# Review of Recent Developments in Short-Term Mine Planning and IPCC

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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 increasing fuel cost, labor cost and low operating cost of conveyors. This article aims at reviewing 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 there is hardly any short-term planning model that 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 mine planning literature.*

## 1. Introduction

Open pit or surface mining is a highly capital-intensive operation. Studies have shown that about 50% of operating costs in surface mining are allocated to truck-shovel operation and the number can go up to as much as 60% in large open-pit mines (Moradi Afrapoli and Askari-Nasab 2017). Therefore, hauling has the highest operating cost among all the material handling operations in open-pit mines. Short-term planning is concerned with operational activities such as, maximizing the production rate, equipment availability, utilization, minimizing 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 high fuel cost, labor 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 truckless 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 summarized 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 optimized.

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## 1.1. Short-term vs Long-term Planning

Short and long-term planning are different from several aspects. These include but are not limited to the type of block model used as input to the planning process; the time horizon (weekly or shorter time periods vs. longer time periods i.e., quarterly to yearly); the objectives being optimized; the constraints that must be considered during optimization and the level of detail to which mine operations are modelled. In the long-term context, a block model generally consists of millions of equally sized blocks. Precedence exists between the blocks in this model, defining constraints on sequences of blocks to be extracted.

The primary objective of any mining project is to maximize the profit by keeping the cost minimum. While the long-term plan is created at the management level to maximize 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. Short-term planning can be branched into production planning in upper level and dispatching in lower-level stages. The several stages of mine planning are delineated in Figure 1.

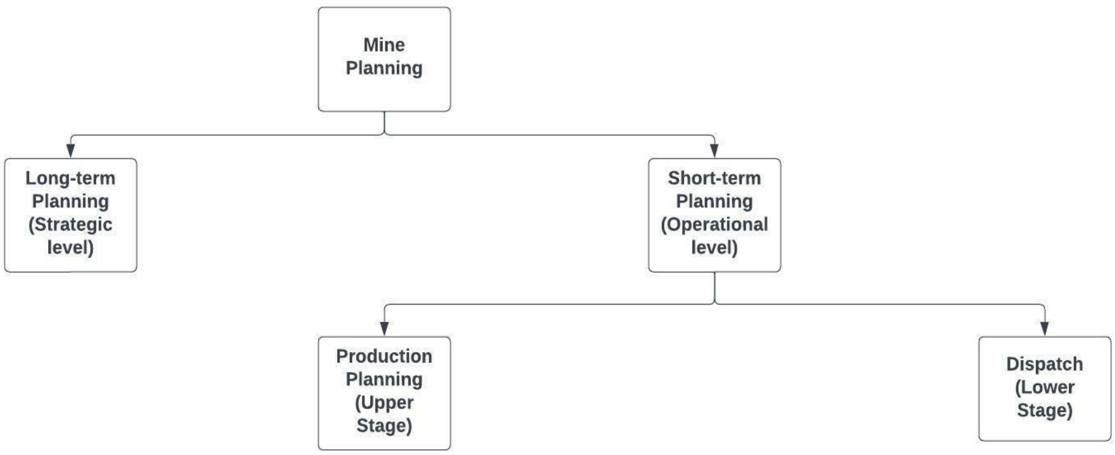


Figure 1. Mine planning stages.

## 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. However, it has thrived in the past two decades for several reasons discussed in the next section of this article. 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).

### 1.2.1. 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 getting deeper resulting in increasing haulage distance and grade of existing reserves getting lower.
- ✔ Increasing diesel price; 10% increase from 2005 to 2018 (2018) and 67% increase from 2019 to 2022 (2022).
- ✔ Availability of equipment, i.e., long lead time for purchasing trucks.
- ✔ Tire shortages and high tire 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 liters per year reduction in diesel consumption which is equivalent to 130,000 tonnes per year reduction in $CO_2$ 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).

### 1.2.2. When to Use IPCC

- ✔ Large mine life of at least 10 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).
- ✔ Large quantity of material movement is required to justify the use of IPCC; 4 to 10 Million ton per year (McCarthy 2011).
- ✔ The difference bw. diesel and electricity cost should be over 25% (Nehring, et al. 2018).

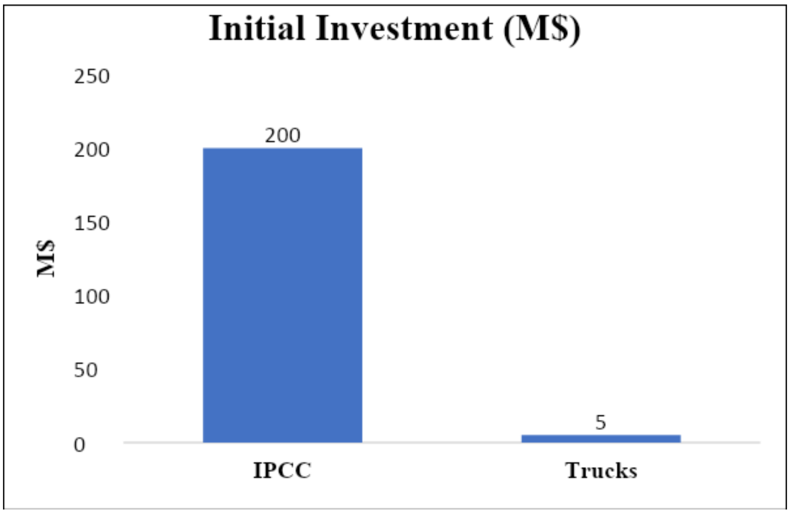


Figure 2. Initial investment for truck vs IPCC.

### 1.2.3. Risks Associated with IPCC

- ✔ IPCC installation results in higher stripping ratio to accommodate the crusher and conveyor belts.
- ✔ Skilled labor is required to operate IPCC systems (especially fully mobile), which might be a challenge as people are habitually avert to new technologies (McCarthy 2011).
- ✔ IPCC system reduces overall flexibility of mining operation because they cannot be scaled to increase or decrease production as required (Osanloo and Paricheh 2020).
- ✔ Failure of one part might shun the complete production because of the interdependency of the conveyor parts.

## 1.3. Motivation

As discussed before, equipment operations comprise more than 50% of the operational cost in mining. Various algorithms have been proposed to optimize mine plan and schedule over the past few decades to deal with this cost. (Blom, et al. 2018) summarized 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 primary motivation of this article is to explore short-term planning of open pit mines with in-pit crushing and conveying to find research gaps and propose a future research direction. IPCC is assumed to be the future of open pit mines, but mine planning with IPCC is an area of research that has not been explored extensively yet. A comprehensive review of short-term planning and IPCC literature after 2010 is done to find the shortcomings of existing methodologies. The findings of the review pave the way to provide logical and scientific suggestions to IPCC integration in short-term mine planning.

# 2. Short-Term Mine Planning

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

## 2.1. 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 minimize deviation between expected and produced grade. (Smith 1998) model is preferred by most researchers while modeling precedence among blocks.

(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.

(Askari-Nasab, et al. 2011) proposed two deterministic MILP models to optimize long-term open pit mining schedule with an objective to maximize NPV by meeting grade blending, mining and processing capacities, and block precedence constraints. The study introduced mining-cuts by combining blocks, to reduce binary variables in the formulation, problem size and solution time. While the first model controls mining in cut level and processing at block level, the second model controls both at mining-cut level. The authors verified the second model with an iron ore mine case study to illustrate that the model is capable of handling large size life-of-mine scheduling problems. Use of mining-cuts or clustering helps reduce the computational expense of MIP models by reducing the number of variables involved.

