Integrated Simulation and Optimization Framework for Quantitative Analysis of Near-face Stockpile Mining[1]

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ABSTRACT

A new conceptual mining method called the near-face stockpile (NFS), which combines the in-pit crushing and conveying IPCC system with a pre-crusher stockpile, has recently been proposed for large open pits with sufficient pit bottom width. In the past, stockpiles mainly act as a "buffer" to improve the stability of the production system. However, in NFS ore will be dumped into the pre-crusher stockpile located at the bottom of the current pit and be fed into the crusher after blending to the desired head grade, instead of being dumped directly into the crusher. Theoretically, this design not only retains the high efficiency and high output of IPCC, but also endows the mining system with better quantity and quality stability. Verifying these advantages and objectively evaluating the NFS method has become a problem worth studying. Since the NFS method exhibits distinctive layout and feeding mechanisms, which distinguish it from other mining methods, a novel simulation model is required for the accurate modeling of the NFS method and quantitatively evaluating the performance of NFS methods. In addition, this paper also proposes an optimization model for short-term production scheduling for NFS method based on the mixed integer linear programming (MILP) method. An oil sands mine case study is implemented to verify the proposed simulation model. One year simulation results reveal that compared to the traditional mining method, the overall production increased by 5.06%, the transporting distance of minerals by trucks was reduced by 17.87%, and the shovels' and crusher's utilization increased by 4.96% and 4.85%, respectively, when using NFS method.

Keywords: *near-face stockpiling; mixed integer linear programming; simulation and optimization; production planning*

1. Introduction

Truck-shovel (TS) system is the most widely used method in open pit mining, and its efficiency and benefits have been significantly improved by the application of large-scale equipment [1]. However, with the increase in the mining depth and transportation distance, the economic benefits of the TS system deteriorated. To address this issue, various improvements have been proposed and applied, among which the in-pit crushing and conveying (IPCC) method has been successful [2]. As the name

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shows, the IPCC method moves the crusher to the bottom of the pit to reduce the trucks' transportation distance and improve its efficiency. The IPCC method offers considerable flexibility in selecting the in-pit crusher. Based on mobility, the crusher can be divided into three types: fully mobile, semi-mobile, and fixed. The crushed material in in-pit crushers is transported to the processing plant or waste dump using conveyor belts. Since the transportation cost of the conveyor belts is only one-fifth to one-third of that of trucks [3-4], a large portion of the operating expenses can be saved. Past research and practices have shown that although the IPCC method has disadvantages, such as heavy initial investment, complex management, and being restricted by terrain, and other constraints, its financial practicality outperforms the traditional TS method in the long run [5].

However, a major drawback of the traditional mining method is its susceptibility to risks, which are not addressed by the IPCC and has prompted the development of the near face stockpile (NFS) mining method, a novel concept that combines IPCC with a pre-crusher stockpile. Specifically, this risk is that the mining subsystem and the crushing subsystem are closely linked. Any accident or unexpected failure in one of the subsystems will affect the other subsystem, which will eventually lead to a reduction in production. To tackle this problem, a stockpile is arranged at the bottom of the open pit, ahead of the crusher. Unlike the IPCC method, where trucks dump the material directly into the crusher, in the NFS method, all materials are first dumped into the stockpile and then fed to the crusher through a reclaim shovel.

It should be pointed out that, regardless of the traditional TS or the IPCC mining method, the connection of the two most significant subsystems of an open pit mine: the mining subsystem and processing subsystem, solely rely on the hauling subsystem. A problem with any of the three subsystems will lead to a chain of shutdowns [6]. As shown in Figure 1, the fundamental difference between the NFS method and the other two methods is that its stockpile can decouple these two subsystems and reduce their mutual influence, improving the fault tolerance of the whole system. In addition, unlike the traditional pre-crusher stockpile, which mainly assumes the role of "buffer", the stockpile in the NFS method can upgrade the traditional truck-by-truck blending to batch blending, reducing the grade deviation fed to the crusher [7]. Besides, in theory, in addition to these new advantages, NFS retains the respective advantages of IPCC and the pre-crusher stockpile itself, such as reduced demand for trucks, transportation distances, and transportation costs. Those benefits will bring enterprises higher equipment utilization, more stable product quality, and better net present value (NPV).

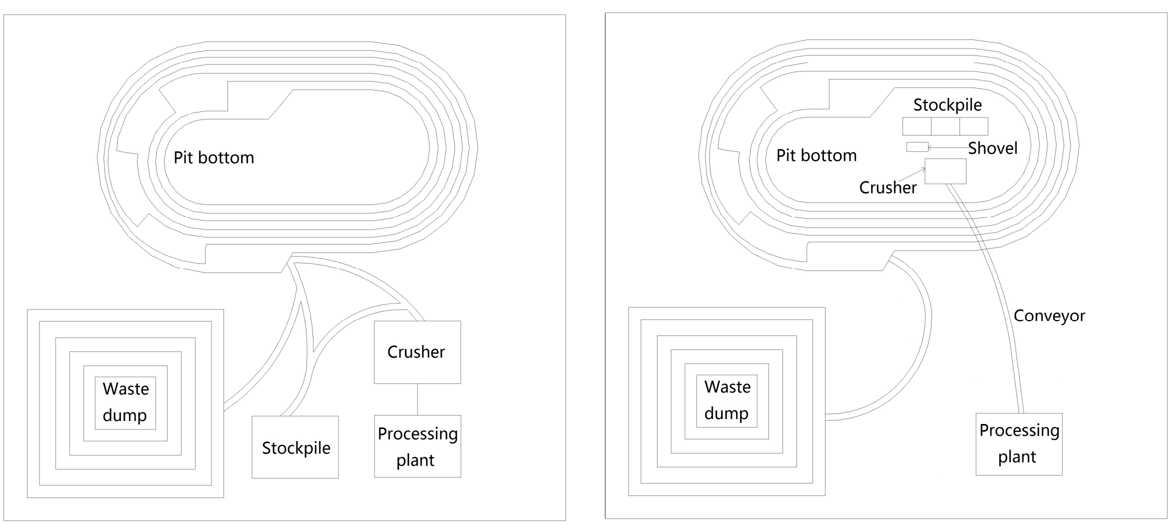

Figure 1. Traditional mining method layout (left) and NFS method mining method layout (right).

Despite the various theoretical advantages of the NFS over other methods, it is still in the conception stage and those advantages are not verified. Therefore, the objective of this study is to understand and measure the performance of the near face stockpile mining method objectively and quantitatively and compared it to the traditional out-pit crusher scenario.

Simulation is a widely used time-saving, cost-saving technology in addressing theoretical "what-if" questions [8]. Therefore, simulation models which can cover the characteristics of the NFS and TS methods and assess uncertainty around the key performance indicators (KPIs) of the mining system are built in this study. Meanwhile, those models can also assist in understanding and measuring the interaction of interrelated activities within the NFS system and TS system and their overall performance.

In addition to the simulation model, an optimal or near-optimal mining schedule is also indispensable for an objective evaluation of a mining method. Therefore, a mathematical short-term mining schedule optimization model based on mixed integer linear programming is also proposed for the NFS method to generate an optimal or near-optimal mining schedule. Through feeding the generated schedule to the proposed simulation model, a comprehensive optimization-simulation framework is completed to evaluate the performance of a mining method.

Afterward, we carry out a case study of an oil sands mine, which adopted the traditional TS method in real operation. The framework is first applied to the traditional TS method and by comparing the simulation results against the real dispatch production data, the framework is validated. The validated simulation results of the TS method are then taken as a benchmark to evaluate the performance of the NFS method under the optimization-simulation framework. The main contribution of this work is creatively proposing a simulation model for the NFS method and combining it with a short-term mining schedule optimization model and quantitatively measuring the performance of the NFS method and verifying its theoretical advantages.

However, in addition to advantages, NFS also has some obvious disadvantages and deficiencies. The first is that the requirements for initial investment are even higher than that of the IPCC method. Secondly, although the operating cost of the conveyor is relatively low, the consequences of its damage are far more serious than the failure of one or two trucks. Besides, the NFS method has higher requirements on the bottom size of the open pit than the IPCC method and is more suitable for ore bodies with lower strip ratios. Furthermore, the added reclaim shovel is an additional risk and also one of the potential bottlenecks of this system. These shortcomings may limit the further generalization of the NFS method.

