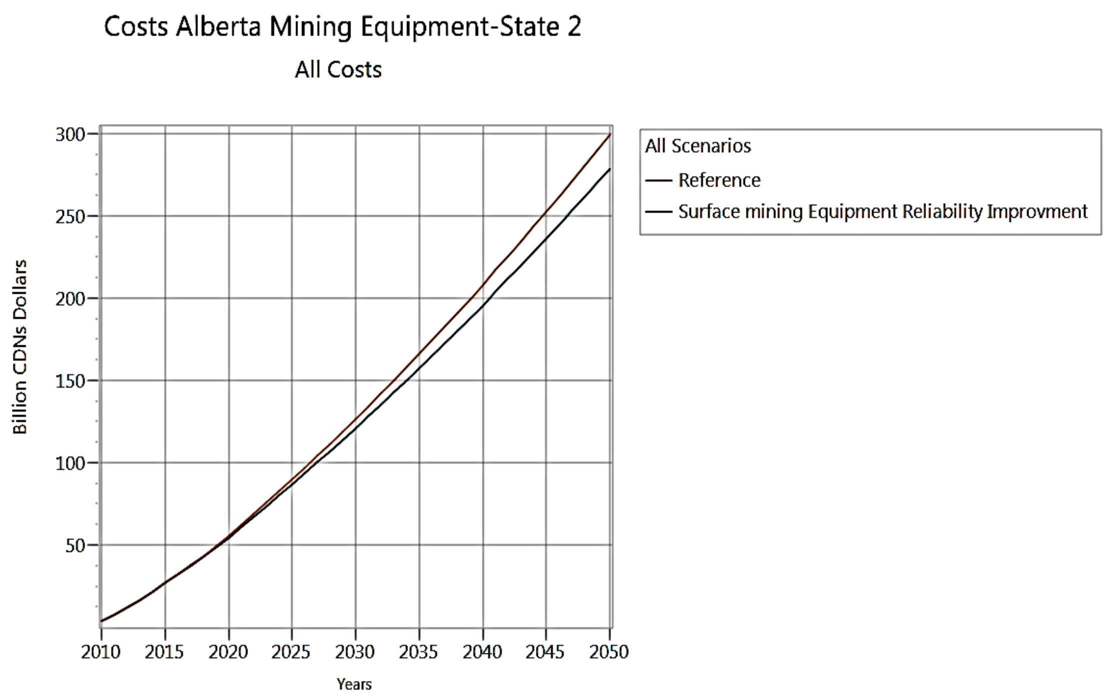



Figure 4-72: Cost saving for Alberta's surface mining equipment: Scenario 2 vs its reference scenario - State 2

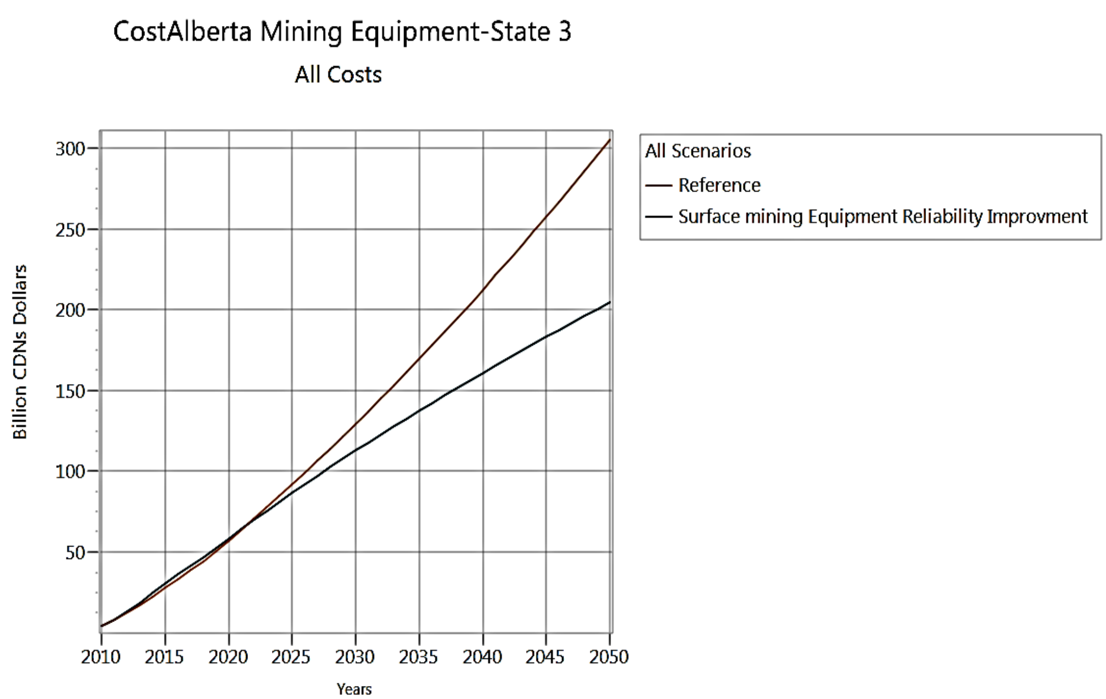



Figure 4-73: Cost saving for Alberta's surface mining equipment: Scenario 3 vs its reference scenario - State 3

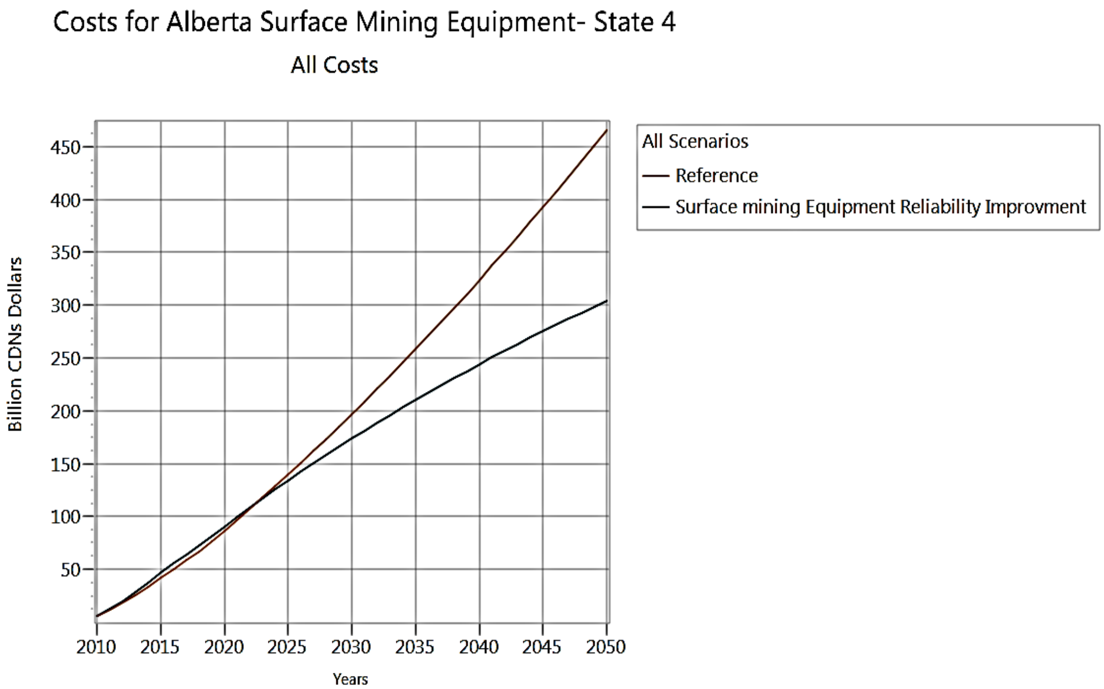



Figure 4-74: Cost saving for Alberta's surface mining equipment: Scenario 4 vs its reference scenario - State 4

### 4.15.4 GHG Emission Saving Results from the E-R Model for Oil Sands Mining Equipment in Alberta Operating Under States 1 to 4

GHG emissions associated with fuel consumption for mining equipment were plotted in LEAP for a 40-year period (2010-2050) in States 1 to 4 and the results are shown in Figures 4-76 to 4-79 and Tables 4-52 to 4-55.

Table 4-52 provides the data obtained from LEAP for both the reference and reliability scenarios for the year 2050. When equipment reliability is improved, GHG emissions can be reduced by an average of 1.05% annually (see Figure 4-76). .

For Scenario 2, there will be on average 0.68% reduction in GHG emissions through improving the reliability of mining equipment (see Figure 4-77 and Table 4-53).

For Scenario 3, there will be on average 0.37 % reduction in GHG emissions through improving the reliability of mining equipment (see Figure 4-78 and Table 4-54).

For Scenario 4 (State 4), there will be on average 0.44% reduction in GHG emissions through improving the reliability of mining equipment (see Figure 4-79 and Table 4-55).