(Eivazy and Askari-Nasab 2012) solved a short-term planning MIP model under several different scenarios, in which the direction of mining varies with different mining precedence constraints. The objective is to minimize the overall cost of mining operations including mining, processing, haulage, re-handling and rehabilitation costs. One major drawback of this model is the use of aggregation of mining blocks prior to optimizing that might lead to suboptimal solutions because aggregation of the blocks ignores the practical selectivity of preferred ore types and cannot deal with the actual hauling process during optimization. This model generates schedules based on cost savings only and does not take the revenue earned into account. Even from a short-term planning perspective, it is important to generate mining sequences the earned revenue.

(L'Heureux, et al. 2013) proposed a detailed mathematical optimization model for short term planning for a period of up to three months by incorporating operations in detail. The objective is to minimize operational costs caused by trucks, shovels, drilling and blasting. They solved the problem for up to 5 shovels, 90 periods and 132 faces. (Kozan, et al. 2013) modelled drilling, blasting and mining of blocks, and allocation of equipment to these activities with an objective of minimizing the make-span that is the elapsed time between the start and end of a schedule. The model takes mine scheduling as a multi-resource multi-stage scheduling problem. An initial schedule is generated using hybrid shifting bottleneck approach (Liu and Kozan 2012) in the form of a disjunctive graph which is re-optimized using neighborhood and tabu search. The process is reiterated until there is no improvement in makespan. A comparison of the proposed approach to CPLEX optimizer in an iron ire mine showed that the solution time is significantly lower with a negligible optimality gap (<5%) for up to 10 jobs.

Later (Kozan and Liu 2016) formulated another short-term planning model to maximize the throughput and minimize the total idle times of equipment at each stage of drilling, blasting and excavation. The optimization was subject to equipment capacity, speed, read times and activity precedence constraints. The MIP model determine 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 an innovative mine management system by integrating a series of mathematical models for long-term ultimate pit limit determination, medium-term block sequencing over quarterly, half-yearly or yearly time periods, and operational level planning of equipment with a job-shop scheduling model to achieve an overall mining efficiency improvement. While the long- and medium-term MIP models maximize the net present value of the blocks to be mined throughout the life of mine and for a specific period respectively, the operational-level MIP minimizes the makespan and tardiness in job completion times. The integrated model combines block sequencing and the scheduling of equipment while minimizing total weighted tardiness in job completion times. This model can act as an efficient tool to synchronize medium-term and operational level planning with long-term planning using a mathematical approach rather than traditional manual ways.

(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 minimize 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. 2016b) proposed an MIP model to minimize the stockpile rehandling cost constrained by upper and lower bounds of ore grade. The objective is attained by maximizing mine-to-processing, minimizing mine-to-stockpile and stockpile-to-processing material flows in each period. The MIP is solved using three metaheuristics: simulated annealing, Tabu search and a hybrid of these two methods. Each method uses a time move to mine a block in a period and a destination move to decide the destination of the mined material. The Tabu search algorithm 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%. The major contribution of this model is to introduce the application of the three metaheuristics in short-term block sequencing problem. A similar study by (Mousavi, et al. 2016a) 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 minimize 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 neighborhood search is applied.

(Blom, et al. 2014) and (Blom, et al. 2016) present a breakdown and MIP-based algorithm for the short-term planning of a supply chain consisting of multiple open-pit iron ore mines and multiple ports. The problem is divided into two parts: mine optimization and port blending. The mine optimization model solves MIPs to generate a set of candidate blocks to be extracted in a short-term planning horizon. The production grade is assumed to be normally distributed about the target given as input. The port-side optimizer solves an MIP to select a single schedule for each time period, assigns trainloads of ore from mine to port and at the same time, minimizes deviation of the average compositions of ore arriving at each port from desired targets. Based on the solution of the port-side problem, new grade targets are generated as input to each mine-side optimizer. The overall objective is to maximize profit by maximizing production of blended products.

Later, (Blom, et al. 2017) presented a rolling planning horizon-based MIP model to generate multiple short-term production schedules to optimize 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 optimizer 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 methodology to optimize multiple hierarchical objectives. The objectives of this model are minimizing the maximum deviation between ore tonnage sent to plant and the plant capacity, between metal fines and the expected metal fines in processing plant and minimizing the overall shovel fleet movement cost. The authors used weighted sum and hierarchical method (Grodzevich, et al. 2006), two goal programing techniques to optimize the defined objectives. The case study in a Copper mine showed that both methods can produce short-term plans with the same optimum objective function values. This model is strictly deterministic and does not take geological uncertainties into account.

### 2.1.1. 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 (Michael 2015). The next section of this article reviews the simulation optimization 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.

## 2.2. Simulation Optimization Models

Many researchers have focused on simulation optimization of equipment selection and efficiency in mine planning because simulation can handle uncertainty involved in operations. (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 optimization 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 minimize 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 behavior allows the planner to analyze the short-term feasibility or robustness of a long-term schedule.

(Bodon, et al. 2011) and (Sandeman, et al. 2011) proposed simulation optimization models to maximize tonnes mined and shipped, minimize the deviation of the quality of all mine and port stockpiles from their assigned targets and meet blending requirements. The model was constrained by equipment capacity, port capacity and precedence constraints for a supply chain consisting of pit, port and ships. A linear program (LP) is defined to determine the tons of ore to be extracted from each mining face and its destination. The model shows how integrating optimization with simulation allows a more accurate representation of a system, provides a better solution, although with a longer run time. It also demonstrates that simulation optimization models have the ability to examine trade-offs between different options for capital expenditure and assess alternative operating practices, including maintenance options.

(Soleymani Shishvan and Benndorf 2014) and (Soleymani Shishvan and Benndorf 2016) presented a stochastic simulation approach to predict performance and reliability of complex continuous mining operations for optimal decision making in short-term production planning. The authors considered geological uncertainty in the model. The objective function value is the weighted sum of the two key performance indicators (KPIs) defined: penalty due to deviation in production and equipment utilization. The framework can be used as a valuable tool to foresee critical situations affecting supply of material and system performance through the two-fold uncertainty management: geological uncertainty by geostatistical simulation of 20 realizations of the block model, and the operational uncertainty by discrete event simulation. However, the details of the simulation framework are not provided in the article. The developed simulation model was applied in some industrial case studies later by (Soleymani Shishvan and Benndorf 2017).

(Torkamani and Askari-Nasab 2015) developed and verified a stochastic discrete event simulation model to analyze the behavior of truck-shovel material handling and haulage system 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. combination of multiple objectives. It does not get a single optimal solution, but it generates the so-called pareto optimal solutions, meaning that there is no other solution that is better at all of the objectives. (Upadhyay and Askari-Nasab 2016) and (Upadhyay and Askari-Nasab 2017) used goal-programming for a simulation optimization based short-term planning 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, maximize production and equipment utilization.