The second chapter of this article is the related literature review. Since the NFS is a new concept, the literature reviewed in this chapter is mainly about past research on the IPCC simulation and mining schedule optimization with a stockpile. In chapter three, we formulated the optimization model and showed the logic and process of building simulation models. The fourth chapter is the validation of the integrated framework and quantitatively compares the performance between the TS method and the NFS method. In the fifth chapter, we summarize and analyze the comparison results, and conclude. In addition, the limitations and future work of this research are also stated.

2. Literature Review

Stockpile is one of the crucial components of the mining system, series linear optimization models and nonlinear optimization models that consider stockpile were proposed. As Jupp [9] described, the near crusher stockpile plays four roles simultaneously: storing, buffering, blending, and grade separation. The quality of stockpiles is managed manually in the early stage while the on-site operational staff routinely records relevant data of essential stockpiles. A MILP model for long-term optimization production planning that considers grade uncertainty and a stockpile was proposed by Koushavand [10]. Their objective function maximizes the profit while including the cost of uncertainty by considering both under-production and over-production scenarios. Smith and Wicks

[11] proposed a MIP for medium-term production planning with a stockpile in a copper mine. However, the authors avoid nonlinearity by not keeping track of elements' grades going to and reclaimed from the stockpile. Instead of using classical linear programming, in which only one objective can be satisfied, a goal programming model that aims at reducing stockpile fluctuation was proposed by Souza [12]. In the model, minimizing the operating cost and grade deviation were set up as two goals to be achieved. However, although the author claims the model could provide support for short-term and medium-term scheduling, it was only tested by a database from the author and no simulation was conducted.

There are also nonlinear models proposed for optimization which incorporate stockpiles. Bley [13] added a non-convex quadratic constraint for stockpiles in each period and used the primal heuristic method to find feasible solutions for a specific problem. Paithankar [14] proposed a mathematical model based on a genetic algorithm to optimize production sequence and dynamic cutoff grades simultaneously. The final goal is set to generate the highest NPV. The model assumes that the stockpile has infinite capacity and no fluctuation in yearly mining capacity, which is not realistic in actual operation. However, although most of the proposed nonlinear models claimed a higher NPV under the case study, more variables are needed than linear models, especially for stockpiles which caused inefficiency issues. Besides, overall optimal or near-optimal results are not guaranteed, and the time consumption is much higher than those linear models.

The IPCC was first proposed and applied in 1956 in Germany [15]. Ever since, academic research on IPCC has continued, and simulation technology's support has promoted the development and maturity of the IPCC method. The simulation of the IPCC mining method involves modeling the process of extracting materials and transporting them to a processing plant using a combination of mobile/semi-mobile/fixed crushers, conveyor belts, and trucks. One of the earliest IPCC simulation studies was carried out in the early 1980s for a copper mine. The study investigated the mining fleet optimization problem under IPCC conditions and used simulation to decide the number of trucks required to increase efficiency [16]. In the late 1990s, the Australian mining company, Rio Tinto, began a series of studies to evaluate the use of IPCC systems in their operations. These studies used simulation technology to model different scenarios for haulage distances, equipment selection, and production rates [17]. Since then, IPCC simulation has continued to play an essential role in the design and optimization of mining operations and is widely used by mining companies and consulting firms to evaluate the feasibility of different mining methods and equipment configurations. Relevant research includes but is not limited to 1. IPCC economic benefit analysis over the traditional TS system, which proves that IPCC can achieve higher profits within the scope of life of mine [18, 19]; 2. Crusher and other equipment’s selection and corresponding capacity determination[20–22]; 3. Optimization of the location of the crusher, which can minimize operating costs and increase profits [4, 23, 24]; 4. Assessment of different truck dispatch rules [25, 26]. Those studies helped to optimize the IPCC system's design by evaluating different scenarios in a virtual environment before implementation, resulting in improved productivity, reduced operating costs, and enhancement in the safety. With the aid of those studies, it has become common knowledge that IPCC can achieve better economic benefits in deeper open pit mines than the TS system. Nowadays, IPCC has been implemented in more than 500 mines [5].

In summary, the common shortcomings found in the literature are 1. Linear optimization models and corresponding simulation models that consider stockpiles adopt perfect blending assumption, leading to a difference between real reclaimed material grade and hypothesized reclaimed grade.; 2. Simulation models build for IPCC are not suitable for NFS; 3. Nonlinear optimization models cannot guarantee overall optimal or near-optimal results. The first and second drawbacks are addressed in this research by proposing a new optimization model and simulation model, in which material grade reclaimed from the stockpile can be tracked precisely.

3. Framework and Formulations

Figure 2 shows the integrated optimization-simulation framework and the interactions between the optimization model and the simulation model. The importance of mining scheduling and its optimization cannot be overstated. No mining method can deliver its value without a practical production schedule and cannot be measured objectively and fairly. Therefore, before building and running a simulation model, it is necessary to build an optimization model to optimize its mining schedule according to the characteristics of the NFS method. The MILP approach is selected to optimize the short-term schedule due to its flexibility, efficiency, and guarantee of optimality. It should be noted that the MILP optimization model we proposed in this section is based on Tabesh and Askari-Nasab's previous work [27].

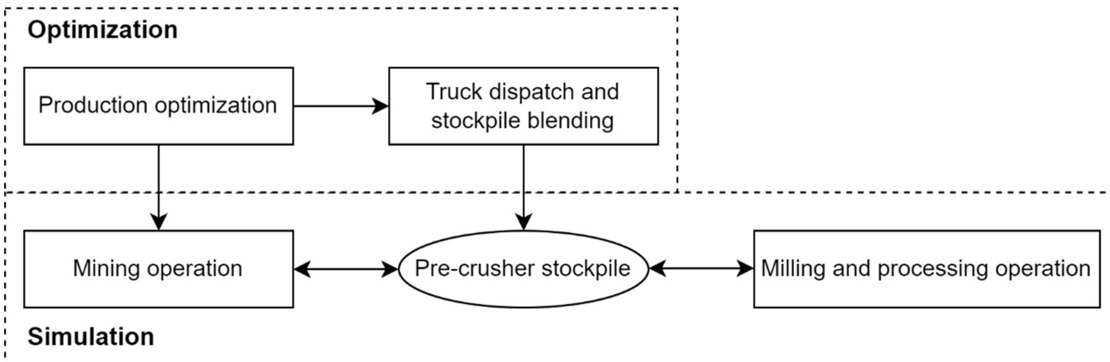

Figure 2. Integrated optimization-simulation framework.

3.1. Optimization Model

In the following, the defined indices, sets, parameters, decision variables, the objective function, and the constraints of the optimization model are presented.

Indices

k	Block indices ($k \in \{1, 2, \ldots K\}$)
t	Period indices ($t \in \{1, 2, \ldots T\}$)
d	Destination indices (stockpile or waste dumps)
s	Zone indices ($s \in \{1, 2, \ldots S\}$)

Sets and parameters

r_s^t	Discounted revenue generated by sending one unit of material from stockpile zone s in period t to crusher minus the dozing, reclaiming, crushing, conveying, processing and selling cost
wt_k^t	Discounted cost of hauling all waste materials to waste dump in block k in period t
ot_k^t	Discounted cost of hauling all ore materials to in-pit stockpile in block k in period t

o_k	Ore tonnage in block k
o_r	Ore tonnage in reserve
w_r	Waste tonnage in reserve
c_s	Capacity of stockpile zone s
g_k	Average grade of material in ore portion of block k in percent
gcu^t	Upper bound of crusher acceptable grade in period t in percent
gcl^t	Lower bound of crusher acceptable grade in period t in percent
pu^t	Upper bound on ore processing capacity in period t in ton
pl^t	Lower bound on ore processing capacity in period t in ton
mu^t	Upper bound on mining capacity in period t in ton
ml^t	Lower bound on mining capacity in period t in ton
C_k	Set of the blocks that must be extracted prior to mine block k
n_k	Number of blocks in set C_k

Decision variables

$x_k^t \in [0,1]$	continuous variable, representing the portion of block k to be mined in period t, fraction of x characterizes both ore and waste included in the block
$b_k^t \in \{0,1\}$	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
$f_s^t \geq 0$	continuous variable, representing the tonnage of material reclaimed from stockpile zone s in period t

