Review of Recent Developments in Short-Term Mine Planning and IPCC with a Research Agenda[1]

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ABSTRACT

Equipment allocation is an integral part of short-term planning. In the past few decades, In-Pit Crushing and Conveying (IPCC) has gained much momentum to replace trucks partially or fully in large open pit mines because of the increasing fuel and labour cost of the shovel-truck system, low operating cost and less greenhouse gas emissions of conveyor systems. This article aims to review the work done on short-term mine planning and IPCC in open pit mines to find research gaps and future research opportunities in short-term planning with IPCC as the prime means of material handling. The most recent literature since 2010 on short-term planning, based on different formulation and solution approaches, and IPCC, based on primary objectives such as optimum crusher location, economic/environmental comparison etc., have been reviewed. The review reveals that hardly any short-term planning model can generate mine extraction sequences with IPCC integration. The authors propose a theoretical problem formulation to explore this research gap as a future research direction. One of the key contributions of this article is to point out the fact that developing a short-term planning methodology considering the IPCC system would be a pioneering step in the mine planning literature.

Key words: *Short-term mine planning and scheduling, simulation-optimisation, IPCC*

1. Introduction

This article is intended to do a review of short-term mine planning and IPCC to provide an idea about the prospects that IPCC may have on short-term planning of open pit mines. The review reveals that short-term planning with IPCC has hardly been explored yet by any researcher. Hence, a theoretical short-term planning methodology by IPCC integration is proposed as a future research opportunity. The appendix section of the paper contains the tabular summary of the reviewed short-term planning and IPCC related paper, their key features, missing attributes, constraints etc.

Open pit mining is a highly capital-intensive operation. Studies such as, Moradi Afrapoli and Askari-Nasab (2017), Osanloo and Paricheh (2020), Rodovalho, et al. (2016), Bozorgebrahimi, et al. (2003) etc. have indicated that about 50% of the operating costs in surface mining is allocated to truck-shovel operation. Therefore, hauling has the highest operating cost among all the material handling operations in open-pit mines. Short-term planning is concerned with meeting production with proper head grade requirements at the mill and minimising ore-waste misclassification. These objectives can be achieved by operational activities such as maximising the production rate, equipment availability, utilisation, minimising grade deviation from plant target by grade blending, minimising equipment movement and cost of ore extraction etc. In-pit crushing and conveying (IPCC) has gained much momentum in the past few decades because of

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the high fuel cost, labour cost and low operating cost of conveyors (McCarthy 2011). Many mines have been employing IPCC in recent years with a comparatively smaller fleet of trucks. S11D, the largest iron ore mine in Brazil, valued at $14.3 billion, started its operation in 2017 with a truck less IPCC operation. The total length of the conveyor belts operating in the mine and the plant is an astounding 68 km (Topf 2017). A list of all mines from 1956 to 2014 with in-pit crushing and conveying has been summarised by Ritter (2016). Researchers are now looking to integrate IPCC systems in mine planning and scheduling. Mine planning can be divided into long-term and short-term planning based on the planning time-horizon and the objectives being optimised. The next section briefly describes the purposes of short-term mine planning.

1.1. Short-Term Planning

The primary objective of any mining project is to maximise the net present value (NPV) by minimising the cost. While the long-term plan is created at the management level to maximise the net present value (NPV) throughout the life of mine, the short-term planning aims at optimizing the operational activities like shovel allocation, grade blending, truck requirement etc. to help achieve the ultimate long-term schedule. The time horizon of short-term planning can be monthly, weekly or even daily. The output of short-term planning is used as a basis for day-to-day mine operations, and adjustments are made as needed to respond to changing conditions or unexpected events. Effective short-term mine planning is crucial for ensuring the profitability and sustainability of a mining operation.

1.2. In-Pit Crushing and Conveying (IPCC)

In-pit crushing and conveying is not a new concept in mining. It has been in use since 1956 (Osanloo and Paricheh 2020) in mines to partially or fully replace trucks in mining operation. IPCC can be divided into three categories: fully mobile, semi-mobile and fixed. Fully mobile IPCC can be loaded directly from shovels, which completely eradicates the need for off-highway trucks. However, it is the least flexible and not quite suitable for deep metalliferous mines (Dean, et al. 2015). Semi-mobile IPCC (SMIPCC) systems are the most flexible. They retain a small haulage fleet for transferring material from the shovel to the crusher, which makes them the most suitable option for mines that have been being actively extracted for years (McCarthy 2011). These crushers are relocated once every one to ten years and have the highest potential for being the most popular IPCC system in large mines in coming years because of its increasing capacity and flexibility (Osanloo and Paricheh 2020). Fixed-type in-pit crushers are placed inside the pit and are not relocated at least for a period of 15 years or more. They are also typically installed in a concrete structure and fed by trucks. Up until 2014, 209 fully-mobile, 213 semi-mobile and 25 fixed in-pit crushers were in use around the world (Osanloo and Paricheh 2020).

1.3. Why IPCC is Thriving in Open Pit Mines

McCarthy (2011) explained the advantages, disadvantages and the reasons of using IPCC in open pit mines. We will review some of these reasons for the readers' ease and to shed light on IPCC integration to existing and new mines:

- ✓ Mines are becoming deeper resulting in increasing haulage distance and the grade of existing reserves becoming smaller.
- ✓ Increasing diesel price; 10% increase from 2005 to 2018 (2018) and 67% increase from 2019 to 2022 (2022a).
- ✓ Availability of equipment, i.e., long lead time for purchasing trucks.
- ✓ Tyre shortages and high tyre costs resulting in inability to adequately utilize truck fleet.
- ✓ Personnel shortages for trucking operations. IPCC systems require fewer operating personnel.
- ✓ Environmental considerations: IPCC offers 60 million litres per year reduction in diesel consumption which is equivalent to 130,000 tonnes per year reduction in CO2 emissions and lesser noise pollution (Nehring, et al. 2018).

- ✓ Less operational risk due to fewer mobile vehicles and simpler maintenance.
- ✓ Lower operating cost in most applications because of lower personnel requirement and higher energy efficiency; 81% of the consumed energy is used to transport material compared to 39% by trucks (Nehring, et al. 2018).

1.4. When to Use IPCC

- ✓ Large mine life of at least ten years because IPCC is capital intensive and short mine life cannot make up for the capital investment by lower operating cost. The initial investment for an IPCC system is about $220M compared to $5M for a 360-ton truck (Osanloo and Paricheh 2020). Therefore, the capital requirement for one IPCC system is equivalent to the capital requirement for a fleet size of forty trucks as shown in Figure 1 .
- ✓ Large quantity of material movement is required to justify the use of IPCC; four to ten Million ton per year (McCarthy 2011).
- ✓ The differential between diesel and electricity cost should be 25% or more (Nehring, et al. 2018).

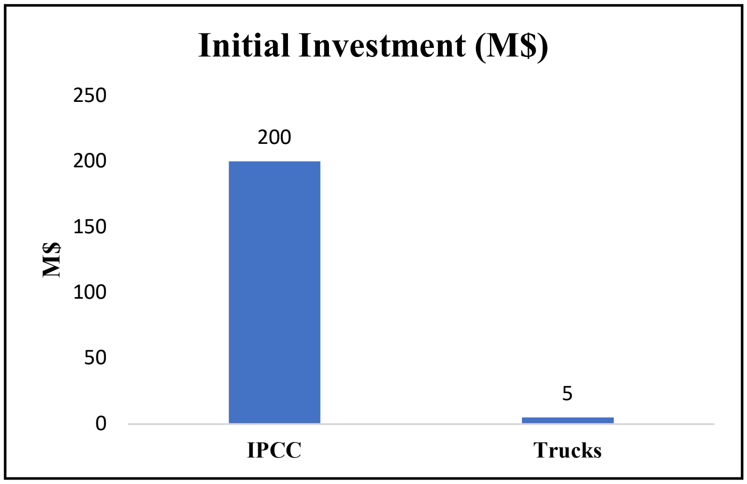

Figure 1. Initial investment for truck vs IPCC.

1.5. Risks Associated with IPCC

- ✓ IPCC installation results in higher stripping ratio to accommodate the crusher and conveyor belts.
- ✓ Skilled labour is required to operate IPCC systems, especially the fully mobile IPCC. Training employees to learn IPCC operation might be a challenge as people are habitually averse to accepting new technologies (McCarthy 2011).
- ✓ IPCC system reduces overall flexibility of mining operation because unlike trucks, IPCC cannot be scaled to increase or decrease production as required (Osanloo and Paricheh 2020).
- ✓ The conveyor system of IPCC is complex and the parts of the conveyor are dependent on each other. Failure of one conveyor part might shut the complete operation because of the interdependency of the parts.

1.6. Impact of Carbon Tax on IPCC

Environmental sustainability is getting more and more importance for every industry including mining. Traditional mining haulage by trucks is not environment friendly because of trucks' dependency on fossil fuel (Nehring, et al. 2018). Canada recently announced that it plans to increase its carbon tax rate to $170 per tonne of greenhouse gas emissions by 2030, up from the current rate of $40 per tonne (2023b). The new carbon tax rule can impact in-pit crushing and conveying (IPCC) in mines in several ways.

Firstly, IPCC can reduce greenhouse gas (GHG) emissions associated with truck haulage and therefore, reduce the carbon footprint of mining operations (Norgate and Haque 2013). As such, IPCC systems may become more economically viable due to the carbon tax incentives to reduce GHG emissions.

Secondly, the cost of implementing and operating IPCC systems may increase due to the additional costs associated with complying with the new carbon tax rule. For example, there may be additional costs for the installation and operation of emissions control systems, monitoring equipment, and carbon credits. These additional costs may impact the feasibility of IPCC systems for some mining operations.

Thirdly, the new carbon tax rule may lead to changes in mine planning and operations to reduce GHG emissions. Mining companies may be incentivized to reduce energy consumption, improve efficiency, and incorporate renewable energy sources to reduce their carbon footprint. This may lead to changes in mine design and planning to incorporate IPCC and other low-carbon technologies.

Overall, the new carbon tax rule can impact IPCC in mines in both positive and negative ways. While the reduction of GHG emissions is desirable, the additional costs associated with compliance may impact the feasibility of IPCC systems for some mining operations. However, the incentives to reduce GHG emissions may also lead to innovation and new opportunities for low-carbon mining technologies like IPCC.

