Short-Term Planning for Open Pit Mines: A Review

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Abstract

This review examines the current state-of-the-art in short-term planning for open-pit mines, with a granularity that spans days, weeks, or months, and a horizon of less than one to two years. In the academic literature, the short-term planning problem for open-pit mines has not been as widely considered as that for the medium- and long-term horizons. We highlight the differences between short- and longer-term planning in terms of both the level of detail to which a mine site is modelled, and the objectives that are optimised when making decisions. We summarise the range of techniques that have been developed for generating short-term plans, capturing both mathematical programming-based methods and heuristic approaches using local-search and decomposition. We identify key challenges and future directions in which to advance the state-of-the-art in short-term planning for open-pit mines.

Keywords: open-pit mining, short-term planning, operations research

1 Introduction

An open-pit mine consists of a set of pits, in which horizontal layers of material (benches) are extracted from the top down. Open-pit mining is suitable for orebodies located close to the surface, with underground mining techniques typically applied where this is not the case. Metal ores including iron, copper, and gold, and other materials such as coal, diamonds, limestone, and uranium, are commonly extracted using the open-pit mining method. A hierarchy of planning activities take place over the life of an open-pit mine – from operational or day-to-day decision-making on the positioning of equipment, truck dispatch, and control of crusher feed characteristics or quality; to long-term and strategic decision-making on the timing of expansions, the introduction or building of new infrastructure, and the opening or closing of regions of the mine site. At each horizon (day-to-day to life-of-mine), a planner selects blocks or regions of material (from a block model) to be extracted in each period (or across multiple periods) of the horizon. The nature of this block model, and the timespan represented by these time periods, varies across the planning hierarchy.

In long-term (or life-of-mine) planning, the block model divides an orebody into a grid of equally sized blocks, where each block is assigned an estimate of its grade (metal content in the context of mining metal ores) and other relevant quality attributes. A planner selects regions of this model (subsets of blocks) to be extracted during each year of the mine's life. The horizon of interest for a short-term planner, in contrast, spans several weeks to months (and typically no more than one to two years). The block model at this horizon divides relevant regions of the orebody into irregularly shaped blocks, generally referred to as ore and waste blocks in the literature. Blocks are blasted (via explosives inserted into drill holes) to form the broken stock of the mine – material that is available and ready for extraction. Prior to extraction, a geologist partitions ore blocks according to grade – areas of, for example, low grade, and high grade ore – on the basis of extracted samples. At the level of day-to-day or shift-to-shift planning, decisions around what material (from available broken stock) is fed into each crusher or processing plant are made, with the objective of achieving a daily production target and meeting other relevant key performance indicators (KPIs).

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1.1 Scope

In the academic literature, the short-term planning problem for open-pit mines has not been as widely considered as that for the medium- and long-term horizons. This review examines the current state-of-the-art in short-term planning for open-pit mines, with a granularity that typically spans a week (to a month) and a horizon of less than one to two years. Caccetta (2007), Osanloo et al. (2008), Newman et al. (2010), Lambert et al. (2014), and Musingwini (2016) summarise the literature, challenges, and solution techniques that exist in the context of long-term planning for both open-pit and underground mines. Lambert et al. (2014) present formulations of a series of commonly solved long-term planning problems, ranging from ultimate pit limit to block sequencing problems. Espinoza et al. (2012) present a library of data sets (MineLib) suitable for evaluating techniques for solving such problems. Newman et al. (2010) review the use of operations research in mine planning, covering work on both underground and open-pit mines, and multiple horizons (from day-to-day decision-making, to mine design and long-term planning). We restrict our attention to the short-term planning of open-pit mines, with horizons of at least one week to at most one to two years. Research related to shift-to-shift or day-to-day planning, equipment selection (selecting fleet sizes and equipment configurations), and truck dispatch, fall outside of the scope of our review. Alarie and Gamache (2002) and Moradi Afrapoli and Askari-Nasab (2017) present reviews on fleet management in open-pit mines. Alford et al. (2007) and Musingwini (2016) provide recent reviews on underground mine planning.

1.2 Overview

We highlight the key differences between short- and long-term planning, and the range of activities that take place across different short-term horizons, in Section 2. Early (pre 2000) work on short-term planning for open-pit mines is discussed in Section 3. Literature tackling weekly and fortnightly build planning is considered in Section 4. The remainder of the paper covers short-term planning methods applied to horizons of several months, grouped according to their underlying methodology. In Section 5, we describe modern mixed-integer programming (MIP) based methods. These approaches capture equipment behaviour, stockpiling, multiple processing pathways, multiple objectives, practical mining rules, and mining precedences. Metaheuristics for short-term planning, typically embedding the solving of MIP models within local search, are considered in Section 6. Management of uncertainty, from various sources, is prevalent in the long-term planning literature. Conditional simulation of orebodies, and the expected outcomes of a long-term plan across different realisations of this uncertainty, is common. We describe the extent to which uncertainty has been modelled in short-term planning in Section 7, with simulation and stochastic programming commonly applied across these works. Section 8 summarises the different approaches used for multi-objective optimisation in the short-term context. The extent to which multi-horizon planning, or the integration of planning across horizons, has been considered in the short-term planning literature is discussed in Section 9.

We compare the short-term planning approaches cited in this review in terms of: the level of detail to which they model mine operations; the objectives they optimise; and the types of uncertainty (if any) modelled. Table 1 compares the features modelled across the short-term planning methods discussed in Sections 5–7. This table identifies, for each approach: the activities modelled (drilling, blasting, excavation – of single blocks or aggregates of blocks, equipment schedules – truck and shovel, rail operations, port operations, and multiple mines); constraints enforced; objectives optimised; and types of uncertainty modelled (if any). Enforced constraints include: demand (minimum production levels); mining precedences (over extraction or other activities); capacities; blend constraints (on the quality of production, and process feeds); utilisation of infrastructure; and longer-term plan alignment (enforcing the mining of blocks as stipulated in a longer-term plan). Capacities on trucks and shovels can be defined in terms of the maximum tons of material that can be hauled, or extracted, in each time period, or in terms of the trucking and shovel hours (or tons per hour) available for use. Objectives optimised include: the minimisation of costs, deviation present in the quality of produced ore from targets, shovel moves, deviation from longer-term goals, or deviation from production targets; the minimisation or maximisation of equipment utilisation; the maximisation of revenue; and minimising makespan (the time required to complete a set of mining activities). While some approaches seek to maximise the utilisation of equipment and infrastructure (with a view to maximising production or throughput), others set minimum demands on production and seek to minimise the operational requirements (such as the number of trucks) to achieve this. Various sources of uncertainty are modelled in short-term mine planning, including: geological uncertainty; equipment-based uncertainty (in cycle times, productivities, availability, and reliability); and economic uncertainty (in metal prices, for example). Geological and equipment-related uncertainty are most commonly considered, while economic uncertainty is not typically emphasised (playing a greater role in work on longer-term horizons).

Plan generation is not the focus in all of the work highlighted in Table 1. Li and Knights (2009), for example, consider how waste dump selection should vary given current fuel prices – simulating an existing mine plan under different policies. Paduraru and Dimitrakopoulos (2017) focus on designing policies for real-time block selection, in place of generating a complete plan in advance. Consequently, the level of detail to which mine operations are modelled varies significantly. Similarly, different aspects of the short-term planning problem are modelled by each of the approaches described in this paper. Liu and Kozan (2012), Liu et al. (2013), and Kozan and Liu (2014, 2016), for example, focus on scheduling a set of drilling, blasting, and extraction activities for a set of blocks so that makespan (the time required to complete the set of activities) is minimised. This work does not model the processing side of mine operations (including the destination to which material is sent), but focuses on scheduling a known set of extraction activities over a horizon spanning several months. The work of Thomas et al. (2012, 2014), in contrast, focuses on the operations of a rail network connecting multiple mine sites to a port. Mine operations are not modelled in detail, with the key variable denoting the quantity of ore produced in each time period. The optimisation determines how this produced material is railed to the port over a network with limited capacity.