Objective function and constraints

$$\max \sum_{t=1}^{T} \left\{ \underbrace{\sum_{s=1}^{S} (r_s^t \times f_s^t)}_{\text{Discounted revenue}} - \underbrace{\sum_{k=1}^{K} (wt_k^t \times x_k^t)}_{\text{Discounted waste haul cost}} - \underbrace{\sum_{k=1}^{K} (ot_k^t \times x_k^t)}_{\text{Discounted ore haul cost}} \right\} \tag{1}$$

$$ml^t \le \sum_{k=1}^{K} (o_k + w_k) \times x_k^t \le mu^t \qquad \forall t \in \{1,...,T\} \tag{2}$$

$$\sum_{t=1}^{T} \sum_{k=1}^{K} o_k \times x_k^t \le o_r \qquad \forall k \in \{1,...,K\}, \quad t \in \{1,...,T\} \tag{3}$$

$$\sum_{t=1}^{T} \sum_{k=1}^{K} w_k \times x_k^t \le w_r \qquad \forall k \in \{1,...,K\}, \quad t \in \{1,...,T\} \tag{4}$$

$$pl^t \le \sum_{s=1}^{S} f_s^t \le pu^t \qquad \forall t \in \{1,...,T\} \tag{5}$$

$$\sum_{k=1}^{K} o_k \times x_k^t - S \times c_s \le \sum_{s=1}^{S} f_s^t \qquad \forall t \in \{1,...,T\} \tag{6}$$

$$\sum_{s=1}^{S} f_s^t \le \sum_{k=1}^{K} o_k \times x_k^t + S \times c_s \qquad \forall t \in \{1,...,T\} \tag{7}$$

$$(\sum_{k=1}^{K} g_k \times o_k \times x_k^t) / (\sum_{k=1}^{K} o_k \times x_k^t) \ge gcl^t \qquad \forall t \in \{1,...,T\} \tag{8}$$

$$(\sum_{k=1}^{K} g_k \times o_k \times x_k^t) / (\sum_{k=1}^{K} o_k \times x_k^t) \le gcu^t \qquad \forall t \in \{1,...,T\} \tag{9}$$

$$\sum_{t=1}^{T} x_k^t = 1 \qquad \forall k \in \{1,...,K\} \tag{10}$$

$$n_k \times b_k^t - \sum_{b \in C_k} \sum_{i=1}^{t} x_{\mathrm{b}}^i \le 0 \qquad \forall k \in \{1,...,K\}, \quad t \in \{1,...,T\} \tag{11}$$

Equation (1) is the objective function. Its goal is set to produce the best discounted net present value of a project in the given period. The expression of NPV in this formula is the sum of discounted revenue minus discounted waste hauling cost by truck minus discounted ore hauling cost by truck in each period. It should be pointed out that the dozing and reclaiming cost of ore material in the stockpile, as well as the subsequent crushing, conveying, processing, and selling costs, have been deducted from the discounted revenue. Equation (2) ensures that total material mined in each period matches the mining capacity. Equation (3) and Equation (4) enforce that the total tonnage of ore and waste being mined will not exceed the available reserve in the deposit. Equation (5) ensures that the material reclaimed from the stockpile matches the desired processing capacity. Equation (6) and (7) limits ore tonnage reclaimed from stockpile in each period. The reclaimed tonnage should not be less than ore material mined in that period minus stockpile capacity, or more than ore material mined in that period plus stockpile capacity. We defined equations (8) and (9) for grade control. Constraint (8) ensures that the average grade of material reclaimed from stockpile in each period does not fall below the lowest acceptable head grade for the processing. Similarly, constraint (9) ensures that the average grade reclaimed from stockpile does not exceed the upper bound of the required processing head grade. Equation (10) requires all blocks to be fully extracted without leftovers. Equation (11) ensures that all predecessor blocks are fully extracted before mining the current block.

3.2. Simulation Model

To simulate mining operations in the IPCC or the traditional TS mining method, the mining, transportation, crushing, and processing processes, are closely related and cannot be considered separately. Figure 3 shows the typical framework for simulating traditional open pit mining operations. However, since in the NFS method, the mining part is decoupled from the milling part, making them two independent subsystems, it is possible to simulate them separately. The two subsystems are connected through the stockpile. This paper proposes a combination of relatively independent but interrelated frameworks to simulate an open pit mining operation that uses the NFS method in Figure 4 (framework of the mining process in the NFS method), Figure 5 (the inner logic of the dumping zone decision sub-model that is shown in Figure 4), and Figure 6 (framework of the crushing and processing processes).

Figure 3 illustrates that in the traditional mining process, trucks play a pivotal role in connecting various processes. Once the shovel is assigned to each working surface as required, the truck first interacts with the shovel to complete the loading of materials and then drives along the completed road network to the crusher/waste dump. Subsequently, upon reaching the destination, the materials are dumped in order, and the truck is emptied to the next loading location as required. However, in this setting, the efficiency of trucks is tied to the flow of materials, and the longer the road, the less efficient the truck becomes. Moreover, the link between the mining system and the crushing system is fragile, and trucks can easily cause them to affect each other or be impacted by them. For instance, if the shovel stops working unexpectedly, the truck will have no material to deliver, resulting in the crushing system's stoppage. Additionally, if there is a problem with the truck or road, even if it is a short-term issue, the mining system and crushing system will come to a halt simultaneously. Although the IPCC method addresses the low efficiency of long-distance transportation, the NFS method further enhances the system's ability to withstand uncertainty while also improving its stability.

Figure 4 depicts that the direct transfer of materials from the truck to the crusher has been replaced with the transfer of materials to a pre-established stockpile. This alteration has resulted in the mining-related activities and the stockpile forming a relatively closed subsystem. Although the stockpile still experiences material exchanges with outside, the system can operate autonomously for a considerable duration, which is positively correlated to the stockpile's capacity. Additionally, the stockpile comprises multiple zones (three zones in this model, each with four dumping spots) which necessitate the addition of a logical judgment module to determine the zone for receiving materials each time. The capacity of each zone can feed the crusher for 8 hours without a new supply.

Figure 5 illustrates the proposed logical judgment module, which aims to enhance communication efficiency with external systems by sequentially dumping materials by area. For safety, each zone can only receive new dumping after the reclamation is fully finished. If the other two zones meet their capacity during this period, the dumping trucks will wait in line until the reclamation of the current zone is completed. At the same time, if a zone is in the refill phase and the other two zones are empty, the reclaim activity will be suspended until the current zone is fulfilled. Dumping and reclaiming must be performed strictly from zone 1 to zone 3. The incorporation of this module enables effective stockpile management and improves safety.

Similarly, the stockpile, crusher, conveyer, and other processing equipment form another relatively closed system, as shown in Figure 6. It is noteworthy that, in contrast to other mining methodologies, the NFS approach requires additional equipment to effectively reclaim materials from the stockpile. Furthermore, the reclaiming activity demands the incorporation of a logical module that facilitates a harmonious interplay with the dumping decision reclaim module. The objective is to ensure an optimal reclaiming sequence and avert potential conflicts between the two systems. The logic module is encapsulated in a dotted box in the figure for clarity. Notably, the post-crushing process in NFS follows the same sequence as the IPCC approach.

The truck request module and dispatch module in the two charts share the same principles. Specifically, the truck request module prioritizes the minimum travel distance, while the truck dispatching module favors the minimum queue length at the shovels. In scenarios where the queue lengths are identical, the shortest distance between the empty truck and the shovels assumes the highest priority. These criteria are instrumental in ensuring the efficient and expedient allocation of resources, thereby optimizing the productivity and profitability of the mining operations.