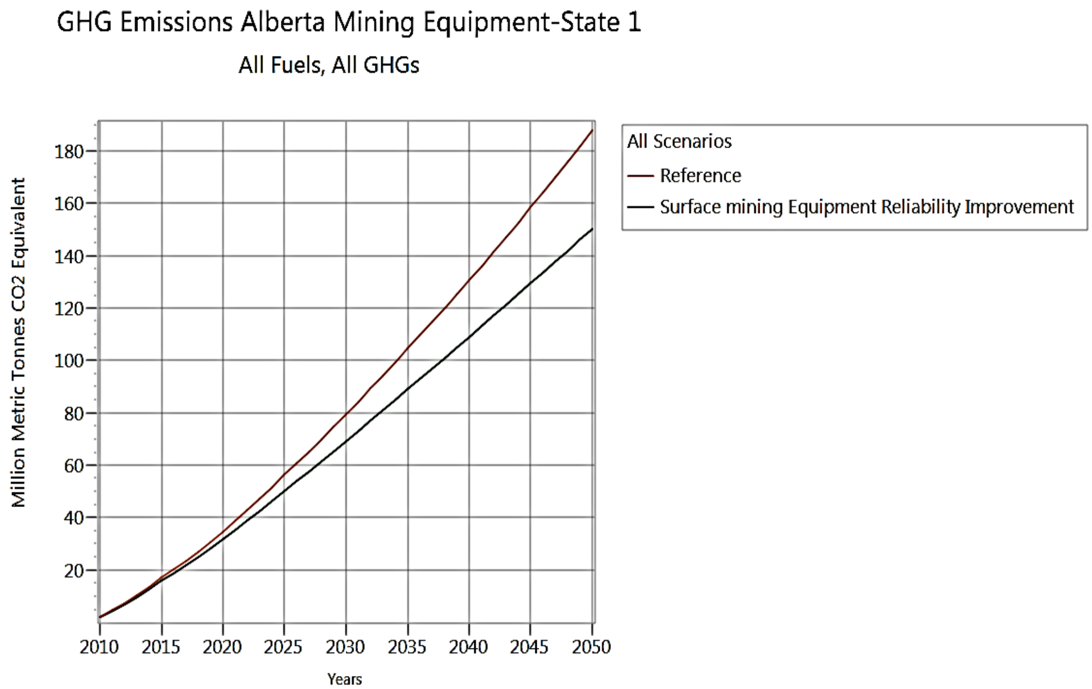



Figure 4-75 GHG emissions for Alberta's mining equipment: Scenario 2 vs reference scenario - State 1

Table 4-52: GHG emissions for oil sands mining equipment, 2010-2050 - State 2 (thousand metric tonnes $CO_2$ equivalent)

| Scenarios | Nitrous Oxide | Methane | Carbon Dioxide Non Biogenic | Total |
|---|---|---|---|---|
| Reference | 15.28 | 3.45 | 5,961.54 | 5,980.28 |
| Surface mining Equipment Reliability Improvement | 10.61 | 2.40 | 4,139.34 | 4,152.35 |
| Total | 25.90 | 5.85 | 10,100.88 | 10,132.62 |

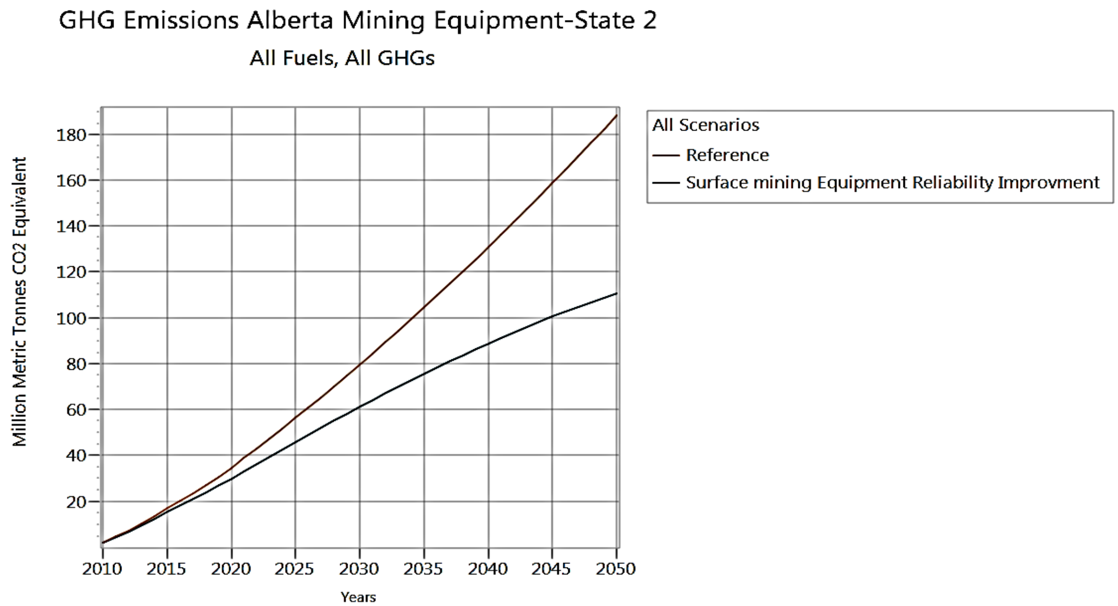



Figure 4-76 GHG emissions for Alberta's mining equipment: Scenario 2 vs reference scenario - State 2

Table 4-53: GHG emissions for oil sands mining equipment, 2010-2050 - State 2 (million metric tonnes $CO_2$ equivalent)

| **Scenario** | **Nitrous Oxide** | **Methane** | **Carbon dioxide non biogenic** | **Total** |
|---|---|---|---|---|
| Reference | 0.48 | 0.11 | 187.47 | 188.06 |
| Surface mining equipment reliability improvement | 0.28 | 0.06 | 110.32 | 110.67 |
| Total | 0.76 | 0.17 | 297.79 | 298.72 |

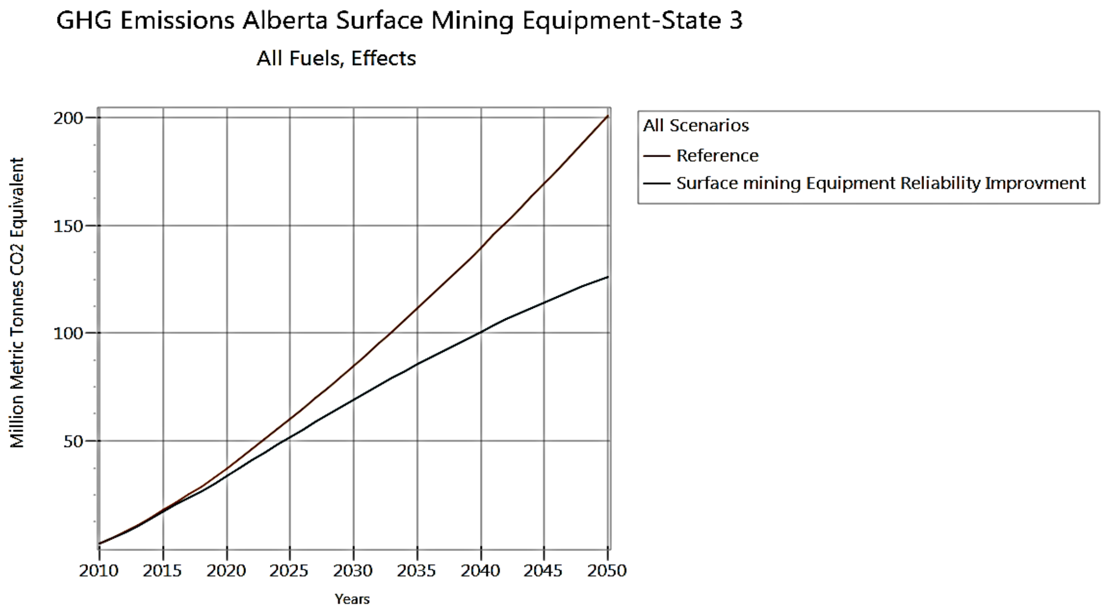



Figure 4-77: GHG emissions saving for Alberta's mining equipment: Scenario 3 vs reference scenario - State 3

Table 4-54: GHG emissions for oil sands mining equipment, 2010-2050 - State 3 (million metric tonnes $CO_2$ equivalent)

| Scenario | Nitrous Oxide | Methane | Carbon dioxide non biogenic | Total |
|---|---|---|---|---|
| Reference | 16.32 | 3.69 | 6,366.48 | 6,386.49 |
| Surface mining equipment reliability improvement | 5.62 | 1.27 | 2,193.40 | 2,200.29 |
| Total | 21.95 | 4.96 | 8,559.88 | 8,586.78 |

