Optimising the operational energy efficiency of an open-pit coal mine system

by

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Abstract

Mining companies are increasingly being challenged to improve energy efficiency, as a method of reducing both the cost and environmental impact of their operations. This thesis addresses this issue by investigating the operational energy efficiency of open-pit coal mining. The presented approach uses integrated mathematical programming and metaheuristics to model and optimise operational decisions of mine systems in order to support operators in making energy efficient decisions.

Open-pit coal mining methods are reviewed to select the most common subsystems that represent the primary operation and energy consumption; excavation and haulage; stockpile; processing plant; and belt conveyor. Due to the apparent lack of operations research literature modelling mine energy efficiency, production system literature is drawn upon by considering an open-pit coal mine as a continuous flow production system. A literature review of production system energy efficiency and how it relates to mine operations is conducted to identify the most important factors to consider in operational models of mines - asset usage and planning. Integrated modelling is introduced as an effective way of considering all the relevant subsystems and factors together.

Using these findings, a framework for creating an integrated model of an operating open-pit coal mine is proposed and used to formulate an integrated Mixed Integer Linear Programming (MILP) model of the four subsystems. A process for applying the framework and model to new mines is also described.

Accuracy issues are identified with the allocation based formulation of the excavation and haulage subsystem that was developed based on recent literature. An improved scheduling formulation of the subsystem is developed to overcome these issues. However, the complexity of the improved model means exact methods are unable to provide solutions for practical sized problems. A hybrid tabu search and simulated annealing metaheuristic is developed so that good quality solutions can be found in reasonable time for practical use.

A case study is conducted of an open-pit coal mine in South East Queensland, Australia. Comprehensive sensitivity analysis is presented to verify and validate that the model and solution technique provide valuable opportunities for supporting decision makers in their pursuit of energy efficiency improvements.

Contents

List of Figures

List of Tables

List of Abbreviations

AHP	Analytic Hierarchy Process
BC	Belt Conveyor
CH	Constructive Heuristic
CHPP	Coal Handling and Processing Plant
CPP	Coal Processing Plant
CVRP	Capacitated Vehicle Routing Problem
DES	Discrete Event Simulation
DOE	Department of Energy
DRET	Department of Resources Energy Tourism
EE	Energy Efficiency
EEO	Energy Efficiency Opportunities
EEX	Energy Efficiency Exchange
EWO	Enterprise Wide Optimisation
GA	Genetic Algorithm
GJ	Gigajoules
GUI	Graphical User Interface
hr	Hour
HSI	Horizontal Shaft Impactor
IGVA	Industry Gross Value Added
kL	Kilolitre
KPI	Key Performance Indicator
LOM	Life-of-Mine
LP	Linear Programming
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
MPC	Model Predictive Control
MW	Megawatt
MWh	Megawatt Hour

NPV	Net Present Value
PFD	Process Flow Diagram
PP	Processing Plant
ROM	Run-of-Mine
SA	Simulated Annealing
SCOR	Supply Chain Operations Reference
SP	Stockpile
t	Tonne
TS	Tabu Search
VSI	Vertical Shaft Impactor
WD	Waste Dump

Statement of Original Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

QUT Verified Signature

Signed: ____

Date: 30/03/2016

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1 Introduction

Mining operations consume high amounts of energy and there are economic, environmental, social and political pressures being placed upon mining companies to improve energy efficiency and reduce their carbon footprint. It is well recognised as an area that requires significant attention from both industry and research (Laurence, 2011; Whitmore, 2006). However, the research and development of quantitative models to help tackle the issue is deficient. This is despite its potential for significant benefit, as seen in many other fields, not least production systems (Jeon et al., 2014; Li et al., 2014), with relatively low cost compared to traditional alternatives, such as capital investment in new technology.

This chapter first expands on the challenges facing mining companies to improve energy efficiency in Section 1.1. The research questions that this study focuses on to address the problem are then presented in Section 1.2. Section 1.3 describes the aims, significance and contribution of the research. The hypotheses are listed in Section 1.4. Section 1.5 describes the research approach that was followed to address the questions, achieve the aims and test the hypotheses. Finally, the remaining chapters of the thesis are outlined in Section 1.6.

1.1 Problem outline

Energy usage is one area that has become the focus in high cost economies for efficiency improvements and cost reductions. Energy consumption of mining operations can have negative effects on both environmental performance and operating costs (Levesque et al., 2014). Across a wide variety of fields, research has shown that using sound environmental management techniques can also help improve overall production efficiency (Lindsey, 2011; Ngai et al., 2013), another problem area for Australian mining operations (Lala et al., 2015; Topp et al., 2008).

Coal mining is an important part of the Australian mining industry. Australia was the second largest exporter of coal in 2011, a year when exports accounted for approximately 86% of the coal mined in Australia (International Energy Agency, 2012). Domestically, it is the largest fuel source for electricity generation, in 2011-12 an estimated 70% of electricity in Australia came from coal fire power plants (Bureau of Resources and Energy Economics, 2013). The importance of coal mining to the Australian economy is clear. However, the economic viability of coal mines has been put under pressure by falling prices and increased costs in recent years (Lala et al., 2015). This forms an economic challenge for mining companies to become more efficient at extracting and processing minerals.

The Australian mining industry accounts for 14% of domestic energy use (Australian Bureau of Statistics, 2010a). Between 1976-77 and 2006-07, energy intensity, expressed as gigajoules per million dollars of Industry Gross Value Added (GJ/$ m IGVA), increased in the mining industry by 99%, as reported in "Australia's Environment: Issues and Trends" (Australian Bureau of Statistics, 2010b). Other major industries apart from agriculture have experienced decreases in energy intensity over the same period.

This increase can be primarily attributed to the declining grade quality of minerals being extracted over time (Mudd, 2007). Lower grade quality makes the raw mineral harder to process and therefore requires more energy to produce the same amount of product. Along with lower ore grades, miners are digging deeper into the ground for raw material, which also consumes more energy.

The Australian Federal Government's Department of Industry and Science, in association with state and territory governments, administers the Energy Efficiency Exchange (EEX), which provides guidance for energy intensive businesses to improve energy efficiency. Mining companies are a particular focus of the content provided by EEX, that recommends accurate analysis and reporting from mining businesses in relation to both the current energy consumption and the efforts being made to improve energy efficiency.

The combination of rising energy intensity of the mining industry; increased cost of energy; and increased socio-political pressure for companies to reduce energy consumption and greenhouse gas emissions; makes energy efficiency an excellent candidate for optimisation. However, as will be explained in Chapter 2, mining literature that uses good practice operations research techniques to address the issue falls behind the more general field of production systems. This motivates research into how methods of modelling used for production systems can be applied to a mining system to support energy efficient decisions.

1.2 Research questions

The overarching research question for this study is:

How can the energy efficiency of a mining production system be modelled effectively?

In order to answer this, the following sub-questions are proposed:

1. How can the energy efficiency of mining production systems benefit from an integrated modelling approach?
   (a) Why is improving energy efficiency a concern for mining operations?
   (b) How can an open-pit coal mine be considered as a production system?
   (c) What factors impact the energy efficiency of a mine?
   (d) What are the benefits of using a quantitative optimisation model of energy efficiency?
   (e) Why take an integrated optimisation approach?
2. What integrated optimisation model of energy efficiency is appropriate for an open-pit coal mine production system?
   (a) What level of detail is required of the model?
   (b) Where are the main points of model complexity?
   (c) How general should the model be?
   (d) What is an appropriate process for applying the model to a real life mine?
3. What solution techniques will be appropriate for solving the model in real-time?
   (a) How hard is it to solve the developed model? Is the optimisation NP hard?
   (b) Are new techniques required?
   (c) What impact do any new solution techniques have on optimality and speed?

1.3 Aims, significance and contributions

As stated in the problem outline, increasing energy efficiency is an important goal for a mining operation from economic, environmental, social and political perspectives. Tied with an apparent lack of operations research looking optimising energy efficiency of open-pit coal mines, the primary aim of this research project is to:

> *Identify key factors influencing energy efficiency in open-pit coal mines and develop an integrated model that can be used as an energy efficiency decision support tool.*

To achieve this aim, a mining operation will be treated as a continuous flow production system and literature from the production system field will be drawn upon. The intent of this approach is to provide a substantial academic foundation for using knowledge from the production system field to address the problem studied in this thesis. It will also serve as an example for how to tackle similar problems where research falls behind the methods used in production system literature.

Based on these findings, a conceptual framework for developing integrated models of continuous production systems will be contributed. The framework will be based around modelling the subsystems of the system separately and connecting them via material mass flow connections, an approach more commonly seen in the production system field and suggested by the Australian Government EEO legislation, now under the EEX name (Department Resources Energy and Tourism, 2010). Being able to formulate the subsystem models separately will be an important feature of the approach as it allows for distinct differences in the operation of the subsystems. For example, it allows for a more discrete formulation to model the transactional nature of the excavation and haulage subsystem while a more continuous formulation can model the nature of the processing plant operation.

The generalisability of the approach is designed to be a useful contribution for future work and means it can be applied to a wider set of problems than the one specifically considered in this study. To foster this, a model application process will also be developed to allow for easy application of the model to new mines, with steps included for extra modelling effort if it is required, an important contribution both for future academic work on the model and for applying it in practice.

Using the modelling framework and application process, an original integrated formulation of a general open-pit coal mine operation will be developed and applied to an operating mine as a case study. This will be a significant extension upon the current mining literature, where modelling is mainly centred on silo optimisation of subsystems and lacks energy efficiency optimisation models.

As is typical with integrated modelling of operations in other production systems, the complexity of the model can become an issue when accurate models are required. The model will therefore be analysed with respect to its accuracy and complexity and an innovative solution technique to overcome the expected complexity will be developed and applied. This will ensure that good quality solutions can be found quickly enough for practical use.

The case study will be used to verify and validate the developed contributions are significant both academically and practically. The contributions of this study will be evaluated based the opportunities they present for supporting decision makers to improve energy efficiency.

1.4 Hypotheses

The hypotheses of this research are as follows:

1. Mining operations can benefit from modelling techniques commonly used in production systems literature.
2. Integrated modelling is an effective approach to modelling the energy efficiency of mining production system.
3. Mixed Integer Linear Programming (MILP) is appropriate for formulating an integrated model of the energy efficiency of an open-pit coal mine.
4. A complex model is required to accurately model the operation of an integrated open-pit coal mine system, in particular the operation of the trucks.
5. A hybrid metaheuristic-based solution technique is able to overcome complexities in the model to provide solutions quickly without significant loss of solution quality.
6. The developed model and solution technique can be used as a decision support tool for making more energy efficient decisions.

1.5 Research approach

The following approach, visualised in Figure 1.1, will be taken to answer the research questions; achieve the aims; provide original contributions with academic and practical significance; and test the hypotheses. As previously explained, open-pit coal mine energy efficiency as it exists as an issue in the problem domain will first be abstracted to be considered a general continuous flow production system, seen in the top left quadrant of Figure 1.1. Literature will be reviewed to confirm the validity of the abstraction and that integrated MILP modelling is an effective method of translating the problem into the solution domain. A modelling framework will then be designed for creating an integrated MILP model of a continuous flow production system along with a general process for applying developed integrated models to operating production systems. This framework will be used to model the specific open-pit coal mine energy efficiency problem addressed in this research. The top right quadrant of Figure 1.1 shows these.

As is theorised by hypothesis 4 and 5, it is expected that the developed model will be too complex to solve with a commercial solver and a new solution technique will be required to find good quality solutions in a reasonable timeframe. A hybrid metaheuristic will be designed to achieve this. This is shown in the bottom right quadrant of Figure 1.1.

In order to verify and validate the developed methodologies, model and solution technique, an operating mine will be used as a case study. The model application process will be applied to the mine and a comprehensive sensitivity analysis will be conducted. Using this, the research outcomes will be studied with respect to the opportunities it presents for improving energy efficiency of an open-pit coal mine, particularly as a decision support tool for operators. This can be seen in the bottom left quadrant of Figure 1.1.

The research approach is structured as an improvement loop to allow the study to iteratively progress towards achieving the aims, answering the research questions and testing the hypotheses. It also fosters a path for future work on the problem and other related problems. The next section outlines how two iterations of the research approach have been applied throughout the remaining chapters of the thesis.

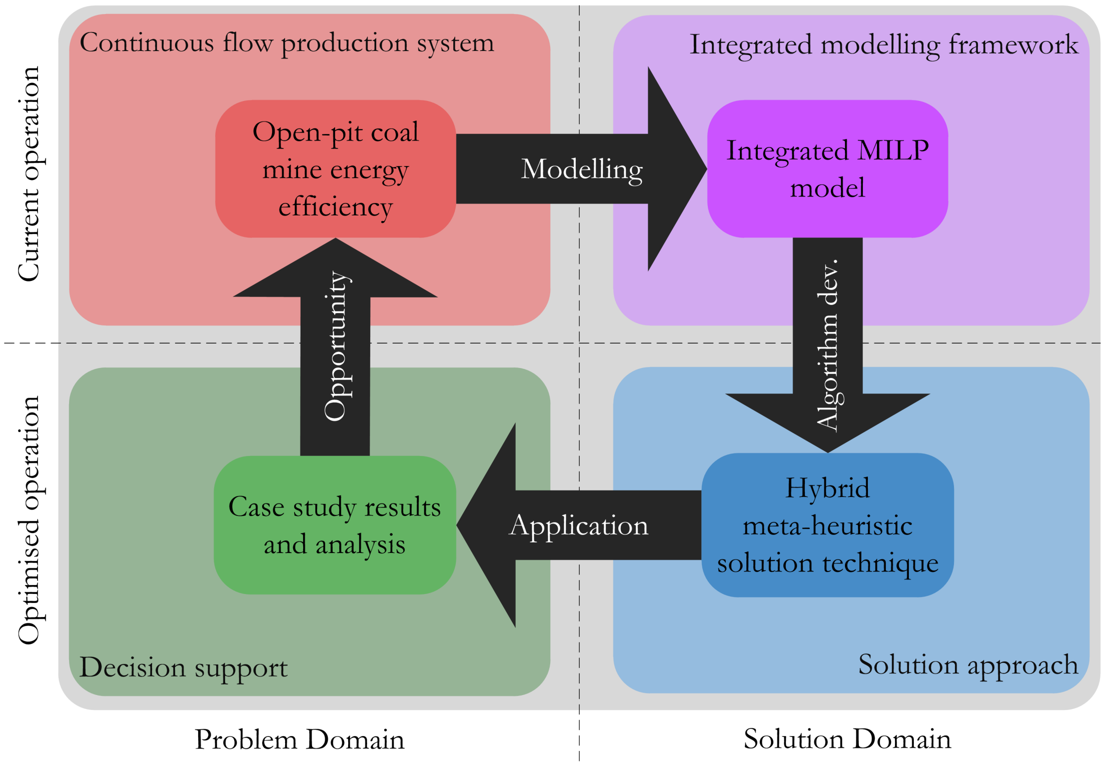

Figure 1.1. Research approach

1.6 Thesis outline

Chapter 2 details the literature review conducted to form a basis for the research approach. Open-pit coal mining methods are reviewed to help define the problem and find the most common subsystems of a mine. The general concept of production system energy efficiency and how a mine can be seen as a production system are described. Factors that impact energy efficiency of production systems in general are presented and how these apply to the four subsystems is studied. Integrated modelling is then reviewed from literature on both production systems and mining. Finally, solution techniques required to solve complex models, similar to the one developed in this study, are reviewed.

Chapter 3 presents the approach developed by this research to devise the integrated model. A framework for modelling subsystems separately and integrating them into a single model is presented. Conceptual models for each subsystem are then introduced. The developed process for applying the integrated model to a mine is also presented.

Chapter 4 then puts these concepts into practice and presents the developed integrated mathematical programming model of a generic open-pit coal mine. Preliminary model validation is done using a simple example and some potential drawbacks are highlighted.

Chapter 5 introduces Meandu Mine, an open-pit coal mine in South East Queensland, as a case study. The application process is followed to apply the integrated model to the mine using information provided in-kind by Downer EDI Mining. Scenario analysis is conducted to further verify and validate the developed model and their results confirm that the issues highlighted in Chapter 4 emerge in practice.

Chapter 6 presents modifications to the excavation and haulage subsystem formulation in order to overcome the issues displayed in the previous two chapters. A scheduling formulation for the subsystem is presented and the simple example from Chapter 4 is used to verify that it overcomes the issues found with the allocation formulation. However, the increased complexity of the scheduling formulation is found to make the model NP-hard and cannot be solved for practical sized problems.

Chapter 7 outlines the solution approach developed to overcome the complexities. A solution representation, neighbourhoods, evaluation algorithms and constructive heuristic are innovated to aid the application of tabu search and simulated annealing metaheuristics to deal with the specific complexities of this model. The two metaheuristics will then be hybridised in a novel example of how software architecture principles can aid the development of efficient and effective solution techniques.

Chapter 8 revisits the case study to provide comprehensive sensitivity analysis with the new Chapter 6 model, to show that the highlighted issues have been overcome and to verify and validate that the model and solution technique provide useful results to the problem.

Chapter 9 discusses the findings of the study. The opportunities that the research presents are examined. It addresses how the hypotheses have been tested and the aims accomplished, to deliver significant contributions from a theoretical and practice perspective. Limitations and future work are outlined, followed by a conclusion.

2
Literature Review

Several key topics are addressed in this literature review in order to establish the relevance and appropriateness of the proposed approach. Initially, a brief introduction to open-pit coal mining is given in order to classify the most important parts of an open-pit coal mine; this inventory will be used to define where the logical boundaries of the model in this project should be. The concept of a production system is then defined, and the importance of energy efficiency in production systems generally and for mining specifically is discussed. Key factors that impact energy efficiency are then selected from production system literature, and papers from relevant mining literature that consider them are reviewed. The concept of integrated modelling with respect to production systems and mines is introduced and reviewed, as it is an effective way to consider all the relevant factors together in one model. Finally, solution techniques are reviewed to select ones that are appropriate for finding good quality solutions to complex integrated models, in reasonable time, for practical use.

2.1 Open-pit coal mining

Though the overarching research question motivating this study is about mining in general, open-pit coal mining is chosen as a specific form of mining on which to focus. This section will first describe most of the different forms of mining as a way of distinguishing what open-pit coal mining is, then look closely into the most common subsystems that make up an open-pit coal mining operation. The excavation and haulage fleet, processing plant, stockpile and belt conveyor are analysed in detail to show they are the most common subsystems and serve as a good basis for creating a model to provide operational decision support.

2.1.1 General overview

In general terms, mining is the process of extracting raw geological material from the earth. It represents the primary stage of the majority of industrial supply chains in the modern world. There are many types of materials mined across the world and a wide array of methods that are used to mine them. Australia's mining sector comprises a broad spectrum of operations using various methods to extract a number of different materials for both domestic use and export to other countries.

Mines can be classified into two extraction techniques - surface mining and underground mining. The type of mine is decided upon through an economic study of the deposit being extracted (Blackham, 1993; Darling, 2011).

Surface mining involves removing the soil and rock, referred to as overburden, above the deposit to uncover and extract it, and is used when the deposit is relatively close to the surface. There are several types of surface mining techniques for coal, listed below, which are selected according to what is being mined, where the deposit is and what shape the deposit is (Fung, 1981; Kininmonth & Baafi, 2009).

- Strip mining
- Open-pit
- Mountaintop removal
- Highwall

Australian coal most commonly uses either strip or open-pit mining, so mountaintop and highwall will not be discussed here beyond their brief explanations below.

Strip mining is used when the whole ore body is close to the surface and mostly flat and horizontal. In its most simple form, it involves removing the overburden in a long 'strip', extracting the exposed mineral seam, then moving along, creating an adjacent seam and placing the overburden from the new strip over the previous strip (Westcott et al., 2009).

Open-pit mines are for less conveniently positioned and shaped deposits of minerals. In simple terms again, a pit is excavated to follow the mineral seam(s) into the earth and overburden must be placed to the side to fill in or partially fill in the pit once the mining is finished (Fung, 1981; Westcott et al., 2009).

Mountaintop removal is much the same, although, as the name suggests, it is used where there is a mountain on top of the deposit. This makes for some distinct differences in the way miners have to handle and store overburden (Fung, 1981). This type of surface mining is more common in North America.

Finally, in layman's terms, highwall mining is used when the side of a horizontal mineral seam has been exposed but still has overburden over it. A specific piece of machinery is placed at the exposed end of the seam to extract the seam without the need to remove the overburden (Seib, 2009).

Underground mining involves digging tunnels into the earth to reach the desired material and is for deposits located deeper in the ground. Depending on the type of material being extracted, there are many different techniques and configurations of digging the tunnels and getting the ore out. Hard minerals, such as copper, gold and other metals, use techniques such as declines, shafts and adits. Miners of soft minerals, such as coal, use methods such as longwall and room-and-pillar bines (Darling, 2011).

This research is concerned with open-pit surface mining, and will not investigate underground techniques beyond this brief introduction.

Australia is the world's second largest exporter of coal, after Indonesia, exporting 284.5 million tonnes in 2011, which accounts for roughly 86% of the coal mined in Australia in that year (International Energy Agency, 2012). Exports are primarily to East Asia. Domestically, it is primarily used as fuel for electricity generation, with an estimated 70% of electricity in Australia coming from coal fire power plants in 2011-12 (Bureau of Resources and Energy Economics, 2013). The majority of coal is mined in the eastern states - Queensland, New South Wales and Victoria - though there are coal mines in all Australian states (Bureau of Resources and Energy Economics, 2012).

Coal is formed as dead biotic material is buried deep into the ground and put under high pressures and temperatures over time (Taylor et al., 2009). Under the various different conditions under which it can be placed, there are a number of different types of coal deposits which can form. These have different chemical makeups, which result in different thermal properties (Thomas, 2012). Besides electricity generation, coal in its solid state can be used as a fuel for producing steel and cement and in many other industrial situations where heat is required, such as the production of steel and cement.

In Australia, there are two main types of coal that are mined, bituminous and lignite. Bituminous coal, commonly referred to as black coal, is a high quality type of coal. It is mined in Queensland and New South Wales and used domestically for electricity production, steel production as well as being exported. Lignite, referred to as brown coal, is lower quality coal which is the primary coal mined in the other states, mainly for electricity generation (Hutton & Wootton, 2009).

Depending on the quality of the raw coal being extracted from the ground, and what its intended use is, a number of processing stages may be required for its sale as product. Raw coal extracted from the ground is known as run-of-mine (ROM) coal; this is the input into what is typically referred to as the Coal Preparation Plant (CPP) or Coal Handling and Preparation

Plant (CHPP). In some cases, when high quality coal is being extracted, there may be no requirement for processing before it is sold to the customer; therefore it is common for a mine to have a bypass around the CHPP, but as the high quality coal is depleted from the deposit, processing will be required to bring the quality up to a product level (Darling, 2011; Horrocks et al., 2009).

The basic function of the CHPP is to wash the ROM coal to remove soil and rock, resulting in improved quality. This is also known as beneficiation. ROM coal is usually first crushed to smaller, more consistent sizes, to make for easier and more stable handling and processing steps downstream. Screening is a process of separating the crushed coal based on size. This can be used at various stages of the overall process if the plant is set up with specific equipment groups for processing different particle sizes. Separation parts the coal and rock (rejects) by distinguishing between them based on density. Before the product coal is stored, the water is removed from it; this is referred to as dewatering. The rejects can also be dewatered before they are discarded as a way of recycling water (Darling, 2011; Horrocks et al., 2009).

Once the coal has been transformed into a product and is ready for sale, there are a number of different ways of delivering it to the customer. If it is being exported, it will be put on a train, taken to a port and put on a ship destined for the country to which it is being sold. If it is being used domestically, then it may be transported by train to the location where it is being used, or, if they are close enough, simply carried on a belt conveyor to the customers (Horrocks et al., 2009; , U.S.).

Energy is consumed in many different ways across an open-pit coal mine. Diesel, petrol, electricity and explosives are the most common sources. Bogunovic et al. (2009) propose a system for monitoring energy consumption across a mine to help identify areas to focus on when making improvements. Kecojevic et al. (2014) also conduct data analysis of energy usage across an open-pit bituminous coal mine. The study proposes a methodology for investigating the relationships between energy production, consumption and cost. For the case study mine it analyses, it finds the diesel sources are the highest energy consumers, while explosives represent the highest energy cost. While the methods of these two papers present significant opportunities to help industry improve energy efficiency, they both only give a picture of where the current energy is being consumed in an operation. They do not provide a way to examine the impact of any potential improvements.

Now that the general concepts of open-pit coal mining have been introduced, some specifics can be examined to identify the most common subsystems of an open-pit coal mine. Descriptions of how energy is used across the subsystems will be given, along with citations of literature studying their energy efficiency. This will form the initial basis for the modelling efforts being undertaken in this project.

2.1.2 Excavation and haulage

The system responsible for digging up material from the ground, be it waste or ROM coal, and transporting it to its next location, is referred to here as 'excavation and haulage'. In its simplest form, there are two main pieces of equipment, shovels and trucks; grouped together they are often referred to as shovel and truck fleets. There are many different types of shovels and trucks that can be used, depending on a number of factors. It is not uncommon to see two fleets of shovels and trucks, one dedicated to removing overburden, the other dedicated to removing ROM coal (Darling, 2011; Westcott et al., 2009). Currently, trucks and shovels are typically operated by human employees, though recent technologically advances have enabled remote control of machinery, leading towards a goal of completely autonomous control. This is expected to lead to significant improvements in productivity and reductions in operating costs (Bellamy & Pravica, 2011).

Truck payload, typically measured in tonnes, varies significantly. Payload can range anywhere between 40 to 400 tonnes and is selected based on the size of the mine and the required production rate (Darling, 2011).

There are two main types of truck frames, rigid and articulated. The difference is that articulated trucks are all-wheel drive and are hinged between the cab and trailer, which is used for steering, whereas rigid frame trucks are rear-wheel drive, have conventional front-wheel steering and do not have a hinge between the cab and dump box. Articulated frame trucks are more suited to rough road conditions and tight corners. Rigid frame trucks are the more commonly used type in open-pit coal mining (Darling, 2011; Westcott et al., 2009).

Trucks most commonly unload by tipping their trailer and dumping the material behind them. This is the most versatile way to unload material. An alternate type of dumping mechanism is the bottom dump, or belly dump, which has openings underneath the trailer that unload the material beneath them. This can be useful for dumping directly into a hopper to go onto a belt conveyor into the CHPP (Darling, 2011; Westcott et al., 2009).

The term ‘shovel’ has been used so far to describe the generic piece of equipment that digs the material, however when talking about the specifics of equipment, the term ‘shovel’ implies a particular type of machinery also known as a front end loader. The other type of machinery that is used to load trucks with material is an excavator or digger. The difference between these two types of equipment is in how they pick up the material. Front end loaders sit on the same level as the truck, at the bottom of the material they are digging, and scoop the material up from in front of them and then into the truck. Excavators sit on top of the material being removed and scoop it up from below them into the truck on the level below (Fung, 1981; Westcott et al., 2009). Here, for simplicity, the term ‘shovel’ is used to refer to either type of digging equipment.

The digging equipment is selected in accordance with long-term plans, often known as the life-of-mine (LOM) plan, and policies for pit design and extraction. Then, once owned, short-term planning and pit design takes into consideration the types of machinery available (White et al., 2009).

Alongside shovels, dozers are used at the pit to service the area, keeping the material together in a form that makes it easy to scoop for the digging equipment and away from the driving paths of trucks (Darling, 2011; Norgate & Haque, 2010).

There are a number of other pieces of auxiliary equipment used in the pit to assist with the operations of the trucks and shovels. Common pieces of equipment include, among others, water trucks for keeping roads wet and dust minimal; mobile refuelling trucks for refuelling trucks and shovels; sump pumps to drain water out of the bottom of the pit; and floodlights to light the pit when operating at night (Cairns & Arney, 2009; Norgate & Haque, 2010). These are not covered in detail as part of the scope of this thesis, as they do not perform a primary function for the mining production system.

The other main piece of machinery, which is often seen in large open-pit coal mines, is the dragline. A dragline is used to remove overburden from above coal. A large bucket suspended from a boom is controlled with ropes and chains to scoop overburden material and place it in more convenient locations for the truck and shovel fleet to handle. While the dragline is a very large piece of equipment that uses a lot of energy and is critical to production, it is very slow to move and should therefore have its operation planned well in advance of the day-to-day operational decision making process. This, along with the limitations of case study data, is why it is not being explicitly considered in this study; instead it will be implicitly considered by way of constraints in the model around the current available material for excavating, which the dragline has left for the truck and shovel fleet (Fung, 1981; Mirabediny & Baafi, 1998; Westcott et al., 2009).

Both diesel and electricity are sources of energy for the equipment used in the excavation and haulage system. Dozers and trucks both use diesel as a fuel source for their engines. Some trucks use the diesel to generate power for an electric powertrain, which is more efficient than a conventional diesel engine. Digging equipment can be either diesel powered or electric, smaller shovels and excavators are more typically diesel powered, while large shovels can be powered by electricity. Draglines are powered by electricity. Electricity to equipment in the pit is provided by means of a high voltage cable, which can be moved to the location of shovel or dragline using the electricity. Most auxiliary equipment, such as drainage pumps and floodlights, use electricity and are often powered by mobile diesel generators (Cairns & Arney, 2009; Darling, 2011; Norgate & Haque, 2010).

Truck operation is one area of focus amongst literature analysing haulage and excavation energy efficiency. Siami-Irdemoosa & Dindarloo (2015) develop a neural network approach for creating a prediction model of truck fuel consumption that could be used to compare alternate operating conditions. Kecojevic & Komljenovic (2010) analyse several truck models under different load conditions to find correlation between fuel consumption and engine load and propose opportunities for improved operation. Sahoo et al. (2014) develop a non-linear optimisation model mine road topology and truck dynamics for reducing the fuel consumption of trucks. Salama et al. (2014) use discrete event simulation and mathematical programming to analyse the energy consumption of alternative haulage methods, including in-pit conveyors, a long-term, strategic planning decision.

The operation of shovels is also considered in literature. Vukotic & Kecojevic (2014) conduct analysis of shovel energy consumption data to identify the impact that operators have on energy efficiency. Awuah-Offei & Frimpong (2007) use dynamic simulation of a shovel to identify the specific operation conditions that yield the highest energy efficiency of the equipment.

2.1.3 Processing Plant

As explained previously, the basic set of processing stages used to get the ROM coal to product quality consists of crushing, screening, washing, separating and dewatering. Each plant is designed and configured specifically for the type and quality of coal it is processing and quality of product required. Coal is sampled and tested for various different properties, which will determine how much processing is required, such as its 'washability', which, in simple language, defines how much rock is mixed with the coal and dictates how hard washing will be. Then, an engineering effort, much like in any other plant or factory, is undertaken to select the correct equipment and design the material flow to suit the coal and meet various other objectives, like throughput capacity, flexibility, maintainability, and efficiency (Horrocks et al., 2009).

Comminution is the term used to describe the reduction of particle size of solid materials. A crusher is a machine used in the early steps of coal processing, which achieves comminution by depositing material in a chamber where force is applied to the material to fracture and break it to a smaller size. This general process can be accomplished in a number of different ways (Napier-Munn & Wills, 2011).

One way the crushing happens is by squeezing the material between two solid surfaces in a funnel type configuration, where the material is crushed into smaller sizes as it falls down to where the surfaces are closer. This is the basic principal behind jaw, gyratory and cone crushers. In a jaw crusher, one surface is fixed, while the other moves back and forth to crush the material between them both. Gyratory and cone crushers both do this work by having a moving cone head in the middle of a chamber, set up such that the material is squeezed between the chamber and the cone head as it moves (King, 2001; Napier-Munn & Wills, 2011).

Another common way of achieving comminution is with an impact crusher. There are two types of impact crushers, horizontal shaft impactors (HSI) and vertical shaft impactors (VSI). Impact crushers are fed material from the top, which falls down onto a rotor, propelling the material against the hard surface of the side of the chamber with enough force to break the material. As their names suggest, the difference between them is in the direction of the rotor. Horizontal shaft impactors have the rotor set up with the shaft parallel to the ground like a car wheel, while vertical shaft impactors have the shaft set up perpendicular with the ground, like a helicopter prop citepKing2001, Napier-MunnWills2011.

Mineral sizers or roll crushers are another type of crusher; they typically have two parallel shafts with large teeth on them, which rotate in opposite directions inward to each other, fracturing and breaking the material into a smaller size as it is fed between them citepNapier-MunnWills2011.

Classifying material based on physical size is known as screening. Typically, this involves a mesh 'screen' that, when material is fed over it, splits the material into two sizes by smaller pieces of material falling through the screen and larger pieces remaining on top. This process is useful for recirculating larger material through comminution again to reduce its size or for plants that employ alternate processes for differently sized materials (King, 2001).

Separation techniques are used to classify different grades of coal from the reject material. There are many different types of separation methods, with varying degrees of complexity and accuracy. Gravity can be used to differentiate between densities of coal and rejects. Coal is a low density material compared to rock; the material with density between rock and coal is known as middlings. The cut-off range between what is acceptable, rejected or middlings is set depending on the quality of the coal being input and what quality is required by the customer. Middlings may be discarded or put through extra processing stages to crush or wash them further to get the coal out of them.

A jig is one common type of separator, in which the material is placed in a tank of water and moved, to allow the dense material to sink to the bottom and less dense material to rise. Early jigs placed the material in a basket that moved up and down. There are many different types of jigs today, which all follow the same basic principal. A Baum jig is an example of one of these variants; it uses compressed air to disturb the contents of the tank (Horrocks et al., 2009; King, 2001; Napier-Munn & Wills, 2011).

Dense, or heavy, medium separation also uses gravity to separate coal from rejects. While jigs use water, dense medium separation, as the name suggests, uses a liquid with a higher density than water. Magnetite is often used, mixed with water, to produce this dense liquid. This can be performed in a number of different ways. A common piece of equipment used to apply dense medium separation to coal is a cyclone. A cyclone is a cone-shaped vessel that has the material in the dense medium pumped through it at pressure in a tangential direction, causing a vortex. The centrifugal force from the vortex opposing the drag force on the moving particles causes the particles to be separated, based on their density. Dense medium separation is typically more expensive than other techniques, however it offers finer control over the densities being separated (Horrocks et al., 2009; King, 2001; Napier-Munn & Wills, 2011).

Finely sized coal can be washed using the floatation technique or with spirals. In the floatation method, material is fed into a chemical bath where the fine coal floats and bonds to bubbles at the top of the bath, while the rejects sink. The spiral method mixes the fine material with water and feeds it down a helix; the material is separated based on its density when it is under the centrifugal force. Heavy particles remain in the main flow with the liquid, while lighter particles are pushed outward (Horrocks et al., 2009; King, 2001; Napier-Munn & Wills, 2011).

Dewatering can be performed by a number of different machines. Dewatering screens, centrifuges or cyclones are the common methods these machines implement to remove the water from the coal or rejects (Horrocks et al., 2009; Napier-Munn & Wills, 2011).

Rejects, or tailings, from the CHPP system are most commonly disposed of to a tailings dam. The reject material from the CHPP is transported via belt conveyor or pipeline to a manmade dam, or pond, where it is left to settle and separate from the water which is then removed after time and either disposed of safely or reused. There are a number of different ways to design dams depending on various characteristics of the environment; this is not a topic covered in detail in this study as it is a concern for long term planning and design rather than operational decision making (Napier-Munn & Wills, 2011; Environmental Protection Agency, 1994).

A coal handling and processing plant contributes a significant portion to the overall energy consumption of an operating mine, especially in its comminution processes. Typically, all of the equipment used in a CHPP consumes electricity as an energy source (Napier-Munn & Wills, 2011; Norgate & Haque, 2010).

There are numerous papers that look energy efficiency of processing plants and specific equipment within them. Matthews & Craig (2013), Numbi & Xia (2014) and Numbi & Xia (2015) align the processing plant's operation with the electricity price tariffs to minimise cost. Pothina et al. (2007) develop a model of gyratory crusher energy consumption to identify how blasting impacts the equipment's energy efficiency, as well as its own operating parameters.

2.1.4 Stockpiles

The handling part of CHPP refers to the storage and transportation of ROM coal, in process material, rejects, water and product coal. Material is most commonly transported via belt conveyor, which will be discussed in the next subsection. Storage locations for the coal before and after processing are known as stockpiles. In some circumstances, coal can be stored mid process; for instance a stockpile may be placed between crushing and washing to separate out the two processes as a buffer for production smoothing (Horrocks et al., 2009).

While the general concept of a stockpile is quite simple, they can come in many different forms. Stockpiles are designed to best suit the way they receive material from upstream, what type of feed is required downstream and the capacities of both up and down stream processes. The general terms for adding to and removing from a stockpile are 'stacking' and 'reclaiming', respectively.

The most common stockpile is the ROM stockpile, which acts as a buffer between the variable and discrete nature of dump trucks delivering ROM from the pit, and the continuous demand rate of the CHPP. The other most common stockpile on a coal mine is the product coal stockpile, which would typically be fed by a belt conveyor from the CHPP and then reclaimed for product delivery, such as loading a train. Intermediate stockpiles can exist inside the CHPP to give finer control over the material flow through the plant. A surge bin is a type of stockpile that is used in this scenario (Darling, 2011).

In a simple ROM stockpile, stacking will occur by dump trucks unloading onto the side of the stockpile and dozers pushing the material into a more compact pile. More sophisticated stockpiles will employ machines called 'stackers' to do this, particularly for large stockpiles and where multiple stockpiles are needed, for different grades. These are machines with a large boom with a belt conveyor, which move along rail tracks, to stack coal onto the top of the stockpile (Darling, 2011).

In most circumstances, material being reclaimed from the stockpile will end up on a belt conveyor for transport to its next location; this can happen in a number of different ways. Similar to a stacker, a 'reclaimer' is a large piece of machinery for dealing with large and multiple stockpiles. Reclaimers are also normally on rail tracks; there are many different mechanisms that reclaimers can have to remove material from the stockpile and feed it onto the machine's belt conveyor, which transports the material to the next location. These can also be combined with stackers. For smaller, simpler stockpiles, front-end loaders and dozers can be used to push the coal into machines called feeders, which put the dumped coal onto belt conveyors. Material can also be reclaimed by using special bunkers placed below the stockpile, which give a continuous feed of material onto a tunnelled belt conveyor (Darling, 2011).

An issue with large stockpiles of coal is their exothermic heating reaction to oxygen, even in ambient conditions. In large stockpiles, there is reduced heat loss to the surrounding environment and if the exothermic heating outweighs the heat loss, spontaneous combustion of the coal can occur. This is a problem from both safety and economic perspectives (Arisoy & Akgün, 1994; Horrocks et al., 2009).

Stockpiles represent material being double handled. For this reason, they should be of great importance when studying mine energy efficiency. The method of energy consumption of a stockpile depends on what type of stockpile it is. A stockpile with dozers will, of course, have diesel as its primary energy source. Belt conveyors and surge bins will be powered by electricity. Stackers and reclaimers are most typically powered by electricity as well (Norgate & Haque, 2010).

2.1.5 Belt conveyors

Belt conveyors are the most common way of transporting coal between different parts of the mine once it has been extracted and transported by truck. For instance, from ROM stockpile to processing plant, between machines in the processing plant, or from product stockpile to train loading facility. In some circumstances, not considered in depth here, belt conveyors are positioned in the pit to move ore straight to the stockpile or handling plant, removing the need for trucks to do long trips in and out of the pit (Yardley & Stace, 2008).

Many industries use belt conveyors as an efficient way of transporting material between fixed points. Mines of all types have been using belt conveyors to transport material since the late nineteenth century. Since then, the capacities and carrying distances of belt conveyors used on mines have increased significantly, though the principles have not changed.

Belt conveyors are most typically powered by electric motors. Various different factors affect the energy requirements of belt conveyors. These are mostly static considerations, such as belt design, gradient and distance of the belt, which leaves the amount of material being transported as the main operating variable affecting the energy consumption of the belt (Yardley & Stace, 2008).

Belt conveyor energy consumption is considered in Luo et al. (2014) where model predictive control for improve energy efficiency is proposed. Zhang & Xia (2011) also address belt conveyor energy efficiency by identifying opportunities for improvements under various operating conditions.

2.1.6 Other subsystems

Another subsystem employed in the open-pit coal mining production system is the drill and blast activity. This subsystem is responsible for breaking up the ground where overburden and coal lie, to allow the dragline and loaders to easily scoop and move the material. Arrays of holes are drilled, packed with explosives and detonated in areas that are to be excavated soon. A number of different considerations have to be made here to design the correct blast for the material being extracted, such as hardness, safety, cost and the LOM plan. The blasting activity primarily consumes chemical energy, while the drilling activities consume diesel and electricity as energy sources (Norgate & Haque, 2010).

While the drilling and blasting subsystem is an important process of the open-pit coal mining production system, much like the dragline, its operation is determined by medium-to-long-term plans and is typically run to give weeks of lead time for the downstream excavation processes. This means day-to-day operational decisions don't have a great impact on the extraction of coal or output of product coal. Therefore it is not explicitly considered as part of the scope of this research project. Instead, it is considered implicitly as a constraint of the system through the determination of current availability of material for extraction at the pit faces entered as production targets.

Another energy-consuming activity, which occurs on open-pit mines but is not considered in this project, is rehabilitation. This refers to the important process of restoring land to its original vegetated state. This is an increasingly important duty of mining companies, which are responsible for minimising the long term impact of their operations on the environment. However, since it does not coincide with the day-to-day operations of the mine extracting material and outputting product, it is not considered at all in this study (Bell & Hannan, 2009).

Other activities not mentioned above that can occur in open-pit mines are not considered in this research project, as it is believed that the primary functional and energy-consuming processes of a typical open-pit coal mine have been adequately reflected with the system descriptions in this section.

2.1.7 Summary

From the study of open-pit coal mining methods conducted here, the four main subsystems that will be used in this research will be excavation and haulage, a processing plant, stockpiles and belt conveyors. Using these subsystems as building blocks to create a representation of a mining operation should cover the majority of work done and energy consumed in a typical open-pit coal mine and the case study mine examined later in this thesis.

As seen throughout this subsection, there are a number of papers addressing open-pit coal mine energy efficiency of these four subsystems. However, they are all specific to individual subsystems and therefore only represent opportunities for making silo improvements, rather than the integrated 'whole-of-system' optimisation that is the aim of this thesis.

2.2 Production system energy efficiency

In its most general form, production systems are defined as organisations that transform inputs, such as materials, personnel, equipment, capital, utilities and information into outputs, in the form of a product or products (Holstein & Tanenbaum, 2013; Martinich, 1997).

Systems can either generate physical goods as their output product, such as manufacturing and mining, or can provide a service as their product. This research is concerned with the former type of production system output.

Within the physical goods realm of this field, there are three primary methods of production, listed below (Holstein & Tanenbaum, 2013).

- Flow production
- Batch production
- Project production

Flow production systems are those that process inputs, using a well-defined and mostly identical sequence of processing stages. Some examples of industries that exploit this type of production are the paper, automobile, food, petroleum, metals, mining and electronics industries. Flow production systems hold a number of advantages over the other methods, including the increased efficiency through specialised equipment, simplified production scheduling, easier quality control and reduced requirement for in-process inventory. Some disadvantages are that the systems are usually not very flexible in producing new product types or handling unplanned work or stoppages, and they can also suffer from high initial costs due to the specialised equipment required (Bellgran & Säfsten, 2010; Martinich, 1997).

There are two main types of the flow production system, discrete and continuous. Discrete flow production systems handle the production of individual units, such as books, trucks or televisions, while continuous flow production systems are those that produce an uninterrupted flow of output, such as electricity, petroleum or product coal (Bellgran & Säfsten, 2010; Martinich, 1997).

Batch production systems describe the typical setup for an organisation that produces several distinct products with different inputs, machines, sequences and processes required to produce each different product. This allows for high levels of production flexibility to deal with unpredictable or cyclic demand, but can be more inefficient than a system specially designed for a single product type, and can be harder to optimally plan production (Bellgran & Säfsten, 2010; Holstein & Tanenbaum, 2013; Martinich, 1997).

Organisations which output one-of-a-kind products, such as buildings, highways, prototypes or software, generally fall into the category of project production systems. These products are highly specific to the customer and are therefore typically expensive (Holstein & Tanenbaum, 2013; Martinich, 1997). This type of production system is not considered further in this research.

The most common production systems are batch and flow production systems, which can often be found in combination with each other. This is sometimes referred to as a Cellular production system (Bellgran & Säfsten, 2010; Martinich, 1997). Batch, flow and cellular production systems are the primary subject of this review when referring to production systems. They are mostly represented in literature by the manufacturing industry. Continuous flow production systems are of particular interest, as they are the type of production system a mine is considered as in this study, as will be explained in more detail later.

Thiede (2012) provides a general input-output definition of energy efficiency of a production system as the ratio of the system's output over the total amount of energy input into the system. This definition is made to be adaptable to all the various possible combinations of different outputs that a production system can yield, and suits multiple ways of measuring the amount of energy being used, such as raw energetic value (joules), the cost of energy or even the environmental impact (e.g. CO_2 emissions). Thiede (2012) asserts that there are two clear strategies to increase this definition of energy efficiency. Either decrease energy input for a proportionally small, or no decrease, in product output or increase production with a proportionally small increase in energy consumption.

In this study, the objective value used for modelling is the denominator of this definition. This is used since the produced output of the system is an expected constraint of the model and is therefore fixed. It also ensures linearity in any case where the product output is a decision variable of the model. This means that 'energy consumption' is used as the objective within the model to represent the study's overall objective of improving energy efficiency.

On top of these straightforward strategies, depending on the specific implementation of the efficiency definition being used, more ways could be devised to improve the energy efficiency of a system being studied. For instance, if environment impact or energy cost is being used, changes to the provision of energy, such as using more renewable or cheaper sources, can improve efficiency without changing the production output or energy consumption (Yuan et al., 2012).

The manufacturing sector makes up a large portion of energy consumption across the world (International Energy Agency, 2008). There is a wide range of literature addressing ways to both measure and improve energy efficiency in the manufacturing industry (Bunse et al., 2010; Bunse & Vodicka, 2010; Cannata & Taisch, 2010; Dietmair & Verl, 2009; Thiede, 2012; Yuan et al., 2012). There are also numerous publications looking at energy efficiency of a mining operation (Medved et al., 2012; Middelberg et al., 2009; of Energy, 2007), though to a lesser extent than in the wider field of production systems. It is the intention of this project to draw upon the learnings from production system literature on energy efficiency, to extend upon the less mature field of mining energy efficiency.

Considering an operating mine as a production system has been done in previous related work. Everett (2007) looks at iron ore mining from a production system's perspective when creating a decision support system to aid operational decisions to reach target ore qualities with minimal rehandling and maximal throughput. Jiu et al. (2013) refer to a coal mine as a production system when developing a model for scheduling equipment maintenance across the various subsystems of a coal mine for tactical decision making. Zuñiga et al. (2015) also use the analogy to explain in detail how the supply chain operations reference (SCOR) standardisation framework, commonly used for manufacturing production systems can be applied to the mining production systems. It finds clear benefit to using the SCOR model in a mining application, despite the various differences between manufacturing and mining operations.

Most of the literature on production systems covered in this literature review refers to manufacturing production systems. The primary difference a mining production system has from manufacturing production systems is the uncontrollable variability of the surrounding environment. Production systems that depend on their environment, like mines do, are known as open production systems, whereas typical manufacturing plants that are not highly dependent on their environment are known as closed production systems (Bellgran & Säfsten, 2010). It is easy to see how mines are dependent on their environment in many different ways. The main effect is the variability in the material being extracted, the input into the production system. Along with this, the geography of the mine affects the layout of the system in a number of ways, from haul road distances and gradients to CHPP location, waste dump sites, belt conveyor placement and product delivery methods. Weather also has significant impact on the mine's production. These factors are considered in more detail and related to energy later in Subsection 2.3.7.

This thesis makes the argument that having such uncontrollable variation in a production system means operational decision making is very important for ensuring the whole system overcomes the variability to reach production targets efficiently. This forms the motivation for the approach taken in this research to provide decision support at an operational level, for making improvements to the energy efficiency of a mine by considering it in an open production system frame.

Ngai et al. (2013) develop a capability maturity model for energy and utility management, named EUMMM (Energy and Utility Management Maturity Model). EUMMM aims to be a coherent framework for organisations to assess their maturity and guide them to high levels of energy and utility management maturity. The highest level of maturity in the model is 'optimised'. This level specifies that organisations have strong, well defined, processes for incremental and innovative improvement, with quantitative measures and goals for improvement. Performance baselining, systematic data collection, analytic models, technological improvement, causal analysis and resolution management are some of the key processes organisations have to be following to be at the highest level of the model.

The importance of energy efficiency in the manufacturing sector is also realised in Bunse et al. (2010). It provides a framework for measuring improvements to energy efficiency and using these at the three typical levels of the decision hierarchy of an organisation: strategic, tactical and operational.

Decisions that are made at a strategic level are those that are long-term and mostly business-wide, relating to what markets are going to be targeted, what type of products/services will be provided from what resources at a high level and the overall structure of the company. The tactical level is about realising the strategic decision made in a medium-term time frame, through decisions on plant layout and capacity; equipment provision and maintenance; product design; and preparing their production. Lastly, operational decisions occur in a short-term time frame and are about planning and executing production to meet demand and longer term goals set by the strategic level decision makers. The objectives of operational decisions are typically based around productivity and efficiency (Ballou, 2004). In this thesis, operational decisions are modelled in order to provide an accurate picture of mine activity, which can then be used to aid decisions from any of these three levels.

2.3 Factors that impact energy efficiency in production systems

In order to accurately analyse and ultimately make improvements to the energy efficiency of a production system, using the generic definition for energy efficiency described by Thiede (2012) introduced earlier, all factors that impact on the production output, energy provision and consumption of the system should be considered. These factors can come from areas across both the physical process of the production system and the organisation running it. Based on a comprehensive search of production system literature that looks at energy, a catalogue of seven factors has been synthesised to cover the broad range of specific issues that are focused upon across the literature. This section reviews the literature that was used to build the catalogue of factors. The factors will then be used in the next section to form the basis for what requirements of the model will be needed to provide value to an operating open-cut coal mine.

2.3.1 Asset ownership factors

Many papers discuss the impact that informed and attentive asset selection has upon energy efficiency. A number of factors related to the ownership of assets are often considered, such as the provision of new technologies, maintenance policy, and correct machine capacity.

Göschel et al. (2011) cite replacing machinery and equipment with new, more efficient, technology as a common activity of organisations trying to improve energy efficiency of their manufacturing operations. For example, more efficient electric drives, pumps, compressors and heating/cooling systems are mentioned.

Technology is the first of three dimensional system approaches to environmentally sustainable manufacturing proposed by Yuan et al. (2012). Materials and energy are the other two dimensions in the devised scheme. The technological aspect of their approach is to create a material and energy flow balanced model of a plant to measure both the material utilisation and energy efficiencies of a production system. This allows for scenario analysis to be conducted, investigating the impact that new technologies or changes to process parameters have on material utilisation or energy efficiency, which can be related back to costs for comparison against one another.

Fleiter et al. (2012) consider in depth the energy saving potentials that new technologies could have in the pulp and paper industry. A long timeframe approach is used to give an accurate model of the real saving potentials of each studied technology across the whole sector in Germany until the year 2035. While the paper and its outcomes are not necessarily aimed at providing short term improvements as are the intentions of this project, they nonetheless show the large impact that adoption of new technologies can have on energy consumption in a production environment.

Equipment capacity is also a factor that impacts energy efficiency. It can have an effect on both the individual asset energy efficiency level and the wider system level. Gopalakrishnan et al. (2007) provide examples of types of equipment whereby capacity is an important factor in the energy consumption of the asset. These include chillers; heating, ventilation and air conditioning (HVAC) equipment; and air compressors. When capacity is a major factor in a piece of equipment's energy efficiency function, the planned utilisation of the equipment should be taken into account for equipment provision and then the capacity should be taken into consideration when actually using it Duflou et al. (2012). The impact of utilisation is considered in more detail in the next section.

While the above papers are mainly concerned with the impact capacity has on the individual equipment's energy efficiency when it is being run below capacity, the capacity of assets can impact the overall energy efficiency when it becomes a bottleneck of the overall production system (Arinez et al., 2010; Leachman, 1997; Thiede, 2012). This can have an impact on the production output and energy consumption of the system - both the numerator and denominator, respectively, of the general definition of production system energy efficiency. This is an important reason to have a whole-of-system model, which takes into account material flow through and capacities of all the components of the system (Ellis et al., 2010; Viere et al., 2011), a concept reviewed further in Section 2.5.

Reliability of the asset should be taken into consideration when purchasing equipment. Aside from the functions the assets are performing in the production system, their maintenance also impacts their energy consumption and therefore the energy efficiency of the system. Arinez et al. (2010) suggest using discrete event simulation (DES) as a generic way of modelling and studying production systems in order to find energy efficiency improvements. Maintenance is listed as a key area for investigation, specifically suggesting scenario analysis of the impact on energy consumption that preventative maintenance has.

Önüt & Soner (2007) and Thiede (2012) also list maintenance as an area of opportunity for improving energy efficiency. The analysis of maintenance activity described in the literature is primarily concerned with the effect it has on the energy efficiency of the assets being maintained, however the energy consumed while maintaining will clearly also have an impact on the overall energy efficiency of the system.

Various different maintenance policies exist with different impacts on the asset reliability (Nakagawa, 2008; Wang & Pham, 2006). Preventive maintenance may result in extra time out of service, but usually will run at a lower risk of a major failure and provides more certainty about the equipment availability for planners and operators. These types of maintenance policies have rich history in the literature showing many of their benefits (Barlow & Hunter, 1960; Cheng-Yi, 2004; Liao, 2012; Mine & Nakagawa, 1977). Maintenance activity will also have an impact on the availability of the assets in a production system (Olson, 2007), which is discussed as a factor in itself in the next section.

2.3.2 Asset usage factors

As briefly introduced in the previous section, both utilisation and availability of the assets in a production system impact energy efficiency. The operation and control of equipment is also a factor in the asset's energy consumption and therefore overall system's energy efficiency.

With relation to this project, asset usage, operation and control is a primary consideration, as they make up some of the core controls mining companies have, through operational planning and decision making, to improve the energy efficiency of their mines.

The importance of asset capacity on energy efficiency is described in the previous section from the perspective of asset provision. On the other side of provision decisions, as alluded to earlier, are the decisions around asset utilisation. Over or under utilising an asset is where the actual negative impacts on energy efficiency are seen.

Jain et al. (2013) conduct an energy efficiency study across a supply chain and outline several opportunities for improving energy efficiency by managing machine utilisation. Energy consumption while in standby or idle is a common area which has contributed to poor energy efficiency across the various subsystems as it is a non-value adding cost. Higher utilisation of assets reduces idle time, which can in turn improve efficiency; shutting down unused equipment is also a suggested way of reducing idle consumption.

He et al. (2012) highlight the importance of understanding and characterising how asset energy consumption changes when performing different tasks, including idle, start up and shut down consumption. The paper also mentions the importance of trading off energy consumption improvement against productivity when considering these decisions around asset utilisation. Dietmair & Verl (2009) use similar concepts of machine operating states to create a profile of asset energy consumption as a robust basis for finding improvements.

Modelling the different 'operating states' of each subsystem and its equipment is employed successfully in a number of recent papers on production system energy efficiency (Herrmann et al., 2011; Li et al., 2014; Mousavi et al., 2015; Sproedt et al., 2015). Each finds that significant benefits to energy efficiency are possible by modelling energy consumption for different operating states. Due to its popularity and success, the concept is used in this thesis to describe the model's time dimension as a series of operating states. This is described in more detail in Chapter 3.

Utilisation is also directly related to availability. Since utilisation is typically calculated as a ratio of time used over time available, low availability can be a cause of bottlenecks created by highly utilised equipment rather than low capacity (Stapelberg, 2009). It is important to consider these two performance measures at the same time to get the best picture of how the asset is being used and what impact it is having on the whole system.

Smith & Ball (2012) model a production system using material, energy and waste flows as a way of improving its energy efficiency, which is a concept applied in this research. Their study looks at sustainability of a production system, which includes energy efficiency and suggests reduction of idle time through switching off assets instead of having them in standby, so long as that does not have overly negative impacts on production.

It has already been presented that availability of assets can be related to energy efficiency though time spent performing maintenance, and the amount of maintenance time is related to the reliability of the asset. The previous section explored reliability from the perspective of procurement; the way the asset is used will also impact reliability. Operating at various different loads and under different external conditions will impact the reliability of the asset

(Stapelberg, 2009).

While the utilisation and availability factors described above are mainly concerned with overall decisions about when and how much the asset is being used, more detailed decisions are required once the equipment is in operation. The energy profiling methods from the aforementioned papers, He et al. (2012) and Dietmair & Verl (2009), are also used to gain an understanding of how the different operating loads directly impact the operational energy consumption of each asset.

Operational planning is where these asset operating loads and conditions are considered and set, and is explored later in Subsection 2.3.6. However, energy is consumed and production targets are reached when the production system is being run and assets are operating, which is why it is important to consider the actual asset's operation as a factor when analysing energy efficiency, especially if plans are not made at particularly high resolutions and many more operational decisions are required to use the assets. Depending on the type of asset, decisions relating to operation can be quite wide ranging, from automated control systems of processing plants to the human decisions of operators using the equipment.

In this thesis, the link between asset usage and planning factors is described using the operating state concept previously mentioned. Here, a plan is considered as a series of operating states of the whole system to partition the time dimension of the model. The subsystems and equipment must then work together in their respective operating states to achieve the overall goals. Once again, this is described in detail in Chapter 3.

The research in Dietmair & Verl (2009) notes the role of operators and control systems in impacting energy efficiency. The concept of using the model to assist in 'online' operational decisions is also suggested for improving energy efficiency, even under unplanned conditions. Cannata & Taisch (2010) and Duflou et al. (2012) also identify control systems as important to consider when improving energy efficiency.

2.3.3 Human factors

Many of the factors presented here involve a decision making process, which involves human behaviour. Humans play important roles in decision making all across organisations, from structuring high level strategies to making minute set point adjustments to control systems on operating equipment. Ultimately, humans are responsible for the vast majority of decisions made across even the most automated production systems, making their judgement an important factor in achieving energy efficiency, though hard to quantify and analyse.

The importance of human behaviour in improving energy efficiency is highlighted in Cagno et al. (2013). The study conducts a critical literature review to find a number of behavioural barriers in industry. 'Bounded rationality' is one of these barriers, which sees humans making decisions based on simply satisfying constraints and following rules of thumb that have worked in the past, rather than striving to search for more optimal decisions.

The manner in which information intended to help with making energy efficiency decisions is presented is another factor affecting human behaviour, as identified by Cagno et al. (2013). Other barriers presented in the paper's literature review are the credibility and trust new technology and information hold with employees; 'inertia', which refers to decision making that favours the status quo by *"treating gains differently from losses, giving greater weighting to certain outcomes with respect to those that are uncertain, and minimizing the regret"* (p. 293); and finally, the values of the individuals making the decisions can be barriers if they don't align with the drivers for improving energy efficiency, such as environmental and cost.

Oskouei & Awuah-Offei (2014) look at how dragline operators at a coal mine impact energy efficiency. A statistical approach is proposed for identifying the energy efficiency of each operator. Using this information, management can focus training efforts on the poorer performing operators to improve energy efficiency. The impact of coal mine equipment operators on energy efficiency is also considered in Vukotic & Kecojevic (2014). In that study, shovel operators a ranked by their impact on energy efficiency, leading towards opportunities for targeted training to improve energy efficiency.

These factors are not considered any further for the development of the models for this thesis. However, for further work on this research project in converting it into a tool for the mining industry, these factors play an important part in making the tool provide valuable decision support that will be trusted and used by employees.

2.3.4 Organisational factors

Further to the impact that human behaviour and communication has on the ability to be energy efficient, organisational culture plays a major part in creating the right environment to enable employees to make energy efficient decisions. Positive organisational culture is created and maintained in various ways. Typically this comes from high level management leading by example, through creating a focus on energy efficiency by establishing improvement targets across the business and investing capital in technology, research and development or bonuses to achieve the targets (Cagno et al., 2013; Rudberg et al., 2013; Thiede, 2012).

Cagno et al. (2013), introduced in the previous section, also look at organisational factors in their study of barriers to industrial energy efficiency. Where power and responsibility lies within the organisation, it is listed as a possible barrier if it is placed with departments or employees that do not see energy efficiency as a primary consideration when making decisions. The 'culture' of the organisation is also listed as an important factor in whether energy efficiency is harboured or disregarded.

Rudberg et al. (2013) looks at how energy management can be considered by organisations from a strategic perspective. This can be done in a number of ways, such as treating energy as a 'core' to the business; investing in long term energy saving measures; establishing an energy manager for the business with the responsibility of improving energy efficiency; participating in government programs that encourage implementing energy management systems or giving incentives for energy saving initiatives; and centralising the energy planning to allow a company-wide optimisation, rather than sub-optimisation of business units.

As with the human factors, these are not considered any further in this thesis, however, should be considered for future work into making a tool from the developed methodologies, which will be useful for industry.

2.3.5 Energy provision factors

Since improving energy efficiency is typically motivated by the opportunity to reduce operating costs and environmental impact, it makes sense that organisations should not only look at the consumption of energy by their operations, but also at the cost and environmental impact of the energy they are purchasing or producing to run the business.

Yuan et al. (2012) consider energy supply as a main part of the energy dimension of their three dimensional system approach to improving environmental sustainability in manufacturing. The paper suggests a method for conducting a cost benefit analysis of clean energy supply. It then goes on to apply the model to a case study in nano-scale manufacturing, comparing three clean energy alternatives to the existing fossil fuel-based energy sources being used in the company, solar photovoltaic, wind and fuel cells, with wind being found to have the best cost benefit in this case.

A number of other papers discuss this as an area of opportunity to improve sustainability and energy efficiency of both the individual organisations and whole supply chains (Duflou et al., 2012; Stich et al., 2012; Thiede, 2012; Zanoni et al., 2013). There is also recognition in the literature of the differences in energy pricing across different countries and from different sources, which impact motivation for companies to improve energy efficiency, the specific focuses they have and decisions they ultimately make.

Since these energy provision factors are based around longer term strategy, they do not translate into day-to-day operational decisions and are therefore not being considered in detail for the model developed in this research.

2.3.6 Planning factors

Ultimately, all energy consumption happens during the actual operation of the system. However, it is the strategic, tactical and operational planning stages that influence the actual operation of a production system. It is at these planning stages that the factors relating to asset usage are considered in achieving potential energy efficiency improvements.

Once this is done effectively, actually following through and achieving an energy efficient plan is clearly just as important as creating one. The organisation's ability to execute energy efficient plans will depend on the factors outlined in Subsection 2.3.3 and Subsection 2.3.4, which should also be included in the planning process. These relationships are well known and described in the continuous improvement domain as the Plan-Do-Check-Act (PDCA) cycle model (Walton, 1988).

Zanoni et al. (2013) present a mathematical programming model which finds production rates to minimise energy usage for a two-stage production system with inventory. The paper conducts analysis over several production policy cases and finds that energy has a critical role to play in production planning.

Duflou et al. (2012) focus on discrete part manufacturing to conduct a detailed analysis of methods for improving energy and resource efficiency. A number of their recommendations highlight the benefit of advanced planning techniques for making energy efficiency improvements. In particular, they mention the importance of optimising factory wide planning for making overall reductions to energy consumption. Mousavi et al. (2015) use this concept to develop an integrated simulation framework for modelling production system energy consumption. Two manufacturing case studies are analysed to find significant potential for using the framework for making energy efficiency improvements.

Newman et al. (2010) conduct a review of how operations research has been applied to mine planning. The paper reviews decades of literature on open-pit and underground mining from strategic, tactical and operational planning perspectives primarily using simulation and optimisation techniques. The paper lists a more holistic model of the mine as an emerging area for planning models for reaching overall optimal results rather than sub-optimising individual decisions from different parts of the mine and organisation. Energy is not mentioned in the review, suggesting it is an underdeveloped area for planning in the mining industry.

While the aim of the developed methodology from this research is not to produce plans for the mines being modelled, it is intended to help operators execute their plans in an energy efficient manner. This will be done by taking the existing plan as an 'input' and providing support for the operational decisions that get made to meet that plan, from an energy efficiency perspective. Explaining it using the operating states' concept introduced in Subsection 2.3.2, the model's responsibility will be to determine the various subsystem and equipment operating states that are required to meet an overall plan, with minimum energy consumption.

2.3.7 External factors

Depending on the production system, different external factors will apply to varying degrees. This section covers some of the main externalities that can impact mining operations and their energy efficiency.

Weather is one of these externalities. For various reasons, not least safety, many mines do not operate during wet weather, which in turn means equipment utilisation is reduced (Department Resources Energy and Tourism, 2010).

The geographical location and existing layout of the mine also impact energy efficiency. Pit face locations and haul roads play a large part in haulage and excavation subsystem energy usage (Department Resources Energy and Tourism, 2010).

Past decisions, or 'operational history', are also externalities that impact energy efficiency (Bruckner et al., 2005), one of which for the coal mining industry is the historical determination of what can be considered economical coal. If previously uneconomical coal has been covered with overburden, this overburden must be relocated once again to reach the lower grade coal. Another way this may occur is through the existence of equipment that is not energy efficient, which relates back to the asset ownership factor. Old decisions based on the long term planning for the mine may not be optimal for updated plans made under different economic and environmental conditions.

Variability in the grade of material being extracted is another uncontrollable external factor that impacts the energy efficiency of a mining operation. As mentioned in the introduction, declining material grades is a reason for increased energy intensity (Mudd, 2007).

Product demand is another external factor that can impact energy efficiency in production systems (Zanoni et al., 2013). Uncertainty around demand for the product can lead to changes to the planned operation that may lead to inefficient operation, relating back to the asset usage and planning factors.

2.4 How factors impact the operation of mine subsystems

This section reviews a selection of literature on the four main open-pit coal mining subsystems chosen to be modelled, which do not necessarily discuss energy but do cover factors introduced in the previous section. The mining literature is used to condense these factors down to the most important to operational modelling. Following that, a review of how each subsystem has been modelled operationally in the literature is conducted.

2.4.1 Operationally modelled factors

Recent mine modelling literature has been reviewed in order to identify the key factors to consider when modelling the operation of a mine. The focus for the review was papers examining quantitative models addressing operational decisions on at least one of the four subsystems analysed. Traditional operations research simulation and optimisation models, or combinations of the two, were primarily collected, however, some 'other' types mathematical models were also included, such as partial differential equations.

To summarise the findings of the review, compliance matrices have been compiled. The legend for the entries in the matrix is as follows: explicit mention is marked with an X, minor mention with an M and future work with an F. Table 2.1 shows what factors were considered in each paper.

