A Hybrid Simulation and Optimization Approach towards Truck Dispatching Problem in Surface Mines

by

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ABSTRACT

This PhD thesis has two main objectives. The first objective is to develop, implement, and verify an integrated simulation and optimization framework to study surface mining operations to address important drawbacks of currently available surface mining simulation models. These drawbacks include 1) the treatment of stochastic variables as deterministic ones in material handling systems in surface mines; 2) the deficiency in linking mining systems to mineral processing systems; 3) the inability to integrate fleet management systems with material handling systems; and 4) the lack of flexibility in using different truck-dispatching algorithms in developed simulation systems.

The second objective of this research is to develop, implement, and verify efficient truck-dispatching decision-making models that can cover important drawbacks in truck-dispatching models used in currently available mining fleet management systems as well as models presented in the literature. These drawbacks include 1) neglecting important objectives like meeting the goal of the upper stage; 2) ignoring the importance of one side of a fleet (either shovels or trucks) when making optimal decisions; and 3) treating stochastic variables as deterministic ones.

The integrated simulation and optimization framework was developed using three different types of software. Rockwell Arena was used as simulation modelling software to simulate mining and processing operations. IBM CPLEX was used as optimization modelling software to create a platform to implement the truck-dispatching models. These models include a benchmark model and three new models to solve the truck-dispatching problem in surface mines. The three developed models are multiple objective goal programming model, stochastic mixed integer linear programming model, and fuzzy linear programming model. Microsoft Excel was used as a datafile for the integrated framework to store all required operational data and the production schedule.

The integrated simulation and optimization framework was implemented in an iron ore case study for verification purposes. The framework mimics the mining operation of the case study and interaction of the mining operation with the mine's processing plants and fleet management system. The backbone algorithm of Modular Mining DISPATCH was used as the benchmark fleet management system to evaluate the truck-dispatching models that were developed. A comparison of the implementation of three developed models with the benchmark model in 26 scenarios of single truck-type fleets and multiple truck-type fleets shows that the developed models need an average of 16.5% fewer trucks to meet production requirements.

PREFACE

This thesis is an original work by Ali Moradi Afrapoli. Some parts of this work have been previously published as: Moradi Afrapoli, A. and Askari-Nasab, H., "Mining fleet management systems: a review of models and algorithms," *Int. J. Mining, Reclam. Environ.*, 2017 and Afrapoli, A. M., Tabesh, M., and Askari-nasab, H., "A stochastic hybrid simulation-optimization approach towards haul fleet sizing in surface mines," *Min. Technol.*, pp. 1–12, 2018. 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. Askari-Nasab, H. and Tabesh, M. were the supervisory authors, who were involved with concept formation and manuscript composition.

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Ali Moradi Afrapoli

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LIST OF ABBREVIATIONS

AHP	Analytical Hierarchy Process
BM	Benchmark
DES	Discrete Event Simulation
ESP	Equipment Selection and Sizing Problem
FLP	Fuzzy Linear Programming
FMS	Fleet Management System
LCC	Life-Cycle Costing
LP	Linear Programming
NPV	Net Present Value
MILP	Mixed Integer Linear Programming
MOGP	Multiple Objective Goal Programming
Multi	Multiple Objective Goal Programming

LIST OF NOMENCLATURES

Model presented in section 2.3.3.1

N	the total number of trucks.
M	the total number of service centers (herein: loaders, loaded haul roads, empty haul roads, dump sites).
n_i	the number of trucks in i^{th} service center.
P	the steady state probability.
μ_i	the service rate at i^{th} service center.
η_i	computes the probability that service center i^{th} is working – utilization.
L_{qi}	calculates the expected number of trucks in the queue at the i^{th} service center.
W_{qi}	the expected time a truck spends at service center ($= L_{qi} / \eta_i \mu_i$).
W_i	estimates the expected time that a truck spends in the i^{th} service center.
LCT	the average total cycle time for a truck to complete M service centers.
C_1	the cost per unit of shovel (including capital and operating costs).
C_2	the cost per unit time of truck (including capital and operating costs).
C	the total cost for unit production.

Model presented in section 2.3.3.2

i	index of shovels in ore.
j	index of shovels in waste.

n total number of shovels in ore.

m total number of shovels in waste.

k general shovel index.

CC crusher capacity.

X_i ore production per period of i^{th} shovel.

X_j waste production per period of j^{th} shovel.

P_i priority of i^{th} shovel for production.

Q_j priority of j^{th} shovel for production.

G_u material quality upper limit.

G_l material quality lower limit.

G_i material grade at i^{th} shovel.

$MAXP_k$ maximum digging rate at k^{th} shovel.

$MINP_k$ minimum production rate at k^{th} shovel.

B_k linear approximation for trucks working with k^{th} shovel between $MINP_k$ and $MAXP_k$.

TT total number of available trucks over the time horizon.

R_l lower limit of SR.

R_u upper limit of SR.

Model presented in section 2.3.3.4

S_1	set of ore shovels.
S_2	set of ore discharge points.
S_3	set of stockpile points.
S_4	set of waste shovels.
S_5	set of waste disposing points.
X_{ij}	truck flow over path from i^{th} loading point to j^{th} discharge point.
K_{ij}	total number of segments on path ij .
$D_{ij}^{(k)}$	length of k^{th} segment on ij^{th} route.
$f_{ij}^{(k)}$	road resistance factor of k^{th} segment of ij^{th} path.
Z_1	net truck weight.
Z_2	ore payload.
Z_3	waste payload.
T	planning period over which number of loading and dumping points do not change.
P_i	amount of material to be transported from i^{th} loading point in T time.
Q	total number of ore quality indicator.
$\alpha_i^{(q)}$	ore quality of indicator q at i^{th} loading point.
$\alpha^{(q)}$	required ore quality of indicator q at processing plant.

$S_{.j}$	set of all loading and discharging points that have path to j^{th} discharge point.
$S_{j.}$	set of all loading and discharge points that constitute feasible paths from j.

Model presented in section 2.3.3.52.3.3.6

P_1	priority factor for production.
P_2	priority factor for grade control.
d_i^-	i^{th} shovel production negative deviation variable.
c_{kj}^+ *and* c_{kj}^-	positive and negative deviation from ore grade indicator k at j^{th} crusher.
n_s	number of shovels.
n_q	number of quality identifiers.
n_c	number of the crushers.
n_d	total number of destinations.
n_{os}	number of shovels working at ore faces.
x_{ij}	production to be assigned to the ij^{th} path connecting i^{th} shovel to j^{th} discharge point in each shift.
y_{ij}	is capacity of truck that is to be assigned from j^{th} dumping point to i^{th} shovel per shift.
M_i	maximum production of i^{th} shovel per shift.
B_i	minimum production of i^{th} shovel per shift.
C_j	maximum available capacity of j^{th} discharge point per shift.

G_{ik}	average ore quality indicator k at i^{th} shovel.
Q_{kj}	target ore quality indicator k at j^{th} crusher.
L_{kj}	prescribed lower limit of ore quality indicator k at j^{th} crusher.
U_{kj}	prescribed upper limit of ore quality indicator k at j^{th} crusher.
R_L and R_U	prescribed lower and upper bounds of required stripping ratio.
H_{ij}	average travel time from i^{th} shovel to j^{th} discharge point.
D_j	average dumping time at j^{th} destination including spot time.
R_{ji}	average travel time from j^{th} discharge point to i^{th} shovel.
S_i	average loading time at i^{th} shovel including spot time.
N	number of trucks.
T	weighted average truck payload.

Model presented in section 2.3.3.6

s	shovel type.
d	type of discharge point.
g	truck type.
$K(g)$	cost coefficient of truck type g. For the truck type g with the smallest capacity K(g)=1 and for the rest it is calculated based on that. For example, in a fleet consisting of 240 ton and 320 ton capacity trucks, K(240)=1 and K(320)=1.33).

$X(s,d,g)$	number of truck type g assigned to shovel s and dump d (fractional or theoretical).
$Y(s,d,g)$	number of truck type g assigned to shovel s and dump d (discrete).
$L_o(s,d,g)$	truck type g capacity working on route connecting shovel s to dump d.
$\tau_o(s,d,g)$	ore truck cycle time (minute).
V_o	initial surge volume.
V_{Truck} & $V_{Extraction}$	ore production rates that go in and out of surge per hour.
$C_{Shovel}(s)$	capacity of shovel s (tonnes/hr).
D_w	amount of waste needed to be handled per hour.
$R(g)$	available number of type g trucks.
H	number of hours in each period of concern.
m	used to specify the minimum amount of ore to be mined by the working shovels $(0 \le m \le 1 \quad \text{ton/hr})$.

Model presented in section 3.2.7.23.2.7.3

t_{ts}	time truck t arrives at shovel s.
t_0	current time on the clock that is equal to tNow in the simulation.
xl_t	distance truck t must travel loaded from its current position to the designated dumping point.
vl_t	average velocity of truck t when traveling loaded.

q_t time truck t is expected to spend in queue at its dumping point.

d_t time it takes for truck t to dump its material at dumping point.

xe_{ts} distance truck t must travel empty to reach shovel s.

ve_{ts} average empty velocity of truck t in the road network from to shovel s.

Model presented in section 3.2.7.3

na_s next time shovel s will be available to load a new truck.

NQ_s total number of trucks in queue at shovel s.

ts_q spot time for truck number q in the queue at shovel s.

tl_q loading time for truck number q in the queue at shovel s.

t_0 current time on the clock.

Model presented in section 3.3.1

N_m, N_s, and N_q number of shovels at mining faces, the number of shovels working at stockpile, and the number of quality constraints.

C_m, C_s, C_q, and C_p material transportation pseudo cost (hr/m^3), the stockpile material handling pseudo cost (hr/m^3), the quality pseudo cost (hr/m^3), and the pseudo cost of low feed to plant (hr/m^3).

Q_i material being transported per hour (m^3/hr) that should be determined in the procedure.

L_j quality director: 1 for low crit and -1 for high crit.

X_{ij}, X_jL, X_jA, and X_jU	j^{th} quality factor at i^{th} shovel, the lower limit for quality factor j, the running average value of quality factor j, and the upper limit for quality factor j.
P_t	target rate of plant feed.
R_i	digging rate at i^{th} shovel.
M_c	1st in/1st out average control mass (kg).
SG	specific gravity.
T_c	base control interval (hr).
V	total mine haulage (m^3).
N_p	number of feasible haul routes.
P_i	haulage on path i which should be determined (m^3/hr).
T_i	path i travel time (hr).
N_d	number of dumps for mine haulage.
P_j	net haulage input to dump j (m^3/hr).
D_j	average dump time at dump j (hr).
N_e	number of operating shovels.
T_s	fleet average truck size (m^3).
N_{pi}	number of feasible input paths at node j.

N_{po}	number of feasible output paths at node j.
P_k	input path haulage (m^3/hr).
$P_{k'}$	output path haulage (m^3/hr).
R_j	limiting rate at node j (m^3/hr).

Model presented in section 3.4.1

L_j	time the last truck was allocated to the shovel j.
F_{ij}	flow rate of path i over the total flow rate into shovel j.
A_j	total haulage allocated by time L_j to shovel j.
R_j	haulage requirement of shovel j.
P_i	path flow rate (ton/hr or m^3/hr).

Model presented in section 3.4.2

i	index for set of Trucks: i = {1,...,N}.
j	index for set of Sources: j = {1,...,M}.
k	index for set of Destinations: k = {1,...,D}.
k'	index for set of dumping points that trucks need to dump their load before traveling to the new shovel: k' = {1,...,D}.
t	index for set of weights for individual goals: t = {1, 2, 3}.
q	index for trucks waiting in queue at shovel: q = {1, ..., NTinQS}.
x_{ijk}	incoming flow to source j by assigning truck i to the path of source j to destinations k.

x'_{ijk}	outgoing flow of source j by assigning truck i to the path of source j to destinations k.
c^{-}_{jk}	negative deviation of the met path flow rate for path between source j and destination k compared to desired path flow rate.
c^{+}_{jk}	positive deviation of the met path flow rate for path between source j and destination k compared to desired path flow rate.
S_{ijk}	idle time for shovel j if truck i is assigned to transport material from shovel j to the destination k.
T_{ijk}	wait time for truck i if it is assigned to transport material from shovel j to the destination k.
P_t	normalized weights of individual goals based on priority.
AF	factor balancing available trucks with the required capacity of plants.
PC_k	capacity of the plant k: k = {1, ..., O}: {1, ..., O}⊂ {1, ..., D}.
SC_j	production capacity of shovel j.
MP_{jk}	path flow rate for the path from source j to the destination k that the production operation has met so far.
tc_i	capacity of truck i (ton).
T_i	nominal capacity of truck i (ton).
PT_{jk}	path flow rate for the path from source j to the destination k.
TR_{ijk}	next time truck i reaches shovel j.
SA_{ijk}	next time shovel j is available to serve truck i.
TN	current time of the operation.

$LD_{ik'}$	the distance truck i must travel to reach the dumping point k' to dump its load.
$ED_{ik'j}$	the distance truck i must travel from the dumping point k' to the next expected shovel j.
$\bar{V}_{ik'j-loaded}$	average loaded velocity of truck i traveling to destination k' and will travel to shovel j after dumping its load.
$\bar{V}_{ik'j-empty}$	average empty velocity of truck i traveling from dump k to the next expected shovel j.
$Q@D_{ik'}$	queue time for truck i in the queue of the dump k'.
$D_{ik'}$	dump time for truck i to dump its material in dump k'.
$NTinQS_j$	number of trucks in queue at shovel j.
$TSpotT_q$	spotting time for the truck q in the queue.
$TLoadT_q$	loading time for the truck q in the queue.

Model presented in sections 3.4.3 and 3.4.4

ltt_{td}	loaded travel time from current truck t position to dump d.
qt_{td}	time truck t must spend in queue at dump d to dump its material.
dt_{td}	time truck t spends at dump d to back up and dump its material.
ett_{ts}	time truck t spends to travel empty from the dump location d to shovel s.
$tinq_{t's}$	time a truck of type t' that is already in queue must spend in shovel s queue.
$tenr_{t's}$	time a truck of type t' must travel from its current position to reach shovel s.
$st_{t's}$	spot time for a truck of type t' at shovel s.

$lt_{t's}$	loading time for a truck of type t' at shovel s.
x_{tds}	binary integer variable to assign truck t to the path connecting shovel s to dump d.
tc_t	capacity of truck t.
sc_s	capacity of shovel s.
pc_d	capacity of dump d (ton).
AF	adjustment factor that forces model to evenly distribute extra available trucks among all the possible destinations.
mf	proportion of the cumulative available trucks' capacity to the cumulative required path flow rate that can be met using the available trucks.
pf_{sd}	required path flow rate for path from shovel s to dump d based on upper stage decisions.
$pmsf_{sd}$	met so far path flow rate for path from shovel s to dump d.
ett^r_{tds}	time truck t spends to travel empty from the dump location d to shovel s in r^{th} realization.
r	index referring to a scenario in the stochastic integer model.
nR	number of realizations implemented to generate random variables for empty travel time from its distribution.

CHAPTER 1: INTRODUCTION

1.1. Background

Mine planning is carried out in three time different time horizons (Figure 1.1): 1 – Long-term (life of mine with a yearly resolution); 2 – Medium-term (1 – 5 years, provides more details about extraction of mining areas); 3 – Short-term (1 – 12 months, provides detailed information about mining faces and quality and quantity of processing plant feed [1].

Short-term schedules are divided into operational plans. An operational plan is the shift-based stage of open pit mine production scheduling, which covers dynamic real-time decision-making that includes finding the shortest paths between loading and dumping points, finding the optimum productivity rate of each route, allocating trucks to each route in a way that meets the production target set by the upper stage, and dynamic truck-dispatching (which is the lower stage).

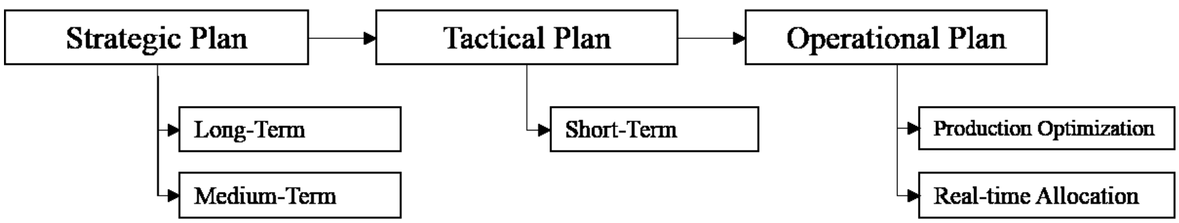

Figure 1.1: Stages of Making Decisions in Mine Production Scheduling

Many researchers believe that 50 percent of operating costs in open pit mines [2] and up to 60 percent in large open pit mines should be spent on materials handling [2]–[8]. Thus, improving the haulage and subsequently decreasing the expenses for this part of the operation by even two or three percent will result in considerable savings.

As Alarie and Gamache [2] found, there are two major approaches to the implementation of operations research techniques to improve materials handling systems in surface mines. A single stage approach, like the one presented by Hauck [9], implements a continuous algorithm to maximize the productivity of the operation and assign trucks to each destination to meet production targets. A multi-stage approach divides the problem into two sub-problems. In the first sub-problem, a static algorithm is implemented to determine the optimal loaders configuration over the mining faces, optimum production rate for the operation, and allocation of trucks to loaders to meet the production target. This stage is called the upper stage and runs at the beginning of the shift and when the mine status changes. The lower stage in a multi-stage approach is a dynamic algorithm, mostly based on an assignment problem analogy and rarely based on a transportation problem analogy. The lower stage assigns the trucks to a proper destination by the time an assignment request is posted by the trucks for a destination to meet the defined targets for this stage.

1.2. Statement of the problem

A fleet management system (FMS) in a mining operation is a connector between strategic level plans and the real-time production operation. Generally, the short-term production target is intended to be met by the operation governed by the FMS. The FMS consists of different levels of dynamic decision-making algorithms that run over the life of the mine and make optimal or near optimal decisions for the materials handling operation. Figure 1.2 illustrates how a FMS is linked with a mining operation. It is worth noting that the FMS in Figure 1.2 is an ideal FMS.

FMSs are used to make decisions primarily on: finding the shortest paths between the loaders and the destinations; determining optimal path flow rates to minimize deviation from the objectives of the strategic plans; and assigning available trucks to active shovels to meet the required path flow rates.

The first problem with the current FMSs comes up in the first step, when a shovel has to be assigned to a new job. In most of the available FMSs, this request is responded to by manually assigning the available shovels to the faces. Current FMSs do not play any role in this step. This problem is usually managed by a mine planner. The result of the assignment varies depending on the level of the mine planner's experience.

Finding the closest distance on the road network for trucks to haul the material to the discharge points is the second problem. This problem is primarily handled by an optimization method such as Dijkstra's algorithm [10]. This problem of finding the shortest path is completely dependent on the shovel's current working face position. The algorithm finds the shortest path from a loader to a destination statically when the loader moves to the next working face. As long as the shovel is working on the same polygon, the shortest path does not change. The problem becomes complicated in large open pit mines with a complex road network. The difference in truck types and their age causes a difference in their velocity. Scheduled or sudden down times for shovels force available trucks to move to an active shovel that causes traffic on specific paths on the road network. The variation in the level of drivers' driving skills and changes in weather conditions are other common factors that complicate the problem.

After determining the optimum combination of available trucks and shovels to meet the desired production in the so-called upper stage of the decision-making procedure, FMSs implement an optimization algorithm each time a truck asks for a new assignment. Most of the algorithms are trying to meet a single, specific predefined objective at this step of the decision-making procedure. These objectives mostly focus on maximizing the utilization of either the truck fleet or shovel fleet in the operation. However, the problem of concern in this step of the decision-making process is to simultaneously maximize the utilization of both trucks and shovels. Also, the models developed so far do not account for the deviation from the desired objectives of the upper stage.

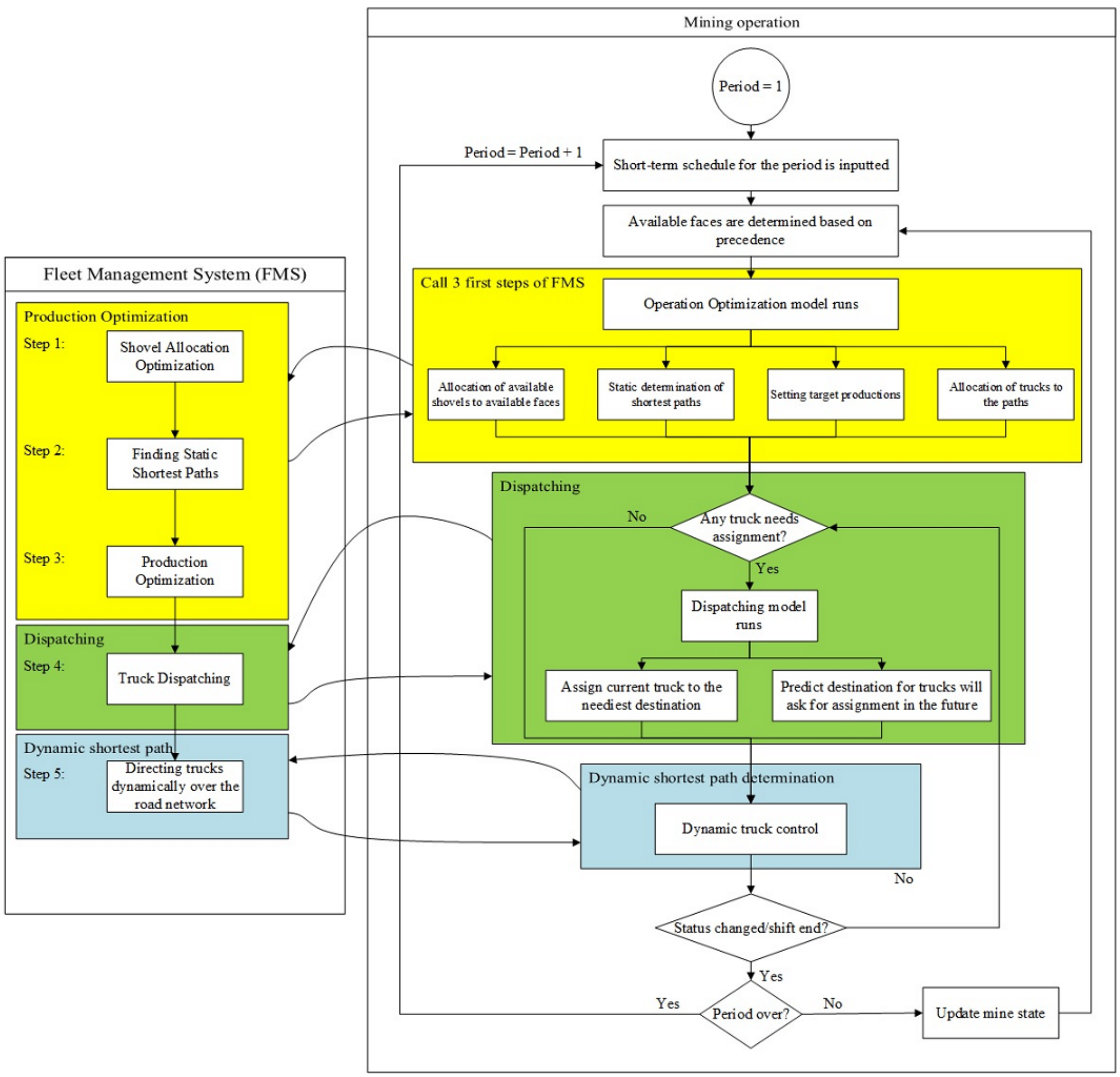

Figure 1.2: schematic illustration of an open pit mine operation.

Researchers have been implementing simulation as a tool to mimic real-world operations in mining engineering-related problems since the early 1960s. Evaluating the effects of what-if scenarios and new developments in mining operations is cheaper and more flexible with simulation. However, the models usually encounter two major problems. The first problem is that the simulations have no connection to the processing operations. Mining operations are directly affected by the failure of downstream assets, change in the throughput capacity, or any change in the processing plant, but, none of the published simulation models take into account an integrated mine and processing plant model. The other major problem with the available simulation models is that they mainly ignore FMSs working in mining operations. However, nowadays almost all open pit mining operations around the world use FMSs, which are core of most e decision-making procedures in any mining operation. The models are developed based on a specific mining operation and there is no possibility of generalizing them to other operations.

A practical FMS is necessary for effective decision-making about available fleet assignments in mining operations. To test and evaluate any fleet management system in the field it is necessary to have a simulation model that integrates both the mining and processing operation in a single framework.

1.3. Summary of literature review

Chapter 2 presents a complete literature review. Herein, I summarize the literature review's two main categories: optimization and simulation. Most of the models in the first category implement different operations research techniques to provide decision makers with choices closest to optimal. The studies in the second category usually implement simulation tools to examine different scenarios and their impacts on the production operation.

1.3.1. Optimization

Most of the literature is about multi-stage decision-making procedures for FMSs. After finding the shortest path, the multi-stage decision-making FMSs usually start with a static production optimization model for the upper stage and end up with a dynamic truck assignment to meet the demands of that stage.

The main limitations of the existing FMSs are that they neglect:

- Linkage to the strategic level production plans;

- The impacts of drilling and blasting operations on the fleet operation;
- The effects of uncertainty and correlation of parameters governing the operation;
- The lost tons caused by mobility and equipment access problems, particularly for shovels;
- The effects of downstream active processes on the transportation operation;
- The impacts of weather and traffic conditions on the shortest path between loaders and destinations;
- The optimum assignment of the available shovels to the active faces;
- Dynamic truck control;
- The incorporation of mixed fleet systems (in most of the models).

These limitations result in decisions that are not optimal.

1.3.2. Simulation

The surveyed literature shows that most of the simulation models were developed based on a specific mine's operation. In these simulation models, some key performance indicators (KPIs) were defined for a specific system based on the requirement. Then, the developed simulation models were run to examine effects of different changes on the defined KPIs. The major limitations of the surveyed simulation models are:

- The models are case-specific, which limits their applicability to problems like the problem for which the model was built;
- The models do not study the operation in a long-time horizon; however most mining companies need to foresee at least one season ahead;
- The models do not incorporate components of processing plants and their up times and down times in the study;
- Most of the models ignore the role that FMSs play in the mining operation. The models are not flexible; different truck-dispatching techniques cannot be implemented.

1.4. Objective of the thesis

This research has two main objectives. The first is to develop a valid simulation and optimization framework to simulate surface mining and processing plant operations. (Figure 1.3). The second is to develop and integrate efficient truck-dispatching decision-making models into the simulation and optimization model developed in the first objective. These dispatching optimization models can be implemented in any multi-stage mining FMS. The simulation model incorporates both the mining operation and processing operation in a single integrated discrete event simulation model and at the same time it communicates to the FMS and asks for path flow rates and truck assignment decisions. The study has five main goals: 1- to develop an integrated simulation and optimization framework to evaluate surface mining operations; 2- to develop efficient truck-dispatching decision-making models to make decisions in the lower stage of any FMS; 3- to embed a currently available FMS in the developed framework to make decisions about the flow rates of paths as well as to dispatch the trucks to be implemented as the benchmark for the study; 4- to embed developed truck-dispatching models in the developed framework; 5- to implement the developed framework with the embedded benchmark and developed truck-dispatching models in a case study.

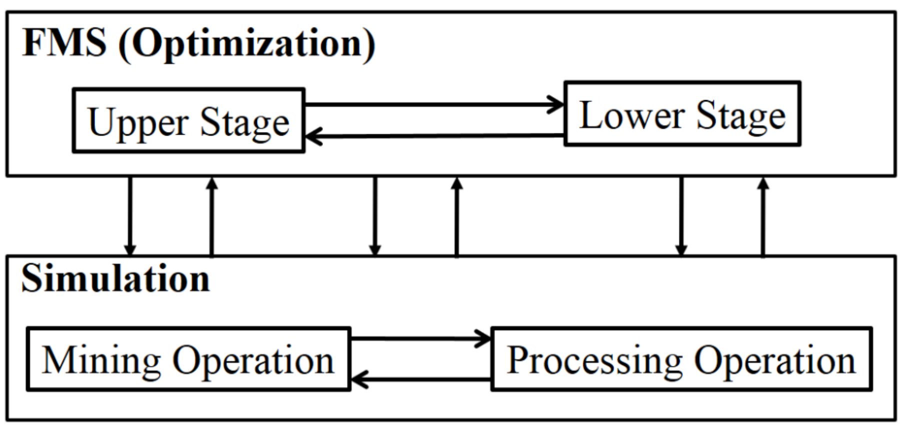

Figure 1.3: Components of the research and their interaction

The research question to address in this study can be divided into two parts and be stated as follows:

Simulation research question: can a simulation and optimization framework be developed to mimic truck and shovel surface mining operations that have an installed fleet management system and is in communication with the processing operation?

Optimization research question: can a decision-making model be developed to solve the truck-dispatching problem in surface mines in a way that minimizes shovel idle time, truck wait time, and the deviation of material path flow rates from the target?

Another major objective of the study is to find a way to approach and consider uncertainties associated with truck and shovel operations in truck-dispatching decision-making models.

To achieve the first objective, a simulation and optimization framework is developed to be implemented in surface mining operation evaluation. Then, the framework was implemented to determine the size of the truck fleet to meet the production requirement dictated by the strategic level planning. Afterwards, the developed framework was used in a mining operation that uses Modular Mining DISPATCH® [11] as its FMS. The framework with the embedded DISPATCH® [11] was used as a benchmark to evaluate the truck-dispatching models developed in this research. Later, the framework was used to evaluate the truck-dispatching models developed in this research as well as to analyze the behavior of the operation system when different scenarios applied.

1.5. Context and scope of work

The research deals with developing a simulation and optimization framework that is capable of mimicking surface mining truck and shovel material handling systems with an integrated FMS. The simulated model considers the effects of processing operations. It also addresses the development of truck-dispatching models that can consider most of the important objectives imposed by strategic level decision makers.

In order to achieve the first objective, we created a system with three major components. The first component is an EXCEL data file. This data file consists of all information from the status of the mine including the production schedule (strategic level short-term schedule of the mine), the shovel fleet and the truck fleet information (obtained from the mining operation database), road network information, etc. The second major component of the integrated system is an Arena discrete event simulation model. The simulation model consists of two main sub-models: a mining operation sub-model, and a stockpile and processing operation conveyor sub-model. The simulation model reads required input data from the EXCEL file. It is also linked to exterior optimization software that contains FMS decision-making models.

To accomplish the second objective, we developed one multiple objective mixed integer goal programming model, one stochastic linear programming decision-making model, and one fuzzy theory-based linear programming model. Each of the truck-dispatching decision-making models is encoded in the optimization software and linked to the simulation model.

The proposed truck-dispatching models consider three major goals of the mining operation, including:

- Minimizing the shovel idle time or, in the other words, maximizing the shovel utilization and subsequently maximizing production;
- Minimizing the truck waiting time or maximizing the total amount of material to be handled in the operation;
- Minimizing the deviation from the target production assigned to each active path using the upper stage model.

The simulation model developed for the study considers a full integration between the mining operation and the downstream processing operations. It is linked to an external optimization environment responsible for fleet management tasks and decision-making processes. Goals of this part of the research are:

- Capturing uncertainty of all random input parameters of the mining operation;
- Embedding an industrially proven mine fleet management system;
- Linking the mining operation with the processing operation;
- Accounting for the effects of the delays in the mining operation of the material handling procedure;
- Accounting for the consequences of the delays in the downstream processes of the material handling procedure.

Although we tried to make the FMS general for the truck and shovel material handling operation in open pit mines, there are always some topics, which fall outside the scope of a research project. Herein, these topics are:

- Changes in product price and operational costs;
- Equipment maintenance;
- Change made by drilling and blasting;
- Equipment failure;
- Equipment matching.

1.6. Research methodology

The study can be divided into five main parts: simulating mining operations with an embedded DISPATCH® [11] optimizer [12], developing mathematical models for truck-dispatching problem in the FMS, developing an integrated mining-processing simulation model, and integrating the FMS with the integrated simulation and optimization model.

When developing each simulation, optimization, and integrated model, the following steps were taken:

- Theoretical model development;
- Encoding and debugging the developed model;
- Verifying the developed model using a case study.

The following lists of tasks were carried out to achieve the research goals. The tasks are categorized into three major areas: operation, simulation, and optimization:

- **Simulation**

  1- Building the mining operation simulation model;

  2- Adding the processing plant connection to the mining operation simulation model;

  3- Preparing the input data file;

  4- Integrating with the optimization model;

  5- Implementing the model into the case study;

  6- Post-processing the integrated framework output for the case study;

  7- Data analysis.

- **Optimization**

  1- Selecting the DISPATCH® [11] optimizer [12] as a benchmark FMS;

  2- Encoding the benchmark model in CPLEX;

  3- Integrating the benchmark optimization model with the simulation model;

  4- Verifying the integrated benchmark model;

5- Developing a multiple objective goal programming mathematical model to solve the truck-dispatching problem in the FMS;

6- Encoding the developed multiple objective goal programming mathematical model to solve the truck-dispatching problem in the FMS in CPLEX;

7- Running different scenarios with the developed multiple objective goal programming mathematical model and comparing the results against the benchmark mathematical model;

8- Developing a stochastic programming mathematical model to solve the truck-dispatching problem in the FMS;

9- Encoding the developed stochastic programming mathematical model to solve the truck-dispatching problem in the FMS in CPLEX;

10- Running different scenarios with the developed stochastic programming mathematical model and comparing the results against the benchmark mathematical model;

11- Developing a fuzzy programming mathematical model to solve the truck-dispatching problem in the FMS;

12- Encoding the developed fuzzy programming mathematical model to solve the truck-dispatching problem in the FMS in CPLEX;

13- Running different scenarios with the developed fuzzy programming mathematical model and comparing the results against the benchmark mathematical model;

14- developing a multiple objective fleet management system by combining the upper stage decision-making model developed by [13], [14] with the lower stage multiple objective goal programming model developed as part of this research;

15- Running different scenarios with the developed multiple objective FMS and comparing the results to the benchmark FMS.

- **Operation**

1- Case study preparation;

2- Preprocessing the required input data;

3- Fleet size determination;

4- Framework implementation;

5- Operation evaluation.

1.7. Scientific contribution and industrial significance of the research

This research has two main contributions. The problem addressed in the optimization part is the truck-dispatching problem in truck and shovel surface mining operations. Three different approaches have been taken to solve the truck-dispatching problem. The first model developed was a multiple objective mixed integer goal programming model. The model is the first truck-dispatching decision-making model in the literature that applied a multiple objective goal programming approach to the truck-dispatching problem. The goal was to meet the production requirement in the mine's schedule by simultaneously minimizing truck wait time, shovel idle time, and the deviation of the path flow rate from the target rate. Our second approach involved developing a new deterministic model for this study. After that, the uncertainties in the input parameters in the truck-dispatching decision-making procedure were taken care of for the first time with two different approaches: stochastic programming approach and fuzzy linear programming approach. Developing the stochastic programming model required a number of scenarios and the implementation of the recourse method [15], [16]. We captured the stochastic behavior of the empty travel time in the truck-dispatching decision-making procedure. We then implemented the fuzzy linear programming approach as the second approach to account for the uncertainty of the input parameters in the truck-dispatching model.

The second main contribution of this research is the development of an integrated simulation and optimization framework for a surface mining operation. This framework consists of the mining FMS, materials handling operation, and processing plants that work in the uncertain mining environment. The framework simulates an open pit truck and shovel operation. The framework also provides a connection between all components of the operation with the FMS and maintains consistent active communication between the FMS and the shovels, roads, trucks, hoppers, and conveyors.

The framework enables the mining industry to determine the minimum number of trucks to meet the production requirement for the operations that have processing plants as well as an FMS in place. Thus far, simulation methods to determine a truck fleet size are not able to consider the effects of processing plants as well as the FMS on the size of the required fleet. The framework also makes it possible for mining companies to evaluate different operational scenarios in the mines that are using an FMS as their operational decision maker. Moreover, the framework helps the industry to examine different decision-making tools and their effects on the operation of the mining system.

1.8. Organization of the thesis

Chapter 1 is a general overview of the research. It discusses the background of the research topic. It then states the problem of concern and provides a brief summary of the literature review. It also explains the objectives of the thesis and introduces the research methodology and contributions.

Chapter 2, the literature review, provides an overview of mining FMSs and simulation of mining systems. Categorizing the FMSs into two main categories, industrial and academic, the thesis extensively studies the developed algorithms for each specific level of publicly available decision-making procedures. It also provides an overview of the simulation studies conducted in mining operations. The chapter ends with the rationale for this Ph.D. thesis.

Chapter 3 contains the theoretical framework for the optimization models and for the simulation and optimization framework developed in this thesis. We divided the chapter into nine parts. After a brief introduction, the chapter explains the models used as the upper stage decision-making tools. Afterwards, introducing the lower stage truck-dispatching decision-making models, the chapter provides information about the simulation model. Then, the chapter discusses the integrated simulation and optimization framework, and the models' assumptions and limitations.

Chapter 4 discusses the implementation of all the developed truck-dispatching models and the developed simulation and optimization framework. The chapter introduces the case study, model verification, design of experiments, determination of optimum fleet size, and implementation of the developed framework with different truck-dispatching decision-making models.

Chapter 5, the last chapter, provides a summary of the thesis and contains concluding statements. It also restates the contributions and limitations of this research and provides recommendations for future works in truck-dispatching in open pit mining operations as well as a simulation of mines' material handling systems.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

Mining projects and more especially surface mines are known as high cost expenditures that need millions of dollars or in the large mines billions of dollars to be expend on them in both capital and operating costs. Materials handling is the main component of the operating cost and plays a critical role in the mining projects' decision-making procedure. A large portion of total mining costs in an open pit mine must be allocated to excavating and transporting the excavated materials from the mining faces to different destinations out of the pit rim. As it is believed by many researchers, 50% of operating costs in open pit mines [2] and even in some cases especially in large open pit mines up to 60% of the operation costs is to be spent on material handling [2]–[4], [17]–[19]. Thus, improving the transportation operation and subsequently decreasing expenses of this part of the operation even by 2 or 3 percent will save stockholders a huge amount of money. There are two important ways along with others to improve material transportation efficiency in open pit mines [2]. The first way is to implement large size trucks in the truck fleet with the capacity of transporting more material in each payload, the point current truck manufacturers have been reached to the maturity. The second principle way to reduce the cost of material transported is to implement operations research techniques to enhance productivity of the operation. Although as Alarie & Gamache [2] considers, there is a single stage approach like the one was presented by Hauck [9]. In this approach, Hauck [9] implements a continuous algorithm to maximize productivity of the operation and send trucks to the destination in a way that minimize deviation from the production target simultaneously. Based on Alarie & Gamache [2], there is also a multi stage approach of the open pit operation optimization that is of the most interest. In the multi stage approach, the problem is divided into two sub problems. In the first sub problem, a static scheduling algorithm is implemented to determine the optimal loaders configuration over the mining faces, optimum production rate for each route connecting loading points to discharge points, and allocation of truck resources to meet production target. This stage called upper stage and runs at the beginning of the shift and when the mine status changes. As the lower stage, an algorithm mostly based on assignment problem or rarely based on transportation problem assigns the trucks to a proper destination by the time the trucks ask for a destination.

The systems containing decision-making models to do upper and lower stage decisions are called Fleet Management Systems (FMS). These decision-making tools make three major sets of decisions: finding the shortest path, determining the optimum path flow rate, and dispatching trucks. In the next section we provide summary of published literature in FMS.

Another area of concern is minimum size of the truck fleet to handle the material handling operation. This is a part of Equipment Selection and Sizing Problem (ESP) that should be solved prior to start of the mining operation.

2.2. Truck fleet sizing problem

Loader related sub problems including loader type and capacity selection and its fleet size determination and hauler type selection and its fleet size determination are two main sets of sub problems that are dealt with in the Equipment Selection and Sizing Problem (ESP) in surface mine planning [20]. To solve the ESP in surface mines different deterministic mathematical models and deterministic and stochastic simulation studies have been conducted thus far.

2.2.1. Mathematical estimation methods

Markeset & Kumar [21] implemented Life-cycle costing (LCC) technique to solve the ESP in surface mines. Later, Samanta et. al. [22] solved the ESP in surface mines using a combination of LCC technique and Analytical Hierarchy Process (AHP) method. Based on [20], [23] the LCC technique does not consider components of a mining operation other than cost in its estimation process. Thus, it is not a qualified and reliable method to be implemented in this area.

Match factor is a value calculated based on the relation between trucks' cycle time and shovels' loading time. A detailed explanation of the procedure of computing the match factor for different types of truck and shovel mining operation can be tracked in [24]–[26]. Results of the match factor computation categorizes any mining operation into three different groups (Table 2.1).

Table 2.1: Mining operation systems based on match factor

No.	Mining operation system	Match Factor
1	Under-truck system	< 1
2	Balanced system	= 1
3	Over truck system	> 1

Implementation of conventional estimation methods countinued by Edwards et. al. [27] using LP model, Krause and Musingwini [28] with implementing machine repair modelling, and Ercelebi and Bascetin [29] who used queuing theory to solve the ESP.

Beside the conventional estimation methods, mining experts have used a variety of methodologies developed based on recent developments in computer science and operational research [20]. These studies can be listed as expert system [30], [31], fuzzy set theory [32], genetic algorithm [33], and multiple criteria decision-making [31], [33], [34].

However, there are two major drawbacks in implementing conventional deterministic models to solve the ESP in surface mines. The first drawback is that the developed models do not consider uncertainties in the input parameters. Dindarloo et al. [35] explains that even if the deterministic modelling of the ESP in surface mine is possible, the modeller encounters serious difficulties due to presence of uncertainties in the input parameters. The second drawback is that the solution methodologies for ESP are not robust methodologies. This is because results of the deterministic model for surface mining material handling system which is stochastic in nature is not reliable and trustworthy [35], [36].

2.2.2. Simulation methods

As most of the conventional methods to solve ESP in surface mines do not provide robust solutions, researchers started to use discrete event simulation (DES) to solve ESP problems that helps to capture impacts of uncertainty of the input parameters on ESP.

Highlights of DES application in surface mining operation studies are the works by Kolonja & Mutmansky [37], Ataeepour & Baafi [38], Yuriy & Vayenas [39], Dindarloo et al. [35], Que et al. [40], Upadhyay & Askari-Nasab [7], Chaowasakoo et al. [41], Chaowasakoo et al. [42], and Zeng et al. [43]. To find out more about application of DES in mining operations, readers are encouraged to read Moradi Afrapoli & Askari-Nasab [44].

Although one of the main concerns about the ESP have been mitigated by implementing DES, the thus far developed DES models usually contain two major disadvantages that force the solutions to be far from optimality. These two major drawbacks are ignoring presence of 1) mining fleet management systems, and 2) downstream processing plants.

2.3. Fleet Management Systems (FMS)

2.3.1. Some of the available FMS in the market

Some of the mining and software engineering companies, those provide decision-making services for mining operations, deliver fleet management system to surface mining operations. Although variety of locally established companies exist that install and support their own fleet management systems for local small mines, there are some FMS providers that are in the business for a while and are world widely recognized. Some of the highlighted companies are: Modular Mining Systems with more than 236 installation [11], Jigsaw Software with more than 130 active installation [45], Wenco (Canadian company headquartered in Vancouver, BC) with about 70 installation [46], TATA consultancy services that claims of 10% to 15% improvement in the production [47], Micromine [48], and CAT® MINESTAR™ FLEET [49]. Table 2.2 represents the FMS names, its provider company, number of mines it has been installed thus far, and some advantages that is claimed by the provider company.

Table 2.2: Industrial mine fleet management systems, summary and stats ([44])

FMS	**Company**	**Installed**	**Advantages**
DISPATCH®	Modular Mining Systems	Over 200	• Haulage Optimization • Qualifications Management • Fuel Service Management • Auxiliary Equipment Management • Remote Supervision • Payload Analysis • Ore Blending Control • Real-Time Web Reporting
Jmineops	Leica Geosystems	130	• OEM independence • Universal Software Platform • Ability to harnesses any industry standard IP-based wireless network • Identical on-board SQL databases & office server that replicate in real-time • Distributed database architecture • Instantaneous data relay • Real-time compliance control • Automated cycle logic
Wencomine	Wenco Mining Systems	65	• Real-time views of location and activity for all equipment at the mine • Assignments sent to operators based on current mine parameters • Roads and detours updated as equipment travels through site • Operators kept on task with onscreen work details • Status of all shovels, trucks, drills, dozers, and other equipment monitored • Ongoing events monitored with customizable, real-time alerts • Observe machine performance with data direct from OEM systems • Boost communication between operators and dispatchers with onscreen messaging • Maintain data integrity with on board store and forward • Follow trends in KPIs with real-time and historical data reporting • Connect over 3G or 802.11 Wi-Fi for data transfer • Operate in an open architecture environment based on Windows

CAT® MINESTAR™ FLEET	Caterpillar	Not available	• Enhancing the management of all types of equipment operations, across one mine site or multiple sites. It also allows you to easily drill down for more detailed views and analysis, from reporting on selectable groups of assets down to individual machines. • With the capability to run scenarios that help determine the impact of operational changes prior to implementing them, Fleet makes it easy to keep your operation running safely and at peak performance, with real-time control. • It also can work with data from all types of assets and equipment—including off-highway trucks, wheel loaders, motor graders, wheel dozers, shovels, light duty vehicles and equipment from other manufacturers—helping you reduce costs per ton, enhance productivity and boost overall site profitability.
Pitram	Micromine	Not available	• Suitable for the underground operations engaging automated mining practices • The solution's intuitive and sophisticated functionality also makes it ideal for open pit mines • Providing an overall view of the current mine status • Increasing clients' control over their operations • Its greater control allows sites to increase production • Reduce costs • Improve safety and business intelligence capabilities
Dynamine	TATA	Not available	• Minimizing the cycle time for open pit mine operations and improving mine productivity • Efficient queue management and monitoring of mobile assets • Effective visualization throughout the operational boundaries within a mine • Monitoring of critical parameters of HEMMS and auxiliary equipment for CBM and safety • Ability to integrate with mine surveys, mine planning and enterprise applications • Ability to be configured with open standard hardware and software platforms such as Microsoft Windows or Linux • Monitoring of the performance of draglines with respect to the swing angle, overload, etc. to maximize operating efficiency

As companies do not have willingness to disclose the algorithms and decision-making models they are using in their developed FMS, reviewing literature for the companies FMS is impossible. The only company that revealed the algorithms and decision-making models of its FMS is Modular Mining System that in two papers ([50], [51]) disclosed their decision-making algorithms working behind the scene in DISPATCH® [11] FMS.

Based on disclosed information regarding the backbone algorithms of DISPATCH® [11] FMS, Figure 2.1 and Figure 2.2 show decision-making procedure in the DISPATCH® [11] FMS and the tasks it accomplishes to take every decision, respectively. In the first step, mine's current status information is inputted to DISPATCH® [11] using some forms. Implementing the Dijkstra algorithm, the FMS finds the shortest paths that trucks can deliver material from loaders to the dumps in the next step. A two segment LP determines the optimal material flow rate in each path. In the last step, using a Dynamic Programming (DP), the FMS dispatches trucks to the right destination and updates the status of the mine [44].