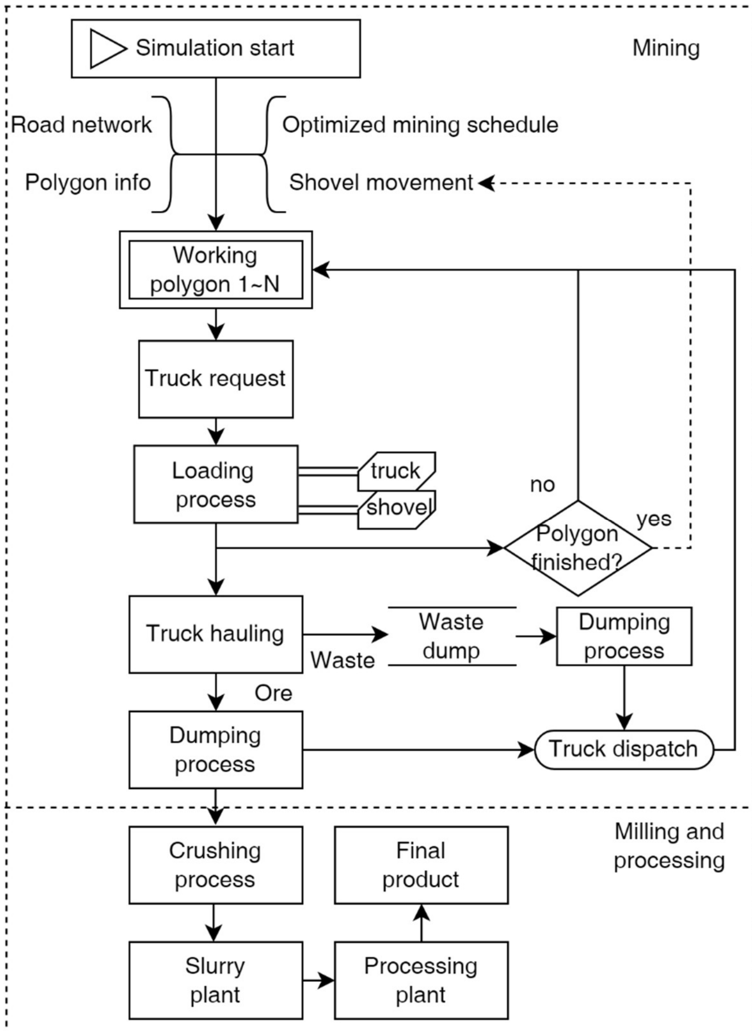

Figure 3. Flow chart of traditional out-of-pit crusher mining method.

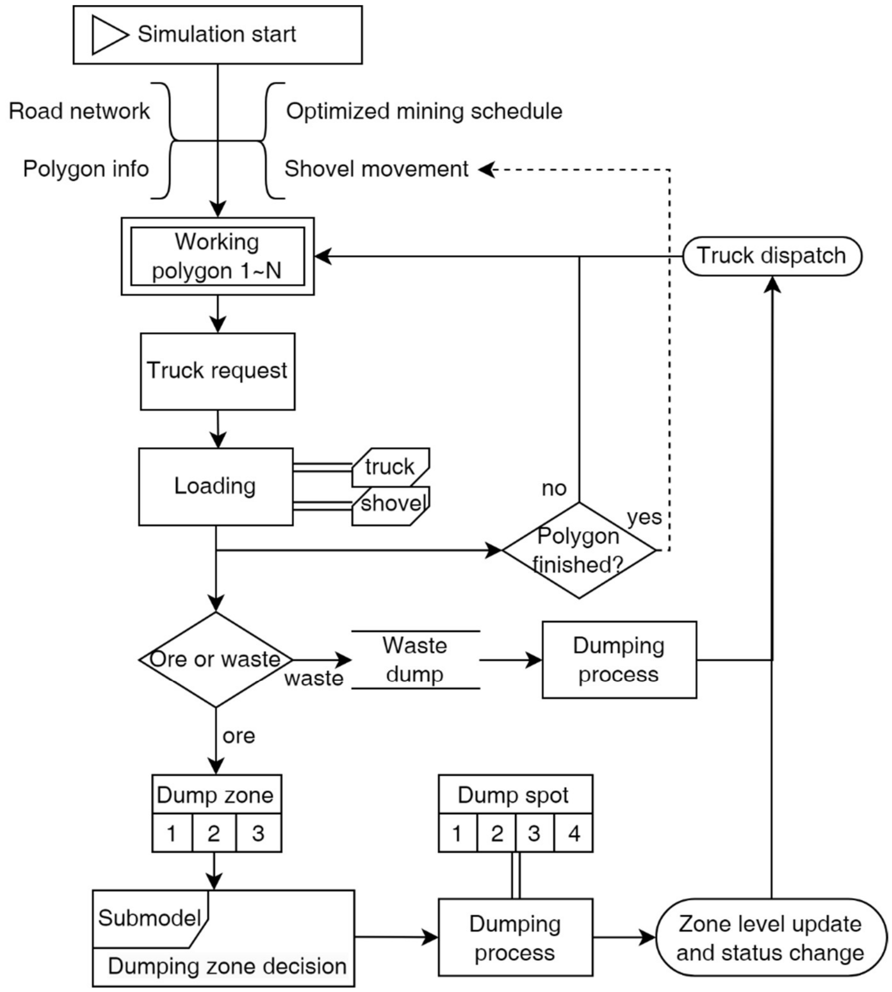

Figure 4. Diagram of mining process in the NFS method.

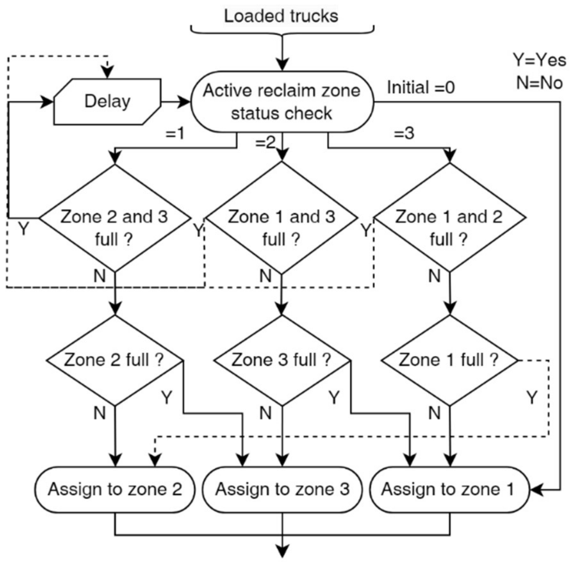

Figure 5. Logic of dumping zone decision sub model.

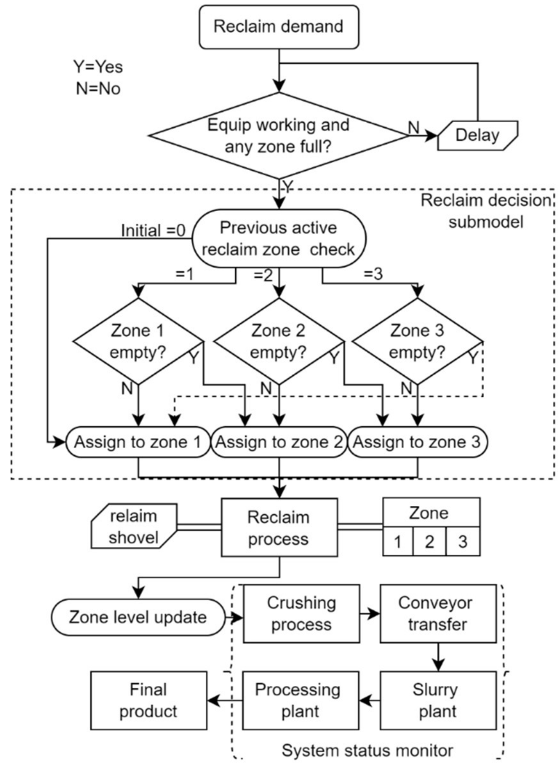

Figure 6. Diagram of crushing and processing process in the NFS method.

Once the optimization and simulation models are developed, they will be incorporated into a comprehensive framework capable of assessing the performance of a mining method. Specifically, the integration process involves importing the output of the optimization model, which is an optimized mining schedule, into the simulation model as an input parameter. This ensures that the mining sequence of blocks remains both reasonable and practical throughout the simulation process. In this study, Arena [28] is chosen as the simulation software to facilitate the simulation of various operations associated with different mining methods. The complete procedure for running the optimization-simulation framework is depicted in Figure 7.