1.7. Importance of IPCC in Short-term Mine Planning

Haulage is one of the largest sources of expense in any open pit mine. Traditional truck haulage is expensive and environmentally harmful because of the dependency on fossil fuel. IPCC has the potential to reduce this cost and provide a more environmentally sustainable haulage option. Hence it is crucial to explore the effects of IPCC on short-term planning of open pit mines. Several key decisions regarding IPCC, such as optimum location, relocation time, conveyor design and length etc., are made in the strategic level of mine planning. Therefore, it is important to investigate the changes that will occur in short-term mining sequences because of housing and moving a crusher inside the pit over time. It is also important to verify if the operational plans can sync with the long-term plan to deliver the desired NPV of the mine in presence of IPCC.

1.8. Research Question and Motivation

As discussed before, equipment operations comprise more than half of the operational cost in mining. Various algorithms have been proposed to optimise mine plan and schedule over the past few decades to deal with this cost. Blom, et al. (2018) summarised the range of techniques developed and used for generating short-term plans, capturing both mathematical programming-based methods and heuristic approaches. Moradi Afrapoli and Askari-Nasab (2017) reviewed mining fleet management algorithms used in both academic and industrial purposes. Osanloo and Paricheh (2020) reviewed the development in IPCC literature. The research questions that this review article poses are:

Is there existing methodologies that can generate short-term mine plan with IPCC? How does IPCC affect mine plan on the operational level?

In order to answer the research questions, a comprehensive review of short-term planning and IPCC literature, mainly post 2010 has been performed. Table 1 summarises the number of different types of short-term planning and IPCC papers based on some key features. The detailed summary of the papers in a tabular format is available in Table 2 and Table 3 of the Appendix.

Table 1. Count of different types of Short-term planning and IPCC papers post 2010 based on decisive features.

Category	Key attributes	Number of papers
	Strictly Deterministic	14

Short-term planning	Stochastic	15
	Designed for Truck Haulage	29
	Designed for IPCC	0
IPCC	Crusher location/relocation time optimization	14
	Economic or environmental comparison	14
	Integration with long-term plan	4
	Integration with short-term plan	0

IPCC is assumed to be the future of open pit mines, but a glaring research gap that exists in mine planning is the integration of IPCC to short-term mine planning. Our review reveals that there is hardly any short-term planning model that can generate mining extraction sequence with IPCC as a haulage option. This paper provides a brief research proposal in the form of a theoretical framework for short-term planning with IPCC integration to fill in the research gap. The framework upon implementation will be a pioneering work in short-term mine planning which will provide a tool for mine planners to select a better haulage option, in terms of cost saving, between trucks and IPCC for open pit mines for a specific year of mine life.

2. Review of Short-Term Mine Planning

Researchers have used several methodologies, such as, linear programming, mixed integer programming, simulation, stochastic programming etc. to optimise short-term schedules. The most recent short-term planning articles are reviewed in this section based on the methodologies used.

3. Mixed Integer Programming (MIP) Based Models

Most of the modern short-term planning models are MIP based with explicit precedence constraints applied. Smith (1998), was the first to use the precedence constraints in mine planning and scheduling. The authors used an MIP for constructing short-term schedules with explicit accessibility constraints, requiring the nine blocks above a block to be mined before that block can be accessed. The objective of this MIP is to minimise deviation between expected and produced grade.

Gholamnejad (2008) proposed a binary integer programming model to solve the short-term mine scheduling problem to decide which blocks of ore and waste to be mined in which period (shift, days, weeks or months) by satisfying several operational and geometrical constraints simultaneously. This model ensures that all the blocks have been opened and the material can be loaded and transported by shovels and trucks respectively.

Eivazy and Askari-Nasab (2012) proposed a short-term planning MIP model with varying mining directions and precedence constraints to minimize overall mining costs, including processing, haulage, rehandling, and rehabilitation costs. However, the model's use of aggregated mining blocks may result in suboptimal solutions as it ignores preferred ore type selectivity and actual hauling processes. Additionally, the model only prioritizes cost savings, disregarding profit. Therefore, considering profit when generating mining sequences is important, even for short-term planning.

L'Heureux, et al. (2013) developed a detailed math model for short-term planning (up to 3 months) that includes truck, shovel, drilling, and blasting operations to minimize operational costs. The model was solved for up to 5 shovels, 90 periods, and 132 faces. Kozan, et al. (2013) created a multi-resource, multi-stage scheduling problem to minimize makespan or the time between the start and end of a process by modelling drilling, blasting, mining of blocks, and allocating equipment. An initial schedule was generated using a hybrid shifting bottleneck approach, then re-optimized using tabu search metaheuristic algorithm, used particularly in combinatorial optimisation, until there was no improvement in makespan, which is the time required for a production process from start to end. The approach was compared to CPLEX optimiser in an iron ore mine, showing significantly lower solution times and negligible optimality gap (<5%) for up to 10 jobs.

Later Kozan and Liu (2016) formulated another short-term planning model to maximise the throughput and minimise the total idle times of equipment at each stage of drilling, blasting and excavation. The optimisation was subject to equipment capacity, speed, read times and activity precedence constraints. The MIP model determines how and when the mining equipment will be allocated to the selected block units to perform the mining tasks at various operational stages. Variables in the MIP model assign pieces of equipment to each job, with binary sequencing variables indicating whether job ‘i’ just precedes job ‘j’ on a particular equipment. The resulting timetable generated for an Australian iron ore mine is confusing because the time units have not been clarified and the optimality gap of the model's results has not been disclosed.

The latest contribution of Liu and Kozan (2017) is a mine management system that integrates long-term, medium-term and operational level mathematical models to improve mining efficiency. The system includes long-term ultimate pit limit determination, medium-term block sequencing, and operational-level equipment planning with a job-shop scheduling model. The long- and medium-term models maximize net present value, while the operational-level model minimizes makespan and tardiness. The integrated model combines block sequencing and equipment scheduling while minimizing total weighted tardiness in job completion times, improving planning efficiency using mathematical modelling instead of manual methods.

Thomas, et al. (2013) formulated an integrated planning and scheduling problem for a coal supply chain with multiple independent mines where they have to share the limited transportation capacity available. The objectives are to minimise the total earliness, tardiness and operation cost constrained by due dates and transportation capacity. The proposed Lagrangian Relaxation-based solution approach performs better than traditional MILP models in terms of upper and lower bounds generation and the lower CPU time. Later, Thomas, et al. (2014) presented a column generation based solution approach for a similar case study.

Mousavi, et al. (2016a) proposed an MIP model to minimize stockpile rehandling costs by optimizing material flows while adhering to ore grade upper and lower bounds. The model uses three metaheuristics: simulated annealing, Tabu search, and a hybrid approach. Tabu search yields the best results when a pre-defined lower bound is used as a termination criterion. The hybrid approach performs better for large instances with an optimality gap of less than 4%. This model introduces the application of the three metaheuristics to the short-term block sequencing problem, making it a significant contribution. A similar study by Mousavi, et al. (2016b) presents a comprehensive mathematical formulation model for a short-term block sequencing problem constrained by precedence relationship, machine capacity, grade requirements and processing demands, which aims to minimise the total cost including rehandling, holding, misclassification and drop-cut costs. The authors presented a hybrid solution approach of branch and bound and simulated annealing which is able to yield solutions with less than 1% optimality gap compared to CPLEX solution, when large neighbourhood search is applied.

Blom, et al. (2014) and Blom, et al. (2016) propose a breakdown and MIP-based algorithm to optimise the short-term planning of a multi-mine, multi-port supply chain for iron ore. The algorithm is divided into two parts: mine optimisation and port blending. The mine optimisation model generates candidate blocks for extraction using MIPs, assuming normally distributed production grades. The port optimiser selects schedules and assigns trainloads of ore from mine to port, minimising deviation from desired composition targets. The algorithm maximises profit by maximising blended product production.

Later, Blom, et al. (2017) presented a rolling planning horizon-based MIP model to generate multiple short-term production schedules to optimise equipment use and shovel movement, constrained by precedence relationships, blending requirements, equipment availability and trucking hours considering multiple processing paths. Multiple schedules are generated using a split-and-branch approach where the optimiser makes several different choices on activities performed in period ‘t’ and a new schedule is generated for each of these sets of choices. The model produces weekly extraction schedules for a three-month planning horizon.

Manriquez, et al. (2019) developed a short-term planning approach to optimize multiple hierarchical objectives in mining. Objectives include minimizing maximum deviation between ore tonnage and plant capacity, metal fines and expected metal fines, and shovel fleet movement cost. They used two goal programming techniques, weighed sum and hierarchical method (Grodzevich and Romanko 2006) and found both to produce plans with the same optimal values in a Copper mine case study. The model does not consider geological uncertainties and is deterministic. Another goal programming based short-term planning model by optimal shovel allocation over continuous time frame has been formulated by Upadhyay, et al. (2021). The objectives of the model are to maximize production, minimize mill grade deviation and shovel movement. The allocation of shovels on mining cuts over a continuous time frame makes the optimization more practical than their previous model (Upadhyay and Askari-Nasab 2017), where shovel allocation was done on a discrete time frame. However, the case study in an iron ore mine shows that the use of continuous time frame makes the model computationally expensive and the solution time increases exponentially with the number of faces.

Nelis and Morales (2022) presents an optimization model for defining mining cuts and scheduling for short-term open-pit planning, which maximizes profits while satisfying operational and scheduling constraints. The model was applied to a real Copper mine and evaluated based on operational considerations, production plans, and optimization runtime. Results show that the model successfully defined the mining cut configuration and production plan simultaneously, providing useful shapes for mining cuts and flexibility to handle different cases in the short-term. The model is computationally very efficient as it could generate representative mining cuts in less than fifteen minutes, which could take days to do it manually.

3.1. Drawbacks of MILP Models

While MILP models guarantee convergence to optimality, it has several shortcomings.

- One general shortcoming of the MIP models is that they are generally strictly deterministic except for the two-stage stochastic programming, which requires a higher level of mathematical understanding. The Mining operations have inherent uncertainties that cannot be captured by deterministic models.
- Non-linearity is beyond the limits of MIP formulations (Urbanucci 2018).
- Big MIP models are computationally very expensive if the planning horizon or solution space is large.

Some strategies that researchers use to overcome these difficulties are clustering, rolling planning horizon etc., that reduce the number of variables involved (Urbanucci 2018). Another approach that researchers frequently use is a combination of simulation with MIP models that enables the models to consider operational uncertainties (Fu 2015). The next section of this article reviews the simulation optimisation approaches used in short-term mine planning. A summary of the short-term planning models showing the key aspects, objectives and constraints, time horizon, tools used etc., has been presented in Table 3 in the Appendix.