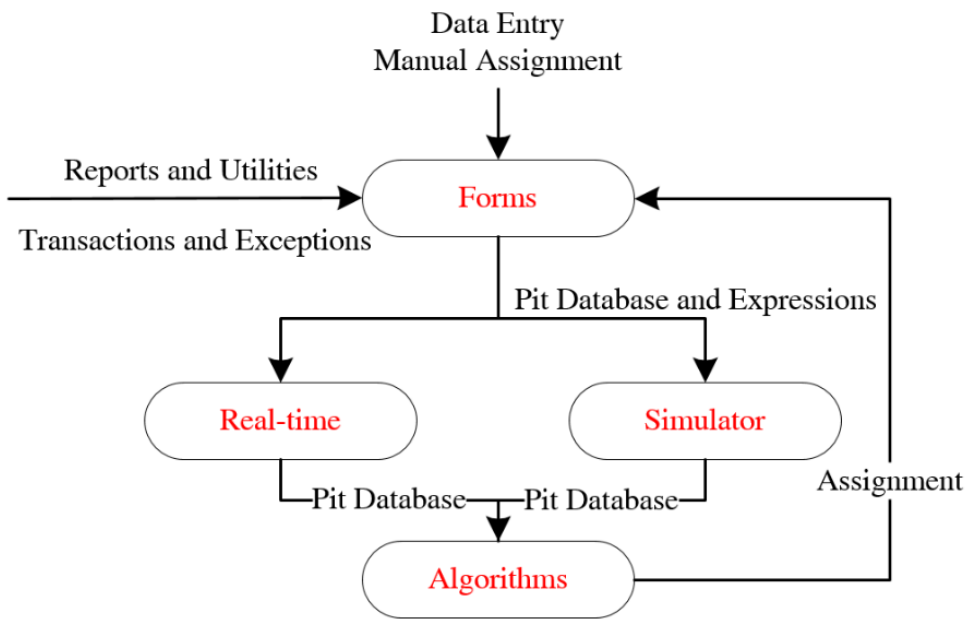

Figure 2.1: Schematic representation of DISPATCH® block diagram [51]

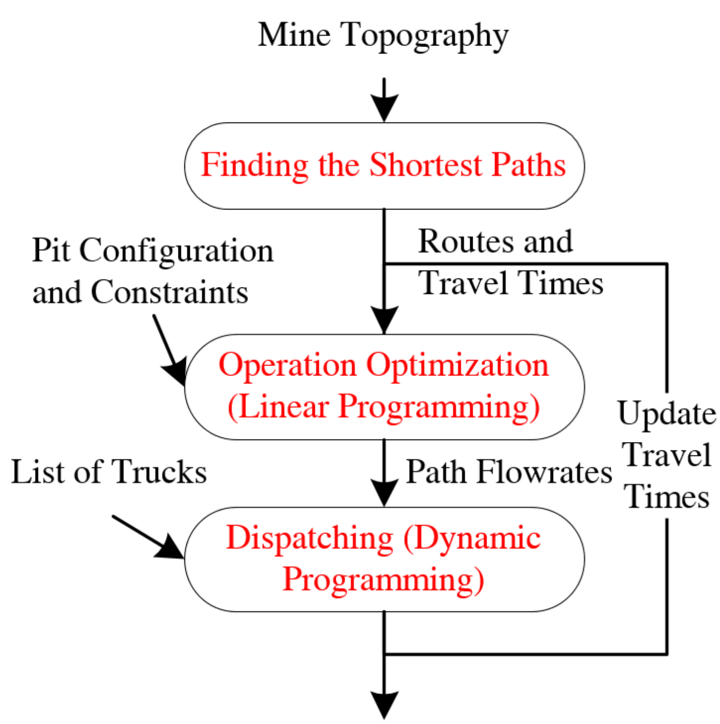

Figure 2.2: Procedure through with DISPATCH® assigns trucks [51]

2.3.2. Finding the shortest path

The shortest path problem is the problem of finding a path between two vertices (or nodes) in a graph such that the sum of the weights of its constituent edges is minimized [52]. Several algorithm have been developed in operational research for finding the best (shortest) path. Some of the most important ones are: Dijkstra [10], Bellman – Ford [53]–[55], A* search [56], Floyd – Warshall [57], [58], Johnson [59], an Viterbi [60]. Despite the variety of the algorithms available to solve the shortest path problem, as claimed by Jaoua et al. [61], the road network in surface mine is not that complex to implement any specific algorithm. Thus, in mining industry, most of the FMS use Dijkstra algorithm.

For instance, DISPATCH® [11] uses Dijkstra's algorithm. The FMS has objective of minimizing travel time for transporting material from a loading face to a dumping area or travelling from a dumping area to a loading face. After solving the shortest path problem, the FMS provides the total minimum distance and travel time for each specific transport and the nodes trucks must pass through to reach the destination for the upper stage decision-making model.

Beside DISPATCH® [11], most of the FMS developed thus far, such as the one presented by Temeng et al. [62] and Temeng et al. [63], also use Dijkstra's algorithm. Hauck [9] defined the shortest path as the shortest travel-time route from loading to the tipping point. Then solved it as an LP sub problem using Dijkstra's algorithm.

However, some FMS in the literature implement a different algorithm to find the shortest path between shovels and dumps. In one of them, in their non-linear model of solving upper stage problems as a network problem, Elbrond and Soumis [64] and Soumis et al. [65] solved a non-linear programming (NLP) network problem to find the shortest path between all loading and discharge points.

2.3.3. Upper stage – production optimization

After finding the shortest path between all the loading mining faces and the dumping points, next level of the decision-making in surface mining operation comes into effect. FMS implement a mathematical model to make the best decision regarding this operational problem. Solving all of the mathematical models in the literature result in either optimum tonnage of material to be transformed from each specific path or optimum number of truck travel to be made on each path. To solve upper stage problem, several researchers implemented different operational research approaches. In following subsections, we present some highlighted contributions categorized based on their solution approaches.

2.3.3.1. Queuing theory approach

Gross et al. [66] defines a queueing system as system in which a customer arrives for a service, if the server is not available immediately, the costumer waits for it, and after taking the service from the server, it leaves. Erlang [67] developed queueing theory for the first time to predict the systems that attempt to provide services. The queueing theory that is defined as the mathematical study of the customers' waiting lines in front of the servers [68].

Koenigsberg [69] is known as the first researcher who used queueing theory concept in mining fields. In his research, Koenigsberg [69] modeled a room and pillar underground mine and a surface mine haulage system using queuing theory. By increasing the number of trucks in the fleet, solving model developed by Koenigsberg [69] will be computationally time consuming [70].

With respect to the truck and shovel operation, some researches have been published in the literature that approach to different problems using queueing theory. Among the studies following queueing theory approach the works of Barnes et al. [54], Dallaire et al. [55], Carmichael [56], Kappas and Yegulalp [57], and Xi and Yegulalp [58] can be highlighted.

Moradi Afrapoli and Askari-Nasab [44] summarized the implementation of queueing theory by Dallaire et al. [55]. Dallaire et al. [55] used an analogy of sestem of many networks for mining operation. they used mean value analysis method founded on recursive relation of the waiting times to compute the truck cycle time for each individual truck as well as capacity of truck fleet. The developed queueing theory based model has two major shortcomings [44]. The model fails to incorporate travel time as an infinite server queueing system that is similar to the drawback of the queueing theory model developed by Barnes et al. [71]. It also leaves the final dispatching decision to be made by the human dispatcher. The model developed by Barnes et al. [71] has another disadvantage that comes from its Erlang distribution characteristics. The distribution can only accept variation in the interval time coefficient to be less than one that is simply violated in mining operations.

Implementing analogy of a production network for truck and shovel material handling operation in surface mine, Kappas and Yegulalp [72] considered trucks as customers and all the serving area in mine like roads, discharge points, loading points, and maintenance areas as servers in their queueing theory model. Although they consider that, the developed model behaves stochastically, the assumption of a mining operation with Markovian nature is not acceptable based on [44]. Moradi Afrapoli and Askari-Nasab [44] notified that as totally different distributions can be fit on the service times in different area of the mining operation, such an operation is not Markovian.

Stochastic truck behavior in queue at dump was considered in the queueing theory model introduced by Najor and Hagan [73]. Results of implementation of their model in a case study in Australia show that neglecting the queue at hoppers leads to misestimating of the total production.

Based on the queueing theory model developed by Carmichael [74], a truck allocation model capable of approximating number of truck required, equipment idle time, and processing plants' feed rate was developed by Ercelebi and Bacetin [29]. We present their developed model below from Eq. (1) to Eq. (12):

$$\left(\frac{N+M-1}{N}\right)=\frac{(N+M-1)!}{(M-1)N!} \tag{1}$$

$$P(n_1,n_2,\mathrm{k},n_M)=\frac{\mu_1^{N-n_1}}{\mu_2^{n_2}\mu_3^{n_3}\Lambda\mu_M^{n_M}}P(N,\mathrm{O},K,\mathrm{O})=\left(\frac{\mu_1}{\mu_1}\right)^{n_1}\left(\frac{\mu_1}{\mu_2}\right)^{n_2}\Lambda\left(\frac{\mu_1}{M_1}\right)^{n_M}P(N,\mathrm{O},K,\mathrm{O}) \tag{2}$$

$$\sum P(n_1,n_2,K,n_M)=1 \tag{3}$$

$$P(N,O,...,O)=\left[\sum\left(\frac{\mu_1}{\mu_1}\right)^{n_1}\left(\frac{\mu_1}{\mu_2}\right)^{n_2}\Lambda\left(\frac{\mu_1}{M_1}\right)^{n_M}\right]^{-1} \tag{4}$$

$$\sum_{i=1}^{M}n_i=N \tag{5}$$

$$\Pr[\textit{phase i is working}]=\eta_i=1-\sum P(n_1,n_2,K,n_{i-1},\mathrm{O},\mathrm{n}_{i+1},K,n_M) \tag{6}$$

$$L_{qi}=\sum n_iP(n_1,n_2,K,n_M)-\sum P(n_1,n_2,K,n_M) \tag{7}$$

$$W_i=W_{qi}+\frac{1}{\mu_i} \tag{8}$$

$$LCT=\sum_{i=1}^{M}(W_{qi}+\frac{1}{\mu_i}) \tag{9}$$

$$\text{Production} = \frac{\textit{time period of } \text{interest}}{\textit{average cycle time}} \times N \times \textit{truck capacity} \tag{10}$$

$$\text{Production} = \text{time period of interest} \times \eta_{shovel} \times \mu_{shovel} \times \textit{truck capacity} \tag{11}$$

$$C = \frac{C_1 + C_2 N}{\textit{unit production} \times \textit{truck capacity}} \tag{12}$$

Where:

N	is the total number of trucks;
M	is the total number of service centers (herein: loaders, loaded haul roads, empty haul roads, dump sites);
n_i	is the number of trucks in i^{th} service center;
P	is the steady state probability Eq.(4);
μ_i	is the service rate at i^{th} service center;
η_i	computes the probability that service center i^{th} is working – utilization – Eq.(6);
L_{qi}	calculates the expected number of trucks in the queue at the i^{th} service center Eq.(7);
W_{qi}	is the expected time a truck spends at service center ($= L_{qi} \;/\; \eta_i \mu_i$);
W_i	estimates the expected time that a truck spends in the i^{th} service center Eq.(8);
LCT	is the average total cycle time for a truck to complete M service centers Eq.(9);
C_1	is the cost per unit of shovel (including capital and operating costs);
C_2	is the cost per unit time of truck (including capital and operating costs);
C	is the total cost for unit production.

Average cycle time is the sum of load time, dump time, queuing time at the shovel, queuing time at the dump, loaded haul time, and empty haul time. Eq.(1), (2), (3), (4), and (5) show the procedure from which the probability of each phase utilization is calculated. Eq.(10) or (11) are implemented to find production per unit of time and Eq.(12) computes total cost per ton of material extracted.

The developed model has some drawbacks. The model assumes Markovian behavior for all the uncertain parameters. It also assumes homogeneity of the mining fleet in the operation, and it calculates transporter's cycle time based on fixed truck allocation meaning that each truck can only travel from a single loader to an specific destination [44].

2.3.3.2. Linear programming approach

Most of the thus far developed FMS implement Linear Programming (LP) approach to solve upper stage problem. Modular Mining Systems FMS DISPATCH® [11] implements a two segment LP model to make optimal decisions on the production requirement (upper stage problem) in surface mining operations. LP model of the first segment results in optimal digging rate at each active loader or shovel. The optimal shovel production rate from the first segment LP is directly used in the second LP segment as an input set of parameters. Then in the second LP segment, DISPATCH® [11] determines minimum required transportation capacity to meet the shovel digging rate requirement [44].

Two main advantages of the model developed by White and Olson [50] and Olson et al. [51] which the FMS of DISPATCH® [11] uses are using information from current status of mining operation as input parameters and resulting in tonnage of capacity required to meet the production requirement rather than number of trucks to meet it [44]. However, as all the researches have their own drawbacks, two major drawback of their model are: 1- not considering required stripping ratio in the operation, and 2- allowing variation of the plants' head grade in a range causing short-term impacts on product quality.

Bonates and Lizotte [75] introduced an LP model for handling upper stage decision-making procedure that maximizes shovel productivity as its objective. The mathematical model developed by Bonates and Lizotte [75] is presented here as a base for all LP type upper stage decision-making models (Eq. (13) to Eq. (21)).

$$\max Z = \sum_{i=1}^{n} P_i X_i + \sum_{j=1}^{m} Q_j X_j \tag{13}$$

Subject to:

$$\sum_{i=1}^{n} X_i \leq CC \tag{14}$$

$$\sum_{i=1}^{n} [G_u - G_i] X_i \geq 0 \tag{15}$$

$$\sum_{i=1}^{n} [G_i - G_l] X_i \geq 0 \tag{16}$$

$$X_k < MAXP_k \quad for \;\; k = 1,2,...,n+m \tag{17}$$

$$X_k > MINP_k \quad for\ k = 1, 2, ..., n+m \tag{18}$$

$$\sum_{k=1}^{n+m} \left[X_k / B_k \right] \leq TT \tag{19}$$

$$R_u \sum_{i=1}^{n} X_i - \sum_{j=1}^{m} X_j \geq 0 \tag{20}$$

$$R_l \sum_{i=1}^{n} X_i - \sum_{j=1}^{m} X_j \leq 0 \tag{21}$$

Where:

i	is the index of shovels in ore
j	is the index of shovels in waste
n	is the total number of shovels in ore
m	is the total number of shovels in waste
k	is the general shovel index
CC	is the crusher capacity
X_i	is the ore production per period of i^{th} shovel
X_j	is the waste production per period of j^{th} shovel
P_i	is the priority of i^{th} shovel for production
Q_j	is the priority of j^{th} shovel for production
G_u	is the material quality upper limit
G_l	is the material quality lower limit
G_i	is the material grade at i^{th} shovel
$MAXP_k$	is the maximum digging rate at k^{th} shovel
$MINP_k$	is the minimum production rate at k^{th} shovel
B_k	is the linear approximation for trucks working with k^{th} shovel between $MINP_k$ and $MAXP_k$
TT	is the total number of available trucks over the time horizon
R_l	is the lower limit of SR
R_u	is the upper limit of SR

Constraint (14) makes sure that total production of shovels working in ore does not exceed the maximum capacity of the crusher. Eq.(15) and (16) guarantee that the ore quality is within the prescribed limits. Constraints (17) and (18) ensure that the total production of each shovel over the period will not deviate from the minimum and maximum digging rate of the shovel. Eq. (19) ensures that the total number of trucks used over the solution time horizon does not exceed total number of available trucks. Constraints (20) and (21) ensure the stripping ratio requirement will be met.

The model presented in Eq. (13) to Eq. (21) can be used as a general LP model to handle upper stage decision-making in FMS. The model accounts for stripping ratio requirement as well as shovels' priorities. Nonetheless, there exists a wrong assumption in developing the model regarding increase in shovel production by increasing the transporters' fleet size. The assumption is that the production rate of shovel has a linear relation with the size of the transporter fleet that is not correct in terms of heterogeneous fleet of trucks. Adding stockpile and re-handling to the objective function is necessary in the model that Moradi Afrapoli and Askari-Nasab [44] refers it as the model's second drawback.

Despite all the efforts, there had been no linkage between the operational level decision-making and the strategic level decision-making in mining operations until the model presented by Gurgur et al. [76]. In their proposed model, Gurgur et al. [76] contribute in assigning shovels to the mining faces. The main objective of the model is to minimize deviation of the production from target set by the strategic level. Based on Moradi Afrapoli and Askari-Nasab [44] the model has two major pros. The model considers availability of trucks in each time span it makes decision for. The model considers mining operation as a multi-period operation and solves the upper stage problem for several periods at the same time. This results in accounting for the influences of the decisions made in current period in the next period decision-making procedure [44].

In a recent research that has its case study from oil sands mining, Ta et al. [77] developed a mixed integer linear programming (MILP) model to solve the upper stage problem in FMS. The model has objective of minimizing total number of trucks required to meet the production schedule. The developed model is not capable of handling a heterogeneous fleet of trucks [44].

Using a knapsack problem LP approach, Mena et al. [78] developed a mathematical model to be implemented in upper stage problem solving procedure in FMS. The model maximizes cumulative truck fleet production for a specific period. The equipment mechanical availability is considered in the decision-making model presented by Mena et al. [78]. The mechanical availability is used as a multiplier for the productivity of the trucks on each specific route in the mine. A mining operation simulated for evaluating their model. Results of their implementation showed that their developed model represents more accurate decisions in comparison to the model where the fleet availability was not considered. The major drawback of the model as claimed by Moradi Afrapoli and Askari-Nasab [44] the problem turns into infeasibility in a certain time of the operation when more than a specific number of trucks are out of operation for the maintenance repair. Another disadvantage of the model is that only availability of the trucks is inputted in the optimization problem. However, the priority in the mining system is the use of bigger equipment and adding availability of all the equipment which plays a role in the production procedure is needed. Along with the above concerns, the blending requirement of the plant feed is not considered in the model as well.

The most resent model based on the LP has been presented by Chang et al. [66]. The model schedules trucks over a shift by implementing MILP with the objective of maximizing transportation revenue. Then a heuristic rule is implemented to solve the model. They also take into account transport priority. The model is based on a homogenous truck fleet that is far from reality and causes non-optimality of the model results in a real system. The model does not consider the stripping ratio requirement, as well as ignores the stochastic nature of the grade distribution. Plant capacity and feed head grade are ignored as well.

One of the major drawbacks of all models developed based on linear programming is that to consider the limitations of the operation, such as the stripping ratio and required feed grade, the models have to define an acceptable range. However, defining a range pushes the operation far behind optimality, especially if the plant feed grade requirement changes. To clarify, let us assume that the objective is to maximize the production. Then probability of truck assignment to the shovel closer to the crusher, resulting in a shorter truck cycle time, will be higher. If the average grade at these closer faces is fairly close to one of the allowed grade boundaries, then whatever the dispatching algorithm is the feed grade within the interval is difficult to control. As a result, the existing of stockpile and subsequently re-handling cost associated with it is undeniably increased.

2.3.3.3. Non-linear programming approach

Most of the models presented in fleet management systems are focusing on upper stage or shovel and truck allocation. The model developed by Soumis et al. [65] performs the upper stage in two steps. As the first step, it fixes the shovels' location by implementing a combinatory mixed integer linear programming (MILP) model with respect to available trucks and the objective of maximizing the production subject to quality constraints. The MILP model solution lists preferred locations for shovels on the computer screen. Now the dispatcher makes decisions on the shovels' allocation based on the list appearing on the screen. Subsequently, as the second step of the algorithm, Soumis et al. [65] represent the truck travel plan between shovels and dumping points by solving a non-linear programming (NLP) model. The model's objective function consists of three components: 1) shovel production objective – computed shovel production; 2) available truck hours – computed truck hours – which includes truck waiting time as well; and 3) penalty for the deviation of the produced ore material from the blending objectives. Munirathinam and Yingling [79] claim that there is an advantage of using NLP versus LP where the solution points of the paths will not be on the extreme points of the solution space, since solution methods for solving LP models always look for the optimum solution on the corner of the feasible regions, whereas NLP solution methods search for the optimum solution over the entire feasible region. As a result of implementing the NLP model, the flow rate will be split over paths, helping to achieve blending goals easier. Beside the advantage of the model, it is assumed that all trucks in the fleet have the same capacity, a homogenous truck fleet. However, generally the truck fleet in mines is heterogeneous with different types and capacity of trucks. The second drawback of the Soumis et al. [65] model is the assumption of fixed grade material in each mining face. However, the stochastic nature of the ore material quality even in a single block is not ignorable [1]. The third disadvantage of the Soumis et al. [65] model is that the model was not presented clearly in the paper.

2.3.3.4. Transportation approach

Although the transportation modelling approach solves the production optimization problem based on an LP model, because of providing a different definition for the problem this modelling approach is being considered as a separate subsection. Li [80] presents a model with the objective of minimization of total transportation work on a travel path, Eq.(22), subject to ensuring meeting a targeted stripping ratio, Eq.(23) and (24), meeting the head-grade requirement, Eq.(25), and ensuring that the number of trucks entering into a loading or dumping node is equal to the number of trucks leaving that node, Eq.(26). Transportation work is defined as the distance that material is transported multiply by the amount of the material. The transportation model was presented by Li [28] for five shovels as follows:

$$\min W = \sum_{i \in S_1} \sum_{j \in S_2 \cup S_3} X_{ij}(Z_1 + Z_2) \sum_{k=1}^{K_{ij}} f_{ij}^{(k)} D_{ij}^{(k)} + \sum_{i \in S_4} \sum_{j \in S_5} X_{ij}(Z_1 + Z_3) \sum_{k=1}^{K_{ij}} f_{ij}^{(k)} D_{ij}^{(k)} + \sum_{i \in S_2 \cup S_3 \cup S_5} \sum_{j \in S_1 \cup S_4} X_{ij} Z_1 \sum_{k=1}^{K_{ij}} f_{ij}^{(k)} D_{ij}^{(k)} \tag{22}$$

Subject to:

$$P_i / T \le \sum_{j \in S_2 \cup S_3} X_{ij} Z_2 \quad for\, i \in S_1 \tag{23}$$

$$P_i / T \le \sum_{j \in S_5} X_{ij} Z_3 \quad for\ i \in S_4 \tag{24}$$

$$\sum_{i \in S_1} \alpha_i^{(q)} \sum_{j \in S_2} X_{ij} = \alpha^{(q)} \sum_{i \in S_1} \sum_{j \in S_2} X_{ij} \qquad for\ q = 1,2,...,Q \tag{25}$$

$$\sum_{i \in S_{.j}} X_{ij} = \sum_{k \in S_{j.}} X_{jk} \qquad for\ j \in \bigcup_{i=1}^{5} \tag{26}$$

Where:

S_1	is the set of ore shovels
S_2	is the set of ore discharge points
S_3	is the set of stockpile points
S_4	is the set of waste shovels
S_5	is the set of waste disposing points
X_{ij}	is the truck flow over path from i^{th} loading point to j^{th} discharge point
K_{ij}	is the total number of segments on path ij
$D_{ij}^{(k)}$	is the length of k^{th} segment on ij^{th} route
$f_{ij}^{(k)}$	is the road resistance factor of k^{th} segment of ij^{th} path
Z_1	is the net truck weight

Z_2 is the ore payload

Z_3 is the waste payload

T is the planning period over which number of loading and dumping points do not change

P_i is the amount of material to be transported from i^{th} loading point in T time

Q is the total number of ore quality indicator

$\alpha_i^{(q)}$ is the ore quality of indicator q at i^{th} loading point

$\alpha^{(q)}$ is the required ore quality of indicator q at processing plant

$S_{.j}$ is the set of all loading and discharging points that have path to j^{th} discharge point

$S_{j.}$ is the set of all loading and discharge points that constitute feasible paths from j

The method implements the abovementioned LP model to allocate the optimal number of trucks to a route meeting its productivity rate. The model presented is based on a five shovel fleet, but the author claims that the model can be implemented in a mine with a higher number of loading points as well. The model considers the productivity of each shovel and also blending requirements. One major drawback of the model is that the total model operational plan, including upper and lower stages, is based on a homogenous fleet. However, this model will not guarantee optimality in real projects where the fleet is heterogeneous because it allocates trucks to each shovel based on the assumption of the same capacity. Another major drawback is that the model does not consider truck breakdowns as a major event that changes the mine status.

2.3.3.5. Goal programming approach

The Goal Programming (GP) was first introduced by Charnes and Cooper [81] and Charnes and Cooper [82]. In the simplest version of GP, the designer prepares some goals he or she wishes to achieve for each objective function. Then, the optimum solution is the set that minimizes deviations from the goals that have been set, meaning that this solution does not maximize or minimize a specific objective, but tries to find a specific goal value of those objectives [83]. In the mining operation optimization, there exists a variety of goals to be achieved, such as production maximization and maintenance of ore quality between the desired limits [63], optimization of the processing plant utilization, and minimization of the trucks' and shovels' movement costs [18]. Temeng et al. [63] formulated a model of open pit mine operation optimization based on GP that is presented below:

$$\min P_1\sum_{i=1}^{n_s} d_i^- + P_2\sum_{k=1}^{n_q}\sum_{j=1}^{n_c}(c_{ij}^+ + c_{kj}^-) \tag{27}$$

Subject to:

$$\sum_{j=1}^{n_d} x_{ij} + d_i^- = M_i \qquad for \quad i = 1,\ldots,n_s \tag{28}$$

$$\sum_{j=1}^{n_d} x_{ij} \ge B_i \qquad for \quad i = 1,\ldots,n_s \tag{29}$$

$$\sum_{i=1}^{n_s} x_{ij} \le C_j \qquad for \quad i = 1,\ldots,n_d \tag{30}$$

$$\sum_{j=1}^{n_d} y_{ji} = \sum_{j=1}^{n_d} x_{ij} \qquad for \quad i = 1,\ldots,n_s \tag{31}$$

$$\sum_{i=1}^{n_s} x_{ij} = \sum_{i=1}^{n_s} y_{ji} \qquad for \quad i = 1,\ldots,n_d \tag{32}$$

$$\sum_{i=1}^{n_{os}} G_{ik}x_{ij} + c_{kj}^- - c_{kj}^+ = Q_{kj}\sum_{i=1}^{n_{os}} x_{ij} \qquad for \quad \begin{array}{l} k = 1,\ldots,n_q \\ j = 1,\ldots,n_c \end{array} \tag{33}$$

$$c_{kj}^- \le (Q_{kj} - L_{kj})\sum_{i=1}^{n_{os}} x_{ij} \qquad for \quad \begin{array}{l} k = 1,\ldots,n_q \\ j = 1,\ldots,n_c \end{array} \tag{34}$$

$$c_{kj}^+ \le (Q_{kj} - U_{kj})\sum_{i=1}^{n_{os}} x_{ij} \qquad for \quad \begin{array}{l} k = 1,\ldots,n_q \\ j = 1,\ldots,n_c \end{array} \tag{35}$$

$$R_L \le \frac{\sum_{i=n_{os}+1}^{n_s}\sum_{j=n_c+1}^{n_d} x_{ij}}{\sum_{i=1}^{n_{os}}\sum_{j=1}^{n_c} x_{ij}} \le R_U \tag{36}$$

$$\sum_{i=1}^{n_s}\sum_{j=1}^{n_d} H_{ij}x_{ij} + \sum_{i=1}^{n_s}\sum_{j=1}^{n_d} D_j x_{ij} + \sum_{j=1}^{n_d}\sum_{i=1}^{n_s} R_{ji}y_{ji} + \sum_{j=1}^{n_d}\sum_{i=1}^{n_s} S_i y_{ji} \le N.T \tag{37}$$

$$d_i^-, x_{ij}, y_{ij}, c_{kj}^+, c_{kj}^- \ge 0 \tag{38}$$

Where:

Where:

P_1	is the priority factor for production
P_2	is the priority factor for grade control
d_i^-	is i^{th} shovel production negative deviation variable
c_{kj}^+ *and* c_{kj}^-	are the positive and negative deviation from ore grade indicator k at j^{th} crusher
n_s	is the number of shovels
n_q	is the number of quality identifiers
n_c	is the number of the crushers
n_d	is total number of destinations
n_{os}	is the number of shovels working at ore faces
x_{ij}	is the production to be assigned to the ij^{th} path connecting i^{th} shovel to j^{th} discharge point in each shift
y_{ij}	is capacity of truck that is to be assigned from j^{th} dumping point to i^{th} shovel per shift
M_i	is the maximum production of i^{th} shovel per shift
B_i	is the minimum production of i^{th} shovel per shift
C_j	is the maximum available capacity of j^{th} discharge point per shift
G_{ik}	is the average ore quality indicator k at i^{th} shovel
Q_{kj}	is the target ore quality indicator k at j^{th} crusher
L_{kj}	is the prescribed lower limit of ore quality indicator k at j^{th} crusher
U_{kj}	is the prescribed upper limit of ore quality indicator k at j^{th} crusher
R_L *and* R_U	are the prescribed lower and upper bounds of required stripping ratio
H_{ij}	is the average travel time from i^{th} shovel to j^{th} discharge point
D_j	is the average dumping time at j^{th} destination including spot time

R_{ji}	is the average travel time from j^{th} discharge point to i^{th} shovel
S_i	is the average loading time at i^{th} shovel including spot time
N	is the number of trucks
T	is the weighted average truck payload

The model maximizes shovel production and ensures the ore grade requirement achieved as much as possible by Eq. (27), Eq. (28) and Eq. (29) ensure that the total material transported from i^{th} shovel cannot exceed the shovel's digging rate and will not be less than its minimum digging rate. Eq. (30) makes sure that the total material dumped in each dumping point cannot surpass its maximum capacity. Eq.(31) and Eq. (32) ensure that the number of trucks entering a node is equal to the number of trucks leaving the node. Eq. (33), Eq. (34), and Eq. (35) guarantee the ore quality requirements at the plant. Eq. (36) conserves the production between the required stripping ratio. Eq. (37) ensures that total production cannot exceed total truck capacity available. The main advantage of the GP model developed by Temeng et al. [63] is that it optimizes two major goals of the open pit operation simultaneously without neglecting either of them. Besides covering the objective function drawbacks of previous models, this model compensates for another disadvantage of the LP models, that is, defining the upper and lower limits for the target grade of material sent to the plant. However, the model has some disadvantages. It does not consider all the goals supposed to be met in an open pit mine operation, such as equipment movement costs and so on.

2.3.3.6. Stochastic programming approach

Ta et al. [84] implemented a chance-constrained stochastic optimization to allocate trucks in an open pit mine as a part of the upper-stage of a fleet management system. They also used an updater to renew the model and parameters by the time shift or status of the mine changes. The presented model considers truck-load and its cycle time as stochastic parameters. The decision variables in the model are number and types of trucks allocated to the shovels. The authors claim that their stochastic model can be solved by converting it to a quadratic deterministic model and implementing mixed integer nonlinear programming techniques and solvers. However, solving the model using NLP techniques is time consuming. Thus, the initial model was divided into two sub-models. The sub-models were solved to allocate a discrete number of trucks to each loader. The main model is as follows:

$$\text{Minimize Truck Resource} = \sum_s \sum_d \sum_g K(g)X(s,d,g) \qquad \text{(truck units)} \tag{39}$$

Subject to:

$$\text{Prob}\left\{V_o + H\left[V_{Truck} - V_{Extraction}\right] \geq V_{Min}\right\} \geq \alpha \tag{40}$$

$$V_{Truck} = \sum_s \sum_d \sum_g \frac{60}{\tau_o(s,d,g)} L_o(\text{s,d,g})\,\text{X(s,d,g)} \qquad \text{(tonnes/ hr)} \tag{41}$$

$$\sum_d \sum_g \frac{60}{\overline{\tau}_o(s,d,g)} \overline{L}_o(\text{s,d,g})\,\text{X(s,d,g)} \leq C_{Shovel}(s) \qquad \text{(tonnes/ hr)} \tag{42}$$

$$\sum_s \sum_d \text{X(s,d,g)} \leq R(g) \tag{43}$$

$$X(s,d,g) \geq 0 \tag{44}$$

Eq. (40) ensures that the confidence level in the model is more than or equal to the predefined level α. Eq. (41) calculates the total volume of material that a truck can transport in a unit of time (hr). Eq. (42) aims to limit trucks at shovel based on the shovel capacity. Eq. (43) and Eq. (44) limit the number of trucks in use to the available trucks in the fleet. The first sub-model, which is a probabilistic chance-constrained model, is as follows:

$$\text{Minimize Truck Resource}(1) = \sum_s \sum_d \sum_g K(g)X(s,d,g) \tag{45}$$

Subject to:

$$V_{Truck} = \sum_d \sum_g \frac{60}{\overline{\tau}_o(s,d,g)} \overline{L}_o(\text{s,d,g})\,\text{X(s,d,g)} \tag{46}$$

$$\text{Prob}\left\{V_o + H\left[V_{Truck} - V_{Extraction}\right] \geq V_{Min}\right\} \geq \alpha \tag{47}$$

$$V_{Truck} \leq C_{Shovel}(s) \tag{48}$$

$$V_{Truck} \geq mC_{Shovel}(s) \quad \textit{where } 0 \leq m \leq 1 \tag{49}$$

$$\sum_s \sum_d \text{X(s,d,g)} \leq R(g) \tag{50}$$

$$X(s,d,g) \geq 0 \tag{51}$$

The first sub problem is almost the same as the general chance-constrained problem, except for the constraint (49) that maintains the solution from the assignment of zero trucks to shovels. Also, a minimum ore throughput from the shovels is maintained by using m. The model must be simplified as a non-linear deterministic model and be solved by use of nonlinear techniques. The model provides a continuous amount for the truck number, which must be a discrete number. To determine this number, a second sub problem was presented:

$$\text{Minimize Truck Resource}(2) = \sum_s \sum_d \sum_g K(g) Y(s,d,g) \tag{52}$$

Subject to:

$$\sum_s \sum_d \sum_g K(g) Y(s,d,g) \geq \text{Truck Resource}(1) \tag{53}$$

$$\sum_d \sum_g \frac{60}{\overline{\tau}_o(s,d,g)} \overline{L}_o(\mathrm{s,d,g})\,\mathrm{Y(s,d,g)} \leq C_{Shovel}(s) \tag{54}$$

$$\sum_d \sum_g \frac{60}{\overline{\tau}_o(s,d,g)} \overline{L}_o(\mathrm{s,d,g})\,\mathrm{Y(s,d,g)} \geq mC_{Shovel}(s) \tag{55}$$

$$\sum_s \sum_d \mathrm{Y(s,d,g)} \leq R(g) \tag{56}$$

$$\begin{aligned} &i=1: Y^{(i)}(x,d,g) \geq 0 \\ &i=2,3,\ldots: Y^{(i-1)}(x,d,g) - 1 \leq Y^{(i)}(x,d,g) \leq Y^{(i-1)}(x,d,g) + 1 \end{aligned} \tag{57}$$

$$Y(s,d,g) \geq 0 \tag{58}$$

Where:

s	is the shovel type; d is type of discharge point
g	is the truck type
$K(g)$	is the cost coefficient of truck type g. For the truck type g with the smallest capacity *K(g)*=1 and for the rest it is calculated based on that. For example, in a fleet consisting of 240 ton and 320 ton capacity trucks, *K(240)*=1 and *K(320)*=1.33)
$X(s,d,g)$	is the number of truck type g assigned to shovel s and dump d (fractional or theoretical)

$Y(s,d,g)$	is the number of truck type g assigned to shovel s and dump d (discrete)
$L_o(s,d,g)$	is the truck type g capacity working on route connecting shovel s to dump d
$\tau_o(s,d,g)$	is the ore truck cycle time (minute)
V_o	is the initial surge volume
V_{Truck} & $V_{Extraction}$	are the ore production rates that go in and out of surge per hour
$C_{Shovel}(s)$	is the capacity of shovel s (tonnes/hr)
D_w	is the amount of waste needed to be handled per hour
$R(g)$	is the available number of type g trucks
H	is the number of hours in each period of concern
m	is the used to specify the minimum amount of ore to be mined by the working shovels $(0 \le m \le 1$ ton/hr)

Constraint (53) defines the lower bound of the objective function. Eq. (54), Eq. (55), and Eq. (56) are the same as Eq. (48), Eq. (49), and Eq. (50) in the first sub-model with the exception of number of trucks being discrete. Eq. (57) helps to move to the next time period realistically.

The objective function value of the first sub problem helps to define a lower limit for the objective function value of the second sub problem. To move to the next time horizon, constraint (57) is defined to ensure gradual transition of allocation from the current period. Although the model provides a good conceptual background for the stochastic optimization approach to solve the multi-stage optimization problem, the model takes into account only the probabilistic nature of truck travel times. In addition, the model formulation is very much specific to a specific mining case and cannot be generalized to other mining systems.

2.3.4. Lower stage – real-time dispatching

Real-time decision-making on the destination of trucks in a mining operation was first used in the early 1960s with implementation of radio communication tools to link between dispatcher and trucks operators in a fixed truck allocation mine. However, based on the utilization of the modern computer, real-time fleet management in mining operation systems are divided into three major categories: locked-in or fixed allocation, semi-automated, and fully automated systems. In the locked-in method, there is no effort for dispatching the transportation units. Semi-automated dispatching, which has been developing by increasing the computer usage in the mining sector, is divided into two different classes: passive and active. In the earlier class, the computer just displays the current mine operation information and does not have any role in the decision-making procedure. However, in the latter class, computers use current mine status information as inputs and process them based on predefined models and suggest a list of assignments for the dispatcher's decision. In the automated dispatching, the data of the current mine status and condition and position of the equipment within the operation are collected into a main computer server, which then sends the assignment to trucks after solving some heuristics or mathematical programs. What we review here is the last class where computers receive data, process them and assign the trucks to their next destinations.

There are two major approaches governing dispatching procedure: the assignment problem approach and transportation problem approach. The first approach itself is a subcategory of the transportation problem in the operations research.

2.3.4.1. Assignment problem approach

A general assignment problem is a balanced transportation problem in which all demands and sources have capacity of one unit. In each assignment problem, there is a cost matrix that consists of the costs associated with assigning each supply to each demand. The objective of each assignment model is to minimize the cost of allocating supplies to demands. In the mining context, the assignment problem has been used mostly to dispatch trucks as supply to shovels or dumping points as demand. The objective in mining truck-dispatching, based on the assignment model, is to minimize shovel idle time, truck waiting time, inter-truck time, and so on. In comparison with the other approach, almost all real-time truck-dispatching models in both industrial and academic research areas are based on the assignment problem.

After solving the upper stage – operation optimization – LP problem by implementing the simplex method [85], resulting in the optimum material flow rate on routes, White and Olson [50] and Olson et al. [51] employ the dynamic programming (DP) [53] approach to send trucks to the proper destination. To do so, two lists and three parameters are defined. A list of needy shovels or LP-selected paths and a list of trucks dumping material at discharge points or en-route from a loading point to a destination are provided. In addition, need-time, which is defined as the expected time for each path's next truck requirement, is calculated.

Then, the neediest path, which is on the top of the neediest shovels list, will be the one with the shortest need-time. Then lost-ton is defined and formulated as a criterion to find the best truck for the neediest path from the truck list.

Considering the lost-ton definition, the best truck is the truck covering lost-ton of neediest shovel the most. After the best truck is assigned to the neediest shovel, it is moved to the last position on the needy paths' list and the procedure is repeated for the second neediest, which is now the neediest until all trucks on the list are assigned.

Defining a rolling time horizon when a sequence of assignment is needed is a benefit of the model. The information of the mine status used in the model is always up to the minute. However, the model does not consider the effect of current truck assignment on the forthcoming truck matching, though all trucks previously sent to the shovels are considered. Another drawback of the model is that despite the authors' claim, the solution method is not a DP. It is a heuristic rule solving each sub-problem based on the best solution of previous sub problems. Based on Alarie and Gamache [2], the solution method's misnaming as a DP is perhaps because of the authors' misunderstanding of Bellman's principal of optimality. However, the DISPATCH® [11] system has been implemented in about 200 mines all around the world and is to most dominant player in the FMS market. Table 2.3 summarizes the procedure with which DISPATCH® solves a mine production problem.

Table 2.3: Summary of the models DISPATCH® uses in the fleet management systems

Category	Shortest Path	Allocation	Dispatching
Objective	Minimize travel time	Minimize total trucks required	Minimize lost-tons caused by the assignment
Constraints	Intermediate call points a truck should pass	Shovels' digging rate Dump area capacity Continuity at each loading and discharge point Total number of trucks available in the fleet Blending limits of grades Targets of material category blending	Proximity of truck that asks for an assignment to the destination
Solution Method	Dijkstra	Simplex	Dynamic Programming

Advantages	Algorithm often does not have to investigate all edges Dijkstra's algorithm has an order of n^2 so it is efficient enough to use for relatively large problems	Model is up to the minute Flowrate of each route is based on the volume of the material rather than number of trucks	Progressing time horizon when order of assignment is required Under-/Over-truck conditions considered
Disadvantages	Model is time consuming Failure in cases of negative edges Global information of the road network required	Appropriate when a few variables are at play Non-negative constraints for all variables	Definition of a progressing time horizon for an order of assignment Consideration of under-/over-truck conditions

Hauck [9] implemented a sequence of assignment problems to dispatch the trucks need destination. The objective function of his model is to minimize total idle time of shovels to minimize a lost ton of the operation. The sub problem solved in each assignment request is as follows:

$$\min \sum_i \sum_j W_{ij}(t_k) X_{ij}(t_k) \tag{59}$$

Subject to:

$$\sum_j X_{ij}(t_k) \le 1 \qquad for \quad i = 1,...,m \tag{60}$$

$$\sum_i X_{ij}(t_k) = 1 \qquad for \quad j = 1,...,n \tag{61}$$

$$X_{ij}(t_k) \in D_k \tag{62}$$

Where:

$$X_{ij}(t_k) = \begin{cases} 1 & if\ truck\ i\ is\ loaded\ by\ shovel\ j\ and\ departed\ at\ time\ t_k \\ 0 & otherwise \end{cases}$$

$W_{ij}(t_k)$ is a lost ton due to idle time caused by assigning x_{ij} truck to j^{th} shovel at time t_k; D_k is representative of a situation that will be explained later on.

The model tries to minimize a lost ton due to idle periods. Constraint (60) guarantees that each truck is assigned to at most one shovel, whereas constraint (61) ensures that each shovel is assigned exactly to one truck. Eq. (62) ensures that a truck to be assigned meets all requirements.

Two main disadvantages of the dispatching part of Hauck's model are first, the assignment is not as accurate as possible because the decisions made now will not be recomputed unless the number of available trucks changes. As a result, the assignment decision is not up to the minute. Secondly, the model is a sub-model of a larger model that uses the result of the last stage of the total model for dispatching. The last stage above the dispatching decision-making model itself is an optimum result of its previous sub-model. Thus, the dispatching model is not able to use DP to solve the assignment problem because it does not have the possibility of using all possible solutions of the previous stages and only uses the optimum solution of those stages.

Soumis et al. [86] developed an assignment model that considers 10-15 forthcoming trucks and their effects on the current assignment. The objective of the model is to minimize the sum of the squared deviation of the estimated waiting time of trucks from the planned waiting time. The model tracks 10-15 trucks based on average travel time, discharge time, and loading time and shovel inter-truck waiting time. After the assignment of the current truck, the data of all 10-15 trucks used for the assignment are erased. The procedure will repeat when the next assignment is requested. The main advantage of the method is that it considers the effects of forthcoming trucks on the current assignment. However, the assumption of a homogeneous fleet is a drawback of the model. Assuming a homogenous fleet of trucks in a multi-stage truck-dispatching model causes a considerable deviation from the reality. The reason behind such a deviation is that to use a homogenous fleet in the lower stage (real-time dispatching level), it is necessary to model the upper stage (operation optimization level) considering a homogenous truck fleet as well. Consequently, the optimized production rate resulting from the upper stage is far from the one in reality because in reality trucks in the fleet range in different sizes in most of the fleets [2]. However, , based on Lizotte et al. [87], to implement a multi-stage dispatching algorithm for an open pit mine operation, the production plan should represent the mine as close to reality as possible to have an optimal plan. The second major drawback of the model that happens in almost all of the dispatching models based on the assignment problem is that, although the models account for upcoming trucks for the current assignment request, the effects of the current assignment on forthcoming trucks are not accounted for.

Li [80] proposed a dispatching rule based on the difference between the actual and optimal trucks' interval times over a route to a destination. The algorithm is run whenever a truck needs to be assigned to a destination and sends the truck to the loader/crusher where the deviation between the actual and the optimal truck interval times on that route are maximum. The author claimed that the proposed algorithm keeps truck flows as close to optimum as possible. However, there is an important drawback for the model, which is the ignoring of the queue of the trucks in the destinations, especially in the loading points. The model, by ignoring the trucks' queue at the destination, underestimates the lost tons caused by this truck waiting time.

Ercelebi and Bascetin [29], after providing optimum truck allocation by using the queuing theory, implemented the assignment problem approach based on the model presented by White and Olson [50] and Olson et al. [51] to dispatch trucks requesting a new destination. Lizotte et al. [87] presented a semi-automated model that first provided a simulation model of the case study where, by the time a truck needs assignment, three dispatching heuristic assignment problems are solved. The results of the simulation are presented on the board in a table beside the result of fixed allocation method and leave the decision for the dispatcher.

All dispatching heuristic rules in the literature are grounded on maximized truck utilization by which a truck is sent to the shovel where it is supposed to be loaded first follow assignment problem. Although such an objective improves production in comparison with a locked-in non-dispatching operation, dispatching heuristic rules have some drawbacks, including how ore quality and stripping ratio are not taken into account. Another major drawback of these types of algorithms is that they tries to send trucks to the shorter routes and as a result, the shovels sitting on the further mining faces will idle longer [75], [88]. In all the dispatching rules in the literature based on maximum utilization of the shovels a truck is sent to the shovel that is supposed to idle longer by the time truck reaches the face. These dispatching rules are following assignment problem as well.

To sum up, although implementing an assignment problem provides a fast solution for real-time truck dispatching in mining operations, this strategy has two major drawbacks arising from the nature of the assignment problem: The main drawback of algorithms based on an assignment problem is that each time only one truck is assigned to each shovel, even if a shovel is far behind its production target and needs more than one truck. The second drawback is that despite the claims of some authors, the model is not able to consider the effects of forthcoming trucks.

2.3.4.2. Transportation problem approach

A transportation problem in the optimization context is described as follows [89]:

1) A set of supply points (m);

2) A set of demand points (n);

3) Cost associated with transporting material from the supply point *i* to the demand point *j*.

Let x_{ij} represent the number of units shipped from the supply point *i* to the demand point *j*, then the general formulation of the transportation problem is as follows:

$$\text{max or min } \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}x_{ij} \tag{63}$$

Subject to:

$$\sum_{j=1}^{m} x_{ij} \le s_i \qquad for \quad i=1,\dots,n \qquad \text{Supply constraints} \tag{64}$$

$$\sum_{i=1}^{n} x_{ij} \ge d_j \qquad for \quad j=1,\dots,m \qquad \text{Demand constraints} \tag{65}$$

$$x_{ij} \ge 0 \qquad for \quad \begin{matrix} i=1,\dots,n \\ j=1,\dots,m \end{matrix} \tag{66}$$

To have a feasible solution, each transportation model must be constrained as follows:

$$\sum_{i=1}^{m} s_i \ge \sum_{j=1}^{n} d_j \tag{67}$$

The model tries to minimize total costs of the decision to be made, Eq. (63). Constraint (64) makes certain that the total material sent to different sink points cannot exceed i^{th} source capacity. Constraint (65) ensures that j^{th} sink will meet its demand. Constraint (66) limits the material to be handled to non-negativity. One of the reliable algorithms of the real-time truck dispatching in an open pit mine is the model developed by Temeng et al. [62] based on a transportation problem. The procedure of truck dispatching by using the Temeng et al. [62] transportation algorithm is as follows:

First, a needy shovel is defined as a shovel using a route that up until now has a cumulative production behind its production target. Alternatively, on the other hand, a non-needy shovel is a shovel that registers a cumulative production of all routes ending to it as above or equal to the target.