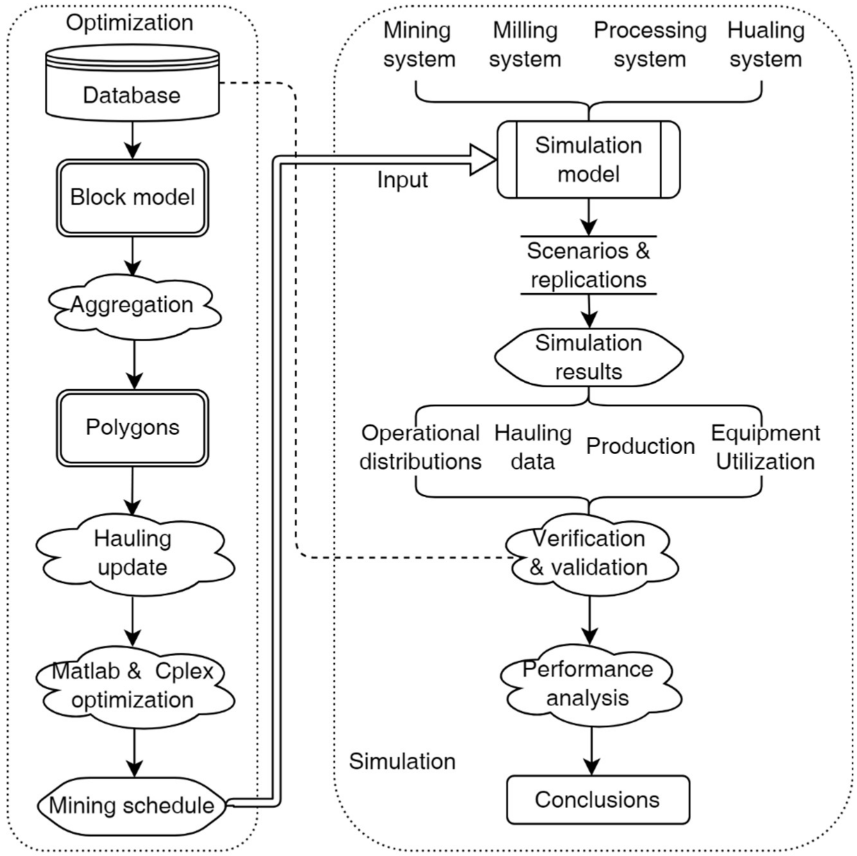

Figure 7. Optimization and simulation procedures needed to complete the case study.

4. Framework validation and NFS evaluation

In the preceding chapters, the author established a comprehensive optimization-simulation framework to evaluate the performance of a mining method. However, prior to using this framework to assess the NFS method and address the research objective, its effectiveness must be verified. To validate the framework, we will implement an oil sands mine case study using the traditional method and take the resulting outcomes as a benchmark for further evaluation. The validation process will entail running the optimization model according to the block model and obtaining a near-optimal and practical mining schedule. Subsequently, we will use this optimized schedule as the input of to the simulation model and run it for ten replications to reduce errors and enhance result reliability. Finally, we will compare the simulation results with actual operating records across multiple dimensions to verify the effectiveness of the framework. After the validation, a detailed comparison between the NFS model and the traditional model is conducted, leading to a conclusion that the NFS mining method outperforms the traditional mining method across multiple metrics.

4.1. Validation

An oil sands mine case study, with two working shovels and sixteen trucks is implemented to verify the proposed simulation and optimization model. The historical data retrieved from the mining fleet management system reveal that, in 2016, the enterprise mined a total of 93.09 million tons of material, consisting of 60.73 million tons of ore material with an average density of 2.1 ton/m3 and average grade of 11.38%. The remaining is different types of waste and the density fluctuate between 2.0 to 2.5 ton/m3.

The total material is assumed to be excavated from 1773 blocks, each with a child size of 50m (length) by 50m (width) by 10m (height), and the total assumed volume is 44.325 million cubic meters. Combining with the total tonnage excavated in reality, the overall density is 2.1 ton/m3, which is close to reality. It is noteworthy that the enterprise's mining and processing capabilities are limited to a monthly output of 9.4 million tons and 6 million tons, respectively. Meanwhile, the minimum acceptable mining tonnage per month is 5.4 million tons. These upper and lower limits are crucial in determining the feasibility and effectiveness of the mining operations and must be considered in any operational strategy or planning. The discount rate of revenue and costs in the case study is set to one percent per month.

Although 1773 blocks are insignificant, when put into the optimization model, 42588 decision variables will be generated, dramatically slowing down the optimization speed. Therefore, the author aggregates the blocks into mining cuts, which have a bigger size. The hierarchical clustering algorithm adopted in this paper was developed by Tabesh [29]. Their algorithm considers max cluster size, the distance between blocks, block grade difference, rock type difference, and many other factors. Different weights could be given based on preference. The mining cuts obtained using this algorithm can maintain the relative physical position between the original blocks so that the mining sequence generated after aggregation remains reasonable. After aggregation, thirty-eight new "blocks" were obtained. Then, two short-term near-optimal mining sequences are generated for the case study. One is for the traditional out-of-pit crusher mining method, and the other is for the NFS mining method. Formulations used for TS optimization are proposed by Tabesh and Askari-Nasab, as referenced earlier. The traditional one is taken as a benchmark, and its formulations are listed in [30]. Both optimization models are formulated in MATLAB [31] and solved by CPLEX [32] through API. Meanwhile, a simulation model for traditional method is also developed based on the flow chart shown in Figure 3. The processes needed to finish the simulation and optimization-model are shown in Figure 7. Six independent variables and two dependent variables are defined as key performance indicators (KPIs) in Table 1 to validate the proposed simulation model.

Table 1 KPIs to be measured and compared.

Type	Variables
Independent variables	Average tonnage/truck (ton)
	Loading time (min)
	Dumping time (min)
	Empty speed (km/h)
	Full speed (km/h)
	Haul distance (km)
Dependent variables	Cycle ready time (min)
	Ton per gross operating hour (TPGOH) (ton/h)

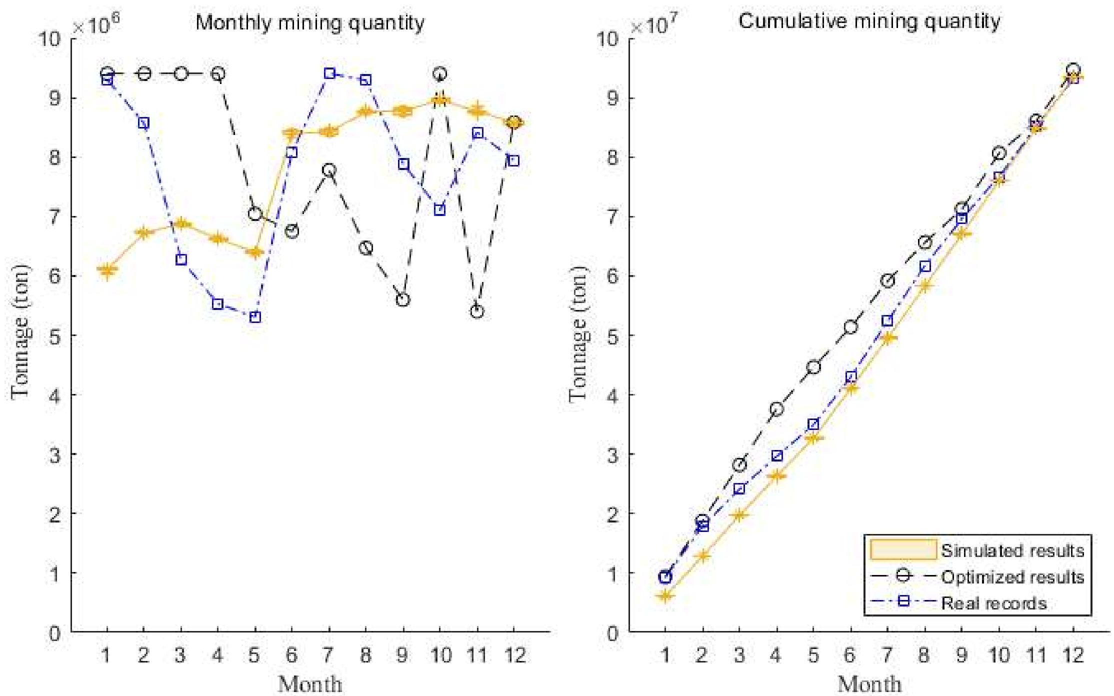

Figure 8. Monthly mining quantity (left) and cumulative mining quantity (right) of traditional mining method under three scenarios: optimized mining schedule, simulated mining schedule and original mining schedule.