4. Simulation-based Optimization Models

Simulation-based optimization is a computational approach that combines simulation modelling and mathematical optimization techniques to solve complex problems. In this approach, a simulation model is used to represent the system under study and to generate performance data for different sets of input parameters. These data are then used as inputs to a mathematical optimization model to find the best set of input parameters that optimize a given performance metric or objective function. Many researchers have focused on simulation-based optimisation for short-term mine planning.

Fioroni, et al. (2008) used simulation in conjunction with a MIP model to reduce mining costs by optimal production planning. The objective is to demonstrate how simulation and optimisation models can be combined, with simultaneous execution, in order to achieve a feasible, reliable and accurate solution.

Ben-Awuah, et al. (2010) developed a discrete event simulation model to minimise discrepancies between long and short-term planning in the context of a life-of-mine planning problem considering uncertainties associated with mining and processing capacities, crusher availability, stockpiling strategy and blending requirements. The simulation model could bridge the gap between the deterministic long-term plan and the dynamic short-term plan. Comparison of the simulated schedule and the expected behaviour allows the planners to analyse the short-term feasibility or robustness of a long-term schedule.

Bodon, et al. (2011) and Sandeman, et al. (2011) The authors proposed simulation-based optimization models to maximize tonnes mined and shipped while meeting blending requirements and minimizing deviation from assigned targets for mine and port stockpiles. The model was subject to constraints such as equipment and port capacity and precedence constraints for a pit-to-port supply chain. An LP determined the amount of ore to be extracted from each mining face and its destination. The model integrates optimization with simulation, providing a more accurate representation and better solution, albeit with a longer run time. It also shows how simulation models can assess trade-offs between capital expenditures and alternative operating practices, including maintenance options.

Shishvan and Benndorf (2014) and Shishvan and Benndorf (2016) proposed an approach to combine geostatistical and discrete event simulations for short-term production planning in complex continuous mining operations. They accounted for geological uncertainty by simulating twenty realizations of the block model and operational uncertainty by discrete event simulation. The objective function considered two key performance indicators: penalty due to deviation in production and equipment utilization. This approach can help predict critical situations affecting supply of material and system performance. However, the article does not provide detailed information about the simulation framework. The developed simulation model was applied in industrial case studies by the authors in Shishvan and Benndorf (2017).

Torkamani and Askari-Nasab (2015) developed and verified a discrete event simulation model to analyse the behavior of truck-shovel material handling and haulage systems in open pit mining. The authors developed an MIP model to deal with the optimum allocation of trucks and shovels in mining faces, and then linked the solutions to the simulation model.

Linear programming only focuses on a single linear objective function with linear constraints. Goal programming is an extension of linear programming that is capable of handling multiple and conflicting objectives. The objective function of the model, therefore, is usually a combination of multiple objectives. It does not get a single optimal solution, but it generates the so-called pareto optimal solutions, a set of points in a multi-dimensional space, where each point represents a solution that is optimal or efficient in terms of the multiple objectives. Upadhyay and Askari-Nasab (2016) and Upadhyay and Askari-Nasab (2017) used goal-programming for a simulation based short-term planning optimization model, to illustrate how proactive decisions can be made in dynamic environment of mining and operational plans and how they can be synced with long-term planning to reduce opportunity cost, maximise production and equipment utilisation.

Manríquez, et al. (2020) proposed a simulation-based optimization framework to increase short-term mining schedule adherence to execution. The framework generates an initial schedule using a MILP model embedded in UDESS, which is then simulated using any discrete event simulation (DES) software to estimate equipment utilization. The utilization of each iteration is fed as input to the next iteration, and the process continues until the material adherence index is less than 5%. The framework was tested in an underground bench and fill mine, showing increased schedule adherence with each iteration without compromising overall NPV (less than 1%). The simulation accounts for equipment uncertainty in an otherwise deterministic model and is applicable to open pit mines. However, the optimization model only considers maximizing extraction the value of each extraction without accounting for operational costs.

4.1. Limitations of Reviewed Simulation-based Optimisation Models

While simulation is a powerful tool to mimic operations and capture uncertainties, simulation-based optimisation models have their limitations.

- A truly representative simulation model is hard and time consuming to develop (Dellino, et al. 2014). Mining operations like dispatching, shovel movement are difficult and time consuming to model.
- Truck and shovel operation in mining is a continuous process. A continuous process should be modelled with continuous data type. The discrete event simulation models developed by Upadhyay and Askari-Nasab (2016), Upadhyay and Askari-Nasab (2017) and Manríquez, et al. (2020) model continuous events like shovel operation by discrete event simulation.
- A simulation model is just as good as the data fed to it. The selection of distribution for the random activities modelled is a major challenge in simulation modelling. The fit will be better if a lot of historical data is available on the activity being modelled. However, identifying and removing outliers, running statistical tests like Kolmogorov-Smirnov test, chi-square test to test the goodness of fit of available data to different distributions is time consuming.
- Due to the confidentiality requirements of the mining companies, it is often very difficult to extract and publish data from a real mining operation (Ritter 2016). If enough data is not available on the event being modelled, the distribution fit will hardly be representative of the real-life event. This is a prime reason why most of the simulation model discussed in this paper have been implemented in hypothetical mines.
- Most simulation models provide less user flexibility towards various stochastic parameters of the system, such as shovel bucket cycle time, truck spotting, hauling on various gradients, payload, dumping, and queuing etc. Truck haulage is a major part of the total production time. It involves a lot of uncertainties due to failure probability, road conditions etc., and needs more attention than what it has got so far in mine planning.
- The runtime for simulation optimisation models is generally higher than mathematical optimisation models. Short-term mine planning requires models to generate results quickly as any change in state, such as an equipment failure, a mined out face etc., calls for a re-optimisation on the schedule (Upadhyay and Askari-Nasab 2017).

Despite the limitations involved in simulation-based optimisation, it is a preferred method in mine scheduling to get the best of both worlds: dealing with uncertainties involved in equipment operation and haulage by simulation and the guarantee of convergence of mathematical models (Fu 2015). Refer to Table 3 of Appendix for a comparison among the reviewed short-term planning literature.

5. Stochastic Optimisation Models

Stochastic programming is a method for solving optimization problems when there is uncertainty in the environment. There are different types of stochastic optimization models, including stochastic optimization with recourse, robust optimization, and stochastic integer programming. Stochastic optimization with recourse involves making decisions at different points in time, with uncertain outcomes of previous decisions. The goal is to maximize the expected value of an objective function. Robust optimization considers uncertain parameters and seeks to find a solution that is optimal for all possible scenarios. Stochastic integer programming involves making decisions under uncertainty with integer-valued variables and is useful in many applications such as production planning and transportation planning. It is commonly used in short-term mine planning.

Dimitrakopoulos and Jewbali (2013) and Jewbali and Dimitrakopoulos (2018) proposed a multi-stage planning process that considers short-term variability in long-term planning. Short-term schedules deviate from long-term plans due to a lack of grade control data. The proposed stochastic integer programming model maximizes NPV and minimizes deviation in planned production by generating possible future observations of grade control data based on mined material's grade. The model integrates these sets of potential observations into conditionally simulated realizations of the mine's orebody, with each realization forming a different scenario. Compliance between short- and long-term schedules is expected to increase the probability of meeting production targets and productivity. The approach generated substantially more ore and NPV when applied to a large gold mine.

Matamoros and Dimitrakopoulos (2016) formulated a stochastic integer programming model that simultaneously optimises fleet and production schedules by taking uncertainty in orebody metal quantity and quality, fleet parameters and equipment availability. They divided the objective function into eight components to minimise the cost of extraction, haulage time under uncertainty of trucks' availability, loss of shovel production and geological risks. The authors claim that this model improves the overall production performance and minimises the production scheduling changes required during operation, compared to the deterministic models because of their simultaneous optimisation approach by considering the uncertainties of the input parameters.

Quigley and Dimitrakopoulos (2019) proposed an improvement of Matamoros and Dimitrakopoulos (2016) model to generate short-term schedule to minimise cost of shovel movement and production deviation, deviation of tonnage and grade sent to plants and maximise truck hours of the allocated fleet, constrained by processing capacity, equipment availability, shovel performance and truck cycle time. The model considers uncertainty of geology by geostatistical simulation.

Paduraru and Dimitrakopoulos (2018) demonstrated how updated grade estimates can be integrated into short-term planning through adaptive policies for assigning destinations to mined blocks. These policies are state-dependent, with a state being a numerical vector describing the block's attributes. As new estimates become available, the policy reassigns a destination to the block that yields the largest immediate improvement in profit or cost. The use of state-dependent policies led to better cash flows and mill usage. The approach is expected to help mill operators decide when to close the mill for maintenance.

Both and Dimitrakopoulos (2020) developed an optimisation model for simultaneous optimisation of short-term extraction sequence and fleet management, in contrast to the traditional approach of optimizing production schedule first and then allocating the fleet. The objectives are to maximise total profit and production by minimising the risk of underproduction by shovels and trucks. The model is constrained by precedence relationships, production targets and number of trucks available over a 12-month planning horizon under geological and equipment performance uncertainty.

5.1. Drawbacks of the Reviewed Stochastic Short-term Planning Models

Stochastic programming is a powerful methodology to deal with the dynamic and uncertain environment of open pit mining. The stochastic models discussed here are stochastic integer programming models and some of them involve geostatistical simulation to account for grade uncertainty. Some of the limitations that the proposed stochastic integer programming has are:

- Stochastic integer programming is computationally expensive. The solution time can increase exponentially with problem size and number of scenarios. Short-term mine planning optimization usually involves thousands of variables for a large sized deposit. The dynamic environment of mining operation demands scheduling models that offer quick convergence. The solution times for the discussed model are substantially higher than deterministic mixed integer programming models.
- Solving stochastic integer programming problems can be challenging because the presence of integer variables often leads to a combinatorial structure that makes the problem non-convex. Moreover, the addition of uncertainty to the problem further complicates the optimization problem, potentially leading to multiple local optima (Can and Grossmann 2021).

- Most of the reviewed stochastic models involve geostatistical simulation of the ore body or block model to generate different realisations of the deposit. If the spatial correlation is poorly understood, the accuracy of the model may be compromised. Knowing the spatial correlation structure of the mining blocks for a real deposit with certainty is difficult (Chilès and Delfiner 2012). This is the reason why most of the reviewed models have been applied on hypothetical mines instead of a real mining data set.
- Generating a scenario tree that has a low error in practice requires high fidelity and accurate historical data, which is very difficult to attain and use in capital sensitive mining industry (Can and Grossmann 2021).