To find the needy shovels, we first calculate the current mean of tonnage ratio by using of Eq. (68) :

$$R = \frac{1}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m} R_{ij} \tag{68}$$

Where:

$R_{ij} = x_{ij} / T_{ij}$; x_{ij} is the current cumulative tonnage on path ij ; T_{ij} tonnage is assigned to the path ij that links i^{th} shovel to j^{th} dump.

Set current mean as the target ratio of each route. Then for each route define d_{ij} (Eq. (69)) as a deviation of the route ij from the target production:

$$d_{ij} = R_{ij} - R \tag{69}$$

Now, a needy shovel is a shovel with $d_{ij} < 0$ (negative deviation).

Secondly, the number of trucks each needy shovel requires is determined. At first, Eq. (70) or Eq. (71) is being implemented to calculate y_{ij} as the tonnage behind the target of the route ij :

$$\frac{x_{ij} + y_{ij}}{T_{ij}} = R \tag{70}$$

$$y_{ij} = RT_{ij} - x_{ij} \tag{71}$$

Before, the demand of each route is found by using of Eq. (72) a basic truck capacity (small, large, or an average of them) is chosen based on some statistical analysis.

$$M_{ij} = \left\lceil \frac{y_{ij}}{C_1} \right\rceil \tag{72}$$

Where:

M_{ij} is the demand of each route ij ; C_1 is the larger truck capacity in the fleet consisting of two different truck sizes; $\lceil x \rceil$ is the smallest integer $\geq x$.

Finally, the demand for each shovel will be Eq. (73):

$$D_i = \sum_{j=1}^{m} M_{ij} \qquad i = 1,\ldots,n \tag{73}$$

And if the demand of i^{th} shovel is D_i, then Eq. (74) is being used to calculate the total demand of the operation at current status:

$$D = \sum_{i=1}^{n} D_i \tag{74}$$

In which D must be less than or equal to the number of trucks available for the assignment and if it is not, a cut-off value for required tonnage should be used that selects those shovels as needy ones with a relatively higher negative tonnage.

Finally, Eq. (75) to Eq. (78) present the model to assign trucks that tries to minimize total cumulative waiting time associated with the assignment based on transportation algorithm:

$$\min \sum_{k=1}^{l} \sum_{i=1}^{n} W_{ik} X_{ik} \tag{75}$$

Subject to:

$$\sum_{i=1}^{n} X_{ik} \le S_k \qquad for \quad k = 1,\ldots,l \tag{76}$$

$$\sum_{k=1}^{l} X_{ik} \ge D_i \qquad for \quad i = 1,\ldots,n \tag{77}$$

$$X_{ik} \ge 0 \tag{78}$$

Where:

$W_{ik} = L_i(N_i + E_i) - (t_k + d_j + e_j + r_{ij})$ is the waiting time associated with assigning truck k to shovel *i*; X_{ik} is the decision on assigning truck k to i^{th} shovel; S_k is supply of truck k; D_i is the demand of i^{th} shovel; L_i is the mean loading time of i^{th} shovel; N_i is the number of trucks at i^{th} shovel; E_i is the number of trucks en route to i^{th} shovel; t_k is the expected travel time of truck k to reach discharge point; d_j is the expected waiting time of a truck at the discharge point *j*; c_j is the average dumping time of a truck at the discharge point *j*; r_{ij} is the average empty travel time from the discharge point j to i^{th} loader.

Eq. (76) ensures that the total number of trucks assigned cannot exceed the number of available trucks. Eq. (77) ensures that trucks sent to the i^{th} shovel will cover their lost ton as much as possible. In addition, Eq. (78) ensures that the number of type k trucks assigned to i^{th} shovel is non-negative. The model assumes a heterogeneous truck fleet; as a result, this model will be as close to reality as the upper stage model is. The model also considers the situation that a shovel is far behind its target production and needs to be assigned more than one truck. In such a situation the model easily assigns more than a single truck to those needy shovels further behind the schedule without any limitation occurring by implementing the assignment model.

However, there are two major drawbacks with the model. The first major drawback is that the mean of production rate for all routes is the basis for calculating the deviation of routes. Based on the upper stage plan, however, sometimes it is required to extract much more of some specific materials to maximize the production rate of the transport routes of those materials. Then during the assignment, the transportation problem based dispatching model will send more trucks to those with higher negative deviation. The second major drawback is in the cost of any arising transportation problem when transporting costs of any unit of material is calculated as constant and independent of supplier centers. However, each truck waiting time at the shovel or crusher is depending on the trucks previously assigned, especially in over-truck systems. Also the waiting time accounting for in transportation method is based on trucks currently at their destination or en route to the destination, and there is no way to account for the waiting time caused by trucks assigned in the future that may reach the destination earlier [2].

2.3.4.3. Single stage approach

One of the first algorithms introduced to solve truck allocation and dispatching problems in open pit mines is a single stage algorithm presented by Hauck [9]. The main feature of the presented algorithm is a combination of the operation plan and real-time scheduling in a single model. The model is based on solving a sequence of assignment problems by using DP. The model considers the stripping ratio, blending objectives, capacity of the plant, and stockpile. The objective of the model is to maximize the production by minimizing the lost ton caused by shovel idle time:

$$\min \sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{q(j)=1}^{Q(j)} W_{ij}(t_{ij}(p(i),q(j)))X_{ij}(t_{ij}(p(i),q(j))) \tag{79}$$

Subject to:

$$r_L \le \frac{\sum_{l=1}^{k}\sum_{i}\sum_{j\in J_1} C_i X_{ij}(t_l)+a}{\sum_{l=1}^{k}\sum_{i}\sum_{j\in J_2} C_i X_{ij}(t_l)+b} \le r_U \qquad \textit{for each } k \tag{80}$$

$$\sum_{l=1}^{k}\sum_{i}\sum_{j\in J_2} C_i X_{ij}(t_l) + (V(t_0) - V(t_k)) \le R_U t_k \qquad \textit{for each } k \tag{81}$$

$$\sum_{l=1}^{k}\sum_{i}\sum_{j\in J_3} C_i X_{ij}(t_l) + (\sum_{l=1}^{k}\sum_{i}\sum_{j\in J_2} C_i X_{ij}(t_l) + (V(t_0) - V(t_k))) \ge R_L t_k \qquad \textit{for each } k \tag{82}$$

$$\sum_{i}\sum_{j\in J_3} C_i X_{ij}(t_k) \le V(t_k) \qquad \textit{for each } k \tag{83}$$

Where:

m is the number of available trucks; *n* is the number of shovels; C_i is the average haulage capacity of truck *i*; J_1 is the set of shovels *j* working at waste; J_2 is the set of shovels *j* working at ore mining faces; J_3 is the set of shovels *j* working at stockpile; doubly subscribed *J* is the union of two sets; t_k is the time a shovel has just loaded a truck (assuming discrete points in time to keep track of the process); $Q(j)$ is the total number of loads completed by j^{th} shovel in *T* working cycle; $p(i)$ is p^{th} load of truck *i*; $q(j)$ is q^{th} load of shovel *j*; $t_{ij}(p(i),q(j))$ is the earliest time p^{th} load of truck *i* which is q^{th} load of shovel *j* is loaded by shovel *j* on truck *i*;

$$W_{ij}(t_{ij}(p(i),q(j))) = \begin{cases} E_j \Gamma_{ij}(t_{ij}(p(i),q(j))) & j \in J_{12} \\ 0 & j \in J_1 \end{cases} \tag{84}$$

E$_j$ is the loading rate of j^{th} shovel (ton/time); $\Gamma_{ij}(t_{ij}(p(i),q(j)))$ is the idle time incurred by j^{th} shovel when it loads its $q(j)$ load as the truck's $p(i)$ load into the truck. r_L and r_U are the lower and upper limits of SR; *b* is a suitable quantity of ore; $a = b(r_L + r_U)/2$; R_L *and* R_U are minimum and maximum processing plant rate; $V(t_o)$ and $V(t_k)$ are stockpile inventory at the beginning of the cycle and at time t_k , respectively. For each k^{th} decision, an assignment problem is solved as a sub problem by implementing DP, which has been presented in Eq. (79) to Eq. (83).

Eq. (80) ensures meeting the SR requirement; Eq. (81) and Eq. (82) guarantee that the processing plant is always being fed; Eq. (83) ensures that total material handling at the stockpile cannot exceed the amount of current stockpile inventory. D_k is the assignment domain satisfying Constraints (81) to Constraints (83). The algorithm presents an optimal combinatorial intractable assignment procedure. Although it is a complex algorithm containing all limitation satisfaction criteria, it runs fast. However, assuming the problem as a completely deterministic procedure shows that the stochastic properties of truck waiting time is ignored. Meeting all the production requirements is not the goal of the operation for each assignment and if they can be satisfied in a longer period of the time, their short term violation is acceptable. As previously mentioned, DP tries to find the optimal solution from all of the feasible solutions of the previous sub problems rather than from the best solution among them.

2.3.5. Some Other Efforts

Krause and Musingwini [90] used a machine repair analogy to analyze and choose truck fleet size for an open pit mine. They chose Arena for the simulation part "because it can be programmed with any number of probability distribution fitted to an unlimited number of cycle variables and is therefore a very flexible model for use in analyzing several variables in shovel-truck analysis".

He et al. [91] implemented a genetic algorithm to optimize truck-dispatching problems in open pit mines. They tried to find a route and assign an upcoming truck to it based on minimized transportation and maintenance costs. In that model, it has been assumed that truck velocity in both loaded and empty conditions are the same, which is a drawback of their model. Although their major focus was on minimizing the costs, by assuming the same velocity for both loaded and unloaded trucks, they underestimated costs. Another major drawback, similar to almost all other models is the assignment of trucks to routes rather than to shovel-destinations. They claimed that truck maintenance cost becomes higher with the age of the truck by a constant coefficient, whereas Topal and Ramazan [92] and Topal and Ramazan [93] revealed that maintenance cost behaves in a fluctuated manner during its life and by each main repair the equipment's maintenance cost will decrease considerably.

Another model provided by Subtil et al. [94] is used in the commercial package SmartMine® marketed by Devex SA [95]. It uses LP in the upper stage to determine the maximum production capacity of the mine and the optimal size of the truck fleet required to meet the target production. The allocation planning stage does not provide any information for shovel assignments, which still completely remain the task of the planner. In addition, the model does not take into consideration other desired characteristics, such as grade blending, constant desired feed to plants, etc. The dynamic allocation or the truck-dispatching is achieved by adopting M trucks for N shovels strategy. Using M trucks, the best possible solutions based on undisclosed criteria are generated and each solution is simulated 50 times to achieve a desired confidence interval. The best solution is found using a multi-criteria optimization, which maximizes productivity of the transport fleet and minimizes queue time at shovels and idle time of shovels. A fuzzy logic expert system is then used to evaluate the solution and, if passed, dispatch the truck to the allocated shovel. The major drawback of the approach can be the cumbersome time consuming methodology adopted at the dynamic allocation stage, which requires real- time decisions. The authors of this study mention some situations where fuzzy logic rejects the best solution, which demands re-running of the entire model to obtain another solution. The alternate solution generated after rejecting the first one will be the second best solution, which may again get rejected, leading the method into a time-consuming loop.

Ahangaran et al. [17] used a two stage model for truck dispatching the trucks, where the first stage uses a network analysis technique to determine the best routes between departure and destination points and second stage provides dynamic truck assignments. The second stage adopts a binary integer-programming model to minimize the function of the total cost of loading and transportation. This dispatching model is significantly different compared to previous models in terms of the objective function and the mixed fleet considerations in the modelling equations. One of the major drawbacks of this model is that it does not consider traffic over the routes during the procedure to find the shortest path. Another drawback is that, although their objective function is to minimize total truck cycle time, they do not take into account truck spot time and truck waiting time at both shovels and crusher. They did not show the practicality of their model in at least one open-pit mine.

A brief summary of the models and algorithms developed for solving the problems in both production optimization and real-time dispatching are presented in Table 2.4 and Table 2.5, respectively.

Table 2.4: Summary of the algorithms to solve production optimization problem

Model Type	Researcher	Year	Objective	Advantages	Disadvantages
Queuing Theory	Xi and Yegulalp Ercelebi and Bascetin	1993 2009	Minimize total costs of the production	Simplicity is the main advantage of the models based on queueing theory. Waiting in queue is very common for trucks working in mine sites, so queueing theory can be modelled as an elegantly simplistic mathematical equation	Production rate underestimation Requiring a significant engineering judgment to implement the model in the operation Using Erlang queuing model Assuming homogeneous truck fleet Ignoring of equipment idling

					Assuming mine as a system with Markovian nature
Transportation	Li	1990	Minimize total transportation work	Taking into account the productivity of each shovel Considering ore quality requirement	Assuming homogeneous truck fleet Ignoring of equipment idling Disregarding equipment breakdown as an event that change the mine's status
Linear Programming	Hauck	1973	Maximize the production by minimizing the lost ton caused by equipment idle time	Considering stripping ratio requirement Accounting for plant and stockpile capacity Trying to meet blending objectives Although performing all the procedure of allocation and real-time assignment together, it runs fast	Not considering stochastic properties of truck waiting time in the objective function Restricting the flexibility of the operation by solving the upper stage model in each and every assignment request Implementing a DP approach to solve each sub-problem without considering all solutions of previous problems
	White and Olson	1986	Maximizes the fleet production by minimizing total required volume to be handled	Being up to the minute Flowrate of each route is based on the volume of the material rather than number of trucks	Disregarding required stripping ratio Defining a range for grade of material to be fed into the plant which consequently will cause either the final product or shovels utilization Ignoring modelling of the equipment idling
	Lizotte and Bonates	1992	Maximize shovel productivity	Considering stripping ratio Relative priority of loading equipment, especially the ones working on mining faces, are taken into account in the model	Necessity of adding stockpile or re-handling to the objective function Assuming linear correlation between production at each face and number of available trucks in the fleet
	Gurgur, Dagdelen and Artittong	2011	Maximize total net value per ton of material handled	Assigning the shovels to the proper faces as a link between short-term plan and operational level Accounting for available trucks in each time period Considering the mine as a multi period task Being a lifelong model	Ignoring costs associated with shovel movement Disregarding lost tons caused by shovel movement Using continuous variables in the discrete operations in heterogeneous fleet allocation is not realistic
	Ta, Ingolfsson and Doucette	2013	Minimize number of trucks required to meet the target	Capturing shovel idling in the objective function Performing Fast and being useable for large mining systems	Not having the capability of providing a reliable allocation in an open-pit operation Defining upper and lower bounds for the head grade Not being able to offer allocations based on a realistic or even near to realistic combination of different types of trucks available in the fleet Missing linkage with any of strategic level plans

Non Linear Programming	Rodrigo, Enrico, Fredy and Adolfo	2013	Maximize the overall productivity of the fleet	Considering availability of the trucks directly in the objective function	Showing infeasibility by the time a certain number of trucks fail or go for maintenance repair Ignoring availability of loaders which results assumption of 100% availability of all shovels Disregarding blending requirement of the plant
	Chang, Ren and Wang	2015	Maximize total revenue obtained from transported material	Accounting for the transportation priority	Assuming homogeneous fleet Ignoring stripping ratio requirement Ignoring the plant capacity requirement Disregarding head grade of the material fed to the plant
	Soumis and Elbrond	1989	Minimize the sum of weighted pseudo-costs of deviation from maximum production due to equipment idling and grade deviations	Allocating shovels to the faces Not having extreme flowrate on each route because of the results being provided by NLP method	Assuming homogenous truck fleet Ignoring stochastic nature of ore grade extracted from each mining face
Goal Programming	Temeng, Otuonye and Frendewey	1998	Minimize deviation from two goals including production rate and material quality	Optimizing two major goal in open-pit operations simultaneously Covering the limitation of the grade requirements of LP-based models	Not providing optimal results because the model is trying to satisfy all the goals simultaneously Not considering shovel allocation Ignoring some of the objectives of an open-pit operation which should be met Not having any linkage to any of the strategic level plans
	Upadhyay and Askari-Nasab	2015	Minimize deviation from four goals including maximum production of the whole operation, target production at processing plant, required head grade at plant and shovels and trucks operating costs	Optimizing four major goals of the open-pit operation Providing a linkage between operational stage and short-term strategic plan by allocating the shovels to the available mining faces	Not providing optimal results because the model is trying to satisfy all the goals simultaneously Ignoring the costs associated with processing plant and other mining costs except for shovels and trucks
Stochastic Programming	Ta, Kresta, Forbes and Marquez	2005	Minimize truck resources needed	Considering trucks loading and cycle time as stochastic parameters Upgrading based on changes in mine’s status	Ignoring the randomness of all other parameters coming from stochastic nature Being case specific and not having capability of being generalized into other mines

Table 2.5: Summary of the models have been presented to solve Real-time dispatching problem

Model Type	Researcher	Year	Objective	Advantages	Disadvantages
Assignment	Hauck	1973	Minimizing the net loading time lost due to idle periods	Internally assuring that the assignment will not violate operation requirements	Limiting shovels' capacity for truck assignment to one truck per assignment Not considering forthcoming trucks Ignoring the stochastic nature of some parameters such as truck cycle time Implementing DP approach Meeting all production requirement in each assignment
	White and Olson	1986	Minimize lost-tons caused by the assignment	Considering forthcoming trucks in the assignment procedure	Using heuristic enumeration to evaluate trucks and shovels combinations
	Lizotte and Bonates	1989	Arbitrary decision based on the results of simulation under for different dispatching rules	Allowing the dispatcher to decide on the scenarios	Not being fully automatic and needs someone to conduct it Not considering the forthcoming trucks during the assignment procedure Ignoring lost ton due to queue
	Soumis and Elbrond	1989	Minimize sum of squared deviation of estimated waiting time of trucks from the expected idling	Considering the trucks need to be assigned in the near future Solving an optimization problem to find the best combination of trucks and shovels	Restricting the capacity of shovels to one truck per assignment
	Li	1990	Maximize inter-truck time deviation	Being easily applicable in real mining operations	Ignoring the production lost caused by queuing Disregarding effects of forthcoming trucks to the current assignment Restricting the capacity of shovels to one truck per assignment
Transportation	Temeng, Otuonye and Frendewey	1997	Minimizing the total waiting time of both shovels and trucks Maximizing the production	Accounting the trucks heterogeneity Considering the time a shovel is far behind its scheduled target and needs more than one truck to cover its lost ton	Assuming equal route flowrate for all routes in the network Assuming constant and independent costs associated with unit of material transported

2.4. Simulation of mining systems

Simulation is the imitation of the operation of a real-world process or system over time [96]. The power of simulation as a tool to evaluate operating systems has been accepted worldwide. In the literature of the simulation, it origins in a simple mathematical problem called the Buffon's needle dated to 1777. The application of simulation in the mining sector can be traced back to 1940s. However, credit of the first use of discrete event simulation was given to Rist [97] who used Monte Carlo simulation technique to solve hauling problem in mining operations.

Developments in the capabilities of computers in the 1980s helped researchers conduct vast studies on the models and observe deficiencies, through the use of computer programs and simulations [98]. After the first usage of the simulation in the mining operation, several studies have been done by different researches in the field. The studies including [75], [88], [99]–[109] are selected studies aiming different simulator tools to evaluate and analyze mining operations over the late second millennium. To evaluate various dispatching techniques and prove positive impacts of implementing dispatching techniques in mining operations Sturgul and Eharisson [106], Bonates and Lizotte [75], Forsman et al. [110], Kolonja and Mutmansky [37], and Ataeepour and Baafi [104] implemented simulation modeling.

Awuah-Offei et al. [111] implemented simulation modeling for determination of fleet size in case of both truck and shovels a mine. To mimic dynamic expansion of an open pit mine, Askari-Nasab et al. [112] developed a simulator called open pit production simulator (OPPS).Their study shows that in the cases of modeling dynamicity of the processes and randomness of the input parameters, artificial intelligent simulators can be very efficient and helpful. Fioroni et al. [113] used discrete event simulation and linked it with an optimization model to deal with the short-term production plan. The goal of the study was to show how simulation and optimization are integrated in order to achieve a reasonable solution for this problem. To analyze and evaluate effects of equipment breakdown on utilization of the resources and production of the operation, Yuriy and Vayenas [114] combined discrete event simulation with genetic algorithm based reliability assessment model.

from 2010 to 2015 all simulation studies in the field of truck and shovel mining system including Jaoua et al. [115], Jaoua et al. [116], Mena et al. [78] , Ta et al. [77], Hashemi and Sattarvand [117], Torkamani and Askari-Nasab [118], Upadhyay and Askari-Nasab [13], and Upadhyay and Askari-Nasab [119] are using the simulation as a tool to evaluate results of the developed optimization algorithm in their studies without incorporating a new component into their system.

Dindarloo et al. [35] provides an step by step discrete event simulation guideline for truck-shovel mining system equipment selection. The claim in the study is that the framework helps to minimize errors caused by inaccurate assumptions as well as procedures.

In one of the latest simulation study of a truck-shovel mining system Que et al. [120] investigated how ignoring correlation between the input parameters will impact on the results of the study. The research presents a new approach to detect and import correlated parameters into the truck-shovel simulation study. Instead of the independent distributions the new approach generates a multivariate random vector representing input parameters into the simulation modeling.

Beside all above-mentioned efforts, some review studies related to implementation of the simulation in the mining sector have been done since late 1990s. Sturgul [107] provides a historic review of discrete mine system simulation in United States. Vagenas [121] provide a review of application of simulations in Canada and Konyukh et al. [122] did a review study over the application of the simulation in Asia. Raj et al. [123] reviewed the application of simulation in production optimization in mines. Hodkiewicz et al. [124] reviewed the simulation studies in both fields of underground and surface mining and highlighted lack of an integrated mining simulation model which incorporate truck workshop as part of the mining system.

2.5. Rationale for the PhD research

Some of the operational level decisions to be made are decisions about the size of the haulage fleet, and semi-dynamic and dynamic decisions made by FMS including decisions about the paths' flow rate and truck-dispatching.

The literature review showed that there are several deterministic and stochastic methods for making decisions about the size of the fleet. In recent years, most mining operations have implemented FMSs and the mining sector has been interacting closely with the processing plants. However, in decision-making procedures none of the available methods takes into account the effects of processing plants and mining FMSs. In this research we present a stochastic simulation and optimization framework that is capable of making decisions about the size of material handling fleets in presence of the mine's FMS and its processing plants.

Our literature review showed that the mathematical models developed to make decisions about truck-dispatching have some drawbacks, including with required objectives. The objectives include minimizing the trucks' wait time, shovel idle time, and deviation from the production targets. The required objectives do not have to be met at the same time in the mathematical models that we found. Another major drawback is that the models neglect the impacts of uncertainties on the input parameters. This research introduces two different decision-making models. The first is a multiple objective mathematical model that has all of the aforementioned objectives in a single model and solves the problem using a goal programming approach. The second set of the mathematical models developed to make truck-dispatching decisions considers uncertainties in input parameters. The second set of the models solves the truck-dispatching problem by implementing two different approaches: a stochastic programming approach and a fuzzy linear programming approach.

2.6. Summary and conclusions

The literature recognizes eight main approaches for dealing with the operational level decision-making procedure during a mining operation. Most of the models are based on the mathematical optimization techniques. The simulation models have been used to evaluate the strategies and validation of the developed models. A summary of the existing systems' major shortcomings is presented in two main categories of optimization and simulation as follows:

➢ **Optimization**

- The real-time decisions in the operation are not linked to the strategic level short-term production schedule of the mine;
- The published researches have not considered the impacts of drilling and blasting operations on the material handling fleet availability;
- The models are usually solved based on information from the independent parameters and the effects of uncertainty and the correlation of parameters governing the operation are not accounted for;
- With the exception of the works of Upadhyay and Askari-Nasab [13], [119], there is nothing in the literature about the tons lost due to mobility and equipment access problems, particularly in the case of shovels;
- Although the downstream processes, including processing plants, play an important role in mining operations, the existing truck-dispatching models do not consider the effects of the downstream processes on the mining operation;
- None of the models developed to date address the impact of weather and traffic conditions on travel time between loaders and destinations;
- None of the models consider dynamic truck controls over the time trucks are travelling from the source to the destinations;
- Most of the models do not incorporate different truck sizes in the mine's transportation fleet.

- **Simulation**

  - The simulation models are case-specific based on the mine they are developed for, which limits their applicability; they are only useful in addressing problems identical to the one for which they were developed;
  - Most of the simulation models are not capable of accepting changes in the input distributions for the random parameters required to run the simulation for the system;
  - Although most of the companies working in the field of mining operations need to forecast a long time ahead, the simulation models do not study operations over a long-time horizon;
  - One of the major shortcomings of the existing models is that they do not incorporate the mineral processing sector in the simulation study, nor do they incorporate downstream processing plants and their up times and down times. However, the effect of a down plant on the operation is undeniable;
  - Most of the models ignore the role that a mine's FMS plays in the simulation. However, nowadays almost all large open pit mines around the world use at least one FMS.
  - The simulation models are not flexible in terms of using different truck-dispatching strategies. They were built based on either non-dispatching or a single logic dispatching strategy and it is impossible to use them to test different dispatching strategies.

CHAPTER 3: THEORETICAL FRAMEWORK

3.1. Introduction

This chapter focuses on the theoretical frameworks of simulation and optimization of truck and shovel surface mining operations as well as different decision-making models to solve the truck-dispatching problem. The chapter introduces the conceptual theoretical frameworks, mathematical models, and connections between different models to achieve the objectives of the presented thesis are introduced. The research focuses on two main objectives. The first one is the development, analysis, and implementation of an integrated simulation and optimization framework for truck and shovel surface mining operations (presented in Figure 3.1). The second objective is the development, analysis, and implementation of mathematical models to deal with the truck-dispatching decision-making problem in surface mining operations.

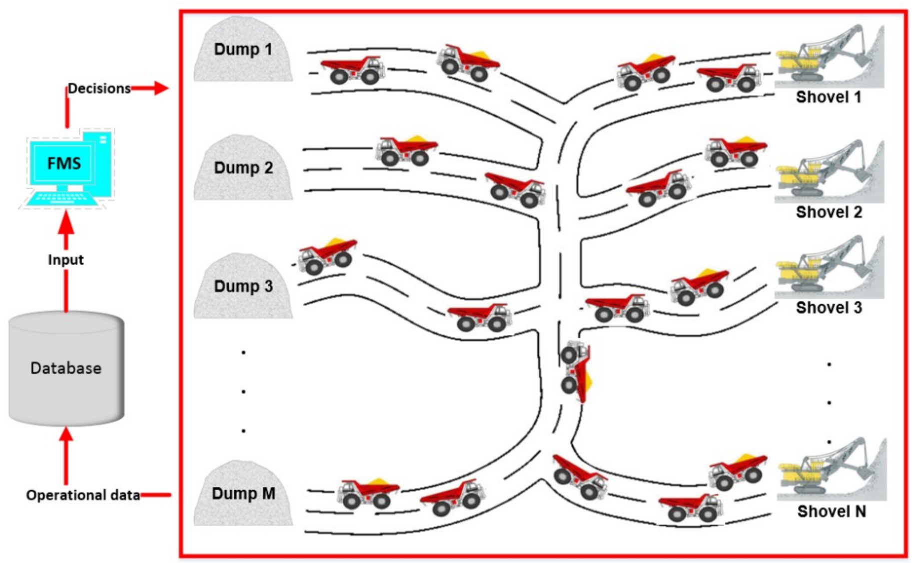

Figure 3.1: Components of a surface mining operation material handling system

Figure 1.3 in Chapter One illustrates the basic components of the integrated simulation and optimization framework developed, analyzed, and implemented in this thesis. In the framework, the mining operation, processing plants, and operational decision-making tools communicate with each other. The framework was implemented to solve equipment selection and sizing problem in a truck and shovel surface mining operation integrated with the fleet management systems and processing plant components. The framework was also used to evaluate the truck-dispatching models which were developed as part of this research.

Alongside development of the integrated framework for the mining operation of surface mines, this chapter focuses on developing multiple objective mixed integer goal programming

(MOMIGP), stochastic mixed integer linear programming (SMILP), and fuzzy mixed integer linear programming (FMILP) models to solve the truck-dispatching problem.

The MOMIGP model aims to maximize production by minimizing the idle time of equipment and minimizing deviations from the planned production requirement. The SMILP solves a truck-dispatching decision-making model with uncertain input parameters. The FMILP model implements a fuzzy approach to solve the truck-dispatching problem by assuming that the input parameters behave fuzzy.

3.2. Integrated simulation and optimization framework

The integrated stochastic simulation and optimization framework developed here consists of four main components: two optimization and two simulation sub-models. The two optimization components are decision-making tools in fleet management systems that solve the paths' flow rate and truck-dispatching problems [12], [125]. The simulation components in the framework are mining operation and material flow into downstream processes. Figure 3.2 shows how the developed framework integrates the four components.

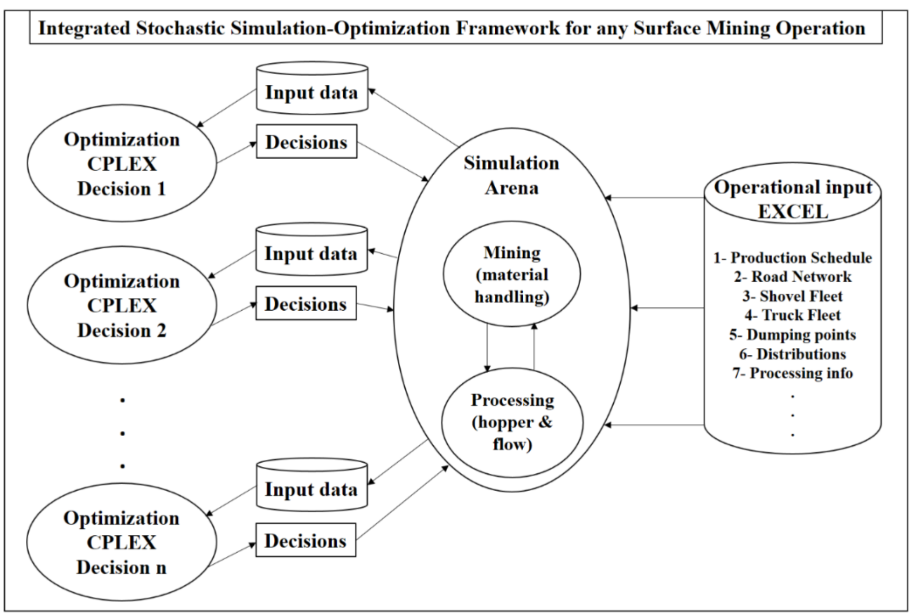

Figure 3.2: Integration of different components of a mining operation in the developed framework

3.2.1. Input data file

The integrated framework requires input parameters and information such as the short-term production schedule, road network of the mine with the expected expansion by the end of the simulation time, shovel and truck types, capacities and performance parameters of the materials handling equipment, information regarding the location and capacity of the dumping points, as well as the number of discharge points at each dumping point. Fitted distributions for the input parameters, and information regarding the processing plants such as capacity of hoppers and conveyor belts are required as well. It is worth noting that, most of the required input parameters such as loading time, dumping time, haul time, traveling empty, backing time, spot time, shovels' bucket capacities, and trucks' loading capacities are stochastic input parameters. Therefore, different probability density functions are fitted on the historical data of such random variables. Goodness-of-fit for the best fitted theoretical or empirical distributions were tested by Chi-Square or Kolmogorov Smirnov tests [126] using Arena Input Analyzer [127] software.

3.2.2. Components of framework's input data file

The input data file into the framework is a Microsoft Excel that consists of several worksheets each of them storing a category of input data. Table 3.1 lists the required worksheets for the input data file.

Table 3.1: Components of the input data file

No.	Worksheet	Category	Description
1	Schedule	Strategic planning	Strategic level schedule for the mining operation
2	Routes' info	Road network	Information on routes, their origin and destinations, distances, etc.
3	Nodes	Road network	x, y, and z coordinates of each node in the road network
4	Dump locations	Road network	x, y, and z coordinates and nodes' information for each dumping location on the road network
5	Links	Road network	Information on links in each route, their origin and destinations, distances, etc.
6	Transporters	Fleet	Information on number, type, capacity, etc. of transporters in the fleet
7	Shovels	Fleet	Information on number, type, capacity, etc. of loaders in the fleet
8	Dumps	Strategic planning	Information on hourly feed rate requirement and acceptable head grade ranges for each dumping point
9	Spot time	Fleet	Fitted distributions on spot time historical data when a specific shovel type loads a specific truck type
10	Bucket count	Fleet	Fitted distributions on number of passes historical data when a specific shovel type loads a specific truck type
11	Bucket tonnage	Fleet	Fitted distributions on historical data of tonnage of material in each load of shovel bucket when a specific shovel type loads a specific truck type
12	Loading cycle time	Fleet	Fitted distributions on loading cycle historical data for shovels when a specific shovel type loads a specific truck type

13	Backing time	Fleet	Fitted distributions on trucks' backing time historical data for each specific truck type
14	Empty velocity	Fleet	Fitted distributions on trucks' empty velocity historical data for each specific truck type
15	Loaded velocity	Fleet	Fitted distributions on trucks' loaded velocity historical data for each specific truck type
16	Dumping time	Fleet	Fitted distributions on trucks' dumping time historical data for each specific truck type

Each of the worksheets in the input data file contains its required columns. Giving the schedule worksheet as an example, it contains information regarding each polygon in the operation including coordinates of the center of the polygon, total tonnage of material, grade of different elements, period that it should be mined, digging locations nodes, shovel assigned to the polygon, ID of the mine polygons, and precedent among mining polygons.

3.2.3. Simulation model

The simulation model is developed in Arena software [127] and consists of two main sub-models: mining and processing operation. The two simulation sub-models are linked to each other using the hoppers (Figure 3.3).

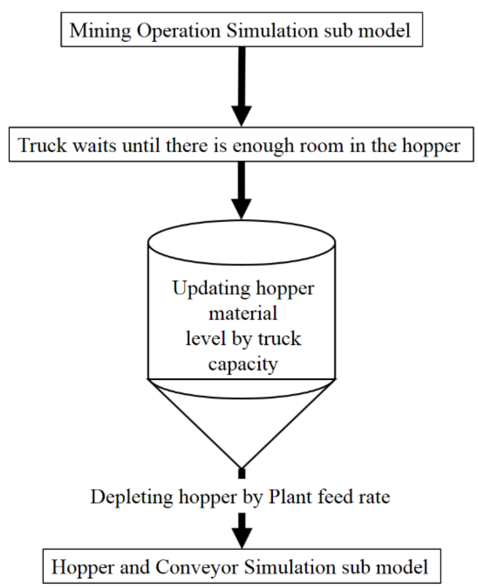

Figure 3.3: Linkage between two simulation sub-models in the developed framework

3.2.4. Optimization models

As mentioned before, the developed framework consists of two optimization components, which imitates the decisions made by the fleet management system in the mining operation. These optimization components are integrated with the simulation model using VBA and OPLrun [128]. Figure 3.4 shows how the simulation models and the optimization models communicate with each other in the developed framework.

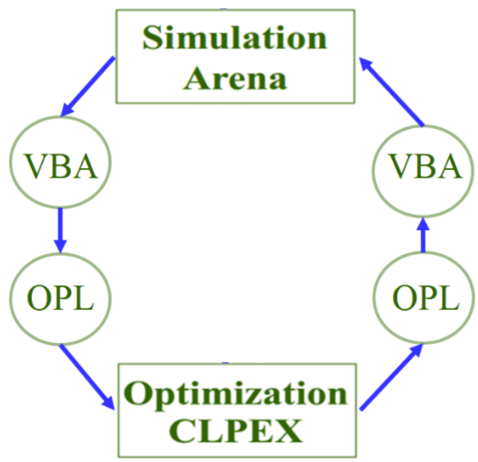

Figure 3.4: Integration of the simulation and optimization models in the developed framework

One of the major advantages of the developed framework is that the number of decision-making models that can be integrated into the framework is not limited. However, in this research, the decisions to be made by the optimization tools are upper stage (production optimization or truck allocation) and lower stage (truck-dispatching) decisions in a multiple stage mining fleet management system [125]. The goal here is to incorporate the dispatching decisions that are made in the real mining operation into the simulation model and develop a more accurate simulation model of the surface mining operations that use fleet management systems. Readers are encouraged to read Alarie & Gamache (2002) and Moradi Afrapoli & Askari-Nasab (2017) for more detailed information regarding the mining fleet management systems.

3.2.5. Upper stage decision-making model

Over the last 50 years, several mathematical models have been developed to decide how much material must be transferred through a specific transportation path over a specific period. Various approaches of linear programming, mixed integer programming, nonlinear programming, and queueing theory are presented. However, in this thesis, we selected two models. The model developed by White and Olson [12] since it is the backbone of the upper stage decision-making model in Modular Mining DISPATCH [11], the most popular fleet management system in the market. The upper stage in this model is divided into two linear programming segments. In the first segment, the model maximizes shovels' production by minimizing total costs. Solving the first segment LP model to minimize the total costs results in the shovel dig rate required to meet the plant's capacity and its material quality requirement with respect to the maximum shovels' dig rate. The second segment of the model minimizes total truck capacity required to transfer material from each path using the obtained shovel dig rate from the first segment.

The second LP model obtains the amount of material required to be transported from each path. However, it is limited by the following two constraints: the equality of the flow rate at each node in the road network and the equality of the transporters capacity allocated to a shovel at a mining face with the shovel's dig rate. The model also needs to meet the production demand at the stockpile, and equality of material transported from each shovel with the shovel dig rate. The upper stage model is called from the simulation at a specific time interval to determine the path flow rate (30 minutes in this case). We also implemented the model developed by Upadhyay and Askari-Nasab [18] to make required decisions on the upper stage problem. The model is a mixed integer goal programming model that provides the operation with the required path flow rate based on objective functions and constraints presented in [13], [14], [129].

3.2.6. Lower stage decision-making models

The lower stage of the fleet management system is activated whenever a truck asks for a new assignment. This research developed four different truck-dispatching decision-making models to be used in the integrated framework. The four different decision-making models are used in this research to make required lower stage decisions in FMSs of the simulation and optimization framework. The first decision-making model that is used in this research to make lower stage decisions is the dynamic programming model developed by White and Olson [12] and Olson et al. [51] since it is the backbone of the upper stage decision-making model in Modular Mining DISPATCH [11]. The model developed by White and Olson [12] and Olson et al. [51] is used as the benchmark model to evaluate three other models that we developed in this research. The three other models are mathematical models we developed to cover the existing shortcoming in the literature of lower stage decision-making models in mining FMSs. The first model we integrated in the framework for making the lower stage decisions is a deterministic multiple objective mixed integer goal programming decision-making model that we developed to cover all the required objectives of this level of decision-making. Two other models that we integrated with the simulation model in the developed framework are stochastic mixed integer linear programming and a fuzzy linear programming approach.

3.2.7. Input from simulation to optimization models

In the developed simulation and optimization framework, the decision-making models in the FMSs responsible for making upper and lower stage decisions need information regarding status of the mining operation being simulated in the framework. These are used as input in the decision-making models to make required decisions for the operation.

3.2.7.1. Current needy paths

We first need to define current available paths to determine needy paths in a surface mining operation. We define any road from any pair of source and destination nodes in the mining network as a path. It is possible that there is more than one path from a loading point to a dumping point based on the complexity of the mining road network. Moreover, the paths' length has to be updated based on the distance from the loader's position to each individual dumping location whenever the loader relocates to a new mining face. Next, the shortest path from any loading point to all of the dumping points are determined based on time differences between them, implementing Dijkstra's algorithm [130]. Every time the loaders or dumping points are relocated or if a blockage occurs in the current shortest path, the Dijkstra's algorithm is recalled to recalculate the shortest path. An $n \times m$ zero – one matrix of available paths, as shown in Eq. (85), is created where n represents the number of loading and m represents the number of dumping points. Si stands for loader i in the fleet and Dj stands for dumping point j.

$$\Gamma = \begin{array}{c c} & \begin{array}{ccccc} D_1 & \dots & D_j & \dots & D_m \end{array} \\ \begin{array}{c} S_1 \\ \vdots \\ S_i \\ \vdots \\ S_n \end{array} & \begin{bmatrix} e_{11} & \dots & e_{1j} & \cdots & e_{1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ e_{i1} & \dots & e_{ij} & \cdots & e_{im} \\ \vdots & \ddots & \vdots & \ddots & \ddots \\ e_{n1} & \dots & e_{nj} & \dots & e_{nm} \end{bmatrix} \end{array}; e_{ij} = \begin{cases} 0 & if\ there\ is\ not\ a\ path\ between\ Si\ and\ Dj \\ 1 & if\ there\ exists\ a\ path\ between\ Si\ and\ Dj \end{cases} \quad (85)$$

The available paths matrix (Γ) is a zero and one matrix. If the element e_{ij} in the matrix is equal to one, it means that the path connecting loading point i *(Si)* to the dumping point j *(Dj)* is available. If the path between loading point i *(Si)* and the dumping point j *(Dj)* is not available, then e_{ij} is equal to zero.

The current needy paths are defined among the available paths. The required *path flow rate* (pf_{ij}) for each available path is calculated every 30 minutes by solving the upper stage or production optimization stage problem using the linear programming model developed by White and Olson [12]. Next, *path met so far* ($pmsf_{ij}$), the summation of the material handled from each available path from the start of the current 30-minute time span up to now, is calculated. Then, the list of current needy paths is a subset of the *available paths* where:

$$needy\ paths = \left\{ \Gamma : e_{ij} = 1 \& \frac{pf_{ij} - pmsf_{ij}}{pf_{ij}} > \frac{tid - (tNow - tSci)}{tid} \quad \forall i \in \{1,...,N\} \ \& \ \forall j \in \{1,...,M\} \right\} \tag{86}$$

In Eq. (86) *tid* stands for duration of a time span in hour; *tNow* is the current time on the clock; and *tSci* represents time on the clock when the current interval has started. The left-hand side of inequality represents the portion of the required material to be transferred in the remaining time of the time interval, whereas the right hand side of the inequality represents remaining time portion of the time interval. If the inequality condition in Eq. (86) is met, which means that the path from loader *i* to dump *j* is behind its planned required material transfer, then the path is called a *needy path* and will be considered in the current truck-dispatching model solving procedure.

3.2.7.2. Current set of trucks to be dispatched

Not all the trucks in the fleet are available to be dispatched at a time due to several reasons such as scheduled maintenance, break down, etc. The set of current trucks to be dispatched is generated by calling the truck-dispatching decision-making tool for an assignment using the following algorithm.

Algorithm 1: generate current set of trucks to be dispatched

Inputs:
Truck fleet (id, type, capacity);
status of trucks (available or not);
current position of available trucks in the network (dump, loader, traveling empty, traveling loaded)

Begin
$Z = 0$
for $h \in$ H **do**
If $s_h = 1$ **then**
$Z \leftarrow Z + 1$
$id_Z \leftarrow$ Truck ID $_h$
endif;
$t = 0$
for z = 1 to Z **do**
If $CP\ id_z \in \{ll \parallel ttd \parallel dad \parallel rfdc\}$ **then**
$t \leftarrow t + 1$
$sdT_{t1} \leftarrow id_z$
	H = {1, …, Hauler} is set of trucks;
	s_h is status of the truck *h* and $s_h \in$ {0 (not available),1 (available)};
	id_Z is id number of the truck *Z* in the set of available trucks;
	CP id $_z$ stands for current position of truck with id equal to id of z;
	ll is leaving the loader; *ttd* stand for travelling to the dump; *dad* is dumping at the dump and *rfdc* stands for returning from a down condition;
	sdT is the *setofdispatchingTrucks*;
	t_{ti} is the time it takes truck *t* to reach shovel *i*

```
        sdT_t2 ← tt_z
        sdT_t3 ← tc_z
        for i ∈ S do
            sdT_t(i+3) ← t_ti
    endif;
```

Algorithm 1 creates a matrix consisting of a list of trucks that are available to be assigned, their types, capacities, and the time it takes each specific truck to travel to a shovel from its current position (Eq. (87)).

$$T = \begin{array}{c} \begin{array}{cccccccc} id & TT & TC & S_1 & \dots & S_i & \dots & S_n \end{array} \\ \begin{bmatrix} id_1 & tt_1 & tc_1 & t_{11} & \dots & t_{1i} & \dots & t_{1n} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ id_t & tt_t & tc_i & t_{t1} & \dots & t_{ti} & \dots & t_{tn} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ id_T & tt_T & tc_T & t_{T1} & \dots & t_{Ti} & \dots & t_{Tn} \end{bmatrix} \end{array} \tag{87}$$

The first three columns in the matrix are truck related specifications for the trucks selected using Algorithm 1. id_t is identification number truck t in the fleet; tt_t stands for truck type for the truck t; and tc_t represents truck capacity of the truck t. Rest of the columns in the T matrix are the time it takes for truck t to travel to each of the paths' starting points. t_{ti} is equal to the time it takes truck t to travel from its current position in the road network to the loader i by taking the shortest path possible and is calculated using:

$$t_{ts} = t_0 + \frac{xl_t}{vl_t} + q_t + d_t + \frac{xe_{ts}}{ve_t} \tag{88}$$

Where:

t_{ts}	time truck t arrives at shovel s
t_0	current time on the clock that is equal to *tNow* in the simulation
xl_t	distance truck t must travel loaded from its current position to the designated dumping point
vl_t	average velocity of truck t when traveling loaded
q_t	time truck t is expected to spend in queue at its dumping point
d_t	time it takes for truck t to dump its material at dumping point
xe_{ts}	distance truck t must travel empty to reach shovel s
ve_{ts}	average empty velocity of truck t in the road network from to shovel s

3.2.7.3. Current set of shovels that require trucks

If a path is available, it means that the shovel working on the mining face to serve that specific path is active. The next time an active shovel will be ready to load a new truck is calculated using Eq. (89):

$$na_s = t_0 + \sum_{q=1}^{Q_s} \left(ts_q + tl_q \right) \tag{89}$$

Where:

na_s	next time shovel *s* will be available to load a new truck
NQ_s	total number of trucks in queue at shovel *s*
ts_q	spot time for truck number *q* in the queue at shovel *s*
tl_q	loading time for truck number *q* in the queue at shovel *s*
t_0	current time on the clock

Algorithm 2 runs when a dispatching request is posted by a truck and generates the set of active shovels (S) matrix in Eq. (90).

Algorithm 2: generate current set of active shovels requiring new truck-dispatching

Inputs:
Shovel fleet (id, type, capacity); status of shovels (available or not); info of current trucks in queue (id, type, capacity), info of trucks being loaded (id, type, capacity), info of trucks en route to the shovels (id, type, capacity, time distance)

Begin
$n = 0$
for s ∈ S **do**
if $A_s = 1$
$n \leftarrow n+1$
$saS_{n1} \leftarrow id_s$
$saS_{s2} \leftarrow st_s$
$saS_{s3} \leftarrow sc_s$
$saS_{s4} \leftarrow na_s$
endif

n is a counter;
S is set of shovels working in the mine;
saS is the *setoffactiveShovel* matrix;

$$S = \begin{array}{c} \begin{array}{cccc} id & ST & SC & na \end{array} \\ \begin{bmatrix} id_1 & st_1 & sc_1 & na_1 \\ \vdots & \vdots & \vdots & \vdots \\ id_s & st_s & sc_s & na_s \\ \vdots & \vdots & \vdots & \vdots \\ id_S & st_S & sc_S & na_S \end{bmatrix} \end{array} \tag{90}$$

In the S matrix, id represents shovel identification number, ST (or st) comes as the shovel type, SC stands for shovel capacity, and na is the next availability of the shovel. The dispatching models are then built upon the T and S matrices.