(Manríquez, et al. 2020) proposed a simulation optimization framework to increase the adherence of short-term mining schedules to execution. The model generates an initial schedule based on an MILP model embedded in UDESS and then simulated in any data encryption standard (DES) software to replicate the schedule and estimate equipment utilization. The utilization of each iteration is fed as input to the next iteration. The user runs the iterations until a termination criterion is satisfied, which in this case, is a material adherence index less than 5%. A case study in an underground bench and fill mine, with a monthly schedule and horizon of 1.5 years, shows that the adherence of the schedule to execution increases with each iteration without any significant compromise (less than 1%) in the overall NPV of the mine. The integration of simulation accounts for the uncertainty of equipment in this strictly deterministic model. It is a generic framework, therefore, applicable to open pit mines too. One shortcoming of the model is that the optimization model generates the schedules with just a single objective of increasing the value of each extraction without considering any costs associated with operations.

### 2.2.1. Limitations of Simulation-optimization

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

A true representative simulation model is hard and time consuming to develop (Dellino, et al. 2014).

A simulation model is just as good as the data fed to it.

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, which needs more attention.

All situations can not be evaluated using simulation. Without randomness in a candidate of interest, all simulated scenarios would produce the same result (Wang, et al. 2021).

The runtime for simulation optimization models is generally greater than mathematical optimization models.

Despite the limitations involved in simulation-based optimization, 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 (Michael 2015).

## 2.3. Stochastic Optimization Models

Stochastic programming models solve optimization problems under uncertain environment. Variables that would be constant in a deterministic approach, follows a probability distribution in stochastic programming models. A stochastic program may be formulated with probabilistic constraints (constraints that must hold with a specified probability) or alternative realizations. In a stochastic program with recourse, possible alternative realizations of the stochastic parameters in the problem are defined with first and second stage variables. In the context of scheduling, while the first-stage decision variables define the plan, the second-stage variables define the alternative scenarios that could arise, and adjustments required for each of these alternative scenarios. Several algorithms have been used to solve stochastic minimization or maximization problems.

(Dimitrakopoulos and Jewbali 2013) and (Jewbali and Dimitrakopoulos 2018) proposed a multi-stage planning process that incorporates potential short-term variability in the long-term planning process. Short-term schedules usually deviate from the long-term plans due to the unavailability of grade control data at the time of long-term planning. This simulation based stochastic integer programming model maximizes NPV and minimizes 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. These sets of potential future observations are integrated into a set of conditionally simulated realizations of the mine's orebody, with each orebody forming a different scenario. The compliance of short-to long term production schedules and performance is expected to augment the probability of meeting production targets and increased productivity. Application of this approach at a large gold mine generated substantially higher amount of ore and NPV.

(Matamoros and Dimitrakopoulos 2016) formulated a stochastic integer programming model that simultaneously optimizes 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 minimize 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 minimizes the production scheduling changes required during operation, compared to the deterministic models because of their simultaneous optimization 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 minimize cost of shovel movement and production deviation, deviation of tonnage and grade sent to plants and maximize 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) showed how new information, such as updated estimates on the grades of extracted material, can be integrated into the short-term planning process. This integration is achieved via the use of adaptive short-term policies for assigning destinations to mined blocks. These policies are state dependent. A state, in this context, is a numerical vector describing the attributes of the block. A policy selects a destination for the block that yields the largest immediate improvement in revenue or cost for each destination. As new estimates become available for the contents of a block, a new state is formed and the short-term policy reassigns a destination to the block. New data typically results in a reduction of local uncertainty. The use of state-dependent destination policies led to better cash flows and more reliable mill usage. The approach is expected to help mill operators decide in advance when the best time to close the mill for maintenance would be.

(Both and Dimitrakopoulos 2020) developed an optimization model for simultaneous optimization 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 maximize total profit/revenue and production by minimizing 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. Table 3 in appendix contains a summary comparison of short-term planning models.

### 2.3.1. Drawbacks of Stochastic Optimization Models

Stochastic programming is a powerful methodology to deal with dynamic and uncertain environment of open pit mining. However, there are several problems associated with it, including:

- Dealing with non-linearity is computationally expensive and mathematically convoluted (Can and Grossmann 2021).
- Handling non-convexity is still a major challenge for stochastic optimization of scheduling.
- 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 optimization is still not very common in mine planning. Most of the available models are tested on hypothetical data sets under simplified assumptions that might not hold true in real mining operations.

## 3. 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 3.

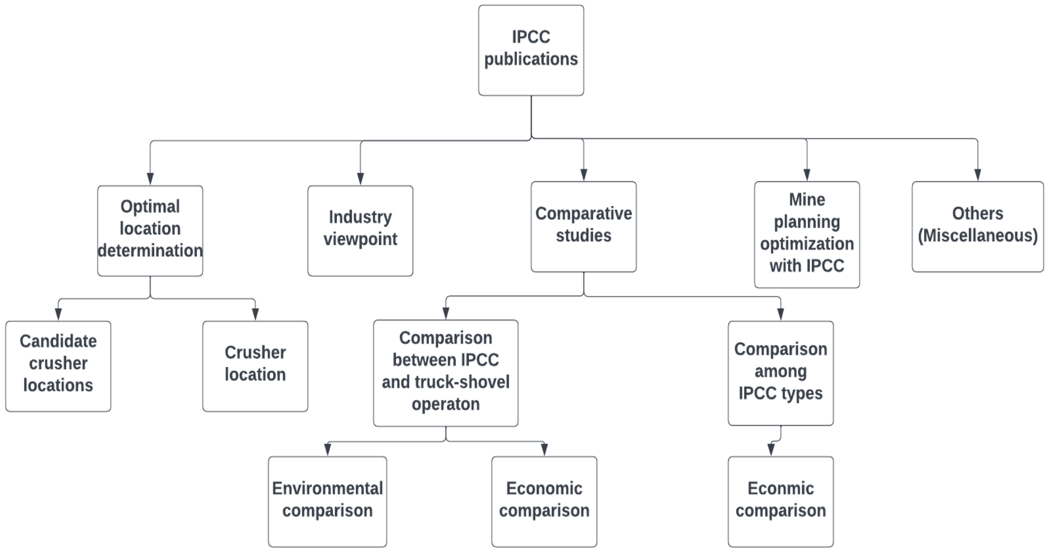


Figure 3. Categories of IPCC research.

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 1 and Table 2 of the Appendix section.

## 3.1. Crusher Location Optimization

(Konak, et al. 2007) worked on selecting an optimum crusher location based on minimum haulage distance for an aggregate production plant in Turkey. The authors considered both stationary and semi-mobile crusher cases to find the optimum in pit location. The developed algorithm calculates the average haulage distance to crusher from mine for all the possible crusher locations, for up to three relocations of the crusher during the life-of-mine. The problem with this model is that it oversimplified the calculation by taking haulage distance as the only decision variable. The significant cost savings shown by the model might be offset by the capital or relocation cost 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. Three alternatives were considered as the crusher location in a hypothetical mine with a life of 18 years. The net present value of the haulage and installation costs were calculated for each of these candidate locations throughout the life of the mine. The one with the minimum cost was selected as the optimum location. The assumptions of this model are too facile because no uncertain costs that might occur due to crusher breakdown or shovel downtime were deliberated. The model also includes systematic approach towards selecting the candidate crusher 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) came up with a more systematic approach to find an optimum in pit crusher location with an objective of minimizing haulage cost by formulating it as a single hub location problem. The crusher location is the hub which will be connected to all the destinations and source locations. Using hubs in a transportation network increases haulage capacity by not increasing the number of trucks proportionally that offers more control over traffic. Although the decision variables are haulage and installation cost like (Taheri, et al. 2009) model, the candidate locations are selected using analytical hierarchical process (AHP) by considering 6 economic factors, such as, haulage distance, reinstallation cost etc. and 11 technical factors including mine plan, geography and safety. The candidate locations are the ones that best satisfy these factors in consideration, which implicitly makes the model consider variables beyond the decision variables used in the objective function. AHP gives quantitative estimates for qualitative factors, which makes it a good tool to select the candidate locations for crushers. One potential disadvantage of using hub-spoke network is the delay and queueing during transshipment at the hubs, which is not considered in the proposed model.