The most common factors studied, by far, are asset usage and planning. Asset usage features in all 36 papers, while planning explicitly featured in all but eight of the reviewed papers. The other factors were all much less prevalent. Energy provision was the next most featured factor with only four explicit mentions. This suggests that asset usage and planning the most important factors to consider when modelling the operation of a mining production system. Hence, they will be the primary focus of the modelling efforts taken out in this thesis and used to analyse the results of the developed model.

Table 2.1. Factors considered in mining literature with operational models

Paper	Asset ownership	Asset usage	Human	Organisational	Energy provision	Planning	External
Castillo & Cochran (1987)	-	X	-	-	-	X	-
Soumis et al. (1989)	-	X	-	-	-	X	-
Li (1990)	-	X	-	-	-	X	-
Kolonja et al. (1993)	-	X	-	-	-	-	-
Munirathinam & Yingling (1994)	-	X	-	-	-	X	-
Everett (1997)	-	X	-	-	-	X	-
Lebedev & Staples (1998)	X	X	-	-	-	X	-
Binkowski & McCarragher (1999)	-	X	-	-	-	X	M
Hodouin et al. (2001)	-	X	M	-	-	X	-
Alarie & Gamache (2002)	-	X	-	-	-	X	-
Robinson (2004)	-	X	-	-	-	X	-
Ta et al. (2005)	-	X	-	-	-	X	X
Blouin et al. (2007)	-	X	-	-	-	M	M
Everett (2007)	-	X	M	-	-	X	-
Tie et al. (2007)	-	X	-	-	-	-	-
Ercelebi & Bascetin (2009)	M	X	-	-	-	X	-
Middelberg et al. (2009)	-	X	-	-	X	X	-
Mitra (2009)	-	X	-	-	-	X	X
Arelovich et al. (2010)	-	X	M	-	-	M	M
Meyer & Craig (2010)	-	X	-	-	-	-	-
Mohanty & Das (2010)	-	X	-	-	-	-	-
Remes et al. (2010)	-	X	-	-	-	X	-
Souza et al. (2010)	-	X	-	-	-	X	-
Bastos et al. (2011)	-	X	X	-	-	-	-
Hulthén & Magnus Evertsson (2011)	-	X	-	-	-	M	F
Zhang & Xia (2011)	-	X	-	-	-	X	-
Hanoun et al. (2013)	-	X	M	-	-	X	-
Matthews & Craig (2013)	-	X	-	-	X	X	-
Mena et al. (2013)	-	X	-	-	-	X	M
Ta et al. (2013)	-	X	-	-	-	X	-
Zhao & Chai (2013)	-	X	-	-	-	X	-
Luo et al. (2014)	-	X	-	-	-	X	-
Numbi & Xia (2014)	-	X	-	-	X	X	-
Sahoo et al. (2014)	-	X	-	-	-	X	-
Chang et al. (2015)	-	X	-	-	-	X	-
Numbi & Xia (2014)	-	X	-	-	X	X	-

2.4.2 Excavation and haulage

In total, 16 of the reviewed papers modelled the operation of the haulage and excavation subsystem. Productivity, production and cost were the objectives or constraints most modelled, with grade and maintenance only considered in few papers. Only one paper considered energy as a part of their respective models. All papers considered asset usage factors explicitly and twelve considered planning factors explicitly. Ten papers contained optimisation models, eight contained simulation models, with three crossing over with both optimisation and simulation models. Table 2.2 summarises these findings.

Table 2.2. Excavation and haulage operational modelling summary

Paper	Sim. or Opt.	Energy	Cost	Production/ throughput	Grade	Maintenance	Productivity	Asset usage	Planning
Castillo & Cochran (1987)	Sim.	-	-	X	-	-	X	X	X
Soumis et al. (1989)	Both	-	M	X	-	-	X	X	X
Li (1990)	Opt.	-	M	-	-	-	X	X	X
Kolonja et al. (1993)	Sim.	-	-	X	-	-	M	X	-
Munirathinam & Yingling (1994)	Opt.	-	X	-	M	-	X	X	X
Alarie & Gamache (2002)	Opt.	-	X	-	-	F	M	X	X
Ta et al. (2005)	Opt.	-	X	-	-	-	-	X	X
Blouin et al. (2007)	Sim.	-	-	X	-	-	X	X	M
Ercelebi & Bascetin (2009)	Opt.	-	X	X	-	-	X	X	X
Arelovich et al. (2010)	Sim.	-	M	-	-	-	X	X	M
Souza et al. (2010)	Opt.	-	M	X	X	-	X	X	X
Bastos et al. (2011)	Sim.	-	X	X	-	-	X	X	-
Ta et al. (2013)	Both	-	X	X	X	M	X	X	X
Mena et al. (2013)	Both	-	-	-	-	X	X	X	X
Sahoo et al. (2014)	Opt.	X	-	X	-	-	X	X	X
Chang et al. (2015)	Opt.	-	-	X	-	-	X	X	X

The primary assets that are used in the haulage and excavation subsystem are trucks and shovels. Most of the recent optimisation models from the literature are equipment allocation-based formulations that provide decision support for managers and operators to assign the trucks to 'trips' between pits and destinations (plants, stockpiles or waste dumps) and shovels to pits (Mena et al., 2013; Sahoo et al., 2014; Souza et al., 2010; Ta et al., 2013). Truck allocation is by far the most modelled operational decision amongst the papers, while the allocation of shovels is less featured. The shovels' slow movement and high criticality to achieving desired production rates means that allocation is more likely dealt with at a medium term decision making level rather than operational.

The asset usage factor is sometimes even more accurately considered by modelling the truck and shovel fleet heterogeneously (Mena et al., 2013). That is, parameterising equipment behaviour on an individual basis from actual performance, rather than considering them all to be the same. This allows the model to more accurately represent the actual operation of the subsystem, which leads to results that provide better decision support to the operators.

The planning factor is considered in the allocation models through constraints ensuring that predefined extraction or demand rates are achieved. These rates are typically worked out during medium and long term (tactical and strategic) planning stages and fed down as targets for the actual operation to meet. In this configuration, the plan is considered an input into the model. Extending upon this concept, more factors from plans are included as inputs in some papers, such as material grade control, minimum stockpile levels or equipment availability.

While allocation models are popular and provide useful results, they are limited in their ability to provide a very accurate representation of the truck and shovel equipment behaviours. Since allocation formulation cannot provide sequencing or scheduling information about the trips that trucks are making, they cannot guarantee shovel and truck synchronicity. Along with this, the models in the literature only consider constant demand rates and produce allocations for a single, steady 'operating state' that the mines work at to meet demand. None of the allocation models are integrated with the whole mine system either. These issues are dealt with throughout this thesis.

Chang et al. (2015) is the only paper to present a scheduling MILP model of the truck and shovel operation. The paper bases its formulation on a model of truck scheduling at container terminals (Tang et al., 2014). The model is formulated around a sequencing variable that decides the order that trucks are loaded by shovels. The constraints ensure that trucks and shovels are synchronised and there is enough driving times between jobs. The objective of their model is to maximise revenue of throughput of the subsystem and does not consider operating costs. It also treats all trucks as equal, which cannot provide an accurate reflection of actual operation. As with the other models, it also only solves for a single operating state and is not integrated with other subsystems at the mine.

Due to these limitations and the fact that the Chang et al. (2015) model is the only one of its kind, the modelling effort in this study will be first based on the more common and established allocation model. This is done to make a useful contribution to the allocation formulation and highlight its drawbacks in detail before formulating a scheduling model to deal with them. The allocation formulation will also be used to estimate the quality of scheduling solutions and aid the solution techniques required to solve the scheduling formulation.

2.4.3 Processing plant

Models of the processing plant subsystem were found in 14 of the reviewed papers. The majority of explicit model features are related to the production or throughput of the plant and grade of the product being produced by the plant. Energy consumption was explicitly modelled in four papers, including one that integrated the processing plant with stockpile and belt conveyor decisions Middelberg et al. (2009), and there were minor mentions in six other papers. The planning factor is considered explicitly in six of the papers that modelled the processing plant. Optimisation models appeared in five of the papers, simulation models appeared in three, while two presented other types of mathematical models. Table 2.3 summarises these findings.

Table 2.3. Processing plant operational modelling summary

Paper	Sim. or Opt.	Energy	Cost	Production/ throughput	Grade	Maintenance	Productivity	Asset usage	Planning
Hodouin et al. (2001)	Opt.	M	M	M	M	M	-	X	X
Tie et al. (2007)	Sim.	M	M	-	X	-	-	X	-
Middelberg et al. (2009)	Opt.	X	M	M	-	-	-	X	X
Mitra (2009)	Opt.	M	M	X	X	-	M	X	X
Remes et al. (2010)	Sim.	M	X	X	X	-	-	X	X
Meyer & Craig (2010)	Sim.	-	-	X	X	-	-	X	-
Mohanty & Das (2010)	Opt.	-	-	-	X	-	-	X	-
Hulthén & Magnus Evertsson (2011)	Other	M	M	X	M	-	-	X	M
Hanoun et al. (2013)	Opt.	-	-	X	-	-	-	X	X
Matthews & Craig (2013)	Opt.	X	X	X	X	-	X	X	X
Zhao & Chai (2013)	Other	M	-	X	X	-	M	X	X
Numbi & Xia (2014)	Opt.	X	X	X	X	-	M	X	X
Numbi & Xia (2015)	Opt.	X	X	X	X	-	M	X	X

The most common decision variables considered in the research, which covers the asset usage factor, are the feed rates of raw material and water entering the processing plant. This is because they are the main controls that operators have over the operation of the plant. These flow rates are usually expressed in tonnes/hour for the raw material or litres/hour for water. The maximum throughput capacity is also considered in models as a constraint on the plant's operation.

Most of the models reviewed here are intended for automatic control systems, in a model predictive control (MPC) methodology. For this reason, many include non-linear equations to account for the dynamics of the specific circuit being modelled. The non-linearity introduced by this level of modelling detail cannot be achieved with MILP and would make integrating the subsystem with the rest of the mine difficult. Two papers that model the processing plant as part of a whole system model considered the overall load of the plant, rather than the non-linear dynamics of it (Hanoun et al., 2013; Middelberg et al., 2009). The Hanoun et al. (2013) model is limited, however, it treats the plant's operation as an input, coming from higher levels of planning, and primarily optimises the handling facilities connected to the plant.

As with the haulage and excavation subsystem, the planning factor is taken into account in processing plant subsystem models by mainly considering planned targets as inputs to the model for constraining the operation. Grade quality targets are the most commonly considered planned variable; others also take planned production rates as an input. The two models that integrated the processing plant's operation with other subsystems (Hanoun et al., 2013; Middelberg et al., 2009) included a time dimension in their formulation to allow for multiple operating states. The other three models that explicitly considered energy (Matthews & Craig, 2013; Numbi & Xia, 2014, 2015) also included a time dimension to allow for changes in operating state. This indicates the importance that considering changes to operating state has on energy efficiency.

2.4.4 Stockpile

Eight of the papers contained models of the stockpiles used on a mine. Grade, production/throughput and cost were the most common model features. Energy was considered in only one paper (Middelberg et al., 2009), which covers the processing plant, stockpile and conveyor belt subsystems. The planning factor is considered in all of the stockpile subsystem papers. Three papers presented optimisation models of the operation, while two were simulation models and the remaining were other forms of mathematical models. These finding are summarised in Table 2.4.

Table 2.4. Stockpile operational modelling summary

Paper	Sim. or Opt.	Energy	Cost	Production/ throughput	Grade	Maintenance	Productivity	Asset usage	Planning
Everett (1997)	Sim.	-	M	X	X	-	-	X	X
Lebedev & Staples (1998)	Sim.	-	X	X	-	M	X	X	X
Binkowski & McCarragher (1999)	Other	-	X	X	X	M	-	X	X
Robinson (2004)	Other	-	-	-	X	-	-	X	X
Ta et al. (2005)	Opt.	-	X	-	-	-	-	X	X
Everett (2007)	Other	-	X	X	X	-	-	X	X
Middelberg et al. (2009)	Opt.	X	M	M	-	-	-	X	X
Hanoun et al. (2013)	Opt.	-	M	X	X	M	X	X	X

The operation of the stockpile subsystem is often modelled via inlet and outlet material flow rates and standard inventory balance equations (Ta et al., 2005; Middelberg et al., 2009). Minimum stockpile levels are often included as a constraint of the subsystem. Since stockpiling represents double handling, the most efficient operations use a stockpile as little as possible. However, in practice, they are used as buffers to reduce the risk of an upstream disturbance impacting downstream processes. For instance, a minimum level of ROM coal should be maintained so that any unplanned stoppage in the haulage and excavation fleet does not mean the processing plant has to stop operation.

Much like the haulage and excavation and processing plant subsystems, the planning factor for the stockpile subsystem is considered by having information from the plan as input into the model. This usually comes in the form of production rate targets and/or material grade targets.

2.4.5 Belt conveyor

Five of the reviewed papers directly modelled the operation of the conveyor belt subsystem and Table 2.5 summarised the models. Production throughput and productivity were major features of two out of the five papers, while energy featured in Middelberg et al. (2009) and Luo et al. (2014). The planning factor is considered explicitly in all three papers. Optimisation modelling was used in two papers and one paper used a simulation model.

Table 2.5. Belt conveyor operational modelling summary

Paper	Sim. or Opt.	Energy	Cost	Production/ throughput	Grade	Maintenance	Productivity	Asset usage	Planning
Lebedev & Staples (1998)	Sim.	-	X	X	-	M	X	X	X
Middelberg et al. (2009)	Opt.	X	M	M	-	-	-	X	X
Zhang & Xia (2011)	Opt.	X	X	M	-	-	-	X	X
Hanoun et al. (2013)	Opt.	-	M	X	X	M	X	X	X
Luo et al. (2014)	Opt.	X	X	M	-	-	-	X	X

Conveyor belts are modelled relatively simply in the literature. Conveyor belt throughput flow rates is the main variable used to define the operation of the machinery, or even simply a binary variable indicating whether it is in service or not, along with an assumption of a fixed flow rate. They also include maximum capacity of the conveyor belt as a constraint of the subsystem. Luo et al. (2014) contains the most advanced model by considering nonlinearity of the energy consumption in a MPC approach to reducing the energy consumption when changes in operating state occur.

Similarly with the other three subsystems, a plan is taken as input to the operational models for the conveyor belt subsystem as their consideration of the planning factor.

2.4.6 The operational energy model gap

There is a lack of operational optimisation models across the reviewed papers that include energy consumption. The apparent gap in research, along with the need for industry to address the problem, forms the motivation for this research. Only a handful of papers explicitly consider energy in their operational models. Here they are reviewed to gain an insight into how this research will contribute to the area with original and substantial contributions.

Luo et al. (2014) demonstrate significant improvements to belt conveyor energy efficiency by applying MPC. They highlight the operational decision making level as an important area for practical application of the approach. The results only demonstrate a silo optimisation of a single subsystem instance, and do not study the impact on upstream or downstream subsystems.

Zhang & Xia (2011) recognise the problem with optimising the belt conveyor on its own without considering other systems. The paper presents a model of a belt conveyor subsystem that includes constraints that other subsystems place on belt conveyors. They show significant potential for energy efficiency improvement of the belt conveyor under various different operating conditions that other subsystems place it in. While this is a good step towards whole-of-mine optimisation, it does not integrate the decisions of all subsystems together in a single model and hence cannot guarantee a whole-of-mine optimal result.

Due to the detailed nature of these two belt conveyor models, they require very detailed information about the subsystem being optimised. This means a sizable data gathering and parameter fitting effort is required to apply the model to any given belt conveyor subsystem before it can be of use. This decreases the practical applicability of the model as it increases upfront cost, extending the payoff period.

Matthews & Craig (2013), Numbi & Xia (2014) and Numbi & Xia (2015) all make similar contributions. They optimise the plant's operation over time to align with the electricity price tariffs, without sacrificing demand requirements to minimise cost. This is known as load shifting; it is employed to take into account the energy provision factor. While these three papers show this to be an effective method of reducing cost, they can be considered silo optimisations as they do not consider constraints of the other subsystems that make up a mine. As with the belt conveyor models, these three models also require a detailed amount of information about the specific plant being modelled. For a processing plant, this can be even more complicated to gather and fit, as they come in many different shapes and sizes.

Middelberg et al. (2009) considers the processing plant and load-shifting as a way to reduce operating costs. However it also models the stockpile and conveyor belt subsystems in a single integrated model, but does not include the haulage and excavation subsystem. The paper proposes a model for deciding the operation of a system of assets to reduce the total cost of electricity to meet train loading demand constraints in a setting where there are different electricity costs at different times.

In its case study, it reduces the problem fairly significantly to only consider the subgroup of conveyors that feed the train loaders, and makes the assumption that conveyor belts should be run only at design load. While the results of the case study demonstrated an improvement, solving the model on a subset of equipment pieces can lead to a suboptimal result from a whole-of-system perspective.

Sahoo et al. (2014) models the excavation and haulage subsystem. It does this by considering a very detailed view of the mine road topology and truck dynamics and creating a non-linear optimisation model to reduce the fuel consumption of trucks. To handle the complexity of the realistically sized, multiple pit and truck problems, it first solves the non-linear model to find the 'specific fuel consumption' for each route and truck, then applies a reduced, linear programming, version of the model to find the truck allocations required to meet demand. While the model is very accurate with regards to energy consumption and is demonstrated to provide useful results for the case study it was applied for, it requires a large amount of data about the trucks and mine.

The papers above all demonstrate the clear benefit that optimisation modelling can bring to mines for making energy efficiency decisions at an operational level. However, compared to manufacturing and the broader field of production systems, there is a definite lack of state-of-the-art operation research models addressing the issue. Each of these papers does not sufficiently integrate all of the studied subsystems. Only Middelberg et al. (2009) attempts to model several subsystems, but then reduces the problem down to a very small subset of equipment. The detailed data required to fit the models to operating mines is also a significant drawback from a practical perspective. It will also be important to ensure various operating states are possible over an optimisation period to best reflect the actual operation of the mine.

As well as the energy gap, it is noted here that maintenance is another area lacking operational modelling. While this is not a consideration of this thesis at all, future work could apply similar approaches to those developed and applied in this study to fill this gap.

2.5 Integrated modelling

Both Subsection 2.1.7 and Subsection 2.4.6 conclude that existing literature surrounding this problem is lacking integrated optimisation modelling techniques. The mining literature studying energy efficiency cited throughout Section 2.1 represented silo studies of the equipment within subsystems (Awuah-Offei & Frimpong, 2007; Kecojevic & Komljenovic, 2010; Pothina et al., 2007). The operational modelling literature throughout Section 2.4 also primarily considered subsystems individually (Luo et al., 2014; Numbi & Xia, 2015; Sahoo et al., 2014). Of the papers that did consider several subsystems (Hanoun et al., 2013; Middelberg et al., 2009; Ta et al., 2005), none integrated all of the four considered here. The importance of considering production systems as a whole when studying energy efficiency is introduced throughout Section 2.2 and Section 2.3. These findings form the motivation for the integrated modelling approach used in this thesis. This section reviews literature to first define the concept of integrated modelling in this thesis, and then describe how it has been used in research.

Sarmiento & Nagi (1999) conducted a review of the application of integrated analysis for optimisation of production-distribution systems at varying levels of decision making. The paper defines integrated analysis as the use of models which simultaneously optimise varying decisions coming from separate parts of a production system. This reflects the way 'integrated' is used in this research. The integrated model developed in this is built by joining operational models of different subsystems within the wider mining system. That is, each subsystem is modelled based on the decisions that need to be made about its operation, then these models are being 'integrated' together to optimise the whole system simultaneously.

Pujari (2005) uses the term in a similar fashion to describe the approach of modelling a whole supply chain by joining models of separate parts of the supply chain together into one framework. An integrated model of a supply chain is also developed by Gunnarsson et al. (2007) for application on a pulp mill company in Europe. Hung & Kim (2011) and Liu et al. (2011) also use 'integrated' to explain how subsystems of water networks can be combined into a single model of the whole water network.

As it is a fairly generic term, alternate definitions of 'integrated' can be also found in the literature. Gamberini & Gebennini (2009) uses the term to describe their approach of combining system models of three different planning levels; strategic, tactical and operational. Cheng & Liu (2013) have used a similar definition, when describing their work in creating an optimisation model for a manufacturing setting for both production planning and control decision support. While the concept of combining models of different planning levels is similar to what is being done in this research, it is important to make the distinction between the two. The papers cited above are describing the integration of different planning models of the same system whereas this project is about combining operational planning models of different subsystems.

Another definition of the term 'integrated' is used in Hooker (2012), who uses it to describe the approach of bringing together multiple solution techniques to solve an optimisation model. Ehie & Benjamin (1993) use the term in a similar fashion, when explaining their approach of combining optimisation models and the analytic hierarchy process (AHP) together into a single solution framework. These two usages differ from the way 'integrated' is used here, as they are explaining integration of techniques to solve the problem rather than the integration of separate models.

The alternate definitions presented above are acknowledged here to ensure they are not confused with this thesis's use of the term 'integrated' and are not used elsewhere in this thesis.

Jang & Kim (2007) formulate and solve an integrated model of a supplier that needs to plan production, inventory and distribution functions of its business. These three business functions must be considered in an integrated setting in order to get a solution, which results in overall minimum cost to the supplier. The paper develops a model and solution techniques to take stochastic demand and customer specific waiting costs into account. In order to solve the problem, a number of different heuristics, including ones they developed, are applied to the three business functions, which are being modelled and compared against one another to compare optimality. The algorithmic solution technique presented in the paper performed well and was suggested as a viable alternative to analytic solution techniques for reaching close to optimal solutions in reasonable time, however a real life case study was not considered.

Bertazzi & Zappa (2012) presented a model that integrated two business functions of a supplier: production and transportation. This paper applied the optimisation model to a set of problem instances using ILOG CPLEX, which represent several possible production policies of a real life case study. The resulting solutions, sensitivity analysis, solution robustness and computation times are all used to compare the different possible production policies. This provided the case study company with a number of model variant options for managers to consider, based on the desired optimality, simplicity and speed of the model for use when planning. CPLEX was efficient at solving the simpler forms of the model, while for other problem instances, the solution times grew unreasonable when the time horizon was increased.

Integrated production and transport planning optimisation is a well-developed area. Mula et al. (2010) present a fairly recent review of mathematical models collected from over 100 references spanning 25 years. This suggests very valuable results have been accomplished using the approach of integrating decisions from separate business functions together into the same optimisation for reaching overall optimal results. This is a key element of the methodologies being developed in this thesis.

Waldemarsson et al. (2013) extend upon previous research into integrated modelling of supply chain planning (Gunnarsson et al., 2007) for a pulp company to include energy aspects of their business, both consumption and revenue from selling excess energy. The formulation collects a number of different decisions, revenues and costs into a single integrated MILP model that maximises profit. The model is implemented in AMPL and solved using CPLEX on several scenarios from a case study on a real life pulp company in Europe. The scenarios show that incorporating energy costs and revenue into the system model has a significant impact on the optimal supply chain plan. The developed model was formulated for a particular company; future research is suggested in the conclusion to generalise the integrated model to allow it to be easily adapted to more companies.

Soylu et al. (2006) applied supply chain optimisation models to energy systems using an integrated MILP model to minimise total cost of investment and operation of the whole system. Their approach to developing and representing the whole integrated model is similar to the one taken in this thesis. The energy system was broken up into subsystems – such as boilers, turbines, fuel tanks and mixer – which were then modelled generically and separately so that they could be joined up in the integrated model to represent the various structures of different companies.

As introduced before, Hung & Kim (2011) and Liu et al. (2011) both use an integrated modelling approach to optimising the design of water networks. Hung & Kim (2011) developed a mixed integer non-linear programming (MINLP) model of the problem, which also took into account uncertainty of process conditions by including process buffer components in the network. In order to solve the problem in reasonable time, decomposition techniques were applied to break the problem down into MILP and LP sub-problems, which are solved iteratively to provide a non-linear optimiser with a close starting point for refining the solution of the original MINLP. Two case studies were assessed using the developed model and solution technique. Both were used to highlight the importance of including buffers in the integrated model to handle uncertainty in the operating conditions of the network, which in turn highlights the importance of optimising the system as a whole. Since buffers are components which represent double handling, the extra cost they represent must be considered alongside constraints and costs from the overall network.

Liu et al. (2011) developed a MILP model of the water network optimisation problem to minimise the annualised total cost of constructing and operating the network. Real life case studies of two Greek island water networks are solved using the model implemented in GAMS and solved with the CPLEX optimiser. Several scenarios for the two case studies were analysed and compared to show the ability of the model to find optimal solutions to real life problem instances. The paper suggests future work to create more efficient solution approaches, such as decomposition, as opposed to simply using CPLEX to solve the model.

Decomposition is a common method for making large integrated optimisation models easier to solve. Hasan & Raffensperger (2007) studied the integrated planning optimisation model of a fishery. The integrated model is difficult to solve using standard solution techniques, and was also found to be slow using existing decomposition techniques. The paper then developed a new decomposition method for the problem, which resulted in much faster computation.

Elkington & Durham (2011) propose an integrated MILP model of an open-pit mine at a strategic planning level. Decisions based around mining capacity, processing capacity, block extraction, stockpiling and processing activity over a number of years are integrated into a single model for maximising the net present value (NPV) of the mine's operation over the time horizon. A case study of a hypothetical copper mine is solved using CPLEX to demonstrate the power of the model. The computation times for solving the model were shown to be quite slow and the paper suggested further research to develop and apply techniques to improve solution speed in order to suit more commercial application. Future work to incorporate uncertainty in the geological makeup of the ore body and in the market was also suggested to increase its value to mines. While this research did not look at operational decisions or energy efficiency, it shows the importance of integrating decisions across the mine as a whole system when providing decision support to mine owners.

Ellis et al. (2010) have developed an integrated modelling approach of optimising the operation of an assembly facility. The developed model connects the various parts of the facility with material flow. This material flow approach is being taken in the research presented in this thesis. As well as decision variables for the material flow through the overall system between subsystems, there are also decision variables representing decisions made for each of the subsystems, which is also the approach of the work in this thesis. The paper developed a heuristic for solving the integrated model which, in simple terms, breaks the problem up into the subsystem models and the overall network flow model and iteratively solves them using simulated annealing to converge on an acceptable solution. The model and solution technique are used on a real life case study of a truck assembly facility. The developed methodology is packaged into a decision support tool and run on several scenarios for the facility, which can be used by managers to make informed and valuable decisions. Though applied to a different domain, this paper represents a good example of the type of work being carried out in this thesis.

Viere et al. (2011) also has a modelling methodology which aligns well with the research being conducted for this thesis. While the paper only develops a simulation model of the production system it analyses, the concepts used to formulate the model are similar to the proposed methodology in this research. As with Ellis et al. (2010), material flow is used to connect subsystems in order to define the whole system. An iterative approach is suggested for applying the modelling methodology to businesses, whereby the primary material flows of each business unit (or subsystem) are modelled and connected initially, then effort in modelling each business unit's energy, waste and cost can be focused where it is needed. This type of iterative approach to defining a system model is being used in this thesis. The paper also notes the importance of visualisation of the results tailored to the various employees who will use the results for decision support. The modelling methodology developed in the paper is applied to a case study for scenario analysis to provide strategic decision support.

Smith & Ball (2012) have used material and energy flow as the basis for analysing production systems from a sustainability perspective. While their developed model is not optimisation or simulation, it shows another example of the power of using material and energy flow in achieving energy efficiency improvements.

Chatfield et al. (2006) also applies similar modelling concepts to simulating supply chains. The paper presents a thoroughly developed software system for modelling and simulating supply chains called SISCO (Simulator for Integrated Supply Chain Operations). There are several aspects to the developed system, which have been designed to allow for it to be a useful system beyond other existing commercial supply chain simulators. Supply chain models are defined using a visual 'drag and drop' style editor, which allows the user to connect up functional blocks to represent the wider system. This is done to allow for easy model building so users can focus on creating the right supply chain structure rather than specific modelling tasks. The concept of using the 'flowsheeting' analogy of defining simulation models from component building blocks (or modules) is not new in the field of simulation (Luna, 1992; Mize et al., 1992; Nidumolu, 1998; Pidd & Castro, 1998). This research draws upon this concept when formulating the modelling and application methodologies.

Zülch et al. (2002) is another piece of work that uses similar concepts to those used in this research. The paper proposes a modelling technique for simulation of production systems, which involves coupling together sub-models with different levels of detail. This approach was taken so the various sub-models can be created to suit the various levels of detail of data available to the processes being modelled. The advantage of this is that there isn't expensive effort required in gathering more detailed data for some areas to match the detail of others, or the model isn't over simplified to the level of the least detailed data being collected. It also allows for specific modelling focus on known problem areas. These separately modelled sub-models are connected to their upstream and downstream neighbours and placed in a hierarchy to represent the total production system being modelled. The modelling methodology presented in Zülch et al. (2002) also includes polymorphism in its analysis, whereby the computation of key data, such as key performance indicators (KPI), can be customised depending on the level in the hierarchy the analysis is being performed at. This allows for the user of the simulation to see a view of the results specific to their position in the process being modelled.

Grossmann (2012) reviews the application of mathematical programming for Enterprise-Wide Optimisation (EWO) in process industries. The paper defines EWO as, "the coordinated optimisation of the operations of a supply chain" in order to maximise the various value streams of the business, such as financial profit, customer value, societal value and environmental value. In process industries, the main activities where optimisation takes place are in planning, scheduling and real-time process optimisation. In order to coordinate the optimisation of these three activities, Grossmann (2012) notes that integrated information and decision-making is required. While information is becoming more available across businesses, decision support tools are required to use this information to allow decision makers to operate the processes of the business for maximum value output. Further to this, decision support integrated across the various processes and operations of a business allows for decisions that benefit the whole system, rather than just the individual processes.

In some circumstances, different subsystems' models which are desired to be integrated together can have varied objectives. Biswal & Acharya (2013) consider a production planning optimisation of a steel production plant, which optimises the production plan for the various subsystems that work together to make up the whole production system. The developed model is a multi-choice multi-objective mathematical programming model. The multi-choice modelling strategy is used to avoid non-linearity of certain decisions that are modelled, and the multi-objective modelling strategy is employed to take into account the differences in objectives from each subsystem planning optimisation. These modelling methodologies will not be required for this research though, since the developed subsystem models will be designed to all be linear and minimise energy consumption, so there will be no need for multi-choice or multi-objective modelling. However, it is important to note these techniques, as it may be a useful tool for future development of the concepts established in this thesis.

The concept of using material flow for analysing the performance of a mining operation is echoed in the guidelines, which go along with the Australian Government's EEO legislation introduced earlier. Performing energy and mass balances across a mining operation is the recommended approach for complying to the EEO legislation Department Resources Energy and Tourism (2010). Thus it follows that using material flow balancing in the model is a sensible approach for making the research useful for mining companies required to comply with the legislation.

2.6 Solution approaches

In order to solve the various types of integrated models reviewed in Section 2.5, a wide variety of solution approaches can be used to find solutions to these models. Subsection 2.6.1 introduces the most common solution techniques used in the operations research for solving such optimisation models. Hybridisation, the use of multiple techniques within the same algorithm, is also introduced in Subsection 2.6.1 as a common way of solving complex models and handling model generality. Subsection 2.6.2 then reviews literature containing models of mines, energy and production systems in general, to identify trends and justify the solution approach developed for this study, described in Chapter 7.

2.6.1 Common solution techniques and hybridisation

Two main streams of solution techniques exist for solving MILP optimisation models, exact methods and heuristic methods. Exact methods, such as the branch and bound algorithm (Lawler & Wood, 1966), explore a tree of solution nodes for the complete search space of a problem by solving linear relaxation sub-problems of the MILP, using algorithms such as the simplex algorithm (Dantzig et al., 1955), and are guaranteed to find optimal solutions. However, they do not deal with model complexity issues at all. Practical-sized instances of complex NP-hard models are often too hard for exact methods to find optimal solutions for in any sort of reasonable time for practical use, especially for operational use, where solutions are required in minutes (Talbi, 2009).

For this reason, heuristics and metaheuristics are used to find good quality feasible solutions in reasonable time, sacrificing the guarantee of optimality for the ability to get solutions quick enough for practical use. Heuristics are algorithms that employ sensible strategies for traversing and/or reducing the solution space of a problem efficiently in order to either build new solutions, known as constructive heuristics, or find improved solutions, known as search or improvement heuristics (Zäpfel et al., 2010).

Metaheuristics are algorithms that implement a high level framework for iteratively applying smaller heuristic functions and perturbations to explore the search space of a complex problem efficiently. They come in many forms with varying levels of intelligence and behaviour that suit different problems (Blum & Roli, 2003; Talbi, 2009).

Examples of metaheuristics popular across a broad range of application are tabu search (Glover, 1989); simulated annealing (Kirkpatrick, 1984); particle swarm optimisation (Eberhart & Kennedy, 1995); variable neighbourhood search (Mladenović & Hansen, 1997); ant colony optimisation (Dorigo et al., 1996); and genetic / evolutionary algorithms (Goldberg, 1989).

An increasingly popular approach to solving complex optimisation models is to create algorithms which combine several algorithms into one. This is referred to as hybridisation (Blum & Roli, 2008).

Talbi (2002) presents a taxonomy of metaheuristic hybridisation to serve as a guide for classifying the various forms that hybridisation takes. The taxonomy is split into two sections, design and implementation. The former refers to the algorithm itself, its structure and functionality; the latter refers to how it is implemented in software and run on hardware.

Jourdan et al. (2009) use this taxonomy to describe hybridisations that also include exact methods, such as the branch and bound and simplex algorithms mentioned above. Algorithms that hybridise metaheuristics and exact mathematical programming model solvers are often referred to as 'matheuristics' or 'model-based metaheuristics' (Ball, 2011; Boschetti et al., 2009).

The taxonomy describes the design of hybrid algorithms in two ways, hierarchical and flat. Two dichotomies are used to classify algorithms' hierarchical structures:

- Low level vs High level
- Relay vs Teamwork

Low level hybridisation refers to when a particular function of a technique is replaced by another technique, such as a tabu search being used as the mutation function of a genetic algorithm. On the other hand, high level hybridisation refers to when the two techniques are executed separately, such as two metaheuristics cooperatively searching different neighbourhoods.

Relay hybridisation refers to when the techniques are configured to run after one another by taking the output from the last as input into the next. Teamwork hybridisation is used to describe the algorithm when techniques cooperate to find solutions, rather than simply running after one another.

The flat classification is based on three dichotomies:

- Homogeneous vs Heterogeneous
- Global vs Partial
- General vs Specialist

The homogeneous classification describes hybridisation of the multiple instances of the same technique, such as two genetic algorithms working together, while a heterogeneous algorithm is one that hybridises two different techniques.

The global vs partial dichotomy refers to the search space which is explored. Global hybrids use techniques that search the entire search space of the problem whereas partial hybrids split the search space up to be searched separately by the different techniques.

Finally, a general hybrid algorithm is one where all hybridised techniques are solving the same optimisation problem. On the other hand, specialist hybridisation describes when the hybridised techniques are solving different problems, such as two decompositions of a problem or the case where a heuristic is employed to optimise the heuristic solving the problem at hand.

The implementation side of the Talbi (2002) taxonomy is also split into hierarchical and flat sections. Specific software and hardware implementation details of solution approaches are not typically considered part of the operations research field. For this reason, the literature studied in the review does not, for the most part, publish these details and they are not a focus of the solution approach developed. As such, this part of the taxonomy won't be looked at in detail here or used in the next section to review the literature.

Michalewicz et al. (2006) describe the importance of using a hybrid solution approach for finding quality solutions quickly, particularly for general models where differences in input can alter how the model behaves in particular metaheuristics. The book demonstrates this concept with a simple car distribution scheduling problem that has a different set of inputs for each day. The problem is solved for each day with seven common techniques, such as Tabu Search and Genetic Algorithms, and the optimal result comes from different techniques on different days. While it is clearly an oversimplified example, it demonstrates their point that there isn't necessarily a best technique for a particular model; it can depend on the specific input as well. This is particularly the case for generalised models, like the one proposed in this study, where differences in input data can mean significant differences in the behaviour being optimised. For instance, changes to the layout of a mine can greatly impact where bottlenecks and double handling occur across the system.

Much more literature exists that defines hybrid solution approaches and their various forms and examines their ability to solve optimisation models (Blum & Roli, 2008; Crainic & Toulouse, 2003; Raidl, 2006). There is also a large amount of work describing how hybrid algorithms have been used to solve specific models from a wide variety of problems with both academic and practical outcomes. The next section reviews such papers that relate to the problem presented in this study.

2.6.2 Solution techniques used in related literature

To aid the design and implementation of the solution approaches used in this study, a review of solution approaches solving complex models from related literature is conducted here. The search focused on papers that solved integrated and/or complex MILP optimisation models of mining operations, energy efficiency or production systems in general. Using the format applied in Section 2.4, a compliance matrix, Table 2.6, has been compiled to summarise the results of the review. The papers reviewed here by no means represent an exhaustive list of papers in the mining, energy or production system literature that use solution techniques to solve their model, rather, they serve as a good cross section of the fields over recent history.

Cases where multiple techniques are used but not hybridised, are those that compare different techniques against each other in the paper. On the other hand, the papers that are marked as employing a single solution technique and hybridisation use the homogeneous hybridisation method, as described in the Talbi (2002) taxonomy.

In all, solution approaches from 53 papers have been reviewed and summarised in Table 2.6. A mining system was the focus of the model being solved in 15 of the papers. Energy was considered in the model in 11 papers, and 38 papers contained models of other production systems. Several papers considered multiple of these three modelling areas.

Among the papers reviewed, metaheuristics is clearly a popular approach; it is employed in 31 of the 53 papers. Hybridisation is also commonly used amongst the papers, featuring 21 times. Exact solution techniques, such as branch and bound, are also common, appearing in 19 papers.

Breaking the metaheuristics group up into individual techniques, the most popular techniques in the papers are tabu search, simulated annealing and genetic algorithms (or evolutionary algorithms).

Of the 21 hybrid algorithms, 16 use metaheuristics. Once again, tabu search, simulated annealing and generic algorithms are the most common metaheuristics techniques involved. There are seven papers that use a matheuristic approach, that is, hybridising exact techniques with other techniques. The papers with hybrid solution approaches in Table 2.6 have been classified using the Talbi (2002) taxonomy described in Subsection 2.6.1, and this can be seen in Table 2.7.

Table 2.6. Summary of solution techniques used in related literature

Paper	Model area	TS	SA	GA/EA	GRASP	VNS	PS/PSO	ACO	LS	Heuristic	Other	Exact	Hybrid
Le Bouthillier & Crainic (2005)	PrdSys	X	-	X	-	-	-	-	-	X	-	-	X
Ta et al. (2005)	Mine	-	-	-	-	-	-	-	-	-	X	X	-
Mishra et al. (2005)	PrdSys	X	X	-	-	-	-	-	-	-	-	-	X
Soylu et al. (2006)	Enrg&PSys	-	-	-	-	-	-	-	-	-	-	X	-
Hasan & Raffensperger (2007)	PrdSys	-	-	-	-	-	-	-	-	-	X	X	X
Gunnarsson et al. (2007)	PrdSys	-	-	-	-	-	-	-	-	-	-	X	-
Jang & Kim (2007)	PrdSys	-	-	-	-	-	-	-	-	X	-	-	-
Loukil et al. (2007)	PrdSys	-	X	-	-	-	-	-	-	-	-	-	-
Altiparmak & Karaoglan (2008)	PrdSys	X	X	-	-	-	-	-	-	-	-	-	X
Mouzon & Yildirim (2008)	Enrg&PSys	-	-	-	X	-	-	-	-	-	-	-	-
Ai & Kachitvichyanukul (2009)	PrdSys	-	-	-	-	-	X	-	-	-	-	-	-
Gajpal & Abad (2009)	PrdSys	-	-	-	-	-	-	X	-	-	-	-	-
Middelberg et al. (2009)	Mine&Enrg	-	-	-	-	-	-	-	-	-	-	X	-
Mitra (2009)	Mine	-	-	-	-	-	-	-	-	-	X	-	-
Repoussis et al. (2010)	PrdSys	X	-	X	-	-	-	-	-	-	-	-	X
Shimizu & Fujikura (2010)	PrdSys	X	-	-	-	-	-	-	-	-	-	X	X
Ellis et al. (2010)	PrdSys	-	X	-	-	-	-	-	-	-	-	-	-
Çatay (2010)	PrdSys	-	-	-	-	-		X	-	-	-	-	-
Subramanian et al. (2010)	PrdSys	-	-	-	-	-	-	-	X	-	-	-	X
Li et al. (2010)	PrdSys	-	-	X	-	-	-	-	-	X	-	-	X
Souza et al. (2010)	Mine	-	-	-	X	X	-	-	-	-	-	-	X
Soltani & Sadjadi (2010)	PrdSys	-	X	-	-	X	X	-	X	-	-	-	X
Yu et al. (2011)	Mine&PSys	X	-	X	-	-	-	-	-	-	-	-	X
Mirzapour Al-E-Hashem et al. (2011)	PrdSys	-	-	-	-	-	-	-	-	-	-	X	-
Elkington & Durham (2011)	Mine	-	-	-	-	-	-	-	-	-	-	X	-
Liu et al. (2011)	PrdSys	-	-	-	-	-	-	-	-	-	-	X	-
Hung & Kim (2011)	PrdSys	-	-	-	-	-	-	-	-	-	X	X	X
MirHassani & Abolghasemi (2011)	PrdSys	-	-	-	-	-	X	-	-	-	-	-	-
Burt et al. (2011)	Mine	-	-	-	-	-	-	-	-	-	-	X	-
Lamghari & Dimitrakopoulos (2012)	Mine	X	-	-	-	-	-	-	-	-	-	-	-
Erdoğan & Miller-Hooks (2012)	Enrg&PSys	-	-	-	-	-	-	-	-	X	-	-	-
Bertazzi & Zappa (2012)	PrdSys	-	-	-	-	-	-	-	-	-	-	X	-
Ramezanian et al. (2012)	PrdSys	X	-	X	-	-	-	-	-	-	-	-	-
Katsigiannis et al. (2012)	PrdSys	X	X	-	-	-	-	-	-	-	-	-	X
Toledo et al. (2013)	PrdSys	-	-	X	-	-	-	-	-	-	-	-	X
Villegas et al. (2013)	PrdSys	-	-	-	X	-	-	-	X	-	-	X	X
Waldemarsson et al. (2013)	Enrg&PSys	-	-	-	-	-	-	-	-	-	-	X	-
Lee et al. (2013)	PrdSys	X	-	-	-	-	-	-	-	-	-	-	-
Dai et al. (2013)	Enrg&PSys	-	X	X	-	-	-	-	-	-	-	-	X
Hanoun et al. (2013)	Mine	-	-	-	-	-	-	-	-	X	-	-	-

Paper	Model area	TS	SA	GA/EA	GRASP	VNS	PS/PSO	ACO	LS	Heuristic	Other	Exact	Hybrid
Ramezanian & Saidi-Mehrabad (2013)	PrdSys	-	X	-	-	-	-	-	-	X	-	-	X
Blom et al. (2014)	Mine	-	-	-	-	-	-	-	-	X	X	X	X
Lamghari et al. (2014a)	Mine	-	-	-	-	-	-	-	X	-	-	X	X
Choi & Xirouchakis (2014)	Enrg&PSys	-	-	-	-	-	-	-	-	-	-	X	-
Lamghari et al. (2014b)	Mine	-	-	-	-	-	-	-	X	-	-	-	-
Liu et al. (2014)	Enrg&PSys	-	-	X	-	-	-	-	-	-	-	-	-
Sahoo et al. (2014)	Mine&Enrg	-	-	-	-	-	-	-	-	-	-	X	-
Ibrahimov et al. (2014)	Mine	-	-	X	-	-	-	-	-	-	-	-	-
Khan et al. (2014)	Mine	-	-	-	-	-	X	-	-	-	-	-	-
Masoud et al. (2014)	PrdSys	X	X	-	-	-	-	-	-	X	-	-	X
Fung et al. (2014)	Mine	-	X	-	-	-	-	-	-	-	-	X	X
Wang et al. (2015)	Enrg&PSys	-	X	X	-	-	X	-	-	-	-	-	-
Nilakantan et al. (2014)	Enrg&PSys	-	-	-	-	-	X	-	-	-	-	-	-
	Total	11	11	10	3	2	6	2	5	8	5	19	21

Table 2.7. Summary of solution techniques used in related literature

Paper	Model area	High level	Low level	Relay	Teamwork	Homogeneous	Heterogeneous	Global	Partial	Specialist	General
Le Bouthillier & Crainic (2005)	PrdSys	X	-	-	X	-	X	X		-	X
Mishra et al. (2005)	PrdSys	-	X	-	X	-	X	X	-	-	X
Hasan & Raffensperger (2007)	PrdSys	X	-	X	-	X	-	-	X	X	-
Altiparmak & Karaoglan (2008)	PrdSys	-	X	-	X	-	X	X	-	-	X
Repoussis et al. (2010)	PrdSys	-	X	-	X	-	X	X	-	-	X
Shimizu & Fujikura (2010)	PrdSys	X	-	X	-	-	X	-	X	X	-
Subramanian et al. (2010)	PrdSys X	-	-	X	X	-	X	-	-	X	
Li et al. (2010)	PrdSys	-	X	X	-	-	X	X	-	-	X
Souza et al. (2010)	Mine	X	-	X	-	-	X	X	-	-	X
Soltani & Sadjadi (2010)	PrdSys	-	X	-	X	-	X	X	-	-	X
Yu et al. (2011)	Mine&PSys	-	X	-	X	-	X	X	-	-	X
Hung & Kim (2011)	PrdSys	X	-	X	-	X	-	-	X	X	-
Katsigiannis et al. (2012)	PrdSys	X	-	X	-	-	X	X	-	-	X
Toledo et al. (2013)	PrdSys	-	X	-	X	X	-	X	-	-	X
Villegas et al. (2013)	PrdSys	-	X	-	X	-	X	X	-	-	X
Dai et al. (2013)	Enrg&PSys	X	-	X	-	-	X	X	-	-	X

Amongst the 21 hybrid solution approaches reviewed and summarised with respect to the Talbi (2002) taxonomy in Table 2.7, there is a fairly even split between the two hierarchical categories, high versus low level and relay versus teamwork. Meanwhile, for the flat categories, there was a trend towards heterogeneous, global, general hybridisation. That is, alternate techniques were hybridised together more often than hybridising one technique with itself; the whole search space was searched by the techniques more than the techniques searching different spaces; and finally, the hybridised techniques were designed to solve the same model.

This review suggests that the state-of-the-art for solving complex/integrated models of mines, energy efficiency or other production systems is centred on the hybridisation of metaheuristics. In particular, tabu search, simulated annealing and genetic algorithm metaheuristics, along with exact algorithms, are hybridised in heterogeneous, global, general hybridisation at either high or low level with either relay or teamwork cooperation.

It must be noted that these findings are over a wide range of different problems and therefore do not necessarily serve to suggest a perfect approach for the problem in this study. Rather, they have been compiled to serve as a sound footing for the design and development for a solution approach that will be effective for the particular model in this study, which is presented in Chapter 7. The particular technique developed and presented there is a high level, teamwork hybrid between tabu search and simulated annealing.

To implement the hybrid technique, software architecture principals will be employed. The publisher-subscriber design pattern (Gamma et al., 1994) is implemented using a popular message queue library, ØMQ or ZeroMQ (Hintjens, 2013). The result is a level communication between the two metaheuristics running in parallel, enabling the type of cooperation Michalewicz et al. (2006) describes. It is an approach successfully employed in a number of papers from both software and operations research literature.

Malek (2009) describes a system architecture for the parallel execution of metaheuristics that pass messages between each other. The genetic algorithm (GA) and tabu search (TS) metaheuristics are implemented to solve the travelling salesman problem and hybridised using the proposed system. The hybrid GA+TS approach was compared to running the two metaheuristics on their own and was found to outperform them in terms of optimality across the majority of problem instances tested. This is a similar approach to how the hybrid solution technique is developed and tested in this thesis.

Ouelhadj & Petrovic (2010) propose a cooperative solution hyper-heuristic framework that uses the Microsoft Message Queuing (MSMQ) library to enable communication between lower level heuristics. While it doesn't work at the high level hybridisation, like this thesis proposes, it is a good demonstration of how message queue libraries can be used to enable cooperative searches amongst parallel search processes. While their developed technique was shown to be competitive at finding good quality solutions in reasonable time compared to sequential non parallel equivalents, it was not found to be better than state-of-the-art metaheuristics. This suggests low level cooperative parallelisation may not be the best area in which to focus this thesis. Rather, cooperation between metaheuristics will be the focus of the solution technique development.

Jin et al. (2014) use message passing communication between several tabu search threads that cooperatively search for the best solution to the capacitated vehicle routing problem (CVRP). New solutions are published and received via MPI (Message Passing Interface) and the different tabu search threads are set up to either intensify or diversify the pool. The technique was tested against 32 well tested CVRP problem instances and found improved solutions to 10 instances within reasonable computation time. Barbucha (2012) also investigates this cooperative approach for solving the vehicle routing problem and finds significant benefits in terms of solution quality.

Georgiev & Atanassov (2014) use the approach to implement the genetic algorithm metaheuristic in a distributed computing environment. The paper describes a framework for using MPI alongside ØMQ to coordinate separate genetic algorithm searches running on separate processes throughout a grid cluster. The implemented framework was found be effective at increasing the number of individuals evaluated when more search processes were added.

Halme (2014) uses the approach to develop a parallel search algorithm to find solutions to the single source shortest path problem, called A!. By instantiating several search agents to run in parallel and communicate via a message queue library, the resulting cooperative behaviour led the algorithm to outperform the traditional single agent algorithm, A*, and a non-cooperative parallel variant. It also found that more agents increase performance, though with diminished returns.

2.7 Remarks

This literature review has delivered a number of outcomes which form a solid grounding for the developed methodologies presented throughout the rest of the thesis. Initially, the review of open-pit coal mining methods in Section 2.1 found four common and important subsystems, which will benefit from operational decision support. These are excavation and haulage, processing plant, stockpile and belt conveyor. They form a focus for the modelling throughout the rest of this study.

Section 2.2 defined production systems, energy efficiency and how a mine can be considered an open continuous flow production system to provide a basis for using production system literature to fill the apparent shortage of research looking at mine energy efficiency. This conjecture was used throughout the remaining sections of the literature review as a way of expanding the search beyond mining literature and as motivation for the generalised modelling and solution approaches developed for the study. It could also very well be useful for tackling other mining-related problems that lack existing literature.

Section 2.3 reviewed production system literature to find factors which affect energy efficiency. These were broadly defined as asset ownership; asset usage; human; organisational; energy provision; planning; and external. The classifications made throughout this section serve as worthy contributions for approaching energy efficiency improvement problems for mining and production systems other than mining.

To condense these factors down to ones particularly important to operational mining decisions, Section 2.4 reviewed how they have been considered in mining literature so far for each subsystem, even if not directly for the purpose of improving energy efficiency. The search also gives a good indication as to the state-of-the-art of modelling for the four subsystems, which will be used to formulate the model for this study.

The literature reviewed in Section 2.4 that did analyse energy efficiency demonstrated the significant potential for benefit that can be achieved using optimisation techniques. However, the amount of research looking at the problem using state-of-the-art operations research techniques clearly falls behind production system literature. In particular, a general integrated model of the four subsystems is missing. Operational scheduling of truck and shovel activity is in its infancy and is not at all considered from an energy perspective. As well as this, the models that do consider energy require a lot of detailed data about the equipment and operation. This makes it a costly exercise to apply them to new mines, decreasing their practical benefit.

Section 2.5 then reviewed literature on integrated modelling in production systems and mining literature to find that it is a sensible approach to take for this research project. In particular, it finds that MILP is an appropriate modelling language and that material flow is an appropriate variable to use for connecting subsystems in an integrated model.

Finally, Section 2.6 gave an overview of different methods that are employed to find solutions to complex models, then looked at how these techniques are applied in literature from mining, energy and other production systems. It found that metaheuristics are commonly employed to successfully solve these models. In particular, tabu search, simulated annealing and generic algorithms were found to be the most common metaheuristics in the papers. Exact methods, such as branch and bound, were also found to play an important role in the reviewed solution approaches. The approach of hybridising these three techniques was also shown to be a common methodology amongst the reviewed papers, including the application of matheuristics, the hybridisation of exact and (meta)heuristic algorithms. These findings gave a strong grounding for the development of the solution approaches used in this study, detailed in Chapter 7.

Referring back to the research approach described in Section 1.5, this chapter has further defined the open-pit coal mining energy efficiency problem and abstracted it out into the context of the more general production systems field (top left quadrant of Figure 2.1) and fruitfully used that abstraction to form a comprehensive foundation for the remaining work. This leads into the next stage of the approach, the top right quadrant of Figure 2.1, in Chapter 3, where outcomes from this chapter will be used to specify a conceptual framework for creating the integrated model presented in Chapter 4.

By working through this part of the research approach, this chapter has addressed research question 1b from Section 1.2, seen below, begun to address questions 1c, 1d and 1e and formed a strong foundation for the later work looking at the remaining questions. Section 2.1 and Section 2.2 worked together to describe how an open-pit coal mine can be considered as a continuous production system. Section 2.3 and Section 2.4 explain in detail how the factors that impact energy efficiency of a mine focused on in this study have been devised. Section 2.5 suggests that quantitative, integrated modelling will bring numerous benefits to the modelling efforts carried out for this thesis. Lastly, Section 2.6 demonstrates a sound basis for appropriateness of hybrid metaheuristics for overcoming modelling complexities.

1. *How can the energy efficiency of mining production systems benefit from an integrated modelling approach?*

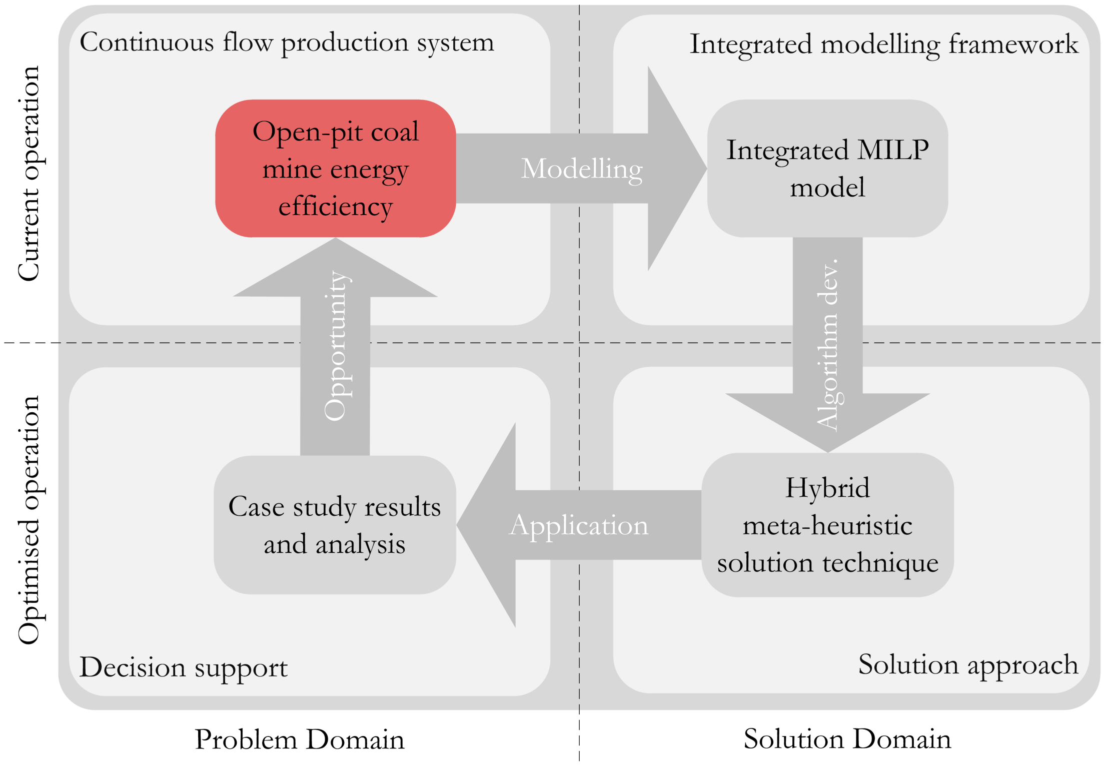

Figure 2.1. Role of Chapter 2 in the research approach

(a) *Why is improving energy efficiency a concern for mining operations?*

(b) *How can an open-pit coal mine be considered as a production system?*

(c) *What factors impact the energy efficiency of a mine?*

(d) *What are the benefits of using a quantitative optimisation model of energy efficiency?*

(e) *Why take an integrated optimisation approach?*

3

Modelling Approach

This section explains the modelling framework developed for undertaking this study. The overall approach is to divide a continuous production system into its respective subsystems, model them separately as 'subsystem modules', then integrating them using material flow connections between their boundaries.

As alluded to in Section 1.5, conceptually, the framework has been designed for creating general continuous production system models, but is put into practice to model the specific problem this thesis is tackling - the energy efficiency of an open-pit coal mine operation. Therefore, throughout this chapter, the energy efficiency of an open-pit coal mine production system will be used to explain the methodology.

This chapter first explains the integrated modelling methodology conceptually in Section 3.1. A more detailed description of what a subsystems module is and how the four specific mining subsystems will be modelled is given in Section 3.2. Section 3.3 then details a general process for applying the model to a production system. This is done using an example of a simple open-pit coal mine, which is used throughout the rest of the thesis. Finally, Section 3.4 concludes the chapter with comments on the benefits, drawbacks and implications of the developed methodology.

3.1 Modelling concepts

The concept of integrated modelling is a primary element of this research. It has been introduced in the literature review as a useful approach for modelling production systems and energy efficiency. This section details the developed framework for formulating an integrated model of a continuous production system, using open-pit coal mine energy as a specific example.

3.1.1 Defining the subsystems of a production system

Production systems are often made up of many diverse subsystems, with a wide variety of processes and behaviours. A mine is no different, for example, the transactional behaviour of a truck's interaction with a shovel at a pit is quite different to the continuous nature of the processing plant. This means that coming up with a single model formulation structure that represents all these different behaviours can be difficult, especially one that is easy to maintain or adapt to new production systems.

Instead, the approach taken in this thesis is to first break the production system down into a series of subsystems that represent the primary operations relating to the objective, and model them separately. This way, modelling effort can be focused and suited specifically to the processes and behaviours of each subsystem, independently of one another.

In order to show the process of reducing a production system into subsystems, consider the simple mine represented in Figure 3.1. It has two pits, a waste dump, a ROM stockpile, a CHPP and two belt conveyors.

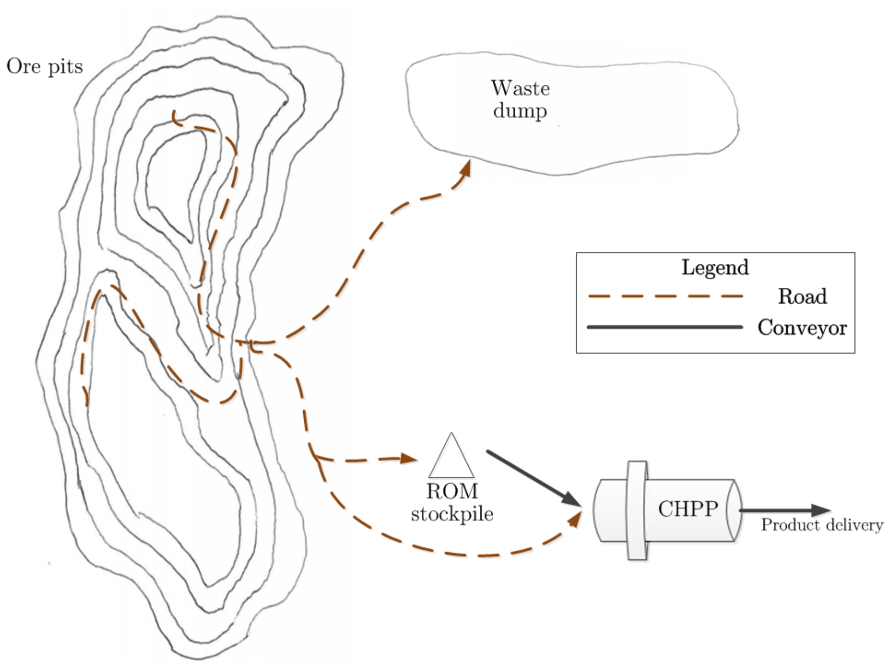

Figure 3.1. Simple mine map

To examine this mining operation in the production system frame of mind, it can be divided into a number of connected subsystems that consume energy and perform functions to achieve production targets of the whole mine. This breakdown can be seen in Figure 3.2, where borders are drawn around subsystems, and various material and energy flows are represented by arrows.

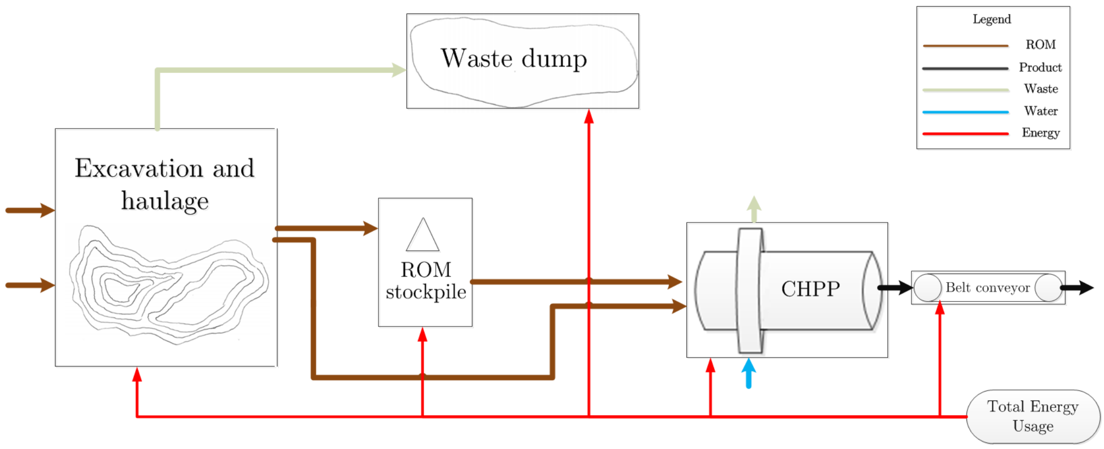

Figure 3.2. Mine process flow diagram

From this subsystem breakdown, there are five subsystems connected to each other using four different material flows, ROM, product, waste and water. Each of the subsystems also has an energy consumption that can be summed up to represent the total energy consumption of the system. For simplicity, the belt conveyor drawn in Figure 3.1 between the stockpile and processing plant is considered here as part of the stockpile reclaiming activity.

3.1.2 Subsystem concepts

The simple explanation of this study's approach so far has explained that these subsystems can now be modelled separately. However, upon further inspection, it can be seen that these five subsystems can be categorised as one of the four subsystems analysed in the literature review. There is one each of excavation and haulage, processing plant and belt conveyor and two stockpiles – thinking of the waste dump points as a stockpile. For larger, more complex, mines, the other subsystems may be replicated in the same way the stockpile has been here. This means, if the subsystem formulations are general enough, only four subsystems modules should need to be formulated. Their replications on site are then parameterised separately.

The most important prerequisite of a subsystem is that the connection points on its boundaries, which connect it to other subsystems, are 'material flow' connections. A well-defined specification of the boundaries of subsystems is required to properly allow for connecting them together in any fashion necessary to represent a wide variety of mine layouts.

Using 'material flow' as the type of connection between subsystems is a key design feature of the modelling framework developed in this research. It has been decided upon under the conjecture that typical analysis and decision making for continuous production systems are based around the flow of material. This is supported by literature reviewed in Section 2.5.

Ideally, a set of subsystem modules can be formulated generally enough to be used to represent the vast majority of subsystems that are used in actual open-pit coal mines. The term 'general' is used here to indicate that the specifics of a subsystem's operation are adaptable through parameters of the model rather than structural changes to the formulation. For instance, a general excavation and haulage subsystem formulation should be scalable, within reason, to any number of pits, destinations, trucks, shovels that may arise at an operating mine. More specifically, the operational detail of the trip times, loading times and energy consumption should also be parameters that can be changed to suit the particular mine being modelled. Similarly, a stockpile should be modelled generally enough to be able to have a number of different inlet and outlet connection points, store any material type and allow for different limits on stacking, reclaiming and overall inventory, all through parameters.

With this set of general subsystems, a library of these generic models can be assembled. This means the effort of subsystem modelling can be performed once then reused across new mines being modelled. The idea behind this is to reduce the effort of applying the developed methodology to a new mine, enabling any potential value to be realised sooner at a lower cost. It also means problem domain experts, such as mine operators, can modify the model of their operation using the appropriate parameters, without needing to change the mathematical formulation.

More specific details about the concepts behind modelling subsystems, along with information about each particular subsystem module, are presented in Section 3.2.

3.1.3 Integrating the subsystems

Once the subsystems modules have been formulated, they are then integrated into single formulation, the integrated model. This has been designed to be a simple process, with the intention being that it can be performed by a domain expert, such as a mine manager or operator, as opposed to a mathematical modeller. This concept is explored further in Subsection 9.1.2. The basic process of creating the 'top level' model of the mine can be summarised by the following steps:

1. Select subsystems used on the mine
2. Connect subsystems to one another
3. Parameterise the subsystem operation
4. Combine their objectives in a function

The first two steps turn the mine into a structured process flow representation. Their purpose is to convert the mine's physical operation into a logical representation of the subsystems and their connections, a transformation represented by the changes between the physical map in Figure 3.1 and the process flow diagram in Figure 3.2.

It is easy to imagine how the first two steps could be implemented into a flowsheeting-style, software application. Users could drag and drop subsystems from a library and connect them up to represent the process flow of the mine being modelled.

The third step in this process is to fit the selected subsystems to their actual operation. This involves setting various parameters on each subsystem based on data taken from the mine's current operation. Accurate parameterisation of subsystems is a key step to getting realistic and useful results from the model. Fitting the parameters to the latest available data means the model will best represent the actual operation of the mine, and therefore search the most realistic space for an optimal solution. A less accurate selection of data for parameterisation, such as old data or design information, will mean the models will poorly represent the actual operation and find solutions that may be inferior for the current mine's behaviour.

Ideally, these parameters should come from up-to-date data, collected on-site as often as possible. This way, any changes to the behaviour of the subsystems can be accounted for in the next run of the optimisation. For instance, if a particular truck has degraded in efficiency, then its energy consumption parameterisation should be updated as data becomes available, which will then impact upon the model's decision to use that truck over other trucks.