3.2.8. Output from upper stage optimization models to simulation

After solving the upper stage problem, the decision-making model that is integrated into the simulation model provides the operation's simulation model with the optimal decisions. The output from the upper stage decision-making models are stored in a text file as a list of tonnage of material that must be handled in the next period from each loading point to each dumping point. Then, using VBA, the stored list is transferred into the simulation model to be stored in the path flow rate variable. Next, the simulation model uses the current optimum values for the flow rates whenever it needs to calculate anything based on that.

3.2.9. Output from lower stage optimization models to simulation

Each time a truck asks for a new assignment, the lower stage decision-making model uses information provided by the simulation model from the status of the operation and make a decision on the next destination of each available truck. Solving the lower stage decision-making model provides a two-column list. The first column in the list represents the truck ID of the truck to be assigned and the second column provides the path ID that the truck in the same row must travel to. The solution is then read into the simulation model using VBA and is stored in a variable. Next time the truck dumped its material, it uses the saved value and travel to the designated destination.

3.3. Upper stage optimization models

3.3.1. Benchmark model

DISPATCH® [11] uses linear programming approach to optimize the production target within a specific time horizon by dividing it into two separate but weakly coupled models. The first one, Eq. (91), optimizes the total production of the operation, including mining, processing, and stockpiling, and the second part, Eq. (95), maximizes the fleet production by minimizing the total required volume to be handled. The second part generates a theoretical haulage master plan that considers production and operational constraints and is later used as a reference to generate real-time truck assignments. White and Olson [12] and Olson et al. [51] describe the model as follows:

$$\min C = \sum_{i=1}^{N_m}(C_m \times Q_i) + C_p \times (P_t - \sum_{i=1}^{N_m+N_s} Q_i) + \sum_{i=1}^{N_s}(C_s \times Q_i) + \sum_{i=1}^{N_m+N_s}\sum_{j=1}^{N_q}(L_j \times C_q \times X_{ij} \times Q_i) \tag{91}$$

Subject to:

$$0 \le Q_i \le R_i \tag{92}$$

$$P_t \geq \sum_{i=1}^{N_m+N_s} Q_i \tag{93}$$

$$X_jL \leq X_jA + \sum_{i=1}^{N_m+N_s} \left(X_{ij} - X_jA\right) \times Q_i \times T_c / \left(M_c / SG\right) \leq X_jU \tag{94}$$

Where:

N_m, N_s, and N_q	are the number of shovels at mining faces, the number of shovels working at stockpile, and the number of quality constraints
C_m, C_s, C_q, and C_p	are the material transportation pseudo cost (hr/m^3), the stockpile material handling pseudo cost (hr/m^3), the quality pseudo cost (hr/m^3), and the pseudo cost of low feed to plant (hr/m^3)
Q_i	is the material being transported per hour (m^3/hr) that should be determined in the procedure
L_j	is the quality director: 1 for low crit and -1 for high crit
X_{ij}, X_jL, X_jA, and X_jU	are the j^{th} quality factor at i^{th} shovel, the lower limit for quality factor *j,* the running average value of quality factor *j,* and the upper limit for quality factor *j*
P_t	is the target rate of plant feed
R_i	is the digging rate at i^{th} shovel
M_c	is the 1st in/1st out average control mass, kg
SG	is the specific gravity
T_c	is the base control interval (hr)

All pseudo costs are chosen arbitrarily with respect to ($C_m < C_q < C_s < C_p$).

As the second segment of the LP model, DISPATCH® [11] tries to minimize total haulage capacity needed to meet shovel production coverage:

$$\min V = \sum_{i=1}^{N_p} \left(P_i \times T_i\right) + \sum_{j=1}^{N_d} \left(P_j \times D_j\right) + N_e \times T_s \tag{95}$$

Subject to:

$$\sum_{k=1}^{N_{pi}} P_k = \sum_{k=1}^{N_{po}} P_{k'} \tag{96}$$

$$R_j = \sum_{k=1}^{N_{po}} P_{k'} \qquad \text{for mining shovels} \tag{97}$$

$$R_j \leq \sum_{k=1}^{N_{po}} P_{k'} \qquad \text{for stockpiles} \tag{98}$$

$$P_j = Q_i \tag{99}$$

$$0 \leq P_i \tag{100}$$

Where:

V is the total mine haulage (m^3)

N_p is the number of feasible haul routes

P_i is the haulage on path *i* which should be determined (m^3/hr)

T_i is the path *i* travel time (hr)

N_d is the number of dumps for mine haulage

P_j is the net haulage input to dump *j* (m^3/hr)

D_j is the average dump time at dump *j* (hr)

N_e is the number of operating shovels

T_s is the fleet average truck size (m^3)

N_{pi} is the number of feasible input paths at node j

N_{po} is the number of feasible output paths at node j

P_k is the input path haulage (m^3/hr)

$P_{k'}$ is the output path haulage (m^3/hr)

R_j is the limiting rate at node j (m^3/hr)

The model, Eq. (91), introduces the first segment of the operation optimization as a pseudo cost-based LP, which is established on the summation of costs in all four operational sectors of the mine. The solution of the first segment presents the shovels' production rates with respect to the maximum digging rate for a shovel, Eq. (92), the maximum capacity of the plant, Eq. (93), and the lower and upper bounds of the blending grade, Eq. (94). The second segment's LP maximizes the production of the operation by allocating a minimum number of trucks to each active route, Eq. (95) to meet the routes production rate. Eq. (96) makes sure that the input and output flow at each shovel and each dumping point are equal. Eq.(97) and (98) guarantee that the amount of material handled meets the grade requirements at the plant cannot exceed the amount produced by the mine and stockpile. Coupling segments of the operation plan is attained by constraining total production of all routes servicing a shovel to be greater or equal to the shovel production, Eq.(99). It should be mentioned here that both P and Q in Eq. (99) are vectors. Finally, Eq. (100) ensures that all haul rates in the mine are nonnegative. One benefit of the model is that it follows the status of the mine by using real-time data. Another advantage of the model is that the optimum production rate of each route is based on the volume of material, not based on the number of trucks. That helps the dispatching step to send the proper truck to cover the shortage. A major drawback of the model is that it does not consider stripping ratio limitation in the operation. By limiting the lower bound of digging rates at each shovel to zero, they allowed the model to ignore a shovel operating at waste mining face. Another disadvantage of the model is that the plant head-grade requirement is constrained to a range of grade between predefined upper and lower limits. It will cause an undeniable short-term influence on both plant output (final product) quantity and its input (utilization of some specific shovels which must be met up to the minute) [63]. However, most of the drawbacks of DISPATCH® [11] will arise in the real-time dispatching model that will be explained in more detail in the next section.

3.4. Lower stage optimization models

3.4.1. Benchmark model

After solving the upper stage – operation optimization – LP problem by implementing the Simplex method [85], resulting in the optimum material flow rate on routes, White and Olson [12] and Olson et al. [51] employ the dynamic programming (DP) [53] approach to send trucks to the proper destination. To do so, two lists and three parameters are defined. A list of needy shovels or LP-selected paths and a list of trucks dumping material at discharge points or en-route from a loading point to a destination are provided. In addition, need-time, Eq. (101), which is defined as the expected time for each path's next truck requirement, is formulated as follows:

$$need-time_i = L_j + F_{ij} \times \left(A_j - R_j\right) / P_i \quad (101)$$

Where:

L_j	is the time the last truck was allocated to the shovel j
F_{ij}	is flow rate of path i over the total flow rate into shovel j
A_j	is total haulage allocated by time L_j to shovel j
R_j	is haulage requirement of shovel j
P_i	is path flow rate (ton/hr or m^3/hr)

So, the neediest path, which is on the top of the neediest shovels list, will be the one with the shortest need-time. Then lost-ton is defined and formulated as a criterion to find the best truck for the neediest path from the truck list with Eq.(102):

$$lost-ton = \frac{truck\,size \times total\,rate}{required\,trucks} \times \left(truck\,idle + excess\,travel\right) + shovel\,rate \times shovel\,idle \quad (102)$$

Where:

Truck size is the size of truck being assigned; Total rate is total digging rate of all shovels in the mine; Required trucks is total required trucks in the LP solution; Truck idle is expected truck idle time for this assignment; Excess travel is extra empty travel time to neediest shovel; Shovel rate is sum of all path rates into neediest shovel; And shovel idle is expected shovel idle time for this assignment.

Considering the lost-ton definition, the truck covering lost-ton of neediest shovel the most is the best truck. After the best truck is assigned to the neediest shovel, it is moved to the last position on the needy paths' list and the procedure is repeated for the second neediest until all trucks on the list are assigned.

Defining a rolling time horizon when a sequence of assignment is needed is a benefit of the model. The information of the mine status used in the model is always up to the minute. However, the model does not consider the effect of current truck assignment on the forthcoming truck matching, though all trucks previously sent to the shovels are considered. Another drawback of the model is that despite the authors' claim, the solution method is not a DP. It is a heuristic rule solving each sub-problem based on the best solution of previous sub problems. According to [2], the solution method's misnaming as a DP is perhaps because of the authors' misunderstanding of Bellman's principal of optimality. However, the DISPATCH® system has been implemented in more than 230 mines all around the world [11].

3.4.2. Multiple objective model

We have developed a multiple objective model to dispatch trucks to shovels in a multi-stage FMS. The model deals with decisions required in the lower stage of FMS by looking at the path production requirements (tonnage of material required to be moved from a specific path) set by the upper stage and other operational parameters such as stripping ratio requirements, available transporters' capacity, required plants' throughput, and loaders' digging rate. The model is to be solved every time a truck requires a new assignment – that happens when a truck dumps its load, or any time a loader that the truck has already been assigned to breaks down before loading that truck (Figure 3.5).

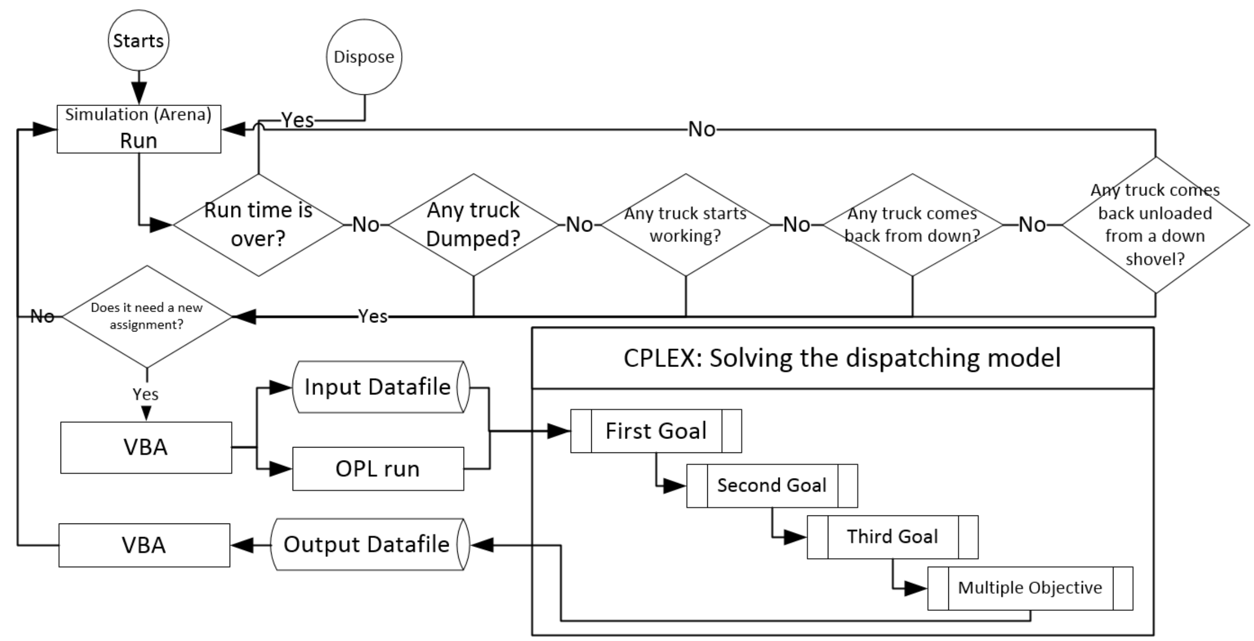

Figure 3.5: Schematic view of the lower stage model call time in the framework

The model is also solved when there is a change in the schedule for the next hour of the operation. We use the following notations to formulate the truck-dispatching model. Indices used in the model to address elements of different sets including set of trucks, set of shovels, set of dumping points, set of goals, and set of trucks waiting in queue at shovels are as follows:

i	Index for set of Trucks: $i = \{1,...,N\}$;
j	Index for set of Sources: $j = \{1,...,M\}$;
k	Index for set of Destinations: $k = \{1,...,D\}$;
k'	Index for set of dumping points that trucks need to dump their load before traveling to the new shovel: $k' = \{1,...,D\}$;
t	Index for set of weights for individual goals: $t = \{1, 2, 3\}$;
q	Index for trucks waiting in queue at shovel: $q = \{1, ..., NTinQS\}$;

The decision variables used are as follows:

x_{ijk}	Incoming flow to source j by assigning truck i to the path of source j to destinations k;
x'_{ijk}	Outgoing flow of source j by assigning truck i to the path of source j to destinations k;
c^-_{jk}	Negative deviation of the met path flow rate for path between source j and destination k compared to desired path flow rate;

c_{jk}^{+} Positive deviation of the met path flow rate for path between source j and destination k compared to desired path flow rate;

The parameters used in the truck-dispatching model and the procedure of calculating objective functions' coefficients of the model are explains as follows:

S_{ijk} Idle time for shovel j if truck i is assigned to transport material from shovel j to the destination k;

T_{ijk} Wait time for truck i if it is assigned to transport material from shovel j to the destination k;

P_t Normalized weights of individual goals based on priority;

AF A factor balancing available trucks with the required capacity of plants;

PC_k Capacity of the plant k: $k = \{1, ..., O\}$: $\{1, ..., O\} \subset \{1, ..., D\}$;

SC_j Production capacity of shovel j;

MP_{jk} Path flow rate for the path from source j to the destination k that the production operation has met so far;

tc_i Capacity of truck i *(ton)*;

T_i Nominal capacity of truck i *(ton)*;

PT_{jk} Path flow rate for the path from source j to the destination k;

TR_{ijk} Next time truck i reaches shovel j;

SA_{ijk} Next time shovel j is available to serve truck i;

TN Current time of the operation;

$LD_{ik'}$ The distance truck i must travel to reach the dumping point k' to dump its load;

$ED_{ik'j}$ The distance truck i must travel from the dumping point k' to the next expected shovel j;

$\bar{V}_{ik'j-loaded}$ Average loaded velocity of truck *i* traveling to destination *k'* and will travel to shovel *j* after dumping its load;

$\bar{V}_{ik'j-empty}$ Average empty velocity of truck *i* traveling from dump *k* to the next expected shovel *j*;

$Q@D_{ik'}$ Queue time for truck *i* in the queue of the dump *k'*;

$D_{ik'}$ Dump time for truck *i* to dump its material in dump *k'*;

$NTinQS_j$ Number of trucks in queue at shovel *j*;

$TSpotT_q$ Spotting time for the truck *q* in the queue;

$TLoadT_q$ Loading time for the truck *q* in the queue.

Objective function coefficients for the multiple objective model are calculated as follows:

Firstly, truck arrival time for each truck *i* to shovel *j* is calculated using Eq. (103).

$$TR_{ijk} = TN + \frac{LD_{ik'}}{\bar{V}_{ik'-loaded}} + Q@D_{ik'} + D_{ik'} + \frac{ED_{ik'j}}{\bar{V}_{ik'j-empty}} \tag{103}$$

It is worth noting that index *k'* in Eq. (103) is referring to the dumping point where the truck *i* needs to first dump its material there and then move to the shovel *j*.

Secondly, the next time shovel *j* will be available to serve truck *i* is calculated using Eq. (104).

$$SA_{ijk} = TN + \sum_{q=1}^{NTinQS_j} \left(TSpotT_q + TLoadT_q \right) \tag{104}$$

Finally, using Eq. (105) and Eq. (106) objective function coefficients for two of the objectives are calculated.

$$S_{ijk} = TR_{ij} - SA_{ij} \qquad \forall i \in \{1,...,N\} \& \forall j \in \{1,...,M\} \& \forall k \in \{1,...,D\} \tag{105}$$

$$T_{ijk} = SA_{ij} - TR_{ij} \qquad \forall i \in \{1,...,N\} \& \forall j \in \{1,...,M\} \& \forall k \in \{1,...,D\} \tag{106}$$

3.4.2.1. Objective function

The real-time multiple objective truck-dispatching model follows the *m-trucks-for-n-shovels* strategy introduced by Alarie and Gamache [2]. The multiple objective model consists of three different objectives. The first objective function minimizes the summation of the active shovels' idle time (Eq. (107)). The second objective function minimizes summation of truck wait time in the operation (Eq. (108)). The third objective function is a goal programming objective that minimizes summation of deviation from paths' flow rates (Eq. (109)). These objectives are of different scales and have different levels of influence on the system. Apart from that, the third objective is to minimize deviation from a target (or goal) value. The model is also an MILP model. Thus, to solve the model we chose a non-preemptive mixed integer linear weighted sum goal programming approach. The three objectives of the model are presented as follows:

$$f_1 = \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{D} S_{ijk} x_{ijk} \tag{107}$$

$$f_2 = \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{D} T_{ijk} x_{ijk} \tag{108}$$

$$f_3 = \sum_{j=1}^{M}\sum_{k=1}^{D} \left(c_{jk}^{-} + c_{jk}^{+}\right) \tag{109}$$

However, since all the objectives do not belong to the same dimensions, we normalize them to dimensionless objectives using Nadir and Utopia points explained by Grodzevich and Romanko [131]. In this method, Utopia point sets a lower bound on individual objective. Nadir point sets an upper bound on the objectives. The results of determination of these points will provide us the lower bound and upper bound of the interval that the objective functions will vary in the Pareto optimal set. Optimizing the system (minimizing) considering only one objective will result in the Utopia point (z^U) which provides the lower bound of values for individual objectives (Eq. (110)). The upper bounds are derived using the components of a Nadir point presented in Eq. (111):

$$z_i^U = f_i\left(x^{[i]}\right):\ x^{[i]} = \arg\min_x \left\{ f_i\left(x\right): x \in \Omega \right\} \qquad i \in objectives \tag{110}$$

$$z_i^N = \max_{1 \le j \le k}\left(f_i\left(x^{[j]}\right)\right):\ x^{[j]} = \arg\min_x \left\{ f_j\left(x\right): x \in \Omega \right\} \quad \forall i = 1,\ldots,k;\ k = total\ number\ of\ objectives \tag{111}$$

Using Nadir and Utopia points objectives are normalized within a range between 0 and 1 using the Eq. (112).

$$\bar{f}_i\left(x\right)=\frac{f_i\left(x\right)-z_i^{U}}{z_i^{N}-z_i^{U}} \qquad \forall\, i\in objectives \tag{112}$$

After normalization of the objectives they can only vary somewhere between 0 and 1 (Eq.(113)):

$$0\le \bar{f}_i\left(x\right)\le 1 \tag{113}$$

The priority weights to be multiplied by the objectives will be obtained using weighted sum method representing in Eq. (114):

$$\sum_i p_i = 1 \qquad i\in objectives \tag{114}$$

Finally, the multi-objective normalized objective function is as follows:

$$Minimize\, Z = p_1\bar{f}_1 + p_2\bar{f}_2 + p_3\bar{f}_3 \tag{115}$$

Each component of the objective function in Eq. (115) is a weighted normalized version of an individual objective presented in Eq. (107) to Eq. (109).

3.4.2.2. Constraints

Constraints limiting the objective function of the truck-dispatching model are listed in Eq. (116) to Eq. (125).

$$\sum_{i=1}^{N}\sum_{k=1}^{D} x'_{ijk} = \sum_{i=1}^{N}\sum_{k=1}^{D} x_{ijk} \qquad \forall\; j\in\{1,...,M\} \tag{116}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ijk} = \sum_{i=1}^{N}\sum_{j=1}^{M} x'_{ijk} \qquad \forall\; k\in\{1,...,D\} \tag{117}$$

$$\sum_{i=1}^{N}\sum_{k=1}^{D} tc_i x_{ijk} \le T_i \qquad \forall\, i\in\{1,...,N\} \tag{118}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} tc_i x_{ijk} \ge AF\times PC_k \qquad \forall\, k\in\{1,...,O\} \tag{119}$$

$$\sum_{i=1}^{N}\sum_{k=1}^{D} tc_i x_{ijk} \le SC_j \qquad \forall\, j\in\{1,...,M\} \tag{120}$$

$$\sum_{i=1}^{N} tc_i x_{ijk} + MP_{jk} + c_{jk}^{-} - c_{jk}^{+} = PT_{jk} \qquad \forall\; j\in\{1,...,M\}\ \&\ \forall\; k\in\{1,...,D\} \tag{121}$$

$$x_{ijk} \in \{0,1\} \qquad \forall\, i \in \{1,...,N\}, \forall\, j \in \{1,...,M\} \; and \; \forall\, k \in \{1,...,D\} \tag{122}$$

$$x'_{ijk} \in \{0,1\} \qquad \forall\, i \in \{1,...,N\} \,\&\, \forall\, j \in \{1,...,M\} \;\&\, \forall\, k \in \{1,...,D\} \tag{123}$$

$$c^{-}_{jk} \geq 0 \qquad \forall\, j \in \{1,...,M\} \;\&\; \forall\, k \in \{1,...,D\} \tag{124}$$

$$c^{+}_{jk} \geq 0 \qquad \forall\, j \in \{1,...,M\} \;\&\; \forall\, k \in \{1,...,D\} \tag{125}$$

Constraint (116) ensures that the number of incoming trucks to each shovel is equal to the number of outgoing trucks from the same shovel, meaning that whatever truck capacity arrived into a shovel queue will leave that shovel. Constraint (117) makes sure that the total incoming haulage capacity into a dump area equals the empty capacity leaving that specific dump location. Constraint (118) limits the tonnage a truck can transport in one payload to its maximum nominal capacity. Constraint (119) ensures that material hauled to the processing plants using all the trucks meet a portion equal to AF times of the required processing target of each plant. AF is the adjustment factor that adjusts the required amount of material at each processing plant. The adjustment factor is calculated using Eq. (126).

$$AF = \sum capacity\; of\; available\; trucks \Big/ \sum required\; flow\; rate\; at\; paths \tag{126}$$

This means that only AF portion of the requirement of the plants can be met. Constraint (120) limits the total haulage capacity sent to a shovel to the nominal digging rate at that shovel. Constraint (121) calculates the deviation of the path flow rate for each path connecting a source to a destination point from the desired path flow rate. Finally, constraints (122) and (123) make sure two first set of the decision variables are binary and constraints (124) and (125) ensure non-negativity of the goal programming variables. After the model has been solved, it will dispatch trucks to shovels.

3.4.3. Stochastic model

3.4.3.1. Deterministic truck-dispatching model

The goal in presenting this model is to develop a dispatching model that minimizes cumulative lost time for the entire active material handling fleet including both the loader fleet and the transporter fleet considering operational limitations such as truck capacity, shovel digging rate, and processing plants feed rate requirements while incorporating the truck travel time uncertainties. However, we first present the deterministic model with the objective function, decision variables and the constraints and present the stochastic model in the next subsection. The model presented in this section is a deterministic model with all its input parameters taking deterministic values. It can also be categorized as a mixed integer linear programming model based on transportation problem. The objective function of the model, presented in Eq. (127), minimizes the cumulative absolute time difference between the times truck *t* will reach shovel *s* after dumping at dump *d* (t_{ts}) and the time shovel *s* will be available to load the next truck (na_s). The second part of the objective function tries to maximize the adjustment factor (*AF*) encouraging the model to maximize a balanced material delivery to all destinations. AF will be explained later on. Finally, VBN stands for very big number.

$$\min Z = \sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{s=1}^{S} C_{tds} x_{tds} + VBN(mf - AF) \qquad \forall t \in \{1,...,T\}, \forall d \in \{1,...,D\}, and\ \forall s \in \{1,...,S\} \tag{127}$$

The objective function coefficient for each of the variables is calculated using Eq. (128):

$$\begin{aligned} C_{tds} &= \left| t_{ts} - na_s \right| \\ &= \left| T(t, 3+s) - S(4, s) \right| \\ &= \left| ltt_{td} + qt_{td} + dt_{td} + ett_{tds} - \sum_{t'=1}^{TT} \left(tinq_{t's} + tenr_{t's} \right) \times \left(st_{t's} + lt_{t's} \right) \right| \\ &\forall t \in \{1,...,T\}\ \&\ \forall s \in \{1,...,S\}\ \&\ \forall d \in \{1,...,D\} \end{aligned} \tag{128}$$

Where:

ltt_{td} loaded travel time from current truck *t* position to dump *d*

qt_{td} time truck *t* must spend in queue at dump *d* to dump its material

dt_{td} time truck *t* spends at dump *d* to back up and dump its material

ett_{ts} time truck *t* spends to travel empty from the dump location *d* to shovel *s*

$tinq_{t's}$ time a truck of type t' that is already in queue must spend in shovel s queue

$tenr_{t's}$ time a truck of type t' must travel from its current position to reach shovel *s*

$st_{t's}$ spot time for a truck of type t' at shovel *s*

$lt_{t's}$ loading time for a truck of type t' at shovel *s*

Moreover, the decisions need to meet operational constraints such as trucks' and shovels' supply (Eq. (129) and Eq.(120)), destination demand constraint (Eq. (119)), balancing truck distribution over the paths (Eq. (132)), and binary constraints (Eq. (133)).

$$\sum_{d=1}^{D}\sum_{s=1}^{S} x_{tds} \leq 1 \qquad \forall\, t \in \{1,...,T\} \tag{129}$$

$$\sum_{t=1}^{T}\sum_{d=1}^{D} tc_t x_{tds} \leq sc_s \qquad \forall\, s \in \{1,...,S\} \tag{130}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S} tc_t x_{tds} \geq AF \times pc_d \qquad \forall\, d \in \{1,...,D\} \tag{131}$$

$$0 \leq AF \leq mf \tag{132}$$

$$x_{tds} \in \{0,1\} \qquad \forall t \in \{1,...,T\},\ \forall d \in \{1,...,D\}, and\ \forall s \in \{1,...,S\} \tag{133}$$

Where:

x_{tds} binary integer variable to assign truck *t* to the path connecting shovel *s* to dump *d*

tc_t capacity of truck *t*

sc_s capacity of shovel *s*

pc_d capacity of dump *d (ton)*

AF adjustment factor that forces model to evenly distribute extra available trucks among all the possible destinations

mf proportion of the cumulative available trucks' capacity to the cumulative required path flow rate that can be met using the available trucks

pf_{sd} required path flow rate for path from shovel *s* to dump *d* based on upper stage decisions

$pmsf_{sd}$ met so far path flow rate for path from shovel *s* to dump *d*

Constraint (129) makes sure that truck *t* cannot be assigned to more than one shovel. Constraint (120) ensures that summation of nominal capacity of all the trucks assigned to shovel *s* does not exceed the shovel's nominal digging rate (capacity). *AF* in constraint (119) is defined as adjustment factor. The adjustment factor is a variable that is forcing the model to evenly distribute the truck fleet capacity between all the destinations and is constrained by *mf* as in Eq. (132). *mf* is a matching factor that is calculated based on cumulative available truck capacity and cumulative path material handling requirement using Eq. (134). This factor is equal to 1 when the total truck fleet capacity is less than the required path flow rate and is equal to the proportion of the available truck capacity to the total path requirements when there is extra fleet capacity available. The adjustment factor is constrained by *mf* to uniformly distribute the extra truck fleet capacity among all the needy paths to balance ore and waste production.

$$mf = \max\left\{1\ ,\ \frac{\sum_{t=1}^{T} tc_t}{\sum_{s=1}^{S}\sum_{d=1}^{D}(pf_{sd} - pmsf_{sd})}\right\} \qquad \forall t \in \{1,...,T\}, \forall d \in \{1,...,D\}, and\ \forall s \in \{1,...,S\} \tag{134}$$

Where:

tc_t	truck capacity for truck t in the fleet
pf_{sd}	path flow rate for path linking shovel s to dump d
$pmsf_{sd}$	Path flow rate for path linking shovel s to dump d that has been met so far

3.4.3.2. Stochastic truck-dispatching model

The presented model uses expected (deterministic) values for the input parameters. However, most of the parameters affecting the truck-dispatching decisions are associated with uncertainties. In this thesis, we formulated our model as a stochastic integer programming model with recourse [16] to capture uncertainty of one of the major parameters affecting the operation (trucks' empty travel time). Reason to capture uncertainty in trucks' empty travel time is that more than 90% of trucks' cycle time in each cycle is spent in traveling. From that time, about 50% is spent in travel empty. As most of the time a truck needs to be dispatched has already passed some portion of its loaded travel or even completed its loaded travel, the most important parameter where the uncertainty associated with it needs to be captured is empty travel. Thus, the objective function of the stochastic model that captures empty travel time uncertainty is (Eq. (135)):

$$\min Z = \overbrace{\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{s=1}^{S} C_{tds}x_{tds}}^{1st} + \overbrace{VBN(1-AF)}^{2nd} \tag{135}$$

$$+\overbrace{\frac{1}{nR}\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{s=1}^{S}\sum_{r=1}^{nR}\left|ltt_{td} + qt_{td} + dt_{td} + ett_{tds}^{r} - \sum_{tt=1}^{TT}(tinq_{t's} + tenr_{t's}) \times (st_{t's} + lt_{t's})\right| x_{tds}}^{3rd}$$

Where:

ett_{tds}^{r} time truck t spends to travel empty from the dump location d to shovel s in r^{th} realization

r is an index referring to a scenario in the stochastic integer model

nR number of realizations implemented to generate random variables for empty travel time from its distribution.

In the developed model, the first two components of the objective function are the same as the deterministic model. The third component is the minimization of the truck or shovel idle time in material handling given the uncertainty in trucks empty travel time. The model is constrained with Eq. (129) to Eq. (133). For each of the realizations r in the stochastic model with nR number of realizations, a random value is being sampled from the fitted distribution of the historical data of the empty truck velocity. The sample is then imported into the model after preprocessing procedure that calculates required travel time and is used during the decision-making procedure.

3.4.4. Fuzzy model

Under the multi-stage truck-dispatching approach [70], [125], we developed a deterministic ILP mathematical model to make decisions on the trucks' next destination. After solving the model using stochastic programming approach, we identified fuzzy parameters and based on those fuzzy parameters we improved the crisp model to a fuzzy model. Herein, we present the fuzzy model development and defuzzification procedure.

Zimmermann [132] and Zimmermann [133] for the first time implemented fuzzy set theory in conventional LP models [134]. Then after, several FLP models have been developed to deal with different real-world problems and more specifically in mining industries. The most recent FLP model developed in a mining operation context can be credited to [135] where the authors developed a FLP model to solve surface mines short term planning problem. Even though all of the input parameters to solve the optimization models in the truck-dispatching problem might behave in a fuzzy manner, none of the thus far developed models to solve the truck-dispatching problem have considered that fuzzy behavior. Thus, in this thesis, we developed the fuzzy version of our deterministic model as follows:

$$\min \tilde{Z} = \sum_{t=1}^{T} \sum_{d=1}^{D} \sum_{s=1}^{S} \tilde{C}_{tds} x_{tds} + VBN(1 - AF) \tag{136}$$

Subject to:

$$\sum_{d=1}^{D} \sum_{s=1}^{S} \widetilde{tc}_t x_{tds} \leq \widetilde{TC}_t \qquad \forall t \in \{1, \dots, T\} \tag{137}$$

$$\sum_{t=1}^{T} \sum_{d=1}^{D} \widetilde{tc}_t x_{tds} \leq \widetilde{sc}_t \qquad \forall s \in \{1, \dots, S\} \tag{138}$$

$$\sum_{t=1}^{T} \sum_{s=1}^{S} \widetilde{tc}_t x_{tds} \geq AF \times \widetilde{pc}_d \qquad \forall d \in \{1, \dots, D\} \tag{139}$$

And Eq. (132) and Eq. (133) where:

$$\tilde{C}_{tds} = \left| \widetilde{ltt}_{td} + \widetilde{qt}_{td} + \widetilde{dt}_{td} + \widetilde{ett}_{ts} - \sum_{tt=1}^{TT} (tinq_{tts} + tenr_{tts}) \times (\widetilde{st}_{tts} + \widetilde{lt}_{tts}) \right| \tag{140}$$

It is worth noting that $\tilde{x}$ represents fuzzy parameter x in the model.

3.4.4.1. Defuzzification

The uncertainties in the input parameters of any fuzzy programming problem force two main problems: the problem of extracting optimum objective function value for the objective function containing fuzzy parameters, and the problem of relationship between fuzzy sides of constraints. Solving these two problems is tied to the process of ranking fuzzy numbers [134]. Several approaches have been introduced in the literature of application of fuzzy set theory to rank fuzzy numbers. A detailed explanation of these approaches can be found in [136], [137]. In this research we implement method developed by Jiménez et al. [138] to rank fuzzy constraints and objectives. Despite some other methods, as claimed by authors, the method developed by Jiménez et al. [138] verifies all of the properties implemented in other approaches. The developed method uses concept of optimality to deal with the fuzzy objective functions and concept of feasibility to deal with the feasibility of constraints. Another advantage of the ranking fuzzy numbers developed by Jiménez et al. [138] is that by implementing this method, linearity of the LP model will be preserved which helps to have a computationally efficient model to solve. In addition to aforementioned advantages, it is capable of not increasing the number of constraints or the objective functions [139]. Thus, it can be implemented in solving large scale FLP models [134]. The method is based on two mathematically strong concepts of expected value and expected interval of fuzzy numbers [140] that initially presented by [141] and [142] and was developed later on by [143] and [144].

To start with the Defuzzification process, we first define some required terms. A fuzzy number is defined as a fuzzy set on the real line R that has membership function presented in Eq. (141).

$$u = \mu_{\tilde{a}} = \begin{cases} 0 & \forall x \in (-\infty, a_1] \\ f_a(x) & \forall x \in (a_1, a_2], increasing \\ 1 & \forall x \in [a_2, a_3] \\ g_a(x) & \forall x \in [a_3, a_4], decreasing \\ 0 & \forall x \in [a_4, +\infty) \end{cases} \quad ; \quad \tilde{a} = (a_1, a_2, a_3, a_4) \tag{141}$$

A cut through the fuzzy number produces a nonfuzzy set and is defined as presented in Eq. (142).

$$a_\alpha = \{x \in R;\ \mu_{\tilde{a}}(x) \geq \alpha; 0 \leq \alpha \leq 1\} \ or \ a_\alpha = [f_a^{-1}(u), g_a^{-1}(u)] \tag{142}$$

The membership function for cases where the f_a and g_a are linear functions, is trapezoidal and in cases where $a_2 = a_3$ and the f_a and g_a are linear functions, is triangular (in this paper all the parameters are assumed to follow the later membership function as due to its easy data acquisition and computational efficiency this type of possibilistic distribution is the most common tool that is used to model fuzzy parameters [145]) [134], [139], [140], [144]. The expected interval and the expected value of a fuzzy number which first been introduced by Heilpern [143] can be calculated using Eq. (143) and Eq. (144), respectively for a triangular fuzzy number.

$$EI(\tilde{a}) = [E_1^a, E_2^a] = \left[\int_0^1 f_a^{-1}(u)du, \int_0^1 g_a^{-1}(u)du\right] = \left[\frac{a_1 + a_2}{2}, \frac{a_2 + a_3}{2}\right] \tag{143}$$

$$EV(\tilde{a}) = \left[\frac{E_1^a + E_2^a}{2}\right] = \frac{a_1 + 2a_2 + a_3}{4} \tag{144}$$

According to the ranking method developed by Jimenez [146] $\tilde{a}$ is greater than or equal to $\tilde{b}$ in the degree defined by Eq. (145) [140].

$$\mu_M(\tilde{a}, \tilde{b}) = \begin{cases} 0 & if\ E_2^a - E_1^b < 0 \\ \dfrac{E_2^a - E_1^b}{E_2^a - E_1^b - (E_1^a - E_2^b)} & if\ 0 \in [E_1^a - E_2^b, E_2^a - E_1^b] \\ 1 & if\ E_1^a - E_2^b > 0 \end{cases} \tag{145}$$

If $\mu_M(\tilde{a}, \tilde{b}) \geq \alpha$ then it is said that at least in degree of α , $\tilde{a}$ is greater than or equal to $\tilde{b}$. Based on Parra et al. [147] $\tilde{a}$ and $\tilde{b}$ are equal in degree of α if:

$$\frac{\alpha}{2} \leq \mu_M\left(\tilde{a}, \tilde{b}\right) \leq 1 - \frac{\alpha}{2} \tag{146}$$

Implementing all aforementioned definitions, any generalized fuzzy linear programming model where the fuzzy parameters follow triangular or trapezoidal fuzzy numbers (presented in Eq. (147)) can be converted to its equivalent crisp model (presented in Eq. (148)) using methods developed by Jimenez [146] for treating fuzzy objective function and Parra et al. [147] to treat fuzzy constraints.

$$\min z = \tilde{c}x \tag{147}$$

Subject to

$$\tilde{a}_i x \leq \tilde{b}_i, i = 1, \ldots, t$$

$$\tilde{a}_i x = \tilde{b}_i, i = t+1, \ldots, l$$

$$\tilde{a}_i x \geq \tilde{b}_i, i = l+1, \ldots, m$$

$$x \geq 0$$

$$\min EV_\gamma(\tilde{Z}) = EV_\gamma(\tilde{c})x$$

s.t.

$$\begin{array}{ll} [(1-\alpha)E_1^{a_i} + \alpha E_2^{a_i}]x \leq \alpha E_1^{b_i} + (1-\alpha)E_2^{b_i}, & i = 1, \ldots, t \\ [(1-\alpha)E_2^{a_i} + \alpha E_1^{a_i}]x \geq \alpha E_2^{b_i} + (1-\alpha)E_1^{b_i}, & i = t+1, \ldots, l \\ [(1-\frac{\alpha}{2})E_2^{a_i} + \frac{\alpha}{2}E_1^{a_i}]x \geq \frac{\alpha}{2}E_2^{b_i} + (1-\frac{\alpha}{2})E_1^{b_i}, & i = l+1, \ldots, m \\ [\frac{\alpha}{2}E_2^{a_i} + (1-\frac{\alpha}{2})E_1^{a_i}]x \leq (1-\frac{\alpha}{2})E_2^{b_i} + \frac{\alpha}{2}E_1^{b_i}, & i = l+1, \ldots, m \\ x \geq 0 & \end{array} \tag{148}$$

Where based on the generalized approach of Jimenez [146], with γ degree of optimism the $EV_\gamma(\tilde{Z}) = EV_\gamma(\tilde{c})x$ with $\tilde{Z} = (Z_1, Z_2, Z_3, Z_4)$ is defined as presented in Eq. (149).

$$EV_\gamma\left(\tilde{Z}\right) = \gamma E_2^Z + (1-\gamma)E_1^Z = \gamma\frac{Z_3+Z_4}{2} + (1-\gamma)\frac{Z_1+Z_2}{2} \tag{149}$$

According to Eq. (141) to Eq. (148), the equivalent crisp model of the developed fuzzy model for the truck-dispatching problem in this paper can be formulated as follows:

$$Z^p = \sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{s=1}^{S}\left|\left(ltt_{td}^p + qt_{td}^p + dt_{td}^p + ett_{ts}^p\right) - \sum_{tt=1}^{TT}(tinq_{tts} + tenr_{tts}) \times \left(st_{tts}^p + lt_{tts}^p\right)\right| \tag{150}$$

$$Z^m = \sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{s=1}^{S}\left|\left(ltt_{td}^m + qt_{td}^m + dt_{td}^m + ett_{ts}^m\right) - \sum_{tt=1}^{TT}(tinq_{tts} + tenr_{tts})\times\left(st_{tts}^m + lt_{tts}^m\right)\right| \tag{151}$$

$$Z^o = \sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{s=1}^{S}\left|\left(ltt_{td}^o + qt_{td}^o + dt_{td}^o + ett_{ts}^o\right) - \sum_{tt=1}^{TT}(tinq_{tts} + tenr_{tts})\times\left(st_{tts}^o + lt_{tts}^o\right)\right| \tag{152}$$

$$\min EV_{\gamma}(\tilde{Z}) + VBN(1-AF) = \gamma\frac{Z^m+Z^o}{2} + (1-\gamma)\frac{Z^p+Z^m}{2} + VBN(1-AF) \tag{153}$$

Subject to

$$\sum_{d=1}^{D}\sum_{s=1}^{S}\left[(1-\alpha)\frac{tc_t^p+tc_t^m}{2} + \alpha\frac{tc_t^m+tc_t^o}{2}\right]x_{tds} \le \alpha\frac{TC_t^p+TC_t^m}{2} + (1-\alpha)\frac{TC_t^m+TC_t^o}{2} \qquad \forall t\in\{1,...,T\} \tag{154}$$

$$\sum_{t=1}^{T}\sum_{d=1}^{D}\left[(1-\alpha)\frac{tc_t^p+tc_t^m}{2} + \alpha\frac{tc_t^m+tc_t^o}{2}\right]x_{tds} \le \alpha\frac{sc_s^p+sc_s^m}{2} + (1-\alpha)\frac{sc_s^m+sc_s^o}{2} \qquad \forall s\in\{1,...,S\} \tag{155}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S}\left[(1-\alpha)\frac{tc_t^m+tc_t^o}{2} + \alpha\frac{tc_t^p+tc_t^m}{2}\right]x_{tds} \ge AF\times\left(\alpha\frac{pc_d^m+pc_d^o}{2} + (1-\alpha)\frac{pc_d^p+pc_d^m}{2}\right) \qquad \forall d\in\{1,...,D\} \tag{156}$$

$$AF \begin{cases} \le mf & \text{if } mf > 1 \\ \le 1 & \text{otherwise} \end{cases} \tag{157}$$

$$x_{tds}\in\{0,1\} \qquad \forall t\in\{1,...,T\},\ and\ \forall d\in\{1,...,D\} \tag{158}$$

$$mf = \frac{\sum_{t=1}^{T} tc_t x_{tds}}{\sum_{s=1}^{S}\sum_{d=1}^{D}(pf_{sd} - pmsf_{sd})} \qquad \forall t\in\{1,...,T\}, \forall d\in\{1,...,D\}, and\ \forall s\in\{1,...,S\} \tag{159}$$

γ is degree of optimism of the decision maker and α is degree of the minimum acceptable feasibility of the decision vector.

3.5. Simulation models

Rockwell discrete event simulation software Arena [127] is used to develop simulation models of the mining operation. We extensively used VBA capability of Arena to build the simulation models. In Step 1 (Figure 3.6), using VBA macro written in Arena all the required input into Arena for the simulation are read into it. The VBA macro written in Arena as the first input reads readable input generated from the .dxf file of the road network by MATLAB. The same VBA macro also reads short-term production schedule, mine's road network, distributions fitted on the historical data of the required parameters (such as velocity, load time, dump time, spot time, etc.), type of equipment in the shovel and truck fleets, etc. from the data file and import them into the simulation model. By building the simulation model, rest of the framework do not require any human intervention to proceed the operation's simulation study. The system general operational parameters such as fitted distributions, equipment types and capacities, size of fleet, etc. can be readily changed in the input file without any interruption of the linkage between the input data file and the simulation model.

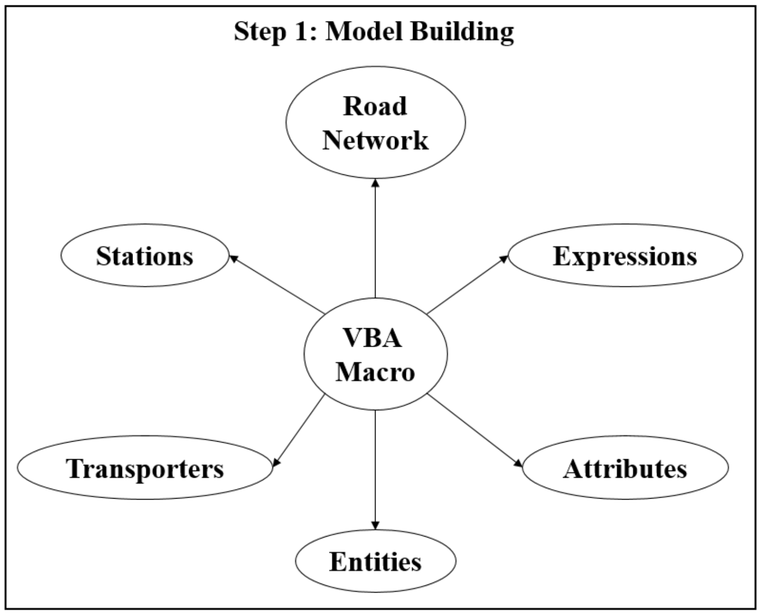

Figure 3.6: Building components of the simulation model using VBA macro (Step 1)

In Step 2 (Figure 3.7), the integrated simulation and optimization framework runs for the designated time frame. During the run, each time a decision is needed to be made, required information from the simulation are exported to a text file. Then, using CPLEX [148] linker (OPLrun) the decision-making model that is stored in a .mod file is recalled into CPLEX [148] software at the same time as the stored text file. Then, CPLEX [148] runs the mathematical model and make the simulation model aware of the decisions made by using of VBA. Afterwards, the simulation model implements the decisions made by CPLEX [148] in the operation.

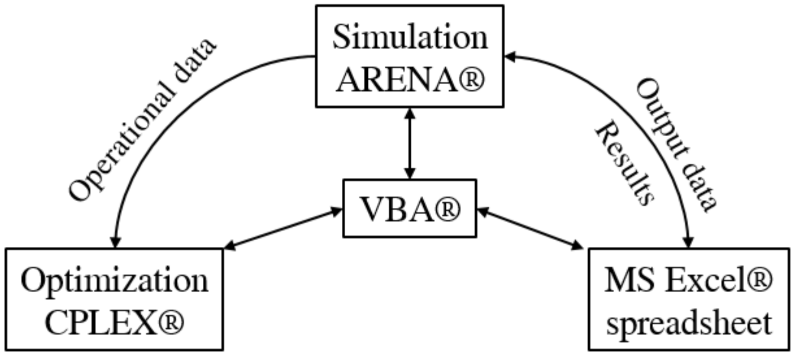

Figure 3.7: Schematic of the framework during the run (Step 2)

In Step 3 (Figure 3.8), after the simulation run reaches to full completion, using a .xml file and a .csv file that contains all the output of the simulation run, VBA macro transfers all the recorded information into an SQL database for further analysis. Using MATLAB and OriginPro software, required graphs and statistical summaries of the data from the simulation study are exported.