The above-mentioned shortcomings and difficulties are reasons why stochastic scheduling optimisation is still not very common in mine planning. Most of the available models are tested on hypothetical data sets under simplified assumptions. It is impossible to guarantee that a model tested on hypothetical data will verify in real life situations without validating it with real data. However, taking certain measures like ensuring resemblance of hypothetical data to real world event, testing the model on a diverse range of test data, monitoring the performance of the model over time etc., increase the likelihood that the model will perform well in real-world scenarios (Elkan C. and Noto 2008). Eventually, more research contributions and improvements in the existing models will make them applicable to real mining operations.

6. IPCC Review

In-pit crushing and conveying related research has increased in recent times as mines are looking into IPCC as a feasible alternative to traditional truck-shovel operations. The IPCC articles have been divided into the following categories depicted in Figure 2.

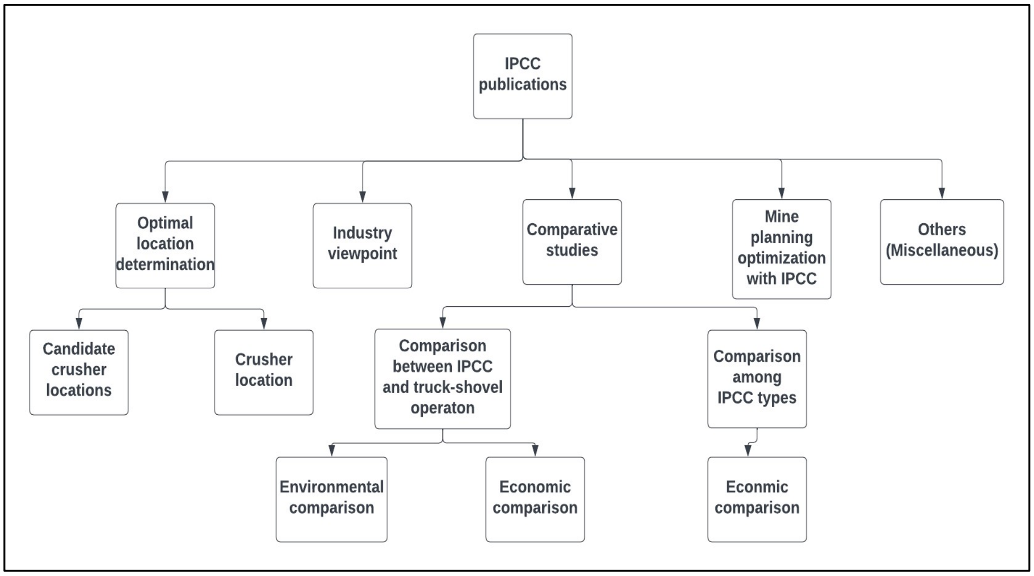

Figure 2. Categories of IPCC research.

The most recent publications will be discussed under the above-mentioned categories to find the progress and research opportunities in the field of IPCC. A summary of the IPCC models has been presented in Table 2 of the Appendix section.

7. Crusher Location Optimisation

Konak, et al. (2007) studied the selection of an optimal crusher location for an aggregate production plant in Turkey based on minimum haulage distance. They considered both stationary and semi-mobile crusher cases and developed an algorithm to calculate the average haulage distance to the crusher from the mine for all possible crusher locations, with up to three relocations during the mine's lifetime. However, the model oversimplified the calculation by only considering haulage distance as the decision variable, and the cost savings shown by the model may be offset by the capital or relocation costs of the in-pit crusher.

A similar but comparatively simpler approach was used by Taheri, et al. (2009) to determine optimum crusher location in deep open pit mines. This approach is simpler than Konak, et al. (2007) because it only considers the case of a stationary in-pit crusher, which would remain in the same location throughout the life of the mine and thus substantially reduces the possible alternative routes. The model calculates the NPV of haulage and installation costs for three candidate locations and selects the one with the lowest cost. However, it does not account for uncertain costs due to crusher breakdown or shovel downtime and lacks a systematic approach to selecting candidate locations. Unlike Konak, et al. (2007), this model added IPCC installation costs along with haulage costs to find the total cost associated with the in-pit crusher.

Rahmanpour, et al. (2013) Proposed a systematic approach to find the optimal in-pit crusher location, by formulating it as a single hub location problem to minimize haulage costs. Candidate locations were selected using analytical hierarchical process (AHP), considering six economic and eleven technical factors, beyond just haulage and installation costs unlike Taheri, et al. (2009). Hub-spoke network was used to connect all destinations and source locations, increasing haulage capacity. AHP provides quantitative estimates for qualitative factors, making it an effective tool for selecting candidate locations. However, delays and queuing during trans-shipment at hubs were not considered in the model.

Roumpos, et al. (2014) The authors developed an iterative method to minimize total transportation cost by finding the optimal location for a belt conveyor distribution point in a mine's perimeter. They used simulation to verify the model and found that the location of the waste dump and conveyor distribution point directly affect transportation costs. This model has advantages over Taheri, et al. (2009) and Konak, et al. (2007) from the context that it continuously calculates costs without requiring initial candidate locations. However, it only considers operating and capital costs and not operational uncertainties or irregular geometries, which can affect conveyor downtime and operating costs.

Paricheh, et al. (2016) proposed a heuristic model to find the optimum locations and movement time of the in-pit crusher in open pit mines hierarchically. The crusher location is optimised by a linear dynamic facility location model with an objective of minimising cost of haulage. The transfer time of crusher is optimised by maximizing the discounted cash flow throughout the life of the mine. This is an iterative model that keeps repeating the steps until the solution improves. Later, Paricheh, et al. (2017) developed another model with the objective of finding out the optimum in-pit crusher location to minimise the haulage cost by modelling it as a dynamic location problem based on the prime factors, such as haulage distance, that affect IPCC location. The results of the model in a case study of a hypothetical mine show that the application of IPCC will reduce cost by six percent from sixth year of mining, saving a total of one hundred and fifty million dollars throughout the mine life.

The models discussed so far are all strictly deterministic. Paricheh and Osanloo (2016) proposed a stochastic approach to determine the optimal crusher location for open pit mines under production and haulage cost uncertainty using stochastic facility location model. The authors formulated the model as a p-median problem with an objective of minimising the expected loss across all scenarios. P-median problem is a kind of a facility location problem where for a set of n demand points or customers and a set of m potential facility locations, the objective is to choose p (where $p \leq m$) facility locations from the set of m locations, such that the sum of distances between each customer and the nearest facility is minimised. The expected loss is the difference between the optimum haulage cost and the p-median haulage cost from each candidate location to the destinations. A case study using the model at Sungun Mine, Iran, to find two crusher locations across nine different equally likely scenarios for fixed, increasing and decreasing production and cost showed that the model is capable of minimising deviation between optimal and p-median haulage cost. However, the model does not work well if the value of p is less than 2.

There has not been many research formulations on finding the best candidate locations from which the optimum in-pit crusher location can be chosen. Paricheh and Osanloo (2019b) explored this opportunity to propose a search algorithm to identify practical and cost-effective candidate locations for in-pit crusher placement in open pit mines. In addition to conventional rules, such as topography and ramp intersection, the authors used block aggregation policies and six specific rules to significantly reduce the number of candidate locations. These rules included depth, pushback, required space, radius of influence, and economic value constraints. The algorithm was validated in Sungun mine and showed a reduction in candidate locations from two hundred and eighty-three to twenty-three. The algorithm does not consider geotechnical or shape restrictions when defining candidate locations.

7.1. Drawbacks of Crusher location Optimisation Models

- ✓ The major problem of the crusher location optimisation models is that the mine plan is not considered for location optimisation. Hence, it cannot guarantee NPV maximisation in the long term.
- ✓ The case study results are not reliable because most of them have been applied in hypothetical mines with simplified geometrical assumptions.
- ✓ There is not enough research work on finding the candidate crusher locations systematically. While Paricheh and Osanloo (2020) proposed a hierarchical approach to finding feasible candidate locations, most of the other models choose candidate locations randomly or based on shortest path without considering a real road network.
- ✓ IPCC design aspects need to be considered for optimal location determination (Dean, et al. 2015).

8. Contributions from Industry Professionals

Morris (2008) provides an overview of productivity issues in semi-mobile (SMIPCC) and full-mobile IPCC (FMIPCC) in real mining operations, without rigorous mathematical modelling. SMIPCC tends to have better overall utilisation than FMIPCC due to lesser dependence on shovel feed. The high service meter unit in IPCC systems, defined as the ratio of engine run time and effective working time, leads to distorted results while predicting fuel consumption from historic data. FMIPCC shows slightly better throughput than SMIPCC. This article is a good introduction to IPCC concerns and industry perspective.

McCarthy (2011) discussed the risks and challenges of implementing IPCC in place of truck shovel haulage systems in mining operations. The author highlighted the importance of proper management planning and training to overcome employee aversion to new technologies like IPCC, and provided information on the types, advantages, and risks associated with IPCC. However, the use of IPCC in large deep mines can be risky due to loss of slope stability and mobility. To address areas of uncertainty, the author recommended probabilistic risk assessment using Monte Carlo simulation during the planning stage and presented examples of decision-making based on risk assessment in the Sandvik mine by Snowden Mining Company. Overall, the article offers valuable insights for beginners to understand IPCC and its industry perspectives. Utley (2011) published a similar article that focused mostly on general ideas and challenges associated with implementing IPCC in large mines.

Dean, et al. (2015) discussed the benefits of using FMIPCC in deep mines such as cost savings and reduced emissions, but also acknowledged the challenges such as large investments and loss of flexibility. They proposed a theoretical design approach for implementing FMIPCC in deep mines using hydraulic excavators, with a model that includes pit widening by conveyor systems and mine sinking by truck-shovel. The use of hydraulic shovels allows for narrow bench widths to maintain high ramp angles necessary for deep mines, and the model proposes radial and parallel belt conveyor movements to minimize the frequency of belt extensions. While the model is innovative, it has not been practically executed in any deep mines, making it difficult to determine its usefulness and feasibility.

The efforts of the members of industry to address existing issues with introducing IPCC in new and existing mines can prove handy because it will help the companies to switch to IPCC with more confidence and assurance.