(Roumpos, et al. 2014) developed an iterative method to find the optimal location of the belt conveyor distribution point in the mine perimeter with the objective of minimizing the total transportation cost throughout the life-of-mine. They used simulation to verify the model in a mine with simplified geometric assumptions and showed that the location of external waste dump and belt conveyor distribution point directly affect transportation cost. This model has advantages over (Taheri, et al. 2009) and (Konak, et al. 2007) from the context that it does not need to specify a few initial candidate locations among which the best one is to be selected. It keeps calculating the total transportation cost for all the points on the mine perimeter until the minimum cost value is attained. The authors claim that the model can be used for mines with irregular geometry. However, no case study is illustrated without the simplified geometric assumptions. The only decision variables used in the model are the operating and capital investment cost without considering any operational uncertainties, which can be viewed as a flaw of this model, because conveyor downtime by unplanned and scheduled maintenance affects the operating cost of the conveyor system.

(Paricheh, et al. 2016) proposed a heuristic model to find the optimum locations and movement time of in-pit crusher in open pit mines hierarchically. The crusher location is optimized by a linear dynamic facility location model with an objective of minimizing cost of haulage. Transferring time of crusher is optimized 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 keeps getting better. Later (Paricheh, et al. 2017) developed another model with the objective of finding out the optimum in-pit crusher location to minimize the haulage cost by modeling 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 6% from 6th year of mining, saving a total of $150 million 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 formulated the model as a P-median problem with an objective of minimizing the expected loss across all scenarios. 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 in Sungun Mine, Iran, to find 2 crusher locations across 9 different equally likely scenarios for fixed, increasing and decreasing production and cost showed that the model is capable of minimizing 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 works 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 new search algorithm to find the best candidates for in-pit crusher locations, in terms of practicality and less opportunity cost. Apart from the general rules that are used conventionally to find candidate locations, such as topography prohibition or intersection with ramps etc., the authors proposed a block aggregation policy and six specific rules to bring down the number of candidate locations significantly. The proposed model aggregates blocks located within the same phase, bench and azimuth domain to account for mining direction. The depth, pushback, required space, radius of influence and frozen economic values constraints are used to reduce the number of feasible candidate locations. The depth restriction makes sure that the minimum depth of a candidate location is the maximum distance that can be economically hauled by trucks. The first pushback is eliminated from consideration by pushback limitation because IPCC investment is not recommended before payback which is usually returned once the first pushback is mined. Blocks that cannot provide enough space for the facility are eliminated by the required space rule. The number of candidates is further reduced by only keeping the blocks having the lowest economic value underneath a block. Validation of the algorithm in Sungun mine, with 79000 blocks and 2063 pushback-bench-slices yielded only 23 candidate locations, while applying the general rule showed 283 candidates. The results also indicated that the number of pushbacks and origin selection affect the number of candidate locations notably. This algorithm does not consider geotechnical (adjacency of blocks) and shape restrictions which are important factors to define a candidate location.

### 3.1.1. Drawbacks of Crusher location Optimization Models

The major problem of the crusher location optimization models is that the mine plan is not considered for location optimization. Hence, it cannot guarantee NPV maximization in the long run.

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).

## 3.2. Industry Perspective

(Morris 2008) explained a few industry practices on several productivity issues of semi-mobile (SMIPCC) and full-mobile IPCC (FMIPCC) and the effect of IPCC's interaction on the availability and utilization of trucks and shovels. While this article does not involve any rigorous mathematical modeling, it gives readers a general idea on how large mining companies are dealing with in-pit crushers in real mining operations. The author also explained that semi mobile IPCC tends to have a better overall utilization than fully mobile IPCC because of its lesser dependence on shovel feed. The article highlighted that the service meter unit, defined as the ratio of engine run time and effective working time, is high in IPCC systems. The reason is that they are hardly shut down when idling, unlike trucks or shovels, to avoid queuing at dump pocket. Because of the high service meter unit, prediction of fuel consumption from historic data might lead to distorted results while planning if there is substantial idle time during operation. A comparison of instantaneous and average throughput between SMIPCC and FMIPCC demonstrated that FMIPCC gains slightly better throughput than SMIPCC. This is a good article for beginners to get along with some IPCC concerns and understand the industry perspective.

Another non-academician (McCarthy 2011) highlighted the risks and scopes of replacing truck shovel haulage system by IPCC and the ways to deal with the difficulties that exist in introducing IPCC. As an industry member, the author explained how employees might be avert to new technologies such as IPCC despite the financial gains it provides and the importance of proper management planning and training to overcome this aversion. This article is a commendable effort that edifies beginners on the type of IPCC, the difference between them, the advantages of IPCC and the numerous risks associated with it. While increasing oil price and labor cost favor the introduction of IPCC, the loss of slope stability and mobility makes the use of IPCC in large deep mines dicey. The author recommended probabilistic risk assessment for the areas of uncertainty associated with IPCC, such as supply prices and availability, differences between oil and electricity price etc., during the planning stage by using Monte Carlo simulation, and presented two examples of decision making based on risk assessment used in Sandvik mine by Snowden Mining Company. This article helps readers to get an initial understanding about 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) addressed the pros, such as, cost savings, less emission etc., and challenges, i.e., large investment, loss of flexibility etc., of employing FMIPCC in deep mines and proposed a theoretical design approach to implement FMIPCC in such mines using hydraulic excavators. The model proposes mine sinking by truck-shovel and pit widening by conveyor system. The use of hydraulic shovel allows narrow bench width to facilitate high ramp angles which is necessary for deep mines to keep the stripping ratio in check. The model proposes radial and parallel belt conveyor moves to minimize the frequency of belt extensions. The authors definitely explored an aspect of IPCC through implementing it in deep mines, which has not been in practice before. However, the problem with this model is that it is still a theory and there has not been any practical execution of the idea in any deep mines yet to examine 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.

## 3.3. Comparative Studies

### 3.3.1. 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 tradition 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 results that were contradictory to (Norgate and Haque 2013).

(Erkayaoğlu and Demirel 2016) investigated the environmental impact of trucks and conveyors, used in mining during utilization stage, in terms of climate change and acidification by life cycle assessment in a Turkish mine. The authors selected these two categories because they have the maximum impact on human health and environment compared to the other categories, such as, land use, eco toxicity etc. Another reason to use these factors for this comparative study is that the data required for LCA study is not readily available because of the confidentiality of mining companies and the uncertainty in data for these two categories is usually minimum. The study revealed that trucks are more environmentally burdensome than conveyors in acidification category because of its dependence on diesel fuel during operation, which produces nitrogen and Sulphur oxides, major components causing acidification, upon burning. On the contrary, conveyors are more detrimental than trucks from climate change perspective because the electricity used to run the conveyors is produced primarily from lignite coal, which produces greenhouse gas like carbon dioxide when burns. Studies like this show the importance of LCA as a powerful tool for equipment selection in mining. However, this study is case specific, and the assumptions used apply in Turkish mines only. Therefore, using the results of the study without appropriate modifications in assumptions for equipment selection of other countries' mines might be inappropriate and erroneous.