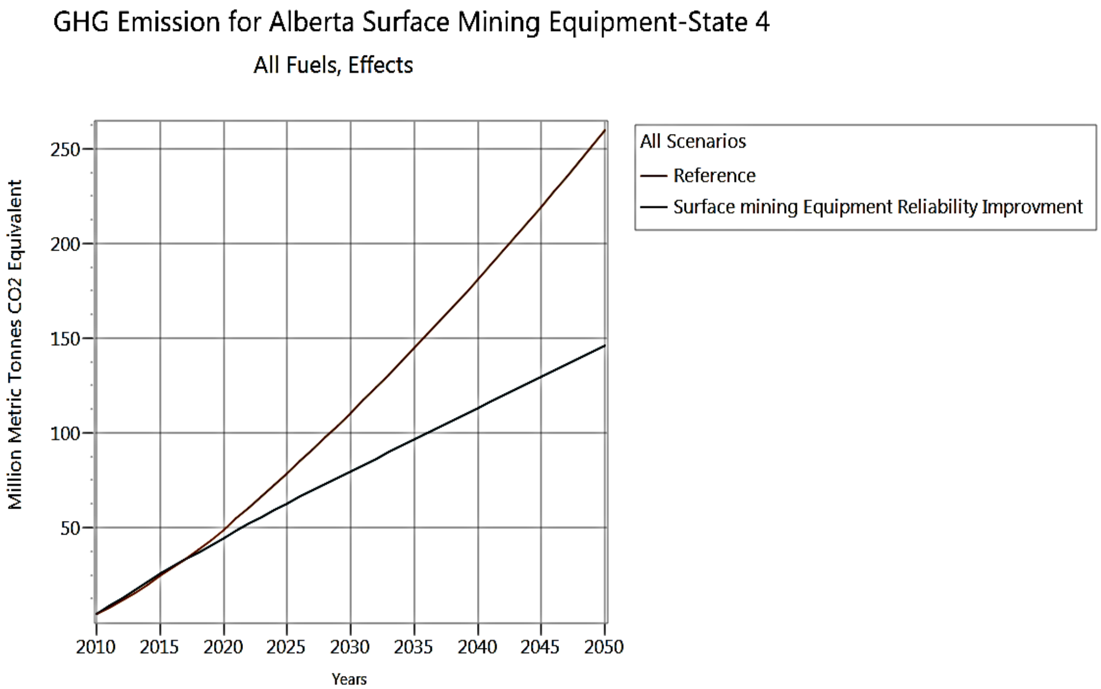



Figure 4-78: GHG emissions saving for Alberta's mining equipment: Scenario 4 vs reference scenario

Table 4-55: GHG emissions for oil sands $_{mining}$ equipment, 2010-2050 - State 4 (million metric tonnes $CO_2$ equivalent$_{)}$

| **Scenario** | **Nitrous Oxide** | **Methane** | **Carbon dioxide non biogenic** | **Total** |
|---|---|---|---|---|
| Reference | 21.05 | 4.75 | 8,211.18 | 8,236.99 |
| Surface mining equipment reliability improvement | 8.55 | 1.93 | 3,333.97 | 3,344.44 |
| Total | 29.60 | 6.68 | 11,545.15 | 11,581.43 |

## 4.16 Validation of the E-R Model

LEAP's projected energy consumption for the surface mining industry in Alberta was compared with NRCan's and statistic Canada data for the year 2010.

Table 4-56: Validation of LEAP model results for the base year (2010)

| Fuel | LEAP (PJ) | NRC (PJ) |
|---|---|---|
| Electricity | 6.85 | 9.64 |
| Diesel | 29.07 | 30.94 |
| Total | 41.9 | 35.45 |

As Table 4-56 shows, LEAP's electricity and diesel consumptions levels are comparable to NRCan's and statistic Canada.

In addition, a Monte Carlo simulation can be used to assess the reliability of E-R model results. The data required for this simulation consist of mining equipment main component failures. A Monte Carlo simulation randomly generates failure samples for each mining equipment sub-component based on the information in the RBD and the reliability function distribution of mining equipment obtained from the failure data. The process is repeated with new random numbers from the same input probability distribution functions to calculate new reliability values. After many iterations, an accepted system reliability will be obtained, wherein reliability assessments for the mining equipment illustrated in the RBD (Figure 4-64) can be represented by a probability distribution function for the system.

## 4.17 Sensitivity Analysis

Sensitivity analyses were performed for haul truck engines and tires of as well as slurry pumps to find the impacts of various technical parameters.

### 4.17.1 Sensitivity Analysis for the Haul Truck Engine

The engine is an important component of the haul truck. Diesel fuel is used to operate the engine. Therefore, a sensitivity analysis of the effects on diesel consumption of changing various parameters of the haul truck's engine is important. In this study, three parameters were selected: truck capacity, cycle time, and availability. Variations of $\pm$ 40% were used in the input parameters. The following assumptions were made:

- The truck was a CAT model 797 from Caterpillar Inc. with a capacity of 345 tonnes, a (diesel) fuel consumption of about 579 l/hr and a velocity of 45 km/hr;
- Cycle time, defined as the required to load, unload, turn and dump, return (empty), wait and delay, was estimated to be 9 minutes. In this thesis, cycle time for five fleets was estimated to be 18.5 minutes (106).
- Energy density in diesel were assumed to be 40.76 GJ/$m^3$ and 36.2 MJ/L, respectively (107).

Figure 4-80 illustrates the sensitivity analysis results for the haul truck's engine in terms of diesel consumption. Diesel consumption moderately increases non-linearly with changes in truck loads, truck cycle time and truck availability as related variables for haul truck engine. This figure shows that with a 10% decrease in truck load, and truck availability, diesel consumption increases by 7.6%, 4.9% and 5.2%, respectively.

In addition, truck cycle time drops by 4.9%.

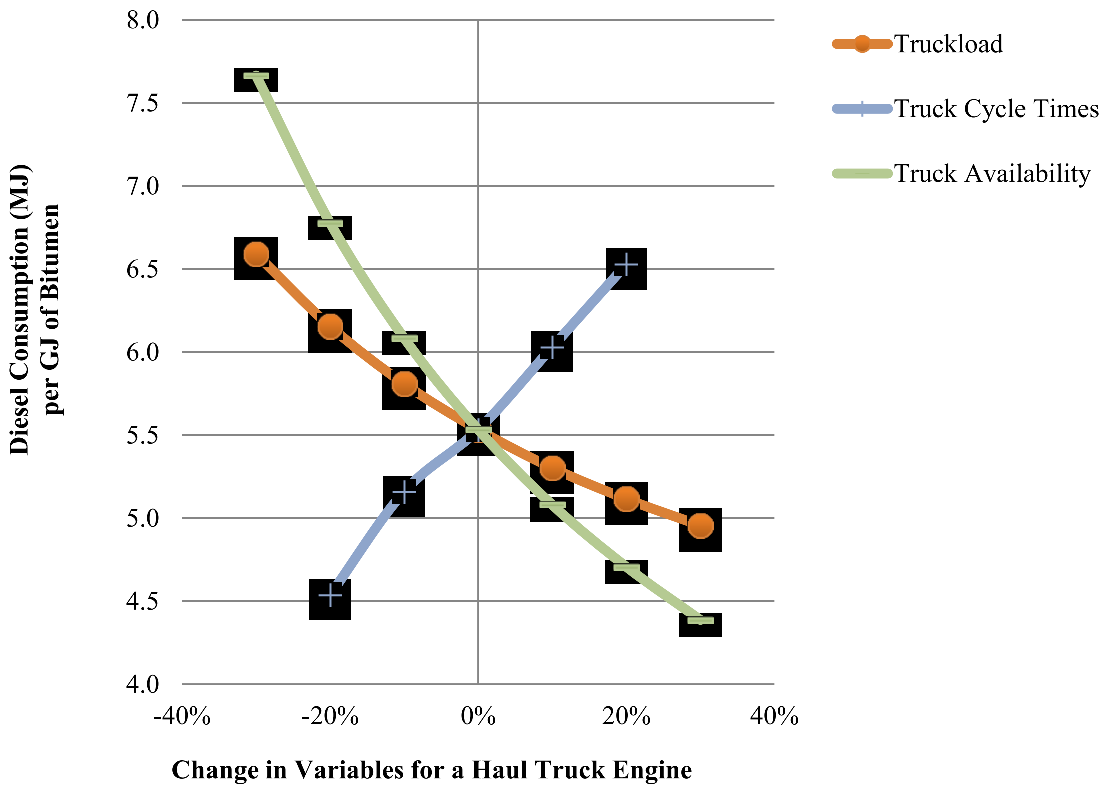



Figure 4-79: Sensitivity analysis for a haul truck engine diesel consumption

## 4.17.2 Sensitivity Analysis for Tires

To verify the effects of changing various parameters of haul truck tires on diesel consumption, a sensitivity analysis was performed. Tire load-carrying capacity, pressure and temperature were the considerations in the sensitivity analysis. These parameters were varied from -20% to +20% to find changes in energy consumption. Tire load capacity can exceed 10-15% related to deviations in loading without any reduction in tire life. If a tire is underinflated or the truck load increases tire pressure, then the tire load capacity increases. If tires are underinflated, heat results are built-up. If tires are overinflated, the rubber tires cuts and their traction increase. Tire pressure is another influential parameter. If tire pressure is low, the truck can still operate but requires more energy. The optimum pressure in cold weather for bias ply/nylon tires is 483 kPa and for radial tires is 586 kPa. If tire inflation pressure increases above 40 PSI, fuel consumption increases by 2%. The temperature of the mining operations also has effect on tires and on energy consumption. Temperature varies with the location of the mine. Tires start to deteriorate at -35°C, and this deterioration leads to sidewall damage (64, 106).

Tire rolling resistance accounts for roughly one quarter to one third of the truck's overall fuel consumption (108). Figure 4-81 demonstrates the sensitivity analysis for haul truck's tire.