9. Comparative Studies

9.1. Environmental Comparison

Norgate and Haque (2013) looked at the advantages of using IPCC over Truck-shovel system in open pit mining from a different perspective. They presented a life cycle assessment for IPCC and ore sorting to highlight the potential of reduced greenhouse gas emission these technologies offer. Environmental regulations have made it imperative for large mining companies to ponder about CO2 emission reduction in mining and mineral processing stage. The study showed that IPCC offers 5% and 22% reduction in CO2 emission compared to traditional truck-shovel system for black coal based and natural gas-based electricity respectively. The problem with such studies is that they are highly subjective and the assumptions used might change the outcome of the result.

Awuah-Offei and Askari-Nasab (2009) presented a similar life cycle assessment (LCA) study which gleaned contradictory results to Norgate and Haque (2013). The results for a coal mine case study show that, for acidification potential, the truck system has thirty-two kg of equivalent sulphur dioxide per functional unit, compared to eight kg for the conveyor system. However, for global warming potential, the conveyor has two thousand eight hundred twenty kg of equivalent carbon dioxide per functional unit, compared to six hundred forty-eight kg for the truck option.

Erkayaoğlu and Demirel (2016) conducted a life cycle assessment of trucks and conveyors used in mining for their environmental impact in terms of climate change and acidification. They chose these categories as they have the maximum impact on the environment and human health, and data for these categories is usually reliable. Trucks are found more environmentally harmful than conveyors in terms of acidification due to their dependence on diesel fuel, while conveyors are more detrimental in terms of climate change as they use electricity produced primarily from lignite coal, which, upon burning, produces greenhouse gasses like CO2. This study highlights the importance of LCA as a tool for equipment selection in mining but should be used with caution as it is specific to Turkish mines and assumptions made in the study may not apply to other countries' mines.

A similar life cycle assessment study was presented by Fuming, et al. (2015) that concluded IPCC system to be more energy efficient and environment friendly compared to traditional truck-shovel system. The outcomes of the study reveal that the energy consumption of truck transportation was four to twelve times higher than that of the belt conveyor, the CO2 emissions from truck transportation were three to ten times higher than those of the belt conveyor and with the increase in the slope angle for transportation, the ratio of truck to belt conveyor for both energy consumption and carbon emissions gradually decreased in open-cut coal mines in China. A general outcome of these life cycle assessment studies is that IPCC is more environmentally sustainable than diesel trucks because of less dependence on fossil fuel.

9.2. Economic Comparison

The economical comparative studies mainly focus on the advantages and disadvantages of truck-shovel and IPCC systems in terms of the cost associated with them. Some studies present a financial comparison between fixed, semi-mobile and mobile IPCC systems. Koehler (2003), Schroder (2003) highlighted the technical and economic aspects of IPCC system to demonstrate the advantages it offers over the traditional truck-shovel system.

Klanfar and Vrkljan (2012) compared stationary and mobile crushers and plants in quarrying stone in terms of cost of processing, loading and transportation by a case study at Sungun mine, Iran. The results showed that mobile crusher offers about 11% cost saving compared to stationary crusher mostly because of its significant cost saving in transportation of material. This article assumes that all the costs are known with certainty, which hardly happens in real operations. The results might vary substantially based on the size of the mine.

Londoño, et al. (2013) explored alternative configurations for pre-stripping in an open pit coal mine using IPCC and found that introducing parallel conveyor lines with spreaders can boost productivity by 9.4 – 12.6% and generate more profit compared to a single conveyor line, despite the higher equivalent unit cost. Simulation of five different IPCC configurations demonstrated that an IPCC system with three conveyors and four parallel conveyor lines could increase annual production by 20%, which compensates for the 15% higher operating cost than the single conveyor line. However, assumptions about process delay and failure distribution are crucial, and changes to these assumptions could affect the results significantly.

Dzakpata, et al. (2016) compared shovels, trucks, and IPCC based on operating time and productivity. Results showed that introducing IPCC can improve shovel productivity by 20-25% as shovels spend 40% of the operating time spotting for trucks, while conveyors offer 25% higher valuable operating time than trucks due to trucks' empty travel time. Although the study used multiple metrics, it is case-specific, and the authors did not disclose their data. Therefore, using the study's results without proper assumptions and modifications for other mines may not be useful.

De Werk, et al. (2017) compared Semi-mobile IPCC (SMIPCC) and traditional truck-shovel (TS) systems in terms of haulage cost in a hypothetical iron ore mine. Results show that although IPCC has higher capital cost, its total cost is lower due to lower operational cost. Sensitivity analysis indicates that TS is more sensitive to fuel prices than IPCC due to the smaller number of required trucks. While electricity price has not been as stable as it has been since 2016, the recent hike in electricity prices (25%) from 2020 to December 2022 is still lower than diesel price increase (97%) in this time frame in the USA (2022b; 2023a). Risk analysis via Monte Carlo Simulation in terms of electricity and fuel prices, TS and IPCC availability and truck fill factor shows that the range of minimum and maximum unit operating costs of IPCC is 10% narrower than TS. While this article verifies most of the cost advantage assumptions of IPCC over TS, the case study was run in a perfectly cone shaped hypothetical mine. The outcome of the comparison might vary substantially in real mines.

Another decision making method to choose between TS and SMIPCC was proposed by Nunes, et al. (2019). The aim of this study is to develop a methodology to compare transportation alternatives (TS and SMIPCC) and select the best one in terms of cost saving and environmental sustainability. The results from a Copper mine show that while the CAPEX of SMIPCC is 60% higher than TS, the OPEX is 43% lower because of low maintenance and labour cost, which results in a 34% saving in net present cost over a LOM of 20 years.

Bernardi, et al. (2020) used an ARENA simulation model to compare semi-mobile and fixed IPCC systems for open pit mines in terms of NPV and proximity to target production rate. The simulation was run for a simplified cone-shaped hypothetical mine with hourly costs, and results showed that semi-mobile IPCC generated 10% higher NPV and was closer to production targets. While the model yields quick results and can help decide on the type of IPCC system, the simplified cost model and mine geometry used may not represent typical mining project complexity. Further work is needed on the cost and geometrical assumptions to make this model applicable to a real and complex mine site.

9.3. Shortcomings of the Comparative Studies

- ✓ Environmental comparison via life cycle assessment is highly case sensitive and qualitative. The results of one case study is not applicable for another mine.
- ✓ Data required for life cycle assessment studies is difficult to get. If data collection is poor, the study will not lead to solid conclusions (Curran 2014).
- ✓ Contradictory outcomes to similar studies on environmental sustainability of IPCC and truck-shovel operations may result based on the type and geographical location of the mine (Awuah-Offei and Askari-Nasab 2009; Norgate and Haque 2013).

- ✓ Economic comparison between IPCC and TS systems is also case specific. The cost of labour and haulage vary substantially based on the geological location of a mine.

Despite the limitations of the life cycle assessment and economic comparison studies, they provide valuable insight on the environmental sustainability and economic viability of IPCC system compared to traditional haulage.

10. Simultaneous Optimisation of IPCC and Mine Plan

The most recent addition to IPCC literature is the simultaneous optimisation of mine planning, IPCC location and relocation. This integration is very important from the aspect of mine planning. The inclusion of IPCC affects the number of required haulage equipment, mining direction, availability of mineable faces or cuts which need to be considered while formulating the strategic or even operational plan. Otherwise, the NPV calculation and generated mining sequence could end up being sub-optimal.

Samavati, et al. (2018) explored the fact that there is almost no study for optimizing the operations with IPCC in open pit mines and estimating the costs of IPCC systems. This makes large mining companies averse to using IPCC system despite the advantages, such as, the low operating cost it offers over traditional trucks and shovels. This article points out the fact that while researchers mostly focus on finding an optimal in-pit crusher location for IPCC, there is not much concern about the integration of IPCC with mine planning and scheduling, without which it is very hard to estimate the costs and savings that might be generated by IPCC throughout the mine life. The authors proposed a research direction to discover the optimal location of the conveyors and how open pit mine planning would be affected by the modified precedence constraints due to the location of the conveyors and crushers inside the pit. This is a descriptive article that raised concerns about a few research agendas that must be explored to make IPCC integration more lucrative and risk free for large mining companies.

The research gap pointed out by Samavati, et al. (2018) has been explored by Paricheh and Osanloo (2019a), who proposes a MILP model to optimize the location of the in-pit crusher to minimize total haulage cost, fleet requirement, and maximize the NPV of the mine, taking into account the dynamic changes in block sequencing caused by the IPCC location and relocation. The model determines block destinations and extraction sequences while comparing to two existing benchmark models. Results showed a 2 to 4% increase in NPV, a 75% decrease in fleet requirement, and changes in extraction sequence from the existing benchmarks models. However, the model is deterministic, and its reliability could be improved by incorporating uncertainties associated with vital parameters like grade, price, and cost in real mines.

A more comprehensive approach to integrate long-term plan with fully-mobile IPCC (FMIPCC) conveyor locations was proposed by Samavati, et al. (2020). Their research proposes a mathematical model that simultaneously generates long time mine planning with optimum crusher and conveyor locations for IPCC with an objective of maximizing net profit over the life of mine. They solved the model with three different relaxation techniques using their proposed heuristic and direct MILP solver, where the heuristics required only 10% time of exact solver to find near optimal solution. While the model has not been applied to a real mine yet, the case study was run in a hypothetical mine that is geologically similar to copper porphyry deposits in Australia.

A framework for simultaneous optimisation of long-term mine scheduling with semi-mobile IPCC was developed by Liu and Pourrahimian (2021). The authors proposed an integer linear programming model that maximises NPV by maximizing block values and minimising haulage and crusher relocation cost. They solve the model for several candidate conveyor and crusher locations and the one that generates the maximum NPV is considered as the optimum conveyor/crusher location. The candidate crusher locations are determined using a pit rotation approach developed by Hay, et al. (2020). Assuming the conveyor locations to be fixed in one side of the pit throughout the mine life, this model shows that the conveyor location can significantly impact the NPV of a mine.

The latest attempt to integrate long-term plan with IPCC location and relocation time has been proposed by Shamsi, et al. (2022). The objective of this study is to maximise the NPV of an open pit mine, considering SMIPCC, TS capital and operating cost, and find the optimum locations and relocation time of crushers constrained by mining and processing capacity, blending requirements etc. Unlike Samavati, et al. (2020), this model does not consider the location and relocation of the conveyors. The case study in a copper mine shows that while the capital is $74M higher for SMIPCC than the traditional truck-shovel system, it generates 70% higher NPV over the life of mine. This model can be used as decision making tool to choose between TS and SMIPCC systems in large open pit mines.

10.1. Areas to Improve

The simultaneous optimisation of mine planning with IPCC is very new and requires a lot of work to be put in to make them suitable to be applied in a real mining project. The major limitations to be overcome are summarised below.

