Optimization and simulation-based verification of near face stockpile mining method

by

Hongshuo Gong

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Department of Civil and Environmental Engineering
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ABSTRACT

The downturn of the world economy and the increasingly severe competition among mining giants puts forward higher requirements for open-pit mining, which is the dominant method for humans to obtain minerals from the earth. Among these so-called higher requirements, reducing mining costs as much as possible is the most important one. Only by reducing mining costs can the profit margin of the enterprise be improved, so that the enterprise can survive the fierce market competition. Fundamentally speaking, there are two main ways to reduce mining costs. The first is to increase the utilization rate of existing equipment under existing conditions, that is, to achieve the expected benefits by formulating efficient long-term, medium- and short-term plans. The other is to improve the current mining methods. This needs to improve the deficiencies of the existing conventional mining methods from the system level to further improve production efficiency. Near face stockpile mining method is an innovative open-pit mining method based on this condition. Compared with traditional mining methods, this method creatively uses the approach of the in-pit-near-crusher stockpile to isolate or decouple the mining process from the crushing and processing process, so as to minimize the problem of low equipment utilization caused by mutual influence between the two procedures.

Several models and algorithms have been put forward to reduce the operational cost by using the first approach but not all major concerns are satisfied, and the results are not optimally guaranteed. Meanwhile, there is no model has been published for the second approach. Therefore, the problem to be addressed in this research is:

> *Can a simulation-optimization framework be developed for near face stockpile mining method that (1) generates an optimal or near-optimal schedule, and (2) captures mining and processing operations' uncertainties, to measure its performance quantitively and compare it with regular out-of-pit mining method?*

The following tasks are going to be considered in this research: (i) to establish, implement and verify a theoretical optimization model for near face stockpile method mining schedule generating while considering multiple practical constraints, (ii) to establish, implement and verify a simulation model that could accurately capture the characteristics of the near face stockpile method, (iii) integrate the optimization model and simulation model and validate the integrated framework and use it to quantitively evaluate the performance of near face stockpile method. To satisfy those tasks listed, the following procedures would be applied: (i) establish a mathematical model for mining schedule optimization, (ii) translate the math model into MATLAB by coding, (iii) verify the mathematical model by case study, (iv) develop simulation model by discrete event simulation software, (v) test and verify the simulation model, (vi) integrate the mathematical model and simulation model into a comprehensive framework, (vii) test and verify the integrated framework, (viii) validate the integrated framework by case study, and (ix) compare the simulated results of near face stockpile method against traditional simulation results and evaluate its performance.

The main scientific contribution of this study would be: (i) establish a mathematical optimization model that can generate optimal or near-optimal mining schedule for near face stockpile method with limited human intervention, (ii) propose a simulation model that can capture mining and processing operations' uncertainties of near face stockpile mining method, (iii) develop a comprehensive simulation-optimization framework that can be used to quantitatively measure the performance of different mining methods from multiple aspects.

PREFACE

This thesis is an original work by Hongshuo Gong. Some parts of this work are published as:

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Gong, H., Afrapoli, A. M., & Askari-Nasab, H. (2023). Integrated Simulation and Optimization Framework for Quantitative Analysis of Near-face Stockpile Mining. Simulation Modelling Practice and Theory, 102794.

I was responsible for designing the conceptual model, the algorithms and case studies, running the case studies, documenting and analyzing the results and writing the manuscripts. H. Askari-Nasab was the supervisory author, who was involved with concept formation and manuscript composition.

DEDICATION

This thesis is proudly dedicated to

My beloved wife Mrs. Jing Ren

My dear son Jiayou Gong

My father Mr. Baoxiang Gong

My mother Mrs. Guihua Gong

I love you all

deeply and thoroughly

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I am grateful to China Scholarship Council for providing financial support for my research and living. Your support has been instrumental in enabling me to conduct my research and complete my studies.

Finally, I would like to give a big thank you to my wife, Jing Ren. My wife and I were separated for three years due to Covid-19. In the past three years, she has worked tirelessly to take care of our son alone, assumed the responsibilities I should have, and paid unimaginable hard work and sweat. Her love, care, and dedication have been my rock and inspiration throughout this journey. If it were not for her unwavering support and sacrifice, I would not be able to complete my studies. Next, I will assume the responsibilities of a husband and father with even greater love and devotion. Thank you, Jing Ren, for being my partner in life and the reason for all my achievements.

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LIST OF ABBREVIATIONS

3G	Third generation of wireless mobile telecommunications technology
4G	Fourth generation of broadband cellular network technology
AR	Augmented reality
CA	Cellular automata
CI	95% Confidence interval
DES	Discrete event simulation
GA	Genetic algorithm
GAMM	Gamma distribution
GASP	General activity simulation program
GIS	Geographic information system
GP	Goal programming
GPRS	General packet radio services
GPS	Global positioning system
GPSS	General purpose simulation system
ID	Identification
ILP	Integer linear programming
IPCC	In pit crushing and conveying
IQR	Interquartile range
KPI	Key performance indicators
LOGN	Lognormal distribution
LP	Linear programming
LTOPP	Long-term optimization production planning
MILGP	Mixed integer linear goal programming
MILP	Mixed integer linear programming
MIP	Mixed integer programming
MR	Mixed reality

MTBF	Mean time between failure
MTBR	Mean time between repair
MWT	Magnetic weight
NFS	Near face stockpile
NLP	Nonlinear programming
NORM	Normal distribution
NPV	Net present value
QMASTOR	Quality management and stockpile tracking optimization routine
QQ	quantile-quantile
QT	Queueing theory
R.A.M.	Reliability, availability and maintainability
SA	Stochastic algorithm
SIMAN	Simulation language
SLAM	Simulation language for alternative modeling
SMIP	Stochastic mixed integer programming
SMU	Selective mining units
SPS	Symbolic program system
SR	Stripping ratio
STD	Standard deviation
TBF	Time between failures
TKM	Ton-kilometer
TPGOH	Ton per gross operating hour
TS	Truck shovel
VBA	Visual basic for application
VR	Virtual reality
WEIB	Weibull distribution

LIST OF NOMENCLATURES

Sets

B^p	A set of polygons that must be extracted before mining polygon p to adhere to slope and precedence constraints.
U^p	Represents all the clusters that are encompassed within polygon p

Indices

$d \in \{1,...,D\}$	Destinations (waste dump, crusher, or stockpile) index
$p \in \{1,...,P\}$	Polygons index
$k \in \{1,...,K\}$	Clusters index
$e \in \{1,...,E\}$	Elements index
$t \in \{1,...,T\}$	Periods index
$s \in \{1,...,S\}$	Stockpile zones index

Parameters

$\overline{MC}^t$	The upper bounds of the mining capacity in different time periods t
$\underline{MC}^t$	The lower bounds of the mining capacity in different time periods t
$\overline{PC}^t$	The upper bounds of the processing capacity in different time periods t
$\underline{PC}^t$	The lower bounds of the processing capacity in different time periods t
$\overline{G}^{t,e}$	Maximum grades allowed of element e sent to processing plant in different time periods t
$\underline{G}^{t,e}$	Minimum grades allowed of element e sent to processing plant in different time periods t
s_p	Total number in S^p
o_p	Ore tonnage in polygon p
w_p	Waste tonnage in polygon p
o_k	Ore tonnage in cluster k
w_k	Waste tonnage in cluster k
o_r	The total reserve tonnage of ore material
w_r	The total tonnage of waste material that needs to be moved

c_p^t	The discounted costs of mining one unit of material from polygon p in period t and sent to its destination (both ore and waste)
$r_k^{t,e}$	Discounted revenue generated from processing one unit of element e from cluster k in period t minus the crushing, processing, and selling costs
$r^{t,e}$	Discounted revenue generated from processing one unit of element e from stockpile in period t minus the rehandling, crushing, processing, and selling costs
$r_s^{t,e}$	Discounted revenue generated from processing one unit of element e from stockpile zone s in period t minus the rehandling, crushing, processing, and selling costs
g_k^e	Average raw ore grade of element e in cluster k
ε	Tonnage flexibility
$gr_s^{t,e}$	Average grade of element e in stockpile zone s in period t
$y_p^t \in [0,1]$	The portion of polygon p extracted in period t (both ore and waste). Continuous variable
$x_k^t \in [0,1]$	The portion of cluster k extracted in period t (both ore and waste). Continuous variable
$b_p^t \in \{0,1\}$	If all the predecessors of polygon p are extracted by or within period t. Binary variable
f^t	Reclaimed tonnage from the stockpile in period t. Continuous variable
f_s^t	Reclaimed tonnage from the stockpile zone s in period t. Continuous variable
$gr^{t,e}$	Grade of element e reclaimed from stockpile in period t

1. INTRODUCTION

1.1. Background

Mining, the process of obtaining desired substances from the ground by various means, has an extremely long history - even as long as human beings. New research findings indicate that the earliest mining activity dates back to 43,000 years (contributors, 2022). So far, the mining industry still provides an endless stream of material for the development of human civilization and is also an essential cornerstone for the continuation of human society.

During the last three decades, much mining research has been carried out on large open-pit mines, and the production of open-pit mines increased considerably. An example is the Escondida mine in Chile. At the beginning of the 1990s, about 90% of minerals were extracted by underground methods, whereas by 2000, more than 85% of minerals were extracted by the open-pit method. Although the operations in open-pit mines nowadays still look the same as decades ago, the scale of the mines and the equipment size is much bigger than they used to be. For example, in 1970, the average truck size employed by open-pit mines was only 90 t, while by 2008, the number went up to over 180t (Darling, 2011). Moreover, Caterpillar and Bucyrus have released oversized trucks with a capacity of over 360t that are being used worldwide (contributors, 2022).

Open-pit mining is capital intensive in order of billions of dollars to support daily operation and maintenance. Moreover, like most other companies in the world, almost all mining companies aim to maximize their profits, in terms of the net present value (NPV) and expand their market share. However, the mining industry is very cyclical. Therefore, when the price of mineral products cannot be effectively raised and even sold at a lower price, the primary method to ensure the company's profitability is to reduce operational costs like mining and management costs (Askari-Nasab et al., 2007). Furthermore, a well-organized mine plan is required to optimally reduce unnecessary equipment movement and increase equipment utilization. Therefore, detailed geological surveys and reasonable mine mining plans in different time resolutions have crucial economic significance for mining companies.

Mine planning is a crucial aspect of mining operations and is typically conducted in three phases based on different time resolutions. The first phase is the long-term plan, which covers a plan for decades or the entire life of the mine. This plan is based on geological models and economic predictions, which reflect the feasibility of the mine. The outputs of this phase guide the latter phases of planning. The second phase is the medium-term plan, which is more detailed compared to the long-term plan. It covers a range of about five years or less and provides information such as benches, pit shells, or equipment requirements. The medium-term plan provides more specific details to help ensure efficient and effective mining operations. The last phase is the short-term plan, which covers a plan from one month to quarters or up to a year. During this phase, the mining operation is subdivided into faces or blocks, and constant feed to the crusher and processing plant is considered. (Osanloo et al., 2008).

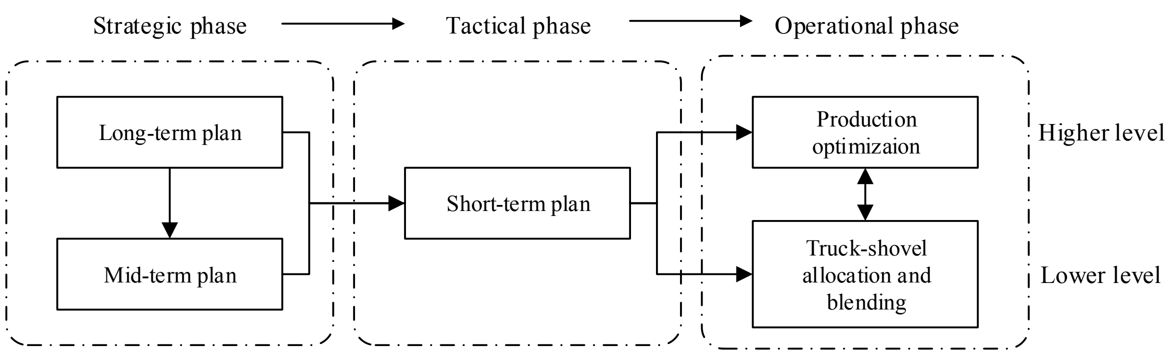

Figure 1.1 Phases of the mine planning

As seen in Figure 1.1, the short-term plan can also be divided into two sub-levels: the higher and the lower levels. The higher level is about production optimization based on short-term plan targets and the capacity of excavation, transportation, and processing equipment and the capacity of each path between shovel to the processing plant, shovel to stockpile, and shovel to dump. The lower level is about real-time truck and shovel allocation under the higher-level optimization, and stockpile blending to feed the plant constantly. The feedback from the lower operational level could also affect the higher level and lead to re-optimization to match the limitations in actual operations. There is

no doubt that the targets of the medium and long term can only be met when the goals of the short-term planning are met. However, due to geological uncertainty, price fluctuation in the market, and operational uncertainties, short-term plans need to be adjusted based on reality. Therefore, the actual output and cash flows of the mine might be very different from the forecast.

Despite all this, on-site mine staff will do their best to accomplish or even exceed the key performance indicators (KPI) targets set in the long-term mining schedule. To achieve the KPIs, minimizing unscheduled downtime is the top goal for managers. The failure of shovels and trucks caused by mechanical problems, weather, or road conditions will lead to an extra unplanned idle time of the crusher and processing plant, which will seriously affect the mine output. As a sequence, stockpile, which is initially used in many mines for low-grade ore inventory but can also act as a “buffer” for production, has received widespread attention from researchers. Nowadays, stockpiles are widely used for different reasons and are placed in various locations in various mines. For example, when the price of the final product in the market is relatively low, the cut-off grade will be higher than average. As a result, some mines will stockpile the material under cut-off grade and wait to re-handle it when it has positive economic value.

Among different types of stockpiles, near face stockpile (NFS) or near crusher stockpile is the focus of this research. According to Jupp et al. (2013), the near-crusher stockpile usually plays four roles simultaneously, storing, buffering, blending, and grade separation. Nevertheless, the near face stockpile with an in-pit crusher could shorten the transportation time significantly and reduce the operating costs in two aspects. First, it requires a smaller number of trucks in the fleet. Second, shortening the haulage distance will dramatically reduce the operation cost, considering that the truck and shovel operating costs make up to 50 percent or even more in operation costs in open-pit mines (Alarie and Gamache, 2002).

1.2. Statement of the problem

1.2.1 Introduction

The pursuit of maximum profit is the nature and mission of every enterprise. However, given the current downturn of the international economy and the high competition among mining enterprises, product prices are highly uncertain and cannot be accurately predicted. Therefore, mining companies have put forward higher requirements for open-pit mining to reduce costs as much as possible. Reducing mining costs could improve the companies' profit margin and help the enterprise survive in the fierce market competition.

There are two common cost-reduction methods. The first is to increase the utilization rate of existing equipment without changing the mining method to obtain a higher production rate. More specifically, by doing some optimization in the operation level to generate more profit by minimizing equipment idle time. However, with years of effort on optimization done by researchers and the standardization of company management getting higher and higher, the room left for increasing the utilization is very limited. The other way to reduce mining costs is to optimize the current mining methods, which means improving the deficiencies of the widely used conventional mining methods to further improve production efficiency. The near face stockpile mining method is a proposed open-pit concept to fulfill this goal.

Unlike typical open-pit mines where the crusher and stockpile are always permanently located outside the pit limit, the near face stockpile with an in-pit crusher requires those facilities to be movable and situated at the bottom of the pit. Meanwhile, the in-pit crusher and the stockpile could be relocated once needed, which means that the equipment could be replaced and reassembled in different benches with the development of the pit while the mine expands yearly. Finally, it is worth mentioning that the conveyor belts play an essential role in transporting material from the pit to the processing plant.

Figure 1.2 and Figure 1.3 show the typical layout of the near face stockpile mining method. As can be seen from the figures, the various activities involved in the NFS approach are as follows:

1. Shovels are allocated to working polygons and request trucks
2. Empty trucks haul to shovels
3. Shovels start digging the assigned polygons and loading the trucks

4. Loaded trucks with ore material travel in-pit to the stockpile located in pit bottom and unload material to the stockpile

5. Loaded trucks with waste material travel to the waste dump located out of pit and unload carried material

6. Emptied trucks dispatched to shovels for next round

7. Reclaim shovel reclaim material from the in-pit stockpile and feed the crusher

8. Crusher crushes ore material received to an acceptable particle size

9. Crushed ore material transferred to the processing plant through conveyor

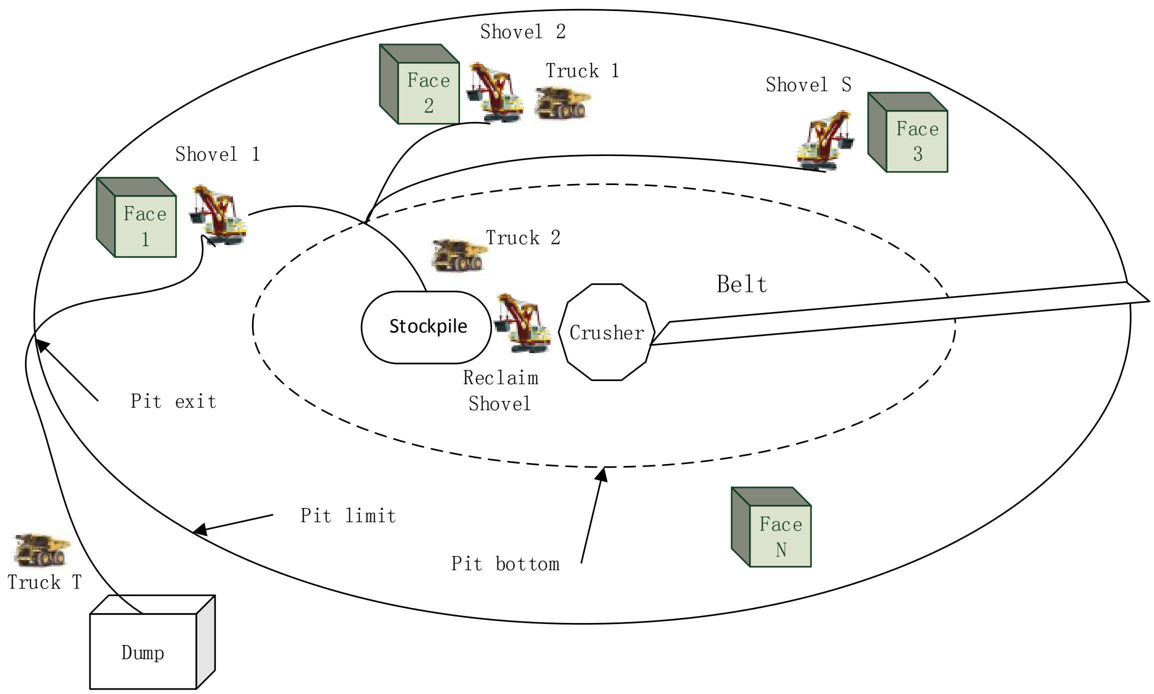

Figure 1.2 A typical overview of the near face stockpile mining method

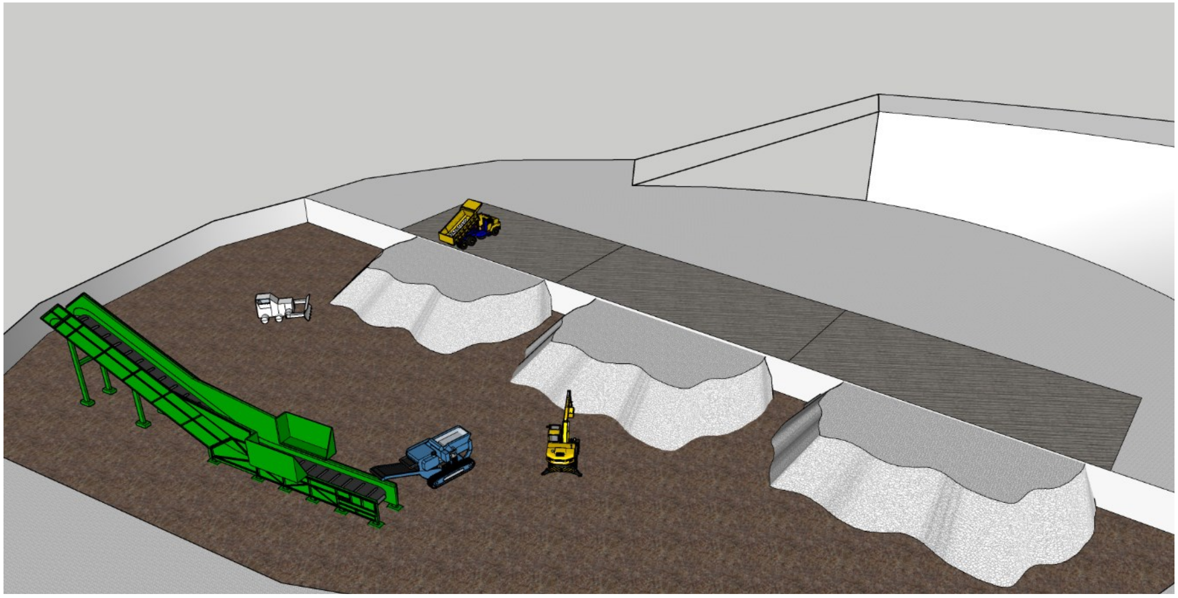

Figure 1.3 A typical pit bottom layout of the near face stockpile mining method

The size of the stockpile in the NFS method is not the usual infinite size. This is because the area of the pit bottom is usually relatively small for cost considerations. The larger the stockpile, the larger the area it occupies. Therefore, the capacity of the stockpile in the NFS method is limited to satisfy the continuous operation of the crusher for 24 hours. That is to say, if the stockpile is fulfilled, even if no new dumping is received, the reclaim process can support the crusher to work for a whole day. Similarly, if the stockpile is empty, it can continue to receive more material until it becomes full, and there is no need to worry about trucks queuing up before the dumping spot before it is full. The stockpile is usually divided into three zones to avoid hidden dangers caused by dumping and reclaiming occurring in the same place. In this way, each zone can independently support the crusher working for eight hours. Taking oil sands mine as an example, its bulk density is about 2.1 metric tons per cubic meter, and its natural repose angle is around 33°. Assuming that the capacity of the crusher is 6000 tons per hour and the height of the stockpile is 15 meters, about 21827 metric tons of ore material can be stored for every 60 meters, and the total length of the required stockpile is 396 meters, that is, the footprint of the stockpile is 9143 square meters, as shown in Figure 1.4.

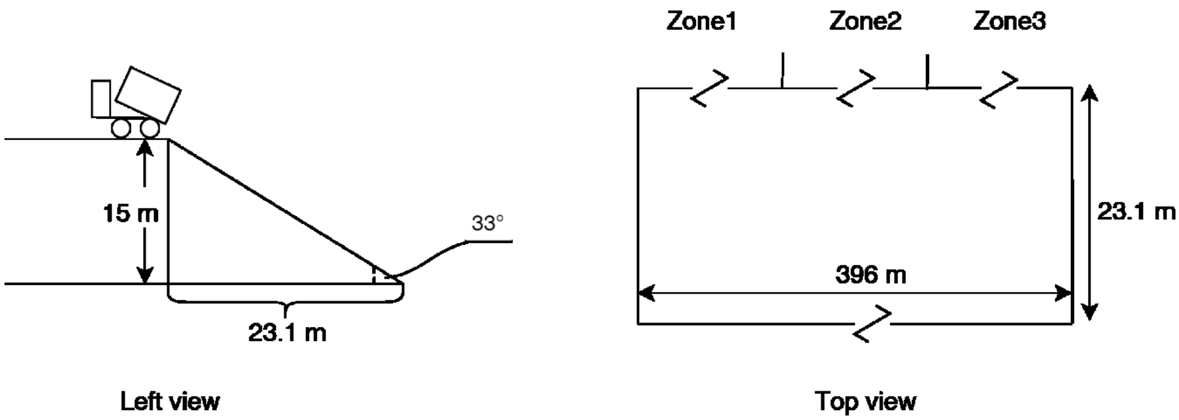

Figure 1.4 An example of stockpile footprint on oil sands mine

The stockpile at the pit bottom decouples the mining and milling process. The decoupling makes it possible that when the mining or hauling system stops for scheduled or unscheduled reasons, the crusher could still work for desired periods to avoid shutdowns of the whole system. It can also be seen that the essential difference between the NFS mining method and traditional out-of-pit crusher mining methods is that the ore materials are hauled only within the pit (from working face to pit bottom stockpile), which shortens the hauling distance and reduces the operational cost. Unfortunately, there is limited research in this area in literature.

It is widely acknowledged in the mining industry that a mining method, regardless of its suitability, may not achieve its intended objectives without a well-conceived mining plan. Thus, the assessment of mining methods should rely on the prudent execution of a near-optimal mining plan. As previously mentioned, the primary objective of a mine plan is to identify the optimal sequence of individual blocks or selective mining units (SMUs) for extraction while taking into account the physical and operational limitations, with the aim of maximizing the net present value. Inherently, this approach prioritizes the acceleration of higher net cash flows over time.

1.2.2 Research question

Despite the various advantages of NFS listed above, since NFS is still in the conception stage and has not been practically applied, the reliability of its benefits is still questionable. Therefore, the main problem to be addressed in this study is to understand the performance of the near-face-stockpile mining method compared to the traditional out-pit crusher scenario. The research question can be stated as follows:

Can a simulation-optimization framework be developed for near face stockpile mining method that (1) generates an optimal or near-optimal schedule, and (2) captures mining and processing operations' uncertainties, to measure its performance quantitively and compare it with regular out-of-pit mining method?

The above statement is a generalization of this study but does not contain all the details. It is easy to build an optimization or a simulation model but building a logical and practical model is a challenge. Therefore, this research problem can be broken down into the following three sub-problems with additional conditions.

The first question: Is it possible to establish a mining sequence optimization model for the NFS mining method that satisfies the following requirements?

- Not case specific.
- Generates the highest NPV.
- Generates optimal or at least near optimal and practical mining sequence.
- Minimizes the unnecessary operation costs caused by human intervention.
- Satisfies milling and mining capacity.
- The feed can stably match the capability of the crusher.
- Not over-utilizing or under-utilizing the stockpile.
- Ore material blended within the stockpile has a stable grade range.
- Can be solved within a reasonable time.

The second question: Is it possible to build a simulation model for the NFS mining method that satisfies the following conditions?

- Captures as many details as possible of the near face stockpile mining method and traditional out-of-pit mining methods.
- Captures the associated cost of each mining operation.
- Captures the uncertainties like equipment failures and working time distributions.
- Captures the production loss caused by shovel movement.

The third question: Is it possible to develop a comprehensive simulation-optimization framework that can quantitatively measure the performance of different mining methods and evaluate it from multiple aspects?

- Integrates the proposed optimization model and simulation model.
- Measures the performance of the target mining method from multiple aspects.
- Has the capability for evaluating different mining methods.
- Can be verified and validated by case study.

1.3. Summary of literature review

As mentioned above, mining enterprises face tremendous pressure to survive and compete due to the deterioration of the economic situation. Therefore, the cooperation between mining enterprises and the scientific research community has become more extensive and profound. Accordingly, in the past few decades, the research on the optimization of the mine operation process has been significantly developed. However, it is worth noting that mining is a complex set of activities, and the shape and grade of the deposit may be very different from the predicted results. It is unrealistic at this stage to incorporate all uncertainties into research optimization and simulation. Therefore, many elements were ignored in the original research over the past few decades. With the study going more profound over time, more and more details are incorporated into various models, providing reliable guidance for the development of actual mining activity plans.

For example, according to the literature reviewed in Chapter 2, although stockpiles are widely used in fundamental operations, most of the optimization models proposed in the past did not consider using stockpiles. In recent years, some studies have begun incorporating stockpiles into their models due to the improvement of computational abilities and optimization software. Despite this fact, most of these models only take regular out-of-pit stockpiles into account, and very few consider pre-crusher stockpiles. For those few models, the stockpile size is relatively small. The primary purpose is to decrease the grade variability of materials sent to the crusher, not for decoupling the mining and milling process (Everett et al., 2015). As for the near-face pre-crusher mining method, no relevant optimization model has been found since it has not been concretely implemented.

Simulation, a technology used to mimic real-world activities over time, has become one of the essential tools in modern research. It is widely used in all walks of life, such as engineering, economics, education, military, training, and even games. To meet the requirements of many different fields, people have developed various simulation models, such as physical simulation, continuous simulation, discrete-event simulation, stochastic simulation, deterministic simulation, and many others (Morgan, 1984). Among these simulation models, discrete-event simulation (DES), and to be more specific, the computer-based discrete-event simulation, is best suited for simulating the mining industry and understanding the behaviors of each process, which is the focus of this research.

However, due to the inherent uncertainty of the mining system, any optimization or simulation modeling of the mining system has some limitations. The following will introduce the general weaknesses of the reviewed models for mining sequence optimization and simulation.

1.3.1 Mining schedule optimization

1. Dispatch and production optimization

Usually, an optimized mine operation plan consists of two main parts. The first part is the pit limit optimization, which defines the final shape of the open pit, is the basis for the following optimization, and affects the value of a mine the most. Although different mathematical models have been published over the past years, the Lerch-Grossman (LG) algorithm is still the dominant method most researchers adopt (Lerchs and Grossmann, 1965; Askari-Nasab et al., 2007; Dimitrakopoulos et al., 2007). The other part is mining sequence optimization. One of the most critical objectives of optimizing a mining complex is to design a mining sequence to maximize the NPV concerning various mining requirements like grade blending, plant capacity, and other constraints (Askari-Nasab et al., 2008; Askari-Nasab and Awuah-Offei, 2009; Askari-Nasab et al., 2011; Ben-Awuah et al., 2015; Lamghari, 2017). Different mathematical models based on various approaches such as Linear Programming, Mix Integer Linear Programming, Goal Programming, Nonlinear Programming, Genetic Algorithm, Stochastic Algorithm, and Queueing Theory were proposed. Meanwhile, various dynamic truck dispatch logics were adopted by different models. However, some common drawbacks are shared in the literature reviewed in Chapter 2:

- The rock type and particle size of the minerals significantly affect equipment efficiency but are not considered by most of the models.
- Shovel relocation will lead to loss of production, but most of the models proposed assume that shovels could 'teleport' to the newly assigned digging place.
- Stockpiles and blending requirements, which are essential in the NFS mining method, are not considered in most linear programming models.
- The optimized short-term or long-term plans under different nonlinear mathematical algorithms based on heuristics or meta-heuristic methods are not guaranteed to be near-optimal and, in some cases, are even unrealistic. Meanwhile, most nonlinear models are not verified or only verified on tiny instances. Therefore, no nonlinear model can give creditable near-optimal results in a short period.
- All the proposed models, except one or two, cannot deal with heterogeneous shovels and trucks, which are common in real mines.
- Most optimization models use only one criterion, while real mines have several different objectives to balance.

2. Optimization with stockpile

Stockpile is one of the critical components of the mining system. It can be helpful to achieve economic goals like reducing the deviation of feed to crusher compared to target as well as minimizing the quality deviation of materials feed to plant concerning the desired grade. However, most optimization models proposed in the past did not incorporate stockpiles for various reasons such as reducing the problem size, solution time, and computational power limitations.

The stockpile plays an inevitable and essential role in open pit mine production scheduling. As Jupp et al. (2013) described, the pre-crusher stockpile plays four roles simultaneously: storing, buffering, blending, and grade separation. Linear models (Caccetta and Hill, 2003; Ramazan and Dimitrakopoulos, 2013; Smith and Wicks, 2014) and nonlinear models (Tabesh et al., 2015) that consider stockpile were proposed, but most of them are either based on unrealistic assumptions or no guarantee of a global optimum:

- Stockpiles in most models are located out-of-pit, capacity stays unclear, and what to do with the material remaining in the stockpile is not stated.
- In most models, stockpiles are far from the crusher, which introduces extra hauling costs into the system that is neglected.
- The reclaiming process will either require an extra cost on equipment like shovels or affect routine mining operation efficiency, which are not considered by the models reviewed.
- Stockpiles in the reviewed models are based on the first-in-last-out principle, and the materials are not blended as assumed.
- Lack of tracking of material in the stockpile, often with large surpluses at the end of the mine.

1.3.2 Mining operation simulation

It is widely believed that simulation applications in mining areas can date back to the 1940s. However, the first use of the Monte-Carlo method in mining dates back to Rist (1961), in which the number of trains needed in an underground mine is determined. After that, different software based on various languages appeared in the market and are widely used, such as General-Purpose Simulation System

(GPSS) and ARENA (automation, 2019). With the further improvement of technology, the application of mixed reality (MR), virtual reality (VR), and Augmented Reality (AR) to the mining industry has begun to attract widespread attention. However, at this stage, the computer simulation technology still cannot fully simulate reality, and there are still some deficiencies in the application examples of mines:

- Different mines have different features, which led to the phenomenon that most of the simulation models successfully implemented in one mine are unsuitable for another, meaning the models are case-specific.
- Due to the multidimensional complexity of the real case, no simulation model can incorporate all the uncertainty conditions. For example, almost all the stockpile models assume that reclaimed material from the stockpile is heterogeneous.
- Simulation offers minimal flexibility to users, and once the input parameters are set up, they cannot be changed before the simulation stops.
- It is unsuitable for long-term prediction since the topography, paths, and many other mine components will be changed while the operation continues.
- The building of a simulation model needs a large number of inputs, while the mine does not track many inputs among them. Moreover, the simulation model has high requirements for the authenticity of the input data. Therefore, if the input data is very different from the actual situation, the simulation results will likely deviate significantly from the actual situation and have no credibility.
- Sometimes, running simulation models with many details is time-consuming, and real-time decisions cannot be made – this is fatal for truck dispatching.
- Most importantly, in all simulation models proposed earlier, the crushing process either does not exist or is connected with the mining system through the traditional truck-crusher relationship, which is not suitable for the NFS method.

1.3.3 Summary

Former sections of this paper summarized the common shortcomings of current research in related fields. Despite the authors' best efforts, this study still does not address some issues adequately. The followings are the shortcomings to be addressed in this research:

- Adding near face stockpile into the linear optimization model.
- Adding reclaim cost and blending requirements into the optimization model.
- Materials sent to stockpile are trackable in the simulation model.
- Average material grade reclaimed from a stockpile can be generated daily.
- Materials in the stockpile will be fully reclaimed in the end.

1.4. Objective of the study

The primary objective of this study is to quantitatively measure and evaluate the performance of the near face stockpile mining method under a near-optimal mining schedule while capturing operational uncertainties. Meanwhile, the blending results, hauling system, and other KPIs of the near face stockpile method will be compared against a typical out-of-pit crusher mining method to verify its advantages and disadvantages.

Three tasks are set to fully address the research problem defined in section 1.2 and achieve the overall objective stated above:

1. Build a mixed-integer linear programming optimization model for the near face stockpile mining method which can generate optimal or near-optimal mining schedule.
2. Build discrete-event simulation models for the near face stockpile method and traditional mining method with an out-of-pit crusher, in which both mining and milling processes are simulated.
3. Integrate the optimization model and simulation model into a comprehensive simulation-optimization framework and use it to quantitively measure and evaluate the performance of the near face stockpile mining method.

A reasonable and near-optimal mining sequence is the basis for evaluating any mining method. At the same time, a proper mining sequence arrangement can maximize the profits of mining companies. Therefore, the objective of the mathematical optimization model is to generate a near-optimal mining schedule with respect to sequence and capability constraints.

Besides, mining is a complex, highly uncertain and interdependent combination of multiple tasks. Therefore, building a simulation model is the best choice to better understand and evaluate the performance of NFS mining methods under the condition of controllable cost. The objective of the discrete-event simulation models is to capture mining and milling associated operational uncertainties and quantitatively measure their performance correspondingly.

Finally, the objective of integrating optimization model and simulation model is to establish a framework that can be used to measure and evaluate different mining methods from multiple aspects. The conclusions drawn through this framework are more standardized and more credible.

1.5. Scope, limitations and assumptions

It should be pointed out that although NFS has many theoretical advantages, it is by no means a perfect mining method. As mentioned above, NFS as a new mining concept that combination of IPCC and stockpile, not only inherits the advantages of IPCC and stockpile but inevitably also inherits the disadvantages of IPCC and stockpile. First of all, it is well known that IPCC Compared with the traditional truck-shovel system requires a large amount of capital in the early stage. On this basis, NFS requires a larger investment than the IPCC method to meet the purchase of extra equipment. In addition, this method requires a larger strip ratio due to the larger bottom operation space needed. Due to the need to arrange equipment such as crushers and conveyor belts at the bottom, IPCC already requires a large space at the bottom. The space requirement is even several times that of the IPCC method. At the same time, due to the limitation of the maximum angle of the operation of the conveyor belt, this method is only suitable for the ore deposit with a small inclination and shallower burial depth of the ore body and is not suggested for other situations. In addition, compared to the situation where one or two truck damages have little impact on the entire system in the traditional method, damage to the conveyor belt or reclaim shovel will cause great harm to the system and will greatly affect the stability of the system, becoming an additional bottleneck. Moreover, this method requires relatively high skills for operators and field engineers. These shortcuts limit the application and promotion of this method, but these are beyond the scope of this research. The precondition of this study is that all conditions such as ore body, personnel, and funds meet the requirements of applying for NFS.

In order to achieve the main research goal of quantitatively measuring the performance of the near face stockpile mining method, this research mainly makes efforts in the following three aspects:

- Establish a general MILP mathematical optimization model for the near face stockpile mining method to generate a practical near-optimal mining sequence.
- Build simulation models for the NFS mining method and the general out-of-pit crusher mining method to capture the uncertainties associated with different mining operations and gain a deeper understanding of the interrelationships between the various activities in the NFS mining method.
- Validate the simulation-optimization framework by case study and compare the simulation results of the near face stockpile method with the benchmark, thus evaluating its performance and drawing conclusions.

1.5.1 Optimization model

The MILP mathematical optimization model's objective is to obtain an optimal or near-optimal mining schedule concerning precedence and capability constraints within a reasonable time range. Despite the author's best efforts to do this research to develop a reliable and convincible model, some factors that may affect the results are not included in the discussion:

- The objective function in the MILP model proposed is to maximize the net present value among various criteria, as the NFS method can effectively improve blending results and feed the crusher more stable than the traditional out-of-pit mining method. Therefore, this model is not suitable for optimization aimed at other interests.

- Before optimization, homogeneous blocks with values and attributes are used as basic pre-determined parameters. However, obtaining detailed geological data and converting it into qualified homogeneous block models is beyond the scope of this paper.
- The final pit limit is taken as a deterministic value before running the optimization model. That is to say, all blocks within the limit, no matter whether ore or waste block, will be entirely removed in the time range, but the technology to decide the final pit limit is not part of this paper.
- Blocks are aggregated into the mining cut and panel levels to shorten the optimization time required and avoid frequent shovel movement. The aggregation algorithm adopted in this paper was developed by Tabesh and Askari-Nasab (2019). However, discussion of the aggregation principles and their advantages and disadvantages is beyond this article's scope.
- The shovels' travel time and corresponding production losses, truck hauling distance, and cost were not factored into the optimization process.
- The material stack in the stockpile is assumed to be homogeneous. Therefore, instead of track grade as a variable or fixed number, in this research, the uniform reclamation grade from the stockpile is recalculated after each dump based on perfect blending.

1.5.2 Simulation model

After the optimization model generates the mining sequence at a higher level, a simulation model is adopted to simulate the actual mining operation while capturing as many details of the near-face stockpile method as possible. Almost all device data that can be collected, such as loading cycle time, dumping time, equipment uptime and downtime, and the road network, will be used as model input to mimic the natural operation process and generate reliable results. By analyzing the results of the simulation models of these two control groups, one can quantitatively conclude whether the near-face-stockpile method has application and promotion value compared to the traditional method.

- Although drilling and blasting are essential parts of surface mining, they are not within the scope of this research. In the simulation model, all blocks are assumed to be in a state that can be mined at any time, and the system will allocate shovels in the optimized order.
- Different dispatch logic has a significant impact on truck utilization efficiency. However, the truck dispatch logic adopted in the proposed simulation model only prioritizes the minimum queue length before the shovel and may not be the most suitable logic.
- Simulation models are highly relying on the accuracy of input parameters. Therefore, there is no doubt that the more comprehensive and reliable the input data, the more credible the simulation results will be.
- Instead of tracking material grade in the stockpile as a variable or fixed value, this research considered a homogeneous near face stockpile. Its grade is recalculated after each dump.
- Some assumptions are made to simplify the simulation model, such as steady-state oil consumption of equipment, ideal road condition, independence of mining and milling operations from weather conditions, and no human-related accidents.
- The application of the NFS mining method heavily relies on the stability of the open-pit slope since the failure of the slope will cause a considerable loss of equipment than expected, and it has a higher requirement for minimum working width. However, these are not discussed in this research.
- Since the NFS method has not yet been implemented, its up-front arrangement and related costs are unknown. Therefore, the calculation and comparison of the NPV of the two methods are limited to the operation level without considering equipment purchasing cost.

1.5.3 Assumptions

It is worth pointing out that the optimization and simulation models are proposed under the following assumptions:

- Block is the minimum operational unit and is treated as a homogeneous unit. To be more specific, any block is either a pure ore or pure waste block, and any material dug from that block has the same attributes as grades for elements, density, and rock type.
- Blocks in the optimization model are clustered to bigger-size mining cuts and panels based on rock type, grade difference, and distance concerning pushback limitations. The adoption of the aggregation process is to decrease the optimization run time and avoid frequent movements of shovels.
- The coordinates of blocks, mining cuts, and panels are their center locations. The calculation of their center point coordinates is the arithmetic mean of all block's center points within that mining cut and panel. Meanwhile, shovel movement within blocks is neglected.
- Vertical sequence mining constraints calculated in the optimization model are assumed to be 45 degrees. Specifically, if one block in the lower bench needs to be mined, at least nine nearest blocks in the upper bench must be fully excavated earlier.
- The distance between blocks on the same bench is the straight-line distance between their center point coordinates. The distance between blocks in different benches is the sum of the distance between the block point and the corresponding ramp connecting point in each bench plus the hauling distance in the ramp.
- During whole mining periods, one block can only be assigned to one shovel, and the shovel cannot move before that block is wholly mined.
- The mining period, attributes of blocks, moving cost of trucks and shovels, mining and crushing capabilities, final product price, and interest rate are deterministic and predetermined. It means that the optimization model can only generate a mining sequence based on those data but cannot optimize them.
- The optimized mining sequence will be used as an input to the simulation model, and its sequence will be strictly adhered to throughout the simulation.

1.6. Research methodology

This study is mainly composed of three parts:

- Developing a mining schedule optimization model to decide the mining sequence and effectively allocate the shovels. The optimization model is a mixed-integer linear programming model and is solved by a widely accepted and applied linear optimization solver, CPLEX.
- Developing two simulation models. One contains an in-pit near the crusher stockpile that decouples the mining and milling process. The other has a traditional out-pit fixed crusher, meaning the mining and grinding processes are directly connected. The two simulation models are developed in the commercial discrete event simulation software, ARENA.
- Integrating the optimization model and the simulation model and analyzing the results. Firstly, run the optimization model to generate an optimal or near-optimal mining sequence based on predetermined constraints. Secondly, the sequence will be loaded into the simulation model as input to start the simulation process. Thirdly, a case study is implemented to verify the integrated model and quantitatively measure the performance of the near face stockpile mining method by comparing the simulation results of the two models.

For all the stages listed above, some general steps will be taken:

- Establish relevant theoretical models.
- Coding and debugging the established theoretical models.
- Verifying the model through case study.

Figure 1.5 describes the interactions between the optimization and simulation models, and the interactions inside each model. For example, the proposed optimization model in this study focuses on optimizing the allocation sequence of shovels to available faces to maximize the overall NPV. Meanwhile, the in-pit stockpile in the proposed simulation model, aiming at decoupling the mining and milling processes, has a vital role in the actual mine and directly affects the overall performance.

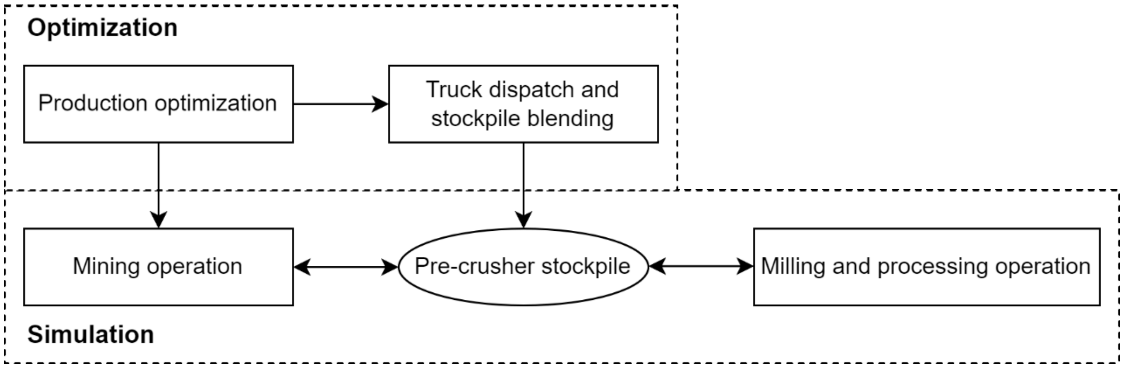

Figure 1.5 Integrated simulation-optimization framework

In order to obtain a meaningful interpretation of the performance of the near face stockpile method, some key performance indicators will be defined to quantitatively measure its performance under near-optimal mining schedule while capturing uncertainties by simulation. Furthermore, the performance of the near face stockpile mining method could be verified through comparing the blending results and hauling system and equipment utilization against a typical out-of-pit crusher mining method.

1.7. Scientific contribution and industrial significance

Over the past decades, with the explosion of computing power, many researchers in the mining area focused on the optimization and simulation of open-pit mines. These studies have brought considerable profits to enterprises and laid a solid foundation for developing large-scale equipment. However, the stockpile as a vital part of open-pit mining has not received much attention, and the research is still at an early stage. Given that optimization and simulation instances are becoming more complex, and the computing power has become a bottleneck again, research on the practical application of stockpiles has strong practicability. It is likely to help companies reduce costs and further improve their revenue.

This research is proposed under this situation. In the past, the mine was regarded as a holistic system. However, if the mining work becomes discontinuous due to weather affection, equipment maintenance, or failure, the corresponding beneficiation work will have to be interrupted due to a lack of materials. Therefore, it is time that the stockpile could eliminate the stereotype that it can only function as a low-grade material repository and can only be located outside of the pit. Instead, it can be located near the crusher to store and blend materials to be processed.

Further, the stockpile can also split the system that was regarded as one into two weakly related sub-systems: the mining and milling systems. In this case, the cessation of mining or grinding operations will not affect another activity directly since the stockpile's capacity can act as a buffer to keep the other process running. In this way, the overall operation of the holistic system can be maintained to the greatest extent, thereby increasing the mine's output, improving crushing efficiency and other equipment utilization, and boosting the stability and profitability of the entire mine.

Given that any suitable mining method will most likely fall short of its desired goals without a reasonable and practical mine plan, all evaluations of mining methods should be based on a well-managed near-optimal mining plan. That is why an optimization model that can help to determine a realistic mining schedule is needed in this research. Moreover, the integration of the optimization and simulation models could ultimately minimize the affection for human intervention and increase the reliability of the study.

Despite the various advantages of the NFS mining method listed above, since it is still in the conception stage and has not been practically implemented, the reliability of its advantages is still questionable with no credible verification. Therefore, the unique scientific contributions of this research are the following:

- Establishing a general mixed-integer linear programming mathematical model for near face stockpile mining method that can generate practical near-optimal mining sequence concerning required constraints.
- Establishing a general simulation model for near face stockpile mining method, which can be helpful to deeper and more intuitively understand the interactions of each process in the NFS method while capturing as many uncertainties as possible.

- Integrating the proposed optimization model and simulation model into a comprehensive simulation-optimization framework. This framework provides a multi-faceted evaluation of mining methods in terms of performance.
- Verifying the superiority of the NFS mining method by comparing the simulation result against typical out-of-pit crusher methods, in terms of blending results, hauling efficiency, and equipment utilization.

The verification of the effectiveness of the near face stockpile method has great industrial significance and could guide the large-scale implementation of this method in the future. To the best of the author's knowledge, the current research on the NFS method is still at the initial level, and there is still a certain distance until it has industrial practicality since many details are not considered. However, what is certain is that this study will provide excellent references and significance for future studies, enhance the body of knowledge, and lay a foundation for future research.

1.8. Organization of thesis

The first half of Chapter 1 of this paper mainly introduces the background of this research, gives a detailed explanation of the research problem to be addressed, and expounds on the primary purpose of this research and the methods and steps taken to achieve the purpose. The second half of Chapter 1 mainly sorts out and summarizes some of the deficiencies of past research published in related fields, as well as the basic assumptions and scope of this research. Finally, the scientific significance and application prospects of this research are summarized.

The second chapter mainly reviews the papers published by other scholars in related research fields over the past few decades. This part is divided into three subsections: the first subsection expounds on and summarizes the development process and achievements of the optimization model at the production level and truck dispatch level; the second subsection focuses on the optimization models that incorporate stockpiles in past research; and the last subsection reviews the applications of simulation models in the mining industry. Finally, Chapter 2 summarizes limitations of the reviewed publications.

The first half of third chapter of this paper establishes the mining sequence mathematical optimization model for the NFS method. It contains the formulation process of the objective function and constraints, as well as a detailed explanation of each mathematical formulation. The results from the implementation of the proposed optimization model on an iron ore mine case study show that the average crusher feeding grade deviation is reduced by 20%. The second half of the third chapter describes the establishment process of the two simulation models and the setting of various parameters in detail. The in-pit and out-pit road networks integrated in two models are the same, and the only difference is the location of the crusher. Other than that, all devices' operating parameters, capacities and downtimes are the same.

At the beginning of the fourth chapter, the proposed simulation-optimization framework is verified and validated through comparing the simulation results of traditional mining method against real historical records and the simulation results is then taken as the benchmark. After that, the framework is implemented to the NFS method. A multi-factored detailed comparison between the NFS simulation results and benchmark is conducted quantitatively and the performance of NFS method is evaluated based on the comparison.

The fifth chapter of this paper summarizes this research and the conclusions based on the previous analysis and proves that the objective of this research has been achieved. Meanwhile, the specific contribution of this research is also summarized. In the end, limitations of this research and recommendations for future research are listed.

2. LITERATURE REVIEW

2.1. Introduction

Since the economic crisis, the mining industry has been very depressed. This is because the prices of most common mineral products such as iron, coal and oil sands are relatively low compared to the prices before the crisis, which significantly affects the profits of mining enterprises. As a result, to survive in the harsh market environment and fierce market competition, the mining industry is studying ways to reduce costs while increasing production to avoid layoffs and bankruptcy. Hence, open-pit mining, that requires high investment and energy consumption and dominates the production of metallic and nonmetallic minerals, has attracted most intentions from scholars (Hartman and Mutmansky, 2002).

Approximately 50% to 60% of the operating costs in open pit mining are related to trucks and shovels moving (Kennedy, 1990; Alarie and Gamache, 2002; Upadhyay and Askari-Nasab, 2016; Moradi Afrapoli and Askari-Nasab, 2017), which means even a small increase in equipment utilization will yield significant benefits for mining enterprises.

Undoubtedly, optimizing the mine plans is among the important and effective ways to improve equipment utilization. One of the most critical objectives of optimizing a mining complex is to design a mining sequence to maximize the NPV while meeting mining requirements such as blending constraints, plant capacity and other constraints (Lamghari, 2017). Due to the inherent complexity of mining activities and computational limitations, from the past to the present, researchers have to divide the entire mining process into three different phases of short-term, medium-term and long-term. Then, the three phases are optimized separately to obtain relatively optimized results in a limited and reasonable time (Hustrulid et al., 1995).

As the optimization of the long-term plan has a more intuitive impact on the overall cash flow and NPV and affects the feasibility of the mine the most, the results are of great significance. Therefore, most of the previous scholars' research focused on the long-term plan, while the development of short- and medium-term plans is not as mature as long-term plans. However, due to the unpredictability of the geological deposit shape and future economic conditions, it isn't easy to make a breakthrough in long-term plan optimization under the state of computational power. On the contrary, the optimization of mine's short-term plan has significant advantages in improving the utilization of existing equipment and reducing unnecessary costs and its economic benefits have become increasingly precious in the fierce market competition. Several different methods that scholars have used in mining plan optimization will be reviewed in this chapter.

Besides, because the mine requires a large amount of investment, the cost of trial and error is too high, leading to the mine managers not wanting to take responsibility and become conservative. They will not trust any new methods that are not verified in real mines. Luckily, with the continuous progress of computers, simulation technology has also experienced development from scratch to maturity. Especially after the maturity of discrete event simulation (DES), simulation became more and more critical in the mining industry. Now, almost all new mining methods or any optimization to existing mines are simulated for hundreds to thousands of replications for different scenarios to predict all possible outcomes to the greatest extent possible. Some applications of simulation, especially the discrete event simulation, which have been used in mining optimization in past decades, are also reviewed in this chapter.

2.2. Mining optimization

As stated in the former section, the optimization of the mining plan consists of two levels. The higher level is production optimization under different constraints, while the lower level is truck-shovel allocation or dispatch.

2.2.1 Dispatch optimization (lower level)

The dispatching problem is a problem not exclusive to mining - many other industries will encounter this problem as well, such as the express delivery industry, taxi industry, food delivery industry and sales industry. However, this literature review only concentrated on the papers related to mining.

Before the 1970s, dispatching in mines was all manual and the results highly depended on the dispatcher's experience and intuition. In the late 1970s, automated computer-based dispatching systems were developed to overcome the limitations of human intervention and make more effective decisions (Munirathinam and Yingling, 1994). In general, there are two different dispatching methods: fixed and dynamic.

Fixed truck assignment, which locks several trucks to a shovel until failure, was adopted by many mines in its early years. However, it is widely believed to be the least productive method nowadays and is considered a baseline for measuring the effectiveness of other dispatch optimization methods (Munirathinam and Yingling, 1994; Moradi Afrapoli and Askari-Nasab, 2017).

As for dynamic dispatch, trucks are independent and can be assigned to different shovels, even different pits. Commonly, the dynamic dispatch strategy has two patterns based on several stages needed - single-stage dispatch and multistage dispatch. Compared to the fixed assignment strategy, the dynamic dispatch system can significantly reduce the operational cost by reducing trucks' and shovels' idle time and the number of needed trucks (Koryagin and Voronov, 2017).

2.2.1.1 Single stage dispatch

A single-stage dispatch strategy is an approach that dispatches the trucks only based on one requirement while failing to consider the production and operation constraints. A typical dispatch method under this category is the 1-truck-for-n-shovel strategy. As shown in its name, this strategy has n available shovels and dispatch one truck at a single time while considering one chosen criterion like minimum cost or maximum production (Munirathinam and Yingling, 1994). Therefore, the standard chosen is quite crucial, otherwise may lead to the opposite results than expected. However, this strategy is considered short-sighted since the interaction between adjacent trucks is ignored. Meanwhile, the criterion chosen is difficult because they dominate each other (Alarie and Gamache, 2002).

Some efforts have been made to make this strategy more practical. Integrated dispatching systems were developed using a simulator to compare the possible results under different criteria. The result will offer guidance for the criterion chosen, which will be repeated by every shift to make the decisions suitable for the current status (Bonates and Lizotte, 1988; Alarie and Gamache, 2002).

It is worth pointing out that all the criteria are not guaranteed to be met in all situations and sometimes even don't help to improve production (Munirathinam and Yingling, 1994).

2.2.1.2 Multistage dispatch method

The limitations and instabilities of single-phase dispatches have led scholars to study more effective ways of dispatching. The revolution in information technology, including computers and GPS, has made it possible to deliver more efficient, accurate and practical multi-phase dispatches in recent decades. More specifically, the development of GPS, GIS, GPRS, 3G and 4G technologies made it easy for mines to collect historical mining data (Alarie and Gamache, 2002; Gu et al., 2008). The data gathered can be used to analyze the implementation of past strategies and as input data to predict the future performance of the mines. Besides, the explosive rise of the computational power of computers made lots of calculations and comparisons in a short time become a reality, helping people find the optimal or near-optimal solutions.

The so-called multistage dispatching method splits the dispatch problem into two (in some cases three, but not widely adopted) related sub-problems (Soumis et al., 1989). In the first phase, the production rate is optimized based on factors such as shovel allocation, shovel digging rate, plant capability and truck capability. While in the later stage, the trucks are assigned to the shovels in real-time to minimize the deviation of shovel rate, grade requirement and production from targets recommended from the first phase (Upadhyay, 2017). Multistage dispatch combines the optimization of higher and lower levels to achieve a higher NPV, and comprehensive approaches have been employed to tackle this problem. The details of optimizations will be reviewed in later literature reviews.

2.2.2 Production optimization (higher level)

Over the decades, open pit mining optimization has received widespread attention, and it is one of the essential tasks for the engineers of mining ventures. In current practice, before optimization, the deposit of interest and its surrounding rocks and overburden will be divided into continuous geological blocks. Then, those blocks, which contain different geological and economic values, will be the basis for all mining optimizations.

Typically, optimization consists of two central parts. The first part is pit limit optimization, which defines the final shape of the open pit, is the basis for the following optimization and affects the value of a mine the most. Although different mathematical methods and models have been published in the past years, Lerchs-Grossman (LG) algorithm is still the dominant method most researchers adopt (Lerchs and Grossmann, 1965; Dimitrakopoulos et al., 2007). The other part is production optimization. To be more specific, the production optimization is to decide the sequence of blocks to be mined annually and address two main problems – when the blocks should be excavated and where the materials from blocks should be sent to, stockpile, waste dump or crusher? Although the research on production optimization started in the last century, many of the proposed optimization algorithms are still not implementable due to the complexity of mining operation which contains too many binary variables and exceeds current computational power (Dagdelen, 2001; Caccetta, 2007). Therefore, the following part focuses on the second part, the production optimization.

2.2.2.1 Linear programming (LP)

LP is one of the exceptional cases of mathematical optimization, and its constraints are formulated as linear relationships. LP and its extension, the mixed integer linear programming (MILP) have been widely used in mining production optimization. The use of LP in the mining industry to optimize mining schedules can be traced back to 1969 after (Johnson, 1968) introduced the 'block concept.'. After that, White and Olson (1986) introduced LP into multi-stage truck-shovel dispatching based on MILP. The authors formed an effective commercial package called DISPATCH. Their approach divided the dispatch problem into two weakly-related LP parts. The solution of the first LP segment helps optimize the production rate while considering constraints such as shovels, stockpiles, plant and blending requirements. For the second LP segment, minimizing the number of trucks needed while covering the production rate on each shovel-dump combination is the only objective. The link between the two LP segments is to make sure the sum of assigned truck capacity on paths that serve one shovel will not be under the production rate of the shovel set by the first LP segment. The main drawback of their model is that it fails to consider the interaction between adjacent dispatched trucks (Munirathinam and Yingling, 1994).

Li (1990) proposed an LP model to minimize the haulage cost by determining the best truck flows of each route in the transportation network. The primary goal of this model is to reduce transportation work, which is defined as the product of material moved and the relevant moving distance. In the first phase, the optimum number of trucks needed is decided based on the number of working shovels and crushing capacity. The dispatching rule in the second phrase is called the maximum inter-truck time deviation. Their results are only related to the time at which the last truck on each route was dispatched. However, this method did not consider the travel time on the path and feasible traffic jams. Besides, as in other models, economic objectives such as blending requirements and practical constraints like heterogeneous fleets are not considered.

Similarly, the closed queuing network theory was adopted by Ercelebi and Bascetin (2009) for the first phase to optimize the number of shovels needed. An LP model was proposed in the second phase under ideal conditions (no truck queues) to minimize the number of trucks required and guarantee maximum shovel utilization. The best number of trucks needed by each valid route was also determined. The author claimed that the results of the LP model matched the queuing network solution from the first stage and led to the minimum loading and hauling cost. The main drawback of this model is that the ideal situation is not practical in actual operation. Nevertheless, truck and shovel breakdowns and maintenance are not considered.

Commercial package SmartMine® is another software for solving optimization problems in real mines. Unlike DISPATCH, the first stage of SmartMine® is to determine the number of trucks needed to cover the optimal production by solving a series of LP models. The second stage use simulation and multi-criterion optimization as heuristic dynamic dispatching to make dispatch decisions (Subtil et al., 2011; Moradi Afrapoli and Askari-Nasab, 2017). However, one of the main drawbacks is that the shovel allocation is regarded as input (i.e., not calculated by the package), meaning that the planner should do it before using the software. Furthermore, characteristics that mines are concerned about, such as blending requirements, are not considered. Although the author claimed a 12% increase in total haulage after using this package in simulation, under certain circumstances, SmartMine® dismisses the best solution and leads to a rerun of the whole model.

An LP model that contains trucks and shovels' reliability, availability, and maintainability (R.A.M) was introduced by Mena et al. (2013) to make optimization strategy more realistic. By comparing the equipment's operating performance, the trucks with the best performance could be assigned to the most productive routes to minimize the deviation from the target. Compared to the ideal condition (maximum availability), this model has less productivity and requires more trucks. However, as the author claimed, due to the less flexibility, the system fails to find a dispatching solution when some trucks stop working simultaneously.

Instead of mainly focusing on reducing equipment idle time, an integer linear programming (ILP) model was formulated to meet the production rate (Zhang and Xia, 2015). At the same time, operational cost is reduced by determining the number of trips needed for each load-dump combination in a shift. The experience results showed a 15.65% cost saving. However, one of the disadvantages of this model is that it only considers truck moving while the lost tons caused by shovels relocation is not considered. In addition, blending requirements and constant feed to the plant are also neglected.

Based on the m-trucks-for-n-shovels strategy, a MILP model was developed for optimizing the routes choices and reducing both trucks and shovels' fuel consumption, thus decreasing the operational costs under the under-truck situation. Furthermore, the technical specifications of all equipment are considered, making the model capable of being used in both homogeneous and heterogeneous fleets (Bajany et al., 2017). However, this model is only tested in the case with only three shovels and two dumps. Therefore, the capability of being implemented in large mines and over-trucked situations stays unknown. Other than that, the typical shortcomings of the MILP model remained in this model: neglecting the blending requirements and constant feeding to the plant.

In Askari-Nasab et al. (2011), the author stated the main shortcomings of MILP used in mining scheduling, inability to solve real-size instances of mining operations. The author proposed a new method that aims to reduce the number of mineable blocks to reduce binary variables. By introducing the concept of 'mining cuts,' adjacent small blocks were grouped into larger units, leading to a significant reduction of variables. A small mining instance was tested in the paper, and the results showed that the method lowered the time needed to solve optimization problems. However, it must be pointed out that this method is not tested and verified for real-size instances. The clustering method is also unclear, and stockpile and blending requirements are not considered.

As discussed above, almost all the LP models mentioned ignored the economic objectives, such as constant feed, blending requirement and stripping ratio. Other than that, heterogenous fleets problems that widely exist in real mines are not addressed. Finally, the inherent nature of LP or MILP constrains the results of models to be found at the edges of the feasible area, which is not necessarily to be the optimal solution in real situations since many relations are not linear at all.

2.2.2.2 Nonlinear programming (NLP)

As the name shows, in NLP, one or some of the constraints or the objective function are not linear. Compared to the widely used LP, the NLP did not gain much attention from mining researchers in the past decades. In their three stages model, Soumis (1989) implemented an NLP model in the second stage based on the results of an LP model used in the first stage, which determined the number of trucks and shovels' locations. Two factors were considered in this step, deviation of shovel production, truck available hours, which include waiting hours and penalties for blending grade deviation. The author believed that the relationship between the number of trucks sent to a shovel and the corresponding truck waiting time is not linear. Although heterogeneous fleet problems remain unsolved, according to Munirathinam and Yingling (1994), NLP can help overcome some of the inherent shortcomings of LP and search for all feasible solutions.

Besides, Pendharkar and Rodger (2000) claimed that the relationship between unit operation cost and production cost is not linear. Therefore, an NLP model was created for coal production optimization concerning economic values like blending. A genetic algorithm was also used to improve an acceptable solution to an optimal solution. For this model, except for the time-consuming problem, only a hypothetical case was tested before the author claimed it could solve complicated problems. The NLP model aggravates the search space, and no algorithm could guarantee finding an optimal solution if there exists one.

2.2.2.3 Queueing theory (QT)

QT was developed for customers and servicers and initially extended to the truck-shovel mining system in the middle of twenty century (Koenigsberg, 1958). It was emphasized and developed mainly in the early years, and most of the work that had been done was focused on a steady-state solution, which does not contain variability for any shift.

Typically, most of the distributions used in QT that represent truck back cycle times and shovel service times were exponential (M), constant (D) and erlang (Eh). Other distributions are not suggested due to the intractability. The commonly adopted notation of the finite source models is (-/-/-)/-, in which the first two slots represent truck back cycle times and shovel service times and the last two slots represent shovel numbers and fleet size.

Griffis (1968) used the exponential model to optimize the truck fleet under one shovel situation. Cabrera and Maher (1973) used a general probability distribution model and optimized the fleet number under four conditions: constant service time and hauling time, random service time and hauling time, random service time and constant hauling time and constant service time and random hauling time.

Kappas and Yegulalp (1991) assumed that the truck/shovel system contains several activities that happen in different service centers, but all located in a closed network. The transportation lanes were also deemed as servers and trucks repair and maintenance were considered. However, their model is only built for trucks with the same capacity and is based on some properties of the Markovian network, which is not a valid assumption.

Muduli and Yegulalp (1996) used queueing theory in truck allocation optimization by finding the nonlinear relationship between shovel productivity and the number of trucks employed and integrating it into a linear allocation model. Different truck sizes had been considered, but it will lead to the nonlinearity of productivity; therefore, in this model, shovels were only assigned to trucks of the same size.

Although QT was believed to give engineers an inner sight of mining operations and is an effective supplement to computer simulation, it is put aside by most mining researchers. That might be because it is mainly used in straightforward cases, while with the models becoming more complicated and practical, researchers turned to other approaches like simulation (Bonates and Lizotte, 1988; Upadhyay and Askari-Nasab, 2018).

2.2.2.4 Goal Programming (GP)

A.Charnes and W.W.Cooper first proposed GP in 1955, developed based on LP (Charnes et al., 1955). It is mainly used to solve practical problems such as the economy and military where LP cannot be used. Its basic principle and mathematical model structure are the same as LP. The difference is that it solves the problem by trying to minimize the deviation of the target from the specified value. Besides, variables are defined to represent the deviation from the target under the corresponding constraints, and all variables will be given a weight to achieve the final goal. In the mining industry decision-making, there are a variety of sub-goals that are mutually constrained or even opposite. These goals may be performed by setting a good GP and giving different weights to different targets.

Temeng et al. (1998) presented a GP model that contains two essential and conflicting goals: quality control and production maximization. Besides, trucks with different capacities were considered in the model, although the average payload of trucks was considered. Based on this model, a mixed integer goal programming (MILGP) model was proposed by (Upadhyay and Askari-Nasab, 2016). This model is based on four goals: minimizing the operation cost including shovel and truck movement cost, minimizing the deviation feed to the plant, minimizing the deviation of grade and maximizing the production. In addition, shovel allocation and a mixed fleet system were considered. A case study in an iron mine shows that the plant utilization is over 99 percent, and both shovels' and trucks' utilization is above 90 percent.

Although GP overcame some of the shortcomings of LP and is widely used in decision-making, young researchers paid less attention to GP. This is mainly because the prior determined goals and preemptive weighting might be too arbitrary (Zeleny, 1981). Besides, the inherent shortcomings still exist in GP, like finding extreme solutions.

2.2.2.5 Stochastic Algorithm (SA)

It is a typical method that gained attention from some scholars. However, all approaches mentioned above did not consider the stochastic nature of mining. The grade of the orebody is not homogenous even in one block, and trucks and shovels break down randomly.

Two uncertainty parameters were considered in the model built by Ta et al. (2005), the truck cycle time and the truck loading tonnage. One of the two mainstream methods of SA is the chance-constrained optimization. This model's objective function was to minimize the number of trucks needed while covering the production target. In addition, a real-time reallocation updater was proposed to deal with the shutdown of shovel or crusher and help to allocate trucks at the beginning of each shift. However, the objective function was based on the mean value of random parameters, and the actual mining operation included more stochastic parameters than the two.

Matamoros and Dimitrakopoulos (2016) proposed a stochastic mixed integer programming (SMIP) model to optimize the short-term mining sequences and the fleet. A single formulation, which contains eight components such as mining constraints, ore grade uncertainty, number of trucks and capacities, availability, and penalties for deviation, were used. Each element was expressed and evaluated by a corresponding cost to meet the target. In addition, five components of the formulation contain decision variables which could change the fleet parameter or the quality accordingly. The application of this model in simulation showed a 15 million CAD dollars increase in mining operation than models without uncertainty. However, as the author claimed, the robustness of the single formulation relies highly on the detailed original schedule because many parameters used in the formulation need to be predefined, which is not practical for most of the mines.

2.2.2.6 Genetic Algorithm (GA)

GA, proposed by Holland in 1975, is a method of searching for optimal solutions by simulating natural evolutionary processes (Holland, 1992). The goal of the model described by He et al. (2010) was also to minimize truck numbers required to cover the production target to eliminate possible queueing time under a fixed transporting path. The difference is that the author used the GA method, and quality requirements were also considered. In this model, the network is fixed, and trucks are assigned to the routes to minimize the truck operation and maintenance cost. Different weights were given to each component of the expression, and in the later stage, higher weights are given to maintenance to reflect the reality. The length of each string (chromosome) is defined as the number of shovels times the number of dumping points times the number of trucks assigned to the specific route. The population is generated randomly with the size of 50. The fitness function was defined as the negative value regarding costs and weights. However, the GA method is time-consuming if the population is too large. Meanwhile, trucks' speed on different routes is assumed to be the same, regardless of the status of trucks. Too much human intervention might be the problem that almost no researcher is using GA to solve natural mining optimization.

2.2.2.7 Other approaches

The look-ahead procedure was proposed by Faiz Fadin (2017). As one can infer from the name, the principle behind this procedure is using historical mining data to 'look ahead' what will happen in early stage and allocate the truck existing in the back of the queue based on the look-ahead results. This method aims to find optimal routes for trucks in real-time. However, the methodology is only tested in small mines with very limited trucks and routes. With five trucks and three routes, the number of scenarios is 243, and real-time dispatching is still possible. But when it comes to real-size mines with dozens of load-dump routes and trucks, using the Look-Ahead algorithm will lead to a considerable number of calculations which will take hours or even days to make only one decision. As a consequence, real-time decision-making is no longer practical.

Implementing machine learning is another attempt by scholars to improve the efficiency of optimization. In this procedure, historical mining data are collected and used to predict the distributions of mining activity duration, thus improving the dispatch confidence (Ristovski et al., 2017). However, road conditions, equipment status, and regulations keep changing over time, so the past pattern learnt by machines is not convincing, and the results are not verified.

2.2.3 Optimization with stockpile

Stockpile is one of the crucial components of the mining system. It can be helpful to achieve economic goals like minimizing the deviation of feed to crusher compared to target as well as reducing the quality deviation of materials feed to plant concerning the desired grade. However, most optimization models proposed in the past did not incorporate stockpiles for various reasons such as reducing model size, model running time and computational limitations.

In this study, stockpile, which decouples the mining and mill process, is the essential difference between the method of interest and other methods. Therefore, the stockpile is listed as a separate section, and relevant papers are reviewed from early years to the latest rather than integrated with the former optimization section.

To maximize the NPV, Lane (1988) suggested a series of economic cutoff grades higher than the breakeven grade. Many mines adopted this method; however, due to the uncertainty of mineral market price and other constraints, the material between the two grades may bring substantial profits. Therefore, the two-stage mining process became popular in the early years. The mine operates based on Lane's theory but uses a stockpile to stack minerals between economic grade and breakeven grade and, in the second stage, reclaim the stacked minerals after depletion (Zhang and Kleit, 2016). With the further research and optimization of the stockpile, it has taken on more roles in the mining process and gained extensive attention in mining design to achieve a higher return.

The quality of stockpiles is managed manually in the early stage while the on-site operational staff routinely records relevant data of essential stockpiles. After that, to have a more reliable product control and reduce costs related to stockpiling, like sampling, quality management and stockpile tracking optimization routine (QMASTOR) system was proposed by Keleher et al. (1998). The system has three components, a remote positioning system (GPS), a central computer and an optimization model for reclaimation. The model aims to offer the best reclamation schedule to meet predefined quality specifications based on up-to-date economic indexes and materials available in the stockpile. Compared to the conventional method, the QMASTOR system reduced the variance in grade and made it possible for mines to have overall quality control of the stockpile. However, the system's stochastic nature of mining, blending requirement, and possible chemical reaction are not considered.

A queueing model was proposed for iron and coal mining stockpile design in Binkowski and McCarragher (1999). In this model, the number and size of the stockpile were determined to maximize the system's output based on an Er /Ek/1/N queue. However, to simplify the model, only the blending requirement was considered, and the truck arrival time, truck size and current grade of the stockpile were neglected. Meanwhile, all cases in that article fail to find a global maximum and only a local optimum was adopted.

Stockpiling with two or more minerals is also a practical situation many mines face. Asad (2005) proposed an optimized cutoff grade determination method for two minerals based on Lane's theory, and a hypothetical copper-gold deposit was used to verify the algorithm. The main drawback of this algorithm is that it is based on an ideal condition where the price and cost are constant. Besides, real operational problems like degrading and oxidizing significantly influence the stockpile, which was not considered in the reference.