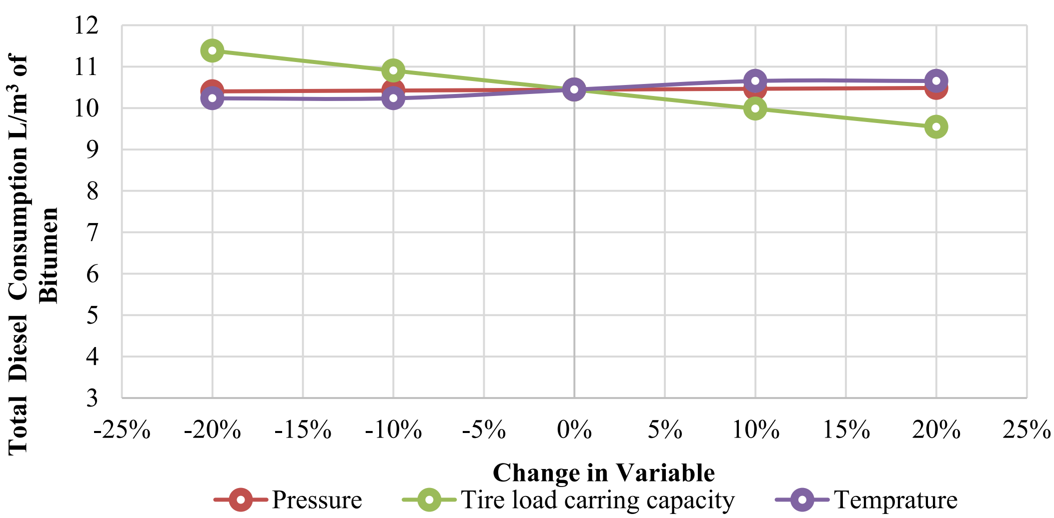



Figure 4-80: Sensitivity analysis for a haul truck's tires

## 4.17.3 Sensitivity Analysis for the Slurry Pump

Parameters used to conduct a sensitivity analysis for a slurp pump were motor efficiency, pump efficiency, pump rotation speed, and slurry pressure differential. Energy consumption based on these variables were calculated based on the assumption that the slurry pump has a 300 HP power motor and operates at 88% efficiency. Annual energy consumption was calculated with Equation 4-4:

Energy consumption (kwh) = (300 HP*0.745 kw*365day*24hr/day)/0.88 [4-4]

=2,224,840.909 kwh

Energy consumption=8009.42 GJ

Second, a slurry pump with 85% efficiency, a pressure differential of 20 bar, and a capacity of 320 m3/h was assumed. Energy consumption for such a pump is calculated with Equation 4-5:

$$\text{Energy consumption}=\frac{Q*\Delta P}{\eta_{PUMP}*\eta_{MOTOR}*36} \qquad [4\text{-}5]$$

Energy consumption= 237.67 kw*365 day*24 hr/1 day=2081989.2 kwh= 7495.16 GJ

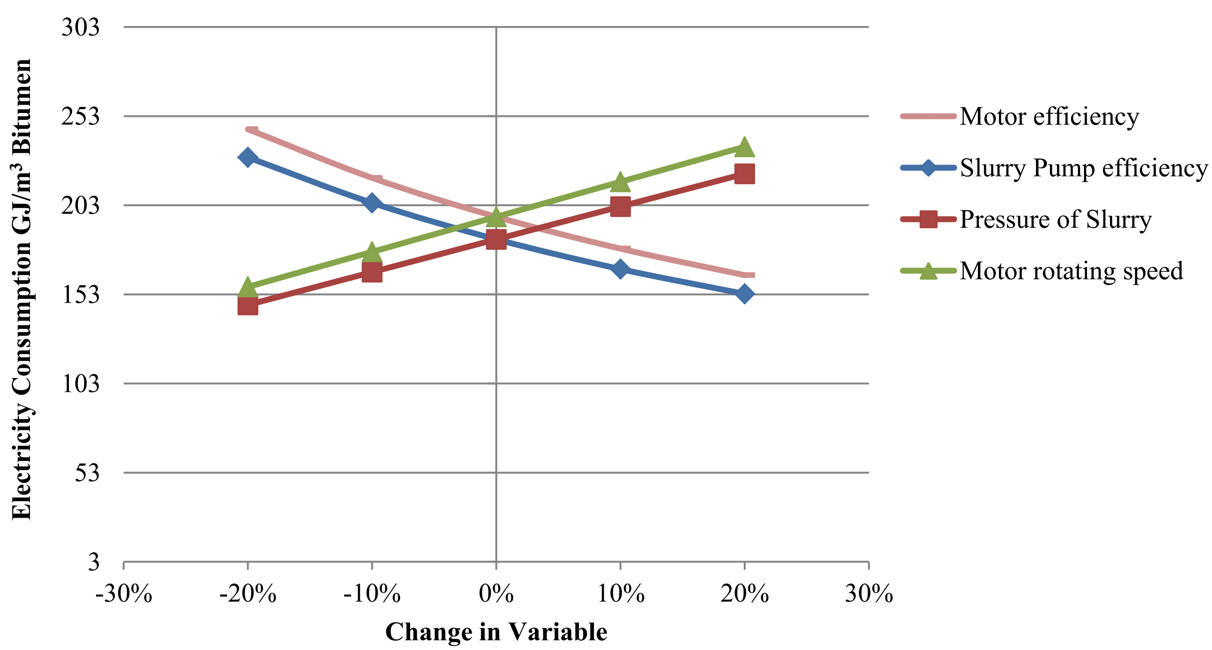



Figure 4-81: Slurry pump electricity consumption sensitivity analysis

Figure 4-82 shows that with a 10% increase in efficiency, energy consumption decreases by 9.15%. With a 20% drop in slurry pump pressure, electricity consumption will increase by 19%.

## 4.18 Uncertainty Analysis for Expert Opinion Data for the Fraction of Loss

An uncertainly analysis is done by performing a variety of tests on the information provided by the experts. There are several means of getting expert responses, such as through structured or informal interviews, with the questions and answers communicated in person, by email, or by telephone. In this research, face-to-face and telephone interviews were conducted on the reliability of equipment in Canada's mining industry with experts from three broad groups: professionals (reliability engineers and managers), supervisors (maintenance coordinators), and trades people. The first two groups had four experts each and the third had six experts. Tables 4-57, 4-58, and 4-59 refer to experience and option on fraction of loss of mining equipment. Interviews were informal and no personal or private information was collected.

Table 4-57: Group 1's experience and opinion on mining equipment fraction of loss (time during which equipment is not available for use)

| Expert | Title | Years of experience | Experience in failure analysis in years (especially mining equipment fraction of loss) | Fraction of loss (%) |
|---|---|---|---|---|
| 1 | Reliability engineer | 5 | 3 | 10 |
| 2 | Maintenance engineer | 10 | 5 | 10 |
| 3 | Reliability manager | 20 | 15 | 10.5 |
| 4 | Reliability engineer | 7 | 5 | 9.9 |

Table 4-58: Group 2's experience and opinion on mining equipment fraction of loss (time during which equipment is not available for use)

| Expert | Title | Years of experience | Experience in failure analysis in years (especially mining equipment fraction of loss) | Fraction of loss (%) |
|---|---|---|---|---|
| 1 | Senior reliability specialist | 17 | 10 | 9.8 |
| 2 | Failure analysis | 4 | 2 | 11.2 |
| 3 | Reliability manager | 7 | 4 | 10 |
| 4 | Reliability analyst | 6 | 1 | 10.1 |

Table 4-59: Group 3's experience and opinion on mining equipment fraction of loss (time during which equipment is not available for use)

| Expert | Title | Experience | Experience in failure analysis in years (especially mining equipment fraction of loss) | Fraction of loss (%) |
|---|---|---|---|---|
| 1 | Manager integration Maintenance and reliability | 27 | 9 | 10 |
| 2 | Reliability engineer | 30 | 7 | 10.1 |
| 3 | Reliability manager | 8 | 2 | 10.2 |
| 4 | Team leader, R&D reliability & performance improvement | 10 | 6 | 11 |
| 5 | Reliability engineering lead | 15 | 5 | 9.5 |
| 6 | Senior mechanical engineer | 11 | 5 | 10.2 |

As both group 1 and 2 have the similar numbers of experts (refer to Tables 4-66 and 4-67)., therefore to be able to compare their decisions regarding fraction of loss of mining equipment, the least significant range ($R_p$) needs to calculate from Equation 4-6.

$$R_p = r_p \times \sqrt{\frac{s^2}{2}} \qquad [4\text{-}6]$$

$S^2$ is the variety in samples (expert opinion on quantitative data) and $r_p$ is the least studentized range, which is obtained from Milton and Arnold's table (see Appendix) (40).

To compare the experts decisions regarding fraction of loss of mining equipment in group 3 to group 1 and 2, the least significant range ($R_p$) calculates from Equation 4-7.

$$R'_p = r_p \times \sqrt{s^2} \qquad [4\text{-}7]$$

P calculates from Equation 4-8 (109). :

$$p = j - i + 1 \qquad [4\text{-}8]$$

The degree of freedom (f) from the sample is calculated from Equation 4-9 (109):

$$f = k \times (n-1) \qquad [4\text{-}9]$$

Where k is the number of groups and n is the number of experts in each group.

Table 4-60 presents the mean value and variance of the data for each group. Table 4-61 displays the least studentized range value ($r_p$) according to F and P from Milton and Arnold's graph.