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.

### 3.3.2. 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 in 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) investigated alternative IPCC configurations for pre-stripping application in an open pit coal mine to demonstrate that introducing parallel conveyor lines with spreaders can improve IPCC productivity by 9.4–12.6% and provide more profit compared to single conveyor line despite having a higher equivalent unit cost. Simulation of five different IPCC configurations with and without parallel conveyor lines assuming 25% loss due to unavoidable delays and a weibull failure model for conveyor and spreader showed that an IPCC system comprised of 3 conveyors with 4 parallel conveyor lines generated 20% higher annual production which makes up for the 15% higher operating cost compared to its single conveyor line counterpart. The assumed constant process delay and weibull failure distribution are subject to the type of operation and any changes to these assumptions might affect the results substantially.

(Dzakpata, et al. 2016) presented a numerical comparative study among shovel, trucks and IPCC based on utilized time, operating time and valuable operating time. The results showed that shovels lose about 40% of its operating time spotting trucks, which demonstrate that introduction of IPCC system can significantly improve the performance of shovel by improving the productivity by 20 to 25%. The study also showed that while trucks attain higher utilization and operating time than conveyors, the conveyors offer 25% higher valuable operating time than trucks because trucks travel empty about 38% of their operating time. The use of multiple performance metrics makes this study a reasonable tool for equipment selection decision. However, the authors did not reveal the data and mining data is highly case specific and context dependent (mine condition, haul routes etc.). Therefore, using the results of this study for any mine without further appropriate assumptions and modifications might not help taking the best decision.

(de Werk, et al. 2017) presented the Comparison of two material handling systems, Semi-mobile IPCC(SMIPCC) and traditional truck-shovel (TS) system in terms of haulage cost in a hypothetical iron ore mine. Results indicate that although the capital cost of IPCC is higher than that of TS, the total cost of IPCC is lower due to its lower operational cost. Sensitivity analysis showed that while both methods were sensitive to production rate, TS is more sensitive to fuel prices than IPCC because of the smaller number of trucks needed with IPCC. As electricity prices are more stable than fuel prices historically, IPCC has less risk compared TS in terms of operational cost. Risk analysis via Monte Carlo Simulation in terms of electric 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 labor cost, which results in a 34% saving in net present cost over a LOM of 20 years.

(Bernardi, et al. 2020) developed 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. They ran the simulation model for a simplified cone shaped hypothetical mine with 1500m depth and 15 benches with an initial number of trucks, maintenance, operating and capital costs on an hourly basis. The simulated cost results are used to calculate NPV and the number of trucks is adjusted based on the difference between target production and actual production. The simulation was run for five iterations and the results improved significantly with semi-mobile IPCC generating 10% higher NPV and more proximity to production targets. The model yields quick results which is helpful to decide on the fleet and type of IPCC system requirement in open pit mines. However, the cost model and mine geometry used here are too simple and the input parameters are too inaccurate to represent any typical mine project complexity.

### 3.3.3. 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 (Ben-Awuah, et al. (2010); (Norgate and Haque 2013).

- ✔ Economic comparison between IPCC and TS systems is also case specific. The cost of labor 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.

### 3.4. Simultaneous Optimization of IPCC and Mine Plan

The most recent addition to IPCC literature is the simultaneous optimization 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, which makes large mining companies avert 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 research in finding out 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 agenda that need to 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 proposed an MILP model to simultaneously optimize crusher location inside the pit to minimize total haulage cost. The model also optimizes fleet requirement and eventually maximize the NPV of the mine by considering the dynamic changes in block sequencing by the location and relocation of the IPCC. One main feature of the proposed model is that it determines the block destination in or external pit crusher/waste dump along with the extraction sequences. A comparison of the proposed model with two existing long term planning models without IPCC was presented. The model showed substantial increase in NPV, decrease in fleet requirement and changes in extraction sequence compared to the two benchmark models M2 and M3, that optimize scheduling and fleet simultaneously and separately, respectively. The proposed model increased NPV by 2.3% and 3.4% compared to M2 and M3, respectively. The required fleet size was 75% less than the required fleet size of M3. The improvements shown in the model surely proves the value of IPCC in open pit mines. However, this model is strictly deterministic because all the parameter values related to costs in consideration, grade and tonnage of each block etc., are known with certainty, which is hardly the case in real life mines. The reliability of this model can be enhanced by incorporating uncertainties associated with some of the vital parameters such as grade, price and cost.

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 the 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 optimization 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 maximizes NPV by maximizing block values and minimizing 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 maximize 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.

### 3.4.1. Areas to Improve

The simultaneous optimization 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 summarized below.

The simultaneous optimization 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 summarized 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 optimization 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).

Following the footsteps of the limited research work exist will lead to more comprehensive simultaneous optimization model in future.

## 3.5. 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 behavior. Another significant contribution of this thesis is the list of all the IPCC systems employed across the world by different companies in different mines.

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 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 modeling to determine the optimum transition time from Truck-shovel to IPCC. The model 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.

# 4. Non-departmental Analogies Suitable for Mine Planning

Vehicle routing problem, more specifically capacitated vehicle routing problem (CVRP), which is a commonly used idea in industrial engineering, can be useful for mine planners because the analogy of vehicle routing can be brought into the haulage management to minimize cost of material handling. The basic idea of vehicle routing problem is to meet the demand of customers with limited resources. The objective in general is to choose the best or shortest possible route to minimize the cost of movement. We will review a few vehicle routing problem literatures here to put light on the fact that these ideas can be useful in mining engineering too.

(Xiao, et al. 2012) proposed a CVRP model to minimize 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 tradeoff 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 behavior 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 the total fixed cost and fuel consumption. The non-linear objective function is linearized which can be solved quickly using solvers like CPLEX when the number of customers (destinations) is small. An improved simulated annealing algorithm has been proposed to achieve optimal or near optimal solutions which outperforms CPLEX and simulated annealing approach when the number of destinations is high (n>=50). The maximum optimality gap is always reasonable (<5%) and the CPU time is remarkably short when n is large. Model shows that the fuel consumption is always larger for stochastic vehicle speed than that with fixed speed model which indicates that assuming fixed speed would result in underestimation of cost of fuel consumption is always larger than that with fixed speed model. Model does not account for randomness of demand and Vehicle speed is not necessarily normally distributed.

(Feld, et al. 2019) proposed a hybrid solution approach to CVRP to minimize total distance travelled using quantum annealer device. The challenge is to translate the CVRP into a quadratic unconstrained binary optimization problem so that it can be mapped to D-wave quantum annealer. Comparison of the hybrid solution approach to classical 2-phase heuristics method shows that it does not offer any patent advantage in terms of solution quality or computation time in its current state. However, the approach shows how to split complex combined problems and solve them in a hybrid way using a quantum annealer. Future research should investigate the effect of the of the hardware on efficiency of the problem mapping, the necessity of using additional tools like QBSolv etc.