Even across more recent work, the way in which the short-term planning problem is modelled varies. This is likely a result of variation in how individual mine sites operate. The set of constraints and objectives that are most important, and emphasised in a short-term model, are likely to vary from site to site, and from commodity to commodity. Table 2 records the largest problem sizes (such as the number of blocks available for selection, and the number of units of equipment modelled) considered during evaluations of the work in Table 1, where this information was available.

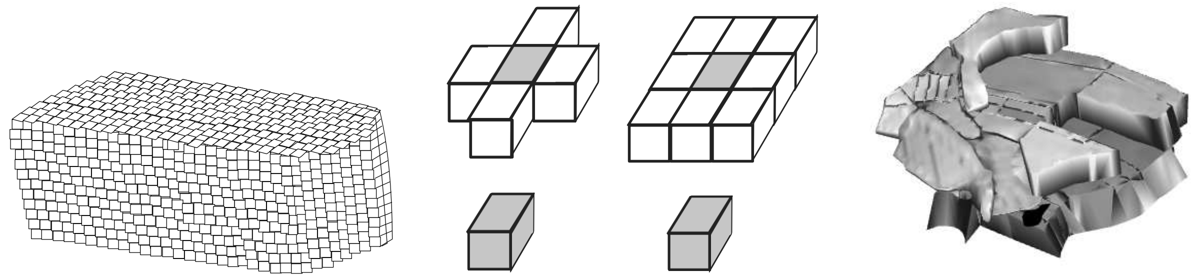
We conclude in Section 12 with an analysis of commercial tools available for short-term planning, and an assessment of the current challenges and unanswered research questions in the field.

2 Short vs Long Term Planning

Short and long-term planning differ in several key dimensions. These include: the type of block model used as input to the planning process; the discretisation of time (weekly or shorter time periods versus quarterly to yearly); the objectives, and number of objectives, being optimised; the constraints that must be considered during optimisation; and the level of detail to which mine operations are modelled.

In the long-term context, a block model consists of (typically) millions of equally sized blocks. Precedences exist between the blocks in this model, defining constraints on which blocks must be extracted before others. Typically, the 5 (or 9) blocks directly above a block (see Figure 1b–1c) are its predecessors, and must be extracted before it can be accessed. These precedences ensure that constraints on the slope of pit walls are respected during mining. Recall that the block model used by short-term planners divides relevant portions of an orebody (the regions being mined in the near future) into ore and waste blocks. Figure 1d shows an example of a portion of an orebody divided into blocks according to grade. These blocks are irregularly shaped. Mining precedences, in this setting, must consider how each block can be accessed from the mining face.

The term 'short-term planning' can be used to capture a range of activities. Shift-to-shift and day-to-day decision-making determines the number of truckloads of material to extract from each available block, and the crusher to which the material is sent, in order to meet daily quantity and quality targets on production. In these time frames, the allocation and sequencing of truck movements is a key lever for controlling the characteristics of crusher feed and maintaining appropriate crusher utilisation. The focus of weekly and fortnightly planning is the design of a series of builds (or runs). Each build is a stockpile from which



(a) (b) (c) (d)

Figure 1: (a) Section of a typical block model used in long-term planning (equally sized blocks in a grid structure), (b) the 5, and (c) 9, blocks above a block, and (c) part of a grade block model.

material is reclaimed onto trains. Blocks that are available for mining over these time periods are assigned to individual builds, with each build designed to meet a specific quality target. At the monthly horizon, a short term planner selects blocks to be mined in each week of the horizon, and the destination to which this material is sent (a stockpile, waste dump, or processing pathway, for example), to meet weekly targets on the quantity and quality of production. The scheduling of blasts, which determines when certain blocks will become available for mining, also takes place at this horizon.

The objectives being optimised in the short-term vary, and typically include: maintaining the grade of production within desired bounds in each time period; maximising equipment utilisation (and the utilisation of crushers in particular) to meet production targets; minimising rehandling (moving material to stockpiles, and reclaiming that material for processing at a later date); or minimising costs. In practice, decisions that determine the costs of mining, such as the number of trucks (fleet size) available, are made at longer-term horizons. Cost minimisation by avoiding rehandling or inefficient use of equipment is common across the work highlighted in this review. Long-term planning models, in contrast, select subsets of blocks to be extracted during each year of a mine's life such that net present value (NPV) is maximised. Each block b yields an economic value (positive or negative) dependent on the year t in which it is mined. Typically, blocks are aggregated into larger units for the purposes of long-term planning to ensure that constructed models, often in the form of mixed-integer programs (MIPs), can be solved in reasonable time. Capital decisions, such as the introduction of a new plant or conveyor, are also considered in the long-term setting.

Mine operations are modelled in greater detail at shorter-term horizons. Consequently, there are significant differences in the decision variables and constraints that define short- and long-term planning problems. Espinoza et al. (2012) describe the typical form of a long-term planning problem with two sets of variables – one modelling the period in which each block is mined, and the other the quantity of material in each block sent to each available destination – and five sets of constraints. These long-term models enforce mining precedences (a set of blocks, for each block b, that must be mined before b can be accessed) and capacity constraints on both the total quantity of material excavated, and that sent to each plant (processing pathway). Blending constraints – on produced ore and on material sent to plants – are also common.

The behaviour of individual pieces of equipment (such as shovels and trucks) is not commonly modelled in long-term planning exercises. In contrast, Kozan and Liu (2014, 2016) capture the behaviour of individual pieces of equipment in a job-shop optimisation-based approach to short-term planning. Blom et al. (2017) capture the tons of different material types (such as waste, low or high grade) extracted from each block, and sent to each available destination (stockpiles, waste dumps, and processing pathways), by different truck and shovel types.

3 Early Work (Pre 2000)

Much of the early (pre 2000) work in the short-term planning of open-pit mines is linear programming (LP) based. Mutmansky (1979) and Topuz and Duan (1989) present early surveys on the use of Operations Research techniques in mine planning. In the short-term context, early LP-based methods focus on solving a blending problem in each time period. Blending requirements are formulated in terms of: constraints, enforcing lower and upper limits on the amount of relevant attributes in produced ore [Wilke and Reimer (1977); Fytas et al. (1993); Sundar and Acharya (1995)]; an objective to be minimised, summing over deviations in the blend of produced ore from target values [Chanda and Dagdelen (1995); Smith and You (1995)]; or 'rules of thumb' to be embedded in the LP. Gershon (1987) present an example of the latter, describing two heuristics for sequencing blocks that are applicable in a short-term context. The first solves a sequence of single period blending problems (LPs), selecting regions to be mined in each period such that a defined long-term objective is optimised (for example, maximising the amount of a contaminant in each blend, subject to upper limits, to extend the useful life of a deposit). The second computes, for each block that can be mined next, its desirability – repeatedly selecting the most desirable block for mining. The desirability of a block is based on its quality, and position, in the deposit.

Fytas et al. (1993) describe PITSCHED, an interactive tool designed to be applicable for both short- and long-term planning. The user groups blocks into shovel regions, assigning a priority to each region. An LP is solved to compute the fraction of each region to be mined in each time period, maximising an objective designed to support the mining of higher priority regions earlier than lower priority areas. The constraints of this LP set lower and upper bounds on the tons of material (ore and waste) mined and the quality of ore produced. The assignment of priorities to shovel regions is designed to reflect accessibility (mining precedences) and compatibility (with longer-term plan) considerations. The user iteratively adjusts these priorities, and solves the LP, until a satisfactory solution is obtained. For further details on the PITSCHED application, see Fytas (1987) and Fytas et al. (1987). Shovel regions similarly form the basic planning element in the work of Chanda and Wilke (1992), with their LP used to select shovel regions for mining in a single time period model. Their objective maximises the metal content in produced ore, while minimising contaminants, with only the shovel regions that are immediately accessible considered for mining.

