

# Short-Term Scheduling Optimization for In-Pit Crushing and Stockpiling Operations Considering Shovel Movement

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## ABSTRACT

*Efficient short-term production scheduling is essential for maintaining productivity and equipment utilization in truck–shovel mining systems. However, most existing scheduling approaches focus primarily on tonnage and grade requirements while overlooking the operational consequences of excessive shovel movement. This study presents a mixed-integer linear programming (MILP) framework that explicitly incorporates shovel movement into weekly scheduling while ensuring balanced ore and total tonnage allocation across multiple shovels. The model is applied to a two-shovel, 40-block case study, where the optimized schedule reduces one shovel’s weekly travel distance by 17% compared to a baseline assignment that ignores movement. The optimization reallocates longer movements to the other shovel while maintaining overall production targets, demonstrating that strategic scheduling of shovel relocation can increase effective working time, improve equipment utilization, and enhance coordination with downstream processes. These results highlight the practical value of incorporating movement minimization into short-term scheduling to generate more operationally efficient mining sequences.*

## 1. Introduction

In-pit crushing and stockpiling (IPCS) systems are attracting increasing attention in large-scale surface mines as an alternative to truck-haulage-dominated material-handling systems, due to their significant potential to reduce greenhouse gas emissions, fuel consumption, and overall operating costs. Despite these benefits, efficiently integrating IPCS into daily operations remains challenging. Short-term production scheduling in mines is highly dynamic and influenced by localized operational variability, shovel movement decisions, crusher throughput limitations, and unplanned disruptions such as equipment failures, ramp congestion, and face availability. As a result, there is a critical need for robust, optimization-driven decision support tools that can generate practical short-term IPCS schedules while accounting for equipment mobility and operational uncertainty.

A substantial body of research has examined long-term and medium-term mine planning under deterministic or stochastic conditions. Foundational works by Hooman Askari-Nasab, including advances in block sequencing, mixed integer linear programming (MILP) formulations, and stochastic optimization, have laid strong analytical foundations for optimizing material extraction [1-3, 7-11, 13, 21, 22]. These studies highlight the importance of integrating operational constraints and equipment dynamics into mine planning models and demonstrate how mathematical programming can significantly improve resource utilization.

However, long-term mine plans provide limited operational guidance for day-to-day decisions such as shovel deployment, face sequence selection, and material routing to crushers or stockpiles.

Alternatively, short-term mining optimization mainly focused on truck dispatching and shovel allocation. Early work established heuristic and rule-based dispatching, while more recent approaches introduced simulation-based optimization and artificial intelligence (AI), including:

- multi-agent truck dispatching using the distributed constraint optimization (DCO) approach [17, 18, 20],
- integrated optimization and simulation approaches for equipment allocation [15, 16, 23, 24],
- stochastic simulation of shovel-truck performance, including equipment failures and route variability [6, 12, 14, 19].

These studies collectively demonstrate that real-time operational decisions have a significant impact on production rates and system stability. Among those decision variables, shovel movement in IPCS operations is the main interest of this study, because shovel–face switching, travel distances, and relocation times directly influence the stockpile’s feeding stability. Unlike truck-based haulage systems where haul trucks can queue and amplify production variability, IPCS tends to exhibit greater resilience to short-term disturbances because the continuous conveying system smooths fluctuations in shovel output. However, extended interruptions—particularly those related to shovel relocation, crusher downtime, or face access delays—can still significantly affect system performance due to the limited ability to build large buffers near the crusher. Yet, most existing short-term mining optimization models assume fixed shovel positions or do not consider shovel mobility at all. Studies that do consider shovel movement (e.g., task assignment models, stochastic dispatching) generally pertain to truck–shovel systems, which are not suitable for the IPCS mining method.

Rolling-horizon optimization techniques have shown promise in short-term mining operations due to their ability to handle evolving system states [4, 5]. Their findings consistently show that dynamic adjustments significantly outperform static plans when operational variability is high.

Given the maturity of simulation tools and the demonstrated effectiveness of mixed-integer programming for mine planning, there is a clear opportunity to combine these techniques into a dynamic short-term scheduling framework for IPCS that incorporates shovel movement explicitly. Such a framework can improve crusher utilization, reduce shovel idle times, and stabilize material flow. Integrating this framework within a rolling-horizon control loop allows it to adjust to disturbances in real time, thus providing a practical decision support tool for daily operational control.