The last step is to create an overall objective based on the objective values coming from the subsystem formulations. For this study, energy consumption, measured in MWh, is used. It is simply the sum of all subsystem energy consumptions. As introduced in Section 2.2, only the denominator, energy consumption, of energy efficiency is used as the objective of the optimisation model since the planned production is an input to the model. It is also selected to ensure linearity of the objective function. More information on how the objective value is selected and defined is given with the subsystem concepts in Section 3.2.

3.1.4 Capacity

The capacity of a production system is a function of its subsystems capacities, which are in turn functions of their respective asset capacities, a factor that impacts production system energy efficiency, as introduced in Section 2.3. This reflects how the modelling framework developed here handles capacity. There is no explicit whole-of-system level modelling feature that deals with capacity. The capacity of the whole system is implicitly described by the particular subsystems that have been connected to create the integrated model, as explained in the previous subsection.

As subsystems interact with each other through material flow connections, the capacities of subsystems must be modelled to constrain the material flow. This will mean connected subsystems will implicitly be constrained by one another and hence the whole system will have an implicit capacity. Since subsystem formulations are distinct from each other and have few requirements, the specifics of how the capacity constraints are implemented are left completely up to the modeller. Once again, this freedom enables subsystem formulations to best represent their actual operation.

By handling the capacity in this manner, integrated models created using this framework can provide valuable insight into the production system's actual capacity. Sensitivity and scenario analysis can be used to compare the current operation against the maximum capacity and identify where and when bottlenecks may be occurring. These are valuable for examining many types of production system performance measures, including energy efficiency.

3.1.5 Operating states

The literature review, in Section 2.3 and 2.4, mentioned the importance of modelling different operating states of subsystems and equipment when optimising energy efficiency. In particular, it was identified as an area to help link the asset usage and planning factors while modelling. While it was well modelled amongst the processing plant, stockpile and belt conveyor models, it was identified as a deficiency with many of the excavation and haulage models. It is therefore an important and valuable concept to employ within the integrated modelling framework.

In this framework, the time dimension of the optimisation is partitioned into multiple operating states, as indices, that can have different lengths. An operating state, also referred to as a state, is defined as the period of time in which no changes to the overall work being performed by each and every subsystem occur. During which, the amount of material flowing between subsystems remains steady. The term operating state, or state, is used here over more traditional operations research modelling terms such as time step or interval, as it more accurately describes the problem domain being modelled.

The variable length of states gives the model the ability to have increased resolution around times where more changes in operation may occur, and reduce resolution when stable operation is occurring. While they are an input into the model and can't change dynamically within the optimisation, they can be programmatically determined before runtime based on the input plan or other parameters.

This concept can also be used to help reduce the problem instance size to increase solution speed. Though, having varied state lengths instead of having smaller equally sized time steps may inhibit the optimisation from finding a more optimal solution, which is a question of speed versus accuracy with regards to the model formulation.

The concept of operating states can also help reach more realistic solutions for operators to comprehend and follow. For example, using small state lengths of 10 minutes, depending on the detail and correctness of the subsystem models, the optimal solution may be to ramp production of a particular subsystem up and down within the 10 minute states, which may be feasible in the model, but result in unwanted behaviour in real life. Even if it is feasible and optimal in real life, giving such tight instructions to operators may be too hard to follow. In a period where there are no changes to the overall operation of the mine, fewer sets of instructions for that time period will likely be easier for an operator to follow, than a multitude of instructions over small time steps. Measures can be taken when formulating the model to reduce this effect, though these extra measures will likely increase the size of the problem and slow down the solution.

It should also be noted that the length of states doesn't necessarily mean subsystems can't implement their own internal time dimension, so long as they aggregate the internal behaviour up to boundary connection material flows for each state. This is performed later in this thesis, in Chapter 6, to give more accuracy to the modelling of equipment operations within the excavation and haulage subsystem.

3.1.6 Solving

After the integrated model has been created, it now only needs one more piece of information to be solved - the operating plan. This is considered the primary input of the optimisation.

Planning happens across various levels and time scales in mining. In general, as explained in the literature review, long and medium-term plans are based on the NPV of the mine and decide on a required production rate to maximise the NPV. The shorter term plans are then devised to meet these production targets with minimum cost. Short-term planning and scheduling can be done to various degrees on a mine. The short-term plan for the mine is used by managers and operators to determine the daily operation of the mine.

These plans are used to define the work required for the mine to complete over the optimisation horizon. This research conceptualises a plan as a series of 'tasks' that the mine, as a system, must complete. These tasks have start and completion times, and can span across the whole mine. For example, there may be a task to produce a certain amount of product before the end of the day; a task to extract an amount of overburden before halfway through the day; a task to extract the ROM coal after the overburden has been uncovered; or a task to have a certain level of stockpile by a particular time.

The ability to add different types of tasks to different parts of the mine enables push or pull-based modelling. For example, a push-based task would be an extraction target, whereas a target on demand would represent a pull-based task.

Once these tasks are placed on the integrated mine model, it is ready to be optimised. This is where connection material flows are solved alongside subsystem specific decision variables subject to achieve the defined tasks, satisfy constraints internal to each subsystem and minimise energy consumption.

Being able to optimise the collection of all decision variables, and satisfy all constraints, is the key benefit to the integrated approach. Even though each subsystem has been modelled and parameterised separately to suit their particular functions and behaviour, they are now in the same solution space for the optimiser to search for the global optimum across the whole mine, rather than each subsystem individually.

The subsystems are now implicitly constrained by each other and the overall production and demand requirements of the whole mine system. Any change made by the optimiser to reduce energy consumption on one subsystem will only be selected if it does not increase the energy consumption on another subsystem by a greater amount or violate any other constraints.

Using this model, decision support provided to the operators of each subsystem can be 'aware' of that subsystem's impact on the whole mine energy consumption, the main benefit behind the concept of whole-of-system modelling. This leads to operational decisions that improve the whole mine's energy efficiency, rather than simply each subsystem on its own, which can result in sub-optimality for the whole system.

3.2 Subsystem modelling concepts

This section details the requirements of subsystem modules to work in the proposed modelling framework. As previously discussed, since the various subsystems that make up a continuous flow production system can be quite different in nature, there is no one mathematical representation for a subsystem. Instead there are requirements for subsystem model formulations to adhere to that allow them to be connected up and solved together.

The generic form of a subsystem module is represented below in Figure 3.3. It has material flow inlet and outlet connections, energy consumption and is characterised by parameters that define its specific behaviour based on actual operation. The operating state time dimension mentioned in Subsection 3.1.5, not shown in Figure 3.3, is also a feature of the subsystem. Each operating state of the integrated model represents the amount of time that the material flow over a subsystem boundary connection is maintained.

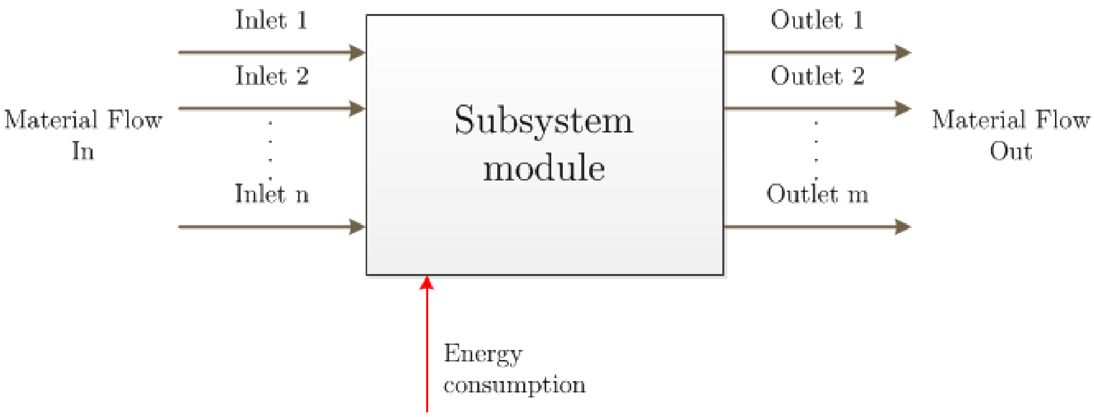

Figure 3.3. Generic subsystem modules

Subsystems can be modelled to various degrees of complexity to represent the functions they perform, depending on a range of different factors. Relatively simple processes, such as belt conveyors, may only require basic linear programming models to meet the requirements of the optimisation, whereas complicated processes, such as truck and shovel fleets, may require much more complicated MILP formulations to provide valuable results to the mine operator. Known problem areas in the production system, where bottlenecks occur, can also be focused on with detailed modelling to make sure they are realistic enough for accurate optimisation. Limited data availability also affects the ability to model subsystems with detail.

The four subsystems modelled in this study are excavation and haulage, processing plant, stockpile and belt conveyor. Each of these haves been modelled using the concepts outlined in this chapter. Knowledge, gained from the research, and experience, from the case study mine examined in this thesis, have been used in order to create a fairly general set of subsystem modules for reusability on new mines.

This section first details the specific requirements of subsystem models in Subsection 3.2.1, then outlines strategies to take and considerations to make when developing subsystem models in Subsection 3.2.2. The remaining four subsections (3.2.3, 3.2.4, 3.2.5 and 3.2.6) outline the modules of the four subsystems being studied in this thesis.

3.2.1 Subsystem model requirements

As explained previously, there are basic requirements of subsystems, in order for them to be connected to each other and used in the integrated modelling framework. These requirements are as follows:

1. That material flow connection points exist on boundaries
2. That they are responsible for constraining the material passing through their connection points
3. That they contain a variable representing the subsystems energy consumption

The first of these requirements ensures all subsystems can be connected to one another in any matter, to allow for representing any configuration of an open-pit coal mine. There are a number of different types of materials that are transported throughout a production system, and the general concept of a connection allows for any number of materials to be transported over it. The main constraint of this requirement is that the connection point represents a 'flow' of the arbitrary material being transported; in terms of modelling, this means it is a continuous variable with a 'per time' unit, such as tonnes/hour or litres/minute. Specifically, hours are being used as the time unit (denominator), as this is what is typically used in the mining industry. The numerator of the flow unit is dependent on the material being transported. For example, tonnes are used for measuring the ROM and product coal, while kilolitres are used for water. The only necessity for the numerator is that each different type of material uses the same unit across the subsystems, not that all materials use the same unit.

This first requirement has the most implications on the design of the framework outlined in this research. It is principally an assumption of both the top level integrated model and the interactions between subsystems. While it allows any subsystem to be trivially connected to any other subsystem at the top level, it assumes that this connection is appropriately represented by a flow of material. The flow connection has been used based on the research into how open-pit coal mines operate as continuous flow production systems, and from industry experience in seeing production rates used at this level of mine management and operation.

In general, there is no restriction on the number of inlet and outlet connection points a subsystem can have. It may be that a specific subsystem has physical limitations on the number of inlets or outlets it has, however that is considered an implementation detail of that specific subsystem model, rather than a limitation of the general subsystem building block definition.

The second requirement asserts that each subsystem model must include any constraints on the material passing in and out through its connection points are defined internally, as introduced in Subsection 3.1.4. This allows for a connection at the top level to be a completely generic concept, so technically any two subsystems can be connected to one another at the top level, but their respective internal model will dictate whether there is any valid material and how much of it can flow between them. This increases the amount of flexibility there is for creating the integrated top level models for specific mine setups.

To explain how this works for constraining the type of material that flows through a subsystem, consider a truck and shovel fleet that transports top soil, overburden and ROM coal and delivers to three different locations: a top soil dump, overburden dump and the ROM stockpile. To keep the model general, the truck and shovel subsystem should not need to be explicitly aware of the type of material it is delivering to each outlet; however, the destination subsystems will be set up with constraints to only receive the type of material they can handle. So once they are connected and being solved in the same model, there will be the implicit constraint on the truck and shovel fleet to only deliver the appropriate material to each of its outlets.

As well as this, the requirement means the capacity of subsystems should constrain the amount of material that can flow in and out of the subsystem to implicitly constrain any connected subsystems. For instance a belt conveyor may have a capacity of 3000t/h but if it is connected to a processing plant that can only take in 2000t/h, it will be implicitly constrained by the processing plant's capacity.

The final requirement is there for use when integrating the models at the top level. Since minimising energy consumption is the objective of the optimisation, each subsystem is assumed to have a common variable for its own energy consumption to be summed up together at the top level in the objective function. The energy unit megawatt hour (MWh) is used as the unit for this variable across all subsystems. This means certain energy sources, such as diesel, must be converted into their energy value, rather than the measured volume or mass, which may be used internally in the subsystem.

The modelling framework is by no means limited to the energy efficiency problem and could easily be suited to alternate problems with other decision variables. For instance, the subsystem module formulations could use greenhouse gas emissions as their objective values to optimise the environmental impact of a mine's operation. It is, however, important to keep all subsystems using the same unit so the addition of their individual values makes sense. A multivariable cost function that assigns dollar values to several different components of a subsystem's operation, such as labour, parts and energy costs, is one way of including more than one component in the optimisation. Other multi-component objective functions, coupled with appropriate solution techniques, could also work within the framework, though are not considered in this study.

With these three requirements satisfied, a subsystem model is ready to be included into the integrated model. Not that it would be particularly useful with just these three requirements satisfied; the intention of this design is to allow for the basic subsystem's building block to be as simple as possible. Then from that building block, the complexity comes from the mathematical modelling, which is done specific to the functions and behaviour of the subsystem. This concept is designed to avoid the effort of trying to fit the functions and behaviours of a new subsystem into an existing, tightly constrained modelling structure.

3.2.2 Subsystem modelling strategies

Modelling the subsystems can be carried out with various degrees of sophistication. This depends on both the production system being modelled and the desired performance of the optimisation.

A primary factor in deciding on the complexity of the model, as with most optimisation model efforts, is the balance between solution speed and accuracy. In order to model the exact operation of a mine with all of the equipment being used, a very large number of variables and constraints would be required, making solving the model in reasonable time unviable. Instead, assumptions must be made and model detail lessened in order to reduce the size of the problem.

The detail of the model may also be limited by the availability of data for the particular subsystem at the mine. In the case study used in this research, there is limited data about where exactly the energy is consumed in the processing plant. This limits the ability to properly model the inner workings of the plant, whereas, with more data, a more detailed representation of its control, equipment and energy consumption could be formulated.

Another factor in deciding how much effort to place on modelling a particular subsystem, is whether it is, or may become, a bottleneck of the whole system. As stated in the literature review, bottlenecks have a major impact on energy efficiency. Making sure there are good representations of possible bottleneck subsystems will allow for the integrated model to take into consideration the increased impact that operation of that subsystem has on the rest of the production system.

In this early stage of the research, another factor in the development of subsystem models is the reusability. Keeping assumptions fairly general and creating relatively simplistic models of the subsystems means that they can form a library of reusable subsystem models which, while not perfectly, should apply to most mine setups. With general models like this in a library, it can be relatively quick to parameterise them and connect them up into the integrated model to get something going.

In order to get a better representation of the specific system being modelled, it may then be appropriate to take one of the standard library subsystem models and alter it to suit particular intricacies of the mine. This follows a more 'agile' style of model development, whereby a running optimisation is always available, with extra effort placed on improving it when required (if at all). This is opposed to the more traditional approach of a large upfront modelling effort across the whole mine. This 'agile' approach of modifying existing subsystems for accuracy improvement is applied in Section 6.1.

The subsystems developed in the following sections take into consideration all of these factors. The case study mine is used as the reference point for data availability, bottlenecks and how general the models can be while still representing the operation well enough to get a quality solution.

In order to develop subsystem models, a number of different resources can be drawn upon. Research papers provide a good source of mathematical models for the various subsystems that are modelled. Even if they do not deal with energy explicitly, the variables and constraints for defining the operation will likely be easily extended to relate to energy consumption.

Industry may also have proprietary optimisation models that could be useful for defining the subsystem modules if access to them is permitted. For instance, CHPPs may have optimisers built into their automated control systems; this could serve as the beginnings of the model developed for this framework.

Another way to build models would be to create extremely general mathematical models that can be empirically fit to operation data, to represent a wide variety of processes.

In general, most formulations for the subsystems will contain some level of empirically derived parameters. For instance, diesel consumption of each truck can come from operational data on the consumption of each truck. Using this type of information in the model, as opposed to design data, is important for getting an accurate representation of the operation of the mine. This means the solution will be the best for the actual operation of the mine, rather than its theoretical operation. Keeping this data up to date is important in making sure the solution stays relevant to the actual operation.

A suggestion for formulating general subsystems is to not use operating states' time indices in parameters, unless the modeller is certain that the states won't change across different instances or that it is completely unavoidable. Since states are designed to come in varying quantity and length, having a parameter that is indexed by state would mean it may have to be updated every time the state length changes.

3.2.3 Excavation and haulage subsystem

The excavation and haulage subsystem developed for this research determines the activity of the trucks and shovels that are working together to dig raw material from the ground and deliver it to its required destination. Due to the complex nature of the excavation and haulage operation, it will require the most sophisticated model of the four subsystems studied in this research. Figure 3.4 outlines the key elements of the excavation and haulage subsystem that will be modelled in Section 4.1. Inlet and outlet connections are also labelled with examples of what the subsystem may be connected to.

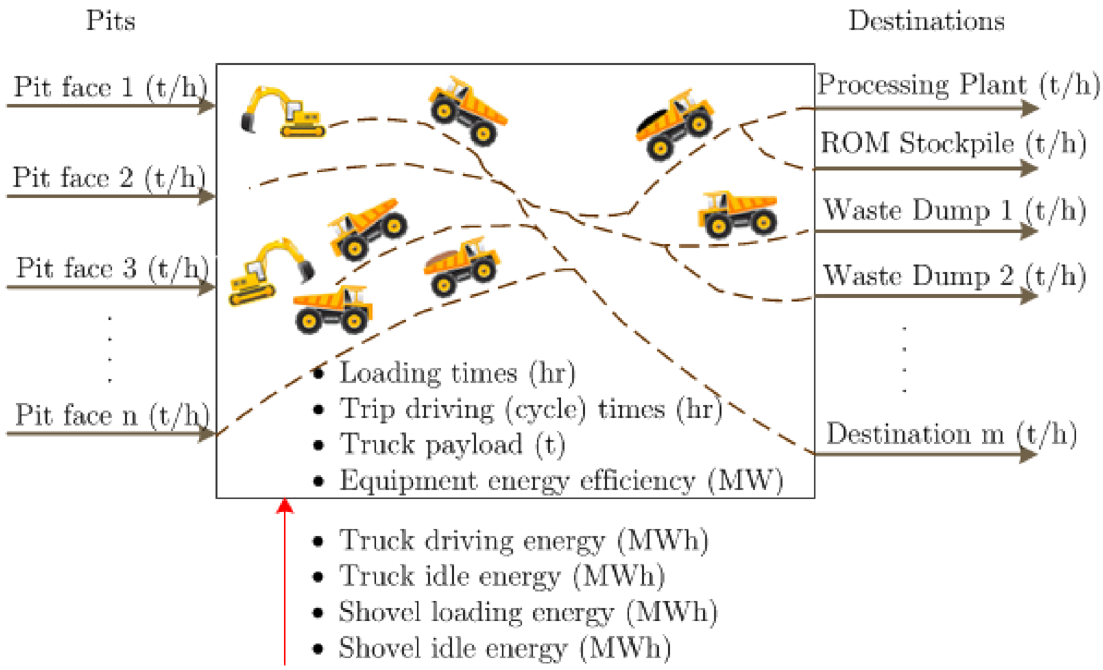

Figure 3.4. Excavation and haulage subsystem overview

The module will be first formulated in Chapter 4 as an equipment allocation type of mathematical model. Integer variables will represent the number of trips that trucks make from certain pits and shovels to destinations over time, and binary variables will represent the allocation of shovels to pits. This is the most common type of formulation present in the recent literature (Mena et al., 2013; Sahoo et al., 2014; Souza et al., 2010; Ta et al., 2013). It will, though, be formulated to a lesser degree of detail than that of Sahoo et al. (2014), due to data availability restrictions and linearity requirements. A scheduling formulation, similar in nature to Chang et al. (2015), will be investigated later in the thesis, in Chapter 6, after the drawbacks of this, more common, approach are studied in detail. Constraints dictate the maximum number of trucks allocated to a shovel and calculate the flow of material being extracted and delivered, based on the activity of the equipment. The energy consumption is represented as the sum of the energy used for the actions each equipment piece is performing: trucks idle (including being loaded); trucks driving; shovels loading; and shovels idle.

The operation of the subsystem is parameterised by the loading and driving times that its equipment achieves when working at particular pits; the truck payloads; and the energy consumption each individual equipment piece has while performing different actions.

The loading and driving times are used to determine the rate at which material is extracted from pits and delivered to destinations. They are also used to determine the maximum number of trips allocated to a single shovel to avoid waiting times. These times should come from operating data to ensure the solution reflects the actual times achieved by the equipment, rather than design or planned times.

It is important to characterise the energy consumption of each truck from real data as well, to ensure the trucks chosen to be allocated will actually use the least amount of energy. This is opposed to using design information, which will not allow the optimisation to realise the difference between trucks and therefore will not necessarily result in a real life optimum. This can also improve the performance of the optimisation, as it reduces the amount of symmetry in the solution space.

3.2.4 Processing plant subsystem

A fairly general model of the processing plant will be developed, similar to that of Middelberg et al. (2009) but still using the same overall, inlet and outlet federate, decision variables at the core of more advanced models (Matthews & Craig, 2013; Numbi & Xia, 2015). This is due to limited data availability for the processing stages in the case study of this thesis as well as to align with the objective of creating a general model to allow for reusability on other mines. Figure 3.5 gives an overview of the processing plant subsystem module, with example inlets and outlets, presented formally in Section 4.1.

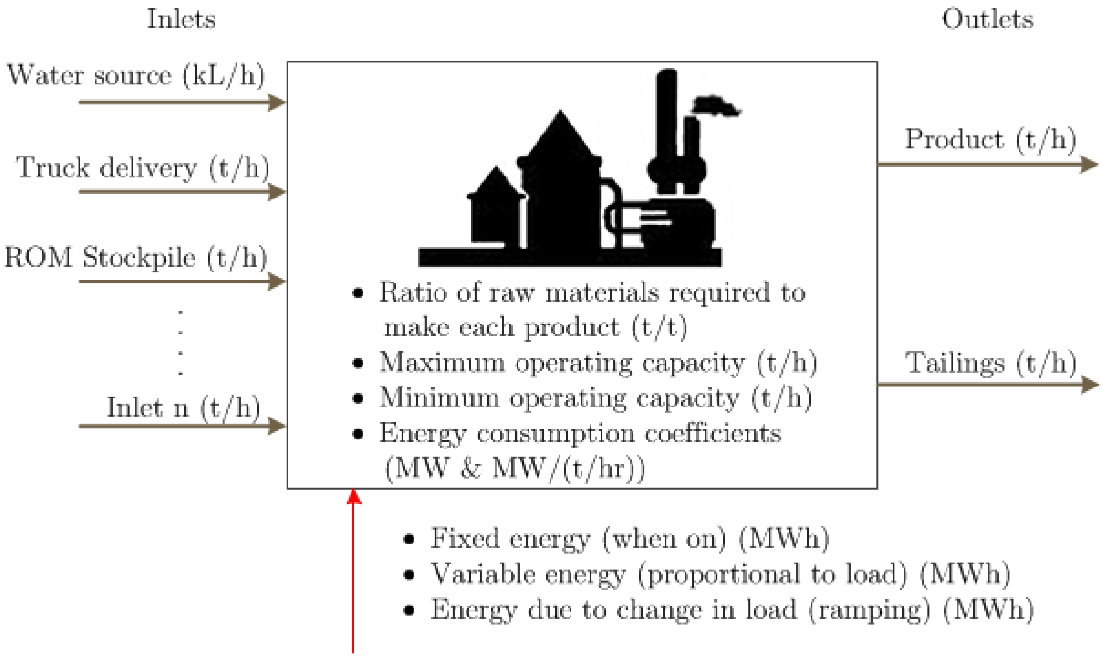

Figure 3.5. Processing plant subsystem overview

The model assumes known ratios for inlet ROM material grades and water to outlet product grades and waste material. It is also constrained by maximum inlet and outlet capacities. The energy consumed by the plant is assumed to be proportional to the grade and amount of ROM it is processing and the grade of product it is producing.

All of these parameters should be able to be fit from real operational data in order to get the best picture of the actual behaviour of the plant. Without detailed data or a detailed model of the subsystem, it is important to get what is available as accurate and up-to-date as possible to allow for the solutions to be close to reality.

3.2.5 Stockpile subsystem

The proposed stockpile model will also been developed to be as generic as possible, so it can apply to many different stockpiles with limited data availability. A network flow model with inventory is used as the basis for the formulation, similar to Ta et al. (2005) and Hanoun et al. (2013). The key elements of the stockpile subsystem module, formulated in Section 4.1, are shown in Figure 3.6 with example connections into and out of the subsystem.

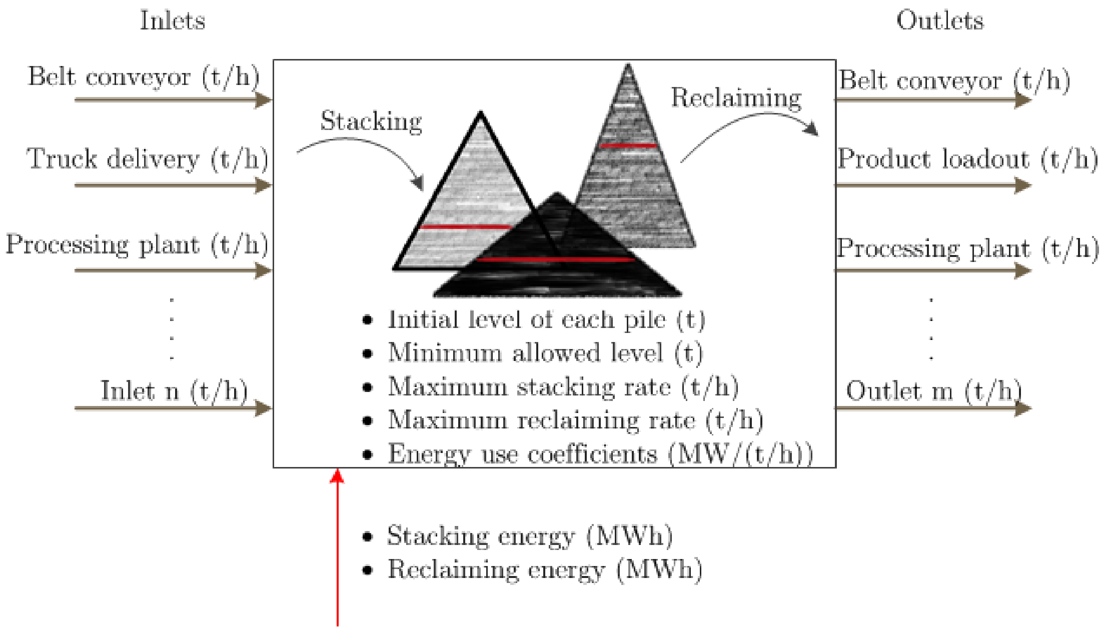

Figure 3.6. Stockpile subsystem overview

Maximum flow rates for stacking and reclaiming are used, along with a minimum stockpile level for each grade being stored. Energy usage is assumed to be proportional to the flow rates of material being stacked and reclaimed from the piles; this is characterised based on the specific equipment used to stack and reclaim for each particular stockpile being modelled.

As with the other subsystems, it is just as important to get accurate and up-to-date operational data for parameters to be able to realise maximum value from the model.

3.2.6 Belt conveyor subsystem

Belt conveyors will also formulated as simple network flow models, but without inventory, in a similar fashion to Middelberg et al. (2009). This is done, as with other subsystems, to be as general as possible to suit a wide variety of belt conveyors and data availability. Figure 3.7 outlines the key elements, with example inlet and outlet connections, of the belt conveyor subsystem formulation that is presented in Section 4.1.

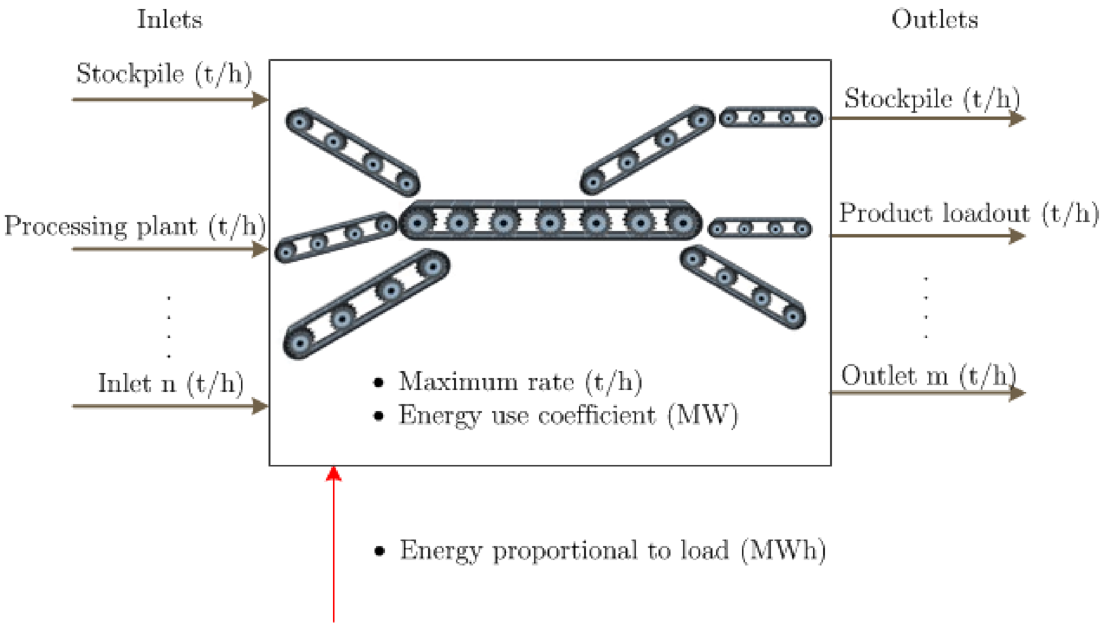

Figure 3.7. Belt conveyor subsystem overview

There will be a constraint on the maximum flow rate of material over the belt and the energy consumption is assumed to be proportional to the flow rate of material.

Fitting the simple parameters of this formulation accurately from up-to-date operational data is also important to get a good representation of the subsystem for best value from the optimisation.

3.3 Process for applying the integrated model

This section details the process developed for applying the modelling methodologies of this research to a continuous production system, and in particular, a mine. Figure 3.8 shows the steps and flow of the developed process.

The process has been designed to enable a problem domain expert to carry out as many steps as possible, rather than a mathematical modeller. Steps that require modelling effort for new subsystems or tasks, highlighted in purple, have been decoupled from the main flow of the process to show the separation of duties.

Ideally, if no new subsystems or tasks are required, a software tool could be developed to allow domain experts at the mine to complete the entire model application process. Done correctly, this could reduce the upfront cost and effort of modelling and give users a better understanding about the details and limitations of the model. This is explored further in Subsection 9.1.2.

There are two main parts to the process; firstly the integrated model is applied to the production system, in this case a mine, then solved using production target inputs to optimise the modelled objective. Partitioning the process like this shows that the initial effort of modelling the system is only needed once before it can be used for many different plans over time. Using the software analogy again, once the user has defined and parameterised the subsystems in the integrated model, the model would be 'saved' as a completed model, then 'loaded' and given a plan to optimise each time it is required.

The remainder of this section steps through the process using a basic hypothetical mine as an example. This example is then used for validation in Chapters 4, 6 and 7. Chapter 5 uses this process to apply the model to an open-pit coal mine in South East Queensland as a case study.

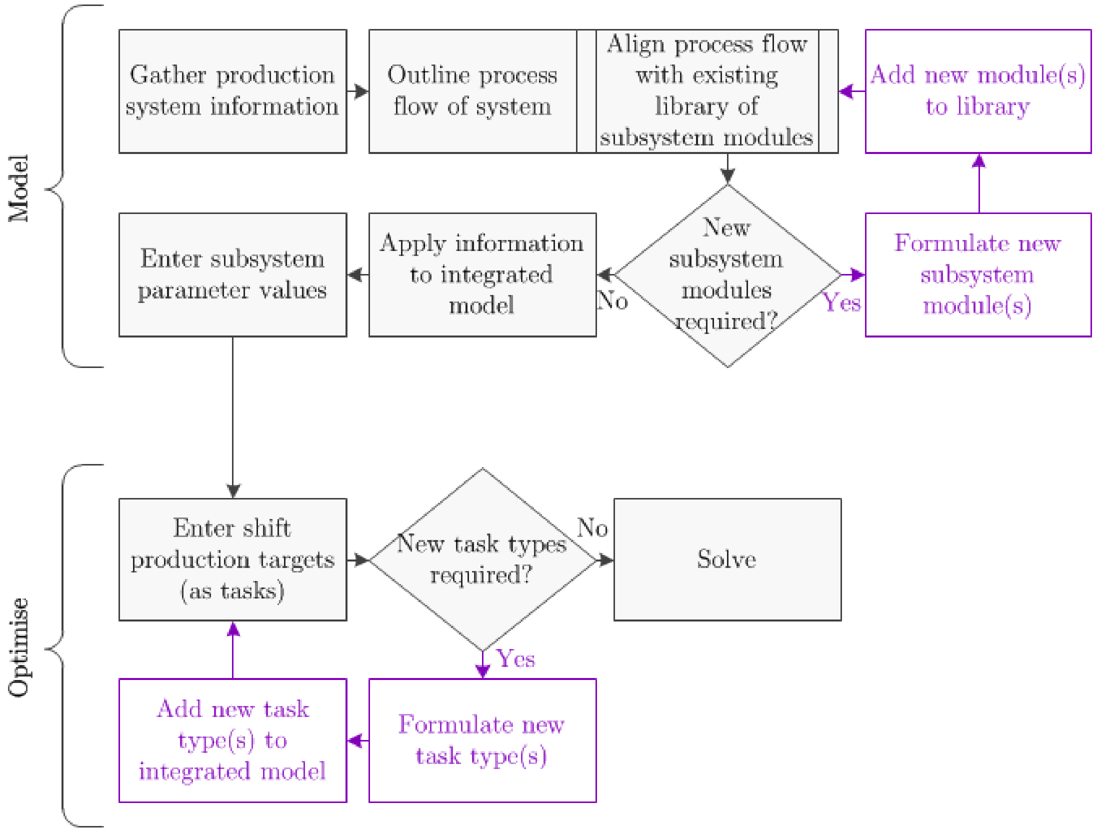

Figure 3.8. Process for applying the integrated model

3.3.1 Gather production system information

The first step of the process is to gather information about the operation of the production system being modelled. Information can come from a number of sources, such as discussion with managers, operators or other employees; operational data; long, medium and short-term plans; maps; and existing models. The work required to carry out this step can vary depending on several factors, such as the modeller's knowledge / experience, availability of data and the complexity of the production system.

Completing this step can be a little open-ended as there are typically a lot of observations to make across a production system to learn its operation, and a mine is no exception. The aim of the step is to get enough of an understanding of the system to help with completing the rest of the process. It is therefore important to focus the effort of making observations to where it will be useful. In reality, this step should be revisited throughout the whole process to make sure the mine model being developed is as good a representation of the system as possible.

In order to provide some rigour around this step, a series of questions have been compiled to help the modeller form useful observations for the later stages of the process. These questions have been created specifically for the mining case studied in this thesis, though they do give an indication of the types of questions that should be being asked of a different type of production system being modelled. They are also by no means exhaustive. The questions are outlined below and answered for a simple hypothetical open-pit coal mine. They are broken up into six parts; the first relates to the mine as a whole, the following four relate to the subsystems that make up the mine and the final one is used to capture knowledge about subsystems that are at the mine but not considered in this research.

The questions are principally about getting the information that is required to create the correct model structure at the whole-system and subsystem level. That is, they focus on finding out what is important and relatively static within the mine and leave the more specific detail for later in the process when each subsystem is parameterised. For instance, the number of shovels is not likely to change often and is important information as it used to define the size of the mathematical formulation, so it is absolutely necessary to solve the model. However, each shovel's idle and loading energy usage is left for the later parameterisation stage. This is because it is likely to change over time as the shovel's efficiency changes, when it degrades or receives maintenance, and can also be estimated based on design data or by other means to solve the model before it is parameterised from real data.

Whole-of-mine questions

These questions help contextualise the mine in a continuous production system setting to define the problem and break it up into a series of connected subsystems.

What are the boundaries of the mine?

A good way to answer this question is to draw a rough map of the mine to see the physical flow of material through the mine, from start to finish. Figure 3.9 shows a rough map of the simple mine being used in this section. In this case, the material is being extracted from one pit face, and either ends up at a common waste dump or delivered via belt conveyor.

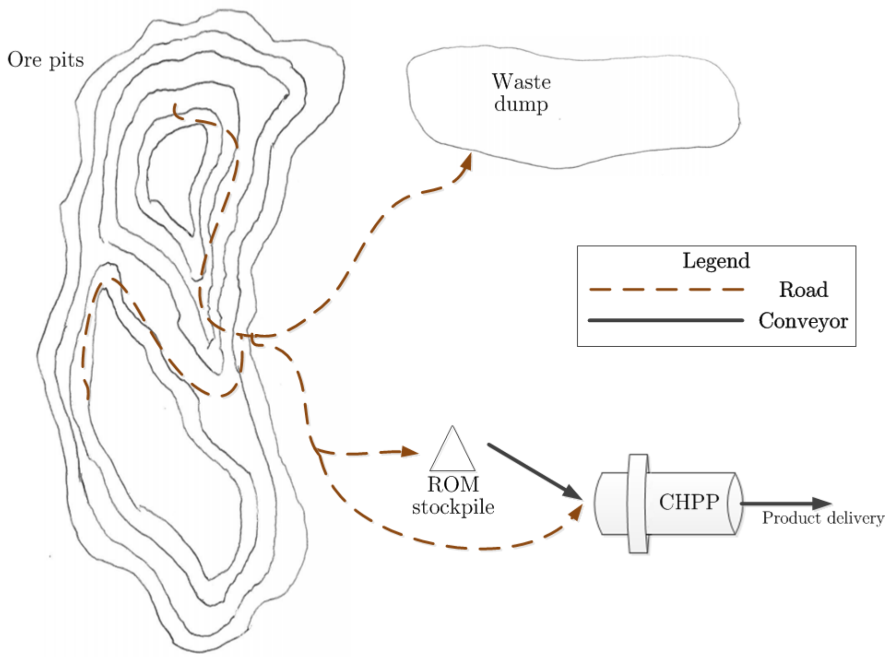

Figure 3.9. Simple hypothetical mine map

In a real life scenario, defining the boundaries may depend on limitations of the responsibility the organisation doing the modelling has. For instance, if a contract miner is only contracted to deliver ROM to a stockpile, the end boundary of their modelling effort may be that stockpile, or even just before it. Alternatively, in a case where two pits are operated by the same organisation and feed the same CHPP and product delivery, then both pits and the delivery loader should be defined as the boundaries.

What systems perform the majority of the work?

Once the boundaries have been defined, the modeller should now look within them to observe what work is being performed to transport and process the materials from the beginning to end boundaries. In this example, we can see that there is excavation and haulage, ROM stockpile, waste dump, CHPP and three belt conveyors. These systems work together to extract the material out of the ground to be transported, processed and delivered.

What are the main energy consumers of the mine?

This question aims to compliment the last and make sure there is no major energy consumption that will be overlooked. The model should aim to include both the main operation and material flow of the mine and the main energy consumption. Typically, and in the case of this example mine, these two go hand in hand; the same systems that contribute to the primary operation of the mine will also be the biggest energy consumers. However, there may be cases where an auxiliary system consumes a large amount of energy, without having much to do with main flow of material and therefore should at least be considered at this point, then evaluated in a later stage as to how it may fit into the model and what value can be achieved at an operational decision making level.

How many different types material are transported between systems?

This question determines what grades of raw ore, waste, product and other materials are being transported and used across the mine. A good starting point to answering this question is to think about what material is transported between the systems that make up the mine, as well as any other material that is consumed, such as water. For the example mine here, there are five types of materials, the ROM coal extracted from the ground; waste in the form of overburden and tailings; product coal output from the CHPP; and water used by the CHPP.

Excavation and haulage questions

These questions should be answered as many excavation and haulage subsystems have been identified in the previous set of questions related to the mine as a whole. They are used to determine the main attributes of the subsystem and its boundaries. The specific operational characteristics are determined and defined in the later, subsystem parameterisation phase of the process.

What are the boundaries of the subsystem?

The answer to this question is used to work out how many inlets and outlets the excavation and haulage subsystem has. The inlets are the pits / faces being extracted from, the outlets are the destinations to which the trucks deliver.

There are two pits being extracted from in this simple example, and three destinations, the ROM stockpile, CHPP and waste dump.

What grades are being extracted?

This is for working out what material grades are extracted by the fleet. It is particularly important in certain cases. For instance if there are two fleets, one for coal and one for overburden, it is important to distinguish what material each fleet is extracting. In this example, the shovels can dig either ROM coal or overburden material from the pit.

How many shovels are there?

This is a straightforward question for defining the number of loaders that the model will have available for parameterisation in later stages. In the simple hypothetical example, there are two shovels.

How many trucks are there?

In a similar fashion to the previous question, this question is for defining the right amount of trucks in the model for the later parameterisation. For this example, there is a fleet of six trucks.

Processing plant questions

Along with the excavation and haulage questions, these are used to gather the general information about the processing plant subsystems at the mine, which enables them to be parameterised in more detail in a later stage of the process.

What are the boundaries of the subsystem?

The processing plant can receive ROM coal from a number of different locations, and typically will also have an inlet of water. The outlet boundaries of the processing plant will usually consist of at least one for product and one for tailings waste, but depending on the complexity of the plant and mine, there could be multiple product and tailings outlets. In this example, there are two ROM inlets, a water inlet, product outlet and a waste outlet.

What materials can be processed?

This is used to define what types of raw material are accepted by the processing plant for transforming into product. In this example, it is the ROM coal material grade that is processed by the CHPP.

What materials are produced?

This question is used to define what product grades are yielded by the processing plant as outputs. The product coal material grade is the answer to this question for this worked example.

Stockpile questions

The questions to answer, relating to the stockpiles, are similar to the other two subsystems. They are focused on defining the basic operating behaviour of the mine, allowing the subsystems to be parameterised in more detail later in the process.

What are the boundaries of the subsystem?

Much like the other subsystems, this question is used to define the inlets and outlets of the stockpile. In this example, there are two stockpile subsystems. The ROM stockpile has one inlet and one outlet, while the waste dump has one inlet and no outlet.

What grades are stored in the stockpile?

This is used to define the grades allowed in and out of the subsystem and also the number of stockpiles in the subsystem. The ROM coal grade in this example is the grade stored by the ROM stockpile, and the waste dump can only accept and store overburden.

Belt conveyor questions

Once again, the questions related to this subsystem are made to simply define the primary operation of the subsystem so it can be parameterised specifically in a later stage of the process.

What are the boundaries of the subsystem?

As with the other subsystems, this question is used to define the inlets and outlets of the subsystem. Belt conveyors are modelled to have a complete mass balance over them, so must have at least one inlet and outlet. The belt conveyor in this example has a single inlet and a single outlet.

What grades can be transported over the belt conveyor?

Depending on the type of belt conveyor, it may be that any grade can be transported over it, but in general it is a good idea to define what the belt conveyor is used for specifically to make sure it is not hooked up incorrectly when it is connected to the upstream and downstream subsystems. In this example the belt conveyor transports product coal.

Other subsystem questions

This final section of questions is for any of the subsystems that have been identified by the whole-of-mine observations but cannot be related back to one of the four general subsystems defined in this research. Depending on their importance, they may or may not need to be developed as new subsystems at a later stage of the process. These questions will help determine whether that effort is actually required, and to help with the modelling if it is. In the simple example being explored here, and ideally, these questions would not be required, so there will only be a description of each question.

What are the boundaries of the subsystem?

Once again, they are used to work out how many inlet and outlet connections the subsystem has.

What materials does the subsystem work with?

This is important to help get an idea of what type of function the subsystem is performing, whether there is any transformation of material happening, or if it performs transport/handling type work.

How is energy consumed on the subsystem?

This question is important in determining how to model the subsystem to ensure it contributes to the objective function; it can also be used as evidence to show that modelling may not be necessary if there is very little energy consumed by the subsystem.

What decisions are made to determine the operation of the subsystem?

In order to determine the structure of the mathematical model to be developed for the new subsystem, answering this question will help scope the required resolution of the decision variables. They may only be the overall flow through the subsystem, or may have to relate to equipment allocation or stock levels.

How do operational decisions on this subsystem impact energy consumption?

This is to help get an idea about what parts of the model impact energy consumption to make sure everything is included in the total energy consumption of the subsystem.

How do operational decisions on this subsystem impact other subsystems?

This question works to both ensure creating the new model is worth it from the perspective of the main operation of the mine, and secondly, to assist in ensuring it will constrain the whole system in a realistic nature.

3.3.2 Outline process flow of system

This step in the process formalises some of the observations made in the first step, about whole-system boundaries and subsystems. This is done by representing the mine as a series of connected subsystems on a Process Flow Diagram (PFD). This has been done to the example mine being used in Figure 3.10.

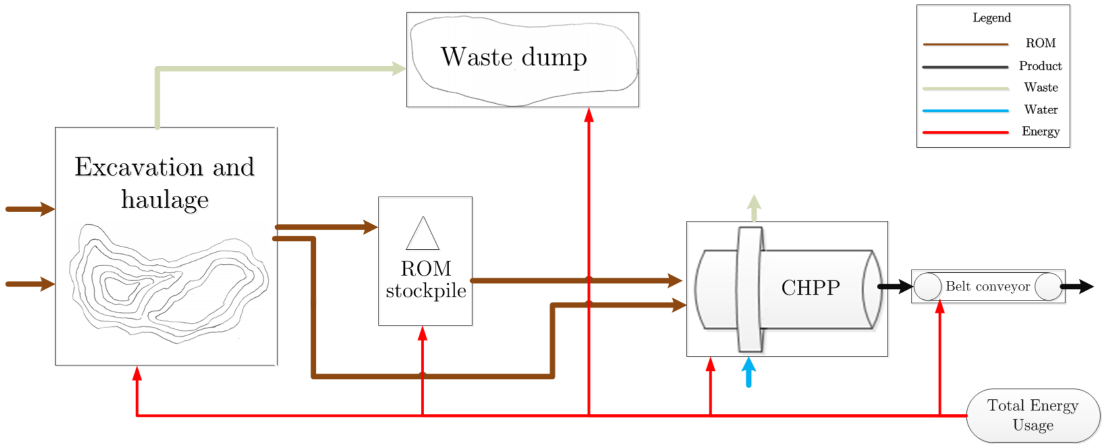

Figure 3.10. Simple mine process flow diagram

The process flow diagram should contain all of the subsystems that were identified as being part of the main flow of material through the mine and/or large contributors to energy consumption.

The sub-step involved in completing this process flow diagram, as seen in Figure 3.8, is to align the subsystems with the standard set, or library, of subsystem models. This research contains four standard subsystem models. As per the next block in the process after this, if there is a subsystem that cannot be represented by one of these four standard models, and depending on its importance and the effort required to model it, a new subsystem may be required to be mathematically modelled before the process can be continued. This is explained in Subsection 3.3.3.

As introduced in previous sections, thinking of this step in a software sense, it is easy to imagine how it could be adapted to a flowsheeting type tool, where the library of standard subsystems can be 'dragged and dropped' onto a canvas and connected up to one another. The PFD created both visually and logically could then be processed by the software to make a start on defining the model in the mathematical modelling language.

3.3.3 Formulate new subsystem model(s) (if required)

As introduced in Subsection 3.3.2, the decision block that asks if any new subsystems are required will determine whether any mathematical modelling will be required for applying this research to the mine. Ideally, for a minimum cost application the answer to this is no. This is the case for the simple example worked through in this section and the case study presented in Chapter 5. However, a description of how to create a new subsystem model will be presented here.

Firstly, the subsystem should be analysed with respect to how necessary a new module of its operation is. Much of this can come from the general observations from the first step of the process, and should be weighed up against the effort required to formulate the new module.

If there are very few operational decisions that impact the subsystem, its energy usage or other subsystems, then it may not be worth including them in the model, as there will be limited operational decision support that the optimisation can provide.

It may be that this process is able to be postponed for later as well. For instance, if the subsystem can be overlooked without impacting much on the other subsystems, a model of the mine could first be created without the new subsystem and value can be realised without the effort of modelling at this stage. The modelling effort can be postponed and re-evaluated in more detail later, without slowing down the upfront effort of getting the initial model up and running.

If it is absolutely critical to have the new subsystem modelled, it may be possible to take a low cost approach to modelling the new subsystem. Creating a very simple mathematical model to represent the subsystem as a black box with basic mass balance constraints and energy consumption related to throughput may be all that is required to continue with the process. Then once it is running, a more detailed study can be conducted into whether further modelling will yield enough value to justify the effort or not.

It may also happen that one of these new subsystems is close to an existing one but does not quite fit the existing model. In this case, the modelling effort may be reduced by duplicating the closest existing subsystem and customising it to suit the new one.

The concepts and requirements described in Section 3.2 are used to define a new subsystem in this part of the process. The standard MILP techniques and modelling procedures can be used to create the parameters, decision variables and constraints, so long as there are boundary connections with material flows and there is a variable for energy consumption for use by the objective function.

After this step is completed for all new subsystems that are deemed to be required at this stage, the process can move onto creating an instance of the integrated model of the mine.

3.3.4 Apply structural information to integrated model

This step is fairly straightforward so long as the process flow diagram aligns with the library of subsystems, plus any new subsystems, and reasonable effort has been carried out in the observation phase. Each subsystem can be added to its relevant set of that subsystem type, connected to the appropriate neighbouring subsystems and configured with the relevant extra information gathered during observations. Details about these are given in the full model formulation presented in Section 4.1.

Going back to the explanation of how this would work in a software tool setting, this stage could possibly be included as part of the process flow diagram creation stage if it is designed well enough to take in the more detailed information about each subsystem, such as the number of shovels of an excavation and haulage subsystem, or the stored grades of a stockpile. A flowsheeting tool that is aware of each subsystem to this degree would be able to create a logical representation of the model with enough detail to be translated into the mathematical modelling language with no user effort.

3.3.5 Enter subsystem parameter values

Once the previous step of defining the structure of the integrated model has been conducted, the model should have enough information to have all of the decision variables defined. The next step required to be completed before it can be run is to parameterise the subsystems to allow for their constraints to become active, along with their respective energy consumption variables for use in the objective function. This will leave the integrated model to only require the planned tasks, for it to be defined completely and be ready to be solved.

Each type of subsystem needs different information as part of this step. Their required parameters will be described one by one below, followed by a general explanation about where this data can come from and what impact it can have on the ability of the model to provide valuable results.

Excavation and haulage parameterisation

In plain English, the parameters required for the truck and shovel operation are as follows, along with the values used for the simple example. These parameters are formally defined in Subsection 4.1.2 of the full integrated model formulation.

- Trip driving time – for each trip – See Table 3.1
- Loading time – for each pit – 3 minutes
- Payload (t) of each truck – See Table 3.2
- Energy consumption rate (MW) of each truck when driving between a pit and destination – See Table 3.2, for this example the energy consumption rate is considered the same between any pit and destination
- Energy consumption rate (MW) of each truck when idle – See Table 3.2
- Energy consumption rate (MW) of each shovel when loading – See Table 3.3
- Energy consumption rate (MW) of each shovel when idle – See Table 3.3

Table 3.1. Simple example trip driving times (minutes)

From row		Inlets		Outlets			Base
to column		Pit 1	Pit 2	Processing plant	ROM Stockpile	Waste dump	Base
Inlets	Pit 1	-	-	7	8	10	7
	Pit 2	-	-	7	8	10	7
Outlets	Processing plant	5	5	-	-	-	-
	ROM stockpile	6	6	-	-	-	-
	Waste dump	7	7	-	-	-	-
	Base	5	5	-	-	-	-

Table 3.2. Simple example truck parameters

Truck	Payload (tonnes)	Idle diesel consumption (MW)	Driving diesel consumption (MW)
1	250	0.34	1.70
2	250	0.32	1.65
3	220	0.37	1.90
4	220	0.30	1.55
5	220	0.33	1.75
6	220	0.34	1.40

Table 3.3. Simple example shovel parameters

Shovel	Loading energy usage (MW)	Idle energy usage (MW)
1	3.10	0.65
2	3.20	0.60

Processing plant parameterisation

The following parameters, formally described in Subsection 4.1.2, are used to describe the processing plant subsystem's operation, with the simple example values listed in Table 3.4 and Table 3.5.

- Ratio of each input material required to produce each product material (t/t)
- Maximum capacity of plant (t/h)
- Minimum capacity of plant when in operation (t/h)
- Fixed energy consumption (of having plant in operation) (MW)
- Variable energy consumption coefficient (related to load of plant) (MW/(t/h))
- Energy due to change in load between operating states (MWh/(t/h))

Table 3.4. Simple example processing plant input ratios

	Produced grade	ROM	Product	Waste	Tailings	Water
Processing plant	Product coal	1.223	0	0	0	0.069148

Table 3.5. Simple example processing plant parameters

	Maximum capacity of plant	Minimum capacity of plant	Fixed energy consumption (MW)	Variable energy consumption coefficient (MW/(t/h))	Energy consumption from change in load (MWh/(t/h))
Processing plant	500	3,500	1.5	0.0023225	0.0023225

Stockpile parameterisation

To parameterise the stockpile subsystem's operation, the following values are required. Table 3.6 provides the values used in the simple example and Subsection 4.1.2 presents them formally.

- Maximum rate of stacking (t/h)
- Maximum rate of reclaiming (t/h)
- Minimum level of each stockpile (t)
- Current/initial level of each stockpile (t)
- Stacking energy consumption coefficient (MW/(t/h))
- Reclaiming energy consumption coefficient (MW/(t/h))

Table 3.6. Simple example stockpile parameters

	Stored grade	Max. rate of stacking (t/h)	Max. rate of re-claiming (t/h)	Min. level of pile (t)	Current level of pile (t)	Stacking energy consumption coefficient (MW/(t/h))	Reclaiming energy consumption coefficient (MW/(t/h))
ROM stockpile	ROM	5,000	5,000	20,000	22,000	0.00066	0.00014666
Waste dump	Ovrbdn	5,000	5,000	0	0	0.00066	0.00014666

Belt conveyor parameterisation

The parameters required to describe the belt conveyor subsystem operation are as follows, along with their values for the simple example in Table 3.7. They are mathematically described in Subsection 4.1.2 of the model formulation.

- Maximum rate of material flowing over belt (t/h)
- Energy consumption coefficient (related to load) (MW/(t/h))

Table 3.7. Simple example belt conveyor parameters

	Maximum rate of material flowing over belt (t/h)	Energy consumption coefficient (MW/(t/h))
Belt conveyor	5,000	0.000146

General parameter considerations

Section 3.1.3 introduces some of the considerations which should be made when finding values for these parameters with regards to the ability for the optimisation to provide valuable results. The idea is that the more up-to-date and accurate these parameters are, the more the model will realistically represent the actual mine operation and therefore will be able to be solved to more realistic optimal solutions.

The ability to get accurate values for each of these parameters will depend on a number of factors. These include how well the modules represent the operation of the specific subsystem, the level detail of data being collected for each subsystem and how easy it is to use this data to update the parameters.

If there is sufficient data available and easily available across the subsystems, then these parameters should be updated on the model as often as the data is collected to maintain the most up-to-date picture of the mine's operation. Ideally, this could happen as an automated step by some sort of software application, which collects, processes and sets the parameters automatically.

Realistically, to get through this stage and move on through the process, the parameterisation could occur using very limited amount of data, be it through design information, educated estimates or even sensible default values. This level of data will not provide maximum value back to the user, however could be used as a stepping stone to move on through the process to get at least some value from the model before this step can be revisited at a later stage and completed in more detail.

Once this step has been undertaken, the process has completed the first of the two main phases, where, in the software analogy, it can be 'saved' out at a point ready for the next phase where the input (current plan) is entered, creating a concrete problem instance to be solved.

3.3.6 Enter shift production targets and define operating states

The remaining steps fall under the second of the two main phases of the process. This phase is where an existing plan for the mine's operation is defined and entered into the model and the model is solved to optimise the total energy consumption while completing the plan. This step is about converting a plan into a form that can be used by the mathematical model.

Subsection 3.1.6 describes some of the concepts formulated for how plans are represented in the model by breaking them up into a series of 'tasks' that become constraints on the model. At the moment, there is only one type of 'task' allowed for in the model. This is the basic task, explained in Subsection 3.1.6 and formulated in Section 4.1, to transport an amount of a particular material grade over a connection within a defined start time and stop time.

If there is an activity in the plan that cannot be represented using this type of task, then a new task type will need to be formulated mathematically and added to the model. Within the developed process, this is handled in a similar fashion to the steps that go back to the modelling domain and add new subsystems in.

The other part of this step is to define the length of operating states to optimise for. As explained in Subsection 3.1.5, the time dimension for the optimisation model is defined by the number and lengths of operating states that are appropriate for the problem being solved. This is directly related to the shift being optimised and the tasks that represent the shift plan. For a mine operating under normal conditions, one to two hour states provide an appropriate resolution to represent mine system decisions. Shorter states may be required around periods where changes in operating are more frequent. Likewise if the system is expected to run at a steady operating point, longer state lengths can suffice.

For this simple example, Table 3.8 below shows the task list entered into the model. Along with these tasks, two one-hour states are used. The specifics of how these values are used in the model are detailed with the full MILP formulation in Section 4.1.

Table 3.8. Simple example task list

Task #	Connection point	Material grade	Amount (t)	Start time (hr)	End time (hr)
1	Excavation and haulage pit 1	ROM	3,000	0	2
2	Excavation and haulage pit 2	Overburden	3,000	0	2
3	Processing plant product outlet	Product	2,000	0	2

This process of converting the plan into tasks could be made much easier for the modeller through a well-developed software tool. Users could be guided to provide the plan in an easy-to-enter format and the software could then convert it to tasks and input them into the model automatically. This would reduce the need for the user to have in-depth knowledge about tasks or other details about the mathematical formulation of the model.

In an ideal scenario, with sufficient technology in place at the mine, it is easy to imagine that plans could be programmatically gathered from planning software, converted to tasks and entered into the model. Along with the ideal automatic parameterisation system, making this stage fully automated would enable the optimisation to be run in an on-line fashion to provide value with minimal effort to the user.

3.3.7 Formulate new task(s) (if required)

If the step of the process explained in Subsection 3.3.6 has found a planned activity that is not able to be converted into an existing task type in the model, a mathematical modelling effort is required in this step to create a new task type. The amount of effort required in this step will depend on the complexity of the planned activities trying to be modelled, how they can be translated into mathematical terms and how many there are.

The modelling of new tasks is done through the addition of parameters and constraints in the 'whole-of-mine' sections of the mathematical model detailed in Section 4.1. Depending on how the states are being determined, new tasks may be required to be developed with them in mind.

The shift plan tasks for the example mine being modelled in this section fit into the formulation presented in the Section 4.1 and therefore do not require this step. Likewise, the shift plans used in the Chapter 5 case study also suit the Section 4.1 task formulation.

3.3.8 Solve

This is the last stage of the developed process. Once the current plan has been entered into the model, all of the parameters, decision variables, objective equation and constraints are active and a concrete problem instance of the model can be instantiated. This is then sent to an optimisation package that solves the problem.

Solving the model can occur in a number of different ways with varying degrees of optimality and speed, depending on the complexity of the formulation. In this research, two solution approaches are used. The first is to solve the model with IBM ILOG CPLEX; this is found to be sufficient for the results in Chapter 4 and 5. The second, required to solve the more complex model introduced in Chapter 6, is to use metaheuristic techniques.

The model can also be solved several times in this step for providing sensitivity or scenario analysis. The specific analysis conducted in this step is dependent on the problem being investigated and the decisions that require support. Operators may only require a single output from the model to help them move towards a more energy efficient operation, whereas tactical or strategic decision makers are more likely interested in comparing the result of several problem instances. Subsection 9.1.2 explains in detail how this step can provide support to a number of different decision makers.

Once the optimisation has run, the results are ready to be returned to the user. This is by no means a trivial task. Results should be presented in an easy-to-read fashion in the domain of the user viewing them. Subsection 9.1.2 also proposes some methods for formatting the results for mine personnel.

The simple example used in this section is solved in Section 4.2 after the complete integrated model formulation is presented.

3.4 Remarks

This chapter has described two of the contributions this thesis makes. Firstly, Section 3.1 and 3.2 describe the conceptual framework for integrated modelling of continuous flow production systems. This was done by referring back to the specific problem and subsystems being examined in this study as a more concrete example of how it works.

Along with this, Section 3.3 outlines a process that has been developed to explain how models created with the framework can be applied to operating systems. The process was followed on a simple mine as an example; this mine will be used for model and solution validation and verification throughout the rest of the thesis.

Academic significance of these contributions comes from being designed for a general continuous flow production system, with a broad class of problems. This means they should be transportable into other fields. They have also been designed to be extensible for allowing future development to make them even more suited to the problems they are being used to solve.

From a practical significance perspective, outlining the general concepts behind creating and applying the integrated model becomes a useful contribution when translating this research into a software tool for providing decision support. The modelling framework has been designed to be highly customisable to suit a wide range of real life problems and the application process has been designed to enable domain experts to apply the model to their system, which is done to reduce upfront configuration costs.

Referring back to the research approach in Section 1.5, this section has defined the conceptual framework for creating integrated models of continuous flow production systems, seen in the top right quadrant of Figure 3.11. It will now be used, in Chapter 4, to formulate the integrated model of the four open-pit coal mine subsystems being examined in this thesis.

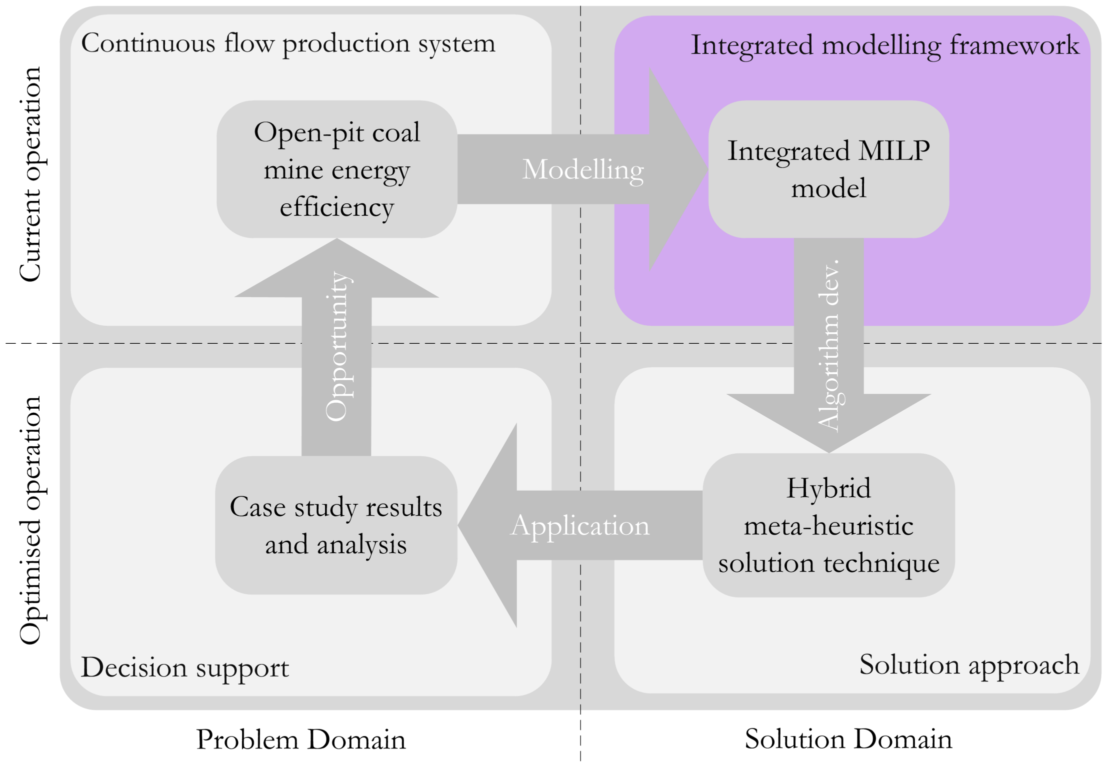

Figure 3.11. Role of Chapter 3 in the research approach

This chapter has begun to address the second research question listed in Section 1.2 and restated below. Various aspects of modelling detail, complexity and generalisability have been examined as key considerations of the developed integrated modelling framework. As well as this, a process for applying the integrated models using this framework has been proposed.

2. *What integrated optimisation model of energy efficiency is appropriate for an open-pit coal mine production system?*
   (a) *What level of detail is required of the model?*
   (b) *Where are the main points of model complexity?*
   (c) *How general should the model be?*
   (d) *What is an appropriate process for applying the model to a real life mine?*

4

Integrated Model

This chapter applies the modelling framework described in Chapter 3. Section 4.1 presents the MILP formulation of the integrated mine model, made up of the top level, 'whole-of-mine', notation, parameters, variables and constraints as well as the variables and constraints used to model each subsystem. Section 4.2 then uses the simple example introduced in Section 3.3 to validate the model. Finally some remarks about the model's benefits and limitations are made in Section 4.3.

4.1 Formulation

The general integrated model of an open-pit coal mine is formulated using the methodologies described in Section 3.1. First, with the aid of the models reviewed in Section 2.4, the subsystem modules that were conceptually defined in Section 3.2 are formulated using MILP. These are then integrated into a single model by modelling the material flow connections, total energy consumption and tasks. To show how the integrated model has been built from the subsystem modules, the representation below is broken up into variable and constraint groups that represent the different subsystems of the formulation, as well a group that represents the system-wide aspects of the formulation, referred to as the 'whole-of-mine'.

As mentioned in Section 3.2, the subsystem modules have initially been formulated to emulate the current standard amongst the models in literature, reviewed in Section 2.4. Despite the potential drawbacks, highlighted in Section 2.4, of the excavation and haulage subsystem allocation models in literature, this study first creates the integrated model using an allocation formulation. Using this, the issues are first confirmed, and then used as motivation for the proposed improvements in Chapter 6.