Sundar and Acharya (1995) present an LP for selecting regions to blast in the next production period, maximising the number of regions blasted subject to constraints designed to ensure that ore of sufficient quality will be available to meet blending requirements. Given a blast schedule, a chance-constrained program is then solved to select the blocks to be mined in each shift of the production period. This program maximises the quantity of ore and waste mined from available blasted regions, subject to blending constraints (lower and upper bounds on the levels of quality attributes in the material mined). The constraints in the program are probabilistic, ensuring that blending and capacity constraints hold with a probability above a specified constant, given uncertainty in ore quality and haulage cycle times. Maximising the utilisation of equipment (for example, by maximising the tons of material mined) is a common short-term objective. The short-term LP of Wilke and Reimer (1977) maximises shovel utilisation (with each shovel weighted with an associated priority), subject to blending and capacity constraints.

Other early LP-based work includes that of Hu et al. (1995), in which a PERT network capturing shovel assignments, accessible blocks, and mining precedences, is used to compute earliest (and latest) start and completion times for the mining of each block. Goal programming (an LP with multiple objectives) is then used to find a mining schedule, with variables (defining the sequence in which blocks are mined) constrained by these earliest (latest) start and completion times. Youdi et al. (1992) use goal programming to generate a medium-term schedule (a yearly or quarterly mine plan), which feeds into a manual short-term planning process using CAD tools.

Early LP-based models for short-term planning do not contain constraints enforcing mining precedences between blocks. These constraints prevent a block b from being mined until all predecessor blocks (that restrict access to b) have also been extracted. Such constraints require the use of integer variables. Some early LP-based models support, but do not explicitly model, the satisfaction of mining precedences by assigning priorities to regions of the mine, and maximising the early mining of higher priority regions (for example, see Fytas et al. (1993)). Chanda and Wilke (1992) avoid the need to express precedence constraints by modelling only a single time period, and considering only immediately accessible regions for mining.

Smith (1998), in contrast, use a MIP for constructing short-term schedules with explicit accessibility constraints, requiring the nine blocks above a block b to be mined before b can be accessed, and that benches are mined 'from the face inwards'. The objective of this MIP minimises deviation between the blend of produced ore and grade targets, with deviation in each quality attribute weighted by an associated penalty.

4 Weekly and Fortnightly Planning

Much of the short-term planning literature, with the exception of work on truck dispatching algorithms, focuses on planning over horizons spanning one to several months. Comparatively, little work exists on the activities that take place in the weekly and fortnightly planning cycles. Plans at these horizons assign portions of available blocks to a sequence of builds, where each build is formed to a defined specification. Lipovetzky et al. (2014) and Burt et al. (2015) consider how to execute a build plan in the context of open-pit mines. Given a set of excavator movements (where each movement represents the extraction of material from a specific block, with an assigned destination), as defined by a given build plan, Lipovetzky et al. (2014) and Burt et al. (2015) investigate a range of approaches (including constraint programming, quadratic programming, and combinations of MIP and automated planning technqiues) for sequencing excavator movements with the objective of completing these activities in the least time, and maximising crusher feed rate.

5 MIP-based Models for Short-Term Planning

Modern short-term mine planning methods are predominantly MIP-based. These methods vary in terms of the level of detail to which mining operations are modelled, and the activities that are scheduled.

5.1 Modelling Mining Precedences

The representation of mining precedences employed by Smith (1998) (in which a set of predecessor blocks must be mined before a given block b can be accessed) is the most commonly applied approach. Blom et al. (2014, 2016, 2017), in contrast, model precedences disjunctively. A block b can be mined only when (at least) one of a number of different sets of blocks are mined (i.e., a block can be accessed in a number of different ways, or from a number of different directions). Eivazy and Askari-Nasab (2012) solve a short-term planning MIP model under a number of different scenarios, in which the direction of mining varies, with different mining precedences enforced. The schedule with the fewest drop-cuts is deemed the most practical. Given a grid-based block model with equally sized blocks, Gholamnejad (2008) require at least 3 (out of 8) of b's neighbouring blocks to be mined before b can be accessed. Gholamnejad (2008) presents an integer program (IP) with binary variables for each block b, and time period t, to indicate whether b is mined during t. Blocks are characterised as containing a proportion of ore (that is sent to the mill when mined) and waste (that is sent to a dump). The objective is to maximise the levels of contaminants in produced ore, while remaining below upper limits. This objective is designed to prolong the life of the mine, by ensuring that enough low contaminant ore is available for mining in the future (following the example of Gershon (1987)).

5.2 Modelling Multiple Destinations

Eivazy and Askari-Nasab (2012) generate a monthly extraction schedule, over a 1 to 3 year horizon, while modelling: multiple destinations for mined material; stockpiling; multiple mining directions; and decisions on which ramps are used to haul material from each block. Their objective is to minimise mining, processing, haulage, and rehandling costs, while adhering (as best as possible) to a longer-term plan (defining the set of blocks to be extracted by the end of the short-term horizon). Rehandling costs are incurred when material is deposited on a stockpile, and reclaimed from that stockpile at a later date. Decision variables are designed to indicate the fraction of each block mined in each period, and sent to each available destination (a waste

Features	Everett (2001); Kamperman et al. (2003); Howard and Everett (2008)	Gholamnejad (2008)	Huang et al. (2009) MineSight Schedule Optimiser	Eivazy and Askari-Nasab (2012)	Liu and Kozan (2012); Liu et al. (2013)	Thomas et al. (2012, 2014)	L'Heureux et al. (2013)	Kozan and Liu (2014, 2016, 2018)	Blom et al. (2014, 2016)	Mousavi et al. (2016a,b)	Blom et al. (2017)	Upadhyay and Askari-Nasab (2017a)	Fioroni et al. (2008)	Li and Knights (2009)	Sandeman et al. (2010); Bodon et al. (2011)	Torkamani and Askari-Nasab (2015)	Shishvan and Benndorf (2014, 2016, 2017)	Rahmanpour and Osanloo (2016)	Matamoros and Dimitrakopoulos (2016)	Paduraru and Dimitrakopoulos (2017)	Osanloo and Rahmanpour (2017)	Upadhyay et al. (2015); Upadhyay and Askari-Nasab (2017b,c)
Activities Modelled																						
Blasting					✓		✓	✓														
Drilling					✓		✓	✓														
Excavation (blocks)	✓	✓	✓	✓					✓	✓	✓							✓	✓	✓		
Excavation (benches/regions)					✓		✓	✓				✓	✓	✓	✓	✓	✓				✓	✓
Equipment schedules			✓		✓		✓	✓		✓		✓	✓	✓		✓	✓		✓			✓
Rail	✓					✓			✓						✓							
Port	✓								✓						✓							
Multiple Mines	✓					✓			✓													
Destinations																						
Stockpiling	✓		✓	✓					✓	✓	✓	✓			✓		✓			✓		
Multiple processing paths	✓		✓	✓					✓	✓	✓	✓								✓		✓
Single processing path		✓					✓						✓		✓	✓	✓	✓	✓		✓	
Constraints																						
Demand		✓				✓	✓		✓	✓		✓	✓					✓			✓	
Precedences		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓			✓	✓			✓	✓		✓
Capacities	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓
Blending	✓	✓	✓	✓			✓			✓	✓				✓	✓		✓	✓		✓	✓
Equipment utilisation		✓		✓			✓		✓	✓	✓	✓				✓					✓	✓
Trucking hours			✓								✓	✓				✓			✓			✓
Dig unit/shovel hours			✓									✓				✓	✓		✓			
Longer-term plan alignment			✓	✓																		
Objectives																						
Minimise costs				✓		✓	✓			✓				✓		✓		✓	✓	✓	✓	
Meet blending targets	✓	✓	✓						✓		✓	✓	✓		✓		✓		✓			✓
Min/max equipment use									✓		✓	✓	✓		✓		✓		✓			✓
Minimise shovel moves												✓	✓						✓			✓
Maximise revenues			✓																	✓		
Align with long-term plan											✓											
Minimise makespan					✓			✓														
Meet production tons targets												✓				✓	✓		✓			
Uncertainty Modelled																						
Geological													✓		✓		✓	✓	✓	✓	✓	✓
Equipment related													✓		✓	✓	✓		✓		✓	✓
Economic														✓							✓	

Table 1: Comparison of features present in short-term planning models described across Sections 5–6.