A simulator called SPSim, which is used to analyze stockpile quality distribution and realize real-time simulation, was developed by Lu and Xu (2010). The main component of the simulator is a simulation engine composed of cellular automata (CA) model, and the second part is the visualization component. The CA model is also composed of two parts, one for the heap of stockpiles and one for the material falling to the stack. Unfortunately, no case study was presented in the literature. Another drawback is that it relies heavily on data input and requires lots of parameters like particle size and environmental parameters, which are not practical to track or determine in the early stage.

The stockpile is inevitable and vital in open pit mine production scheduling. As Jupp et al. (2013) described, the near crusher stockpile plays four roles simultaneously: storing, buffering, blending and grade separation. Linear models (Caccetta and Hill, 2003; Ramazan and Dimitrakopoulos, 2013; Smith and Wicks, 2014) and nonlinear models (Tabesh et al., 2015) that consider stockpile were proposed, but most of them are either based on unrealistic assumptions or lack of mathematical formulation or no guarantee of a global optimum.

A MILP model for long-term optimization production planning (LTOPP) that considers grade uncertainty, and a stockpile was proposed by Koushavand et al. (2014). Their objective function maximizes the maximize profit while including the cost of uncertainty by considering both under-production and over-production scenarios. Smith and Wicks (2014) propose a MIP strategy for a copper mine that incorporates stockpiling. Their proposed approach involves categorizing ore into different groups based on grade and primary element recovery. They establish a stockpile specifically for handling low-grade ore when necessary. However, to simplify the process, the authors do not account for variations in element grades when materials are deposited into or reclaimed from the stockpile, thus avoiding nonlinear complexities. Similarly, Mousavi et al. (2016) also address the issue of stockpiling with a predetermined grade, using a non-exact method to tackle the problem. They compare their findings with results obtained through an exact method and demonstrate the proximity of their solutions to the optimal solution. However, the authors do not investigate the errors that may arise from assuming a fixed reclamation grade for the stockpile. Furthermore, their most extensive case study only involves a relatively small number of 2,500 blocks. Kumar and Chatterjee (2017) propose a mathematical formulation for production scheduling in a coal mine, incorporating stockpiling. Their approach aligns with the aforementioned strategies, assuming a fixed and predetermined reclamation grade for the stockpile. Their findings indicate that the observed head grades of the elements remain within the required limits. 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 et al. (2018). 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. Gholamnejad and Kasmaee (2012) proposed a linear goal programming model with a stockpile. However, it is mainly focused on stockpile reclaim, to be more specific, material blending between two stockpiles with low-grade and high-grade phosphorus. Mining schedule optimization, which heavily affects the materials being sent to the stockpile, is not included. Although the stockpile is incorporated for those models listed above, an automatic perfect blending assumption is adopted. The main drawback of perfect blending is that it would introduce errors into the result and make it not credible. The introduction of error is because stockpiles in traditional open-pit mining will not be fully reclaimed, so there will be a difference between real reclaimed material grade and hypothesized reclaimed grade.

There are also nonlinear models proposed for LTOPP optimization which incorporate stockpiles. Bley et al. (2012) 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 et al. (2020) 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 the linear models. Waqar Ali Asad and Dimitrakopoulos (2012) explored the incorporation of stockpiling in determining the cutoff grade, specifically considering the presence of uncertainty. Instead of using planning units, they employed grade-tonnage curves and developed a model that accounted for grade ranges and tonnages of material within each field of the stockpile. Ramazan and Dimitrakopoulos (2013) proposed a production scheduling model that accounted for uncertain supply and included stockpiling. Their model utilized a predetermined constant grade for reclaiming material from the stockpile. Additionally, it allowed blocks to be sent to the stockpile based on the probability of the block grade falling within an acceptable range for the stockpile. However, the authors did not compare the actual grade of material in the stockpile with the predefined rate.

In order to keep the plant constantly working, avoiding the mining and beneficiation processes constraining each other, reducing grade variation and improving the prediction of output, a near face pre-crusher stockpile model that decouples the integrated system into two weak-related subsystems is proposed in this study.

2.3. Mining simulation

A simulation model mimics the real operations of a system or process. Still, the explosive growth of the application of this method happened only after the invention of the digital computer. Up to now, simulation has become one of the most essential and effective tools for researchers in almost all fields. It is adopted to evaluate the corresponding system performance after changing parameters, thus helping to optimize the system operation.

Typically, the system to be simulated has two distinct types, discrete and continuous. If the system's state changes on discrete points over time, the system is defined as a discrete system. Oppositely, when the system state changes continuously, it will be described as a continuous system (Banks et al., 2005). Undoubtedly, the nature of the mining industry matches the discrete system perfectly.

Over the past years, the Monte Carlo method has been adopted by most the discrete event simulation, which generates random numbers from expected distributions, and the sampled numbers will be used to process the system state change (Sturgul, 1999).

It is widely believed that simulation applications in mining areas date back to the 1940s. However, the credit for the first use of the Monte-Carlo method in mining simulation is credited to Rist (1961). In that model. The number of trains needed in an underground mine is determined. A superannuated language known as Symbolic Program System (SPS) was used in the literature. Based on Rist's work, Harvey (1964) introduced General Purpose Simulation System (GPSS) into mining simulation. After that, Fortran was employed by Cross and Williamson (1969) when simulating the mining process. The simulator was written by GASP V, a forerunner language of SLAM. In 1985, SIMAN (simulation analysis), a discrete-continuous simulation language, started getting the attention of mining researchers (Pegden, 1985; Mutmansky and Mwasinga, 1988; Banks et al., 1994). Since then, ARENA (SIMAN) (The Rockwell automation, 2019) and GPSS have been the two main languages adopted among mining researchers due to their high capability to data from other software.

The development of simulation in mining in Australia, Asia, Europe, the United States and South Africa are reviewed by Basu and Baafi (1999), Panagiotou (1999), Konyukh et al. (1999), Sturgul (1999) and Turner (1999), respectively. Different models with different purposes used for simulation in various mines in the second half of the 20th century are comprehensively introduced. According to the literature, the simulation in mining most focused on production optimization, bottleneck analysis, truck shovel dispatch and equipment selection.

As stated earlier, since Cross and Williamson (1969), many dispatch strategies have been simulated, and the results show that most of them positively impact the increase of production compared to the fixed method (Bonates and Lizotte, 1988; Soumis et al., 1989; Forsman et al., 1993; He et al., 2010; Newman et al., 2010; Subtil et al., 2011; Lin et al., 2012; Zhang and Xia, 2015; Faiz Fadin, 2017). Therefore, there is no doubt that the trucks' and shovels' utilization is improved by using those dispatch strategies.

It is worth pointing out that all the results of the literature reviewed in Chapter 2.2 (published within twenty years), in the field of production optimization, are obtained by running corresponding simulation models. Other than that, more and more components and constraints like stockpile, product quality, and equipment availabilities have been added to simulation models to make them more and more in line with reality, and the results are more credible (Hodkiewicz et al., 2010; Camargo et al., 2018).

Recently, the application of mixed reality (MR), virtual reality (VR) and Augmented Reality (AR) in the mining field has attracted some attention from mining scholars. Those new technologies could be beneficial in offering real-time information, equipment maintenance and repair, remote assistance and make it easier for personnel to have an overall understanding of how the mine works (Jacobs et al., 2016; Zhang, 2017; Bellanca et al., 2019; Stothard et al., 2019). However, those techniques are still in the early stages of development, and there are no uniform equipment and protocols standards. Moreover, implementing those techniques requires detailed information input, which is beyond the capability of mines to collect, especially for those large-scale mines.

2.4. Literature Summary

Different truck-shovel dispatch strategies and mining production optimization models proposed over the past decades were reviewed in this section. Besides, models that analyzed the positive effect of stockpiles on short-term mining production optimization were also studied. It can be seen that most of the models are tested using discrete event simulation – the best and cheapest way to validate those models before implementation in a real mine.

However, due to the flexibility of mining procedures, no model in the current stage could perfectly cover all elements in mining. Moreover, even if there is one, no meaningful results could be obtained since it cannot be simulated due to the limitations of computational power. Therefore, those models inevitably have different shortcomings. To the best knowledge of the author, the shortcomings are summarized in three categories as follows:

2.4.1 Optimization shortcomings

- The rock type and particle size of the minerals significantly affect equipment efficiency but are not considered by most models.
- Shovel relocation, which will lead to loss of production, is not addressed in most of the proposed models, assuming that shovels could 'teleport' to the new assigned digging place.
- Stockpiles and blending requirements are not considered in most linear programming models.
- Optimized short-term or long-term plans under different nonlinear mathematical algorithms based on heuristics or meta-heuristics methods are not guaranteed to be near-optimal and, in some cases, even unrealistic. Meanwhile, most nonlinear models are not verified or only verified on small datasets. Therefore, no nonlinear model can give creditable near-optimal results in a short period.
- All the models proposed, except one or two, cannot deal with heterogeneous shovels and trucks, which are common in real mines.
- Most optimization models use only one criterion while real mines have several different objectives to be balanced.
- Stockpiles in most models are located out-of-pit, the capacity stays unclear, and what to do with the material remaining in the stockpile is not stated.

- Stockpiles in most models are far away from the crusher, which introduces extra hauling costs into the system that is neglected.
- Reclamation processes will either require an extra cost on equipment like shovels or affect routine mining operation efficiency, which are not considered by models reviewed.
- Stockpiles in reviewed models are based on the first-in-last-out rule, and the materials are not blended as assumed.

2.4.2 Simulation shortcomings

- Different mines have different features, which led to the phenomenon that most of the simulation models successfully implemented in one mine are unsuitable for another, which means models are case specific.
- Due to the multidimensional complexity of reality, no simulation model can incorporate all the uncertainty conditions. For example, almost all the stockpile models assume that the reclaimed material from the stockpile is heterogeneous.
- Simulation offers minimal flexibility to users, and once the input parameters are set up, they cannot be changed before the simulation stops.
- It is unsuitable for long-term prediction since the topography, paths, and many other mine components will be changed while the operation continues.
- The simulation model building needs plenty inputs, while most of the mines do not track that many inputs among them. Moreover, the simulation model has high requirements for the authenticity of the input data. Therefore, if the input data is very different from the actual situation, the simulation results are likely to deviate significantly from the real situation and have no credibility.
- Sometimes, running simulation models with many details is time-consuming, and real-time decisions cannot be made – this is fatal for truck dispatch.

2.4.3 Shortcomings addressed

This section summarized the common shortcomings of current research in related fields. Despite the authors' best efforts, this study still does not address some issues adequately. The followings are shortcomings addressed in this research:

- Add near-face-stockpile into the linear optimization model.
- Add stockpile-associated cost and blending requirements into the optimization model.
- Materials sent to stockpile are trackable in the simulation model.
- Average material grade reclaimed from a stockpile can be generated daily.

3. THEORETICAL FRAMEWORK

3.1. Introduction

One of the objectives of this research is to establish a complete optimization-simulation framework that can quantitatively measure and evaluate the performance of a mining method. This framework is shown in Figure 3.1.

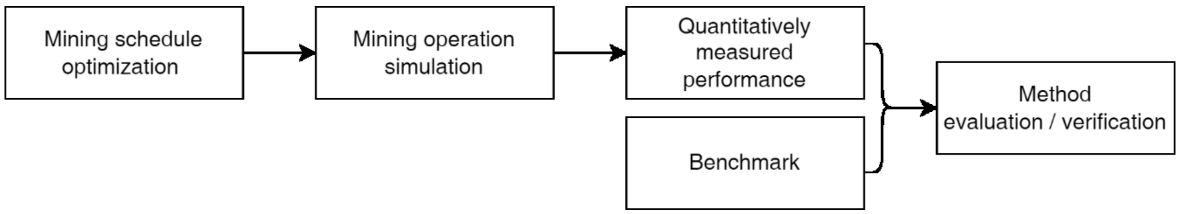

Figure 3.1 The optimization-simulation framework for mining method evaluation

Therefore, theoretical work mainly includes two aspects, mining schedule optimization and mining operation simulation. The following work is involved in this chapter: First, based on mixed integer linear programming, establish a mathematical optimization model that can generate an optimal or near-optimal mining schedule for the NFS method. Second, based on the discrete simulation software ARENA, develop a simulation model suitable for the NFS method, in which the mining system and the milling system are relatively independent.

As reviewed in Chapter 2, the existing literature has presented various mathematical optimization models, both with and without stockpiles. In this chapter, the near face stockpile is modeled utilizing the piecewise linearization technique (Markowitz and Manne, 1957) to circumvent nonlinear constraints. The introduction of three stockpiles, each with distinct acceptable grades, enables the assignment of fixed reclamation grades to individual stockpiles. The determination of input grade ranges and reclamation grades is based on preexisting records.

Furthermore, the reduction of problem size is achieved through the utilization of two sets of aggregates to inform mining and processing decisions: polygons and clusters. Mining operations are conducted at the polygon level, while destination decisions are made at the cluster level. The polygons and clusters are generated using a clustering algorithm proposed by Tabesh and Askari-Nasab (2013). This algorithm is employed to establish processing units within the boundaries of the benches. Consequently, all benches are subdivided into smaller units characterized by similar rock types and grades, forming the foundation for processing and stockpiling determinations. The mathematical formulation and notations employed in this study represent improved and customized versions of the model initially presented in Tabesh et al. (2015).

In addition to the optimization models, the simulation model must meet the following conditions: Captures as many details as possible of the near face stockpile mining method and traditional out-of-pit mining methods; Captures the associated cost of each mining operation; Captures the uncertainties like equipment failures and working time distributions; Captures the production loss caused by shovel movement.

3.2. Optimization model – traditional

3.2.1 Notations

- Sets

B^p	A set of polygons that must be extracted before mining polygon p to adhere to slope and precedence constraints.
U^p	Represents all the clusters that are encompassed within polygon p

- Indices

$d \in \{1,...,D\}$	Destinations (waste dump, crusher, or stockpile) index
$p \in \{1,...,P\}$	Polygons index
$k \in \{1,...,K\}$	Clusters index
$e \in \{1,...,E\}$	Elements index
$t \in \{1,...,T\}$	Periods index
$s \in \{1,...,S\}$	Stockpile zones index

- Parameters

$\overline{MC}^t$	The upper bounds of the mining capacity in different time periods t
$\underline{MC}^t$	The lower bounds of the mining capacity in different time periods t
$\overline{PC}^t$	The upper bounds of the processing capacity in different time periods t
$\underline{PC}^t$	The lower bounds of the processing capacity in different time periods t
$\overline{G}^{t,e}$	Maximum grades allowed of element e sent to processing plant in different time periods t

$\underline{G}^{t,e}$	Minimum grades allowed of element e sent to processing plant in different time periods t
s_p	Total number in S^p
o_p	Ore tonnage in polygon p
w_p	Waste tonnage in polygon p
o_k	Ore tonnage in cluster k
w_k	Waste tonnage in cluster k
o_r	The total reserve tonnage of ore material
w_r	The total tonnage of waste material that needs to be moved
c_p^t	The discounted costs of mining one unit of material from polygon p in period t and sent to its destination (both ore and waste)
$r_k^{t,e}$	Discounted revenue generated from processing one unit of element e from cluster k in period t minus the crushing, processing, and selling costs
$r^{t,e}$	Discounted revenue generated from processing one unit of element e from stockpile in period t minus the rehandling, crushing, processing, and selling costs
$r_s^{t,e}$	Discounted revenue generated from processing one unit of element e from stockpile zone s in period t minus the rehandling, crushing, processing, and selling costs
g_k^e	Average raw ore grade of element e in cluster k
ε	Tonnage flexibility
$gr_s^{t,e}$	Average grade of element e in stockpile zone s in period t

- Decision Variables
  Model 1 – Nonlinear model

$y_p^t \in [0,1]$	The portion of polygon p extracted in period t (both ore and waste). Continuous variable
$x_k^t \in [0,1]$	The portion of cluster k extracted in period t (both ore and waste). Continuous variable
$b_p^t \in \{0,1\}$	If all the predecessors of polygon p are extracted by or within period t. Binary variable
f^t	Reclaimed tonnage from the stockpile in period t. Continuous variable
$gr^{t,e}$	Grade of element e reclaimed from stockpile in period t

3.2.2 Model 1 – traditional nonlinear

Initially, we introduce the initial optimization model that incorporates a mathematical formulation for stockpiling, featuring a non-linear calculation for stockpile grade. This model employs two distinct sets of units to facilitate decision-making pertaining to mining and processing activities. The first and third sets of decision variables are specifically designed for polygons. As the number of polygons is typically lower than that of blocks and clusters, employing polygons for controlling precedence results in a reduced number of binary variables and a lower resource consumption when solving the model. Additionally, the use of polygons as mining units is a widely adopted practice in the mining industry. However, for more accurate material destination decisions, a more precise unit is necessary, which is achieved by employing smaller-sized units known as clusters.

- Objective Function

$$\max \sum_{t=1}^{T}\left(\sum_{e=1}^{E}\sum_{k=1}^{K}(r_k^{t,e}\times o_k\times x_k^t)-\sum_{p=1}^{P}(c_p^t\times\left(o_p+w_p\right)\times y_p^t)+\sum_{e=1}^{E}\left(f^t\times gr^{t,e}\times r^{t,e}\right)\right) \tag{1}$$

- Constraints

$$\underline{MC}^t \le \sum_{p=1}^{P}\left((o_p+w_p)\times y_p^t\right)\le\overline{MC}^t \qquad \forall t\in\{1,...,T\},\forall p\in\{1,...,P\} \tag{2}$$

$$\sum_{k\in U^p}\left(o_k\times x_k^t\right)\le\left(o_p+w_p\right)\times y_p^t \qquad \forall t\in\{1,...,T\},\forall p\in\{1,...,P\},\forall k\in\{1,...,K\} \tag{3}$$

$$\underline{PC}^t \le \sum_{k=1}^{K}\left(o_k\times x_k^t\right)+f^t\le\overline{PC}^t \qquad \forall t\in\{1,...,T\},\forall k\in\{1,...,K\} \tag{4}$$

$$\underline{G}^{t,e}\le\frac{\sum_{k=1}^{K}\left(o_k\times g_k^e\times x_{k,p}^t\right)+f^t\times gr^{t,e}}{\sum_{k=1}^{K}\left(o_k\times x_{k,p}^t\right)+f^t}\le\overline{G}^{t,e} \qquad \forall t\in\{1,...,T\},\forall e\in\{1,...,E\},\forall k\in\{1,...,K\} \tag{5}$$

$$gr^{t,e} = \frac{\sum_{t'=1}^{t-1} f^{t'} \times G^{t',e}}{\sum_{t'=1}^{t-1} f^{t'}} \qquad \forall t \in \{1,...,T\}, \forall e \in \{1,...,E\} \tag{6}$$

$$\sum_{t'=1}^{t} f^{t'} \leq \sum_{t'=1}^{t-1} \sum_{k=1}^{K} \left(o_k \times x_{k,s}^{t'} \right) \qquad \forall t \in \{2,...,T\}, \forall k \in \{1,...,K\} \tag{7}$$

$$\sum_{t=1}^{T} y_p^t = 1 \qquad \forall p \in \{1,...,P\}, \forall t \in \{1,...,T\} \tag{8}$$

$$\sum_{i=1}^{t} y_p^i \leq b_p^t \qquad \forall p \in \{1,...,P\}, \forall t \in \{1,...,T\} \tag{9}$$

$$s_p \times b_p^t \leq \sum_{i \in B^p} \sum_{j=1}^{t} y_i^j \qquad \forall p \in \{1,...,P\}, \forall t \in \{1,...,T\} \tag{10}$$

$$b_p^t \leq b_p^{t+1} \qquad \forall p \in \{1,...,P\}, \forall t \in \{1,...,T-1\} \tag{11}$$

Equation (1) is the objective function, which calculates the discounted revenue derived from sending material from the clusters to the processing plant and the discounted revenue generated from reclaiming ore material from the stockpile. The summed revenue is then subtracted by the total cost of mining and hauling. It is worth noting that the objective function is a non-linear equation. Equations (2) and (4) control the portion of polygons and clusters to be extracted in each period with respect to mining and processing capacities. The constraint of Equation (3) restricts the tonnage sent from the clusters to the processing plant and stockpile during a period to be less than the total tonnage mined from polygons during the period. Equation (5) controls the overall average head grade of material processed in each period by averaging the material grade from clusters and stockpile. To maintain linearity, the equations are rearranged before being transformed into matrix format. Equation (8) constrains that all polygons within the pit limit need to be fully mined. Equations (9) to (11) constrains the mining sequence of polygons.

Equation (6) is used to calculate the average grade of element e in stockpile in different periods t in the stockpile. Equation (7) ensures that the cumulative tonnage reclaimed does not overpass the cumulative tonnage sent to the stockpile. Note that equation (6) and (7) assumes that material sent to the stockpile will not be reclaimed in same period.

3.2.3 Model 2 – traditional linear (base model)

In order to establish a linear optimization model incorporating stockpiling, we make the assumption that multiple stockpiles exist, each with narrow ranges specified for acceptable element grades. This enables us to assign an average reclamation grade and determined revenue to each stockpile. It is important to note that as the number of stockpiles defined increases, the model incurs a smaller error. However, it is essential to consider that incorporating more stockpiles may compromise the assumption of complete blending, which is typically expected in most stockpiling scenarios. Therefore, it is crucial to make reasonable assumptions regarding the number of stockpiles required to define the acceptable element grade ranges, as this decision greatly influences the meaningfulness and accuracy of the obtained results. The optimization model can be linearized by using convincible averaged grade. Therefore, $gr^{t,e}$ is no longer a decision variable and can be replaced by determined $gr_s^{t,e}$. And f^t is still a decision variable but replaced by f_s^t. Meanwhile, $r^{t,e}$ is replaced by $r_s^{t,e}$ which represent discounted revenue generated from processing one unit of element e from stockpile zone s in period t minus the rehandling, crushing, processing, and selling costs.

In this way, the objective function of Model 1 can be replaced with equation (12). Equations (4) to (7) will be replaced by equations (13) to (16) respectively. In addition, we incorporate a constraint to control the element content of the material sent to the stockpile and the material reclaimed from it. Equation (17) is introduced to halt the reclamation process from the stockpile when the element of interest reclaimed tonnage reach the overall element tonnage sent to the stockpile. For example, if the total mass sent to the stockpile was 50 tons with an average grade of 7%. Then if the reclaimed material has an average grade of 14%, at most 25 tons of materials can be reclaimed from the stockpile.

$$\max \sum_{t=1}^{T}\left(\sum_{e=1}^{E}\sum_{k=1}^{K}(r_k^{t,e} \times o_k \times x_k^t) - \sum_{p=1}^{P}(c_p^t \times \left(o_p + w_p\right) \times y_p^t) + \sum_{s}^{S}\sum_{e=1}^{E} f_s^t \times gr_s^{t,e} \times r_s^{t,e} \right) \tag{12}$$

$$\underline{PC}^t \leq \sum_{k=1}^{K}\left(o_k \times x_k^t\right) + \sum_{s=1}^{S} f_s^t \leq \overline{PC}^t \qquad \forall t \in \{1,...,T\}, \forall k \in \{1,...,K\} \tag{13}$$

$$\underline{G}^{t,e} \leq \frac{\sum_{k=1}^{K}\left(o_k \times g_k^e \times x_k^t\right) + \sum_{s=1}^{S}\left(f_s^t \times gr_s^{t,e}\right)}{\sum_{k=1}^{K}\left(o_k \times x_k^t\right) + \sum_{s=1}^{S} f_s^t} \leq \overline{G}^{t,e} \qquad \forall t \in \{1,...,T\}, \forall e \in \{1,...,E\}, \forall k \in \{1,...,K\} \tag{14}$$

$$\underline{G}_s^{t,e} \leq \frac{\sum_{k=1}^{K}\left(o_k \times g_k^e \times x_{k,s}^t\right)}{\sum_{k=1}^{K}\left(o_k \times x_{k,s}^t\right)} \leq \overline{G}_s^{t,e} \qquad \forall t \in \{1,...,T\}, \forall e \in \{1,...,E\}, \forall k \in \{1,...,K\} \tag{15}$$

$$\sum_{i=1}^{t}\sum_{s=1}^{S} f_s^i \leq \sum_{i=1}^{t-1}\sum_{k=1}^{K}\left(o_p \times x_{k,s}^i\right) \qquad \forall s \in \{1,...,S\}, \forall t \in \{2,...,T\}, \forall k \in \{1,...,K\} \tag{16}$$

$$\sum_{i=1}^{t} gr_s^{t,e} \times f_s^i \leq \sum_{i=1}^{t-1}\sum_{k=1}^{K}\left(o_k \times g_k^e \times x_{k,s}^i\right) \qquad \forall s \in \{1,...,S\}, \forall t \in \{2,...,T\}, \ \forall k \in \{1,...,K\} \tag{17}$$

3.2.4 Case Study - traditional

To assess the efficacy of the proposed model and quantify the approximation error resulting from linearizing the stockpile grade calculation, we conducted an implementation on an iron-ore mine. The dataset comprised 430 million tons of material within the final pit, discretized into 19,561 blocks. Our objective was to derive a 20-year production plan. The blocks were aggregated into 40 polygons and 1,870 clusters using a hierarchical clustering algorithm proposed by Tabesh and Askari-Nasab (2013).

The processing plant capacity was set at 7.5 million tons per year, commencing from the fourth year. Meanwhile, the mining capacity started at 32 million tons and gradually decreased to eight million tons towards the end of the mine's lifespan. The block model considered three distinct elements, namely iron content, sulfur, and phosphorus. The iron content was measured as a mass percentage relative to the magnetic weight (MWT), while sulfur and phosphorus were tracked in mass percentage units. The specifications of the processing plant dictated that the ore should possess certain quality criteria. Specifically, the minimum required MWT was set at 78%, and the maximum allowable sulfur and phosphorus contents were 0.14% and 1.7% respectively. These specifications ensured that the processed ore met the desired quality standards.

To formulate the models, we utilized MATLAB and employed the CPLEX optimization engine to solve them optimally. This approach allowed us to effectively evaluate and analyze the proposed model's performance, taking into account the specific constraints and requirements of the iron-ore mining scenario.

3.2.4.1 Original Schedule - benchmark

In the initial phase, we executed the mixed-integer linear programming (MILP) without imposing any constraints on the head grade. This allowed us to adjust the mining capacity to obtain an acceptable schedule. The same settings were subsequently employed for the subsequent scenarios to demonstrate the benefits of incorporating stockpiling into the mine planning process. The generated schedule yields a net present value (NPV) of 2,615 million dollars. It is worth noting that the sulfur head grade constraint at the processing plant did not pose any restrictions in any of the scenarios and has been omitted in the following analysis.

Subsequently, we introduced head grade constraints for the three elements and re-executed the MILP. However, results show that in most years, the utilization rate of the processing plant is not ideal. Additionally, due to strict restrictions on the grade, the ore material grade of the shallow layer mined in the fourth year is low and does not meet the requirements of the processing plant, so the output in the fourth year is zero. Consequently, the generated net present value (NPV) declined to 2,109 million dollars, representing a 23% decrease compared to the previous scenario.

3.2.4.2 Adding stockpile

In order to address the head grade challenges, we incorporated three stockpiles into the operation. These stockpiles were defined with different acceptable grade ranges and corresponding reclamation grades, as outlined in Table 3.1. The revenue generated from reclaiming material from the stockpile was calculated using the MWT reclamation grade and an average rehandling cost of $0.5 per ton. It is important to note that the cost of the mining fleet on reclamation is not considered. As depicted in Figure 3.2, the plant utilization remained below maximum capacity for several years, indicating a scarcity of high-quality ore to sustain plant operations. However, thanks to the stockpile, ore was stored and subsequently reclaimed in later years. This reclaimed material, mixed with higher-quality ore, was then fed to the plant. The resulting net present value (NPV) amounted to 2,155 million dollars, representing a 9% improvement compared to the scenario without stockpiling. Figure 3.3 visually presents the variation between the actual grade of material in the stockpile and the predetermined reclamation grade. It can be observed that the average absolute error in grade amounted to 3%. Moreover, over the mine's lifespan, a total of 6 million tons of material were reclaimed from the stockpiles.

These results demonstrate the benefits of incorporating stockpiles in managing head grade constraints. By strategically storing and reclaiming material, the operation can enhance plant utilization, overcome grade limitations, and ultimately improve the project's economic performance. However, it is essential to acknowledge the slight grade discrepancies between the actual material in the stockpile and the predetermined reclamation grade.

Table 3.1. Summary of the stockpiles' parameters

Stockpile	Element	$\underline{G}_s^{t,e}$ (%)	$\overline{G}_s^{t,e}$ (%)	$gr_s^{t,e}$ (%)
1	P	0.10	0.11	0.10
	S	1.00	2.00	1.59
	MWT	70.00	74.00	71.83
2	P	0.11	0.13	0.12

	S	1.00	2.00	1.59
	MWT	74.00	78.00	76.47
3	P	0.13	0.15	0.14
	S	1.00	2.00	1.59
	MWT	78.00	82.00	80.34

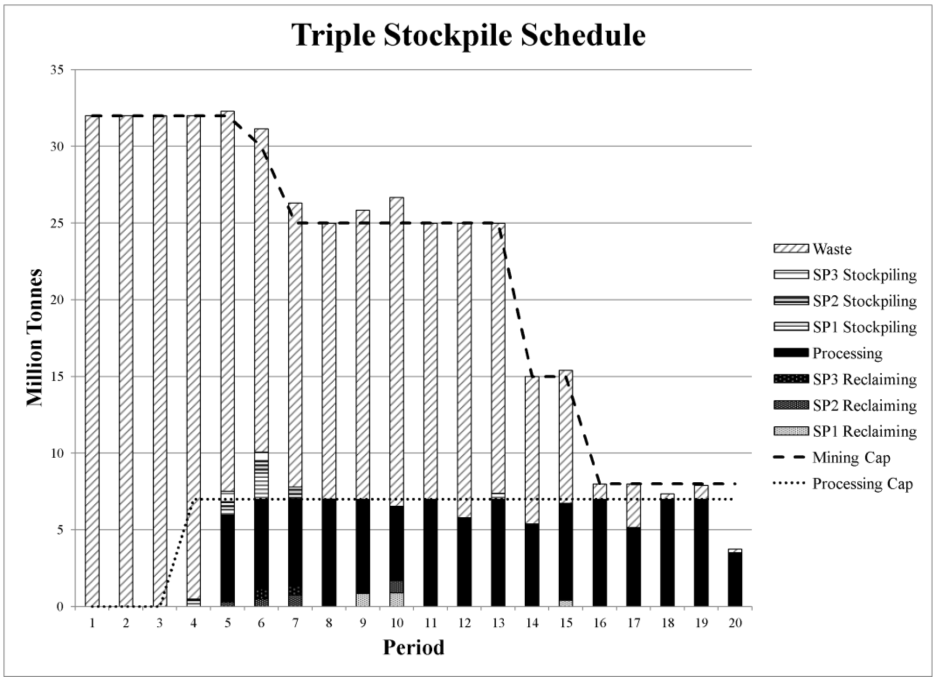

Figure 3.2 Mining schedule with three linearized stockpiles

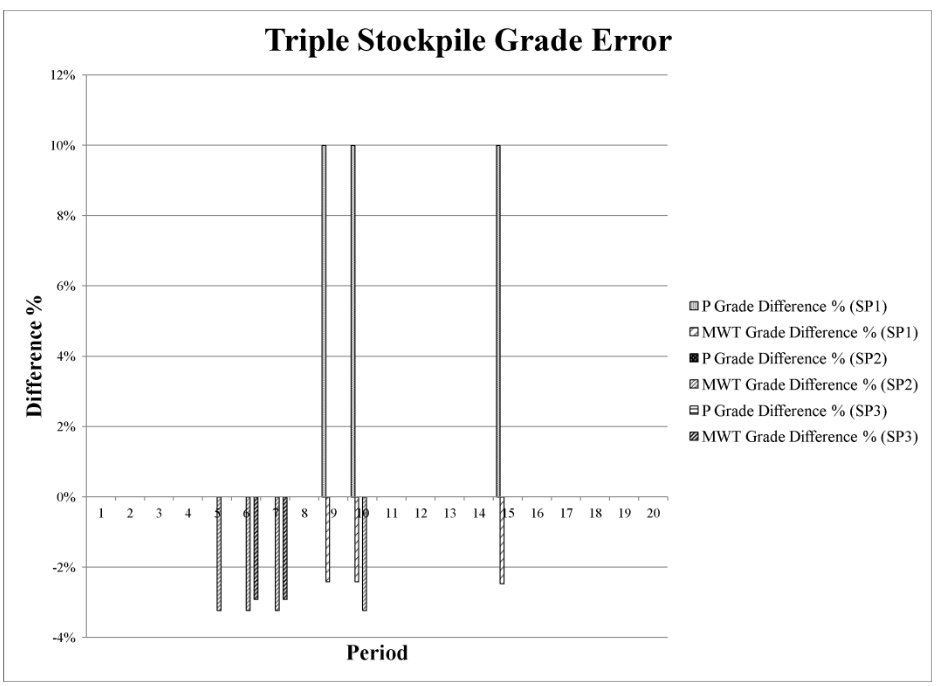

Figure 3.3 Grade error of iron and phosphorus between real grade and predefined grade

3.2.4.3 Summary of the results

We conducted a case study on an iron ore mine to evaluate the performance of our proposed optimization model. Table 3.2 presents the results of the scenarios tested, including the "no stockpile" scenario, which resulted in a lower net present value (NPV) and inadequate feed to the plant. To address this issue, we introduced three stockpiles with predetermined grade range and reclamation grade. The inclusion of stockpiles in the scenario led to higher NPV and increased total tonnage of material sent to the crusher, as illustrated in the table. However, it is important to note that the grade error also increased due to the material reclaimed from the stockpiles exhibiting a higher degree of grade deviation. As we discussed in earlier sections, the precise control of multiple element grades for the stockpile inputs plays a crucial role in defining the stockpiles and estimating reclamation errors accurately.

The case study provided confirmation of the effectiveness of our proposed optimization model. The addition of stockpiles resulted in an overall NPV increase of 2.23% with minimal grade deviation increased. This demonstrates the potential of stockpiling as a valuable strategy to enhance the economic performance of mining operations, while also highlighting the importance of carefully defining stockpile parameters and managing grade variations. In conclusion, our case study validated the efficacy of the proposed optimization model by showcasing the positive impact of stockpiling on NPV improvement, despite the limited increase in grade deviation.

Table 3.2.Summary of the results

Scenario	NPV ($M)	Diff (%)	Reclaimed Tonnage (MT)	Average Grade Error (%)
Original - benchmark	2108	-	-	-
Optimized	2155	2.23%	5.7	3.0

3.3. Optimization model – NFS

3.3.1 Model 3 – NFS

As mentioned earlier, model 2 is built to optimize a typical mining layout where stockpiles are located out of the pit, and only materials that cannot feed the crusher directly are sent to the stockpile.

For the NFS mining method, all material within acceptable range will be sent to stockpiles in the pit bottom, and then a reclaim shovel starts feeding the crusher from the stockpile. NFS mining method results in an even better blending since more materials are mixed, and the grade limitations for the stockpile can also be relaxed. To quantitatively study the blending performance, in this part, we will extend model 2 to the NFS mining method scenario.

The objective function for model 3 keeps the same as equation (12). Equation (13) and (14)are replaced by equation (18) and (19). Equation (20) to (22) are added on the foundation of model 2.

$$\underline{PC}^t \le \sum_{s=1}^{S} f_s^t \le \overline{PC}^t \qquad \forall t \in \{1,...,T\} \tag{18}$$

$$\underline{G}^{t,e} \le \frac{\sum_{s=1}^{S}\left(f_s^t \times gr_s^{t,e}\right)}{\sum_{s=1}^{S} f_s^t} \le \overline{G}^{t,e} \qquad \forall t \in \{1,...,T\}, \forall e \in \{1,...,E\} \tag{19}$$

$$\sum_{t=1}^{T}\sum_{p=1}^{P} o_p \times y_p^t \le o_r \qquad \forall p \in \{1,...,P\}, \quad t \in \{1,...,T\} \tag{20}$$

$$\sum_{t=1}^{T}\sum_{p=1}^{P} w_p \times y_p^t \le w_r \qquad \forall p \in \{1,...,P\}, \quad t \in \{1,...,T\} \tag{21}$$

$$\sum_{k=1}^{K} o_k \times x_k^t - \varepsilon \le \sum_{s=1}^{S} f_s^t \le \sum_{k=1}^{K} o_k \times x_k^t + \varepsilon \qquad \forall t \in \{1,...,T\} \tag{22}$$

Equation (20) and Equation (21) enforce that the total ore and waste tonnage mined should be less than the total reserve available. Equation (22) puts a limitation on tonnage reclaimed from different zones in each period. The reclaimed tonnage in each period should be located within the range of ore material mined in that period plus/minus flexibility tonnage.

3.3.2 Case study – NFS

The same dataset and software are used in this section to verify the blending performance of the NFS mining method. Since the former analysis already proved that three stockpiles could achieve better blending results, the near-face stockpile will be divided into three zones in this case study.

3.3.2.1 Schedule

We can see from Table 3.9 that the pre-stripping takes about four years, and after that, ore material starts being excavated, sent to the stockpile and crushed. Note that all material sent to stockpile will be crushed, and in year four, unlike the former model, there is no material sent to stockpile – grade constraints rejected material mined in early years, and they are sent to waste dump. Coorespondingly,

The final net present value generated is 2355 million dollars, which is higher than the all scenarios presented in model 2. Meanwhile, the amount of materials processed each year is almost stable at a high level close to the capacity, and the annual difference level is relatively low, as seen in Table 3.3. As a consequence, the yearly strip ratio shows a decreasing trend. Although only one near-face stockpile is considered during the life of mine, it consists of three zones representing low-grade, medium-grade and high-grade.

Table 3.3 Tonnage of ore delivered to the processing plant on the yearly basis

Year / Case	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Benchmark (Mt)	7	7.5	7.5	7.5	7.5	7.3	7.5	6.9	7.5	6.7	7.5	7.5	6.5	7.5	7.5	4.8
Error (%)	-7	-	-	-	-	-3	-	-8	-	-11	-	-	-13	-	-	-36
NFS (Mt)	7.5	6.4	7.5	7.5	7.5	7.5	7.5	7.2	7.0	7.0	7.0	7.0	7.5	7.5	7.5	7.2
Error (%)	0.0	-15	-	-	-	-	-	-4	-7	-7	-7	-7	-	-	-	-4.3

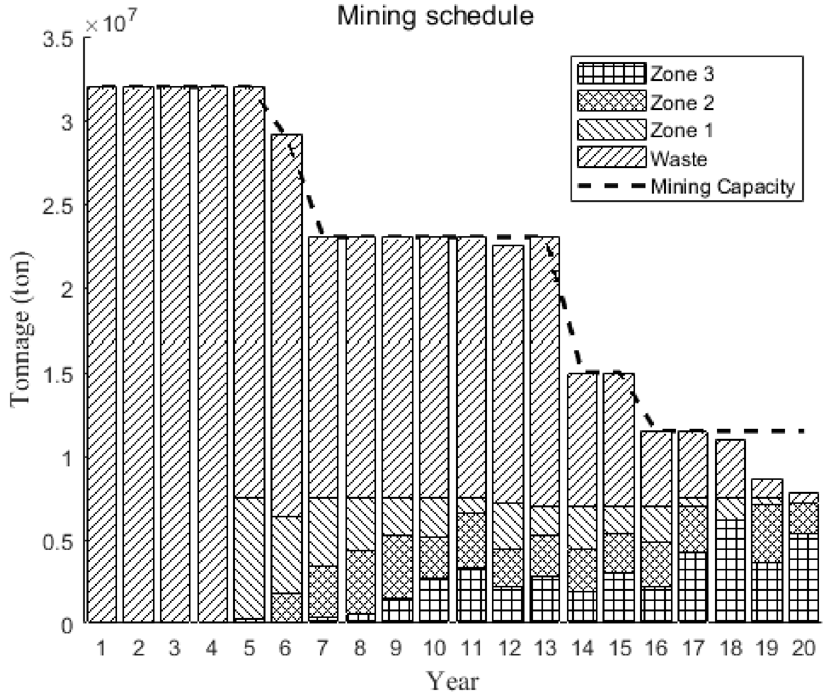

Figure 3.4 Generated mining schedule for NFS method

3.3.2.2 Grade error

Due to the particularity of the NFS mining method, all target minerals excavated from cuts will be sent to the stockpile located at the bottom of the pit and then reclaimed by another shovel. This process does not require an additional truck fleet and is completed by belt transportation. The cost of reclamation is set at \$0.5/ton. In order to use each area of the stockpile more evenly, two values were selected as the threshold by calculating the material tonnage and grade in each block. Those two values will distinguish the stockpile into three zones, which are under76.65%, between 76.65% and 80.23% and over 80.23%, as seen in table 2. The lowest MWT grade, 41.22% and the highest MWT grade, 84.52%, are the actual lowest and highest grades retrieved from the dataset, as shown in Table 3.4. The threshold value is selected based on MWT grade since the grade of Sulphur and Phosphor are not the main interest of mining companies and meet the processing requirement in most of the period.

Figure 3.5 and Figure 3.6 show the average grade of Phosphor and Sulphur of processed material by year and by zone, and Figure 3.7 shows the yearly average MWT grade of each zone in the stockpile and the overall MWT grade processed each year. Figure 3.8 depicts the yearly grade error of MWT and Phosphor sent to processing plant.

Table 3.4 Stockpile zoning parameters for the NFS case and benchmark case

Case	Number	Lower MWT (%)	Upper MWT (%)	Avg MWT (%)	Lower P (%)	Upper P (%)	Avg P (%)	Lower S (%)	Upper S (%)	Avg S (%)
Benchmark	Zone1	41.22	76.65	71.83	0.10	0.18	0.12	1	2	1.43
	Zone2	76.65	80.23	76.47	0.14	0.18	0.15	1	2	1.66
	Zone3	80.23	84.52	80.34	0.14	0.18	0.15	1	2	1.59
NFS	Zone1	41.22	76.65	70.02	0.1	0.18	0.14	1	2	1.31
	Zone2	76.65	80.23	78.68	0.1	0.18	0.13	1	2	1.69
	Zone3	80.23	84.52	81.26	0.1	0.18	0.14	1	2	1.60

Table 3.5 Yearly grade error of processed material

Year	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
S grade	1.6	1.4	1.7	1.7	1.6	1.6	1.7	1.5	1.8	1.7	1.7	1.7	1.7	1.8	1.5	1.5
Error (%)	-	-	-	-	-	-	-	-	3.5	-	1.2	-	-	5.9	-	-
P grade	.14	.12	.17	.13	.16	.16	.13	.11	.12	.12	.16	.14	.14	.13	.13	.14
Error (%)	-	-	23	-	14	11	-	-	-	-	14	-	-	-	-	-
MWT grade	66	71	74	74	76	80	80	79	80	75	76	75	80	80	81	81
Error (%)	-15	-9.6	-5.6	-4.6	-2.4	2.3	2.7	1.8	3.0	-3.6	-2.1	-4.2	2.1	3.0	3.9	4.1
S grade	.89	1.5	1.7	1.7	1.6	1.6	1.6	1.5	1.5	1.8	1.6	1.7	1.6	1.6	1.5	1.5
Error (%)	-	-	-	-	-	-	-	-	-	3.2	-	-	-	-	-	-
P grade	.14	.18	.14	.15	.14	.14	.14	.14	.14	.13	.13	.13	.13	.13	.13	.13
Error (%)	-	29	2.1	7.1	-	-	-	-	-	-	-	-	-	-	-	-
MWT grade	65	70	75	76	77	78	80	76	77	76	77	78	80	81	80.	81
Error (%)	-17	-10	-3.5	-2.3	-0.9	0.4	1.9	-2.1	-1.3	-2.1	-1.8	0.5	3.0	3.2	2.4	3.3

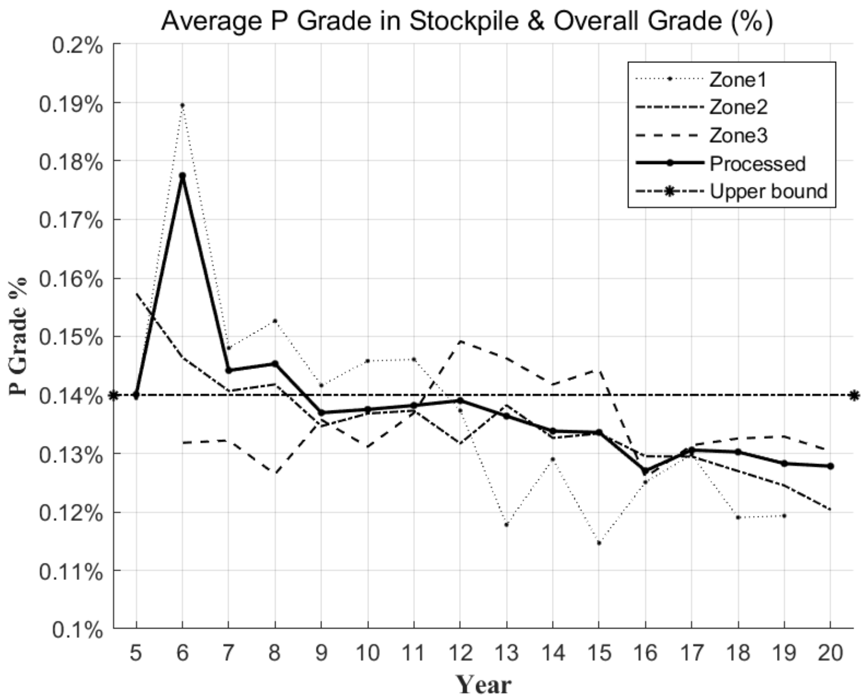

Figure 3.5 Phosphor grade delivered to each zone of the stockpile and the phosphor grade of final blend reclaimed from the stockpile by year of the mine life

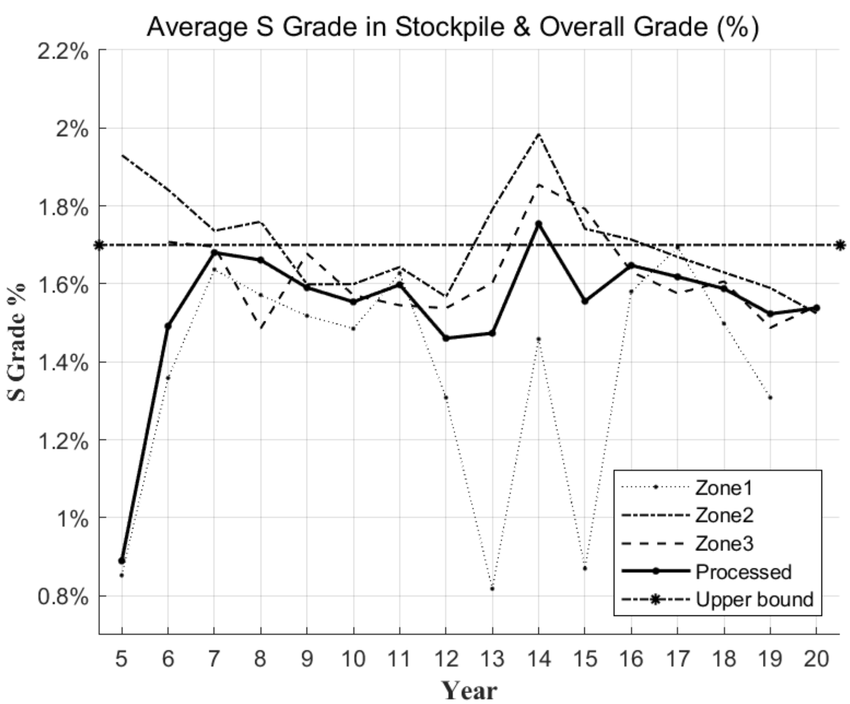

Figure 3.6 Sulfur grade delivered to each zone of the stockpile and the sulfur grade of final blend reclaimed from the stockpile by year of the mine life.

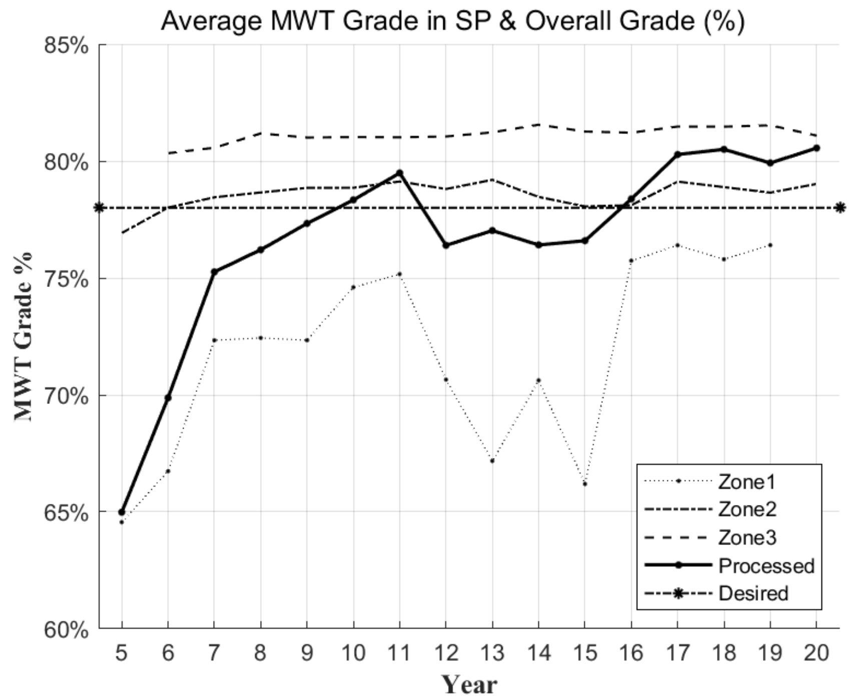

Figure 3.7 MWT grade delivered to each zone of the stockpile and the MWT grade of final blend reclaimed from the stockpile by year of the mine life.

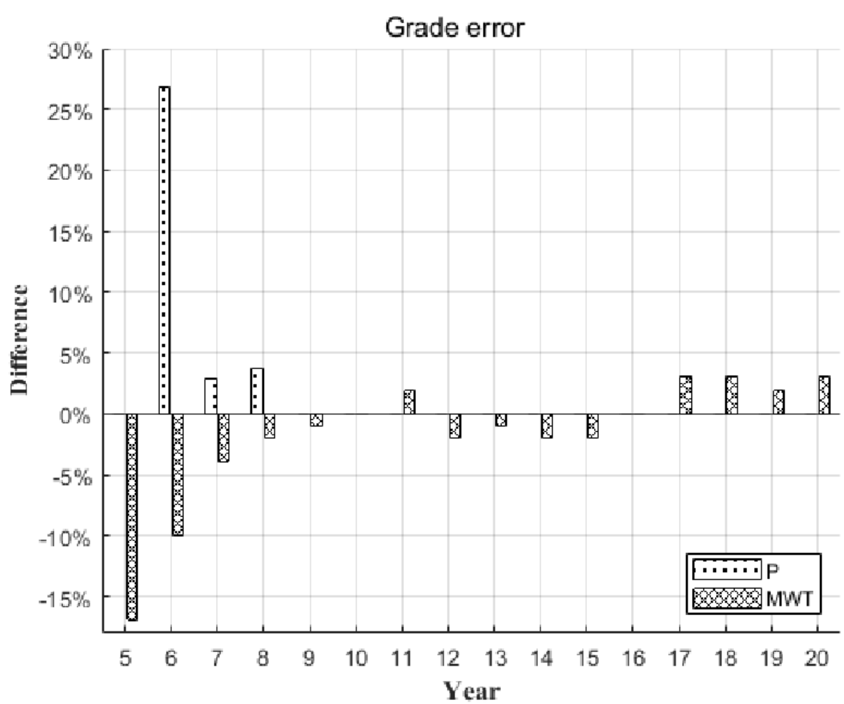

Figure 3.8 Grade error of MWT and Phosphor sent to processing plant on a yearly basis

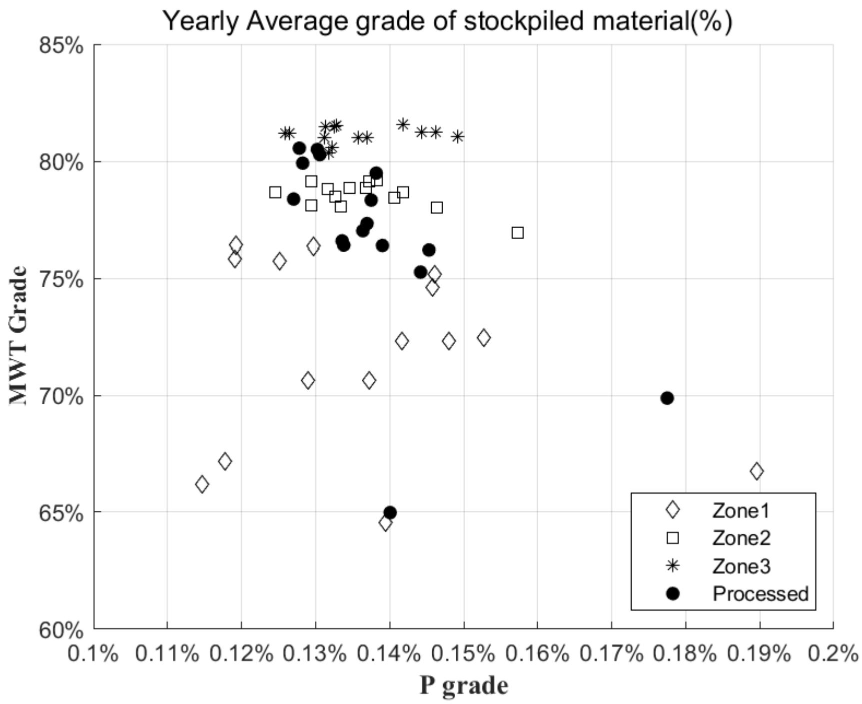

Figure 3.9 Grade distribution of stockpiled and processed material

Figure 3.9, Table 3.4 and Table 3.5 clearly show that inside the near face stockpile, zone 1 has the most comprehensive grade range for both MWT and phosphor and is the dominant zone to be reclaimed and processed in the first two years, leading to a higher grade error in early years. However, with the development of the pit limit, the average excavated material grade keeps rising, and the grade error for both MWT and phosphor is narrowed down, which means, zone 3 has the narrowest grade range for MWT and phosphor and is the dominant zone in later years.

3.3.3 Comparison

The results of the MILP model proposed in this article for the NFS mining method and the MILP model for the usual open-pit mining method accomplished (model 2) are compared in Table 3.6.

Table 3.6 Optimization results comparison between NFS method and traditional method

Category	Average grade error (%)	NPV
Traditional method	3.0	2155
NFS method	2.0	2355
Difference (%)	-33.3%	+9.28%

To evaluate the performance of the NFS open pit mining method, we compared results of our proposed optimization model with the results of the benchmark case in two important KPIs (the NPV and the absolute grade deviation). In the benchmark model, the case study generates $2155 million dollars of NPV with an average absolute MWT grade deviation of 4.36%. The number of the NFS case is $2355 million dollar and the hypothetical material grade deviation is 3.48%. This means that by switching from conventional open pit mining to the NFS open pit mining method the NPV generated by the case study will increase by 9.3% and the hypothetical grade variation of material sent to the crusher is reduced by 33.3%. For MWT, the hypothetical grade deviation reduction is 20%. This is mainly due to the higher turnover rate of near face stockpile since material in different zones are fully reclaimed in a predetermined time range while in traditional mining method, stockpile is only reclaimed when material mined in that period is not enough and rarely does stockpile realize a fully turnover in life of mine. To be more specific, high stockpile turnover rate has a strong positive effect on the blending results since with higher turnover rate, the tolerance for ore grade fluctuations will increase, and some relatively extreme high-grade and low-grade ore material will become acceptable. This is particularly beneficial to those mining companies whose material of interest comes with associated impurities – just as the iron mine used in the case study. Moreover, with more materials becoming acceptable for processing, higher production is expected (for this case, 1.8% higher production) which will eventually bring higher revenues and profits to the company.

3.4. Simulation model

Typical mining simulation models consist of only the mining system, while milling and processing are dispensable. However, for the NFS method, the stockpile is the essential difference from traditional mining method and is the critical component to be simulated. Therefore, after the production optimization model has been established above, this chapter will take an oil sands mine using the traditional crusher-out-of-pit mining method as an example to establish a simulation model to simulate the production status of the mine in 2016. Satellite view and Gems rebuild topography is shown in Figure 3.10 and Figure 3.11. On this basis, a second simulation model is established. Based on consistent ore body conditions and equipment capabilities, the layout of this mine was changed to the NFS mining method, and the corresponding road network and equipment location were also changed to adapt to the new mining method.

Figure 3.10 Satellite view of the targeted oil sand mine

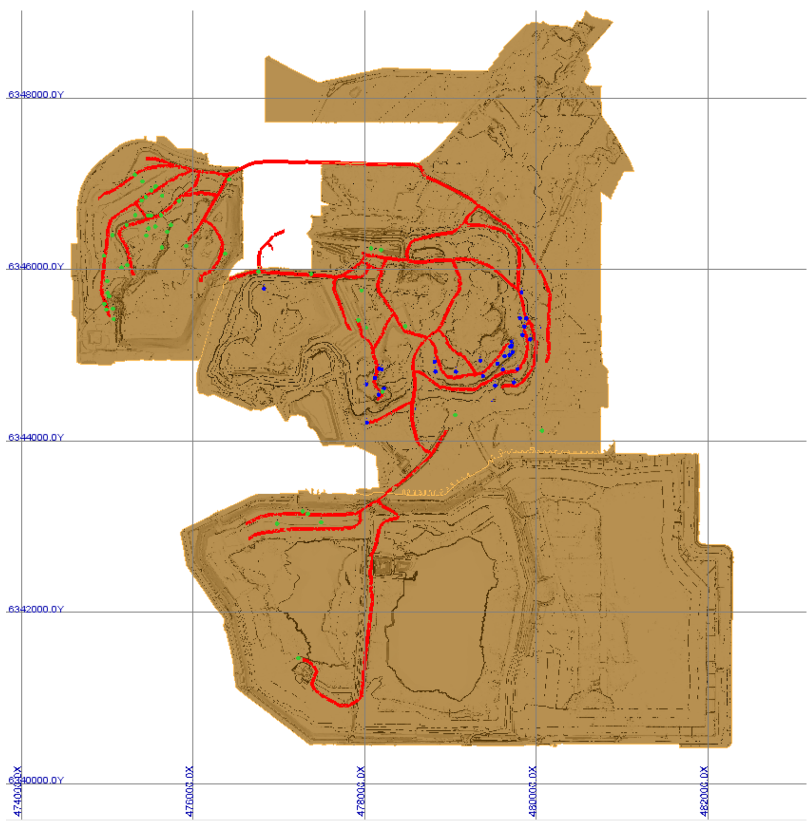

Figure 3.11 Gems rebuild topography of targeted oil sand mine

The first simulation model was built to compare with the actual mining situation to verify the validity of the simulation model. The simulation results combined with the corresponding optimization model will also be used as a benchmark to represent the best results that traditional mining methods can achieve. Furthermore, the results of running the second simulation model represent the main research objective of this paper, the performance of the NFS mining method. The next chapter will evaluate the NFS method and draw some conclusions by quantitatively comparing the simulation results of the NFS model and the benchmark model. Based on the discontinuity of mining activities, compatibility with VBA programming, and the ability to read and store data externally, a mature discrete simulation software called Arena is adopted to build the simulation models in this research.

A general disadvantage of simulation models is that most are case-specific and 'hard coded,' and it is almost impossible to transfer them to other cases. Many factors cause this situation. First, the burial conditions and physical properties of minerals of different varieties in different regions are vastly different. Meanwhile, different equipment choices can also significantly impact the final extraction boundary. In addition, differences in environmental policies, mining methods, capital costs, workers' capabilities, engineers' experience, and many other reasons will also affect mining activities. So, its corresponding simulation model is challenging to generate automatically by defining a few key parameters.

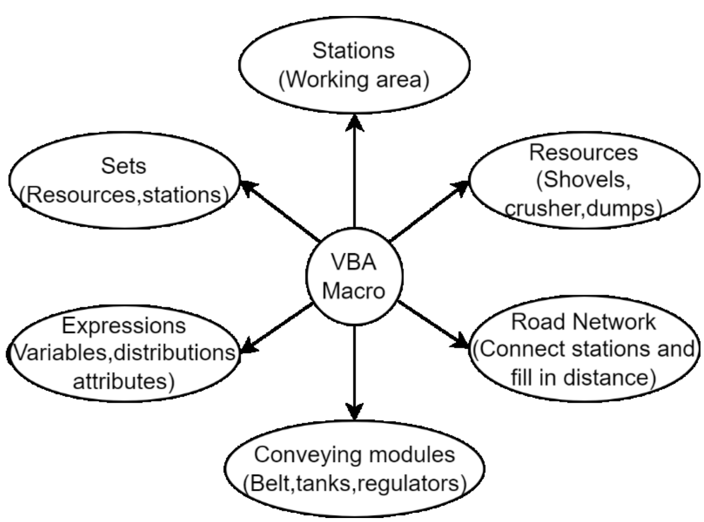

Figure 3.12 Components of simulation models created by VBA macro

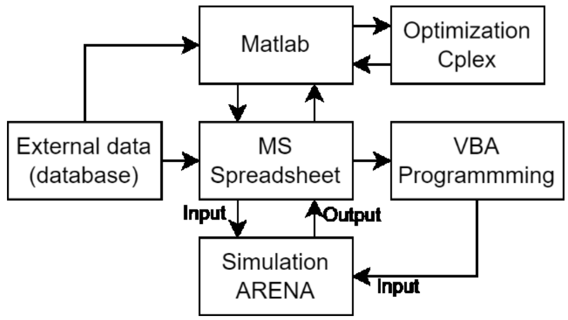

Figure 3.13 Schematic of data flow

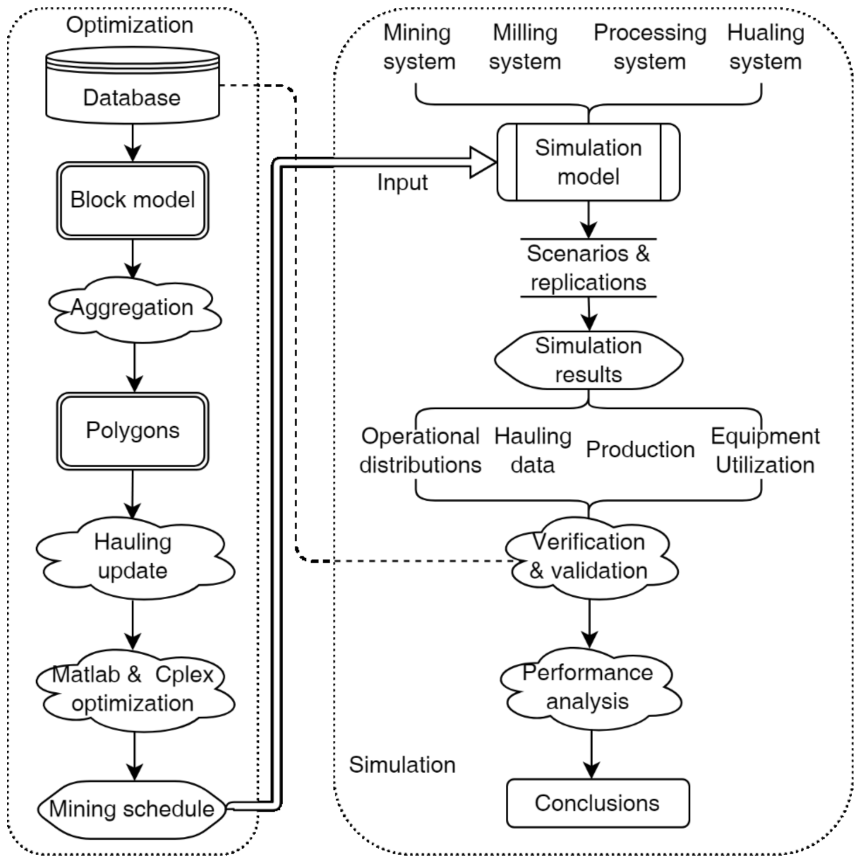

Figure 3.14 Simulation-optimization procedures

Although complete automation is not realistic at this stage, using semi-automation can also significantly improve the simulation efficiency and the case-specific status of the simulation model. Considering that the NFS mining method has a relatively common bottom structure, this paper will establish a semi-automatic model to simulate the NFS mining method. Therefore, the author takes the compatibility of the simulation software for VBA programming as one of the selection criteria.

Figure 3.12 shows the parts of the simulation model that need to be built with VBA macros to achieve semi-automation.

Besides, as mentioned above, the simulation model proposed in this chapter is based on the optimized mining sequence proposed above to achieve the best simulation results. Therefore, choosing the simulation software Arena with the ability to read external data can assist in establishing semi-automatic simulation models and greatly simplify the workload required to modify the model. Figure 3.13 shows how data is transferred between different programs. Figure 3.14 demonstrates procedures needed to complete the proposed optimization and simulation model.

3.4.1 framework

Generally, the working area of a conventional surface mining system mainly consists of the following elements: polygons (also known as blocks or faces to be moved), several electric shovels, a fleet of trucks, a growing road network, crusher(s), processing plant(s) and stockpile(s) (being placed in different locations based on different needs). Meanwhile, mining is not a specific activity but the sum of all the activities of the elements mentioned above. The activities of these elements are mainly connected in series by trucks and affect each other. Take the oil sand mine as an example. These activities can be mainly summarized as follows:

10. Follow a predetermined mining schedule and decide on working polygons
11. Shovels are allocated to working polygons and request trucks
12. Trucks haul to shovels
13. Shovels start digging the assigned polygons and loading the trucks
14. Full trucks travel to determined destinations (crusher, waste dump, or stockpile) based on materials grade
15. Trucks unload material carried at the designated location
16. Trucks assigned to a shovel for the empty return trip and being loaded at shovel locations again

17. Crusher crushes ore material received to an acceptable particle size
18. Crushed ore material being sent to the slurry plant
19. Slurry plant grinds minerals into smaller sizes and prepares a slurry
20. The slurry is transferred to the processing plant to produce the final product
21. Crude oil comes from the processing plant and is sold in the market or sent to a refinery plant

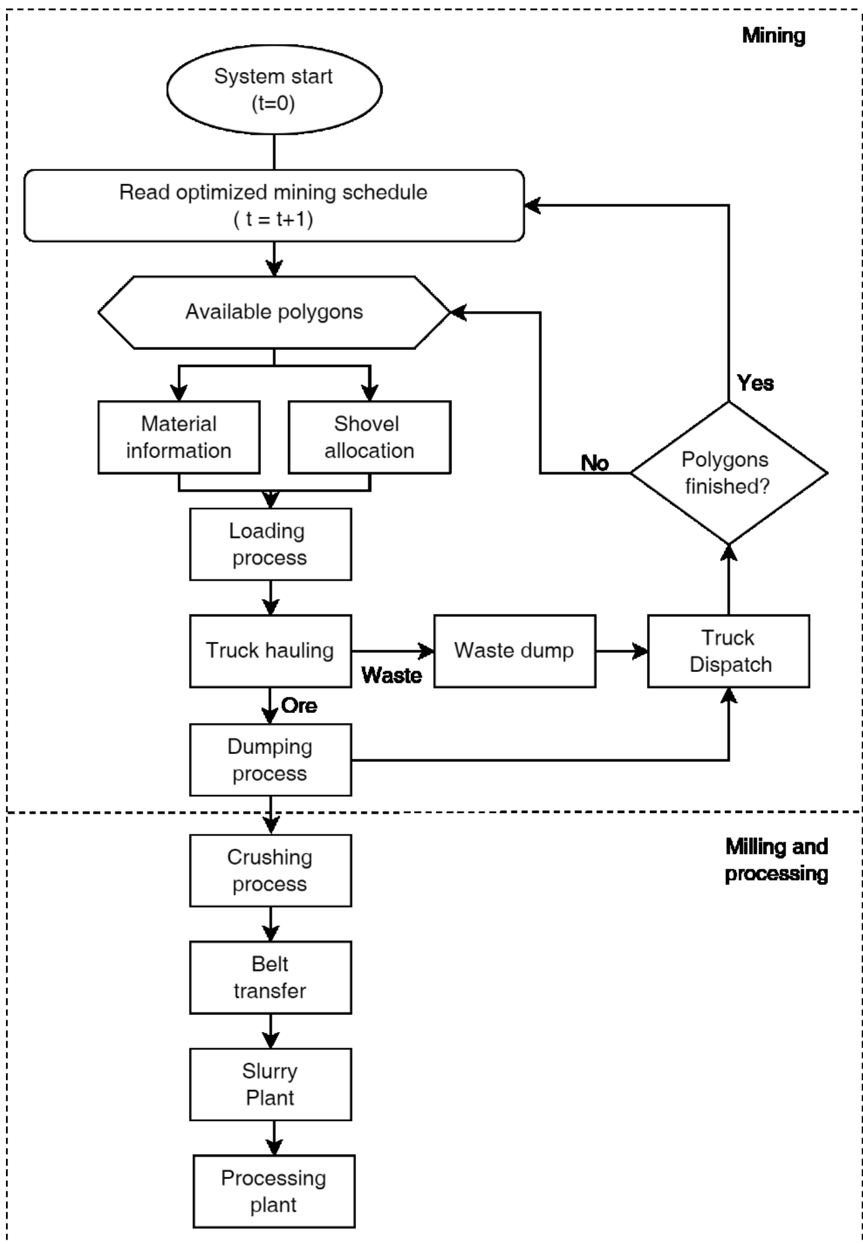

Figure 3.15 Frame of traditional mining method

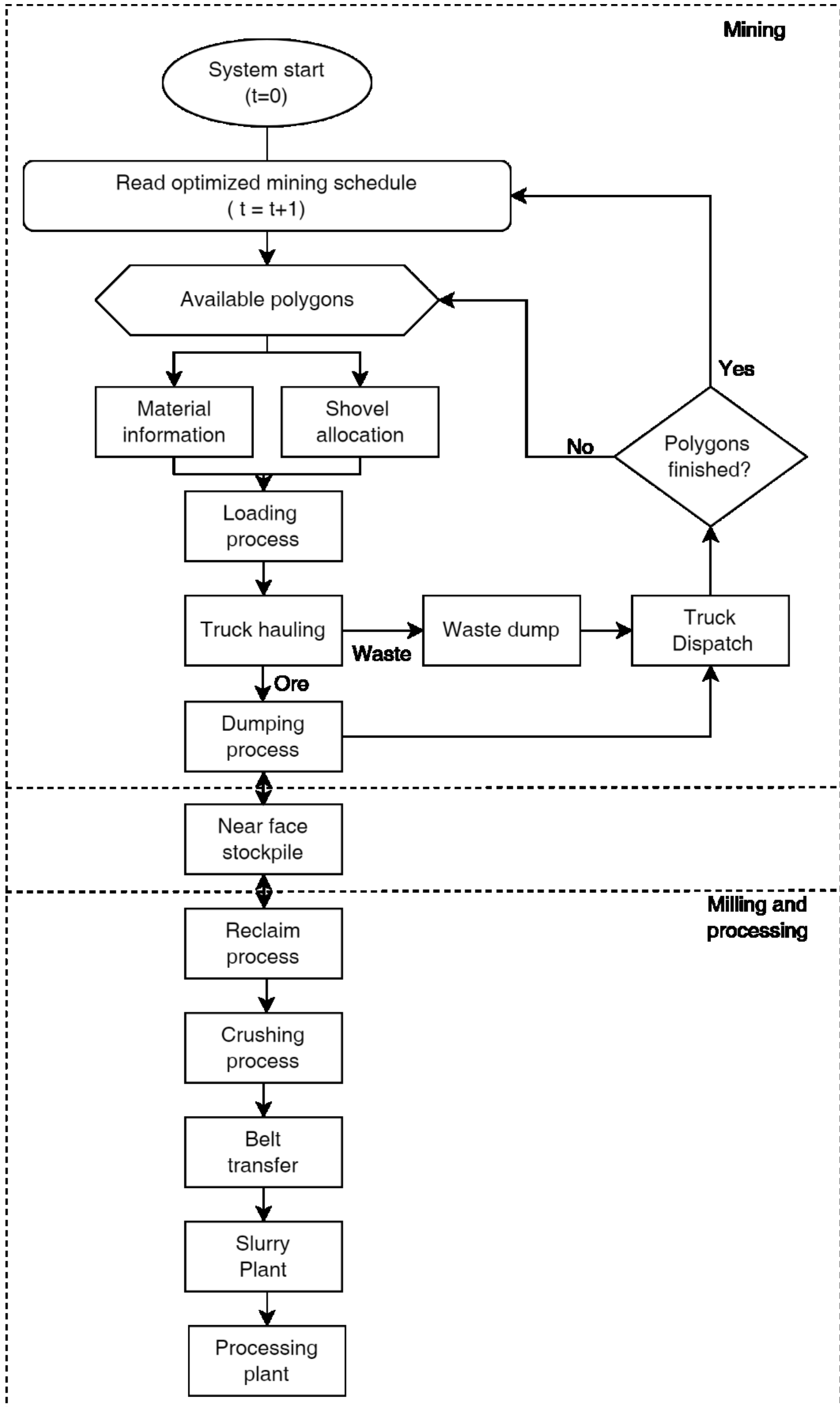

Figure 3.16 Frame of near-face-stockpile mining method

Although the basic logic of the traditional and near-face-stockpile mining methods is the same, in step 6, the designated locations for loaded trucks to dump in the two methods are quite different. For the waste materials, dumping trucks in both methods are hauling to the exact predefined waste dumps. However, things are different for ore materials. Trucks dump directly to the crusher in the traditional method, while in the near-face-stockpile method, dumping trucks dump to the stockpile in front of the crusher. In this way, trucks are no longer the direct feeder to the crusher, and an extra shovel is required to feed the crusher as needed. The NFS simulation model proposed in this chapter contains only one stockpile but is divided into three zones. Four dumping spots are available for each zone. The reclaim shovel keeps reclaiming materials from stockpile zones in a specific order. Afterward, materials will go through the crusher, belt, and slurry plant and be pumped out of the pit. In the software ARENA, Conveyor is an incorporated ready-to-use module. The modeling of conveyors within the software does not necessarily necessitate the utilization of specialized simulation constructs. Instead, conveyors can be effectively modeled using either a PROCESS module or a DELAY module, incorporating a deterministic delay. This delay parameter is employed to accurately represent the time required for an entity to transition from one location to another during sliding.