4.1.1 Notation

Whole-of-mine

Q	Set of subsystems
E	Set of excavation and haulage subsystems $\subseteq Q$
P	Set of processing plant subsystems $\subseteq Q$
V	Set of stockpile subsystems $\subseteq Q$
B	Set of belt conveyor subsystems $\subseteq Q$
I_q	Set of inlet connection points on subsystem $q \in Q$
J_q	Set of outlet connection points on subsystem $q \in Q$
K	Set of all connection points $\bigcup\limits_{q \in Q} I_q \cup J_q$
C	Set of connections (a pair of one outlet and one inlet connection point)
A	Set of tasks
T	Set of operating states
G	Set of material types / grades
q	Subsystem $\in Q$
q_e	Excavation and haulage subsystem $\in E$
q_p	Processing plant subsystem $\in P$
q_v	Stockpile subsystem $\in V$
q_b	Belt c"onveyor subsystem $\in B$
i	Inlet connection point $\in I_q$
j	Outlet connection point $\in J_q$
k	Connection point, $\in K$
c	Connection, $\in C$
c^{in}	Inlet connection point of connection $c \in C$
c^{out}	Outlet connection point of connection $c \in C$
a	Task, $\in A$
t	Operating state, $\in T$
g	Material type / grade, $\in G$

Excavation and haulage, $\forall q_e \in E$

D_{q_e}	Set of grades extracted from pits $\subseteq G$
R_{q_e}	Set of trucks
S_{q_e}	Set of shovels
r	Truck, $\in R_{q_e}$
s	Shovel, $\in S_{q_e}$

Processing plant, $\forall q_p \in P$

$B_{q_p}^{\text{raw}}$	Set of raw ore grades able to be processed, $\subseteq G$
$B_{q_p}^{\text{prod}}$	Set of product grades, $\subseteq G$
$p_{q_p}^{\text{prod}}$	Product outlet connection point, $\in J_{q_p}$
$p_{q_p}^{\text{waste}}$	Waste outlet connection point, $\in J_{q_p}$
$b_{q_p}^{\text{waste}}$	Grade of waste output from $p_{q_p}^{\text{waste}}$, $\in G$

Stockpile, $\forall q_v \in V$

$B_{q_v}^{\text{stocked}}$	Set of ore grades stockpiled, $\subseteq G$

There are no belt conveyor sets or indices.

4.1.2 Parameters

Whole-of-mine

H_t	Time span of state t (hours)
ζ_a^{start}	State which task a starts in, $\in T$
ζ_a^{stop}	State which task a stops in, $\in T$
ζ_a^{min}	Minimum mass transferred for task a (tonnes)
ζ_a^{max}	Maximum mass transferred for task a (tonnes)
ζ_a^{grade}	Material type / grade transferred for task a, $\in G$
$\zeta_a^{\text{con.p}}$	Connection point of transferred mass for task a, $\in K$

Excavation and haulage, $\forall q_e \in E$

$c_{jiq_e}^{\text{dt}}$	Trip time of trucks driving from j to i (hours)
$c_{ijq_e}^{\text{db}}$	Trip time of trucks driving from i to j (hours)
$c_{igsq_e}^{\text{l}}$	Loading time of shovel s at pit i extracting grade $g \in D_q$ (hours)
γ_{rq_e}	Payload of truck r (tonnes)
$\alpha_{jirq_e}^{\text{tdt}}$	Truck r energy usage per hour driving from j to i (MW)
$\alpha_{ijrq_e}^{\text{tdb}}$	Truck r energy usage per hour driving from i to j (MW)
$\alpha_{rq_e}^{\text{tl}}$	Truck r energy usage per hour idle (MW)
$\alpha_{sq_e}^{\text{sl}}$	Shovel s energy usage per hour loading (MW)
$\alpha_{sq_e}^{\text{si}}$	Shovel s energy usage per hour idle (MW)

Processing plant, $\forall q_p \in P$

$\sigma_{gg'q_p}$ Fraction of $g \in G$ required to produce $g' \in B_q^{\text{prod}}$ (tonnes/tonne)
$\eta_{q_p}^{\min}$ Minimum rate of production output (tonnes/hour)
$\eta_{q_p}^{\max}$ Maximum rate of production output (tonnes/hour)
$\alpha_{q_p}^{\text{ppfixed}}$ Fixed energy usage of plant when operating (MW)
$\alpha_{q_p}^{\text{ppvar}}$ Variable energy usage of plant when operating (MW/(t/h))
$\alpha_{q_p}^{\text{pppc}}$ Energy usage of positive changes to plant load (MWh/(t/h))
$\alpha_{q_p}^{\text{ppnc}}$ Energy usage of negative changes to plant load (MWh/(t/h))

Stockpile, $\forall q_v \in V$

$\pi_{q_v}^{\text{stack}}$ Maximum rate of stacking (tonnes/hour)
$\pi_{q_v}^{\text{reclaim}}$ Maximum rate of reclaiming (tonnes/hour)
$\lambda_{gq_v}^{\min}$ Minimum level of grade $g \in B_{q_v}^{\text{stocked}}$ pile (tonnes)
λ_{g0q_v} Initial (state 0) level of grade $g \in B_{q_v}^{\text{stocked}}$ pile (tonnes)
$\alpha_{q_v}^{\text{stack}}$ Energy usage coefficient of stacking (MW/(t/h))
$\alpha_{q_v}^{\text{reclaim}}$ Energy usage coefficient of reclaiming (MW/(t/h))

Belt conveyor, $\forall q_b \in B$

$\pi_{q_b}^{\text{belt}}$ Maximum rate of flow over belt (tonnes/hour)
$\alpha_{q_b}^{\text{belt}}$ Energy usage coefficient of belt conveyor (MW/(t/h))

4.1.3 Decision variables

Whole-of-mine

θ_{kgt} Mass flow of grade g through connection point k in state t (tonnes/hour)
z_{tq} Energy usage of subsystem q in state t (MWh)

Excavation and haulage, $\forall q_e \in E$

$n_{ijgsrtq_e}$ number of trips r takes of g from s at i to j in state t
v_{ijgrtq_e} Flow of g truck r moves from i to j in state t (tonnes/hour)

$$y_{isq_e} = \begin{cases} 1 & \text{when shovel } s \text{ is allocated to pit } i \\ 0 & \text{otherwise} \end{cases}$$

$$u_{rtq_e}^{\text{truck}} = \begin{cases} 1 & \text{when truck } r \text{ is allocated in state } s \\ 0 & \text{otherwise} \end{cases}$$

Processing plant, $\forall q_p \in P$

$$w_{gtq_p} = \begin{cases} 1 & \text{when plant is producing grade } g \in B_{q_p}^{\text{prod}} \text{ in state } t \\ 0 & \text{otherwise} \end{cases}$$

$d^{+}_{gtq_p}$ Positive change in production of grade $g \in B^{\text{prod}}_{q_p}$ (tonnes/hour)
$d^{-}_{gtq_p}$ Negative change in production of grade $g \in B^{\text{prod}}_{q_p}$ (tonnes/hour)

Stockpile, $\forall q_v \in V$

λ_{gtq_v} Level of $g \in B^{\text{stocked}}_{q_v}$ pile at the end of state t (tonnes)

There are no belt conveyor decision variables, its operation is determined by the mass flow through its connection points, represented by θ_{kgt}, the whole-of-mine decision variable.

4.1.4 Objective

Minimise

$$\sum_{\forall t,q} z_{tq} \tag{4.1}$$

The objective function, (4.1), represents the total energy usage, in MWh, of the mine for minimisation. Each subsystem is responsible for defining its energy usage, z_{tq}; these are all expressed as equality constraints in the following section.

4.1.5 Constraints

Whole-of-mine

These constraints apply at the top, whole-of-system, level of the model where subsystems are connected to one another and work together to achieve the planned tasks.

$$\theta_{c^{\text{out}}gt} = \theta_{c^{\text{in}}gt} \qquad \forall c, g, t \tag{4.2}$$

$$\sum_{t=\zeta_a^{\text{start}}}^{\zeta_a^{\text{stop}}} \left[H_t \theta_{\zeta_a^{\text{con.p}} \zeta_a^{\text{grade}} t} \right] \geq \zeta_a^{\min} \qquad \forall a \tag{4.3}$$

$$\sum_{t=\zeta_a^{\text{start}}}^{\zeta_a^{\text{stop}}} \left[H_t \theta_{\zeta_a^{\text{con.p}} \zeta_a^{\text{grade}} t} \right] \leq \zeta_a^{\max} \qquad \forall a \tag{4.4}$$

$$\theta_{kgt} = 0 \qquad \forall k, t, g \tag{4.5}$$

$$z_{qt} = 0 \qquad \forall q, t \tag{4.6}$$

Constraint (4.2) balances the inlet and outlet connection points of each connection in the model. Constraint (4.3) and (4.4) set the minimum and maximum amount of work required by each task, respectively. Constraint (4.5) and (4.6) ensure non-negative mass flows and energy consumptions, respectively.

Excavation and haulage

As mentioned previously, the excavation and haulage subsystem is first modelled using an allocation formulation based on recent literature (Mena et al., 2013; Sahoo et al., 2014; Souza et al., 2010; Ta et al., 2013). Shovels are allocated to pits and trucks are allocated trips from shovels at those pits to destinations. They work together to dig raw material from the ground and deliver it to the required destinations. Due to the complex nature of the excavation and haulage operation and data availability for the case study, it has the most sophisticated formulation of the four subsystems.

The operation of the subsystem is parameterised by the loading and driving times its equipment achieves when working at particular pits; the truck payloads; and the energy each individual equipment piece consumes while performing different activities. It is important to characterise the energy parameters of each truck individually to ensure the allocated trucks will be the most energy efficient. This can also improve the performance of the optimisation, as it reduces the amount of symmetry in the solution space.

$$\sum_{\forall i,j,g,s} n_{ijgsrtq_e}\left(c^{\mathrm{dt}}_{jiq_e}+c^{\mathrm{l}}_{igsq_e}+c^{\mathrm{db}}_{ijq_e}\right)\le H_t u^{\mathrm{truck}}_{rtq_e} \qquad \forall r,t,q_e \tag{4.7}$$

$$\sum_{\forall i} y_{isq_e}\le 1 \qquad \forall s,q_e \tag{4.8}$$

$$\sum_{\forall j,r} n_{ijgsrtq_e}\le \left\lfloor \frac{H_t}{c^{\mathrm{l}}_{igsq_e}}\right\rfloor y_{isq_e} \qquad \forall i,g,s,t,q_e \tag{4.9}$$

$$\nu_{ijgrtq_e}=\frac{\gamma_{rq_e} n_{ijgsrtq_e}}{H_t} \qquad \forall i,j,g,r,t,q_e \tag{4.10}$$

$$\theta_{igt}=\sum_{\forall j,r}\nu_{ijgrtq_e} \qquad \forall i,g,t,q_e \tag{4.11}$$

$$\theta_{jgt}=\sum_{\forall i,r}\nu_{ijgrtq_e} \qquad \forall j,g,t,q_e \tag{4.12}$$

$$\begin{aligned}
z_{tq_e}=&\sum_{\forall r}\alpha^{\mathrm{tl}}_{rq_e}\left[H_t u^{\mathrm{truck}}_{rtq_e}-\sum_{\forall i,j,g,s} n_{ijgsrtq_e}\left(c^{\mathrm{dt}}_{jiq_e}+c^{\mathrm{db}}_{ijq_e}\right)\right]\\
&+\sum_{\forall i,j,g,s} n_{ijgsrtq_e}\left(\alpha^{\mathrm{tdt}}_{jirq_e}c^{\mathrm{dt}}_{jiq_e}+\alpha^{\mathrm{tdb}}_{ijrq_e}c^{\mathrm{db}}_{ijq_e}\right)\\
&+\sum_{\forall i,j,g,s,r}\alpha^{\mathrm{sl}}_{sq_e}c^{\mathrm{l}}_{igsq_e}n_{ijgsrtq_e}\\
&+\sum_{\forall i,s}\alpha^{\mathrm{si}}_{sq_e}\left[H_t y_{isq_e}-\sum_{\forall j,g,r}c^{\mathrm{l}}_{igsq_e}n_{ijgsrtq_e}\right]
\end{aligned} \qquad \forall t,q_e \tag{4.13}$$

Constraint (4.7) ensures a truck isn't allocated for more than the available time in each state. Constraint (4.8) ensures shovels are allocated only once. Constraint (4.9) sets the relationship between $n_{ijgsrtq_e}$ and y_{istq_e} and limits the number of trucks allocated to a pit over time to avoid wasteful queues and over allocation of shovels. Constraints (4.10), (4.11) and (4.12) translate the allocations into mass flow rates for the subsystem's inlet and outlet connection points. Constraint (4.13) represents the energy consumption of the excavation and haulage subsystem; made up of truck idle energy consumption, truck driving energy consumption, energy from shovel loading and the idle energy consumption of the shovel. Trucks are considered idle for all times they are not driving, during a state they're used in.

Processing plant

A general formulation of the processing plant, extended from Middelberg et al. (2009), has been developed to align with the objective of creating a generic enough model for reusability on other mines and to suit the limited data available for the case study in this thesis. The formulation assumes known ratios for inlet grades (including water) to outlet product grades and waste and decides the product grade output and how much is produced.

$$\theta_{p_{q_p}^{\text{prod}} g t} \geq w_{g t q_p} \eta_{q_p}^{\min} \qquad \forall g \in B_{q_p}^{\text{prod}}, t, q_p \tag{4.14}$$

$$\theta_{p_{q_p}^{\text{prod}} g t} \leq w_{g t q_p} \eta_{q_p}^{\max} \qquad \forall g \in B_{q_p}^{\text{prod}}, t, q_p \tag{4.15}$$

$$\sum_{\forall g \in B_{q_p}^{\text{prod}}} w_{g t q_p} \leq 1 \qquad \forall t, q_p \tag{4.16}$$

$$\sigma_{g g' q_p} \theta_{p_{q_p}^{\text{prod}} g' t} = \sum_{\forall i} \theta_{i g t} \qquad \forall g, g' \in B_{q_p}^{\text{prod}}, t, q_p \tag{4.17}$$

$$\theta_{p_{q_p}^{\text{waste}} b_{q_p}^{\text{waste}} t} = \sum_{\forall i, g} \theta_{i g t} - \sum_{\forall g \in B_{q_p}^{\text{prod}}} \theta_{p_{q_p}^{\text{prod}} g t} \qquad \forall t, q_p \tag{4.18}$$

$$d_{g t q_p}^{+} - d_{g t q_p}^{-} = \theta_{p_{q_p}^{\text{prod}} g t} - \theta_{p_{q_p}^{\text{prod}}, g, t-1} \qquad \forall g \in B_{q_p}^{\text{prod}}, t < |T|, q_p \tag{4.19}$$

$$\begin{aligned} z_{t q_p} = H_t \sum_{\forall g \in B_{q_p}^{\text{prod}}} \Big[& \alpha_{q_p}^{\text{ppfixed}} w_{g t q_p} + \alpha_{q_p}^{\text{ppvar}} \theta_{p_{q_p}^{\text{prod}} g t} \\ & + \alpha_{q_p}^{\text{pppc}} d_{g t q_p}^{+} + \alpha_{q_p}^{\text{ppnc}} d_{g t q_p}^{-} \Big] \end{aligned} \qquad \forall g \in B_{q_p}^{\text{prod}}, t < |T|, q_p \tag{4.20}$$

Constraints (4.14) and (4.15) sets the minimum and maximum operating capacity, respectively, as well as the boolean variable for the operating mode of plant, $w_{g t q_p}$. This boolean variable is further constrained in (4.16), which ensures a maximum of one grade is produced at a time. Constraints (4.17) and (4.18) are mass balances for product output and waste output, respectively. Constraint (4.19) sets the positive and negative changes in production rate between states. Constraint (4.20) sets the energy consumption of the plant, made up of fixed consumption when in operation, a variable consumption proportional to the plant load and the extra energy consumed due to changing the plant load between states.

Stockpile

The stockpile formulation has been developed to apply to many different stockpiles. A network flow model with inventory is used as the basis for the formulation, similar to Ta et al. (2005) and Hanoun et al. (2013). Multiple grades can be stored by each stockpile subsystem.

$$
\begin{aligned}
\sum_{\forall i,g} \theta_{igt} \leq& \pi^{\text{stack}}_{q_v} && \forall t, q_v && (4.21)\\
\sum_{\forall j,g} \theta_{jgt} \leq& \pi^{\text{reclaim}}_{q_v} && \forall t, q_v && (4.22)\\
\lambda_{gtq_v} \geq& \lambda^{\min}_{gq_v} && \forall g \in B^{\text{stocked}}_{q_v}, t, q_v && (4.23)\\
\lambda_{gtq_v} =& \lambda_{g,t-1,q_v} m + H_t \sum_{\forall i} \theta_{igt} - H_t \sum_{\forall j} \theta_{jgt} && \forall g \in B^{\text{stocked}}_{q_v}, t, q_v && (4.24)\\
z_{tq_v} =& H_t \alpha^{\text{stack}}_{q_v} \sum_{\forall i,g} \theta_{igt} + H_t \alpha^{\text{reclaim}}_{q_v} \sum_{\forall j,g} \theta_{jgt} && \forall t, q_v && (4.25)
\end{aligned}
$$

Maximum stacking and reclaiming rates are enforced by constraints (4.21) and (4.22) respectively. Constraint (4.23) places a minimum allowable stockpile level for each stored grade. Constraint (4.24) represents the mass balance of the subsystem, including the holdup of stocked material. The energy consumption of the stacking and reclaiming activity is expressed in Constraint (4.25).

Belt conveyor

Belt conveyors are formulated as network flow models without inventory constraints, similar to Middelberg et al. (2009).

$$
\begin{aligned}
\theta_{\forall i,g} \leq& \pi^{\text{belt}}_{q_b} && \forall t, q_b && (4.26)\\
\sum_{\forall i} \theta_{igt} =& \sum_{\forall j} \theta_{jgt} && \forall g, t, q_b && (4.27)\\
z_{tq_b} =& H_t \alpha^{\text{belt}}_{q_b} \sum_{\forall i,g} \theta_{igt} && \forall g \in B^{\text{stocked}}_{q_v}, t, q_b && (4.28)
\end{aligned}
$$

Constraint (4.26) represents the maximum mass flow rate over belt conveyor. Constraint (4.27) is the mass balance equality for the subsystem and the energy usage, proportional to load, is set in Constraint (4.28).

4.2 Validation

In this section the simple example mine that demonstrated the application process in Section 3.3 will be used to validate the results of the integrated model presented in the previous section. For all instances in this section, the model has been solved using IBM CPLEX

Optimizer on an Intel i7 CPU with 16GB of RAM. The first problem instance comes from fitting the model with the parameters and tasks as they are described in Section 3.3. Two 1-hour time states are used and the tasks are re-listed below in Table 4.1. The problem instance has 928 variables and 789 constraints; it is solved to optimality in 468.43 seconds.

Table 4.1. Simple example task list

Task #	Connection point	Material grade	Amount (t)	Start time (hr)	End time (hr)
1	Extraction pit 1	ROM	3,000	0	2
2	Extraction pit 2	Overburden	3,000	0	2
3	Processing plant product outlet	Product	2,000	0	2

The subsystem energy usages are reported in Table 4.2. It can be seen that the largest consumers of energy are the extraction subsystem and processing plant, which is consistent with expectations.

Table 4.2. Energy consumption (MWh)

Subsystem	State 1 (0-1hr)	State 2 (1-2hr)	All time
Belt conveyor	0.15	0.15	0.29
Extraction	9.03	7.72	16.75
Pit 1	0.00	0.00	0.00
Pit 2	0.00	0.00	0.00
Processing plant	8.52	8.52	17.05
Stockpile	0.29	0.15	0.44
Waste dump	1.06	0.93	1.99
Whole mine	19.05	17.47	36.52

Table 4.3 shows the material transferred over each connection between the subsystems and on the model's boundary connection points. The three production targets, underlined, that are entered as input into the model as tasks have all been met. The overall excavation and haulage work is fairly evenly split between the two hours, with slightly more work being done in the first state. This is reflected in where the processing plant gets its ROM input. The processing plant input is supplemented by the ROM stockpile more in the second hour when the haulage and excavation reduces its ROM extraction, which is the expected behaviour of an operating mine. This validates that the mass balance constraints across the various subsystems are working as expected.

Table 4.3. Total material transferred (tonnes)

Connection	Grade	State 1 (0-1hr)	State 1 (1-2hr)	All time
belt conveyor out	Product	1,000.00	1,000.00	2,000.00
extraction→processing plant	ROM	1,220.00	1,190.00	2,410.00
extraction→stockpile	ROM	440.00	220.00	660.00
extraction→waste dump	Ovb.	1,600.00	1,410.00	3,010.00
extraction pit 1 in	ROM	1,660.00	1,410.00	3,070.00
extraction pit 2 in	Ovb.	1,600.00	1,410.00	3,010.00
processing plant→belt conveyor	Product	1,000.00	1,000.00	2,000.00
processing plant tailings out	Tailings	292.15	292.15	584.30
processing plant water in	Water	69.15	69.15	138.30
stockpile→processing plant	ROM	3.00	33.00	36.00

Table 4.4 shows the truck allocations over the period. The number of times it makes a particular trip (inlet/outlet pair) is displayed for each state. There are 26 trips made across the two hours. ROM is being extracted from pit 1; ten trips are made to the processing plant (PP) and three are made to the stockpile (SP). The remaining thirteen are transporting overburden (Ovb.) from pit 2 to the waste dump (WD). Truck 3, the least efficient truck, is not used at all, while truck 5 is only used in the first hour. The other trucks all make six trips each, three in each hour.

Table 4.4. Truck allocation

State	State 1 (0-1hr)			State 1 (1-2hr)			
Shovel	1	2		1	2		All
Grade	Ovb.	ROM		Ovb.	ROM		time
Inlet	Pit 2	Pit 1		Pit 2	Pit 1		&
Outlet	WD	PP	SP	WD	PP	SP	trips
Truck 1	1	2	0	0	3	0	6
Truck 2	1	2	0	3	0	0	6
Truck 3	0	0	0	0	0	0	0
Truck 4	2	0	1	1	1	1	6
Truck 5	1	0	1	0	0	0	2
Truck 6	2	1	0	2	1	0	6
All trucks	7	5	2	6	5	1	26

To further analyse the model, instances of varying sizes have been solved. Table 4.5 shows the objective values and CPU times from solving several small instances based on the simple example introduced in Section 3.3. They have been solved to optimality with CPLEX, the computation times are also listed.

Table 4.5. Computational results (simple example instances)

id	states	shovels	trucks	pit target (t)	product target (t)	obj. (MWh)	CPU sec.
4.01	1	1	2	(1500)	1,000	12.70	0.27
4.02	1	1	4	(2500)	2,000	22.34	0.26
4.03	1	1	6	(3250)	2,000	24.15	0.27
4.04	1	2	2	(750, 500)	500	9.75	0.34
4.05	1	2	4	(1000, 1000)	500	12.94	0.36
4.06	1	2	6	(1500, 1500)	1,000	19.10	0.26
4.07	2	1	2	(3000)	2,000	25.39	0.26
4.08	2	1	4	(5000)	4,000	43.19	0.26
4.09	2	1	6	(7000)	6,000	61.54	0.26
4.10	2	2	2	(1000, 1000)	500	16.77	0.37
4.11	2	2	4	(2000, 2000)	1,000	24.38	1.16
4.12	2	2	6	(3000, 3000)	2,000	36.52	468.43

As these instances do not reflect practically sized problems, they do not give an indication of the effectiveness of CPLEX as a solution approach. Using the case study, described in detail in Chapter 5, several more instances are solved to examine the quality and speed of CPLEX for a more realistic problem size. Table 4.6 describes the problem instances to give an indication of size. For these problems, 2 hour operating states are used. Table 4.7 presents the results of solving the CPLEX with a 1-hour and 2-minute time limit, as well as the best known lower bound (LB) reported by CPLEX.

Table 4.6. Case study instance descriptions

id	states	shovels	trucks	pit target (t)	product target (t)
4.13	2	2	10	(5000, 5000)	1,000
4.14	2	2	15	(7500, 7500)	2,500
4.15	2	2	20	(10000, 10000)	5,000
4.16	2	4	10	(2500, 2500, 2500, 2500)	1,000
4.17	2	4	15	(3750, 3750, 3750, 3750)	2,500
4.18	2	4	20	(5000, 5000, 5000, 5000)	4,000
4.19	4	2	10	(10000, 10000)	2,500
4.20	4	2	15	(15000, 15000)	5,000
4.21	4	2	20	(20000, 20000)	10,000
4.22	4	4	10	(5000, 5000, 5000, 5000)	2,000
4.23	4	4	15	(7500, 7500, 7500, 7500)	5,000
4.24	4	4	20	(10000, 10000, 10000, 10000)	8,000

Table 4.7. Computational results (case study instances)

id	Best known LB (MWh)	CPLEX 1hr time limit obj. (MWh)	CPLEX 1hr time limit % gap	CPLEX 2min time limit obj. (MWh)	CPLEX 2min time limit % gap
4.13	65.40	65.40	0.00%	65.40	0.00%
4.14	90.01	90.19	0.20%	90.20	0.21%
4.15	128.27	128.54	0.21%	128.55	0.22%
4.16	73.11	73.27	0.22%	73.27	0.22%
4.17	99.34	99.51	0.17%	99.51	0.17%
4.18	132.85	133.09	0.18%	133.09	0.18%
4.19	130.75	131.01	0.20%	131.01	0.20%
4.20	179.76	180.15	0.22%	180.23	0.26%
4.21	255.98	256.82	0.33%	256.82	0.33%
4.22	145.08	145.38	0.21%	145.38	0.21%
4.23	197.49	197.95	0.23%	198.01	0.26%
4.24	265.13	265.79	0.25%	265.79	0.25%

It is clear from Table 4.7 that CPLEX is able to find a good quality solution within 2 minutes to these instances. This indicates it is an appropriate method for solving the model for practical sized problems. It will therefore be used to solve the case study analysis in Chapter 5.

4.2.1 Issues

While the model produces sensible solutions and justifies its application to a real life case study, there are a number of drawbacks of using allocation to model the excavation and haulage subsystem that will impact its accuracy, as mentioned in Subsection 2.4.2 of the literature review. They relate to the lack of sequence and time information considered in the formulation.

The issues can be demonstrated using the first instance, 4.01, from the above computational analysis. For this instance, the optimal result involves 6 trips, three from each truck. Table 4.8 shows the trips they are required to make.

Table 4.8. Instance 4.01 truck allocations

State	State 1 (0-1hr)	
Shovel	1	
Grade	ROM	
Inlet	Pit 1	
Outlet	PP	SP
Truck 1	3	0
Truck 2	2	1
All trucks	5	1

Since these trips are all to a single shovel, they physically cannot happen at the same time. This means they must happen in sequence. However, the current, allocation based, model formulation doesn't indicate the sequence. This results in accuracy limitations that impact both optimality and feasibility.

The first is that the time between different trips may be different, which will therefore impact the amount of time the truck is driving. This is illustrated in Figure 4.1 by considering two of the trips truck 2 needs to make – pit 1 to the processing plant and pit 1 to the ROM stockpile – and applying the driving time parameters outlined in Subsection 3.3.5. From this simple example, it is clear that different trip sequences may result in differences in driving times. By not considering this properly, the accuracy of the objective and feasibility are both impacted. Firstly, the truck driving component of the objective will not take into consideration the potential differences in driving times. Secondly, if these differences in times are large enough, it may be the difference between enough and not enough time for a trip to happen feasibly.

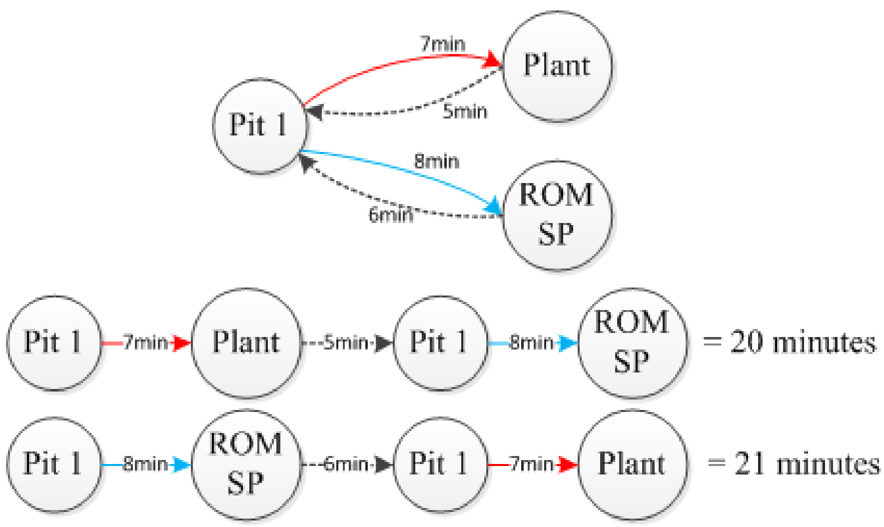

Figure 4.1. Driving time differences between trip orders

The second issue is that the model cannot properly account for truck waiting time. This can be demonstrated by manually scheduling the trips described in Table 4.8. Figure 4.2, Figure 4.3 and Figure 4.4 illustrate three possible schedules that result from sequencing the optimal truck allocations from instance 4.01. Black indicates the times when trucks are being loaded by shovels; the coloured blocks represent when trucks are loaded and driving to the destination; grey blocks of time are when the truck is then driving from its last destination to the next pit; time between grey and the next loading is when trucks are waiting. It is clear from these three possible schedules that the sequence can have a large impact on truck waiting time. This will impact accuracy of both the optimality and feasibility. Trucks waiting at shovels will consume idle energy that isn't currently accurately being accounted for in the objective function. Depending on the amount of truck waiting time, the ability for a given trip to happen in a state can also be impacted, which may cause infeasibilities.

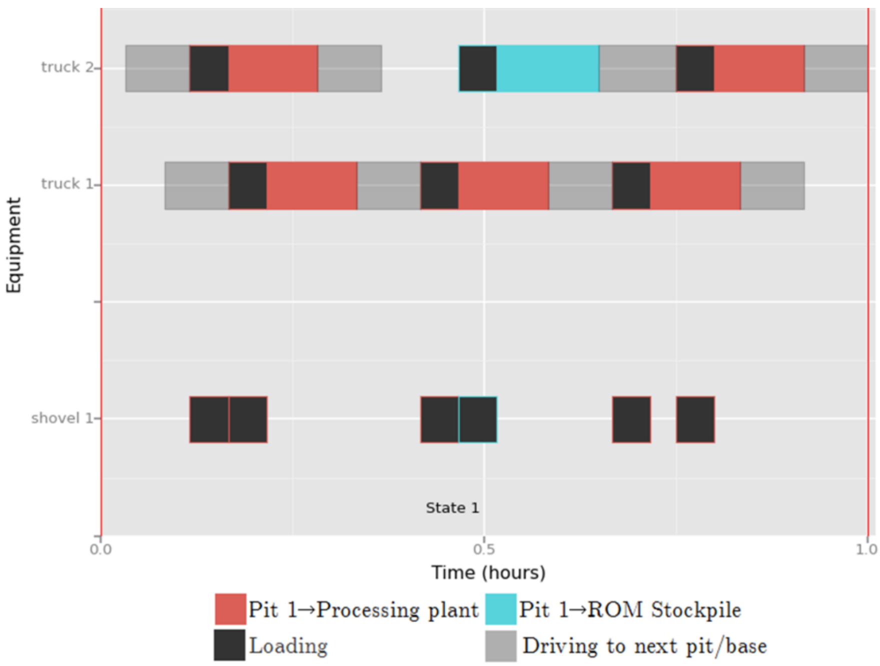

Figure 4.2. Instance 4.01 – Feasible schedule 1

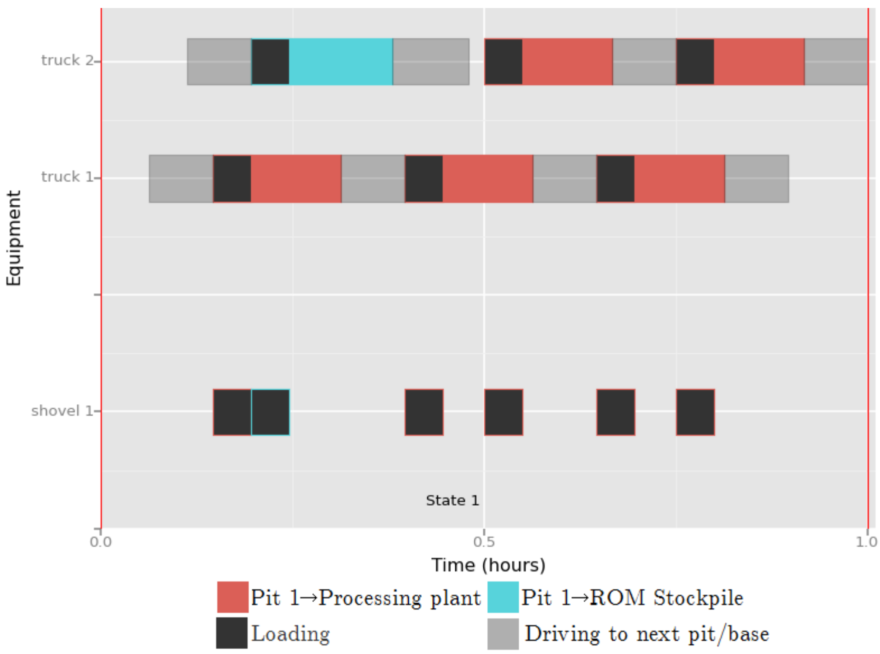

Figure 4.3. Instance 4.01 – Feasible schedule 2

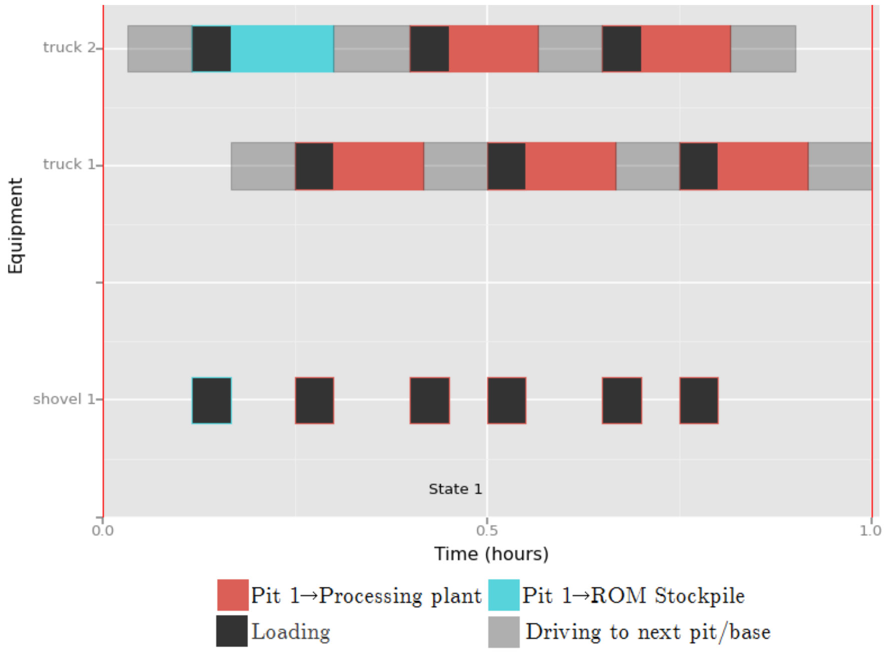

Figure 4.4. Instance 4.01 – Feasible schedule 3

Another issue that is demonstrated in the above schedules, is the ability to properly consider the trucks travelling from base at the start, back to base at the end, and potentially to and fro during the shift. This is also not being considered by the current formulation.

4.3 Remarks

This chapter has successfully applied the conceptual methodology described in Chapter 3 and presented an integrated model of an open-pit coal mine. The four subsystems have been formulated in line with models from recent literature and integrated into a single MILP formulation. The modelling framework has been shown to be effective at decoupling subsystem formulations and supporting model generalisation to allow for application to different mines.

While validation of the model showed it produces sensible results, issues with the excavation and haulage allocation formulation have been highlighted. A small problem instance has been analysed to demonstrate the issues. They relate to the fact that the allocation formulation does not give the sequence or times of truck trips from shovels to destinations.

The first is that a truck making different trip types may drive for different amounts of time depending on the sequence in which it does the trips. Since the time of a trip being allocated to a truck isn't known for sure without sequence, the energy of driving cannot be accurately modelled in the objective, and the feasibility of assigning trucks to trips cannot be guaranteed.

The second issue is related to the synchronicity between trucks and shovels. Without knowing the order and time of trips, the formulation cannot properly model the loading interaction between the shovels and trucks. Most importantly this means waiting times are not accounted for, which also impacts the objective value and feasibility.

While these issues are important to overcome, the model can still give useful results for providing decision support to operators for making energy efficiency improvements, as do the other models in literature with similar limitations. Hence before they are overcome, a real life case study will be analysed with the model presented in this chapter. This will also be useful for reinforcing the importance of improving the model by asserting their existence in a real life application.

The contribution of this chapter, referring back to the research approach described in Section 1.5, relates to the inner part of the top right quadrant of Figure 4.5. Since the model in its current form does not appear too complex for exact techniques to solve optimally in practical time for real life sized problems, the bottom right quadrant of Figure 4.5 can be trivially replaced with the IBM CPLEX Optimizer for now. This does not mean the complexity and solution approach related hypotheses have been disproved. Rather, the research approach was designed to be an iterative process. Due to the limitations of the model presented in this chapter and expanded upon in the next, the model will be revisited in Chapter 6 to formulate an improved, complex model, which will require the work earmarked by the bottom right quadrant of Figure 4.5 to properly further test the hypotheses.

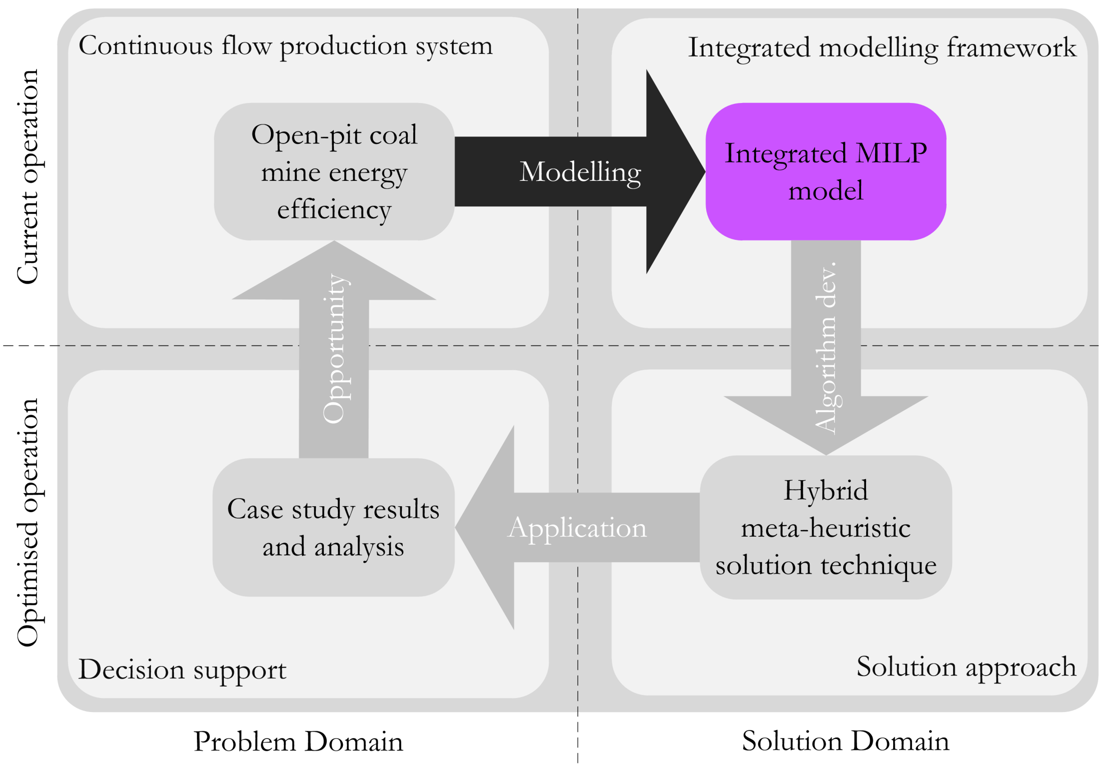

Figure 4.5. Role of Chapter 4 in the research approach

This chapter has further addressed research questions 2a, 2b and 2c from Section 1.2, listed below, by using the modelling framework to build a formulation with various levels of detail, complexity and generalisability. The excavation and haulage subsystem is where the majority of detail and complexity exists in the model and is also where accuracy issues have arisen. This will be the focus of later improvements where these questions will be revisited again.

2. *What integrated optimisation model of energy efficiency is appropriate for an open-pit coal*

mine production system?

(a) *What level of detail is required of the model?*

(b) *Where are the main points of model complexity?*

(c) *How general should the model be?*

5

Case Study

This chapter conducts a case study on a real life open-pit coal mine to verify and validate the developed model and methodologies. The mine being studied is an open-pit coal mine in south east Queensland, Australia, named Meandu Mine.

All of the product coal produced by Meandu Mine is delivered via belt conveyor to Tarong Power Station, an adjacent coal-fired power station. The mine and power station are both owned by Stanwell Corporation, a Queensland Government owned corporation. A private, company, Downer Mining, a subsidiary of Downer EDI Limited, is contracted by Stanwell to operate the mine. The data and information provided for this case study has come from contacts within Downer Mining working at Meandu Mine.

This chapter first follows the process described in Section 3.3 to fit the integrated model presented in Section 4.1 to the mine. It then details the results of a scenario analysis that has been conducted to verify and validate the accuracy of the model and its solutions. The chapter concludes by highlighting issues with the current model that were found throughout the results which motivate modifications made in the next chapter.

5.1 Apply the integrated model

5.1.1 Gather production system information

Information about Meandu Mine was gathered from a number of different sources. Various reports and plans were provided upfront from the mine. This was followed by a mine visit that involved discussion with managers from both the extraction and CHPP sides of the mine and a tour of the mine through the majority of its operations. The initial provision of data was very useful in ensuring relevant and valuable discussion could be had during the mine visit. Together, these formed enough information to answer all the necessary questions in the first step of the application process, and were valuable for the later stage of parameterising the model.

The remainder of this section will outline the answers to the questions described in Subsection 3.3.1.

Whole-of-mine questions

What are the boundaries of the mine?

> The following figures are satellite images of Meandu Mine. Figure 5.1 shows the whole mine, while Figure 5.2 shows just the CHPP setup of the mine, boxed in red in Figure 5.1).
>
> The mine extracts from five pit faces, and has one product load out belt conveyor.

Figure 5.1. Meandu mine satellite image (Maps, 2014)

Figure 5.2. Meandu mine CHPP satellite image (Maps, 2014)

What systems perform the majority of the work?

Meandu is a fairly typical open-pit coal mine, it has a drilling and blasting operations, dragline, loaders extracting the material from the face, trucks transporting it to be handled or dumping waste, and a CHPP.

The CHPP at Meandu Mine could be considered as a single subsystem, however, there is a stockpile between the crusher and wash plant, and so for the purposes of this case study, to get a better picture of the activity of the CHPP operation, two processing plants will be considered (a crusher and a wash plant) along with the intermediate stockpile and a number of belt conveyors.

What are the main energy consumers of the mine?

The energy is primarily consumed by the operations listed in the above question.

How many different types material are transported between systems?

There are a number of different materials which are handled throughout the main operations of the mine, these are:

- Run of Mine (ROM) coal
- Crushed ROM coal
- Product coal
- Overburden
- Spoil (similar to overburden)
- Top soil
- Tailings
- Water

Note: Spoil is overburden material that has been dumped on previously uneconomical coal, which has now been determined to be economical. The distinction between spoil and overburden is made by the mine since spoil is already soft and does not need to be blasted. This is an example of the external factor, 'operational history', mentioned SubSection 2.3.7, having an impact on current operation.

Excavation and haulage questions

What are the boundaries of the subsystem?

There are five pit faces that are extracted from. These make up the inlets to the extraction subsystem.

The ROM coal is delivered either to a stockpile or directly to a belt conveyor going to the CHPP; these make up the first two outlets of the extraction system.

On top of those outlets, there are a number of places that are used to dump waste material. While there are more than five destinations for waste it is not normal for the mine to be delivering to all of them, so only a few are required; for the purposes of this model, there will be three waste dumps for overburden and spoil, and one top soil waste dump.

This makes for six outlets.

What grades are being extracted?

ROM coal, overburden, spoil and top soil are the grades being extracted from the pits.

How many loaders are there?

There are four loaders: two EX3600 Hitachi Excavators, one EX5500 Hitachi Excavator and one EX3500 Hitachi Shovel.

How many trucks are there?

> There are 20 trucks, six Komatsu 830E DC, eight Komatsu 630E DC and six Komatsu 830E AC.

Processing plant questions

As mentioned earlier, two processing plants are being considered for this modelling exercise: the crusher and wash plant.

What are the boundaries of the subsystem?

> The crusher is fed a belt conveyor and outputs to another belt conveyor.
>
> The wash plant is also fed input material from a single conveyor, has another input for water and has two outputs, one for product and the other for tailings.

What materials can be processed?

> The crusher processes ROM coal from the pits.
>
> The wash plant processes crushed ROM coal and also consumes water.

What materials are produced?

> Crushed ROM coal is produced by the crusher.
>
> Product coal and tailings are output from the wash plant.

Stockpile questions

There are seven stockpile subsystems being considered for the model, five of which are different waste dumps, the sixth is for ROM coal and the seventh is for crushed ROM coal. There is no storage of product at Meandu Mine.

What are the boundaries of the subsystem? / What grades are stored in the stockpile?

> The five waste dumps each have only a single input, delivering the waste material from either trucks (for the top soil dump and three waste dumps) or from the conveyor transporting tailings out of the wash plant. The top soil dump is filled with top soil material. The three regular waste dumps are filled with either overburden or spoil material. The tailings dump is filled with tailings material.
>
> The ROM stockpile has a single inlet, being fed from the extraction subsystem and a single outlet feeding the crusher inlet conveyor. It stores ROM coal material.
>
> The crushed ROM stockpile has a single inlet from the crusher outlet conveyor and a single outlet to the wash plant inlet conveyor. It stores crushed ROM coal straight from the crusher.

Belt conveyor questions

There are five conveyors being considered for the Meandu Mine mode.

What are the boundaries of the subsystem? / What grades can be transported over the belt conveyor?

> The conveyor transporting ROM coal to the crusher has two inlets coming from the extraction subsystem and the ROM stockpile and has a single outlet feeding the crusher. It transports ROM coal.
>
> Crushed ROM coal can bypass washing and be fed directly to the product load out conveyor; therefore the conveyor that has the crusher output as its inlet has two outlets, one going to the crushed ROM stockpile, the other to the product delivery conveyor. It transports crushed ROM coal.
>
> The conveyor between the crushed ROM stockpile and the wash plant has a single inlet and a single outlet. It transports crushed ROM coal.
>
> The conveyor transporting tailings out of the wash plant to the tailings dump also has a single inlet and a single outlet. It transports tailings material.
>
> The product delivery conveyor is fed by either the crusher outlet conveyor or from the wash plant and has a single outlet to Tarong Power Station, which represents the output boundary of the whole mine model. It transports either product coal or crushed ROM coal.

Other subsystem questions

There are no other subsystems required to be modelled for this case study.

5.1.2 Outline process flow of system

Using the information gathered in step one of the process, the process flow of the system being modelled can be determined. Figure 5.3 is a process flow diagram (PFD) representing each subsystem that will be modelled and the material connections between them.

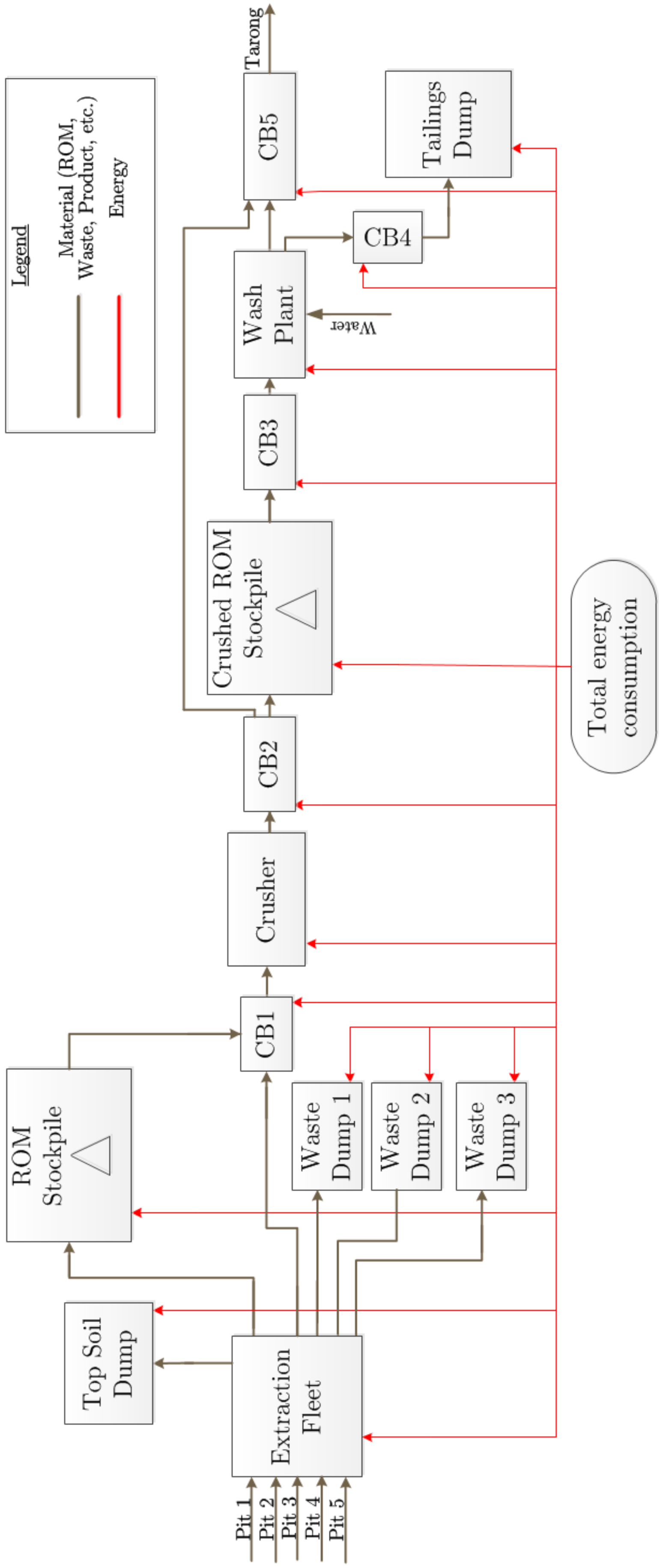

Figure 5.3. Meandu mine process flow diagram (Maps, 2014)

5.1.3 Formulate new subsystem model(s) (if required)

Each of these subsystems can be modelled with one of the four modules developed for this research, so there is no requirement for new subsystem modelling.

5.1.4 Apply structural information to integrated model

By examining the gathered information and generated process flow diagram, each of the sets, which define the structure of the integrated model, can now be defined. The tables in Appendix A show the values entered for each of the sets.

5.1.5 Enter subsystem parameter values

See Appendix B for data tables containing the parameter values for each subsystem.

5.1.6 Enter shift production targets and define operating states

A monthly production plan was provided by Meandu Mine. A typical 8 hour time period was selected from the plan and the activities relevant to the modelled operations of the mine were entered as tasks, seen in Table 5.1.

Table 5.1. Production target tasks

Task #	Start time (hr)	Stop time (hr)	Grade	Connection	Mass (t)
1	0	8	Overburden	Extraction pit 1 inlet	8,000
2	0	8	ROM	Extraction pit 2 inlet	10,000
3	0	8	Spoil	Extraction pit 3 inlet	14,000
4	0	8	Product	Wash plant outlet	8,000

A time resolution of two-hour steps over the eight hour period of production will be used for this case study. This has been selected as a reasonable resolution to reflect the on-site decisions which the model aims to provide assistance for.

5.1.7 Formulate new task(s) (if required)

Each of the four tasks detailed above fit into the existing model of a task, so no new tasks are required to be modelled for this case study.

5.1.8 Solve

Solving this model can be performed with IBM ILOG CPLEX. An Intel i7 CPU with 16GB of RAM for 2 minutes is used to find the solutions. Section 5.3 presents the results obtained by solving the model using the production targets mentioned previously, along with some scenario analysis.

5.2 Additional constraints

Following the model application process worked well for creating the integrated model of the primary operations of the case study mine. There are, however, three extra sets of constraints that the model has been appended with, to make it represent the case study mine's operation more realistically.

The first additional constraints, 5.1–5.4, set the shovel allocation decision variables to known locations. This was done since Meandu already knows their shovel allocations in advance as part of their plan, and is therefore not an operational decision, so not required to be a decision variable for this particular model. Constraint 5.1 allocates shovel 1 to pit 2; Constraint 5.2 allocates shovel 2 to pit 3; Constraint 5.3 ensures shovel 3 is allocated to no pits; and Constraint 5.4 allocates shovel 4 to pit 1.

$$y_{\text{pit 2,shovel 1},t,q_e} = 1 \qquad \forall t \tag{5.1}$$
$$y_{\text{pit 3,shovel 2},t,q_e} = 1 \qquad \forall t \tag{5.2}$$
$$y_{i,\text{shovel 3},t,q_e} = 0 \qquad \forall i,t \tag{5.3}$$
$$y_{\text{pit 1,shovel 4},t,q_e} = 1 \qquad \forall t \tag{5.4}$$

The second set of constraints that have been added, Constraints 5.5 and 5.6, blocks the extraction subsystem from delivering waste to waste dump 2 and 3. Much like the shovel allocation constraint added, the destination of waste is known in advance as part of the mine plan and is therefore not an operational decision to be made. For this operating shift, all waste is delivered to waste dump 1, and hence the flow into the other two waste dumps is set to zero.

$$\theta_{\text{extraction} \to \text{waste dump 2},g,t} = 0 \qquad \forall g \in D_{q_e}, t \tag{5.5}$$
$$\theta_{\text{extraction} \to \text{waste dump 3},g,t} = 0 \qquad \forall g \in D_{q_e}, t \tag{5.6}$$

The final extra constraints, 5.7 and 5.8, ensures the wash plant and crusher, respectively, are always on. This has been done to better reflect the actual operation of the two subsystems at the mine.

$$w_{\text{crushed ROM},t,\text{crusher}} = 1 \qquad \forall t \tag{5.7}$$
$$w_{\text{product},t,\text{wash plant}} = 1 \qquad \forall t \tag{5.8}$$

5.3 Results

The case study is first solved to find a benchmark for the analysis. Sensitivity to product demand is then investigated, followed by an analysis of the impact each truck has on the solution, and a look at the current issues with the model. IBM CPLEX Optimizer on an

Intel i7 CPU with 16GB of RAM for 2 minutes is used to find the solutions. The CPLEX solution gaps were below 1% for all instances.

5.3.1 Benchmark solution

Using the information provided by the mine's operator, the benchmark solution for the rest of the analysis was found. Table 5.2 shows the energy consumption of each subsystem. Using the general definition of energy efficiency introduced in Section 2.2 (product output divided by energy input) the energy efficiency of this result is 35.46 product tonnes per megawatt hour (Product t/MWh). The extraction subsystem accounts for the large majority of energy consumption, which is in line with information from site. Second and third are the crusher and wash plant, respectively, which is also consistent with expectation.

Table 5.2. Benchmark energy consumption (MWh)

Subsystem	State 1 (0-2hr)	State 2 (2-4hr)	State 3 (4-6hr)	State 4 (6-8hr)	All time
ROM stockpile	0.00	0.29	0.01	0.01	0.32
CB1	0.12	0.12	0.12	0.12	0.46
CB2	0.46	0.46	0.46	0.46	1.85
CB3	0.39	0.39	0.39	0.39	1.54
CB4	0.67	0.67	0.67	0.67	2.66
CB5	0.59	0.59	0.59	0.59	2.36
Crushed ROM stockpile	1.97	1.97	1.97	1.97	7.89
Crusher	7.18	7.18	7.18	7.18	28.72
Extraction	35.36	31.88	34.34	31.40	132.98
Tailings dump	0.06	0.06	0.06	0.06	0.23
Top soil dump	0.00	0.00	0.00	0.00	0.00
Wash plant	6.15	6.15	6.15	6.15	24.58
Waste dump 1	6.00	5.00	5.85	5.17	22.02
Waste dump 2	0.00	0.00	0.00	0.00	0.00
Waste dump 3	0.00	0.00	0.00	0.00	0.00
Whole mine	58.94	54.75	57.78	54.16	225.63

Table 5.3 shows the amount of material transferred over each connection. The demand and production targets have all been met and are marked in bold in the last column. The ROM stockpile increases from 21000 tonnes to 21256 tonnes, 1.2%, over the 8 hour period, indicating that the extraction targets are fairly well balanced with the product demand well.

Table 5.3. Benchmark material transfer over connections (tonnes)

Connection	Grade	State 1 (0-2hr)	State 2 (2-4hr)	State 3 (4-6hr)	State 4 (6-8hr)	All time
ROM Stockpile→BC1	ROM	26	6	76	76	184
BC1→Crusher	ROM	2446	2446	2446	2446	9784
BC2→Crushed ROM stockpile	Crushed ROM	2446	2446	2446	2446	9784
BC2→BC5	-	0	0	0	0	0
BC3→Wash plant	Crushed ROM	2446	2446	2446	2446	9784
BC4→Tailings dump	Tailings	584.3	584.3	584.3	584.3	2337.2
BC5 outlet	Product	2000	2000	2000	2000	8000
Crushed ROM stockpile→BC3	Crushed ROM	2446	2446	2446	2446	9784
Crusher→BC2	Crushed ROM	2446	2446	2446	2446	9784
Crusher waste outlet	-	0	0	0	0	0
Extraction→ ROM stockpile	ROM	0	440	0	0	440
Extraction→ BC1	ROM	2420	2440	2370	2370	9600
Extraction→ Top soil dump	-	0	0	0	0	0
Extraction→ Waste dump 1	Overburden & Spoil	6000	5000	5850	5170	22020
Extraction→ Waste dump 2	-	0	0	0	0	0
Extraction→ Waste dump 3	-	0	0	0	0	0
Extraction pit 1	Overburden	2020	1700	2550	1750	8020
Extraction pit 2	ROM	2420	2880	2370	2370	10040
Extraction pit 3	Spoil	3980	3300	3300	3420	14000
Extraction pit 4	-	0	0	0	0	0
Extraction pit 5	-	0	0	0	0	0
Wash plant→BC5	Product	2000	2000	2000	2000	8000
Wash plant water in	Water	138.3	138.3	138.3	138.3	553.2
Wash plant→BC4	Tailings	584.3	584.3	584.3	584.3	2337.2

Table 5.4 shows the truck allocations for the benchmark problem instance. A total of 158 trips are made by trucks in the excavation and haulage subsystem, made up of 46 trips transporting overburden from pit 1, 47 trips transporting ROM coal from pit 2 and 65 trips transporting spoil from pit 3. This is split over 10 trucks; these are trucks 1, 2, 4, 6, 8, 9, 12, 13, 15 and 18.

Table 5.4. Benchmark truck allocations (# trips)

State	State 1 (0-2hr)			State 2 (2-4hr)				State 2 (4-6hr)			State 4 (6-8hr)			
Shovel	1	2	4	1		2	4	1	2	4	1	2	4	All
Grade	ROM	Spoil	Ovb.	ROM		Spoil	Ovb.	ROM	Spoil	Ovb.	ROM	Spoil	Ovb.	trips
Inlet	Pit 2	Pit 3	Pit 1	Pit 2		Pit 3	Pit 1	Pit 2	Pit 3	Pit 1	Pit 2	Pit 3	Pit 1	&
Outlet	PP	WD1	WD1	PP	WD1	WD1	PP	WD1	WD1	ROM SP	PP	WD1	WD1	times
Truck 1	2	3	-	1	1	3	-	2	3	-	2	3	-	20
Truck 2	2	-	3	-	2	3	-	2	3	-	2	2	1	20
Truck 3	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 4	2	3	-	1	1	3	-	2	3	-	2	3	-	20
Truck 5	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 6	2	3	-	-	2	3	-	2	3	-	2	3	-	20
Truck 7	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 8	-	-	4	-	2	-	3	-	-	4	-	-	4	17
Truck 9	-	4	-	-	2	-	3	-	-	4	-	2	2	17
Truck 10	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 11	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 12	-	-	4	-	-	-	4	-	-	4	1	-	3	16
Truck 13	-	-	-	-	-	-	-	1	-	3	-	-	-	4
Truck 14	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 15	2	3	-	-	2	3	-	2	3	-	2	3	-	20
Truck 16	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 17	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 18	1	3	-	-	-	-	-	-	-	-	-	-	-	4
Truck 19	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 20	-	-	-	-	-	-	-	-	-	-	-	-	-	-
All trucks	11	19	11	2	12	15	10	11	15	15	11	16	10	158

5.3.2 Demand analysis

Sensitivity to the mine's planned product output/demand, represented by task 4, is analysed here by varying the demand by ±40%, or from 4800 tonnes to 11200 tonnes. The analysis demonstrates how the planning factor, described in Section 2.3, is being taken into account in the model and that it has a clear impact on energy efficiency. Figure 5.4 shows the results of this scenario.

The energy efficiency of the mine improves with increased demand, and becomes worse with less demand. However, after a certain point, around +115%, the efficiency gains begin to diminish. This is once the ROM stockpile starts to be worked down rather than increased, and the excavation and haulage subsystem must increase the ROM coal extraction to meet the demand. This effect can be seen in the stockpile level and shovel utilisation trends in Figure 5.4. This is the expected behaviour, and shows that the current benchmark operation has room for energy efficiency improvement before extra excavation and haulage work is required.

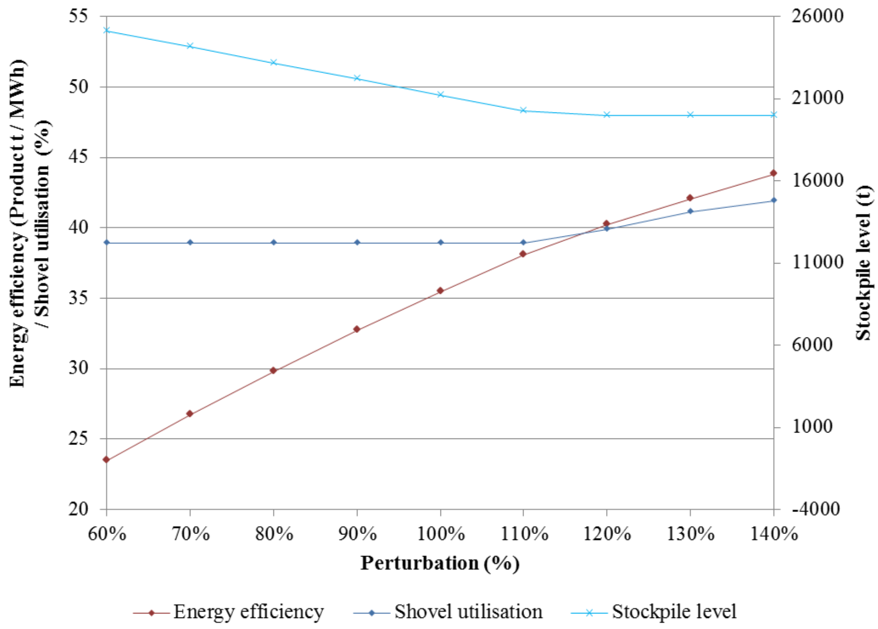

Figure 5.4. Product demand sensitivity analysis

5.3.3 Truck analysis

In this scenario, the trucks that were used in the benchmark solution are removed from the model and the model is re-solved in order to find the truck most critical to the energy efficiency of the system. It highlights the importance and power of using a heterogeneous model of the trucking fleet. Solving the model without a truck will replace its workload with another less optimal allocation, the next best. Figure 5.5 shows a simple hypothetical example for explanation purposes. The optimal truck allocations are shown in Figure 5.5 (a), which uses four out of five trucks. In choosing truck 2 to perform this analysis, it is removed from the model, meaning the workload needs to be redistributed among the other trucks, seen in Figure 5.5 (b), which will be a less optimal solution. Doing this for all the trucks and comparing the resulting energy consumption will indicate which trucks are the most critical to achieving the optimal solution.

Truck	0-1hr	1-2hr	2-3hr	3-4h
1	X	X	-	-
2	X	X	X	X
3	-	-	-	-
4	-	X	X	X
5	X	X	-	-

(a)

Truck	0-1hr	1-2hr	2-3hr	3-4h
1	X	X	X	-
2	-	-	-	-
3	-	-	-	-
4	X	X	X	X
5	X	X	X	X

(b)

Figure 5.5. Truck analysis methodology

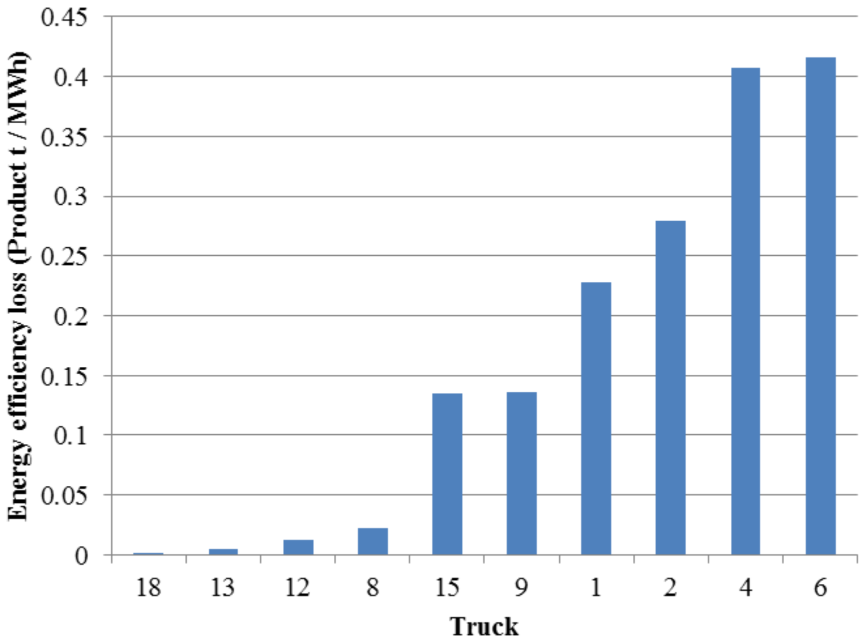

Figure 5.6. Effect of taking out each truck from benchmark solution

The results of this scenario are seen in Figure 5.6, ordered by increasing energy efficiency loss. They show that the largest loss of energy efficiency is encountered when truck 6 is removed, indicating it is most critical to achieving energy efficiency, closely followed by truck 4. In contrast, trucks 18, 13 and 12 and 8 have a very small impact on the energy efficiency, indicating their usage is not as critical to achieving an energy efficient operation. It demonstrates an example of how the model can be used to aid decisions relating to the asset usage factor introduced in Section 2.3.