MIP-BASED METHODS (SECTION 5)	
Howard and Everett (2008)	Network with 4 mines, 1 plant, and 1 port (the BHP Billiton Iron Ore Newman Joint Venture, consisting of the Mt Whaleback, Orebody 19, Jimblebar, and Orebody 23 & 25 sites).
Eivazy and Askari-Nasab (2012)	Case study mine with 20 benches, 3,000 blocks aggregated into 150 mining cuts, 6 destinations (2 plants, 2 stockpiles, and 2 waste dumps).
Thomas et al. (2012, 2014)	Train dispatching model with 4 train classes, up to 3 trains in each class, 200 time periods, and 15 mines.
Liu et al. (2013)	Case study with 18 drilling and blasting jobs to schedule, up to 6,000 blocks, 2 units of drill equipment, 2 units of blast equipment, and 5 excavators.
Kozan and Liu (2014, 2016, 2018)	Job-shop scheduling model with up to 54 mining jobs, 3 stages in each job (drill, blast, and excavate), an 18 week horizon, 2 units of blast equipment, 2 units of drill equipment, up to 3,000 blocks.
Blom et al. (2016)	Network of 8 mines, 2 ports, a 13 week horizon with weekly time periods, 2,095 blocks in total across the network (up to 437 blocks at each mine).
Blom et al. (2017)	Case study mine with 838 blocks, 5 material types, 5 quality attributes, 10 stockpiles, 4 plants, 4 dig unit types, and 3 truck types.
Upadhyay and Askari-Nasab (2017a)	Case study mine with 4 benches, 174 mining faces, 2 crushers, 2 shovel types (with 5 shovels in total), 33 trucks of two types, and a horizon of 6 time periods.
METAHEURISTICS (SECTION 6)	
Liu and Kozan (2012)	Case study with 18 drilling and blasting jobs to schedule, up to 6,000 blocks, 2 units of drill equipment, 2 units of blast equipment, and 5 excavators.
L'Heureux et al. (2013)	Case study mine with a 90 time period horizon, 192 faces, 5 shovels, 864 block aggregates (MIP model has 2,541,024 variables and 627,178 constraints).
Mousavi et al. (2016a,b)	Experiments with up to 2,500 blocks, 6 excavators, 6 destinations for mined material, and 12 time periods.
SIMULATION-BASED (SECTION 7.1)	
Fioroni et al. (2008)	Case study mine with 26 mining areas (12 ore areas, and 14 waste areas), 9 quality attributes, 9 units of loading equipment, 2 truck types (MIP model has 330 variables and 265 constraints).
Torkamani and Askari-Nasab (2015)	Case study mine with 6 destinations (2 waste dumps, 2 stockpiles, and 2 plants), up to 4 shovels and 15 trucks, 330 mining cuts each containing 5 blocks on average, and up to 10 blocks.
Shishvan and Benndorf (2014, 2016)	Case study coal mine with 6 excavators, 2 spreaders, and up to 6,000 blocks.
Benndorf (2014)	Walter Lake data set (Issaks and Srivastava (1989)).
Upadhyay et al. (2015); Upadhyay and Askari-Nasab (2017b,c)	Case study mine with 4 benches, 174 mining faces, 2 crushers, 2 shovel types (with 5 shovels in total), 33 trucks of two types, and a horizon of up to 26 time periods.
Shishvan and Benndorf (2017)	Case study coal mine with 8 excavators, 7 spreaders, 8 benches, and 90 time periods (shifts).
STOCHASTIC (SECTION 7.2)	
Matamoros and Dimitrakopoulos (2016)	Case study mine with 734 blocks, 2 shovels, 10 trucks, 5 quality attributes, 12 time periods (1 year).
Osanloo and Rahmanpour (2017)	Case study limestone mine with 5 mining areas (faces), 1 plant with a capacity of 41,000 tonnes per month, and 3 modelled quality attributes.

Table 2: Largest problem size considered in the evaluation of short-term planning methods.

dump, stockpile, or processing pathway), and the amounts of extracted material from each block hauled along each available exit ramp. The choice of exit ramp for mined material has implications on haulage costs. Solutions of this MIP identify the location of the best ramps to be used over the course of the horizon.

Blom et al. (2017) generate multiple, diverse short-term schedules while optimising with respect to a customisable, prioritised sequence of objectives. A rolling horizon-based algorithm solves a MIP representation of the short-term planning problem for each time period in the planning horizon. For each time period t, the remainder of the horizon is aggregated into increasingly coarse time periods. A MIP is solved over this aggregation of time, and the activities of the focus period, t, are fixed to those in the resulting solution. The algorithm then rolls forward to the next time period, $t + 1$, and repeats the process of aggregating the remainder of the horizon, and solving a MIP representation of the scheduling problem. The MIP of Blom et al. (2017) models precedence constraints, multiple processing pathways for mined material, stockpiles and waste dumps, multiple truck and dig unit types, truck cycle times and available trucking hours, constraints on the characteristics of ore fed into each plant and stockpile, and constraints on the use of specific types of equipment across the mine site. Multiple, different schedules (in which blocks are extracted in different sequences) are formed via a split-and-branch approach. At predefined time periods t across the scheduling horizon, the optimiser makes several different choices on activities performed in period t. For each of these sets of choices, a new schedule is generated, and the algorithm proceeds to progress multiple schedules.

5.2.1 Scheduling with Shovel Allocations

Upadhyay and Askari-Nasab (2017a) take a shovel-allocation-based approach to short-term schedule generation. Their model uses binary variables to allocate shovels to faces (collections of blocks) in each period. Integer variables define the number of trips made by trucks between faces and destinations (such as processing plants), and continuous variables define the quantities mined from each face in each period. A weighted sum of several objectives (maximising production, meeting desired feed characteristics in each plant, meeting blending requirements, and minimising shovel movements) is optimised. In a similar vein, Morales and Rubio (2010) consider the use of mathematical programming, in the context of short-term planning for a copper mine, to control the characteristics of plant feeds. Shovel-allocation-based methods are common across the literature on operational (daily and shiftwise) planning (for example, see Souza et al. (2010)).

5.3 Drilling, Blasting, and Excavation – Multi-stage MIPs

The MIP of L'Heureux et al. (2013) models both drilling, blasting, and extraction activities, precedences between these activities, and shovel assignment. Shovels are assigned to small sets of blocks called *faces* in each shift of a horizon spanning days to several months. Drilling and blasting decisions (i.e., which blocks are drilled or blasted in each time period) are made with respect to collections of faces. Binary variables are used to model shovel-to-face assignments, face-to-face movement of shovels, and drilling, blasting, and extraction decisions in each period. Continuous variables model the amount of material mined from each face, in each period. Constraints enforce precedences between drilling, blasting, and mining activities, and capacities on equipment. Their objective minimises the cost of mining operations (incurred by shovel movement, blasting, and drilling activities). L'Heureux et al. (2013) solve their model under varying problem sizes, ranging from 10 to 90 periods, 30 to 192 faces, and up to 5 shovels.

Liu and Kozan (2012) and Liu et al. (2013) model the drilling, sampling, blasting, and mining of blocks, and allocation of equipment to these activities. Given a set of mining activities to be completed, a schedule for these activities that minimises makespan (i.e., minimising the time required to complete the set of activities) is desired. Their MIP resembles that of a job-shop scheduling problem. A shifting-bottleneck algorithm is presented for finding near-optimal solutions. This algorithm builds a schedule, in the form of a disjunctive graph, for each piece of equipment (or resource). The problem is decomposed into several single-resource scheduling problems, whose solutions are consequently combined. The resulting schedule is re-sequenced and re-optimised with a metaheuristic (based on neighbourhood and Tabu search). This process is iterated, with the current best found solution used to set release and delivery times for activities in each single-resource scheduling problem. Limits on solution time, iterations, and successive iterations without improvement in makespan, provide stopping conditions for the algorithm. On instances with up to 10 mining jobs (where each job requires the execution of drilling, sampling, blasting and mining activities), the optimality gaps of discovered solutions range from 0.3% (6 jobs) to 4.3% (10 jobs).