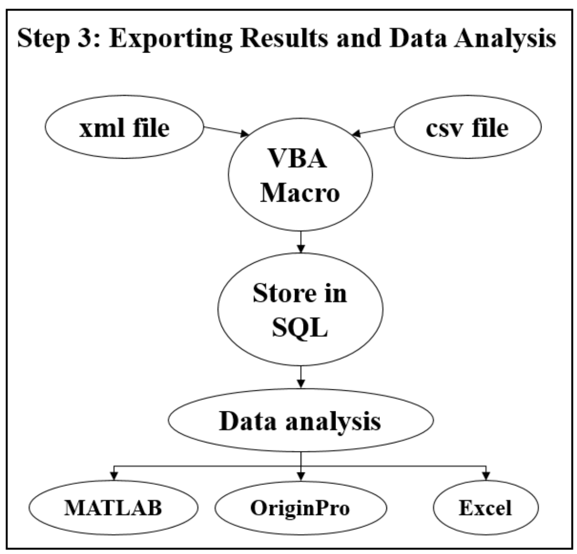

Figure 3.8: Exporting, storing, and analyzing results (Step 3)

3.5.1. System

The system includes one open pit mine operation, its haul network, the fleet management system that makes semi-dynamic and dynamic decisions, its two processing plants and one waste dump. At the beginning of the operation, signal is sent to the upper stage decision-making model to make decision on the required production. Then, based on the decisions made on the upper stage, the simulation sends signal to the second optimization model to make decisions on the trucks' destinations. By solving the lower stage (truck-dispatching) decision-making model, trucks are assigned and travel to shovels from the bay. This is the start of the operation.

In the operation simulation, the loading process is done by the shovel. Afterwards, loaded material is transported to one of the destinations based on the short-term plan. As the next step in the system, the truck reaches the destination and backs up to the exact dumping location to dump the material. Here is the time lower stage decision-making part of fleet management system (FMS) finds the best trucks among those just dumped their material into a dump and the trucks en-route to a dumping point by calling CPLEX. At the same time, it finds the neediest shovels and matches the best trucks with the neediest shovels. After finding its best destination, the truck travels to the shovel where dispatching system assigned it to. Figure 3.9 illustrates the flow diagram of the operation in the simulation model.

In the processing plants sub-models, a logical entity was defined for each of the plants. The logical entity enters to the simulation at the start of the simulation, seizes a regulator and after delivering plant's flow requirement (which is set to continue for entire time of the simulation) leaves the system. Along with it, a tank is being used to simulate performance each hopper.

3.5.2. Key Performance Indicators

To evaluate the performance of the developed truck-dispatching models, we need to use some key performance indicators (KPIs). Any mining complex encompasses two major parts of operation: mining operation and processing operation. Any FMS has a major influence on the performance of mining and processing. The important KPIs, based on which we evaluate the performance of our FMSs in the results chapter of this thesis, are listed in Table 3.2.

Table 3.2: Key Performance Indicators (KPI) to evaluate performance of the developed model in different scenarios

No.	Area of Concern	KPI to evaluate
1	Processing Plants	total production
2	Processing Plants	Hourly feed rate
3	Processing Plants	Hourly head grade
4	Shovels or Loaders	Utilization of the equipment
5	Trucks or Transporter	Queue length at sources
6	Trucks or Transporter	Queue time at sources

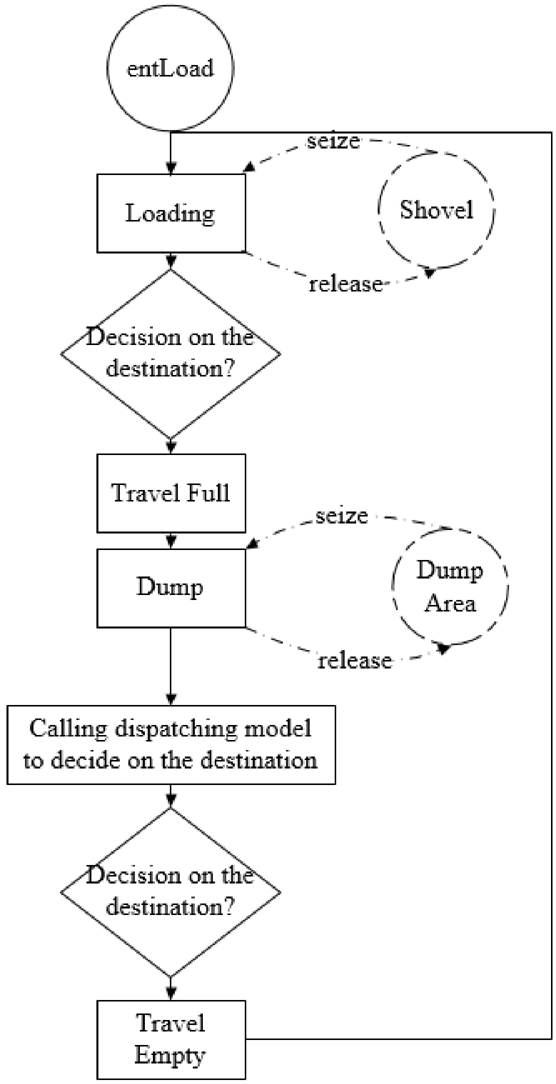

Figure 3.9: A simple flow diagram of the mining operation simulation model

3.5.3. Model inputs

The simulation model input can be illustrated within three categories of short-term schedule, technical characteristics, and fleet management systems decisions. The required inputs from the first category are including: coordinates and node IDs for the digging locations, total tonnage of the blocks, material average grade for each block, ID of the destinations the materials are supposed to be sent to, Shovel number, sequence number for each shovel, precedence, and distances from the digging location to the dumping locations. The second category of inputs are decisions on optimal paths flow rates, imported from the solution of the upper stage mathematical model, and decisions on the optimal trucks assignments, imported from the solution to the lower stage decision-making model. The required technical inputs are: shovels' ID, bucket capacities, loading cycle time, availability, trucks' ID, number of trucks of each type, capacities, dump time, spot time, availability, average speed of trucks when empty and when loaded, backing time, desired grade of each material type at processing plants, maximum rate of processing at processing plants, geographical information regarding dumping locations, all information regarding coordinates of the nodes connecting different parts of the road network, information regarding activity of any paths within sources and destinations, bucket count for each combination of shovel type-truck type, and seasonal loading cycle times for each and every shovel type-truck type combination.

3.5.4. Simulation sub-models

The simulation model consists of eight different sub-models. Table 3.3 lists the sub-models developed to perform the simulation of the mining complex operation.

Table 3.3: List of sub-models used to develop simulation model

No.	Sub-model	Task's description
1	Operation starting	Recalls available trucks from the bay and assigns them to the available shovels
2	Loading	Imitates the operation from the time a truck reaches to a shovel up until that truck leaves the shovel
3	Dumping	Imitates the process of dumping truck payloads into the dumping areas
4	Hopper and conveyor	Simulates the stockpile, hopper, and the conveyor that feed processing plants
5	Season change	This sub-model simulates change of the season and thus corresponding changes in the parameter distributions affected by it.
6	Shift change	Simulates change of the operation shifts as well as days
7	Path flow rate	Prepares required input parameters to run the decision-making model making decisions on the optimum path flow rate
8	Truck dispatching	Prepares required input data to run the truck-dispatching decision-making model

Each of the simulation sub-models listed in Table 3.3 plays a crucial role in the simulation of the mining complex. The procedure that developed simulation model to mimic the operation are listed below:

Step one: at the start of the simulation sub-model 1 that handles the start of the operation process is responsible for the process of trucks travel from the bay to the available shovels.

Step two: at each shovel station, trucks are loaded by a shovel already assigned to the polygon in that specific position, all the required information are transferred from the polygon to the material loaded onto the truck, truck leave the shovel and polygon (coming from the short-term schedule) remains there until it is fully depleted.

Step three: the loaded truck travel on the road network taking the shortest path from the shovel to the dump destination.

Step four: if the destination is a waste dump, the truck backs up and dumps its material in the designated area, otherwise, a decision is made based on current line up in front of each hopper, then the truck is assigned to the hopper with the least number of trucks in its queue. Then, as soon as all the trucks in the line are done with the dumping process, the hopper capacity is tested, if it has enough room for the truck, truck is allowed to dump its material. Otherwise, the truck needs to wait for hopper to open enough room for its material.

Step five: if the truck is already assigned to a shovel, it leaves the dumping area to start travel to the designated shovel. Otherwise, the simulation model prepares required input data for the truck-dispatching decision-making model. Once the decision is made by solving the truck-dispatching model, the truck is assigned to a shovel.

Step six: the truck travels to the shovel it is assigned.

Step seven: go to step two.

The procedure explained above consists of sub-models 1, 2, 3, and 8. Sub-model 4 controls stockpiles, hoppers, and conveyors. It accepts discrete truck loads in hopper and by simulating the conveyor that connects the hopper to the downstream processing operation, it continually feeds the plant based on the required hourly feed rate. Sub-model 5 runs using a logical entity to change all the required input parameters when the simulation runs over two different seasons. In sub-model 6, a logical entity works toward changing shifts of the operation when the simulation time reaches to the end of each shift. The process of production optimization (upper stage) decisions that must be made within a time interval are handled using sub-model 7. This sub-model collects required data from the status of the mining operation and sends them to an external decision maker tool to make required decisions regarding optimum path flow rate.

3.6. Models' general assumptions

Although we tried to make the fleet management system (FMS) general for the truck and shovel material handling operation in open pit mines, there are always some topics, which fall outside the scope of a research project. Herein, these topics are:

- During the time of mining a polygon, grade of mineral stays constant without any change;

- Mining faces geographical position will not change during the time of mining that polygon to depletion;
- Decisions made in upper stage will not change until a big event happens and there is not any possibility of human intervention into it;
- Road network remains the same throughout the simulation time and re-construction or maintenance are not considered;
- Mine operates 24 hours a day without any shift change or coffee break;
- Equipment maintenance is not included in the simulation time or optimization model;
- Change made by drilling and blasting are excluded from the research;
- We excluded equipment failure for both truck fleet as well as shovel fleet;

3.7. Scope and limitations of models

The scope of the research is limited to application of multiple objective mixed integer goal programming, stochastic integer programming, and fuzzy integer programming models in conjunction with a stochastic discrete event simulation model for uncertainty-based truck fleet size determination and truck-dispatching in open pit mines. Although the models developed here consider most critical objectives and constraints, so many factors in actual open pit mining operations exist that need to be accounted for such as changing dump location, equipment failure, drilling and blasting, road development, etc. decision-making

3.8. Truck fleet size determination

Haul fleet size determination is a critical task in any surface mining operation where material is handled using truck and shovel system. Although the problem of finding the optimum haulage fleet size has been widely studied, three important shortcomings are still in effect: neglecting uncertainties associated with the input parameters, disregarding downstream processes' effects on the operation, and ignoring effects of the fleet management system being used.

Any mining operation needs loading and haulage equipment to meet the planned production requirement. Making decisions for selection and sizing of the loading and haulage equipment to handle both ore and waste material throughout the life of mine such that it minimizes the total material handling costs is called equipment selection and sizing problem *(ESP)* [36], [149], [150].

Decision on the ESP [23], [151] and, more specifically, size of the haulage fleet that handle the material [125], [150] has a significant direct impact on the fleet efficiency and operation costs and any non-optimal decision will decrease performance in the mine. Thus, determining the optimum fleet size with which the production requirement is met is critical. There exist several approaches to find optimum haul fleet size in a truck-and-shovel surface mining operation. The common approaches are: Match Factor (MF) and discrete event simulation (DES). MF was developed by Douglas (1964) for homogenous haulage fleet and modified by Burt and Caccetta [26] for a heterogeneous haulage fleet. The DES approach is implemented by several researchers to deal with different operational problems in surface mines [70]. Although Darling [152] argues that the best effective way of determining the material handling system productivity and fleet size in surface mines is DES, there are some drawbacks in published literature of DES implementation in surface mining studies which may cause the fleet size to be far from optimal. Three of the main drawbacks of the current models are: 1- ignoring effects of downstream processes on the mining operation; 2- underestimating the effects of fleet management systems on the performance of the truck fleet; and 3- disregarding uncertainties in input parameters.

To address the abovementioned drawbacks, we implement the simulation and optimization framework for haulage fleet size determination.

3.9. Summary and conclusions

In this chapter we presented a hybrid simulation and optimization framework along with three different decision-making models to solve the truck-dispatching problem in surface mines. The hybrid simulation and optimization framework mimics material handling in the surface mining operation. The framework links the mining operation with the FMS and the processing plants in an integrated environment. The decision-making models to solve truck-dispatching problem are part of the FMS in the integrated framework. Each time a truck needs an assignment, the optimization dispatching model is called.

We showed how these sub-systems work individually and how they are linked to each other in the integrated framework. We also presented the connection between the framework and the data file that provides all the required information. In addition, we introduced components of the framework. The simulation sub-model that mimics the materials handling operation and the simulation sub-model that mimics the processing plants' input conveyor and hopper, the components of FMSs including the upper stage decision-making optimization model as well as the lower stage decision-making models.

For the upper stage decision-making, the benchmark model that we introduced is based on model developed by White and Olson [12]. For the lower stage decision-making in FMSs, we offered three mathematical models. The first one solves the lower stage problem using multiple objective goal programing. The second one implements a stochastic programming approach to solve the lower stage problem, and the third one uses a fuzzy linear programming approach to deal with the lower stage problem. We presented all of the above-mentioned decision-making models with their objective functions and constraints. We explained, in detail, the variables and parameters needed to develop the models. Our models maximize production using the available fleet while simultaneously satisfying the upper stage decisions and minimizing the shovels' idle time and the trucks' wait time. Operational constraints limit the decisions of the lower stage models, including, truck capacity, shovel dig rate, and processing plant capacity.

Finally, this chapter presented the simulation model linked to the FMS. The simulation model consists of eight sub-models, two of which are main sub-models. One of those sub-models mimics the truck and shovel operation and one sub-model mimics the processing plants. We defined the systems in the simulation model, the inputs to the sub-models, and the required Key Performance Indicators (KPIs) to be captured sub-model.

CHAPTER 4: VERIFICATION, IMPLEMENTATION, AND DISSCUSSION OF RESULTS

4.1. Introduction

In this chapter we focus on presenting results of the implementation of the hybrid simulation and optimization framework as well as the developed decision-making models to solve the lower stage (truck-dispatching) problem in an iron ore case study. We introduce the location of the iron ore mine, its production schedule, and its road network in the next sub-section. We present the verification of the framework with a detailed analysis and compare the individual process values. Because historical data from the case study is not available, a full validation study of the developed framework is not presented in this thesis. The chapter also presents the procedure of scenario development and determination of optimum fleet size for both homogeneous and heterogeneous fleets.

The chapter also presents the implementation of the framework with five different dispatching algorithms in the case study. First, we present the results of implementing the benchmark dispatching system. Then, by replacing the lower stage decision-making model with the multiple objective model (MOGP), we present a comparative analysis of the MOGP and the benchmark model. In the next sections, we continue to assess the performance of the stochastic mixed integer linear programming model and the fuzzy linear programming model in comparison to the benchmark model. Table 4.1 shows a summary of the scenarios developed to evaluate the models.

Table 4.1: Summary of the scenarios used to evaluate the developed models

Scenario No.	# of shovels		# of trucks		# of dumps		Dispatch model			
	Type 1	Type 2	Type 1	Type 2	Ore	Waste	BM	Multi	Stochastic	Fuzzy
1	3	2	20	0	2	1	✓	✓	✓	✓
2	3	2	22	0	2	1	✓	✓	✓	✓
3	3	2	24	0	2	1	✓	✓	✓	✓
4	3	2	26	0	2	1	✓	✓	✓	✓
5	3	2	28	0	2	1	✓	✓	✓	✓
6	3	2	30	0	2	1	✓	✓	✓	✓
7	3	2	32	0	2	1	✓	✓	✓	✓
8	3	2	34	0	2	1	✓	✓	✓	✓
9	3	2	36	0	2	1	✓	✓	✓	✓
10	3	2	0	15	2	1	✓	✓	×	×
11	3	2	0	16	2	1	✓	✓	×	×
12	3	2	0	17	2	1	✓	✓	×	×
13	3	2	0	18	2	1	✓	✓	×	×
14	3	2	0	19	2	1	✓	✓	×	×
15	3	2	0	20	2	1	✓	✓	×	×
16	3	2	0	21	2	1	✓	✓	×	×

17	3	2	0	22	2	1	✓	✓	×	×
18	3	2	8	16	2	1	✓	✓	×	×
19	3	2	10	15	2	1	✓	✓	×	×
20	3	2	12	14	2	1	✓	✓	×	×
21	3	2	14	13	2	1	✓	✓	×	×
22	3	2	16	12	2	1	✓	✓	×	×
23	3	2	18	12	2	1	✓	✓	×	×
24	3	2	20	10	2	1	✓	✓	×	×
25	3	2	22	8	2	1	✓	✓	×	×
26	3	2	24	7	2	1	✓	✓	×	×

4.2. Case study

To test the developed framework in a case study we need two types of data, the strategic schedule and the technical operational data. However, because of unavailability of required data from the operating mine, the strategic production schedule was borrowed form Upadhyay [129] and the operating equipment are assumed. Using operational data of an existing mine, the required distributions for processes of truck and shovel operation were fitted.

4.2.1. Mine location and its operational data

Gol-E-Gohar iron ore mine is located in Kerman Province of Iran. The project lies in southwest of the province, approximately 50 km southeast of the city of Sirjan (Figure 4.1). Mining operation in Gol-E-Gohar is being handled by a truck and shovel material handling system.

The equipment that we assessed consists of Hitachi EX2500 and Hitachi EX5500Ex excavators and rigid frame rear dump Cat 785C and 793C trucks (Table 4.2). There are three main dumping points for the loaded trucks including two processing plants and one waste dump, each of which has two hoppers (or dumping point in the case of waste dump). Figure 4.2 shows the location of loading and dumping points as well as the road network for the year 11 of the operation.

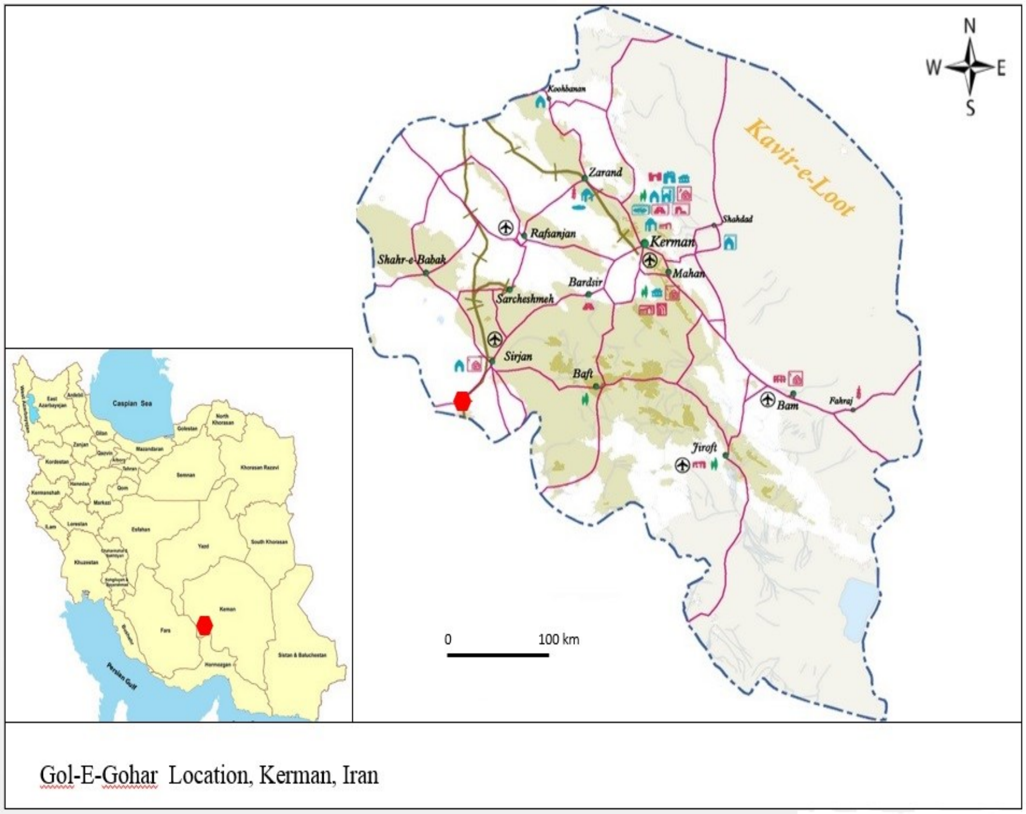

Figure 4.1: Location of the Gol-E-Gohar Project in Kerman Province of Iran

Table 4.2: General specifications of the production fleet

No.	Loading Point	Destination	Starting Distance (m)	Loader	Hauler
1	Shovel 1	Plant 1	4129	Hitachi EX2500	Cat 785C & Cat 793C
		Plant 2	3626		
2	Shovel 2	Plant 1	4196	Hitachi EX2500	Cat 785C & Cat 793C
		Plant 2	3693		
3	Shovel 3	Waste Dump	1930	Hitachi EX5500	Cat 785C & Cat 793C
4	Shovel 4	Waste Dump	1850	Hitachi EX5500	Cat 785C & Cat 793C
5	Shovel 5	Waste Dump	4295	Hitachi EX2500	Cat 785C & Cat 793C

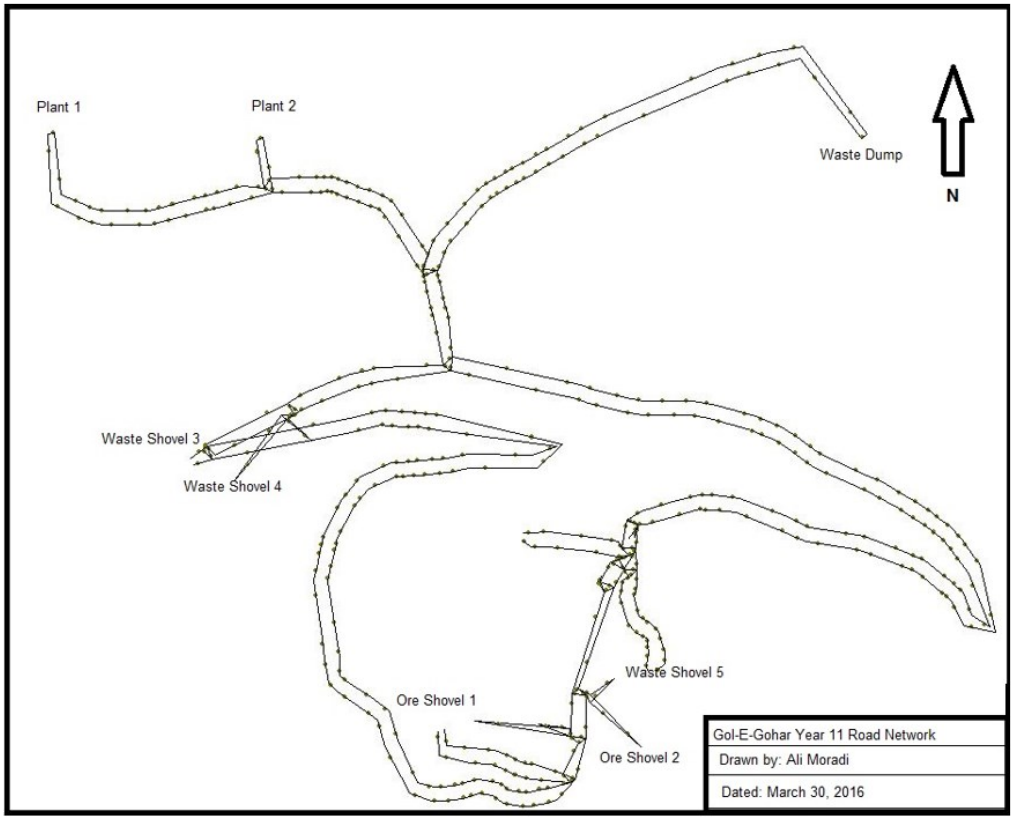

Figure 4.2: Gol-E-Gohar Iron Ore Mine Year 11 Road Network and loading and dumping locations

Five shovels are working in the case study to meet the production schedule requirement. characteristics of the shovels used in the case study are listed in Table 4.3.

Table 4.3: Characteristics of shovels working in the mining operation of the case study

Equipment	Type	Number in use	Bucket capacity (t)	Cycle time (s)
S1, S2, and S5	Hit 2500	3	NORM(14, 1)	NORM(17, 0.5)
S3 and S4	Hit 5500Ex	2	NORM(21, 2)	NORM(16, 1)

To transport the mined material from the mining faces to the destinations, the mining operation employs two types of trucks as mentioned above. Table 4.4 provides information regarding the characteristics of these two truck types.

Table 4.4: Characteristics of trucks working in the mining operation of the case study

Equipment	Type	Capacity (t)	Spot time (s)		Dump time (s)
			Hit 2500	Hit 5500Ex	
Truck Type 1	Cat 785C	140	LOGN(32, 26)	LOGN(69, 94)	NORM(60, 27)
Truck Type 2	Cat 793C	240	LOGN(42, 41)	LOGN(79, 114)	NORM(52, 21)

The mine operates with two processing plants. Each of the processing plants have one crusher that has a hopper to provide a continuous feed. The trucks haul the removed waste material into a waste dump where two scrapers are working to make it possible to have two trucks dumping at the same time. Table 4.5 presents information regarding the processing active plants in the operation.

Table 4.5: Operational characteristics of the active processing plants

Dumping point	Desired MWT grade	Target feed rate (tph)	Hopper Capacity (t)
Plant 1 Crusher	65%	2300	500
Plant 1 Crusher	75%	2300	500

Failure of the equipment are not considered in this study.

4.2.2. Strategic schedule

The yearly schedule that was created based on drill hole data using GEOVIA GEMS [153] and GEOVIA Whittle [154] by Upadhyay [129] is given in Figure 4.3. With an average stripping ratio of 1.99, the yearly production schedule requires to mine 172.654 Mt of ore for which the material handling system needs to move 344.309 Mt of waste from the pit. The deposit consists of Iron (MWT), Sulfur (S), Phosphorous (P), and waste, where MWT is the material of interest with S and P as impurities [129].

10 days of operation from year 11 of the production schedule was selected to be used in our model implementation. This period selection leads to requirement of production of ore and waste material as listed in Table 4.6.

Table 4.6: Scheduled tonnage and grade of material to be handled during the period of simulation

Year 11	Total material (t)	Ore (t)	SR	MWT Grade (%)
10 days production requirement	1269600	552000	1.3	68.58

The pit, access roads, blocks to be mined in year 11 of the mine life, and location of discharge points are shown in Figure 4.4.

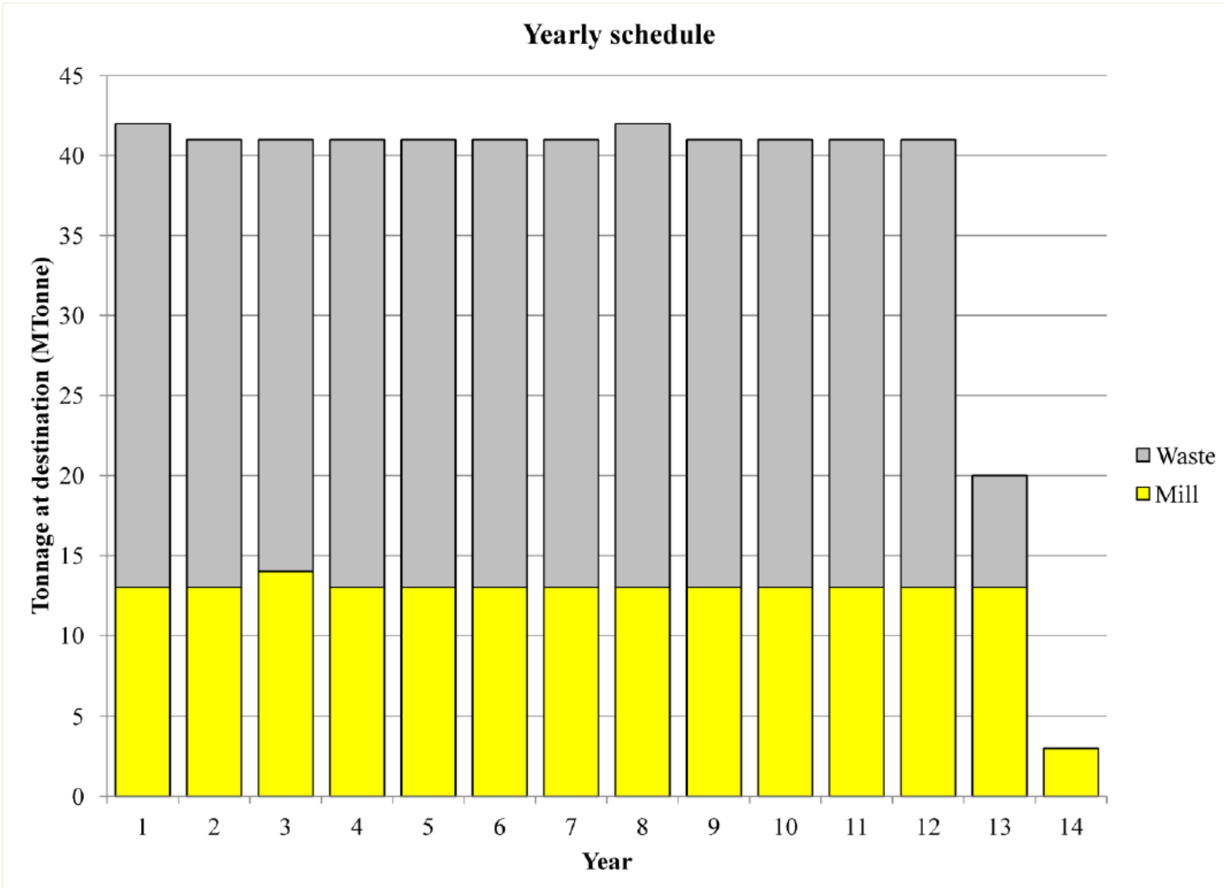

Figure 4.3: Yearly schedule of the case study created using GEOVIA Whittle [129]

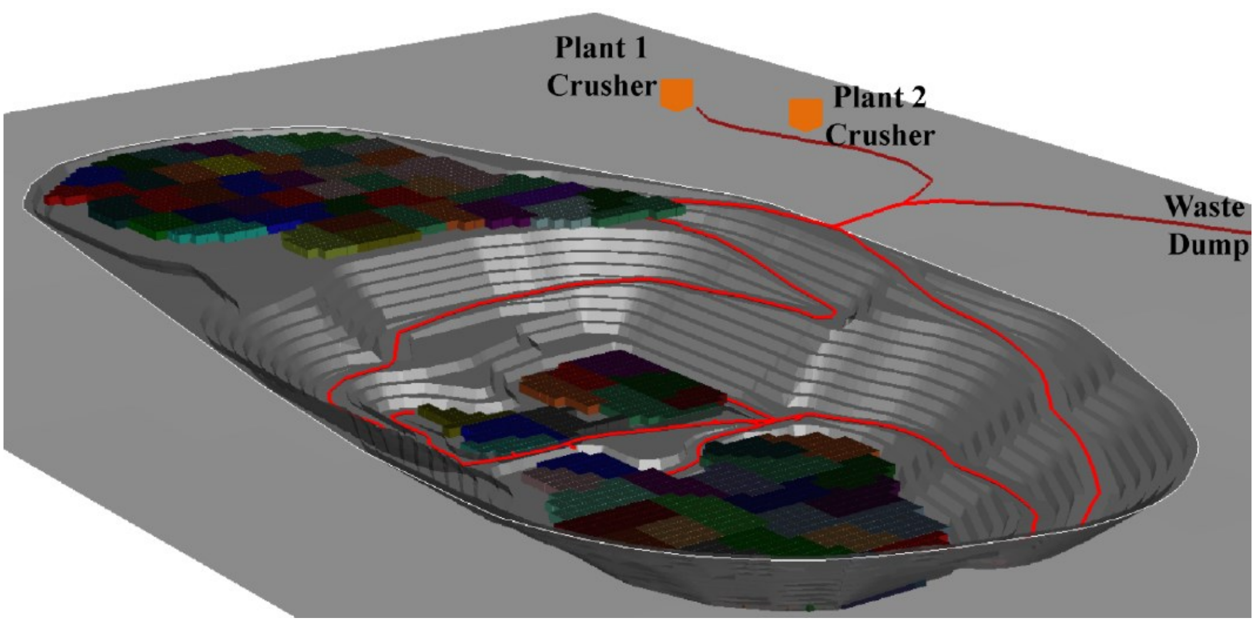

Figure 4.4: The pit designed to mine scheduled material in year 11 of mine life [129]

4.3. Models verification

To verify the integrated framework, distributed time between different processes of the shovels fleet including loading, spotting, and hanging (idling) times are presented in Figure 4.5, Figure 4.6, and Figure 4.7 for different size of small, large, and mixed trucks fleets listed in Table 4.1, respectively. Cumulative operation time for all the five shovels in the fleet for 10 days of operation with one 12-hour shift in each day is calculated as 5×10×12=600 hours. This 600 hours operation of truck fleet as shown in Figure 4.5, Figure 4.6, and Figure 4.7 are fulfilled using the integrated framework. Figure 4.5, Figure 4.6, and Figure 4.7 also show that by increasing the number of trucks in the material handling fleet, cumulative idle time of shovels fleet are transferred to cumulative spotting time and cumulative loading time in all three cases of small truck fleet, large truck fleet, and mixed truck fleet.

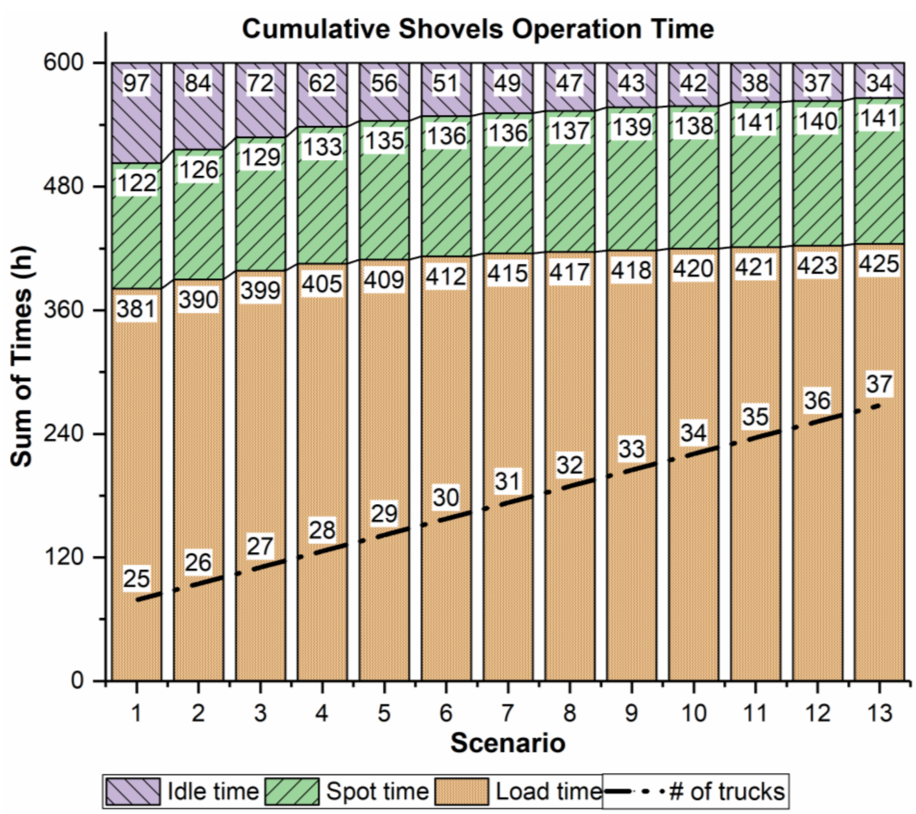

Figure 4.5: Summation of shovel fleet operation time with different fleets of small trucks

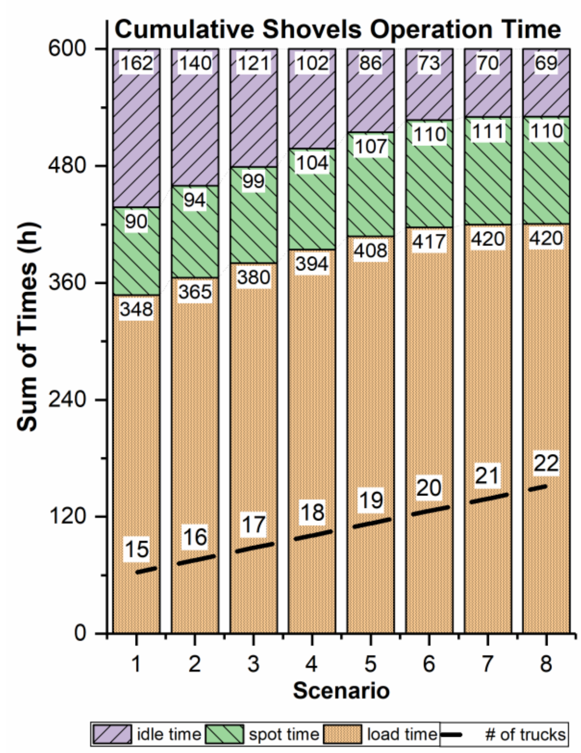

Figure 4.6: Summation of shovel fleet operation time with different fleets of large trucks

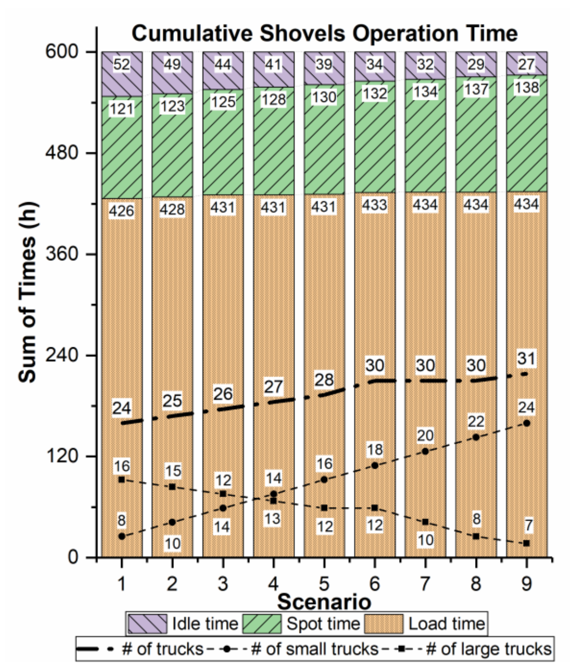

Figure 4.7: Summation of shovel fleet operation time with different mixed fleets of trucks

All other characteristics of the operation including individual shovel loading, spotting, and idling times, along with truck dumping, empty velocity, loaded velocity, loaded tonnage and other characteristics are also verified by comparing against data fed to the integrated framework.

4.4. Scenario development

To define operational scenarios, we deterministically calculated the required fleet size using a match factor definition introduced by Burt and Caccetta [26] and evaluated by Chaowasakoo et al. [155]. It is worth noting that the logic behind the match factor is dividing any mining operation into three different categories as listed in Table 4.7.

Table 4.7: Mining operation systems based on match factor

No.	Mining operation system	Match Factor
1	Under-truck system	< 1
2	Balanced system	= 1
3	Over truck system	> 1

Match factor calculation for our case study shows that to have a balanced system (match factor equals 1) – we need to have a truck fleet of 37 trucks of Cat 785C with a nominal capacity of 140 tons or a truck 28 trucks of Cat 793C with a nominal capacity of 240 tons to meet the production schedule. However, there are some limitations in finding truck fleet size using match factor. Firstly, the match factor does not account for any uncertainties in the input parameters. The second limitation is that it determines the size of the fleet based on locked-in dispatching approach (where the operation is not using any FMS), which is not the case in most of the currently active surface mines. In other words, the match factor does not consider effects of decision-making tools (fleet management systems) on the size of the fleet. To address (or overcome) these shortfalls, using the deterministic fleet size determination procedure, we defined different scenarios in the range of under-truck systems (readers are encouraged to refer to [26] for more details about mining fleet systems) for both fleet of small trucks and fleet of large trucks. Then, the simulation model of the case study was run for each of the scenarios. The rationale behind choosing under-truck systems is that the deterministic match factor does not account for effects of the FMSs on the fleet size and, consequently, it overestimates the required fleet size.

The truck loading in all the scenarios is handled using five active shovels. The integrated simulation framework was set up for five replications to reach the required half widths for total material sent to each of the processing plants of within a confidence interval of 95%. We ran the simulation model for 12 hours per shift and 10 shifts for each scenario. However, as any other simulation work, this work has some assumptions and limitations. We assumed that over the run time of the simulation model, the ore polygons have consistency in material quality and tonnage. Another assumption is that all the machineries are mechanically available for entire simulation time. This assumption was made to make sure that the productivities reported by different dispatching algorithms are comparable. The last assumption of the simulation model is that drivers' errors do not have any effect on operation.

To transport the materials from the shovels to the designated destinations to meet the production requirement, it is possible to choose a homogeneous fleet of small trucks, homogeneous fleet of large trucks, or a Heterogeneous fleet of small and large trucks combined as listed in

Table 4.8,

Table 4.9, and Table 4.10, respectively. For each of the defined scenarios we used the integrated simulation and optimization framework in the case study.

Table 4.8: Homogeneous small truck scenarios with their associated fleet size.

Scenario	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Fleet Size	20	22	24	26	28	30	32	34	36

Table 4.9: Homogeneous large truck scenarios with their associated fleet size.

Scenario	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
Fleet Size	15	16	17	18	19	20	21	22

In the fleet of heterogeneous trucks, we started with a scenario with eight small trucks in the fleet to meet a portion of the required production. After calculating the required number of large trucks to meet the rest of the production requirement deterministically, we used the simulation framework to find the minimum number of large trucks required to meet the production using the fleet management systems (either benchmark or multiple objective FMSs). We then added two more small trucks to the fleet and followed the same procedure until we had 24 small trucks in the fleet. Table 4.10 lists the optimum number of trucks when using the benchmark fleet management system and when substituting it with the multiple objective model.

Table 4.10: Heterogeneous truck scenarios with their associated fleet size.

	Scenario	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
Fleet size	Small	8	10	12	14	16	18	20	22	24
	Large-BM	16	15	14	13	12	12	10	8	7

Large-Multi	14	14	12	11	10	8	6	4	2

4.5. Implementation of the developed framework

After defining scenarios for the operation of the case study, the developed hybrid simulation and optimization framework was implemented with four different combinations of FMSs including:1) the benchmark FMS, 2) the FMS developed by combining upper stage model of the benchmark FMS and our lower stage MOGP, 3) the FMS developed by combining upper stage model of the benchmark FMS and our lower stage stochastic programming model, and 4) the FMS developed by combining upper stage model of the benchmark FMS and our lower stage fuzzy linear programming model.

4.5.1. Benchmark FMS

The benchmark (BM) FMS that we implemented in this thesis is the backbone algorithm of the Modular Mining DISPATCH® [11] FMS that was developed by White and Olson [12] and Olson et al. [51]. We coded both of the upper stage decision-making model and the lower stage decision-making model in IBM CPLEX [128] and linked it to the simulation model of the mining operation in the developed framework. Since DISPATCH® [11] is a proprietary software, the details of heuristics behind it and the changes into the dispatch algorithms and upgrades since it is introduction in White and Olson [12] is not publicly available. We are using White and Olson [12] as the benchmark to have a fair measure for verification of our developments. We do not claim that the algorithms developed in this thesis will outperform Modular Mining DISPATCH® because we do not have any means to assess such comparison. Results of implementation of the developed integrated framework in different homogeneous and heterogeneous scenarios in the case study where the BM FMS makes required semi-dynamic and dynamic decisions are presented in following sections.

4.5.1.1. Homogeneous fleet of small trucks

The integrated framework with BM FMS as the decision maker was implemented first on the scenarios listed in

Table 4.8 for the fleet of small trucks. By increasing the number of trucks in the fleet, each important KPI has been evaluated and comparisons are presented in Figure 4.8 to Figure 4.11.

Figure 4.8 shows how cumulative plant feed requirement is met by increasing the number of trucks in the fleet. The blue dash lines in the graph stands for the required cumulative input for plant 1 and the total ore to be delivered. The graph shows that it is not possible for the fleet to meet the plants requirement in scenario 1 with 20 small trucks in the fleet to scenario 8 with 34 small trucks in the fleet. The only scenario that is capable of meeting the plants input requirement is scenario 9 with 36 small trucks. Scenario 1 can only meet 64% of the required plants feed. By adding 2 trucks in each successive scenario, the fleet can meet an extra 5.5% of the plants requirement up to being able to meet 97.5% of the plant's requirements in scenario 8.

By increasing the number of trucks, the shovel fleet was utilized with an average increase of 3%. As depicted by Figure 4.9, by 25% increase in utilization of the shovel fleet, the operation can only meet the production requirement using 98% of the shovel fleet available time. Regarding the truck fleet, by increasing number of trucks in the fleet with fixed number of shovels, the trucks in the fleet spent more time in the queue at shovels waiting for loading to start (Figure 4.10). Each truck spent an average of 37 hours out of 120 available hours (31% of its available time) waiting in queue. Increase in the number of trucks also caused an increase in the percentage of the time a truck reaches to a shovel and faces a line-up of at least one truck (Figure 4.11). With a jump of 55%, in scenario 9, 86% of the times a truck reached to a shovel, it faced lineup in front and needed to wait in queue to be loaded.