Inspired by the gaps identified in the literature and building on previous optimization–simulation advancements, this research proposes a novel short-term scheduling framework for IPCS using mixed-integer programming combined with discrete-event simulation. This integrated approach aims to provide operationally feasible, high-resolution schedules that account for shovel movement, variable productivity, crusher capacities, and stochastic operational disruptions. The resulting methodology not only advances the state of the art in IPCS optimization, but also contributes to the broader field of dynamic short-term mine operations management.

## 2. Framework and Formulations

### 2.1. Problem Scope

We consider a short-term scheduling problem in an open-pit mine with an IPCS layout and a set of shovels  $S$  that can be assigned to extraction blocks  $k$ . Decisions include shovel-to-face assignments

and shovel relocation actions. The simulation captures stochastic digging rates, relocation travel times, equipment downtime, and queue formation.

### 2.1.1. Key Assumptions

1. Shovels can be relocated between faces, but relocation consumes time (lost production).
2. Crusher and conveyor capacities are deterministic per time unit but subject to stochastic downtime modeled in the simulator.
3. The operating performance of shovels and trucks—including swing time, dump time, spot time, and travel speed—is sampled from predefined statistical distributions, and equipment is subject to potential failures during the simulation.
4. All decisions implemented at the beginning of simulation rolling horizon are enforced; subsequent decisions are advisory and may be revised in later re-optimizations.

## 2.2. Methodology

### 2.2.1. Rolling-Horizon Control Loop (Overview)

1. Initialize system state from the digital twin (shovel positions, stockpile levels, crusher status).
2. Solve the MIP for the first time interval.
3. Implement decisions in the simulation model.
4. Simulate system evolution using Arena, with stochastic realizations.
5. Update system state and repeat from step 2 until the entire operational period is complete.

### 2.2.2. Mixed-Integer Programming Formulation

1. Indices

$k$  Block indices ( $k \in \{1, 2, \dots, K\}$ )

$s$  Shovel indices ( $s \in \{1, 2, \dots, S\}$ )

$t$  Period indices ( $t \in \{1, 2, \dots, T\}$ )

2. Sets and parameters

$r^t$  Revenue generated by sending one unit of material from the stockpile in the period  $t$  to the crusher minus the dozing, reclaiming, crushing, conveying, processing, and selling costs

$wt^t$  Cost of hauling one ton of waste material by one kilometer in the period  $t$

$ot^t$  Cost of hauling one ton of ore material by one kilometer in the period  $t$

$D_k$  Distance of the block  $k$  to its destination, waste dump, or stockpile

$D_{i,j}$  Distance between block  $i$  and block  $j$  through the road network

$S_s$	Shovel moving cost by kilometer
$O_k$	Ore tonnage in the block $k$
$w_k$	Waste tonnage in the block $k$
$O_r$	Ore tonnage in reserve
$w_r$	Waste tonnage in reserve
$c$	Capacity of stockpile
$pu$	Upper bound on ore processing capacity in tons
$pl$	Lower bound on ore processing capacity in tons
$mu$	Upper bound on mining capacity in tons
$ml$	Lower bound on mining capacity in tons
$su$	Upper bound of shovel $S$ mining capacity in tons
$sl$	Lower bound of shovel $S$ mining capacity in tons
$C^k$	Set of blocks that must be extracted prior to mine block $k$
$n^k$	Number of blocks in set $C^k$

### 3. Decision variables

$x_k^t \in [0,1]$	continuous variable, representing the portion of block $k$ to be mined in period $t$
$b_{s,k}^t \in \{0,1\}$	binary integer variable controlling the precedence of extraction of blocks. $b_k^t$ is equal to one if extraction of block $k$ has started by or in period $t$ , otherwise it is zero
$f^t \geq 0$	continuous variable, representing the tonnage of material reclaimed from stockpile $S$ in period $t$
$C_{i,j}^s \in \{0,1\}$	binary integer variable. $C_{i,j}^s$ is equal to one if shovel $S$ moves from block $i$ to block $j$ , otherwise it is zero

### 4. Objective function

$$\max \sum_{t=1}^T \left\{ \underbrace{(r^t \times f^t)}_{\text{Revenue}} - \underbrace{\sum_{k=1}^K (wt_k^t \times x_k^t \times D_k)}_{\text{Waste hauling cost}} - \underbrace{\sum_{k=1}^K (ot_k^t \times x_k^t \times D_k)}_{\text{Ore hauling cost}} - \underbrace{\sum_{s=1}^S \sum_{i \neq j} (S_s \times D_{i,j} \times C_{i,j}^s)}_{\text{Shovel moving cost}} \right\} \quad (1)$$