(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 whole point of introducing IPCC in big mines is to reduce the number of trucks to minimize haulage cost. The fleet management in mine planning might be optimized 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 minimization 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 needs to be explored more is 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 opportunities to formulate more efficient models to optimize IPCC location and relocation using this particular field of study.

## 5. Future Research Direction

As discussed in the previous sections, mines are getting 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. The comparisons among most recent short-term planning and IPCC literature show that while very few models can generate a strategic plan with IPCC in place ((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 (Samavati, et al. 2018), 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.

Commercial tools like Geovia Whittle, Minesched, XPAC, Leapfrog etc., can generate long and short-term production schedule for traditional truck-shovel 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 IPCC which is considered to the future of open pit mines but 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 maximize 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 optimization with Semi-Mobile IPCC.

### 5.1. A Brief Research Proposal

The authors would like to develop a mixed integer linear programming model with the objective of generating monthly production schedules that minimize the haulage cost with IPCC system in place. The assumptions are:

1. The IPCC system is semi-mobile.
2. The optimum locations and relocation time of the crusher is known throughout the life of mine from strategic planning.
3. There is no waste crusher. Waste material goes directly to external waste dumps.
4. The ore and waste faces are labelled. Hence, ore shovels will be assigned to ore faces and waste shovels will go to waste faces only.
5. The time horizon is 12 to 36 months.

6. The tonnage and grades of each mining cut location is known with certainty.

The objective function will have two components. The first component will calculate the cost of hauling waste material to waste dumps and ore material to crusher using regular diesel trucks. The second part calculates the cost of conveying ore material from crusher to processing plant. The following Figure 5 shows the transportation of waste and ore with and without in-pit crusher in place.

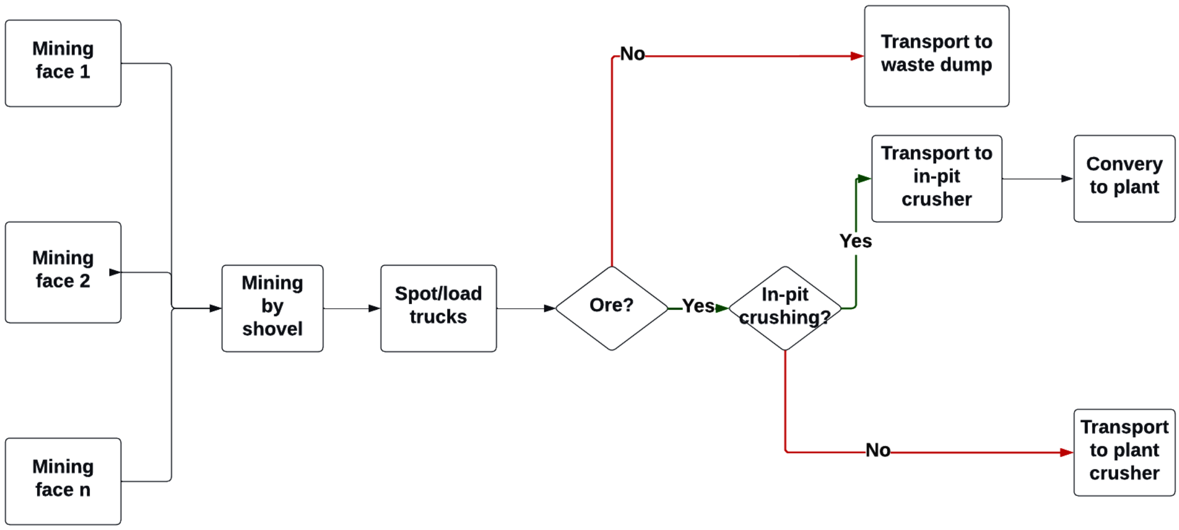


Figure 4. Flow of material from mine to crusher, plant and waste dump.

Obj function, f = cost of transporting material to crusher or waste dump from mine by trucks + cost of conveying ore material from crusher to processing plant

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 optimized 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 case study will be run for two cases: one with IPCC system with reduced number of trucks and the other with traditional truck-shovel haulage system without IPCC. The comparison of these two scenarios will verify whether the SMIPCC offers cost benefits by meeting long-term production targets within short-term planning horizon of 1 to 3 years. A mathematical formulation with case study will follow.

## 6. Conclusions

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.

## 7. References


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## 8. Appendix

Table 1:Comparison among key aspects of IPCC publications

| **Comparison of post 2007 IPCC papers** | **Key Aspects** | | | | |
|---|---|---|---|---|---|
| | Integration with Long-term Planning | Integration with Short-term planning | Type of IPCC | Case study | Uncertainty |
| Konak et al. (2007) | No | No | Fixed, Semi-mobile | √ | × |
| Phil Morris (2008) | No | No | Fixed, Semi-mobile | × | × |
| Taheri et al. (2013) | No | No | Fixed | √ | × |
| McCarthy (2011) | No | No | Fixed, semi-mobile, fully mobile | × | × |

| **Comparison of post 2007 IPCC papers** | **Key Aspects** | | | | |
|---|---|---|---|---|---|
| | Integration with Long-term Planning | Integration with Short-term planning | Type of IPCC | Case study | Uncertainty |
| Utley (2011) | No | No | Fixed, semi-mobile, fully mobile | × | × |
| Klanfer, Vrkjln (2012) | No | No | Fixed, fully mobile | √ | × |
| Rahmanpour et al. (2013) | No | No | Semi-Mobile | √ | × |
| Roumpos et al. (2014) | No | No | Fixed, semi-mobile, fully mobile | √ | × |

| **Comparison of post 2007 IPCC papers** | **Key Aspects** | | | | |
|---|---|---|---|---|---|
| | Integration with Long-term Planning | Integration with Short-term planning | Type of IPCC | Case study | Uncertainty |
| Londono et al. (2013) | No | No | Fixed, semi-mobile, fully mobile | √ | × |
| Norgate, Haque (2013) | No | No | Fixed, semi-mobile, fully mobile | √ | × |
| Dean et al. (2015) | No | No | Fully Mobile | √ | × |
| Erkayaoglu, Demirel (2016) | No | No | Fixed, semi-mobile, fully mobile | √ | × |
| Ritter (2016) | No | No | Semi-mobile | √ | √ |

| **Comparison of post 2007 IPCC papers** | **Key Aspects** | | | | |
|---|---|---|---|---|---|
| | Integration with Long-term Planning | Integration with Short-term planning | Type of IPCC | Case study | Uncertainty |
| Paricheh, Osanloo (2016) | No | No | Semi-mobile | √ | √ |
| Paricheh et al. (2016) | No | No | Semi-mobile | √ | × |
| De Wark et al.(2017) | No | No | Semi-mobile | √ | × |
| Paricheh et al. (2017) | No | No | Semi-mobile | √ | × |
| Abbaspour et al. (2018) | No | No | Fixed, semi-mobile, fully mobile | √ | × |

| **Comparison of post 2007 IPCC papers** | **Key Aspects** | | | | |
|---|---|---|---|---|---|
| | Integration with Long-term Planning | Integration with Short-term planning | Type of IPCC | Case study | Uncertainty |
| Abbaspour, Carsten (2019) | No | No | Fully mobile | √ | × |
| Nunes et al. (2019) | No | No | Semi-mobile | √ | × |
| Paricheh, Osanloo (2019a) | Yes | No | Semi-mobile | √ | × |
| Paricheh, Osanloo (2019b) | No | No | Fixed, Semi-mobile | √ | × |
| Bernardi et al. (2020) | No | No | Fixed, Semi-mobile | √ | × |

| **Comparison of post 2007 IPCC papers** | **Key Aspects** | | | | |
|---|---|---|---|---|---|
| | Integration with Long-term Planning | Integration with Short-term planning | Type of IPCC | Case study | Uncertainty |
| Samavati et al (2020) | Yes | No | Fully Mobile | √ | × |
| Shamsi, Nehring (2021) | No | No | Semi-mobile | √ | × |
| DingBang, Yahsar (2021) | Yes | No | Semi-mobile | √ | × |
| Wachira et al. (2021) | No | No | Semi-mobile | √ | × |
| Shamsi et al. (2021) | Yes | No | Semi-mobile | √ | × |