Kozan and Liu (2014, 2016, 2018) model equipment, and its use, in detail, capturing: operating capacities; ready times; speeds; block-sequence-dependent movement times; equipment-dependent operational times; and the use of equipment in different stages of mining (drilling, blasting, and excavation). Their objective minimises completion time (makespan) and total weighted tardiness of mining jobs (where each mining job has a desired completion time, as a parameter). Variables in their MIP model assign pieces of equipment to each job, with binary sequencing variables indicating whether a job i just precedes another j on a particular equipment unit. Sequence-dependent movement times are modelled, with varying amounts of time being consumed when equipment is moved between different locations.

5.4 Pit-to-Port Optimisation

A number of works optimise the operation of a mining supply chain (across short-term horizons) in a pit-to-port fashion. Everett (2001) outlines a number of algorithms and tools for aiding decision-making at each stage of the mining supply chain: scheduling the mining of material at mines; railing mined material to ports; stockpiling ore at ports; and loading ore from stockpiles onto ships. Underpinning this work is the concept of 'stress' from a target specification. For each attribute of interest, the deviation between the actual and desired level of this attribute forms a quadratic contribution to total stress. Everett (2001) propose a quadratic programming formulation for selecting available blocks to mine while minimising the stress of produced ore from a desired target. A train dispatching algorithm is presented that selects the next train to depart from a mine on the basis of minimising a running average of aggregated stress of the material arriving at the port from a desired target. The train that, when aggregated with a running measure of stress, minimises total stress is selected as the next train to depart. The selection of a stockpile on which to deposit each trainload of ore at the port is similarly made with the objective of minimising stress in the composition of each stockpile from a desired target. A quadratic programming formulation is proposed for allocating ore to ships while minimising total stress of material on each ship from targets. Kamperman et al. (2003) highlight the application of these ideas at a case study open-pit iron ore mine. Everett (2007) extends this work by modelling the split of iron ore into lump and fines components, and presenting a mechanism for adjusting blasthole assays on the basis of later sampling of mined material. Howard and Everett (2008) describe the application of these ideas in a case study network of open-pit iron ore mines.

Blom et al. (2014, 2016) present a decomposition and MIP-based algorithm for the short-term planning of a supply chain composed of multiple open-pit iron ore mines and multiple ports. The short-term planning problem is decomposed into a set of mine-side optimisation problems, and a port-side blending problem. Given a series of grade targets to achieve over the short-term planning horizon, the mine-side optimisers solve a series of MIPs to form a set of candidate extraction sequences. The grade of production across these sets of schedules is normally distributed about the target provided as input. The port-side optimiser solves a MIP to select a single schedule to be implemented at each mine, assigning trainloads of ore from each mine to each port, while minimising deviation between the average composition of ore arriving at each port from desired targets. On the basis of the solution found to the port-side problem, new grade targets are provided, as input, to each mine-side optimiser. The solving of mine and port-side optimisation problems is iterated until a stopping criterion, based on a lack of improvement in the best solution found by the port-side optimiser over a defined number of successive iterations, is satisfied.

Thomas et al. (2012, 2014) consider a resource constrained scheduling problem with multiple producers and a single linking constraint, applied to the scheduling of multiple mines in a coal supply chain. In this case study, mines share a single railway network to deliver orders (quantities of ore of a specific composition) to a terminal. An integrated MIP schedules production in each mine, and the delivery of orders from each mine, while minimising operating costs. Constraints ensure that orders are delivered by their due dates, and that the total number of trains of any type running at any given time is less than or equal to the number of available trains of that class. Thomas et al. (2012) consider the use of Lagrangian relaxation for solving this integrated MIP, while Thomas et al. (2014) present a column-generation based approach.

6 Metaheuristics

Large neighbourhood search (LNS) forms part of most metaheuristic-based approaches for short-term planning. Local search describes a class of algorithms that move from solution to solution (by making local changes) until a stopping criterion is reached (such as a solution of sufficient quality being discovered, a lack of improvement in the best found solution over successive iterations, or a time limit being exceeded). Neighbourhood-based search is a local search method. Given an initial solution to a scheduling problem, s, neighbourhood search techniques search for an improved solution, s', in a neighbourhood of s. A neighbourhood is typically defined as the set of solutions that can be reached from s by applying one of a number of 'change operators'. An example of such a change operator, in the context of a mine plan, is swapping the mining of a block from one period to another. Search proceeds by moving from each solution s, to the best solution s' in a neighbourhood of s, until a stopping criterion is reached.

Mousavi et al. (2016a) present and compare three metaheuristics (simulated annealing, Tabu search, and a hybrid of these two methods) applied to short-term planning with equipment assignment, multiple processing options, and stockpiling. A MIP modelling of the problem is defined, with binary variables indicating whether a block b is mined by a piece of equipment i in period t and sent to destination d (a stockpile or processing option). The objective is to minimise operating costs (rehandling and holding costs associated with stockpiling), while respecting lower and upper bounds on the quality of production. Each metaheuristic uses neighbourhood search, with the neighbourhood of a solution defined in terms of 'time' and 'destination' move operators. Given a solution s, a 'time' move changes the period in which a selected block is extracted in s. This operator is designed to push the mining of processable blocks into periods where there is available processing capacity (reducing the number of processable blocks that are stockpiled), and postpone the stockpiling of material to later time periods. A 'destination' move changes the destinations to which blocks are sent. For each time period, a MIP is solved to select new destinations for each of the blocks mined in that period. The objective of this MIP is to maximise mine-to-processing, and minimise mine-to-stockpile and stockpile-to-processing, material flows. The hybrid simulated annealing/Tabu search approach applies Tabu search (maintaining a search history, preventing a previously found solution from being revisited, and prioritising exploration of the search space when selecting new solutions to move to), while incorporating some concepts from simulated annealing (allowing moves to inferior solutions to avoid local optima). This hybrid method was found to yield superior solutions given larger problem instances (with 900 to 1200 blocks, 4 to 6 excavators, and 6 time periods) finding solutions within 4% of the optimal.

Similar work is developed by Mousavi et al. (2016b), modelling multiple processing pathways, stockpiling, equipment assignment, and mining rules (minimum mining width, feasibility of drop cuts, prioritisation of waste extraction, and constraints on the maximum number of benches being mined). Total operating costs (associated with stockpiling, drop cuts, and misclassification – in which waste is sent to processing and ore to a dump) are minimised. A combination of branch-and-bound, simulated annealing, and LNS form the basis of this approach. The algorithm explores the solution space, moving from one solution s to a solution in the neighbourhood of s, using the principles of simulated annealing. The neighbourhood of a solution is the set of solutions that can be reached by applying one of two operators: swapping k blocks between two periods (changing the period in which a set of k blocks are mined); and reassigning the destinations of each block in a single period. The rescheduling of blocks from one time period to another follows the principles of Mousavi et al. (2016a). The latter operator considers the blocks that have been moved from one period to another, and uses branch-and-bound to determine the best reassignment of destinations to these blocks. Mousavi et al. (2016b) compare this hybrid simulated annealing, branch-and-bound, and LNS-based approach to solving a MIP modelling of the scheduling problem with CPLEX. Given a 6 hour time limit applied to experiments, the presented heuristic is competitive with CPLEX on all instances (finding solutions within 1% of the best solution found by CPLEX, on average). Where CPLEX finds an optimal solution in the 6 hour timeframe, this optimal solution is also found by the hybrid heuristic.

Liu and Kozan (2012) apply Tabu and neighbourhood-based search to improve existing solutions to a short-term planning problem with equipment assignment. Their approach, described in Section 5.3 in the context of multi-stage MIP-based methods, forms (and subsequently combines) schedules for each piece of equipment in an iterative process. In each iteration, the metaheuristic of Liu and Ong (2004) and Liu et al. (2005) is applied to improve the quality of this combined schedule. This metaheuristic is defined with respect to a job shop representation of the planning problem, and is domain independent.