- The existing models are all still in theoretical level. They have not been applied to a real mine yet.
- The models developed so far are all deterministic and cannot consider uncertainties associated with geology or IPCC operations.
- We are yet to find out the effect of IPCC on short-term or operational level planning. Most of the simultaneous optimisation models are concerned with strategic mine planning.
- IPCC integration to mine planning is difficult because of the complex design of conveyor, belt distribution points and dynamic crusher locations (Samavati, et al. 2018).

Building upon the limited research work that exists will lead to more comprehensive simultaneous optimisation model in future.

11. Others

Some of the recent research work related to IPCC fall outside the five categories discussed above. For example, a significant contribution to IPCC literature was made by Ritter (2016), who proposed a method for calculating the annual capacity of SMIPCC system considering the random delays that occur due to system performance and inter connection between several parts. The system induced delays have been determined by a discrete event simulation model. The case study shows that the SMIPCC capacity is substantially affected by system delays and the capacity has an inversely proportional relationship with mean repair time. An economic comparison between TS and IPCC system proved SMIPCC to be cheaper than TS for the same annual capacity. This method of determining SMIPCC annual capacity is the first numerical method that considers random system behaviour. A simulation of the proposed numerical model of in a hypothetical coal deposit show that the capacity of a SMIPCC system reaches an optimum in terms of cost per tonne, which is 24% lower than a truck and shovel system (Ritter and Drebenstedt 2019).

A comparative study was published by Abbaspour, et al. (2018), where the different types of transportation systems (truck-shovel and IPCC) are evaluated based on safety (such as accidental death) and social indexes (higher number of employees). FMIPCC presented the highest safety index in contrast with SMIPCC, which showed the lowest. In addition, Truck-Shovel and SMIPCC systems demonstrated the highest social index because of benefiting from higher number of employees and hours of training. In contrast, FMIPCC ranked the last in the social index. Such system dynamic models are highly dependent on the variables, which depend on the judgement of the modeler. Hence, the results are not always reliable. The model has not been applied to any real mine yet.

Abbaspour and Drebenstedt (2020) used system dynamics modelling to determine the optimum transition time from Truck-shovel to IPCC. The case study shows that whereas TS system is preferable at the first five years of a mining project, FMIPCC system shows a better economic performance in the rest of the mine's life.

Shamsi and Nehring (2021) determined the optimum depth at which it is the most convenient to switch to SMIPCC from truck-shovel by scenario analysis. The economic analysis in a cone shaped hypothetical mine with 4 pushbacks showed that switching to IPCC from truck-shovel from the second phase at a depth of 335m generates the maximum discounted cost savings. This model is based on a lot of simplified assumptions on mine geometry and the results will vary depending on the depth and phases of mine.

Wachira, et al. (2021) developed a methodology to determine SMIPCC performance based on mine productivity index. The study found that a reduction in loading equipment (shovel) reduces the truck requirement by 33%. The mine productivity is higher with multiple loading equipment than a single shovel. The case study in a hypothetical mine shows mine productivity index is higher for SMIPCC system than traditional TS system. Table 2 in Appendix presents a detailed comparison of the aspects and objectives optimised among IPCC publications post 2007.

Gong, et al. (2023a) and Gong, et al. (2023b) introduced a new concept called near face stockpile (NFS) mining, which combines the in-pit crushing and conveying IPCC system with a pre-crusher stockpile. This idea of NFS showed an overall improvement in production quantity and NPV compared to traditional mining method.

12. Relevant Optimization Models Suitable for Mine Planning

The capacitated vehicle routing problem (CVRP), a well-established concept in industrial engineering, holds potential for mine planners, as it allows for the optimization of material handling costs through the application of vehicle routing principles to haulage management. Essentially, the vehicle routing problem seeks to fulfil customer demands while working with finite resources, with the ultimate aim of selecting the most efficient or shortest route to minimize movement costs. This section will explore a selection of vehicle routing problem literature to demonstrate the value of these concepts in mining engineering.

Xiao, et al. (2012) proposed a CVRP model to minimise fuel consumption by considering Fuel Consumption Rate (FCR) as a load dependent function using simulated annealing algorithm with a hybrid exchange rule. Experimental results show that the proposed model can reduce fuel consumption by 5% on average compared to the classical CVRP model. This model can be used to manage the trade-off between the total distance and the priorities of serving customers with larger demands. The model in its current state of art cannot assume factors such as road condition, driver behaviour etc. on fuel consumption.

A similar model was proposed by Feng, et al. (2017) with normally distributed vehicle speed and fixed vehicle cost to minimize fixed cost and fuel consumption using a non-linear objective function that is linearized. They used a simulated annealing algorithm to achieve optimal or near optimal solutions, which outperforms CPLEX and simulated annealing approach when there are many destinations. The model shows that fuel consumption is always larger for stochastic vehicle speed than for fixed speed model. However, the model does not account for randomness of demand and the speed distribution is not necessarily normal.

Feld, et al. (2019) proposed a hybrid solution approach using a quantum annealer device to minimize total distance in CVRP. However, the comparison with classical 2-phase heuristics method did not show any significant advantage in terms of solution quality or computation time. The study suggests a method to split complex problems and solve them in a hybrid way using a quantum annealer, but further research is needed to assess the effect of hardware on problem mapping efficiency and the use of additional tools like QBSolv, a software tool developed to solve large scale optimisation problems.

Sarasola, et al. (2016), Errico, et al. (2016), Marinaki and Marinakis (2016) and many other researchers have worked on capacitated vehicle routing problem formulation. The objective of introducing IPCC in big mines is to reduce the number of trucks to minimise haulage cost. The fleet management in mine planning might be optimised by applying the CVRP approach because the basic idea of meeting production target (mill demand) by limited resource (fleet) with minimum cost is the same in both cases.

The emission minimisation vehicle routing problem (EVRP) formulation methodologies similar to Bektaş and Laporte (2011), Figliozzi (2010), Franceschetti, et al. (2013), Jabali, et al. (2012) etc., might be applicable to life cycle assessment studies for IPCC and TS system in mines because the general objective of EVRP is to reduce the greenhouse gas emission while solving the CVRP.

Another arena of operations research that must be explored more is the facility location problem. While Paricheh, et al. (2016), Rahmanpour, et al. (2013) used facility location models to find optimum in-pit crusher locations, there is still a lot of opportunity to formulate more efficient models to optimise IPCC location and relocation using this particular field of study. Other significant research work that can be looked at are Nikbin and Moradi Afrapoli (2023), Moradi-Afrapoli and Askari-Nasab (2022) etc.

13. Future Research Direction

As discussed in the previous sections, mines are becoming deeper and the average ore grade is depleting (McCarthy 2011; Osanloo and Paricheh 2020), which leaves mines with only two options going ahead: switching to underground mining which is not feasible in most cases because the total setup needs to be changed or introducing IPCC to exploit the benefits of a lower operating cost and longer life span than truck-shovel system. This detailed review of the short-term planning and IPCC literature shows that, while most of the articles concerning IPCC are focusing typically on conveyor design or finding an optimal crusher location inside mines based on the cost of traveling from crusher to destinations assuming a predefined and fixed strategic mine plan, some articles are comparing the pros and cons of IPCC with traditional truck-shovel system to promote IPCC system to the mining industry.

This review highlights the fact that the majority of the case studies pertaining to IPCC have been based on hypothetical mines, with simplified assumptions made about mine geometry or operational costs. The widespread adoption of IPCC technology by mining companies has been limited, leading to a scarcity of data on IPCC installation and capital costs, as well as on how changes in mine geometry can accommodate a crusher inside the pit. This lack of data has made it difficult, if not impossible, to validate research formulations against real data. Without such validation, it is challenging to comment on the scalability of any research model. To promote more comprehensive and realistic mine planning with IPCC, it is crucial for mining companies and researchers to collaborate and facilitate the free exchange of data. This will not only aid in validating existing models but also support their improvement.

The comparisons among the most recent short-term planning and IPCC literature show that while very few models can generate a strategic plan with IPCC in place, such as Paricheh and Osanloo (2019a), Samavati, et al. (2020), Shamsi, et al. (2022), Liu and Pourrahimian (2021) etc., there is hardly any short-term planning model with IPCC integration. To make things worse, there is no study that can help mine planners estimate the cost of IPCC systems in a systematic manner considering all the variables and uncertainties associated with it, forcing mine planners to use intuition and experience to come up with a cost estimate that are mostly error-prone and affect the planned NPV in a negative manner (Samavati, et al. 2018).

Commercial tools like Geovia Whittle, Minesched, XPAC etc., can generate long or short-term production schedule for traditional truck-shovel haulage systems but to the best of our knowledge, there is no such commercial tool that can do the same for IPCC system in place. Therefore, it is evident that while IPCC is considered to the future of open pit mines, production sequencing (both long and short-term) considering in-pit crusher is still under-developed and neglected. While strategic planning with IPCC needs to find out the optimal locations of IPCC as a function of time to maximise the NPV, short-term sequencing needs to consider the effects of IPCC location and relocation over time, such as, change in production capacity, haulage distance etc. to come up with a practical production schedule that will sync with the long-term plan.

Operations research tools, such as, transportation problem, vehicle routing, facility location etc. need to be used more rigorously in mining literature so that the existing gaps can be filled in and mathematical models and commercial tools capable of generating strategic and short-term planning with IPCC can be developed. The following sub-section will propose a brief research proposal for short-term planning optimisation with Semi-Mobile IPCC.

14. A Brief Research Proposal

The authors propose a methodology to generate a near optimal short-term planning schedule by optimal allocation of shovel. The schedule can be generated for both IPCC and traditional truck shovel haulage. The goal is to develop a short-term planner that can compare scenarios with IPCC and traditional truck-shovel mining method in terms of profits earned and cost of haulage in a specific period of mine life to decide on the optimal material handling system. Some of the existing issues this research work intends to address are:

1. Reduce or eliminate manual intervention in shovel allocation to dig locations.
2. Considering profit maximisation for optimum shovel allocation unlike existing short-term planning models that consider cost minimisation only.
3. Demonstrate the effect of IPCC on short-term planning.

The model assumptions are:

- The IPCC system is semi-mobile.
- Uncertainty of ore grade and price is not taken into account in the initial stages of the study.
- The optimum locations, relocation time of the crusher and conveyor length and design are known throughout the life of mine from strategic planning.
- There is no waste crusher. Waste material is hauled to waste dump by trucks.
- The ore and waste faces are known from long-term plan.
- There is no stockpiling. Material goes to either waste dump or processing plant.
- Queuing models, as applied by some researchers, will not be applied in this study, although it may provide further improvement in the solutions.
- This study does not focus on the dispatching stage in its current state of art.
- The shovel allocations are made based on haulage cost minimisation and profit maximisation. Capital investment for IPCC system, shovel movement cost etc. are not considered.
- Lost production due to equipment failure and planned maintenance is not considered at the current stage of the model.