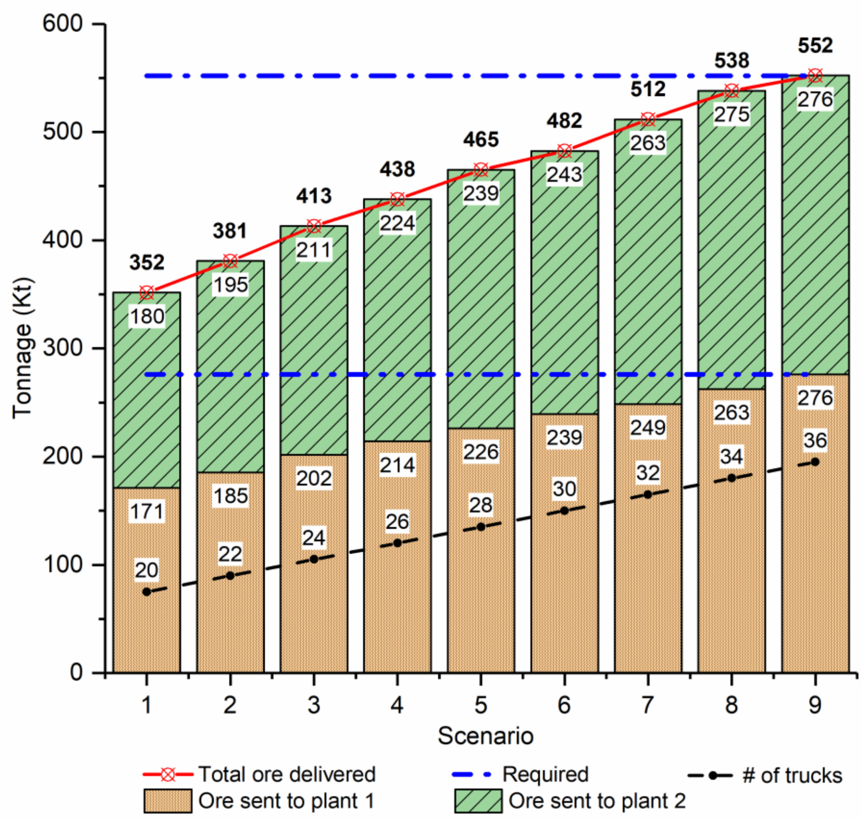

Figure 4.8: Total tonnage of ore delivered to the processing plants with increasing number of trucks – BM – small fleets

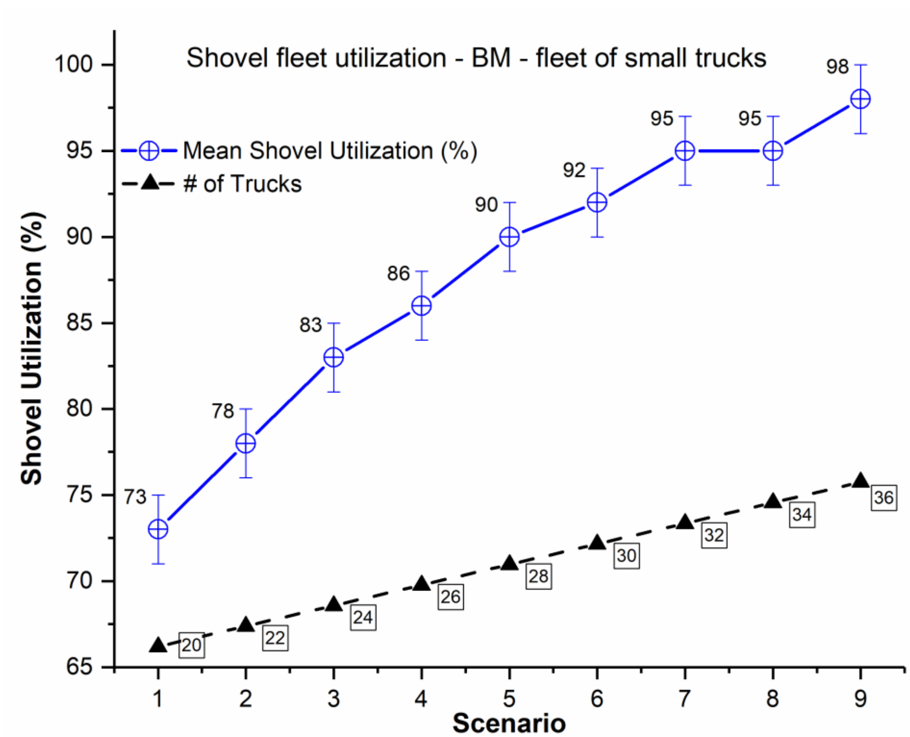

Figure 4.9: Shovel utilization with increasing number of trucks – BM – small fleets

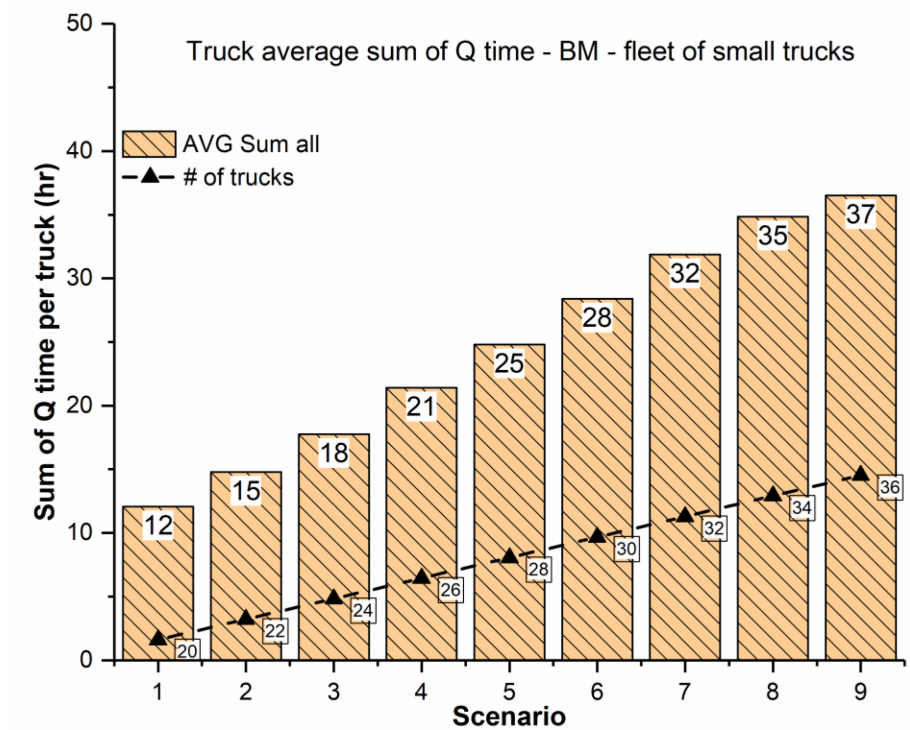

Figure 4.10: Cumulative average queue time for trucks in the operation – BM – small fleets

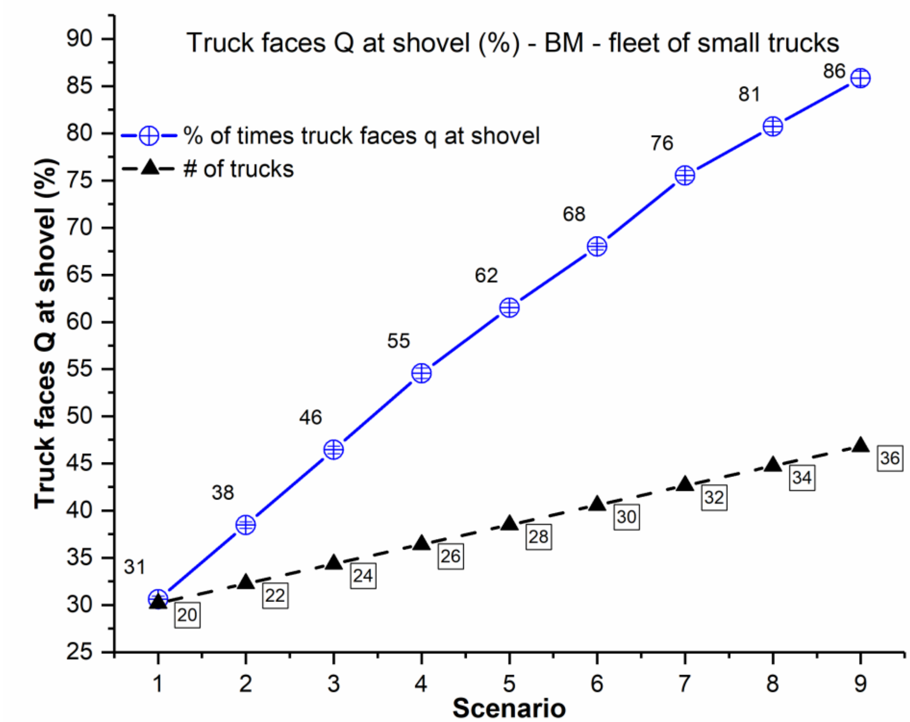

Figure 4.11: Percentage of the times a truck faces line up in front of shovel – BM – small fleets

4.5.1.2. Homogeneous fleet of large trucks

In scenario 10 to scenario 17, instead of having small size trucks in the fleet, we replace them with large trucks. Tonnage of material sent to the processing plants using different fleet of large trucks are presented in Figure 4.12. The production requirement of the operation was met using a fleet of 21 large trucks. The fleet size that by increasing its size to 22 large trucks, the shovel fleet was utilized the same (Figure 4.13). due to a decrease in total number of active trucks in the operation, amount of time spent by a truck at queue decreased dramatically comparing to the scenarios where material was being handled by fleets of small trucks (Figure 4.14). however, by increasing number of trucks in the fleet, the percentage of time a truck encountered lineup in front of shovel increased by about 30% (Figure 4.15).

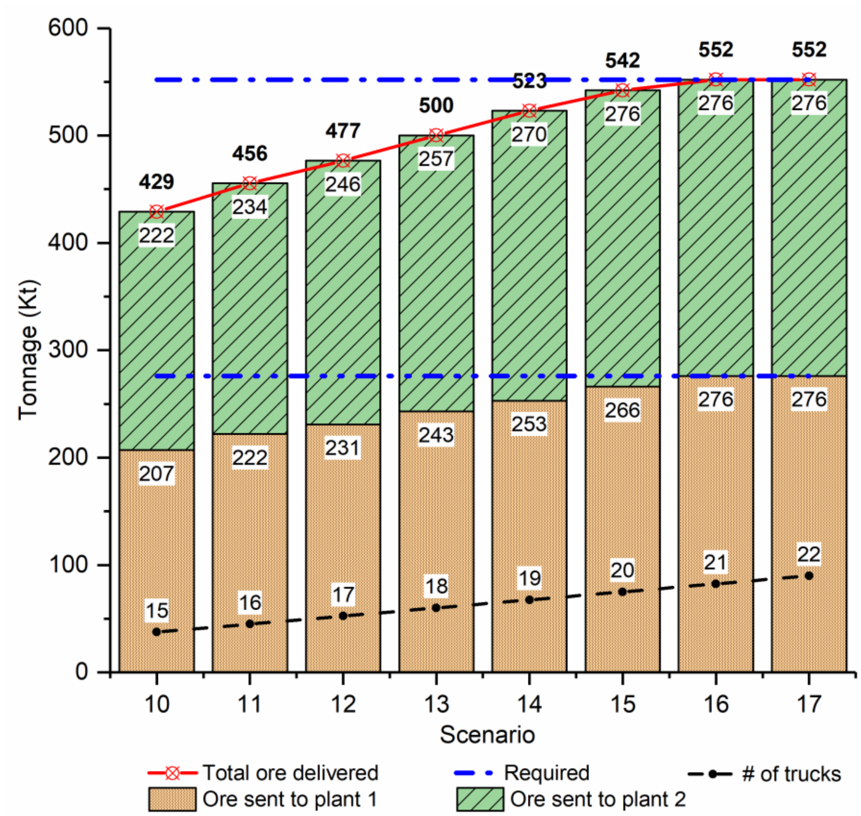

Figure 4.12: Total tonnage of ore delivered to the processing plants with increasing number of trucks – BM – large fleets

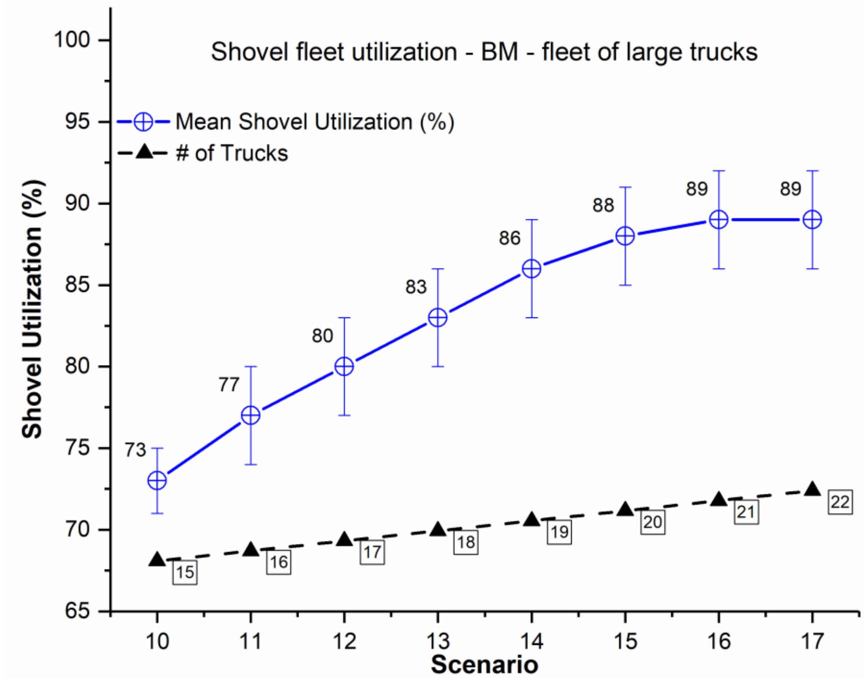

Figure 4.13: Shovel utilization with increasing number of trucks – BM – large fleets

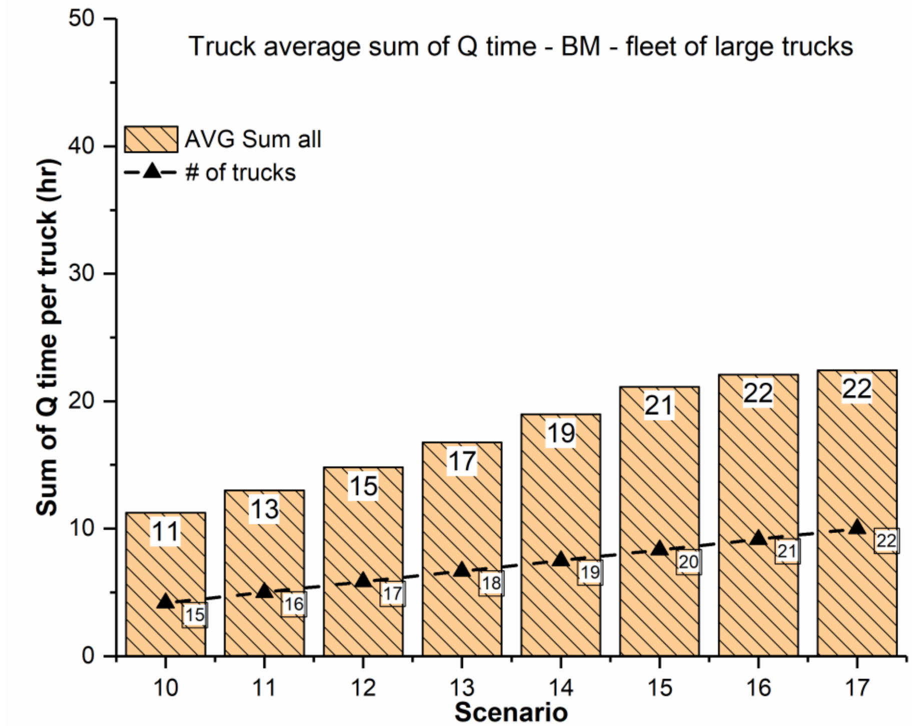

Figure 4.14: Cumulative average queue time for trucks in the operation – BM – large fleets

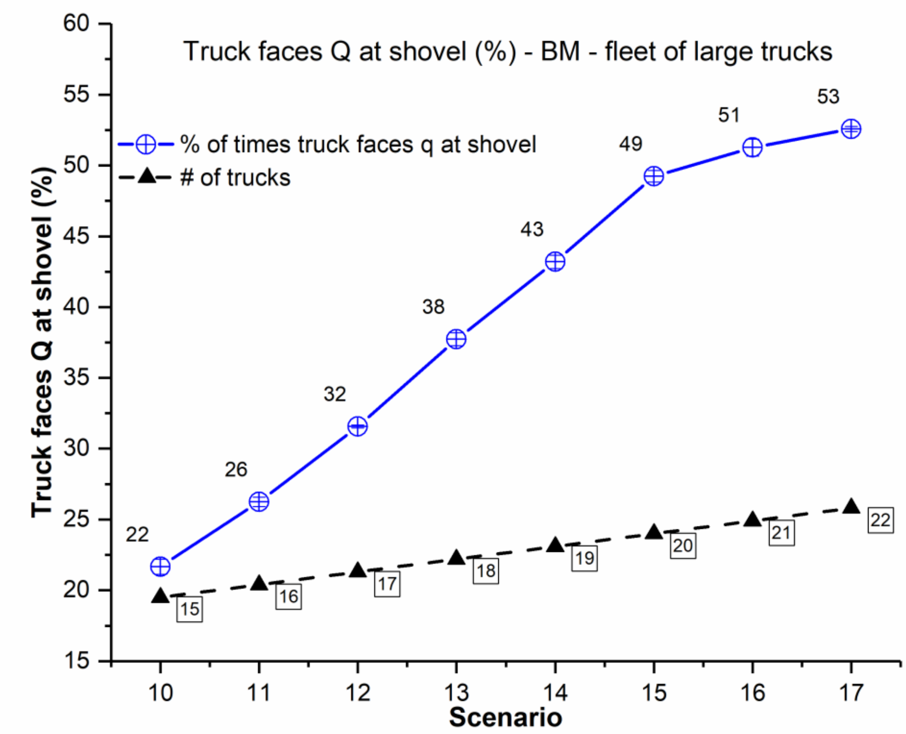

Figure 4.15: Percentage of the times a truck faces line up in front of shovel – BM – large fleets

4.5.1.3. Heterogeneous fleet

In scenarios 18 to 26, starting from a fleet of small trucks that meets production requirement, by reducing number of small trucks in fleet and adding large trucks instead, we tried different mixed fleet scenarios. Herein, results of scenarios of mixed fleet that meet the production requirements. All the scenarios in the heterogenous fleet with the combination of trucks represented in Figure 4.16 meet plants' capacity requirements. Above 90% of the shovel fleet available time were utilized by the truck fleet in all the scenarios (Figure 4.17). However, the truck fleet spent 28% more time in queue at shovels in scenario 26 with 24 small trucks and 7 large trucks than the fleet spent in scenario 18 with 8 small trucks and 16 large trucks (Figure 4.18). The percentage of the time a truck faced lineup in front of a shovel increased by 13% from scenario 18 to scenario 23 because of increase in number of trucks in the fleet and after that, as the fleet size did not change, the percentage of times trucks faces lineup at shovels did not experienced any big variation (Figure 4.19).

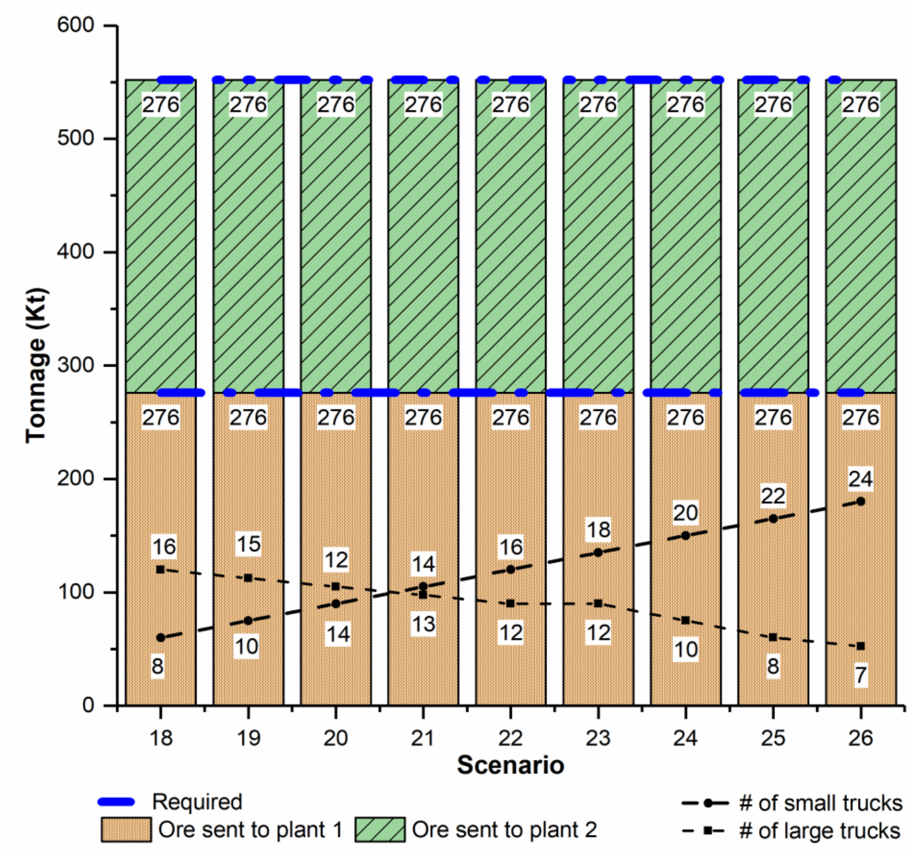

Figure 4.16: Total tonnage of ore delivered to the processing plants with increasing number of trucks – BM – mix fleets

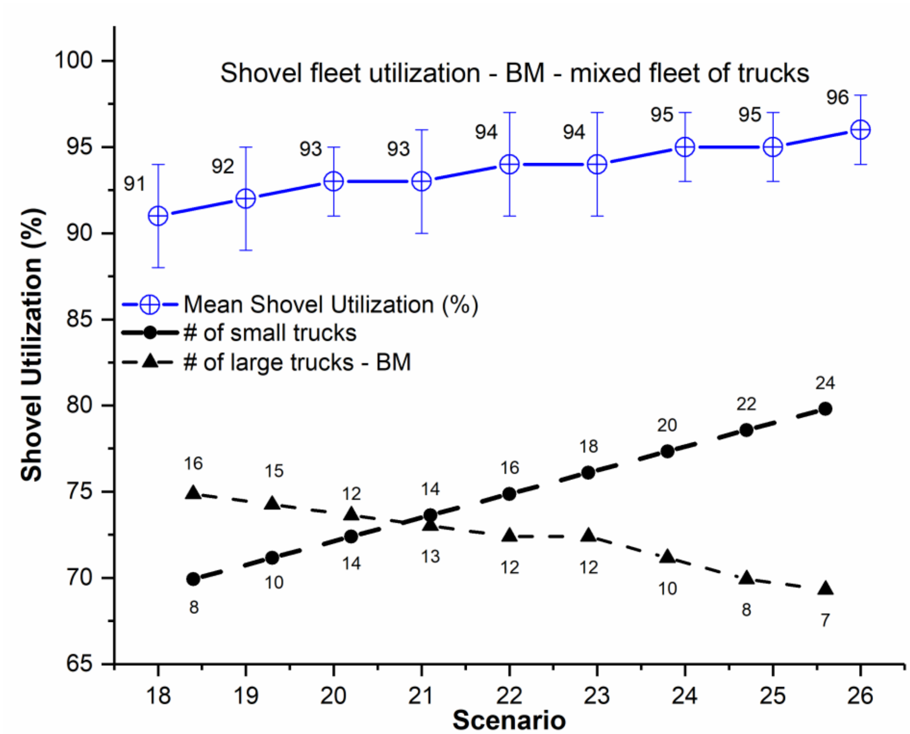

Figure 4.17: Shovel utilization with increasing number of trucks – BM – mix fleets

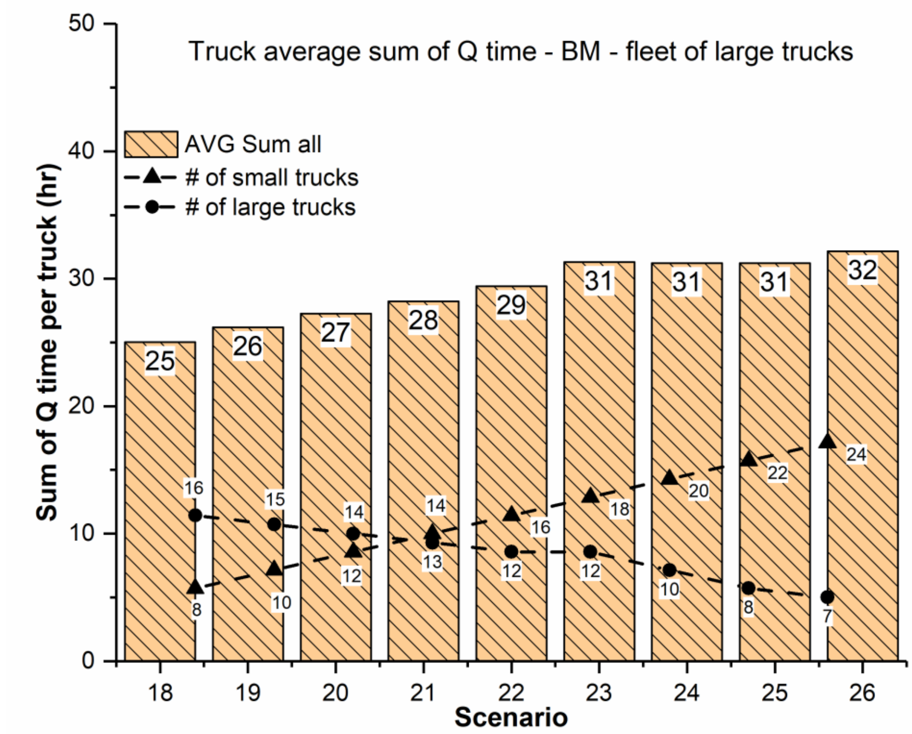

Figure 4.18: Cumulative average queue time for trucks in the operation – BM – mix fleets

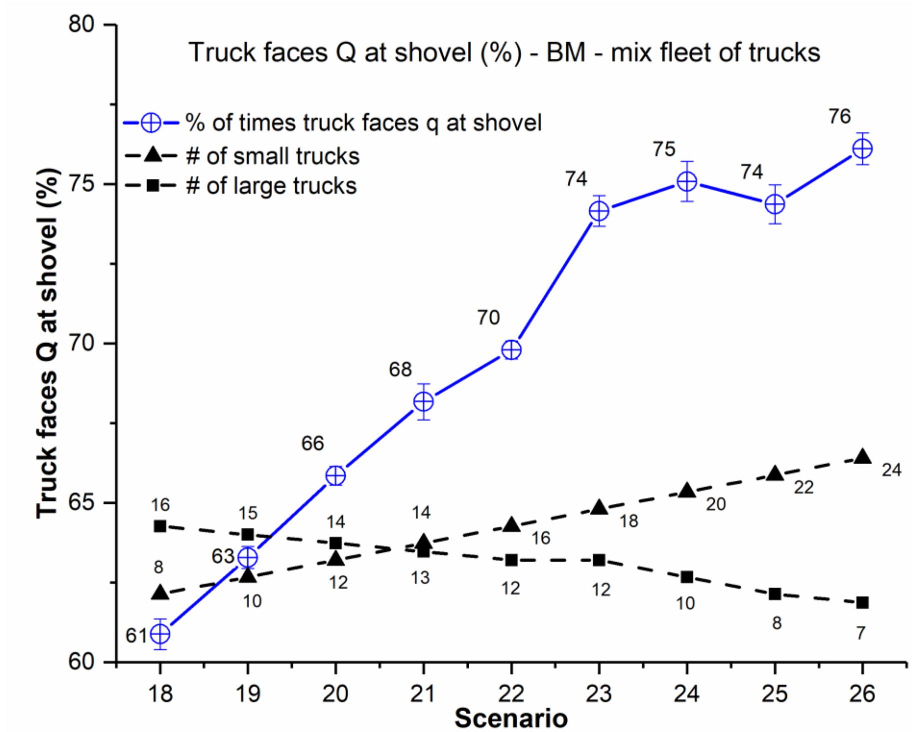

Figure 4.19: Percentage of the times a truck faces line up in front of shovel – BM – mix fleets

4.5.2. Lower stage MOGP model

After running the integrated simulation and optimization framework developed in this research for the case study with algorithm of modular mining DISPATCH® [11] as its FMS and analyzing the key performance indicators of the operation, we replaced the truck-dispatching part of the FMS with the MOGP mathematical model that was developed in this research. We ran the simulation for all the scenarios listed in

Table 4.8,

Table 4.9, and Table 4.10. Results of implementation of the integrated simulation and optimization framework with MOGP mathematical model as its truck-dispatching decision maker are presented in this section.

4.5.2.1. Homogeneous fleet of small trucks

In scenarios 1 to 9 where the material was handled by a fleet of small trucks, results of the evaluation show that the operation can meet the plants' production requirements from scenario 6 with fleet of 30 trucks to scenario 9 with a fleet of 36 small trucks (Figure 4.20). The shovel fleet utilization increases for 20% by increasing number of trucks from 20 in scenario 1 to 36 in scenario 9 (Figure 4.21). Regarding the truck fleet, Figure 4.22 and Figure 4.23 show that, although percentages of the time a truck faces queue at shovels increased by 200% from scenario 1 to scenario 9, summation of the time a truck spent in queue had only increased by less than 50%.

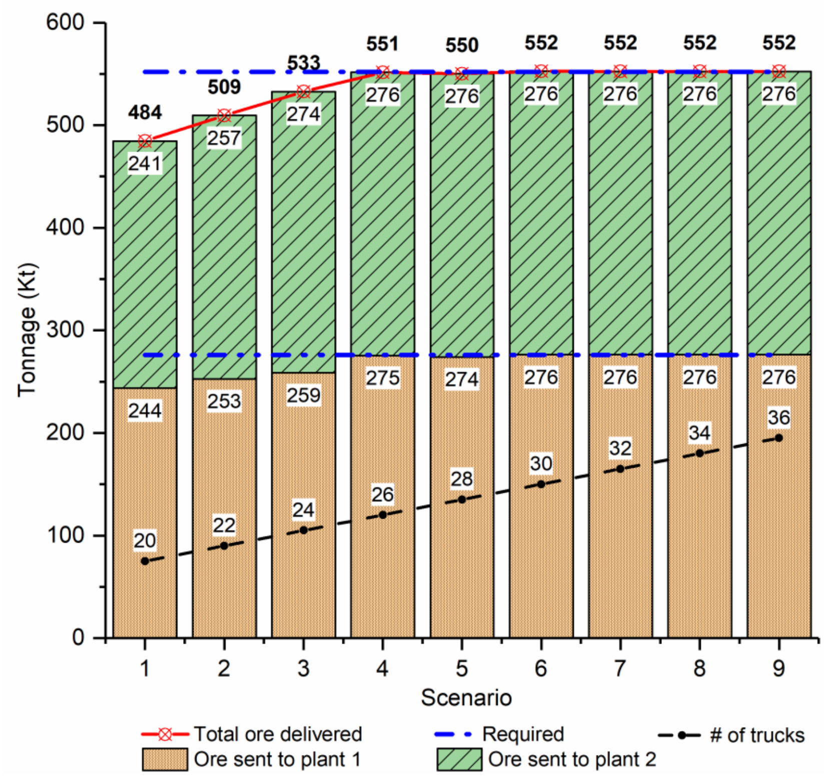

Figure 4.20: Total tonnage of ore delivered to the processing plants with increasing number of trucks – MOGP – small fleets

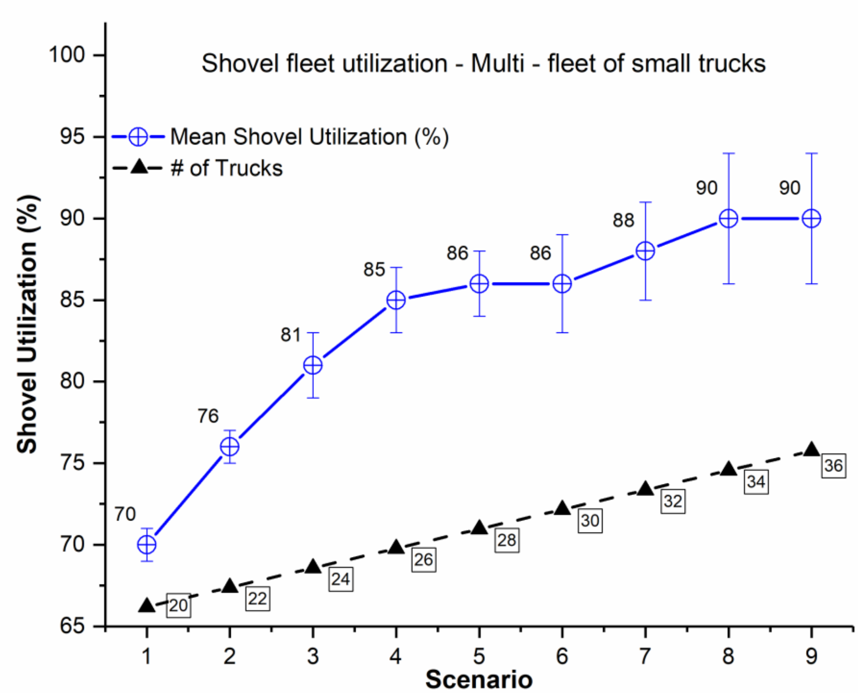

Figure 4.21: Shovel utilization with increasing number of trucks – MOGP – small fleets

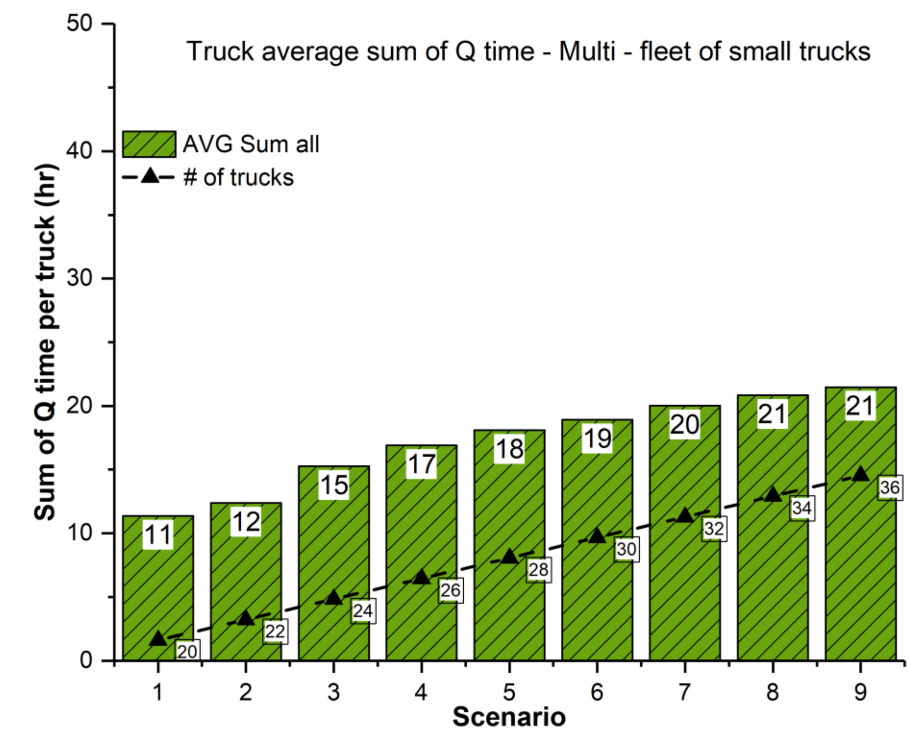

Figure 4.22: Cumulative average queue time for trucks in the operation – MOGP – small fleets

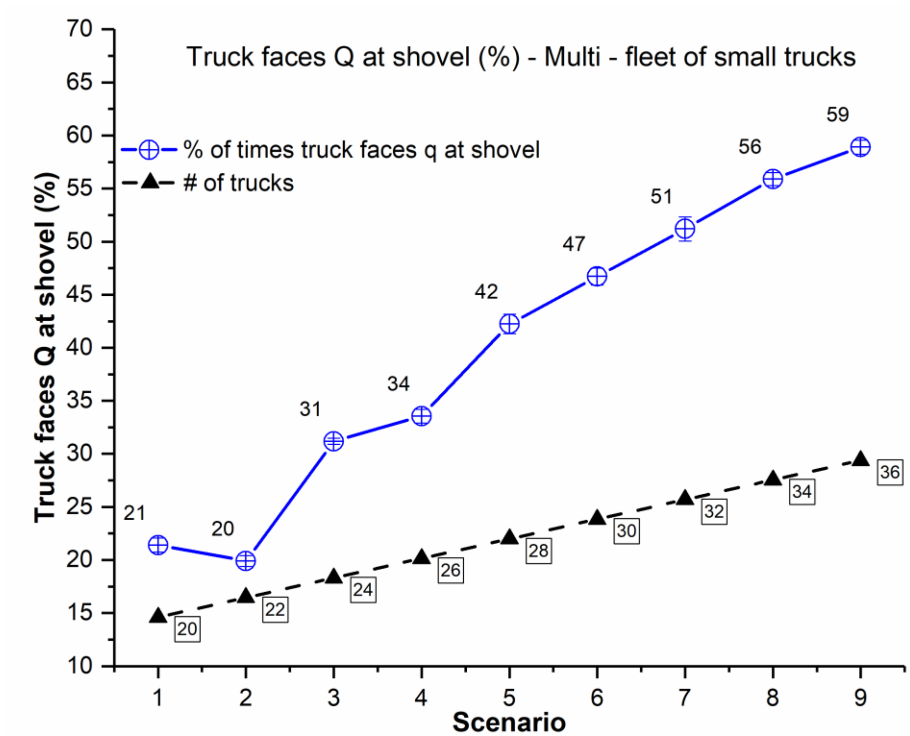

Figure 4.23: Percentage of the times a truck faces line up in front of shovel – MOGP – small fleets

4.5.2.2. Homogeneous fleet of large trucks

In scenario 10 to scenario 17 where the material was handled by fleets of large trucks instead of fleet of small trucks in scenario 1 to scenario 9, operation showed to be able to meet the production requirement from scenario 12 with 17 large trucks in the fleet to scenario 17 with 22 trucks in the fleet (Figure 4.24). As the number of trucks in the fleet decreased in comparison to the scenarios of the small fleets, both shovel fleet utilization (Figure 4.25) and truck fleet queue time (Figure 4.26) were reduced dramatically. Figure 4.27 shows that percentages of the time a truck faces lineup at shovels increases only 7% from scenario 10 with 15 trucks to scenario 17 with 22 trucks.

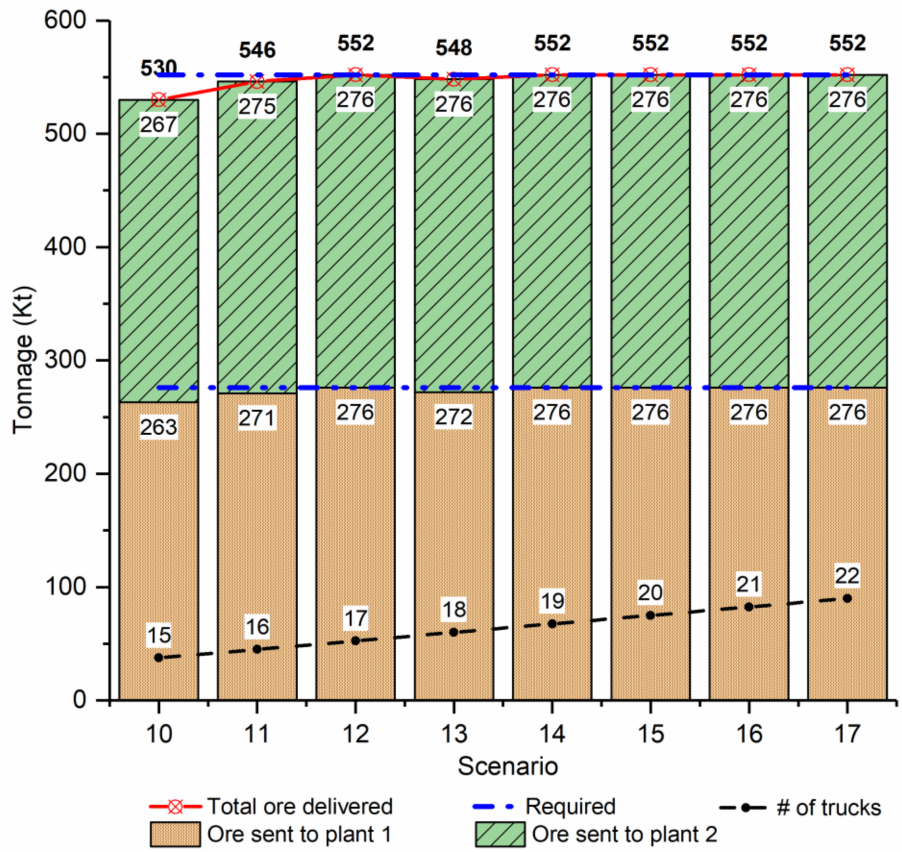

Figure 4.24: Total tonnage of ore delivered to the processing plants with increasing number of trucks – MOGP – large fleets

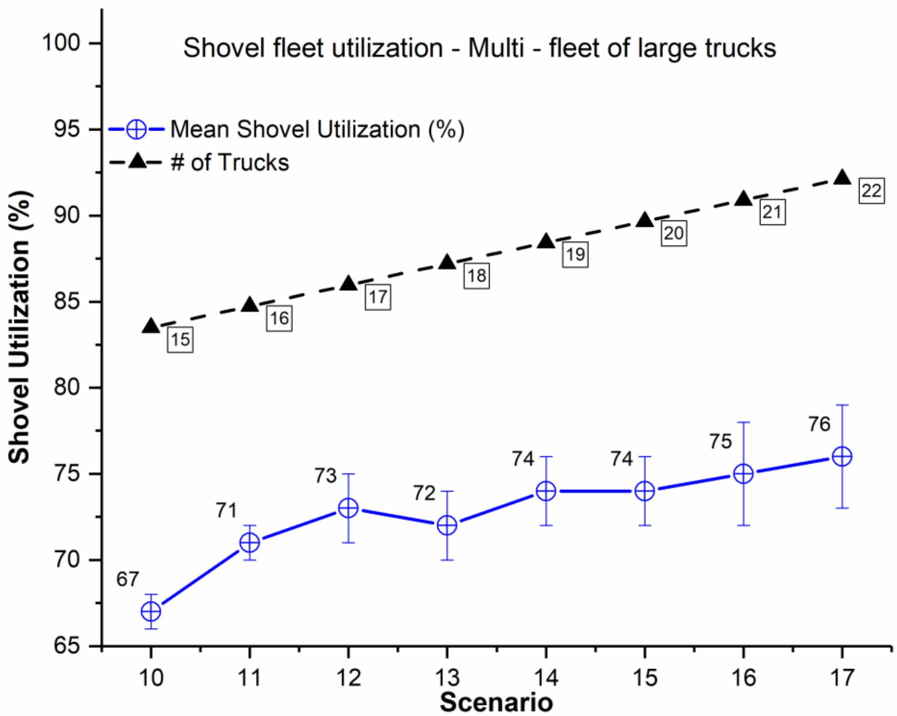

Figure 4.25: Shovel utilization with increasing number of trucks – MOGP – large fleets

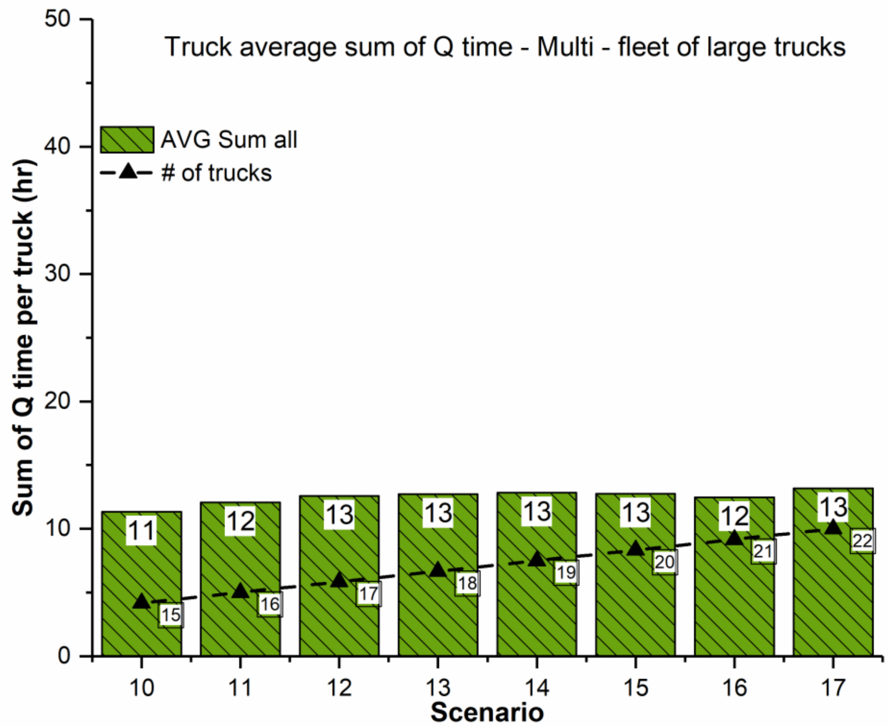

Figure 4.26: Cumulative average queue time for trucks in the operation – MOGP – large fleets

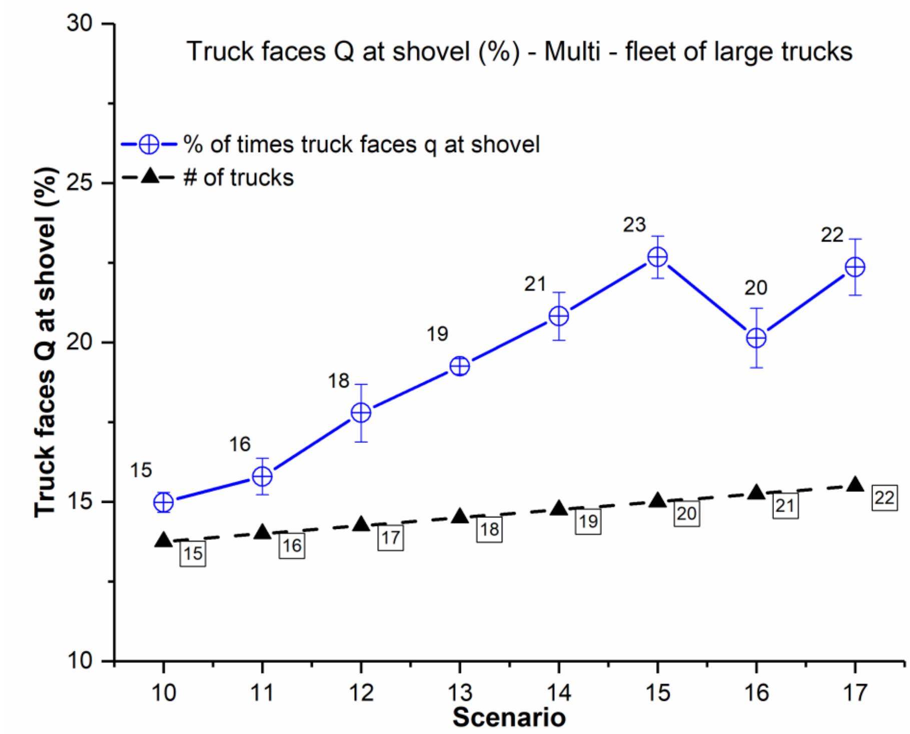

Figure 4.27: Percentage of the times a truck faces line up in front of shovel – MOGP – large fleets

4.5.2.3. Heterogeneous fleet

As explained in section 4.5.1.3, although we evaluated different combination of the mixed fleet scenarios, herein we only present scenarios that met the production requirement with 8 small trucks and up to 24 small trucks in the fleet. Figure 4.28 shows how the production requirement of processing plants were met in scenario 18 to scenario 26. Figure 4.29, Figure 4.30, and Figure 4.31 depict that as total number of trucks in the fleet did not change from scenario 22 to scenario 26, thus, utilization of shovels and wait time for trucks did not show any variation.