7 Managing Uncertainty

Mine planning, at any horizon, is performed given estimates of relevant parameters or variables. Ore body models estimate the characteristics of each block on the basis of drill samples and assays, with the most accurate assessment of its contents not available until after it has been extracted. The available capacity of equipment and infrastructure may be impacted by unplanned maintenance, and planned activities may be derailed by adverse weather, rendering previously feasible schedules infeasible. In the majority of short-term planning methods described thus far, decisions are made on the basis of estimated models and parameters, without being influenced by the uncertainty present in the values of these inputs. A number of approaches for short-term planning take this uncertainty into account when forming solutions, with the aim of forming schedules that are robust under different realisations of the underlying uncertainty, or maximise the expected value of an objective, across a range of most likely realisations.

We describe two contrasting approaches for managing this uncertainty: the combination of simulation and optimisation (Section 7.1); and stochastic optimisation (Section 7.2).

7.1 Simulation and Optimisation

A number of early surveys characterise the use of simulation in the modelling and operation of mines: in Europe [Panagiotou (1999)]; South Africa [Turner (1999)]; Australia [Basu and Baafi (1999)]; the United States [Sturgul (1999)]; South America [Knights and Bonates (1999)]; and Canada [Vagenas (1999)]. Sturgul (2001) and Govinda et al. (2009) provide a more recent review on the use of simulation for optimising varying aspects of production in both underground and open-pit mines. An earlier review on the use of simulation in the minerals industry is presented by Sturgul and Li (1997). A number of works focus on the use of specific modelling languages for designing simulation software (for example, the GPSS language [Sturgul and Harrison (1987)], Arena [Kelton (2002)], and SLAM [Pritsker (1986)]). Many authors consider the use of simulation to evaluate systems for dispatching trucks in open-pit mines. We restrict our attention, in this section, to approaches that use simulation for the purposes of short-term planning.

Simulation is commonly used to understand the behaviour or result of a given mine plan under different realisations of varying sources of uncertainty. A number of such approaches embed planning or optimisation procedures (of varying degrees of sophistication) within the simulation when events arise that require a change in plan. Given an initial mine plan, these methods can be used to analyse the extent to which it allows a mine to adapt or recover desired behaviour over the course of a horizon. Upadhyay et al. (2015) and Upadhyay and Askari-Nasab (2017a,c,b) present a shovel allocation-based approach for short-term planning. A MIP assigns each of a number of available shovels to a face in each time period, and controls the tons of material mined from each face, in each period. Given an initial assignment, simulation is used to evaluate the degree to which objectives are satisfied across a planning horizon. Upon specific events arising in the simulation (such as shovel failures, or the completed mining of a block), a new shovel allocation is computed (i.e., the system reoptimises). Fioroni et al. (2008) present similar work, embedding shovel reallocation within a simulation, and demonstrating the approach at Vale's Aguas Claras mine complex. A distinction between the two approaches is that Upadhyay and Askari-Nasab (2017a) model mining precedences within their optimisation, allowing them to simulate over longer horizons.

Sandeman et al. (2010) and Bodon et al. (2011) present similar ideas in the context of a supply chain comprised of a mine, rail, and port system. A linear program (LP) is defined to determine: the tons of ore to be extracted from each mining face, and its destination – one of a number of mine stockpiles; and the tons of material, from each mine stockpile, to transport to each of a number of port stockpiles, in each time period. In addition, this LP models port stockpile to ship movements. The primary objective of this model is to maximise throughout of material from pit to ship, while secondary objectives minimise deviation between the quality of ore loaded onto each ship and desired targets, and encourage the timely loading of material onto ships. The simulation model of Sandeman et al. (2010) and Bodon et al. (2011) solves the LP to generate an initial schedule for the first two weeks of a year-long horizon. These activities are executed, and at the end of the two week simulation, the LP is solved to generate a short-term plan for the next two weeks, given the current state of the system. Activities are executed, as best possible, during the simulation, with some 'intelligence' in-built to deal with unexpected events (such as operational shut downs or equipment failures). While the details of the in-built procedures are not provided, a potential intervention is to re-solve the LP to reschedule activities in the portion of the two week period remaining. Sandeman et al. (2010) and Bodon et al. (2011) examine the use of their approach for evaluating trade-offs between varying capital decisions (infrastructure options), operating practices, and maintenance options.

Simulation is commonly used to evaluate the performance or reliability of a schedule in the presence of geological uncertainty (uncertainty in the estimates of block characteristics). In the context of an open-pit lignite mine, Shishvan and Benndorf (2014, 2016) use conditional simulation to generate a set of equally probable realisations of the orebody. Simulation of a short-term plan (describing the time periods in which each block is mined, and the excavator used) over these realisations is used to quantify the impact of geological uncertainty on the satisfaction of a set of relevant key performance indicators (KPIs). Such KPIs include meeting targets on production (in terms of both quality and tons) and equipment utilisation. The weighted sum of these KPIs forms the objective to be maximised. The result of this simulation is used to assess the robustness of a given schedule. Shishvan and Benndorf (2017) highlight several case studies in which this simulation application has been applied in industrial settings. Torkamani and Askari-Nasab (2015) similarly evaluate mine performance, under a given short-term plan, with uncertainty present in truck cycle times, tons of material in each truck load, and the reliability of trucks and shovels.

Rahmanpour and Osanloo (2016) utilise simulation to analyse the ability of a given short-term schedule to meet desired KPIs (around production quality and tons) given varying realisations of geological uncertainty in orebody estimates. The short-term planning problem is modelled as a precedence-constrained knapsack problem with capacity, quality, and demand constraints, with an objective to minimise operating costs. Given a candidate schedule, its behaviour is analysed by simulation over a set of conditionally simulated block model realisations. On the basis of observed fluctuation in production (quality and tons), Rahmanpour and Osanloo (2016) show how improvements can be implemented in the original schedule to reduce the severity of these fluctuations. For example, if underproduction is likely in certain time periods, an increase in mining rate, or the building of a stockpile to compensate for a lack of available feed, may be considered. The impact of these alterations can be examined by simulating the new schedule across the set of block model realisations.

Benndorf (2014) similarly utilise geostatistical methods for managing uncertainty in the short-term planning process. The differences between the realised behaviour of an executed plan, and that predicted during the planning process, is used to create a revised model of the orebody. This new model is used to form the next short-term plan. In place of using simulation to understand the likely results of plan execution, Benndorf (2014) use the results of plan execution to maintain a more accurate orebody model.

7.2 Stochastic Optimisation

Stochastic programming is an approach for modelling and solving optimisation problems under uncertainty. Stochastic programs are linear, non-linear, or mixed-integer programs that are parametrised with random variables (i.e., what would be constant parameters in a deterministic program now take on values drawn from a probability distribution). A stochastic program may contain probabilistic constraints (constraints that must hold with a specified probability) or may be formulated as a recourse problem. In a stochastic program with recourse, a set of possible realisations (scenarios) of the uncertain or stochastic parameters in the problem are defined, alongside first and second stage variables. In the context of a scheduling problem, the first stage decision variables define the plan to be executed. The second stage variables are defined with respect to each scenario that could arise, and represent adjustments that must be made to the plan in the event that the associated scenario is realised. Specialised algorithms are used to solve stochastic programs, minimising or maximising an *expected* objective value given varying probabilities of each scenario arising.

Much recent work in stochastic optimisation for open-pit mines involves the solving of stochastic programs with recourse (defined over a set of scenarios). Much of this work is concerned with long-term planning (see Dimitrakopoulos (2011) for a recent review). Matamoros and Dimitrakopoulos (2016) present a stochastic program with recourse for the short-term planning problem. First stage decision variables define: which blocks are mined in each period; and allocate shovels to mining areas. Second stage decision variables define the number of trips made by each truck to each mining area. Geological estimates for each block, and equipment availabilities, vary across a defined set of scenarios. The objective of this stochastic program is to minimise expected total mining costs and deviation in the quality of production from desired targets.

The application of stochastic optimisation to link short-term variability with long-term planning is discussed by Dimitrakopoulos and Jewbali (2013) and Jewbali and Dimitrakopoulos (2018). Dimitrakopoulos and Jewbali (2013) and Jewbali and Dimitrakopoulos (2018) emphasise that short-term schedules typically deviate from the guidelines defined by long-term plans due to the availability of new estimates of orebody characteristics (not available at the time of long-term planning). Short-term schedules will necessarily deviate from long-term plans to satisfy constraints on production. A multi-stage planning process is proposed that incorporates potential short-term variability in the long-term planning process. A set of possible realisations of future grade control data is generated on the basis of the grade of material in mined out areas of the mine site. These sets of potential future observations are integrated into a set of conditionally simulated realisations of the mine's orebody. Stochastic integer programming, with each realisation of the orebody forming a distinct scenario, is applied to generate a long-term schedule that maximises net present value (NPV) while minimising the cost of deviations from desired production targets.