Figure 3.15 and Figure 3.16 illustrate the basic frame of simulating the traditional mining method and the near-face-stockpile mining method. From these two figures, we can see again that the near-face-stockpile divides the integrated (strongly connected) mining and the processing processes into two relatively independent (weakly connected) processes. In other words, the near-face stockpile acts as a buffer that allows the reclaiming and milling system to keep working for hours when no trucks dump materials into the stockpile for any reason. Besides, when the milling system shuts down unexpectedly, the mining system could also keep digging and dumping ore material to stockpile as usual for hours. This "buffer" brings extra stability to the system and can effectively improve equipment utilization, resulting in a better production rate. From the perspective of the independence of each subsystem, Figure 3.17, Figure 3.18, Figure 3.19can better reflect the difference between NFS and traditional mining methods at the operation level.

Figure 3.17 shows that, compared with the process of the traditional mining method, due to the increase in the number of dumping zones and dumping spots, it is necessary to add a selection strategy to determine the dump location of the truck. This selection strategy is shown in Figure 3.18. The fundamental purpose is not affecting other subsystems' operating and improve the security of whole system. From the perspective of risk management, if a certain zone is in the state of dumping and reclaiming simultaneously, it will threaten the safety of personnel and equipment, and lead to significant economic losses. Therefore, on the operation level, a fundamental principle is that zones under the reclaiming state cannot receive material from trucks simultaneously, and vice versa. Figure 3.19 shows the flow of the reclaim process and the inner logic of reclaiming zone determination in detail, as well as the crushing and processing subsystem. Therefore, the traditional shovel-truck-crusher connection has become two roughly independent connections: shovel-truck-stockpile connection and shovel(reclaim)-crusher connection, which bears more uncertainties.

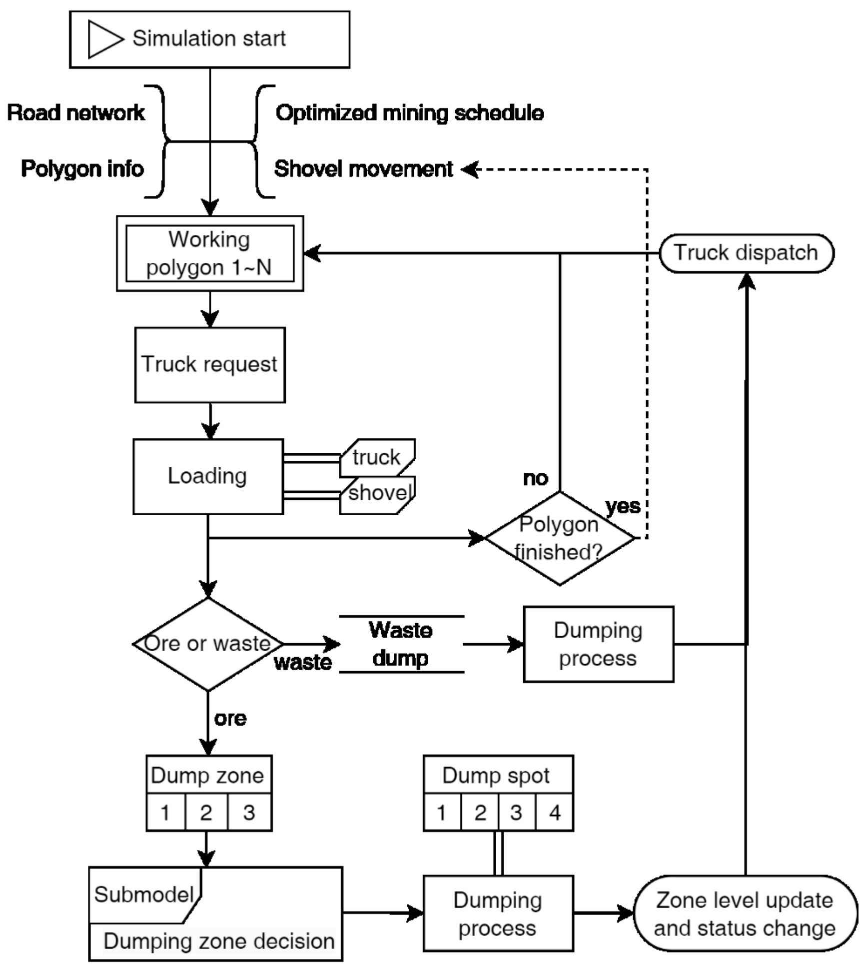

Figure 3.17 Diagram of mining sub-system of the NFS method

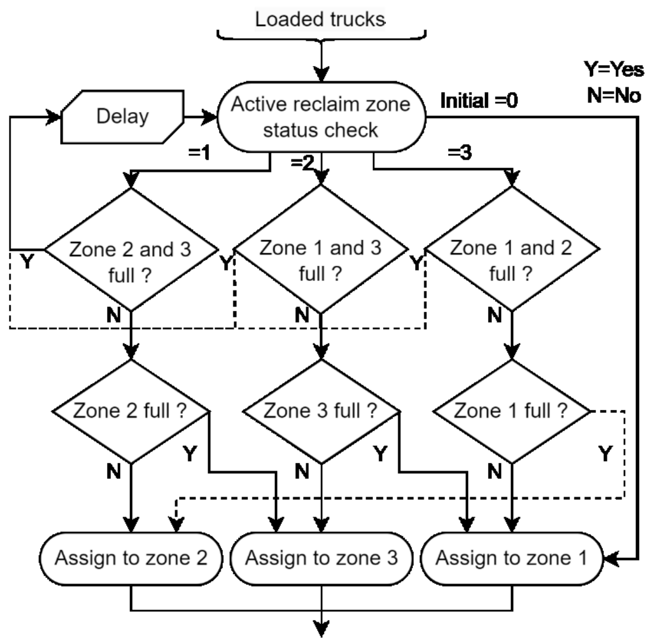

Figure 3.18 Logic of dumping zone decision

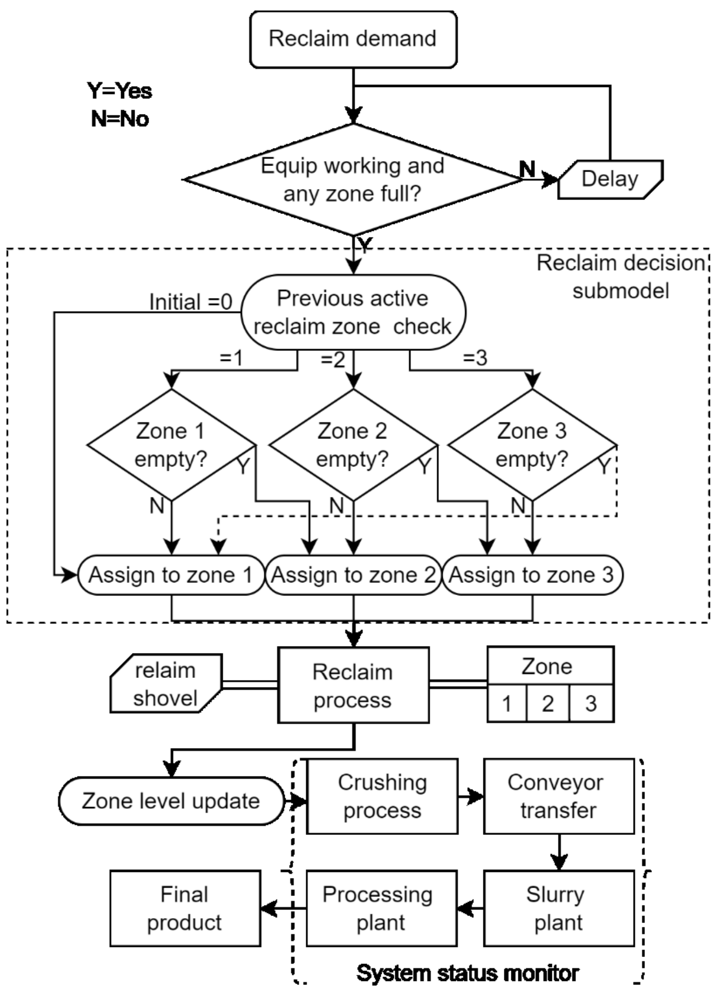

Figure 3.19 Diagram of reclaiming, crushing, and processing process of the NFS method

It is important to note that the traditional truck shovel mining system represents a typical amalgamation of discrete events, wherein the alteration of system state is discontinuous, rendering it suitable for discrete event simulation. Conversely, in the near face stockpile mining system, the stockpile is emulated through the employment of a tank module, and the transportation of crushed ore material to its destination is facilitated by a conveyor belt, making it more appropriate for continuous event model simulation. This observation further substantiates that the simulation of the NFS method encompasses a hybrid simulation, encompassing both the discrete simulation of the truck-shovel subsystem activities and the continuous event simulation of the crushing and conveying subsystem. These two subsystems are interconnected via a sensor, whereby the sensor, upon detecting that the material within the stockpile has attained the predetermined threshold, proceeds to close the corresponding zone within the stockpile and open the adjacent zone to enable the continued reception of truck dumping.

3.4.2 Inputs

Human movement is inseparable from the support of bones. Similarly, the framework proposed above supports the operation of the simulation system like bones. On its basis, this system also needs various details to fill in the parts between the bones, like flesh and blood, to make the system more vivid and realistic and simulate the actual situation better.

Under ideal conditions, when all the details of reality can be captured and fed into the simulation system, the simulation results will be infinitely close to the actual operating results. This is one of the most important meanings of simulation, that is, to make predictions about the performance of a system. In addition, it can also be used to identify the impact of some changes on the system behavior and, in turn, guide the actual operation to obtain better system performance. However, the reality is not always ideal. The actual operation faces many unpredictable uncertainties, such as the distribution of minerals, the shape of the deposit being different from the expected, the possible damage to the transportation road, the landslide caused by slope instability, and the extreme weather and other uncontrollable factors. To be more specific, simulation and reality will not be exactly the same.

However, that's not to say that simulations aren't useful. It is undeniable that many of the above-mentioned factors are only small-probability events that can be reduced or even eliminated through better management and averaging the results of multiple replications. Honestly, when we incorporate the main uncertainties of mining activities into the simulation system, run multiple replications, and average the results, the simulation results already have a high degree of confidence and are close to what would happen in reality. In other words, the simulation results do not represent an exact value that actual operations will generate but provide a narrow range with high confidence that actual operating results will most probably be located.

On this basis, after completing the setup of the basic framework, various operating details and uncertainties of two mining methods. Typically, two different kinds of inputs are needed by the simulation model. The first category is the schedule information, which include but are not limited to: blocks and faces, coordinates and nodes, number of equipment, ore and waste tonnage, ore grade, transport network, precedence of blocks, stripping ratios, shift times, ore recover rate, and distances between nodes. These data can be derived from the optimization model proposed in the previous chapter.

The second category of information needed by the simulation model is technical inputs, which include but are not limited to: shovels’ operating information (such as ID, bucket capacity, movement speed, swing speed, availability, acceptable utilization, and operating cost), trucks’ operating information (such as ID, capacity, empty and loaded movement speed, dumping time, availability, acceptable utilization, operating cost) and crusher’s, belt’s, processing plant’s operating information (such as capacity, acceptable utilization, operating cost). These technique inputs should be defined before any comparisons are made, bringing the simulation models closer to reality and giving the results more confidence. More specifically, the shovels' (mining shovel(s) and reclaiming shovel(s)) loading costs are measured by dollar/ton, and their moving costs are measured by dollar/m. Trucks' moving costs are measured by dollar/km; the spotting and queueing cost is assumed to be zero. Crushing and processing costs are also measured by dollar/ton. Assuming the belt works at a constant cost per hour, i.e., dollar/hour.

In addition to these costs, a simulation model's most important objective is capturing as much uncertainty as possible in real-world operations. In actual operation, the working time of mechanical equipment, such as electric shovels and trucks, is not a fixed value for each cycle but roughly satisfies a certain distribution. These characteristics bring great uncertainty to the system. In addition to the uncertainty in the working cycle, another feature of that mechanical equipment is that even under proper maintenance, they will still fail from time to time, causing the termination of mining activities and bringing more uncertainty to the system. In addition to the operating time, the equipment's operating load per cycle is also not fixed, which brings similar uncertainties into the system.

Therefore, quantifying these uncertainties into quantifiable distribution equations with suitable parameters, and using these equations and parameters as input data, is one of the critical factors in building a high-confidence simulation model.

Normally, the performance of different devices is always very different, even if the same manufacturer produces them. Therefore, to obtain an accurate performance of these devices, the author retrieved the production record from the database of the oil sands mine of the year 2016 and extracted data on equipment cycle time and other performance related records.

These records can be roughly divided into two categories, independent variables, and dependent variables. The independent variables and dependent variables mainly used in this paper are listed in Table 3.7.

Table 3.7 List of independent variables and dependent variables to be compared

Type	Variables
Independent variables	Dumping time (s)

	Loading time (s)
	Measured tonnage per truck(t)
	Truck hauling distance (km)
	Velocity – empty haul (km/h)
	Velocity – full haul (km/h)
Dependent variables	Queue time before shovel (s)
	Empty haul time (min)
	Full haul time (min)
	Cycle ready time (min)
	Ton per gross operating hour (ton/h)

It is worth pointing out that, in actual operations, it is expected that some operators cannot record relevant operations in time, forget to record, or make wrong input records. Even computerized records are not working 100% reliably since GPS and sensors lose connections occasionally. As a result, the data in the database have "null" values and many nonsenses extreme values. For example, only one second is consumed for shovels loading a truck with a 400-ton capacity. Besides, in many cases, trucks haul to waste dump with 0.1 "measured" tonnage. Therefore, before analyzing the uncertainty of these data, the author set up several lower and upper bounds to filter the data. Those "null" and extreme values will be eliminated to better characterize the mechanical equipment operation. The lower and upper bounds are listed in Table 3.8. The truck type used in the oil sands mine is Caterpillar 797B, with a nominal capacity of 345 tons (380 short tons).

Table 3.8 Filters for equipment operation records

Operation variables	Lower bound	Upper bound
Truck payload (t)	10	480
Truck dumping time (s)	20	160
Truck queue time (s)	0	1800
Truck travel distance (km)	2	20

Truck velocity – empty haul (km/h)	5	70
Truck velocity – full haul (km/h)	5	70
Truck empty haul time (min)	2	60
Truck full haul time (min)	2	60
Cycle ready time (min)	5	60
Shovel loading time (s)	60	360

In addition, mechanical equipment will inevitably fail after continuous operation, even if appropriate proactive maintenance has been taken. According to experience, equipment downtime generally satisfies certain distributions. Therefore, by analyzing these devices' historical work and failure times, we can roughly predict these devices' working time and downtime in the next period. It is worth noting that the downtime defined for trucks and shovels in this paper includes regular maintenance time and repair time due to unpredictable mechanical failure. Table 3.9 shows the filters of equipment uptime and downtime.

Table 3.9 Filters for equipment productive and non-productive records

Operation variables	Lower bound	Upper bound
Shovel uptime (h)	0	800
Shovel downtime (h)	12	200

After extracting and filtering the relevant data, the author uses MATLAB software to draw the corresponding frequency distribution histograms and then fit distributions that can represent the histogram characteristics individually and determines the relevant parameters. Figure 3.20 to Figure 3.28 show the histogram of each operation. Figure 3.29 to Figure 3.30 show the resulting ton per gross operating hour (TPGOH) histogram. Figure 3.31 to Figure 3.32 show the fitted density function for shovel's uptime and downtime records. The independent variables' fitted distribution functions are summarized in Table 3.10 and will be used as inputs to the simulation model to control the uncertainty of the entire mining system. It should be pointed out that the failure data in this section are retrieved from the database of 2014-2015 since no failure record is available for year 2016.

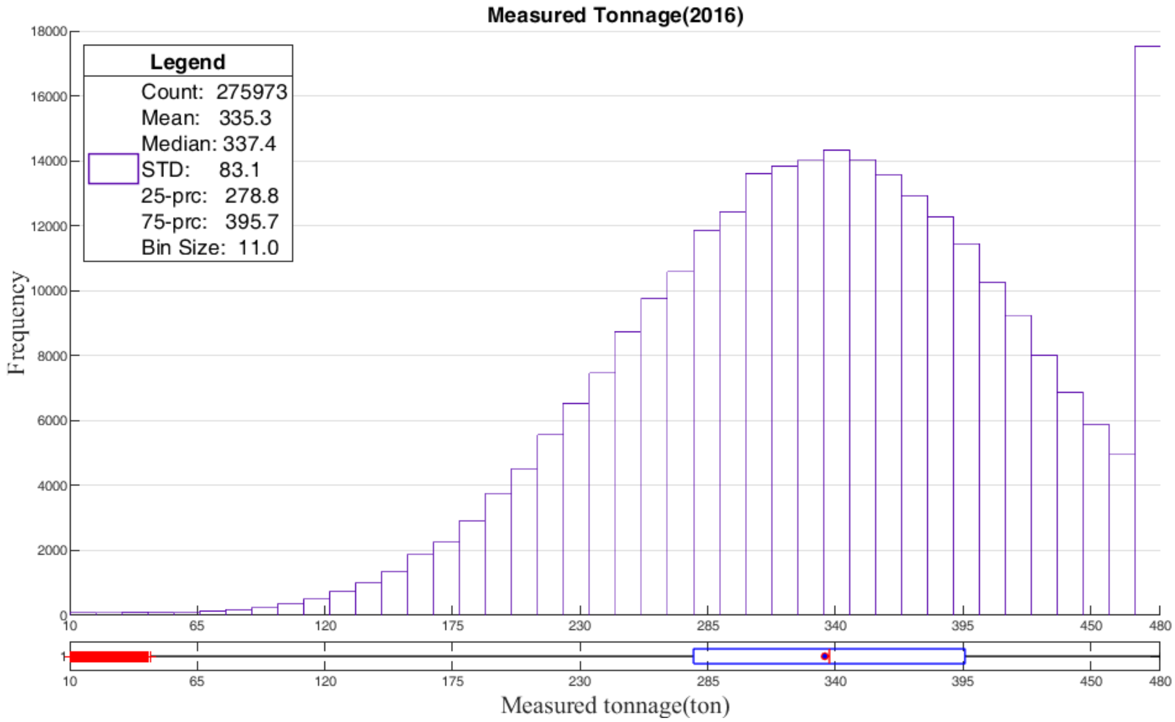

Figure 3.20 Truck payload histogram in record

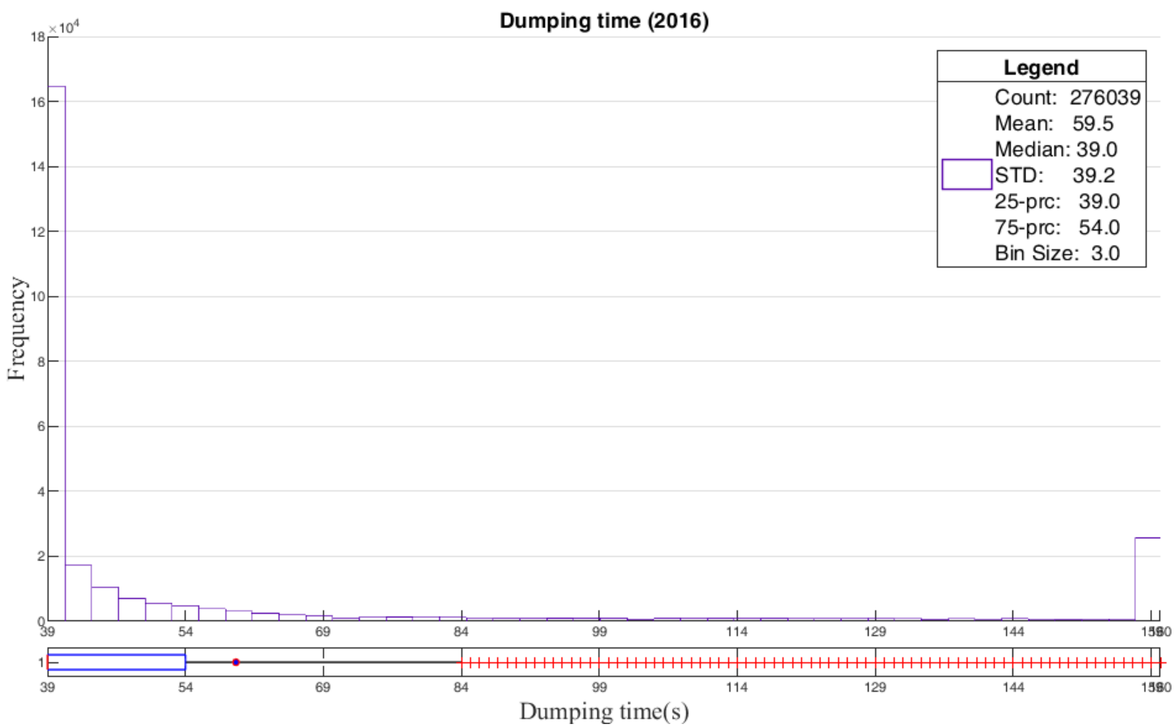

Figure 3.21 Truck dumping time histogram in record

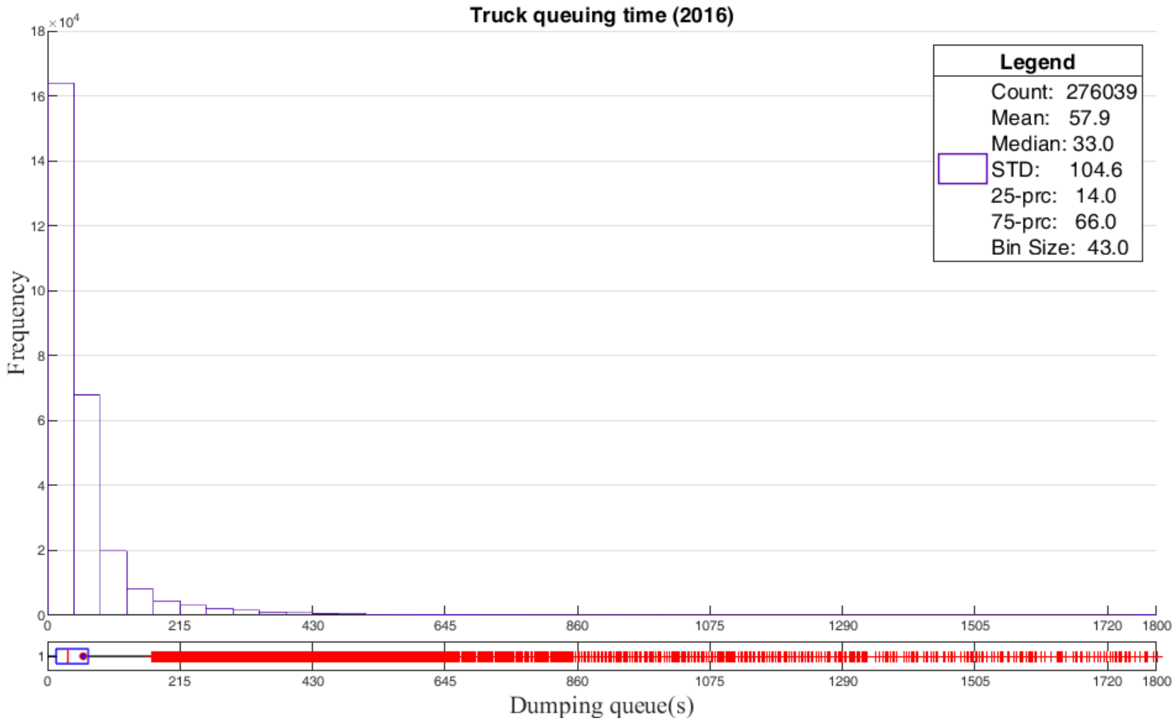

Figure 3.22 Truck queuing time histogram in record

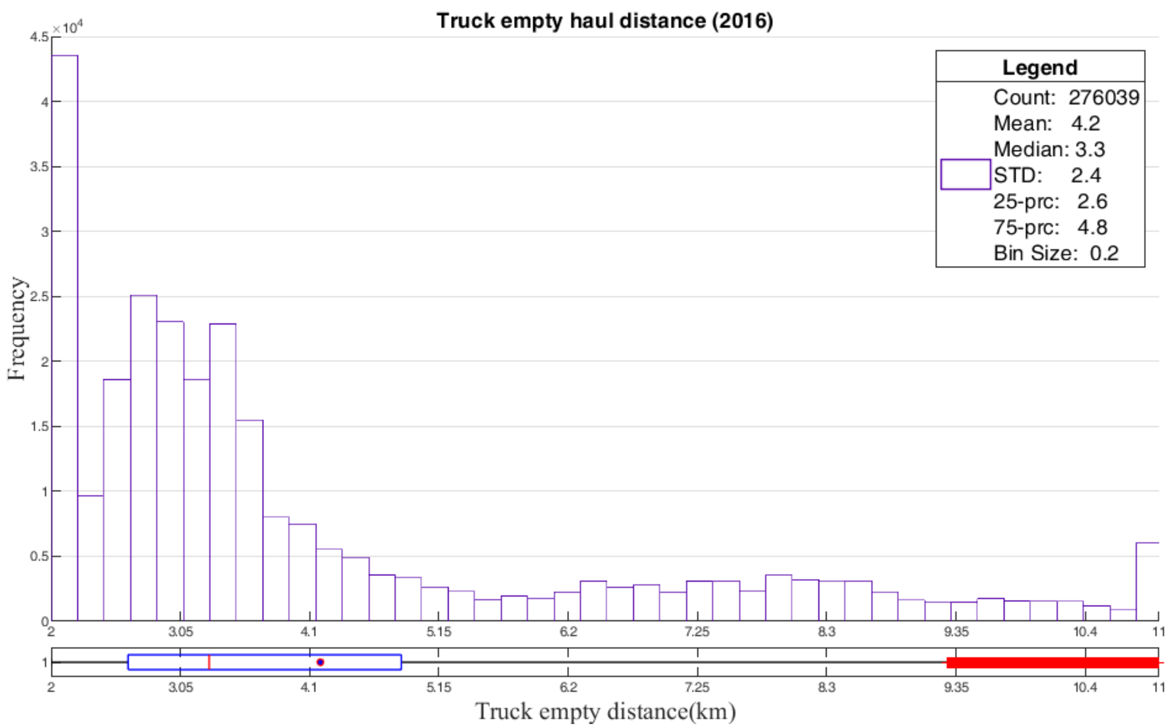

Figure 3.23 Truck empty hauling distance histogram in record

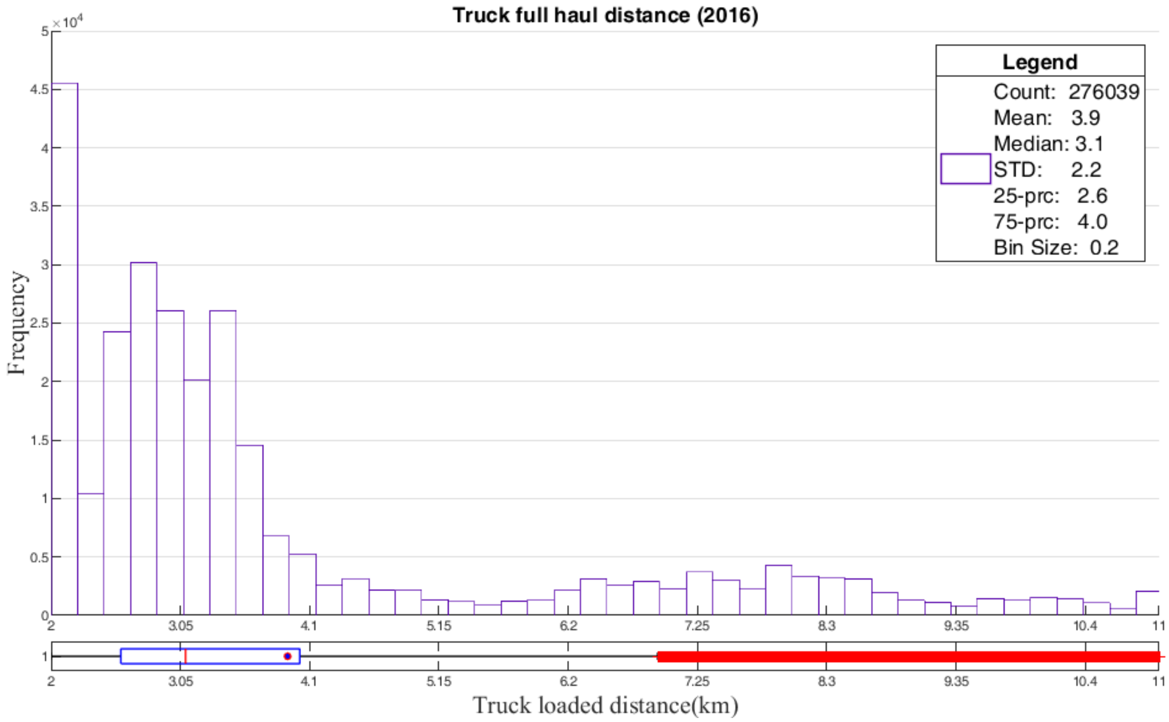

Figure 3.24 Truck loaded hauling distance histogram in record

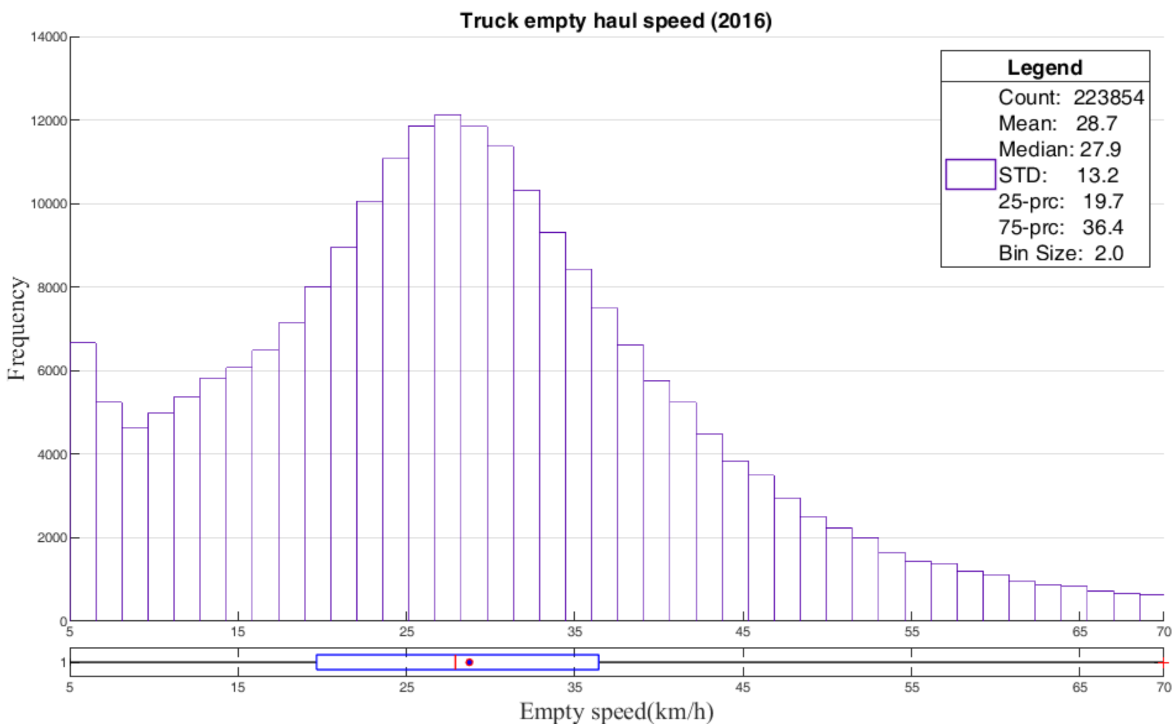

Figure 3.25 Truck empty haul velocity histogram in record

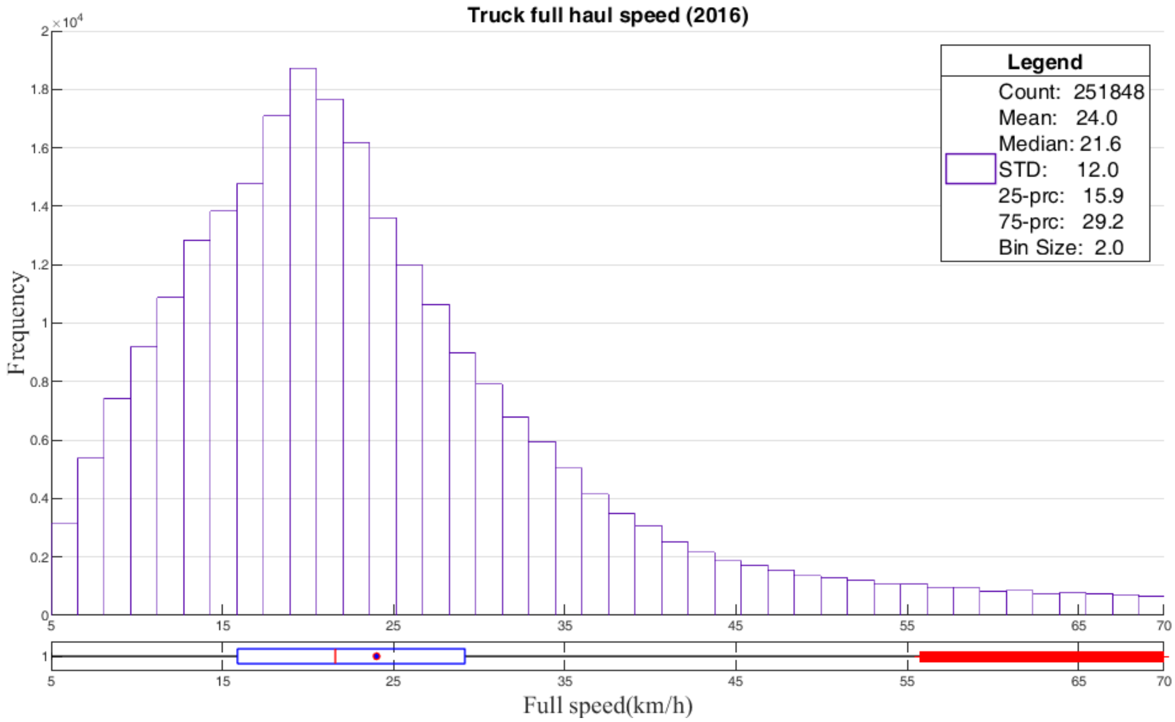

Figure 3.26 Truck full haul velocity histogram in record

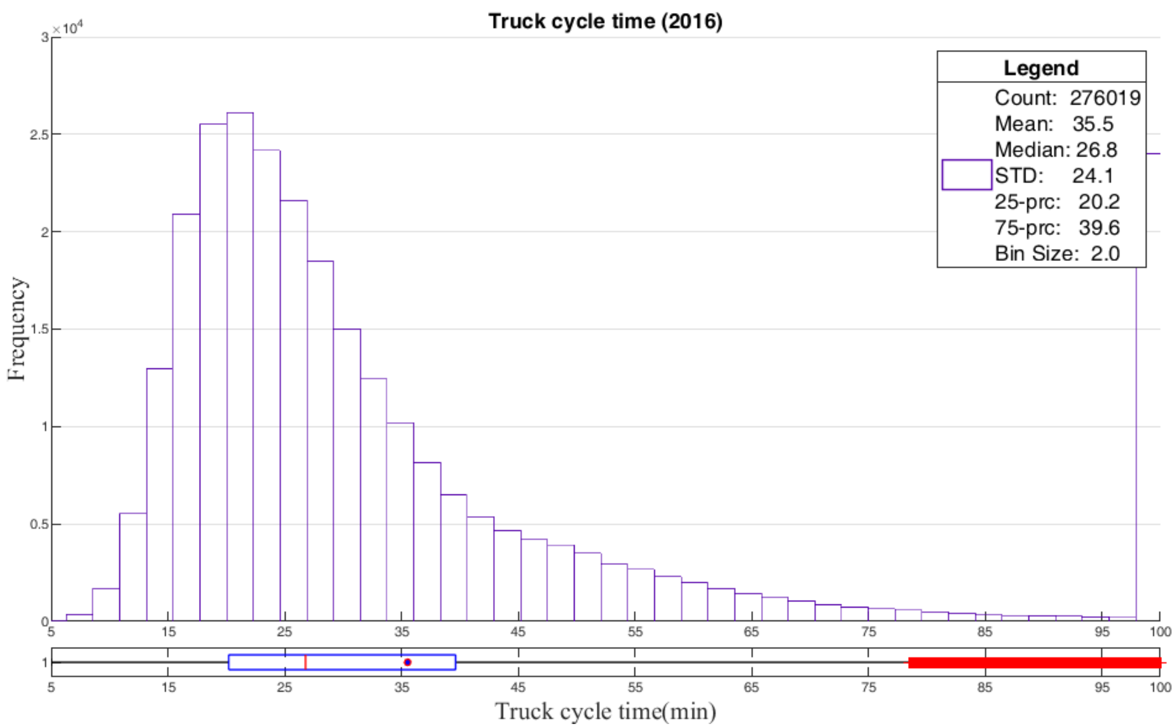

Figure 3.27 Truck cycle time histogram in record

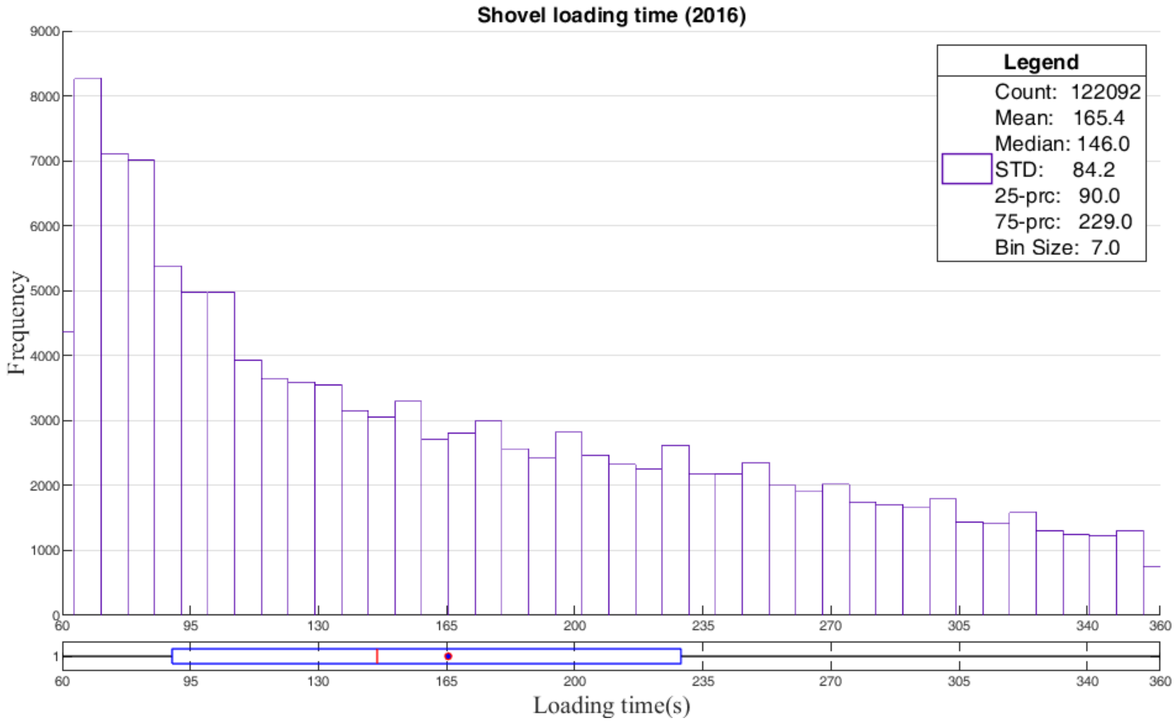

Figure 3.28 Shovel loading time histogram in record

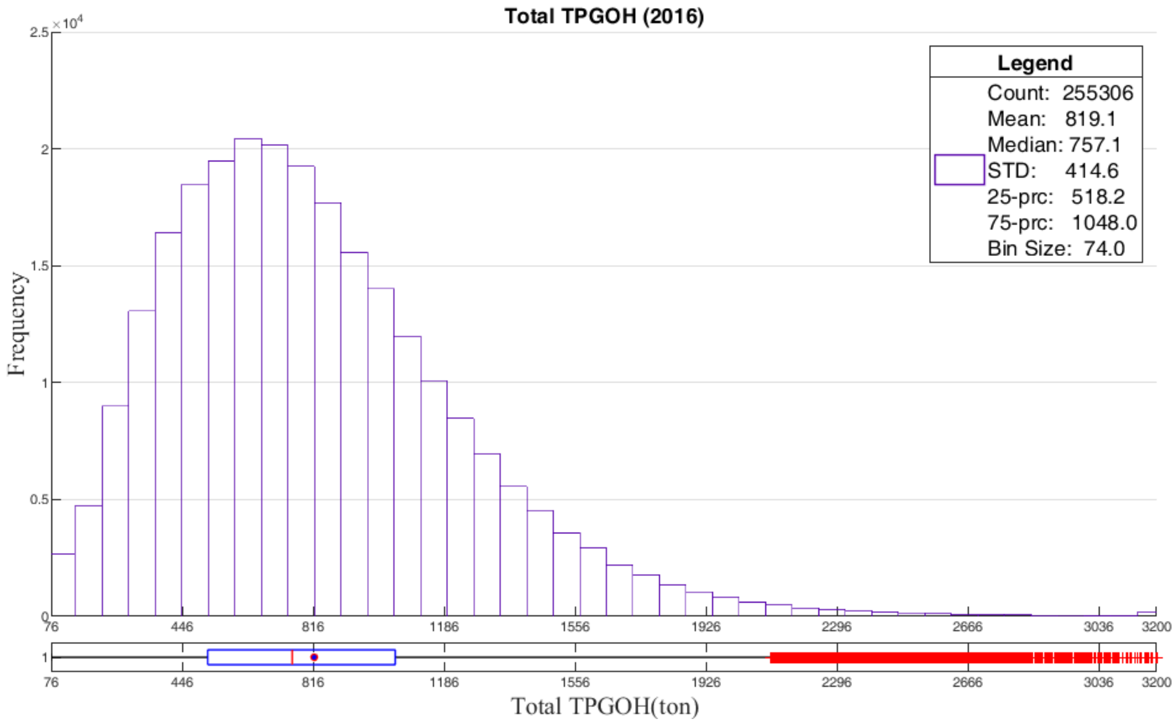

Figure 3.29 Total TPGOH distribution

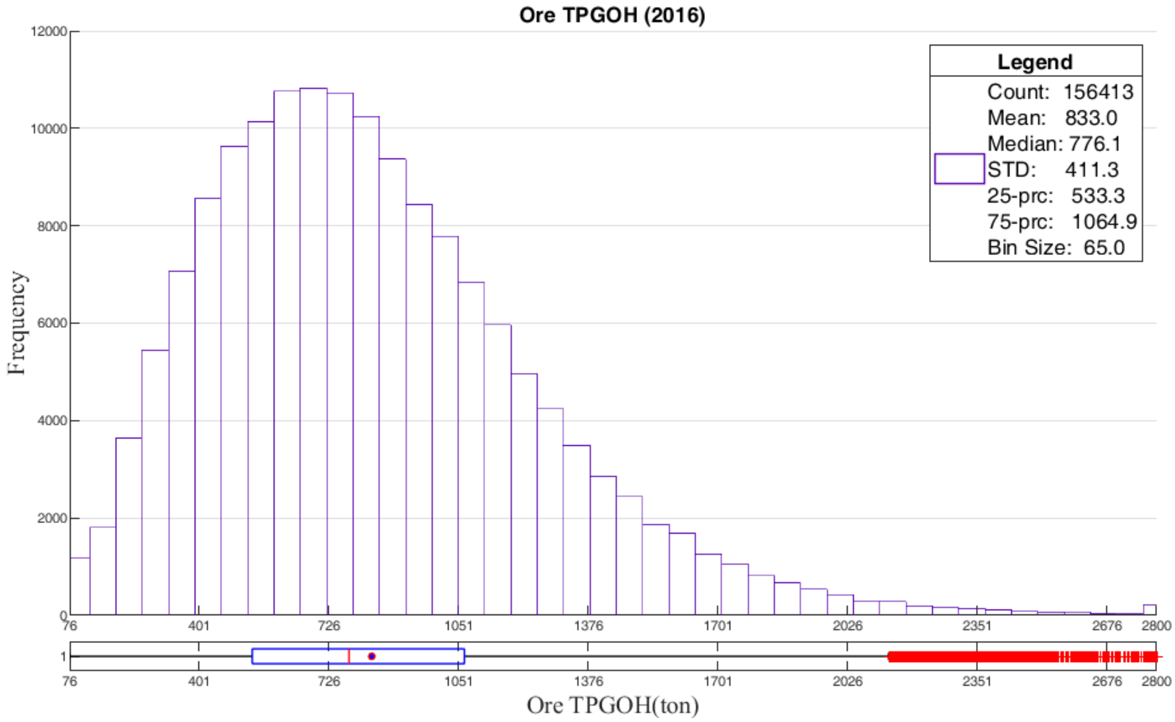

Figure 3.30 Ore TPGOH distribution

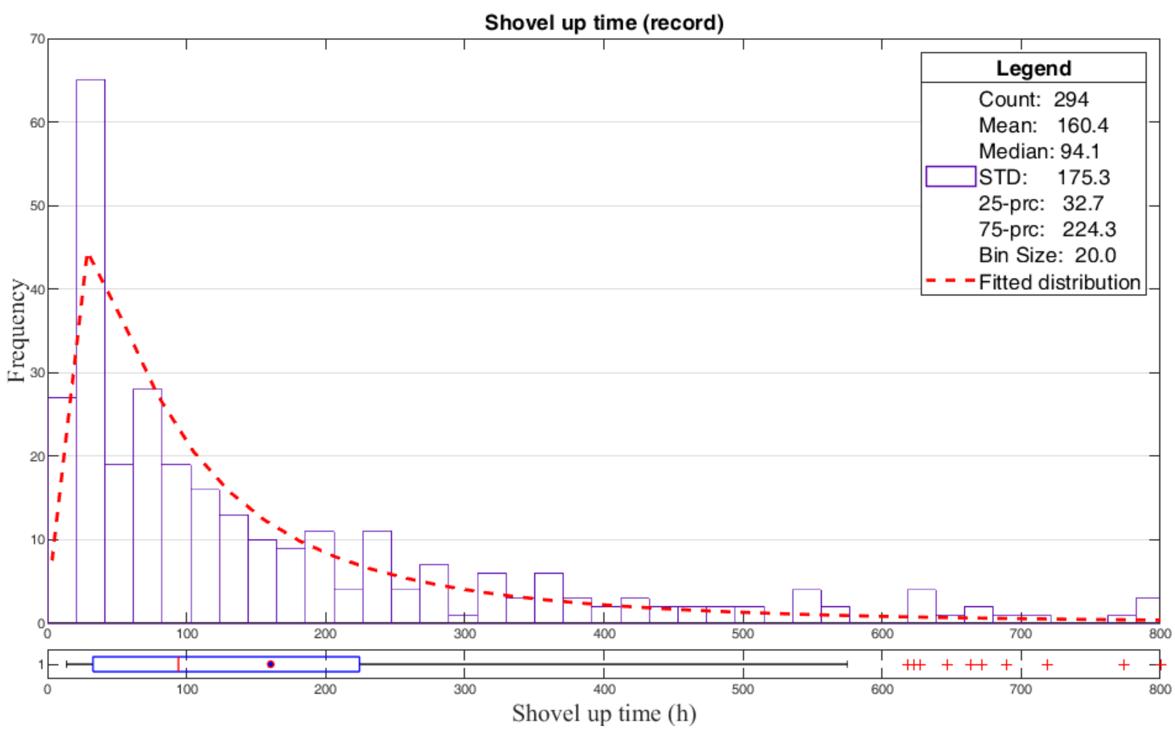

Figure 3.31 Shovel uptime histogram and fitted distribution

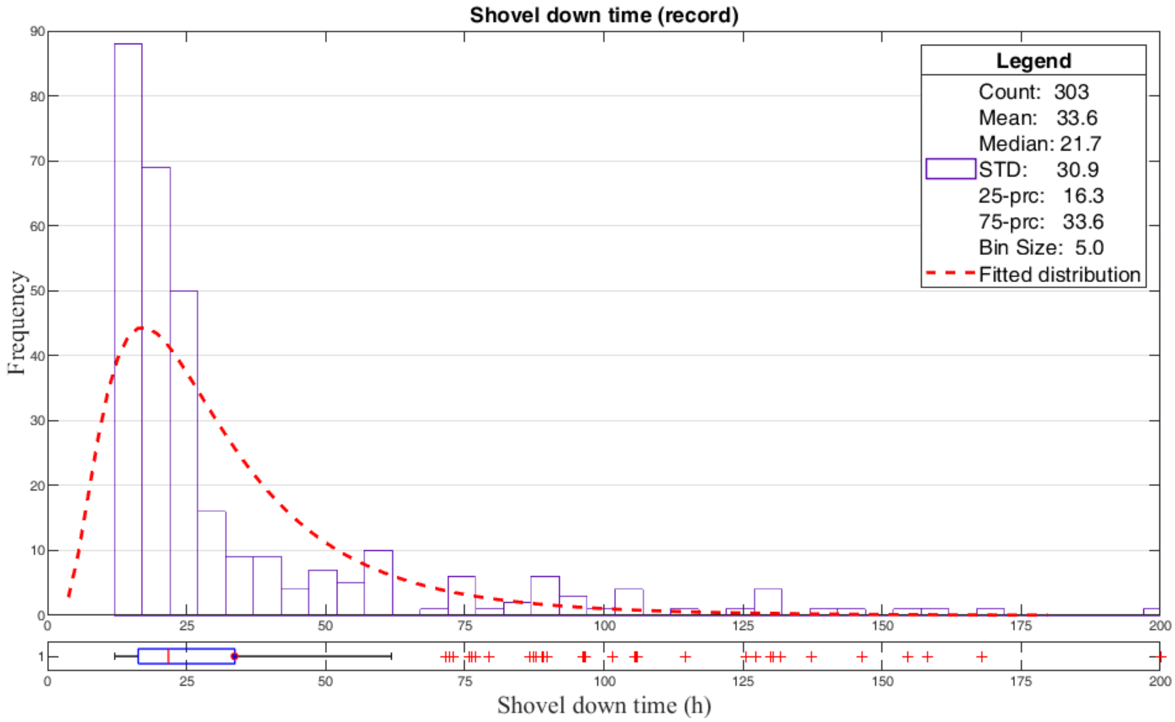

Figure 3.32 Shovel uptime histogram and fitted distribution

Table 3.10 Fitted distribution

Category	Fitted distribution	Arena input
Truck payload (t)	Normal (335.3,80)	NORM(335.3,80)
Truck dumping time (s)	Normal (73.9, 22)	NORM (73.9, 22)
Truck velocity – empty haul (km/h)	Normal(28.61, 9.02)	NORM(28.61, 9.02)
Truck velocity – full haul (km/h)	9 + LOGN(17.1, 7.1)	9 + LOGN(17.1, 7.1)
Shovel loading time (s)	Gamma(25.6, 5.23)+30	GAMM(25.6, 5.23)+30
Shovel uptime (h)	Weibull(131, 0.775)+13	WEIB(131, 0.775)+13
Shovel downtime (h)	Lognormal(3.25, 0.63)	LOGN(23, 49.8)+12

3.4.3 KPIs (Key Performance Indicators)

Just building a model is not the end of the simulation. The author's purpose is to establish a model that reflects the activities of the mine as realistically as possible and to quantitatively predict the impact of changes in mining methods on various processes in the mining process. This result may be good or bad, and the author will make an objective and fair evaluation of the new mining method based on the simulation model results. However, these evaluations are based on a premise: the model is valid and reliable. The data is the best evidence that the simulation model is trustworthy and reliable. Therefore, the author sets out several KPIs that need to be tracked for the simulation model and compares them with the actual operating conditions of the enterprise to verify and confirm the model's validity. Those selected KPIs are listed in Table 3.11.

Table 3.11 Selected KPIs to evaluate the performance of different mining method

No.	Arena of concern	KPI to evaluate
1	Transporter	Utilization
2	Transporter	Queue number at sources
3	Transporter	Queue time at sources
4	Transporter	Average cycle time
5	Transporter	Average payload
6	Transporter	Average dumping time
7	Transporter	Average full/empty speed
8	Stockpile	Tonnage in and out
9	Stockpile	Truck interarrival time
10	Crusher	Utilization
11	Crusher	Production rate of different time frames
12	Crusher	Feeding rate of different time frames
13	Crusher	Truck interarrival time
14	Shovel	Utilization
15	Shovel	Average cycle time

3.4.4 Macro developed

As mentioned earlier, a common disadvantage of simulation models is their lack of generalizability. The flexibility of equipment parameters and numbers is limited or fixed at the beginning of the establishment of the simulation model, making the model case specific. In order to solve this problem and make the model more applicable, AERNA-related VBA macro programming is used to create as many modules as possible. The macro can read the equipment parameter, quantity, and road information of the mine from the prepared excel spreadsheet to ensure that the established model can be easily reconstructed for other mining cases that use the same mining method. The following are the main functions of the macro:

1. Read polygon data (include tonnage, grade, rock type, sequence, coordinates), and build polygon set.
2. Read related data, build "tanks" for dumping zones, crusher and slurry plant, and corresponding regulators based on capacity and other
3. Create variable sets for each dumping point to track status.
4. Create a mining shovel resource set for the mining process.
5. Create the sub-model for dumping decision making
6. Create the sub-model for reclaiming process and corresponding level change (NFS model only)
7. Create a sub-model for crusher's and dumping zones' status check and level change.
8. Build the conveyor system and processing system
9. Create stations for each mining, dumping, and processing location. Create station sets for each branch system and classify these stations into different sets.
10. Create a road network system and read and type the distance between stations

3.4.5 Assumptions

- The polygons are simplified to a point with weight, which is also the polygon's center point in the physical sense. Specifically, the shovel movement within a polygon mining process is not considered, and the trucks are also loaded at the same point.
- All polygons are not allowed to be partially mined. That is to say after a polygon is assigned a shovel, the shovel will only move to the next polygon once the polygon is thoroughly mined. Polygons are allowed not to be mined out during one period, but at the beginning of the next period, the shovel will continue to work on this polygon until the task is completed. One reason for this assumption is that frequently moving shovels can significantly affect equipment

utilization and lead to reduced productivity. In addition, adopting a consistent logic can better reduce the interference of human factors.

- Inside each polygon, the ore part is assumed to be uniform. That is, the physical parameters such as grade and density are constant. The grades of different polygons can be different, determined by the exploration results. This assumption is based on the previous optimization. Before the blocks are grouped into clusters and polygons, the grade differences between different blocks are considered. Therefore, the grade of the polygon can smooth out the grade differences of each internal block on an overall level, which has a positive significance for improving optimization and simulation efficiency.
- It is assumed that ore and waste are different in physical properties and will not affect the equipment. Although a whole truck of ore material and a whole truck of waste are similar in size, their weight may differ, resulting in differences in loading and unloading time. This is because the distribution function used by the simulation system does not distinguish between the loading time, loading weight, and unloading time of ore and waste when fitting the previous historical data.
- The logic of shovel-requesting trucks is set to the minimum distance priority. This is to reduce the average waiting time of trucks and avoid system stagnation caused by trucks not arriving on time.
- The dispatch logic after the truck is unloaded at the destination point is that the minimum number of queues before the shovel is given priority. Similar to the former assumption, this also reduces the average waiting time of trucks and improves equipment utilization efficiency.
- Assume that the road network in the simulation system is fixed. This assumption is based on two points: a. Each polygon has been simplified into one point in the simulation system, and the relative distance between these points is fixed; b. The simulation system simulates a short period (12 months), so the main road changes will not be insignificant. Therefore, although the road

will continue to develop and change with mining activities in actual operation, this assumption is still reasonable.

3.4.6 Scope and limitations

- This simulation model does not have optimization capabilities, cannot optimize the mining sequence of polygons and shovel allocation, and entirely depends on the results of the previous optimization model. If the input mining sequence is not optimized, the simulation results can be far from the optimal plan.

- The road network of this simulation model adopts the free path method, ignoring the truck interaction. This will lead to a scenario: two trucks travel on the same route, but the truck that starts late but runs faster will arrive at the destination before the truck that starts early but runs slow.

- As mechanical equipment, trucks are often faced with maintenance and failure in operation. However, this simulation model uses 'tranporters' instead of trucks. It will not fail and does not require maintenance, so its utilization rate can reach 100% under ideal conditions.

- In actual operation, trucks of different sizes and brands are often used at the same time. However, as mentioned above, this model uses a 'tranporter' to simulate the truck's operation, and its parameters default to the same value. If a heterogeneous fleet situation needs to be handled, different parameters according to the unit number require manual assignment, which cannot be automatically generated.

- Although this model has the flexibility to build simulation models for different mines, it has strict data requirements without any flexibility. Although different equipment and locations can be set up according to different needs, detailed data input is required for each equipment's working parameters and capability range. If the parameters are missing, the simulation model will not work correctly.

3.5. Summary

At the beginning of this section, we introduced the original nonlinear optimization model and demonstrated the advantages of utilizing piecewise linearization techniques to create a linear optimization model. This approach allowed us to simplify the problem and facilitate more efficient optimization. Subsequently, we presented a case study to illustrate the impact of incorporating stockpiles into production plans. Furthermore, we examined the consequences of defining stockpile grade ranges when working with linearized grade estimations in the context of MILP. To scientifically understand the performance of the near face stockpile mining method (especially the blending results) under the optimized mining schedule, the author extends the proposed optimization model to the NFS mining method by making minor modifications. The modified model generated a near-optimal operation schedule for the NFS method while being applied to the same mining instance. The result shows that the near face stockpile mining method achieved a 33 percent drop in overall grade error compared to the traditional open-pit mining method with an out-of-pit crusher.

In the second half of this chapter, the author continues the research on quantitatively measuring the performance of the near face stockpile mining method. Specifically, the author explained the logic and steps needed to build the simulation model that can mimic real operations and capture more uncertainties. The similarities and differences between the NFS simulation model and the traditional simulation model are also presented. Some key indicators needed for evaluating the performance of the mining method are also defined in the second half. Besides, the following aspects are also introduced in detail: the selection of model parameters, macros developed to complete the simulation model, assumptions being made for building the models, and the scope and limitations of the model.

By integrating the proposed optimization model and simulation model, a comprehensive simulation-optimization framework is thus completed. The next step is to verify and validate the proposed framework and apply it to the NFS method.

4. VERIFICATION, VALIDATION, IMPLEMENTATION, AND DISSCUSSION OF RESULTS

4.1. Introduction

In the preceding chapters, the author established a comprehensive simulation-optimization framework to evaluate the performance of different mining methods. However, prior to using this framework to assess the NFS method and address the research objective, its effectiveness must be verified. Thus, in this chapter we will conduct verification and validation of the proposed framework.

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 to the simulation model and run it for ten replications to reduce errors and enhance result reliability. The selection of 10 replications is based on comprehensive consideration of reducing randomness while taking into account efficiency. Finally, we will compare the simulation results with actual operating records across multiple dimensions to verify the effectiveness of the framework. Once the framework validation is complete, we will apply the NFS method to the same oil sands mine. A comprehensive quantitative comparison of the simulation results of the two mining methods across multiple time resolutions and dimensions are conducted. From the comparison, we will draw conclusions about the performance of the NFS method.

4.2. Simulation verification

As stated, an oil sands mine case study with two working shovels and sixteen trucks is implemented to verify the proposed simulation and optimization model. The author obtained a one-year dispatch record from the enterprise. The record contains the timestamp when the trucks started or stopped an action and the truck payload of each cycle. The records show that in 2016, a total of 93.1 million tons of material (60.7Mt ore) from 1,773 blocks were mined, with an average TV: BIP (total volume: bitumen in-place) ratio of 8.7. The cut-off TV: BIP ratio by law is 12. The size of each block is 50m (length) by 50m (width) by 10m (height). The mining capacity and processing capacity of the mine are 9.7Mt per month and 6Mt per month, respectively.

The simulation model built for traditional method which is to be verified in this section is developed based on the flow chart shown in Figure 3.15. The results obtained in this section are only taken from the first two blocks from the database. The two blocks are assumed to contain only ore material with unlimited weight, while the transport distance is consistent with the real situation. The reason for this assumption is that if waste and ore material is included at the same time, the results of the dumping queue time and length will be disturbed, which will affect the verification.

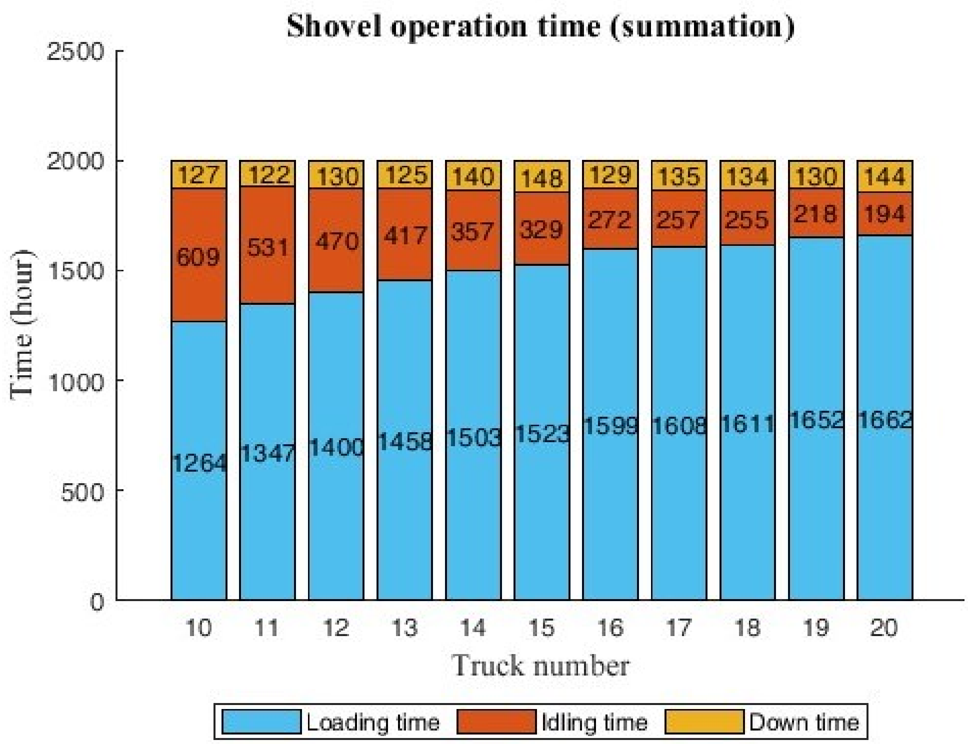

Figure 4.1 Summation of shovel operation times with increasing number of trucks

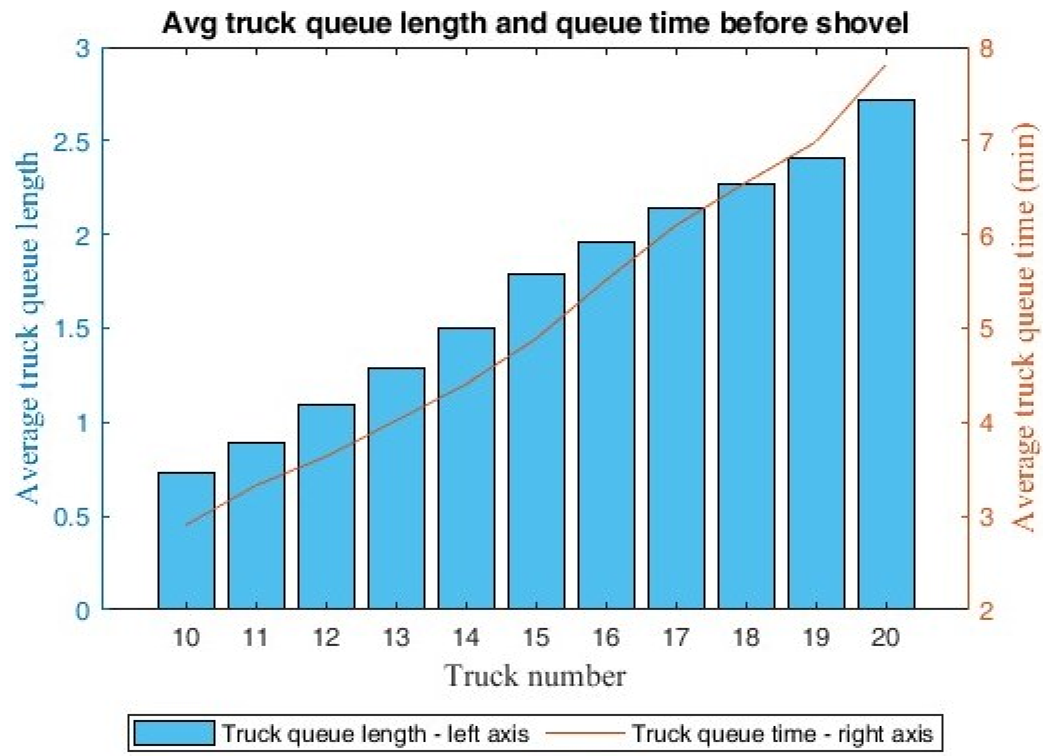

Figure 4.2 Average truck queue length and queue time before shovel

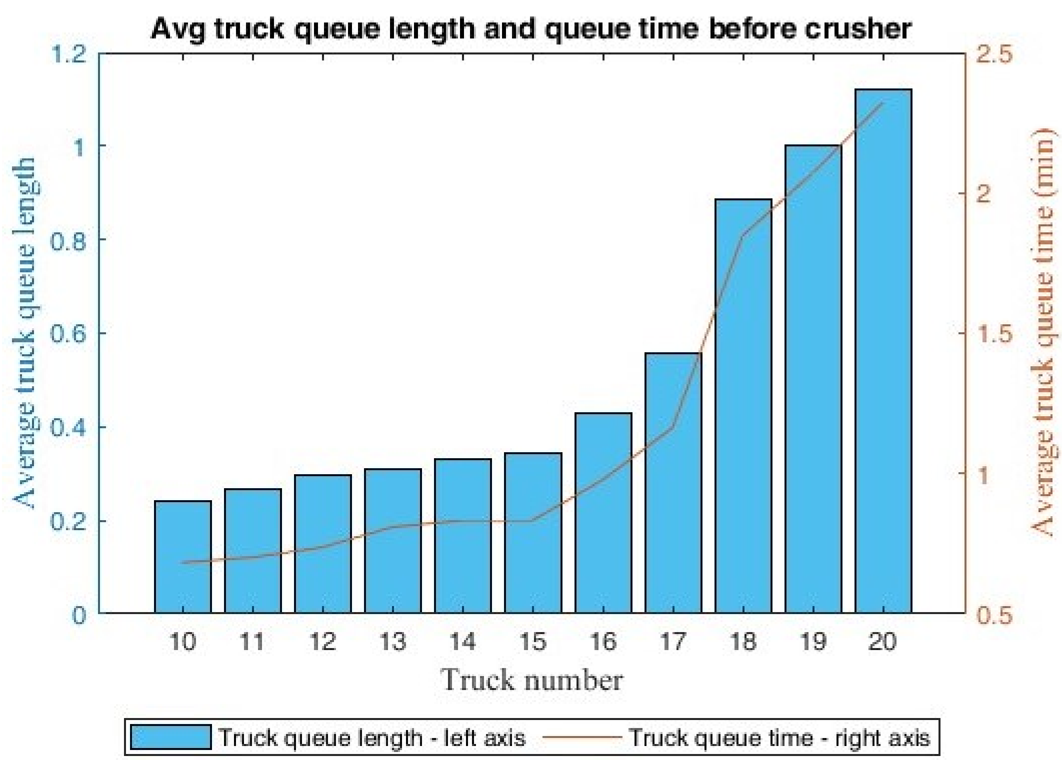

Figure 4.3 Average truck queue length and queue time before crusher

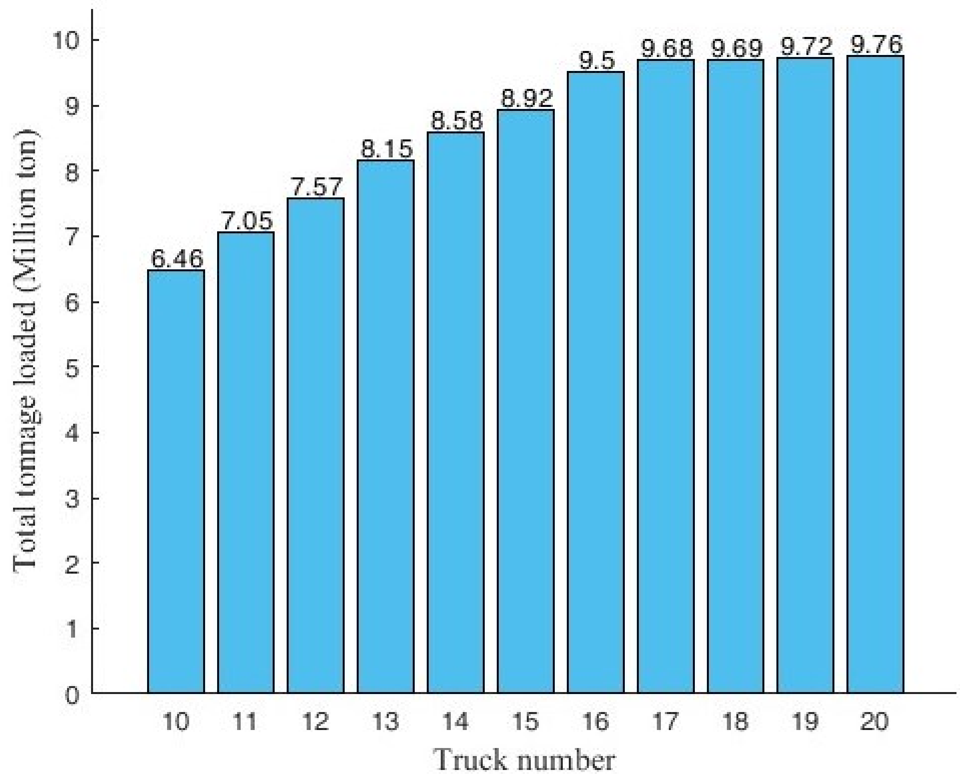

Figure 4.4 Total tonnage excavated with increasing number of trucks

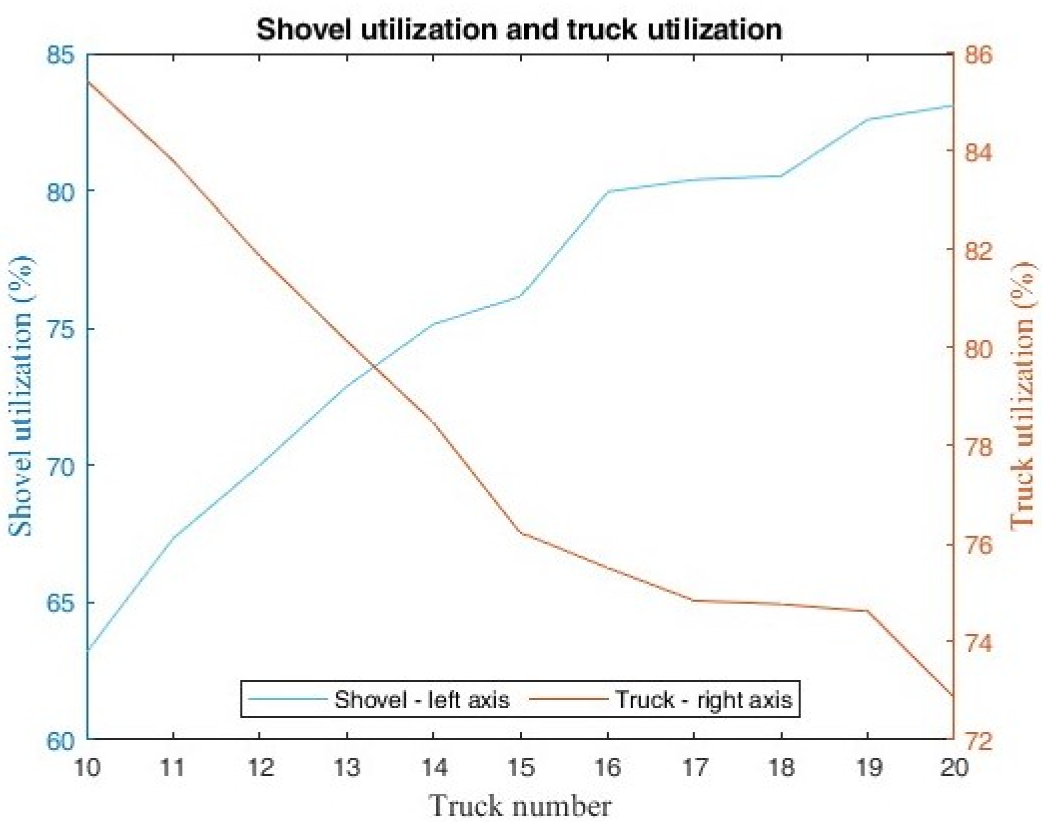

Figure 4.5 Shovel utilization and truck utilization with increasing number of trucks

The inputs of simulation model are listed in Table 3.10. The simulation time is set as 1000 hours. Considering that there are two shovels working at the same time, the actual total working hours is 2000 hours, which can also be seen in Figure 4.1. Meanwhile, it can be seen from the figure that as the number of trucks increases, the working hours of the shovels increase accordingly. It is worth pointing out that the relationship between the two is not a simple linear relationship, which is also in line with the phenomenon observed in the actual operations. The failure time of the shovel is only related to its own mean time between failure (MTBF) and mean time to repair (MTTR), which is an independent distribution and is not related to the increase in the number of trucks. The loading time in Figure 4.1 is pure working time, excluding spot time. Shovels' and trucks' utilization with an increasing number of trucks are shown in Figure 4.5. The two figures show an obvious negative correlation that is in line with engineering cognition. In addition, Figure 4.2 shows the average truck queue length and the average time in the queue before the shovel as the number of trucks increases. There is a clear and nearly linear positive correlation between the two. However, as shown in Figure 4.3, although there is still a positive correlation between the length of the truck queue before the crusher and the average time in the queue, it does not increase linearly. This situation is because the crusher is operating at full capacity. After the number of trucks reaches a certain value, the utilization rate of the crusher will no longer increase linearly and the queue length of the trucks in front of it will increase sharply, which will eventually lead to a sharp increase in queue time. This situation can also be observed in Figure 4.4. When the number of trucks is less than 16, the total material being excavated increases linearly, but when the number of trucks exceeds this threshold, the total mass excavated hardly increases anymore.