Table 4-60: Mean value and variance of each group's sample data

| Group | Number of data | Mean | Variance |
|---|---|---|---|
| 1 | 4 | 10.10 | 0.073 |
| 2 | 4 | 10.28 | 0.396 |
| 3 | 6 | 10.17 | 0.235 |

Table 4-61: Least studentized range value from Milton and Arnold (1)

| | | | | |
|---|---|---|---|---|
| F | 15 | 15 | 9 | 9 |
| P | 2 | 3 | 2 | 3 |
| $r_p$ | 3.014 | 3.16 | 3.2504 | 3.3842 |

The value for the desired significant level α was chosen as 0.05 to find the related $r_p$. Table 4-62 shows the difference between mean values of each group to compare with $R_p$ or $R'_p$.

Table 4-62: The least significant range comparing expert groups' data

| | $m_1$ & $m_2$ compared | | $m_1$ & $m_3$ compare | | $m_2$ & $m_3$ compared | |
|---|---|---|---|---|---|---|
| p | 2 | 2 | 3 | 3 | 2 | 2 |
| f | 9 | 9 | 9 | 15 | 9 | 15 |
| $r_p$ | 3.2504 | 3.2504 | 3.3842 | 3.16 | 3.2504 | 3.014 |
| n | 4 | | | | | |
| $s^2/n$ | $2*10^{-5}$ | | | | | |
| square root of $s^2/n$ | 0.0014 | 0.0014 | 0.0063 | 0.0063 | 0.0048 | 0.0048 |
| $R'_p$ | 0.0044 | 0.0044 | 0.0213 | 0.0199 | 0.0157 | 0.0146 |
| $m_d$ | 0.0035 | | -0.0024 | | -0.0024 | |
| Comparison of $m_d$ & $R'_p$ | 0.0035<0.0044 | | | | | |

Because $m_d$ in each group was smaller than $R'_{p,}$, the difference between the two mean values was considered to be insignificant. Therefore, the mean value of the data, which was 10%, can be used as the fraction of loss (time during which equipment is not available for use) for haul trucks, shovels, crushers, conveyor belts, and slurry pumps.

Chapter 5:

# Conclusions, Engineering Significance, and Recommendations for Future Work

# Chapter 5: Conclusions, Engineering Significance, and Recommendations for Future Work

## 5.1 Conclusions

Alberta's surface mining sector is one of the largest energy-consuming industries in Canada. Energy is consumed primarily by mining equipment through bitumen extraction processes. According to Alberta Energy, there are 166 billion barrels of oil in Alberta's reserves . Oil sands mining equipment has a significant impact on economic assets. Sustainable development in Alberta's oil sands mining industry can be achieved by improving the reliability of mining equipment, which will reduce costs and energy consumption. Energy consumption and equipment reliability have significant risk associated with some main subsystems. When mining equipment reliability is evaluated and improved, costs associated with maintenance and energy consumption can be reduced, which also influences GHG emissions.

In this research, some oil sands mining equipment was selected and failure modes for some main subsystems were defined and studied. The Bayesian belief network (BBN) was used to determine failure probability and reliability values for selected mining equipment subsystems through their failure modes. Those major subsystems that influence energy consumption were analyzed using the Long-range Energy Alternative Planning Systems (LEAP) software. A discrete Markov multi-state model was used to link equipment reliability and energy efficiency.

The key objectives of this research were to develop a demand tree, analyze and assess the reliability modeling of oil sands mining equipment, and make a link between energy consumption and reliability. These objectives will lead to substantial reductions in cost and long-term energy consumption in the oil sands mining sector in Alberta. It is important to determine which mechanical parts have a direct impact on reliability and energy consumption, especially when equipment can continue to work under partial reliability. Therefore, critical subsystems of oil sands mining equipment, that is haul trucks, hydraulic and electric shovels, crushers, conveyor belts, and slurry pumps, were identified and analyzed based on reliability, final energy consumption, and cost. The integrated energy-reliability model (E-R model) developed for oil sands mining equipment provides a detailed reliability-energy analysis. This model helps us understand the relationship between energy and reliability, and clarifies the amount of energy consumption and energy saving possibilities through improving the reliability of equipment.

In order to deal with uncertainty and lack of accessible data, the BBN was used to calculate the failure rate for the selected main subsystems. In addition, failure rate was used to find the partial reliability. Partial reliabilities were calculated for these main parts based on a Markov degraded multi-state model (three states). These there states are defined as:

State 1: the system operates under expected reliability (as defined by manufacturer). State 2: the system operates under low or limited reliability; this is also known as partial reliability. State 3: the system fails.

LEAP software was used to calculate final energy consumption by each main subsystem for the study period 2010 to 2050. Results from this study will elucidate energy saving possibilities in surface mining operations and energy saving influence on cost reduction and profitability for the mining industry.

The E-R model simulates cost and energy in every state of the mining equipment considered and evaluates the energy, cost, and GHG emissions savings by comparing the reference and "improving reliability" scenarios in each state based on a discrete Markov multi-state model, which works under four states. These four states are defined as:

State 1: the mining equipment is fully operational; in other words, its reliability is equal to 1 (it does not encounter any failure; this is the ideal state)

State 2: the mining equipment works under expected reliability. Every piece of equipment has its own reliability value based on its probability density function and its local situation; this is known as expected reliability. The manufacturer defines expected reliability.

State 3: the mining equipment works under partial reliability. If some parts of equipment are damaged but the equipment still can operate, perhaps under lower reliability, this is known as partial reliability.

State 4: the mining equipment fails.

Afterward, partial failure probability and partial reliability were calculated through the reliability function and used in the E-R model. LEAP software calculated energy consumption by each equipment's sub-component and made connections with partial reliability and energy consumption. Failure probability, reliability, and probability density function summaries for each piece of equipment selected are given in Tables 5-1 and 5-2. Through LEAP, energy, cost, and GHG emission savings were determined. The E-R model results for the selected mining equipment for both the reference scenario (that is, the base case for the year 2010) and the “improving reliability” scenarios are summarized in Tables 5-3, 5-4, and 5-5. The evaluation was done by implementing already-developed reliability studies and strategies. The success of this model depends on how well the interactions between energy and reliability are defined.

5-1: Summary of activities performed in the simulation

| Equipment | Main Subsystem | Probability of Failure | Reliability | Failure Rate |
|---|---|---|---|---|
| Mining Haul Trucks | Cab/control | 0.01 | 0.99 | 0.01 |
| | Fuel system | 0.1 | 0.9 | 0.11 |
| | Engine | 0.01 | 0.99 | 0.01 |
| | Transmission | 0.1 | 0.9 | 0.11 |
| | Brakes | 0.12 | 0.88 | 0.14 |
| | Suspension | 0.08 | 0.92 | 0.09 |
| | Tires | 0.17 | 0.83 | 0.20 |
| | Dispatch system | 0.15 | 0.85 | 0.18 |
| | Pneumatics/ Hydraulics | 0.1 | 0.9 | 0.11 |
| | Structure | 0.04 | 0.96 | 0.04 |
| | Final drives (wheel sets) | 0.05 | 0.95 | 0.05 |
| Mining Shovels-Hydraulic | Hydraulic pumps | 0.05 | 0.95 | 0.01 |
| | Shutdown valves | 0.01 | 0.99 | 0.05 |
| | Filter assembly | 0.14 | 0.86 | 0.06 |
| | ZAKO rings | 0.07 | 0.93 | 0.01 |
| | O-rings | 0.07 | 0.93 | 0.10 |
| | Boom and stick | 0.01 | 0.99 | 0.28 |
| | Slew ring bolts | 0.22 | 0.78 | 0.08 |
| | Shovel cab/control | 0.01 | 0.99 | 0.01 |
| | Engine | 0.09 | 0.91 | 0.16 |
| | Brakes | 0.06 | 0.94 | 0.08 |

5-2: Summary of activities performed in the simulation (cont)

| Equipment | Main Subsystem | Probability of Failure | Reliability | Failure Rate |
|---|---|---|---|---|
| Mining Shovels-Electric | Hoist Ropes | 0.02 | 0.98 | 0.27 |
| | Buckets | 0.06 | 0.94 | 10.11 |
| | Teeth | 0.91 | 0.09 | 0.01 |
| | Electric drive motor | 0.21 | 0.79 | 0.06 |
| | Crawler | 0.01 | 0.99 | 0.02 |
| Oil Sands Mining Crushers | Structure | 0.05 | 0.95 | 0.05 |
| | Screen mesh | 0.07 | 0.93 | 0.08 |
| | Teeth | 0.9 | 0.1 | 9.00 |
| | Rolls | 0.12 | 0.88 | 0.14 |
| | Drive system | 0.17 | 0.83 | 0.20 |
| | Apron feeder | 0.04 | 0.96 | 0.04 |
| | Control system | 0.1 | 0.9 | 0.11 |
| Oil Sands Mining Conveyor Belt | Drive motor | 0.01 | 0.99 | 0.01 |
| | Power roller | 0.03 | 0.97 | 0.03 |
| | Head and tail pulley | 0.01 | 0.99 | 0.01 |
| | Idler | 0.06 | 0.94 | 0.06 |
| | Belt | 0.85 | 0.15 | 5.67 |
| | Pulley cleaner | 0.05 | 0.95 | 0.05 |
| Oil Sands Mining Slurry Pump | Surface | 0.10 | 0.9 | 0.11 |
| | Motors | 0.17 | 0.83 | 0.20 |
| | Impellers | 0.07 | 0.93 | 0.08 |
| | Structure | 0.05 | 0.95 | 0.05 |
| | Casings | 0.90 | 0.1 | 9.00 |