5.3.4 Issues

As the literature review in Section 2.4 and the initial model validation in Section 4.2 introduced, using allocation to model the excavation and haulage subsystem has drawbacks. The central issue is that without knowing the order that allocated trips happen in, driving and loading operations cannot be accurately modelled. This results in two particular inaccuracies, each of which is apparent in solutions to the case study model.

Firstly, if the time it takes to drive between two trips is different depending on the order of trips, the allocation model cannot accurately determine the amount of time spent driving between the trips. This occurs in the solutions found for the case study model. Even with the limited resolution of the provided driving time data, the issue can be demonstrated. The time that it takes to travel to the crusher or stockpile from a pit is 6.5 minutes each way and the time it takes 11.9 minutes to travel to the waste dump from each pit. Reusing Figure 4.1 and applying these times in Figure 5.7 shows how the order of trips impacts truck driving time.

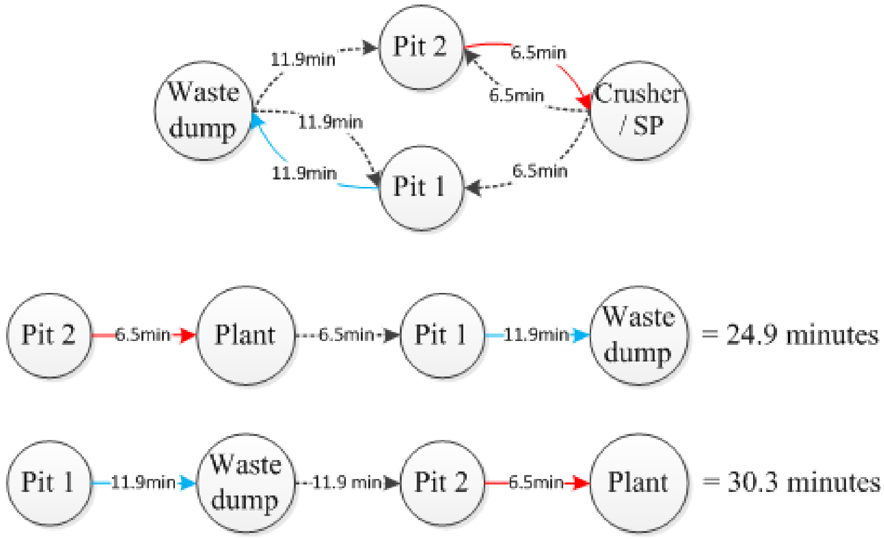

Figure 5.7. Driving time differences between trip orders

Secondly, without knowing the sequence, the times when trucks are being loaded by shovels cannot be known and therefore synchronicity cannot be guaranteed and truck waiting times cannot be accounted for. This can be seen in the benchmark solution.

Of the 65 trips transporting spoil from pit 3 to the waste dump, 19 happen in the first state (0-2hr) across six trucks. In particular, truck 1, 4, 6, 15 and 18 make three trips each and truck 9 makes four trips. Trucks 1, 2, 4, 6 and 15 also make two other trips from pit 2 to the ROM stockpile in the first state. Using this example, it can be demonstrated that different trip orderings will result in times where trucks are waiting for shovels, which will impact energy consumption and feasibility that aren't being accounted for with the current formulation. This can be demonstrated by manually sequencing and scheduling seven jobs, illustrated in Figure 5.8. Here the fourth truck must wait at the pit while the 15th truck finishes being loaded. While this may be avoidable by a better sequence in some circumstances, for practical-sized cases with many trucks it is very unlikely that a sequence with no truck waiting time will exist. Since the allocation model doesn't consider it at all, the cost of waiting or impact on feasibility cannot be calculated or guaranteed, respectively.

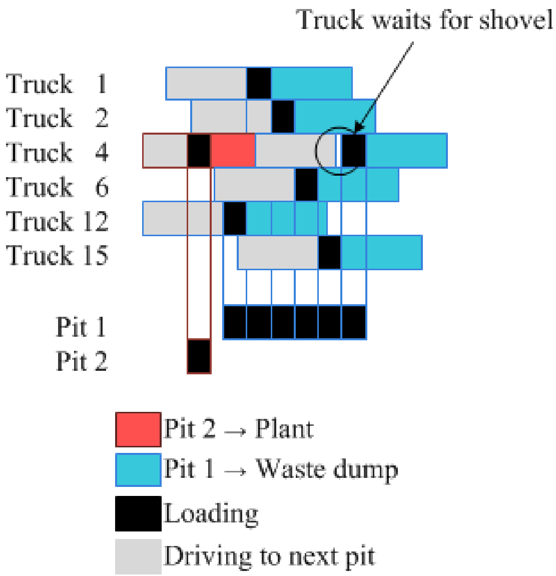

Figure 5.8. Example where truck waits for shovel

One of the main differences between the model presented here and models using the truck allocation formulation in the review literature is that they did not include the time dimension. Instead, they have been modelled to give allocations for 'steady state' production. This study has included the time dimension to give better resolution to the interactions between subsystems to ensure a more accurate, optimal solution. The length of these states will have an impact on the resulting objective values.

For instance, if one 8 hour state was used for the benchmark, the resulting energy consumption would come down to 224.78 MWh. However, this is a less accurate result, since there is less resolution around the material flow between subsystems and this cannot account for their interaction. For example, calculating how much double handling is required from a stockpile becomes less accurate. With one state, the model will only add in trips to the stockpile above the required demand from the CHPP, but if the CHPP trips aren't made at the right time they won't be synchronised with the demand and will therefore have to go to the ROM stockpile. Minimum stockpile levels exist to act as a buffer to ensure the real world feasibility of these solutions but will require extra double handling, an energy cost, so will not be energy efficient. Having a long state length would also not allow for planned changes in operation, such as a new block starting half way through the day or a change in production.

Conversely, for the allocation formulation, decreasing the time period has a negative impact on the objective. Solving with eight one-hour states, the resulting energy consumption increases to 227.54 MWh. Since the allocation formulation cannot accurately model the truck trip sequences or times, it doesn't consider trips that occur over two states and hence, unless trip times fit exactly into the two state lengths being compared, fewer trips per state are allowed in the shorter state length, leading to a less optimal result.

So for the current formulation, the benefits of the increased resolution that the time dimension is bringing are being decayed by the drawbacks of the allocation formulation accuracy. This, along with the other two issues noted above and in Section 4.2, motivates the development of a new formulation for the excavation and haulage subsystem.

5.4 Remarks

This chapter first demonstrated how the application process can be used to create a model of an operating mine from the general integrated formulation, as presented in Chapter 4. The process was used to effectively find the necessary information required to apply the model and solve it for a particular plan. On top of this, extra constraints were added to better model the mine's actual operation.

The model was solved for a typical 8-hour shift plan that was used as a benchmark for analysis. This instance produced sensible results that demonstrate the value of the model for aiding operators to meet targets in an energy efficient manner. Issues with the allocation formulation of the excavation and haulage, first mentioned in Subsection 2.4.2 and raised again in Section 4.2, were shown to exist for real problems, justifying the need for the improvement work carried out in the next chapter.

Besides these issues, initial sensitivity analysis that was conducted to demonstrate the model still produces sensible and valuable results that include impacts from the asset usage and planning factors. These form a basis to be extended upon in Chapter 8 using the improved formulation.

In relation to the research approach described in Section 1.2, this chapter represents the first iteration of the bottom left quadrant of Figure 5.9; it has been used to show the model application process on an operating mine. It also shows that, while the model is mostly logical, its limitations motivate a second iteration of modelling. Chapter 6 will next modify the model to overcome the synchronicity issues in the excavation and haulage subsystem.

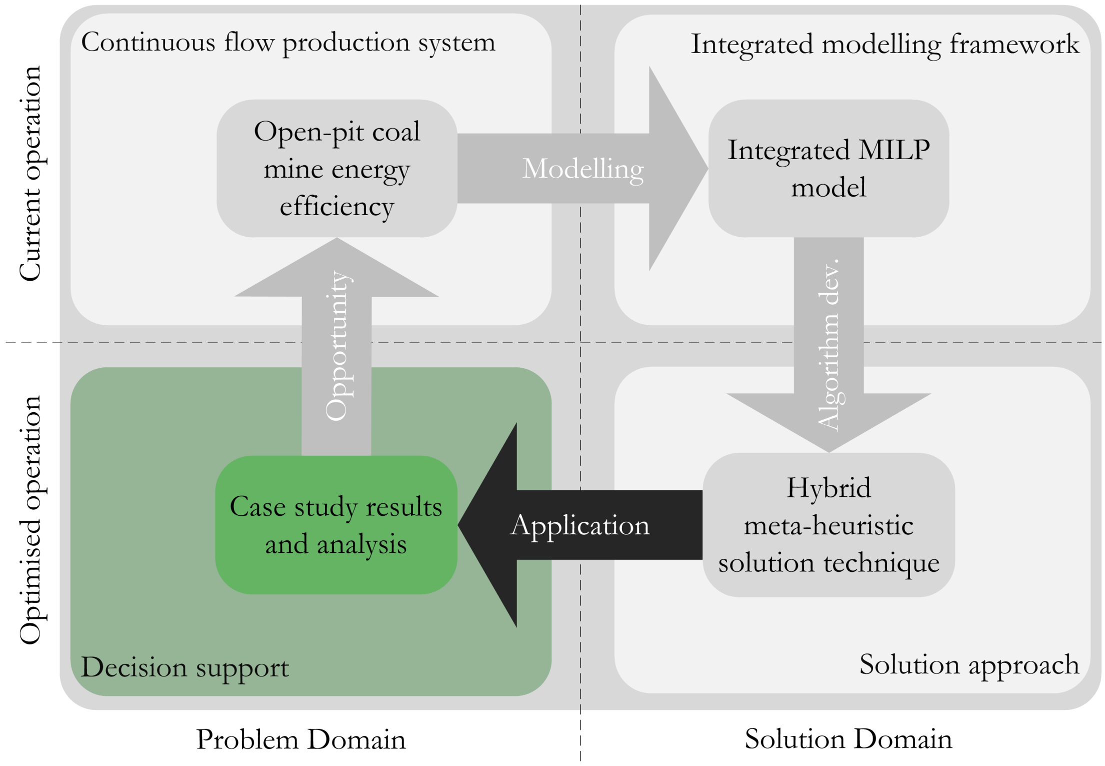

Figure 5.9. Role of Chapter 5 in the research approach

By successfully using the application process to create a model of the case study mine, research question 2d has been addressed in this thesis. As well as this, question 1 and the remaining parts of question 2 have been further addressed through the promising initial results from the case study. The results demonstrate the clear potential for using quantitative, integrated modelling to model open-pit coal energy efficiency and confirm the model takes the asset usage and planning factors into account. In general, the modelling detail and generality fit well with the data received for the case study, however, looking closer at the excavation and haulage, accuracy issues motivate a more detailed complex formulation for that subsystem.

1. *How can the energy efficiency of mining production systems benefit from an integrated modelling approach?*
   (a) *Why is improving energy efficiency a concern for mining operations?*
   (b) *How can an open-pit coal mine be considered as a production system?*
   (c) *What factors impact the energy efficiency of a mine?*
   (d) *What are the benefits of using a quantitative optimisation model of energy efficiency?*
   (e) *Why take an integrated optimisation approach?*
2. *What integrated optimisation model of energy efficiency is appropriate for an open-pit coal mine production system?*
   (a) *What level of detail is required of the model?*
   (b) *Where are the main points of model complexity?*

(c) *How general should the model be?*

(d) *What is an appropriate process for applying the model to a real life mine?*

6

Improving the Model

As a result of the initial testing in Section 4.2 and the case study results in Section 5.4, modifications to the model were earmarked in Section 4.3 and 5.5, respectively. Issues were highlighted with example problem instances to show where the model can be modified to better represent the operation of the excavation and haulage subsystem. The issues relate to the allocation formulation that is currently being used to represent the truck and shovel operation. Without a sequencing element to the formulation, the driving times of trucks, truck and shovel synchronicity and waiting times of trucks cannot properly be modelled.

It is important to note that while the modifications presented here are contained within the excavation and haulage subsystem module, the resulting formulation still fits into the integrated model presented in Chapter 4 by aligning with the Chapter 3 framework's requirements of subsystems. Figure 6.1 shows this relationship. In fact, as explained later in Section 6.1, the input parameters of the two integrated models remain the same after the modifications, a property that will be used in Chapter 7. Since the rest of the integrated model is not affected by these changes, the full formulation is not presented again, but will be referred to as the Chapter 6 model. The work carried out in this chapter serves as a good demonstration of the modelling framework's extensibility.

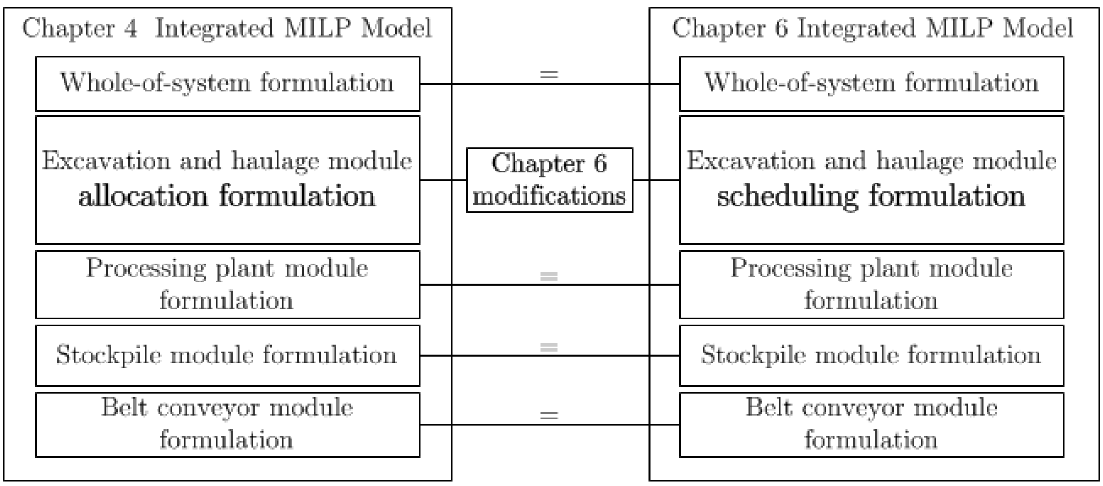

Figure 6.1. Relationship between Chapters 4 and 6 integrated models

This chapter details the modifications in Section 6.1. Initial analysis on a simple mine, similar to those done in Section 4.2, is then conducted in Section 6.2 to demonstrate the modifications make the necessary improvements, and study the implications of the introduced complexity. Finally, Section 6.3 concludes the chapter, and makes the case for a new solution technique to overcome the complexity so real life sized problems, including the case study, can be solved.

6.1 Excavation and haulage formulation modifications

The proposed changes to make the excavation and haulage model more realistic are outlined below as modifications to the Chapter 4 model, detailed in Section 4.1. As previously mentioned, they all occur within the excavation and haulage subsystem module and do not impact the formulation for any other subsystem or anything at the 'whole-of-system' level. The changes are centred on the way truck movements are accounted for.

In the previous model, trucks were assigned work through an integer decision variable representing the number of trips they had to make in each state. This is an equipment allocation style of formulation. As previously mentioned, this decision variable has limited ability to accurately determine the time spent driving between different trips and ensure synchronisation between truck and shovel to account for waiting time, which both impact the subsystem's energy consumption and feasibility.

In the new model, binary decision variables are used to determine the sequence of trucks being loading from each particular shovel, along with continuous decision variables that record the time that each truck starts being loaded at the shovel. It is a scheduling formulation similar in structure to that of the Chang et al. (2015) model, the only other known open-pit coal mine truck scheduling MILP, which was based on Tang et al. (2014). However, the model presented here has a number of differences to the Chang et al. (2015) model.

The new model will utilise similar binary sequencing time and continuous loading time variables as Chang et al. (2015), whereby each truck is loaded by a shovel in a loading sequence. The model formulated here is addressing a different problem to the Chang et al. (2015) model, that maximised revenue. Instead of trying to fit as many trips as possible into the optimisation period, the core problem of this formulation is choosing the correct number of trips to meet demand with minimum energy consumption. The energy consumption objective value requires a more detailed picture of the trucks' operation than what is used in as Chang et al. (2015), as it will explicitly include the truck waiting times and trips back to base.

The other difference is that more flexibility is required from this formulation to properly model the problem being addressed. The trucking fleet is considered to be heterogeneous in this research, to properly account for equipment operating costs. The ability to change demand and operating states over the optimisation period and integrate with other subsystems at the material flow level means the shovel loading sequences have to be split into states. This also means the grade extracted from each inlet must be explicitly considered, as it can change throughout the optimisation. The inclusion of the shovel location decision variable means the inlet and shovel are separated in the truck operation decision variable.

The following subsections will go through the notation, parameters, decision variables and constraints to detail the modifications made to the excavation and haulage module formulation from Section 4.1. The complexity introduced by the modifications will then be noted upon.

6.1.1 Notation modifications

The following set and index are introduced for the excavation and haulage subsystems.

L_{sq_e} Set of possible slots shovel s can load a truck
l Loading slot $\in L_{sq_e}$

The loading slot index represents the sequence of times that a shovel can load a truck. Taking three minutes as a typical loading time, and considering a two-hour optimisation period, there would be 42 loading times steps, slots 1-40 during the optimisation period, slot 0 being a step before the period and slot 41 a step after the period used to give trucks starting and ending locations, respectively.

6.1.2 Parameter modifications

There are two additional parameters introduced to describe the connection between loading slots and states, so the model can know which state each loading slot exists in.

$\tau^s_{tq_e}$ First loading slot in state t
$\tau^e_{tq_e}$ Last loading slot in state t

It is important to note here that these new parameters can be determined programmatically. This means the original Chapter 4 allocation formulation and new scheduling formulation can be implemented to run from the same set of required parameter values. This makes comparing the two models easier. Later in this thesis, in Chapter 7, the solutions to the Chapter 4 model are used to aid the solution technique, finding solutions to the modified model presented here.

As well as these additional parameters, a conceptual/dummy inlet, outlet, grade and shovel are also introduced to represent a base location for trucks. This is done by including them in I_{q_e}, J_{q_e}, D_{q_e} and S_{q_e} and representing them as i^b, j^b, g^b, s^b, respectively. These are used to give trucks a start and finish location for the optimisation. It also allows the model to account for the trucks going back to base, where they can be turned off and not use energy when they are not required. This is done by setting $\alpha^{\text{tdt}}_{i^b j^b r q_e}$, $\alpha^{\text{tdb}}_{i^b j^b r q_e}$ and $\alpha^{\text{tl}}_{i^b j^b r q_e}$ to zero, i.e. dummy trips from base to base have no driving or idle energy consumption.

6.1.3 Decision variable modifications

The integer decision variable $n_{ijgsrtq_e}$ for excavation and haulage in Section 4.1.3 is removed and replaced with:

$$x_{ijgsrlq_e} = \begin{cases} 1 & \text{when truck } r \text{ is allocated to shovel } s \text{ in loading slot } l \text{ doing a trip} \\ & \text{from } i \text{ to } j \text{ moving } g \\ 0 & \text{otherwise} \end{cases}$$

$$x^{\text{seq}}_{rsls'l'q_e} = \begin{cases} 1 & \text{when truck } r \text{ is loaded by shovel } s \text{ in loading slot } l \text{ directly before} \\ & \text{shovel } s' \text{ in loading slot } l' \\ 0 & \text{otherwise} \end{cases}$$

$x^{\text{time}}_{slq_e}$	time that loading slot l on shovel s begins (hour)
$x^{\text{wait time}}_{rslq_e}$	amount of time truck r waits to be loaded by shovel s in slot l (hours)
$z^{\text{tdt}}_{rslq_e}$	energy of truck driving to shovel s loading slot l (MWh)

The $u^{\text{truck}}_{rtq_e}$ decision variable is removed and the remaining decision variables, v_{ijgrtq_e}, y_{istq_e} and $u^{\text{shovel}}_{stq_e}$ remain as they are in the Chapter 4 formulation.

6.1.4 Constraint modifications

Constraint (4.7) is replaced with constraints (6.1) and (6.2). Constraint (6.1) ensures a truck allocated to a shovel and loading slot pair is only allocated to it once. Constraint (6.2) ensures that at most one truck is allocated to each shovel and loading slot pair.

$$\sum_{\forall i,j,g} x_{ijgsrlq_e} \leq 1 \qquad \forall r,s,l,q_e \tag{6.1}$$

$$\sum_{\forall i,j,g,r} x_{ijgsrlq_e} \leq 1 \qquad \forall s \neq s^b, l, q_e \tag{6.2}$$

Constraint (6.3) replaces constraint (4.9) to make sure a truck is only allocated to an active shovel. Where $M_1 = (\tau^s_{tq_e} + \tau^e_{tq_e} + 1)$, the maximum number of truck allocations per shovel for a given state t.

$$\sum_{l=\tau^s_{tq_e}}^{\tau^e_{tq_e}} \sum_{\forall i,j,g,r} x_{ijgsrlq_e} \leq M_1 y_{isq_e} \qquad \forall i, s \neq s^b, t, q_e \tag{6.3}$$

Constraints (6.4)(6.8) set the conditions at the start and end of the optimisation period.

$$x_{i^b j^b g^b s^b r 0 q_e} = 1 \qquad \forall r, q_e \tag{6.4}$$

$$\sum_{\forall i \neq i^b, j \neq j^b, g \neq g^b, s \neq s^b, r} x_{ijgsr0q_e} = 0 \qquad \forall q_e \tag{6.5}$$

$$x_{i^b j^b g^b s^b r, \tau^e_{|T|q_e}+1, q_e} = 1 \tag{6.6}$$

$$\sum_{i \neq i^b, j \neq j^b, g \neq g^b, s \neq s^b, r} x_{ijgsr, \tau^e_{|T|q_e}+1, q_e} = 0 \qquad \forall q_e \tag{6.7}$$

$$x^{\text{time}}_{s, \tau^e_{|T|q_e}+1, q_e} \leq \sum_{\forall t} H_t \qquad \forall s, q_e \tag{6.8}$$

Constraints (6.4) and (6.5) ensure each truck starts at base and is only at base, respectively. Constraints (6.6) and (6.7) ensure that each truck ends up back at base and only at base, respectively. Constraint (6.8) makes sure the last trip back to base occurs before the end of the optimisation period.

Constraints (6.9) – (6.14) work together to make sure that any allocation to base is only at base for all indices. This ensures no base trips are mistakenly counted when working out the boundary flow variables.

$$\sum_{\forall j \neq j^b, g, s, r, l} i^b j g s r l q_e = 0 \qquad \forall q_e \tag{6.9}$$

$$\sum_{\forall j \neq i^b, g, s, r, l} i j^b g s r l q_e = 0 \qquad \forall q_e \tag{6.10}$$

$$\sum_{\forall i \neq i^b, j \neq j^b, s, r, l} i j g^b s r l q_e = 0 \qquad \forall q_e \tag{6.11}$$

$$\sum_{\forall i \neq i^b, j \neq j^b, g, r, l} i j g s^b r l q_e = 0 \qquad \forall q_e \tag{6.12}$$

$$\sum_{\forall g \neq g^b, s, r, l} i^b j^b g s r l q_e = 0 \qquad \forall q_e \tag{6.13}$$

$$\sum_{\forall g, s \neq s^b, r, l} i^b j^b g s r l q_e = 0 \qquad \forall q_e \tag{6.14}$$

Constraint (6.9) ensures that no trips with non-base destination j come from base. Constraint (6.10) ensures no trips from non-base inlet i go towards base. Constraint (6.11) ensures no non-base trips transport the base grade. Constraint (6.12) ensures no non-base trips are loaded by the base shovel. Constraint (6.13) makes sure no base trips use a non-base (real) grade. Finally, constraint (6.14) makes sure no base trips use a non-base (real) shovel.

Constraints (6.15) and (6.16) ensure loading slots have predecessors, besides the first slot, and successors, besides the last slot, respectively. Constraint (6.17) prohibits 'self-looping' trips that precede and succeed themselves.

$$\sum_{\forall i,j,g} x_{ijgsrlq_e} = \sum_{\forall s',l'} x^{\text{seq}}_{rs'l'slq_e} \qquad \forall r,s,l \neq 0, q_e \tag{6.15}$$

$$\sum_{i,j,g} x_{ijgsrlq_e} = \sum_{\forall s',l'} x^{\text{seq}}_{rsls'l'q_e} \qquad \forall r,s,l \neq \tau^e_{|T|q_e}+1, q_e \tag{6.16}$$

$$\sum_{\forall r} x^{\text{seq}}_{rslslq_e} = 0 \qquad \forall s,l,q_e \tag{6.17}$$

The timing of trips is enforced using constraints (6.18) – (6.22).

$$\begin{aligned} x^{\text{time}}_{s'l'q_e} - x^{\text{time}}_{slq_e} = &\sum_{\forall i,g}\left(c^{\text{l}}_{igsq_e} + c^{\text{db}}_{ijq_e}\right) x_{ijgsrlq_e} \\ &+ \sum_{\forall i',j',g'} c^{\text{dt}}_{ji'q_e} x_{i'j'g's'rl'q_e} \qquad \forall j,r,s,l,s',l',q_e \\ &- \sum_{\forall t} H_t\left(1 - x^{\text{seq}}_{rsls'l'q_e}\right) \end{aligned} \tag{6.18}$$

Constraint (6.18) ensures enough time between adjacent trips of the same truck. It is an *if-then* constraint that says if truck r is loaded by shovel s in loading slot l at i and travelling to j immediately before being loaded by shovel s' in loading slot l' at i' then the time between the two jobs must be at least $c^{\text{l}}_{igsq_e} + c^{\text{db}}_{ijq_e} + c^{\text{dt}}_{ji'q_e}$.

$$x^{\text{time}}_{s,l+1,q_e} - x^{\text{time}}_{slq_e} \geq \sum_{\forall i,j,g,r} c^{\text{l}}_{igsq_e} x_{ijgsrlq_e} \qquad \forall s,l,q_e \tag{6.19}$$

$$x^{\text{time}}_{slq_e} \geq \sum_{t'=1}^{t-1} H_{t'} \qquad \forall s,t,\tau^s_{tq_e} < l < \tau^e_{tq_e}, q_e \tag{6.20}$$

$$x^{\text{time}}_{slq_e} < \sum_{t'=1}^{t-1} H_{t'} \qquad \forall s,t,\tau^s_{tq_e} < l < \tau^e_{tq_e}, q_e \tag{6.21}$$

Constraint (6.19) ensures there is enough time between adjacent loading slots for each shovel. Constraint (6.20) and (6.21) make sure shovel loading slots occur in the correct state.

$$
\begin{aligned}
x_{rslq_e}^{\text{wait time}} \geq & x_{s'l'q_e}^{\text{time}} - x_{slq_e}^{\text{time}} \\
& - \sum_{\forall i,g} \left(c_{igsq_e}^{\text{l}} + c_{ijq_e}^{\text{db}} \right) x_{ijgsrlq_e} \\
& - \sum_{\forall i',j',g'} c_{ji'q_e}^{\text{dt}} x_{i'j'g's'rl'q_e} \\
& + \sum_{\forall t} H_t \cdot \left(1 - x_{rsls'l'q_e}^{\text{seq}} \right) \qquad \forall j,r,s,l,s',l',q_e \qquad (6.22) \\
& + \sum_{\forall t} H_t \cdot \left(1 - \sum_{\forall i,g} x_{ijgsrlq_e} \right) \\
& + \sum_{\forall t} H_t \cdot \left(1 - \sum_{\forall i',j',g'} x_{i'j'g's'rl'q_e} \right)
\end{aligned}
$$

Constraint (6.22) calculates the amount of waiting time between jobs. It is another *if-then* constraint that works similarly to Constraint (6.18). It says if truck r is loaded by shovel s in loading slot l at i and travelling to j immediately before being loaded by shovel s' in loading slot l' at i' then the waiting time, $x_{rslq_e}^{\text{wait time}}$, will be greater than the difference between $x_{s'l'q_e}^{\text{time}}$ and $x_{slq_e}^{\text{time}}$ minus the associated driving and loading time $\left(c_{igsq_e}^{\text{l}} + c_{ijq_e}^{\text{db}} + c_{ji'q_e}^{\text{dt}} \right)$.

Constraint (4.10), that converts the discrete equipment operation to the truck flow variable, v_{ijgrtq_e}, becomes Constraint (6.23).

$$
v_{ijgsrtq_e} = \sum_{l=\tau_{tq_e}^{s}}^{\tau_{tq_e}^{e}} \frac{\gamma_{rq_e} x_{ijgsrlq_e}}{H_t} \qquad \forall r,j,g,r,t,q_e \qquad (6.23)
$$

Constraints (4.8), (4.11) and (4.12) remain the same as they do not include the outgoing decision variable. Constraint (4.13), the subsystem energy consumption equality, changes to be Constraint (6.24) and (6.25).

$$
\begin{aligned}
z^{\text{tdt}}_{rslq_e} \geq & \alpha^{\text{tdt}}_{jirq_e} c^{\text{dt}}_{jiq_e} \Big(-2c^{\text{dt}}_{jiq_e} \\
& + \sum_{\forall j'g'} x_{ij'g'srlq_e} \\
& + x^{\text{seq}}_{rs'l'slq_e} \\
& + \sum_{\forall i',g'} x_{i'jg's'rl'q_e} \Big)
\end{aligned}
\qquad \forall j,i,r,s,l,s',r',q_e \tag{6.24}
$$

$$
\begin{aligned}
z_{tq_e} \geq & \sum_{l=\tau^s_{tq_e}}^{\tau^e_{tq_e}} \sum_{\forall s,r} \left[\sum_{\forall i,j,g} \alpha^{\text{tdb}}_{ijrq_e} c^{\text{db}}_{ijq_e} x_{ijgsrlq_e} + z^{\text{tdt}}_{rslq_e} \right] \\
& + \sum_{l=\tau^s_{tq_e}}^{\tau^e_{tq_e}} \sum_{\forall s,r} \alpha^{\text{tl}}_{rq_e} \left[\sum_{\forall i,j,g} c^{\text{l}}_{igsq_e} x_{ijgsrlq_e} + x^{\text{wait time}}_{rslq_e} \right] \\
& + \sum_{l=\tau^s_{tq_e}}^{\tau^e_{tq_e}} \sum_{\forall i,j,g,s,r} \alpha^{\text{sl}}_{sq_e} c^{\text{l}}_{igsq_e} x_{ijgsrlq_e} \\
& + \sum_{\forall i,s} \alpha^{\text{si}}_{sq_e} \left[H_t y_{isq_e} - \sum_{l=\tau^s_{tq_e}}^{\tau^e_{tq_e}} \sum_{\forall j,g,r} c^{\text{l}}_{igsq_e} x_{ijgsrlq_e} \right]
\end{aligned}
\qquad \forall t,q_e \tag{6.25}
$$

Constraint (6.24) calculates the energy consumed by trucks driving from the previous destination to the pit of their next job. It is another *if-then* constraint that says if truck r is loaded by shovel s in slot l at i and that truck's trip is preceded by being loaded by s' in l' and the preceding trip's destination is j, then the driving energy from the previous trip to the (s,l) trip equals $\alpha^{\text{tdt}}_{jirq_e} c^{\text{dt}}_{jiq_e}$.

The first term of Constraint (6.25) represents the truck driving energy consumption; the second term represents truck idle energy consumption proportional to the time each truck is being loaded or waiting to be loaded. The third term represents the shovel loading energy consumption and the final term represents the shovel idle energy consumption.

6.1.5 Complexity

As with the Chang et al. (2015) model and compared to the Chapter 4 model, this new formulation contains a great deal of complexity. This complexity has been introduced by the increase in number of decision variables and constraints. With the inclusion of the shovel loading slots into the index of the decision variable for main decision variable $x_{ijgsrlq_e}$, the number of variables grows rapidly with increases to the optimisation period length. The if-then style constraints, (6.18), (6.22) and (6.24), that compare every shovel loading slot (s,l) against all other shovel loading slots (s',l') represent a significantly large number of constraints proportional to the optimisation period length.

Using the Pinedo (2012) scheduling formulation and complexity classifications, the model can be shown to be NP-hard. The shovels can be considered as unrelated machines in parallel with different speeds. The difference in truck driving times depending on the shovels and destinations they travel between can also be considered sequence dependent setup times. Both of these contribute to making the formulation NP-hard. This will be explored in a practical sense in the next section, where medium-to-large-sized problems will be shown to be intractable for exact methods.

6.2 Validation

The improved model is now validated on the simple example introduced in Section 3.3 and used in Section 4.2. The model is once again solved with IBM CPLEX Optimizer. However, with the complexities added with the truck scheduling improvement, the model is now much harder for CPLEX to solve.

Firstly, instance 4.01 is revisited to demonstrate the issues identified in Section 4.2 are being overcome with the new formulation. Solving this instance with the new model results in the schedule illustrated in Figure 6.2. The same truck allocations are present, seen in Table 6.1, but now the formulation can guarantee a higher level of accuracy in the objective value and feasibility of the solution. The resulting schedule contains no truck waiting time, an energy wasting activity, and the times between different trip types are properly accounted for. It also demonstrates the inclusion of trips from and to base, a new feature of the improved model.

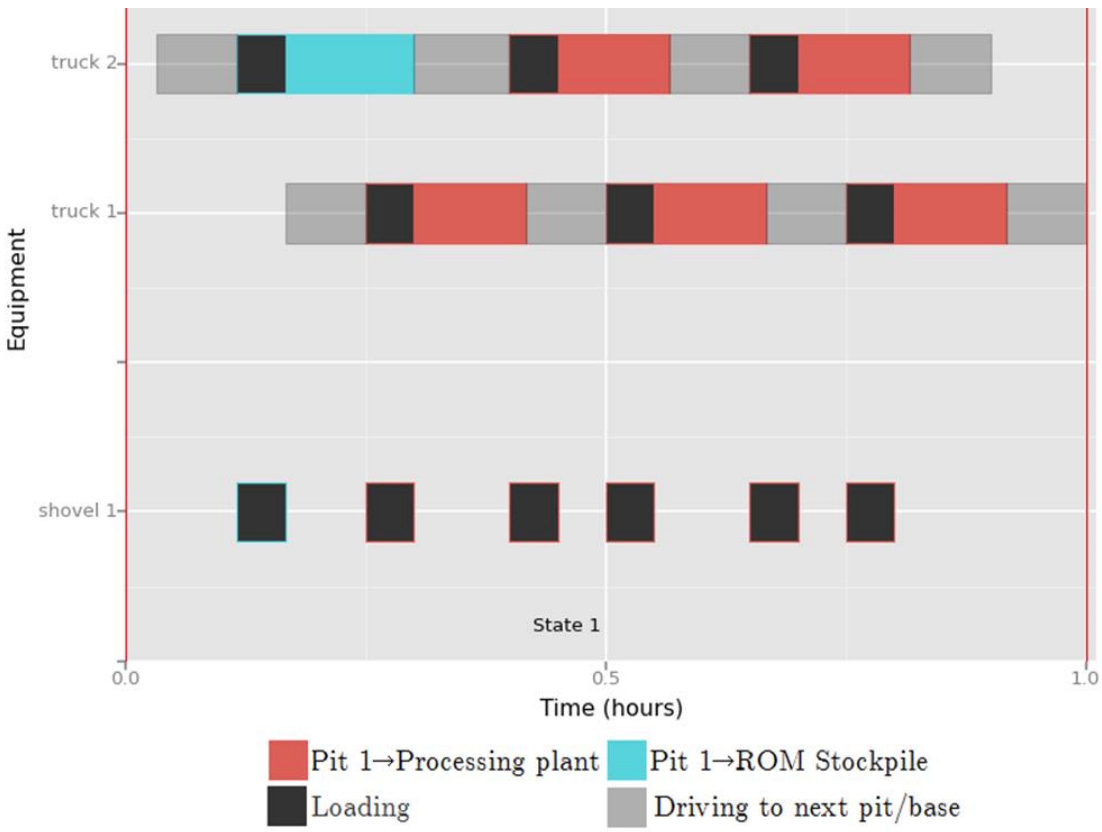

Figure 6.2. Instance 4.01 equipment schedule

Table 6.1. Instance 4.01 truck allocations

State	State 1 (0-1hr)	
Shovel	1	
Grade	ROM	
Inlet	Pit 1	
Outlet	PP	SP
Truck 1	3	0
Truck 2	2	1
All trucks	5	1

To analyse the computational difficulty that CPLEX has solving the model, a superset of the instances used in Section 4.2 are solved. Table 6.2 describes the problem instances to give an indication of size. Table 6.3 presents the results of solving the CPLEX with a 2-hour time limit, the objective of the LP relaxation and the objective value from solving the Chapter 4 MILP for the instance. Rows marked with dashes indicate CPLEX failed to find any integer solution in 2 hours.

Table 6.2. Problem instance descriptions

id	states	shovels	trucks	pit target (t)	product target (t)
6.01	1	1	1	(250,)	500
6.02	1	1	1	(500,)	500
6.03	1	1	1	(750,)	500
6.04	1	1	2	(1000,)	500
6.05	1	1	2	(1500,)	1000
6.06	1	1	4	(2500,)	2000
6.07	1	1	6	(3250,)	2000
6.08	1	2	1	(250, 250)	500
6.09	1	2	1	(500, 250)	500
6.10	1	2	2	(750, 500)	500
6.11	1	2	4	(1000, 1000)	500
6.12	1	2	6	(1500, 1500)	1000
6.13	2	1	1	(1500,)	1000
6.14	2	1	2	(2000,)	1000
6.15	2	1	4	(5000,)	4000
6.16	2	1	6	(7000,)	6000
6.17	2	2	1	(500, 500)	500
6.18	2	2	1	(750, 750)	500
6.19	2	2	2	(1000, 1000)	500
6.20	2	2	4	(2000, 2000)	1000
6.21	2	2	6	(3000, 3000)	2000

Table 6.3. Computational results

id	Ch. 4 MILP obj. (MWh)	LP relaxed Obj. (MWh)	Obj. (MWh)	CPU sec.	LP gap %	Ch.4 MILP gap %
6.01	6.52	5.78	6.41	0.34	10.90%	-1.69%
6.02	6.88	6.32	6.85	0.24	8.39%	-0.44%
6.03	7.49	6.91	7.55	0.4	9.26%	0.80%
6.04	8.39	7.58	8.36	2617	10.29%	-0.36%
6.05	12.7	12.01	12.82	458.4	6.74%	0.94%
6.06	22.34	20.98	-	-	-	-
6.07	24.15	23.07	-	-	-	-
6.08	7.8	6.48	7.8	0.74	20.37%	0.00%
6.09	8.16	6.98	8.25	1.73	18.19%	1.10%
6.10	9.75	8.25	9.84	263.1	19.27%	0.92%
6.11	12.94	10.42	-	-	-	-
6.12	19.1	16.46	-	-	-	-
6.13	14.97	13.95	15	1.84	7.53%	0.20%
6.14	16.44	15.31	16.47	3336	7.58%	0.18%
6.15	43.19	42.11	-	-	-	-
6.16	61.54	60.6	-	-	-	-
6.17	13.94	7.87	13.8	2.34	75.35%	-1.00%
6.18	15.23	9.34	15.32	51.1	64.03%	0.59%
6.19	16.77	10.93	-	-	-	-
6.20	24.38	20.95	-	-	-	-
6.21	36.52	33.1	-	-	-	-

6.3 Remarks

This chapter has successfully overcome the issues with the excavation and haulage subsystem outlined in Section 4.2 and Section 5.3 by modifying it to use a scheduling formulation. The issues were shown to be resolved using the same instances as Section 4.2. The new formulation represents an original, significant contribution to operations research literature in the mining field where only one other paper (Chang et al., 2015), looking at throughput maximisation, contains a scheduling model of the truck and shovel interactions. The model presented here is also integrated at the material flow connection level with other subsystems of the mine across multiple operating states in the time dimension, an important feature of the contribution.

Scheduling is also an important contribution to make in preparation for future developments in the excavation and haulage equipment operation. Autonomous equipment operation is expected in the near future to address productivity problems (Bellamy & Pravica, 2011). This will reduce uncertainty of equipment operation, making it a prime candidate for optimised scheduling.

The improved formulation has come at a cost of combinatorial complexity that means it cannot be solved for practical-sized problem instances. The formulation is NP-hard making it intractable for exact methods to find solutions to anything other than small instances. In order to solve the model, the development and application of metaheuristics solution techniques will be required.

This section represents the second iteration of the modelling effort described in Section 1.5, seen as the inner square of the top left quadrant of Figure 6.3. Revisiting this quadrant has further validated the worth of the modelling methodology described in Chapter 3. Updating an existing subsystem module and adding a new subsystem module formulation in the integrated model was shown to be a clear and simple process, with no impact to the remainder of the subsystem or wider whole-of-system formulations. As expected, the improved model is NP-hard and therefore too hard for exact solution techniques to solve. Another solution approach must therefore be taken, as in the bottom right quadrant of Figure 6.3. This is the focus of Chapter 7.

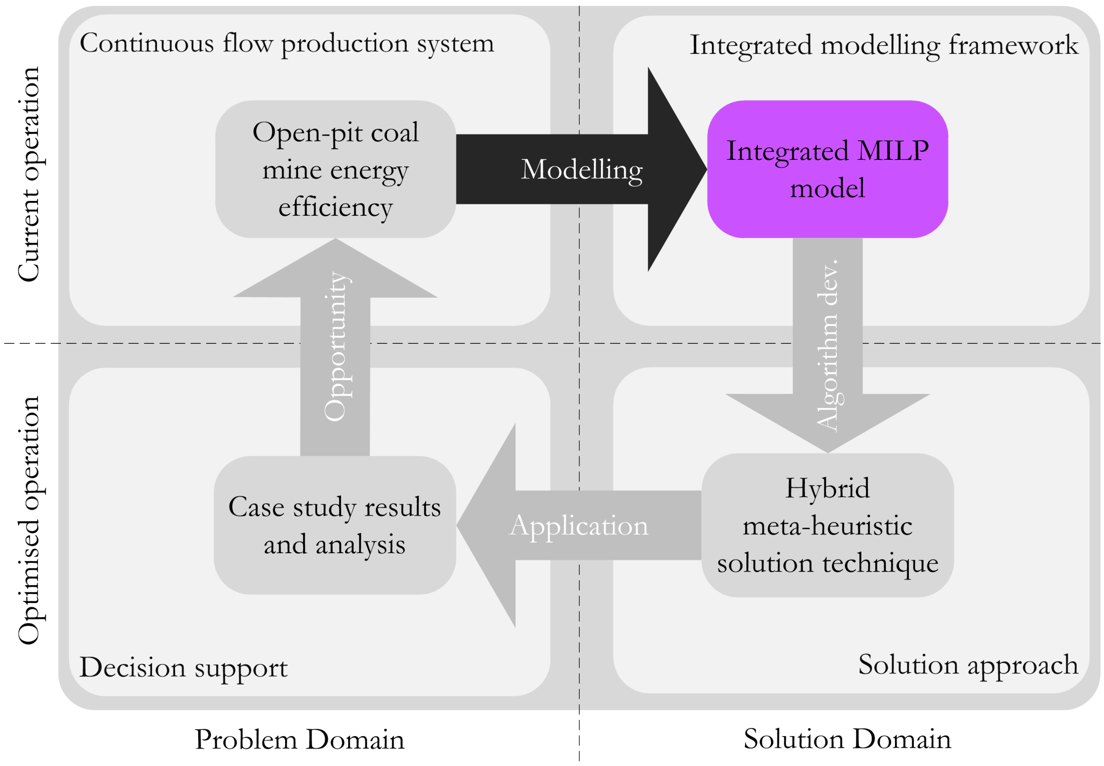

Figure 6.3. Role of Chapter 6 in the research approach

Research questions 2 and 3 from Section 1.2, listed below, relating to the required detail, complexity and generality of the model and solution technique, have been further addressed here. A new formulation for the excavation and haulage subsystem has been developed that is much more detailed than the allocation formulation, introduces a high level of complexity and doesn't sacrifice the generality of the original model. The new formulation, however, is NP-hard, cannot be solved with the existing solution technique and motivates innovation of a new technique to be able to find good quality solutions in reasonable time for practical-sized problems.

2. *What integrated optimisation model of energy efficiency is appropriate for an open-pit coal mine production system?*

   (a) *What level of detail is required of the model?*

   (b) *Where are the main points of model complexity?*

   (c) *How general should the model be?*

   (d) *What is an appropriate process for applying the model to a real life mine?*

3. *What solution techniques will be appropriate for solving the model in real-time?*

   (a) *How hard is it to solve the developed model? Is the optimisation NP hard?*

   (b) *Are new techniques required?*

   (c) *What impact do any new solution techniques have on optimality and speed?*

7

Solution Approach

While the excavation and haulage model improvements detailed in Section 6.1 were shown to overcome the issues outlined in Sections 4.3 and 5.4 on a simple example, they were also shown to introduce NP-hard complexity onto the model that made medium-to-large-sized problems intractable for direct solvers. To provide near optimal solutions in a practical amount of time for real life-sized problem instances of the model, a new solution approach is required. An overview of the approach, made up of the different elements contributed throughout this chapter, is shown in Figure 7.1. The approach focuses on the excavation and haulage subsystem but uses the Chapter 4 MILP and its equivalences to the improved Chapter 6 model to integrate the excavation and haulage schedules back with the whole system, still at a material flow connection level for each operating state.

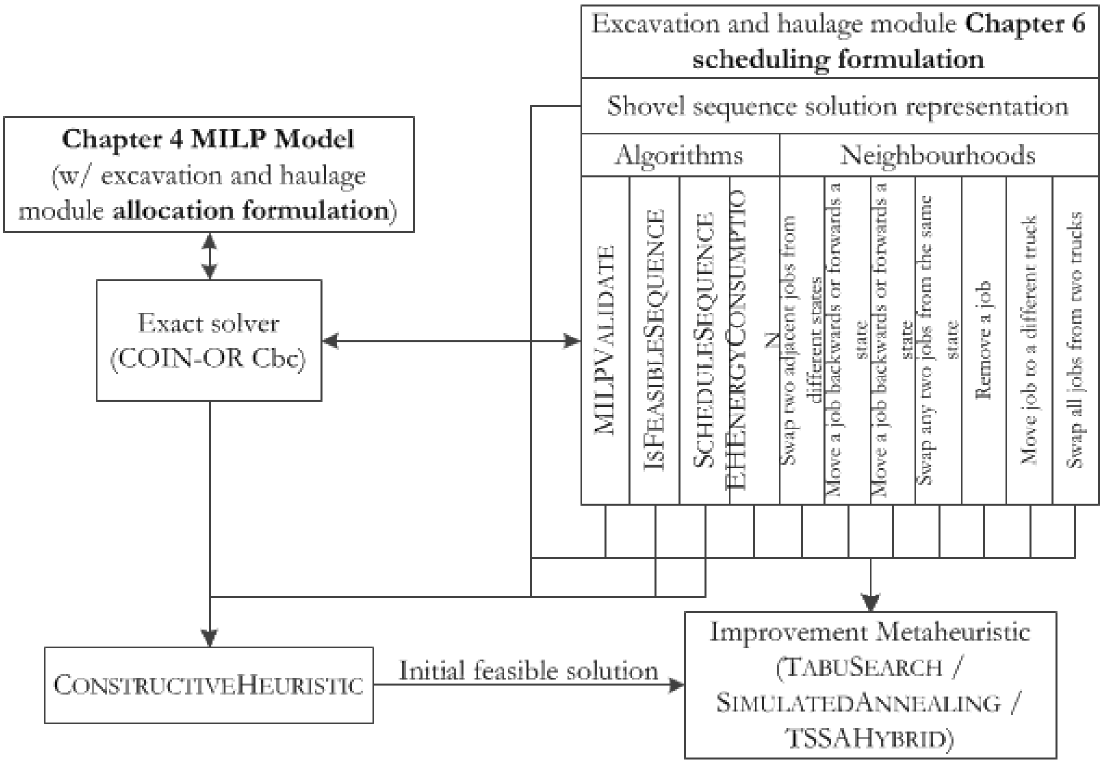

Figure 7.1. Solution approach structure

Two of the popular metaheuristics, tabu search and simulated annealing, outlined in Section 2.6 of the literature review, are implemented to efficiently search for solutions to the new excavation and haulage scheduling formulation. To apply these popular techniques to the formulation, a solution representation, evaluation algorithms, neighbourhoods and a constructive heuristic are innovated. The constructive heuristic uses the Chapter 4 MILP, which can be solved quickly enough using exact methods, to help build an initial feasible solution for the metaheuristics to improve upon. The developed metaheuristics will also contain a low level hybridisation with the exact method solving the Chapter 4 MILP, to ensure new excavation and haulage solutions satisfy constraints from the remaining subsystems in the mine. After implementing these metaheuristics on their own, a high level hybridisation of them will be developed in a novel example of how to use a message queue to efficiently run the two metaheuristics in parallel, and enable communication for the type of cooperative behaviour introduced as an effective approach in Section 2.6.

Section 7.1 describes the various details of the approach mentioned above. Section 7.2 then validates that the developed techniques provide optimal solutions in reasonable time for small sized problems, and tests that they will be able to solve the larger sized problems that CPLEX was not able to solve in Section 6.2. Finally, Section 7.3 will conclude the chapter by remarking on the benefits and limitations of the developed solution technique.

7.1 Solution technique

As mentioned and demonstrated throughout Chapter 6, complexity exists in determining the operation and interactions of the excavation and haulage subsystem equipment. The solution technique must therefore focus on this area, so that quality solutions can be generated in practical time. It must efficiently search and evaluate alternative excavation and haulage equipment operations to find the solution that meets the required demand targets, with the least energy.

As well as focusing on the complexities in the excavation and haulage subsystem, the solution technique must also provide solutions that are feasible to the whole-of-system integrated model. To do this, the constructive heuristic and two metaheuristics make use of the Chapter 4 integrated MILP model, with the allocation excavation and haulage subsystem formulation, for which exact methods can find solutions relatively quickly. The constructive heuristic uses it to give the boundary requirements of the excavation and haulage subsystem for building the initial feasible solution. The two metaheuristics use it to verify that new solutions are feasible solutions to the integrated, whole-of-mine model.

Subsections 7.1.1, 7.1.2 and 7.1.3 explain the solution representation, its validation and evaluation, and its neighbourhoods, respectively. Then Subsections 7.1.4, 7.1.5 and 7.1.6 describe the constructive heuristic, tabu search and simulated annealing algorithms in detail, respectively. Finally Subsection 7.1.7 describes how a high level hybridisation of the developed tabu search and simulated annealing metaheuristic techniques has been designed and implemented.

7.1.1 Representation of a solution

To allow the metaheuristics to efficiently search for new solutions, a much more dense solution representation than the sparse binary decision variables used in the Section 6.1 formulation is required. Job sequences for each shovel are used to represent the equipment activity. A job is identified as a truck arriving at a shovel in a particular state, being loaded and transporting the material to a particular destination. It is represented as a tuple of the state, truck and destination, or (t,r,j) using the notation used in the MILP formulation. It is important to record the state of the job. This is used to keep the synchronicity between subsystems over the material flow connection points for the whole-of-mine integration.

A simple example of the solution representation is shown in Figure 7.2. It shows the sequence list for each shovel, made up of tuples containing the state, truck and destination. Shovel 1 has nine jobs assigned to it over two states, four in state 1 and five in state 2, with trucks 3, 4, and 5 completing transporting material from shovel 1 to destination 3, while shovel 2 has seven jobs over the two states, four in state 1 and three in state 2. Trucks 1 and 2 are loaded by shovel 1 and take material to destinations 1 and 2.

Shovel 1	(1,3,3)	(1,4,3)	(1,5,3)	(1,3,3)	(2,4,3)	(2,5,3)	(2,3,3)	(2,4,3)	(2,5,3)
Shovel 2	(1,1,1)	(1,2,1)	(1,1,2)	(1,2,1)	(2,1,1)	(2,2,2)	(2,1,1)		

Figure 7.2. Solution approach structure

7.1.2 Neighbourhoods

The two metaheuristics explore neighbourhoods within the solution space by applying perturbations or moves to the job sequence solution representation. Seven neighbourhood moves have been developed and implemented to be used within the metaheuristic algorithms. This subsection describes the seven neighbourhood moves and demonstrates them as applied to the example sequence shown in Figure 7.2 with the differences from this schedule highlighted in blue.

Two of the moves change the boundary flows around the excavation and haulage subsystem between states, and therefore can cause infeasibilities across the remaining subsystems. For instance, moving a ROM stockpile truck trip forward into the next state reduces the flow into the ROM stockpile in the earlier of the two states and increases it in the latter one. For the earlier state, this could cause the minimum stockpile constraint to be violated, and could violate the maximum stacking capacity of the stockpile.

As the boundary flows are changed from these neighbourhood moves, the new solutions they generate must be checked for infeasibilities throughout the rest of the integrated model. To do this, the Chapter 4 MILP model is re-solved. More detail about how this is achieved, using the MILPVALIDATE algorithm, is given in Subsection 7.1.3. N1 and N2 are the two moves that require the Chapter 4 MILP re-solve. The remaining five moves do not impact the other subsystems in the integrated model if they have been validated using the ISFEASIBLESEQUENCE algorithm described in Subsection 7.1.3.

N1. Swap two adjacent jobs from different states

This move randomly selects two adjacent jobs that are in different states on a random shovel and swaps them. As this move may modify how much work is done on the boundary by the excavation and haulage system in the two states, the Chapter 4 MILP is required to be re-solved to validate that the new solution is feasible with respect to the rest of the system. Figure 7.3 shows this move applied to the fourth and fifth jobs on shovel 2.

Shovel 1	(1,3,3)	(1,4,3)	(1,5,3)	(1,3,3)	(2,4,3)	(2,5,3)	(2,3,3)	(2,4,3)	(2,5,3)
Shovel 2	(1,1,1)	(1,2,1)	(1,1,2)	(1,1,1)	(2,2,1)	(2,2,2)	(2,1,1)		

Figure 7.3. Job sequence solution representation after swapping two adjacent jobs from different states

N2. Move a job backwards or forwards a state

In this move, only a single job is affected; it selects a random job that is adjacent to a job with a different state and changes the state of the adjacent job. In other terms, it pushes jobs that are on the boundary of a state over into the next or previous state. As it modifies the amount of work being done in a state, it requires the Chapter 4 MILP validation to ensure the rest of the system remains feasible. Figure 7.4 shows the result of pushing the fifth job on Shovel 1 backwards into the first state.

Shovel 1	(1,3,3)	(1,4,3)	(1,5,3)	(1,3,3)	(1,4,3)	(2,5,3)	(2,3,3)	(2,4,3)	(2,5,3)
Shovel 2	(1,1,1)	(1,2,1)	(1,1,2)	(1,2,1)	(2,1,1)	(2,2,2)	(2,1,1)		

Figure 7.4. Job sequence solution representation after moving a job backwards or forwards by one state

N3. Swap two adjacent jobs from the same state

This move selects two adjacent jobs from the same state on a random shovel and swaps their order. Figure 7.5 shows the result of applying the move to the second and third job on shovel 1.

Shovel 1	(1,3,3)	(1,5,3)	(1,4,3)	(1,3,3)	(2,4,3)	(2,5,3)	(2,3,3)	(2,4,3)	(2,5,3)
Shovel 2	(1,1,1)	(1,2,1)	(1,1,2)	(1,2,1)	(2,1,1)	(2,2,2)	(2,1,1)		

Figure 7.5. Job sequence solution representation after swapping adjacent jobs from same state

N4. Swap any two adjacent from the same state

This move randomly selects any two jobs from any shovel in the same state and swaps them. Some extra logic is applied to this move to increase the likelihood of feasibility, if the two jobs are from different inlets with different grades, only the truck is swapped, otherwise the destination is also swapped. For example, applying this move to the sixth job on shovel 1 and the seventh job on shovel 2 results in Figure 7.6. Whereas, applying it to the first and third job on shovel 2 results in Figure 7.7.

Shovel 1	(1,3,3)	(1,4,3)	(1,5,3)	(1,3,3)	(2,4,3)	(2,1,3)	(2,3,3)	(2,4,3)	(2,5,3)
Shovel 2	(1,1,1)	(1,2,1)	(1,1,2)	(1,2,1)	(2,1,1)	(2,2,2)	(2,5,1)		

Figure 7.6. Job sequence solution representation after swapping two random jobs from same state

Shovel 1	(1,3,3)	(1,4,3)	(1,5,3)	(1,3,3)	(2,4,3)	(2,5,3)	(2,3,3)	(2,4,3)	(2,5,3)
Shovel 2	(1,1,2)	(1,2,1)	(1,1,1)	(1,2,1)	(2,1,1)	(2,2,2)	(2,1,1)		

Figure 7.7. Job sequence solution representation after swapping two random jobs from same state

N5. Remove a job

This move selects a random job and removes it. Figure 7.8 shows the effect of applying it to the fourth job on shovel 1.

Shovel 1	(1,3,3)	(1,4,3)	(1,5,3)	(2,4,3)	(2,5,3)	(2,3,3)	(2,4,3)	(2,5,3)
Shovel 2	(1,1,1)	(1,2,1)	(1,1,2)	(1,2,1)	(2,1,1)	(2,2,2)	(2,1,1)	

Figure 7.8. Job sequence solution representation after removing a job

N6. Move job to a different truck

This move selects a random job and changes the truck completing it to a randomly selected truck. Figure 7.9 shows the result of applying the move to the second job on shovel 2.

Shovel 1	(1,3,3)	(1,4,3)	(1,5,3)	(1,3,3)	(2,4,3)	(2,5,3)	(2,3,3)	(2,4,3)	(2,5,3)
Shovel 2	(1,1,1)	(1,3,1)	(1,1,2)	(1,2,1)	(2,1,1)	(2,2,2)	(2,1,1)		

Figure 7.9. Job sequence solution representation after moving a job to be done by a different truck

N7. Swap all jobs from two trucks

The last move selects two random trucks and swaps their workload for all time. Figure 7.10 shows the effect of swapping the workload of trucks 3 and 2.

Shovel 1	(1,2,3)	(1,4,3)	(1,5,3)	(1,2,3)	(2,4,3)	(2,5,3)	(2,2,3)	(2,4,3)	(2,5,3)
Shovel 2	(1,1,1)	(1,3,1)	(1,1,2)	(1,3,1)	(2,1,1)	(2,3,2)	(2,1,1)		

Figure 7.10. Job sequence solution representation after swapping all jobs between two different trucks

7.1.3 Validation and evaluation of a solution

Four algorithms are used by the constructive heuristic and metaheuristics to validate the sequence, convert it into a schedule and evaluate the energy consumption objective value. The first two are used to check that sequences represent feasible solutions to the integrated model. Next, a scheduling algorithm assigns time to jobs in the sequence representation to create a schedule for the equipment. The fourth then uses the schedule to compute the energy consumption of the excavation and haulage subsystem that can then be used to determine the whole-mine energy consumption using the Chapter 4 MILP solution.

Validation algorithm

As introduced in the previous subsection, when moves are made in neighbourhoods N1 and N2, the Chapter 4 MILP (with truck allocation) must be re-solved to check that the new solution does not violate any constraints from the rest of the system. The MILPVALIDATE algorithm conducts this check. Firstly, it takes in the new sequence and corresponding schedule, then converts that to the $n_{ijgsrtq_e}$ truck allocation variable used in the Chapter 4 MILP model. It then re-solves the Chapter 4 MILP with the truck and shovel allocation variables. If that re-solve finds an infeasibility, a false signal is returned, otherwise the MILP variables are overwritten with their new values and a true signal is returned.

MILPVALIDATE$\left(\text{seq}_s^1, \text{sch}^1, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}\right)$

$n_{ijgstrq_e} \leftarrow 0$
for each $\left(\text{lb}, s, r, t, j', i, j, g\right) \in \text{sch}^1$ **do**
  if $j \neq$ base **then**
    $n_{ijgstrq_e} \leftarrow n_{ijgstrq_e} + 1$
feasible, $z_{tq}^{\text{MILP1}}, v_{ijgrtq_e}^{\text{MILP1}}, y_{istq_e}^{\text{MILP1}}, \theta_{igt}^{\text{MILP1}} \leftarrow$ MILPSOLVE$\left(n_{ijgstrq_e}, y_{istq_e}\right)$
if not feasible **then**
  return False
$z_{tq}^{\text{MILP}} \leftarrow z_{tq}^{\text{MILP1}}$
$v_{ijgrtq_e} \leftarrow v_{ijgrtq_e}^{\text{MILP1}}$
$\theta_{igt} \leftarrow \theta_{igt}^{\text{MILP1}}$
$\text{obj}^1 \leftarrow \text{F}\left(\text{sch}^1, z_{tq}^{\text{MILP}}\right)$
return False

For all other sequences, where the boundary conditions of the excavation and haulage subsystem still hold, the ISFEASIBLESEQUENCE algorithm, presented below, applies. It checks that a given job sequence adheres to the excavation and haulage boundary conditions, which guarantees feasibility with respect to the rest of the system.

IsFeasibleSequence$\left(\text{seq}_s, v_{ijgrtq_e}, y_{istq_e}\right)$

1: job_types $\leftarrow \emptyset$
2: mass_req$_{sjt} \leftarrow 0$
3: **for** each $i \in I_{q_e}, j \in J_{q_e}, s \in S_{q_e}, t \in T$ **do**
4:     **if** $y_{istq_e} = 1 \& \sum_{g,r} v_{ijgrtq_e} > 0$ **then**
5:         Append(job_types, (s, j, t))
6:         mass_req$_{sjt} \leftarrow \sum_{g,r} H_t v_{ijgrtq_e}$
7: mass$_{sjt} \leftarrow 0$
8: **for** each $s \in S_{q_e}$ **do**
9:     **for** each $(t, r, j) \in \text{seq}_s$ **do**
10:         **if** $(s, j, t) \notin$ job_types **then**
11:             **return** False
12:         mass$_{sjt} \leftarrow$ mass$_{sjt} + \gamma_{rq_e}$
13: **for** each $(s, j, t) \in$ job_types **do**
14:     **if** mass$_{sjt} <$ mass_req$_{sjt}$ **then**
15:         **return** False
16: **return** True

The IsFeasibleSequence algorithm first, in lines 1–6, iterates through the truck flow, v_{ijgrtq_e}, and shovel allocation, y_{istq_e} decision variables from the Chapter 4 MILP solution to extract the job 'types' (shovel, destination, state) being done and the corresponding amount of mass required to be moved each job. It then, in lines 7–12, iterates over the sequence to check that no new jobs are being performed and accumulates the amount of mass being moved in the sequence representation. Finally, in lines 13–15, the job masses of the sequence are compared with the required masses to check if any job is under the required amount. If any errors are found, the algorithm returns a False signal, otherwise if no errors are found it returns a True signal.

Scheduling algorithm

In ScheduleSequence, presented below, jobs in the sequence are progressively assigned a starting time (time when truck begins being loaded by the shovel) and added into a schedule. The algorithm is a form of discrete event simulation, whereby lower bounds (lb) of time are used to work out what the next possible action is. Here, for readability purposes, three subroutines QJFNSort, IsWorthGoingBackToBase and AnyLateJobs are separated out from ScheduleSequence and presented on their own.

The algorithm iteratively schedules the first element of each shovel's sequence, and removes it from the sequence until no jobs are left in the sequences, as seen in line 10. To resolve any conflicts where two jobs are ready and require the same truck, a heuristic, QJFNSort, which sorts shovels to favour the quickest job to finish first, is used in line 11.

The sorted shovel set is then iterated over, and the next job in the sequence for each shovel is considered in lines 12–30. If the job is scheduled for a later state than the current one being scheduled for, line 18 and 19 increase the shovel's lower bound shovel_lb$_s$ to the next state. If the job is able to be done, evaluated by line 20, the ISWORTHGOINGBACKTOBASE subroutine first checks if it will use less energy than waiting to send the truck base to base first, and includes a trip back to base before the next job if it does. The job is then added to the schedule, removed from the sequence and the equipment lower bounds are updated in lines 24–28. Otherwise, in lines 29 and 30, the shovel's lower bound is increased if it is less than truck that's due to be loaded next.

Lines 31–32 then update the overall lower bound to be the next possible event, and increment the current state if the new lower bound is in the next state. Finally, the schedule is checked, by ANYLATEJOBS, to make sure all jobs will start on time and finish before the end of the last state.

The shovel set sorting heuristic algorithm, QJFNSORT, evaluates the minimum finishing time of each shovel's next job and sorts the shovel set, S_{q_e}, by these times in ascending order, so jobs that will be quickest to finish first are preferred.

The ISWORTHGOINGBACKTOBASE subroutine checks two things. The first is that whether a trip back to base is possible between the truck's last job and the start time of the next job. The second is that driving back to base - where the truck can be turned off and use no energy - then on to the next job, will use less energy than if the truck waits idle for the shovel at the next job. If both of these conditions are satisfied, True is return, otherwise False is return.

The ANYLATEJOBS subroutine iterates through a schedule to make sure each job is starting in the correct state and will get back to base at the end of the last state.

Objective value algorithm

EHENERGYCONSUMPTION, presented below, processes the scheduled job to accumulate the excavation and haulage subsystem's energy consumption, represented by z_{tq_e} and calculated by Constraint (59) in Section 6.1.

The algorithm works by first, in line 1, setting to all equipment being idle for all time in the energy consumption variable, z_{tq_e}. It then iterates through the scheduled equipment activity to add on driving and loading energy and remove idle energy in lines 5–13. As in the model, shovels are only not consuming energy in states where they are not used at all; lines 14 and 15 remove the idle use of these states. Next the idle energy before the first and after the final job for each truck is removed in lines 17–25 and 26–33, respectively. Finally the total energy consumption for all states is returned.

Using this algorithm, the overall energy consumption can be calculated. The following subroutine, F, takes the Chapter 4 MILP solution energy consumption, removes the excavation and haulage energy; calculated using the allocation formulation, then adds the new, scheduling, energy consumption. This is used by the metaheuristics to evaluate the quality of solutions to converge on an optimal solution to the whole integrated model, rather than just the excavation and haulage subsystem.