The above indicators show that the simulation results are highly consistent with the actual operating results, experts' inference and engineering common sense that is in line with expectations. Therefore, the established simulation model can well simulate the actual activities in a mine, thus verifying the correctness of the model.

4.3. Simulation validation

Once the simulation model is verified, it is necessary to further validate that the model can simulate the real operation of the oil sands mine well, so as to endorse the simulation results of the model using the NFS method.

As shown in Figure 3.14, prior to running the simulation model and analyzing the simulation results, it is necessary to complete the mining schedule optimization procedures. Although 1,773 blocks are insignificant, when put into the optimization model, 42,588 decision variables will be generated, that dramatically slows down the optimization speed. Therefore, the blocks are aggregated into clusters with larger sizes. The aggregation methodology is the same as elaborated in Chapter 3, section 3. After aggregation, thirty-eight new 'blocks' were obtained. The optimization model is formulated in MATLAB (The MathWorks Inc., 2018) and solved by CPLEX (CPLEX, 2014) through API.

Figure 4.6 shows the production schedule before and after optimization. Since the objective function is to obtain the maximum discounted cash flow, the new mining strategy is to mine and process ore material as early as possible under the condition of satisfying the physical sequence and other constraints. Figure 4.7 shows the change in the stripping ratio every month before and after optimization. For other inputs of the simulation model such as truck empty and loaded speed, equipment operating time distribution, etc., the distributions obtained from the database are used, as shown in Table 3.10.

Different from the verification stage, the simulation model in the validation will be run for 366 days (2016 is a leap year), 24 hours a day, with two shifts working alternately. Shift breaks and corresponding losses are considered in the simulation. The original road network is also added to the simulation, as shown in Figure 4.8. In addition, in order to reduce the error that may be caused by a single run, this model will run for 10 replications under the same parameter settings. The average value of the KPIs and the corresponding box plots will be calculated and plotted to compare the performance of the simulation results against the historical records. The Arena will automatically use different random factors in each replication and randomly sample values from distributions.

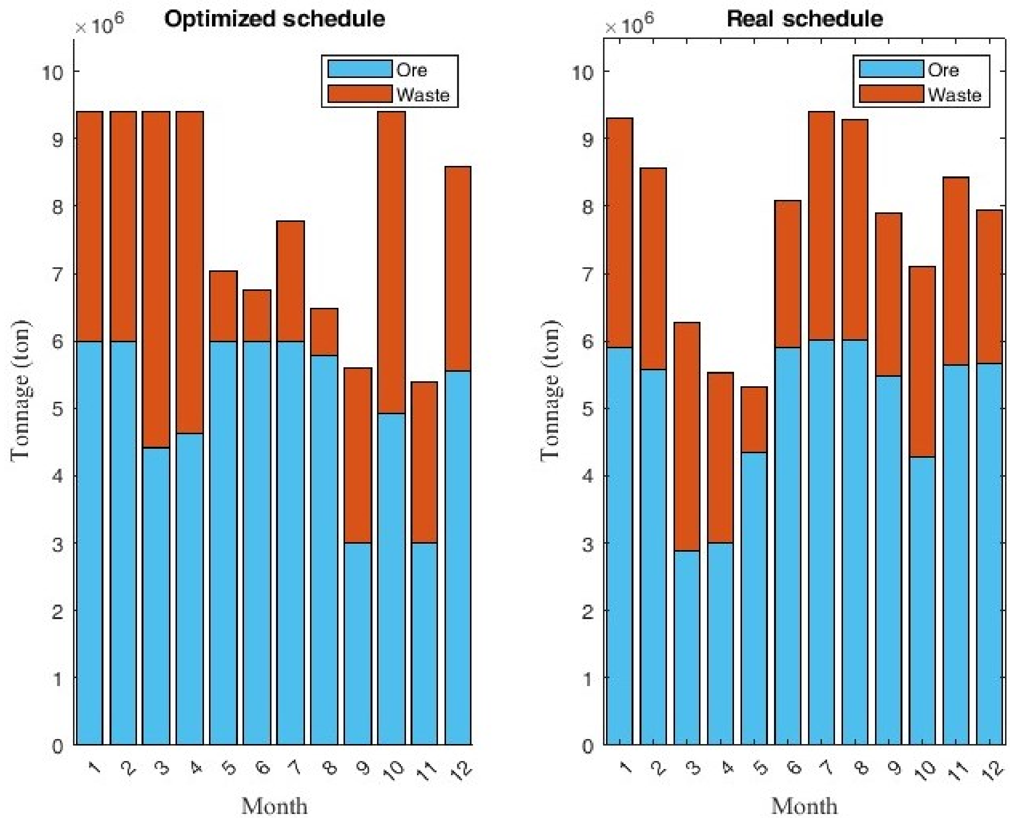

Figure 4.6 Optimized mining schedule and real schedule

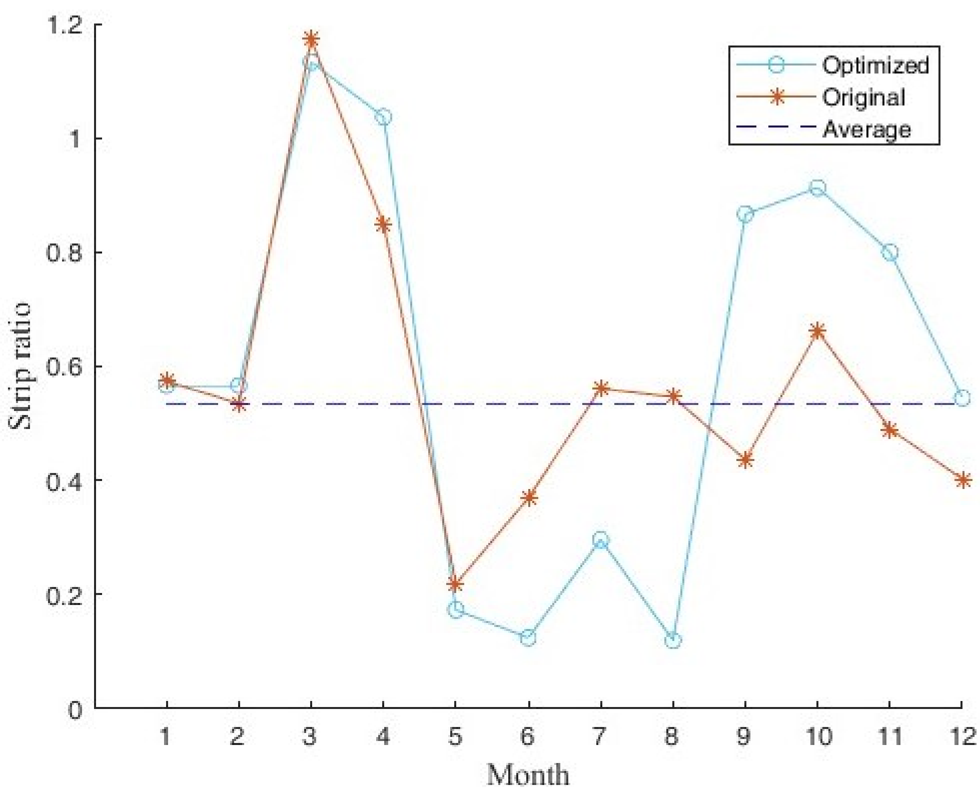

Figure 4.7 Strip ratio of optimized traditional schedule versus record

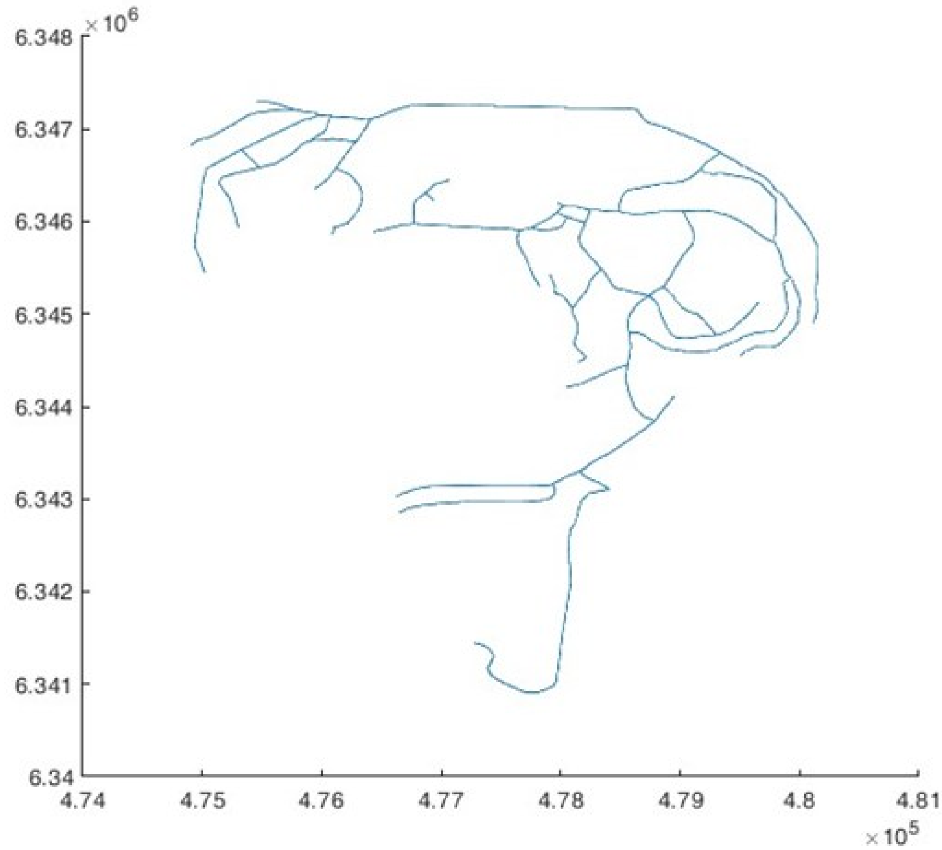

Figure 4.8 Road network of the mine in year 2016

4.3.1 Consistency check

In order to validate whether the results of the simulation model can truly represent the actual operation, it is necessary to check how the distributions of activities match the input distributions. The simulated histogram of different activities' results and corresponding QQ plot against record are shown in Figure 4.9 to Figure 4.18. Corresponding values are summarized in Table 4.1. 'Rec' in the table represents the record and 'SimTra' represents the simulated result of the traditional TS mining method. Taking the average payload of trucks per cycle as an example, the difference between the simulated and the recorded data is 0%, and the difference between the annual mining tonnage is 0.31%. Although the average difference of other independent variables is slightly higher, the difference range only fluctuates in a narrow range, showing the relative consistency of these variables. It is worth mentioning that all the simulation results provided with range in this paper have 95% confidence intervals.

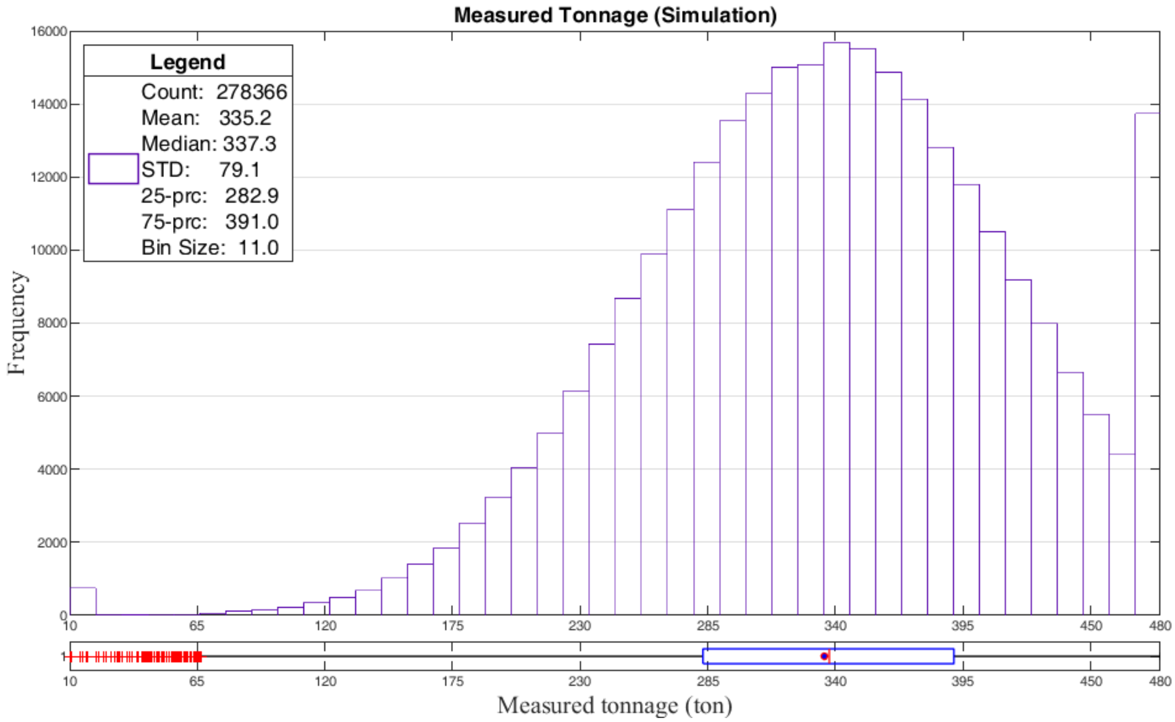

Figure 4.9 Histogram of the simulated truck payload

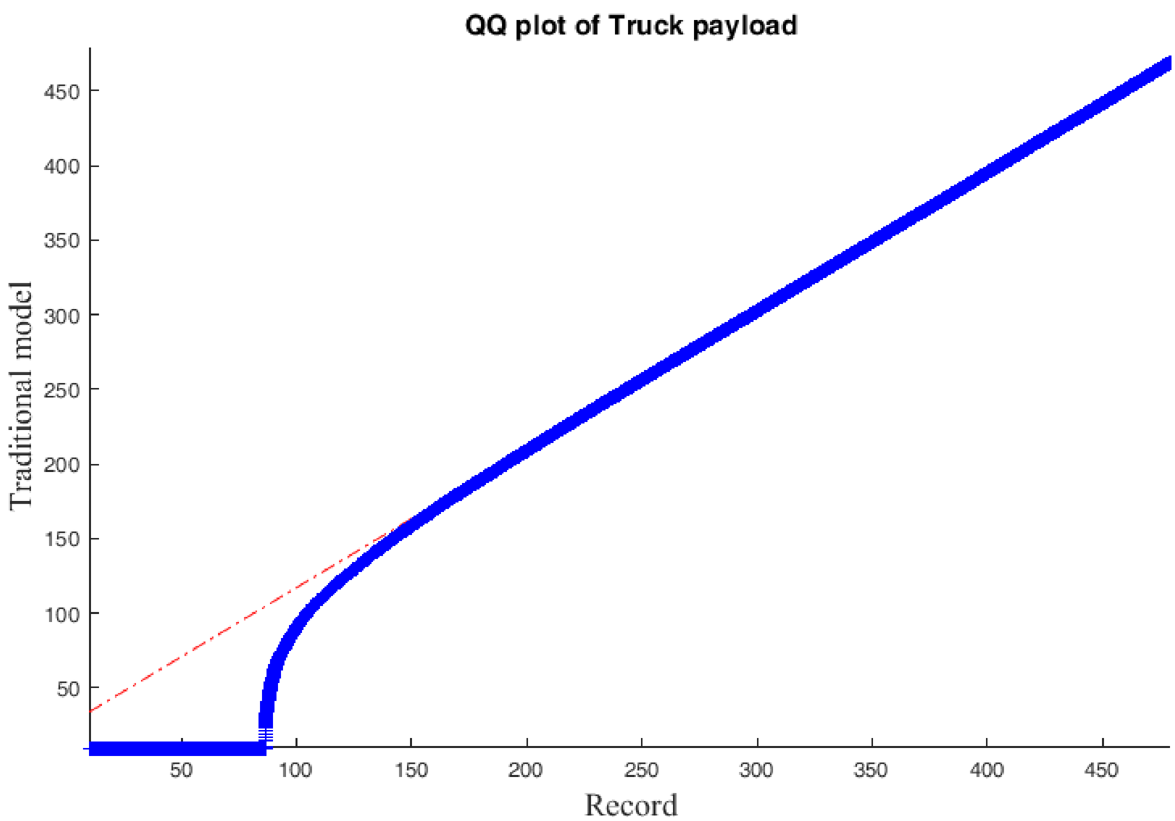

Figure 4.10 QQ plot of truck payload of the traditional simulation model and real operational records

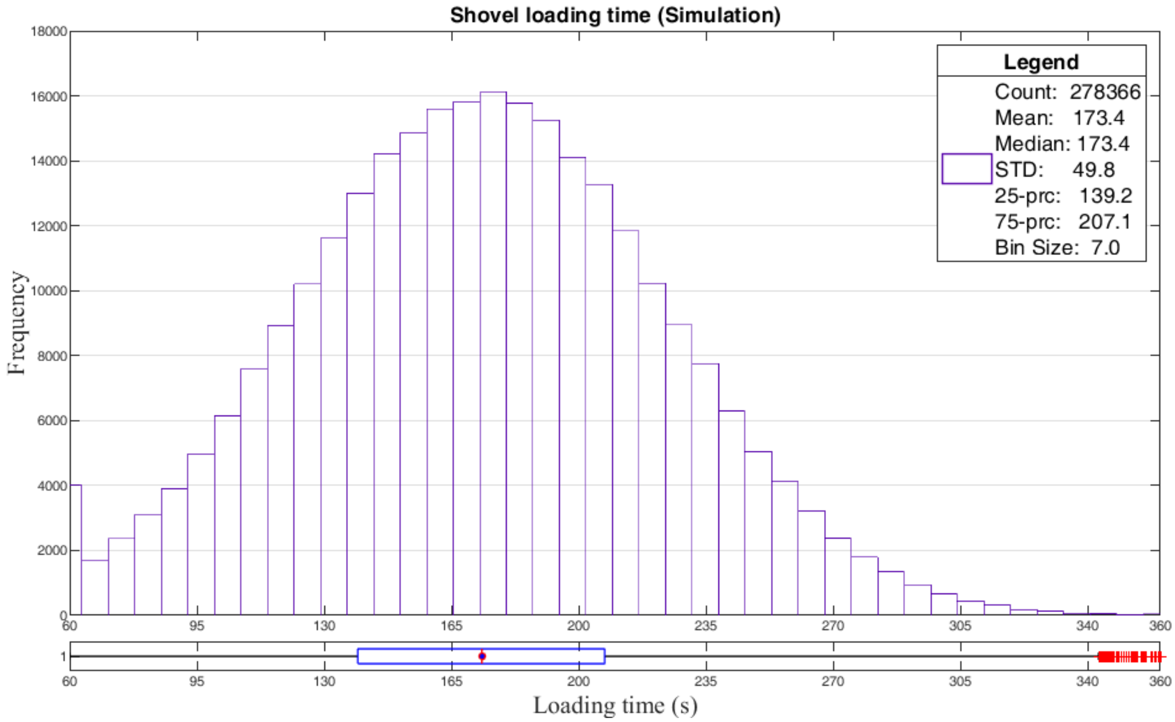

Figure 4.11 Histogram of the simulated shovel loading time

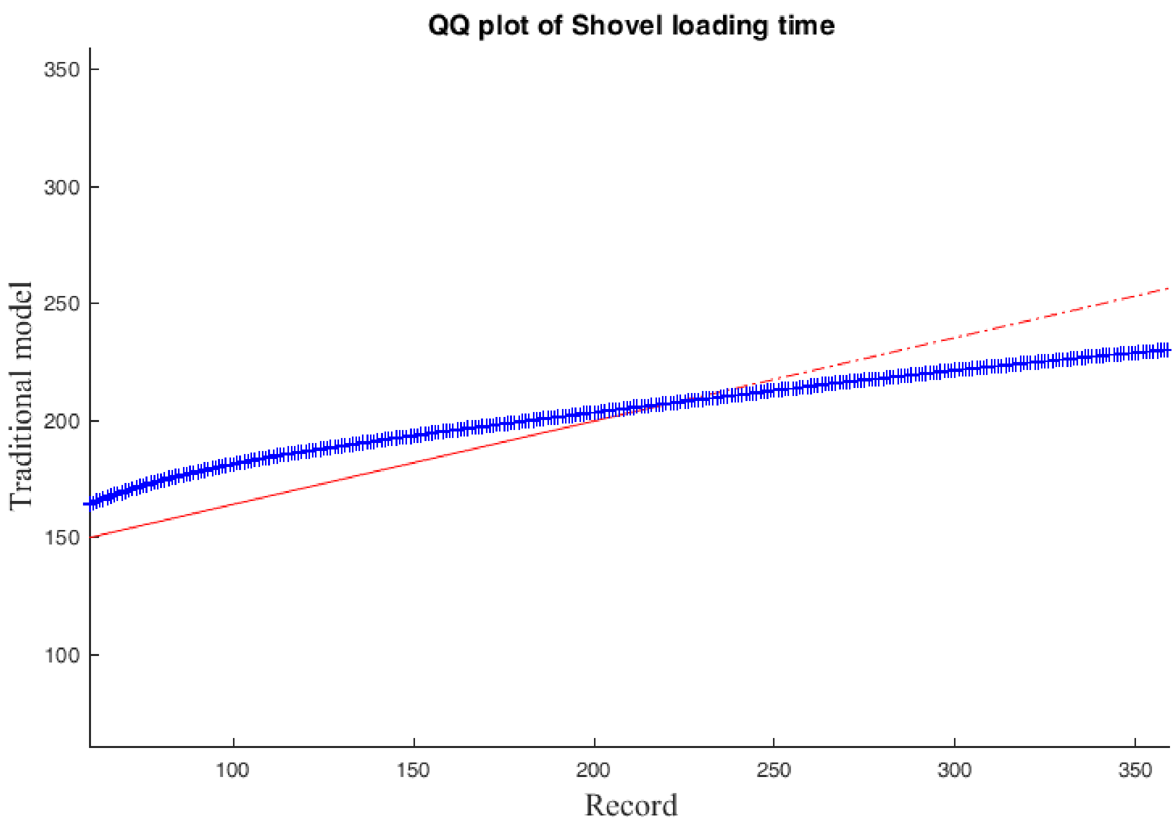

Figure 4.12 QQ plot of loading time of the traditional simulation model and real operational records

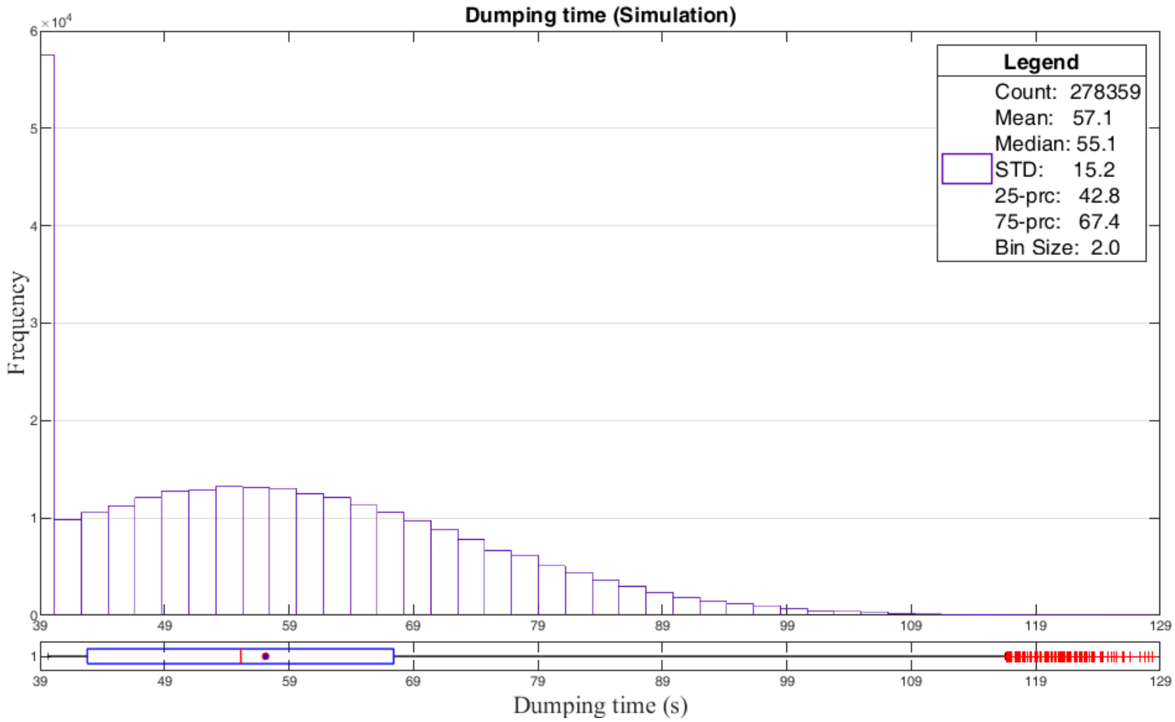

Figure 4.13 Histogram of the simulated truck dumping time

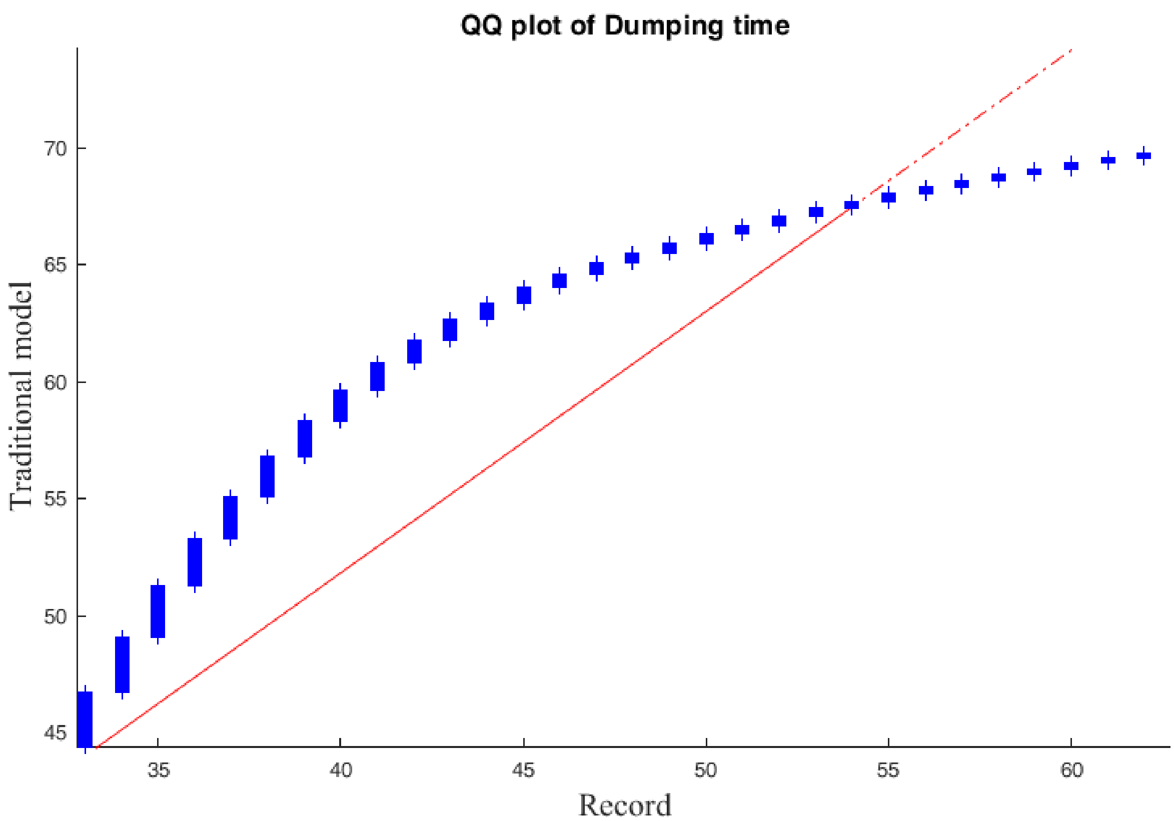

Figure 4.14 QQ plot of dumping time of the traditional simulation model and real operational records

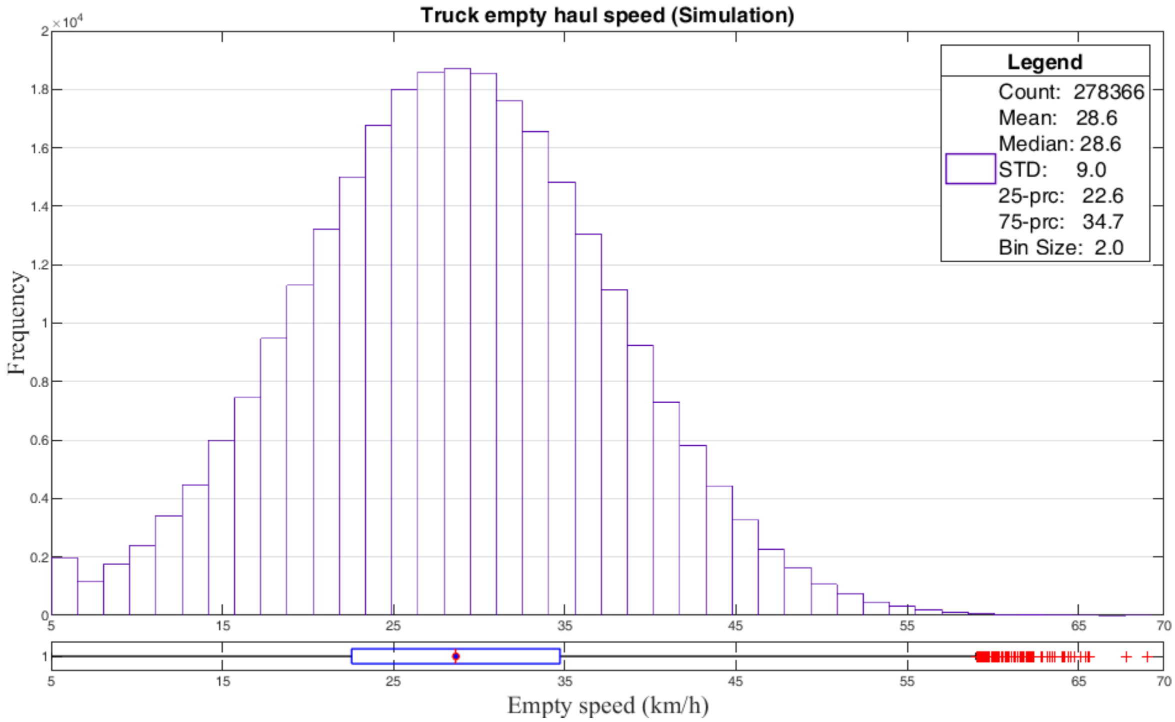

Figure 4.15 Histogram of the simulated truck empty velocity

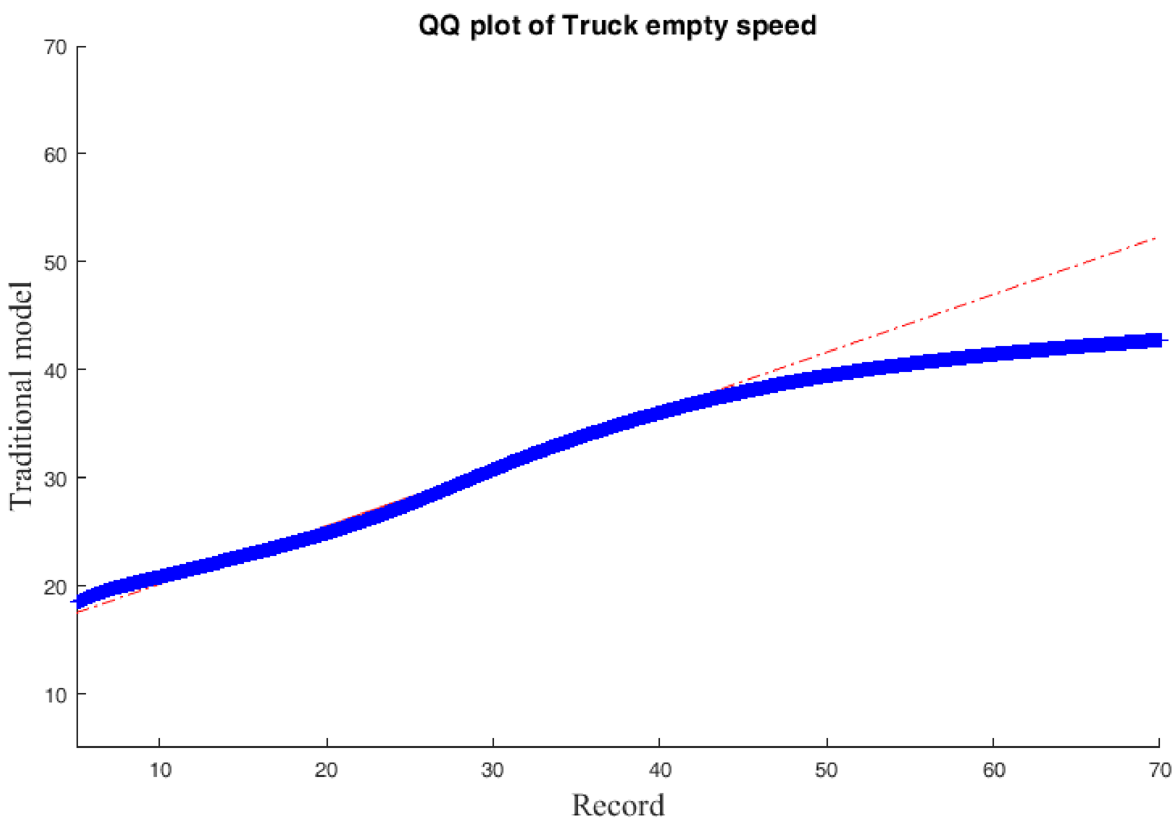

Figure 4.16 QQ plot of truck empty speed of the traditional simulation model and real operational records

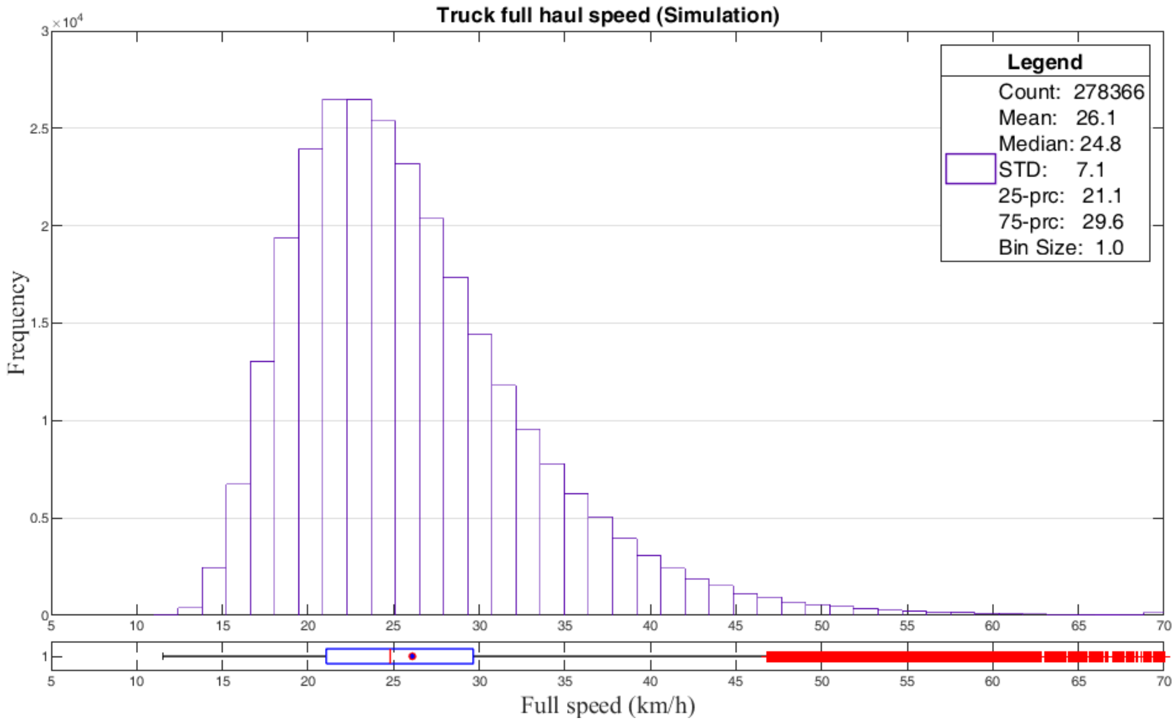

Figure 4.17 Histogram of the simulated truck loaded velocity

Figure 4.18 QQ plot of truck full speed of the traditional simulation model and real operational records

Figure 4.10 depicts the QQ plot of the truck payload in the simulation results and the record. The plot indicates that, except for minor deviations observed when the payload is below 150 tons, the simulation results are in good agreement with the record across the remaining range. Similarly, the QQ plots of Figure 4.12, Figure 4.16, and Figure 4.18, which represent shovel loading distribution, empty truck speed distribution, and loaded truck speed distribution respectively, showed the same trend. However, Figure 4.14 shows a relatively higher fluctuation. The fluctuation mainly comes from a smaller dumping time range and there is no obvious difference in the overall mean and summation of dumping time. It can be concluded that, despite some fluctuations, the simulation results align closely with, or even replicate, the distribution of the record within the main value range. Thus, we can infer that the distribution of independent variables in the simulation results exhibits a strong positive correlation with the distribution of real-world data and provides a more accurate representation of the actual outcomes.

Table 4.1 Comparison of simulated and recorded values for the independent variables

Category	Range	Mean	Summation
Average tonnage/truck(ton) - Rec	470	335.3	93,090,766
Average tonnage/truck(ton) - SimTra	470±0	335±0.32	93,374,636±189,085
Difference	0.00%	0.00%	0.30%
Loading time(min) - Rec	5	2.76	768,739
Loading time(min) - SimTra	5±0	2.89±0	805,227±1,968
Difference	0.00%	4.71%	4.75%
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	7,745,079
Empty speed(km/h) - SimTra	64.3±2.73	28.62±0.02	7,973,113±17,205
Difference	-1.08%	2.00%	2.94%
Full speed(km/h) - Rec	65	26.49	7,293,809
Full speed(km/h) - SimTra	58.44±0.38	26.1±0.04	7,271,881±12,091
Difference	-10.09%	-1.47%	-0.30%

4.3.2 Monthly production

Once the model is validated for independent variables, the next step is to check the validity of the model for dependent variables. The validity of the overall production is the first measure to investigate.

The left graph in Figure 4.19 shows the monthly optimized theoretical production, simulated production, and the recorded production. It can be seen from the graph that the simulated production is smaller than the optimized production in the early months, but greater than the optimized production in the later months and is more stable than it over the cycle. This is due to the travel distance differences and the fixed number of trucks. In the early stages of mining, waste material is the main production, and its transportation distance is much greater than that of the ore. Therefore, in the early months, the total tonnage moved per unit of time is less than expected. In the later stages, after the upper waste stripping is completed, the ore material is the main interest, and the transportation distance becomes shorter, so the production per unit time increases and becomes greater than expected. It can be found that the optimization formulas in the previous chapter did not take the transportation distance as a constraint, and all optimization results obtained are based on the average transportation distance, which leads to this difference.

In order to achieve optimized results, the number of trucks needs to be increased, which will lead to a serious waste of equipment in the later stage and is not in line with the economic principle. The simulation results again illustrate the rationality and correctness of the simulation model. The graph on the right in Figure 4.19 shows the difference in the cumulative tonnage corresponding to the three cases. As can be seen from the figure, optimized production is slightly higher than the other two. This is because equipment maintenance and failures are not considered in the optimization model. However, this is unavoidable in practice. The graph shows that the lines corresponding to the simulated results and recorded data are relatively close, which is a measure of model validation, showing that it can well reflect the actual operations in practice, and the results have high credibility. Corresponding values are listed in Table 4.2, showing that the total difference in production is 0.31%.

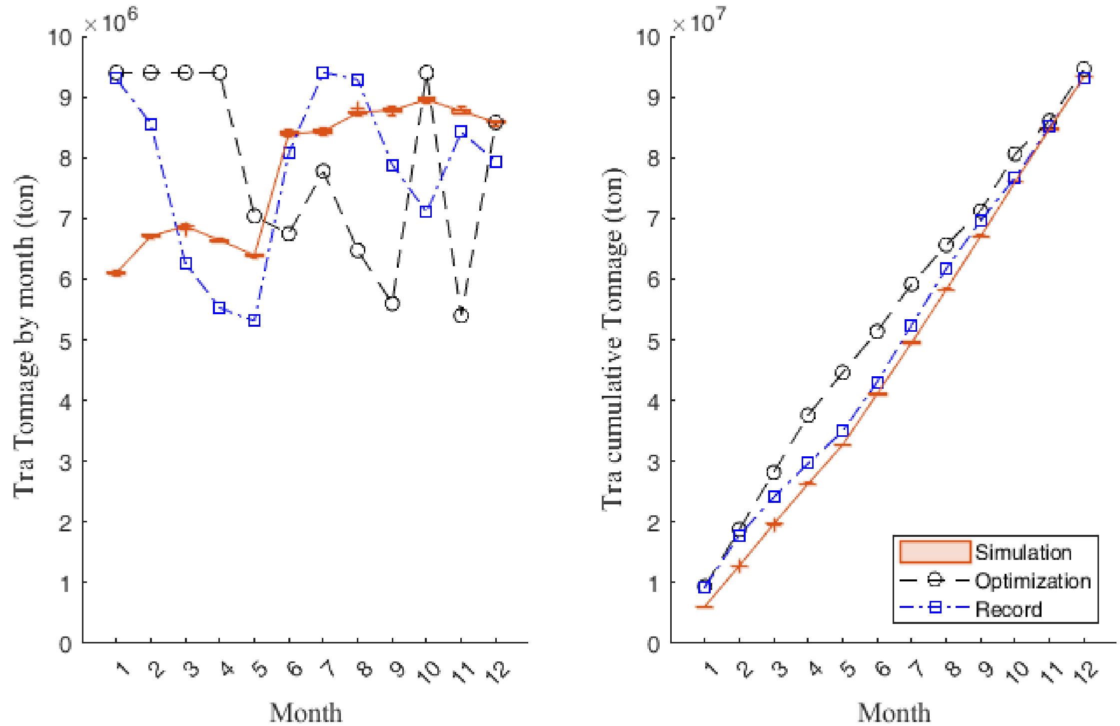

Figure 4.19 Optimized schedule, simulated schedule, and original schedule of the traditional mining method

Table 4.2 Mean of the traditional simulation and the recorded data of the tonnage moved in each month

Month	Recorded	Simulated	Error
1	9,296,384	6,102,097	-34.36%
2	8,562,481	6,708,678	-21.65%
3	6,264,342	6,870,891	9.68%
4	5,530,158	6,641,612	20.10%
5	5,308,889	6,391,948	20.40%
6	8,079,350	8,392,611	3.88%
7	9,406,137	8,432,095	-10.36%
8	9,286,549	8,742,980	-5.85%
9	7,887,197	8,783,730	11.37%
10	7,102,192	8,957,280	26.12%
11	8,417,418	8,770,832	4.20%
12	7,946,804	8,584,725	8.03%
Total	93,087,903	93,379,480	0.31%

4.3.3 Ton-kilometer (TKM)

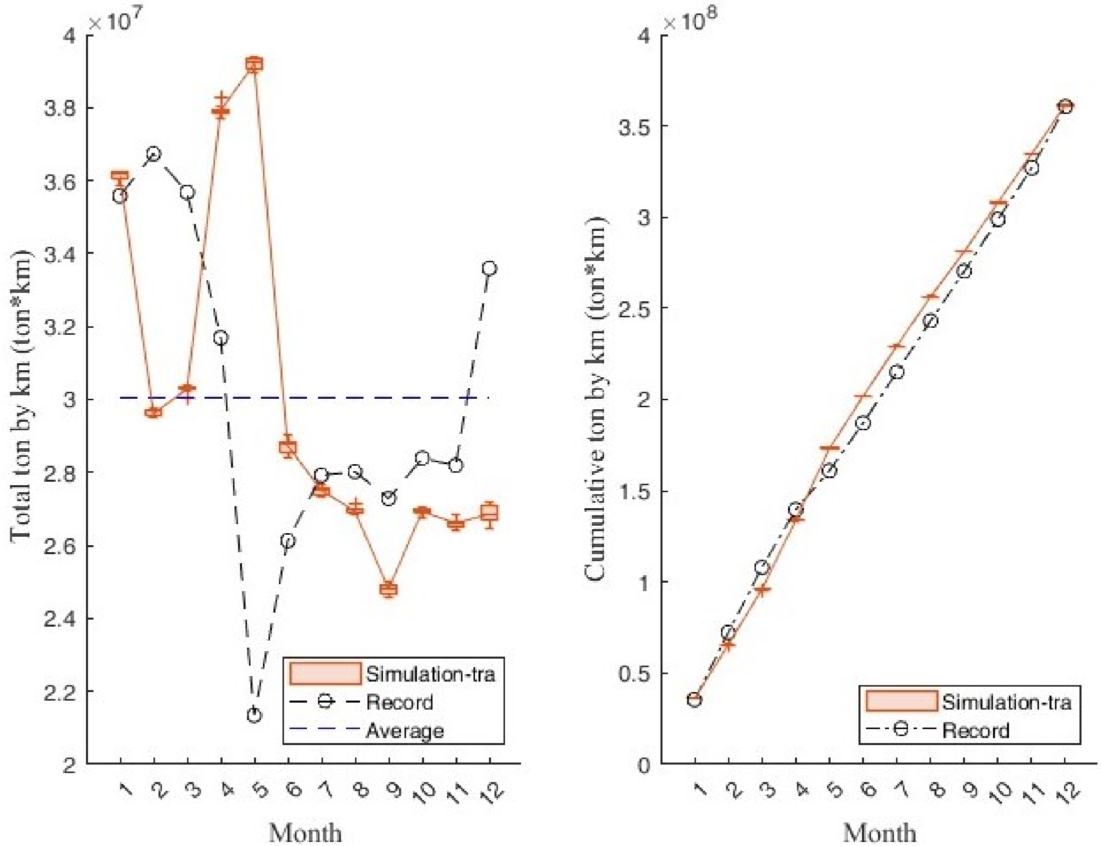

Figure 4.20 Ton-by-kilometer comparison of the traditional model and real operational record

Figure 4.20 shows the TKM difference for each month. This is due to the different mining sequences shown in the previous schedule figure. Although there are some fluctuations (also caused by ore and waste transport distance differences), as can be seen from the right graph, the total value is very close over a year, with a difference of 0.27%. Corresponding values are listed in Table 4.3. In addition to the monthly comparison, matching the average travel distance of the trucks in each cycle is also one of the verification items. The relevant comparison can be seen in Table 4.4. It is not difficult to see that the simulation model maintains a very high positive correlation with the recorded data in terms of truck operation data.

Table 4.3 Traditional simulation result and recorded data of ton-by-kilometer in each month

Month	Record	Simulated result (mean)	Error
1	35,585,400	36,134,422	1.54%
2	36,733,754	29,610,326	-19.39%

3	35,684,595	30,290,172	-15.12%
4	31,694,432	37,916,430	19.63%
5	21,344,821	39,206,429	83.68%
6	26,132,869	28,734,408	9.96%
7	27,925,146	27,516,904	-1.46%
8	28,023,676	26,937,118	-3.88%
9	27,287,164	24,810,607	-9.08%
10	28,390,619	26,936,105	-5.12%
11	28,199,447	26,619,372	-5.60%
12	33,598,857	26,862,698	-20.05%
Total	360,600,780	361,574,995	0.27%

Table 4.4 Comparison of hauling distance between recorded and simulated results

Operational data	Range	Mean	Summation
Haul distance(km) - Rec	8	3.91	1,078,648
Haul distance(km) - SimTra	7.99±0	3.88±0.01	1,079,935±2,252
Difference	-0.12%	-0.77%	0.12%

4.3.4 TPGOH

The primary focus of mining companies has always been on TPGOH, especially for ore material. The calculation of TPGOH is shown in Equation (23). From the equation it can be found that two variables affect the TPGOH, truck payload and truck cycle time. Truck payload distribution is checked in the first section of 4.3.1, and truck cycle time be compared in this section.

$$TPGOH = \frac{Truck\ Payload}{Cycle\ ready} \tag{23}$$

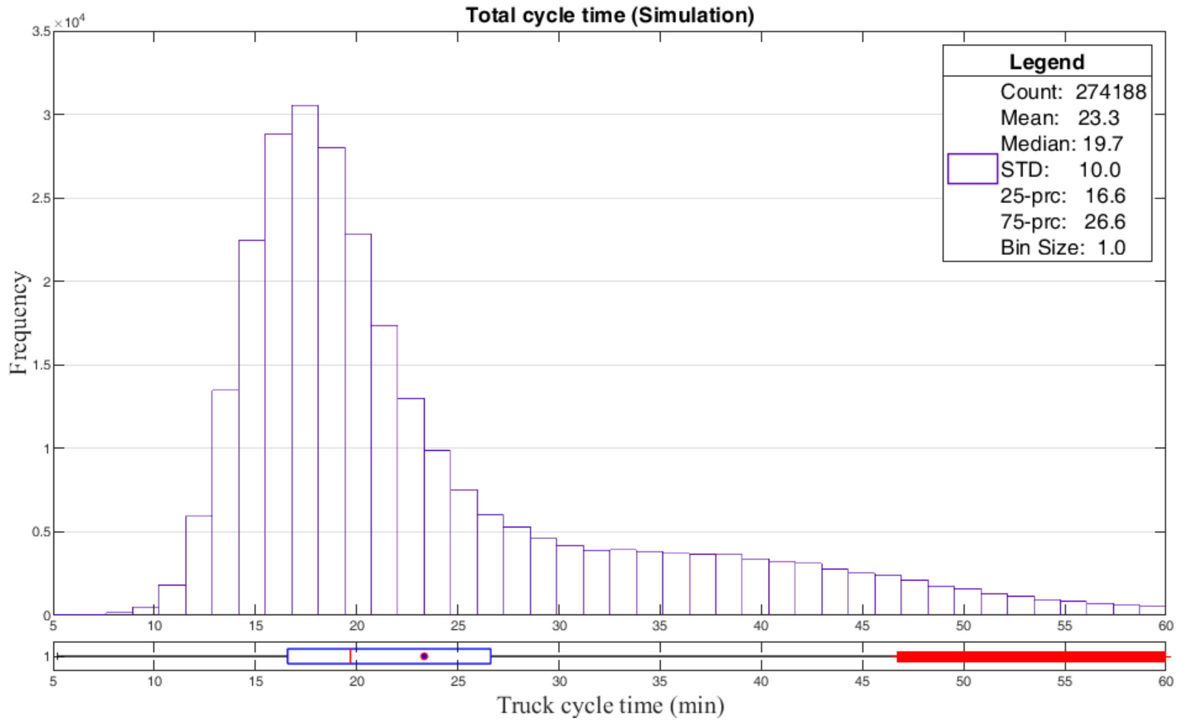

Figure 4.21 Histogram of the simulated truck cycle time

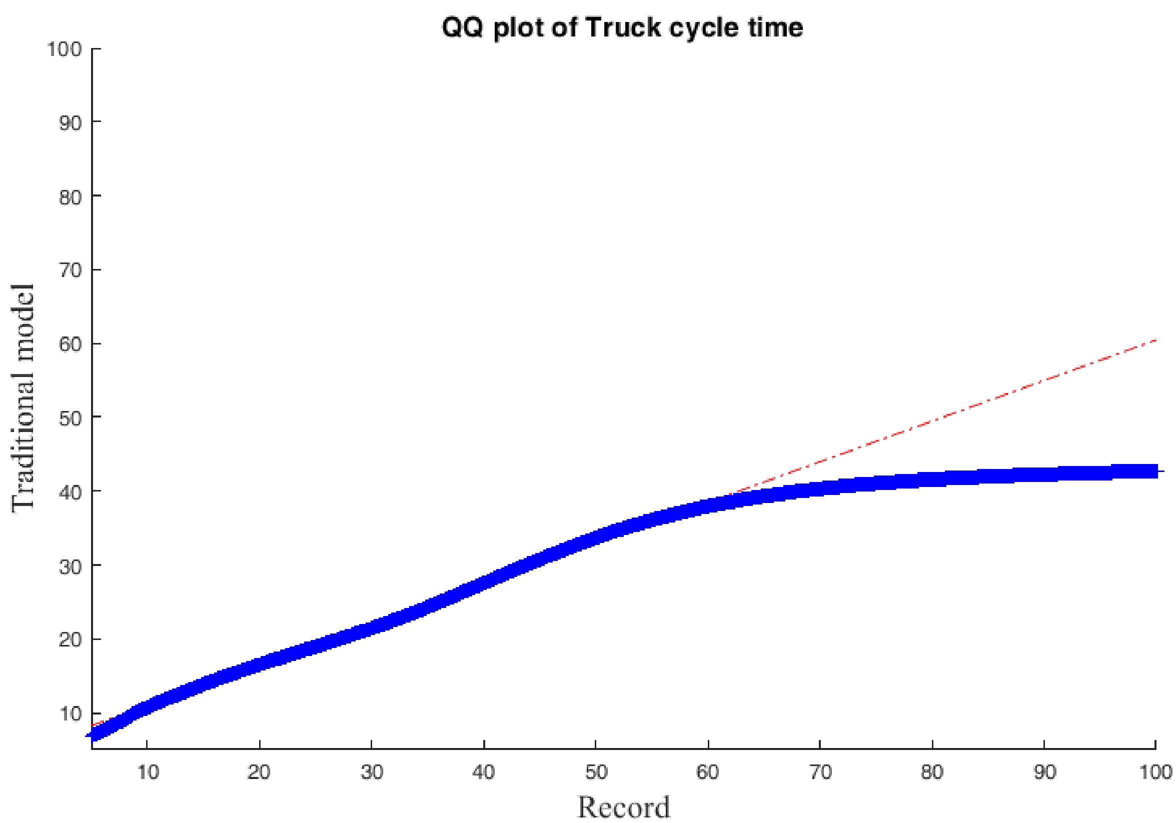

Figure 4.22 QQ plot of truck cycle time of the traditional simulation model and real operational records

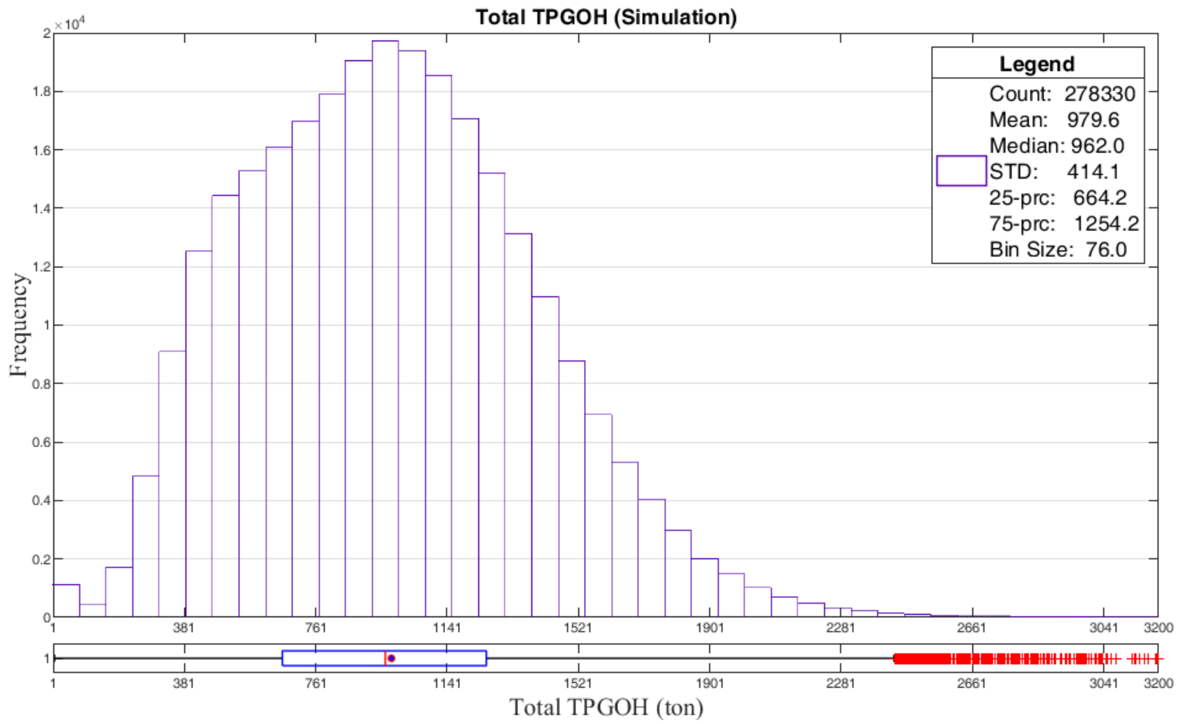

Figure 4.23 Histogram of simulated total TPGOH

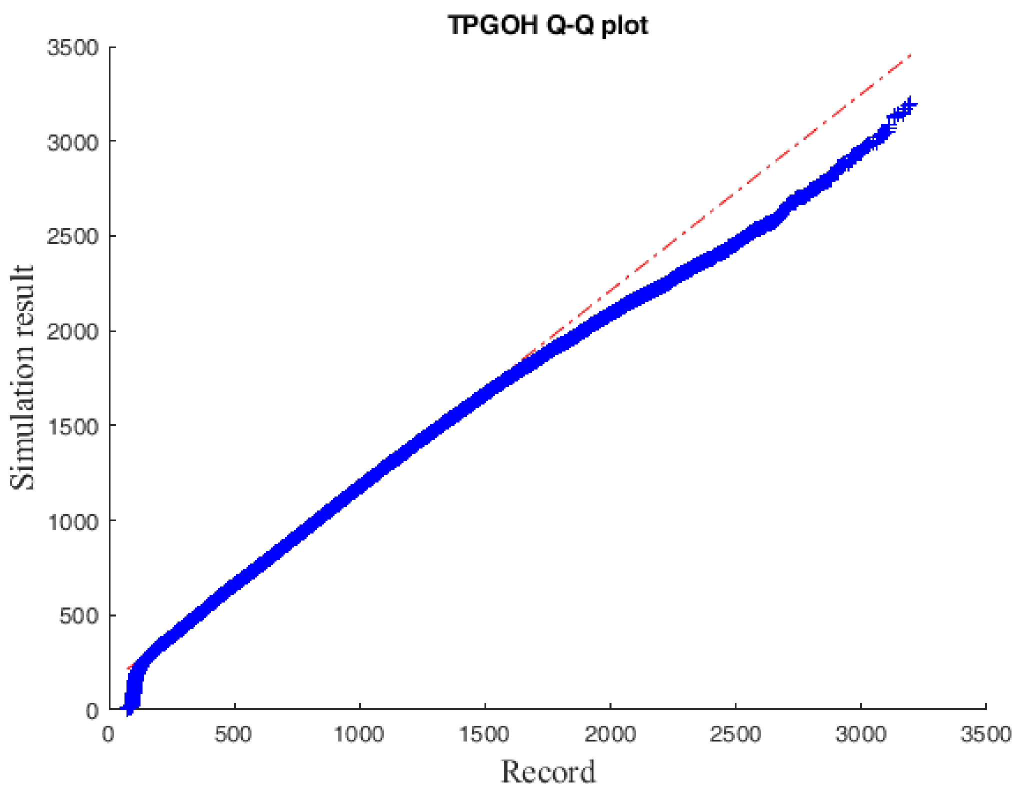

Figure 4.24 QQ plot of total TPGOH of the traditional simulation model and real operational records

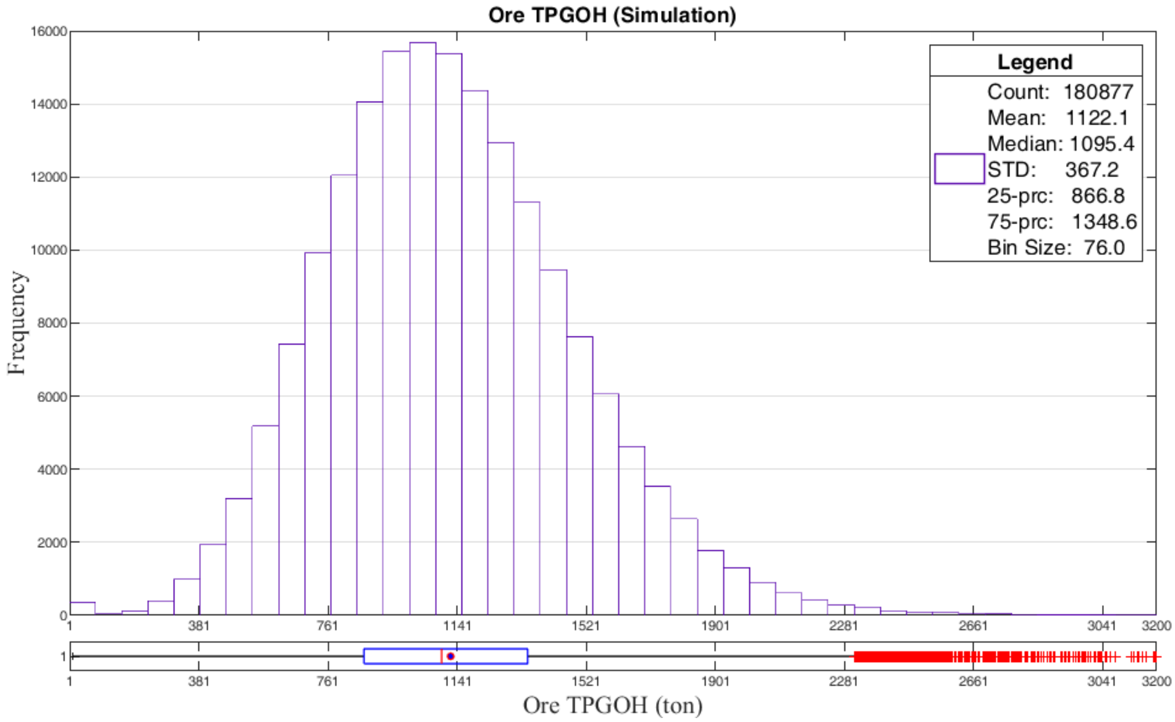

Figure 4.25 Histogram of simulated ore TPGOH

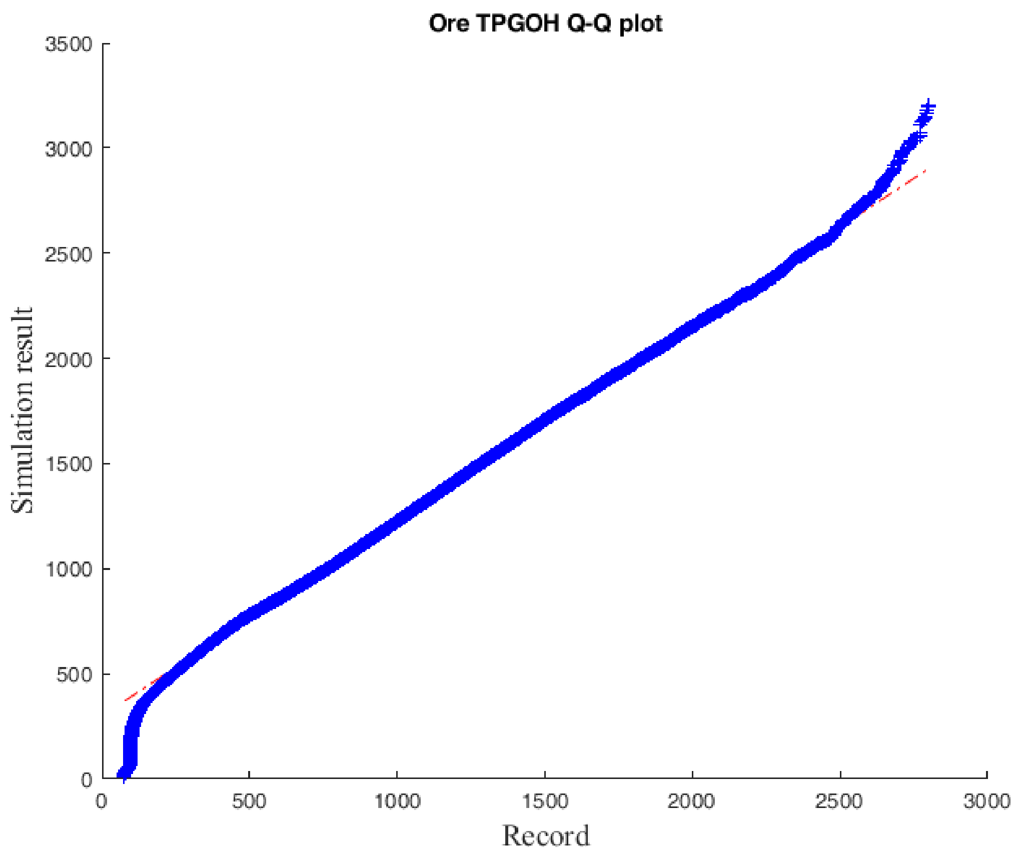

Figure 4.26 QQ plot of ore TPGOH of the traditional simulation model and real operational record

Figure 4.21 shows the histogram of simulated truck cycle time and Figure 4.22 is the corresponding QQ plot versus the record. In the main interval of 5 to 60 minutes, the distributions of the two are the same, but in the range of more than 60 minutes, there are some unconventional records in the historical data, which is not happening in the simulation model. The histograms of the simulated total TPGOH (ore and waste together) and ore TPGOH are shown in Figure 4.23 and Figure 4.25, respectively. By comparing Figure 4.23 and Figure 3.29, it can be seen that the simulation results of total TPGOH have a strong positive correlation with the recorded historical data. From Figure 4.24, which is their QQ plot, we can see that although there are some differences between the simulated and the recorded data on TPGOH when the value becomes greater than 1800 tons. The difference is noticeable but not significant. Given that more than 90% of TPGOH data are less than 1800, this fluctuation is acceptable.

The histogram of more concerned ore material is shown in Figure 4.25. The corresponding QQ plot, as shown in Figure 4.26 shows that the TPGOH of ore material is also highly positively correlated. The primary distribution area does not exhibit any significant differences except for TPGOH values lower than 200 and higher than 2800. The summaries are presented in Table 4.5, which serves as compelling validation for the simulation model. As a dependent variable, the average difference is about 6.39%, which falls within an acceptable range.

Table 4.5 Comparison of KPIs between record and simulated results

Operational data	Range	Mean	Summation
Total cycle time(min) - Rec	75	26.48	7,308,292
Total cycle time(min) - SimTra	100±52	24.6±0.03	6,851,909±13,464
Difference	25.28%	-7.62%	-6.66%
TPGOH- Rec	2,828.5	917.1	253,155,367
TPGOH- SimTra	2,957±662	979.8±1.8	272,966,328±651,926
Difference	-1.93%	6.39%	7.26%

This section validates the proposed simulation model based on four aspects: Input variables' consistency, tonnage excavated in each month, the trucks monthly travel distance, and average TPGOH. These comparisons verify that the proposed simulation model is feasible, credible, and reliable, and provides a solid foundation for the comparison between the traditional mining method and the NFS mining method in the following section.

4.4. Implementation of the NFS method

The establishment process of the simulation model and the verification of the simulation model for the traditional mining method are described in the first three sections of this chapter. In this section, we discuss the application of the NFS method simulation model and its results.

The detailed differences in process and logic between the NFS method and the traditional mining method are shown in Figure 3.16 and Figure 3.17 to Figure 3.19. The input data of the NFS simulation model needs to be adjusted due to these differences. The first modification is the relocation of the crusher from the outside of the pit to the bottom of the pit. The red box in Figure 4.27 indicates the position of the original crusher, and the red dot represents the new position. It should be noted that, like IPCC, NFS can choose fixed, semi-mobile, or fully mobile crushing equipment when needed, but equipment selection is not the research interest of this paper and therefore, is not discussed. We assume that the originally fixed crusher is used, and the parameters remain the same, except for the position.

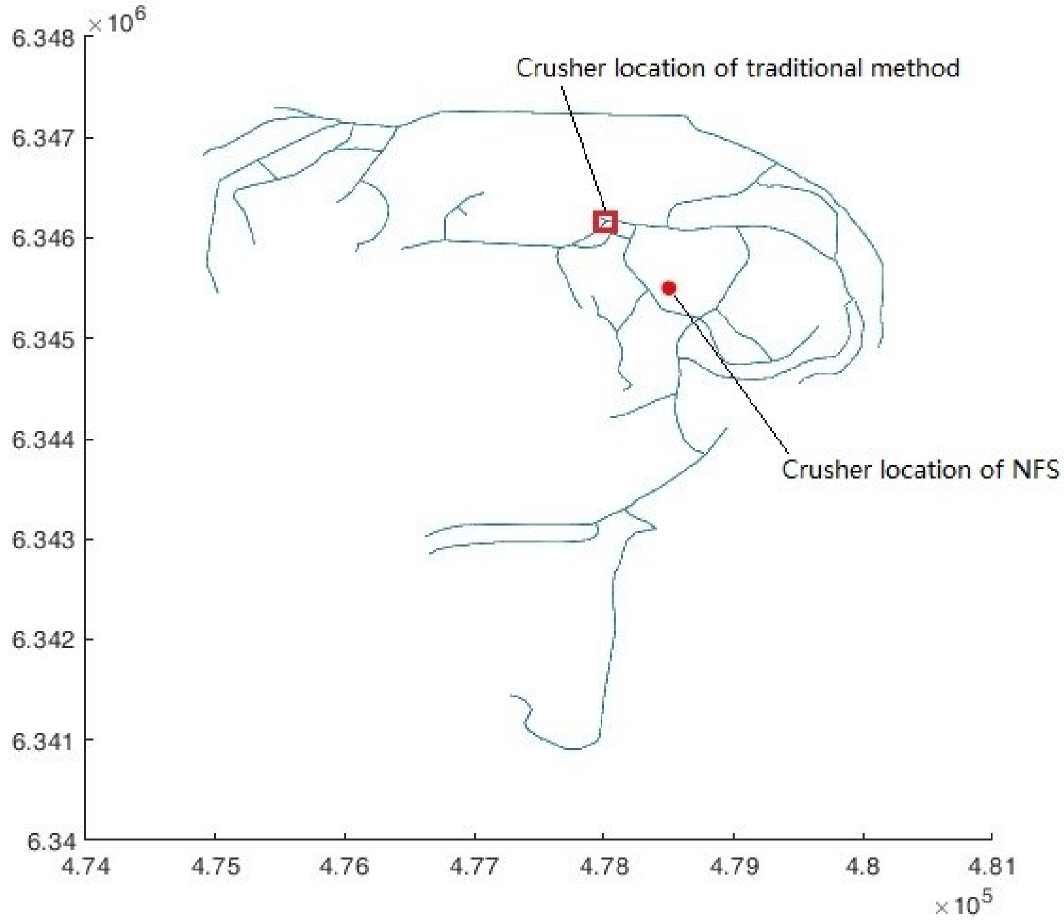

Figure 4.27 Demonstration of crusher location of the NFS model and traditional model

The second modification is the adaptation of the original road network according to the location of the new crusher. The main framework of the original road network remains unchanged since the waste material still needs to be transported to the specified location through the previous route. However, for ore material, trucks only haul inside the pit from the loading location to the in-pit stockpile. Therefore, the travel distance needs to be recalculated and used as input to the simulation model. As mentioned above, the aggregation of the original blocks is only related to its own physical properties, such as mineral grade, rock type, and height, and is not related to the position of the crusher. Therefore, the input blocks used for the NFS model are the same to maintain consistency. Two examples, bench 280 (elevation) and bench 310, with corresponding mining schedules, are shown in Figure 4.28 to Figure 4.29, respectively.