Table 2: Comparison among objectives optimized and solution tool used in IPCC papers

| Comparison of post 2007 IPCC papers | Objectives | | | | | | | | | | | Solution tool |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Economic Comparison with TS | Environmental comparison with TS | Comparison among IPCCs (Economic) | Optimum conveyor design/ exit location determination | Optimum Crusher Location determination | Crusher relocation on time optimization | Candidate crusher location determination | Transportation cost minimization | IPCC risk assessment | NPV maximization | IPCC capacity/performance determination | |
| Konak et al. (2007) | × | × | × | × | √ | × | × | √ | × | × | × | NS |
| Phil Morris (2008) | × | × | √ | × | × | × | × | × | × | × | × | NS |
| Taheri et al. (2013) | × | × | × | × | × | √ | × | √ | × | × | × | NS |
| McCarthy (2011) | × | × | √ | × | × | × | × | × | × | × | × | NS |
| Utley (2011) | × | × | √ | × | × | × | × | × | × | × | × | NS |

| **Comparison of post 2007 IPCC papers** | **Objectives** | | | | | | | | | | | **Solution tool** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Economic Comparison with TS | Environmental comparison with TS | Comparison among IPCCs (Economic) | Optimum conveyor design/ exit location determination | Optimum Crusher Location determination | Crusher relocation on time optimization | Candidate crusher location determination | Transportation cost minimization | IPCC risk assessment | NPV maximization | IPCC capacity/performance determination | |
| Klanfer, Vrkjln (2012) | × | × | √ | × | × | × | × | √ | × | × | × | NS |
| Rahmanpour et al. (2013) | × | × | × | × | √ | × | √ | √ | × | × | × | NS |
| Roumpos et al. (2014) | × | × | × | √ | × | × | × | √ | × | × | × | MATLAB |
| Londono et al. (2013) | × | × | × | √ | × | × | × | × | × | × | × | NS |

| **Comparison of post 2007 IPCC papers** | **Objectives** | | | | | | | | | | | **Solution tool** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Economic Comparison with TS | Environmental comparison with TS | Comparison among IPCCs (Economic) | Optimum conveyor design/ exit location determination | Optimum Crusher Location determination | Crusher relocation time optimization | Candidate crusher location determination | Transportation cost minimization | IPCC risk assessment | NPV maximization | IPCC capacity/performance determination | |
| Norgate, Haque (2013) | × | √ | × | × | × | × | × | × | × | × | × | Simapro |
| Dean et al. (2015) | × | × | × | √ | × | × | × | √ | × | × | × | NS |
| Erkayaoglu, Demirel (2016) | × | √ | × | × | × | × | × | × | × | × | × | Simapro 7.3 |
| Ritter (2016) | √ | × | × | × | × | × | × | × | × | × | √ | ARENA /VBA |
| Paricheh, Osanloo (2016) | × | × | × | × | √ | × | × | √ | × | × | × | CPLEX |

| **Comparison of post 2007 IPCC papers** | **Objectives** | | | | | | | | | | | **Solution tool** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Economic Comparison with TS | Environmental comparison with TS | Comparison among IPCCs (Economic) | Optimum conveyor design/ exit location determination | Optimum Crusher Location determination | Crusher relocation on time optimization | Candidate crusher location determination | Transportation cost minimization | IPCC risk assessment | NPV maximization | IPCC capacity/performance determination | |
| Paricheh et al. (2016) | × | × | × | × | √ | √ | × | × | × | √ | × | GAMS, Excel |
| De Wark et al.(2017) | √ | × | × | × | × | × | × | × | × | × | × | NS |
| Paricheh et al. (2017) | × | × | × | × | √ | × | × | √ | × | × | × | GAMS |
| Abbaspour et al. (2018) | × | √ | × | × | × | × | × | × | √ | × | × | NS |

| **Comparison of post 2007 IPCC papers** | **Objectives** | | | | | | | | | | | **Solution tool** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Economic Comparison with TS | Environmental comparison with TS | Comparison among IPCCs (Economic) | Optimum conveyor design/ exit location determination | Optimum Crusher Location determination | Crusher relocation time optimization | Candidate crusher location determination | Transportation cost minimization | IPCC risk assessment | NPV maximization | IPCC capacity/performance determination | |
| Abbaspour, Carsten (2019) | √ | × | × | × | × | × | × | √ | × | × | × | NS |
| Nunes et al. (2019) | √ | × | × | × | × | × | × | √ | × | × | × | Excel VBA |
| Paricheh, Osanloo (2019a) | × | × | × | × | √ | × | × | √ | × | √ | × | CPLEX |
| Paricheh, Osanloo (2019b) | × | × | × | × | × | × | √ | × | × | × | × | NS |
| Bernardi et al. (2020) | × | × | √ | × | × | × | × | × | × | √ | × | ARENA |

| **Comparison of post 2007 IPCC papers** | **Objectives** | | | | | | | | | | | **Solution tool** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Economic Comparison with TS | Environmental comparison with TS | Comparison among IPCCs (Economic) | Optimum conveyor design/ exit location determination | Optimum Crusher Location determination | Crusher relocation on time optimization | Candidate crusher location determination | Transportation cost minimization | IPCC risk assessment | NPV maximization | IPCC capacity/performance determination | |
| Samavati et al (2020) | × | × | × | √ | √ | × | × | × | × | √ | × | Gurobi |
| Shamsi, Nehring (2021) | √ | × | × | × | × | × | × | √ | × | × | × | NS |
| DingBang, Yahsar (2021) | × | × | × | √ | × | √ | × | √ | √ | × | × | MATLAB/CPLEX 12.7 |
| Wachira et al. (2021) | × | × | × | × | × | × | × | × | × | × | √ | NS |
| | × | × | × | × | √ | √ | × | √ | × | √ | × | CPLEX 12.7 |

| Comparison of post 2007 IPCC papers | Objectives | | | | | | | | | | | Solution tool |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Economic Comparison with TS | Environmental comparison with TS | Comparison among IPCCs (Economic) | Optimum conveyor design/ exit location determination | Optimum Crusher Location determination | Crusher relocation time optimization | Candidate crusher location determination | Transportation cost minimization | IPCC risk assessment | NPV maximization | IPCC capacity/performance determination | |
| Shamsi et al. (2021) | | | | | | | | | | | | |