5-3: Summary of E-R model results in the simulation

| Equipment | Scenarios | States | Energy (Diesel-Electricity) | Addition Cost needs (CAN$/bbl | | | | | Addition Energy needs (lit/bbl or Kwh/bbl | Energy Saving (Yearly) % | Cost Saving (Yearly) % | GHG Emission saving (Yearly) % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mining Haul Trucks | Reference | | Diesel (million GJ) | Fuel System | Engine | Transmission | Suspension | Tires | | | | |
| | | 1 | 1,605.45 | 0.045 | 0.042 | 0.02 | 0.01 | 0.04 | 0 | 0.45 | 0.69 | 0.33 |
| | | 2 | 1,605.54 | 0.045 | 0.042 | 0.02 | 0.01 | 0.04 | 0.15 | 0.57 | 0.61 | 0.94 |
| | | 3 | 1,607.20 | 0.05 | 0.048 | 0.021 | 0.011 | 0.04 | 0.3 | 0.45 | 0.6 | 0.53 |
| | | 4 | 1,622.90 | 0.09 | 0.084 | 0.04 | 0.02 | 0.08 | 3 | 0.16 | 0.52 | 0.78 |
| | Reliability improvement | 1 | 1,236.79 | | | | | | | | | |
| | | 2 | 690.80 | | | | | | | | | |
| | | 3 | 756.92 | | | | | | | | | |
| | | 4 | 360.12 | | | | | | | | | |
| Oil Sands Hydraulic Shovel | Reference | 1 | Diesel million GJ 974.06 | 0 | | | | | 0 | 0.12 | 0.94 | 0.15 |
| | | 2 | 978.44 | 0.0004 | | | | | 0.009 | 0.15 | 0.73 | 0.16 |
| | | 3 | 1607.20 | 0.015 | | | | | 0.36 | 0.11 | 0.71 | 0.15 |
| | | 4 | 1,984.12 | 0.08 | | | | | 2 | 0.15 | 0.67 | 0.16 |
| | Reliability improvement | 1 | 826.56 | | | | | | | | | |
| | | 2 | 829.88 | | | | | | | | | |
| | | 3 | 756.92 | | | | | | | | | |
| | | 4 | 1,651.92 | | | | | | | | | |
| Oil Sands Electric Shovel | Reference | 1 | Electricity million GJ 372.08 | 0 | | | | | 0 | 0.11 | 0.78 | |
| | | 2 | Electricity 375.80 | 0.00415 | | | | | 0.08 | 0.151 | 0.77 | |
| | | 3 | Electricity 429.76 | 0.006 | | | | | 1.24 | 0.152 | 0.76 | |
| | | 4 | Electricity 13,746.94 | 0.0415 | | | | | 18 | 0.11 | 0.73 | |
| | Reliability improvement | 1 | Electricity 315.74 | | | | | | | | | |
| | | 2 | Electricity 318.79 | | | | | | | | | |
| | | 3 | Electricity 364.22 | | | | | | | | | |
| | | 4 | Electricity 12,294.15 | | | | | | | | | |

5-4: Summary of E-R model results in the simulation (cont-1)

| Equipment | Scenarios | States | Energy (Diesel-Electricity) | Addition Cost needs (CAN$/bbl | | Addition Energy needs (lit/bbl or Kwh/bbl | | Energy Saving (Yearly) % | Cost Saving (Yearly) % | GHG Emission saving (Yearly) % |
|---|---|---|---|---|---|---|---|---|---|---|
| Mining Crusher | Reference | | Electricity (million GJ) | Apron Feeder | Drive System | Apron Feeder | Drive System | 0.148 | 0.77 | |
| | | 1 | 11.63 | 0 | 0 | 0 | 0 | | | |
| | | 2 | 11.67 | 0.001 | 0.002 | 0.001 | 0.001 | 0.15 | 0.77 | |
| | | 3 | 421.97 | 0.054 | 0.034 | 0.045 | 0.025 | 0.11 | 0.73 | |
| | | 4 | 23.26 | 0.289 | 0.345 | 0.25 | 0.250 | 0.16 | 0.52 | |
| | Reliability improvement | 1 | 9.87 | | | | | | | |
| | | 2 | 9.91 | | | | | | | |
| | | 3 | 307.23 | | | | | | | |
| | | 4 | 19.73 | | | | | | | |
| Oil Sands Conveyor Belt | Reference | | Electricity (thousand GJ) | Motor | Power Roller | Motor | Power Roller | | | |
| | | 1 | 3,953.38 | 0.47 | 0.046 | 0 | 0 | | | |
| | | 2 | 3,953.38 | 0.471 | 0.047 | 0.0001 | 0 | | | |
| | | 3 | 4,185.93 | 0.55 | 0.053 | 0.017 | 0 | | | |
| | | 4 | 7,906.76 | 0.94 | 0.092 | 0.1 | 0.07 | | | |
| | Reliability improvement | 1 | 3,339.30 | | | | | | | |
| | | 2 | 3,339.30 | | | | | | | |
| | | 3 | 3,552.94 | | | | | | | |
| | | 4 | 6,669.89 | | | | | | | |
| Oil Sands Slurry Pump | Reference | | Electricity (million GJ) | | | | | | | |
| | | 1 | 186.04 | 0.054 | | 0 | | 0.15 | 0.76 | |
| | | 2 | 189.20 | 0.055 | | 0.068 | | 0.15 | 0.75 | |
| | | 3 | 221.39 | 0.064 | | 0.76 | | 0.15 | 0.74 | |
| | | 4 | 372.08 | 0.11 | | 4 | | 0.15 | 0.68 | |
| | Reliability improvement | 1 | 157.87 | | | | | | | |
| | | 2 | 160.58 | | | | | | | |
| | | 3 | 187.75 | | | | | | | |
| | | 4 | 315.74 | | | | | | | |

5-5: Summary of E-R model results in the simulation (cont-2)

| Scenario | 1 | | 2 | | 3 | | 4 | |
|---|---|---|---|---|---|---|---|---|
| **Energy (Million GJ)** | Electricity | Diesel | Electricity | Diesel | Electricity | Diesel | Electricity | Diesel |
| **Reference** | 2,579.51 | 573.71 | 2,583.98 | 580.87 | 2,756.59 | 668.35 | 3,571.01 | 1,147.41 |
| **Reliability improvementc c** | 2,063.35 | 486.82 | 1,520.61 | 492.84 | 1,732.91 | 566.50 | 2,011.72 | 973.97 |
| **Energy Saving (%)** | 0.19 | | 0.36 | | 0.33 | | 0.37 | |
| **Cost Saving (%)** | 0.77 | | 0.07 | | 0.33 | | 0.35 | |
| **GHG Saving (%)** | 1.05 | | 0.68 | | 0.37 | | 0.44 | |

## 5.2 Engineering Significance

In this research, mining equipment reliability was investigated with the aim of improving procedures/protocols for equipment inspection through determining the importance of the equipment's subsystems. This section discusses feasible suggestions for developing mining equipment reliability and monitoring a system. The E-R model provides an integrated approach to analyse functioning reliability scenarios by predicting the amount of energy and cost used in mining equipment operating under partial reliability conditions. This model is flexible and can be easily modified to handle various scenarios. With accurate reliability probability functions for mining equipment, bottlenecks and design improvements can be identified. The E-R model can be used in various mining industries, and it can be improved and further developed to solve complex real-world challenges in the field of reliability and to help identify means by which to reduce GHG emissions, energy consumption, and cost. The following improvements and recommendations for the E-R model can be considered in future studies:

**Maintenance Schedule**

- Early detection of component failure that is operating under minor failure conditions is important, before other parts are affected and damaged. These damages may lead to equipment failure, which may impose the higher operational cost and excessive GHG emissions. Data from maintenance/repair of equipment and inspections need to be recorded and reported for ongoing reliability analysis.

**Operational Cost Estimate**

- Many factors influence operational cost when equipment operates under partial reliability. Although operating under partial reliability postpones repair costs, it may increase operational cost due to higher energy demand. Factors such as equipment type, system set-up, mining site location and condition, monitoring systems, and labour and fuel cost need to be taken into account when estimating operational cost. If operational cost under partial reliability is estimated to be less than the repair cost, then it can be beneficial to use E-R model to determine the risk.

**Preventing Unpredictable Failure**

- To prevent unpredictable failure, it is important to keep a record of the time at which the equipment fails.
- It is necessary to keep the historical failure data and develop preventive and corrective action plans based on the historical failure data. These data are valuable for future reliability studies and improving maintenance and repair schedules.

## 5.3 Future Research

For this research, an energy and partial reliability model for oil sands surface mining equipment was developed. Some assumptions were made and can be used in future investigations. Some of the opportunities for future work are presented below.

- To calculate the probability of failure based on BBN, the reliability function for each sub-subsystem was not considered in this research; however, in the real world, all possible reliability function events influence the process. Therefore, to determine actual reliability, more reliability functions for each positive and negative event need to be considered.