The proposed MILP model has three operational objectives: 1. Maximize profit earned by ore material per period, 2. Meet production requirement to feed the mill to its capacity, 3. Minimize haulage cost. The objective function consists of three components. The first component calculates the cost of hauling ore material to crusher or mill and waste material to waste dumps respectively, using regular diesel trucks. The second part calculates the cost of conveying ore material from crusher to processing plant. The last component calculates the profit earned from selling ore. The model should be solved in mining cut level. The mining blocks can be aggregated using clustering algorithms proposed by Tabesh and Askari-Nasab (2013) or Tabesh and Askari-Nasab (2019). The problem can be formulated as a minimization problem in MATLAB, where the objective is the minimization of, f = cost of transporting material to crusher or waste dump from mine by trucks + cost of conveying ore material from crusher to processing plant – profit

The following Figure 3 shows the transportation of waste and ore with and without in-pit crusher in place. The materials are mined from the mining faces by shovels and then loaded to trucks.

The waste material are transported all the way to the waste dumps by the waste trucks. The ore material will be hauled by the ore trucks to the in-pit crusher from mining faces and then conveyed to plant in the scenario with IPCC. In the scenario without IPCC, the ore material will be hauled all the way by trucks from the pit to the plant crusher.

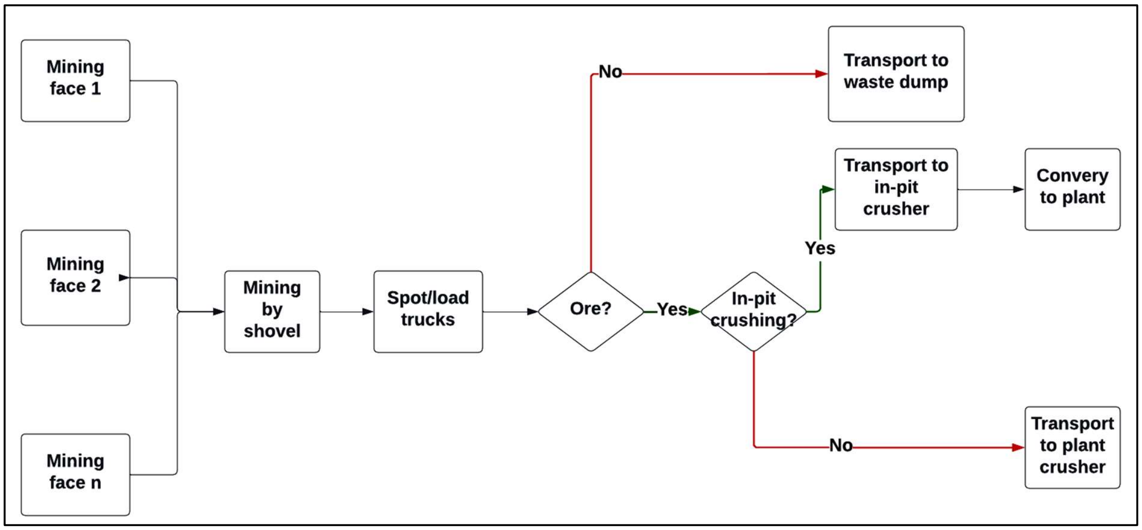

Figure 3. Flow of material from mine to crusher, plant and waste dump.

The distance of each face from the crusher and waste dump will be fed to the model as a road network graph. The objective function will be optimised subject to shovel allocation, grade blending, minimum plant requirement, maximum allowable grade variation and IPCC location constraints to achieve required production and grade targets set by strategic plan through accommodating crusher within ultimate pit limit. Optimum allocation of shovels to mining faces will extract required tonnage of material to feed the plant. The idea is to present two scenarios, one with IPCC and the other one with traditional truck haulage and compare the results to find out the overall revenue generated and haulage cost incurred in each of the scenarios. The comparison of results should enable mine planners to decide on the better haulage option for a specific year of mine life and verify whether the SMIPCC offers cost benefits by meeting long-term production targets within short-term planning horizon of 1 to 3 years.

14.1.1. Expected Outcomes

The proposed research is expected to deliver the following outcomes.

1. The difference in ore and waste production for cases without and with IPCC to see if the monthly production target can be met with IPCC system in place. The total production is expected to drop when IPCC is installed due to the IPCC location constraints. The results should demonstrate how significant is this dip in production and how badly it impacts the profits earned.

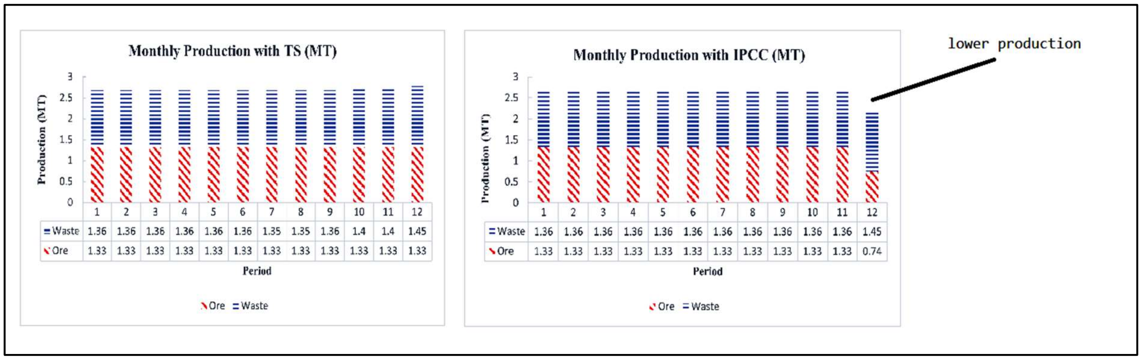

Figure 4. An example of production dip with IPCC.

2. The installation of IPCC will prevent the faces that house the crusher from being mined. It will also impact the mining of the precedence faces too. The results of the proposed model will demonstrate the effect of housing the crusher inside the mine on the short-term schedule.

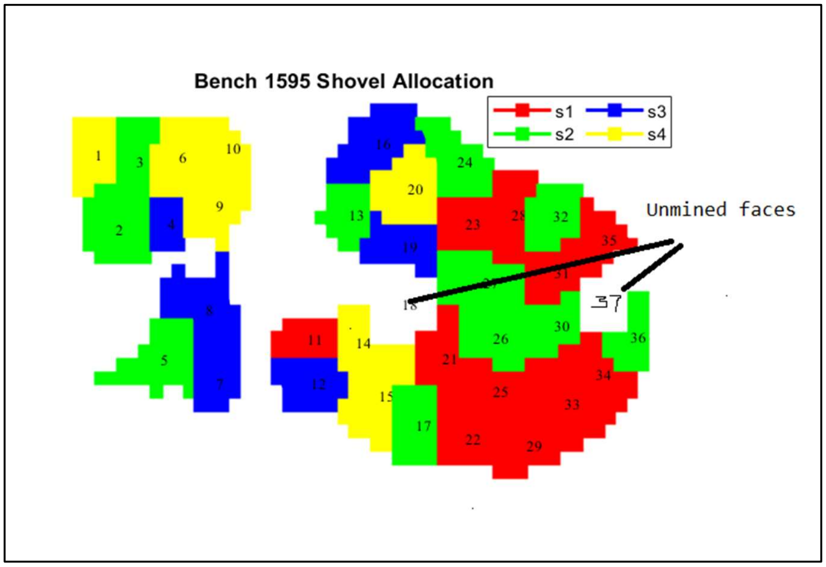

Figure 5. Example of shovel allocation to mining cuts.

3. The results should verify if the cost saving in haulage due per year to IPCC installation is large enough to offset the huge capital investment required for IPCC over the life of mine.

4. The results are expected to delineate the impact of IPCC installation on shovel efficiency.

15. Conclusion

IPCC is the future of open pit mining. For the industry to have a smooth transition from traditional truck-shovel system to IPCC, a lot of work is required to be done in both academic and commercial sectors of mining engineering. Mathematical models and commercial tools that can produce long-term, short-term and operational plans need to be created so that IPCC can be more mainstream in the mining industry and bring about the revolution it can deliver.

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17. Appendix

Table 2. Comparison among key aspects of IPCC publications.

Comparison of post 2010 IPCC papers	Key Aspects					Objectives											Solution Tools
	A1	A2	A3	A4	A5	O1	O2	O3	O4	O5	O6	O7	O8	O9	O10	O11	NS
Konak et al. (2007)	No	No	F,SM	√	×	×	×	×	×	√	×	×	√	×	×	×	NS
Phil Morris (2008)	No	No	F,SM	×	×	×	×	√	×	×	×	×	×	×	×	×	NS
Taheri et al. (2013)	No	No	F	√	×	×	×	×	×	×	√	×	√	×	×	×	NS
McCarthy (2011)	No	No	F,SM, FM	×	×	×	×	√	×	×	×	×	×	×	×	×	NS
Utley (2011)	No	No	F,SM, FM	×	×	×	×	√	×	×	×	×	×	×	×	×	NS
Klanfer, Vrkjln (2012)	No	No	F,FM	√	×	×	×	√	×	×	×	×	√	×	×	×	NS
Rahmanpour et al. (2013)	No	No	SM	√	×	×	×	×	×	√	×	√	√	×	×	×	NS
Roumpos et al. (2014)	No	No	F,SM, FM	√	×	×	×	×	√	×	×	×	√	×	×	×	MATLAB
Londono et al. (2013)	No	No	F,SM, FM	√	×	×	×	×	√	×	×	×	×	×	×	×	NS
Norgate, Haque (2013)	No	No	F,SM, FM	√	×	×	√	×	×	×	×	×	×	×	×	×	Simapro
Dean et al. (2015)	No	No	FM	√	×	×	×	×	√	×	×	×	√	×	×	×	NS
Erkayaoglu, Demirel (2016)	No	No	F,SM, FM	√	×	×	√	×	×	×	×	×	×	×	×	×	Simapro 7.3
Ritter (2016)	No	No	SM	√	√	√	×	×	×	×	×	×	×	×	×	√	ARENA /VBA
Paricheh, Osanloo (2016)	No	No	SM	√	√	×	×	×	×	√	×	×	√	×	×	×	CPLEX
Paricheh et al. (2016)	No	No	SM	√	×	×	×	×	×	√	√	×	×	×	√	×	GAMS, Excel
De Wark et al.(2017)	No	No	SM	√	×	√	×	×	×	×	×	×	×	×	×	×	NS
Paricheh et al. (2017)	No	No	SM	√	×	×	×	×	×	√	×	×	√	×	×	×	GAMS
Abbaspour et al. (2018)	No	No	F,SM, FM	√	×	×	√	×	×	×	×	×	×	√	×	×	NS
Abbaspour, Carsten (2019)	No	No	FM	√	×	√	×	×	×	×	×	×	√	×	×	×	NS
Nunes et al. (2019)	No	No	SM	√	×	√	×	×	×	×	×	×	√	×	×	×	Excel VBA