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 | Multiple processing destinations | Stochastic or Deterministic | IPCC/ Regular TS haulage |
|---|---|---|---|---|---|---|---|
| Eivazy and Askari-Nasab (2012) | Block extraction sequence generation | 12 to 36 months | CPLEX | Minimize cost of mining, processing, material movement and waste rehabilitation **subject to** head grade, precedence and capacity constraints | Yes | Deterministic | TS |
| Liu, Kozan (2012), Liu, Kozan, Wolff (2013,2016) | Block extraction with equipment scheduling; multi-stage, multi-resource scheduling | Not specified | C++ | Minimize makespan of mining activities drilling, blasting and excavation **subject to** capacity of mining equipment and precedence constraints | No | Deterministic | TS |
| L'Heureux et al. (2013) | Block extraction, shovel allocation drilling and blasting schedule. | 3 months | IBM ILOG CPLEX | Minimize cost of shovel movement, drilling and blasting cost **subject to** precedence of activities, capacity and blending constraints | No | Deterministic | TS |

| Comparison of post 2010 short-term papers | key Aspects | Time horizon | Solution tool | Objectives | Multiple processing destinations | Stochastic or Deterministic | IPCC/ Regular TS haulage |
|---|---|---|---|---|---|---|---|
| Mousave et al. (2016b) | Block sequencing problem with equipment scheduling | Six months | CPLEX | Minimize 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, | No | 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 minimize the stockpile rehandling cost **constrained by** upper and lower bounds of ore grade. | Yes | Deterministic | TS |

| Comparison of post 2010 short-term papers | key Aspects | Time horizon | Solution tool | Objectives | Multiple processing destinations | Stochastic or Deterministic | IPCC/ Regular TS haulage |
|---|---|---|---|---|---|---|---|
| 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. | No | Deterministic | TS |

| Comparison of post 2010 short-term papers | key Aspects | Time horizon | Solution tool | Objectives | Multiple processing destinations | Stochastic or Deterministic | IPCC/ Regular TS haulage |
|---|---|---|---|---|---|---|---|
| Liu, Kozan (2017) | An innovative mine management system by integrating a series of mathematical models for long-term (ultimate pit limit determination), mid-term block sequencing (over quarterly, half-yearly or yearly time periods), and operational level planning of equipment (with a job-shop scheduling model) to achieve an | 18 weeks | CPLEX | The long and medium term MIP models maximize 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 minimizes the makespan and tardiness in job completion times **subject to** block precedence and capacity constraints. | No | Deterministic | TS |

| Comparison of post 2010 short-term papers | key Aspects | Time horizon | Solution tool | Objectives | Multiple processing destinations | Stochastic or Deterministic | IPCC/ Regular TS haulage |
|---|---|---|---|---|---|---|---|
| | overall mining efficiency | | | | | | |
| Blom et al. (2014,2016) | A decomposition based heuristic model to solve a set of mine-side (extraction) 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 | Yes | Deterministic | TS |
| Blom (2017) | A rolling planning horizon-based MIP model to generate multiple short-term production schedules | 13 weeks | IMB CPLEX | Optimize equipment use and shovel movement **constrained by** precedence relationships, blending requirements, equipment availabilities and trucking hours considering multiple processing paths. | Yes | Deterministic | TS |

| Comparison of post 2010 short-term papers | key Aspects | Time horizon | Solution tool | Objectives | Multiple processing destinations | Stochastic or Deterministic | IPCC/ Regular TS haulage |
|---|---|---|---|---|---|---|---|
| Upadhyay, Askari-Nasab (2016, 2017) | Simulation optimization model to generate optimum mining schedule by shovel allocation | 12 months | CPLEX, ARENA | Maximizing shovel utilization, minimizing deviation in production and grade from expected/target, minimizing shovel movement **subject to** production capacity, grade blending and precedence constraints. | Yes | Operational uncertainty | TS |
| Manriquez et al. (2019) | A framework to optimize short-term planning of open pit mines | NS | Python | Minimizing maximum deviation between ore tonnage sent to plant and plant capacity, minimizing maximum deviation between metal fines and the expected metal fines in processing plant and minimizing overall shovel fleet movement cost minimization **subject to** grade blending and precedence constraints. | Yes | Deterministic | TS |
| Manriquez et al. (2020) | Simulation optimization model to generate short-term extraction sequence | 18 months | UDESS | Maximize value of extraction **subject to** precedence, blending and equipment availability constraints. | Yes | Deterministic | TS |

| **Comparison of post 2010 short-term papers** | **key Aspects** | **Time horizon** | **Solution tool** | **Objectives** | **Multiple processing destinations** | **Stochastic or Deterministic** | **IPCC/ Regular TS haulage** |
|---|---|---|---|---|---|---|---|
| Matamoros, Dimitrakapoulos (2016) | Simultaneous optimization of fleet and production schedules | 12 months | CPLEX, C++ | Eight component objectives to minimize 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. | No | Stochastic (geological and fleet uncertainty) | 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. | Yes | Geological uncertainty | TS |

| Comparison of post 2010 short-term papers | key Aspects | Time horizon | Solution tool | Objectives | Multiple processing destinations | Stochastic or Deterministic | IPCC/ Regular TS haulage |
|---|---|---|---|---|---|---|---|
| Matamoros, Jewbali (2013, 2018) | A multi-stage planning process that incorporates potential short-term variability in the long-term planning process. | NS | NS | Maximizes NPV and minimizes 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. The compliance of short-to long term production schedules and performance is expected to augment the probability of meeting production targets and increased productivity. | Yes | Geological and operational uncertainty | TS |
| Bodon, Sandman (2010, 2011) | Model shows how integrating optimization within a simulation allows a more accurate representation of the system, providing a better solution although | 9 days | Lingo | Maximize tonnes mined and shipped, minimize 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. | Yes | Operational Uncertainty | TS |

| Comparison of post 2010 short-term papers | key Aspects | Time horizon | Solution tool | Objectives | Multiple processing destinations | Stochastic or Deterministic | IPCC/ Regular TS haulage |
|---|---|---|---|---|---|---|---|
| | with a longer run time. | | | | | | |
| 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 | Minimize production deviation and maximize equipment utilization **subject to** processing capacities and equipment availability. | No | Geological Uncertainty and equipment uncertainty | TS |
| Rahmanpour, Osanloo (2016) | stochastic optimization model to capture the effects of geological uncertainties on short and long | 30 months | NS | minimize cost of mining **subject to** equipment capacity, ore quality and mill demand constraints | No | Geological Uncertainty | TS |

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

| Comparison of post 2010 short-term papers | key Aspects | Time horizon | Solution tool | Objectives | Multiple processing destinations | Stochastic or Deterministic | IPCC/ Regular TS haulage |
|---|---|---|---|---|---|---|---|
| Both, Dimitrakopoulos (2020) | Optimization model for simultaneous optimization of short-term extraction sequence and fleet management, in contrary to the traditional approach of optimizing production schedule first and then fleet allocation | 12 months | NS | maximize total profit/revenue and production by minimizing risk of underproduction by shovel and trucks **constrained by** precedence relationships, production targets and number of trucks available | Yes | Geological and equipment performance uncertainty | TS |

**Abbreviations**

IPCC – In-pit crushing and conveying

SMIPCC – Semi-mobile IPCC

FMIPCC – Fully-mobile IPCC

TS – truck-shovel