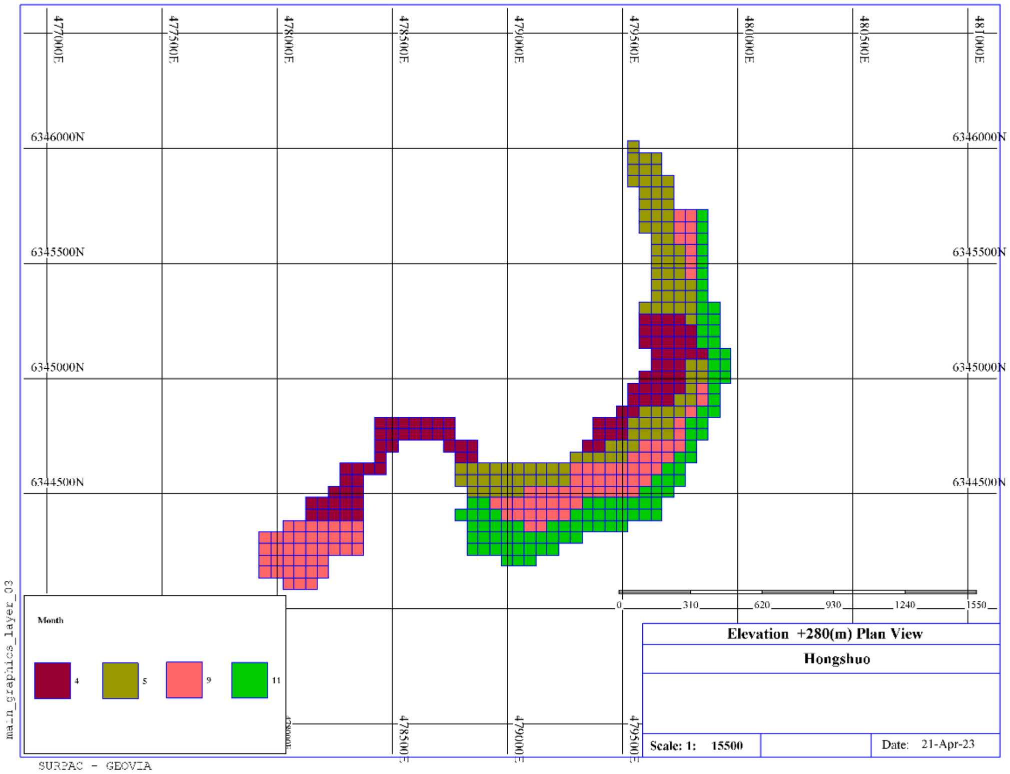

Figure 4.28 Mining schedule of bench 280

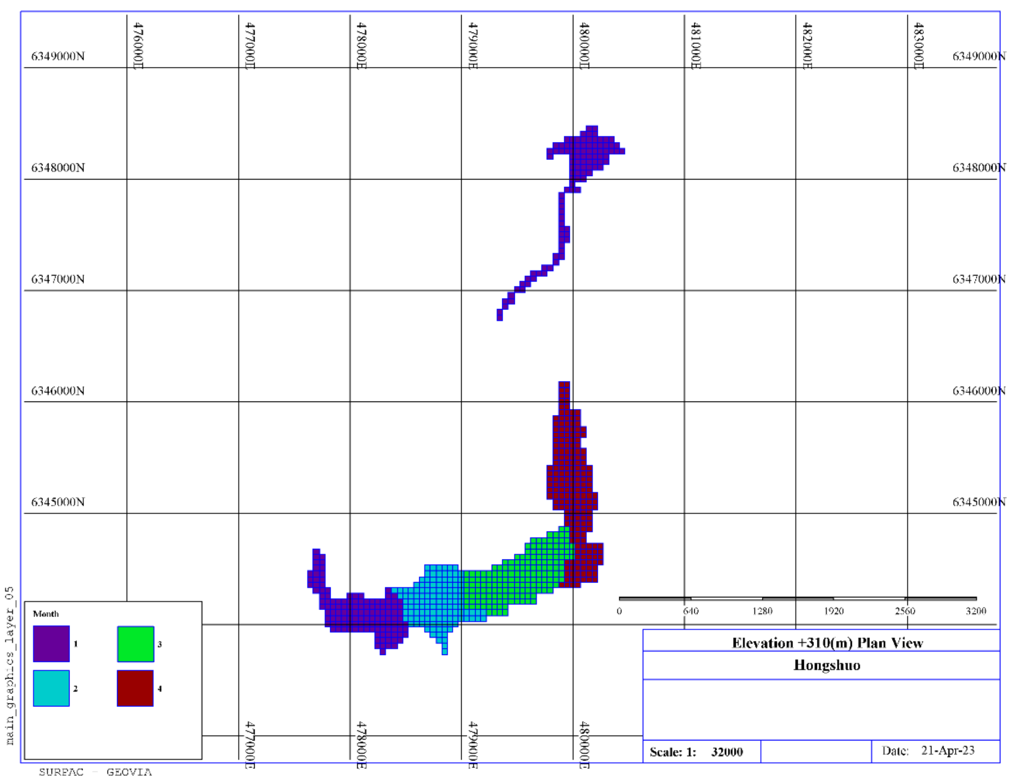

Figure 4.29 Mining schedule of bench310

Although the physical properties of the aggregated blocks have not changed, the values assigned to them have changed. One reason is that some extra tonnage is assigned to avoid possible idling caused by a lack of material. In addition, the average travel distance from each block to the crusher has changed, as shown in Table 4.6. The empty cells in the table indicate that the block is a pure waste block with no ore material sent to the crusher. It should be pointed out that only the average transportation distance of ore material has changed. Since the main framework of the road network and the aggregation of blocks have not changed, the transportation distance of waste remains unchanged from that of the traditional mining method simulation model.

Table 4.6 Ore hauling distances of blocks before and after the movement of crusher

Block No.	Distance original (km)	Distance NFS (km)	Difference
1	-	-	-
2	2.218	1.542	-30.48%
3	2.371	1.204	-49.20%
4	2.635	1.603	-39.14%
5	2.515	1.646	-34.54%
6	2.152	1.485	-30.98%
7	2.591	1.631	-37.07%
8	2.797	1.636	-41.51%
9	2.794	2.163	-22.59%
10	2.445	1.270	-48.07%
11	3.006	1.951	-35.08%
12	2.895	1.855	-35.93%
13	2.695	3.174	17.78%
14	3.043	2.198	-27.78%
15	2.901	2.601	-10.33%
16	3.004	3.092	2.94%
17	2.850	3.102	8.85%

18	3.147	2.895	-7.99%
19	2.727	2.648	-2.88%
20	2.724	2.678	-1.68%
21	2.693	2.851	5.86%
22	2.529	2.812	11.21%
23	3.155	1.680	-46.77%
24	3.341	1.970	-41.04%
25	3.964	3.596	-9.30%
26	3.205	2.934	-8.47%
27	3.295	2.711	-17.73%
28	3.295	3.124	-5.17%
29	3.301	3.806	15.30%
30	-	-	-
31	-	-	-
32	3.555	4.542	27.77%
33	2.679	4.444	65.87%
34	-	-	-
35	-	-	-
36	-	-	-
37	-	-	-
38	-	-	-

Table 4.7 Ore tonnage within each hauling range of the two models

Distance range(km)	Ore tonnage in traditional method (ton)	Ore tonnage in NFS method (ton)	Difference
1.1 to 1.3	1,775,306	0	-
1.3 to 1.5	2,312,704	0	-
1.5 to 1.7	13,008,543	0	-
1.7 to 1.9	2,491,094	0	-

1.9 to 2.1	2,158,453	0	-
2.1 to 2.3	6,653,357	4,192,862	36.98%
2.3 to 2.5	0	2,077,245	-
2.5 to 2.7	6,303,785	8,867,597	-40.67%
2.7 to 2.9	6,945,984	11,130,609	-60.25%
2.9 to 3.1	10,238,007	17,159,104	-67.60%
3.1 to 3.3	7,895,129	12,819,721	-62.38%
3.3 to 3.5	0	3,129,751	-
3.5 to 3.7	967,779	20,158	97.92%
3.7 to 3.9	2,355,512	0	-
3.9 to 4.1	0	936,893	-
4.1 to 4.3	0	0	-
4.3 to 4.5	211,186	0	-

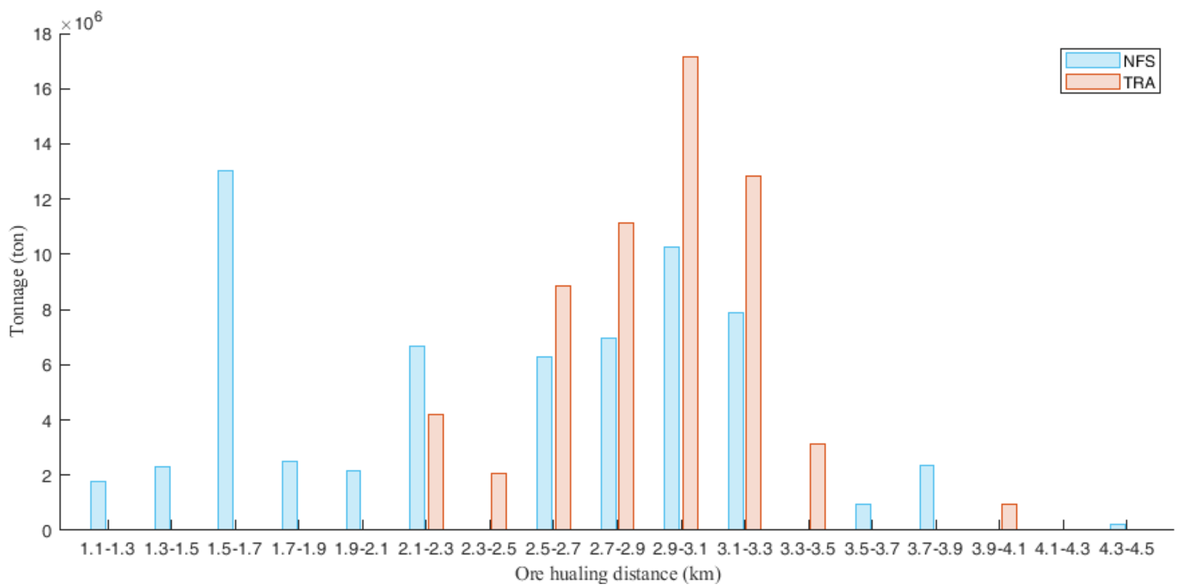

Figure 4.30 Ore tonnage within each hauling range of the NFS model and traditional model

It can be observed from Table 4.6 that among the 38 blocks, the mineral transportation distance of 8 blocks (accounting for 21%) becomes longer. However, when compared with Figure 4.30, only 3.53 million tons of ore material, accounting for 5.57%, experienced increased hauling distance. Besides, when combining Table 4.7 with Figure 4.30, it can be seen that the minimum distance for ore transportation by truck was found to be between 2.1 and 2.3 kilometers before the application of the NFS method, and the number decreased to the range of 1.1 to 1.3 kilometers after implementation of the NFS method. In addition, after applying the NFS method, the transportation distance of more than 21 million tons of ore material becomes less than 2.1 km, which accounts for more than one-third of the total ore material. Hence, we can confidently conclude that 94.43% of the ore mineral is expected to have a shorter transportation distance after the application of the NFS method.

Changing the transporting distance of ore minerals will bring about other changes as well. For example, after running the optimization program shown in Figure 3.14, the resulting mining schedule is somewhat different from the traditional mining method. The detailed mining schedule of the two methods is shown in Table 4.8 and Table 4.9.

Table 4.8 Mining schedule of traditional simulation model

	Desired exaction period (month)											
Block	1	2	3	4	5	6	7	8	9	10	11	12
1												
2												
3												
4												
5												
6												
7												
8												
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Table 4.9 Mining schedule of NFS simulation model

	Desired exaction period (month)

Block	1	2	3	4	5	6	7	8	9	10	11	12
1												
2												
3												
4												
5												
6												
7												
8												
9												
10												
11												
12												
13												
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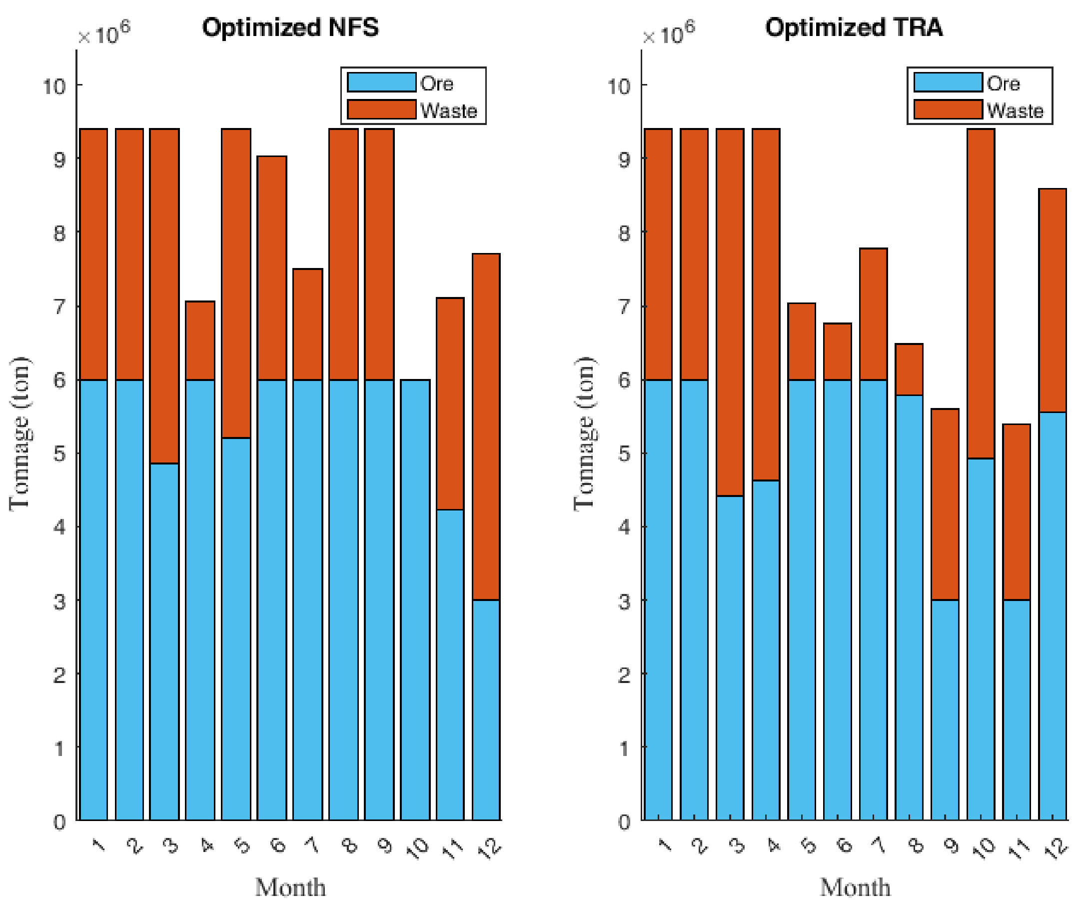

Figure 4.31 Mining schedule of the NFS model and traditional model by month

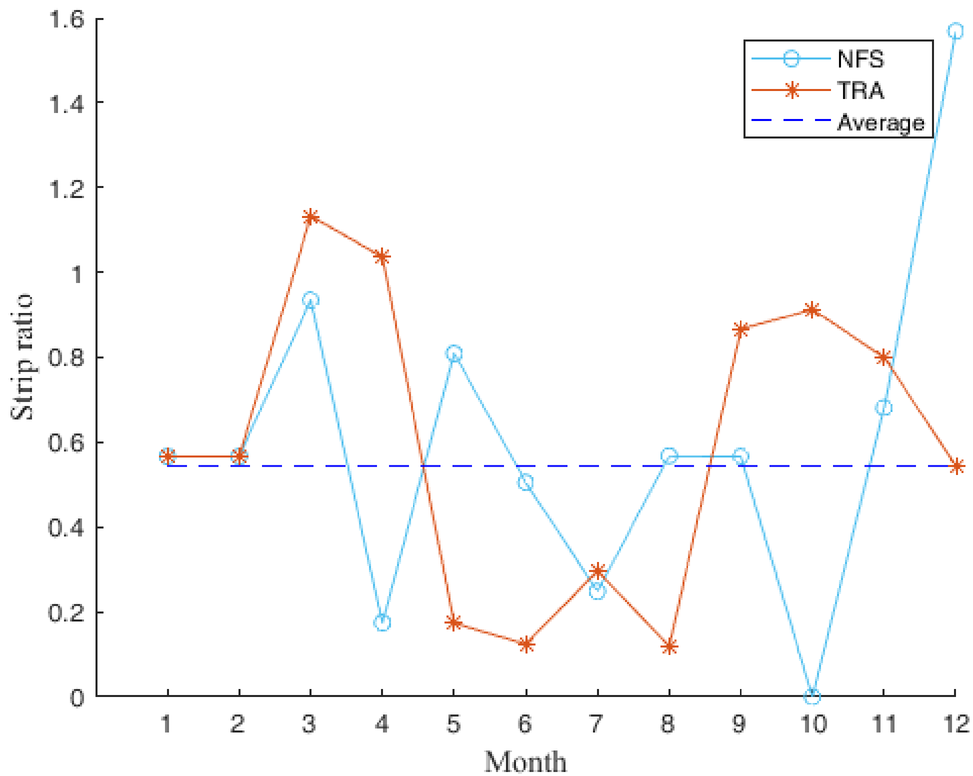

Figure 4.32 Monthly stripping ratio of the NFS model and traditional model

Figure 4.31 shows the optimized monthly ore mineral mining tonnage and waste mining tonnage of the two models under respective schedules. The monthly stripping ratio of the two methods is shown in Figure 4.32, which indicates that with extra materials, the NFS method could maintain a lower strip ratio in early periods to maximize its discounted net present value.

4.5. Simulation results analysis

The various results obtained after applying the optimization procedures will be used as the input to the NFS simulation model. Other independent variables, such as shovel loading time, empty speed, full load speed, dumping time, etc., are consistent with the input data that is used in the traditional simulation model. Meanwhile, the running time of the NFS simulation model for one replication is also set to be 366 days and will be run for 10 replications as the traditional simulation model.

4.5.1 Independent variables

To enhance the credibility of the comparative study between the NFS mining method and the traditional mining method, it is crucial to minimize the differences in all aspects except for the layout of the two methods. This can be achieved by employing the control variable method, which is one of the primary means for comparative studies. In particular, the use of the same mechanical equipment and the consistency of their operating performance are critical prerequisites for an effective comparison.

Although the data presented in Table 3.10 were utilized in both simulation models as the inputs, the simulation software will introduce certain uncertainties. Therefore, to ensure that the operating conditions of all equipment are within a reasonable range and to enhance the credibility of the results of the dependent variables, it is necessary to compare and analyze the distribution of independent variables in the running results of the two models. By doing so, any potential biases introduced by the simulation software can be minimized, leading to more reliable and trustworthy findings.

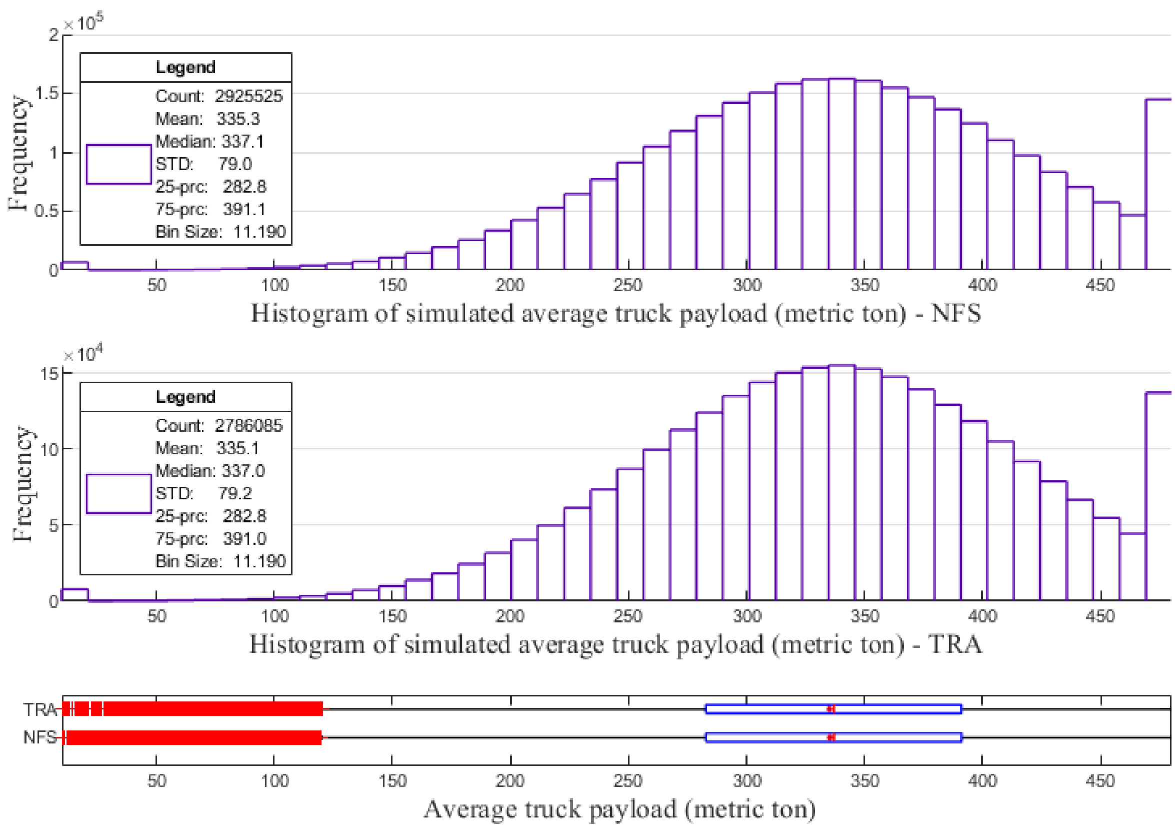

Figure 4.33 Simulated average truck payload of NFS method and traditional method

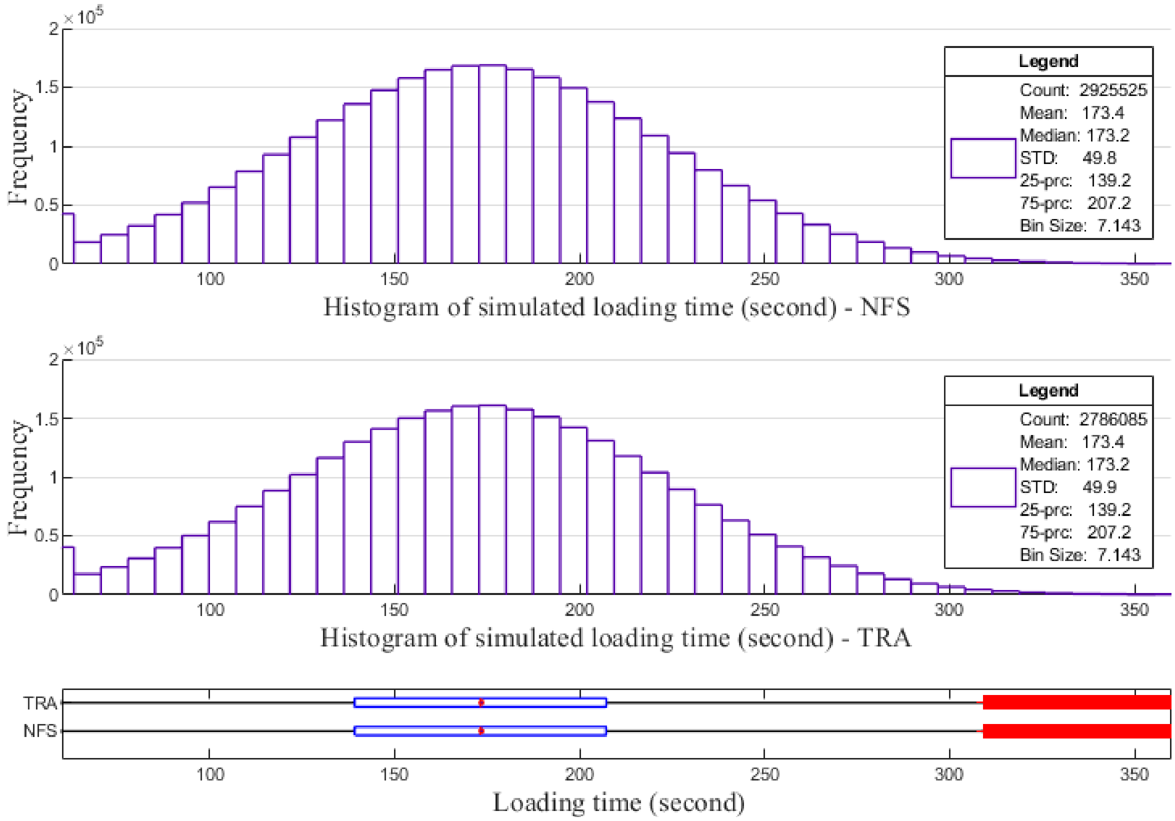

Figure 4.34 Simulated shovel loading time per truck of NFS method and traditional method

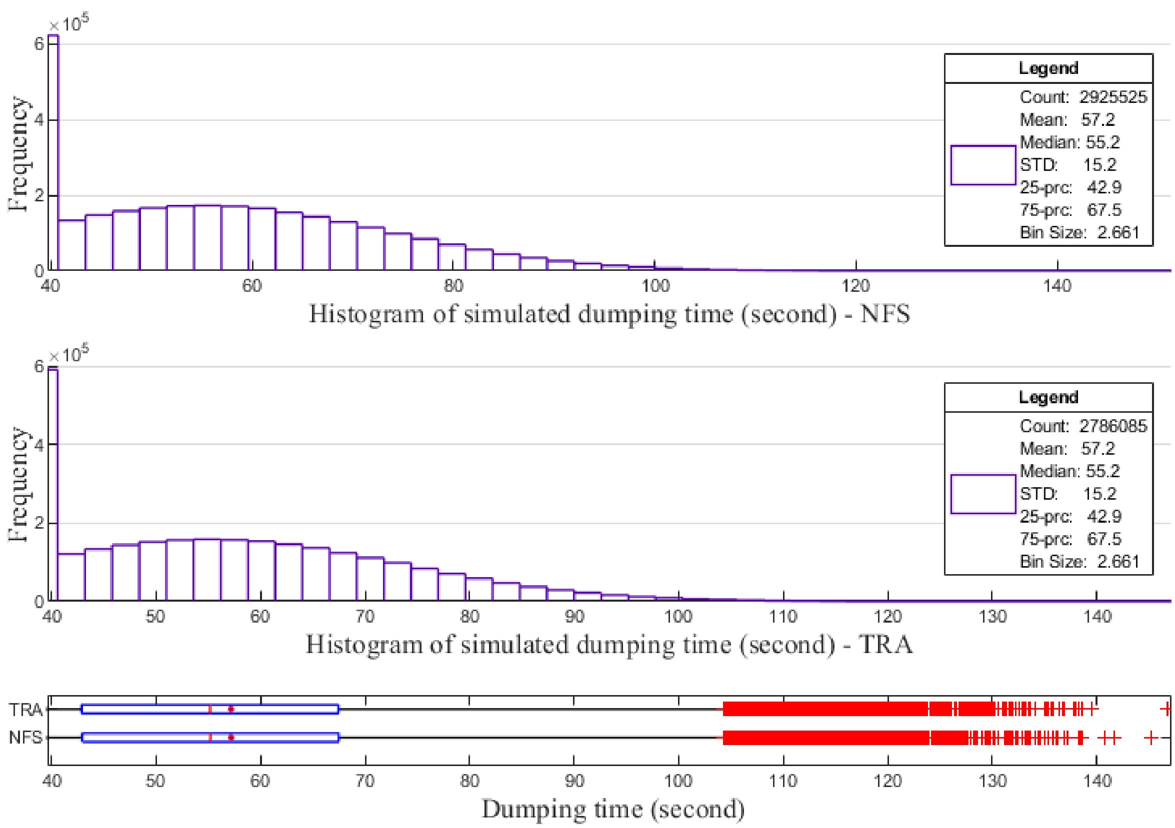

Figure 4.35 Simulated truck dumping time of NFS method and traditional method

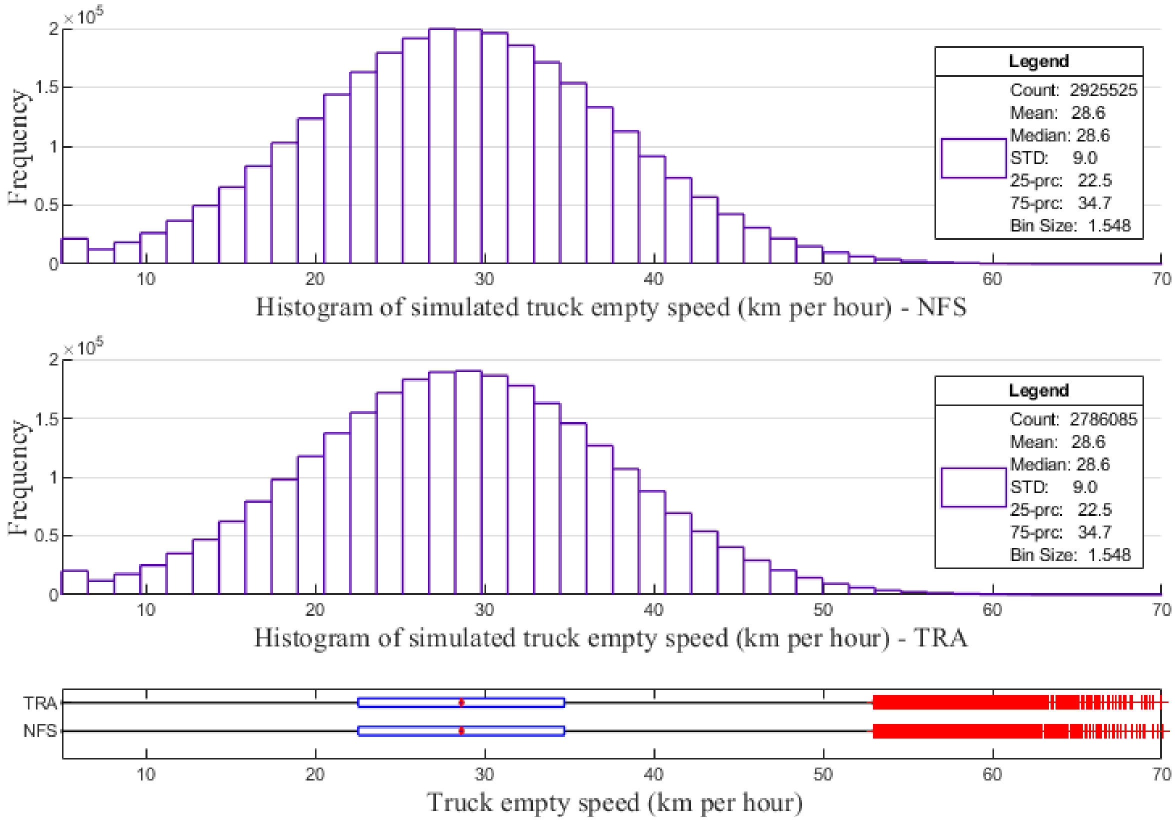

Figure 4.36 Simulated truck empty hauling speed of NFS method and traditional method

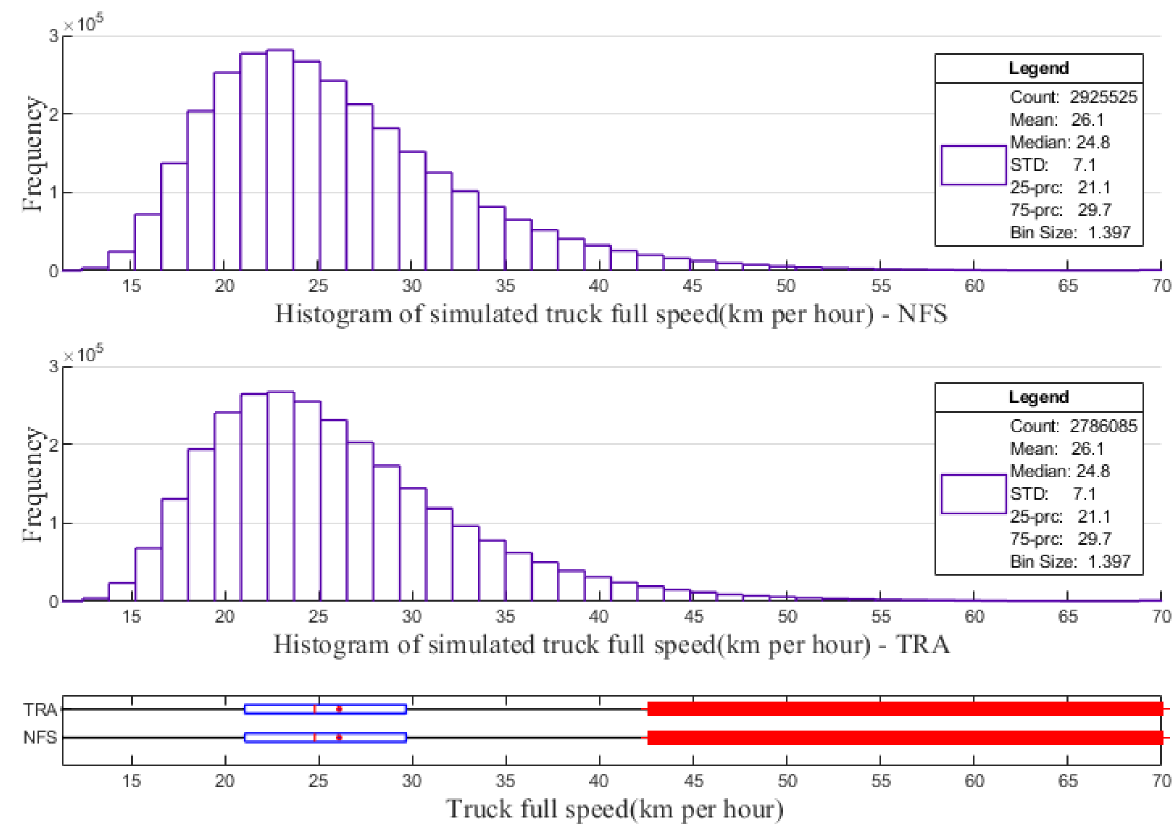

Figure 4.37 Simulated truck loaded hauling speed of NFS method and traditional method

The histograms of five independent variables, namely average truck payload, shovel loading time per truck, truck dumping time, truck empty speed, and truck loaded speed, are presented in Figure 4.33 to Figure 4.37. These histograms illustrate a comparison between the results obtained using the NFS method and the traditional method.

For a more detailed comparison, eight categories are selected to evaluate each variable. The definition of the eight categories is listed in Table 4.10. After the definition, the captured variables' distributions are listed in Table 4.11. Similar to the comparison in the model validation section, 'SimNFS' in the table is short for NFS model simulation results.

Table 4.10 Definition of the categories selected to evaluate the performance of variables

Category name	Definition
Count	The average times that the given variable is recorded in one replication
Range	Ten replication average of variable's maximum value in one replication minus the minimum value in that replication
Mean	Ten replication average of the variable's mean value in each replication
Median	Ten replication average of the variable's median value in each replication
STD	Ten replication average of the variable's standard deviation in each replication
25-prc	Ten replication average of 25 percent value of the variable's dataset
75-prc	Ten replication average of 75 percent value of the variable's dataset
Summation	The average summation of the variable in one replication

Table 4.11 Independent variables results comparison between NFS model and traditional model

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Average truck payload (ton) - SimTra	278,609 ±537	470±0	335± 0.32	337± 0.35	79.18± 0.44	283± 0.26	391± 0.31	93,374,636 ±189,085
Average truck payload (ton) - SimNFS	292,553 ±696	470±0	335± 0.65	337± 0.57	78.95± 0.6	283± 0.61	391± 0.59	98,096,248 ±270,705
Difference	5.00%	0.00%	0.05%	0.02%	-0.29%	0.01%	0.02%	5.06%
Loading time(min) - SimTra	278,609 ±537	5±0	2.89±0	2.89± 0.01	0.83±0	2.32±0	3.45± 0.01	805,227 ±1968

Loading time(min) - SimNFS	292,553 ±696	5±0	2.89±0	2.89± 0.01	0.83±0	2.32±0	3.45± 0.01	845,445 ±1976
Difference	5.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.99%
Dumping time(min) - SimTra	278,609 ±537	1.64± 0.2	0.95±0	0.92±0	0.25±0	0.72± 0.01	1.12± 0.01	265,428 ±398
Dumping time(min) - SimNFS	292,553 ±696	1.7± 0.16	0.95±0	0.92±0	0.25±0	0.72± 0.01	1.12± 0.01	278,813 ±809
Difference	5.00%	3.66%	0.00%	0.00%	0.00%	0.00%	0.00%	5.04%
Empty speed(km/h) - SimTra	278,609 ±537	64.3± 2.73	28.62± 0.02	28.6± 0.04	8.99± 0.02	22.52± 0.04	34.69± 0.03	7,973,113 ±17,205
Empty speed(km/h) - SimNFS	292,553 ±696	63.79± 3.32	28.62± 0.03	28.6± 0.02	8.99±0. 03	22.52± 0.05	34.69± 0.05	8,372,830 ±23,546
Difference	5.00%	-0.79%	0.00%	0.03%	0.00%	0.00%	0.00%	5.01%
Full speed(km/h) - SimTra	278,609 ±537	58.44± 0.38	26.1± 0.04	24.8± 0.05	7.09± 0.04	21.07± 0.03	29.67± 0.04	7,271,881 ±12,091
Full speed(km/h) - SimNFS	292,553 ±696	58.39± 0.37	26.1± 0.04	24.79± 0.04	7.08± 0.03	21.07± 0.05	29.67± 0.04	7634,242 ±21,300
Difference	5.00%	-0.09%	0.00%	-0.04%	-0.14%	0.00%	0.00%	4.98%

The first independent variable to be compared is the average truck payload. As can be seen from the table, there is no noticeable difference between two simulated results in category ‘range’, ‘mean value’, ‘median value’ and ‘standard deviation’. However, when it comes to the category ‘count’ and ‘summation’, the difference increased from 5 per ten thousand level to 5 percent level. The increment means that compared to traditional simulation model, trucks experienced more full-empty cycles in the NFS simulation model. With the average truck payload remaining the same, the increment led to a higher total production in the given period. The reason for the increase will be analyzed in detail in the following sections.

Other independent variables exhibit nearly identical performance to the average truck payload. Figure 4.33 to Figure 4.37 and Table 4.11 demonstrate that the distribution of these variables in both methods is consistent with the set values and the comparison of the corresponding boxplot clearly show a high degree of consistency. The consistency indicates that those independent variables have a negligible impact on the performance evaluation of two methods.

4.5.2 Truck hauling distance and hauling time

It should be pointed out again that the establishment of the two simulation models in this paper does not take into account the mutual influence of trucks during hauling, that is, there will be no traffic jams or fast trucks being limited by slow trucks. Under this premise, truck hauling time is determined by two parts, one is the speed of the truck, and the other is the travel distance. It can be seen from the above that the speed distribution of the truck in the two models is almost the same whether it is empty or fully loaded, so the factor that determines the hauling time is the transportation distance.

Given that the speed of the truck is different when it is empty and fully loaded, the hauling distance and hauling time in the two states need to be compared separately. In addition, while considering the overall situation, this section also divides the data into two additional conditions in more detail: the case of transporting ore material and the case of transporting waste material.

1. Total empty and loaded truck hauling distance and hauling time

This section mainly discusses and analyzes the similarities and differences between the truck's hauling distance and hauling time regardless of ore and waste.

- Empty condition

Figure 4.38 displays the histogram and boxplot of the empty truck hauling distance for two simulation models: the NFS simulation model and the traditional simulation model. The top and middle figures represent the simulation results of the NFS and traditional simulation models, respectively, while the bottom figure shows the boxplot of the two results.

The boxplot in the bottom figure displays the statistical distribution of the data. The red line in the center of the box represents the median value of the results, while the 25th and 75th percentiles of the data are shown at the left and right ends of the box. The valid range of the data is indicated by the black line, with the minimum value of the valid data on the left and the maximum value of the valid data on the right.

Additionally, the interquartile range (IQR) is defined as the distance between the third and first quartiles. The whiskers in the boxplot are based on 1.5 times the IQR and any data point outside the whiskers is defined as an outlier, as indicated by the red plus sign in the figure.

Other figures in this section maintain the same structure and internal picture order as Figure 4.38, and the introduction will not be repeated.

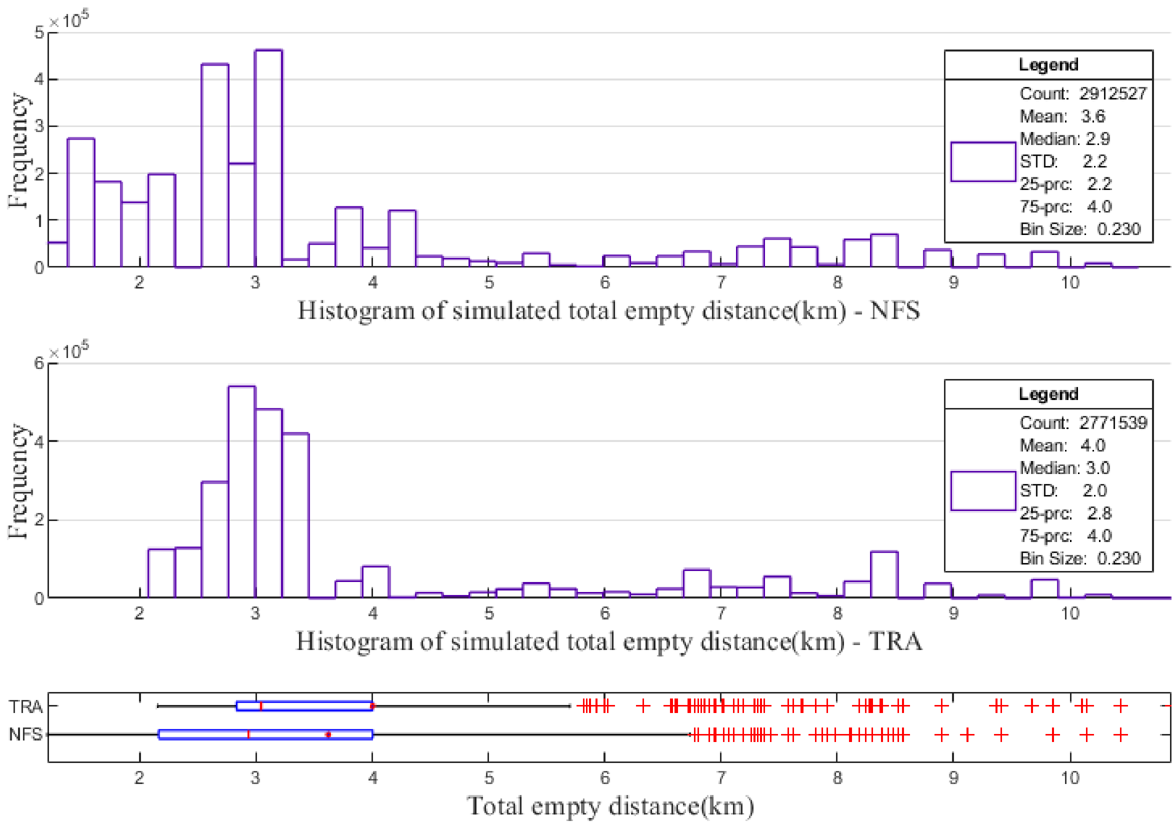

Figure 4.38 Simulated empty truck hauling distance of NFS method and traditional method

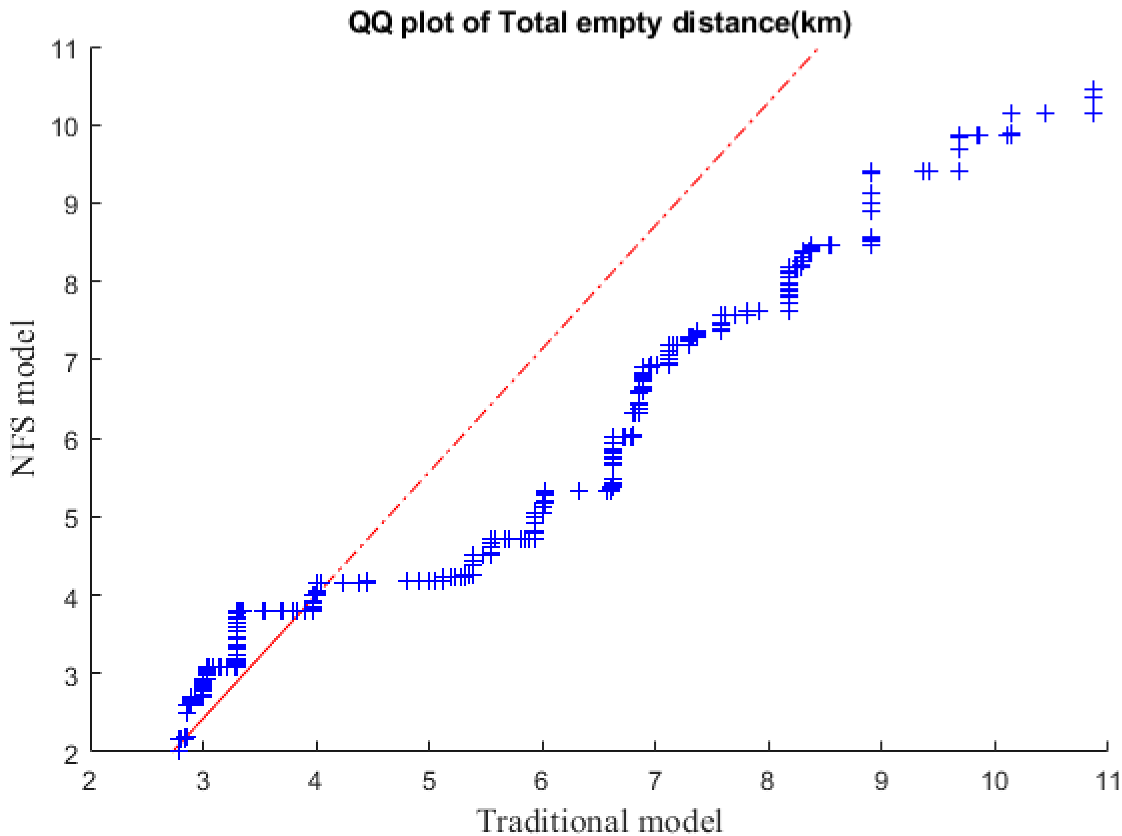

Figure 4.39 QQ plot of empty truck hauling distance of NFS method and traditional method

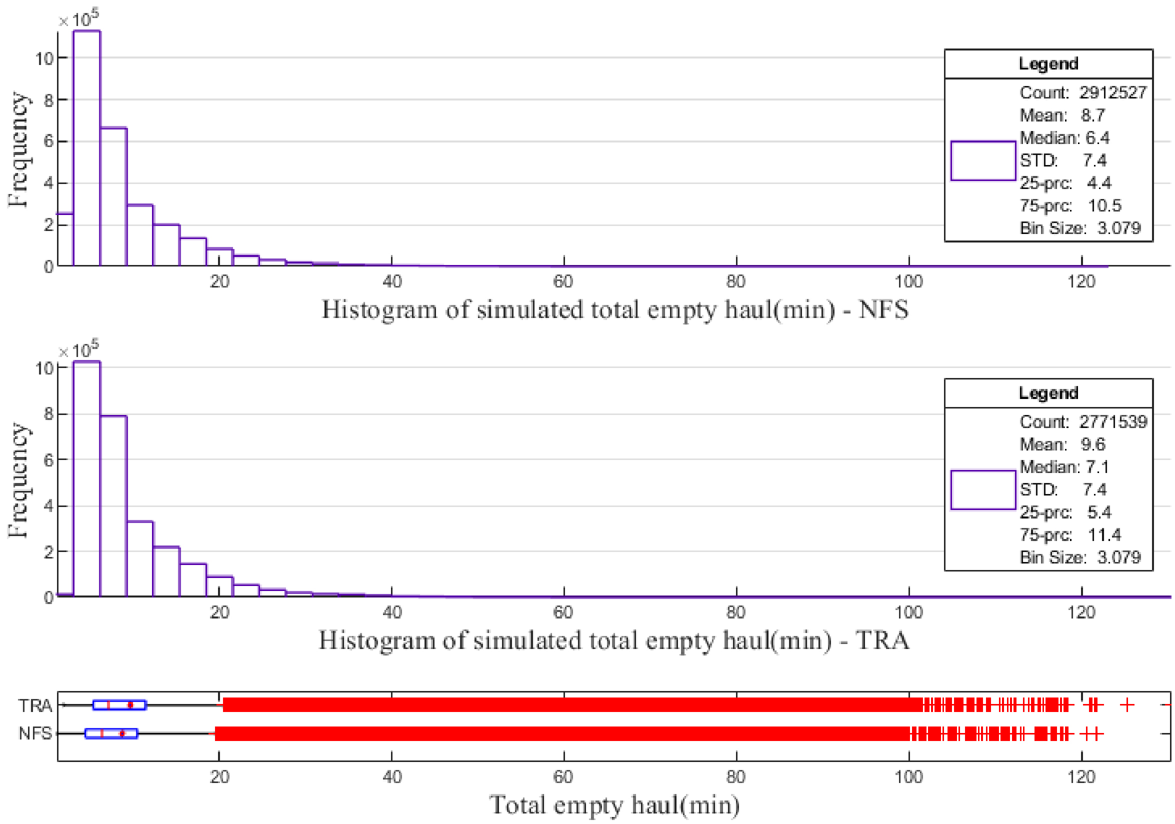

Figure 4.40 Simulated empty truck hauling time of NFS method and traditional method

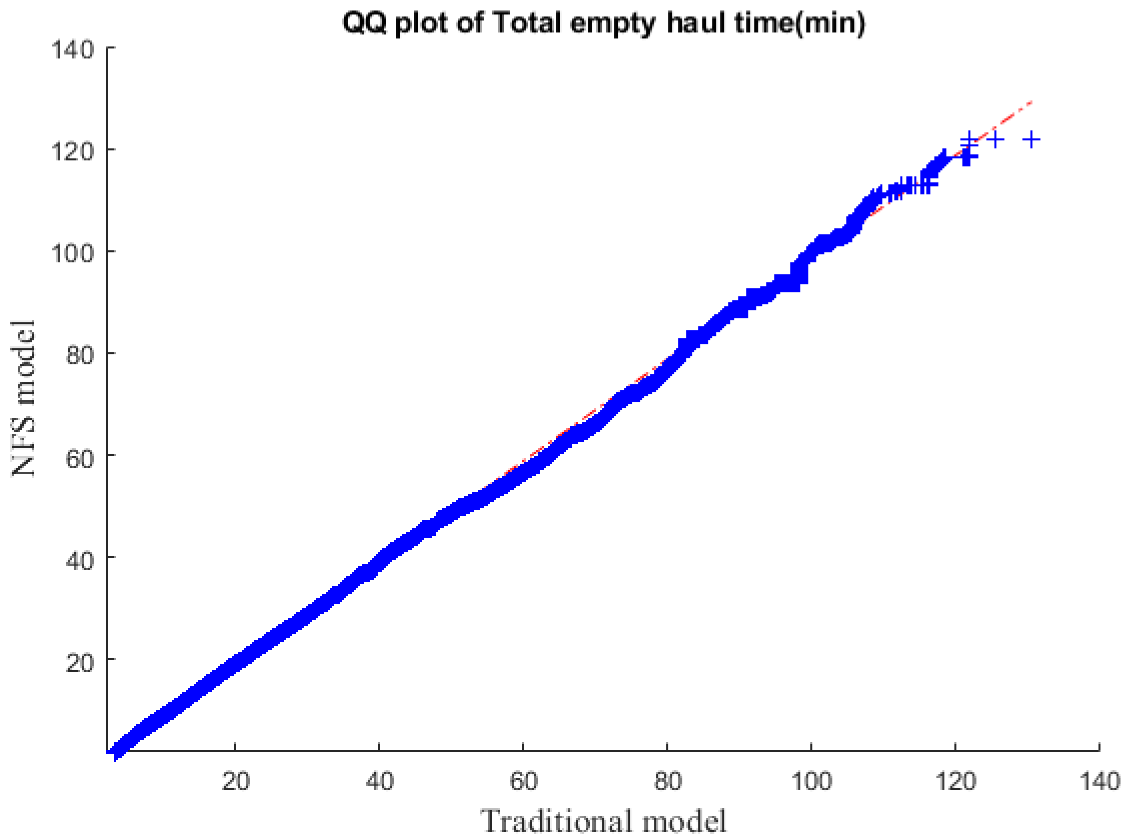

Figure 4.41 QQ plot of empty truck hauling time of NFS method and traditional method

Table 4.12 Simulated total empty truck hauling time and hauling distance comparison of the NFS model and traditional model

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Total empty distance(km) - SimTra	278,609 ±537	10.87 ±0	3.98 ±0	3.04±0	2.03± 0.01	2.8±0	3.99 ±0.01	1,109,237 ±2,053
Total empty distance(km) - SimNFS	292,553 ±696	10.38 ±0.29	3.61 ±0.01	2.93±0	2.17±0	2.16±0	4±0	1,054,643 ±2,547
Difference	5.00%	-4.51%	-9.3%	-3.62%	6.9%	-22.86%	0.25%	-4.92%
Total empty haul time(min)- SimTra	278,609 ±537	123.8 ±8.3	9.6 ±0.02	7.12 ±0.02	7.41± 0.09	5.35 ±0.01	11.39 ±0.05	2,674,328 ±4,709
Total empty haul time(min)- SimNFS	292,553 ±696	121.7 ±0	8.69 ±0.02	6.37 ±0.01	7.4± 0.12	4.41 ±0.01	10.44 ±0.03	2,542,078 ±6,524
Difference	5.00%	-1.70%	-9.5%	-10.5%	-0.13%	-17.57%	-8.34%	-4.95%

In both models, the dispatch logic of the trucks gives the highest priority to the shortest queue number before the shovel. As shown in Figure 4.38, the NFS model reduces the distance between the crusher and blocks, resulting in a significant improvement in the part of the empty truck hauling distance of less than 3km in the NFS model results. According to Table 3.7, the 25-percentile data of the NFS model is 22.86% lower than that of the traditional model. However, there is no significant difference in the part where the empty truck hauling distance is greater than 4km, which mainly corresponds to waste material, resulting in a negligible difference between the two results. Since waste material accounts for nearly one third of the total mining volume, the 75-percentiles of the simulation results of the two models are almost the same. The mean value of the empty truck hauling distance of the NFS model is 3.61km, which is 9.3% lower than that of the traditional model. However, the median value is only -3.62% lower. The corresponding QQ plot, as shown in Figure 4.39, also shows that the NFS has a higher proportion of material at a lower hauling distance. As the rest proportions, the corresponding value in the NFS method is always lower than that of the traditional method.

The difference in transportation distance leads to a difference in truck transportation time, as shown in Figure 4.40. The mean value of the hauling time of the empty truck in the NFS model is 8.69 minutes, which is 9.48% less than the 9.6 minutes of the traditional model. The empty hauling time data of the 25-percentile and 75-percentile decreased by -17.57% and -8.34%, respectively. Although Figure 4.41 shows that the difference is not apparent, this is due to a wide range selected for comparison. Higher hauling times correspond to longer transport distances, and the two models do not differ much over long distances, leading to this result. When the time range is reduced to 2-7 minutes, as shown in Figure 4.22, the difference becomes obvious.

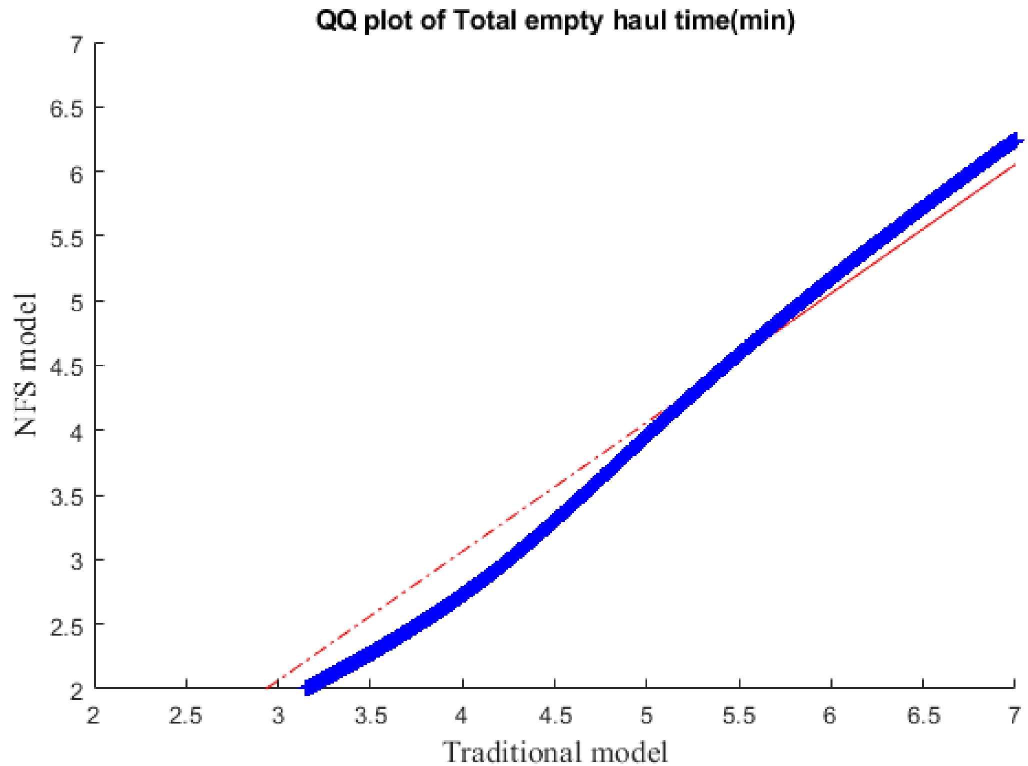

Figure 4.42 QQ plot of empty truck hauling time of NFS method and traditional method (small range)

- Loaded condition

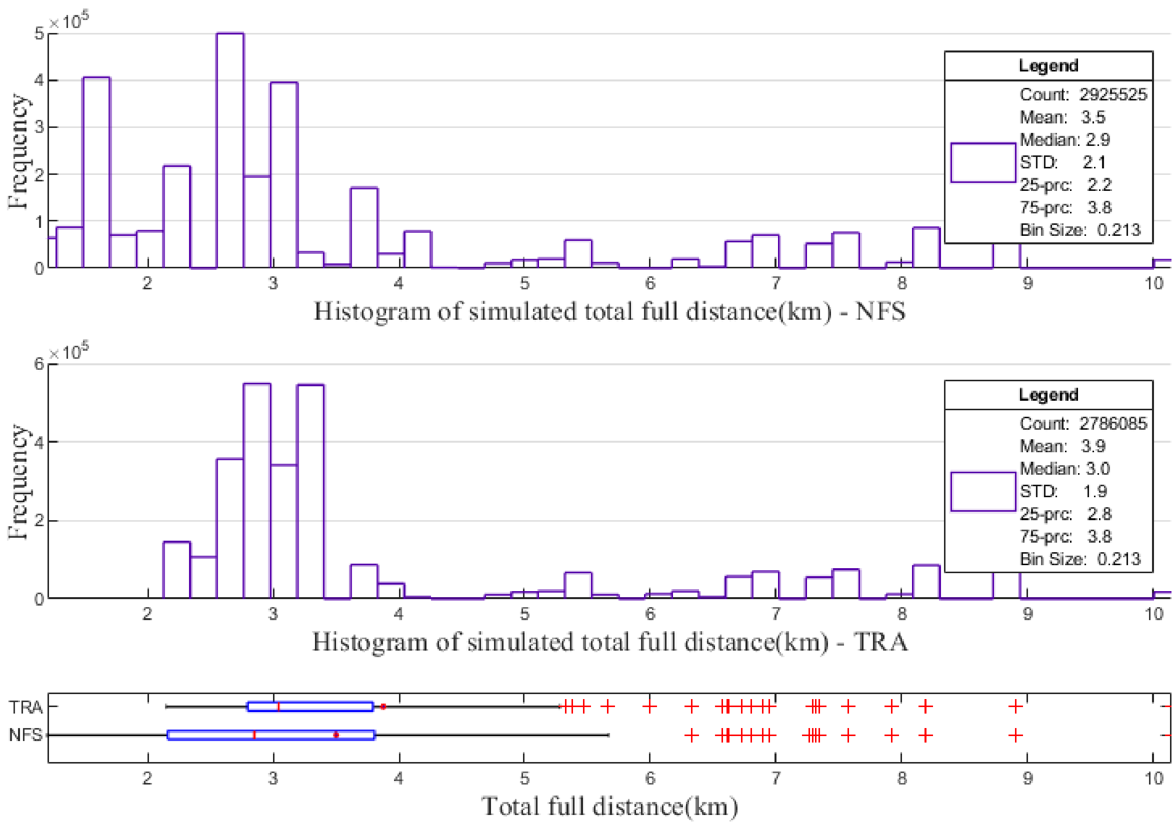

Figure 4.43 Simulated loaded truck hauling distance of NFS method and traditional method

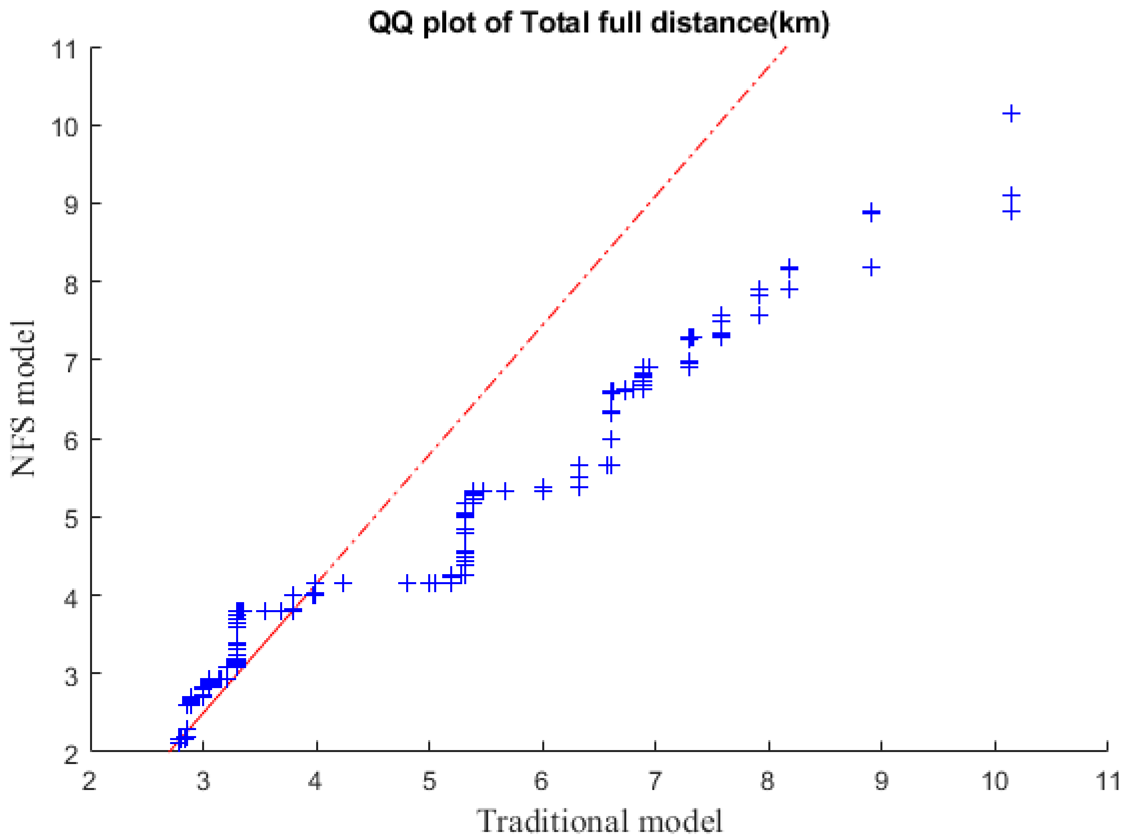

Figure 4.44 QQ plot of loaded truck hauling distance of NFS method and traditional method

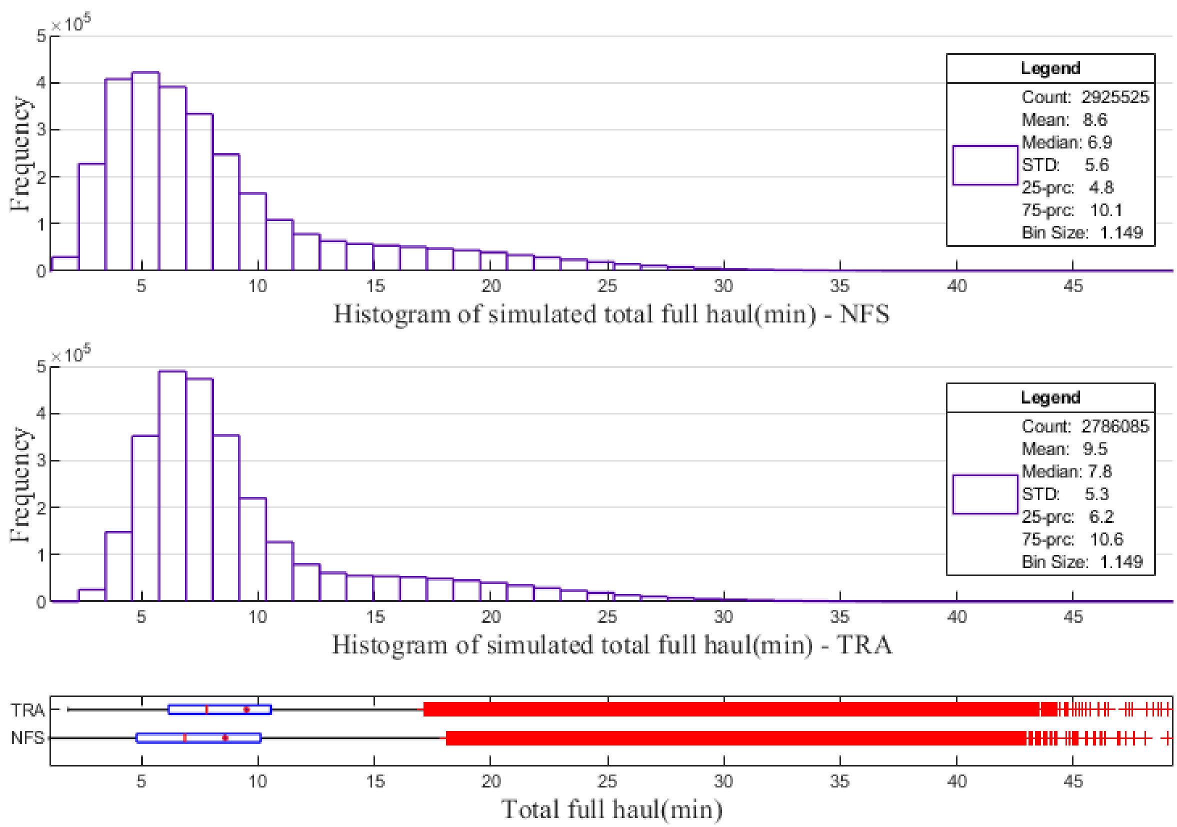

Figure 4.45 Simulated loaded truck hauling time of NFS method and traditional method

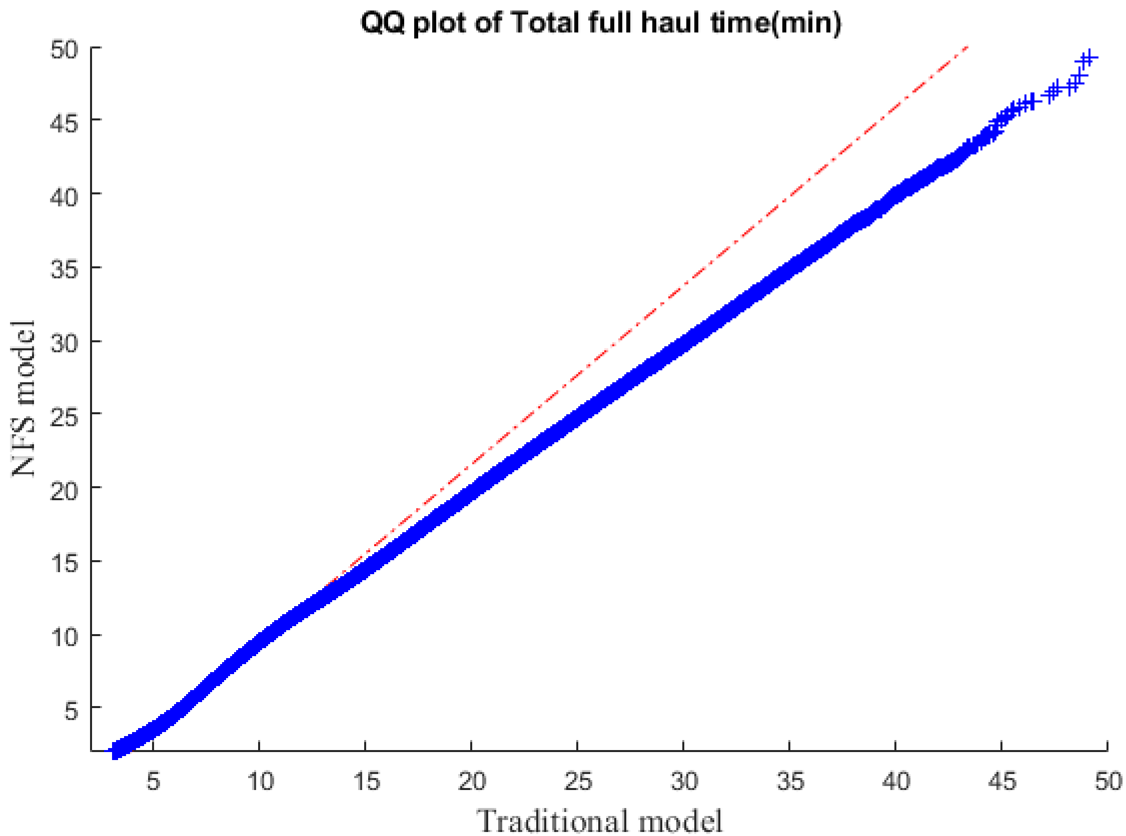

Figure 4.46 QQ plot of loaded truck hauling time of NFS method and traditional method

Table 4.13 Simulated total loaded truck hauling time and hauling distance comparison of the NFS model and traditional model

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Total full distance(km) - SimTra	278,609± 537	7.99±0	3.88 ±0.01	3.04±0	1.87±0	2.8±0	3.79±0	1,079,935 ±2,252
Total full distance(km) - SimNFS	292,553± 696	8.94±0	3.5±0	2.85±0	2.06±0	2.16±0	3.81±0	1,024,348 ±2,315
Difference	5.00%	11.89%	-9.8%	-6.25%	10.16%	-22.9%	0.53%	-5.15%
Total loaded haul time (min) - SimTra	278,609± 537	45.14 ±3.76	9.5 ±0.01	7.8 ±0.02	5.27 ±0.02	6.17 ±0.01	10.55 ±0.02	2,647,558 ±6,881
Total loaded haul time (min) - SimNFS	292,553± 696	45.97 ±3.77	8.59 ±0.01	6.86 ±0.02	5.61 ±0.02	4.78 ±0.02	10.11 ±0.02	2,511,233 ±6,519
Difference	5.00%	1.84%	-9.6%	-12.1%	6.45%	-22.5%	-4.17%	-5.15%

The distinction between loaded truck hauling distance and empty truck hauling distance warrants a separate discussion. Empty truck hauling occurs after the truck has unloaded its contents and is dispatched in real-time to various shovels based on dispatch logic. The randomness in empty truck hauling is determined solely by the number of trucks queued before the shovels. Loaded truck hauling, on the other hand, starts from each block and hauls to different destinations based on the material type. The weight ratio of ore material in the block determines the probability of the loaded truck haul to the crusher, which compared to the waste is considered as a shorter hauling distance.

Figure 4.43 presents a different frequency of each bar in the hauling distance of less than 3 km compared to Figure 4.38. This difference is due to the disparity between the deterministic weight distribution and the uncertain dispatch logic. As shown in Table 4.13, the empty hauling range of the NFS model is 10.87 km, and the loaded hauling range is 7.99 km, whereas in the traditional model, the two numbers are 10.38 km and 8.94 km, respectively. Consequently, the mean value and median value of the loaded truck hauling distance in the NFS model are reduced by 9.79% and 6.25%, respectively, compared to the traditional model. Notably, the standard deviation of the loaded truck hauling distance in the NFS model increases by 10.16% due to the shorter distance between the crusher and the blocks and the unchanged distance between the waste dumps and the blocks. The QQ plots of the two models in this term are shown in Figure 4.44, which is very similar to the Figure 4.39.