Comparison of post 2010 IPCC papers	**Key Aspects**					**Objectives**											**Solution Tools**
	A1	A2	A3	A4	A5	O1	O2	O3	O4	O5	O6	O7	O8	O9	O10	O11	NS
Paricheh, Osanloo (2019a)	Yes	No	SM	√	×	×	×	×	×	√	×	×	√	×	√	×	CPLEX
Paricheh, Osanloo (2019b)	No	No	F,SM	√	×	×	×	×	×	×	×	√	×	×	×	×	NS
Bernardi et al. (2020)	No	No	F,SM	√	×	×	×	√	×	×	×	×	×	×	√	×	ARENA
Samavati et al (2020)	Yes	No	FM	√	×	×	×	×	√	√	×	×	×	×	√	×	Gurobi
Shamsi, Nehring (2021)	No	No	SM	√	×	√	×	×	×	×	×	×	√	×	×	×	NS
DingBang, Yahsar (2021)	Yes	No	SM	√	×	×	×	×	√	×	√	×	√	√	×	×	MATLAB/CPLEX 12.7
Wachira et al. (2021)	No	No	SM	√	×	×	×	×	×	×	×	×	×	×	×	√	NS
Shamsi et al. (2022)	Yes	No	SM	√	×	×	×	×	×	√	√	×	√	×	√	×	CPLEX 12.7

A1 - Integration with long-term plan
A2 - Integration with short-term plan
A3 - IPCC type
A4 - Case study
A5 - Stochastcity
O1 - Economic comparison with TS
O2 - Environmental comparison with TS
O3 - Comparison among IPCCs (Economic)
O4 - Optimum conveyor design/ exit location determination
O5 - Optimum Crusher Location determination
O6 - Crusher relocation time optimisation
O7 - Candidate crusher location determination
O8 - Transportation cost minimisation
O9 - IPCC risk assessment
O10 - NPV maximisation
O11 - IPCC capacity/performance determination
F – Fixed
SM – Semi-mobile
FM – Fully-mobile

Table 3. Comparison among most recent publication on short-term mine planning.

Comparison of post 2010 short-term papers	**key Aspects**	**Time horizon**	**Solution tool**	**Objectives**	**Stochastic or Deterministic**	**IPCC/ TS**
Eivazy and Askari-Nasab (2012)	Block extraction sequence generation	12 to 36 months	CPLEX	Minimise cost of mining, processing, material movement and waste rehabilitation **subject to** head grade, precedence and capacity constraints	Deterministic	TS
Liu, Kozan (2012), Liu, Kozan, Wolff (2013,2016)	Block extraction with equipment scheduling; multi-stage, multi-resource scheduling	Not specified	C++	Minimise makespan of mining activities drilling, blasting and excavation **subject to** capacity of mining equipment and precedence constraints	Deterministic	TS
L'Heureux et al. (2013)	Block extraction, shovel allocation drilling and blasting schedule.	3 months	IBM ILOG CPLEX	Minimise cost of shovel movement, drilling and blasting cost **subject to** precedence of activities, capacity and blending constraints	Deterministic	TS
Mousave et al. (2016b)	Block sequencing problem with equipment scheduling	Six months	CPLEX	Minimise the total mining cost which includes rehandling and holding costs, misclassification and drop-cut costs **constrained by** precedence relationship machine capacity, grade requirements and processing demands	Deterministic	TS
Mousave et al. (2016a)	A comparative study of three meta heuristic approaches (tabu search, simulated annealing and a hybrid of these two) to short-term mine sequencing.	NS	NS	An MIP model to minimise the stockpile rehandling cost **constrained by** upper and lower bounds of ore grade.	Deterministic	TS

Comparison of post 2010 short-term papers	**key Aspects**	**Time horizon**	**Solution tool**	**Objectives**	**Stochastic or Deterministic**	**IPCC/ TS**
Kozan, Liu (2016)	Multi-stage mine production timetabling model for drilling, blasting and excavating operations	18 weeks	IBM ILOG CPLEX	Maximise the throughput and minimise the total idle times of equipment at each stage of drilling, blasting and excavation **subject to** equipment capacity, speed, ready times subject to precedence constraints.	Deterministic	TS
Liu, Kozan (2017)	An innovative mine management system by integrating a series of mathematical models for long-term, mid-term block sequencing and operational level planning of equipment with a job-shop scheduling model to achieve an overall mining efficiency	18 weeks	CPLEX	The long and medium term MIP models maximise the net present value of the blocks to be mined throughout the life of mine and for a specific period respectively and the operational level MIP minimises the makespan and tardiness in job completion times **subject to** block precedence and capacity constraints.	Deterministic	TS
Blom et al. (2014,2016)	A decomposition based heuristic model to solve a set of mine-side optimisation problems and a port-side blending problem	13 weeks	IMB CPLEX	Meeting blending targets and maximizing equipment use in a multi-mine, multiple port network **constrained by** capacity and blending constraints	Deterministic	TS
Blom (2017)	A rolling planning horizon-based MIP model to generate multiple short-term production schedules	13 weeks	IMB CPLEX	Optimise equipment use and shovel movement **constrained by** precedence relationships, blending requirements, equipment availabilities and trucking hours considering multiple processing paths.	Deterministic	TS

Comparison of post 2010 short-term papers	**key Aspects**	**Time horizon**	**Solution tool**	**Objectives**	**Stochastic or Deterministic**	**IPCC/ TS**
Upadhyay, et al. (2021)	Shovel allocation optimization over continuous time frame	20 weeks	CPLEX	Maximizing shovel utilisation, minimising deviation in production and grade from target, minimising shovel movement **subject to** production capacity, grade blending and precedence constraints.	Deterministic	TS
Nelis, Morales(2022)	Optimization of short-term plan by simultaneous generation of mining cuts	5 weeks	Gurobi	Maximizing profit **subject to** mining capacity, precedence, mining cut size and maximum number of mining cuts constraints.	Deterministic	TS
Upadhyay, S., Askari-Nasab (2016, 2017)	Simulation optimisation model to generate optimum mining schedule by shovel allocation	12 months	CPLEX, ARENA	Maximizing shovel utilisation, minimising deviation in production and grade from expected/target, minimising shovel movement **subject to** production capacity, grade blending and precedence constraints.	Operational uncertainty	TS
Manriquez et al. (2019)	A framework to optimise short-term planning of open pit mines	NS	Python	Minimising maximum deviation between ore tonnage sent to plant and plant capacity, minimising maximum deviation between metal fines and the expected metal fines in processing plant and minimising overall shovel fleet movement cost minimisation **subject to** grade blending and precedence constraints.	Deterministic	TS
Manriquez et al. (2020)	Simulation optimisation model to generate short-term extraction sequence	18 months	UDESS	Maximise value of extraction **subject to** precedence, blending and equipment availability constraints.	Operational uncertainty	TS
Matamoros, Dimitrakopoulos (2016)	Simultaneous optimisation of fleet and production schedules	12 months	CPLEX, C++	Eight component objectives to minimise the cost of extraction, haulage time under uncertainty of trucks' haulage time and availability, loss of shovel production and geological risks **subject to** capacities and blending constraints.	Stochastic (geological and fleet uncertainty)	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Stochastic or Deterministic	IPCC/ TS
Paduraru, Dimitrakopoulos (2018)	Shows how new information, such as updated estimates on the characteristics of extracted material, can be integrated into the short-term planning process	50 weeks	NS	Based on the characteristic vector of a block, determining the optimum destination for that block to impose the largest immediate improvement on cash flow **constrained by** block precedences and processing capacities.	Geological uncertainty	TS
Matamoros, Jewbali (2013, 2018)	A multi-stage planning process that incorporates potential short-term variability in the long-term planning process.	NS	NS	Maximises NPV and minimises deviation in planned production, where a set of possible realizations of future grade control data is generated based on the grade of material in mined out areas of the mine site **satisfying** block precedence constraints.	Geological and operational uncertainty	TS
Bodon, Sandman (2010, 2011)	Model shows how integrating optimisation within a simulation allows a more accurate representation of the system, providing a better solution although with a longer run time.	9 days	Lingo	Maximise tonnes mined and shipped, minimise the deviation of the quality of all mine and port stockpiles and meet blending requirements **constrained by** equipment and port capacity and precedence constraints for a supply chain consisting of pit, port and ships.	Operational Uncertainty	TS
Shishvan, Bendorf (2014, 2016, 2017)	Stochastic simulation approach to predict performance and reliability of complex continuous mining operations for optimal decision making in short-term production planning	7days	Arena	Minimise production deviation and maximise equipment utilisation **subject to** processing capacities and equipment availability.	Geological Uncertainty and equipment uncertainty	TS
Rahmanpour, Osanloo (2016)	Stochastic optimisation to capture the effects of geological uncertainties on short-term mine planning	30 months	NS	Minimise cost of mining **subject to** equipment capacity, ore quality and mill demand constraints	Geological Uncertainty	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Stochastic or Deterministic	IPCC/ TS
Quigley, Dimitrakapolous (2019)	Improvement of Matamoros, Dimitrakapolous model (2016)	12 months	CPLEX	Generate short term schedule to minimise cost of shovel movement and production deviation, deviation of tonnage and grade sent to plants and maximise truck hours of the allocated fleet **constrained by** processing capacity, equipment availability considering uncertainty of geology, shovel performance and truck cycle time.	Geological and equipment uncertainty	TS

Table 4. List of acronyms.

Acronym	Abbreviation
NPV	Net present value
OPEX	Operational expense
Capex	Capital Expense
SMIPCC	Semi-mobile IPCC
FMIPCC	Fully-mobile IPCC
LP	Linear programming
MILP	Mixed integer linear programming
DES	Discrete event simulation
GHG	Greenhouse gas