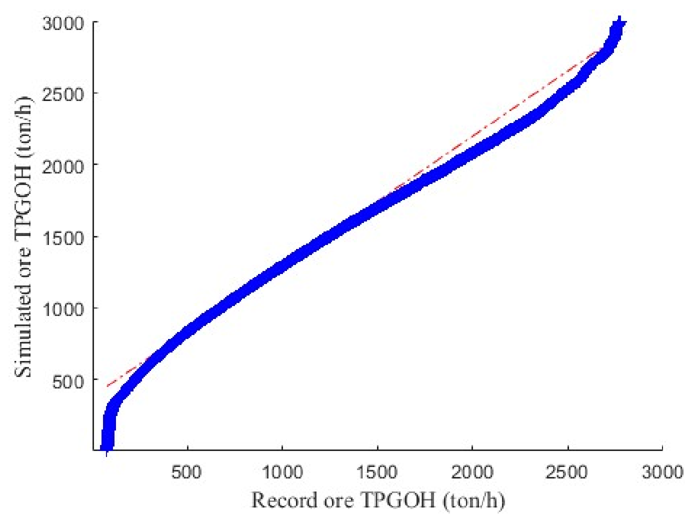

Figure 9 QQ plot of ore TPGOH under real operation versus simulated ore TPGOH under traditional mining method.

The simulation length was set to 12 months and 366 days, considering the leap year of 2016, to obtain results for comparison after running the model for 10 replications. The left graph in Figure 8 displays the total tonnage moved in each month under three schedules: optimized, real, and simulated. Although the simulation model takes the optimized schedule as input, the simulated schedule is not the same due to the incorporation of numerous uncertainties into the system. Nevertheless, in comparison to the other two schedules, the simulation model performed well, with results fluctuating within a reasonable range and never exceeding its nominal capacity or falling below the minimum acceptable value. The right graph in Figure 8 shows the cumulative tonnage excavated within the given period. The simulation results followed the same trend as operations under the real schedule and achieved almost the same level of production, which clearly validated the simulation model.

However, the primary focus of mining companies has always been on the ore material. In this regard, Figure 9 displays the QQ plot of the TPGOH distribution of ore between the simulated and recorded results. The primary distribution area does not exhibit any significant differences except for TPGOH values lower than 200 and higher than 2800. This consistency in the results demonstrates that the simulation model can effectively represent real operations.

Besides, the comparisons of predetermined KPIs between simulated results and record are presented in Table 2, which also serves as compelling validation for the simulation model. 'Rec' in table represents record and 'SimTra' in tables and ‘TRA’ in figures represent the simulated result of the traditional mining method. Taking the average payload of trucks per cycle as an example, the difference between the simulated data and the records is only 0.62%, and the difference between the annual mining tonnage is 0.31%. Although the average difference of other independent variables increased slightly, the difference range only fluctuates in a narrow range, indicating that the consistency of these variables is confirmed. As for the dependent variables, the difference is about 7%, which also falls within an acceptable range. These observations clearly demonstrate the model's ability to capture real mining operations. It worth mentioning that all the simulation results provided in this paper have 95% confidence intervals.

Table 2. Comparison of KPIs between record and simulated results.

Operational data	Range	Mean	Summation
Average tonnage/truck(ton) - Rec	470	337	93,090,766
Average tonnage/truck(ton) - SimTra	470±0	335±0.32	93,374,636±189,085
Difference	0.00%	-0.59%	0.30%
Loading time(min) - Rec	5	2.42	668,739
Loading time(min) - SimTra	5±0	2.89±0	805,227±1,968
Difference	0.00%	19.42%	20.41%
Dumping time(min) - Rec	2.67	0.95	263,116
Dumping time(min) - SimTra	1.64±0.2	0.95±0	265,428±398
Difference	-38.58%	0.00%	0.88%
Empty speed(km/h) - Rec	65	28.06	-
Empty speed(km/h) - SimTra	64±2.7	28.62±0.02	-
Difference	-1.54%	2.00%	-
Full speed(km/h) - Rec	65	26.49	-
Full speed(km/h) - SimTra	58.44±0.38	26.1±0.04	-
Difference	-10.09%	-1.47%	-
Haul distance(km) - Rec	8	3.91	1,078,647
Haul distance(km) - SimTra	7.99±0	3.88±0.01	1,079,935±2,252

Difference	-0.12%	-0.77%	0.12%
Cycle ready time (min) - Rec	75	26.48	7,308,292
Cycle ready time (min) - SimTra	100±52	24.6±0.03	6,851,909±13,464
Difference	33.33%	-7.10%	-6.24%
TPGOH- Rec	2,829	917.1	253,155,367
TPGOH- SimTra	2,957±662	980±1.81	272,966,328±651,926
Difference	4.35%	6.39%	7.83%

4.2. Distance and TPGOH

After the validation of the simulation model, the following sections will compare the results of the simulation model of the NFS method the traditional method from various aspects and quantitatively analyze the performance of the NFS method. Like the IPCC method, the crusher in the NFS method is located at the pit bottom, which can significantly reduce the truck transportation distance of the ore material. In this case study, compared to the traditional method, the average ore moving distance by truck in the NFS method decreased significantly.

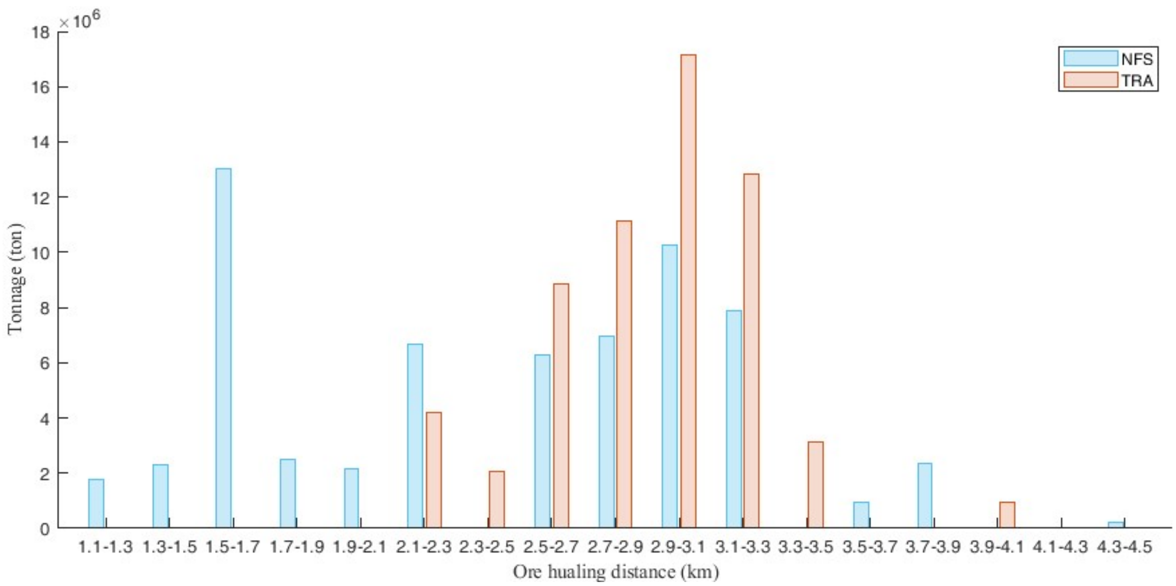

Figure 10. Cumulative ore tonnage comparison in each hauling range under NFS mining method and traditional mining method