The difference in hauling time is more noticeable than that in hauling distance. A comparison of Figure 4.40 and Figure 4.45 shows a considerable reduction in the outlier of the loaded truck hauling time. This is still because the destination of the loaded truck is more deterministic. Furthermore, the mean value and median of the loaded truck hauling time in the NFS model are 8.59 minutes and 6.86 minutes, respectively, representing a reduction of 9.58% and 12.1%, respectively, compared to the traditional model. Conversely, the standard deviation of the loaded truck hauling time increased by 6.45%. Loaded truck hauling time QQ plots of the two methods are shown in Figure 4.46, which is similar to Figure 4.41. However, comparing the two QQ plots, it can be seen that the part of the loaded truck in the small hauling time is higher than that of the empty truck. Therefore, in Figure 4.46, the slope of the line connecting the points is less than 45 degrees.

2. Empty and loaded ore truck hauling distance and hauling time

The previous section discussed and analyzed the differences between the NFS model and the traditional model in terms of hauling distance and hauling time as a whole. This section will focus on the analysis and discussion of the performance of the most affected ore material in terms of hauling distance and hauling time under the two model conditions. Similarly, the two states of the truck: empty and loaded, will still be analyzed separately.

- Empty condition

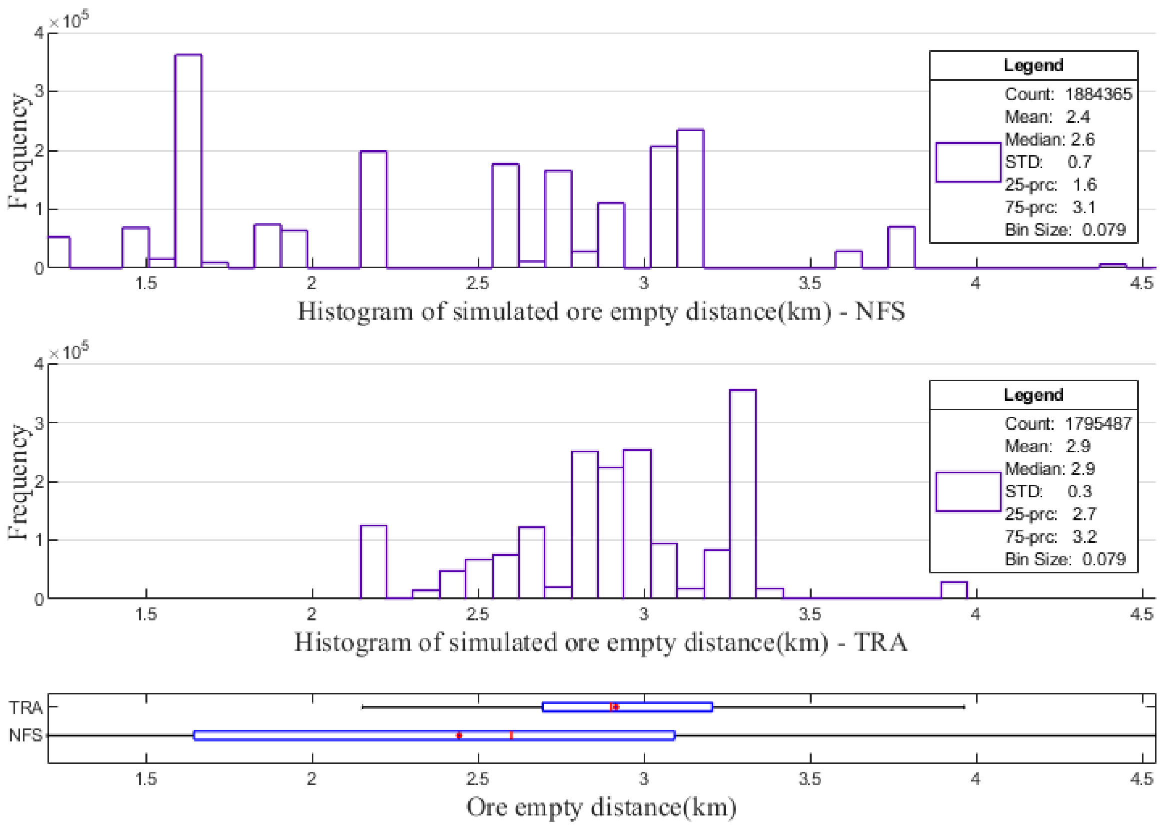

Figure 4.47 Simulated empty ore truck hauling distance of NFS method and traditional method

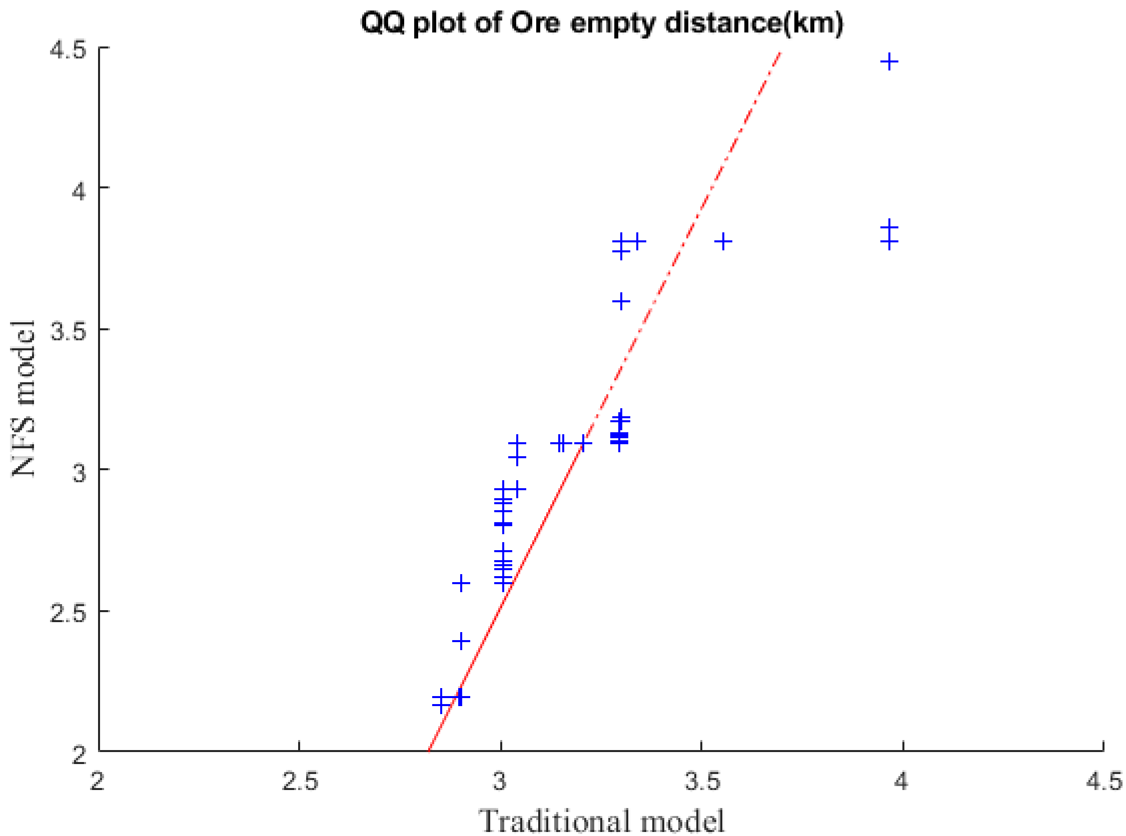

Figure 4.48 QQ plot of empty ore truck hauling time of NFS method and traditional method

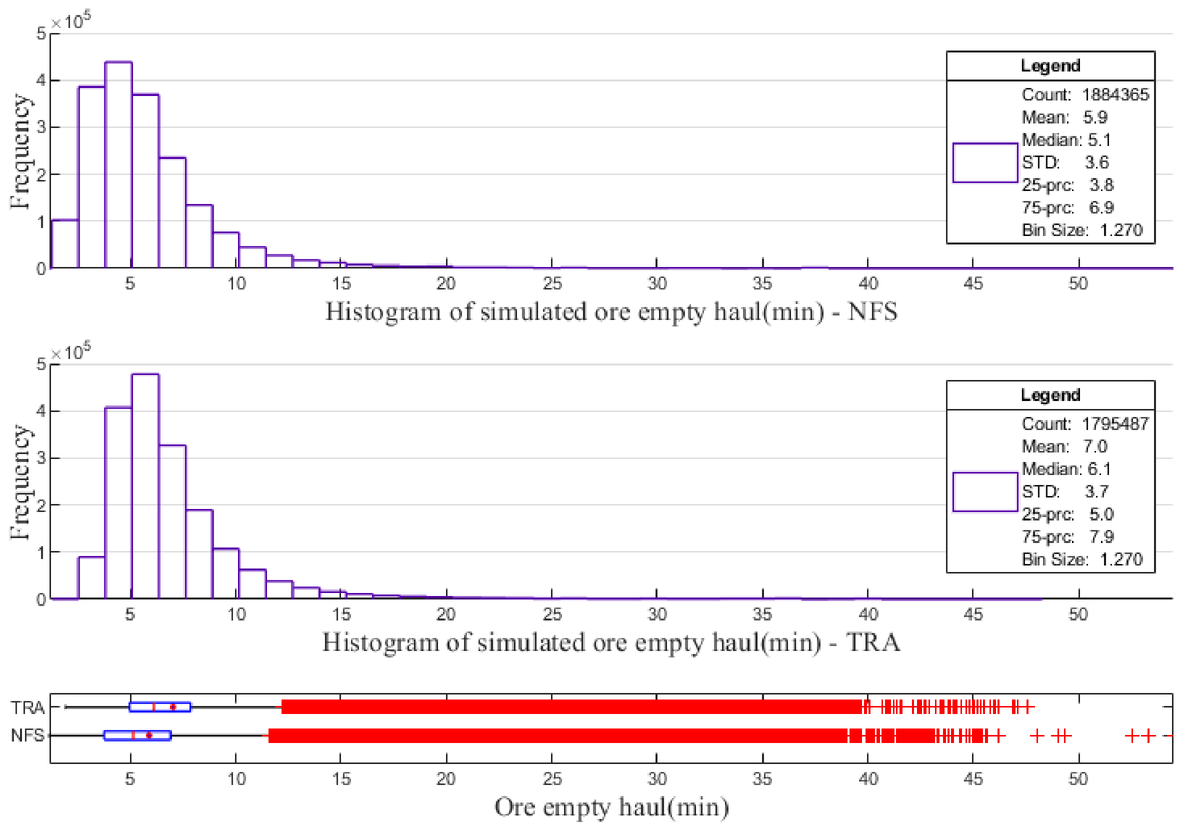

Figure 4.49 Simulated empty ore truck hauling time of NFS method and traditional method

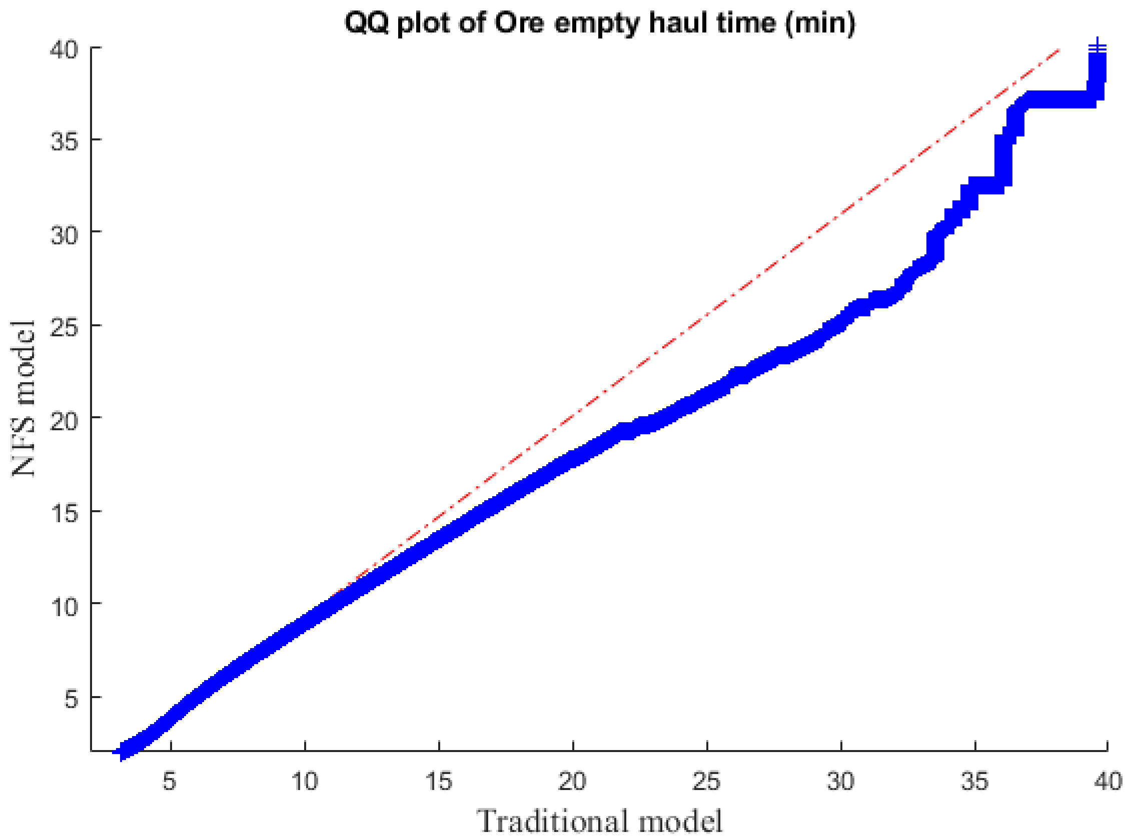

Figure 4.50 QQ plot of empty ore truck hauling distance of NFS method and traditional method

Table 4.14 Simulated ore empty truck hauling time and hauling distance comparison of the NFS model and traditional model

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Ore empty distance (km) - SimTra	181,003 ±433	3.96±0	2.89±0	2.9±0	0.43±0	2.7±0	3.21±0	523,506 ±1,218
Ore empty distance (km)-SimNFS	189,736± 512	4.54±0	2.43 ±0.01	2.6±0	0.72 ±0.01	1.65±0	3.09±0	460,412 ±1,046
Difference	4.82%	14.65%	-15.9%	-10.3%	67.44%	-38.9%	-3.74%	-12.05%
Ore empty haul time(min) - SimTra	181,003 ±433	47.57 ±0	6.97 ±0.02	6.1 ±0.01	3.77 ±0.06	4.93 ±0.02	7.84 ±0.02	1,261,828 ±4,970
Ore empty haul time(min) - SimNFS	189,736 ±512	53.68 ±1.28	5.85 ±0.02	5.11 ±0.01	3.59 ±0.07	3.73 ±0.02	6.89 ±0.02	1,109,939 ±4,867
Difference	4.82%	12.84%	-16.1%	-16.2%	-4.77%	-24.3%	-12.1%	-12.04%

In this section, the author examines the hauling distances and hauling times of empty ore trucks in two different mining models. The so-called empty ore truck is the truck that transports the ore material to the crusher/stockpile and completes the queuing and dumping process. In the traditional model, the starting point for the empty ore truck is at the crusher, while in the NFS model, the starting point is at the stockpile in front of the crusher. The distribution of frequency in Figure 4.47 is very close to the distribution of ore tonnage in each hauling range in Figure 4.30 because the distribution curve of the mass carried by trucks in each cycle is the same in the two models.

The most obvious change is the change in the number of truck cycles. When ore and waste are considered together, the total number of cycles of the NFS model is 292552, and the number of cycles of the traditional model is 278608. But when the ore material is considered separately, these two numbers become 189736 and 181003, respectively. This verifies again that the mass of ore material accounts for about 65% of the total mass.

The analysis shows that the hauling distance range of the empty ore truck in the NFS model is much lower than that of the total material. Specifically, the range of ore truck empty hauling distance is only 4.54 km in the NFS model and 3.96 km in the traditional model, which represents a reduction of 52.7% and 61.8%, respectively, compared to the range of total empty hauling distance in the two models (10.38 km and 10.87 km separately). Correspondingly, the mean value of the two models dropped by 32.7% and 27.4% and the median value decreased by 11.3% and 4.6%.

In addition to the comparison between total material and ore material, the comparison between the two models on ore truck empty hauling distance is also worth describing. As mentioned above, the transportation distance of about 3 million tons of ore materials has become longer, while the transportation distance of other ore materials has become shorter. Therefore, the hauling range of the empty ore truck in the NFS model has increased from 3.96 km to 4.54 km compared with the traditional, which is 14.65% longer. However, other data show that the NFS model has a huge improvement in hauling distance compared to the traditional model. One proof is a 38.9% decrease in the 25-percentile distance and a 3.74% decrease in the 75-percentile distance. Besides, the mean value decreased from 2.89 km to 2.43 km, which is 15.9% lower. This result is consistent with the above-mentioned conclusion that most of the ore material expected a shorter hauling distance to the crusher. The slope of the extrapolation of the quartile line in Figure 4.48 is greater than 1, which also supports this conclusion.

Furthermore, we found in Figure 4.49 and Figure 4.50 that the hauling time of the empty ore truck in the NFS model decreased significantly compared to the traditional model. Specifically, the average hauling time of the empty ore truck in the NFS model decreased from 6.97 minutes to 5.85 minutes, representing a decrease of 16.1%. The 25-percentile and 75-percentile of empty ore truck hauling time data also showed a significant decrease, corresponding to -24.3% and -12.1%, respectively.

Overall, the comparison highlights the significant differences in the hauling characteristics of empty ore trucks between the traditional model and the NFS model. The NFS model shows a significant improvement in reducing the hauling distance and time of the empty ore truck, which could potentially lead to a more efficient and cost-effective mining operation.

- Loaded condition

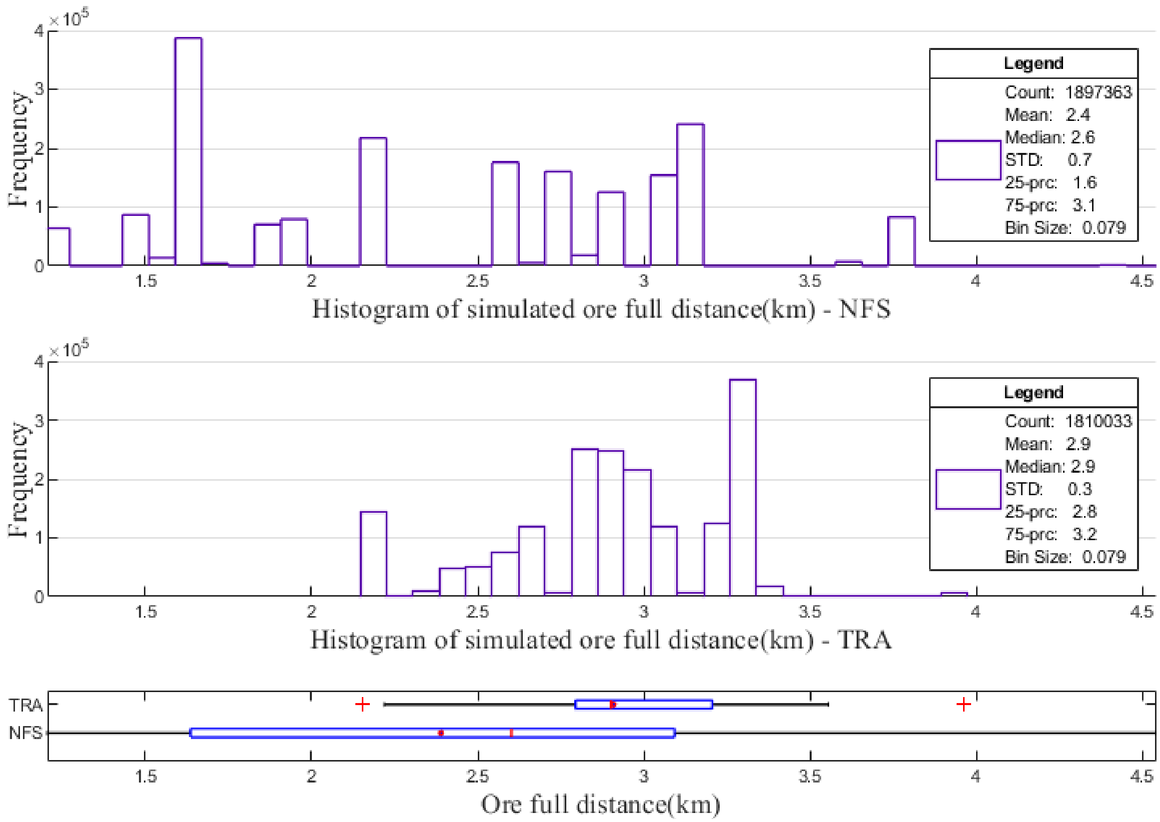

Figure 4.51 Simulated loaded ore truck hauling distance of NFS method and traditional method

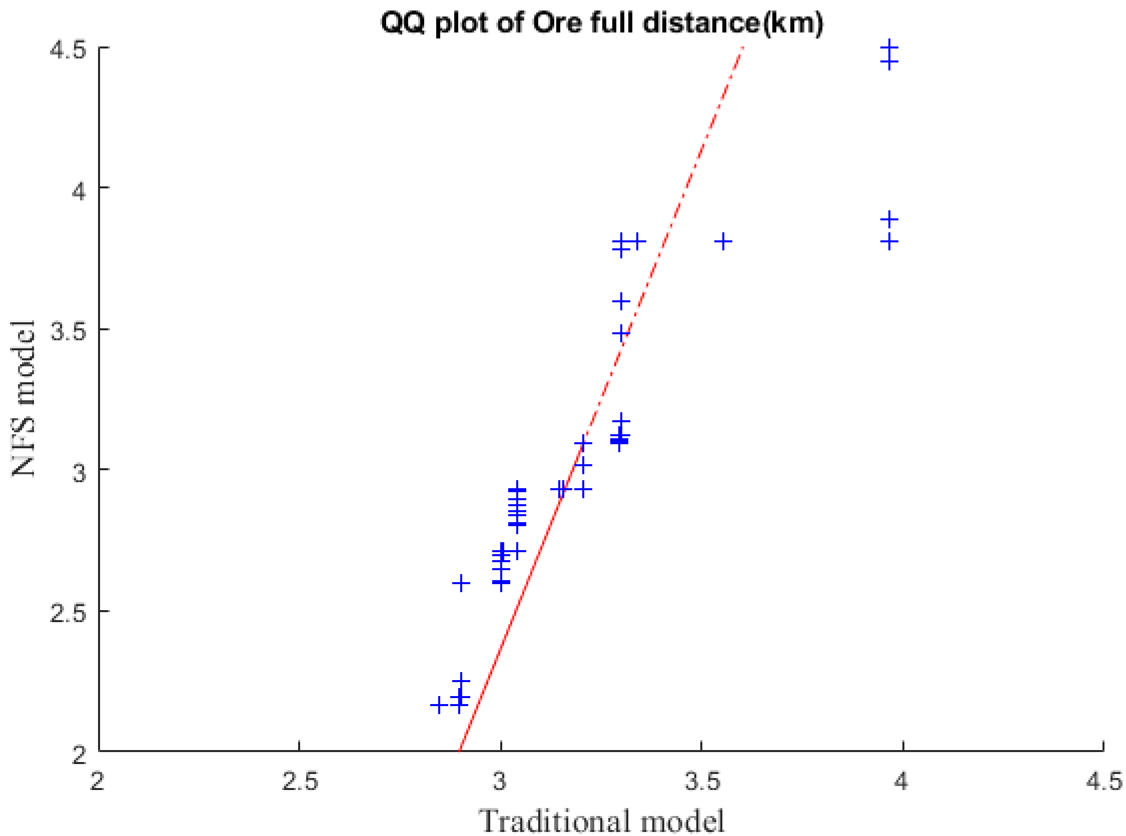

Figure 4.52 QQ plot of loaded ore truck hauling distance of NFS method and traditional method

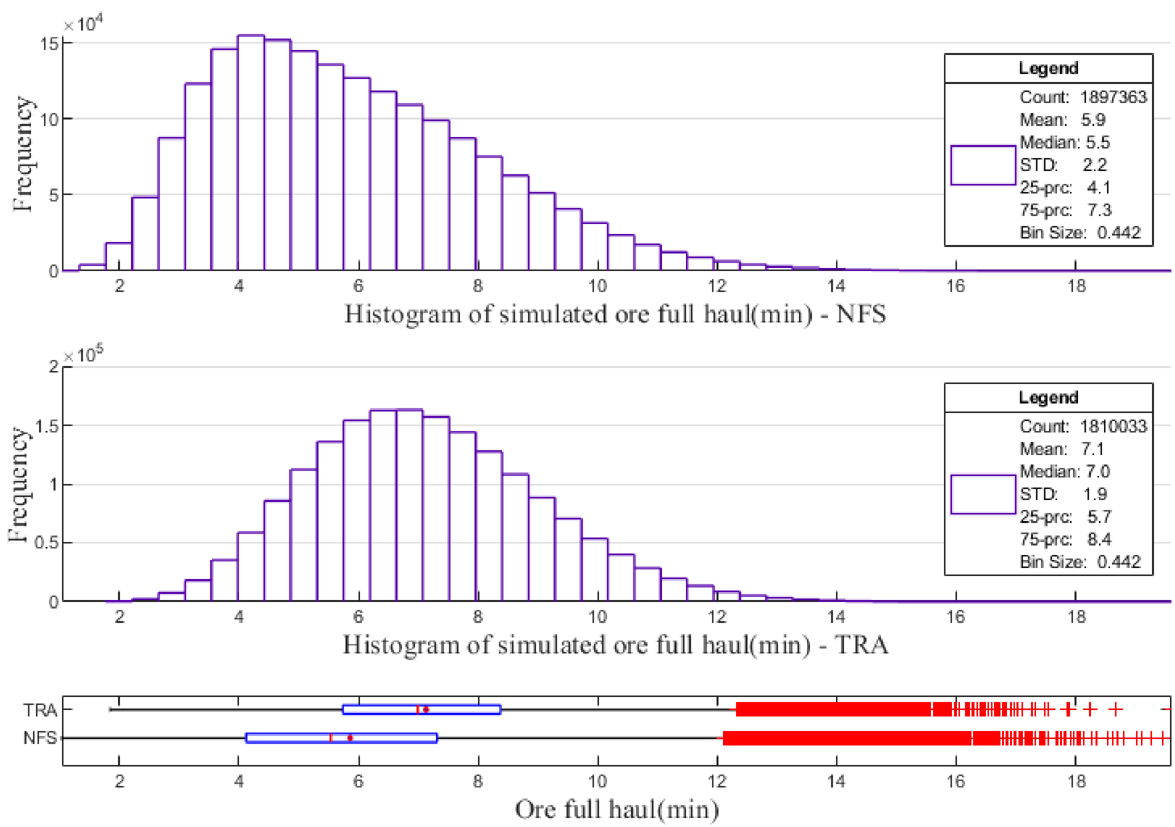

Figure 4.53 Simulated loaded ore truck hauling time of NFS method and traditional method

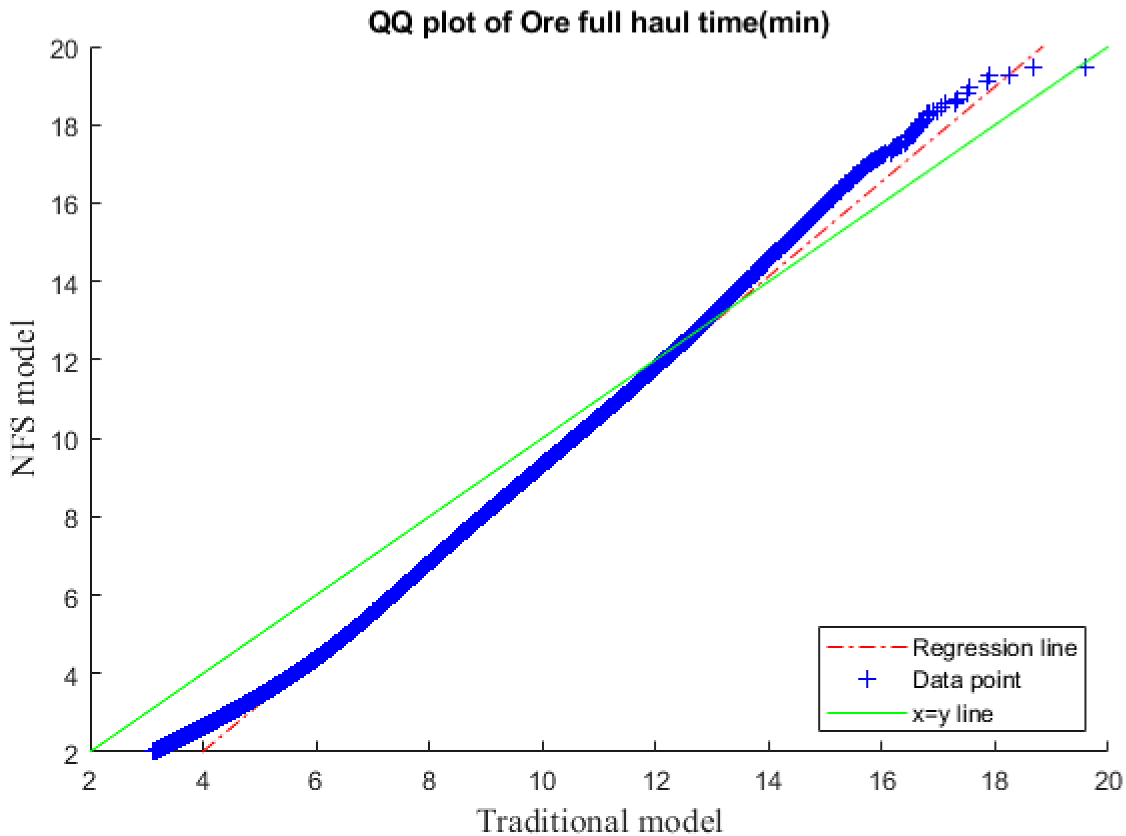

Figure 4.54 QQ plot of loaded ore truck hauling time of NFS method and traditional method

Table 4.15 Simulated loaded ore truck hauling time and hauling distance comparison of the NFS model and traditional model

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Ore loaded distance(km) - SimTra	181,003 ±433	1.81±0	2.91±0	2.9±0	0.33 ±0	2.77 ±0.07	3.21±0	526,510 ±1,209
Ore loaded distance(km) - SimNFS	189,736 ±512	3.34±0	2.39±0	2.6±0	0.69 ±0	1.64±0	3.09±0	453,376 ±864
Difference	4.82%	84.5%	-17.9%	-10.3%	109%	-40.8%	-3.74%	-13.89%
Ore loaded haul time (min) - SimTra	181,003 ±433	15.82 ±2.03	7.13 ±0.01	6.99 ±0.01	1.93 ±0.01	5.74 ±0.01	8.38± 0.01	1,290,390 ±4,438
Ore loaded haul time (min) - SimNFS	189,736 ±512	17.82 ±1.26	5.86 ±0.02	5.53 ±0.02	2.25 ±0.01	4.12 ±0.02	7.32± 0.02	1,111,681 ±3,031
Difference	4.82%	12.6%	-17.8%	-20.9%	16.6%	-28.2%	-12.7%	-13.85%

In this section, the author presents the results of comparing the loaded ore truck hauling distance and hauling time under two simulation models. Figure 4.51, which shows the loaded ore truck hauling distance is very similar to, but not identical to Figure 4.47, which shows the empty ore truck hauling distance. It should be noted that the former is a deterministic distribution, while the latter contains randomness caused by dispatch logic. Similarly, QQ plots, Figure 4.52 and Figure 4.48 show them same trend.

To further compare the two models, the author lists the simulated data in Table 4.15. The average loaded ore truck hauling distance of the NFS model is found to be 2.39 km, which is lower than that of the traditional model, which is 2.91 km. However, the average empty ore truck hauling distance in the two models is 2.43 km and 3.04 km, respectively. The randomness of dispatch logic has been found to introduce differences of 1.17% and 4.38% in the two models, respectively.

When considering only the loaded ore truck hauling distance, the mean and median values of the NFS model are found to be respectively reduced by 17.87% and 10.34% compared to the traditional model. It is worth noting that, compared to the range of 1.81 km in the loaded ore truck hauling distance in the traditional model, the range in the NFS model is 3.34 km, with an increase of 84.53%. The increase in this value is mainly because the transportation distance of some ore materials has been shortened and the transportation distance of the others has been increased.

Furthermore, although the difference in the average transportation distance between loaded ore trucks and empty ore trucks is small, the distribution of hauling time under the two conditions is more visible, as shown in Figure 4.53. The most obvious difference is the significant reduction of outliers with larger values. This is evident from the fact that the range of loaded ore truck hauling time is reduced to 17.82 minutes and 15.82 minutes in the NFS and traditional models, respectively, a drop of 66.8% and 66.7% compared to the range of empty ore truck hauling time. When comparing only the loaded condition, the mean loaded ore truck hauling time of the NFS model is 17.81% lower than that of the traditional model. The QQ plot of this item shows this more clearly. As shown in Figure 4.54, in more than 90% of overall results (hauling time less than 12.3 minutes), the hauling time of the loaded ore truck in the NFS model is shorter than that of the traditional model.

In conclusion, compared to the traditional model, the NFS model shows significant improvements in ore material transportation distance and transportation time under both empty conditions and loaded conditions, which increases the utilization of the truck per cycle.

3. Empty and loaded waste truck hauling distance and hauling time

This section mainly discusses and analyzes the performance of waste truck under the empty and loaded conditions in the two models.

- Empty condition

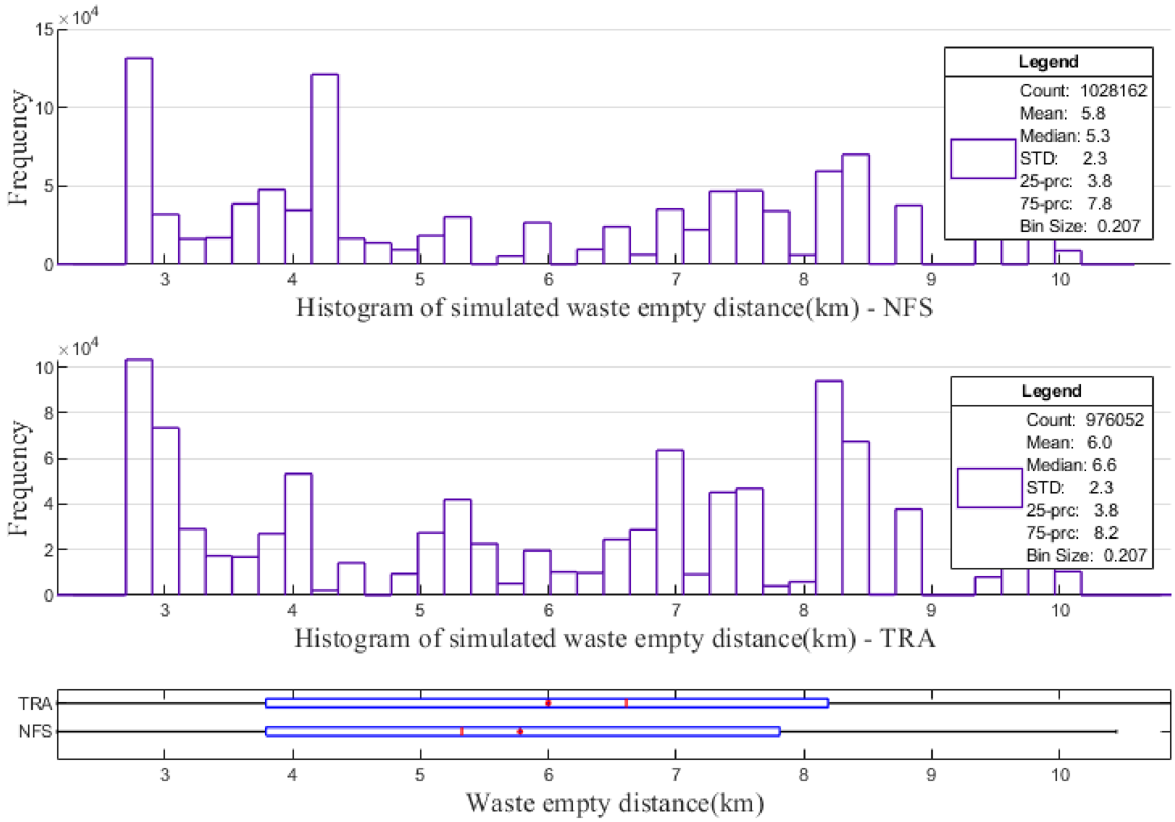

Figure 4.55 Simulated empty waste truck hauling distance of NFS method and traditional method

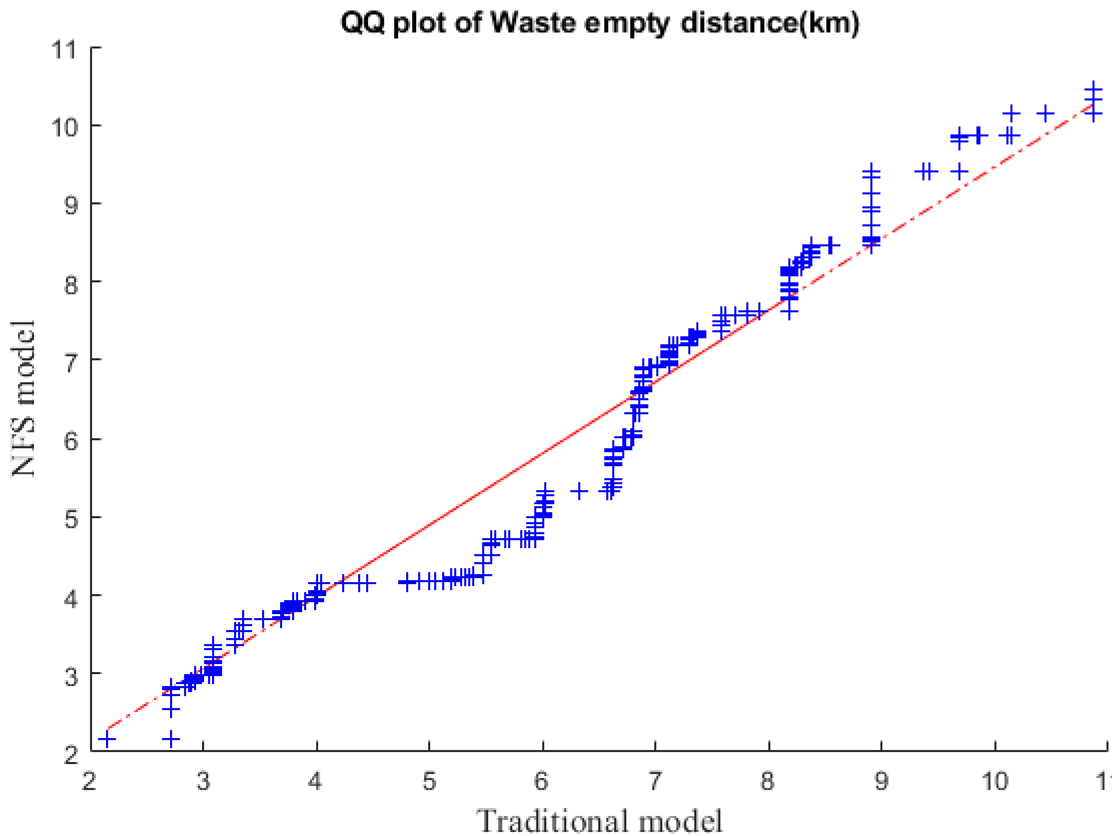

Figure 4.56 QQ plot of empty waste truck hauling distance of NFS method and traditional method

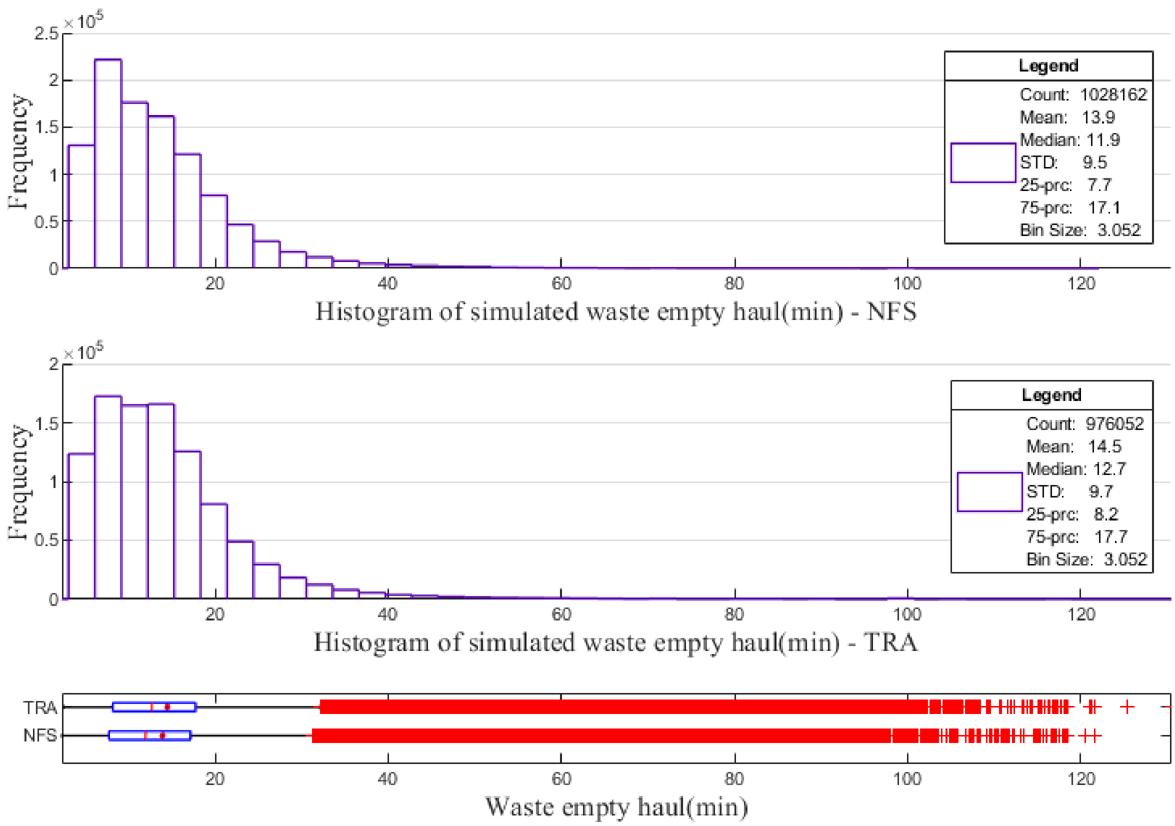

Figure 4.57 Simulated empty waste truck hauling time of NFS method and traditional method

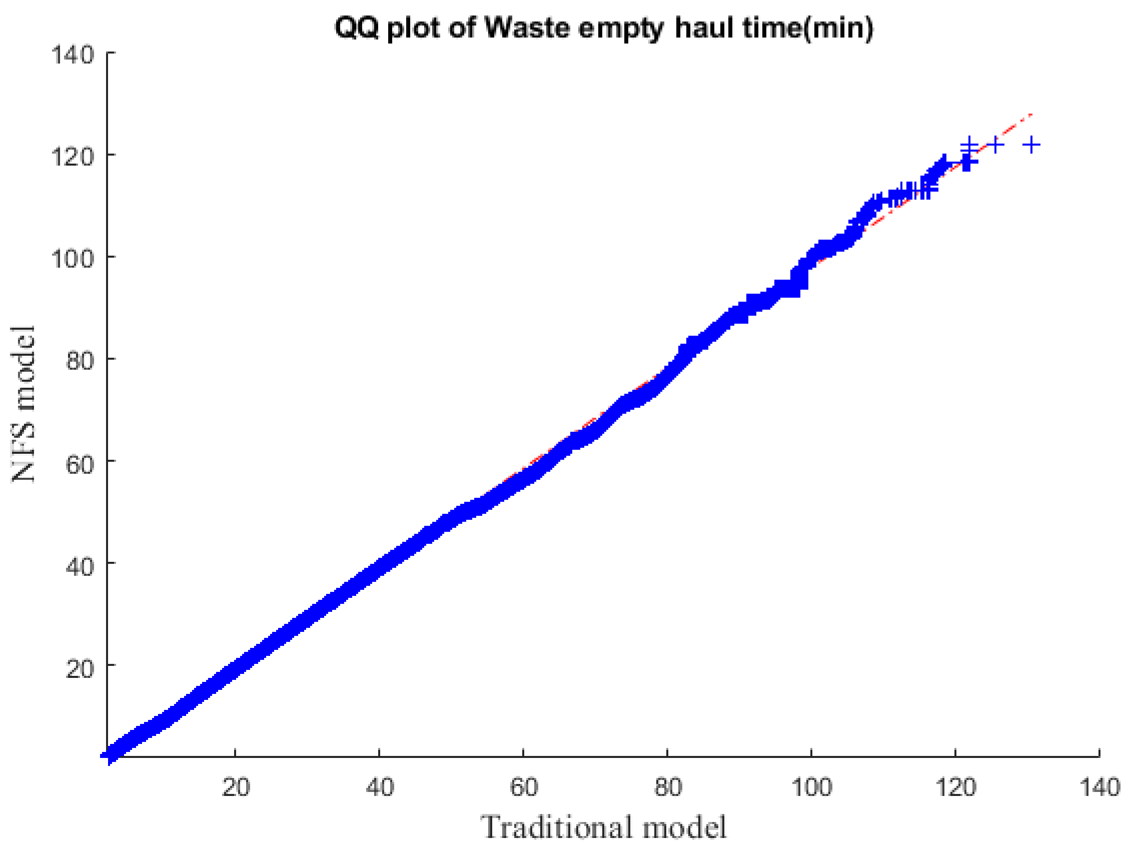

Figure 4.58 QQ plot of empty waste truck hauling time of NFS method and traditional method

Table 4.16 Simulated waste empty truck hauling time and hauling distance comparison of the NFS model and traditional model

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Waste empty distance (km) - SimTra	97,605 ±354	8.71±0	6±0.01	6.61±0	2.28± 0.01	3.79±0	8.19±0	585,731 ±2,282
Waste empty distance (km) - SimNFS	102,816 ±379	8.22± 0.29	5.78 ±0.01	5.33 ±0.06	2.27±0	3.79±0	7.81±0	594,231 ±2,278
Difference	5.34%	-5.63%	-3.67%	-19.4%	-0.44%	0.00%	-4.64%	1.45%
Waste empty haul time(min) - SimTra	97,605 ±354	121.2 ±8.34	14.47 ±0.06	12.7 ±0.04	9.7± 0.16	8.16 ±0.07	17.74 ±0.07	1,412,500 ±5,756
Waste empty haul time(min) - SimNFS	102,816 ±379	119.2 ±0.25	13.93 ±0.06	11.95 ±0.05	9.46 ±0.2	7.74 ±0.04	17.15 ±0.07	1,432,139 ±4,373
Difference	5.34%	-1.66%	-3.73%	-5.91%	-2.47%	-5.15%	-3.33%	1.39%

Similar to empty ore truck, the empty waste truck is defined as a truck that transports waste material to the designated waste dump and completes the unloading procedure, with its hauling starting point at the waste dump. In contrast to the ore material, the waste material in each block is transported to the waste dump without a change in distance. As a result, the difference in simulation results between the two models with regard to transportation distance aspect is minor, primarily influenced by the uncertainty of dispatch logic. According to Figure 4.55 and Table 4.16 as the QQ plot Figure 4.56, the average empty waste truck hauling distance for the NFS model and the traditional model is 5.78 km and 6.0 km, respectively, with a gap of 3.67%. The discrepancies in the relevant data at the 25th and 75th percentiles are 0.00% and -4.64%, respectively. However, on the median value, the gap between the NFS model and the traditional model is 19.36%, indicating that the NFS model has a higher concentration in the middle distance.

A minor difference in the hauling distance leads to a correspondingly minor difference in the hauling time distribution, as shown in Figure 4.57 and Figure 4.58. The average difference in the empty waste truck hauling time range is only 1.66%. Therefore, although the NFS model shows slightly better performance than the traditional model in the hauling distance and hauling time of the empty waste truck, the difference is not statistically significant.

- Loaded condition

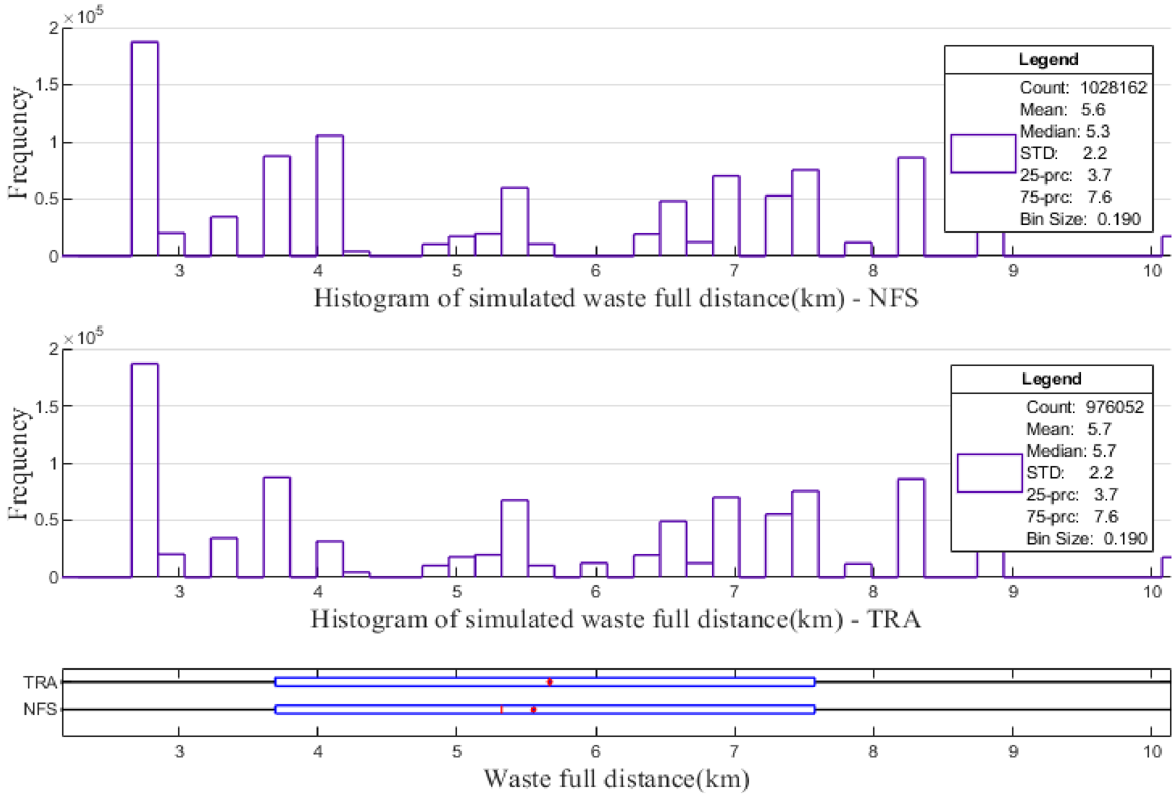

Figure 4.59 Simulated loaded waste truck hauling distance of NFS method and traditional method

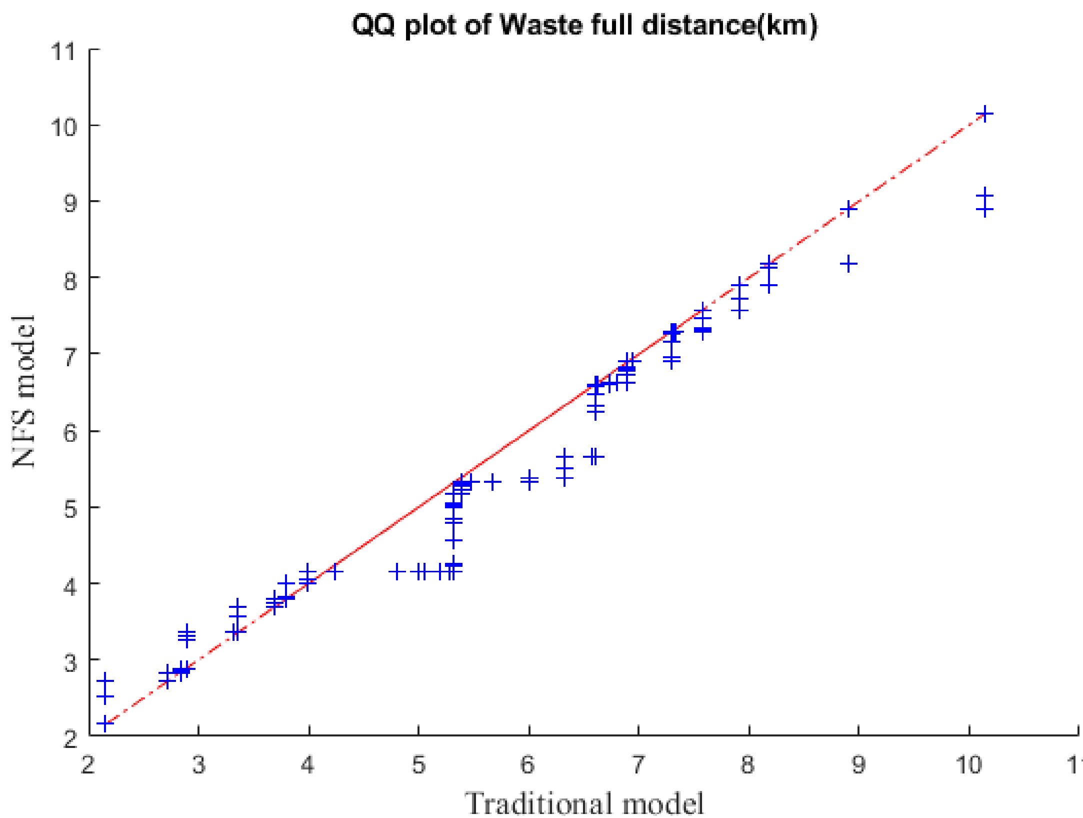

Figure 4.60 QQ plot of loaded waste truck hauling distance of NFS method and traditional method

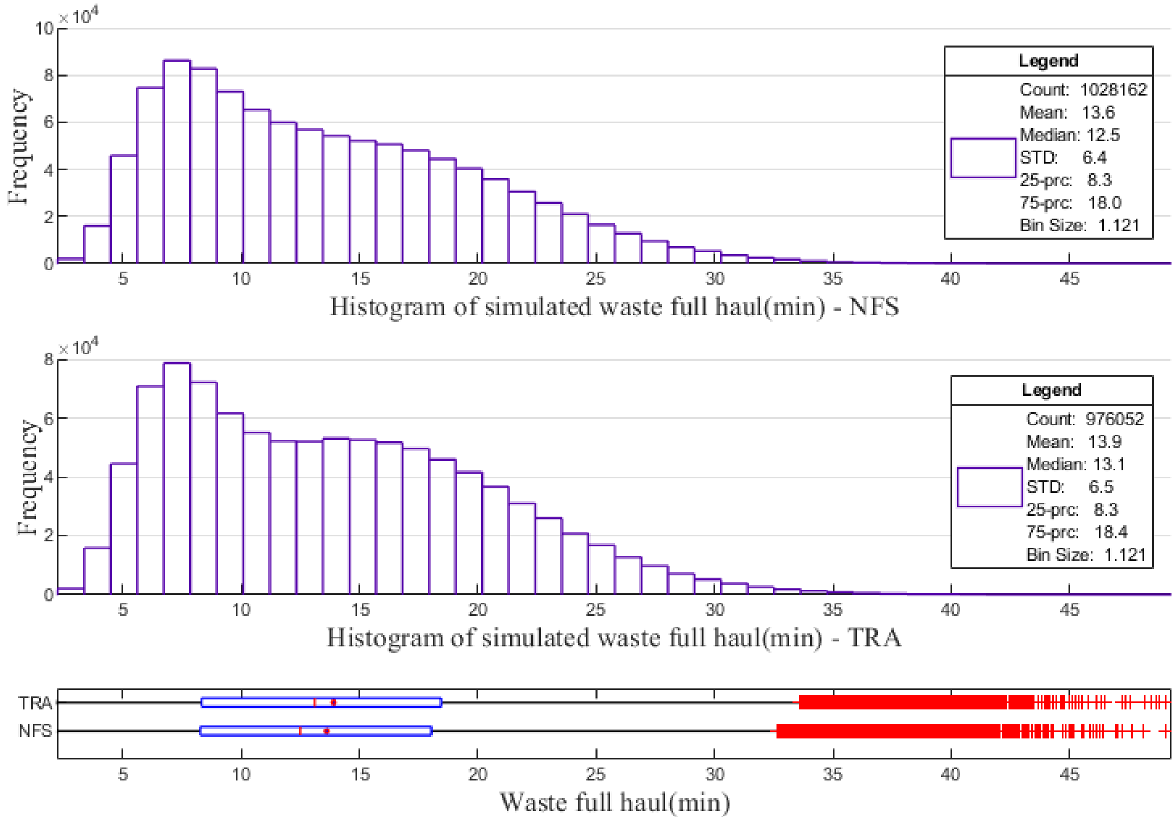

Figure 4.61 Simulated loaded waste truck hauling time of NFS method and traditional method

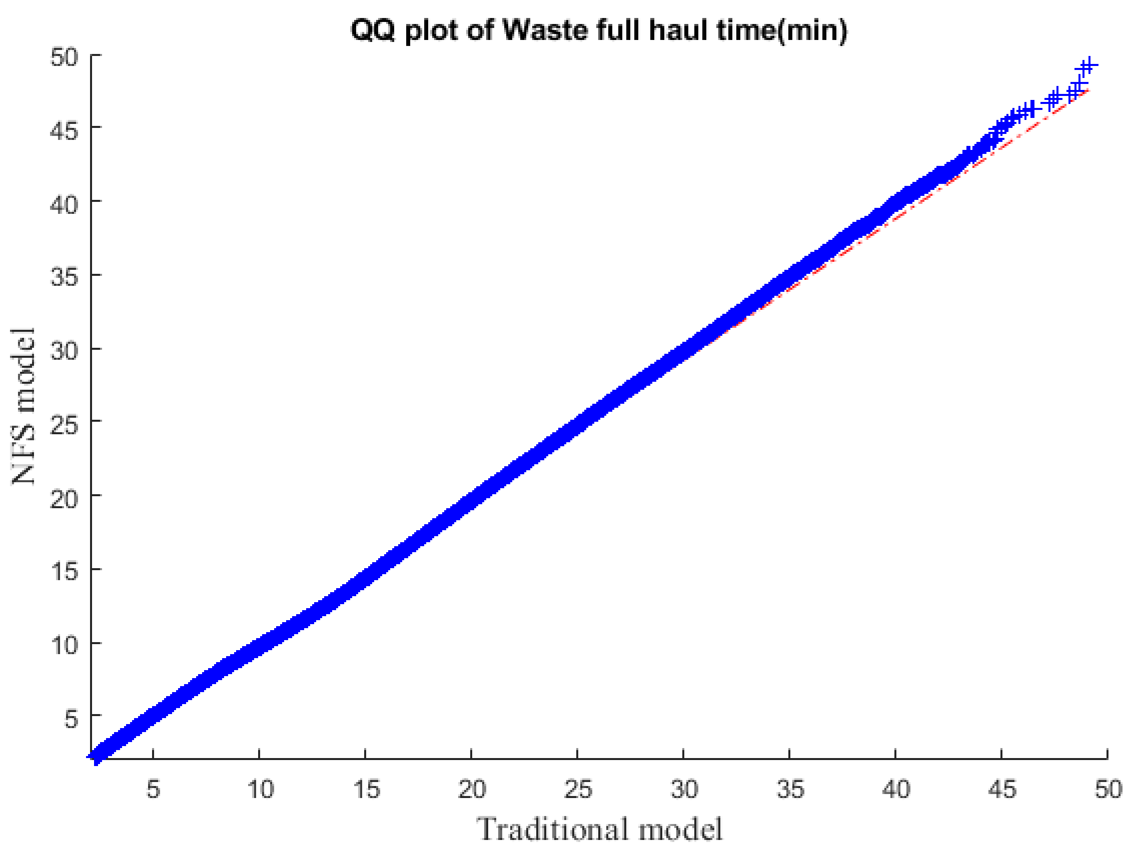

Figure 4.62 QQ plot of loaded waste truck hauling time of NFS method and traditional method

Table 4.17 Simulated waste loaded truck hauling time and hauling distance comparison of the NFS model and traditional model

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Waste loaded distance (km) - SimTra	97,605 ±354	7.98±0	5.67±0	5.67±0	2.2± 0.01	3.7±0	7.58±0	553,425 ±22,05
Waste loaded distance (km) - SimNFS	102,816 ±379	7.98±0	5.55 ±0.01	5.32±0	2.18±0	3.7±0	7.58±0	570,972 ±2,014
Difference	5.34%	0.00%	-2.12%	-6.17%	-0.91%	0.00%	0.00%	3.17%
Waste loaded haul time(min) - SimTra	97,605 ±354	44.7 ±3.8	13.9 ±0.03	13.1 ±0.05	6.5± 0.03	8.3± 0.04	18.5± 0.06	1,357,168 ±5,447
Waste loaded haul time(min) - SimNFS	102,816 ±379	44.7 ±3.7	13.6 ±0.03	12.5 ±0.03	6.4± 0.03	8.3± 0.03	18.0± 0.06	1,399,552 ±5,844
Difference	5.34%	0.13%	-2.16%	-4.73%	-1.38%	-0.72%	-2.28%	3.12%

In this section, the author investigated the hauling distance and time of loaded waste trucks and compared the performance of the traditional model with that of the NFS model. Our results indicate that the hauling distance under loaded conditions is more certain than under empty conditions, as represented by the total distribution of waste material in each hauling distance range (Figure 4.59). Furthermore, due to the further improvement in certainty, a reduction in the difference between the two models compared to the empty condition is expected and observed by comparing Figure 4.55 and Figure 4.59. More specifically, Table 4.17 shows that the 25-percentile and 75-percentile results of the NFS model are identical to those of the traditional model, indicating a high degree of similarity in their performance. The comparison between Figure 4.60 and Figure 4.56 also shows that the distribution of hauling distance of loaded waste trucks is closer than that of the empty waste truck.

In terms of hauling time, we observed a similar trend of decreased difference between the two models under loaded conditions, as shown in Figure 4.61 and Figure 4.62. Specifically, the difference in hauling distance range between the two models drops from 1.66% to 0.13%, while the difference in average hauling time drops from 3.73% to 2.16%. These results suggest that the performance of the NFS model is superior to that of the traditional model even on waste trucks, despite only small differences in hauling distance and time being observed between the two models.

4.5.3 Truck queueing time

Queue time is also an important indicator to objectively evaluate a mining method. The queue time here is mainly for trucks because the amount of other equipment is much smaller than the number of trucks. A longer queue time will reduce truck utilization and driver efficiency, indirectly increase unnecessary operating costs, and result in lower profits.

In this mining activity, the queue will mainly occur in two places: the dumping area and the loading area. These two parts will be discussed separately in this section. Since the destinations of ore material and waste material are different and the dumping environment is different, the queue time of ore and waste will be discussed separately.

1. Dumping queue time

This section mainly discusses and analyzes the performance of ore and waste truck on the dumping queue under the two models.

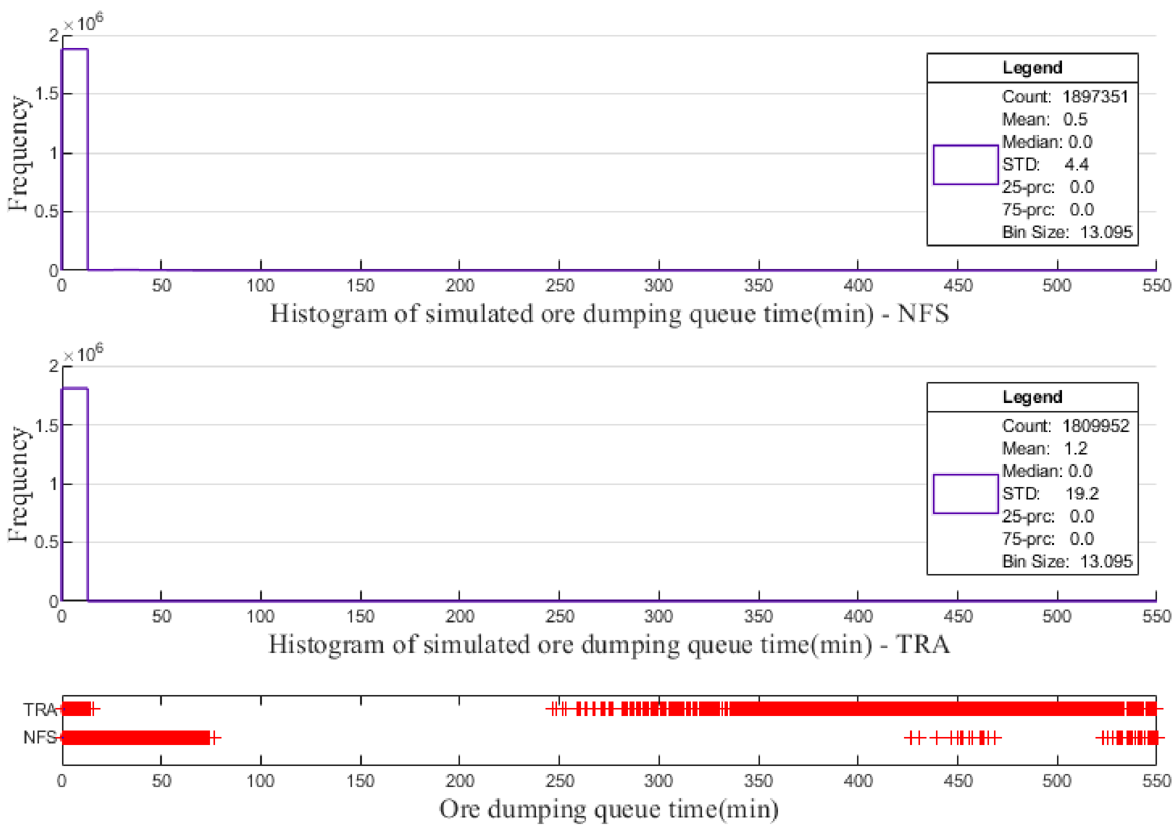

Figure 4.63 Simulated ore truck dumping queue time of NFS method and traditional method

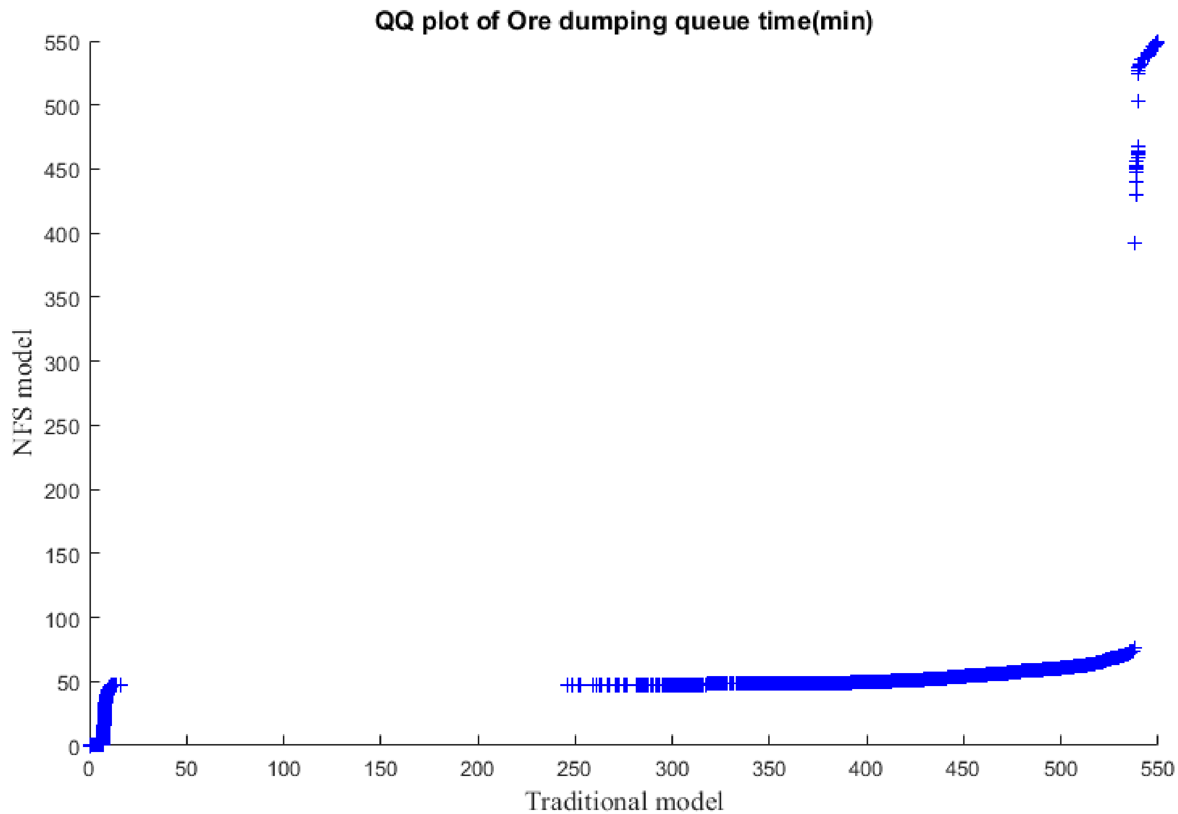

Figure 4.64 QQ plot of ore dumping time of NFS method and traditional method

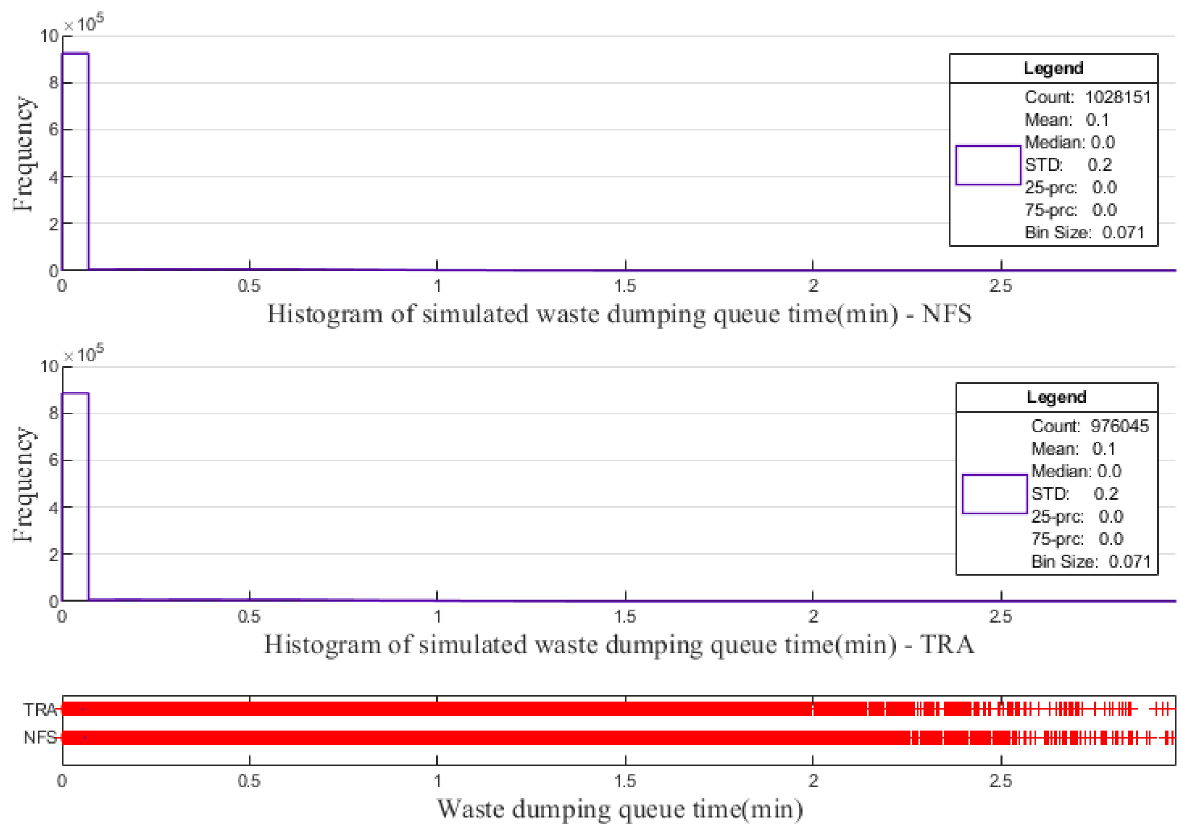

Figure 4.65 Simulated waste truck dumping queue time of NFS method and traditional method

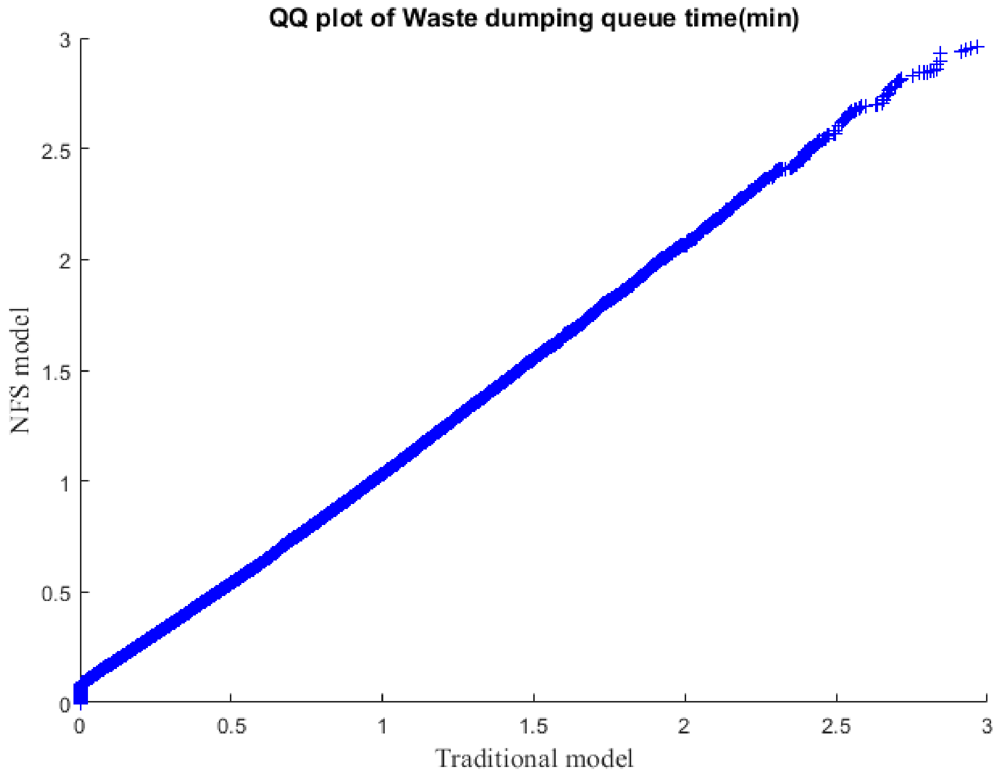

Figure 4.66 QQ plot of waste dumping time of NFS method and traditional method

Table 4.18 Ore and waste dumping queue comparison between NFS method and traditional method

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Ore dumping queue time(min) - SimTra	181,003 ±433	553 ±55	1.26± 0.06	0±0	19.5 ±0.73	0±0	0±0	227,631 ±9,818
Ore dumping queue time(min) - SimNFS	189,736 ±512	292± 232	0.54± 0.07	0±0	4.6 ±2.6	0±0	0±0	102,180 ±12,652
Difference	4.82%	-47.3%	-57.1%	-	-77%	-	-	-55.11%
Waste dumping queue time(min) - SimTra	97,605 ±354	3.05± 0.88	0.06± 0.01	0±0	0.2 ±0	0±0	0±0	5,458 ±139
Waste dumping queue time(min) - SimNFS	102,816± 379	3.12± 0.58	0.06±0	0±0	0.2 ±0	0±0	0±0	6,273 ±203
Difference	5.34%	2.30%	0.00%	-	4.8%	-	-	14.94%

It can be seen from Figure 4.63 and Figure 4.64 that in most cases, the ore trucks in the two models do not need to wait in the queue and can directly dump the carried ore material into the crusher/stockpile. The data in Table 4.18 shows that the length of the ore truck dumping queue over 75-percentile is zero. However, the probability of trucks waiting in the dumping queue for a long time (greater than 20 min) in the traditional model is much greater than that in the NFS model. There are mainly two reasons for the long waiting in the dump queue. One is that the crusher is working at full capacity at that time, and the trucks needed to wait in the queue until there is enough room for dumping. Another reason, which is also the main reason, is that the crusher is in a state of failure or maintenance and stops working, so the trucks have to wait until the crusher resumed its working state before unloading the ore material they carried.