### 5. Constraints

- Mining capacity constraints

$$ml^t \leq \sum_{k=1}^K (O_k + w_k) \times x_k^t \leq mu^t \quad \forall t \quad (2)$$

- Ore reservation tonnage constraints

$$\sum_{t=1}^T \sum_{k=1}^K o_k \times x_k^t \leq o_r \quad \forall k, t \quad (3)$$

- Waste reservation tonnage constraints

$$\sum_{t=1}^T \sum_{k=1}^K w_k \times x_k^t \leq w_r \quad \forall k, t \quad (4)$$

- Crushing capacity constraints

$$pl^t \leq f^t \leq pu^t \quad \forall t \quad (5)$$

- Ore mining tonnage relation with ore reclaiming tonnage from the stockpile

$$\sum_{k=1}^K o_k \times x_k^t \leq f^t + c \quad \forall t \quad (6)$$

$$f^t \leq \sum_{k=1}^K o_k \times x_k^t + c \quad \forall t \quad (7)$$

- All blocks must be mined and can only be mined once:

$$\sum_{t=1}^T x_k^t = 1 \quad \forall k \quad (8)$$

- Mining sequence constraint:

$$n^k \times \sum_{s=1}^S b_{s,k}^t - \sum_{b \in C_k} \sum_{i=1}^t x_b^i \leq 0 \quad \forall k, t \quad (9)$$

- Assignment consistency (one block can only be assigned to one shovel):

$$\sum_{s=1}^S C_k^s = 1 \quad \forall k \quad (10)$$

- Link shovel assignment with shovel movement

$$\sum_{i \neq j} C_{i,j}^s = \sum_{t=1}^T b_{s,i}^t \quad \forall s \quad (11)$$

$$\sum_{i \neq j} C_{i,j}^s = \sum_{t=1}^T b_{s,j}^t \quad \forall s \quad (12)$$

- Shovel productivity balance constraint (shovels should have similar productivity):

$$\sum_{k=1}^K C_k^s \times (o_k + w_k) \leq \sum_{k=1}^K (o_k + w_k) / S \times 1.1 \quad \forall k, s \quad (13)$$

$$\sum_{k=1}^K (o_k + w_k) / S \times 0.9 \leq \sum_{k=1}^K C_k^s \times (o_k + w_k) \quad \forall k, s \quad (14)$$

### 2.2.3. Simulation Model

The simulation model that the author previously built for an IPCS scenario is adopted in this paper, while adding some new features [7]:

1. At re-optimization time, Arena exports a CSV file that indicates: shovel current face/block, remaining blocks, stockpile inventories, and equipment breakdowns. After the exports, it calls the optimizer.
2. The optimizer ingests the state file, update available blocks and corresponding sets and parameters, and solves the MILP problem for the next time range and returns an updated assignments (schedule) file.
3. Arena reads the newly generated schedule file and once the shovels finish the current block, assigns them the updated block (the same block may be assigned to the same shovel, but not necessary).
4. Repeat until simulation end time.

### 2.3. Case Study

The proposed optimization–simulation framework is tested using an oil sands case study consisting of two operating shovels and sixteen trucks. The original dataset contains 1,773 mining blocks, each with dimensions of 50 m × 50 m × 10 m. However, this scale is too large for short-term, near-real-time optimization and would significantly impact computational efficiency. The simulation spans a week period, with optimization performed daily and re-optimization occurring every six hours. Given this temporal resolution, only the first 40 blocks are considered in the present study to ensure tractable and timely optimization. The daily mining and processing capacities are set to 288,000 tonnes and 180,000 tonnes, respectively. The optimization model is implemented and solved in MATLAB.

Two scenarios are designed for comparison to verify the proposed optimization method:

- a) Base case: The original static mining sequence used in actual operations.
- b) Optimized case: The mining sequence generated by the proposed optimization method, with the schedule re-optimized at regular intervals.

### 2.4. Results and Discussion

#### 2.4.1. Schedule

The mining sequence of two shovels in the two-scenario is listed in Table 1 and Figure 1. As can be seen, the original weekly schedule distributes mining tasks relatively evenly between the two shovels without considering shovel movement efficiency. As a result, Shovel 1 is assigned approximately 1,030,000 t (including 532,000 t of ore), while Shovel 2 receives 1,026,000 t (including 505,000 t of ore). Although the tonnage is balanced, this allocation does not minimize the travel distance between blocks, leading to unnecessary equipment movement.