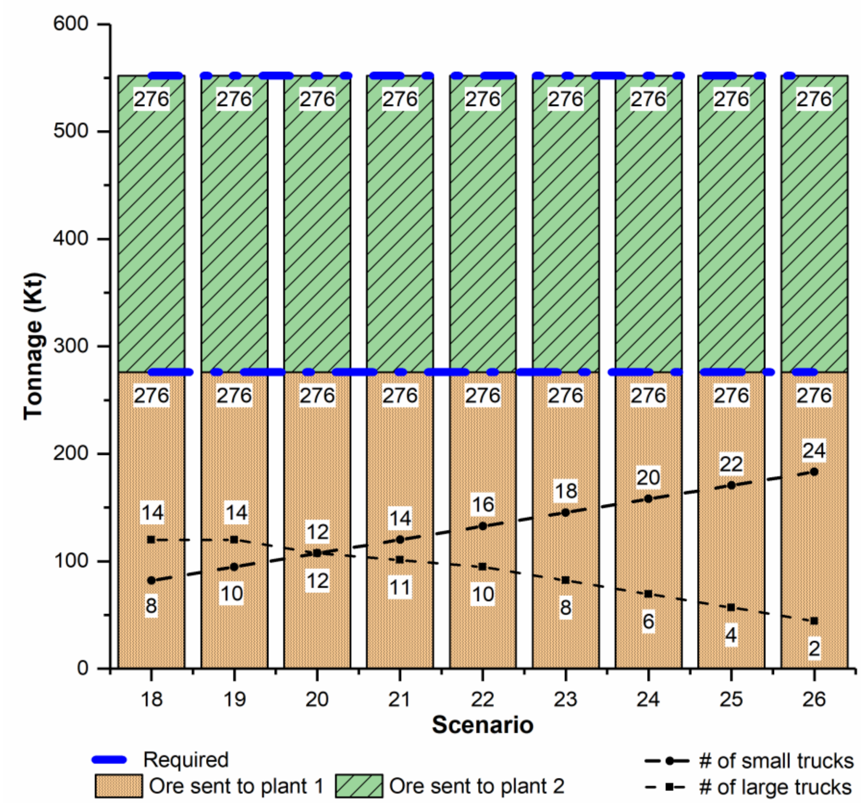

Figure 4.28: Total tonnage of ore delivered to the processing plants with increasing number of trucks – MOGP – mix fleets

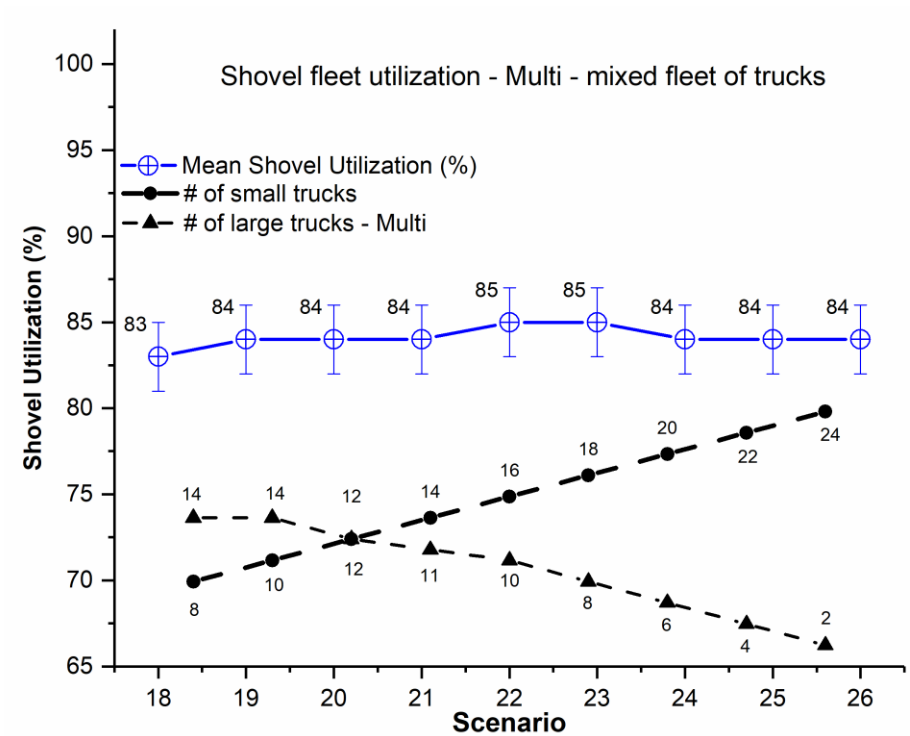

Figure 4.29: Shovel utilization with increasing number of trucks – MOGP – mix fleets

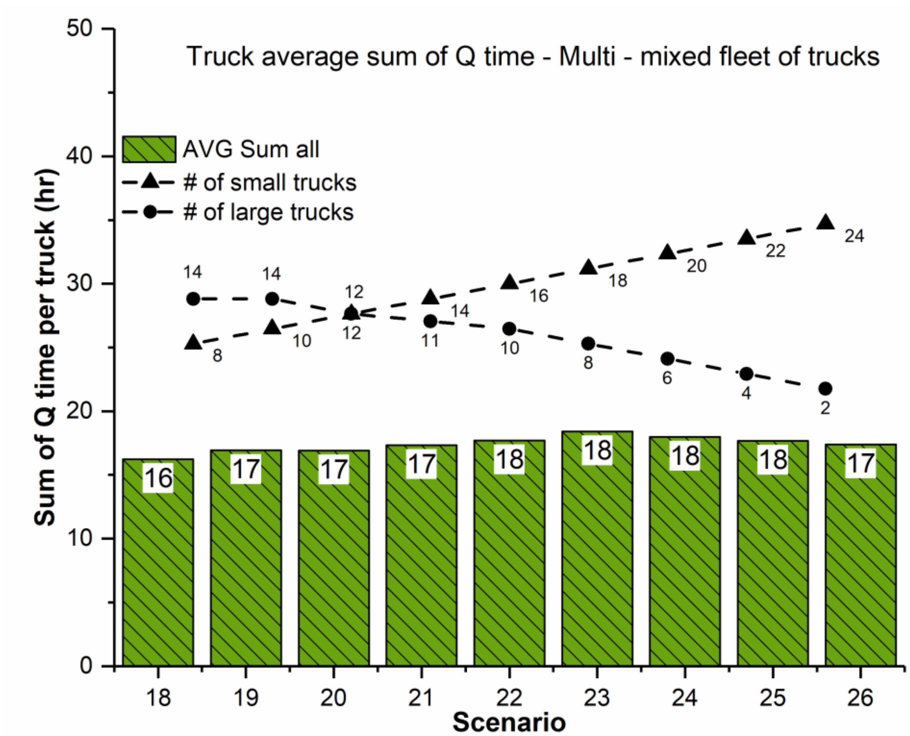

Figure 4.30: Cumulative average queue time for trucks in the operation – MOGP – mix fleets

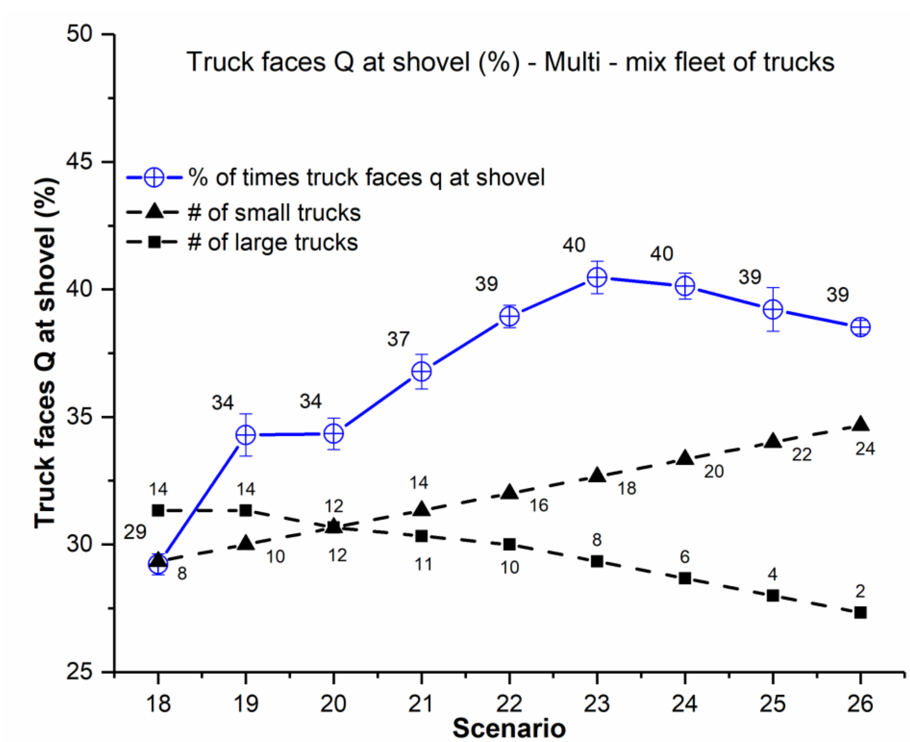

Figure 4.31: Percentage of the times a truck faces line up in front of shovel – MOGP – mix fleets

4.5.3. Comparing MOGP with the benchmark model

Using the deterministic match factor calculation, the total number of the small size trucks and large size trucks required to meet the production demand of the case study's operation were calculated to be 37 and 28, respectively. Then, 17 under-truck scenarios for small trucks and large trucks and 9 balanced scenarios for mixed fleets were developed to implement the integrated framework with MOGP and BM fleet management systems. For each of the developed scenarios, the integrated framework applied to the operation of the case study using both truck-dispatching models (benchmark (BM) model and the multiple objective (multi) model), and after separately analyzing the results in previous sections, the results are compared against each other and are presented in this section.

Implementing small truck fleets, Figure 4.32 shows that when the benchmark decision-making model handles truck dispatching, the operation can meet the production demands with fleets of at least 36 trucks (scenario 9) whereas, using the developed MOGP truck-dispatching model, the operation can meet the production demands with a fleet of 30 trucks (scenario 6). This means that by replacing the benchmark truck-dispatching model with the MOGP truck-dispatching model developed in this study, the mine can operate with 6 trucks (17%) less than the number of small trucks required to meet the production using benchmark (BM) truck-dispatching model. Apart from that, by implementing the MOGP truck-dispatching model instead of BM truck-dispatching model, the fleet of shovels was utilized less for an average of 4% (Figure 4.33), trucks waited less in queues for an average of 22% (Figure 4.34), and they also encountered lineup for an average of 20% less than the time BM truck-dispatching was making required decisions (Figure 4.35).

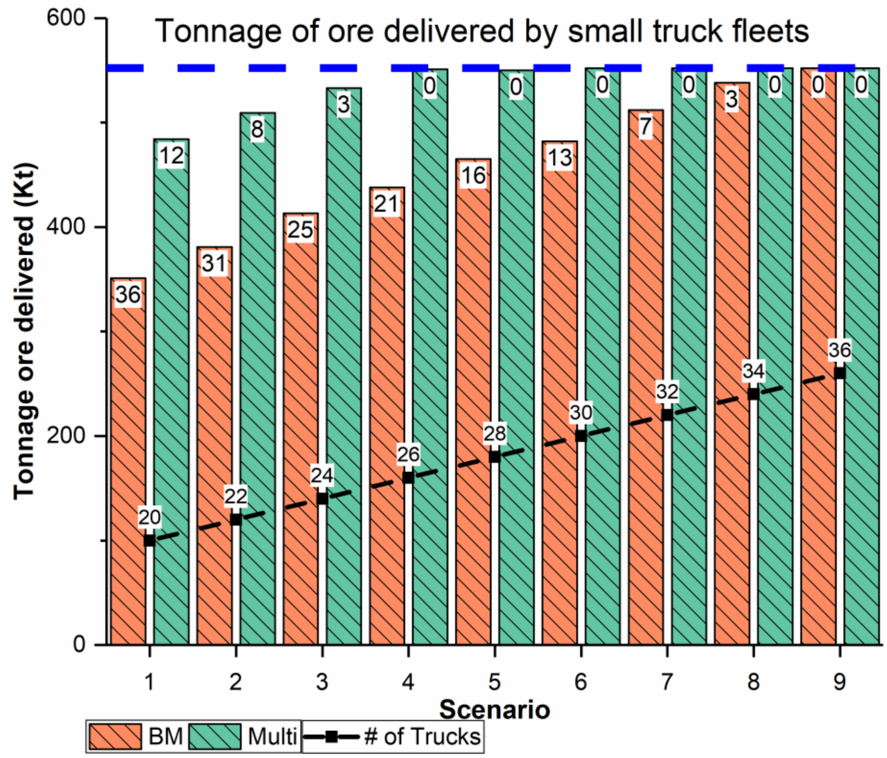

Figure 4.32: Total tonnage of ore delivered to processing plants – small trucks – comparison

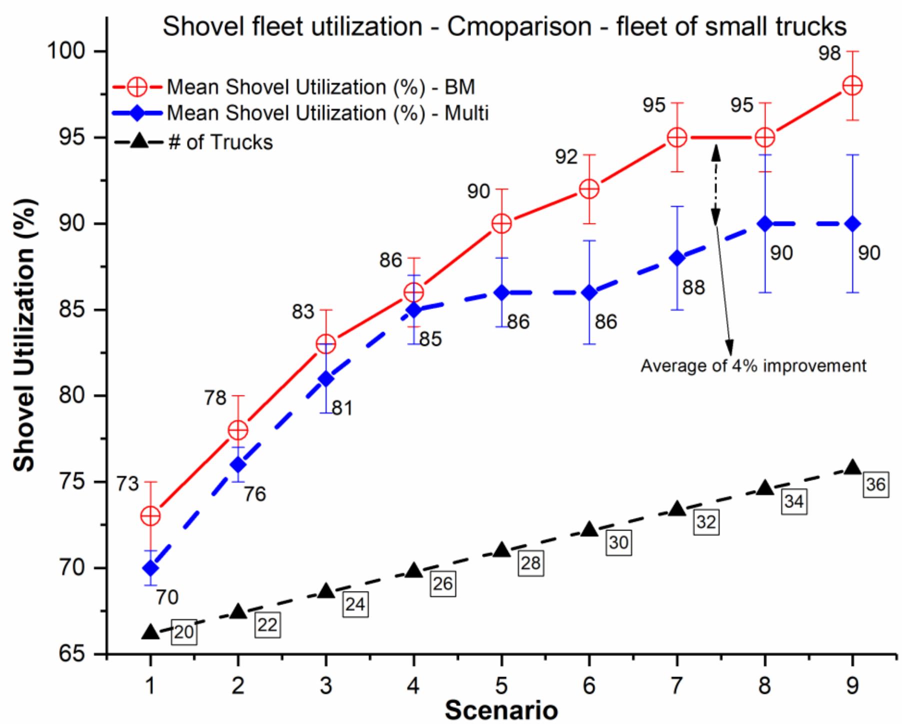

Figure 4.33: Shovel utilization with increasing number of trucks – small trucks – comparison

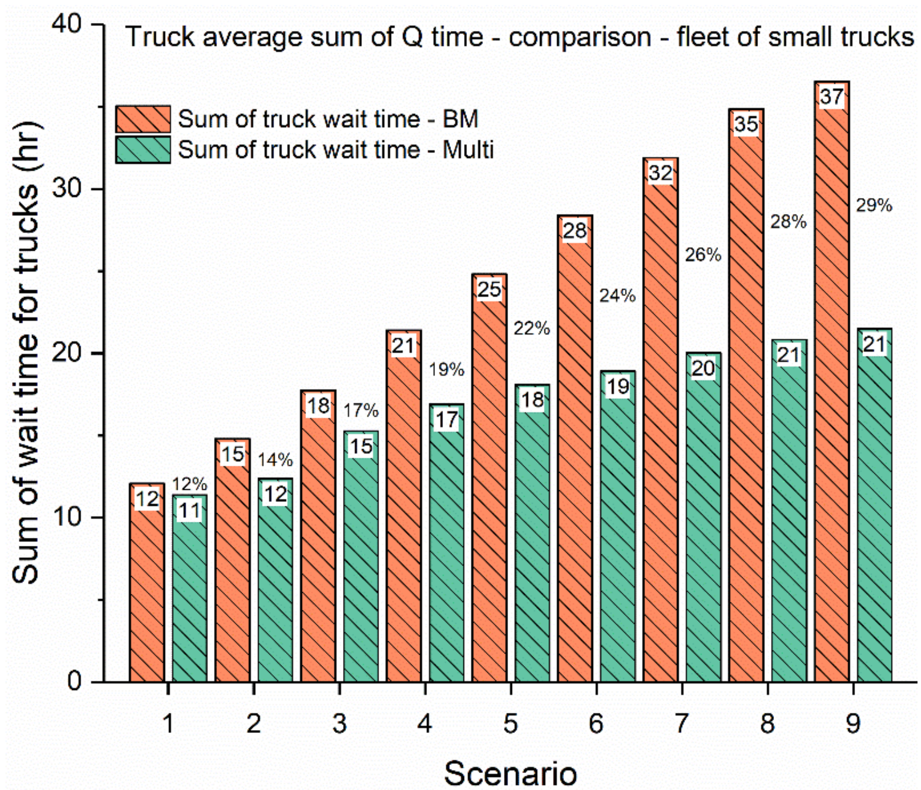

Figure 4.34: Cumulative average queue time for trucks in the operation – small trucks – comparison

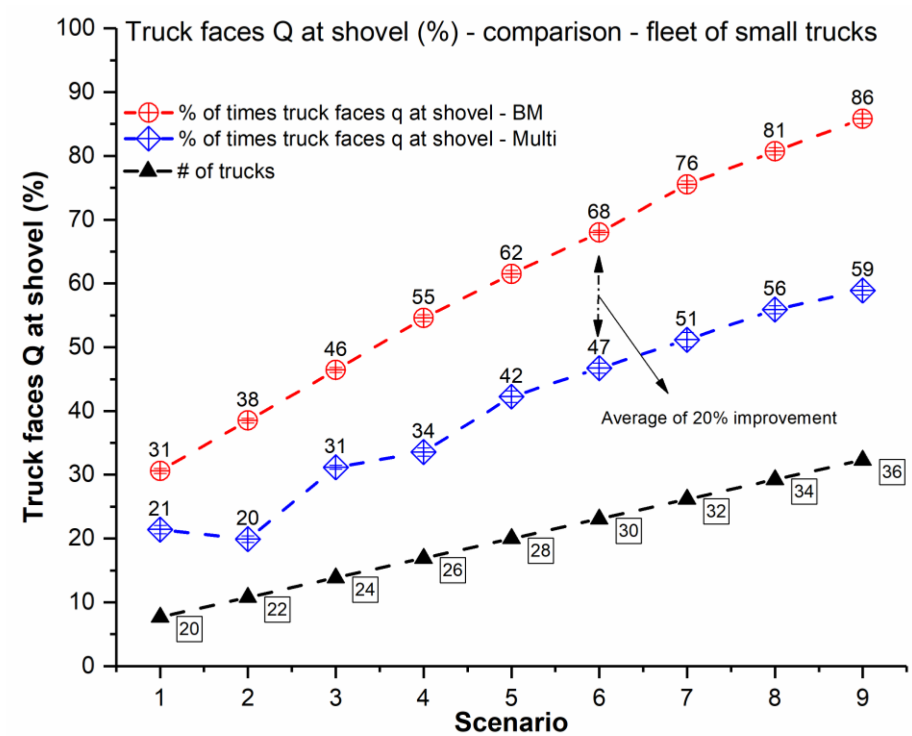

Figure 4.35: Percentage of the times a truck faces line up in front of shovel – small trucks – comparison

For scenarios 10 to 17 where the fleets of small trucks were replaced with the fleets of large trucks, as shown by Figure 4.36, the MOGP model can meet the required processing plants' capacity with a fleet of 17 large trucks (scenario 12) whereas the BM truck-dispatching model can meet the processing plants' requirement with fleet of at least 21 large trucks. The operation utilized shovels fleet for an average of 10% less (Figure 4.37), trucks spent an average of 25% less time in queue at shovels (Figure 4.38), and they encountered lineup at shovels in an average of 20% less times (Figure 4.39) when the BM model was replaced with the MOGP model.

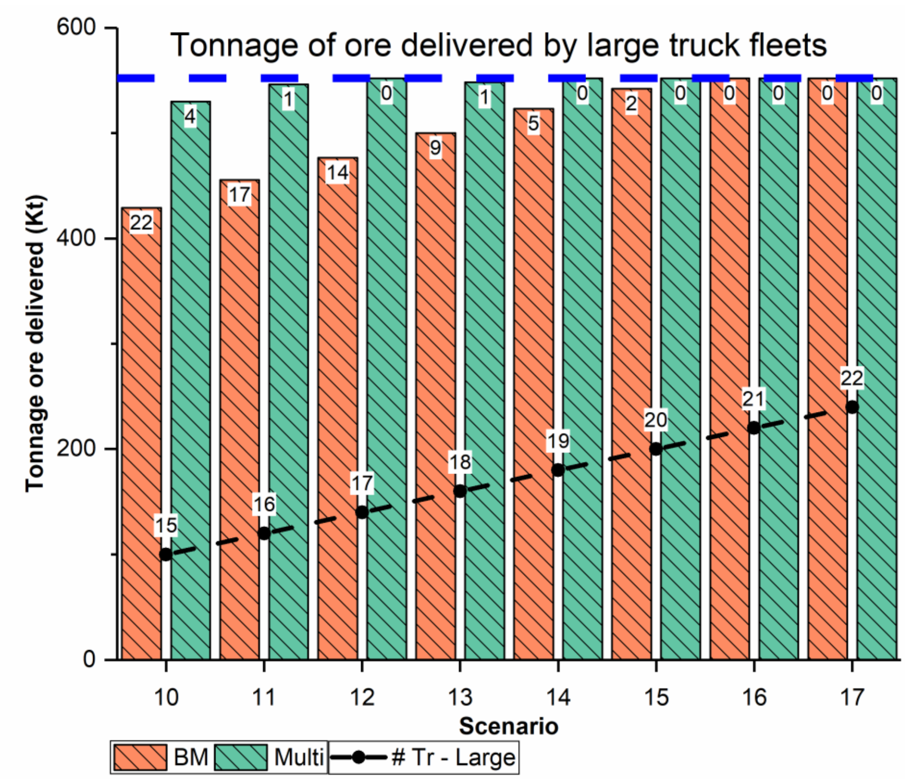

Figure 4.36: Total tonnage of ore delivered to processing plants – large trucks – comparison

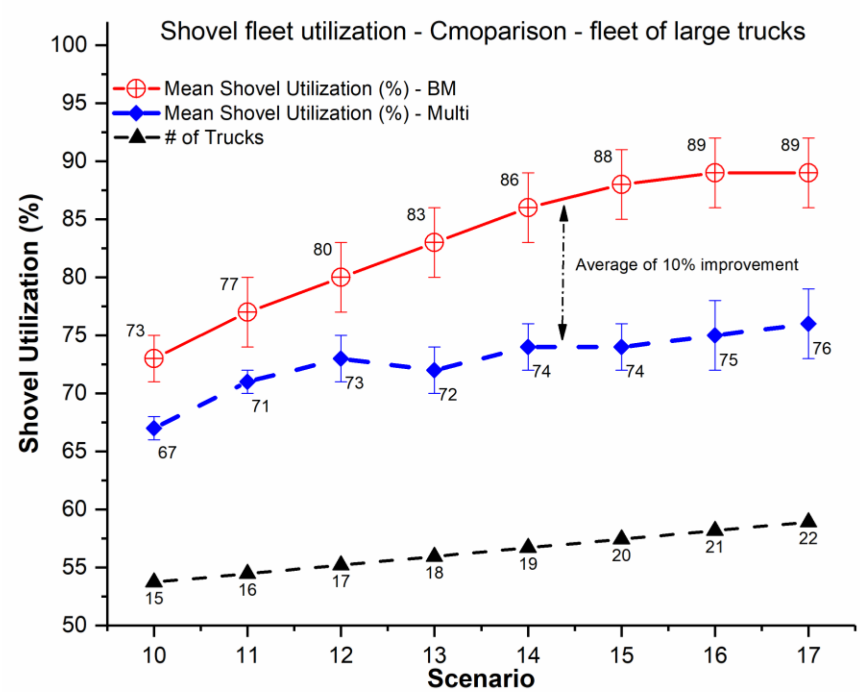

Figure 4.37: Shovel utilization with increasing number of trucks – large trucks – comparison

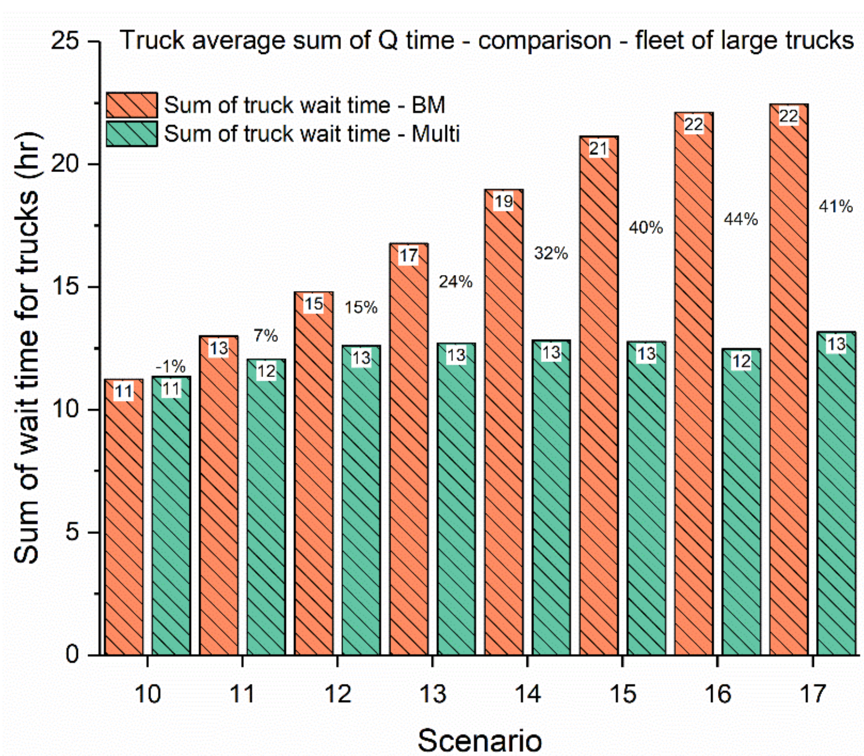

Figure 4.38: Cumulative average queue time for trucks in the operation – large trucks – comparison

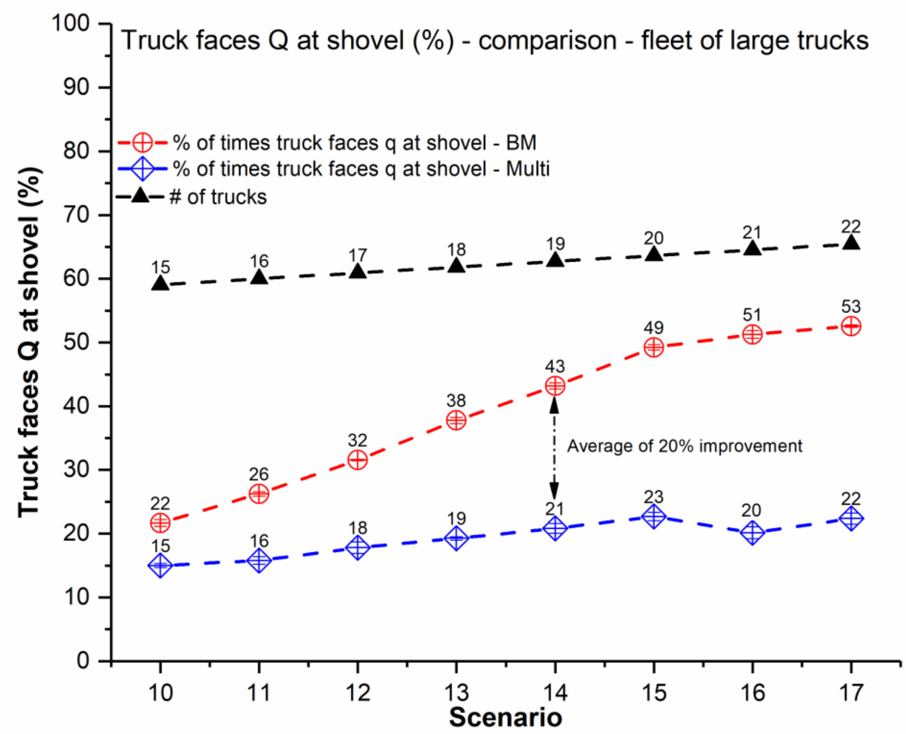

Figure 4.39: Percentage of the times a truck faces line up in front of shovel – large trucks – comparison

Figure 4.40 to Figure 4.43 compare KPIs for implementation of MOGP truck-dispatching model against BM truck-dispatching model using mixed fleet of trucks to handle the material in the case study. Results show that because the MOGP model required less number of trucks in different combinations to meet the production requirements (Figure 4.40), the shovels fleet was utilized 10% less (Figure 4.41), the trucks spent 40% less time in queues (Figure 4.42) and faced lineups at shovels 33% less (Figure 4.43).

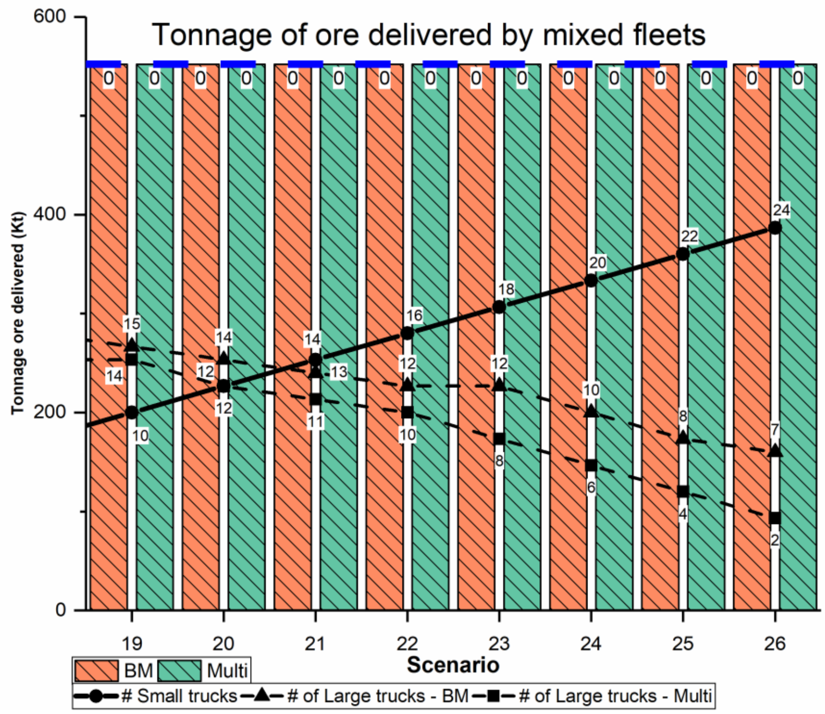

Figure 4.40: Total tonnage of ore delivered to processing plants – mix fleets – comparison

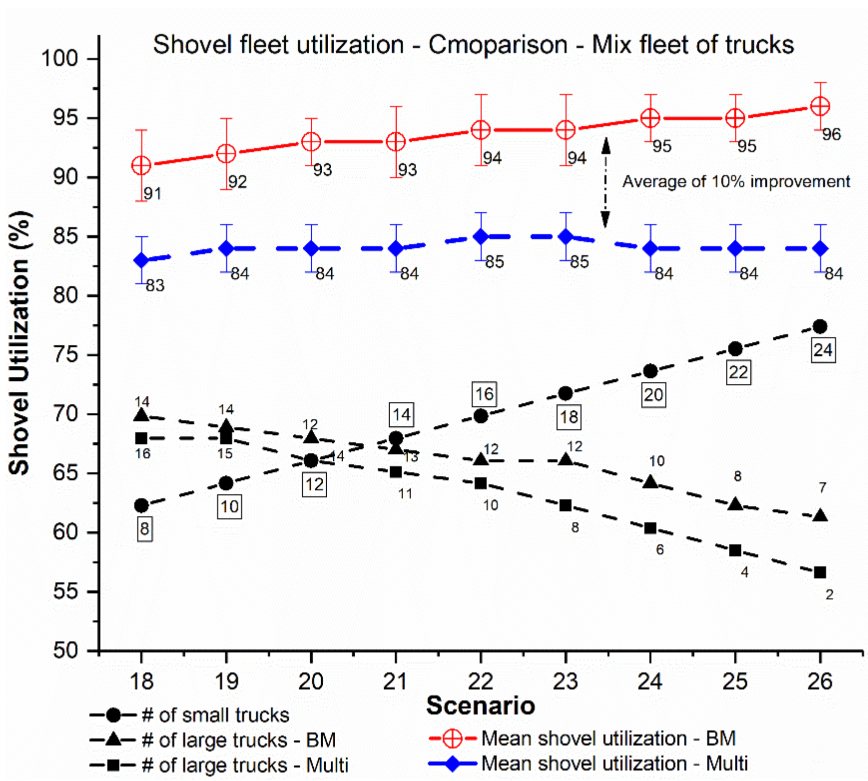

Figure 4.41: Shovel utilization with increasing number of trucks – mix fleets – comparison

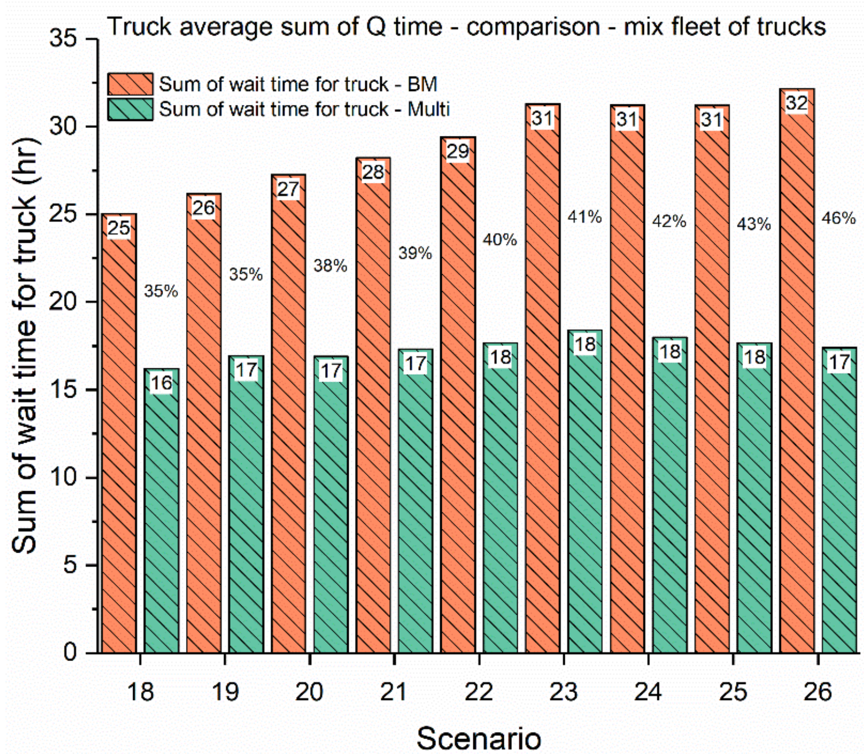

Figure 4.42: Cumulative average queue time for trucks in the operation – mix fleets – comparison

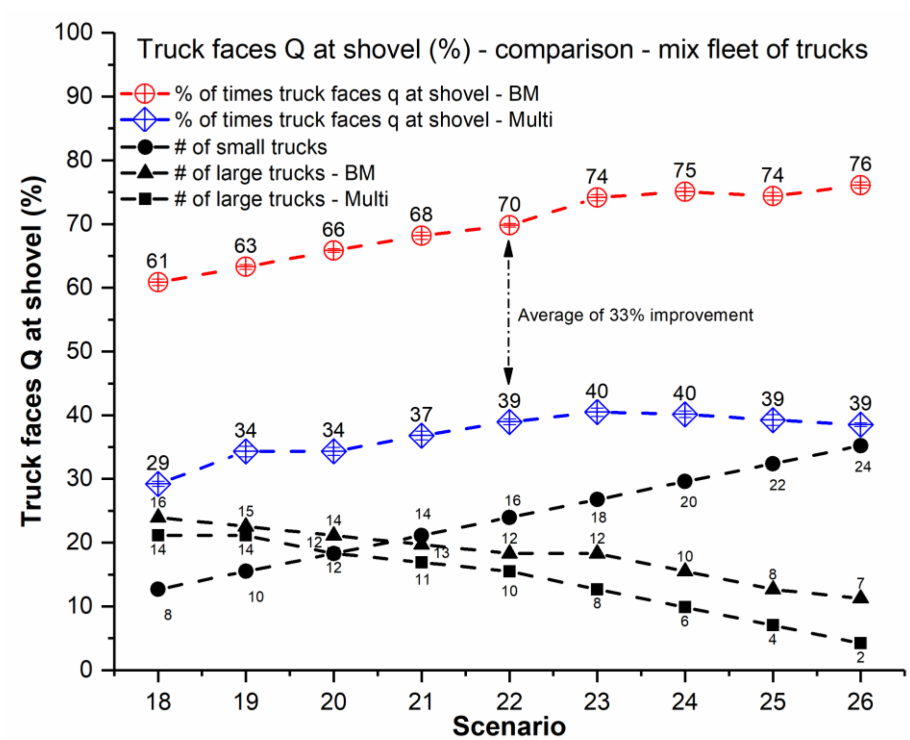

Figure 4.43: Percentage of the times a truck faces line up in front of shovel – mix fleets – comparison

Studying KPIs for different small fleet, large fleet, and mixed fleet scenarios show that implementing the MOGP truck-dispatching model, the operation needs less number of trucks to meet the production targets. In the next section, we present higher resolution analysis of important scenarios.

4.5.4. Higher resolution study on selected scenarios

We implemented the developed integrated simulation and optimization framework in an open pit mine case study with BM truck-dispatching model and MOGP truck-dispatching model. 26 scenarios (in three categories: 9 small truck fleet scenarios, 8 large truck fleet scenarios, and 9 mixed fleet scenarios) were run for both BM and MOGP truck-dispatching models. For small trucks and large trucks fleets, results of implementing MOGP is compared against results of implementing BM in the best scenario when using BM model, the best scenario when using MOGP model, and comparison of best scenarios in a shift by shift resolution manner that are being presented in this section. It is worth noting that although the simulation study was run for 10 shifts and 12 hours per shifts, we did our shift by shift evaluations by considering the first shift as the warm up shift. Thus, the analysis being presented in the following sub sections are presented for 9 shifts.

4.5.4.1. Fleet of 28 small trucks

In scenario 5 listed in

Table 4.8 we implemented fleet of 28 small trucks to handle the material transportation. Results of implementation show that the fleet can meet the processing plants capacity requirement if it is being used with MOGP model as the truck-dispatching decision-making tool in the operation's FMS.

Figure 4.44 depicts that using the BM truck-dispatching model, although the fleet transported more tonnage that required in each shift, the capacity requirement for none of the processing plants were met. The BM model met 79% of plant 1 capacity (Figure 4.46) and 84% of plant 2 capacity in each shift (Figure 4.47). The reason that it can meet the plant 2 capacity more than plant 1 is that plant 2 is located closer to the loaders than plant 1. In contrast, using MOGP truck-dispatching model, each of the processing plants were fed in their full capacity. However, the total production capacity was not met for 100% (Figure 4.45). the MOGP met the plants' capacity requirements for 100%, though. Figure 4.48 and Figure 4.49 show that implementing the MOGP truck-dispatching model, the material handling system was able to meet the hourly feed rate requirement for each processing plants whereas the BM model was not able to meet the hourly feed rates for any of the plants while using a fleet of 28 small trucks. Replacing the BM model with the MOGP model helped to improve queue length at shovels from an average of 2 trucks to an average of 1 truck (Figure 4.50) that consequently caused 25% improvement in the time a truck spent in queue at shovels (Figure 4.51 and Figure 4.52).

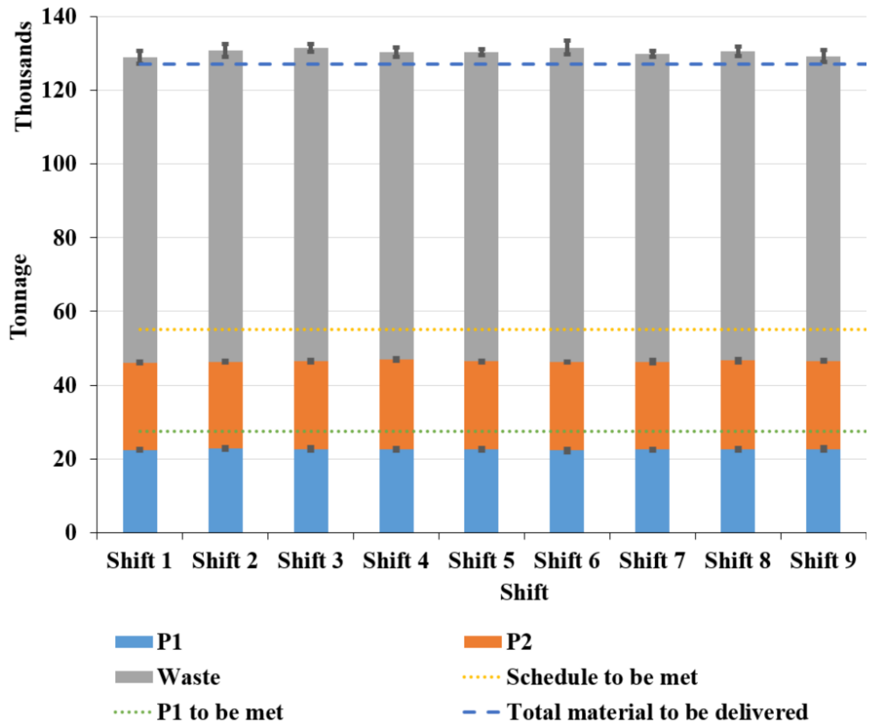

Figure 4.44: Shift by shift production – fleet of 28 small trucks – BM

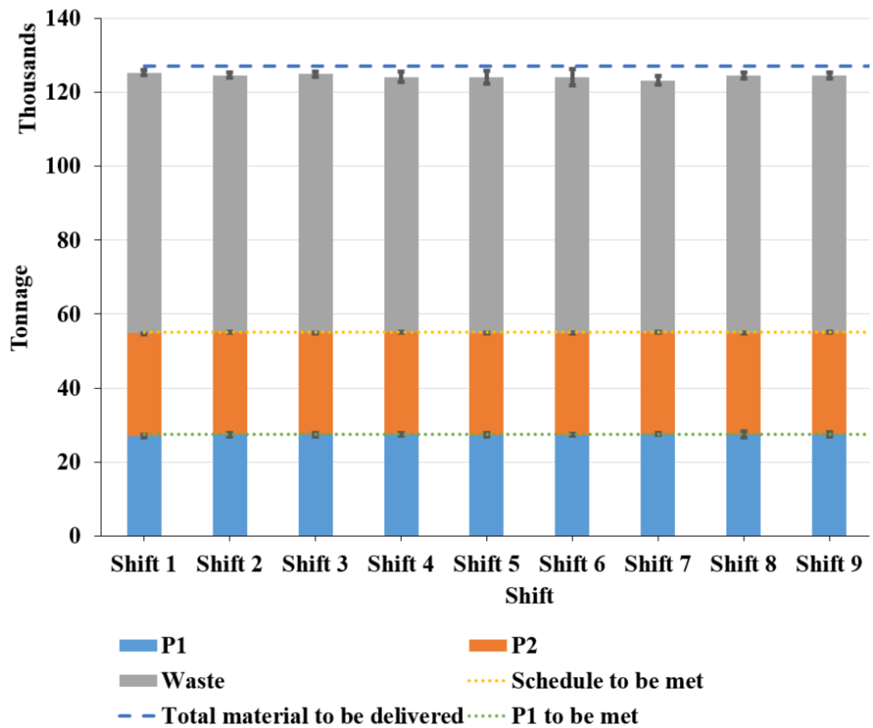

Figure 4.45: Shift by shift production – fleet of 28 small trucks – MOGP

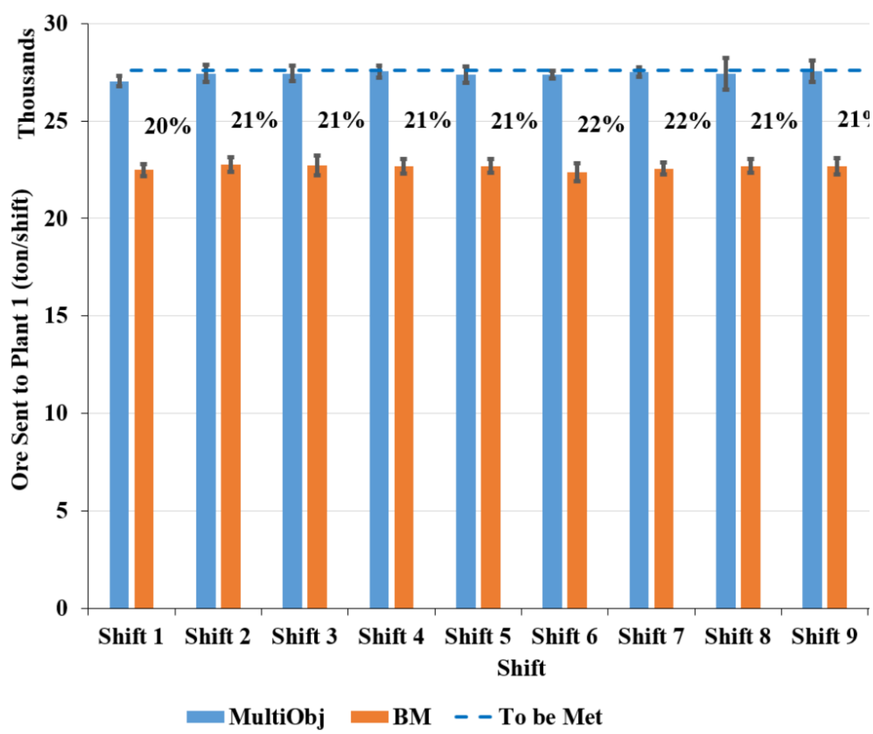

Figure 4.46: Ore sent to plant 1 – MOGP (blue bars) versus BM (orange bars) – shift by shift resolution – fleet of 28 small trucks

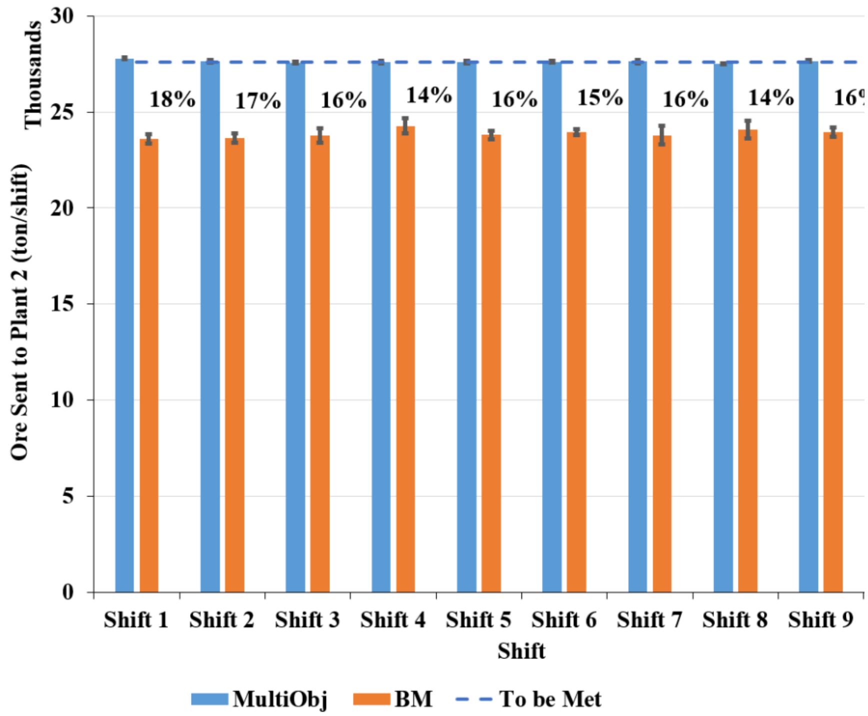

Figure 4.47: Ore sent to plant 2 – MOGP (blue bars) versus BM (orange bars) – shift by shift resolution – fleet of 28 small trucks