Although these two reasons will interfere with the work efficiency of trucks, it can be seen that the impact that the NFS method suffers from is much smaller than that of the traditional model. This is also one of the important theoretical advantages of the NFS method, that is, the mutual impact of the mill process and the mining process is reduced, thereby improving the utilization rate of the truck. As mentioned above, this can be contributed to the existence of the stockpile. When the crusher is not working during scheduled hours or unscheduled hours, trucks can continue to unload minerals into the stockpile instead of waiting in a queue. The data shows that the average waiting time for trucks in the NFS model is 0.54 minutes or 32 seconds. The only situation where the dumping queue is generated in the NFS model is when the three zones of the stockpile are all fulfilled, and trucks need to wait for the reclaim shovel to complete the reclaiming work of at least one zone. The average wait in dumping time for trucks in the traditional model is 1.26 minutes or 76 seconds. The NFS method reduces the dumping queue time by 57.1%, greatly improving the utilization of the trucks.

As for the waste dumping queue, the results of the two models are almost zero and there is no significant difference, as can be seen in Figure 4.65. This is because the waste dump is considered to be in the state of accepting material all the time in the simulation period and will not fail. In addition, since the movement distance of waste material is not changed, this result is in line with expectations.

Overall, the simulation results verify the theoretical advantages of the NFS method and quantitatively conclude that it can reduce waiting time by 57% and improve the utilization rate of the truck and personnel efficiency compared with the traditional crusher out-of-pit mining method. This study provides important insights into the optimization of the mining process and can serve as a reference for future studies.

2. Loading queue time and queue length

This section mainly discusses and analyzes the performance of trucks on the loading queue under two simulation models. In addition to queue time, queue length before each shovel is also compared. The length comparison can be used to assist in judging the effective utilization of the truck. In addition, it can also be used to judge whether the dispatch logic reasonably allocates trucks to each shovel.

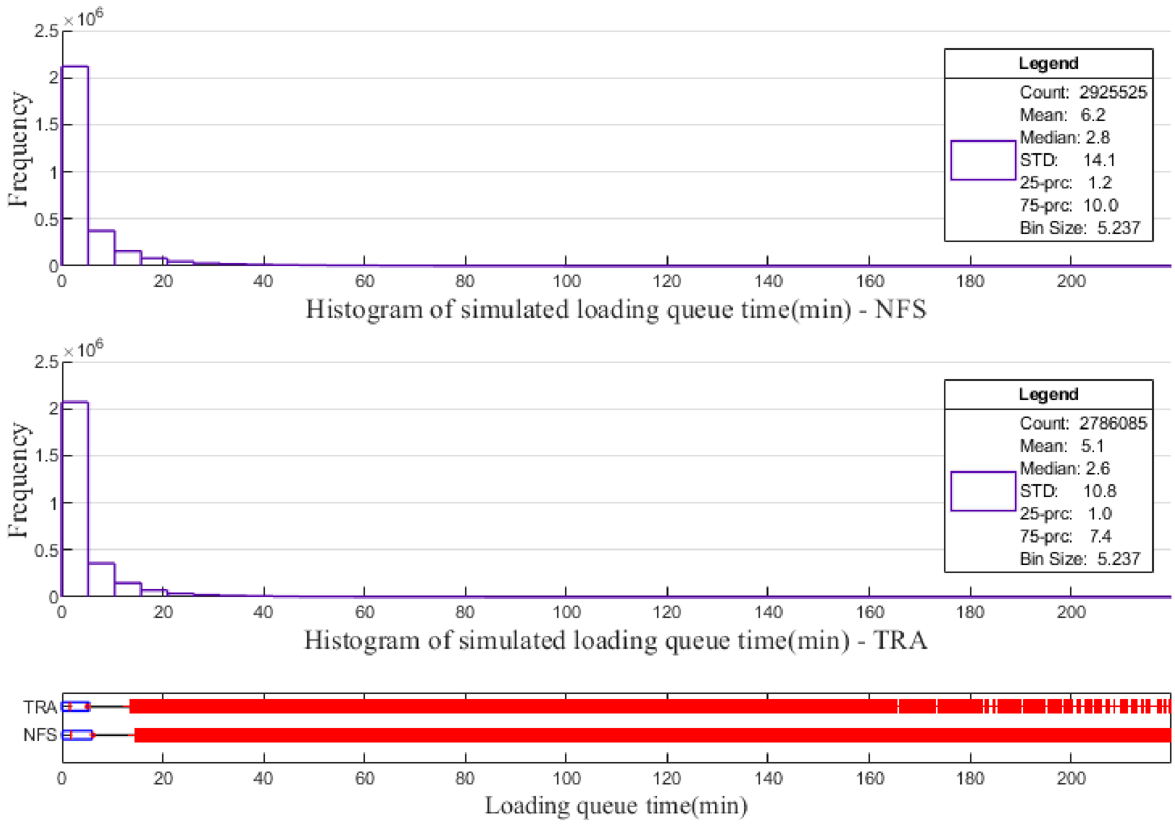

Figure 4.67 Simulated loading queue time of NFS method and traditional method

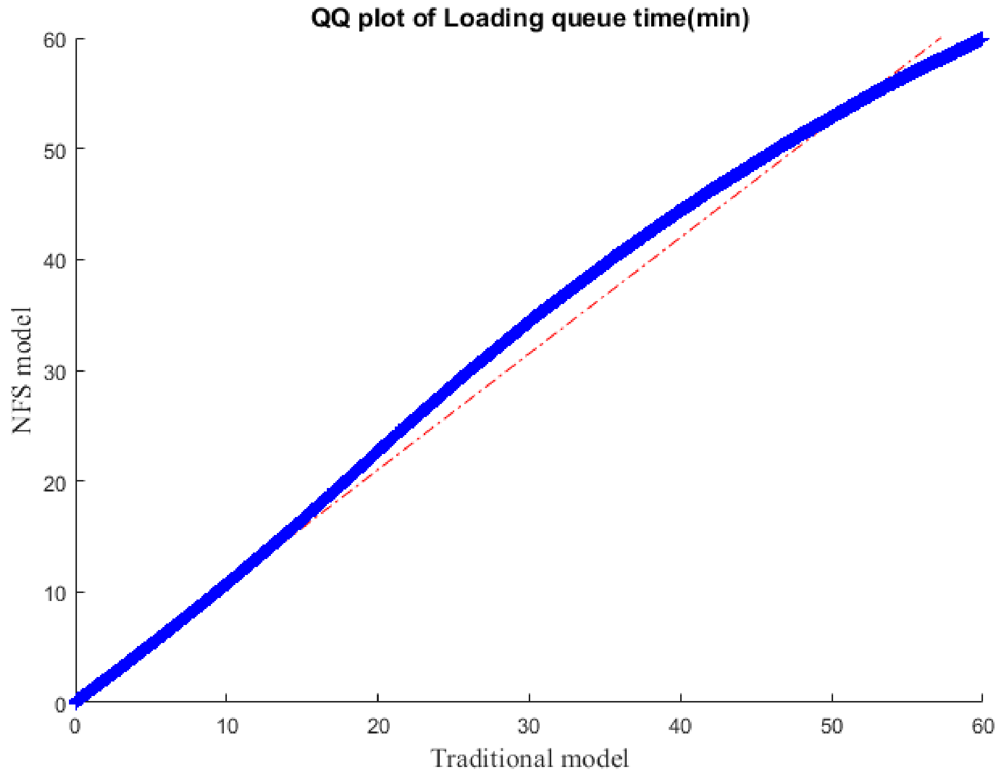

Figure 4.68 QQ plot of shovel loading time of NFS method and traditional method

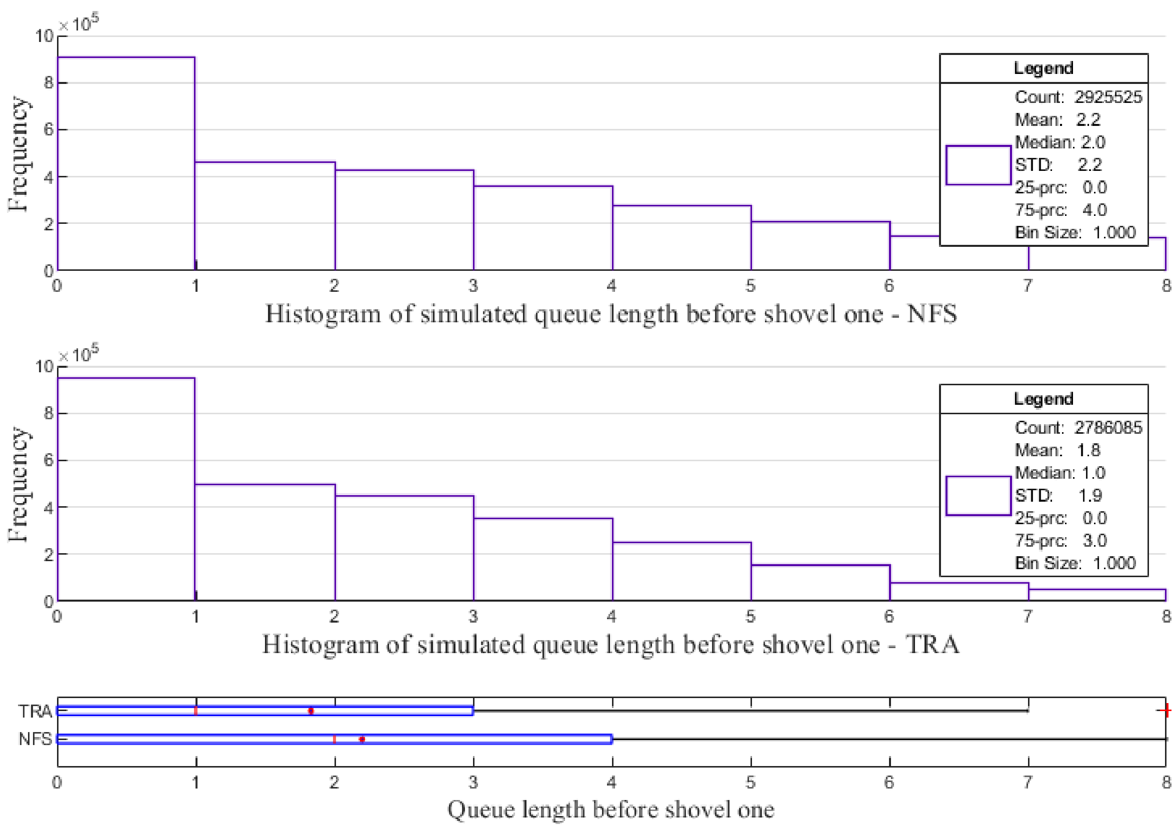

Figure 4.69 Queue length comparison of NFS method and traditional method before shovel one

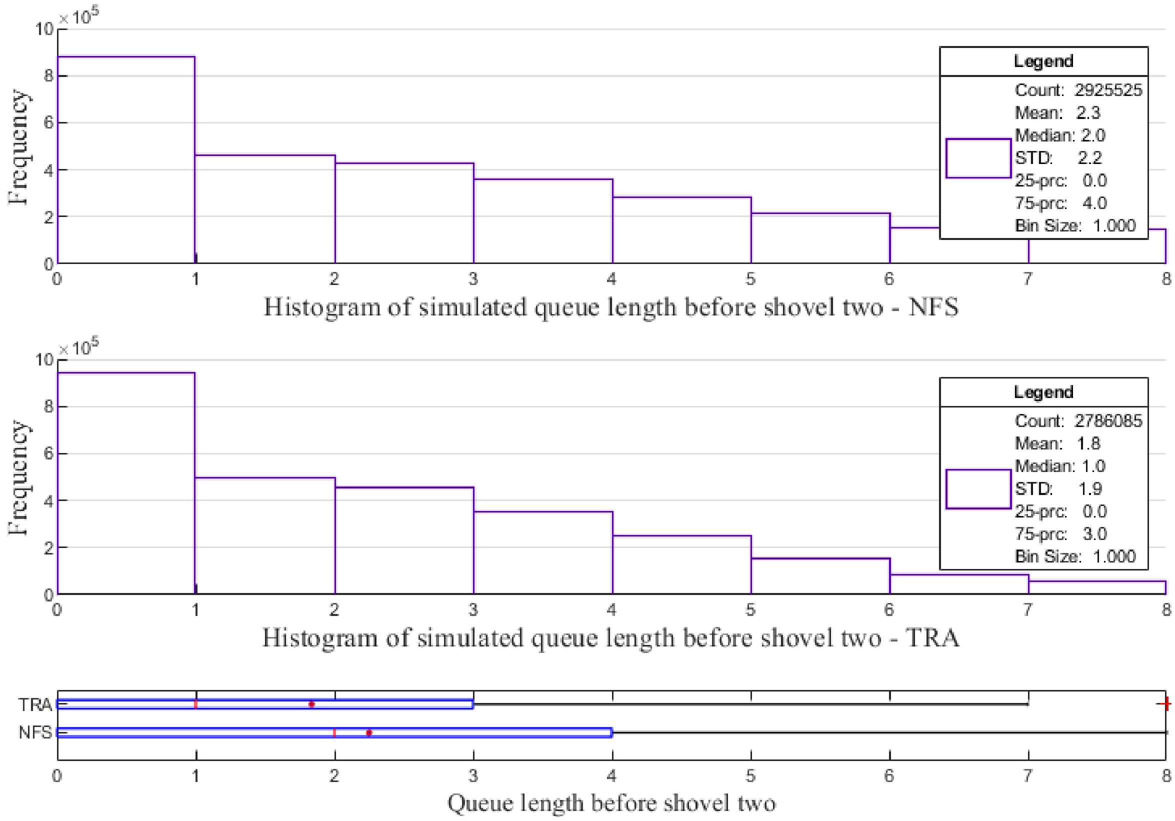

Figure 4.70 Queue length comparison of NFS method and traditional method before shovel two

Table 4.19 Queue time and queue length before shovels comparison between NFS method and traditional method

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Queue time before shovel (min) - SimTra	278,609 ±537	200± 54.03	5.06± 0.07	2.63± 0.02	11.11 ±0.31	1.02± 0.01	7.43 ±0.07	1,409,761 ±16,196
Queue time before shovel (min) - SimNFS	292,553 ±696	200± 12.18	6.24± 0.06	2.8± 0.02	18.18 ±4.07	1.15± 0.01	9.97 ±0.1	1,825,528 ±13,539
Difference	5.00%	0.00%	23.17%	6.46%	63.6%	12.75%	33.2%	29.49%
Queue length-shovel 1 – SimTra	278,609 ±537	8.00± 1.69	1.75± 0.07	1±0	1.94± 0.05	0±0	3±0	487,565 ±18,250
Queue length-shovel 1 - SimNFS	292,553 ±696	8.00± 0.55	2.16± 0.07	2±0	2.23± 0.04	0±0	4±0	631,914 ±20,914
Difference	5.00%	0.00%	23.43%	100%	14.95%	0.00%	33.33%	29.61%
Queue length-shovel 2 – SimTra	278,609 ±537	8± 1.59	1.76± 0.06	1± 0.02	1.93± 0.03	0±0	3±0	490,351 ±16,539
Queue length-shovel 2 - SimNFS	292,553 ±696	8± 0.57	2.16± 0.08	2±0	2.24± 0.07	0±0	4±0	633,381 ±22,929

Difference	5.00%	0.00%	23.43%	100%	14.41%	0.00%	33.33%	29.17%

Figure 4.67 shows the histogram of the queuing time of each truck cycle before shovel. All categories compared in the former sections have a common sense that the number generated by the NFS model is consistently lower than that of the traditional model. However, the comparison in this section is an exception. Both queuing time and queuing length of trucks before shovels in the NFS model no longer follow that pattern. Table 4.19 further demonstrates that the average truck queuing time in the NFS model is 6.24 minutes, an increase of 23.17% compared with 5.06 minutes in the traditional model. Additionally, the total queuing time before the shovels increased by 29.49% within one year of simulation. Its QQ plot, as shown in Figure 4.68, also shows that the loading queue time in NFS model is slightly higher than that of traditional model.

Figure 4.69 and Figure 4.70 demonstrate that both models exhibit a balanced use of shovel one and shovel two, with no overreliance on either. However, the queue length before the shovel in the NFS model is higher than that of the traditional model, as indicated by the mean value increased by approximately 23% and the median queue length is always one truck higher.

While longer queue times and lengths are typically indicative of poor performance, this is not the case here. The NFS model improves the transportation efficiency of the trucks by reducing the transportation distance of the ore material, which ultimately results in a decrease in the demand for trucks. To maintain consistency and minimize the impact of other variables on performance, the NFS model employs the same number of 16 trucks as the traditional model. As such, the increase in queue time and length in the NFS model can be attributed to the excess number of trucks. This growth, however, serves to further support the superior performance of the NFS model over the traditional model.

4.5.4 Truck requesting time

The section focuses on the evaluation of the truck requesting time as a parameter that reflects the efficiency of shovels in a mining operation.

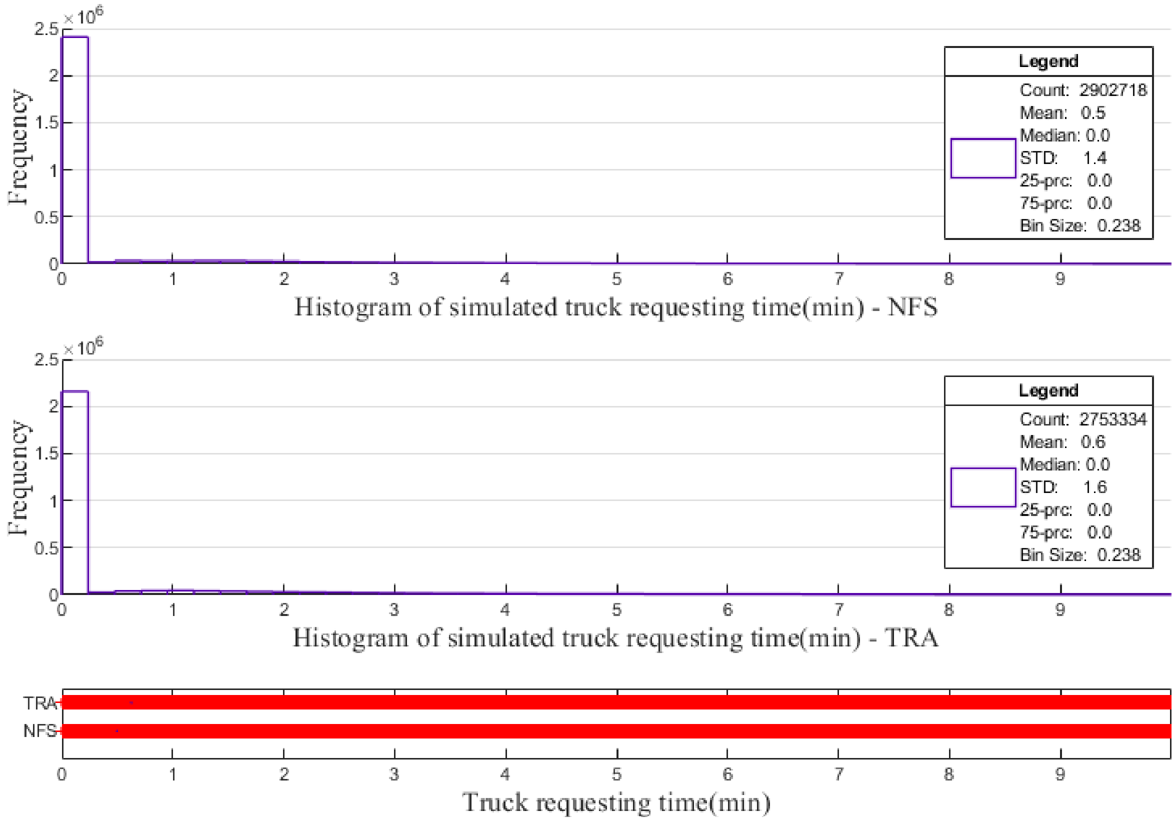

Figure 4.71 Simulated truck request time of NFS method and traditional method

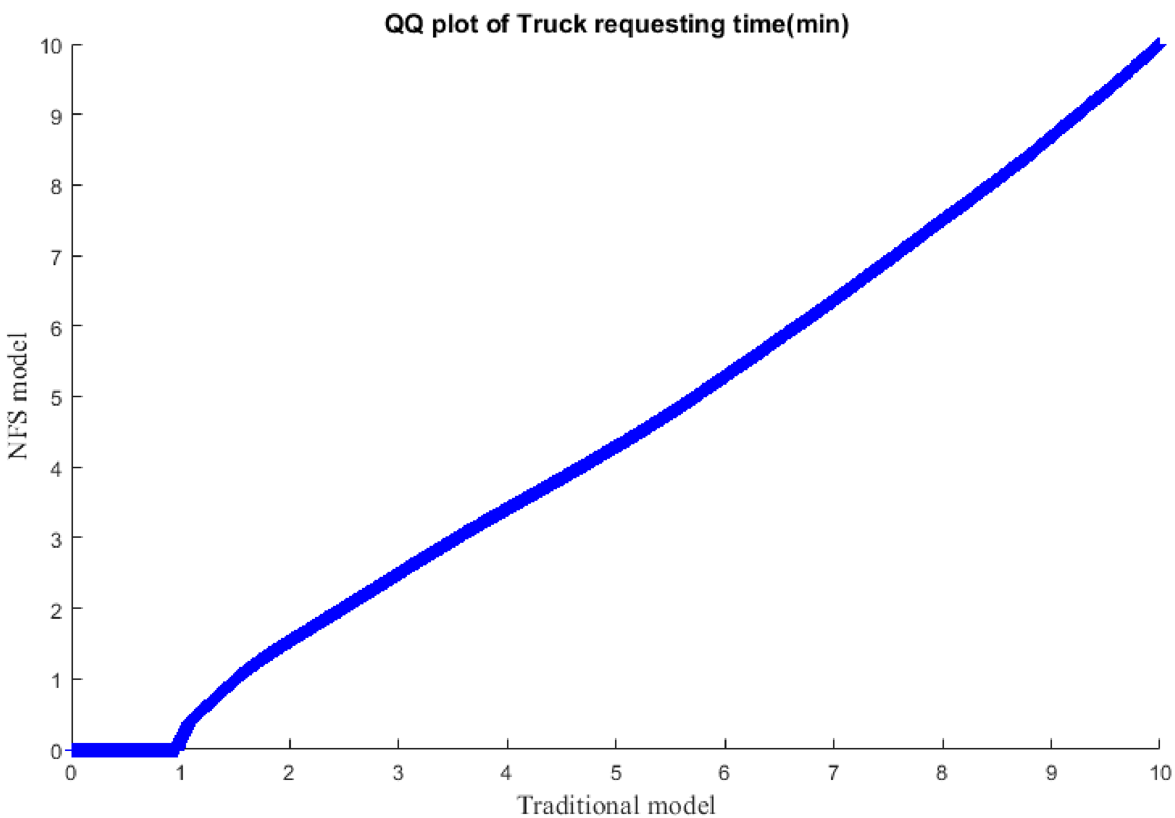

Figure 4.72 QQ plot of truck requesting time of NFS method and traditional method

Table 4.20 Truck requesting time comparison between NFS method and traditional method

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Truck request time (min) - SimTra	278,609 ±537	127.9± 41.3	0.64± 0.03	0±0	1.67± 0.06	0±0	0±0	178,309 ±2,352
Truck request time (min) - SimNFS	292,553 ±696	107.8± 101.2	0.46± 0.02	0±0	1.41± 0.29	0±0	0±0	134,574 ±2,512
Difference	5.00%	-15.7%	-28.1%	-	-15.6%	-	-	-24.5%

This parameter refers to the duration between the readiness of the shovel to begin loading and the readiness of the truck to receive loading. If a truck is not present in front of the shovel or has not vacated the loading spot, the shovel will idle until the truck is ready. Furthermore, the truck requesting time and the queue time, which was discussed in the previous section, are inversely related indicators to some extent. In the case where there is a truck queueing in front of the shovel, the corresponding requesting time is zero. Conversely, if the requesting time is not zero, it indicates that the trucks are in the hauling phase, and the queue time and queue length before the shovel are both zero.

Through the analysis of Table 4.20 , Figure 4.71, and Figure 4.72, it can be observed that more than 75th percentile of the truck requesting time data in both models, is zero. This finding suggests that the shovels are efficiently utilized, and truck shortages are infrequent. Despite being efficiently utilized, the NFS model performs better than the traditional model. Specifically, the average truck requesting time for the NFS model is 0.46 minutes, which is 28% less than the traditional model's average of 0.64 minutes. The overall simulation result indicates that the NFS model reduces the idle time of shovels by 24.5% compared to the traditional model. Truck requesting time can be used as an important parameter to evaluate the efficiency of shovels. The comparison and analysis in this section show that the NFS model significantly exceeds the traditional model in terms of shovel utilization.

4.5.5 Truck cycle time

This section mainly discusses and analyzes the performance of the truck cycle time of the two models.

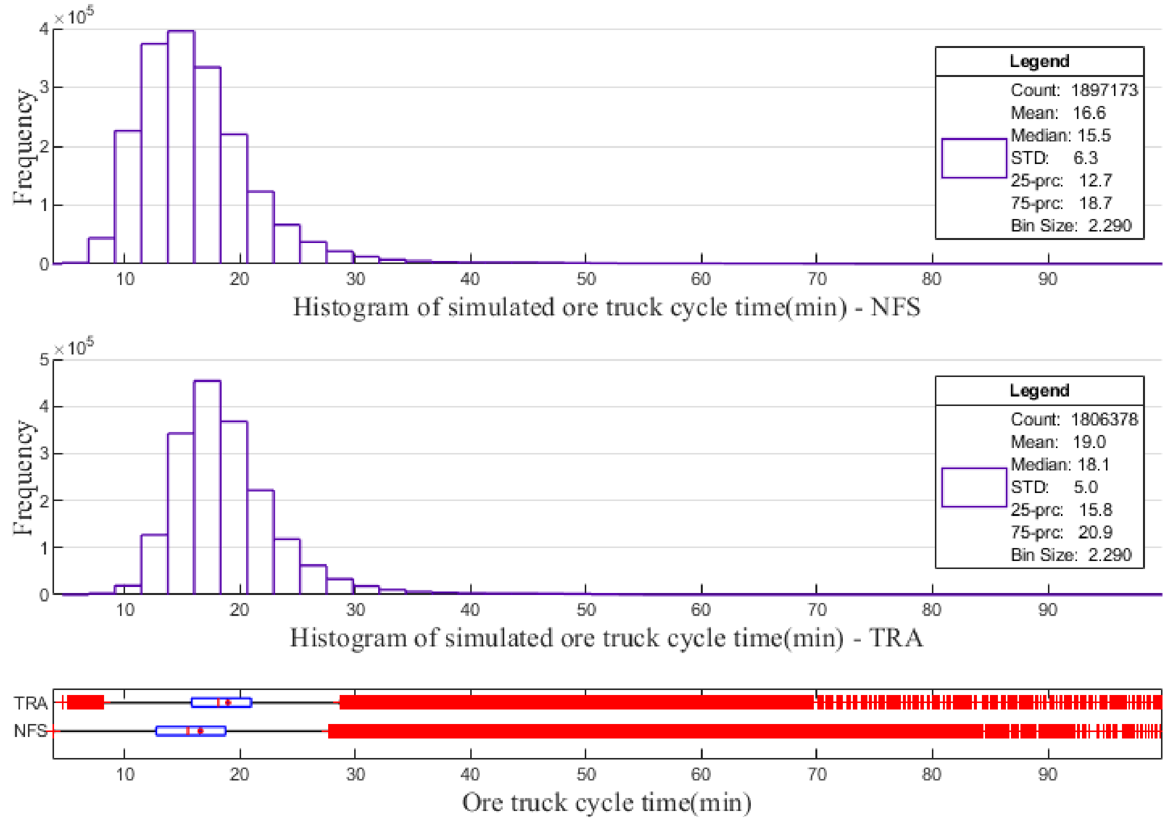

Figure 4.73 Simulated ore truck cycle time of NFS method and traditional method

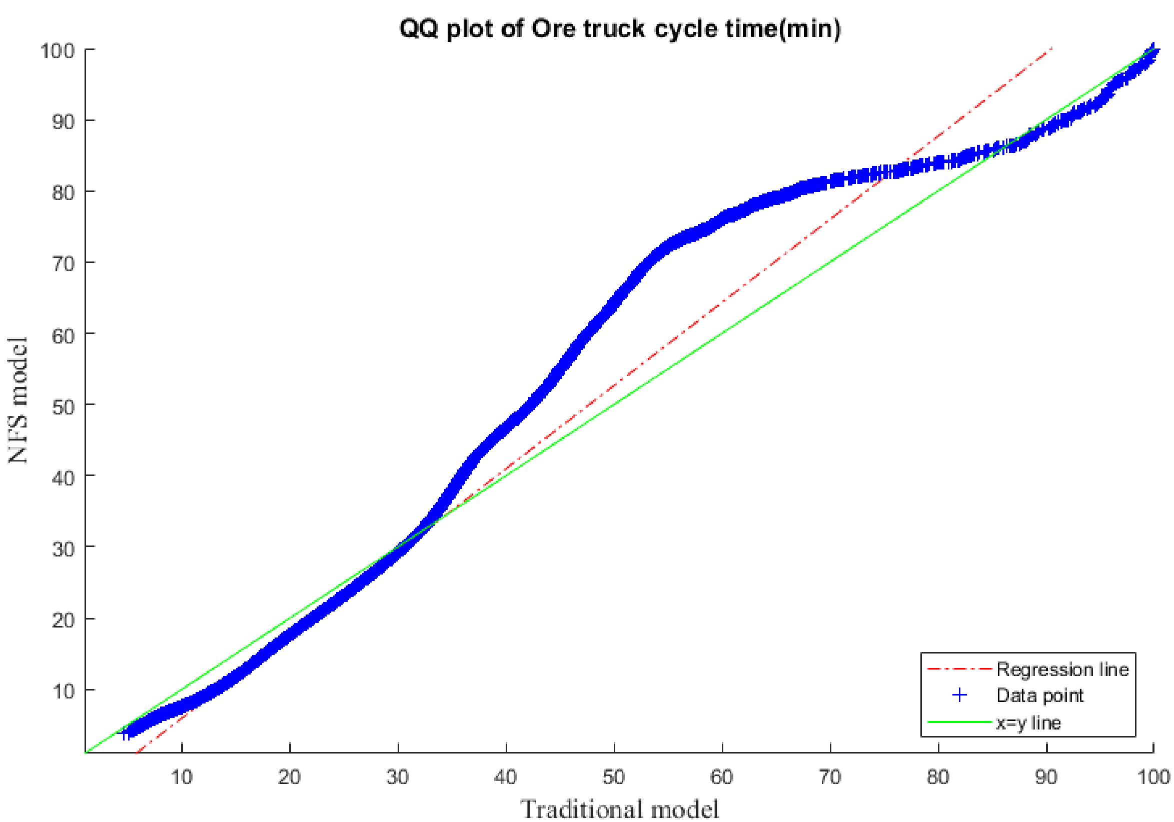

Figure 4.74 QQ plot of ore truck cycle time of NFS method and traditional method

The truck cycle time is a critical indicator that determines the efficiency and utilization rate of trucks in mining operations. It encompasses various activities related to the truck, including shovel loading time, loaded truck hauling time, queuing time before the dump, dumping time, and empty truck hauling time. However, the queuing time before shovel loading is not included in the complete truck cycle time, and its starting point is from receiving shovel loading. The shorter the cycle time, the higher the utilization rate of the truck. Similar to the previous sections, the truck cycle time is divided into three situations for discussion and analysis, the cycle time of ore material, the cycle time of waste material, and the overall cycle time.

The first part to analyze is the cycle time of the ore material since ore is always the main interest of companies that brings profit. As can be seen from Figure 4.73 and Table 4.21, the average ore cycle time of the NFS model is 16.58 minutes, which is 16.3% less than the 19.81 minutes of the traditional model. Furthermore, compared with the traditional model, the NFS model's 25th percentile and 75th percentile of ore truck cycle data are reduced by 19.5% and 10.7%, respectively. In addition, the NFS model's total ore material cycle time decreased by 12.27% despite an increase of 4.82% in the number of cycles. This finding suggests that the change in the layout of the NFS model significantly improves the truck utilization efficiency, which reduces hauling costs for the enterprise. Figure 4.74, the QQ plot of the ore truck cycle time of two methods, also indicates that in most conditions (cycle time less than 33 minutes) the ore truck in the NFS model outperforms the traditional model, with some fluctuations in tailings data.

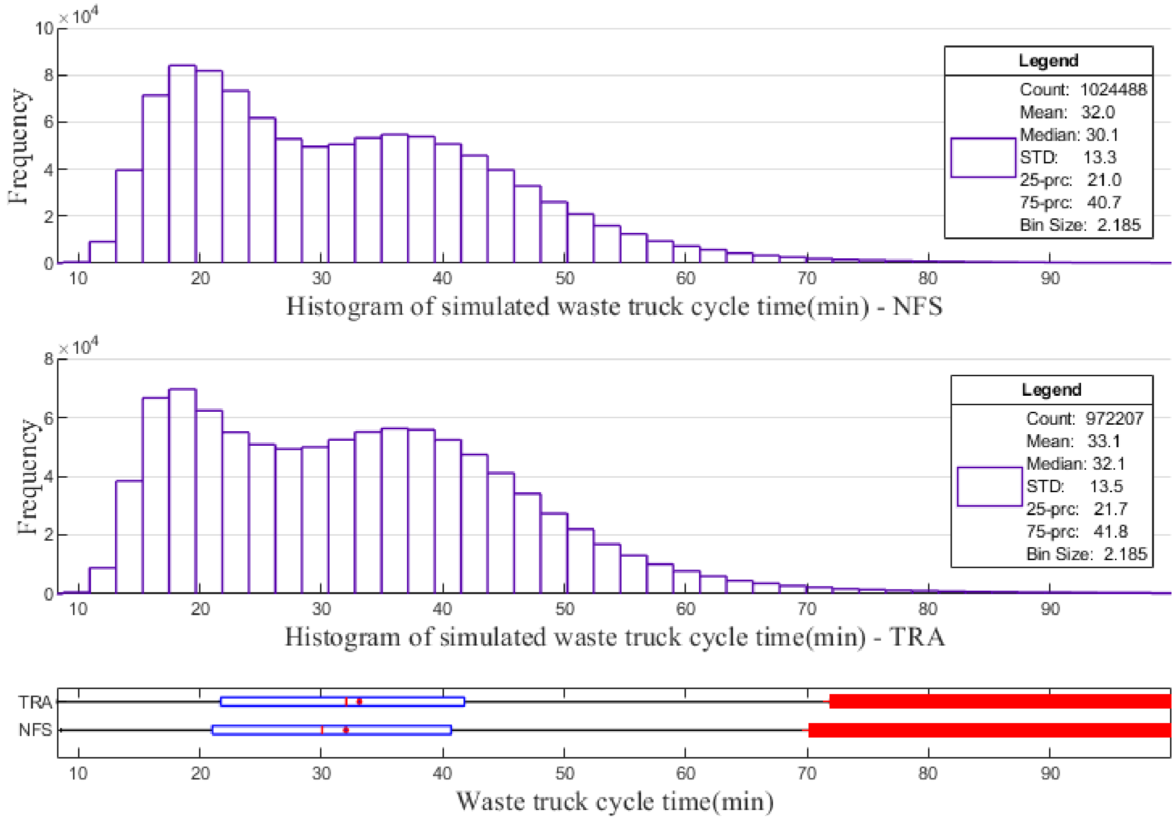

Figure 4.75 Simulated waste truck cycle time of NFS method and traditional method

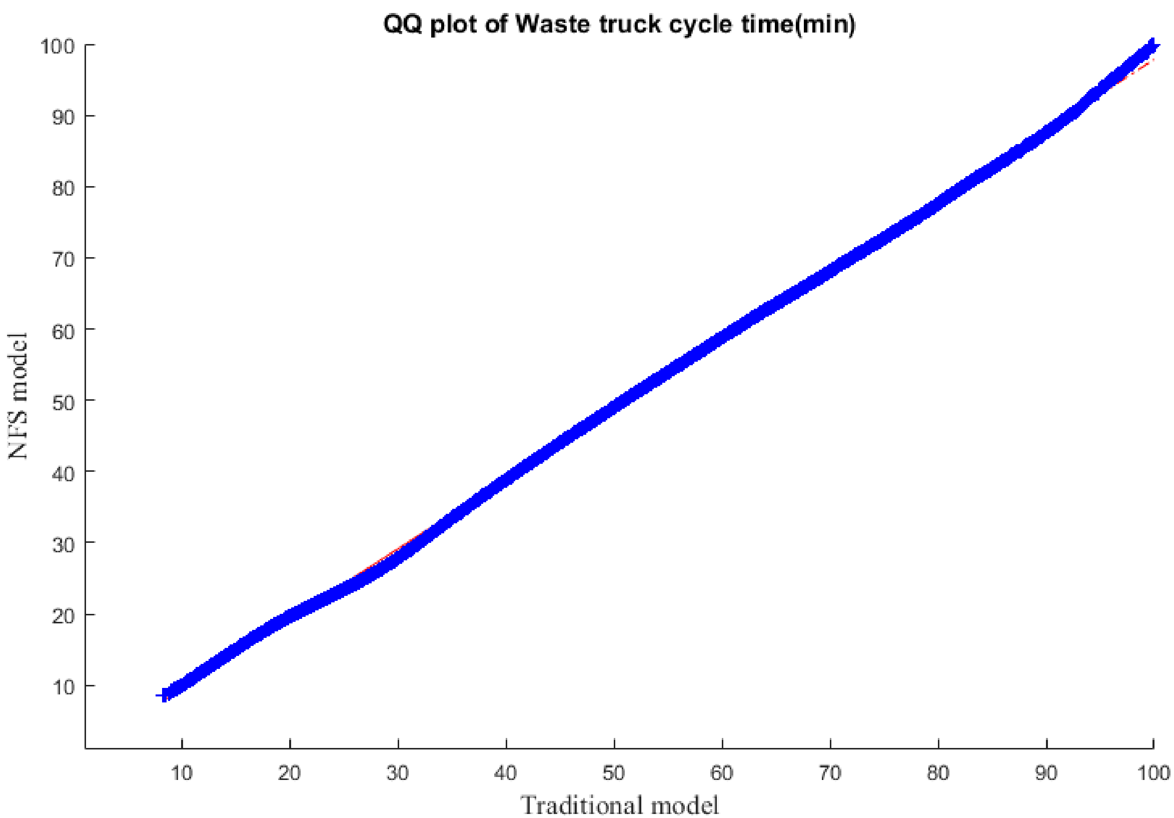

Figure 4.76 QQ plot of waste truck cycle time of NFS method and traditional method

Comparing Figure 4.73 and Figure 4.75, it can be seen that the truck cycle time of waste material is significantly higher than that of ore material. The waste truck cycle time in the NFS model and the traditional model both exceed 30 minutes, which are 32.33 minutes and 33.46 minutes respectively. This is due to a higher hauling distance of waste material compared to ore material. In addition, although the truck cycle time of ore material in the NFS model has been significantly reduced compared with the traditional model, it has relatively no significant change in the improvement of the transportation distance and transportation efficiency of waste material. Relevant data shows that the difference between the truck cycle time of the waste material of the two models is only about 3%. Figure 4.76 also shows that the two distributions are very close.

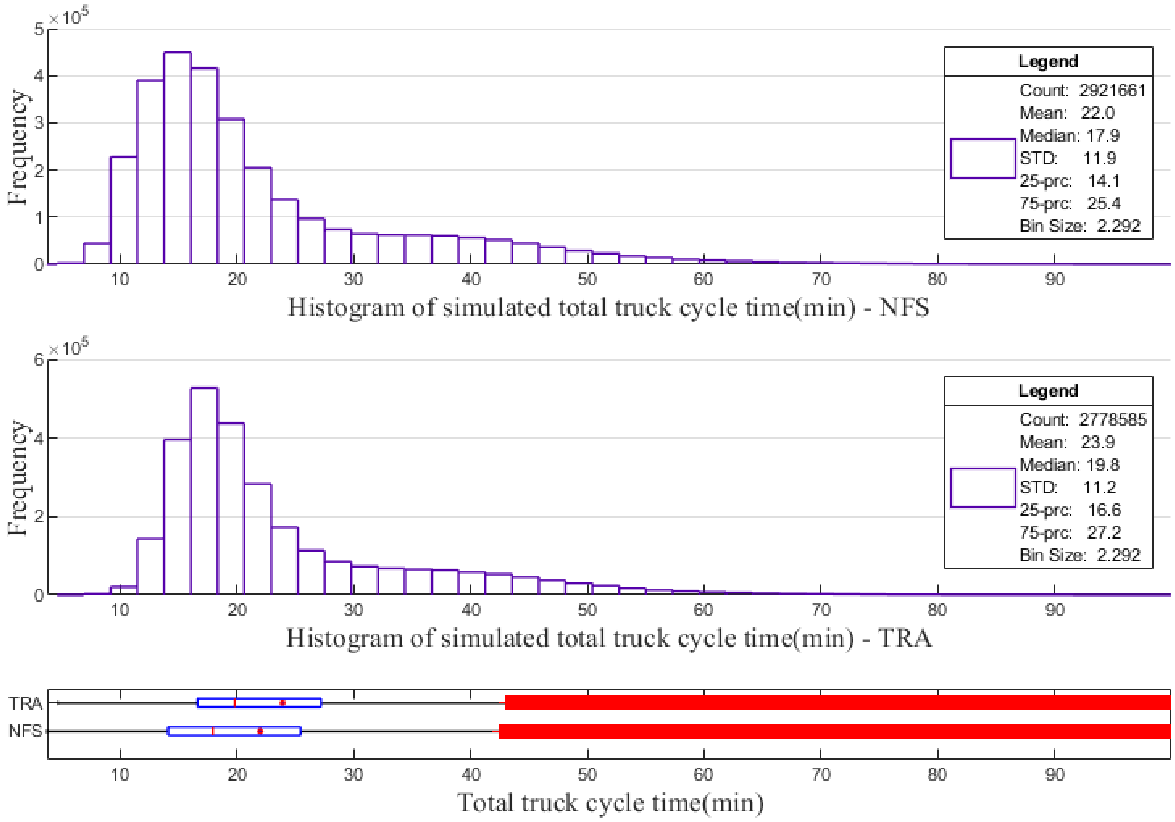

Figure 4.77 Simulated total truck cycle time of NFS method and traditional method

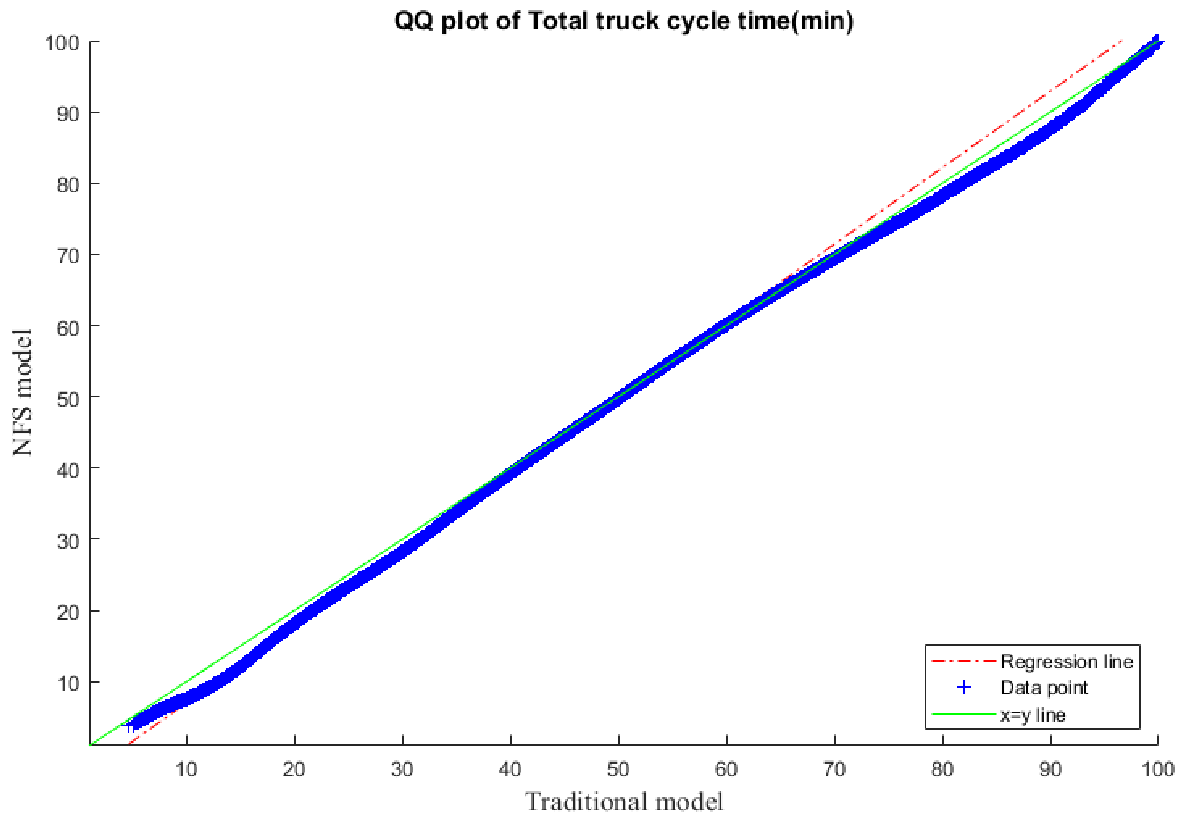

Figure 4.78 QQ plot of total truck cycle time of NFS method and traditional method

Table 4.21 Truck cycle time comparison between NFS method and traditional method

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Ore cycle time(min)-SimTra	181,003 ±433	568±52	19.81 ±0.06	18.11 ±0.04	20.16 ±0.71	15.82 ±0.04	20.97 ±0.06	3,585,891 ±16,839
Ore cycle time(min) - SimNFS	189,736 ±512	332 ±327	16.58 ±0.08	15.49 ±0.04	6.97 ±1.81	12.74 ±0.04	18.73 ±0.03	3,145,992 ±16,078
Difference	4.82%	-41.6%	-16.3%	-14.5%	-65.4%	-19.5%	-10.7%	-12.27%
Waste cycle time(min) - SimTra	97,605 ±354	165±23	33.46 ±0.08	32.14 ±0.1	14.57 ±0.16	21.76 ±0.12	41.9 ±0.11	3,266,018 ±11,407
Waste cycle time(min) - SimNFS	102,816 ±379	169.15 ±51	32.33 ±0.09	30.16 ±0.1	14.23 ±0.2	21.04 ±0.07	40.82 ±0.08	3,324,474 ±8,519
Difference	5.34%	2.71%	-3.38%	-6.16%	-2.33%	-3.31%	-2.58%	1.79%
Total cycle time(min) - SimTra	278,609 ±537	568±52	24.6 ±0.07	19.82 ±0.04	19.51 ±0.45	16.63 ±0.03	27.31 ±0.09	6,851,909 ±13,464
Total cycle time(min) - SimNFS	292,553 ±696	346 ±334	22.12± 0.08	17.93 ±0.03	12.63 ±0.68	14.1 ±0.04	25.5 ±0.05	6,470,467 ±14,332

Difference	5.00%	-39.1%	-10.1%	-9.54%	-35.3%	-15.2%	-6.63%	-5.57%

Since ore material accounts for a larger proportion of the total mining volume, around 65%, when evaluating the performance of the truck cycle time of the two models from an overall perspective, the NFS model still has a significant improvement compared to the traditional model. According to Figure 4.77, the average truck cycle time of the NFS model is 22.12 minutes, which is 10.1% shorter than the traditional model's 24.6 minutes. The 25th percentile and 75th percentile of all simulated data are also reduced by 15.2% and 6.63%, respectively. Similarly, although the overall truck cycle number of the NFS model has increased by 5% compared with the traditional model, its total cycle time has been shortened by 5.57%. The total truck cycle time QQ plot of the two methods is shown in Figure 4.78. It can be seen from the figure that almost all the data are located at or below the green line, indicating that the performance of the truck in NFS is not weaker than that in the traditional method throughout the whole simulation time. In the main hauling time range of 5-30 minutes, the NFS method is obviously better than the traditional method.

The comparisons in this section fully demonstrate that the NFS model improves truck utilization efficiency compared to the traditional model. It not only completes more cycles in the same simulation period, which results in higher production, but also reduces the invalid travel time of the trucks. All of these make it possible to reduce the number of trucks and create the premise for further reducing truck transportation costs.

4.5.6 Ton-kilometer (TKM)

Ton-kilometer (TKM) is a widely used unit of measure for material transport, specifically referring to the transport of one ton of ore or waste by truck over a distance of one kilometer. This metric is included as a comparison item because it serves as a useful indicator of truck operational costs. A lower TKM implies lower fuel consumption, reduced maintenance costs, lower carbon emissions, and higher profits. As such, it is an important metric for evaluating the efficiency and profitability of truck operations in the mining industry. Similarly, the analysis on TKM will still compare and analyze ore material TKM, waste material TKM and total TKM respectively.

1. Ore material TKM

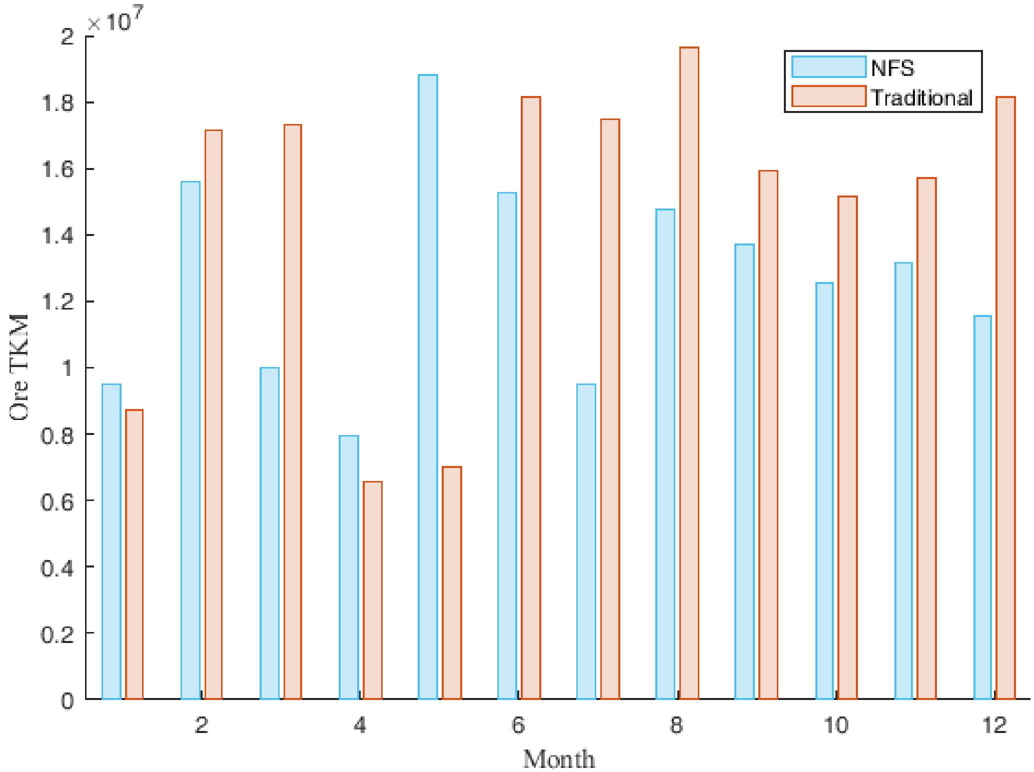

Figure 4.79 Average monthly ore material TKM comparison between NFS method and traditional method

Table 4.22 Average monthly ore material TKM comparison between NFS method and traditional method

Month	Traditional ore TKM (10 replications mean)	NFS ore TKM (10 replications mean)	Difference
1	8,722,008	9,491,645	8.82%
2	17,147,927	15,572,285	-9.19%
3	17,322,607	10,008,352	-42.22%
4	6,580,100	7,936,708	20.62%
5	6,990,037	18,832,114	169.41%
6	18,133,442	15,282,055	-15.72%
7	17,480,249	9,475,146	-45.80%
8	19,613,288	14,770,451	-24.69%
9	15,933,799	13,732,759	-13.81%
10	15,133,729	12,564,172	-16.98%
11	15,723,125	13,175,149	-16.21%
12	18,140,688	11,547,088	-36.35%

Total	176,921,000	152,387,925	-13.87%

The examination of Figure 4.79 and Table 4.22 reveals that, except for three months, the average monthly ore material TKM of the NFS model is consistently lower than that of the traditional model in the remaining three-quarters of the year, with a maximum reduction of 45.8%. Consequently, the annual average ore material TKM is 13.87% lower in the NFS model than in the traditional model. Notably, this reduction is achieved with a 4.86% increase in ore material output in the NFS model. If the output increase is not considered, the ore material's TKM of the NFS method is 20.71% lower than that of the traditional method at the same production level.

It can be concluded that the performance of the NFS method on the ore TKM is significantly better than that of the traditional method, which not only improves the output, but also achieves a lower TKM. This also represents the improvement of NFS method in terms of energy consumption efficiency, which is more suitable for the development concept of modern mines.

2. Waste material TKM

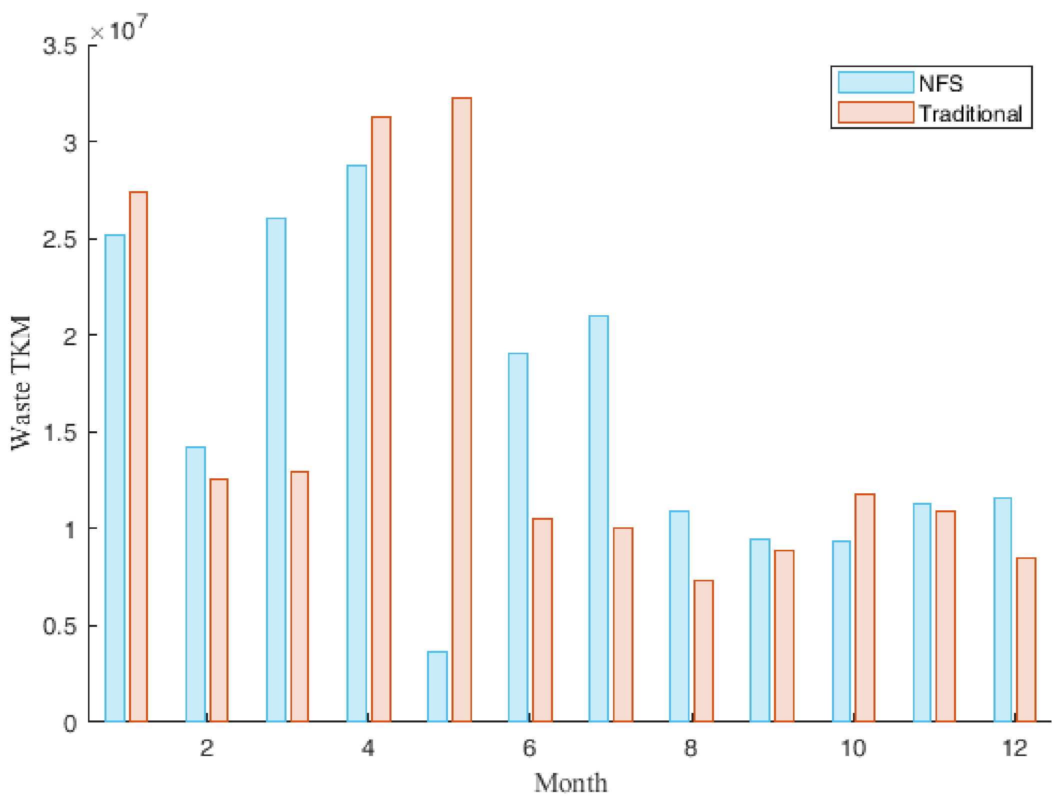

Figure 4.80 Average monthly waste material TKM comparison between NFS method and traditional method

Table 4.23 Average monthly waste material TKM comparison between NFS method and traditional method

Month	Traditional waste TKM (10 replications mean)	NFS waste TKM (10 replications mean)	Difference
1	27,409,883	25,167,390	-8.18%
2	12,599,708	14,223,711	12.89%
3	12,980,087	26,036,967	100.59%
4	31,278,200	28,777,551	-7.99%
5	32,233,020	3,614,659	-88.79%
6	10,509,778	19,063,317	81.39%
7	10,016,118	21,001,921	109.68%
8	7,364,536	10,940,095	48.55%
9	8,847,930	9,444,581	6.74%
10	11,812,760	9,372,947	-20.65%
11	10,953,037	11,259,266	2.80%
12	8,466,056	11,593,473	36.94%
Total	184,471,114	190,495,880	3.27%

In contrast to the analysis of ore material TKM in the preceding section, the performance of the NFS model with respect to waste material TKM does not exhibit a clear superiority over the traditional model after analyzing Figure 4.80 and Table 4.23. For instance, while the monthly waste material TKM of the NFS model dropped by 88.79% in May compared to the traditional model, it increased by 109.68% in July. As the transportation distance of waste material remained constant, the variation in TKM between the two models across different months is primarily attributable to differences in scheduling. The comparison of the annual waste material TKM reveals a 3.27% increase in the NFS model relative to the traditional model. However, considering that the NFS model yielded approximately 5% increasement in waste material output, the difference in the annual average waste material TKM between the two models reduces to roughly 1%, consistent with expectations.

3. Total TKM

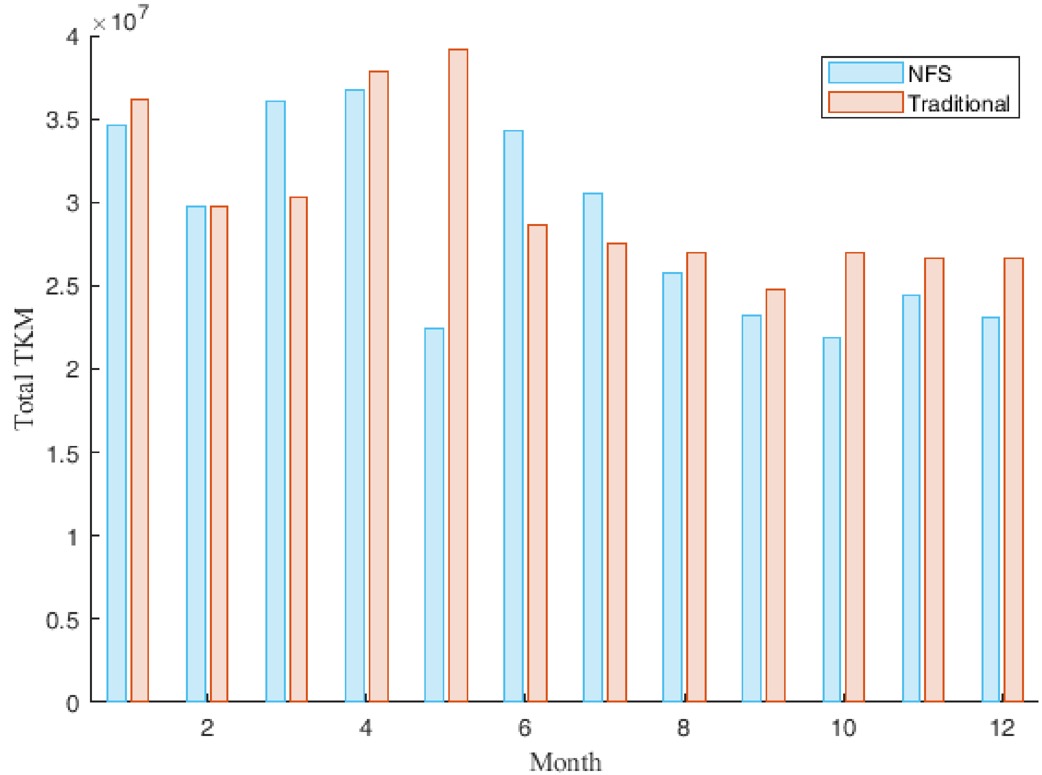

Figure 4.81 Average monthly total TKM comparison between NFS method and traditional method

Table 4.24 Average monthly total TKM comparison between NFS method and traditional method

Month	Traditional total TKM (10 replications mean)	NFS total TKM (10 replications mean)	Difference
1	36,131,892	34,659,035	-4.08%
2	29,747,635	29,795,996	0.16%
3	30,302,694	36,045,319	18.95%
4	37,858,300	36,714,259	-3.02%
5	39,223,057	22,446,774	-42.77%
6	28,643,220	34,345,372	19.91%
7	27,496,367	30,477,067	10.84%
8	26,977,824	25,710,546	-4.70%
9	24,781,729	23,177,341	-6.47%
10	26,946,489	21,937,119	-18.59%
11	26,676,162	24,434,415	-8.40%
12	26,606,744	23,140,561	-13.03%

Total	361,392,114	342,883,805	-5.12%

In this section, the monthly average total TKM of all materials for the NFS and traditional methods were compared using Figure 4.81 and Table 4.24, which are obtained from ten simulation replications. Results showed that the NFS method outperformed the traditional method, with the monthly total TKM of the NFS method being lower than that of the traditional method in 8 out of 12 months. The maximum monthly TKM reduction achieved by the NFS method was 42.77%, while the maximum increase was less than 20% in the remaining 4 months. Therefore, on an annual basis, the NFS method had a 5.12% decrease in total TKM compared to the traditional method. This decrease was achieved on the basis of a 5.06% increase in the overall output of the mining system. When the effect of production increment was removed, the total TKM of the NFS method was reduced by 10.93% relative to the traditional method.

Based on the comparison of the three categories in this section, it is evident that the NFS method has significantly improved the total TKM compared to the traditional method. This improvement offers several advantages, including reduced demand for the number of trucks, cost savings in terms of truck operating costs, and reduced expenses associated with purchasing trucks.

4.5.7 TPGOH

The truck cycle time mainly evaluates the performance of the truck from the effective time, and TKM focuses on general transportation productivity. The ton per gross operating hour (TPGOH) combines the carrying capacity of each cycle truck, thus obtaining the average material transport volume per hour during the simulation time. TPGOH is one of the most important indicators for evaluating the performance of a mining method. Under the premise that the equipment capacity remains unchanged, a higher TPGOH means a higher comprehensive equipment utilization rate and better performance. Similarly, this section still compares the TPGOH of the NFS model and the traditional model from three aspects, that is, the TPGOH of the ore material, the TPGOH of the waste material, and the comprehensive TPGOH.

1. Ore material TPGOH

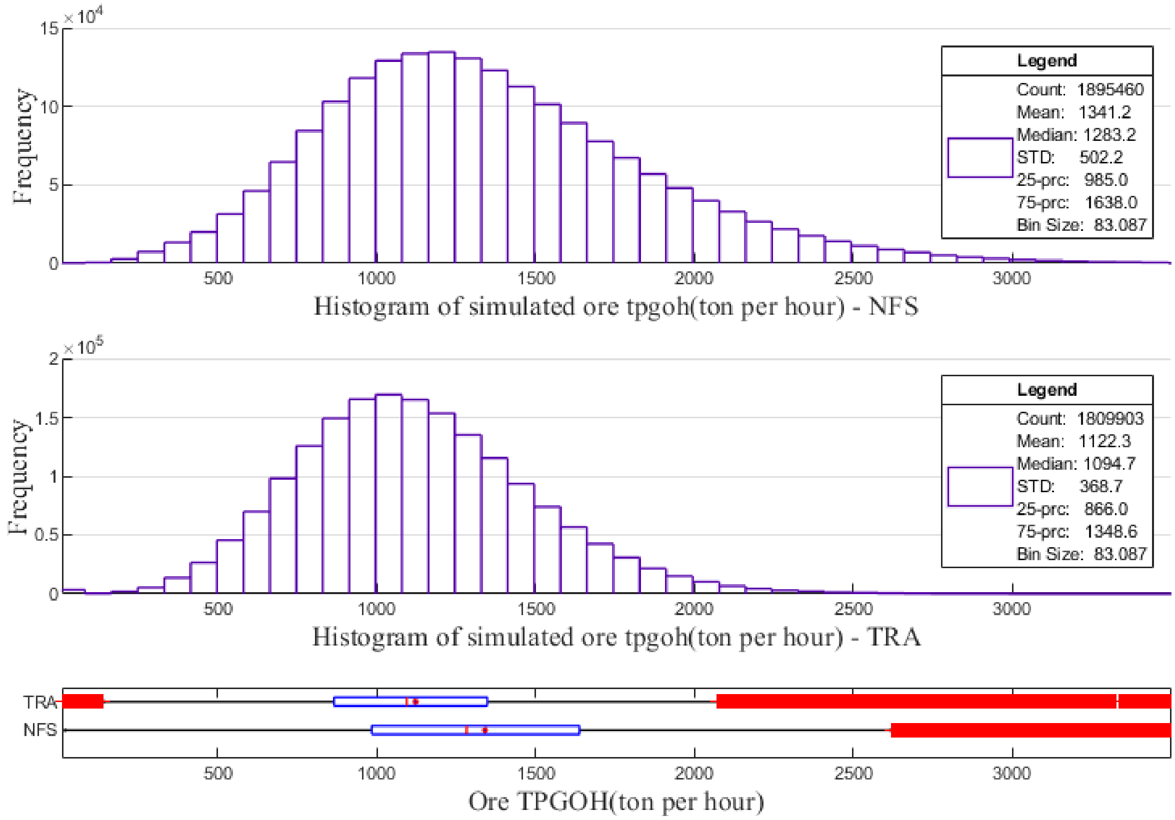

Figure 4.82 Simulated ore material TPGOH of NFS method and traditional method

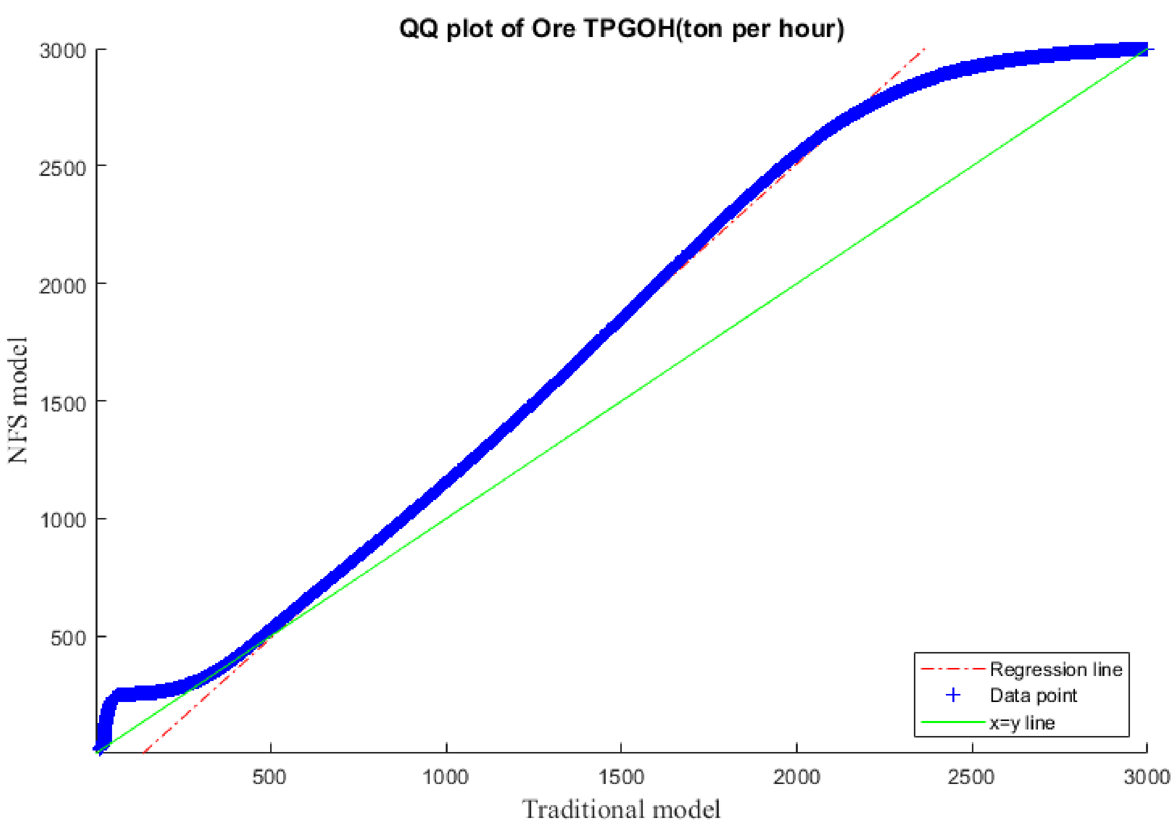

Figure 4.83 QQ plot of ore material TPGOH between NFS method and traditional method

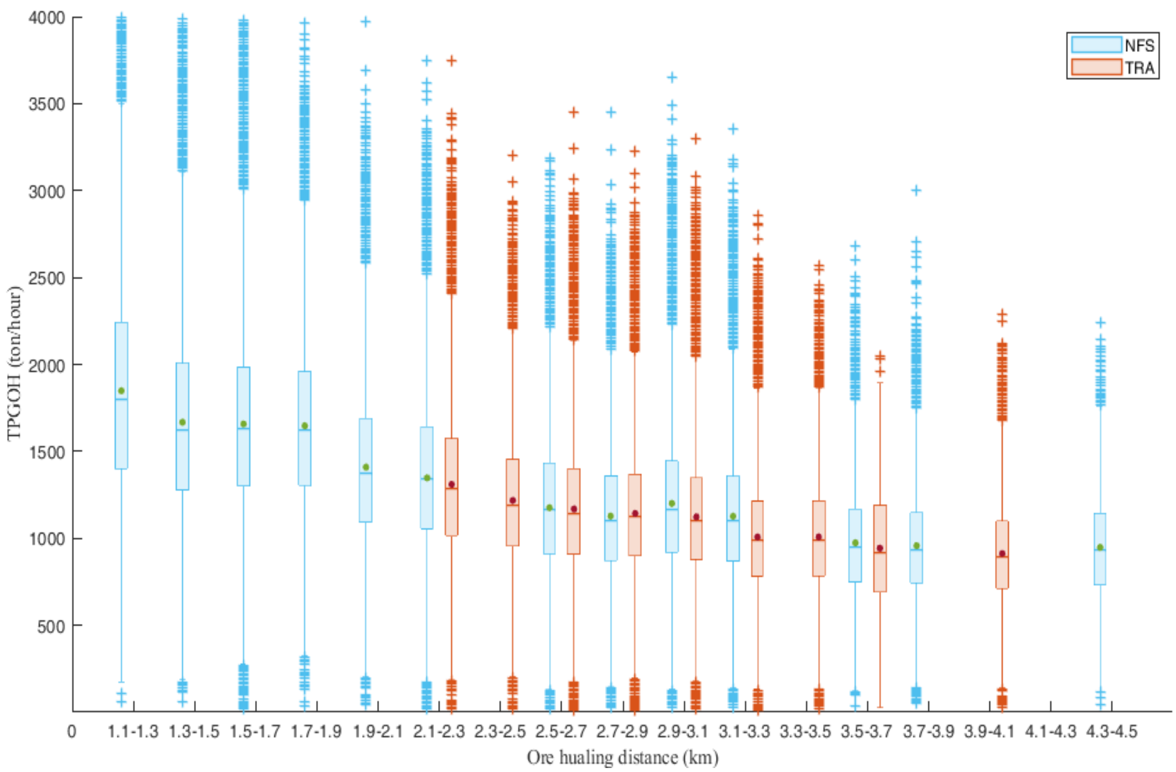

Figure 4.84 Ore TPGOH comparison in each hauling range under NFS mining method and traditional mining method

Table 4.25 Ore material TPGOH comparison between NFS method and traditional method

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Ore TPGOH - SimTra	181,003 ±433	2,726 ±662	1,122 ±3.11	1,095 ±3.49	369.5 ±1.55	866± 1.98	1349 ±4.14	203,170,229 ±455,307
Ore TPGOH - SimNFS	189,736 ±512	3,590 ±1,740	1,341 ±343	1,284 ±4.27	508.4 ±2.84	985 ±2.21	1639 ±5.19	254,435,976 ±1,047,751
Difference	4.82%	22.51%	19.51%	17.26%	37.58%	13.77%	21.55%	25.23%

The section investigates the comparative performance of the NFS model and traditional model in terms of ore truck productivity or ore TPGOH. Figure 4.82 depicts the histogram of TPGOH under the two models, and Table 4.25 provides a detailed data analysis. The findings suggest that the NFS model surpasses the traditional model in all aspects, with an average ore TPGOH of 1341 tons/hour, which is 19.51% higher than the traditional model's 1095 tons/hour. Furthermore, the 25th percentile and 75th percentile of all ore data are 13.77% and 21.55% higher, respectively, and the range of ore TPGOH of the NFS model is 31.68% higher than that of the traditional model. These results indicate that the NFS model significantly enhances the comprehensive utilization of the truck.