SCHEDULESEQUENCE$\left(\text{seq}_s, y_{istq_e}, \theta_{igt}\right)$

$\text{lb} \leftarrow 0$
$\text{current\_state} \leftarrow 0$
$\text{next\_state\_lb} \leftarrow 0$
$\text{shovel\_lb}_s \leftarrow 0$
$\text{truck\_lb}_r \leftarrow 0$
$\text{shovel\_inlet}_{st} \leftarrow \sum_i i y_{istq_e}$
$\text{shovel\_grade}_{st} \leftarrow \sum_g g \left(\theta_{\text{shovel\_inlet}_s t, g, t} > 0\right)$
$\text{prev\_dest}_r \leftarrow 0$
$\text{sch} \leftarrow \emptyset$
while $\left(\text{seq}_s \neq \emptyset \forall s \in S_{q_e}\right)$ **AND** $\text{curent\_state} \leq |T|$ **do**

QJFNSORT$\left(S_{q_e}, \text{truck_lb}_r, \text{prev_dest}_r, \text{shovel_inlet}_{st}\right)$
for each $s \in S_{q_e}$ **do**

$(t, r, j) \leftarrow \text{seq}_s[0]$
$i \leftarrow \text{shovel\_inlet}_{st}$
$g \leftarrow \text{shovel\_grade}_{st}$
$j' \leftarrow \text{prev\_dest}_r$
$\text{temp\_lb} \leftarrow \text{truck\_lb}_r + c^t_{j'iq_e}$
if $t < \text{current\_state}$ **then**

$\text{shovel\_lb}_s \leftarrow \text{next\_state\_lb}$

else if $\text{lb} \geq \text{shovel\_lb}_s$ **AND** $\text{lb} \geq \text{temp\_lb}$ **then**

if ISWORTHGOINGBACKTOBASE$(\text{lb}, \text{truck_lb}_r, \text{temp_lb})$ **then**

$\text{sch} \leftarrow \text{sch} \cup \left\{\left(\text{truck\_lb}_r + c^{\text{dt}}_{j',\text{base},q_e}, s, r, t, j', \text{base}, \text{base}, \text{dummy}\right)\right\}$
$j' \leftarrow \text{base}$

$\text{sch} \leftarrow \text{sch} \cup \left\{\left(\text{lb}, s, r, t, j', i, j, g\right)\right\}$
remove $\text{seq}_s[0]$
$\text{shovel\_lb}_s \leftarrow \text{lb} + c^{\text{l}}_{igsq_e}$
$\text{truck\_lb}_r \leftarrow \text{lb} + c^{\text{l}}_{igsq_e} + c^{\text{db}}_{igsq_e}$
$\text{prev\_dest}_r \leftarrow j$

else if $\text{shovel\_lb}_s < \text{temp\_lb}$ **then**

$\text{shovel\_lb}_s \leftarrow \text{temp\_lb}$

$\text{lb} \leftarrow \max\left(\min\left(\text{shovel\_lb}_s\right), \min\left(\text{truck\_lb}_r\right)\right)$
if $\text{lb} \geq \text{next\_state\_lb}$ **then**

$\text{current\_state} \leftarrow \text{current\_state} + 1$
$\text{next\_state\_lb} \leftarrow \text{next\_state\_lb} + H_{\text{current\_state}}$

if ANYLATEJOBS(sch) **then**

return FAIL

return sch

QJFNSORT$\left(S_{q_e}, \text{truck_lb}_r, \text{prev_dest}_r, \text{shovel_inlet}_{st}\right)$

$\text{next\_finish\_time}_s \leftarrow \sum_t H_t$
for each $s \in S_{q_e}$ **do**
  $(r, j, t) \leftarrow \text{seq}_s[0]$
  $i \leftarrow \text{shovel\_inlet}_{st}$
  $g \leftarrow \text{shovel\_grade}_{st}$
  $j' \leftarrow \text{prev\_dest}_r$
  $\text{next\_finish\_time}_s \leftarrow \text{truck\_lb}_r + c^{\text{dt}}_{j'iq_e} + c^{\text{l}}_{igsq_e} + c^{\text{db}}_{ijq_e}$
for each $s \in S_{q_e}$ **do**
  $s' \leftarrow s$
  while $\left(s' > 0\right)$ **AND** $\left(\text{next\_finish\_time}_{s'-1} > \text{next\_finish\_time}_{s'}\right)$ **do**
    swap s' and $s'-1$ in S_{q_e}
    $s' \leftarrow s'-1$

ISWORTHGOINGBACKTOBASE(lb, truck_lb$_r$, temp_lb)

if$\left(\text{truck\_lb}_r + c^{\text{dt}}_{j',\text{base},q_e} + c^{\text{dt}}_{\text{base},i,q_e} < \text{lb}\right)$ **AND**
$\left(\alpha^{\text{tdt}}_{j',\text{base},r,q_e} c^{\text{dt}}_{j',\text{base},q_e} + \alpha^{\text{tdb}}_{i,\text{base},r,q_e} c^{\text{dt}}_{\text{base},i,q_e} < \alpha^{\text{tl}}_{rq_e} (\text{lb} - \text{temp\_lb}) + \alpha^{\text{tdt}}_{j'irq_e} c^{\text{dt}}_{j'iq_e}\right)$ **then**
  return True
else
  return False

7.1.4 Constructive heuristic

To provide tabu search and simulated annealing with an initial solution a constructive heuristic is required. The algorithm CONSTRUCTIVEHEURISTIC, presented below, uses the Chapter 4 MILP to iteratively build an initial feasible solution.

As noted in Section 6.1, the only change to model parameters for the new excavation and haulage formulation, the inclusion of loading slots, can be programmatically determined. This means the two models can be considered as having the same set of inputs. Since solutions to the Chapter 4 MILP model can be found in reasonable time, it is used to give an initial guess for the operation of the mine for constructing the first solution. The COIN-OR Cbc solver, represented by the MILPSOLVE routine is used to find a near optimal solution to this MILP in reasonable time. The solution is then passed back to the constructive heuristic algorithm.

The algorithm then progressively adds jobs to the sequence, based on the truck and shovel allocation in the MILP result, until the boundary flows achieved in the MILP are satisfied

ANYLATEJOBS(sch)

for each $(\text{lb}, s, r, t, i, j, g) \in \text{sch}$ **do**
  if $\text{lb} \geq \sum_{t' \leq t} H_t$ **then**
    return True
  if $(t = |T|)$ **AND** $\left(\sum_{t'} H_{t'} - \text{lb} < c^{\text{l}}_{igsq_e} + c^{\text{db}}_{ijq_e} + c^{\text{dt}}_{j,\text{base},q_e}\right)$ **then**
    return True
return False

EHENERGYCONSUMPTION(sch)

$z_{tq_e} \leftarrow \sum_s \alpha^{\text{si}}_{sq_e} H_t + \sum_r \alpha^{\text{tl}}_{rq_e} H_t$
shovel_unused_in_state$_{st} \leftarrow 1$
time_before_first_job$_r \leftarrow -1$
prev_end_time$_r \leftarrow 0$
for each $(\text{lb}, s, r, t, j', i, j, g) \in \text{sch}$ **do**
  $z_{tq_e} \leftarrow z_{tq_e} + \alpha^{\text{sl}}_{sq_e} c^{\text{l}}_{igsq_e} - \alpha^{\text{si}}_{sq_e} c^{\text{l}}_{igsq_e}$
  $z_{tq_e} \leftarrow z_{tq_e} + \alpha^{\text{tdt}}_{j'irq_e} c^{\text{dt}}_{j'iq_e} + \alpha^{\text{tdb}}_{ijrq_e} c^{\text{db}}_{ijq_e} - \alpha^{\text{tl}}_{rq_e} \left(c^{\text{dt}}_{j'iq_e} + c^{\text{db}}_{ijq_e} \right)$
  shovel_unused_in_state$_{st} \leftarrow 0$
  if $j' = \text{base}$ **then**
    $z_{tq_e} \leftarrow z_{tq_e} - \alpha^{\text{tl}}_{rq_e} \left(\text{lb} - \text{prev\_end\_time}_r - c^{\text{dt}}_{j'iq_e} \right)$
  prev_end_time$_r \leftarrow \text{lb} + c^{\text{l}}_{igsq_e} + c^{\text{db}}_{ijq_e}$
  if time_before_first_job$_r < 0$ **then**
    time_before_first_job$_r \leftarrow \text{lb} - c^{\text{dt}}_{j'iq_e}$
for each $s \in S_{q_e}, t \in T$ **do**
  $z_{tq_e} \leftarrow z_{tq_e} - \text{shovel\_unused\_in\_state}_{st} \alpha^{\text{tl}}_{rq_e} H_t$
for each $r \in R_{q_e}$ **do**
  if time_before_first_job$_r > 0$ **then**
    for $t = 1 \textbf{to} |T|$ **do**
      if time_before_first_job$_r < H_T$ **then**
        $z_{tq_e} \leftarrow z_{tq_e} - \alpha^{\text{tl}}_{rq_e} \text{time\_before\_first\_job}_r$
        break
      else
        $z_{tq_e} \leftarrow z_{tq_e} - \alpha^{\text{tl}}_{rq_e} H_t r$
        time_before_first_job$_r \leftarrow$ time_before_first_job$_r - H_t$
  $z_{tq_e} \leftarrow z_{tq_e} + \alpha^{\text{tdt}}_{j',\text{base},r,q_e} c^{\text{dt}}_{j',\text{base},q_e}$
  time_after_last_job $\leftarrow \sum_t H_t - \text{prev\_end\_time}_r$
  for $t = |T| \textbf{down to} 1$ **do**
    if time_after_last_job $< H_t$ **then**
      $z_{tq_e} \leftarrow z_{tq_e} - \alpha^{\text{tl}}_{rq_e}$ time_after_last_job
      break
    else
      $z_{tq_e} \leftarrow z_{tq_e} - \alpha^{\text{tl}}_{rq_e} H_t$
      time_after_last_job $\leftarrow$ time_after_last_job $- H_t$
return $\sum_t z_{tq_e}$

$\text{F}\left(\text{sch}, z^{\text{MILP}}_{tq}\right)$

return $\sum_{q \neq q_e} z^{\text{MILP}}_{tq} - z^{\text{MILP}}_{tq_e} + \text{EHENERGYCONSUMPTION(sch)}$

for each state. This is checked by the ISFEASIBLESEQUENCE algorithm, and the SCHEDULESEQUENCE algorithm is used to ensure the schedules feasibility. For improved readability, EXTRACTMILPSOLNINFO and SELECTTRUCK are separated out as subroutines.

CONSTRUCTIVEHEURISTIC($\text{it}^{\max}$)

```
feasible, z_{tq}^{MILP}, v_{ijgrtq_e}, y_{istq_e}, θ_{igt} ← MILPSOLVE()
if not feasible then
    return Fail
shovel_inlet_{st} ← Σ_i i y_{istq_e}
shovel_grade_{st} ← Σ_g g (θ_{shovel_inlet_{st} g t} > 0)
jobs_t^0, mass_req_{sjt}, R_{sjt}^{recommended} ← EXTRACTMILPSOLNEINFO(v_{ijgrtq_e}, y_{istq_e})
seq_s ← ∅; it ← 0
while not ISFEASIBLESEQUENCE(seq_s, v_{ijgrtq_e}, y_{istq_e}) do
    seq_s ← ∅; sch ← ∅; mass_{sjt} ← 0
    jobs_t ← jobs_t^0
    R_t^{available} ← R_{q_e}
    t ← 1
    while Σ_{t'} |jobs_t| > 0 do
        if |jobs_t| = 0 then
            t ← t + 1
        s, j ← RandomChoice(jobs_t)
        i ← shovel_inlet_{st}
        g ← shovel_grade_{st}
        r, trlb_r, shlb, msg ← SELECTTRUCK(s, i, j, g, t, sch, R_t^{available}, R_{sjt}^{recommended})
        if msg = "no trucks for job" then
            R_{sjt}^{recommended} ← R_{sjt}^{recommended} ∪ max_{r ∈ R_t^{available} \ R_{sjt}^{recommended}} γ_{rq_e} / α_{ijrq_e}^{tdb}
            break
        else if msg = "truck can't do job" then
            REMOVE(R_t^{available}, r)
            continue
        sch' ← SCHEDULESEQUENCE(seq_s ∪ (t, r, j), y_{istq_e}, θ_{igt})
        if sch' ≠ FAIL then
            seq_s ← seq_s ∪ (t, r, j)
            sch ← sch'
            if max(trlb_r, shlb) + c_{igsq_e}^{l} + c_{ijq_e}^{db} > Σ_{t' ≤ t} H_t then
                REMOVE(R_t^{available}, r)
            mass_{sjt} ← mass_{sjt} + γ_{rq_e}
            if mass_{sjt} ≥ mass_req_{sjt} then
                REMOVE(jobs_t, (s, j))
    it ← it + 1
    if it > it^{max} then
        return FAIL
return seq_s, z_{tq}^{MILP}, v_{ijgrtq_e}, y_{istq_e}, θ_{igt}
```

The first step solves the Chapter 4 MILP to get the appropriate decision variables, and fails if it isn't a feasible problem instance. It then, in lines 4–7, uses the solution from the Chapter 4 MILP to set up some auxiliary variables and initialises the sequence and iterator variables. Some of this is encapsulated in the EXTRACTMILPSOLNINFO subroutine, presented below. It iterates over the truck flow and shovel allocation variables to determine the types of jobs to be done, along with their mass requirements and trucks recommended to do the jobs.

EXTRACTMILPSOLNINFO$\left(v_{ijgrtq_e}, y_{istq_e}\right)$

1: $\text{jobs}_t^0 \leftarrow \emptyset$
2: $\text{mass\_req}_{sjt} \leftarrow 0$
3: $R_{sjt}^{\text{recommended}} \leftarrow \emptyset$
4: **for** each $i \in I_{q_e}, j \in J_{q_e}, s \in S_{q_e}, t \in T$ **do**
5:     **if** $y_{istq_e} = 1$ **AND** $\sum_{g,r} v_{ijgrtq_e} > 0$ **then**
6:         $\text{mass\_req}_{sjt} \leftarrow \sum_{g,r} v_{ijgrtq_e}$
7:         APPEND$\left(\text{jobs}_t^0, (s,j)\right)$
8:         **for** each $r \in R_{q_e}$ **do**
9:             **if** $\sum_g v_{ijgrtq_e} > 0$ **then**
10:                 APPEND$\left(R_{sjt}^{\text{recommended}}, t\right)$
11: **return** $\text{jobs}_t^0, \text{mass\_req}_{sjt}, R_{sjt}^{\text{recommended}}$

The algorithm then starts the main iteration that continues until a feasible solution is found, or a maximum number of iterations are reached, in which case it returns a fail signal (see lines 37 and 38). For each main iteration, a new solution is built, so lines 9–12 reset the appropriate variables and count the iterator. The inner loop is then begun, which starts at the first state and continues until no jobs remain unfinished, incrementing the state when no jobs remain for the current state (in line 14 and 15).

The algorithm then randomly selects an unfinished job from the current state and using the latest schedule uses the SELECTTRUCK subroutine, presented below, to find a potential truck to do the job. Initially, if there are no trucks available to do the requested job, a message is returned to the main algorithm, which will then add a new recommended truck, that has maximum efficiency, as measured by $\frac{\gamma_{rq_e}}{\alpha_{ijrq_e}^{\text{tdb}}}$, and break out of the inner loop to retry the outer loop again.

If that is not the case, SELECTTRUCK uses the latest schedule to find the lower bounds of the equipment involved with completing the next job in lines 3 – 8, makes sure the job can be done by a truck in line 9 and 10, and then heuristically orders the trucks that are both available and recommended. The heuristic, seen in line 11, sorts these trucks by their readiness and energy efficiency, $(\text{trlb}_r \leq \text{shlb})\frac{\gamma_{rq_e}}{\alpha_{ijrq_e}^{\text{tdb}}}$, first, then by the truck with smallest lower bound. If there are multiple trucks that maximise this heuristic, a random one is selected.

Line 13 and 14 then check to make sure the truck can start the job on time and that it will finish on time if it is in the last state. If it cannot perform the job, the main algorithm will skip the rest of the inner loop and try again. If that is not the case, the truck, lower bounds and an "OK" message are returned to CONSTRUCTIVEHEURISTIC.

SELECTTRUCK$\left(s, i, j, g, t, \mathrm{sch}, R_t^{\text{available}}, R_{sjt}^{\text{recommended}}\right)$

if $\left|R_t^{\text{available}}\right| = 0$ **OR** $\left|R_t^{\text{available}} \cup R_{sjt}^{\text{recommended}}\right| = 0$ **then**

  return 0, 0, 0, "no trucks for job"

$\mathrm{trlb}_r \leftarrow 0$

$\mathrm{shlb} \leftarrow 0$

for each $\left(\mathrm{lb}, s', r, t, j'', i', j', g\right) \in \mathrm{sch}$ **do**

  if $s = s'$ **then**

    $\mathrm{shlb} \leftarrow \mathrm{lb} + c^{\mathrm{l}}_{i'g'sq_e}$

  $\mathrm{trlb}_r \leftarrow \mathrm{lb} + c^{\mathrm{l}}_{i'g'sq_e} + c^{\mathrm{db}}_{i'j'q_e} + c^{\mathrm{dt}}_{j'iq_e}$

if $\max\left(\min\left(\mathrm{trlb}_r\right), \mathrm{shlb}\right) > \sum_{t' \le t} H_{t'}$ **then**

  return 0, 0, 0, "no trucks for job"

$R' \leftarrow \max_{r \in R_t^{\text{available}} \cup R_{sjt}^{\text{recommended}}} \left(\left(\mathrm{trlb}_r \le \mathrm{shlb}\right) \frac{\gamma_{rq_e}}{\alpha^{\mathrm{tdb}}_{ijrq_e}}, -\mathrm{trlb}_r \right)$

$r \leftarrow$ RANDOMCHOICE$\left(R'\right)$

if$\left(\mathrm{trlb}_r > \sum_{t' \le t} H_t\right)$ **OR** $\left(t = |T|\ \textbf{AND} \left(\max(\mathrm{trlb}_r, \mathrm{shlb}) + c^{\mathrm{l}}_{igsq_e} + c^{\mathrm{db}}_{ijq_e} + c^{\mathrm{dt}}_{j,\mathrm{base},q_e} > \sum_{t'} H_{t'}\right)\right)$ **then**

  return r, "truck can't do job"

return r, 0, 0, trlb_r, shlb, "OK"

Using the selected potential truck, CONSTRUCTIVEHEURISTIC then attempts to schedule the sequence with the candidate job appended to the relevant shovel in line 27. If that succeeds, the working sequence and schedule are updated with the new job appended in lines 27–29. If the truck is then found to not be able to do any more jobs in the state, it is removed from the list of available trucks, in lines 31 and 32. Likewise, lines 32–34 assess whether the job type has now satisfied the mass requirements and remove it if it has. Finally, once a feasible sequence is found, the algorithm returns it, along with other relevant MILP information, ready for use by the metaheuristics.

7.1.5 Tabu search

The TABUSEARCH algorithm, presented below, primarily follows a standard tabu search algorithm flow, to search neighbourhoods for more optimal solutions and ignore recently visited solutions, to avoid finding local optima. As mentioned in the introduction of this section, the metaheuristics employ lower level hybridisations with COIN-OR Cbc solving the Chapter 4 MILP for validating certain candidate solutions. For improved readability and because they are reused in the simulated annealing algorithm, SELECTNEIGHBOURHOOD and SELECTCANDIDATE are separated out as subroutines.

The algorithm begins by initialising the best solution variables, an empty tabu list (TL) and zero iterator variables. The main loop is then begun, and runs until a maximum number of iterations have passed, in total or since an improvement has been found. After incrementing the loop iterators, a neighbourhood is then selected from the seven neighbourhoods using the SELECTNEIGHBOURHOOD subroutine, presented below. The subroutine randomly

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TabuSearch$\left(\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}, \text{nc}, \text{TL}^{\text{length}}, \text{it}^{\max}, \text{itsi}^{\max}, \text{mv}^{\text{freq}}\right)$

1: $\text{seq}_s^{\text{best}} \leftarrow \text{seq}_s$
2: $\text{obj}^{\text{best}} \leftarrow \text{F}\left(\text{ScheduleSequence}\left(\text{seq}_s^{\text{best}}, y_{istq_e}, \theta_{igt}\right), z_{tq}^{\text{MILP}}\right)$
3: $\text{TL} \leftarrow \emptyset; \text{it} \leftarrow 0; \text{itsi} \leftarrow 0; \text{mv} \leftarrow 0$
4: **while** $\text{it} < \text{it}^{\max}$ **AND** $\text{itsi} < \text{itsi}^{\max}$ **do**
5: $\quad \text{it} \leftarrow \text{it} + 1$
6: $\quad \text{itsi} \leftarrow \text{itsi} + 1$
7: $\quad N \leftarrow \text{SelectNeighbourhood}\left(\text{Neighbourhoods}, \text{mv}, \text{mv}^{\text{freq}}\right)$
8: $\quad \text{seq}_s^1, \text{obj}^1 \leftarrow \text{SelectCandidate}\left(\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, N, \text{nc}, \text{TL}\right)$
9: $\quad \text{Append}\left(\text{TL}, \text{seq}_s^1\right)$
10: $\quad$ **if** N requires MILP validation **AND**
$\quad$ **not** $\text{MILPValidate}\left(\text{seq}_s^1, \text{sch}^1, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}\right)$ **then**
11: $\quad\quad$ **continue**
12: $\quad$ **if** $\text{obj}^1 < \text{obj}^{\text{best}}$ **then**
13: $\quad\quad \text{seq}_s^{\text{best}}, \text{obj}^{\text{best}} \leftarrow \text{seq}_s^1, \text{obj}^1$
14: $\quad\quad z_{tq}^{\text{MILP best}}, v_{ijgrtq_e}^{\text{best}}, y_{istq_e}^{\text{best}}, \theta_{igt}^{\text{best}} \leftarrow z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}$
15: $\quad\quad \text{itsi} \leftarrow 0$
16: $\quad \text{seq}_s \leftarrow \text{seq}_s^1$
17: **return** $\text{seq}_s^{\text{best}}, \text{obj}^{\text{best}}, z_{tq}^{\text{MILP best}}, v_{ijgrtq_e}^{\text{best}}, y_{istq_e}^{\text{best}}, \theta_{igt}^{\text{best}}$

---

selects a neighbourhood and checks if it is a neighbourhood that requires the MILPValidate check (N1 or N2), and only allows it every mv^{freq} times, to limit the number of calls to MILPValidate required, as they are slower than IsFeasibleSequence.

SelectNeighbourhood$\left(\text{Neighbourhoods}, \text{mv}, \text{mv}^{\text{freq}}\right)$

$N \leftarrow \text{Null}$
while
$\quad$ **do** $N' \leftarrow \text{Random}(\text{Neighbourhoods})$
$\quad$ **if** N' requires MILP validation **then**
$\quad\quad$ **if** $\text{mv} \% \text{mv}^{\text{freq}} = 0$ **then**
$\quad\quad\quad$ **continue**
$\quad\quad \text{mv} \leftarrow \text{mv} + 1$
$\quad N \leftarrow N'$
return N

Using the selected neighbourhood, the algorithm then calls the SelectCandidate subroutine, presented below, to choose a candidate solution to potentially move to. This subroutine populates a set of candidate solutions with non-tabu neighbours from the chosen neighbourhood and returns the one with the lowest objective value. If the move does not require the MILPValidate check, it will use the IsFeasibleSequence validation to check the candidate and reject it if it isn't feasible. Otherwise, since MILPValidate is not quick, the feasibility check will be left for later on the most optimal candidate on line 10 of TabuSearch, rather than checking all candidates.

After a feasible, non-tabu candidate has been selected and added to the tabu list, the al-

SELECTCANDIDATE$\left(\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}, N, \text{nc}, \text{TL}\right)$

candidates $\leftarrow \emptyset$
while |candidates| $<$ nc **do**
  $\text{seq}_s^{\text{candidate}} \leftarrow$ NEIGHBOURHOODMOVE(seq_s, N)
  if $\text{seq}_s^{\text{candidate}}$ **in** TL **OR**
  (**not** (N requires MILP validation) **AND**
  not ISFEASIBLESEQUENCE$\left(\text{seq}_s^{\text{candidate}}, v_{ijgrtq_e}, y_{istq_e}\right)$) **then**
    continue
  $\text{sch}^{\text{candidate}} \leftarrow$ SCHEDULESEQUENCE$\left(\text{seq}_s^{\text{candidate}}, y_{istq_e}, \theta_{igt}\right)$
  if $\text{sch}^{\text{candidate}} = \text{FAIL}$ **then**
    continue
  APPEND$\left(\text{candidates}, \left(\text{F}\left(\text{sch}, z_{tq}^{\text{MILP}}\right), \text{seq}_s^{\text{candidate}}, \text{sch}^{\text{candidate}}\right)\right)$
$\text{seq}_s^1, \text{sch}^1, \text{obj}^1 \leftarrow \min(\text{candidates})$
return $\text{seq}_s^1, \text{sch}^1, \text{obj}^1$

gorithm saves it, and resets the 'iterations since improvement' counter, if it is the best known solution found so far. It is then updated to be the current solution and the main iteration begins again. Once the stopping criteria of the main loop are satisfied, the best solution is returned.

7.1.6 Simulated annealing

As with the TABUSEARCH algorithm, the SIMULATEDANNEALING algorithm, presented below, primarily follows the standard simulated annealing flow, to improve the initial solution provided by the constructive heuristic but also employs a low level, teamwork hybridisation with COIN-OR Cbc solving the Chapter 4 MILP. It also uses the SELECTNEIGHBOURHOOD and SELECTCANDIDATE subroutines introduced with the TABUSEARCH algorithm in Subsection 7.1.5.

The algorithm first initialises the best solution variables, temperature variable and zero iterator variables. It then begins the main 'while' loop, continuing until the temperature reaches a minimum level or a maximum number of iterations have passed since an improvement has been found. A neighbourhood is then chosen using the SELECTNEIGHBOURHOOD subroutine, explained previously in Subsection 7.1.5.

The SELECTCANDIDATE subroutine is also reused here to choose a neighbourhood solution to evaluate, however here only one candidate is selected, rather than a population of them. Once again if required, the MILPVALIDATE check is performed and the candidate is rejected if it isn't feasible.

The main simulated annealing step is then taken, whereby the candidate solution is moved to if it is better than the current solution or if the probabilistic acceptance function, $e^{\frac{\text{obj}-\text{obj}^1}{T}} >$ RAND() , is satisfied. The temperature is then cooled. If the new solution is the best known so far, it is saved out and the 'iterations since improvement' counter is reset. Finally, after the main loop's stopping criteria are satisfied, the best solution is returned.

$\textsc{SimulatedAnnealing}\left(\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}, T^0, T^{\min}, T^{\text{cr}}, \text{itsi}^{\max}, \text{mv}^{\text{freq}}\right)$

$\text{obj} \leftarrow \text{F}\left(\textsc{ScheduleSequence}\left(\text{seq}_s^{\text{best}}, y_{istq_e}, \theta_{igt}\right), z_{tq}^{\text{MILP}}\right)$
$\text{seq}_s^{\text{best}} \leftarrow \text{seq}_s$
$\text{obj}^{\text{best}} \leftarrow \text{obj}$
$T \leftarrow T^0; \text{itsi} \leftarrow 0; \text{mv} \leftarrow 0$
while $\text{T} > \text{T}^{\min}$ **AND** $\text{itsi} < \text{itsi}^{\max}$ **do**
  $\text{itsi} \leftarrow \text{itsi} + 1$
  $N \leftarrow \textsc{SelectNeighbourhood}\left(\text{Neighbourhoods}, \text{mv}, \text{mv}^{\text{freq}}\right)$
  $\text{seq}_s^1, \text{obj}^1 \leftarrow \textsc{SelectCandidate}\left(\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, N, 1, \emptyset\right)$
  if N requires MILP validation **AND**
   not $\text{MILP}\textsc{Validate}\left(\text{seq}_s^1, \text{sch}^1, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}\right)$ **then**
    continue
  if $\text{obj}^1 < \text{obj}$ **OR** $e^{\frac{\text{obj}-\text{obj}^1}{T}} > \textsc{Rand}()$ **then**
    $\text{seq}_s \leftarrow \text{seq}_s^1$
    $\text{obj} \leftarrow \text{obj}^1$
  $T \leftarrow T(1 - T^{\text{cr}})$
  if $\text{obj} < \text{obj}^{\text{best}}$ **then**
    $\text{seq}_s^{\text{best}}, \text{obj}^{\text{best}} \leftarrow \text{seq}_s, \text{obj}$
    $z_{tq}^{\text{MILP best}}, v_{ijgrtq_e}^{\text{best}}, y_{istq_e}^{\text{best}}, \theta_{igt}^{\text{best}} \leftarrow z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}$
    $\text{itsi} \leftarrow 0$
return $\text{seq}_s^{\text{best}}, \text{obj}^{\text{best}}, z_{tq}^{\text{MILP best}}, v_{ijgrtq_e}^{\text{best}}, y_{istq_e}^{\text{best}}, \theta_{igt}^{\text{best}}$

7.1.7 Hybrid technique

As seen in Section 2.6 of the literature review, a number of papers successfully employ approaches where several solution techniques cooperate to find the optimal solution. In particular, Michalewicz et al. (2006) describe it as an effective way to deal with complex generalised models that can exhibit varied behaviour between specific problem instances, which reflects the nature of this study's modelling methodology. With respect to the Talbi (2002) taxonomy, high level teamwork hybridisation is used here to enable this cooperative behaviour between the tabu search and simulated annealing techniques described in Subsection 7.1.5 and 7.1.6, respectively. This type of hybridisation also enables parallelisation of the solution techniques, without the need for major redesign or reimplementation.

In software architecture terms, a 'publisher-subscriber' design pattern (Gamma et al., 1994) is used to facilitate the hybridisation. The two metaheuristics are run as separate processes that asynchronously communicate newly found best solutions. ØMQ, an open source, lightweight message queue framework (Hintjens, 2013) is used to implement this communication. Much like the papers reviewed at the end of SubSection 2.6.2, in particular Malek (2009), the design and implementation serve as a novel example of how well known software architecture principles can be used to efficiently enable high level hybridisation, for cooperative, asynchronous communication between existing metaheuristic techniques.

TSSAHYBRID encapsulates the parallel execution of the two metaheuristics and the saving of the best found solution. It first runs the constructive heuristic to find the initial feasible solution, then uses this to instantiate the two metaheuristics, as their own processes, in lines 3 and 4. It then listens for solutions and keeps a record of the best found solution. It also listens for the stop messages from the metaheuristics. The 'while' loop ends when both metaheuristics have stopped.

TSSAHYBRID$\left(\text{it}^{\text{CHmax}}, \text{nc}, \text{TL}^{\text{length}}, \text{it}^{\text{TSmax}}, \text{itsi}^{\text{TSmax}}, \text{mv}^{\text{TSfreq}}, T^0, T^{\text{min}}, T^{\text{cr}}, \text{itsi}^{\text{SAmax}}, \text{mv}^{\text{SAfreq}}\right)$

1: $\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt} \leftarrow$ CONSTRUCTIVEHEURISTIC$\left(\text{it}^{\text{CHmax}}\right)$
2: $\text{obj}^{\text{best}} \leftarrow$ F$\left(\text{SCHEDULESEQUENCE}\left(\text{seq}_s^{\text{best}}, y_{istq_e}, \theta_{igt}\right), z_{tq}^{\text{MILP}}\right)$
3: **start** ØMQTABUSEARCH$\left(\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}, \text{nc}, \text{TL}^{\text{length}}, \text{it}^{\text{TSmax}}, \text{itsi}^{\text{TSmax}}, \text{mv}^{\text{TSfreq}}\right)$
4: **start** ØMQSIMULATEDANNEALING$\left(\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}, T^0, T^{\text{min}}, T^{\text{cr}}, \text{itsi}^{\text{SAmax}}, \text{mv}^{\text{SAfreq}}\right)$
5: TSRunning $\leftarrow$ True
6: SARunning $\leftarrow$ True
7: **while** TSRunning **AND** SARunning **do**
8:     msg, data $\leftarrow$ ØMQLISTEN()
9:     **if** msg = "solution" **then**
10:         $\text{seq}_s, \text{obj}, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt} \leftarrow \text{data}$
11:         **if** $\text{obj} < \text{obj}^{\text{best}}$ **then**
12:             $\text{seq}_s^{\text{best}}, \text{obj}^{\text{best}} \leftarrow \text{seq}_s, \text{obj}$
13:             $z_{tq}^{\text{MILP best}}, v_{ijgrtq_e}^{\text{best}}, y_{istq_e}^{\text{best}}, \theta_{igt}^{\text{best}} \leftarrow z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}$
14:     **else if** msg = "TS stopped" **then**
15:         TSRunning $\leftarrow$ False
16:     **else if** msg = "SA stopped" **then**
17:         SARunning $\leftarrow$ False
18: **return** $\text{seq}_s^{\text{best}}, \text{obj}^{\text{best}}, z_{tq}^{\text{MILP best}}, v_{ijgrtq_e}^{\text{best}}, y_{istq_e}^{\text{best}}, \theta_{igt}^{\text{best}}$

Only minor modifications to the TABUSEARCH and SIMULATEDANNEALING algorithms described Subsection 7.1.4, 7.1.5 and 7.1.6, respectively, are required to enable their asynchronous communication. These can be seen below, in blue text, in the updated algorithms ØMQTABUSEARCH and ØMQSIMULATEDANNEALING.

The subroutine ØMQSOLNLISTENER is also presented below to encapsulate the separate process as each metaheuristic starts to listen for new solutions coming from one another. This is started during the initialisation phase of the two metaheuristics, where new variables are introduced to record new solutions published through ØMQ. In the main loop of the two metaheuristics there are two modifications. The first checks if there is a new ØMQ solution and moves to it if it is better than the current best, and non-tabu for the tabu search. The second publishes any new best solutions. Finally, when each metaheuristic is finished its search, a stop message is published through ØMQ.

ØMQSOLNLISTENER$\left(\text{new_ØMQ_soln}, \text{seq}_s^{\text{ØMQ}}, \text{obj}^{\text{ØMQ}} z_{tq}^{\text{MILP ØMQ}}, v_{ijgrtq_e}^{\text{ØMQ}}, y_{istq_e}^{\text{ØMQ}}, \theta_{igt}^{\text{ØMQ}}\right)$

while True **do**
  msg, data $\leftarrow$ ØMQLISTEN()
  if msg = "solution" **then**
    new_ØMQ_soln $\leftarrow$ True
    $\text{seq}_s^{\text{ØMQ}}, \text{obj}^{\text{ØMQ}} z_{tq}^{\text{MILP ØMQ}}, v_{ijgrtq_e}^{\text{ØMQ}}, y_{istq_e}^{\text{ØMQ}}, \theta_{igt}^{\text{ØMQ}} \leftarrow$ data

ØMQTABUSEARCH$\left(\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}, \text{nc}, \text{TL}^{\text{length}}, \text{it}^{\max}, \text{itsi}^{\max}, \text{mv}^{\text{freq}}\right)$

$\text{seq}_s^{\text{best}} \leftarrow \text{seq}_s$
$\text{obj}^{\text{best}} \leftarrow \text{F}\left(\text{SCHEDULESEQUENCE}\left(\text{seq}_s^{\text{best}}, y_{istq_e}, \theta_{igt}\right), z_{tq}^{\text{MILP}}\right)$
$\text{TL} \leftarrow \emptyset; \text{it} \leftarrow 0; \text{itsi} \leftarrow 0; \text{mv} \leftarrow 0$
new_ØMQ_soln $\leftarrow$ False
$\text{seq}_s^{\text{ØMQ}}, \text{obj}^{\text{ØMQ}}, z_{tq}^{\text{MILP ØMQ}}, v_{ijgrtq_e}^{\text{ØMQ}}, y_{istq_e}^{\text{ØMQ}}, \theta_{igt}^{\text{ØMQ}} \leftarrow \text{seq}_s, \text{obj}, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}$
start ØMQSOLNLISTENER$\left(\text{new_ØMQ_soln}, \text{seq}_s^{\text{ØMQ}}, \text{obj}^{\text{ØMQ}}, z_{tq}^{\text{MILP ØMQ}}, v_{ijgrtq_e}^{\text{ØMQ}}, y_{istq_e}^{\text{ØMQ}}, \theta_{igt}^{\text{ØMQ}}\right)$
while $\text{it} < \text{it}^{\max}$ **AND** $\text{itsi} < \text{itsi}^{\max}$ **do**
  $\text{it} \leftarrow \text{it} + 1$
  $\text{itsi} \leftarrow \text{itsi} + 1$
  if new_ØMQ_soln **AND** $\text{obj}^{\text{ØMQ}} < \text{obj}^{\text{best}}$ **AND** $\text{seq}_s^{\text{ØMQ}}$ **not in** TL **then**
    $\text{seq}_s, \text{obj} \leftarrow \text{seq}_s^{\text{ØMQ}}, \text{obj}^{\text{ØMQ}}$
    $z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt} \leftarrow z_{tq}^{\text{MILP ØMQ}}, v_{ijgrtq_e}^{\text{ØMQ}}, y_{istq_e}^{\text{ØMQ}}, \theta_{igt}^{\text{ØMQ}}$
    new_ØMQ_soln $\leftarrow$ False
    $\text{itsi} \leftarrow 0$
  $N \leftarrow$ SELECTNEIGHBOURHOOD$\left(\text{Neighbourhoods}, \text{mv}, \text{mv}^{\text{freq}}\right)$
  $\text{seq}_s^1, \text{obj}^1 \leftarrow$ SELECTCANDIDATE$\left(\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, N, \text{nc}, \text{TL}\right)$
  APPEND$\left(\text{TL}, \text{seq}_s^1\right)$
  if N requires MILP validation **AND**
  not MILPVALIDATE() **then**
    continue
  if $\text{obj}^1 < \text{obj}^{\text{best}}$ **then**
    $\text{seq}_s^{\text{best}}, \text{obj}^{\text{best}} \leftarrow \text{seq}_s^1, \text{obj}^1$
    $z_{tq}^{\text{MILP best}}, v_{ijgrtq_e}^{\text{best}}, y_{istq_e}^{\text{best}}, \theta_{igt}^{\text{best}} \leftarrow z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}$
    ØMQPUBLISH$\left(\text{"solution"}, \left(\text{seq}_s, \text{obj}, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}\right)\right)$
    $\text{itsi} \leftarrow 0$
  $\text{seq}_s \leftarrow \text{seq}_s^1$
ØMQPUBLISH("TS stopped", NULL)
return $\text{seq}_s^{\text{best}}, \text{obj}^{\text{best}}, z_{tq}^{\text{MILP best}}, v_{ijgrtq_e}^{\text{best}}, y_{istq_e}^{\text{best}}, \theta_{igt}^{\text{best}}$

ØMQSIMULATEDANNEALING$\left(\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}, T^0, T^{\min}, T^{\text{cr}}, \text{itsi}^{\max}, \text{mv}^{\text{freq}}\right)$

obj $\leftarrow$ F$\left(\text{SCHEDULESEQUENCE}\left(\text{seq}_s^{\text{best}}, y_{istq_e}, \theta_{igt}\right), z_{tq}^{\text{MILP}}\right)$

$\text{seq}_s^{\text{best}} \leftarrow \text{seq}_s$

$\text{obj}^{\text{best}} \leftarrow \text{obj}$

$T \leftarrow T^0$; itsi $\leftarrow 0$; mv $\leftarrow 0$

new_ØMQ_soln $\leftarrow$ False

$\text{seq}_s^{\text{ØMQ}}, \text{obj}^{\text{ØMQ}}, z_{tq}^{\text{MILP ØMQ}}, v_{ijgrtq_e}^{\text{ØMQ}}, y_{istq_e}^{\text{ØMQ}}, \theta_{igt}^{\text{ØMQ}} \leftarrow \text{seq}_s, \text{obj}, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}$

start ØMQSOLNLISTENER$\left(\text{new_ØMQ_soln}, \text{seq}_s^{\text{ØMQ}}, \text{obj}^{\text{ØMQ}}, z_{tq}^{\text{MILP ØMQ}}, v_{ijgrtq_e}^{\text{ØMQ}}, y_{istq_e}^{\text{ØMQ}}, \theta_{igt}^{\text{ØMQ}}\right)$

while $\text{T} > \text{T}^{\min}$ **AND** $\text{itsi} < \text{itsi}^{\max}$ **do**

  itsi $\leftarrow$ itsi + 1

  if new_ØMQ_soln **AND** $\text{obj}^{\text{ØMQ}} < \text{obj}^{\text{best}}$ **then**

    $\text{seq}_s, \text{obj} \leftarrow \text{seq}_s^{\text{ØMQ}}, \text{obj}^{\text{ØMQ}}$

    $z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt} \leftarrow z_{tq}^{\text{MILP ØMQ}}, v_{ijgrtq_e}^{\text{ØMQ}}, y_{istq_e}^{\text{ØMQ}}, \theta_{igt}^{\text{ØMQ}}$

    new_ØMQ_soln $\leftarrow$ False

    itsi $\leftarrow 0$

  $N \leftarrow$ SELECTNEIGHBOURHOOD$\left(\text{Neighbourhoods}, \text{mv}, \text{mv}^{\text{freq}}\right)$

  $\text{seq}_s^1, \text{obj}^1 \leftarrow$ SELECTCANDIDATE$\left(\text{seq}_s, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, N, 1, \emptyset\right)$

  if N requires MILP validation **AND**
  not MILPVALIDATE$\left(\text{seq}_s^1, \text{sch}^1, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}\right)$ **then**

    continue

  if $\text{obj}^1 < \text{obj}$ **OR** $e^{\frac{\text{obj}-\text{obj}^1}{T}} >$ RAND() **then**

    $\text{seq}_s \leftarrow \text{seq}_s^1$

    $\text{obj} \leftarrow \text{obj}^1$

  $T \leftarrow T(1 - T^{\text{cr}})$

  if $\text{obj} < \text{obj}^{\text{best}}$ **then**

    $\text{seq}_s^{\text{best}}, \text{obj}^{\text{best}} \leftarrow \text{seq}_s, \text{obj}$

    $z_{tq}^{\text{MILP best}}, v_{ijgrtq_e}^{\text{best}}, y_{istq_e}^{\text{best}}, \theta_{igt}^{\text{best}} \leftarrow z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}$

    ØMQPUBLISH$\left(\text{“solution”}, \left(\text{seq}_s, \text{obj}, z_{tq}^{\text{MILP}}, v_{ijgrtq_e}, y_{istq_e}, \theta_{igt}\right)\right)$

    itsi $\leftarrow 0$

ØMQPUBLISH(“SA stopped”, NULL)

return $\text{seq}_s^{\text{best}}, \text{obj}^{\text{best}}, z_{tq}^{\text{MILP best}}, v_{ijgrtq_e}^{\text{best}}, y_{istq_e}^{\text{best}}, \theta_{igt}^{\text{best}}$

7.2 Validation

The simple example introduced in Section 3.3, solved in Section 4.2 with the first model and again in Section 6.2 with the improved model is used here to validate the outcomes of this chapter. The developed solution technique's ability to overcome the intractability issues with the new excavation and haulage module formulation is tested using a variety of instances.

Two sets of problem instances are used to analyse five solution methods. The first, described in Table 7.1, are the simple example instances used in Section 6.2. The second, described in Table 7.5, are the case study instances used to analyse CPLEX solving the Chapter 4 model in Section 4.2.

The methods are CPLEX with a two hour time limit; the constructive heuristic on its own (CH); the constructive heuristic and tabu search (CH+TS); the constructive heuristic and simulated annealing (CH+SA); and the full hybrid constructive heuristic, tabu search and simulated annealing technique described in the previous section (CH+TS+SA). All results were run using a computer with an Intel i7 CPU and 16GB of RAM. The four solution technique methods have been run 20 times and the average objective values are reported.

Table 7.2 presents the objective values of the simple example instances, the best known solutions are highlighted in green. For all instances that CPLEX can find a solution to, the hybrid CH+TS+SA solution technique also finds the same optimal result. In fact, across all of these instances, the hybrid CH+TS+SA solution technique finds the best known solution. Table 7.3 reports the standard deviation of the 20 runs of each solution technique. They are all within acceptable bounds of the objective, below 1%.

Table 7.4 shows the CPU times for the four solution techniques solving the simple example problem instances. The table clearly demonstrates the developed solution techniques are able to find the solutions to these small instances very quickly with acceptable amount of variance. It also shows that the hybrid CH+TS+SA solution technique doesn't take a considerably longer time to find the most optimal solutions.

Table 7.1. Simple example instance definitions

id	states	shovels	trucks	pit target (t)	product target (t)
7.01	1	1	1	(250,)	500
7.02	1	1	1	(500,)	500
7.03	1	1	1	(750,)	500
7.04	1	1	2	(1000,)	500
7.05	1	1	2	(1500,)	1000
7.06	1	1	4	(2500,)	2000
7.07	1	1	6	(3250,)	2000
7.08	1	2	1	(250, 250)	500
7.09	1	2	1	(500, 250)	500
7.10	1	2	2	(750, 500)	500
7.11	1	2	4	(1000, 1000)	500
7.12	1	2	6	(1500, 1500)	1000
7.13	2	1	1	(1500,)	1000
7.14	2	1	2	(2000,)	1000
7.15	2	1	4	(5000,)	4000
7.16	2	1	6	(7000,)	6000
7.17	2	2	1	(500, 500)	500
7.18	2	2	1	(750, 750)	500
7.19	2	2	2	(1000, 1000)	500
7.20	2	2	4	(2000, 2000)	1000
7.21	2	2	6	(3000, 3000)	2000

Table 7.2. Simple example instance objectives

	CPLEX	CH	CH+TS	CH+SA	CH+TS+SA	
id	Obj. (MWh)	Avg. obj. (MWh)	Avg. obj. (MWh)	Avg. obj. (MWh)	Avg. obj. (MWh)	Ch.4 MILP gap %
7.01	6.41	6.41	6.41	6.41	6.41	-1.69%
7.02	6.85	6.85	6.85	6.85	6.85	-0.44%
7.03	7.55	7.55	7.55	7.55	7.55	0.80%
7.04	8.36	8.36	8.36	8.36	8.36	-0.36%
7.05	12.82	12.82	12.82	12.82	12.82	0.94%
7.06	-	22.50	22.49	22.49	22.49	0.67%
7.07	-	24.68	24.65	24.67	24.63	1.99%
7.08	7.80	7.80	7.80	7.80	7.80	0.00%
7.09	8.25	8.25	8.25	8.25	8.25	1.10%
7.10	9.84	9.84	9.84	9.84	9.84	0.92%
7.11	-	13.06	12.84	12.92	12.79	-1.16%
7.12	-	19.23	19.22	19.22	19.22	0.63%
7.13	15.00	15.01	15.01	15.00	15.00	0.20%
7.14	16.47	16.49	16.48	16.48	16.47	0.18%
7.15	-	44.25	44.17	44.20	44.13	2.18%
7.16	-	62.14	62.14	62.14	62.14	0.97%
7.17	13.80	14.11	13.80	13.80	13.80	-1.00%
7.18	15.32	15.32	15.32	15.32	15.32	0.59%
7.19	-	16.86	16.85	16.82	16.82	0.30%
7.20	-	24.62	24.61	24.59	24.57	0.80%
7.21	-	37.77	37.30	37.65	36.98	1.25%

Table 7.3. Simple example instance objective standard deviation

id	CH Obj. std. dev. (MWh)	CH+TS Obj. std. dev. (MWh)	CH+SA Obj. std. dev. (MWh)	CH+TS+SA Obj. std. dev. (MWh)
7.01	0.00	0.00	0.00	0.00
7.02	0.00	0.00	0.00	0.00
7.03	0.00	0.00	0.00	0.00
7.04	0.00	0.00	0.00	0.00
7.05	0.00	0.00	0.00	0.00
7.06	0.01	0.00	0.00	0.00
7.07	0.00	0.02	0.02	0.02
7.08	0.00	0.00	0.00	0.00
7.09	0.00	0.00	0.00	0.00
7.10	0.00	0.00	0.00	0.00
7.11	0.00	0.09	0.11	0.00
7.12	0.00	0.00	0.00	0.00
7.13	0.00	0.00	0.00	0.00
7.14	0.00	0.00	0.01	0.00
7.15	0.14	0.12	0.08	0.15
7.16	0.00	0.00	0.00	0.00
7.17	0.00	0.00	0.00	0.00
7.18	0.00	0.00	0.00	0.00
7.19	0.00	0.00	0.00	0.00
7.20	0.01	0.02	0.02	0.01
7.21	0.35	0.22	0.21	0.09

Table 7.4. Simple example instance computation times

id	CH		CH+TS		CH+SA		CH+TS+SA	
	Avg. CPU sec.	CPU sec. std. dev.	Avg. CPU sec.	CPU sec. std. dev.	Avg. CPU sec.	CPU sec. std. dev.	Avg. CPU sec.	CPU sec. std. dev.
7.01	0.03	0.01	0.66	0.09	0.23	0.01	0.84	0.05
7.02	0.04	0.01	0.23	0.01	0.97	0.08	1.14	0.07
7.03	0.03	0.01	0.23	0.01	1.05	0.07	1.27	0.16
7.04	0.05	0.02	0.52	0.08	2.25	0.25	3.22	0.42
7.05	0.08	0.02	0.46	0.05	1.23	0.07	1.84	0.17
7.06	0.10	0.02	1.00	0.12	0.82	0.20	1.78	1.10
7.07	0.78	0.18	2.68	0.46	1.86	0.29	3.93	0.75
7.08	0.04	0.01	0.36	0.05	0.70	0.08	0.76	0.06
7.09	0.05	0.01	0.36	0.04	1.18	0.08	1.32	0.12
7.10	0.08	0.02	0.57	0.06	2.54	0.50	2.89	0.11
7.11	0.33	0.03	1.56	0.24	1.58	0.46	2.24	0.26
7.12	0.14	0.02	1.45	0.12	1.46	0.22	2.49	0.14
7.13	0.08	0.01	0.38	0.05	1.24	0.42	1.63	0.45
7.14	0.10	0.02	2.26	0.48	1.90	0.80	4.17	0.96
7.15	5.05	0.28	5.68	0.33	5.72	0.69	5.62	0.35
7.16	5.25	0.28	7.01	1.51	8.00	1.09	5.96	0.47
7.17	0.11	0.02	0.32	0.04	1.48	0.11	1.76	0.13
7.18	0.11	0.01	0.38	0.07	0.75	0.10	0.97	0.08
7.19	0.39	0.01	2.18	0.44	2.28	0.63	4.11	0.87
7.20	1.08	0.09	3.31	0.94	1.91	0.28	4.07	0.44
7.21	1.70	0.09	4.27	0.71	2.59	0.38	5.45	0.85

The case study instances are more important for demonstrating the practical applicability of the developed solution techniques. Table 7.6 reports the average objective values from running the four solution techniques 20 times, the best objective is highlighted in green. With the growing problem size, the benefit of the TS and SA hybridisation also becomes clear. This indicates the hybridisation's ability to search through a wider area of the solution space more efficiently. The hybrid technique is able to equal or better the single metaheuristic methods in all instances. This demonstrates the value of solver cooperation between the two techniques that has been enabled by using the developed solution framework.

The Chapter 4 MILP gap is also reported as a measure of optimality. While these gaps are above what was seen in the smaller sized problem instances, they are not unreasonably far away. By plotting the gap against a measure of size (# loading slots × # shovels × # trucks) on a logarithmic scale a relationship is observed, seen in Figure 7.11. The cause of the relationship is unclear. It may be caused by a certain behaviour that's different between the two models or a limitation of the solution technique. However, it is considered out of scope for this thesis as the solutions are considered satisfactory for the purpose of the analysis. More detailed investigation into this relationship is therefore recommended as future work.

Table 7.7 shows the standard deviation of the 20 runs for each case study problem instance. The hybrid CH+TS+SA technique doesn't negatively impact the consistency of results. It achieves satisfactorily low levels of variance, less than 1 MWh or 1% of the objective. Importantly, in some circumstances where the individual metaheuristic methods have a poor variance, it achieves a smaller variance than the other two methods. This is a result of the cooperative behaviour avoiding local optima.

Table 7.8 reports the CPU time for each solution technique method. All instances can be solved within a reasonable amount of time for practical, operational use. The extra computation required for the hybrid CH+TS+SA technique is small enough to justify the improved quality it achieves.

Table 7.5. Case study instance definitions

id	states	shovels	trucks	pit target (t)	product target (t)
7.22	2	2	10	(5000, 5000)	1000
7.23	2	2	15	(7500, 7500)	2500
7.24	2	2	20	(10000, 10000)	5000
7.25	2	4	10	(2500, 2500, 2500, 2500)	1000
7.26	2	4	15	(3750, 3750, 3750, 3750)	2500
7.27	2	4	20	(5000, 5000, 5000, 5000)	4000
7.28	4	2	10	(10000, 10000)	2500
7.29	4	2	15	(15000, 15000)	5000
7.30	4	2	20	(20000, 20000)	10000
7.31	4	4	10	(5000, 5000, 5000, 5000)	2000
7.32	4	4	15	(7500, 7500, 7500, 7500)	5000
7.33	4	4	20	(10000, 10000, 10000, 10000)	8000

Table 7.6. Case study instance computational results

id	CH	CH+TS	CH+SA	CH+TS+SA	
	Avg. obj. (MWh)	Avg. obj. (MWh)	Avg. obj. (MWh)	Avg. obj. (MWh)	Ch.4 MILP gap %
7.22	67.86	67.46	67.34	67.13	2.65%
7.23	96.72	95.71	95.84	93.72	3.90%
7.24	137.44	135.48	135.44	134.15	4.36%
7.25	77.67	76.00	76.24	75.55	3.12%
7.26	104.92	103.31	103.17	102.47	2.97%
7.27	140.85	137.91	138.35	137.59	3.38%
7.28	137.58	136.44	135.92	135.12	3.14%
7.29	196.24	192.89	195.02	188.54	4.61%
7.30	276.02	274.27	274.23	269.66	5.00%
7.31	153.73	148.36	149.78	147.77	1.64%
7.32	209.64	205.13	205.48	204.25	3.15%
7.33	279.81	274.47	274.09	273.46	2.89%

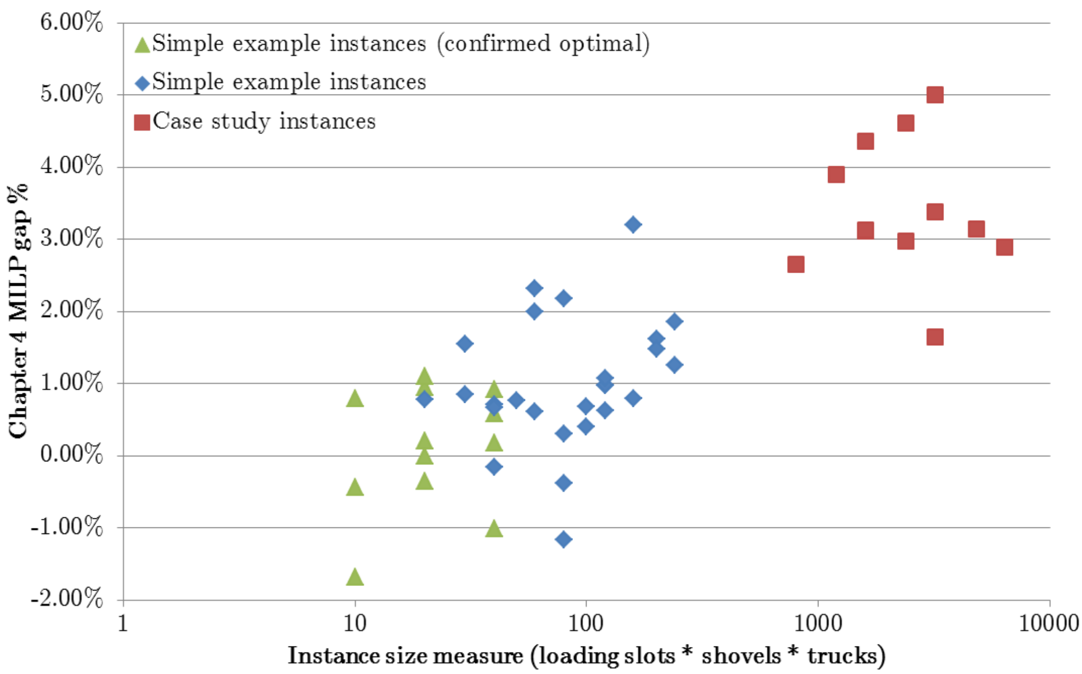

Figure 7.11. Chapter 4 MILP gap % vs instance size measure

Table 7.7. Case study instance objective standard deviation

id	CH Obj. std. dev. (MWh)	CH+TS Obj. std. dev. (MWh)	CH+SA Obj. std. dev. (MWh)	CH+TS+SA Obj. std. dev. (MWh)
7.22	0.06	0.28	0.18	0.23
7.23	0.66	0.38	0.79	0.36
7.24	0.51	0.70	0.50	0.59
7.25	0.41	0.43	0.58	0.37
7.26	0.26	0.38	0.63	0.45
7.27	0.23	0.24	0.79	0.60
7.28	1.70	0.47	0.68	0.92
7.29	1.30	0.73	2.17	0.86
7.30	1.73	1.41	1.47	0.89
7.31	0.46	0.44	1.33	0.94
7.32	0.52	0.75	0.47	0.83
7.33	0.18	1.14	0.33	0.57

Table 7.8. Case study instance computation times

id	CH		CH+TS		CH+SA		CH+TS+SA	
	Avg. CPU sec.	CPU sec. std. dev.	Avg. CPU sec.	CPU sec. std. dev.	Avg. CPU sec.	CPU sec. std. dev.	Avg. CPU sec.	CPU sec. std. dev.
7.22	6.37	0.20	12.07	0.40	0.18	10.85	18.00	1.24
7.23	7.74	0.78	18.72	3.95	0.79	14.70	27.18	2.38
7.24	9.37	0.94	54.44	3.79	0.50	42.77	63.57	2.13
7.25	6.13	0.41	15.44	1.86	0.58	14.05	26.75	2.95
7.26	12.49	0.77	24.98	2.06	0.63	22.35	37.90	4.21
7.27	25.97	0.45	40.87	1.49	0.79	40.59	59.55	8.64
7.28	8.66	0.94	21.50	2.62	0.68	17.39	34.41	6.43
7.29	24.94	3.50	52.03	3.23	2.17	35.71	82.69	8.35
7.30	33.46	3.79	61.32	6.83	1.47	61.15	90.04	8.74
7.31	30.99	2.31	69.51	7.65	1.33	43.82	68.45	7.26
7.32	14.69	0.84	34.87	1.74	0.47	33.39	64.65	7.40
7.33	36.53	6.25	71.39	4.91	0.33	75.63	105.89	7.14

7.3 Remarks

The solution technique presented in this chapter has successfully overcome the modelling complexity that was added in Chapter 6. The development focused on the excavation and haulage subsystem, where NP-hard complexity was introduced, but also ensures the feasibility and optimality of the whole integrated model. By innovating a solution representation, neighbourhoods, validation and evaluation algorithms and a constructive heuristic, the problem was translated into a form suitable for the application of metaheuristics.

The core complexity of the improved excavation and haulage subsystem formulation was the scheduling of truck and shovel interactions. In the formulation, a large number of variables and if-then constraints were required to accurately model this behaviour. The focus of the solution representation was therefore to reduce the size of the solution space to allow for more efficient searching. This was achieved using a sequence of truck 'jobs' for each shovel as the solution representation. Using this solution representation, seven neighbourhoods were developed, two of which were identified as potentially impacting the rest of the integrated model. Two different validation algorithms were therefore required. The first, MILPVALIDATE, to deal with these two moves whereby the whole-system must be checked for feasibility. The other, ISFEASIBLESEQUENCE, only needs to check the excavation and haulage subsystem is okay, since the move won't impact other subsystems.

A scheduling algorithm, SCHEDULESEQUENCE, was then developed and presented to assign times to the jobs happening in the shovel sequences. The resulting schedule is then processed by the EHENERGYCONSUMPTION algorithm to compute the energy consumption of the excavation and haulage subsystem. The algorithm is also accompanied by a subroutine, F, that substitutes the EHENERGYCONSUMPTION result into the Chapter 4 MILP solution to provide the metaheuristics with the overall energy consumption of the whole integrated model.

The CONSTRUCTIVEHEURISTIC algorithm then builds an initial feasible solution for the improvement metaheuristics to use as a starting point. It first finds a solution to the Chapter 4 MILP model using an exact method, COIN-OR Cbc, then uses that as a basis for iteratively building sequences based on some heuristics and random selections, until a feasible one is found.

Two metaheuristics were developed to search for improvements to the initial feasible solution, TABUSEARCH and SIMULATEDANNEALING. They both use their respective standard algorithm flows to apply the aforementioned contributions to search the solution space for near optimal solutions. Due to the use of the MILPVALIDATE algorithm to check certain neighbourhood moves, the two developed metaheuristics are low level, teamwork hybridisations with the exact method used to re-solve the Chapter 4 MILP to confirm the feasibility of the whole-of-mine integrated model.

A high level, teamwork hybridisation was developed to run the two metaheuristics in parallel and facilitate their communication. This enabled the type of cooperative behaviour Michalewicz et al. (2006) describes, as explained in Section 2.6. This was achieved using the publisher-subscriber software design pattern (Gamma et al., 1994) and a popular message queue library ØMQ (Hintjens, 2013). Using these meant relatively minimal modifications to the design and implementation of the two metaheuristics was required to get them running in parallel and communicating with each other asynchronously. It is a novel example of how software architecture good practice can aid in the efficient development of hybrid metaheuristics, similar to that seen in Malek (2009), Georgiev & Atanassov (2014) and other papers reviewed in SubSection 2.6.2.

Using problem instances of the simple example and case study models analysed throughout this thesis, the utility of the developed techniques has been demonstrated. For the small instances that CPLEX could find solutions to, the hybrid technique was able to find the optimal solution very quickly. For larger instances, solutions of good quality, using the Chapter 4 MILP as a rough measure, were found within two minutes. Across all instances, the hybrid TS and SA technique consistently performs best without a significant increase in computation time. It will therefore be used to solve the model for the remaining analysis conducted in the next chapter.

Referring back to the research approach described in Section 1.5, this chapter has resulted in the bottom right quadrant of Figure 7.12. Various elements have been innovated to overcome the complexities of the Chapter 6 formulation and form an effective solution approach for finding good quality solutions for practical-sized instances in a reasonable time frame. The high level, teamwork hybridisation between tabu search and simulated annealing was shown to be the most effective and robust way of finding good quality solutions without an unreasonable increase in computation time. It will therefore be used as the technique for solving the case study model in the next chapter.

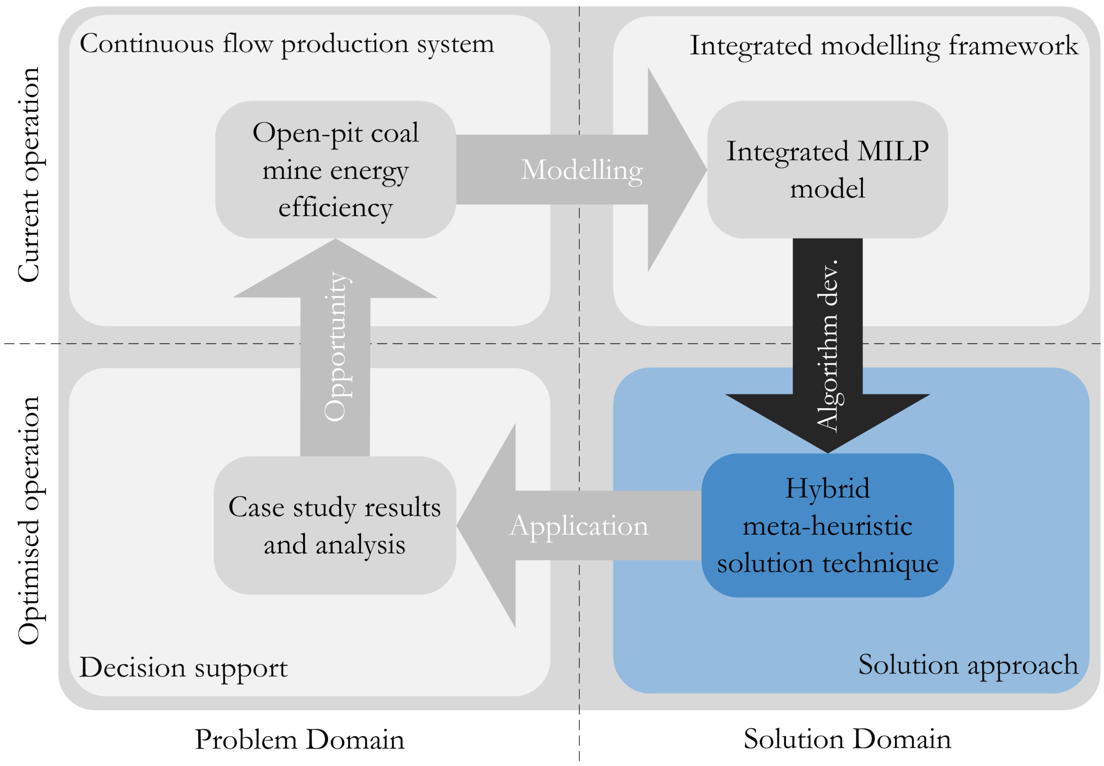

Figure 7.12. Role of Chapter 7 in the research approach

Research question 3 from Section 1.2, listed below, has been addressed in detail throughout this chapter. A new solution technique has been developed and is showing promising results for being able to overcome complexity issues by finding feasible solutions reasonably quickly, with minimal impact on optimality.

3. *What solution techniques will be appropriate for solving the model in real-time?*
   (a) *How hard is it to solve the developed model? Is the optimisation NP hard?*
   (b) *Are new techniques required?*
   (c) *What impact do any new solution techniques have on optimality and speed?*

8
Results

Using the solution technique developed in Chapter 7, the improved model can now be solved on the case study, introduced in Chapter 5, to verify and validate it on a real life problem and show that the improvements made in Chapter 6 are suitable. Section 8.1 first analyses the benchmark solution to inspect the solutions to the improved model, and validate that it overcomes the issues with the original formulation. Sections 8.2 and 8.3 then continue the validation by looking at the model results from the perspective of the planning and asset usage factors, respectively. Finally, Section 8.4 concludes the chapter with a summary of the findings.

8.1 Benchmark solution

Using the developed CH+TS+SA hybrid metaheuristic, the benchmark problem instance introduced in Section 5.3 has been solved with the improved model. Table 8.1 shows the energy consumption of each subsystem and Table 8.2 shows the amount of material transferred over each connection. The new model results in an overall energy consumption of 233.93, up 3.6% from the original model. This increase can be attributed to the excavation and haulage subsystem, which now consumes a total of 140.69 MWh, 60.1

Table 8.3 presents the new truck allocations and Figure 8.1 illustrates the resulting equipment schedule. The increased accuracy of the excavation and haulage model has meant that a few trips from the more efficient trucks are required to be done by the less efficient trucks, which also have smaller payloads, so four more trips are required, 161 in total. There are 47 trips transporting overburden from pit 1, 47 trips transporting ROM coal from pit 2 and 67 trips transporting spoil from pit 3. This is split over 13 trucks: trucks 1, 2, 4, 5, 6, 7, 8, 9, 11, 12, 13, 15 and 18. The ROM stockpile still increases by the same amount, however is used slightly less. The only other change is in the waste dump, with slightly different make up of use over the four states, but the same overall usage.