Table 1: Mining schedule with and without shovel movement.

Shovels	Blocks assigned (base case)	Blocks assigned (after optimization)

Shovel 1	1,4,6,7,8,11,13,15,16,17,18,19, 22,26,27,29,32,35,36,39	1,2,3,4,5,6,7,8,10,12,13,14,15,19, 21,26,29,33,38,40
Shovel 2	2,3,5,9,10,12,14,20,21,23,24, 25,28,30,31,33,34,37,38,	2,3,5,9,10,12,14,20,21,23,24,25, 28,30,31,33,34,37,38,40

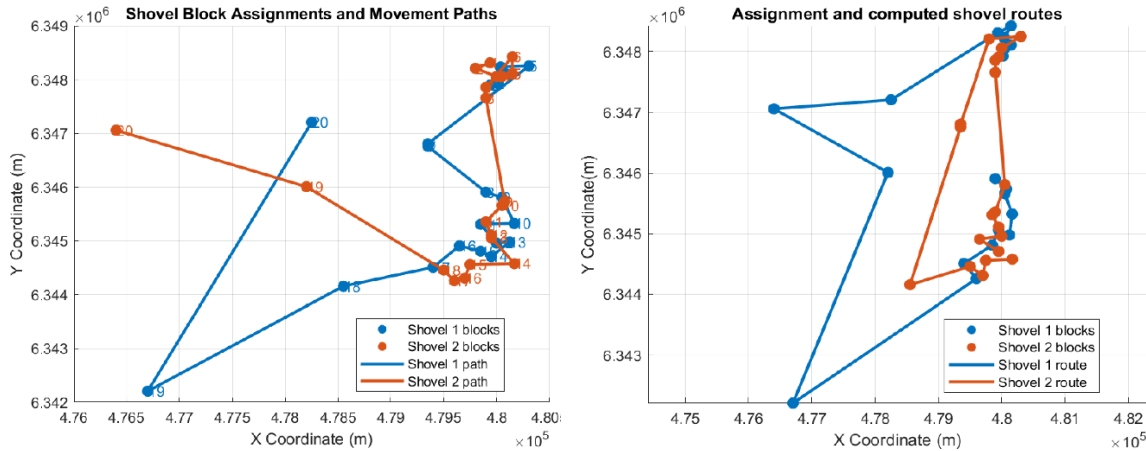


Figure 1: Shovel route before optimization (left) and after optimization (right).

After applying the optimization model, the scheduling pattern changes. The optimizer prioritizes reducing the total shovel movement distance and consequently assigns most of the longer movements to Shovel 1. As a result, Shovel 1 handles 494,000 t of ore, reflecting a shift in ore extraction responsibilities to improve overall haulage efficiency. The optimized schedule thus demonstrates that considering shovel movement explicitly can lead to a more efficient operational plan, even if the resulting distribution of ore and waste differs from the original balanced approach.

### 2.4.2. Shovel move distance

A comparative analysis of cumulative shovel movement distances between the baseline and optimized schedules demonstrates that incorporating movement considerations into short-term planning can yield meaningful operational benefits, as shown in Table 2 and Figure 2.

Table 2: Shovel move distance summary (m).

Shovels	Moving distance (m) (base case)	Moving distance (m) (after optimization)
Shovel 1	16608	16831
Shovel 2	13199	10952