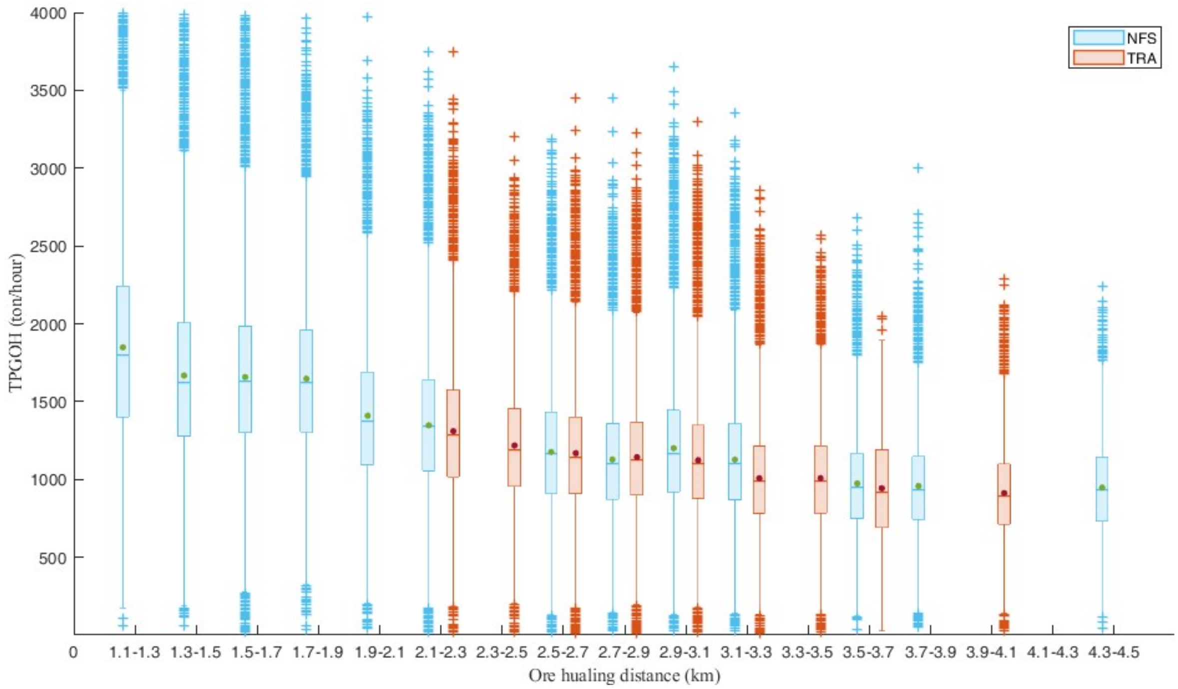

Figure 11. Ore TPGOH comparison in each hauling range under NFS mining method and traditional mining method.

Figure 10 is presented to illustrate the total tonnage of ore material in different distance ranges, before and after applying the NFS method. The minimum distance for ore transportation by truck was found to be between 2.1 and 2.3 kilometers before the application of the method, which decreased to a range of 1.1 to 1.3 kilometers after implementation. With the exception of 3 million tons of ore, most of the material experienced a reduction in haulage, with an average drop of 17.87% as shown in Table 3. The reduction in transportation distance resulted in a direct benefit of a 16.30% decrease in the average cycle time of ore trucks, which significantly improved operational efficiency. Additionally, it is well-known that shorter transport distances lead to higher TPGOH. To demonstrate this, Figure 11 shows the simulation results of ore TPGOH under different hauling ranges and mining methods. Table 3 indicates that the TPGOH of ore material in the NFS method increased by 19.71%.

Since the waste material is still transported to the out-of-pit dump locations only with trucks, there were no significant differences in the transportation efficiency and cycle time of waste material between the two methods, which is consistent with expectations. Similarly, 'SimNfs' in chart and 'NFS' in figure represent simulation results of the NFS model.

Table 3. Distance related simulation data comparison of two methods.

Operational data	Range	Mean	Summation
Ore cycle time(min) - SimTra	568±52	19.81±0.06	3,585,891±16,839
Ore cycle time (min) - SimNfs	331±467	16.58±0.08	3,145,992±16,078
Difference	-41.73%	-16.30%	-12.27%
Waste cycle time(min) - SimTra	165±24	33.46±0.08	3,266,018±11,407
Waste cycle time(min) - SimNfs	169±51	32.33±0.09	3,324,474±8,519

Difference	2.42%	-3.38%	1.79%
Ore haul distance(km) - SimTra	1.81±0	2.91±0	526,510±1,209
Ore haul distance (km) - SimNfs	3.34±0	2.39±0	453,376±864
Difference	84.53%	-17.87%	-13.89%
Waste haul distance (km) - SimTra	7.98±0	5.67±0	553,425±2,205
Waste haul distance (km) - SimNfs	7.98±0	5.55±0.01	570,972±2,014
Difference	0.00%	-2.12%	3.17%
Ore TPGOH - SimTra	2,726±662	1,122±3.11	203,170,229±455,307
Ore TPGOH - SimNfs	3,590±1740	1,344±343	254,946,861±1,047,751
Difference	31.69%	19.79%	25.48%
Waste TPGOH - SimTra	2,957±365	715±1.59	69,796,099±215,856
Waste TPGOH - SimNfs	2,853±245	737±2.53	75,797,750±220,647
Difference	-3.52%	3.08%	8.60%

4.3. Productivity

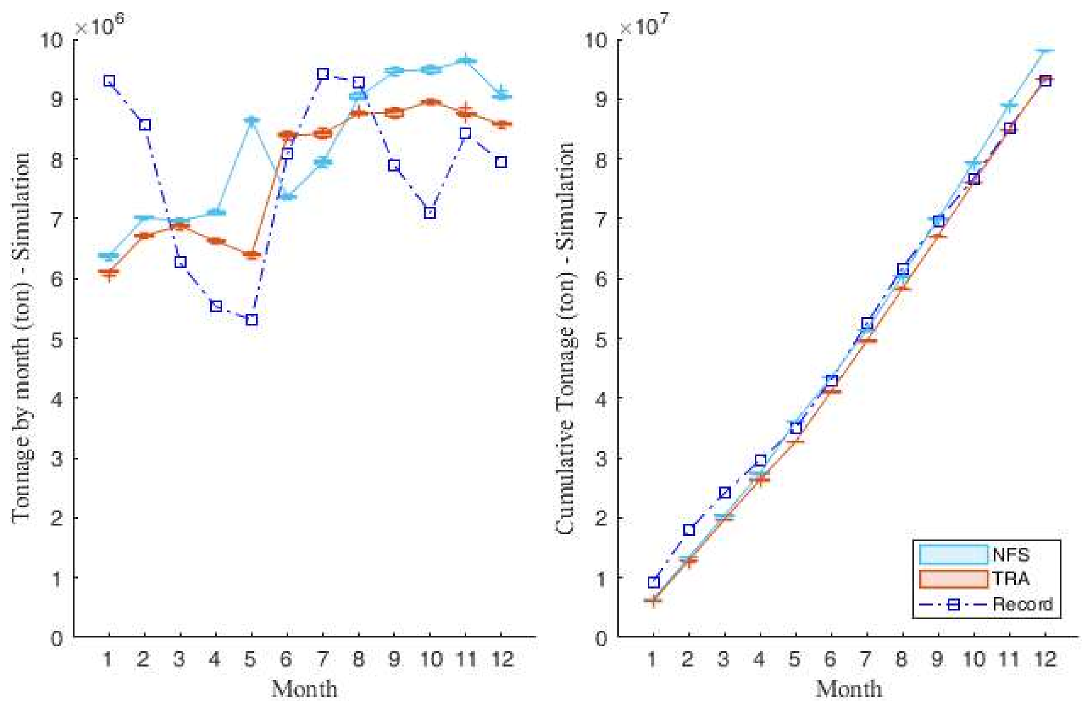

Figure 12 Average monthly production and cumulative production of NFS mining method and traditional mining method compare against record.