- The E-R model was generated for oil sands surface mining in Alberta, Canada. However, this model can be developed and used for other industries such as in situ mining and the chemical and pulp and paper sectors.
- In this research E-R model was assumed steady state, however it can be considered under non steady state condition as well. This can be consider as a new avenue in future work.
- In this research, energy consumption amount for each subsystem was estimated as a fraction of equipment process. More investigations are required to find the precise amount of energy consumption by each main subsystem.
- One of the main challenges in this research was the lack of sufficient data and information on failure rates and cost for each component of equipment. Therefore, it was not possible to use actual cost data in the risk analysis model for components. However, by calculating reliability based on failure rates by running a Monte Carlo simulation through Matlab with improved estimates of system parameters, the E-R model's outcomes can be validated.
- The E-R model for oil sands mining equipment can be improved through optimization techniques, which allow us to minimize the cost of systems based on limitations and constraints. Such techniques can improve the modeling processes by connecting a macroeconomic model with a complete energy supply model, thereby allowing assessments of energy performance standards, demand side management, and renewable/clean technology combinations.

# References

## References

1. National Energy Board. Canada's Oil Sands Opportunities and Challenges to 2015: An Update, An Energy Market Assessment 2006.
2. Ebeling CE. An introduction to reliability and maintainability engineering, 2010.
3. Tyrone L.Jones. Handbook of prediction procedures for mechanical equipment, logistics technology support: Narval Surafce Warfare Cantre; 2011.
4. ZHIGANG TIAN, MING J. ZUO, YAM RCM. Multi-state k-out-of-n systems and their performance evaluation. IIE Transactions. 2007.
5. Tian. Z, GregoryLevitin., MingJ.Zuo. A jointreliability–redundancyoptimizationapproachformulti-state series–parallel systems. ReliabilityEngineeringandSystemSafety. 2009:1568–76.
6. Yi Ding, Ming J. Zuo, Li W. A Framework for Reliability Approximation of Multi-State Weighted K-out-of-N Systems Multi-State Weighted K-out-of-N Systems IEEE TRANSACTIONS ON RELIABILITY. 2010;59.
7. Lipsett MG, Gallardo-Bobadilla R. Modeling Risk in Discrete Multi-State Repairable Systems. Asset Condition, Information Systems and Decision Models. 2013:187-205.
8. Yang Dongpeng, Ran Lun, Jinlin L. Research on Reliability of Complex Coal Mine Ventilation Networks. Management of Innovation and Technology ICMIT 2008 4th IEEE International Conference on: IEEE; 2008. p. 1418 - 22.
9. Lien Y-N, Wu M-H. Partial Reliable TCP. Computer Science Department ,National Chengchi University , Taipei, Taiwan, ROC. 2015.
10. L. Donckers, P.J.M. Havinga, G.J.M. Smit, Smit LT. Enhancing Energy Efficient Tcp By Partial Reliability. Personal, Indoor and Mobile Radio Communications: IEEE; 2002. p. 2424 - 8.
11. T. Nuzialea, Vagenas N. A software architecture for reliability analysis of mining equipment.

International Journal of Surface Mining, Reclamation and Environment. 2007:19-34.
12. Barabady J, Kumar U. Reliability analysis of mining equipment: A case study of a crushing plant at Jajarm Bauxite Mine in Iran. Reliability Engineering and System Safety. 2008.
13. Peng S, Vayenas N. Maintainability Analysis of Underground Mining Equipment Using Genetic Algorithms: Case Studies with an LHD Vehicle. Journal of Mining

2014.
14. Hall. R, Daneshmand LK. Reliability Modeling of Surface Mining Equipment: Data Gathering and Analysis Methodologies. . International Journal of Surface Mining, Reclamation, and Environment. 2003.
15. Samantha B, SARKAR B, Mukherjee SK. Reliability Analysis of Shovel Machine Used in An Open Cast Coal Mine. Mineral Resources Engineering. 2001;10:219-31.
16. Khan MI. An Overview of Reliability and Maintenance Engineering and Management in Oil Sands Mining Industry. University of Alberta, 2013.
17. Rahman Yousefi Moghaddam R, Lipsett MG. RELIABILITY ASSESMENT AND CONDITION MONITORING OF A SHOVEL TEST BED. Engineering Asset Management (WCEAM-IMS),; Beijing, China 2008.

18. Chung H. Ta AI, Doucette J. A linear model for surface mining haul truck allocation incorporating shovel idle probabilities. European Journal of Operational Research. 2013:770-8.
19. Vaghar Anzabi R, Nobes DS, Lipsett MG. Haul truck tire dynamics due to tire condition. J Phys Conf Ser. 2012;364(1).
20. Barabady J. Reliability and Maintainability Analysis of Crushing Plants in Jajarm Bauxite Mine of Iran. Reliability and Maintainability Symposium2005. p. 109-15.
21. Seebregts AJ, Goldstein GA, Smekens K. Energy/Environmental Modeling with the MARKAL Family of Models. Operations Research Proceedings 2010.
22. Subramanyam V. Development of Greenhouse Gas Mitigation Options for Alberta's Energy Sector: Alberta; 2010.
23. Tejas Shah, Deepak Paramashivan, Veena Subramanyam, Saeidreza Radpour, Kumar A. Identification of Best Energy Efficiency Opportunities in Alberta's Energy Sector PHASE II. 2013.
24. Shah T. Development Of Energy Intensity of Mining and Oil And Gas Extraction Industry of Alberta, Canada. 2012.
25. Aumnad Phdungsilp, Wuttipornpun T. Energy and Carbon Modeling with Multi-Criteria Decision-Making towards Sustainable Industrial Sector Development in Thailand. Low Carbon Economy. 2011:165-72.
26. Santosh Kumar Chaudhari, Murthy. HA. Energy Aware Network: Bayesian Belief Networks Based Decision Management System. Journal on Communication Technology: Special Issue on Next Generation Wireless Networks And Applications. 2011;2(2).
27. Gerbec M, Kontic B, editors. Key performance indicators and bayesian belief network based risk model as a management tool-results from the case study. European Safety and Reliability Conference, ESREL 2013; 2014; Amsterdam: shers.
28. Abdo A, Leclère V, Jacques P, Salim N, Pupin M. Prediction of new bioactive molecules using a Bayesian belief network. J Chem Inf Model. 2014;54(1):30-6.
29. M.Swami Das, Ramakanta Mohanty, D.Vijayalakshmi, Govardhan A. Application of Data Mining Using Bayesian Belief Network To Classify Quality of Web Services. International Journal of Computer Science & Informatics. 2012;2(1, 2).
30. Brenda McCab, Goebel R. BELIEF NETWORKS FOR CONSTRUCTION PERFORMANCE DIAGNOSTICS. Journal of Computing in Civil Engineering. 1998.
31. Huang, Hong-Zhong, Zuo MJ, Sun Z-Q. Bayesian Reliability Analysis for Fuzzy Lifetime Data. Fuzzy Sets and Systems. 2006:1674–86.
32. Wimonmas Bamrungsetthapong, Pongpullponsak A. System reliability for non-repairable multi-state series–parallel system using fuzzy Bayesian inference based on prior interval probabilities. International Journal of General Systems. 2014.
33. McCabe. B, AbouRizk. SM, Goebel R. Belief Networks For Construction Performance Diagnostics. 2001.
34. Kwok A, Liu DB. A Bayesian belief network model and tool to evaluate risk and impact in software development projects. Reliability and Maintainability, 2004 Annual Symposium - RAMS2004.
35. Barker GC. Application of Bayesian Belief Network models to food safety science. Bayesian Statistics and Quality Modelling in the Agro-Food Production Chain. 2004;3.
36. Smith M. Dam Risk Analysis Using Bayesian Networks. Engineering Conferences International 2006.

37. Jeon G, Falcon R, Kim D, Lee R, Jeong J. Application of Bayesian Belief Network in Reliable Analysis for Video Deinterlacing. IEEE Transactions on Consumer Electronics. 2008;54.
38. Yuriy G. discrete event simulation of mine equipment system combined with a reliability assessment model: Alberta; 2005.
39. Gerbec M, Kontić B. Key Performance Indicators and Bayesian Belief Network based risk model as a management-tool result from the case study: Taylor and Francis group 2014.