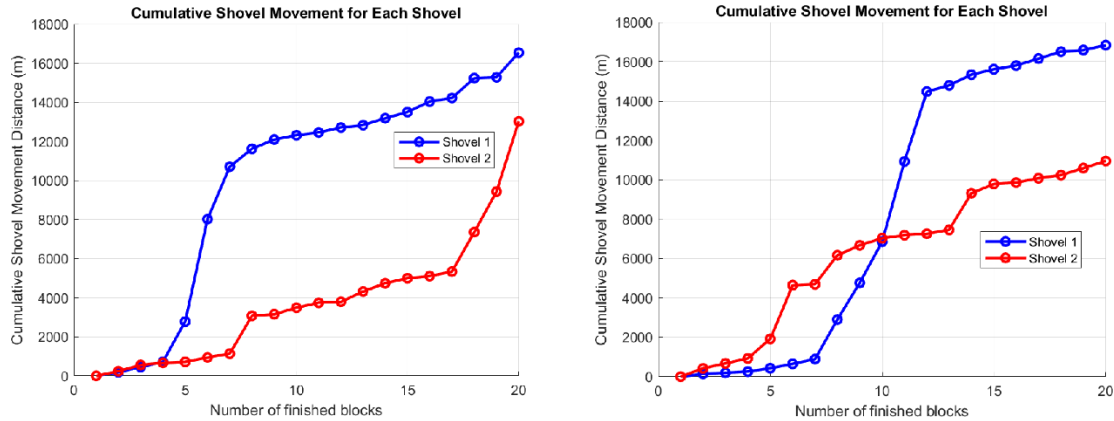


Figure 2: Cumulative shovel movement of base case (left) and optimized case (right).

In the baseline case, Shovel 1 and Shovel 2 travelled 16,608 m and 13,199 m during the study week, respectively. Under the optimized schedule, the total weekly movement of Shovel 1 increased slightly to 16,831 m (a 1.3% increase), whereas the movement of Shovel 2 decreased to 10,952 m, representing a reduction of approximately 17.0%. Although the optimization strategy transfers a portion of longer travel routes to Shovel 1, the substantial reduction achieved for Shovel 2 leads to an overall improvement in relocation efficiency.

The practical implications of these changes are significant. Large electric and hydraulic shovels typically achieve relocation speeds of approximately 40–60 m/min. Assuming an average travel rate of 50 m/min, the 2,247 m reduction in Shovel 2's weekly movement corresponds to a decrease of approximately 45 min in relocation time. This reduction directly increases the proportion of productive loading time available within the same working week, which is particularly valuable in short-term horizons where small improvements in availability can have measurable impacts on downstream production rates. In addition to time savings, shorter relocation distances translate into lower operating costs and fuel consumption. Such reductions become proportionally more substantial for mines operating multiple shovels or planning frequent short-term re-scheduling.

From an operational standpoint, the optimized schedule also promotes improved equipment utilization. Shovel tramming contributes disproportionately to component wear—particularly track chains, rollers, and swing bearings—and extended travel often requires additional supervision and safety clearances. By lessening unnecessary movement, the proposed optimization approach not only lowers direct operating cost but may also extend component life and reduce the likelihood of relocation-related interruptions. These practical advantages complement the production-balancing capability of the MILP formulation, which maintained a nearly even weekly tonnage distribution between the two shovels despite the inclusion of movement-minimization objectives.

## 2.5. Conclusions, Limitations, and Future Work

This study developed a mixed-integer linear programming (MILP) framework for short-term, rolling-horizon production scheduling that explicitly incorporates shovel relocation distances while ensuring balanced ore and total tonnage assignments. Application to a two-shovel, 40-block weekly case study demonstrates that conventional schedules—though balanced in tonnage—induce substantial and operationally inefficient shovel movement. The optimized schedule reduced one shovel's weekly travel distance by 17%, reallocating longer movements to the other shovel while maintaining production targets. These results highlight that incorporating movement minimization in short-term scheduling can increase effective working time, improve equipment utilization, and facilitate more efficient coordination with downstream processes.

Despite these promising outcomes, several limitations exist. The current model does not explicitly consider equipment failures, variable shovel cycle times, or stochastic truck travel, all of which could impact real-world performance. While rolling-horizon scheduling provides adaptability to dynamic conditions, incorporating additional detailed variables—such as individual block attributes, multi-shovel interactions, or finer temporal resolution—would increase the complexity of the MILP and could render real-time optimization infeasible. Furthermore, the present study does not quantify the incremental benefit of combining rolling-horizon re-optimization with equipment failure modeling; although it is apparent that including failures would further improve operational efficiency, the extent of such gains requires further investigation.

Future work will focus on extending the framework to integrate stochastic operational disturbances, including equipment downtime and variable cycle times, to evaluate the robustness of the optimized schedules under realistic mining conditions. Comparative studies between rolling-horizon and static optimization strategies will also be conducted to quantify the benefits of adaptive re-optimization. Additionally, research into computational efficiency—through decomposition techniques, heuristic warm starts, and parallelization—will be necessary to enable the practical implementation of high-fidelity MILP models for near real-time mine scheduling. Finally, expanding the approach to multiple shovels and more complex mine geometries will enhance its applicability to large-scale, operationally representative scenarios.

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