Table 8.1. Benchmark energy consumption (MWh)

Subsystem	State 1 (0-2hr)	State 2 (2-4hr)	State 3 (4-6hr)	State 4 (6-8hr)	All time
ROM stockpile	0.00	0.00	0.00	0.15	0.15
CB1	0.12	0.11	0.11	0.12	0.47
CB2	0.48	0.45	0.45	0.48	1.86
CB3	0.38	0.38	0.38	0.39	1.54
CB4	0.66	0.66	0.66	0.68	2.66
CB5	0.59	0.59	0.59	0.62	2.37
Crushed ROM stockpile	2.03	1.92	1.92	2.02	7.89
Crusher	7.40	7.20	7.00	7.60	29.20
Extraction	32.60	36.14	32.41	39.54	140.69
Top soil dump	0.00	0.00	0.00	0.00	0.00
Wash plant	6.11	6.11	6.11	6.33	24.65
Waste dump 1	5.17	6.05	5.17	5.83	22.22
Waste dump 2	0.00	0.00	0.00	0.00	0.00
Waste dump 3	0.00	0.00	0.00	0.00	0.00
Whole mine	55.60	59.67	54.86	63.81	233.93

Table 8.2. Benchmark material transfer over connections (tonnes)

Subsystem	Grade	State 1 (0-2hr)	State 2 (2-4hr)	State 3 (4-6hr)	State 4 (6-8hr)	All time
ROM Stockpile→BC1	ROM	0.0	0.0	0.0	0.0	0.0
BC1→Crusher	ROM	2540.0	2370.0	2370.0	2540.0	9820.0
BC2→Crushed ROM stockpile	Crushed ROM	2540.0	2370.0	2370.0	2504.0	9784.0
BC2→BC5	-	0.0	0.0	0.0	36.0	36.0
BC3→Wash plant	Crushed ROM	2426.7	2426.7	2426.7	2504.0	9784.0
BC4→Tailings dump	Tailings	579.7	579.7	579.7	598.2	2337.2
BC5 outlet	Product	1984.2	1984.2	1984.2	2083.4	8036.0
Crushed ROM stockpile→BC3	Crushed ROM	2426.7	2426.7	2426.7	2504.0	9784.0
Crusher→BC2	Crushed ROM	2540.0	2370.0	2370.0	2540.0	9820.0
Crusher waste outlet	-	0.0	0.0	0.0	0.0	0.0
Extraction→ ROM stockpile	ROM	0.0	0.0	0.0	220.0	220.0
Extraction→ BC1	ROM	2540.0	2370.0	2370.0	2540.0	9820.0
Extraction→ Top soil dump	-	0.0	0.0	0.0	0.0	0.0
Extraction→ Waste dump 1	Overburden & Spoil	5170.0	6050.0	5170.0	5830.0	22220.0
Extraction→ Waste dump 2	-	0.0	0.0	0.0	0.0	0.0
Extraction→ Waste dump 3	-	0.0	0.0	0.0	0.0	0.0
Extraction pit 1	Overburden	1870.0	1870.0	1870.0	2530.0	8140.0
Extraction pit 2	ROM	2540.0	2370.0	2370.0	2760.0	10040.0
Extraction pit 3	Spoil	3300.0	4180.0	3300.0	3300.0	14080.0
Extraction pit 4	-	0.0	0.0	0.0	0.0	0.0
Extraction pit 5	-	0.0	0.0	0.0	0.0	0.0
Wash plant→BC5	Product	1984.2	1984.2	1984.2	2047.4	8000.0
Wash plant water in	Water	137.2	137.2	137.2	141.6	553.2
Wash plant→BC4	Tailings	579.7	579.7	579.7	598.2	2337.2

Table 8.3. Benchmark truck allocations (# trips)

State	State 1 (0-2hr)			State 2 (2-4hr)			State 2 (4-6hr)			State 4 (6-8hr)				
Shovel	1	2	4	1	2	4	1	2	4	1		2	4	All
Grade	ROM	Spoil	Ovb.	ROM	Spoil	Ovb.	ROM	Spoil	Ovb.	ROM		Spoil	Ovb.	trips
Inlet	Pit 2	Pit 3	Pit 1	Pit 2	Pit 3	Pit 1	Pit 2	Pit 3	Pit 1	Pit 2		Pit 3	Pit 1	&
Outlet	PP	WD1	WD1	PP	WD1	WD1	PP	WD1	WD1	ROM SP	PP	WD1	WD1	times
Truck 1	2	2	-	1	4	-	3	2	-	1	2	2	-	19
Truck 2	3	2	-	3	2	-	4	2	-	-	1	1	2	20
Truck 3	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 4	2	3	-	2	3	-	-	4	-	-	4	1	-	19
Truck 5	-	-	-	-	4	-	-	-	-	-	-	-	-	4
Truck 6	3	2	-	1	4	-	2	3	-	-	1	-	3	19
Truck 7	-	4	-	-	-	-	-	-	-	-	-	-	-	4
Truck 8	-	-	4	1	-	3	1	-	4	-	1	-	3	17
Truck 9	1	-	4	-	-	4	-	-	4	-	-	-	3	16
Truck 10	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 11	-	-	-	-	-	-	-	-	-	-	-	-	3	3
Truck 12	-	-	3	-	-	4	-	-	3	-	-	4	-	14
Truck 13	-	-	-	-	-	-	-	-	-	-	-	4	-	4
Truck 14	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 15	1	3	-	3	2	-	1	4	-	-	2	2	-	18
Truck 16	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 17	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 18	-	-	-	-	-	-	-	-	-	-	1	3	-	4
Truck 19	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Truck 20	-	-	-	-	-	-	-	-	-	-	-	-	-	-
All trucks	12	16	11	11	19	11	11	15	11	1	12	17	14	161

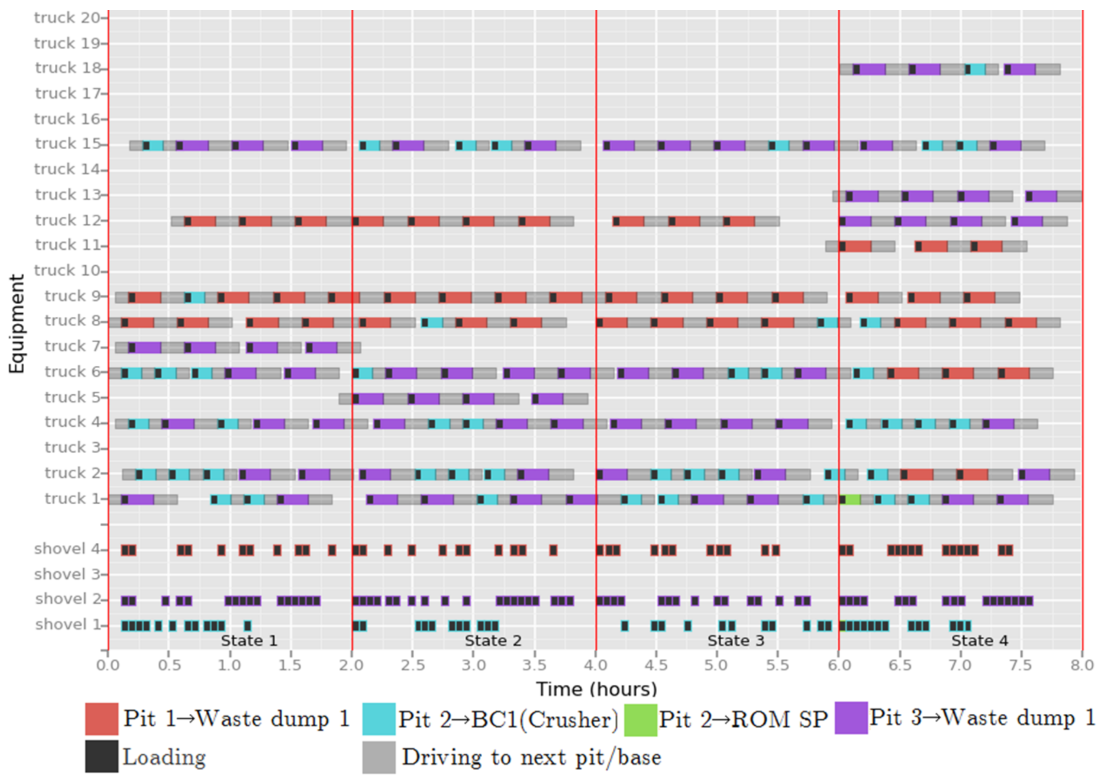

Figure 8.1. Benchmark solution schedule

By focusing on the first 5 trips of truck 15, the two primary issues with the allocation model can be examined and seen to be overcome.

The truck's first and second trip have different driving times; the first is moving ROM from pit 2 to the BC1 while the second is moving spoil from pit 3 to the waste dump. The driving time between the jobs is correctly displayed as 6.5 minutes. Three trips later, the truck then changes back to do a pit 2 job again, however this time it needs to drive for 11.9 minutes to get from the waste dump back to pit 2.

The second issue is also demonstrated amongst these trips. After the truck has driven back to pit 2, it must wait to be loaded. This shows that the formulation is working to correctly model the shovel and truck interaction. The total impact of truck waiting time can now be calculated from the model solutions. Across all trips, the average waiting time is 1.7 minutes, adding up to a total of 4.33 truck hours or 1.335 MWh, which accounts for 0.95% of the excavation and haulage energy consumption and 0.57% of the whole mine's energy consumption.

The other issue found in the original case study analysis in Section 5.3 was the decaying accuracy and objective value with shorter state lengths. Solving the benchmark with eight 1 hour states now reaches a solution with a more comparable objective value of 234.29. This suggests that the new formulation improved upon issue that the allocation formulation had with shorter state lengths. The improved accuracy of the scheduling formulation now allows for more realistic transitions between states. It also suggests that 2-hour states are appropriate for the problem as shorter states aren't able to produce a more optimal result.

Solutions for the problem with smaller state lengths became much harder for the solution technique to find. The computation time increased to 200+ seconds. This is likely because the algorithms used here have been developed and tuned for this particular case study, with four 2-hour time steps. If smaller time steps were required or found to result in more optimal solutions, it is expected that further tuning on the developed techniques would result in more acceptable computation times.

For longer state lengths, the objective still improves; solving the benchmark instance with one 8-hour state results in an objective value of 230.45 MWh. Though, as explained in Section 5.3, this comes at the cost of reduced accuracy from the whole-of-mine perspective. With longer states, the resolution of subsystem interaction is reduced.

8.2 Plan analysis

This section extends upon the preliminary case study analysis using the original model in Subsection 5.3.2 that looked at the effect that demand has on energy efficiency. Here, the same analysis is used on the improved model to study how demand and extraction targets that represent the planning factor identified as an area of focus in Section 2.4, impact the results.

Six scenarios are analysed:

P1. Perturb pit 1 (overburden) extraction target by ±40%

P2. Perturb pit 2 (ROM) extraction target by ±40%

P3. Perturb pit 3 (spoil) extraction target by ±40%

P4. Perturb wash plant (product) output target by ±40%

P5. Perturb pit 2 (ROM) extraction target and wash plant (product) output target by ±40%

P6. Perturb all pit's extraction targets and wash plant (product) output target by ±40%

Figure 8.2 shows the increase in energy consumption as a result of the increased production targets for each scenario. P6 has the largest impact on energy consumption since it increases the work across the whole mine. The other scenarios are more closely grouped. P3 and P5 have the next biggest impact as they represent the largest extraction target and an increase in two targets, respectively.

As applied in Section 5.3 and explained in Section 2.2, a conventional measure of production system energy efficiency is used in this study. This is production system output, product tonnes in this case, divided by energy input, the objective of the model. The resulting unit for efficiency is Product t / MWh.

The impact on energy efficiency of perturbing each of the three extraction targets can be seen in Figure 8.3. The overburden and spoil scenarios reduce energy efficiency as the target is increased since the product output (numerator) isn't changing but more energy is being consumed. This is also seen for the ROM target increases. However, when decreasing the ROM target, the minimum stockpile limit constraint comes into play, seen in the P2 SP trend of Figure 8.3. It forces the excavation and haulage subsystem to maintain the ROM extraction so that the production target can be achieved. This is a good example of the benefit that having a whole-of-system model brings.

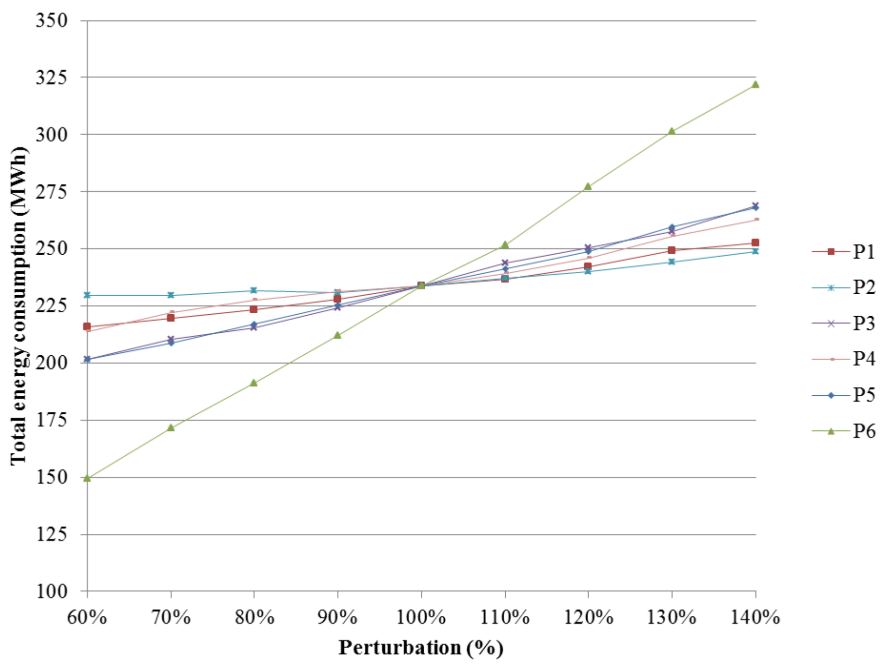

Figure 8.2. Energy consumption of planning analysis scenarios

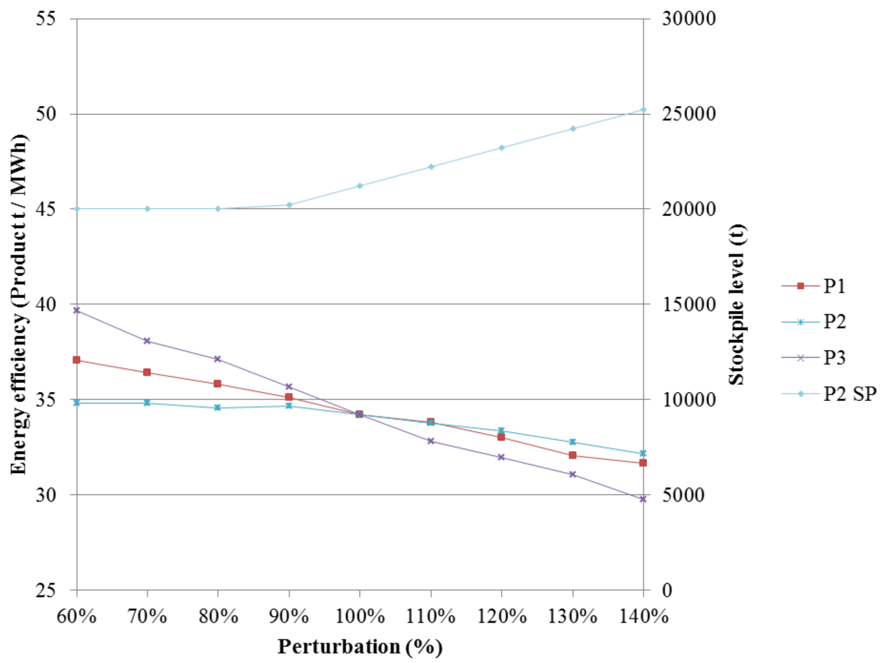

Figure 8.3. Energy efficiency and stockpile level of scenarios perturbing extraction targets

The results from the remaining scenarios also demonstrate the value of having an integrated model of the mine. By perturbing the product target coming out of the wash plant, this shows the interaction between CHPP subsystems and the excavation and haulage and stockpile subsystems. Plotting the scenarios against energy efficiency and stockpile level, Figure 8.4 shows that P4 and P5 improve the energy efficiency of the system, while the energy efficiency remains fairly steady in P6.

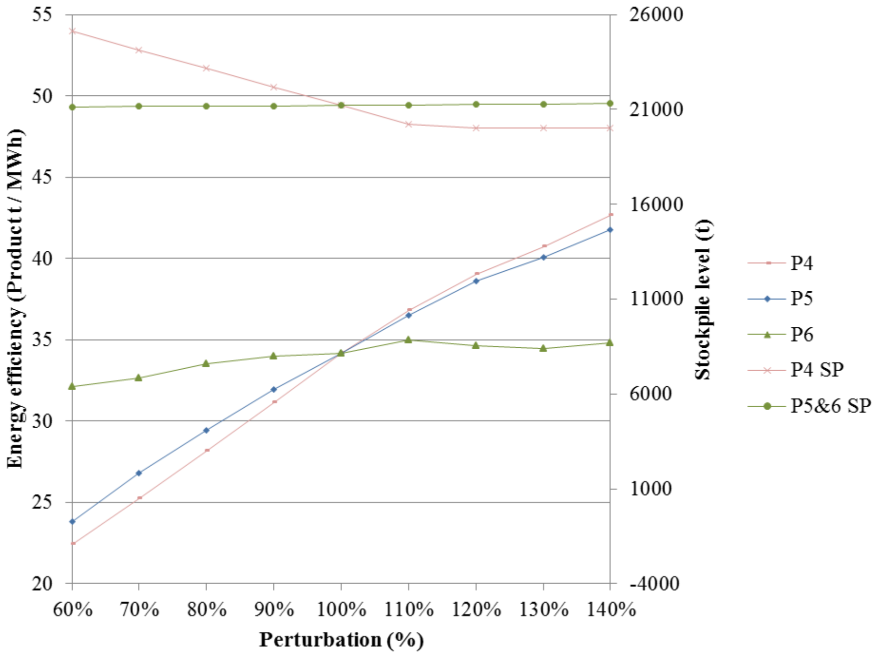

Figure 8.4. Energy efficiency and stockpile level of scenarios perturbing product output

The improving efficiency in P4 and P5 indicates that the increases in production (numerator) outweigh the increases in energy consumption (denominator). Looking closer at P4, a slight drop off in efficiency gain can be observed for targets above 9200 tonnes (115%). This is consistent with the results found with the original model in Subsection 5.3.2. It is due to the stockpile being drawn down to minimum level, also seen in Figure 8.4, which means the excavation and haulage system has to extract more ROM coal to meet the required demand. It is a clear demonstration of the benefit that the integrated approach provides, and bringing all subsystems together allows for analysis of dynamic system wide behaviour like this.

P5 demonstrates that the mine can increase ROM coal extraction and product output together and still receive efficiency improvements. However, from a longer term perspective, this won't last since increasing ROM coal extraction without increasing overburden, spoil and top soil extraction will mean the mine will eventually run out of exposed ROM coal to extract. So, a more realistic scenario where all targets are increased is conducted in P6.

The steady efficiency for the increased production half of P6 indicates the energy efficiency of the current operation is balanced equally between extraction and production. This means that the current equilibrium can be maintained if the overall workload of the system is required to be increased. This equilibrium is also noticed in the steady stockpile level of the scenario instances. For operators of the case study mine, this means they have some flexibility to increase the overall work of the mine to accommodate for disturbances, such as weather events or changes in demand, without necessarily impacting energy efficiency. On the other hand, reducing the overall workload will lead to diminished energy efficiency. This demonstrates the impact that the fixed energy cost of running the shovels, crusher and wash plant have on the energy efficiency.

By fitting a linear function to these results, energy consumption and efficiency costs per kilotonne (scaled up from tonne for readability) modified in each scenario can be derived, seen in Table 8.4. P2, P4 and P6 have been broken into two parts to show their respective diminished returns. The table is a compact way of visualising the results of the analysis conducted in this section. This type of output could be used by mine operators to quickly identify the most critical targets with the respect to energy based on their current operation.

Table 8.4. Marginal cost per kilotonne of plan target

Scenario	MWh / kilotonne	(Product t / MWh) / kilotonne
P1 (pit 1 overburden)	5.89	-0.86
P2 (pit 2 ROM coal) 6000-8500t	0.44	-0.07
P2 (pit 2 ROM coal) 8500-14000t	3.54	-0.49
P3 (pit 3 spoil)	5.93	-0.87
P4 (product) 4800-9200 t	5.71	+3.51
P4 (product) 9200-11200 t	4.71	+1.16
P5 (ROM & product)	4.61	+1.24
P6 (All targets) 60-105%	5.23	+0.14
P6 (All targets) 105-140%	5.87	0.01

Along with the overall energy consumptions and stockpile level, and leading towards the next section that looks at asset usage, these planning scenarios can also be used to analyse elements of asset usage. Section 2.3 explains that these two factors impact each other and this is an example of how the model in this study handles their relationship. Figure 8.5 shows the relationship between energy efficiency and shovel utilisation across the various extraction targets. It shows a negative relationship between energy efficiency and shovel utilisation. As extraction targets are increased and efficiency is diminished shovels are used more. While it is not suggested that this means shovel utilisation always has a negative relationship with energy efficiency, it shows that it shouldn't be used alone as an indicator of energy efficiency.

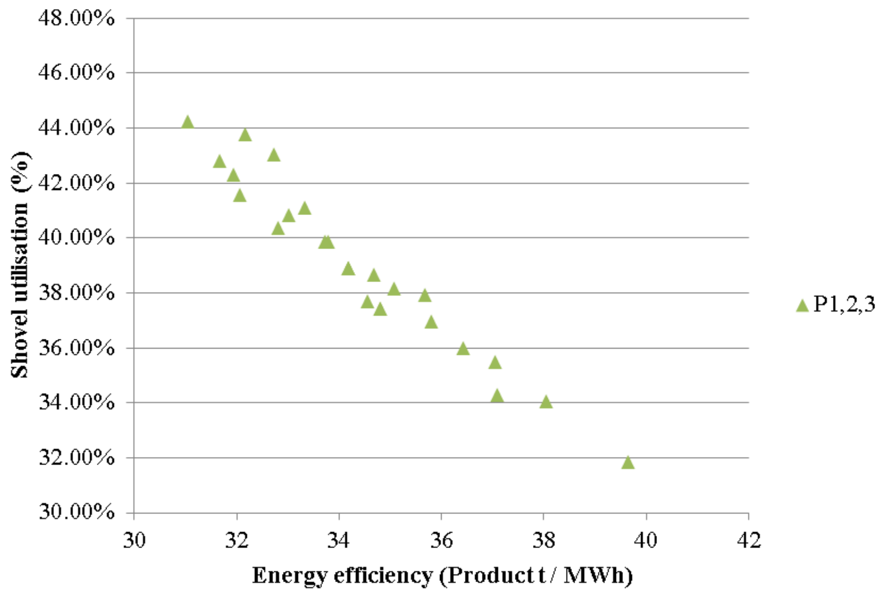

Figure 8.5. Energy efficiency vs shovel utilisation for scenarios perturbing extraction targets

The low levels of shovel utilisation that are required from the current operation are evident in the benchmark solution and this analysis. Without more data about the actual operation that was achieved under this plan, it is not clear about whether this is the level of utilisation that happened. If not, that would suggest the mine is not operating in an energy efficient manner and can benefit from the model results. If they do in fact operate at such low shovel utilisation, it may be that they should either change their planning or reconsider its use as a key performance indicator (KPI). Further analysis with more data and knowledge about the mine's operation would be required to properly analyse this area.

If the mine decided to modify planning to achieve better shovel utilisation, the model would serve as a good tool for verifying the feasibility of the plan. Figure 8.6 shows a the resulting schedule from solving the model with significantly increased targets – 17,000t of overburden from pit 1; 21,000t of ROM from pit 2; and 21,000t of spoil from pit 3. The overall shovel utilisation for this scenario is 76%. This hypothetical scenario demonstrates the capacity limitation that the trucks have on shovel utilisation. Even when only using three of the four shovels, the capacity of the truck fleet is almost exhausted. This suggests the mines trucks and shovels capacities are misaligned for the current operating point.

This is of course not a completely realistic example from a whole-of-system perspective, since no consideration about the stockpile or processing plant has been made. Rather it is a hypothetical scenario to demonstrate how the model could be used to analyse the relationship between planning, utilisation and capacity.

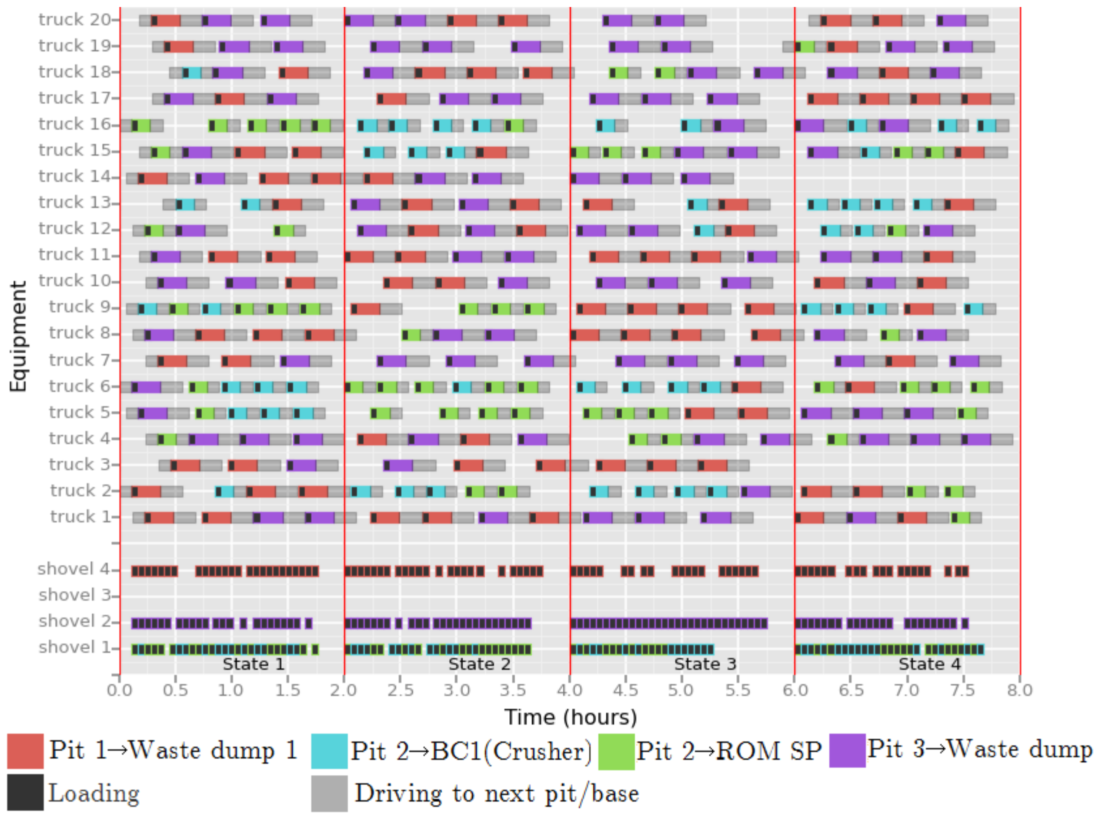

Figure 8.6. Equipment schedule with higher shovel utilisation

8.3 Asset usage analysis

As mentioned in the last section, the second factor that was identified as a focus of this study in Section 2.4 is asset usage. Here, several scenarios are analysed to demonstrate how the model incorporates the asset usage factor.

8.3.1 Truck analysis

The methodology from Subsection 5.3.3 is used here to analyse the criticality of trucks in the benchmark solution. By disabling each of the 12 trucks that appeared in the solution to the benchmark solution, resolving and sorting by the increases in energy efficiency, the trucks most critical to achieving energy efficiency can be determined. Figure 8.7 shows the results of the analysis. The ordering is mostly consistent with the results from this analysis on the original model in Subsection 5.3.3, though there are slight differences. These are because the improved accuracy of the scheduling formulation brings a slightly different mix of trucks into the solution. Trucks 4 and 6 are once again two of the most critical trucks, with trucks 1 and 2 joining them now. The three new trucks (5, 7 and 11) that were added into the solution with the increased accuracy of the new formulation appear towards the bottom, alongside truck 18 and 13.

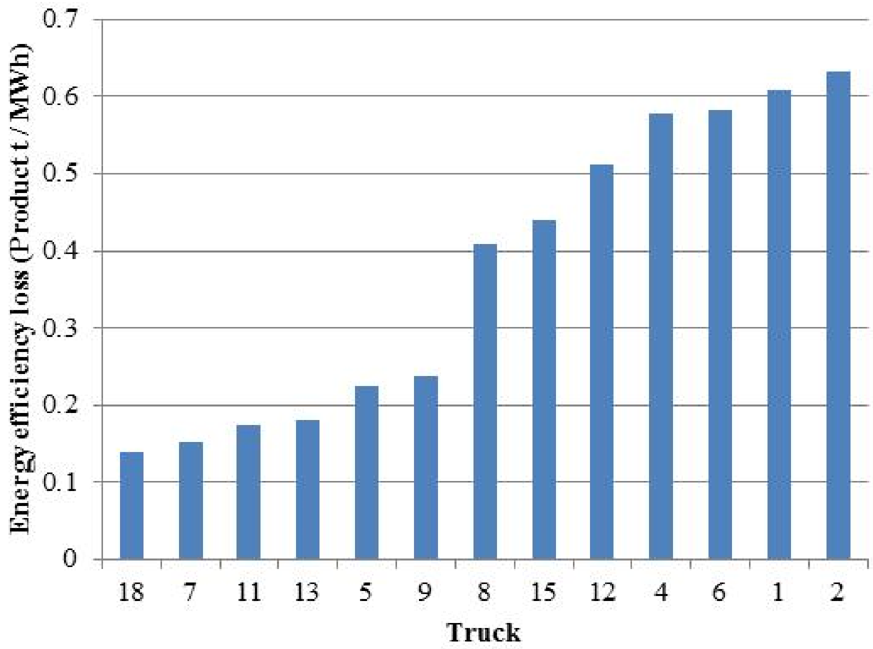

Figure 8.7. Effect of taking out each truck from benchmark solution

Another way that trucks can be analysed is by perturbing their energy consumption coefficient parameters. A similar methodology that was used to get the above results can be applied to analyse the effect of improving each truck's energy efficiency on the overall energy efficiency of the system. Figure 8.8 shows the energy efficiency gain of reducing the energy consumption of each truck by 10%. This shows that improvement to truck 2 would result in the biggest gain in energy efficiency, closely followed by trucks 4, 1 and 13. Reducing the energy consumption of trucks 11, 18, 5 and 7 would result in the least improvement of overall energy efficiency, besides making improvements to trucks that aren't being used.

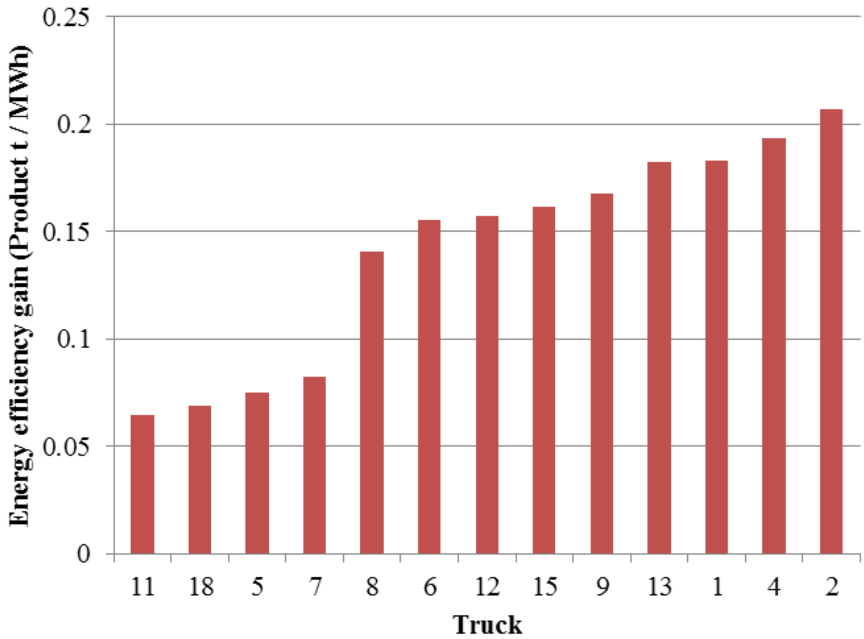

Figure 8.8. Effect of taking out each truck from benchmark solution

These two methods of analysis show useful ways to study the asset usage factor. The first analysis informs operators of the equipment that is most important to achieving energy efficiency for a particular plan, which can assist dispatching decisions. The second could be used to inform decisions about where the most value can be realised by maintenance that improves equipment efficiency.

8.3.2 Cycle time analysis

Key to the operation of the excavation and haulage subsystem and usage of its equipment is the cycle time of trips. In this analysis, the loading times, driving times and both combined are perturbed by ±20%. Figure 8.9 shows the impact that each of these three scenarios has on the energy efficiency of the system and the shovel utilisation. Increasing each of these three parameters has a principally linear impact on energy efficiency, with the relative change to loading time having the least impact, followed by driving and, understandably, the whole cycle time.

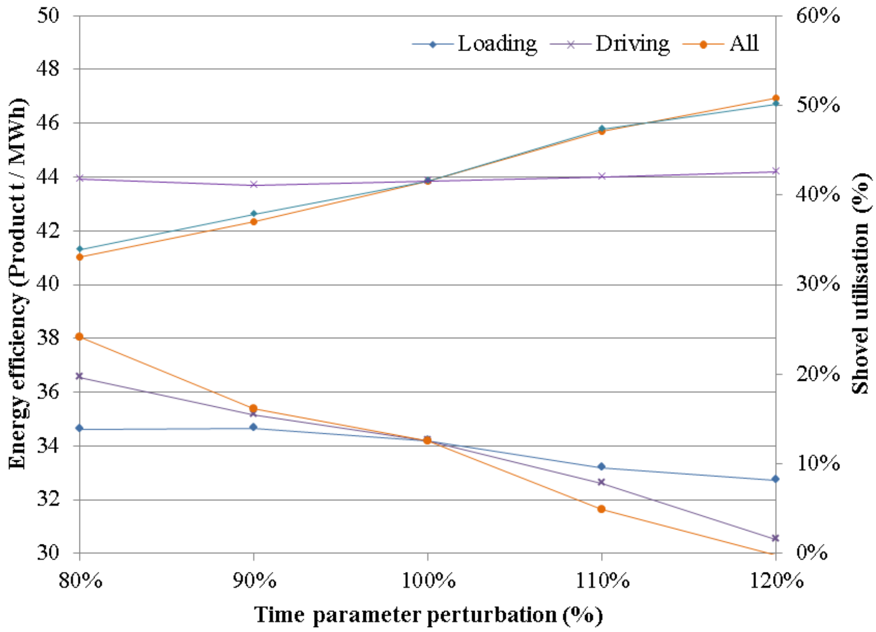

Figure 8.9. Energy efficiency and shovel utilisation of scenarios perturbing cycle time

This however, does not show the relationship on a per minute basis. For instance, an increase of 20% for a 13 minute driving time corresponds to a 2.6 minute increase but to only 0.7 minutes for the loading time. Depending on the context of the analysis it may be more appropriate to compare the impact of changing the times by the same amount of minutes rather than the same relative change.

Table 8.5 has been compiled to show the 'per minute' impact on energy consumption and efficiency that each scenario results in. Average driving and cycle times have been used to weight them, based on the balance of trips that are present in the solution. This was not needed to be done for the loading time as it is the same across all equipment.

Table 8.5. Marginal cost per kilotonne of plan target

Scenario	MWh / minute	(Product t / MWh) / minute
Loading time	10.51	-1.51
Avg. driving time	4.96	-0.69
Avg. whole cycle time	6.69	-0.99

Referring back to Figure 8.9, the shovel utilisation has a negative relationship with efficiency; as loading times increase and energy efficiency decreases, utilisation rises – reiterating the point made at the end of Section 8.2 that shovel utilisation should not be relied upon as a measure of energy efficiency. It does not change when driving times are perturbed.

8.3.3 Truck waiting time analysis

Times where trucks wait to be loaded at the shovel is a common point of interest when inspecting the efficiency or productivity of the truck and shovel fleet. It is a key improvement to the subsystem formulation that this study contributes. As mentioned in the benchmark analysis, truck waiting time only accounts for a small percent, 0.56%, of the total energy consumption. This makes analysing it difficult when perturbing parameters and inputs, as the other analyses have been done in this chapter, since other factors have a much greater influence on the energy consumption of the system. So to analyse its impact, 70 feasible solutions to the benchmark instance have been recorded from 10 runs of the solution technique.

Figure 8.10 shows a correlation between truck waiting energy and overall energy efficiency. Lower truck waiting energy, and hence truck waiting times, are seen as more energy efficient. This indicates the relationship is being taken into account but is a relatively weak correlation with the energy consumption objective for the case study mine. Since truck waiting time is often looked at as a key performance indicator (KPI) of the excavation and haulage activity, this loose correlation suggests it may not be the best KPI for operators to focus on when looking for energy efficiency improvements.

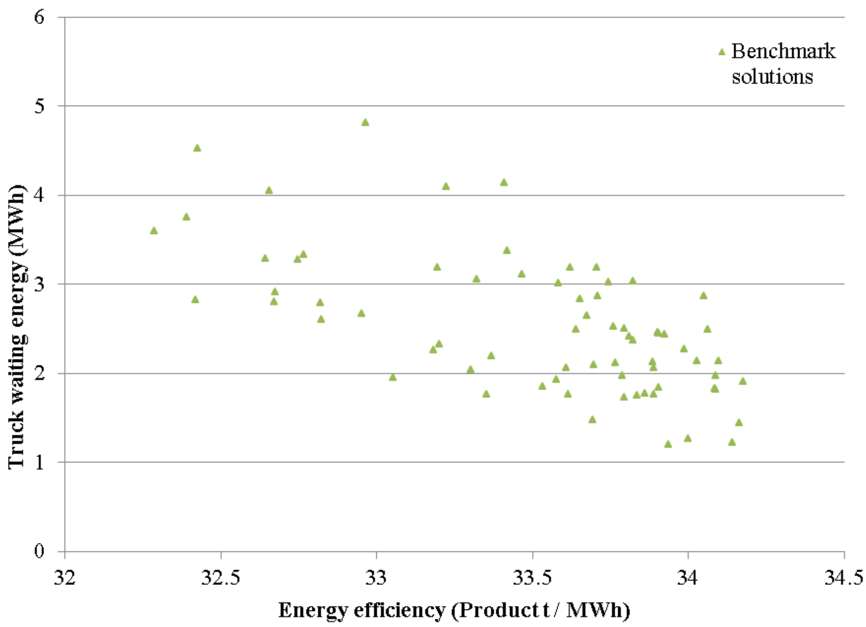

Figure 8.10. Energy efficiency vs truck waiting energy

8.3.4 Shovel availability analysis

The last analysis relating to the asset usage factor identifies the shovel and state most critical to the optimal solution. To do this, a constraint that disables a shovel in a particular state was added to the model and solved for each combination of shovel and state. For the shovel at pit 2, where ROM is being extracted, in state one, this constraint introduced conflicts with the minimum stockpile limit constraint, so the minimum stockpile limit was reduced to 18,800 tonnes for this analysis.

Figure 8.11 shows the energy efficiency loss by disabling each shovel from each state of the benchmark instance. The shovel at pit 2, where ROM is being extracted, in states three and four, has fairly consistent energy loss across the states and has the largest impact on energy efficiency. This is due to the increased double handling required at the ROM stockpile to allow the processing plants to continue operating. The interactions between the various subsystems on display here is another demonstration of the benefit of integrating them all into a single model. Without considering the downstream stockpile and CHPP subsystems, the real cost of the shovel unavailability could not be calculated.

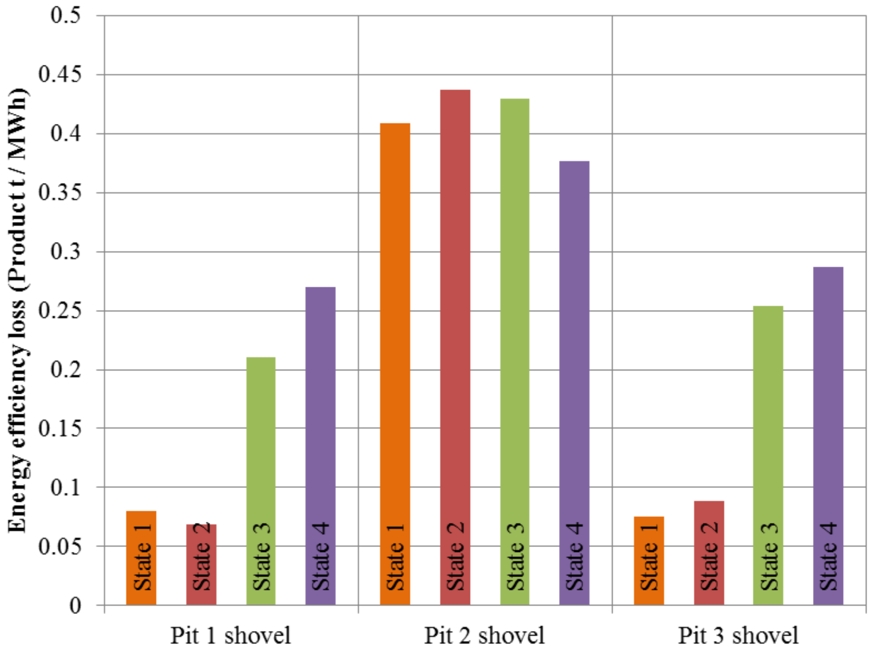

Figure 8.11. Energy efficiency lost from outage of each shovel in each state

The shovels at pit 1 and 2, digging overburden and spoil respectively, exhibit a more varied result. For the first two states, the increase in energy consumption is quite minor. This is because the two targets do not have a direct impact on the rest of the mine and since the excavation and haulage subsystem is operating with excess capacity, it is able to account for the loss evenly throughout the day. However, the reason behind the increased losses of the third and fourth state is not clear. These two states appear to exhibit a more subtle, unexpected, behaviour isolated to within the excavation and haulage subsystem. While trip numbers and shovel utilisation remain unchanged between the state 2 and 3 scenarios, the solutions for the state 3 scenario exhibit the more truck waiting time and hence more energy consumption. The cause of this is unknown at this stage. It is also strange that it doesn't seem to appear in the pit 2 shovel unavailability scenarios. Detailed investigation looking into this phenomenon should be carried out in future work to determine the cause.

This analysis also serves as a demonstration of how the maintenance aspect of asset usage could be considered using the model. As explained in Section 2.3, asset availability is directly impacted by maintenance activity. Running these scenarios and similar could help assist decisions about planned maintenance that will have the least impact on the energy efficiency of the mine.

8.4 Remarks

This chapter has revisited the case study to give practical verification of the improved integrated model and the solution technique that has been innovated to solve it. The model now provides a much more accurate solution for the case study mine's excavation and haulage subsystem, overcoming synchronicity issues experienced in the first run of the case study, in Chapter 5. This is delivered in the form of a shovel and truck schedule, which is an original contribution that is significant both academically and practically. Finally, while the improved model was too hard for exact solution techniques to solve for real life-sized problems, like the case study, the solution technique developed in Chapter 7 was shown here to be able to generate quality solutions in reasonable time.

Several scenarios have been analysed to show these outcomes. These were presented from the context of the two factors introduced in Section 2.4 as areas of focus when modelling operational energy efficiency of a mine. Initially, the planning factor was analysed by extending upon the initial results, using the original model presented in Subsection 5.3.2. Planned targets, inputs to the model, were perturbed and the resulting impact on energy consumption and efficiency were analysed. The model behaved well across the range of instances and provided sensible, consistent results. The benefit of the integration was on display when analysing the diminished returns of due to the ROM stockpile hitting its lower limit. The marginal cost per kilotonne of each target perturbation was also presented as a compact way of interpreting the results. Finally, a look at the impact extraction targets have on shovel utilisation suggested that shovel utilisation is not necessarily a good indicator of energy efficiency.

The asset usage factor was analysed in four ways. Firstly, the truck analysis introduced in Subsection 5.3.3, was used to identify the trucks that are most critical to achieve the most optimal benchmark solution, and how the solution improves with more efficient trucks. Secondly, a sensitivity analysis on the cycle time parameters found that the model behaves well and produces expected results. A look into truck waiting times found that, while the impact of trucks waiting at the shovel is relatively small compared to other factors at play, a relationship does exist with energy efficiency. However, the variance suggests truck waiting time is not necessarily a good indicator of energy efficiency. Finally, scenario analysis that looked at the impact of unavailable shovels throughout the day was conducted. This highlighted the value of the integrated model and also uncovered some interesting behaviour when the shovel at pit 2 is unavailable later in the 8 hour period. This should be the focus of further work, to discover whether it is a problem with the model and solution technique or a physical phenomenon at the mine.

This chapter completes the bottom left quadrant of Figure 8.12 of the research approach detailed in Section 1.5. The case study has been revisited with the improved model and solution techniques, from Chapter 6 and Chapter 7 respectively. The improved model was shown to be superior to the first iteration in practice, and the solution approach provides quality solutions in reasonable time for practical-sized problems. Chapter 9 next completes the loop of the research approach by discussing the outcomes of the research to outline the opportunities that they present and concludes the thesis by revisiting the research questions, aims and hypothesis.

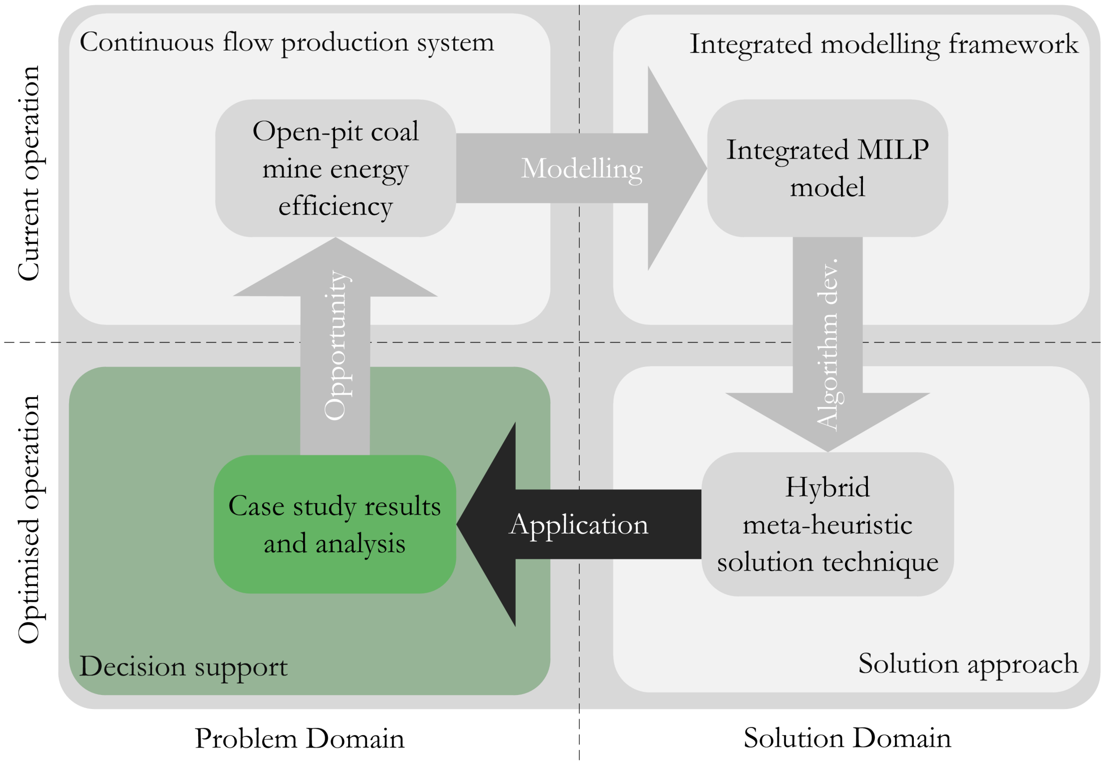

Figure 8.12. Role of Chapter 8 in the research approach

The content of this chapter addresses all three research questions listed in Section 1.2, listed below, by applying the various contributions from the thesis so far in a detailed analysis of the case study mine. The modelling approaches and formulation have been verified in detail with relation to a real life example of the general problem being addressed by this thesis. As well as this, the solution technique's usefulness for practical application has been validated.

1. *How can the energy efficiency of mining production systems benefit from an integrated modelling approach?*
   (a) *Why is improving energy efficiency a concern for mining operations?*
   (b) *How can an open-pit coal mine be considered as a production system?*
   (c) *What factors impact the energy efficiency of a mine?*
   (d) *What are the benefits of using a quantitative optimisation model of energy efficiency?*
   (e) *Why take an integrated optimisation approach?*
2. *What integrated optimisation model of energy efficiency is appropriate for an open-pit coal mine production system?*
   (a) *What level of detail is required of the model?*
   (b) *Where are the main points of model complexity?*

   (c) *How general should the model be?*
   (d) *What is an appropriate process for applying the model to a real life mine?*

3. *What solution techniques will be appropriate for solving the model in real-time?*
   (a) *How hard is it to solve the developed model? Is the optimisation NP hard?*
   (b) *Are new techniques required?*
   (c) *What impact do any new solution techniques have on optimality and speed?*

9

Discussions and Conclusions

This chapter finalises the thesis by first using the case study results to discuss the opportunities for providing support to operating mines for making improved decisions about energy efficiency. Secondly, the contributions of the research are examined from the perspective of their academic and practical implications. The limitations of the outcomes are then highlighted, and future work is earmarked for improving upon the contributions of the study. Finally, concluding statements assert the success of the research.

9.1 Opportunities

The final step of the research approach improvement loop, described in Section 1.5 and highlighted in Figure 9.1, is to identify the opportunities that the results present, to the case study mine and the problem of open-pit coal mine energy efficiency in general. A suite of decision support software tools is also proposed as a way of applying the research findings in practice.

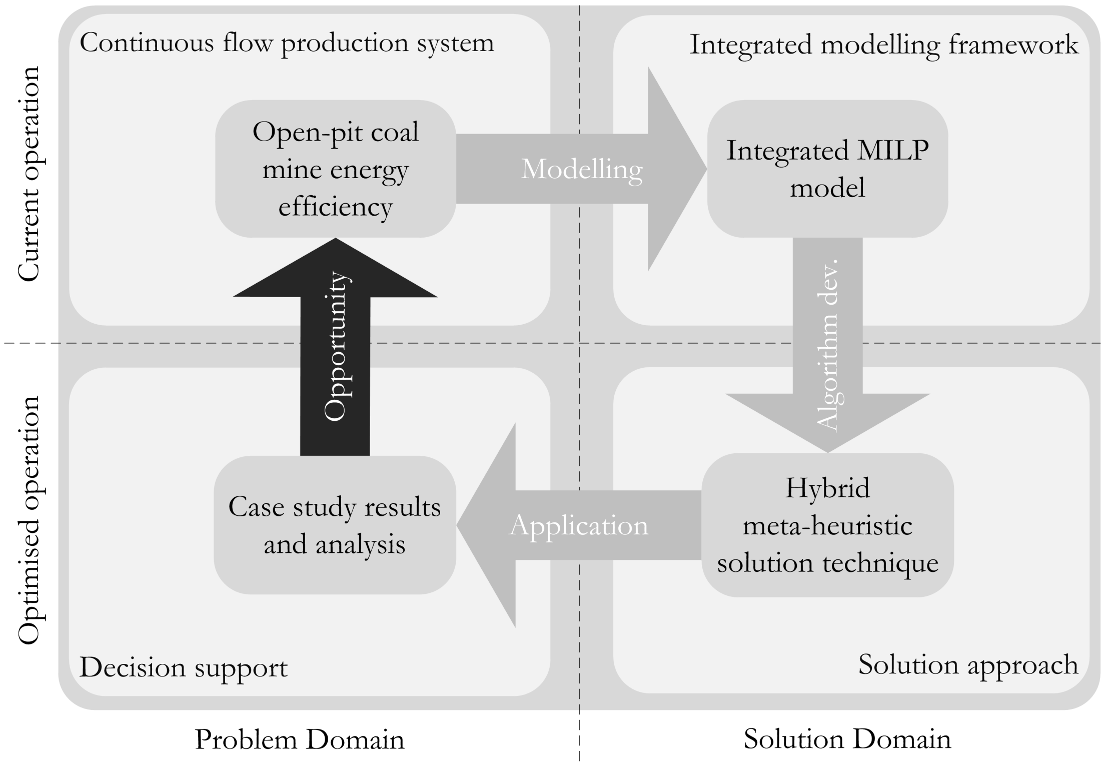

Figure 9.1. Role of Section 9.1 in the research approach

9.1.1 Opportunities for Meandu Mine

Results using both the Chapter 4 and Chapter 6 models, presented in Chapters 5 and 8 respectively, demonstrated clear opportunities for supporting energy efficient decisions at Meandu Mine. Using data that was readily available to the mine operators and information gathered during a mine visit, the application process presented in Section 3.3 was followed to create an integrated model of Meandu Mine. Using information about their current operation, a benchmark shift plan was established. Comprehensive sensitivity and scenario analysis gave insight into how their operators can use the model for making energy efficient decisions.

Excavation and haulage opportunities

Since the excavation and haulage subsystem represented the majority of energy consumption and had the most detailed data, the focus of the analysis primarily centred around how its operation impacts the whole mine energy efficiency. At the current, benchmark, operating point, a relatively high level of excess capacity appears to exist in the excavation and haulage subsystem. Whereby to meet the planned operation, shovels were only required to operate at around 40% utilisation, and several trucks were not required.

This presents two avenues for potential opportunity. Firstly, if the mine's actual operation is not reaching a similar level of utilisation, it is unlikely they are operating in an energy efficient way. They could therefore benefit from directly using the benchmark solutions to the model to guide excavation and haulage subsystem operation, to achieve the extraction targets with less energy consumption. The model provides a detailed picture of energy efficient truck and shovel activity that operators could use to aid their truck dispatching decisions. How this can be achieved is discussed in more detail in Subsection 9.1.2.

The second avenue for opportunity to come out of the low utilisation insight is the potential for better alignment between their planning, capacity and performance measures. This could benefit the mine in more ways than just energy efficiency, as equipment utilisation is a key performance indicator (KPI) used to reflect the productivity of the mine's operation. If the planned operating point can be achieved with relatively low utilisation, either planning should increase extraction to allow operation to achieve higher utilisation or utilisation isn't the best KPI for operation to focus on.

Changing the extraction plan is, of course, not a trivial exercise that should be done based on one finding, rather, this is based on many different variables outside the scope of this research. However, using some simple reasoning, a case can be made to warrant further investigation. Firstly, it is important to realise that the case study mine is in a particular situation. It only has one customer and has well known demand. Therefore, simply increasing the overall extraction targets would only lead to an imbalance with demand and unnecessarily high stockpiles. Rather, it may be beneficial to reduce the operating hours of the mine.

Currently, the excavation and haulage operates 24 hours a day, seven days a week. If these hours were reduced and the excess capacity was employed to increase output during operating hours, the equipment utilisation during the operating hours would increase. This would potentially lead to operating cost reductions, especially if night time and weekends are more expensive to times to operate. The processing plant already uses this strategy by turning off on weekends. Depending on the specifics of how this would be implemented, it may not necessarily lead to increased energy efficiency. However, scenario analysis using the model could be used in a cost benefit analysis to help decision makers investigate options.

On the other hand, if changes to the plan are not suitable options, these results may suggest that utilisation isn't the best KPI for operators of this mine to target. From an energy efficiency perspective, this is supported by the results in Section 8.2 and Subsection 8.3.2, which gave examples of where energy efficiency and shovel utilisation can have a negative relationship. From a broader perspective, focusing on improving the low utilisation KPI may lead the operators to deviate from the medium and long term plans. Perhaps a 'plan corrected' KPI could be developed to give operators a better indicator of their utilisation compared to what utilisation is required to meet the plan. In this case, the model could be used to determine the expected utilisation for a given plan. Using this would enable operators to see that the low utilisation is okay, reducing the risk of them deviating from longer term plans and increasing the importance of other KPIs that will lead to cost reductions, such as energy consumption.

Subsection 8.3.3 addressed another KPI that the mine uses to measure the performance of the excavation and haulage subsystem - truck waiting time. While this KPI isn't necessarily related to the excess capacity discussed so far, the results demonstrated that it too may not be the best measure of energy efficiency. As expected, a positive relationship to energy efficiency was demonstrated, however, the variance was quite high. This indicates that other variables have a much higher impact on energy efficiency. Focusing on truck waiting time is therefore not entirely appropriate for making energy efficiency decisions. It is no doubt a useful indicator of other important costs, but it is important for decision makers to understand the limit of its applicability. Instead, it is suggested that new KPIs be developed based on the results of this research and that of May et al. (2015).

As well as these avenues for opportunity, there is also the possibility that the data provided by the mine is erroneously misrepresenting the mine's capacity and current operating point. Therefore, more data about their current plans and actual operation would be required to exclude this possibility.

Whole-of-mine opportunities

As well as the opportunities contained within the excavation and haulage subsystem, several opportunities present themselves for using the model to aid wider decisions about the whole mine. In Section 8.2, the current operating point of the whole mine was shown to have a degree of flexibility. Increasing all extraction and demand targets across the mine by the same factor did not affect energy efficiency significantly. This means the mine is in a good position to increase its workload to accommodate for disturbances, without impacting energy efficiency. For example, if rain impacted operation for a day, extra work for the remaining workload for the next couple of days to 'catch up' with planned targets could be done without adverse impact on energy efficiency.

Another opportunity identified for the mine is to introduce grade control into their operation. At the moment, they consider all ROM coal equally and process it into a single product grade. The general model presented in this thesis has been designed to account for various types of ROM and product grades. By modifying the current model of the mine to include more material grades, the impact of grade control on energy efficiency could be analysed as well as the impact on the mine's operation.

Taking this idea further and considering downstream from the mine, the power station it provides product coal to could also be included in the model, to achieve an even wider level of system integration. Since the mine only services the power station, operators of the two systems are in a very good position to align their operation to get maximum value out of their interactions. Power stations are also continuous production systems, meaning the integrated modelling framework and application process developed in this research would suit this endeavour well.

By formulating a power station subsystem module and connecting it to the existing model, a number of scenarios could be analysed. For example, various demand profiles for product coal coming out of the wash plant could be analysed to see if less double handling at the power station stockpile could be achieved. This could be used to further analyse the previously mentioned opportunity to operate the excavation and haulage subsystem at reduced hours to increase its utilisation, and synchronise its workload with the demand profile.

Another example would be to analyse the impact that more grades of product would have on the efficiency of the power station. For instance, using lower quality coal when the power station is operating at low loads and higher quality coal at high loads could lead to more overall efficiency of the power station. There is currently legacy wash plant bypass that was previously used for high quality coal and didn't need to be washed, but it is not used anymore. It may be that crushed ROM coal could use this bypass to go straight to the power station when the power station is at low loads, removing the cost of washing.

As well as this, several possibilities for other improvements to various parts of the mine were brought up in informal discussions with operators during a site visit. Large scale strategic investment options were discussed as potential areas of investment. This model could be used to analyse each option's impact on energy efficiency compared to the current operation of the mine. For instance, an obvious double handling cost is the crushed ROM stockpile between the crusher and wash plant. Investing to change this to be a more efficient transfer between subsystems, such as a surge bin, could lead to energy efficiency improvements when the two subsystems are both in operation. Decision makers would be able to use the model to conduct cost benefit analysis around such investment options.

9.1.2 Opportunities for open-pit coal mines

Rather than cutting the problem down to only model the specifics of the case study mine, the practical applicability of the research to other mines has been a focus. Therefore, beyond the opportunities that this thesis presents to the case study mine, there are many opportunities for addressing the problem of open-pit coal mine energy efficiency in general. These are the ease of applying the methods to new mines; the ability to quantify factors that impact energy efficiency; how various levels of decision making can be assisted; and how the model can be developed into a decision support software tool.

Efficient modelling of operating mines

The modelling framework, application process and general integrated model presented in this thesis have all been designed to reduce the upfront cost of modelling new mines. This was demonstrated using the case study mine. With existing, readily available data provided by the operators, an integrated model of the main operations of the mine was able to be created with the integrated modelling framework, using the four subsystem module formulations. This was done with the assistance of the model application process, which proved to be an effective process for efficiently translating from the mine's 'problem domain' into the modelling 'solution domain'.

This is an important outcome as it means creating models of new operations does not require a massive upfront effort in terms of cost or time. Getting value from the model sooner at a lower cost means a shorter payback period on initial investment. This is a design feature of the research outcomes to help ensure their practical viability. Lower initial investment and a shorter payback period are encouraging traits for companies that are considering applying the model to their operations.

The model design also means that mines can use their existing data to form a baseline of their current performance, to measure the progress of improvements. The approach allows for scaling up when more resources and data are available, to make a higher resolution, more accurate model as required. Once again, this reduces the initial investment and therefore the payback period. It also increases the likelihood that any given mine can apply the model, as mines with less available data should still be able to get a model of their operation running. Once the model is running on existing data, any investment that improves the model accuracy can then be directly compared to the previous versions of the model, to help mines see where their efforts may be best spent.

In particular, other open-pit coal mines that solely service a power station are in a very good position to benefit from this research. While the modelling is based around a general open-pit coal mine, the detailed analysis of its application and resulting opportunities were centred on the case study mine. This places similar mines in a good position to apply the model with a higher degree of certainty that the concepts will carry over to their operation and provide them valuable results.

Analysing factors impacting energy efficiency

As Thiede (2012) suggests, energy efficiency modelling and analysis should aim to consider many factors that influence a production system. The modelling effort in this thesis focused on asset usage and planning factors. Their impact on the case study mine was analysed in Chapter 5 and 8. Other factors listed in Section 2.3 can also be analysed using the model, using scenario and sensitivity analysis. An example of this is the investigation of the asset ownership factor also conducted on the case study mine. By using these factors to classify and describe the application of the model, a deeper analysis of the energy efficiency can be conducted.

Framing analysis around these factors is an effective way of applying the learnings of a large body of production system literature to practical application of the model. Rather than looking at results as discrete outputs that only apply to the mine being modelled, relating the results back to these factors allows for deeper insights.

For example, the results in Subsection 8.3.1 provide indication of which trucks are most critical in achieving energy efficiency for the current operation. However, when conducting a deeper investigation into these results, it can be seen that a number of factors are at play. The impact of asset usage for each truck is being quantified for operators to use to prioritise their decisions around keeping the most critical trucks available and working. Maintenance activity, which falls under the asset usage and ownership factors, can also use the results to weigh up the impact of temporarily removing each truck and improving its efficiency. All the while, these results are taking into consideration the current planned operation, another important factor.

Detailed scenario and sensitivity analysis can be performed to separate and quantify the influence of each of these factors on energy efficiency. This is a useful method of identifying opportunities to improve energy efficiency. By using to model to quantify the influence of each factor, companies can see where their efforts may be best spent to make overall improvements to the whole-of-mine energy efficiency. This type of analysis is recommended in the EEX, formally EEO, program that formed part of the motivation for this research Department Resources Energy and Tourism (2010).

Quantifying the influence of the factors is also important when trying to compare the mine's operation to other mines or a best practice. Mines are highly exposed to external variables, such as geography, geology and weather, as mentioned in Section 2.2 and 2.3. This makes it harder to compare one mine against another, which can become a barrier that stops mines from improvement towards best practice. However, being able to quantify then remove the influences of such external, uncontrollable factors, allows mines to put themselves on a more even playing field, to compare against one another or a best practice. This can be useful for identifying opportunities and measuring improvements.

Decision making levels

Central to the primary aim of this study was to present opportunities to assist decision making. Considering energy efficiency at all levels of decision making – operational, tactical and strategic – is a key recommendation of Bunse et al. (2010). Though the model is formulated around operational decision variables, by performing different types of scenario and sensitivity analysis, the model can be used to aid any of these decision making levels. In fact, the ability to use an operational model to aid medium to long-term decision making is an important element of this opportunity. Being able to use an accurate model of the mine's operation fit using recent data of actual operation supports better decision making. Rather than analysing medium to long-term decisions using only historical, design or theoretical data, this methodology enables decision makers to analyse the effect of their decisions on current, actual operation. Figure 9.2 gives examples of how the operational model can be applied to support the three levels of decision making mentioned above.

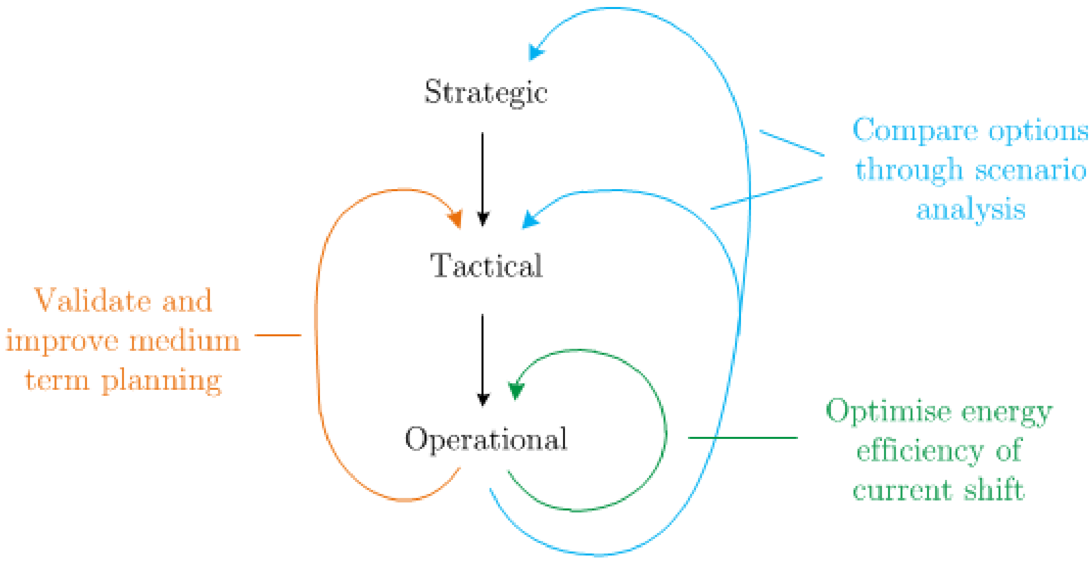

Figure 9.2. Examples of how model can aid different decision levels

Operational decisions, such as subsystem workload and equipment allocation, are the decision variables of the optimisation model. This means that solving the model on the current operation provides a detailed output about the most optimal way to meet planned targets, especially since the model is quick enough to run frequently as new information is gathered. For example, at the start of a shift, mine operators can enter the targets, solve the model and get an idea about the activity required by each subsystem throughout the shift. This could then be rerun when new information is available, such as equipment failure or other unexpected events, to give a new result to follow to meet the planned targets. This would help operators stick to the plan in an energy efficient manner, using quantified justification based on the current operation, rather than theoretic or design information.