To present a more intuitive comparison of the NFS model and traditional model, a QQ plot is also generated, as illustrated in Figure 4.83. The plot highlights that the results of all ore TPGOH generated by the NFS model are consistently upper than those of the traditional model, indicating the superior performance of the NFS model.

Moreover, the study explores the relationship between TPGOH and the load weight and cycle time of the truck. The cycle time of the truck is calculated as the truck hauling distance divided by the truck speed. Figure 4.36 and Figure 4.37 reveal that the distributions of the two models on truck speed are almost identical. Meanwhile, Figure 4.33 depicts the truck loading tonnage distribution is also identical. Therefore, TPGOH is highly negatively correlated with truck hauling distance, as shown in Figure 4.84. The figure suggests that the reduction in hauling distance leads to an increase in ore material TPGOH, whereas the TPGOH generated by the NFS model and traditional model is not significantly different when the truck hauling distance is in the same range. Therefore, the efficiency improvement of the NFS model is entirely attributed to the reduction of hauling distance and not the truck itself.

In conclusion, the study provides comprehensive evidence supporting the superiority of the NFS model over the traditional model in terms of ore truck productivity. The findings highlight the importance of reducing the truck hauling distance for enhancing the efficiency of ore material transportation.

2. Waste material TPGOH

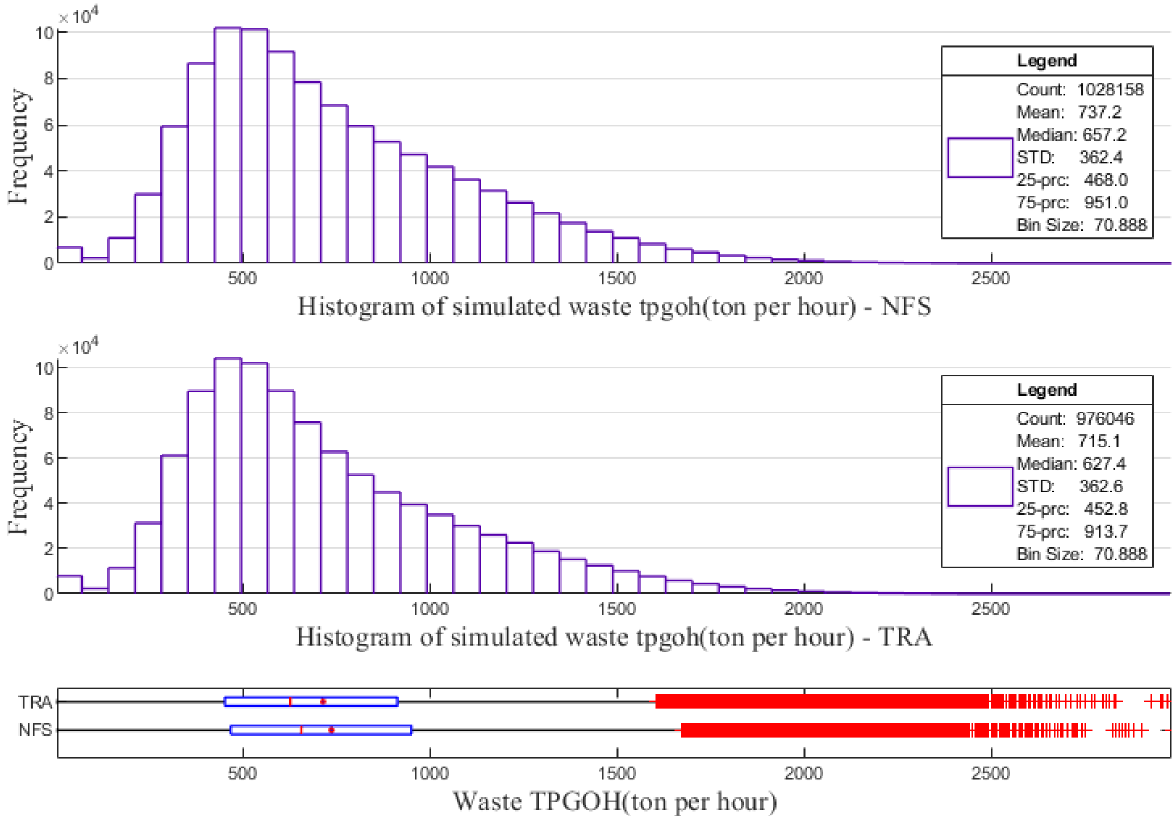

Figure 4.85 Simulated waste TPGOH of NFS method and traditional method

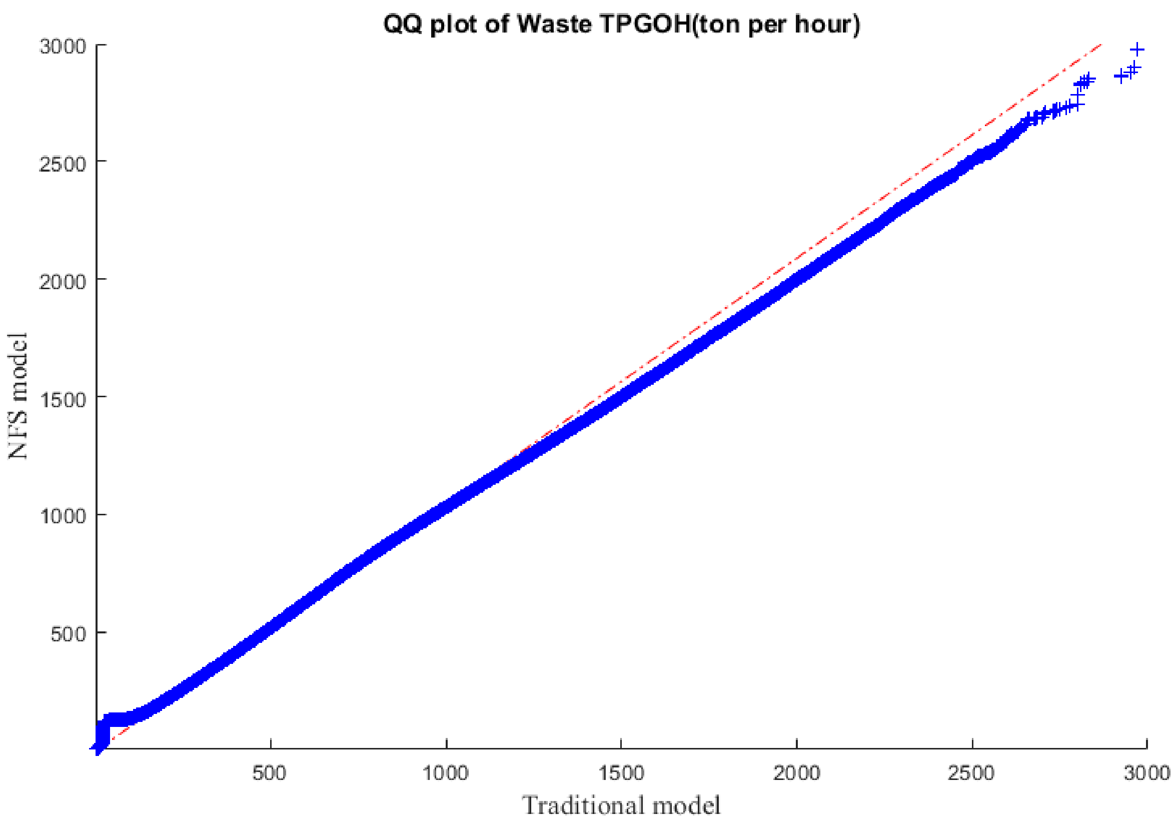

Figure 4.86 QQ plot of waste material TPGOH between NFS method and traditional method

Table 4.26 Waste material TPGOH comparison between NFS method and traditional method

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Waste TPGOH - SimTra	97,605 ±354	2,957 ±365	715 ±1.59	627 ±2.28	363 ±2.8	453 ±1.73	914 ±3.65	69,796,099 ±215,856
Waste TPGOH - SimNFS	102,816 ±379	2,853 ±245	737 ±2.53	657 ±2.46	362 ±2.44	468 ±2.67	951 ±3.25	75,797,750 ±220,647
Difference	5.34%	-3.51%	3.09%	4.75%	-0.04%	3.35%	4.08%	8.60%

Since the hauling distance of the waste material has not changed, theoretically there should be no significant difference between the distributions of the two models on the waste material TPGOH. As shown in Figure 4.85 and Figure 4.86 and Table 4.26, the gap between the two is only about 3%, which is in line with expectations.

3. Total TPGOH

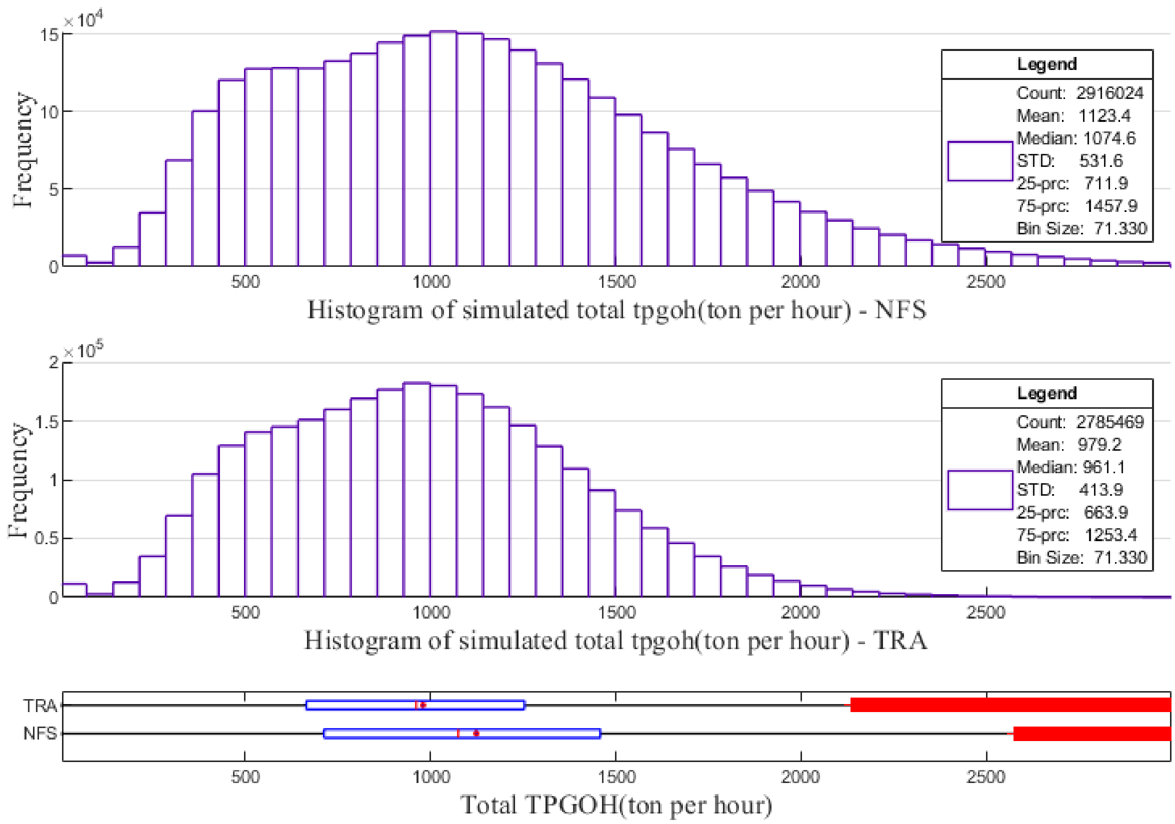

Figure 4.87 Simulated total TPGOH of NFS method and traditional method

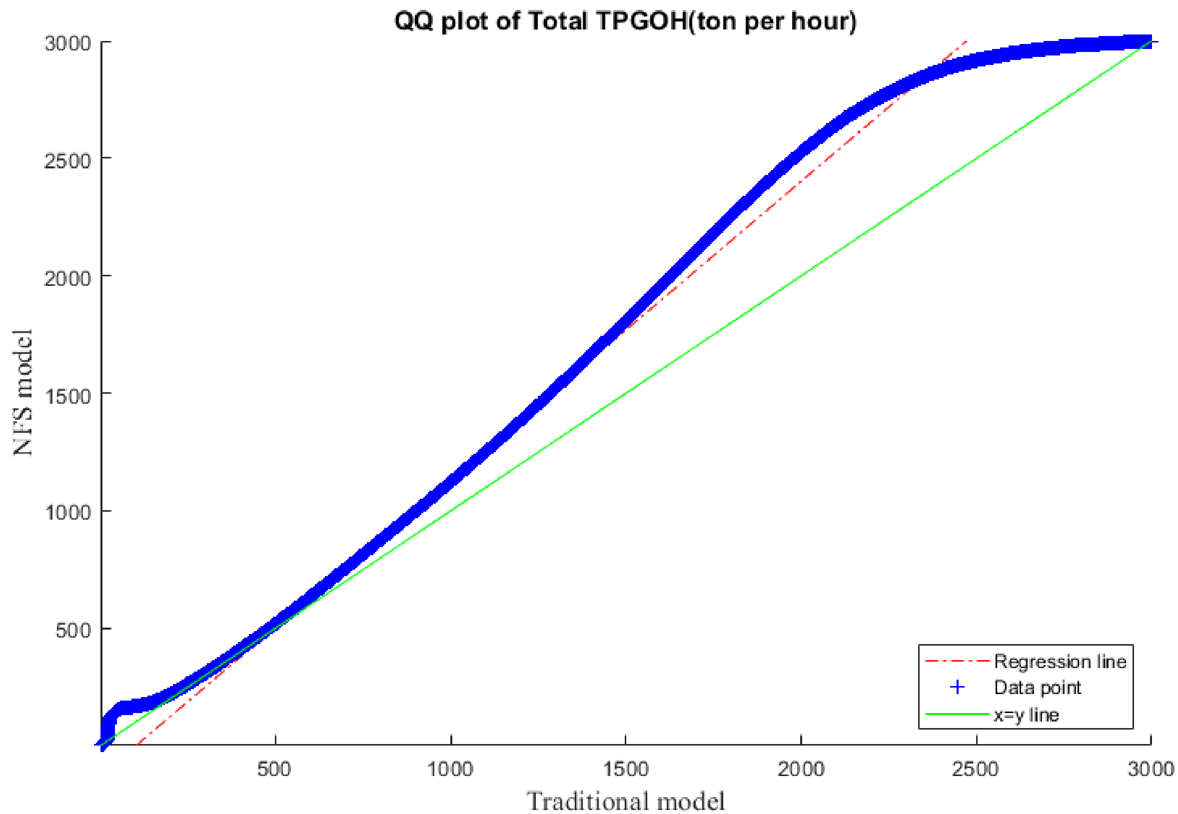

Figure 4.88 QQ plot of total material TPGOH between NFS method and traditional method

Table 4.27 Total TPGOH comparison between NFS method and traditional method

Category	Count	Range	Mean	Median	STD	25-prc	75-prc	Summation
Total TPGOH (ton/h) - SimTra	278,609 ±537	2,957 ±662	979 ±1.81	961 ±2.14	415 ±1.67	664 ±1.31	1,254 ±3.06	272,966,328 ±651,926
Total TPGOH (ton/h) - SimNFS	292,553 ±696	3,590 ±1,735	1,123 ±2.82	1,077 ±2.35	546 ±2.34	713 ±2.06	1,462 ±3.55	328,537,019 ±1,233,888
Difference	5.00%	21.41%	14.68%	12.03%	31.34%	7.41%	16.66%	20.37%

This section further investigates the overall truck productivity by evaluating the total truck TPGOH, which considers all materials without distinguishing ore or waste. Figure 4.87 and Table 4.27 illustrate that although the TPGOH of waste material is not improved, the performance of total TPGOH under the NFS model is still significantly better than that of the traditional model. The mean value, 25th percentile value, and 75th percentile value of total TPGOH under the NFS mining method increased by 14.68%, 7.41%, and 16.66%, respectively. Meanwhile, Figure 4.88 is quite similar to Figure 4.83, which also indicates that the NFS method performs better than the traditional method in overall situations.

Overall, the findings indicate that the NFS model outperforms the traditional model in enhancing truck productivity and improving the utilization rate of the truck. Consequently, the NFS model provides the possibility for higher production with the cooperation of other equipment.

4.5.8 Shovels' production

The previous sections compared and analyzed the performance of the NFS model and the traditional model in terms of the efficiency of the truck in each process. The main reason why companies care about truck efficiency is that high efficiency can help mines achieve higher output of the mining system within the same time frame, thus bringing higher profits to the company. Therefore, this section will compare and analyze the performance of near-face stockpile and traditional mining methods from the aspect of shovels' productivity, which directly reflects the utilization of shovels in a mining method.

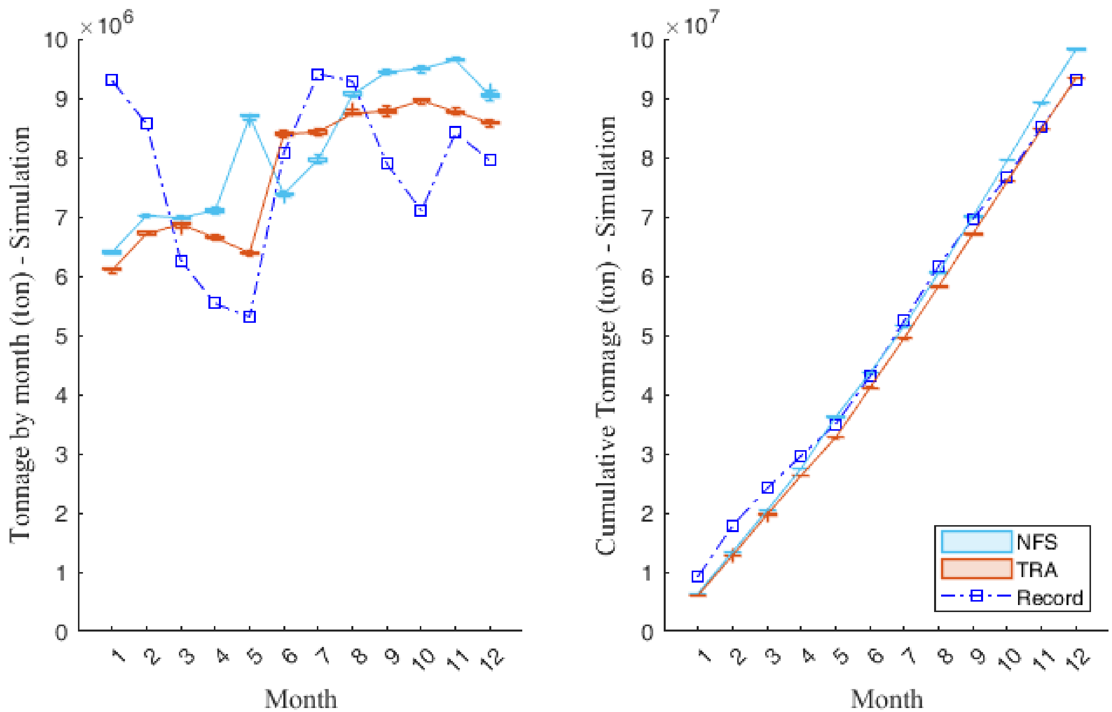

Figure 4.89 Average monthly shovels' productivity and cumulative monthly shovels' productivity of NFS method and traditional method

Table 4.28 Average monthly crusher feeding rate comparison between NFS method and traditional method

Month	Traditional model shovels' productivity (ton) (10 replications mean)	NFS model shovels' productivity (ton) (10 replications mean)	Difference
1	6,107,052	6,380,692	4.48%

2	6,720,483	7,013,867	4.37%
3	6,878,293	6,971,834	1.36%
4	6,626,170	7,094,499	7.07%
5	6,395,779	8,651,223	35.26%
6	8,387,028	7,363,994	-12.20%
7	8,424,225	7,947,315	-5.66%
8	8,753,869	9,036,105	3.22%
9	8,778,200	9,463,109	7.80%
10	8,956,518	9,494,295	6.00%
11	8,770,716	9,634,756	9.85%
12	8,576,304	9,044,559	5.46%
Total	93,374,636	98,096,248	5.06%

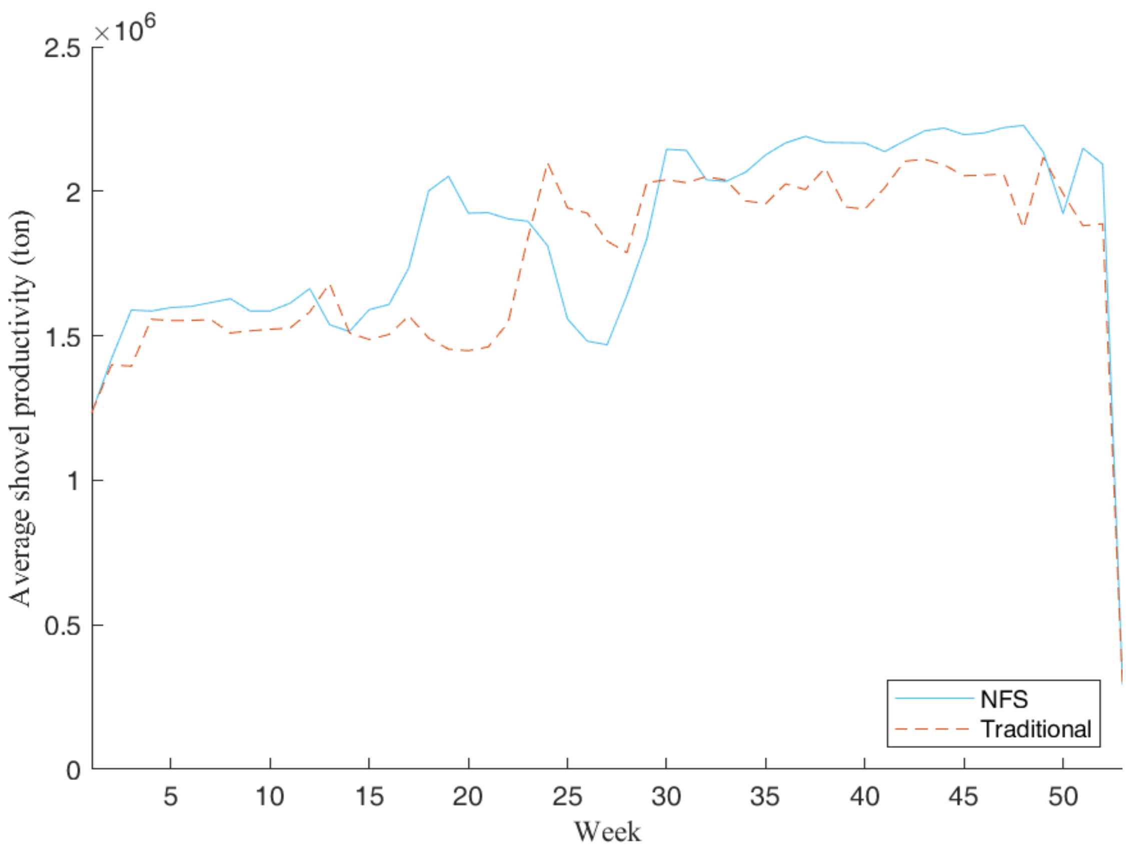

Figure 4.90 Average weekly shovels' production comparison of NFS method and traditional method

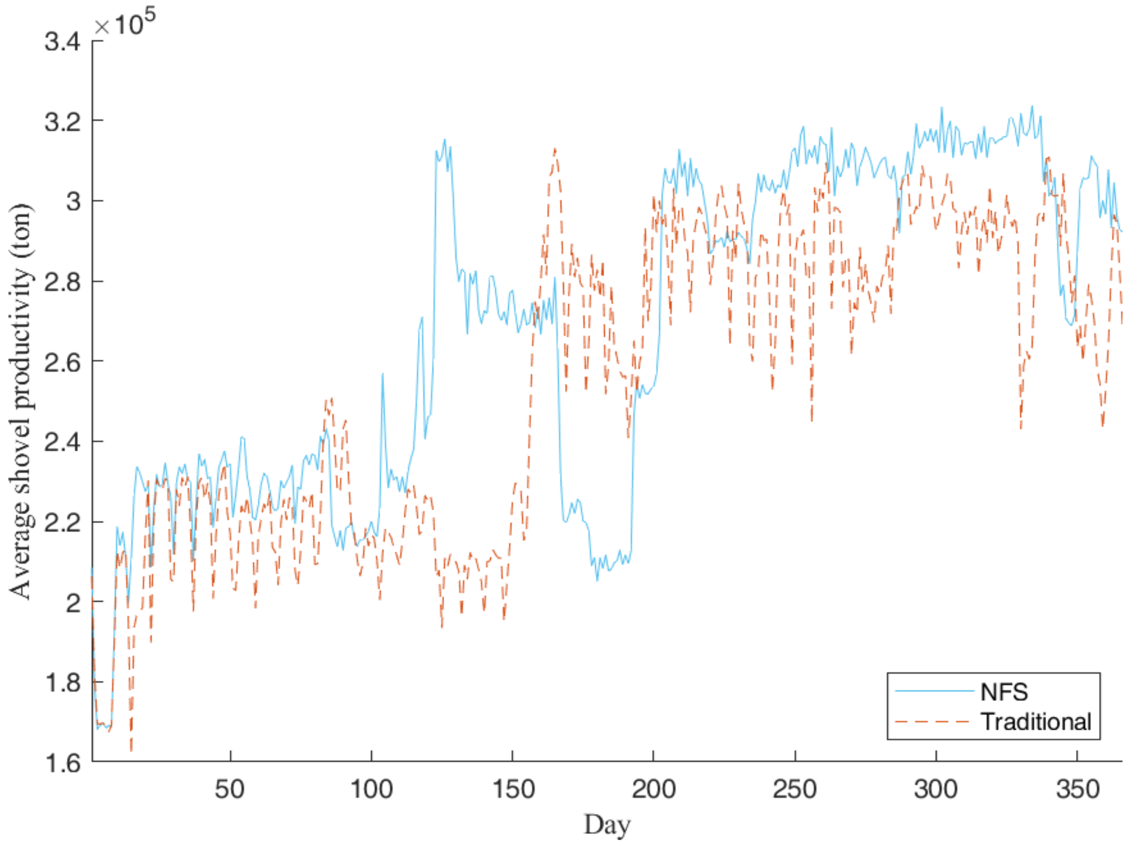

Figure 4.91 Average daily shovels' productivity comparison of NFS method and traditional method

Figure 4.89 displays the 10 replications' average monthly shovels' productivity (left graph) and cumulative monthly shovels' productivity (right graph) of both methods. Corresponding numbers are listed in Table 4.28. The comparison indicates that in most of the months, except June and July, the NFS method yields a higher shovels' productivity. Meanwhile, the total tonnage excavated in the NFS method is 98.10 million tons, which is 5.06% higher than traditional method's 93.37 million tons.

To provide a more detailed analysis of the performance of the two mining methods, Figure 4.90 and Figure 4.91 compare the weekly and daily shovels' productivity of the two methods, respectively. As observed from the trend of the monthly shovels' productivity comparison chart, the NFS method yields higher output from mining system than the traditional mining method in most weeks and days. Furthermore, the output graphs of the three different time resolutions demonstrate a common feature, which is the lower output in the early stage and higher in the later stage. This trend is attributed to the need to complete the work of stripping the waste, which involves long hauling distances and extended truck cycle times, thus resulting in relatively low productivity of shovels. Conversely, the later stage primarily involves mining of the ore material with short distances and high efficiency, resulting in a high productivity. It should be pointed out that in Figure 4.90, the sudden drop in the shovels' productivity of the two methods in the last week is not due to insufficient material or equipment failure, but because the last week only includes two days in the simulation time.

In addition, Figure 4.91 also shows that in the first 50 days of simulations, the shovels' productivity of the NFS method and the traditional model show the same trend, and there is no obvious difference. This is also because the main materials being excavated and transported in the early stage were waste, and the advantages of the NFS method are only reflected in the ore material.

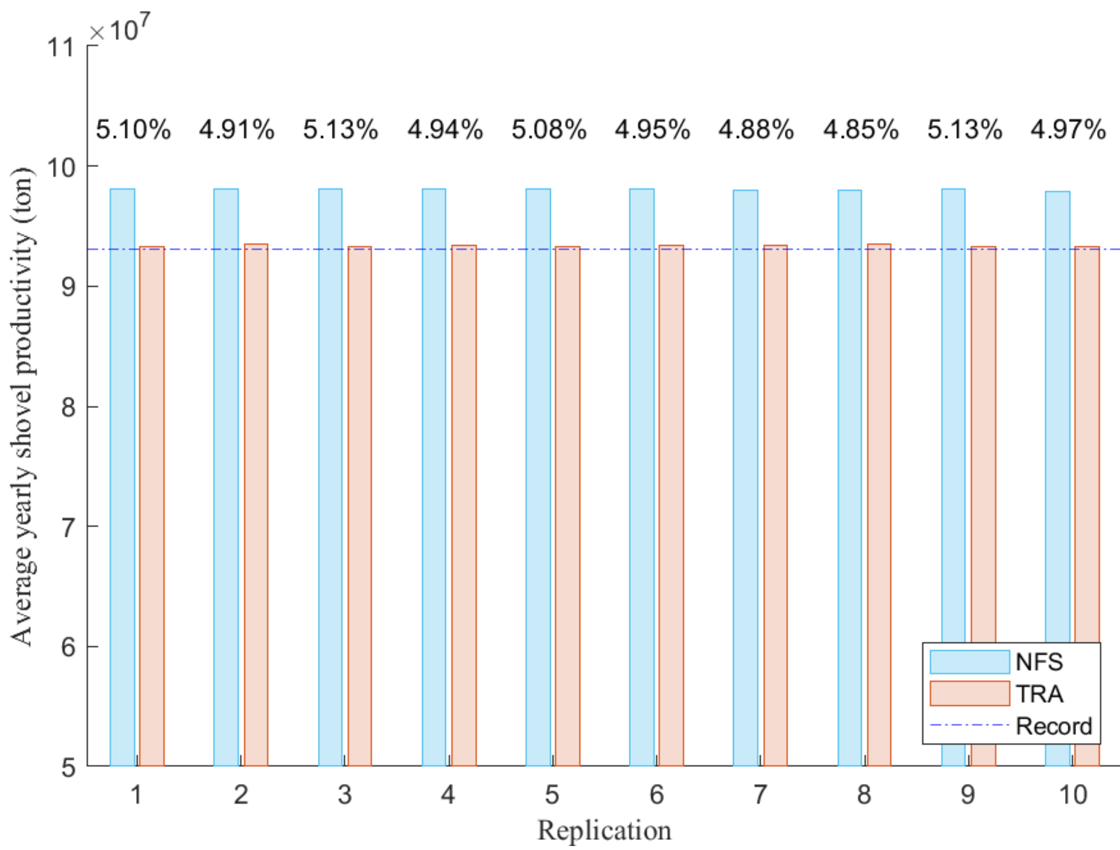

Figure 4.92 Annual shovels' productivity comparison of NFS method and traditional method by replication

After completing the monthly, weekly, and daily productivity comparisons, Figure 4.92 shows the yearly production comparison by replication of the two methods. Undoubtedly, in all replications, the annual shovels' productivity of the NFS method is about 5% higher than that of the traditional method, and its ten-year average productivity of shovels have increased by 5.06% as mentioned above.

4.5.9 Crusher's production

In this section, the author focuses on evaluating the performance of the crusher under the NFS and traditional mining methods in terms of production, which is defined as the output from the crusher. The author notes that while the shovels' productivity is highly correlated with the crusher output, they are not identical to each other. Therefore, the author separates production as a distinct section to analyze the performance of the crusher.

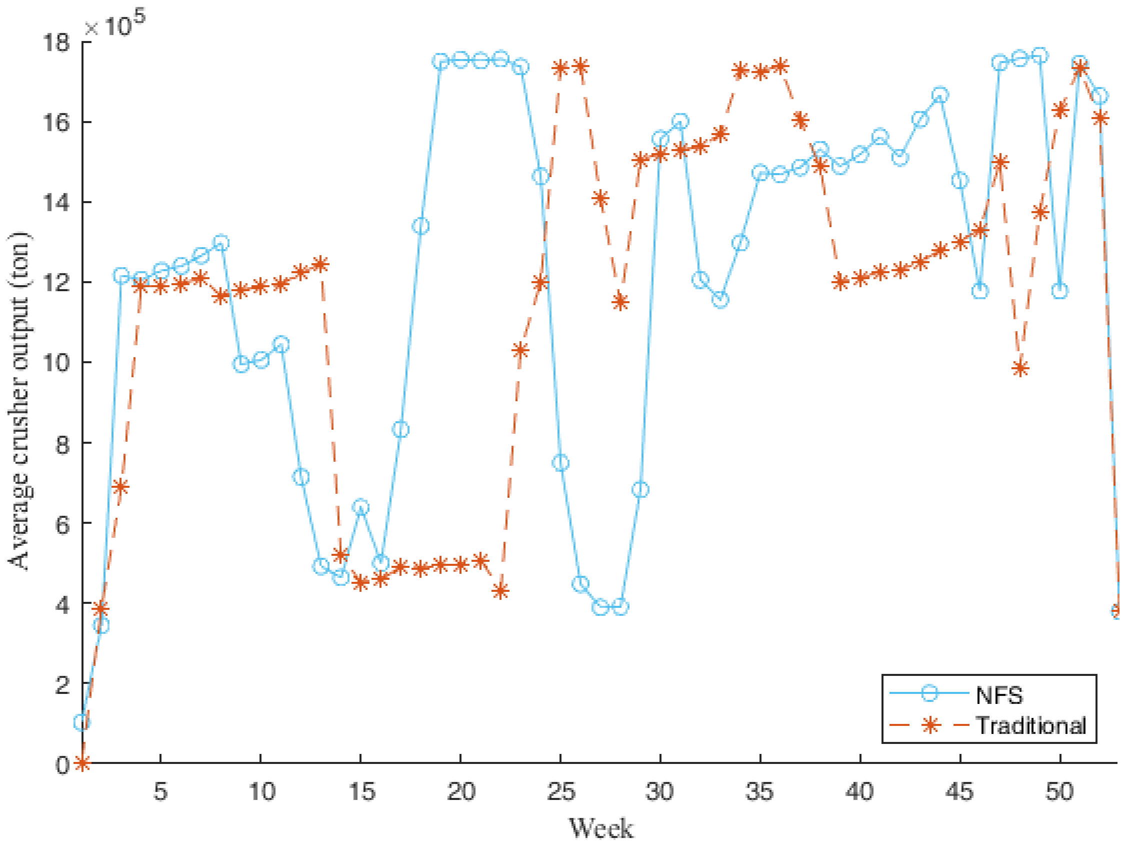

Figure 4.93 Average weekly crusher output comparison between NFS method and traditional method

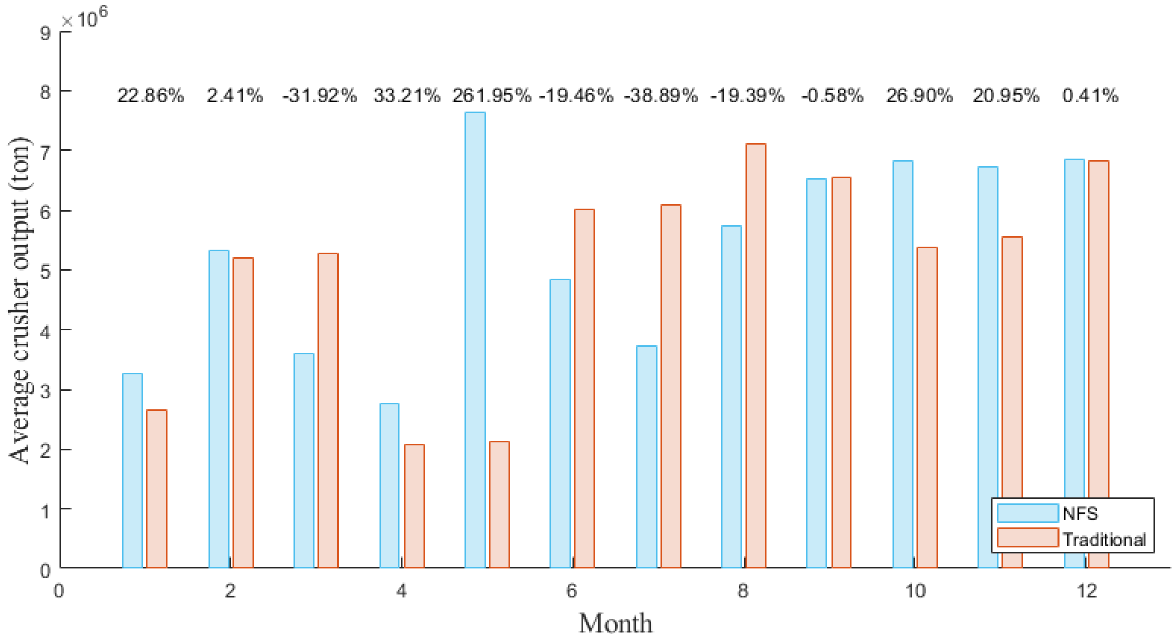

Figure 4.94 Average monthly crusher output comparison between NFS method and traditional method

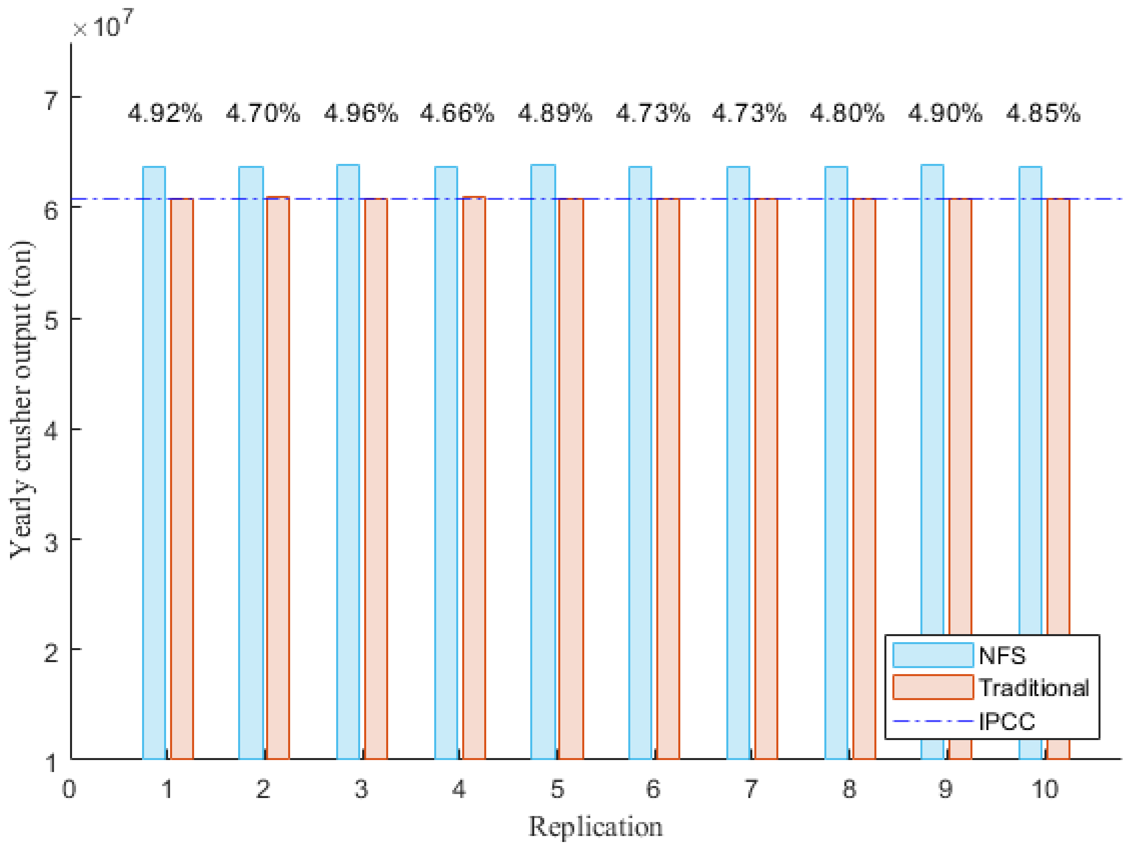

Figure 4.95 Yearly crusher output comparison between NFS method and traditional method

In Figure 4.93 to Figure 4.95, a comparison is presented between the performance of the crusher output under the NFS method and the traditional method across three time resolutions of weekly, monthly, and yearly. Despite the existence of noticeable fluctuations in the short-term (weekly and monthly), the production of the NFS method generally outperforms that of the traditional method. Furthermore, when the timeframe is extended to a yearly basis, the NFS method consistently outperforms the traditional method in terms of crusher output, with an average annual increase of 4.87% across 10 replications.

Considering the difference in layout between the NFS method and the traditional method, it is somewhat arbitrary to completely attribute the increase in crusher output to the increase in the utilization of trucks and other devices. Investigating the existence of the stockpile has made its own contribution to smoothing the fluctuation of the crusher output deserves further discussion and analysis.

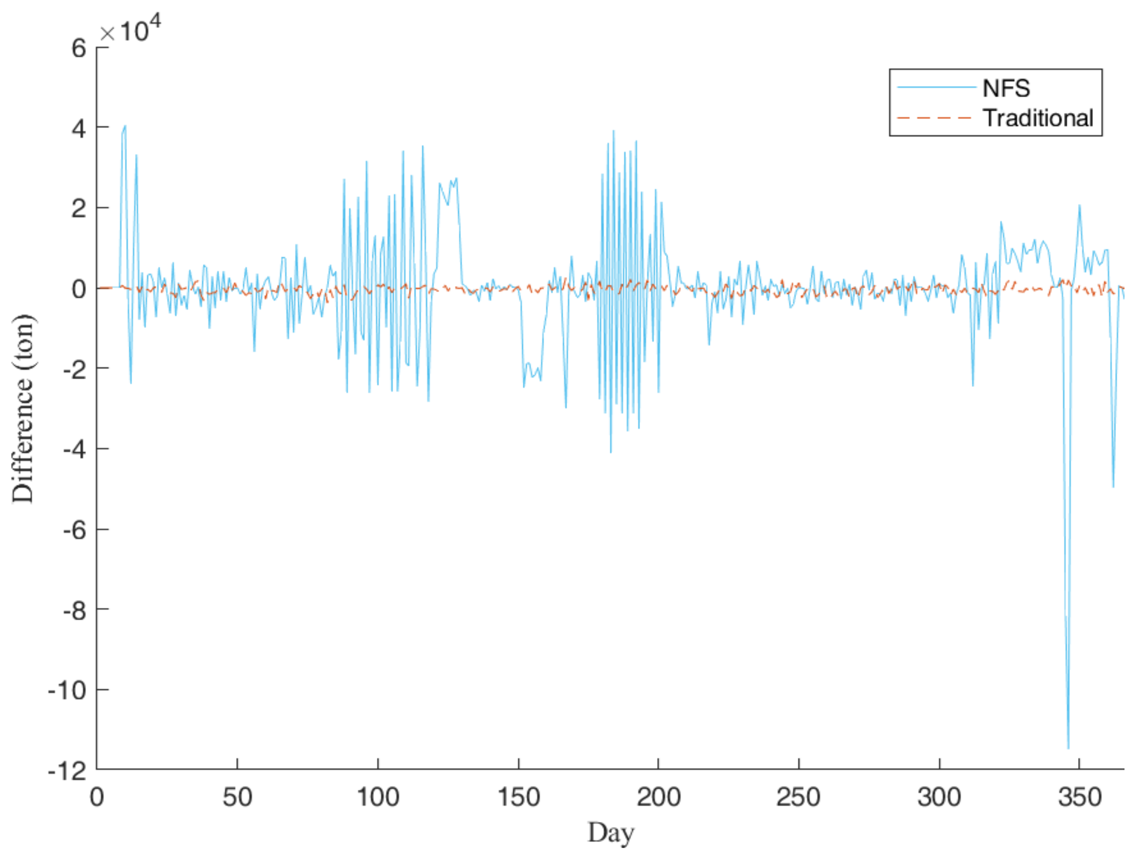

Figure 4.96 Average daily difference between crusher feeding rate and crusher output of NFS method and traditional method

Figure 4.96 presents the average difference between the daily crusher/stockpile feeding rate and crusher productivity for the NFS method and the traditional method. A difference greater than 0 implies that the crusher/stockpile feeding tonnage is higher than the crusher productivity, whereas a negative difference indicates that the productivity of the crusher is higher than the feeding rate. In the traditional method, without a stockpile, the productivity of the crusher per unit of time is expected to be less than or equal to the crusher feeding rate. Consequently, its productivity will fluctuate according to the feeding rate, unless a stable feeding rate is guaranteed. The simulation results of the traditional method, represented by the orange dotted line, confirm this conclusion. The difference between the feeding rate and productivity is small and fluctuates around zero, within one or two loads.

This is a major disadvantage of the traditional mining method and a problem that the NFS method aims to solve. The NFS method features a pre-crusher stockpile that acts as a buffer between the mining and crushing systems. The results, as shown by the blue line in the figure, exhibit noticeable volatility. This indicates that the pre-crusher stockpile functions as expected, with the stockpile carrying redundant ore material when the difference is greater than zero and consuming its own hoarded materials to ensure the crusher operates normally when the feeding rate reduces. This storage and consumption process creates a buffer space for the entire system to cope with uncertain events, significantly enhancing the crusher's ability to maintain stable productivity.

This stability is also the reason why the NFS method yields higher production rates than the traditional method, given the same crusher capacity. The NFS method exhibits remarkable stability, while the traditional method lacks anti-interference ability against uncertain events due to the close connection between the mining and crushing systems.

However, it is worth noting that the stabilizing effect of the pre-crusher stockpile on the crusher productivity gradually weakens as the time resolution is extended to weekly or monthly, as shown in Figure 4.97 and Figure 4.98. This is due to the fact that the size of the stockpile is set to daily turnover. However, this limitation does not diminish the practicality of the NFS method. On the contrary, with a finer daily schedule, the crusher can maintain a stable output within a larger time range, thus maximizing its utilization rate and final productivity.

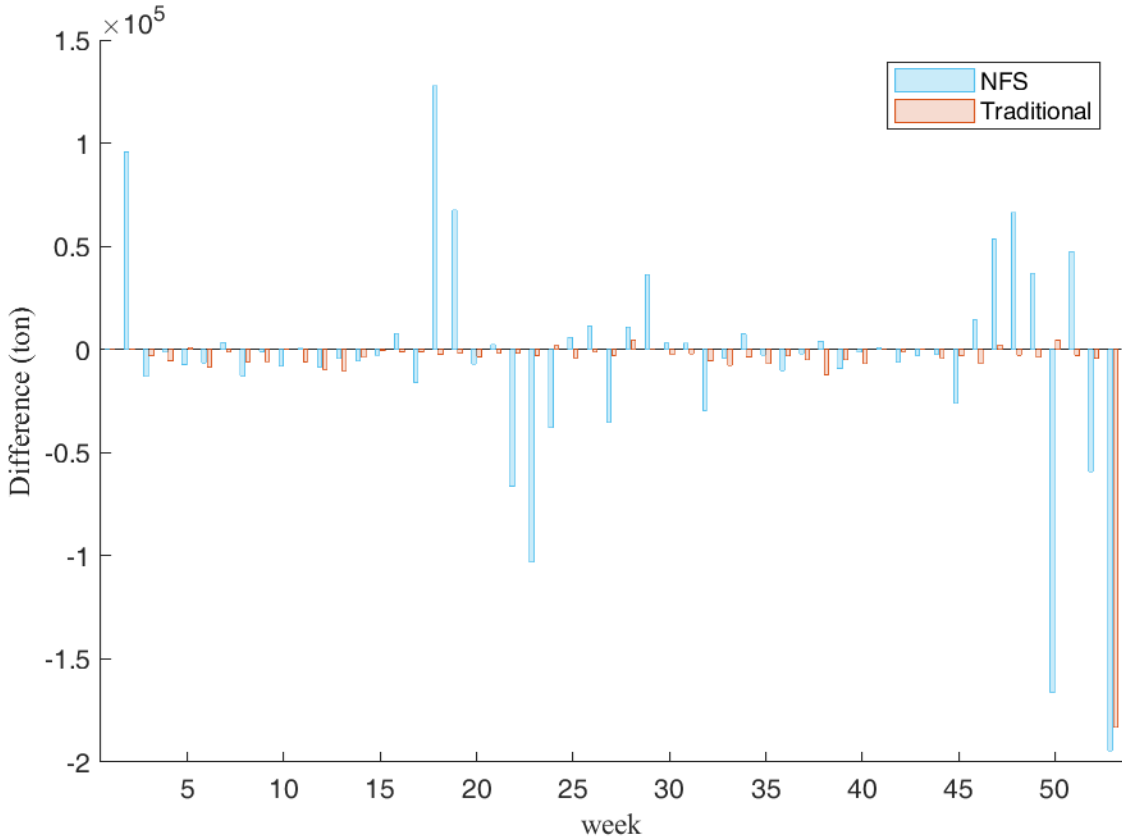

Figure 4.97 Average weekly difference between crusher feeding rate and crusher output of NFS method and traditional method

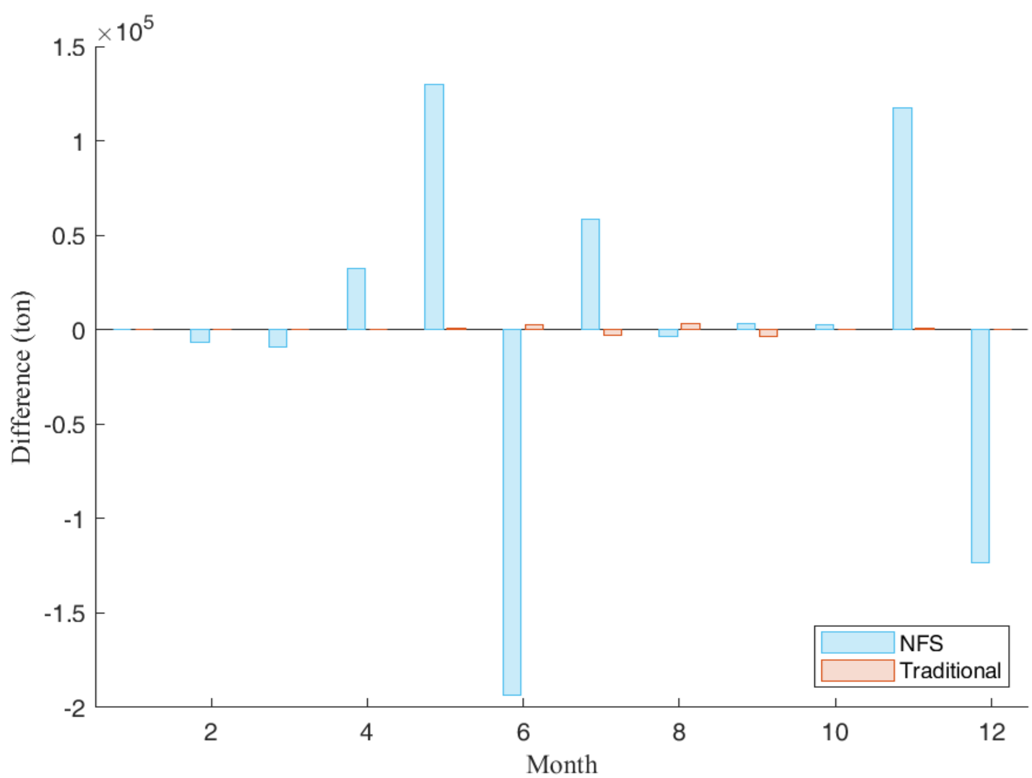

Figure 4.98 Average monthly difference between crusher feeding rate and crusher output of NFS method and traditional method

4.5.10 Equipment utilization

The analyses presented in the previous eight sections have conclusively shown that the NFS mining method is superior to the traditional mining method in terms of truck efficiency, shovel productivity and crusher productivity. The improvement of the efficiency and productivity of these devices can also be demonstrated from the perspective of the utilization rate of each piece of equipment.

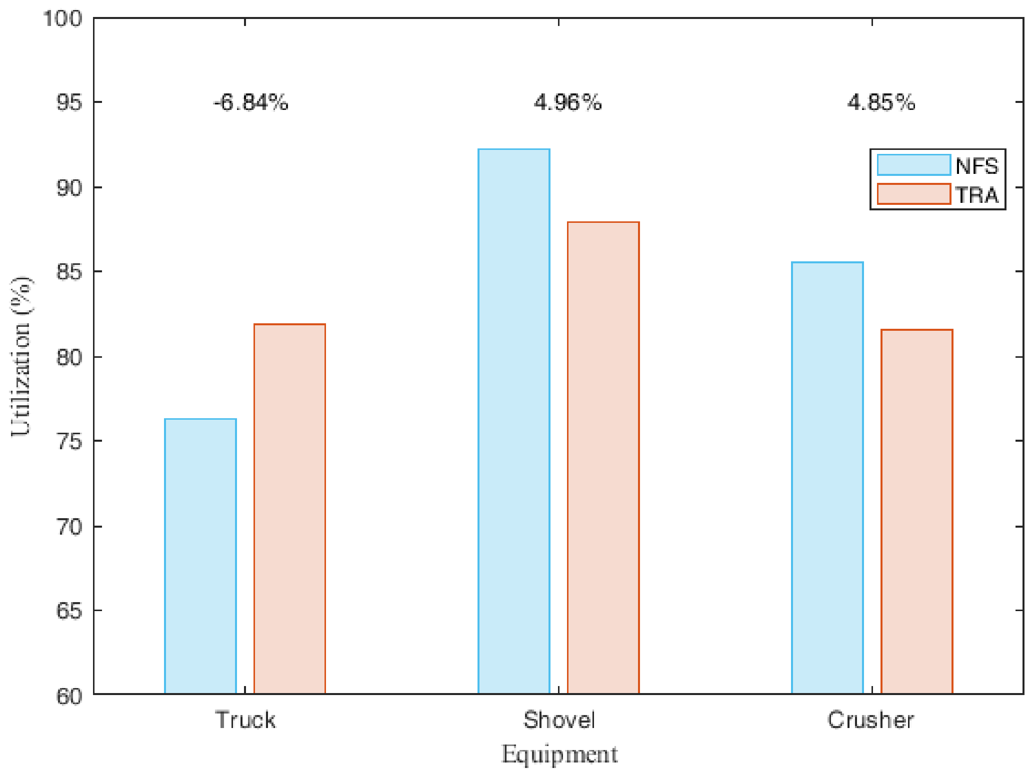

Figure 4.99 Average equipment utilization comparison between NFS method and traditional method

Figure 4.99 provides evidence that the utilization rates of shovels and the crusher under the NFS method are increased by 4.96% and 4.85%, respectively, compared to the traditional method. However, due to the constant number of trucks used for transportation in NFS model, the wait time for trucks has increased despite the reduction in distance covered, leading to a decrease of 6.84% in the overall utilization rate of the trucks, even though the overall production has increased by 5.06%. This demonstrates that the NFS method inherits the advantages of IPCC mining method and reduces the demand for trucks.

The increase in the effective utilization of the crusher, shovels, and trucks can be attributed primarily to the introduction of the near-face stockpile in the layout. In the traditional method, a fully loaded crusher would result in a waiting queue of trucks to dump their loads. Moreover, if shovels are under maintenance or engaged in mining waste blocks at a specific time, the crusher would remain idle. The near-face stockpile mining method was proposed to address these challenges. Although the size of the stockpile may be limited by terrain, cost, or management, the stockpile with a daily mining capacity is sufficient to cover most of the unscheduled shutdowns and minimize the frequency of the problem, thus enhancing the utilization rate of the equipment.

Overall, the NFS mining method outperforms the traditional mining method in terms of equipment utilization, annual production, and TKM moved by truck. It offers the potential for enterprises to reduce carbon emissions, increase production rate, and use equipment more efficiently. Therefore, it is worth going further in research and promotion applications.

4.6. Summary

This chapter first verifies the established simulation model by studying the behavior of scenarios under changing truck numbers. Afterward, the proposed simulation-optimization framework is validated by comparing the simulation results of the traditional model with real data.

After the validation, the simulation-optimization framework is implemented into the NFS method, and the difference between the NFS and traditional models in terms of material transportation distance and mining schedule is compared in detail.

Other than that, a detailed comparison between the simulation results of the NFS and traditional methods in terms of the performance of independent and dependent variables are conducted, and finally draw the following conclusions: Compared with the traditional method,

- The NFS method greatly shortens the truck hauling distance and hauling time of ore material
- The NFS method reduces the total ton-kilometer
- The NFS method greatly reduces the truck's queuing time before the crusher
- The NFS method greatly improves the efficiency of the truck and its TPGOH

- The NFS method reduces the number of trucks required
- The NFS method improves the productivity and utilization of shovels
- The NFS method improves the productivity and utilization of the crusher
- The NFS method can effectively suppress the fluctuation of the crusher’s output
- The NFS method increases the final output of the mine

5. CONCLUSION AND FUTURE WORK

5.1. Summary of the research

The extraction of natural resources through mining, particularly open-pit mining, has remained a crucial approach despite the continuous improvement in the ability to explore and utilize these resources. Although the truck-shovel system was the most prevalent open-pit mining method in the past, it has become increasingly inefficient as mining depths continue to increase, resulting in longer hauling distances and lower economic returns. To address these challenges, in-pit crushing and conveying (IPCC) has gained significant attention due to its ability to reduce truck movement and carbon emissions and increase returns on investment in the life-of-mine cycle. However, a major drawback of the traditional mining method is its susceptibility to risks, which has prompted the development of the near face stockpile (NFS) mining method, a novel concept that combines IPCC with a pre-crusher stockpile.

While the NFS approach has theoretical advantages, there is a need to quantify and evaluate its benefits. Simulation technology has proven to be a reliable and cost-effective approach to evaluate and improve mining methods. However, the existing simulation models have limitations, including a lack of universality, inability to include stockpile, limited flexibility for parameter changes, and unsuitability for simulating the NFS method.

In addition to simulation models, an optimal or near-optimal mining schedule is also indispensable for an objective evaluation of a mining method. This is because no matter how good the mining method is, if there is no optimized mining schedule that matches it, the results may be disastrous. Prior mathematical optimization models have limitations that make them inapplicable to the NFS method, including a lack of consideration for the high turnover of the stockpile. Blindingly applying them will have a significant adverse effect on the objective evaluation of the NFS mining method.

This study has three main objectives. First, establish a mining schedule optimization model that incorporates pre-crusher and is suitable for NFS methods. Secondly, establish a simulation model that can reflect the characteristics of the NFS method, in which the mining subsystem and milling subsystem are relatively independent, to simulate various operations involved in the NFS method.

Finally, integrate the proposed optimization model and simulation model into a complete simulation-optimization framework to evaluate the performance of the NFS method objectively and quantitatively.

The first objective of this research is covered in the first half of Chapter 3. Initially, a mining schedule optimization model was established for traditional mining, incorporating an out-of-pit crusher, utilizing mixed integer linear programming. The objective of the optimization model is to maximize the overall net present value while accounting for constraints of mining capacity, processing capacity, mining-processing inter-relationship, grade control, and procedure control. Aggregations of blocks are implemented to make the optimization model practical for large mines. The algorithm proposed by other scholars is adopted for the implementation of aggregations. Since the optimization process involves extensive data processing, the optimization model is coded in MATLAB and solved by CPLEX through API. An iron mine with 430 million tons of material and 19,561 blocks is introduced as a case study to verify the proposed optimization model for the traditional method, which results in a 2% increase in NPV. On this basis, the author made changes to the optimization model to make it suitable for the NFS mining method. The optimization model for the NFS method is also verified by applying the new optimization model to the same iron ore. Results show that the hypothetical grade variation of material sent to the crusher is reduced by 33.3%. On the basis of only considering the equipment operating cost and not considering the equipment expenditure cost, the overall NPV is increased by 9.3%.

After completing the establishment of the optimization model, in the second part of the third chapter, the author completed the construction of the simulation model of the traditional method and NFS method. The model of the traditional method is based on the truck-shovel system, and the content of the simulation includes shovel moving, loading, truck-loaded haul, truck dumping, truck dispatch, truck empty haul, truck queuing, and other activities in the mining system, as well as crushing and processing in the milling system activity. In addition to the optimized mining schedule, the input items of the simulation model include some independent variables that can significantly affect the simulation results, such as shovel loading time, truck hauling speed, and truck payload. These variables are all taken from the result records of the actual operation, and respectively fitted to the corresponding distribution. In addition, the author also defines some indicators that need to be tracked in the simulation to evaluate its performance. Macros based on Visual Basic language are created to enhance the simulation model's universality by reading equipment parameters and road networks to generate some modules automatically. An oil sands mine with historical activity database is used as a case study to verify and validate the simulation model. The simulation results of the traditional model not only fully follow the distribution of independent variables in actual operation, but also fully match the record of real operation in aspects like crusher feeding rate, ton-kilometer, and TPGOH, indicating a high degree of reliability. Afterward, the author modified the traditional simulation model to fit the NFS method while keeping all equipment parameters unchanged, fulfilling the research's second objective.

The establishment of the simulation models with the completion of the simulation-optimization framework has enabled the objective and quantitative evaluation of the NFS mining method's performance, which is the main focus of this research. A detailed comparison between the NFS model and the traditional model is conducted in Chapter 4, using the validated simulation results of the traditional model as the benchmark. The comparison items include consistency of independent variables' distribution, truck hauling distance and time, truck queuing time and length, truck cycle time, TPGOH, ton-kilometer, shovel productivity, crusher productivity, and equipment utilization. The results of the comparison demonstrate that the NFS mining method outperforms the traditional mining method across multiple metrics. These findings 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.

5.2. Conclusions

Surface mining efficiency and benefits have been significantly improved by the application of large-scale equipment. However, the further improvement of traditional surface mining methods is hindered by bottlenecks. To address this issue, various improvements have been proposed and applied, among which the IPCC method has been successful. Nevertheless, the IPCC lacks the anti-interference ability to deal with uncertain events in mining, milling, and processing, despite effectively reducing the cost of the truck-shovel (TS) system.

To overcome this challenge, the NFS method has been proposed, and its performance evaluation has become an urgent problem to be solved. This paper presents a simulation-optimization based framework to evaluate different mining methods, including the NFS method, in a quantitative and objective manner. Afterward, in Chapter 2, the author reviewed the optimization models for mining schedules and simulation models for different mining methods proposed by various scholars in recent years and identified their respective limitations. Most of the reviewed optimization models do not include the stockpile or only treat it as a marginal auxiliary tool, which is completely inapplicable to the NFS method. In contrast, the NFS method considers the stockpile as a pivot point that connects and separates the mining subsystem and the milling subsystem. Therefore, this research pioneers the efforts to use mathematical programming models in the form of mixed integer linear programming to provide a mining schedule optimization model suitable for NFS methods.

Furthermore, in the simulation models proposed in the past, either the crushing process was not considered, or only the interaction between the truck and the crusher was considered—which does not conform to the characteristics of the NFS method. To address this limitation, this research pioneers the efforts to develop a simulation model suitable for NFS based on discrete event simulation, where the mining subsystem and milling subsystem are relatively independent. The proposed simulation model takes the results of the optimization model as input items to construct a complete simulation-optimization framework for evaluating the performance of mining methods.

To evaluate the performance of different mining methods, an oil sand open pit mine with a traditional mining method is selected as a case study to implement the proposed simulation-optimization framework. First, the framework is applied to the traditional crusher out-of-pit mining method, and its simulation results are compared with real historical data to verify the effectiveness of the framework and serve as a benchmark. Afterward, the framework is applied to the NFS mining method, and the simulation results are compared with the benchmark. By summarizing and analyzing the optimization and simulation results, the following conclusions can be drawn:

1. The optimization model established for the NFS method can generate an optimal or near-optimal mining schedule, which is also a prerequisite for objectively evaluating a mining method.
2. The proposed integrated simulation-optimization framework can well simulate various activities involved in open pit mining, including loading, hauling, dumping, reclaiming, crushing, and processing.
3. The proposed integrated simulation-optimization framework can measure the performance of a mining method from multiple aspects, including but not limited to operating costs, equipment utilization, TPGOH, productivity, queuing time, grade deviation sent to the crusher, etc.
4. The NFS method greatly shortens the truck hauling distance and hauling time of ore material by an average of 17.9%. At the same time, it also reduces the total ton-kilometer transported by trucks by 10.9%, thereby reducing fuel consumption and carbon emissions, and ultimately saving the operating cost of the truck.
5. The NFS method greatly reduces the truck's queuing time before the crusher by 57%, and the truck's cycle time is reduced by an average of 16.3%. These improvements have greatly increased the transportation efficiency of the truck, and the TPGOH of its ore material has increased by 19.5%. In addition, the improvement of truck efficiency also reduces the number of trucks required by the system.

6. Besides trucks, the NFS method also improves the productivity and utilization of shovels by 4.96%. This improvement comes from the reduction of shovels' idle time after the truck efficiency is improved.
7. The existence of the pre-crusher stockpile in The NFS method can effectively suppress the fluctuation of the crusher's feeding rate. The ore material stored in the stockpile can continuously provide materials for the crusher when the ore mining capacity is limited. At the same time, when the ore mining capacity exceeds the crushing capacity, store excess ore material to avoid truck queuing up.
8. Since the NFS method provides a stable crusher feeding rate, the crusher can maintain a stable working state as much as possible, and its output and utilization rate is increased by 4.87% and 4.85% respectively. The increase in the output of the crusher represents an increase in the final production capacity, which can bring higher revenue to the enterprise.
9. The existence of the stockpile not only stabilizes the quantity of ore material fed to the crusher but also stabilizes the quality. This is because the material sent to the crusher has been upgraded from the previous load by load blending to batch blending, which greatly reduces the fluctuation of grade. Simulation results show that the NFS method reduces grade deviation by 20%.
10. Without considering the equipment expenditure, NFS not only greatly reduces the truck operating cost, but also increases the revenue, which can significantly improve the NPV and profit of the enterprise.

To sum up, the performance of the NFS method surpasses the traditional crusher out-of-pit mining method in many aspects. Not only has the utilization rate of trucks, shovels, and crushers been improved, but also the operating cost and carbon emission have been effectively reduced, and the NPV has been increased. It needs to be explained again that the above conclusions are based on the premise that the NFS method is applicable. The NFS method is not suitable for minerals requiring a low stripping ratio and small bottom space. In addition, the above conclusions are based on short-term (one-year) simulation results. Whether the long-term application of NFS maintains the same advantages as the short-term is not clear. In addition, the above conclusions are based on the premise of the perfect work of the conveyor belt. If the belt is damaged or shut down frequently, the results will be far from the simulated results. These premises limit the popularization and application of NFS. However, given its proven advantages, further research on NFS is meaningful.

5.3. Contribution of the research

The present study aims to provide a quantitative evaluation of the performance of the novel NFS mining method that has yet to be applied in practice. To achieve this research objective, the author has undertaken pioneering work during the research period, including a comprehensive analysis of the NFS method and its internal activity interactions. The outcomes of this study lay the foundation for further research and future practical applications of the NFS mining method. The key contributions of this research are summarized as follows:

1. This research presents a novel mathematical optimization model based on mixed integer linear programming, which is capable of generating an optimal or near-optimal mining schedule for the NFS method. To the best of our knowledge, this research is the first to propose such a model for the NFS method.

2. Taking into account the characteristics of the NFS method, this study employs discrete simulation software to create a simulation model. The mining subsystem and the milling subsystem are treated as independent modules, rather than being closely connected through truck-crusher interactions, as is typically done.

3. The proposed optimization model and simulation model are integrated to establish a comprehensive simulation-optimization framework. This framework provides a multi-faceted evaluation of mining methods in terms of performance.

4. This study validates the proposed simulation-optimization framework by comparing the traditional mining method case study with real historical records.

5. By applying the validated simulation-optimization framework to the NFS method, this study quantitatively obtained the performance of the NFS method in terms of transportation efficiency, equipment utilization, productivity, and product quality. Additionally, we provide new insights into how stockpiling can suppress fluctuations in crusher feeder rates.

6. A comparison of the NFS simulation results with benchmark results reveals the significantly better performance of the NFS method compared to the traditional crusher out-of-pit method. It not only enhances transportation efficiency and equipment utilization but also boosts production and reduces operational costs for enterprises, ultimately leading to higher profits.

7. This study confirms the theoretical advantages of the NFS method over traditional mining methods, indicating the potential for further research and practical application. Our work provides a foundation for future studies aimed at promoting the use of the NFS method in the mining industry.

5.4. Limitations and recommendations for future work

In this research, we have innovatively established an optimization model and simulation model that are particularly suitable for the NFS mining method. Using these models, we have constructed a simulation-optimization framework for assessing the mining method's performance. We have then quantitatively evaluated the NFS mining method using this framework and drawn some conclusions. However, these conclusions are based on certain assumptions and have limitations. Therefore, to enhance the body of knowledge and to facilitate a more comprehensive understanding and application of the NFS methods, we present several recommendations:

1. In order to be applicable to tackle the real size mine problem and obtain optimal results, the proposed optimization model aggregates blocks into polygons and assumes a uniform grade of ore material within each polygon. However, with the future increase in computing power, the polygon size can be reduced to improve tracking of the ore material grade, enabling more refined blending results and mining schedules.

2. The optimization model in the proposed simulation-optimization framework is only optimized once at the beginning and then applied to the simulation model as a deterministic result, lacking flexibility. Future work can consider running the optimization model once each polygon is mined to obtain a dynamic and more adaptive mining sequence.

3. The proposed simulation model assumes that trucks haul without any interaction with other trucks. However, in practice, truck interactions with different speeds on the same route are common. To simulate a more realistic truck hauling performance in the NFS method, the road network can be optimized in the future and subdivided into smaller zones.

4. The truck dispatch logic in the proposed simulation model prioritizes the minimum queue length before the shovel. However, different dispatch logic has a significant impact on truck utilization efficiency. Future research can explore the impact of different dispatch logic on NFS transportation efficiency and find the most suitable dispatch logic for the NFS method.

5. The pre-crusher stockpile is a crucial component of the NFS method, and its capacity determines its ability to stabilize crusher feeding rate fluctuations and reduce grade deviations. In this study, it is assumed that its capacity can meet the daily turnover rate of the mine. Future work can establish a methodology to determine the appropriate capacity size that can adapt to different mines and needs, considering construction and maintenance costs and blending requirements, thereby improving the NFS method's practicality.

6. This study's conclusion that the economic efficiency of the NFS method is superior to the traditional method only considers the reduction of truck operating costs and the increase in selling revenue, without factoring in the cost of purchasing different equipment. Although many studies have proven that IPCC can bring investors better returns under life-of-mine conditions, future research can conduct a detailed cost and revenue comparison between the NFS method and the traditional method to verify its superiority.

7. This study only compared the two methods under a short-term simulation of one year. Whether the performance of NFS is still better than the traditional truck shovel method in the whole life cycle is still unknown. Simulating the performance of the NFS method under the full life cycle can greatly improve the understanding of the NFS method and has positive significance for its promotion.

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