Alternative approaches that have been considered for stochastic optimisation in the short-term context include: designing policies for adapting mine plans as new information (geological estimates) arise [Paduraru and Dimitrakopoulos (2017)]; portfolio optimisation [Osanloo and Rahmanpour (2017)]; and real options [Li and Knights (2009)].

Paduraru and Dimitrakopoulos (2017) consider how new information (such as updated estimates on the characteristics of extracted material) can be integrated into the short-term planning process, as it arises. This integration is achieved via the use of adaptive short-term policies for assigning destinations to mined blocks. These policies are state dependent – policies that map states to the decisions that should be made in that state. A state, in this context, is a numerical vector describing the characteristics of the block. A policy selects a destination for the block that yields the 'largest immediate improvement in the objective', which in the case study examined by Paduraru and Dimitrakopoulos (2017) captures revenue and processing costs for each destination. As new estimates become available for the contents of a block, a new state is formed and the short-term policy reassigns a destination to the block.

Portfolio optimisation determines the amount of money to invest in a set of risky assets, with the objective of maximising expected return. Osanloo and Rahmanpour (2017) apply this concept to short-term planning. In this context, mining faces are viewed as risky assets, each with a mean return and risk level (computed on the basis of historical data or simulation). Return, in this context, defines the geological characteristics of the face. A short-term schedule defines the quantities of material extracted from each mining face, representing the extent of investment in each of these assets. A fuzzy linear program (FLP) – a non-linear program with bounded fuzzy numbers appearing as parameters in some constraints – is defined to model the scheduling problem. Its objective is to minimise total mining costs, while satisfying capacity, production quality, and demand constraints. Equipment capacities and face characteristics (grade and recovery) are represented by bounded fuzzy numbers in this model. Each of these parameters has a lower bound (a 'risk-free' value) and an upper bound (a 'risky and possible' value). While non-linear, the presented model can be translated into a linear program, and is demonstrated on a case study limestone mine.

Real options theory is another technique that has been borrowed from economics and applied to short-term mine planning. Li and Knights (2009) describe how real options can be used to adjust the destination of waste material in response to fluctuating fuel prices. In periods of high fuel price, a policy of directing waste to the closest available dump is followed. In periods of low fuel price, waste is directed to dumps with the objective of balancing storage volume across the set of available dumps.

8 Multi-objective Optimisation

Many of the approaches described in this review generate short-term schedules while optimising with respect to multiple objectives. These objectives most commonly include the minimisation of operating costs, the minimisation of deviation present in quantity and quality of produced ore from desired targets, and maximising the utilisation of available equipment (often to achieve maximal production or throughput). Approaches for optimising with respect to multiple objectives vary across the mine planning literature.

A common treatment of multiple objectives is to form, and optimise with respect to, a single weighted sum over each objective. Upadhyay and Askari-Nasab (2017a) compute weights for a series of objectives by solving their short-term planning problem with respect to each objective individually, to 'determine their respective values in pareto optimal space'. The set of objectives is subsequently normalised and combined. The computation of objective weights is a well-discussed topic within the literature on multi-objective optimisation. Coelho et al. (2012), in contrast, seek to find non-dominated (pareto optimal) solutions to an operational planning problem via a series of metaheuristics. For a pareto optimal solution, it is impossible to alter the solution in a way that improves its performance against one objective without reducing its performance on another. The set of all pareto optimal solutions to a problem is denoted its pareto front (or frontier). A third approach is the optimise-and-prune method applied by Blom et al. (2017). Given an arbitrary sequence of prioritised objectives, Blom et al. (2017) solve a MIP modelling of a short-term planning problem with respect to each of these objectives in turn. After solving with respect to the first, and most important objective o, yielding an optimal solution s, constraints are added to the MIP to prune from its solution space all solutions inferior to s with respect to o. The altered MIP is then solved with respective to the next objective in the sequence, and additional constraints added. This process is repeated until all objectives in the prioritised sequence have been considered.

9 Multi-Horizon Planning

The concept of hierarchical planning in which decision-making over high-level or coarse formulations of a problem is used to inform or restrict decisions made at lower-level or finer granularities, is commonly applied across many domains. Existing software, such as that supplied by MineSight (Huang et al., 2009), allow planners to constrain the set of blocks that can be mined in a short-term plan to those scheduled for mining by a longer-term plan. Blom et al. (2017), in contrast, view compliance as an objective to be maximised. Both approaches are designed to prevent or discourage the mining of blocks not scheduled for mining in a relevant longer-term plan.

Compliance of plans at shorter-term horizons with longer-term plans, or an analysis of the expected results or challenges of a longer-term plan when executed in the short-term, are the most common approaches for multi-horizon open-pit planning in the literature. The integration of short- and long-term decisions into single models has had limited traction. Nehring et al. (2012) and Martinez and Newman (2011) present two examples, for the planning of underground mines over periods spanning 1.5 to 3.5 years. Liu and Kozan (2017) consider the integration of a series of mathematical models for open-pit mine design, block sequencing (over quarterly, half-yearly, or yearly time periods), and operational level planning of equipment (with a job-shop scheduling model). Economic objectives are optimised int the first two models, and objectives related to minimising makespan and tardiness in job completion times in the third. A job-shop scheduling-bsaed MIP model, that captures aspects of all three levels of decision-making, is presented. This model schedules mine operations over a series of *operational stages*, where the working benches and equipment available in each stage varies. Variables are defined to represent the size of individual mining jobs (the number of blocks they represent) and the equipment to be allocated to those jobs. The integrated model combines block sequencing (when blocks are mined) and the scheduling of equipment (to what jobs each unit of equipment is assigned) while minimising total weighted tardiness in job completion times. Liu and Kozan (2017) evaluate this integrated model in a case study with 18 mining jobs, over an 18 week horizon.

Simulation provides a tool for analysing the expected results of a schedule, at any horizon, when executed at shorter time scales. This process can be used to inform decision-making at one horizon, by assessing how these decisions may impact the choices available at shorter-term horizons. Ben-Awuah et al. (2010) describe how simulation can be used to link long- and short-term planning in the context of a life-of-mine planning problem. A simulation model is designed to simulate the behaviour of a long-term plan in the context of short-term constraints, and uncertainty in mining capacities, equipment availability, and desired quality targets on production. Comparison of the simulated schedule and expected behaviour allows a planner to analyse the short-term feasibility or robustness of a long-term schedule. Similarly, Torkamani and Askari-Nasab (2015) demonstrate how short-term planning can be linked with day-to-day operations by simulating the performance of a short-term schedule given uncertainty in truck behaviour (cycle times and load tonnages) and equipment reliability.

Dimitrakopoulos and Jewbali (2013) incorporate potential realisations of future grade-control data in the life-of-mine planning process – recognising that short-term schedules (generated on the basis of data not yet available when forming a long-term plan) will necessarily deviate from the goals set out in a long-term plan.

Simulation of schedules, and conditional simulation of orebody models, provide a means for exploring how this deviation may arise. Yarmuch and Ortiz (2011) highlight how the simulation of a medium-term plan, in a short-term context, can be used to adjust parameters used in the longer-term planning process (where there is a lack of compliance between the simulated and original plans).

Vivas and Nava (2014) highlight the challenges of integrating long-, medium-, and short-term planning at the Goldcorp Peñasquito mine, an open-pit gold mine located in Zacatecas, Mexico. The varying assumptions and levels of detail to which the planning problems at each horizon are modelled, the varying sources and representations of data used, and different platforms used for constructing plans, lead to difficulties in reconciliation across plans, and integration of plans. The solution adopted at the Goldcorp Peñasquito mine was to use a single tool – the MineSight Schedule Optimiser [Huang et al. (2009)] – for planning at each horizon. The advantages of this approach is that the data required for planning at each horizon resides in a single database, and seamless integration and information transfer across plans is supported.