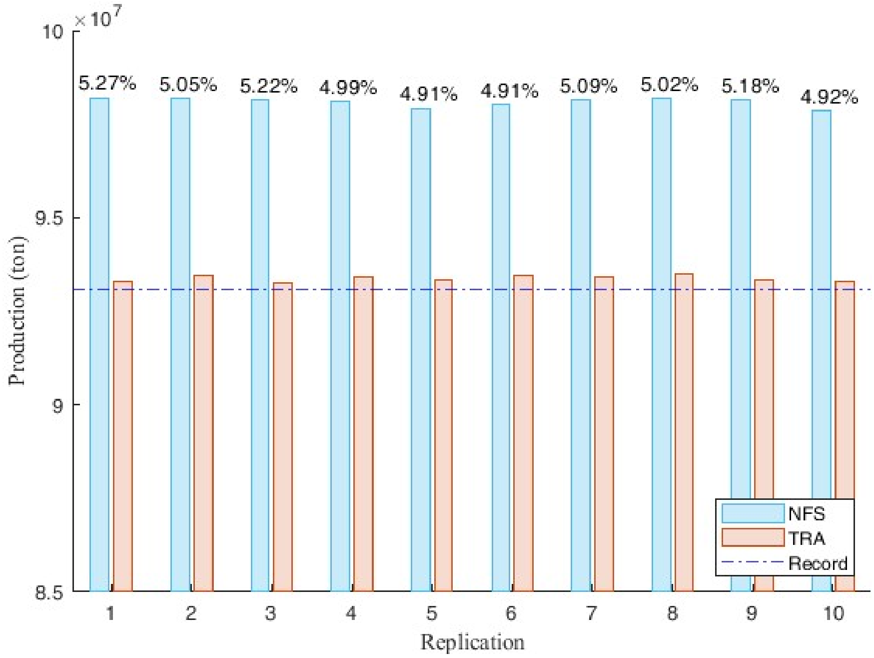

Figure 13 Simulated annual production comparison between NFS mining method and traditional mining method.

In this section, we demonstrate the impact of improved truck efficiency and TPGOH on the tonnage of material transported to the crusher/stockpile per unit of time and ultimately, on production rate. Our results show that with the same number of trucks, the NFS method outperforms the traditional method in terms of production. Figure 12 displays the monthly average and annual production of both methods, indicating that in most months, the NFS method yields higher production and overall cumulative tonnage. The average production results of ten replications are shown in Table 4 and year by year comparison are shown in Figure 13. Our findings indicate that compared to the traditional mining method, the NFS method improves yearly production by 5.06%.

Table 4. Tonnage related simulation data comparison of two methods.

Operational data	Range	Mean	Summation
Average tonnage/truck(ton) - SimTra	470±0	335.15±0.32	93,374,636±189,085
Average tonnage/truck(ton) - SimNfs	470±0	335.31±0.65	98,096,248±270,705
Difference	0.00%	0.05%	5.06%

4.4. Equipment utilization

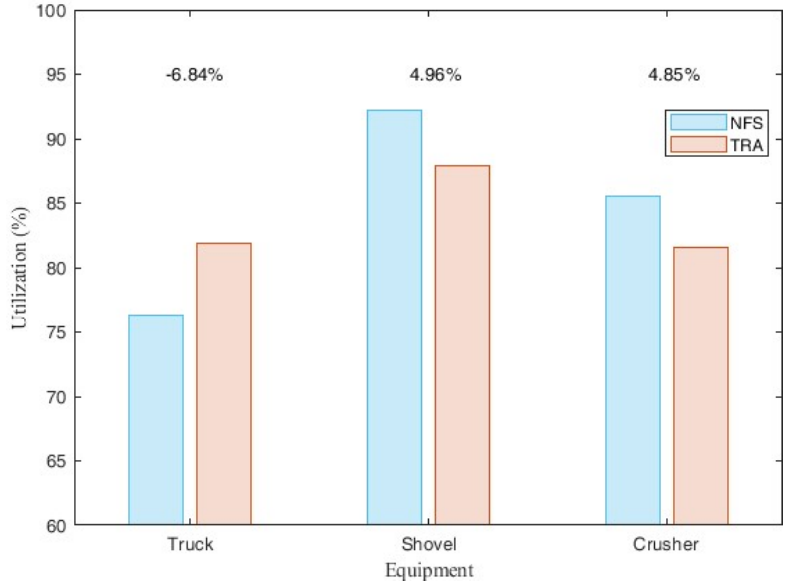

Figure 14 Trucks', shovels', and crusher' utilization comparison between NFS mining method and traditional mining method.

The increase in production can be attributed to the enhanced utilization rates of the crusher and shovels. As shown in Figure 14, demonstrates that the utilization rates of shovels and crusher under the NFS method are elevated by 4.96% and 4.85%, respectively, as compared to the traditional mining method. However, the constant number of trucks used for transportation, coupled with the reduction in the distance covered, has led to an increase in the wait time in queue for trucks. Consequently, there is a decrease of 6.84% in the overall utilization rate of the trucks. It also shows that the NFS method inherits the advantages of IPCC and curtails the demand for trucks. The improved utilization rate of the crusher and shovels can be primarily attributed to the presence of the near-face stockpile. In the traditional method, a fully loaded crusher would result in waiting time for trucks to dump their loads, and if one of the shovels is under maintenance or engaged in mining waste blocks at a specific time, the crusher would remain idle. Although the NFS method cannot entirely eradicate this issue, it has minimized its frequency, thus enhancing the utilization rate of the equipment. Table 5 displays that the average truck waiting time at the crusher/stockpile has reduced by 57.14%. However, the truck wait time at the shovels has increased by 21.05%. Overall, the NFS method has the potential to optimize production efficiency in mining operations while reducing the number of trucks required for transportation.

Table 5. Queue time comparison of two methods.

Operational data	Range	Mean	Summation
Ore Dumping Queue (Min) - SimTra	553±55	1.26±0.06	227,631±9,818
Ore Dumping Queue (Min) - SimNFS	292±532	0.54±0.07	102,180±12,652
Difference	-47.25%	-57.14%	-55.11%
Waste Dumping Queue (Min) - SimTra	3.05±0.88	0.06±0.01	5,458±139
Waste Dumping Queue (Min) - SimNFS	3.12±0.58	0.06±0	5,273±203

Difference	2.30%	0.00%	-3.50%
Queue Time Before Shovel (Min) - SimTra	600±454	5.96±0.07	1,660,660±16,196
Queue Time Before Shovel (Min) - SimNFS	724±562	7.24±0.06	2,117,266±13,539
Difference	17.13%	21.48%	27.50%

5. Summary and conclusion

The NFS mining method is a new mining method that combines IPCC with a pre-crusher stockpile and theoretically has all the advantages of IPCC and stockpile. However, its performance is not verified. To tackle this problem, this paper presents an optimization-simulation based framework that can evaluate a mining method from multiple aspects, in a quantitative and objective manner. Running this framework to evaluate a mining method involves three steps: The first step is to establish and run an optimization model suitable for the target mining method and obtain a practical or even optimal mining schedule. The second step is to create a simulation model suitable for the target method and use the optimized mining schedule as input. Then run the simulation model for multiple replications and quantify the performance of this method. The last step is to compare the simulated results with the benchmark and objectively evaluate the pros and cons of the target method. Specifically, a short-term mining schedule optimization model for the NFS method based on mixed integer linear programming is proposed in this research and. Meanwhile, simulation models for the traditional TS mining method and the NFS method are also built. After that, the established simulation and optimization framework was applied to an oil sand mine, and the validation of the proposed framework was conducted by comparing the simulation results of the traditional mining method with real records. Subsequently, the framework was employed for the NFS mining method, and the simulation results were compared with the benchmark (i.e., the simulation results of the traditional mining method). Through these comprehensive steps, this study provides a novel and quantitative assessment of the NFS method's performance, allowing for the verification of its theoretical advantages.

In comparison to the conventional truck and shovel mining method, the NFS method showcases significant advantages. Notably, it achieves a reduction of 17.87% in the transportation distance covered by trucks, along with a shortened truck cycle time by 16.30%. Consequently, the TPGOH of ore material experiences a substantial increase of 19.79%. Additionally, the NFS method effectively mitigates idle time for shovels and the crusher, resulting in a respective utilization improvement of 4.96% and 4.85%. Simulation results also demonstrate a significant decrease of 57.14% in the dumping queue time preceding the crusher. By enhancing equipment efficiency and utilization, the NFS method ultimately achieves a remarkable production increase of 5.06%.

The findings of this study suggest that the NFS method has significant application value and is worthy of further research. Meanwhile, this research provides important insights into the potential of the NFS method for improving the system’s stability, mining efficiency, and productivity, and highlights the importance of simulation modeling in evaluating and optimizing mining methods.

The current research does not provide verification of quality blending, an essential theoretical advantage of the NFS method. Additionally, the study does not examine the influence of stockpile capacity size and the number of zones on the performance of the NFS method. These aspects hold significant importance in promoting and applying the NFS method, prompting the author to undertake further exploration.

6. Declaration of Competing Interest

None.

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