40. J.S M, Arnold JC. Probability and statiscs in the Engineering and Computer science: Mc Graw hill; 1986.
41. Gabriele Manno, Ferdinando Chiacchio, Lucio Compagno, Diego D'Urso, Trapani N. MatCarloRe: An integrated FT and Monte Carlo Simulink tool for the reliability assessment of dynamic fault tree. Expert Systems with Applications. 2012:10334-42
42. Hoseinie. Sh, Khalokakaie. R, Mohammad Ataei, Ghodrati. B, Kumar U. Monte Carlo Reliability Simulation of Coal Shearer MachineInternational journal of Performability Engineering. 2013;9487-94.
43. R. Billinton, Tang X. Selected considerations in utilizing Monte Carlo simulation in quantitative reliability evaluation of composite power systems. Electric Power Systems Research. 2004:205-11.
44. Herbert J, Neale DJ. The Link between Plant Reliability and Energy Efficiency, and Making a Difference in a Capital Constrained World. Gateway To Reliability Excellence -SMRP2009.
45. Jamshid Abouei J, Brown. D, N. K, Plataniotis., Pasupathy S. Energy Efficiency and Reliability in Wireless Biomedical Implant Systems. IEEE TRANSACTIONS ON INFORMATION TECHNOLOGY IN BIOMEDICIN 2011.
46. Mario Di Francesco, Giuseppe Anastasi, Marco Conti SKD, Neri V. Reliability and Energy-efficiency in IEEE 802.15.4/ZigBee Sensor Networks: An Adaptive and Cross-layer Approach. IEEE Journal On Selected Areas in Communications. 2011;29.
47. Min Chen, Taekyoung Kwon, Shiwen Mao, Yong Yuan, Leung VCM. Reliable and Energy-Efficient Routing Protocol in Dense Wireless Sensor Networks. 2013.
48. Breese J, Koller D. Tutorial on Bayesian Networks.
49. A. A, Van Tol, M. S, AbouRizk. Simulation modeling decision support through belief networks. Simulation Modeling Practice and Theory 2006:614-40.
50. Cebesoy T. Surface mining equipment cost analysis with a developed linear breakeven model. International Journal of Surface Mining, Reclamation and Environment. 2011;11(2).
51. Oil and Gas Industry Paradidsm(2015).
52. Anzabi RV, Lipsett MG. Reliability analysis and condition monitoring methods for off-road haul truck tires. Condition Monitoring and Diagnostic Engineering Managment; U.K2011.
53. Hall RAaD, L.K. Reliability and Maintainability Models For Mobile Underground Haulage Equipment. Canadian Mining & Metallurgical Institute Bulletin. 2003:159-65.
54. Cannon M, Koroluk D, Shuai Y. Oil Sands Bitumen Recovery-Crusher cost. Department of Chemical Engineering University Of Saskatchewan 2007.

55. Vose D. Risk Analysis: A Quantitative Guide. 3 ed2008.

56. 31000:2009 ANZaoI. AS/NZS 4360, Risk management. Standard Austrelia; 2004.
57. M.G.Lipsett, Gallardo-Bobadilla R. Modeling Risk in Discrete Multi-State Repairable Systems. Asset Condition, Information Systems and Decision Models. 2013:187-205.
58. PMI. A Guide to the Project Management Body of Knowledge (PMBOK® Guide) -: Project Management Institute; 2008.
59. Dubai LA-Go. Shovel Operator's Handbook. 2008.
60. Natural Resources Canada's 40-year outlook, forecast and assumptions [Internet]. 2015. Available from: http://www.nrcan.gc.ca/home.
61. Carderockdiv. Handbook of prediction procedures for mechanical equipment, logistics technology support2010.
62. Ebeling C. reliability and maintainability engineering2010.
63. regulator Ae. Alberta Surface Mining. 2015.
64. James T. Extreme cold can be bad news for vehicles. 2015.
65. CAT® 797 -Components of Truck Cost [http://www.miningandexploration.ca/technology/article/haul_truck_tire_drives_more_than_three_and_a_half_times_around_the_globe/]. 2013.
66. Alarie S, Gamache M. Overview of solution strategies used in truck dispatching systems for open pit mines,. International Journal of Surface Mining, Reclamation and Environment. 2002.
67. Batchelor DH. The implementation of a computerised truck dispatch system at Palabora. APCOM 87. Proceedings of the Twentieth International Symposium on the Application of Computers and Mathematics in the Mineral Industries.1987. p. 389-401.
68. Cooney M. Is the CAT 797F Too Expensive? $5 Million, Options Extra.: Industry tap in to news; 2013. Available from: http://www.industrytap.com/.
69. Thompson J. Why Diesel Fuel Injectors Fail2012. Available from: http://www.dieselpowermag.com/tech/1211dp_why_diesel_fuel_injectors_fail/.
70. Heavy Duty- Engines and Vehicles 2010.
71. Council NP. Heavy Duty- Engines and Vehicles http://wwwnpcorg/reports/FTF-report-080112/Chapter_10-HD_Engines-Vehiclespdf2010.
72. Alberta Go. Oilsands Discovery Centre. (n.d). Facts about Alberta's oilsands and its industry 2013.
73. H. A, Bonnett F. Root Cause AC Motor Failure Analysis with a Focus on Shaft Failures. IEEE Transactions On Industry Applications 2000.
74. Authority HS. Crusher. http://wwwhsaie/eng/Your_Industry/Quarrying/Crushing_Sizing_Screening/Clearing_Blocked_Crushers/2015.
75. sizer crusher [http://www.mhhe.com/engcs/chemical/peters/data/ce.html]. 2011.
76. Lodhi G. Operation and maintenance of crusher house for coal handling in thermal power plant. International Journal of Mechanical Engineering and Robotics Research. 2013;2.
77. Ali Nouri.Gharahasanlou, Ashkan Mokhtarei, Aliasqar Khodayarei, Ataei M. Fault tree analysis of failure cause of crushing plant and mixing bed hall at Khoy cement factory in Iran, . Case Studies in Engineering Failure Analysis. 2014;2(1):33–8.
78. Mining M. Processing Crushing Resource 2010.

79. Group A. Screen Mesh Cost. http://wwwalibabacom/showroom/crusher-screen-meshhtml2011.
80. Pennsylvania. Crusher Corporation; Handbook of Crushing1995.
81. Group A. Apron Feeder Cost. http://wwwalibabacom/showroom/apron-feeder-for-salehtm2011.
82. Chinbat U. Risk Analysis in the Mining Industry, in Risk Management in Environment. Production and Economy. 2011.
83. Handling-SAIMH Tsaiom. Conveyor Belt Installations and Related Components-idler. 2015.
84. Sicard MA, Bob Courtwright, Tom Wujcik RI, Kuehne RBaK. Slurry Pump Fundemental 2006.
85. Electric LS. Motor Repair Guideline2015.
86. Andrew L. Mular, Doug N. Halbe, Barratt DJ. Mineral Processing Plant Design, Practice, and Control Proceedings. 2 ed: SME; 2002.
87. Minerals W. WARMAN Slurry Pump Handbook. 2009.
88. Herbert J, Neale DJ. The Link between Plant Reliability and Energy Efficiency, and Making a Difference in a Capital Constrained World. Manufacturing Process Reliability: SMRP; 2009.
89. M.G.Lipsett, R. Gallardo-Bobadilla. Modeling Risk in Discrete Multi-State Repairable Systems. Asset Condition, Information Systems and Decision Models. 2013:187-205.
90. Heaps C. An Introduction to LEAP2008.
91. Veena Subramanyam , Hafiz Umar Shafique , Md. Alam Hossain Mondal , Balwinder Nimana , Zhang X, Kumar A. Identification of Best Energy Efficiency Opportunities in Alberta's Energy Sector Phase III, Development of Energy Efficiency Opportunities for Mining Sector of Alberta, Final Report. Prepared for Alberta Innovates – Energy and Environmental Solutions (AI-EES) and Natural resource Canada: Department of Mechanical Engineering, University of Alberta, 2015.
92. Community For Energy EaD. An Introduction to LEAP http://www.energycommunity.org/default.asp?action=47, .
93. SEI. Stockholm Environment Institute. 2006.
94. Discounat rate for Alberta. In: Agency CR, editor. 2015.
95. Helmer-Hirschberg O. Analysis of the Future- The Delphi Method. Available from: (http://www.rand.org/topics/delphi-method.html).
96. L. Donckers PJMH, G.J.M. Smit, L.T. Smit Enhancing Energy Efficient Tcp By Partial Reliability International Symposium on Personal, indoor and mobile radio communications. 2002.
97. Jenny JA. The Effect of Partial Failure Modes on Reliability Analysis. IEEE Transactions On Reliability. 1969.
98. Idhammar C. Reliability Improvements-Cost Reduction 2015. Available from: http://www.idcon.com/resource-library/articles/reliability-vs-cost/478-reliability-improvements-cost-reduction-2.html.
99. Mine I. Shovel cost 2010.
100. Cebesoy T. Surface mining equipment cost analysis with a developed linear breakeven model,. International Journal of Surface Mining, Reclamation and Environment. 2011;11.

101. Siemens Industry. Crushers for the mining industry. In: siemens, editor. 2013.
102. Evolution of Design and Applications of Apron Feeders, (2002).
103. Cohen P. Cost for Mining Equipments and Parts: Mc GrawHill Education-Engineering; 2015. Available from: http://www.mhhe.com/engcs/chemical/peters/data/ce.html.
104. Loh HP, Lyons J, Charles W. White I. Process Equipment Cost Estimation. National Energy Technology Center 2002.
105. Tejas Shah, Deepak Paramashivan, Veena Subramanyam, Saeidreza Radpour, Kumar. A. Identification of Best Energy Efficiency Opportunities in Alberta's Energy Sector PHASE II,. 2013.
106. Kennedy BA. Surface Mining, Second Edition: Society for Mining, Metallurgy, and Exploration (U.S.); 1990.
107. Nimana BS. Life Cycle Assessment of Transportation Fuels from Canada's Oil Sands through Development of Theoretical Engineering Models: University of Alberta; 2014.
108. Solutions BC. Bridgestone Truck Tires. 2014.
109. Ayyub BM. Uncertainty Modeling and Analysis in Civil Engineering CRC Press; 1997.
110. Cycles JP. Cost of Shovel's engine http://wwwjpcyclescom/product/420-2282015.