The results of the model can also be used to improve communication between operators of different subsystems and shifts. Because it is an integrated, whole-of-mine model, operators can use the model output to see how their subsystem is working as a part of the wider system. It can be used by operators to communicate with each other based on quantified details from the same model, rather than their own silo optimisations. Likewise, the results can be used for communication between the operators of two adjacent shifts. The results give a detailed, quantified, picture of optimal activity for each shift, irrespective of operator's preferences that could be used to promote more consistent operation.

Aside from these operational decisions, medium-term decision support is also possible, as demonstrated by various scenario analyses presented in the results. Planning decisions usually made at a tactical level are the input to the model. The results showed significant opportunity for analysing planning options with respect to energy efficiency by way of scenario analysis. During the planning stages, the model could be run on proposed plans to see the model's resulting energy consumption. This could be used to help make plans that use less energy consumption.

Other medium-term decision making can also be aided using the model. Scenario analysis looking at decisions around equipment availability, efficiency and other parameters of the model could be used to support relevant tactical decisions. Along with these, the aforementioned asset ownership decisions are usually considered at a tactical level on mines.

While it was not analysed in the results chapter, the model also has potential for being used to aid long term, strategic level, decision making. Major changes to the structure or operation of the mine, such as a new processing plant or alternate demand agreements, would benefit from a detailed, accurate model of the mine's current operation. The extensibility of the modelling framework would become useful for taking the model of the current operation and modifying it to reflect the proposed changes. Accurate and up-to-date benchmarking and cost benefit analysis could then be carried out between the two models.

As a decision support software tool

Development of a software tool is proposed to deliver the aforementioned opportunities to decision makers. It is intended that the software is designed to make a positive influence on human and organisational factors, described in Section 2.3, for improving energy efficiency (Cagno et al., 2013). Since there is a broad range of opportunities for many different decision makers across a wide variety of mines, this may be delivered in a variety of different forms. The model application process presented in Section 3.3, represented below in Figure 9.3, can be used to help guide this discussion.

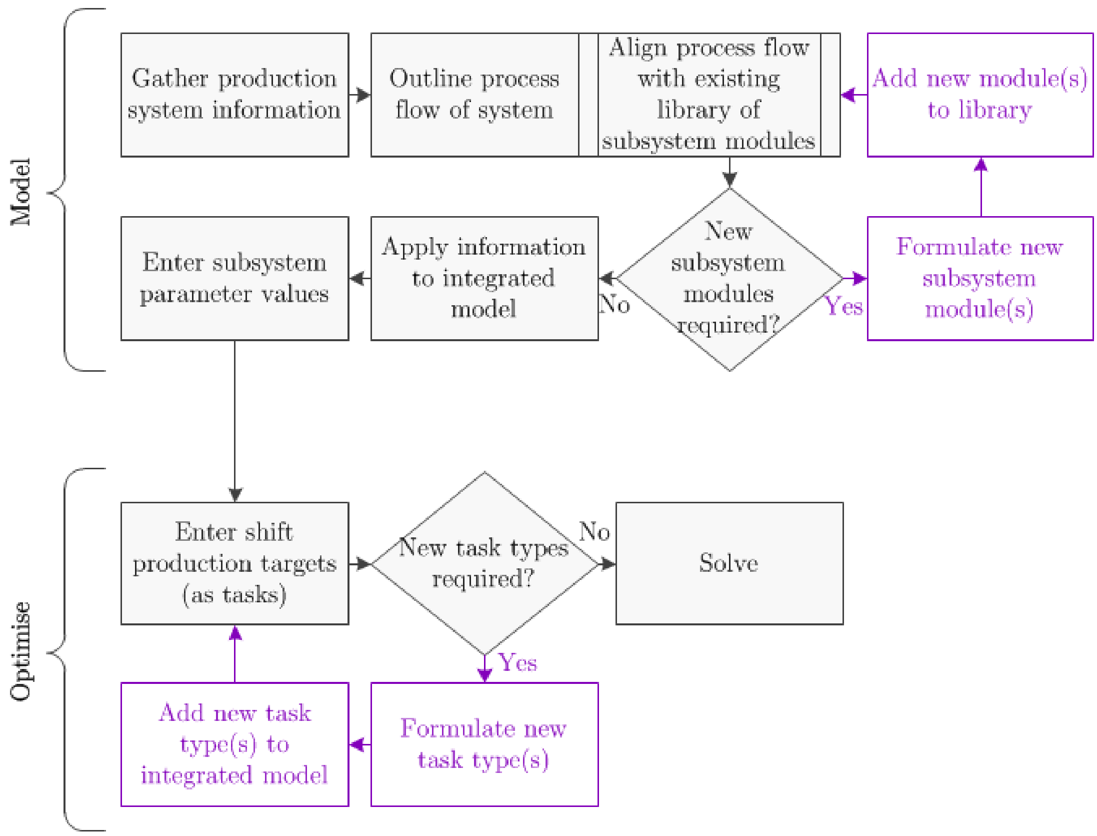

Figure 9.3. Examples of how model can aid different decision levels

Before the general integrated model contributed by this thesis can be used for decision support at a mine, it must first be applied to the mine in question. This is represented by the top half of the application process in Figure 9.3. The first piece of software proposed here is a tool that allows mine personnel, or 'problem domain experts', to fit the general integrated model to their operation; this will be referred to as 'MineModeller'.

Once the general integrated model has been applied to the mine being modelled, it is ready to be used for decision support; this is represented in the bottom half of the application process in Figure 9.3. Extending upon the discussion from the previous section looking at how to aid different decision levels, three conceptual decision support software tools are proposed; a tool to aid operators, ShiftDashboard; a tool to aid planners, EEPlanner; and a 'what-if' scenario tool, EEWhatIf.

MineModeller

A key feature that enables the problem domain experts to apply the model, briefly touched on in Section 3.3, is the concept of a subsystem library. Having a library of generalised subsystem models, currently made up of the four subsystems studied in this thesis, allows for a flowsheet style, 'drag and drop', graphical user interface (GUI) that problem domain experts can interact with, to build the layout of their mine with no modelling expertise required. This is the type of user interface proposed for MineModeller, shown in Figure 9.4. This takes care of the 'Outline process flow of system', 'Align process flow with existing library of subsystem modules' and 'Apply information to integrated model' steps in the application process.

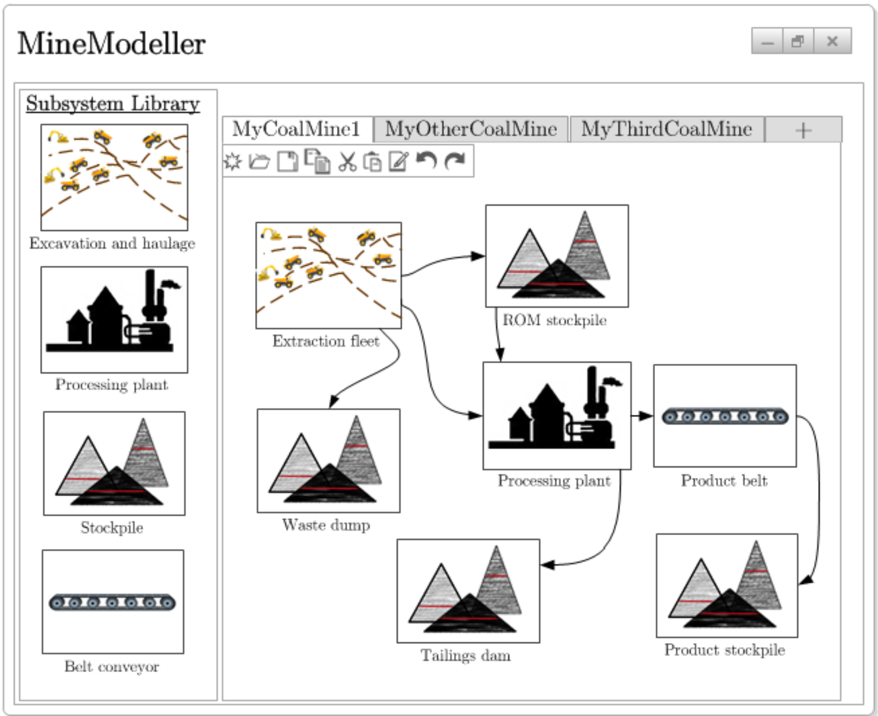

Figure 9.4. MineModeller GUI wireframe

For cases when systems on the mine cannot be represented using one of the generic subsystems in the library, the separation between 'problem domain', grey, and 'solution domain', purple, tasks in the application process, Figure 9.3, becomes important. In these cases, a 'solution domain expert', such as an OR modelling consultant, is required to work with the mine to formulate the new subsystem. Once the new subsystem module formulation is finished and tested, the modeller consultant can then add it back into the module library to allow the users of MineModeller to continue their work.

Once the layout and process flow of mine is configured with the flowsheet interface shown in Figure 9.4, custom forms for each subsystem instance that the user includes in their mine model are required. The various sets and parameters from the mathematical formulation of the subsystems, detailed in Chapter 4, would have to be translated into an appropriate GUI form for users to enter the relevant data. This is represented as the 'Enter subsystem parameter values' step in the application process.

After using MineModeller to complete these steps, the mine's operation has successfully been translated into a form ready to be loaded onto the model formulation, have a production target task set and solved. The remaining software tools proposed here illustrate how this can be done to achieve three different types of decision support.

ShiftDashboard

This tool is designed to achieve the opportunities for decision support at the operational level, mentioned previously. The core concept behind the tool is to present the model's optimal solution along with what is actually happening at the mine. Operators can use it to quickly see how well they are following the result of the model. They can use that information to quantify the impact that their decisions or unexpected disturbances have had on energy efficiency, and use it to make more energy efficient decisions. Depending on the mine using it, the ShiftDashboard may be customised to suit the user requirements and availability of operational data. Here, it is assumed that the mine has detailed data about the current operation that can be fed into the tool in near real-time. In this scenario, the model is re-solved with the updated data, also in near real-time, to update the optimal plan as more data becomes available.

First of all, to solve the models created using MineModeller for a shift, the planned targets for that shift must be entered. This is represented by the 'Enter shift production targets' step of the application process. An example GUI for entering or modifying the shift production targets is shown in Figure 9.5. These could be programmatically fed into the tool directly from the planning software that the mine uses. This could also be used half way through a shift to update the plan and get a new result from the model. For example, after an unexpected disturbance, an operator may decide to increase or decrease a given production target.

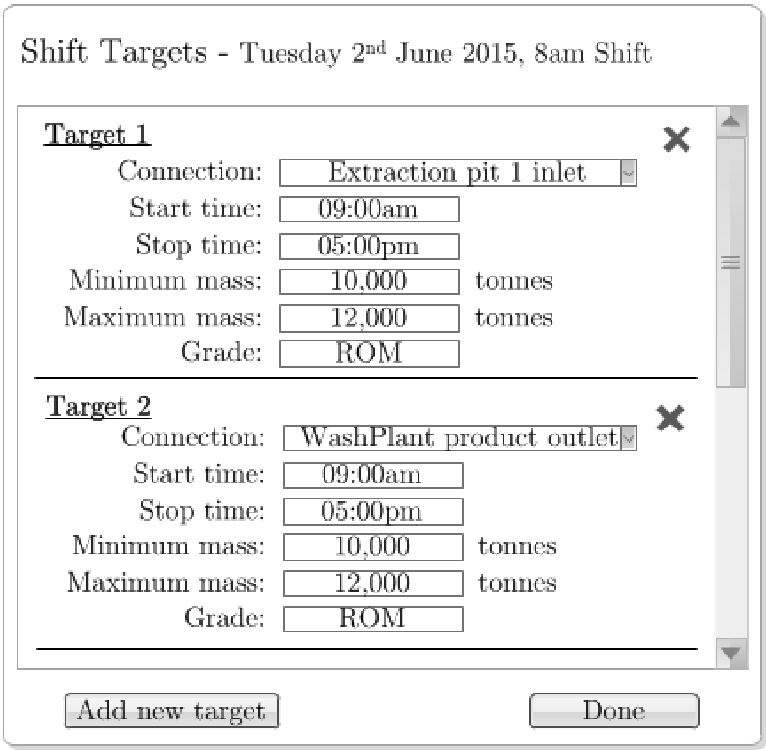

Figure 9.5. ShiftDashboard target input panel wireframe

These targets can also be selected from a library of different types that correspond to tasks in the model. The terms 'target' and 'task' are kept separate here to distinguish that a target is in the problem domain, while a task is in the solution domain. At the moment, in the formulation, there is only a single type of task. This is a constraint requiring a given connection to have a total mass transferred of a particular grade between a minimum and maximum amount during specified states. This translates into a production target that specifies the minimum and maximum mass required of a particular grade between two times. If a different type of target/task pair is required, a solution domain expert is required. This would happen in a similar way to that in which the MineModeller deals with new subsystems. Once the solution domain expert has created the new task in the formulation and integrated it as a target back into the software, the user can continue entering their shift.

Once shift targets are entered, they are loaded into the model as tasks and the model is solved, using the Chapter 7 solution technique, and results are presented alongside the operational data in the form of a hierarchical dashboard. The dashboard has a main overview screen, shown in Figure 9.6, that gives a summary of the energy consumption, production and 'health' of each subsystem. The health is a traffic light indicator that allows users to quickly see where deviations between plan and actual are occurring. The dashboard can be configured to show more detail in areas that require more attention, for example, the excavation and haulage subsystem. It is a screen that would be of particular interest to operators or mine managers that are concerned with the whole-of-mine operation.

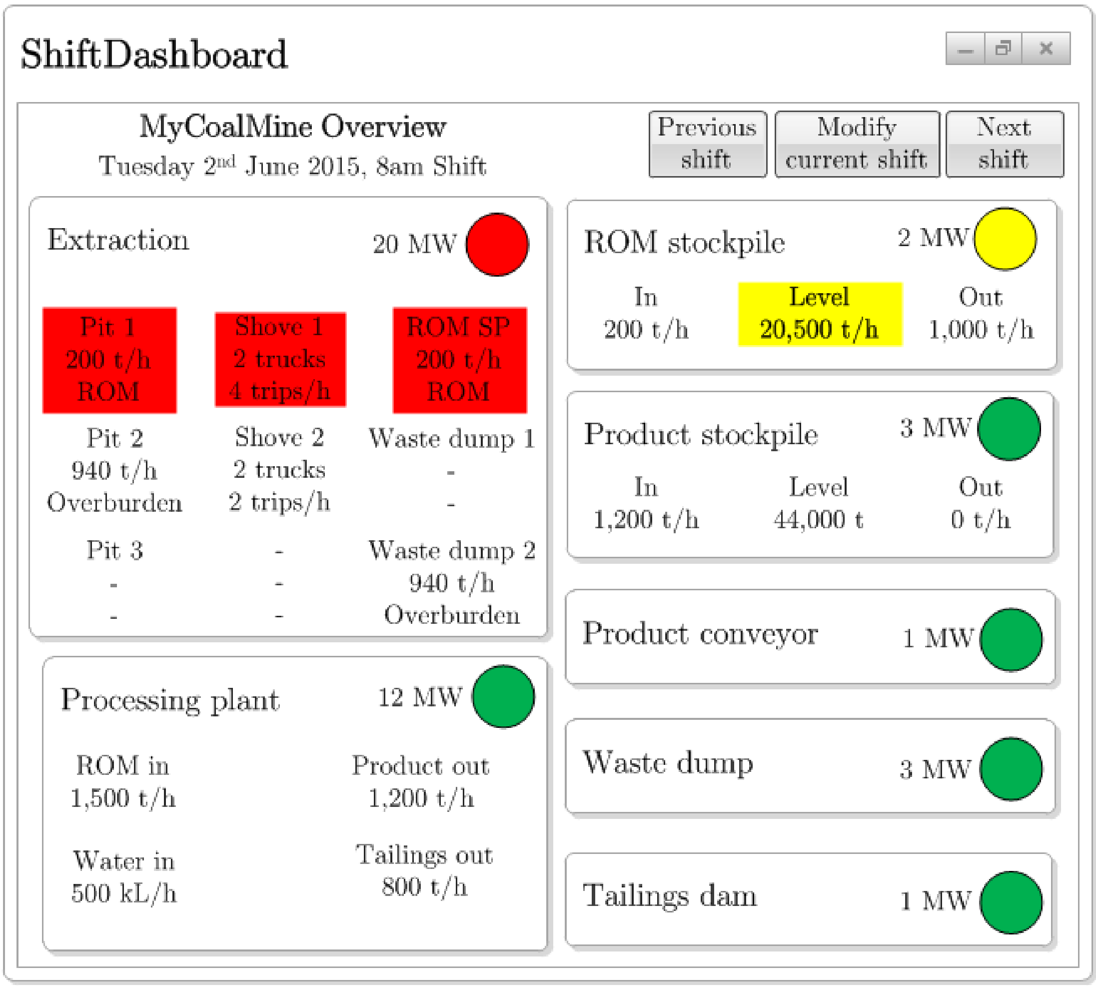

Figure 9.6. ShiftDashboard mine overview wireframe

In the example overview dashboard shown in Figure 9.6, there is an issue with the extraction and ROM stockpile subsystems. The extraction subsystem is red because it has a major change to the plan; it is currently only extracting 200t/h of ROM from Pit 1. The stockpile is marked as yellow, indicating a minor issue; this is because, while there is no current problem inside the stockpile, due to the lower than expected output from the extraction subsystem, the stockpile level is expected to reach minimum, safety level later in the day.

As previously mentioned, the dashboard is hierarchical, meaning users can 'drill down' to subsystem dashboard levels that display more detail. By clicking on a subsystem in the overview, the user is taken to a dashboard for that subsystem. Continuing on with this example, the excavation and haulage subsystem dashboard is shown in Figure 9.7. These subsystem screens of the tool are where operators of the individual subsystems can get a detailed picture of their responsibilities, and a brief insight into subsystems connected to theirs.

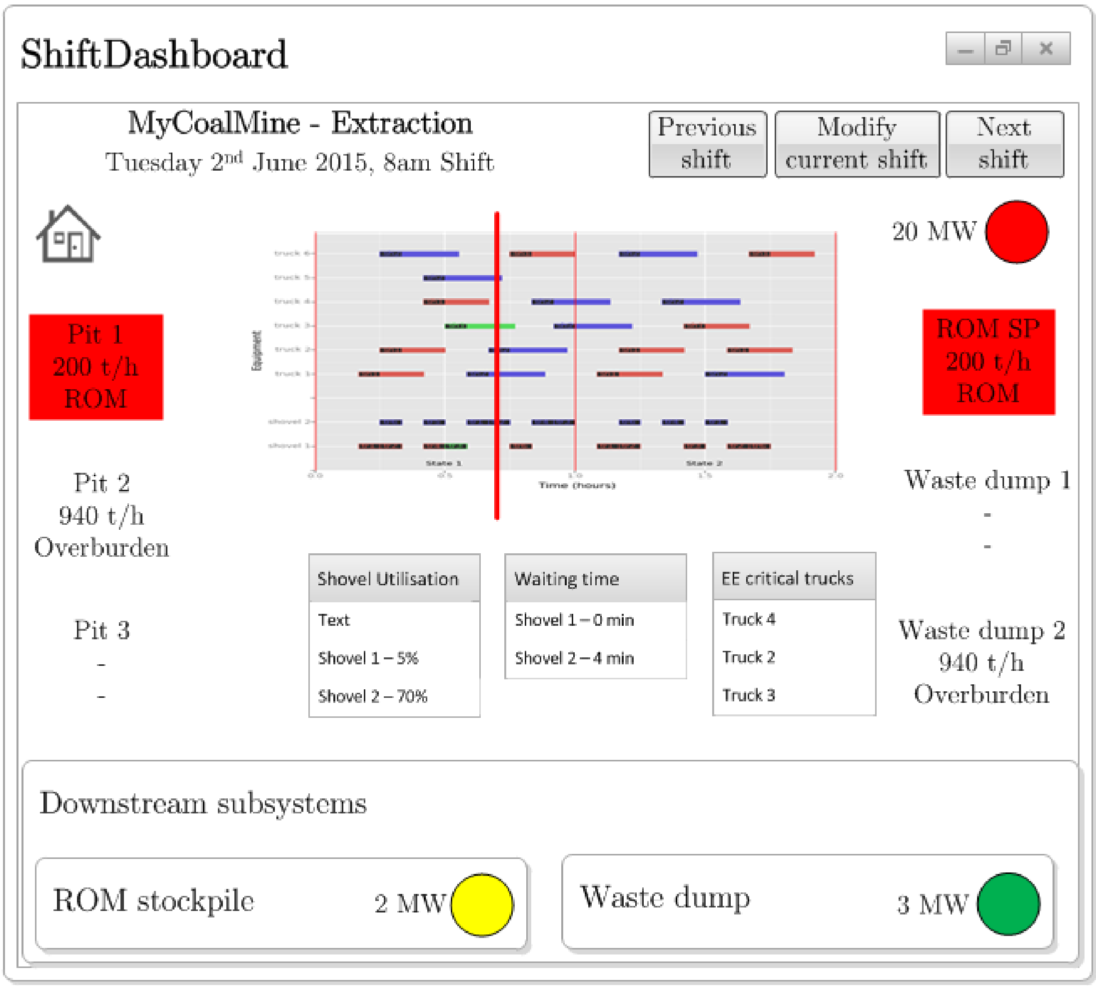

Figure 9.7. ShiftDashboard excavation and haulage subsystem wireframe

These can be customised to suit the requirements of the user. In this example, the user can see a number of different pieces of useful information. In the centre of the screen is the main output of the excavation and haulage subsystem formulation, the equipment schedule. Depending on the availability of real-time data, this could be merged with the actual truck locations to show the user how far away they are from the optimal plan. Other information relevant to the operators can also be seen, such as the shovel utilisations and average truck waiting times. More advanced output from running automated scenario or sensitivity on the model can be displayed, for instance the energy efficiency truck criticality, using the method presented in Subsection 8.3.1.

EEPlanner

The next tool is designed to help planners make more energy efficient plans. It reflects an example of the opportunity to support medium term, tactical level decision makers. It is not as centred around a GUI, rather, it is how software can be used to integrate the model with existing planning processes and software used at the mine. Figure 9.8 exhibits the existing planning systems and data used at the mine and the proposed role of EEPlanner, highlighted in green.

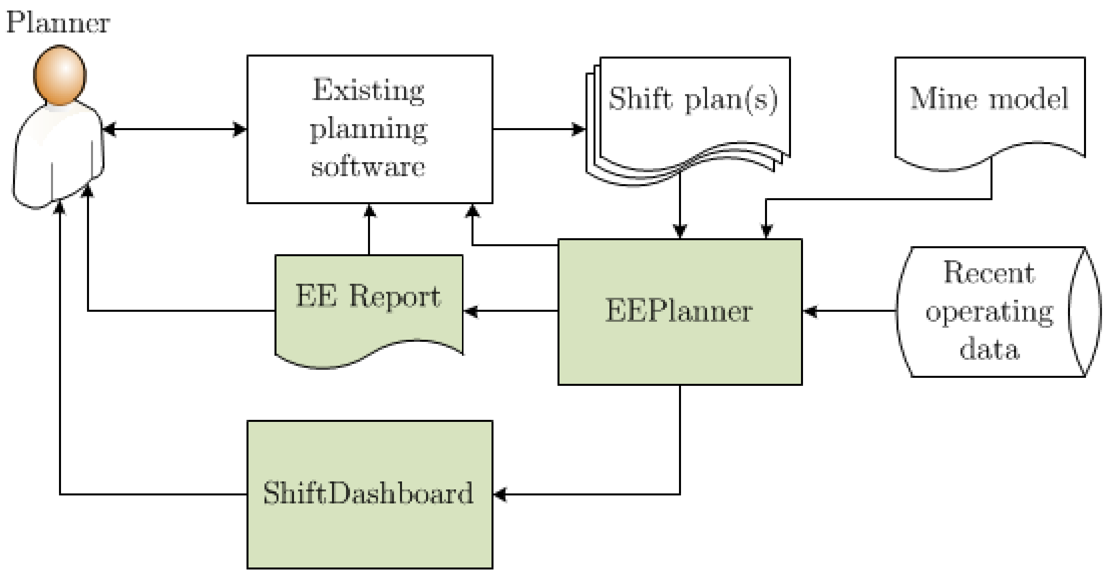

Figure 9.8. EEPlanner workflow diagram

The EEPlanner will be implemented to solve the model using the output of the current planning software as the planner creates it. It may solve one or several shifts depending on the output of the planning software. When solving several shift plans, they will be solved in series to correctly pass certain variables, such as the stockpile levels, between the shifts. Solving the shift(s) using the model validates that the shift can be achieved and gives an optimised energy efficiency achievable for that plan.

The EEPlanner will also use recent data about the operation of the mine, if available, such as equipment efficiency and loading times. This means the model is solved with an up to date picture of the mine's operation to ensure the result accuracy. By bringing this data into the planning phase, the tool helps planners make decisions based on recent operation rather than outdated or theoretical data. This follows the theory of the Plan-Do-Check-Act cycle (Walton, 1988).

The model results can then be delivered back to the user in a number of ways. Firstly, a report can be generated. This would contain high level information about the subsystem workload and energy consumption required to meet the plan. Sensitivity analysis, similar to that presented in Section 8.2, could also be generated and included in the report to give users an idea about what changes could be made to improve the energy efficiency of the plan.

The ShiftDashboard GUI could also be used to present the results of the EEPlanner to the user. This shows the planner exactly what their plan will look like to operators. Having planners see their shifts in this light promotes a deeper understanding of how their outputs are used and the role of operators.

As well as these two options for presenting the EEPlanner results, the third is to publish the results back into the planning software. Depending on what type of integration with the planning software is possible, this could be done by directly feeding the detailed results back to the software for it to process, or by feeding the reports back into the planning software.

EEWhatIf

The final tool presents opportunities to medium to long-term, or tactical to strategic, decision makers, typically managers, for measuring the energy efficiency impact of decisions they are considering. As with the EEPlanner, the core of the EEWhatIf tool is not a new GUI. Rather, it is a hybrid, or 'mashup', of the three tools already presented above, as shown in Figure 9.9. MineModeller is used to make alterations that represent the scenarios being evaluated; EEPlanner is used to run each scenario, and the current model as a benchmark, on a set of shift plans; the results are then presented to the manager in the form of a report or through the ShiftDashboard GUI.

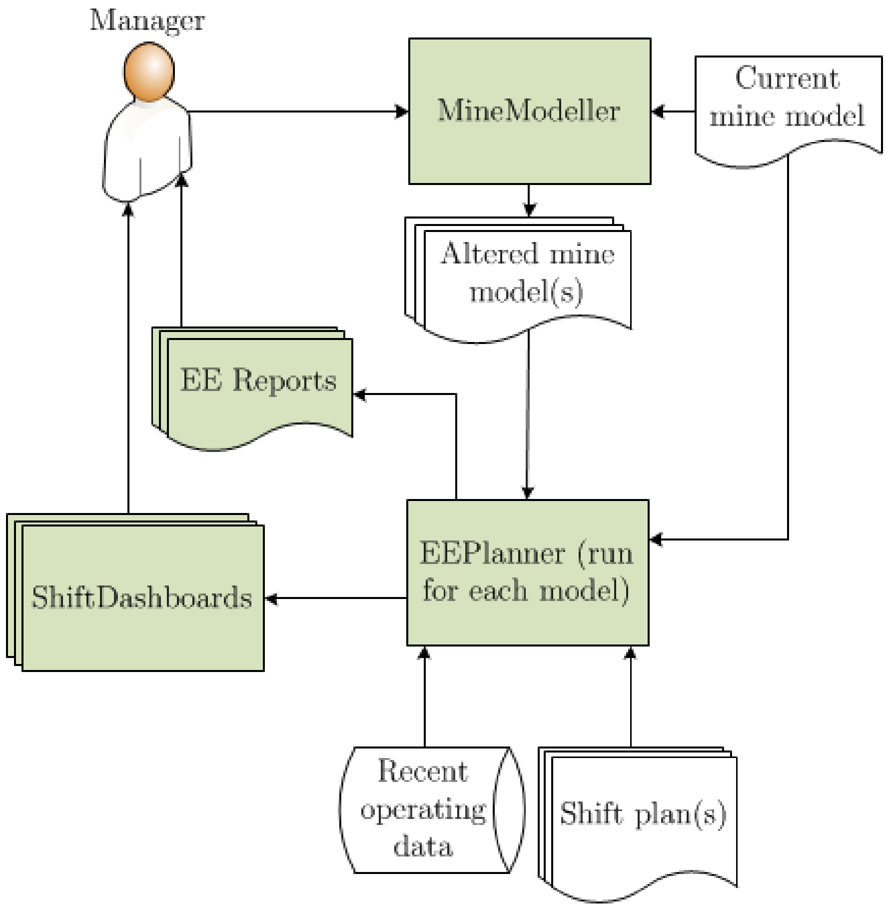

Figure 9.9. EEWhatIF workflow diagram

Scenarios are developed by the user in the MineModeller by starting with the current mine model, altering it and saving it as a separate model. As many scenarios as necessary can be saved out for the analysis. This allows for a wide variety of possible scenarios to suit many different decisions. For example, tactical decisions around asset procurement could be developed as scenarios that replace or add additional equipment pieces into the model. Strategic scenarios about major changes to the mine can also be created, for example, the inclusion of a new pit.

Once the scenarios have been developed, they are each evaluated with the model using the EEPlanner and a set of shift plans. Depending on the questions at hand, any set of shift plans can be used to conduct this analysis. For example, historical plans could be used if the decision maker wants to see the potential impact that scenarios could have had on past operation; current plans to see how the scenarios will impact the immediate operation; and future plans for the impact on longer term operating conditions of the mine.

As explained above, the EEPlanner can provide a more accurate result when using actual operating data, once again supporting users to follow the Plan-Do-Check-Act cycle (Walton, 1988). However, of course, data changed specifically for the scenarios is not to be overwritten by the recent data when running EEPlanner. As well as this, if historical shift plans are being used, data from when the shift plans were used may be appropriate for solving the model.

After the scenarios are run in the EEPlanner, the results are collated into reports that give the user an overview of the energy efficiency and subsystem workload of each scenario. The information in the reports can be used to compare against other measures related to the decision at hand, such as cost. The ShiftDashboard GUI can also be used to look at the result of each scenario in detail. It may be that the results warrant further investigation; in this case the process is followed again with more scenarios or different shift plans.

9.2 Contributions and implications

Throughout this thesis, the remarks sections, 2.7, 3.4, 4.3, 5.4, 6.3, 7.3 and 8.4, detailed how the research approach as described in Section 1.5 and seen in Figure 9.10, was followed to address the research questions listed in Section 1.2. By following the approach and addressing these questions, the thesis has successfully yielded a number of original, significant contributions to knowledge. Broadly defined, these are listed below and numbered on Figure 9.10.

1. The abstraction of mining systems as open continuous flow production systems, used to draw upon advanced production system literature.

2. The framework for formulating integrated models of continuous production systems and process for applying them to operating systems.

3. The integrated MILP formulation of the open-pit coal mine energy efficiency problem developed using the framework.

4. The solution technique innovated to overcome complexity issues with the shovel and truck scheduling component of the integrated model.

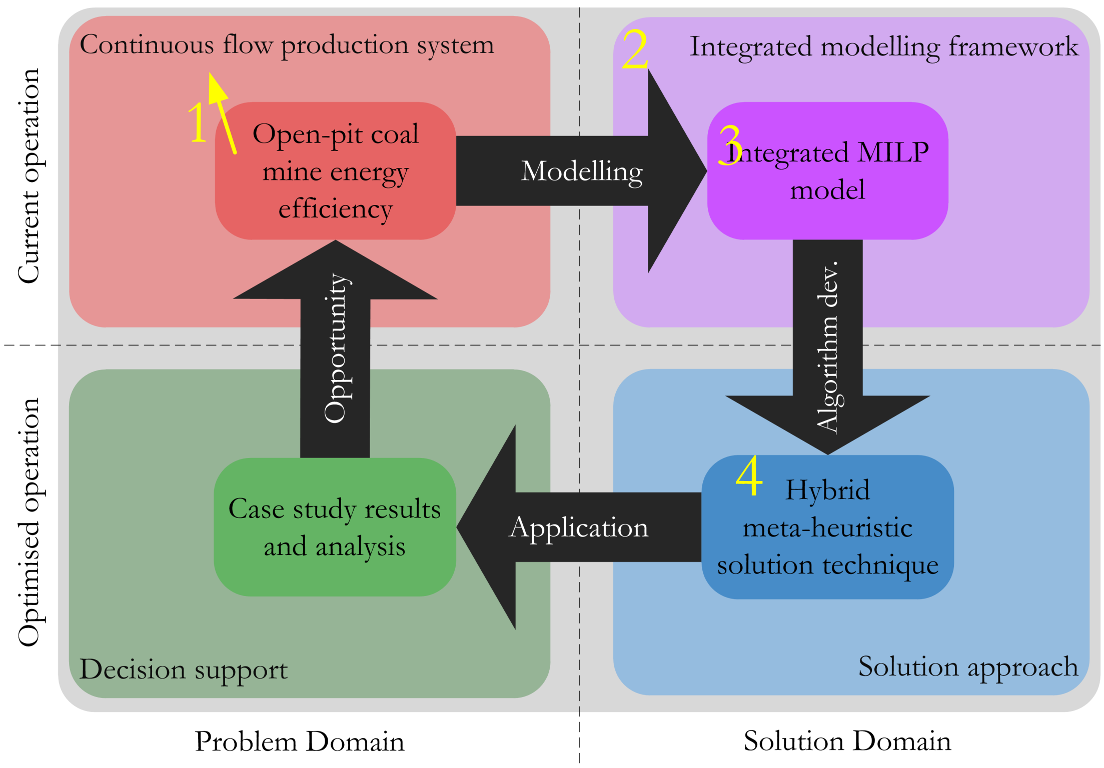

Figure 9.10. Contributions delivered using research approach

In this section, the academic and practical implications of the contributions are discussed, along with an assessment of how they have been used to confirm the hypotheses.

9.2.1 Production system abstraction

Since there is an apparent lack of operations research literature looking at the integrated, operational energy efficiency modelling of mining systems, the mining system was abstracted to the more general field of production systems. This abstraction has been made, with success, in some recent literature (Everett, 2007; Jiu et al., 2013; Zuñiga et al., 2015) but is still in its infancy, relative to the broad range of advanced production system literature that mining may be able to benefit from. It has also not, until now, been formally applied to the specific problem of operational energy efficiency. The contribution is shown in the top left quadrant of the research approach in Figure 9.10. The abstraction and its implications are described in detail throughout Chapter 2.

Section 2.2 described the abstraction by first defining different types of production systems. It then goes on to explain how a mining system can be considered as an open continuous flow production system. Once this is explained, the remaining sections of Chapter 2 employ it to form a sound basis for the rest of the work carried out for the thesis.

Section 2.3 used production system literature to build a catalogue of seven key factors that impact energy efficiency; asset ownership; asset usage; human; organisational; energy provision; planning; and external. Section 2.4 then looked at operational models in mining literature. The factors were used as a way of including models that did not necessarily consider energy efficiency in the review. The review found the two most important factors to consider when formulating an operation model, asset usage and planning. The operational mining models were then reviewed to find appropriate techniques for modelling each subsystem, and the lack of integrated models that focus on energy efficiency was identified.

Production system literature was also drawn upon in Section 2.5. Integrated modelling, material flow connections and MILP formulations were each found to be popular approaches used in relevant production system literature (Ellis et al., 2010; Viere et al., 2011; Zülch et al., 2002). This justifies the modelling approach taken for this research. Section 2.6 also used production system literature to gather a broad range of literature with complex models and reviewed the solution techniques required to solve them. In particular, cooperative hybrid metaheuristics were focused on (Georgiev & Atanassov, 2014; Malek, 2009; Michalewicz et al., 2006; Talbi, 2002). The results of the review have justified the solution technique developed in this research.

Two primary academic implications come out of this contribution. Firstly, the comprehensive literature review presented in Chapter 2 has given a strong foundation for future work looking at the energy efficiency of mining systems, particularly at an operational, integrated optimisation model level, which was lacking in the current literature. Secondly, considering a mining system as a production system was shown to be an effective way to leverage a large body of research to fill gaps in mining literature. This procedure could be replicated to address other mining system issues; for instance, maintenance planning using operational models was identified, in SubSection 2.4.6, as a potential gap in mining literature that could benefit from the application of existing production system literature.

Taking approaches from production systems and applying them to mining systems can also have direct practical implications. Without the need for further research, this procedure could be used to take best practice processes and policies from other similar production systems and apply them to mining problems. While this is likely to have already been done in the industry, being successful in competitive global markets requires continuous improvement of operational procedures, which are much more developed in other production systems such as manufacturing.

The approach could also be useful for other industries. For example, elements of agriculture, the other Australian industry that experienced energy intensity increases between 1976-77 and 2006-07 (Australian Bureau of Statistics, 2010b), could be considered as a continuous production system. Using this abstraction, the same procedure could be used for applying methods from the general production system literature, for making theoretical and practical advances in the agriculture field.

9.2.2 Modelling framework

The second contribution of the thesis is the original modelling framework for developing general, integrated formulations of continuous production systems, and the process for efficiently applying the models to operating production systems. This is represented as the wider region in the top right quadrant of Figure 9.10 and was presented in Chapter 3.

Section 3.1 describes the conceptual framework in detail. The framework works by dividing a continuous production system into subsystem 'modules' with material flow connections between them. The idea is to decouple the subsystem formulations so that they can be very different in nature, to best reflect their respective operations. A time dimension, described as 'operating states', exists at the whole-of-system level of formulation to allow for changing operating conditions through an optimisation, and ensure synchronicity between subsystems. States can be different lengths depending on the required resolution of decision making. The inputs to the integrated model are 'tasks' that describe what work is required by the system as a whole. Solving the model will determine the operation required to best achieve these targets.

Section 3.2 then goes into more detail about the requirements of subsystem module formulations. The main requirement of a subsystem formulation is that it has material flow connection points, so that it can be connected to other subsystems. Subsystem module formulations are also responsible for constraining the material flowing in and out of them. This is an important feature as it means the whole-of-system level of the integrated formulation does not need to be aware of the specific operation of the subsystems. They are also required to provide an objective value, in this case energy consumption, to be included in the whole-of-system objective.

In order to apply this framework to actual production systems, a model application process was also designed. This is presented in Section 3.3. It describes the steps required to gather appropriate data about the operation of the system; define the problem as a system of connected subsystems; use existing subsystem module formulations or formulate new ones to create the integrated model of the problem; apply the gathered data to model parameters; set up the tasks required to be done by the system; and solve the model for analysis of the results. This proved to be useful not only for applying the model to the case study, in Section 5.1, but for exploring opportunities to build a decision support software tool, explained in Subsection 9.1.2.

The academic implications of these contributions are far reaching. While the framework and application process have been used in this study to model the energy efficiency to an open-pit coal mine, they have been designed to apply to continuous flow production systems in general. They have been designed to allow for other objective values, to be applied to other areas of mining, or for application to any other production system that can be represented by a number of subsystems connected by material flow. In particular, the framework could be very useful for taking existing state-of-the-art subsystem formulations from literature, integrating them, without the need for significant reformulation, and efficiently applying them to real-life case studies.

From a practical perspective, the modelling framework and application process promote more efficient, lower cost modelling, allowing for a shorter payback period once the model is running and generating value. This was expanded upon in Subsection 9.1.2. They have been designed to enable the creation of models from a relatively small data set and scale up if more data is available. The reusability of subsystem modules is also important for being able to rapidly apply the framework to new systems. The process has also been designed to separate the responsibilities of problem domain experts from modelling experts, so more of the work can be done by the problem domain expert, also explored in Subsection 9.1.2.

9.2.3 Integrated model

Using the aforementioned modelling framework, two integrated models of open-pit coal mine energy efficiency were presented that represent several contributions. The first is presented in Chapter 4 and an improved formulation is presented in Chapter 6. The modelling done in these two chapters is represented by the inner section of the top right quadrant of the research approach in Figure 9.10.

Chapter 4 presented an integrated model formulation using four common subsystems present in open-pit coal mines, excavation and haulage; processing plant; stockpile; and belt conveyor. This model is an original and substantial contribution as it combines operational models for subsystems across a whole mine into a single integrated model.

These subsystems were designed to reflect the availability of data at the case study mine and models from existing recent mining literature. The detail of the processing plant, stockpile and conveyor belt modules were limited due to data availability constraints. However, they were successfully modelled as general subsystems based on recent literature (Hanoun et al., 2013; Middelberg et al., 2009; Ta et al., 2005) that should be portable to many other open-pit coal mines.

The availability of data for the excavation and haulage subsystem was much better and therefore afforded a more detailed model. The Chapter 4 formulation of the excavation and haulage subsystem was based around using a similar allocation decision variable to that used in the majority of recent operational models of truck activity (Mena et al., 2013; Sahoo et al., 2014; Souza et al., 2010; Ta et al., 2013). The formulation also extended upon these other models by including a time dimension to allow for changing operating conditions throughout the optimisation period. While the Chapter 4 formulation was shown to provide sensible and valuable results on the case study, a number of limitations were found relating to the usage of equipment allocation to model the operation of the excavation and haulage subsystem.

To rectify these issues, Chapter 6 revisited the excavation and haulage formulation. The improved excavation and haulage formulation included truck and shovel interactions and trip sequencing so that the equipment operation could be more accurately accounted for. The new formulation is similar to that of Chang et al. (2015), the only other truck scheduling seen in literature. However, the Chapter 6 formulation is distinct from Chang et al. (2015) as it minimises energy consumption, integrates with other subsystems at a material flow level and allows for changing operating states throughout the optimisation period. The improved accuracy came at a cost however. This model was shown to be NP-hard and demonstrated to be intractable for practical sized problems.

The two models are both useful contributions to academia. While the first has limitations, it is the first of its kind to integrate all four subsystems. It is able to be solved quickly with commercial solvers and, despite accuracy issues, still provide sensible results. Depending on the problem at hand, the accuracy of this model may be more than enough. Meanwhile, the improved excavation and haulage subsystem module formulation represents the state-of-the-art in modelling for that subsystem.

They also have the ability to provide valuable implications in practice. The integrated nature of them means they can be used to help mine operators work toward system wide optimums rather than suboptimal solutions from silo optimisations. Being able to have an operational model of a running mine fit with up-to-date data means the models can provide precise decision support relevant to the mine's current operation, rather than design, theoretical or historical data.

The speed of the first model means it could be used to provide quick answers, with lower accuracy, to users making operational decisions. The improved formulation, along with the developed solution technique presented in Chapter 7 and summarised below, can then be used to provide an even greater level of accuracy to decision makers. Looking towards the future of mining, technological advances in autonomous shovels and trucks are expected to provide significant economic benefits (Bellamy & Pravica, 2011). Advanced operations research techniques, such as those demonstrated in this thesis, will be required for accurate and optimal scheduling of this technology.

9.2.4 Solution technique

A high level, teamwork hybridisation of a simulated annealing and tabu search was innovated to overcome the NP-hard complexities of the Chapter 6 excavation and haulage subsystem formulation. This was presented in Chapter 7 and deals with the inner section of the bottom right quadrant of the research approach in Figure 9.10.

In order to apply the tabu search and simulated annealing metaheuristics to the complex formulation, several elements were innovated. Subsection 7.1.1 described the solution representation that significantly reduces the search space of the model. Subsection 7.1.2 then detailed seven neighbourhoods around this solution. Since the solution representation only represents the excavation and haulage subsystem, it was noted that special consideration must be made for two of these neighbourhoods as they can cause infeasibilities in other subsystems.

Several algorithms were then presented in Subsection 7.1.3. To check solutions that are generated from the aforementioned neighbourhoods that may cause infeasibilities on other subsystems, MILPVALIDATE was designed. This solves the Chapter 4 MILP with allocation set based on the candidate solution to determine if any constraints of other subsystems have been violated. For solutions generated using the other five moves, the ISFEASIBLESEQUENCE algorithm ensures the solution represents enough work from the subsystem. The SCHEDULESEQUENCE algorithm is developed to convert a sequence into a schedule. The schedule is then used by EHENERGYCONSUMPTION and F to calculate the energy consumption of the subsystem and whole-mine, respectively.

Subsection 7.1.4 then presented is the constructive heuristic that builds the initial feasible solution required by the metaheuristics. This also uses the Chapter 4 MILP to ensure the solution is feasible for the whole integrated model and for truck recommendations when building the sequence. It represents a low level, relay hybridisation between the heuristic and exact method solving the MILP, as per the Talbi (2002) taxonomy.

The tabu search and simulated annealing algorithms are then presented in Subsections 7.1.5 and 7.1.6, respectively. They both follow relatively standard algorithm flows. However, the requirement to use the algorithm to check certain solutions makes them low level, teamwork hybridisations between the heuristic and exact method solving the MILP, as per the Talbi (2002) taxonomy.

Drawing upon the concepts and techniques reviewed in Section 2.6 (Georgiev & Atanassov, 2014; Malek, 2009; Michalewicz et al., 2006; Talbi, 2002), the two metaheuristics were hybridised. A novel approach that utilised good practice software architecture theory and implementation resulted in a high level, teamwork hybrid metaheuristic, as per the Talbi (2002) taxonomy. With relatively minimal changes required to their algorithm flow, the publisher-subscriber software design pattern (Gamma et al., 1994) was used to facilitate communication between the metaheuristics running in parallel. They were implemented to communicate asynchronously via ØMQ, an open source, lightweight message queue framework (Hintjens, 2013). This enabled cooperative behaviour between the metaheuristics that resulted in improved solutions without a large increase in computation time.

Using hypothetical problem instances and case study problem instances, in Section 7.2, comprehensive computational analysis was conducted on the solution technique. Firstly, the solution technique was shown to find optimal results to the small problems for which CPLEX could find solutions to the Chapter 6 MILP. It was then demonstrated to curb the complexity issues that CPLEX faces, to provide good quality solutions in reasonable time for medium-to-large-sized problems. Finally, the value of the hybrid technique over the two metaheuristics on their own was demonstrated. It consistently provided the most optimal result, without a great deal of extra computation required.

From an academic perspective, the developed solution technique demonstrates how to overcome the complexity issues with the scheduling formulation of the excavation and haulage subsystem. It also serves as a good example for dealing with localised complexities in integrated models, while still ensuring the feasibility of the overall integrated model. The hybrid tabu search and simulated annealing technique also demonstrated a novel example of how software architecture practices can aid the efficient development of good quality solution techniques.

Practically, this contribution was shown to enable the complex but accurate Chapter 6 integrated model to be solved for real problems. This means the various benefits of the model can be realised on operating mines to provide good quality solutions. The speed of the solution technique also means the model can be solved for a number of different applications, including in an operational setting, as described in Subsection 9.1.2.

9.2.5 Confirmation of hypothesis

The contributions throughout the thesis, summarised throughout this section, have been used to comprehensively test the hypotheses outlined in Section 1.4 and listed below. The vast array of opportunities, detailed in Section 9.1, for the case study mine and the problem in general, confirms each of the hypotheses.

1. *Mining operations can benefit from modelling techniques commonly used in production systems literature.*

The production system abstraction is a critical contribution for forming the strong research foundation presented in Chapter 2. By using this foundation, the research has been able to apply the techniques used in advanced production system literature to the mining problem at hand. The resulting opportunities for making an improvement to open-pit coal mine energy efficiency demonstrate that this was a successful endeavour, confirming hypothesis 1.

2. *Integrated modelling is an effective approach to modelling the energy efficiency of mining production system.*

3. *Mixed Integer Linear Programming (MILP) is appropriate for formulating an integrated model of the energy efficiency of an open-pit coal mine.*

Integrated modelling is an approach that was identified and reviewed in the production system literature mentioned above, as well as in mining literature, though to a lesser degree. This was reviewed in Section 2.5, where MILP was also identified as a popular and successful approach for formulating the integrated models. These findings formed a basis for the integrated modelling framework contribution presented in Chapter 3 and integrated MILP formulation presented in Chapters 4 and 6. After applying these contributions to the case study mine, the opportunities to improve energy efficiency demonstrated the effectiveness of the integrated modelling and MILP formulation approaches. This confirms hypotheses 2 and 3.

4. *A complex model is required to accurately model the operation of an integrated open-pit coal mine system, in particular the operation of the trucks.*

Though the Chapter 4 MILP model exhibited promising results for the case study in Chapter 5, detailed inspection highlighted some inaccuracies with the formulation. In particular, the activity of the trucks interacting with the shovels was shown to be a problem area. This motivated the modifications made in Chapter 6 to improve the accuracy of the excavation and haulage subsystem. A scheduling formulation was proposed and examined to show the accuracy was improved. The results in Chapter 8 then demonstrated the benefit of the improved accuracy. This confirms hypothesis 4.

5. *A hybrid metaheuristic-based solution technique is able to overcome complexities in the model to provide solutions quickly without significant loss of solution quality.*

The drawback of the improved formulation presented in Chapter 6 is its NP-hard complexity. Practical-sized problem instances of the model cannot be solved with exact methods. To overcome this issue, various elements were innovated and detailed in Chapter 7 to be able to apply the tabu search and simulated annealing metaheuristics. These two metaheuristics were also hybridised to allow them to cooperatively find good solutions in reasonable time to practical-sized problems. Computational analysis in Chapters 7 and 8 demonstrated the value of the hybrid solution technique, confirming hypothesis 5.

6. *The developed model and solution technique can be used as a decision support tool for making more energy efficient decisions.*

Finally, Section 9.1 of this chapter covered how each of the contributions can be used for decision support. Numerous opportunities for using the model, solved with the solution technique, to support decisions at the case study mine were outlined in Subsection 9.1.1, confirming hypothesis 6. Subsection 9.1.2 extended upon this to discuss how the model, solved using the solution technique, can be used to aid a decision for the problem in general. In particular, a suite of software tools were proposed to aid decision makers at operational, tactical and strategic levels.

9.3 Limitations

While the original contributions of this study have been shown to have substantial implications, the approach also has a number of limitations. With respect to the modelling framework, the assumption that subsystems can only be connected via material flow connections restricts the ability to model many interactions. This did not cause issues for this problem, and it is suggested that other continuous flow production systems should suit this restriction; it may not always work as well as it has in this study. For instance, modelling other, less continuous operations at a mine, such as drilling and blasting, auxiliary systems, or train loading, may be harder with material flow.

While the modelling framework theoretically allows for different, or more, objectives, it has only been implemented with an energy consumption objective. This means the model results may have detrimental effects on other important measures of mine efficiency. For instance, in the case study results, the truck waiting time seemed relatively high. Since it was shown to only have a minor impact on energy efficiency, it was not a priority of the optimisation to reduce this, which may be a key performance indicator of the subsystem's productivity. Therefore, model results should be verified against other objectives before being acted upon, and eventually, other important objectives should be included in the model.

The other limitation of the objective is that only energy consumption relating to the main operations is being considered. Activities, such as shovel movement, drilling and blasting and maintenance, that are not as closely related to the day-to-day operation of the mine, from a continuous production system perspective, have not been considered in this study, and may not necessarily be straightforward to include in the future. Along with these, other subsystems that have not been modelled here, such as draglines and auxiliary subsystems, will have an impact on energy efficiency that cannot be analysed with the model presented in this study.

The study has also only considered the application of the contributions on one mine. Mines are very dependent on external factors such as environment and demand. As such, results for a particular mine are likely to change for a different mine. For the particular mine studied in this thesis, demand is very well-known as it only produces coal for an adjacent power station. It also is dealing with a specific circumstance where it has to re-extract old overburden to get to previously uneconomic coal. This means mines with very variable demand, different extraction requirements or alternate processing structures can't necessarily take any of the learnings for this case study mine for granted and apply them directly to their mine.

Likewise for the solution technique, since it has been developed and tuned for this application on a particular mine, it may not perform so well on a different mine, operating under different conditions. For example, the solution technique focuses on the excavation and haulage subsystem, which there is only one of in this system; in theory the algorithm concepts should hold for a model with more than one excavation and haulage subsystem, however, it is expected that modifications would be required to effectively search both solution spaces at the same time and ensure feasibility across both subsystems, as well as the mine as a whole.

Another limitation of analysing this mine was that it only considers a single grade of ROM coal and a single grade of product coal. This means the grade control elements of the model are untested and require detailed analysis on a mine that does differentiate between ROM and product coal grades.

This research has also been limited to deterministic methods. It has not explicitly considered the stochastic nature of the mine. It is proposed that the model should be resolved when deviations from plan occur in a reactive scheduling setting.

9.4 Future work

In this section, two broad streams for future work are presented. Firstly, avenues to develop the methods for further application to mining problems are recommended. Secondly, work is outlined to formalise and develop the concepts for addressing other problems that fall under the general area of continuous production systems. Each has promising potential to further benefit academia and industry.

9.4.1 Further analysis of mining systems

As mentioned in the limitations, this research has focused on a particular problem in mining, energy efficiency, and tested its contributions on a single mine case study. Though the outcomes present significant opportunities for the mining industry, generalising the findings to guarantee improvements cannot be done. Therefore, a primary avenue for future work is more application on operating mines. This will further verify the opportunities that face mining operations. In general, due to the strong practical intent of the research, further application on real case studies is central to all future work outlined here.

Initially, for this case study, further analysis is warranted to investigate the issue found in Subsection 8.3.4. It is unclear why increases in energy consumption occurred when the shovels at pits 1 and 3 were made unavailable later in the day as opposed to earlier. More data about the operation would aid the investigation into whether it is an error with the methods or a physical phenomenon.

To improve the generalisability and accuracy of the integrated model, improved and new subsystem modules should be formulated. This would allow for application to a wider set of mines. For example, to apply the methodologies to an underground mine, new subsystem modules would be required to be formulated and integrated with the current subsystem.

New objective terms, such as labour costs and asset degradation could also be added to the objective to improve the accuracy of the model and broaden its usefulness. Another modelling improvement would be to include stochastic techniques, such as chance constrained programming and fuzzy logic.

Continued development of the solution technique would also be required to ensure good quality solutions to the model can be found quickly for practical application. A formal lower bound on the objective would be a useful addition to ensure the quality of solution. This could also assist further algorithm development and tuning to improve speed and reduce variance.

If a new subsystem formulation was found to be complex, like the excavation and haulage subsystem in this thesis, new techniques would be needed to solve it in a reasonable timeframe. The extensibility of the hybrid approach could be exploited to integrate any new techniques with the existing ones.

Improved and new techniques, such as hyperheuristics, population-based metaheuristics and improved constructive heuristics, could provide better solutions even faster for bigger sized problems. Techniques such as rolling horizon, reactive, predictive or proactive scheduling could also be useful for ensuring the schedules can be quickly updated when disturbances occur. The level of communication between hybridised techniques could also be improved to make them more effective at cooperatively and competitively finding optimal solutions.

The development of a product from the contributions is also recommended. This would enable operating mines to realise practical benefits of the contributions. The decision support software tools proposed in Subsection 9.1.2 serve as a good starting point for the development of a commercial product. They have been designed to enable low upfront cost modelling and provide support to various levels of decision making. These tools are also designed to be extended to suit other modelling and solution improvements, for instance, new objectives and subsystems.

9.4.2 Application to other systems

The other main stream of future work is to further generalise the production system abstraction and modelling framework contributions. The broader intentions of these contributions, along with the research approach, are to give direction to researchers looking at similar problems outside of the mining industry. The concepts have been designed to allow development and application on other continuous production systems, such as manufacturing and agriculture. Once again, central to the motivation of the research, future work is recommended to include application on real case study systems to ensure its practical viability.

Applying the modelling methodology to completely new areas would require more effort, as completely new subsystem formulations would be required, though it would more strongly test the developed concepts and framework. Currently, the main current of the integrated modelling framework is the requirement of flow connections between subsystems. Future work looking at adding other types of connections, such as discrete transactions, could widen the potential for application drastically. Extending the methodologies to cope with other modelling techniques, such as chance constrained programming and multiple objectives, would also broaden the range of problems that could be modelled. Further application to new areas would also likely require new solution techniques to be created.

As with the mining problem, for industry to realise the benefit of any future work, the development of software tools is recommended. The core concepts behind the suite of tools proposed in Subsection 9.1.2 have been designed to apply to other production systems. By formalising the modelling framework and constructing a large library of subsystem modules, a generalised modelling tool could be developed to facilitate decision support for a wide set of production systems.

9.5 Conclusions

The importance of improving energy efficiency of mining operations is well-known by research and industry alike. However, there is a lack of literature applying state-of-the-art operations research techniques to the problem. This thesis has addressed the gap by abstracting the problem as a continuous flow production system. The vast production system literature dealing with operational energy efficiency modelling was successfully used to fill the gap in research looking at operational optimisation models of mining energy efficiency.

Formulating the model as an integrated system of subsystems connected by material flow using Mixed Integer Linear Programming (MILP) was shown to be an effective approach for modelling the energy efficiency of a mining production system. The developed integrated modelling framework and application process were successfully employed to define a general MILP formulation of an open-pit coal mine and apply it to a real mine using a limited data set from the mine operator.

The accuracy of the excavation and haulage subsystem was investigated in detail and an original scheduling model of the shovel and truck operation has been formulated to model their interaction accurately. However, by introducing these complexities into the formulation, exact methods were unable to solve the model. The development and application of a hybrid tabu search and simulated annealing solution technique was shown to overcome the complexities and provide good quality solutions to the model in reasonable time for practical application.

The developed model and solution technique have been shown to be suitable for supporting more energy-efficient decisions. The case study results consisted of several examples on a real mine that demonstrated how the model can be used to provide valuable results to decision makers at the mine. Several opportunities were presented for both the case study mine and for addressing the problem in general. Not least, opportunities for using the contributions as a tool for decision support at operational, tactical and strategic levels were discussed.

As a result of this work, each hypothesis has been comprehensively tested and confirmed. A number of original contributions to knowledge have been made that each have significant academic and practical implications. Finally, a promising scope for more significant work to be done in the future, on this specific problem and other similar problems, has also been detailed.

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A

Meandu Mine Model Structure

Table A.1. Set of all subsystems

Set Q		
ID	Subsystem	Abbreviation
1	Extraction (excavation and haulage)	Extraction
2	ROM stockpile	ROMStockpile
3	Top soil dump	TopSoilDump
4	Waste dump 1	WasteDump1
5	Waste dump 2	WasteDump2
6	Waste dump 3	WasteDump3
7	Crusher	Crusher
8	Wash plant	WashPlant
9	Crushed ROM stockpile	CrROMStockpile
10	Belt conveyor 1	BC1
11	Belt conveyor 2	BC2
12	Belt conveyor 3	BC3
13	Belt conveyor 4	BC4
14	Belt conveyor 5	BC5
15	Tailings dump	TailingsDump

Table A.2. Set of excavation and haulage subsystems

Set $E \subseteq Q$		
ID	Subsystem	Abbreviation
1	Extraction (excavation and haulage)	Extraction

Table A.3. Set of processing plant subsystems

Set $P \subseteq Q$		
ID	Subsystem	Abbreviation
7	Crusher	Crusher
8	Wash plant	WashPlant

Table A.4. Set of stockpile subsystems

Set $V \subseteq Q$		
ID	Subsystem	Abbreviation
2	ROM stockpile	ROMStockpile
3	Top soil dump	TopSoilDump
4	Waste dump 1	WasteDump1
5	Waste dump 2	WasteDump2
6	Waste dump 3	WasteDump3
9	Crushed ROM stockpile	CrROMStockpile
15	Tailings dump	TailingsDump

Table A.5. Set of belt conveyor subsystems

Set $B \subseteq Q$		
ID	Subsystem	Abbreviation
10	Belt conveyor 1	BC1
11	Belt conveyor 2	BC2
12	Belt conveyor 3	BC3
13	Belt conveyor 4	BC4
14	Belt conveyor 5	BC5

Table A.6. Sets of connection points, inlets and outlets

Set $C_p, I_q and J_q$			
I_q/J_q	ID	Subsystem	I/O
I_1	1	Extraction	In
	2	Extraction	In
	3	Extraction	In
	4	Extraction	In
	5	Extraction	In
J_1	6	Extraction	Out
	7	Extraction	Out
	8	Extraction	Out
	9	Extraction	Out
	10	Extraction	Out
	11	Extraction	Out
I_2	12	ROMStockpile	In
J_2	13	ROMStockpile	Out
I_3	14	TopSoilDump	In
I_4	15	WasteDump1	In
I_5	16	WasteDump2	In
I_6	17	WasteDump3	In
I_7	18	Crusher	In
J_7	19	Crusher	Out
	20	Crusher	Out
I_8	21	WashPlant	In
	22	WashPlant	In
J_8	23	WashPlant	Out
	24	WashPlant	Out
I_9	25	CrROMStockpile	In
J_9	26	CrROMStockpile	Out
I_{10}	27	BC1	In
	28	BC1	In
J_{10}	29	BC1	Out
I_{11}	30	BC2	In
J_{11}	31	BC2	Out
	32	BC2	Out
I_{12}	33	BC3	In
J_{12}	34	BC3	Out
I_{13}	35	BC4	In
J_{13}	36	BC4	Out
I_{14}	37	BC5	In
	38	BC5	In
J_{14}	39	BC5	Out
I_{15}	40	TailingsDump	In

Table A.7. Set of connections

Set C		
Outlet connection ID		Inlet connection ID
6	→	12
7	→	27
8	→	14
9	→	15
10	→	16
11	→	17
13	→	28
29	→	18
19	→	30
31	→	25
32	→	38
26	→	33
34	→	21
23	→	37
24	→	35
36	→	40

Table A.8. Set of material types

Set G		
ID	Grade	Abbreviation
1	ROM coal	ROM
2	Crushed ROM coal	CrushedROM
3	Product coal	Product
4	Overburden (waste)	Overburden
5	Spoil (waste)	Spoil
6	Top soil (waste)	TopSoil
7	Tailings (waste)	Tailings
8	Water	Water

B

Meandu Mine Model Parameters

B.1 Excavation and haulage

- Cycle time
  - 6.5 minutes from any pit to ROM stockpile or crusher
  - 11.9 minutes from any pit to any waste dump
- Loading time
  - 3.2 minutes at any pit

Table B.1. Meandu Mine truck parameters

Truck	Pay load	Idle diesel consumption (MW)	Driving diesel consumption (MW)
1	220	0.33927	1.69635
2	220	0.32957	1.64784
3	220	0.58172	2.90858
4	220	0.30961	1.54807
5	220	0.38904	1.94518
6	220	0.30766	1.53830
7	170	0.30967	1.54834
8	170	0.27087	1.35436
9	170	0.24885	1.24425
10	170	0.31326	1.56629
11	170	0.28864	1.44321
12	170	0.27258	1.36287
13	170	0.28191	1.40955
14	170	0.35922	1.79610
15	220	0.36122	1.80608
16	220	0.40347	2.01733
17	220	0.40529	2.02643
18	220	0.38789	1.93943
19	220	0.41849	2.09255
20	220	0.42006	2.09004

Table B.2. Meandu Mine shovel parameters

Shovel	Loading energy usage(MW)	Idle energy usage (MW)
1	3.017891	0.603578
2	4.585459	0.917092
3	1.639840	0.327968
4	3.442511	0.688502

B.2 Processing plants

Table B.3. Meandu Mine CHPP input ratios

Processing plant	Produced grade	ROM	Crushed ROM	Product	Ovbn.	Spoil	Top Soil	Tailings	Water
Crusher	Crushed ROM	1	0	0	0	0	0	0	0
Wash Plant	Product	0	1.223	0	0	0	0	0	0.0692

Table B.4. Meandu Mine CHPP parameters

Processing plant	Maximum capacity of plant	Minimum capacity of plant	Fixed energy consumption (MW)	Variable energy consumption coefficient (MW/(t/h))
Crusher	300	2,300	0.75	0.0023225
Wash Plant	500	1,880	0.75	0.0023225

B.3 Stockpiles

Table B.5. Meandu Mine CHPP stockpile parameters

Stockpile	Stored grade	Max rate of stacking	Max rate of reclaiming	Min level of stockpile	Initial level of stockpile	Stacking energy consumption coefficient (MW/(t/h))	Reclaiming energy consumption coefficient (MW/(t/h))
Crushed ROM Stockpile	Crushed ROM	2,300	2,400	20,000	20,000	0.00066	0.0001466
ROM Stockpile	ROM	2,400	2,300	20,000	21,000	0.00066	0.0001466
Tailings Dump	Tailings	5,000	5,000	0	0	0.0001	0
Top Soil Dump	TopSoil	5,000	5,000	0	0	0.001	0
Waste Dump 1	Ovrbrdn	5,000	5,000	0	0	0.001	0
Waste Dump 1	Spoil	5,000	5,000	0	0	0.001	0
Waste Dump 2	Ovrbrdn	5,000	5,000	0	0	0.001	0
Waste Dump 2	Spoil	5,000	5,000	0	0	0.001	0
Waste Dump 3	Ovrbrdn	5,000	5,000	0	0	0.001	0
Waste Dump 3	Spoil	5,000	5,000	0	0	0.001	0

B.4 Belt conveyors

Table B.6. Meandu Mine belt conveyor parameters

Belt conveyor	Maximum rate of material flowing over belt	Energy consumption coefficient (MW/(t/h))
CB1	2,400	0.00004727
CB2	2,400	0.00018907
CB3	2,400	0.00015750
CB4	2,400	0.00113908
CB5	2,400	0.00029544

C
Papers published

An integrated model of an open-pit coal mine: improving energy efficiency decisions

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Abstract

This article contributes an original integrated model of an open-pit coal mine for supporting energy-efficient decisions. Mixed integer linear programming is used to formulate a general integrated model of the operational energy consumption of four common open-pit coal mining subsystems: excavation and haulage, stockpiles, processing plants and belt conveyors. Mines are represented as connected instances of the four subsystems, in a flow sheet manner, which are then fitted to data provided by the mine operators. Solving the integrated model ensures the subsystems' operations are synchronised and whole-of-mine energy efficiency is encouraged. An investigation on a case study of an open-pit coal mine is conducted to validate the proposed methodology. Opportunities are presented for using the model to aid energy-efficient decision-making at various levels of a mine, and future work to improve the approach is described.

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