10 Commercial Tools

A commercial tool that has often been applied in the generation of plans across the short- to long-term horizons is the XPAC Autoscheduler by Runge[1] (or RPM). When using the XPAC Autoscheduler, a mine scheduling problem is modelled in terms of records (which may, for example, represent blocks), dependencies between records, constraints, and resources. If each record represents a mining block, the dependencies amongst them describe block precedences – a set of rules defining which blocks must be mined before others become accessible. Constraints may, for example, relate to processing capacities, amounts mined from different regions of a mine, or restrictions on the mining of blocks within certain time periods. Resources can represent excavators, crushers or even pits. The XPAC Autoscheduler forms a time stamped activity sequence for each resource in the model. If the resource is an excavator, this activity sequence defines the blocks that it mines – each activity the mining of a block, with a start and end time.

Each resource in the XPAC model is associated with targets and objectives. A target for an excavator may, for example, represent a required tonnage to be mined. An objective consists of a target and an upper and lower limit. Objectives may be assigned to individual resources, or shared between resources. An example of a shared objective is the achievement of product quality targets within defined tolerances. The XPAC Autoscheduler uses an event-based greedy algorithm to find activity sequences for each resource. The formation of a mining sequence for an excavator begins by identifying the set of blocks that it can first choose to mine – blocks that are not constrained or dependent on the mining of others. On the basis of the current state of the mine (what, if anything, has been mined so far by each excavator), these blocks are prioritised according the objectives of the excavator (which may be shared). If the excavator has capacity left to mine, it will select the block with the highest priority to mine next (the block that contributes most to the achievement of its objectives). A step-size defines the frequency with which a resource will stop and decide anew what activity to complete – an excavator may continue mining a particular block, or move to a different location.

Two additional short-term planning applications in the RPM suite of tools are XACT and XECUTE. These tools provide support for visualising and constructing schedules while integrating data from multiple sources (such as block models, maintenance and GPS data). Some support for schedule optimisation, in the form of automated assignment of destinations to mined material, is provided.

The MineSight Scheduling Optimiser (MSSO), described by Huang et al. (2009), models: multiple destinations for mined material (stockpiles, processing pathways, and waste dumps); exit ramp decisions; alignment to longer-term plans; mining precedences; and multiple mining directions. MineSight models short- and medium-term scheduling problems, in the context of both open-pit and underground operations, using MIP methods. In the open-pit context, continuous variables represent the fraction of each block mined in each time period, and sent to each available destination, and the quantities of material reclaimed from each stockpile, and sent along relevant processing pathways. Binary variables are used to select which ramps are

[1]http://www.runge.com/software.asp.

to form part of the haulage network in each time period, with variables introduced to represent the quantity of material from each block hauled along each available exit ramp.

Numerous other packages providing short-term planning capabilities exist. MineSched by GEOVIA[2] is designed for use in both long- and short-term planning in both open-pit and underground mines. MineSched supports the automated sequencing of blocks on a bench-by-bench basis, the modelling of stockpiling and multiple processing pathways, and blending across multiple mine sites. Micromine[3] employs MIP solving in its mine planning and design tools, with support for mine design, long-, medium-, and short-term planning. This MIP is designed to find an optimal mining sequence at each horizon. MineMax Tempo[4] supports the integration of scheduling across the long-, medium-, and short-term horizons by measuring the compliance of plans at shorter horizons with longer-term plans. Maintenance scheduling, truck dispatch, and real-time production monitoring can also be integrated within the MineMax solution. Studio OP by Datamine[5] supports the medium and short-term planning of open-pit mines, including: pit and dump design; and the blending of material from different sources given production, haulage, and operating constraints. While many tools incorporate block-sequencing optimisation at different horizons, others focus on providing support for visualisation and comparison of mine designs and plans. Vulcan Open Pit Mine Planning by Maptek[6], for example, includes automated features for generating bench plans ('blocking out' material and assigning destinations based on defined rules) and the visualisation and comparision of alternative short-term plans.

The precise details of the optimisation algorithms used in many commercial tools are not publicly available. Many of these packages are likely to be MIP-based, solving a series of optimisation problems to schedule each period in a rolling horizon fashion (with a 'lookahead' of one or more periods included in the modelling to avoid greedy optimisation). Such approaches solve an N-period MIP, spanning periods 1 to N, for example, to schedule the activities of the first time period. Another N-period MIP, spanning periods 2 to $N+1$, is solved to schedule the activities of the second time period (and so on).

11 Comparing Short-Term Solving Approaches

Standard formulations for long-term planning problems, and associated benchmark problem instances, are available for comparing the performance of different solving approaches (see Lambert et al. (2014) for a series of common formulations, and Espinoza et al. (2012) for benchmark instances). The presence of standard formulations and benchmark problems supports the comparison of different solving approaches (metaheuristic vs MIP-based methods, for example) and provides a way of identifying which methods are the current state-of-the-art. In the context of short-term planning, standard formulations and benchmarks are not currently available. In general, more recent work models mine site operations in greater detail (the scheduling of equipment, ramp design considerations, multiple processing and stockpiling options, multiple stages from drilling and blasting to excavation, railing, and port blending, and multiple objectives). The selection of an appropriate solver for a given case study involves a trade-off between the fidelity to which operations are modelled (scheduling individual pieces of equipment or modelling equipment availability in terms of total capacities, for example), and the problem sizes being tackled. In general, approaches that schedule individual pieces of equipment have been demonstrated on case studies with smaller fleets or aggregated block models, or with a focus on generating extraction schedules (without modelling process-side activities), than methods that model equipment fleets in terms of total available capacities. Tables 1-2 support the selection of an appropriate solving method for a given case study, on the basis of the desired fidelity of operations modelling and the problem sizes these methods have been demonstrated on. The development of standard formulations, and associated benchmark instances, in the short-term context, is a promising area of future work.

[2]www.3ds.com/products-services/geovia/products/minesched
[3]www.micromine.com
[4]www.minemax.com
[5]http://www.dataminesoftware.com/open-pit-planning/
[6]http://www.maptek.com/products/vulcan/open_pit.html

12 Future Directions and Challenges

Short-term planning approaches have become increasingly sophisticated in their modelling of the mining environment over the last two decades, from relatively simple LP-based blending models to MIP-based methods that schedule individual pieces of equipment. Future advances in the current state-of-the-art in short-term mine planning are likely to result in more effective integrated planning across different planning horizons, more agile planning methods in which increasingly rapid data collection leads to real-time adaptation of existing plans, and more powerful stochastic optimisation methods for tackling larger problem sizes. The development of standard formulations, and benchmark instances, for short-term planning problems will support the comparison of different solving approaches, and motivate the development of more efficient methods.

The current state-of-the-art in short-term planning, in deterministic settings (without consideration of geological, equipment-related, or economic sources of uncertainty), is able to generate schedules given thousands of blocks, up to 100 time periods, and dozens of units of equipment. Stochastic optimisation-based methods have been applied to problems with thousands of blocks, up to 12 time periods (a horizon of 1 year), and in the order of a dozen units of equipment.

Increasing support for real-time updates to orebody models, on the basis of new samples, assays and measurements, motivates the need for more agile and adaptive planning processes. Fast, and predominantly automated, scheduling tools can take advantage of these frequent model updates by developing new, or adjusting existing plans, as required. Changes to a plan at one horizon should not be considered in isolation, however, without consideration of their impact on others. Current short- and long-term planning techniques are limited to assessing the impact (or feasibility) of decisions when viewed in the context of shorter-term horizons. While alignment to a longer-term plan is often considered in the short-term planning literature, the impact of choices made in the short-term, on longer-term plans, is not. If a short-term planner must deviate from the guidelines of the longer-term plan, techniques that provide an understanding of how their decisions will impact, or alter, this plan will be significantly valuable. Short-term planning techniques that are able to assess the impact of their decisions on both shorter- and longer-term horizons will represent a significant advance on the current state-of-the-art.

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