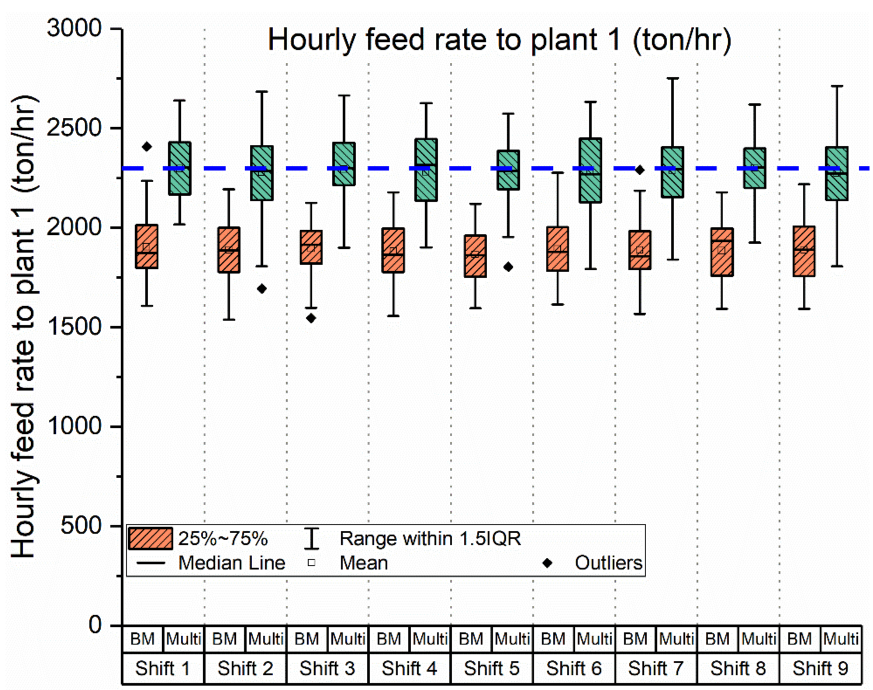

Figure 4.48: Hourly feed rate for plant 1 – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 28 small trucks

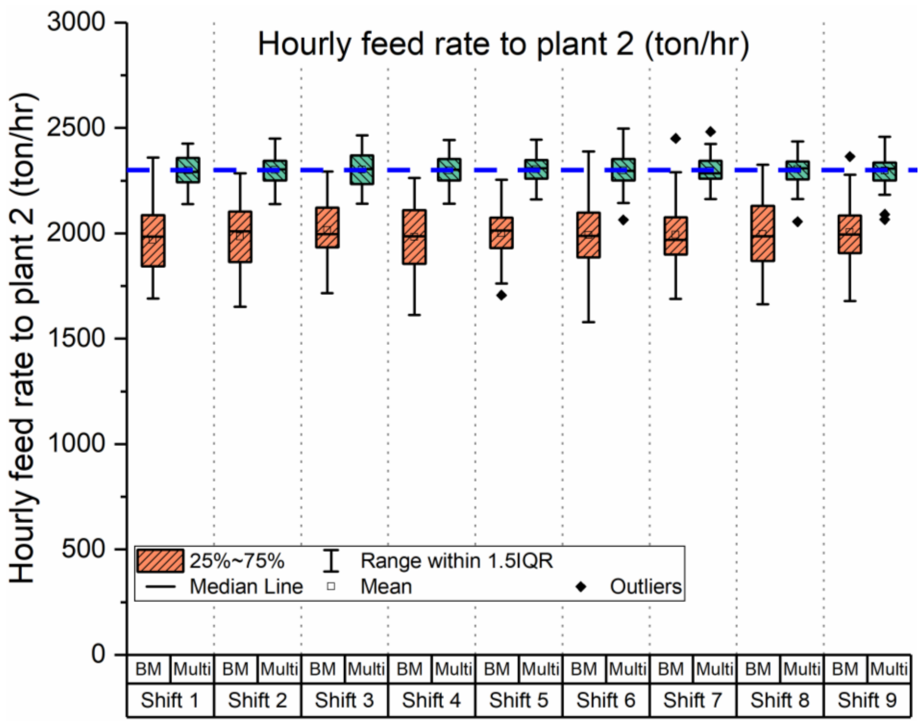

Figure 4.49: Hourly feed rate for plant 2 – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 28 small trucks

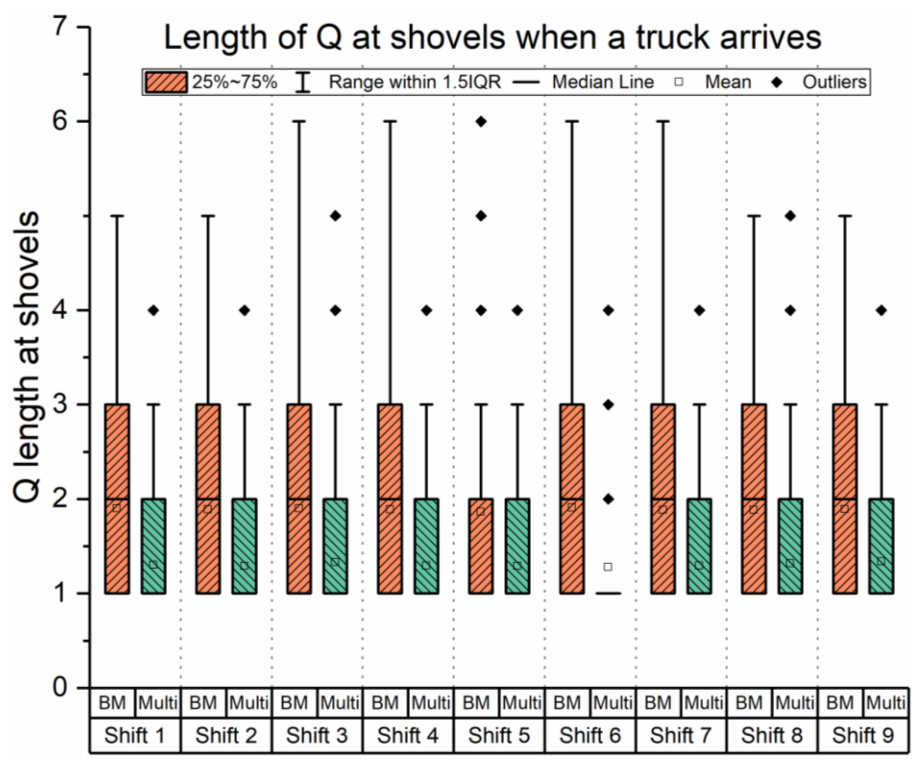

Figure 4.50: Length of queue at shovels – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 28 small trucks

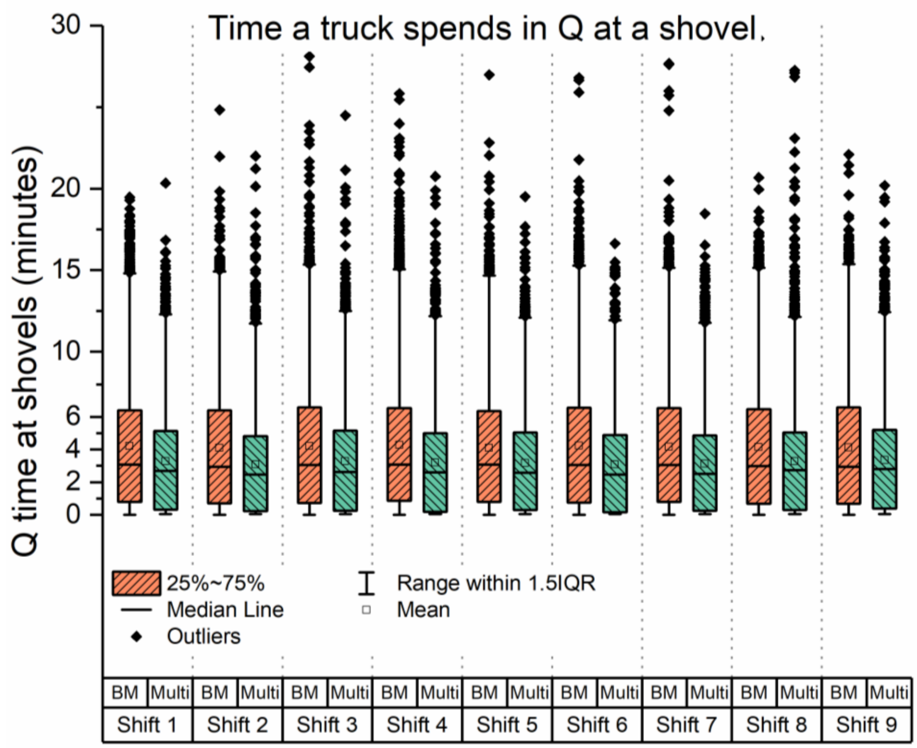

Figure 4.51: Queue time at shovels – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 28 small trucks

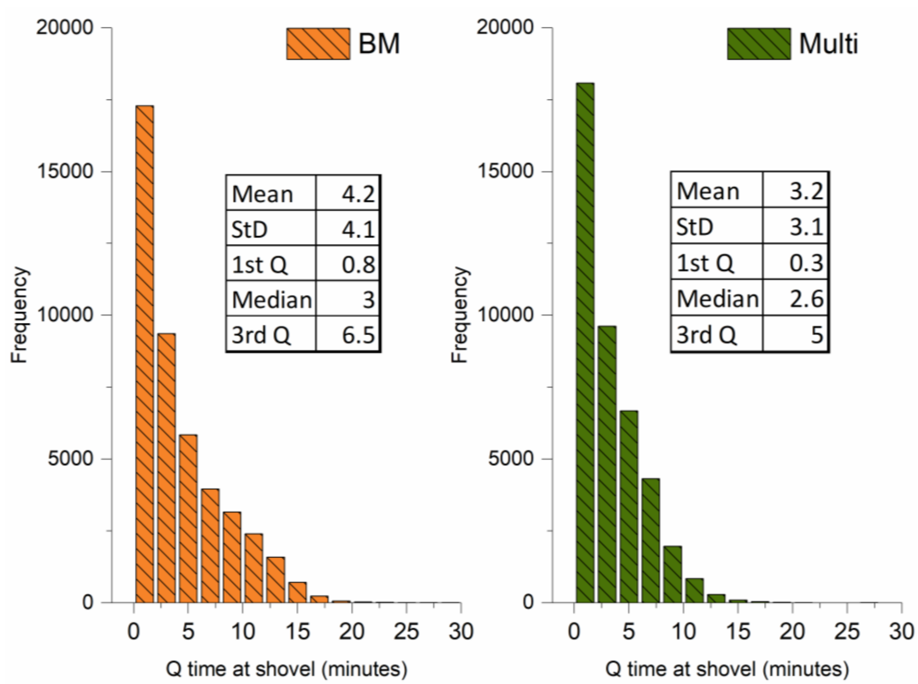

Figure 4.52: Histogram for time a truck spent in queue at shovels – MOGP (green bars) versus BM (orange bars) – fleet of 28 small trucks

4.5.4.2. Fleet of 31 small trucks

In scenario 5 with 28 small trucks in the fleet, although by using of MOGP model the processing plants requirements are met by 100%, the operation cannot meet the stripping ratio requirement. If we use the BM model in the same scenario, the plants' ore delivery requirement will not be met even if the operation can meet the total ore + waste production requirement. Thus, we introduce a new scenario (fleet of 31 small trucks) where the processing plants' requirement as well as ore + waste production requirement are met with minimum number of trucks in the fleet.

Results of implementing the 31 small trucks to handle the material in the case study show that using BM truck-dispatching model, although total production requirement for the case study was met (Figure 4.53), it was not able to deliver required amount of material to meet the processing plants' demands (Figure 4.55, Figure 4.56, Figure 4.57, and Figure 4.58). However, using MOGP truck-dispatching model both the total production schedule for shifts (Figure 4.54) and demand of each processing plant (Figure 4.55, Figure 4.56, Figure 4.57, and Figure 4.58) were met. Comparison of truck queue at shovels show that, with an average queue length of 1.4 in each shift of operation compared to 2.2 of BM (Figure 4.59), using the MOGP trucks spent an average of 2 minutes less in queue in each shift of the operation (Figure 4.60 and Figure 4.61).

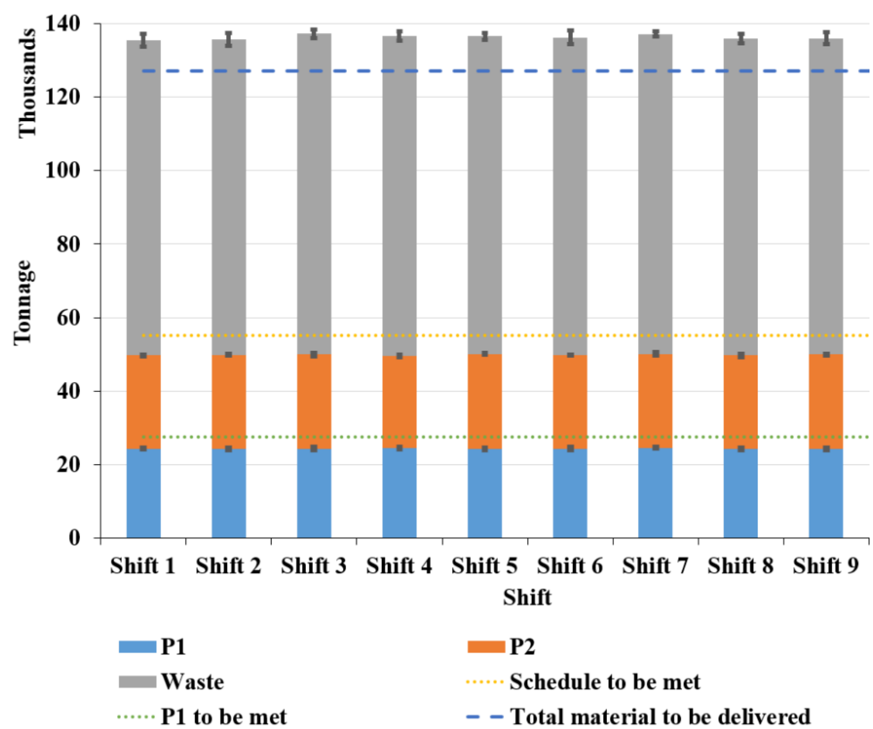

Figure 4.53: Shift by shift production – fleet of 31 small trucks – BM

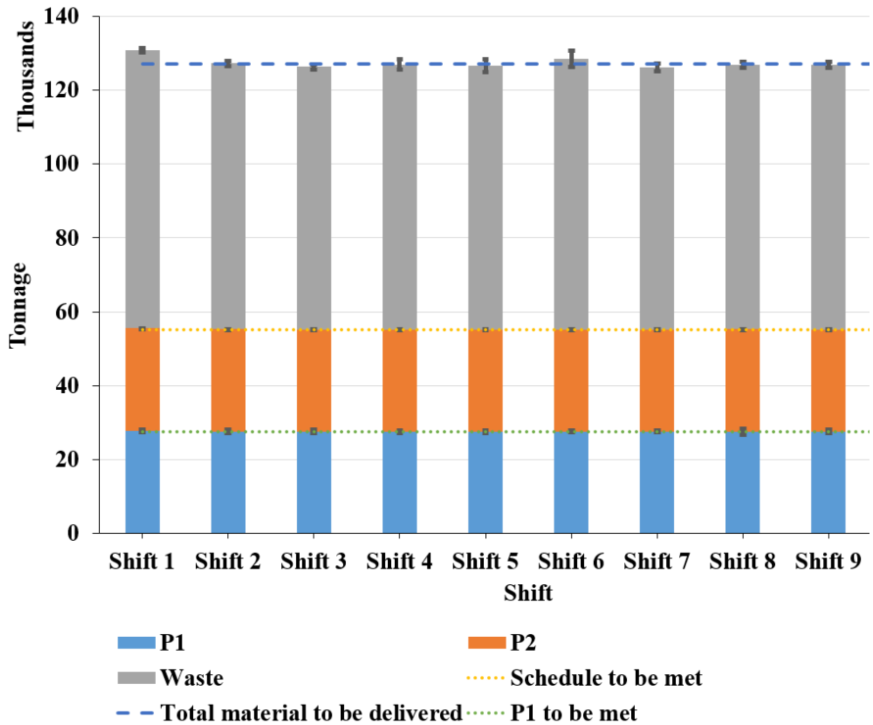

Figure 4.54: Shift by shift production – fleet of 31 small trucks – MOPG

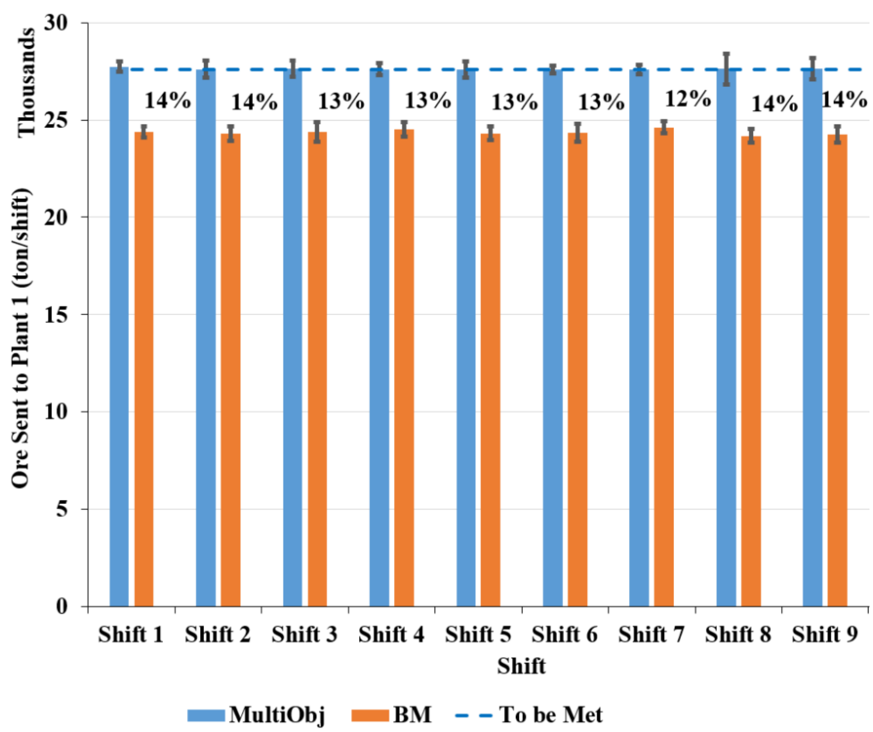

Figure 4.55: Ore sent to plant 1 – MOGP (blue bars) versus BM (orange bars) – shift by shift resolution – fleet of 31 small trucks

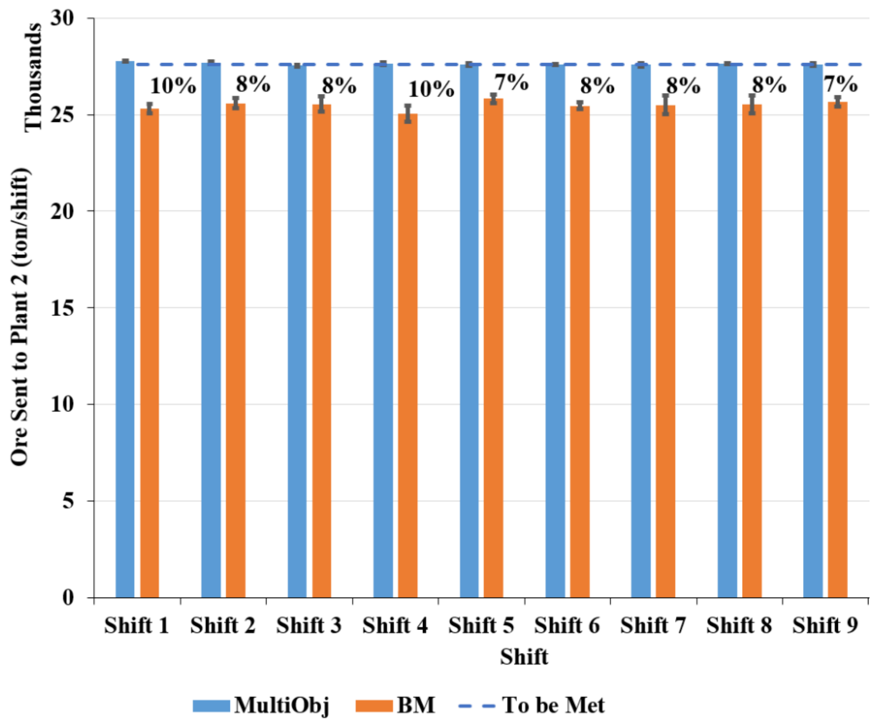

Figure 4.56: Ore sent to plant 2 – MOGP (blue bars) versus BM (orange bars) – shift by shift resolution – fleet of 31 small trucks

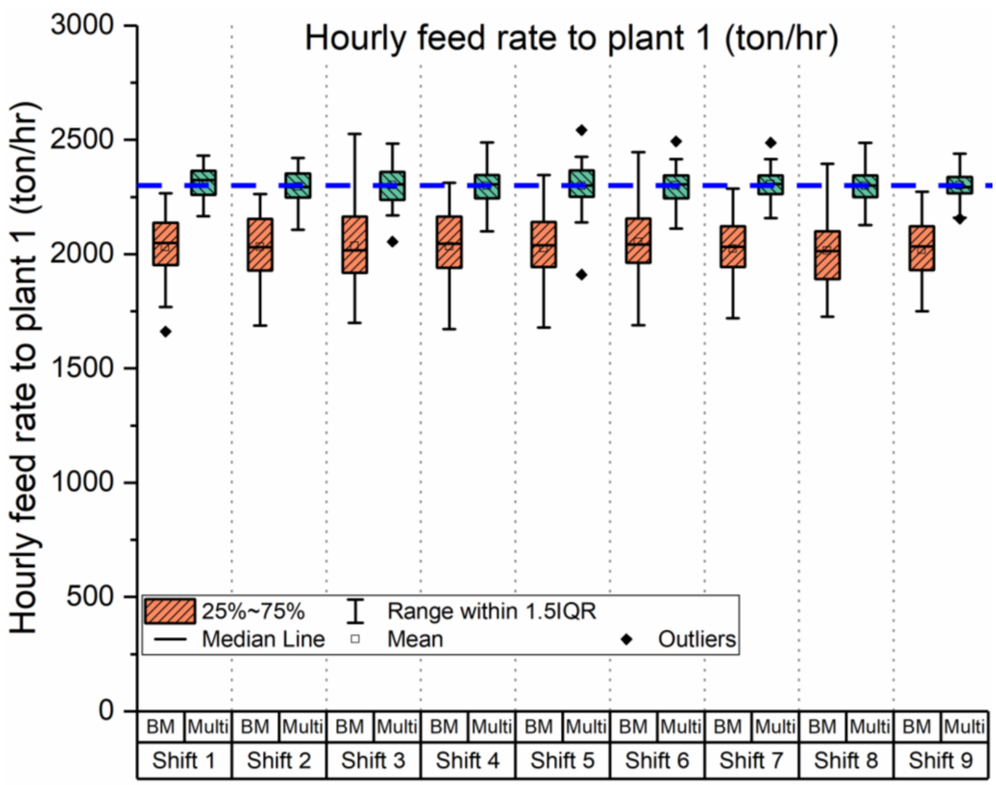

Figure 4.57: Hourly feed rate for plant 1 – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 31 small trucks

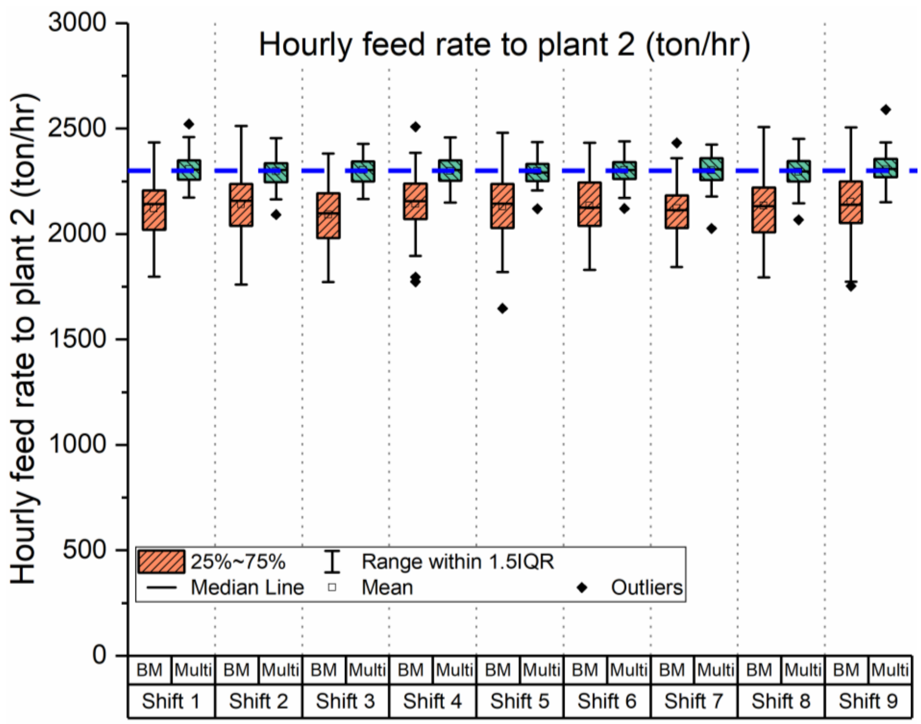

Figure 4.58: Hourly feed rate for plant 2 – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 31 small trucks

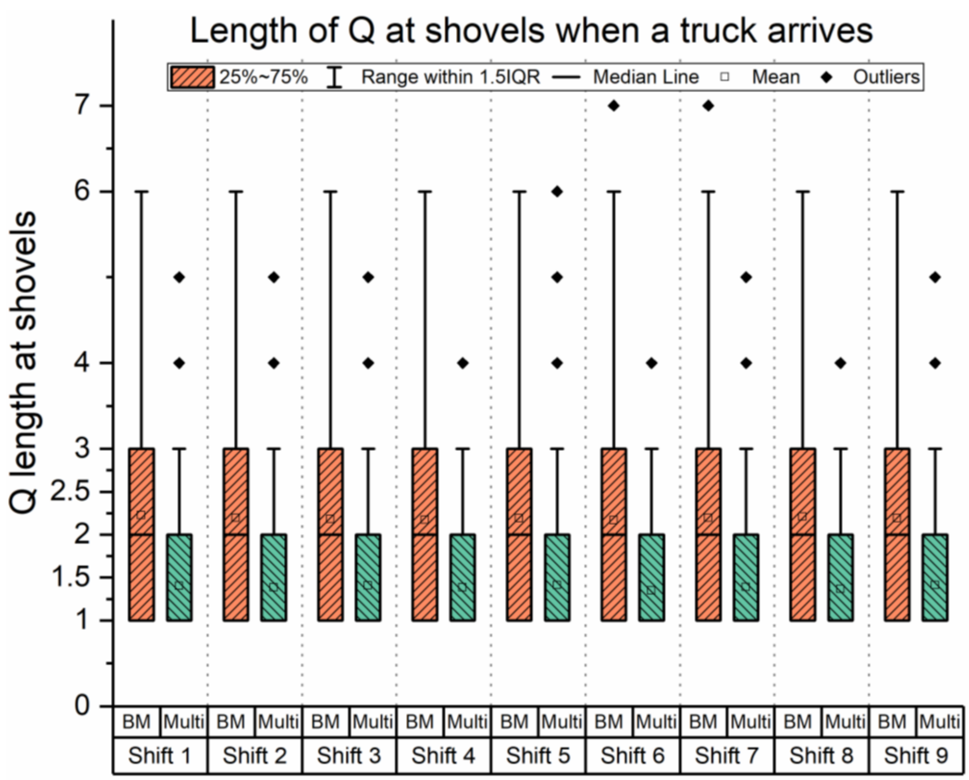

Figure 4.59: Length of queue at shovels – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 31 small trucks

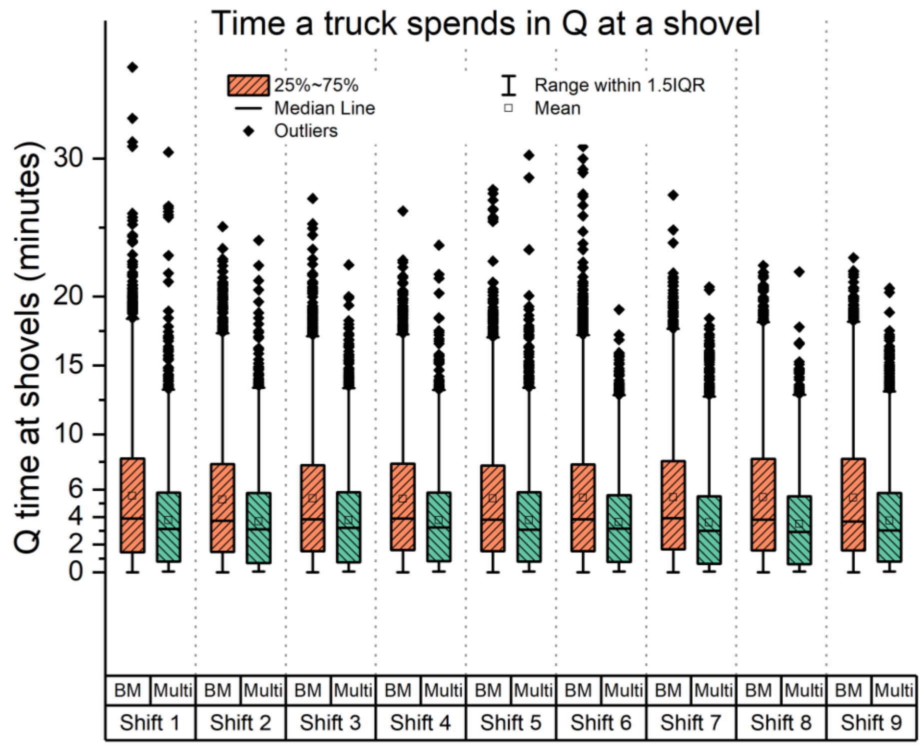

Figure 4.60: Queue time at shovels – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 31 small trucks

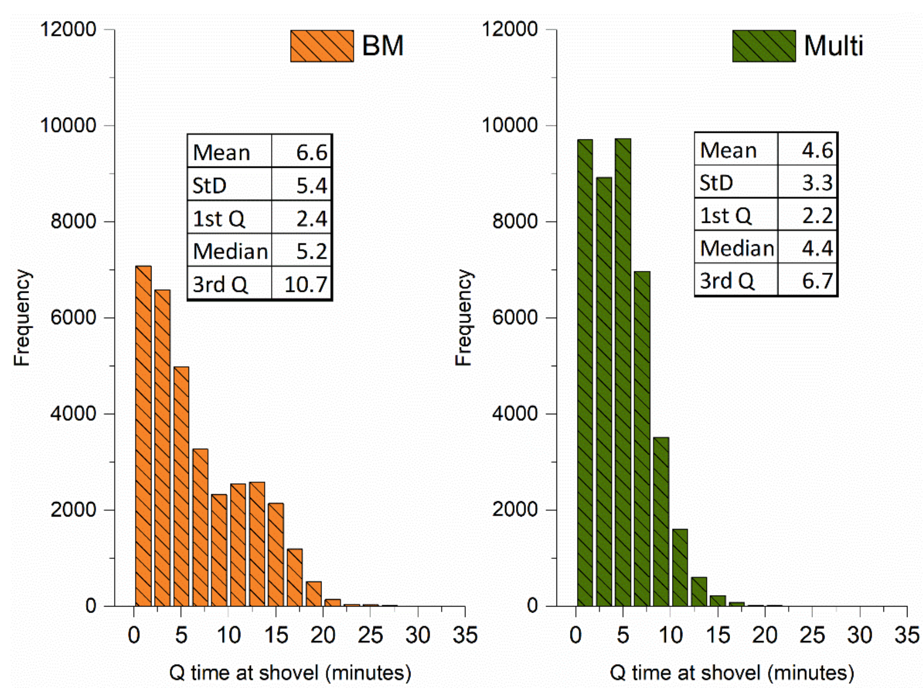

Figure 4.61: Histogram for time a truck spent in queue at shovels – MOGP (green bars) versus BM (orange bars) – fleet of 31 small trucks

4.5.4.3. Fleet of 36 small trucks

Scenario 9 with 36 small trucks in the fleet is the scenario with the least number of trucks in the fleet where using BM truck-dispatching model the operation can meet the production requirement (Figure 4.62), and ore delivered to each processing plant per shift (Figure 4.64 and Figure 4.65) and per hour of operation (Figure 4.66 and Figure 4.67). Replacing the BM model with the developed MOGP model, Figure 4.63 shows how the operation met the production requirement on shift by shift base. Results presented in Figure 4.68, Figure 4.69, and Figure 4.70 compare queue length and queue time at shovels between BM model and MOGP model. The operation met all the production requirement using both of the decision-making models implemented to make decisions on truck-dispatching problem in the case study in this scenario.

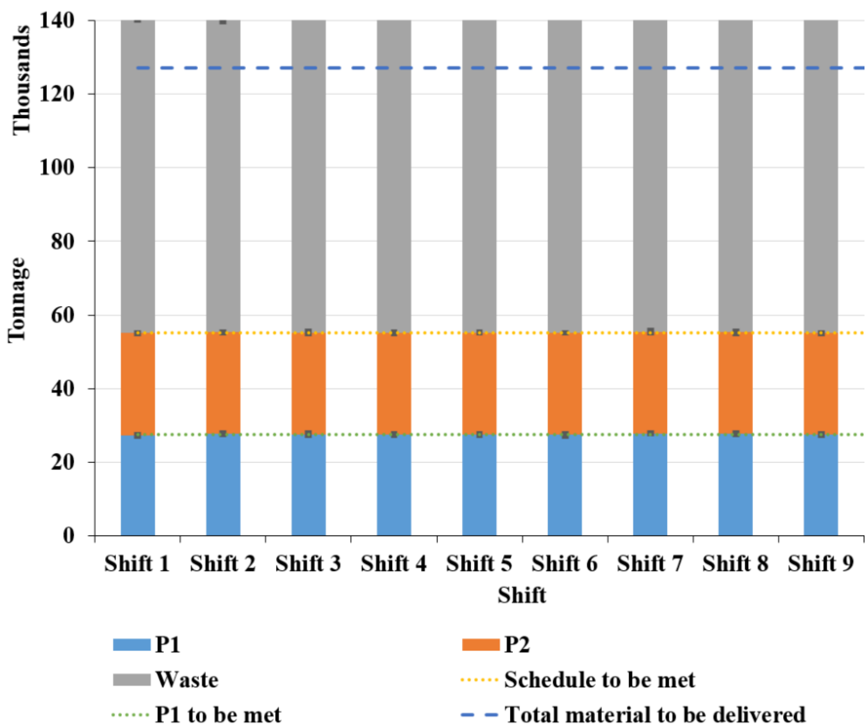

Figure 4.62: Shift by shift production – fleet of 36 small trucks – BM

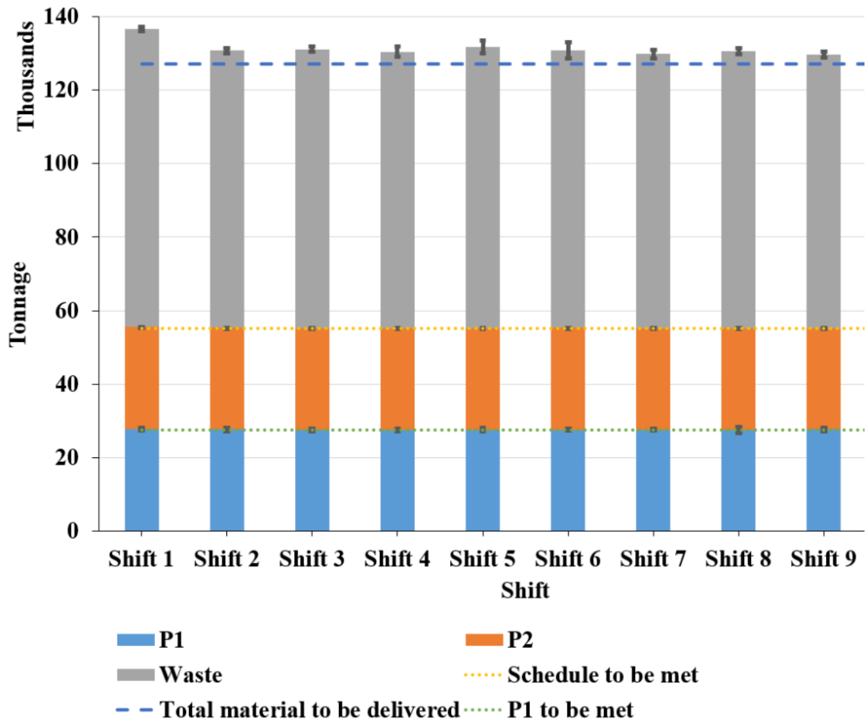

Figure 4.63: Shift by shift production – fleet of 36 small trucks – MOGP

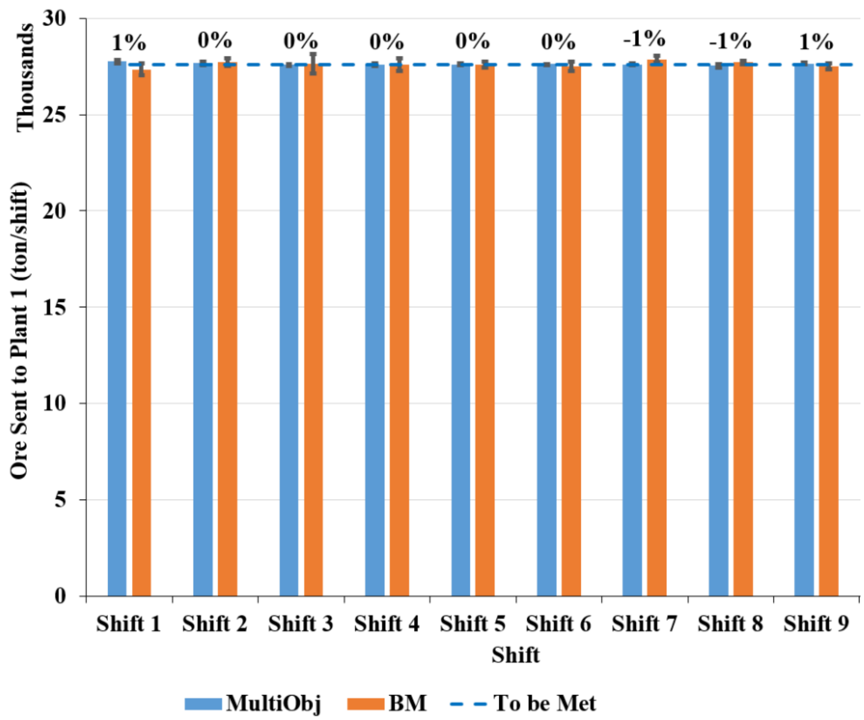

Figure 4.64: Ore sent to plant 1 – MOGP (blue bars) versus BM (orange bars) – shift by shift resolution – fleet of 36 small truck

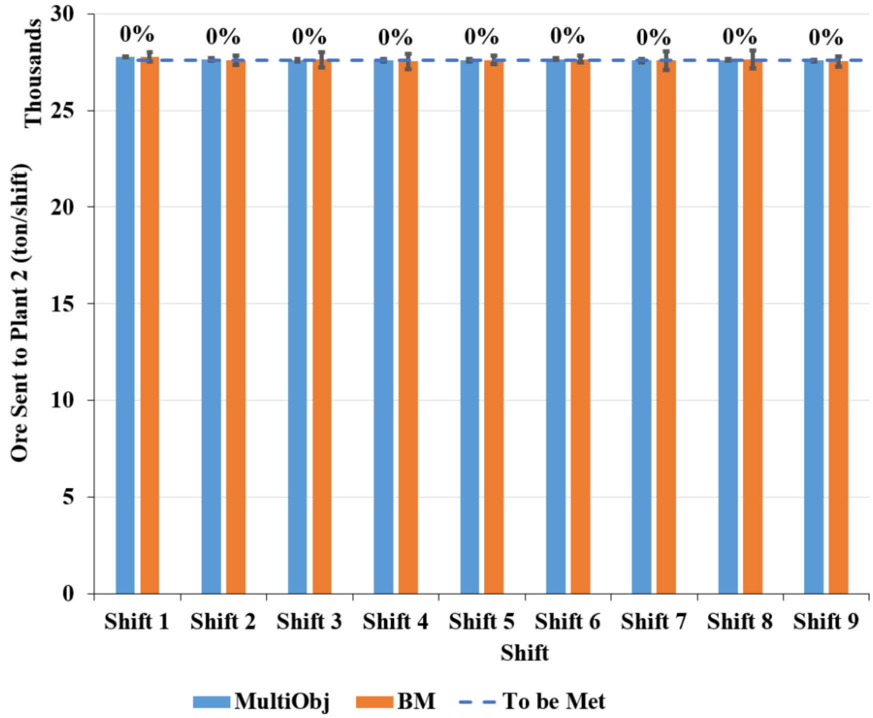

Figure 4.65: Ore sent to plant 2 – MOGP (blue bars) versus BM (orange bars) – shift by shift resolution – fleet of 36 small truck

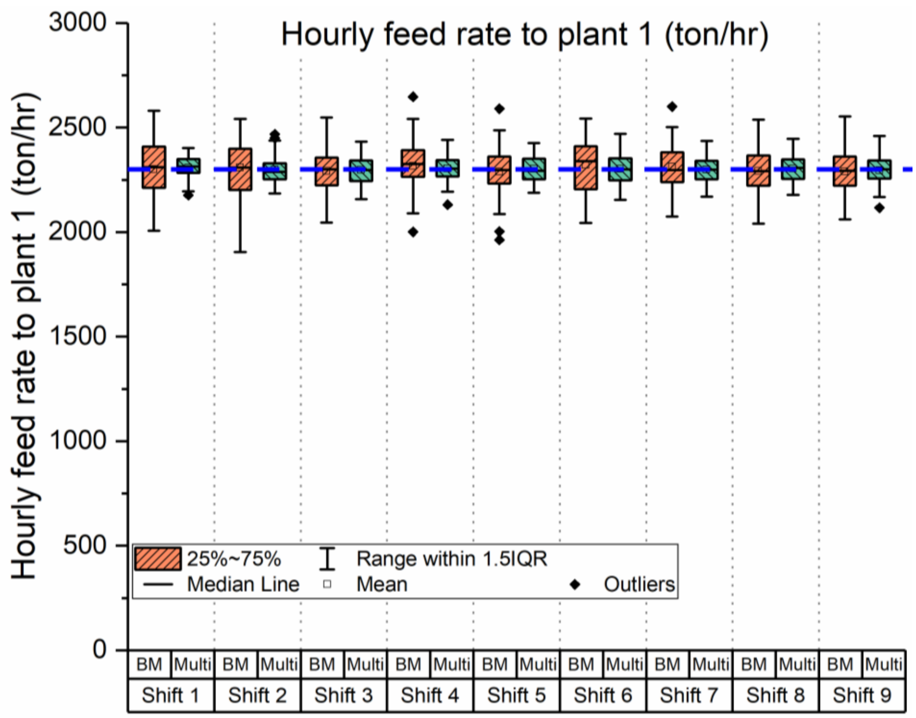

Figure 4.66: Hourly feed rate for plant 1 – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 36 small trucks

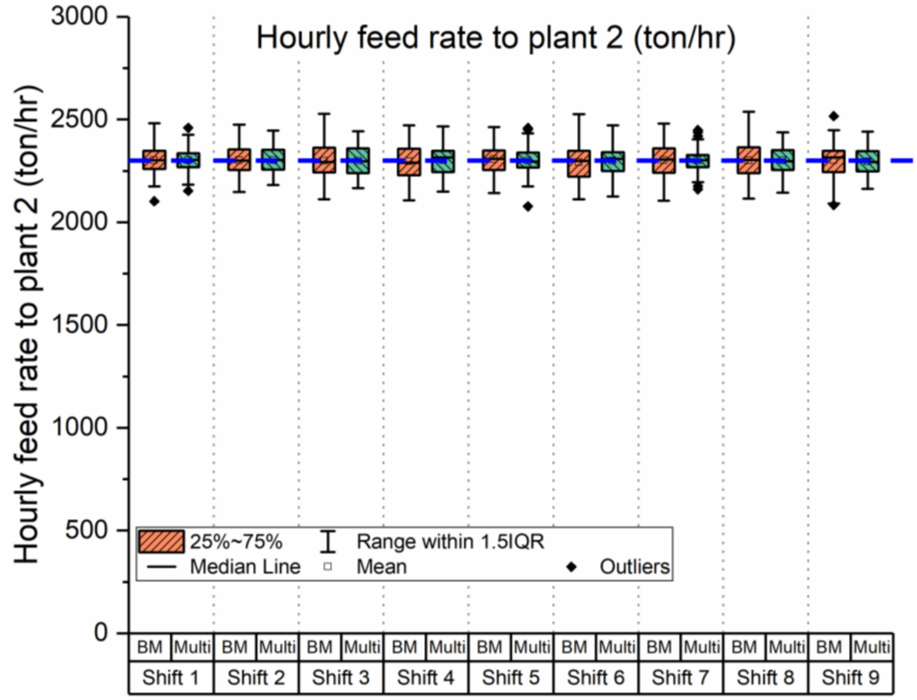

Figure 4.67: Hourly feed rate for plant 2 – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 36 small trucks

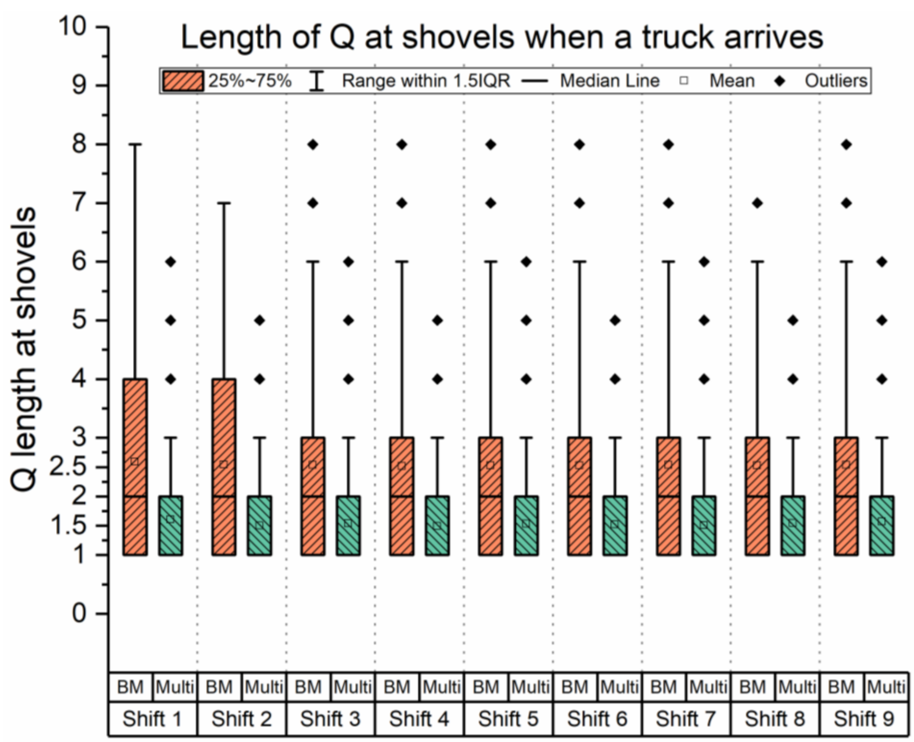

Figure 4.68: Length of queue at shovels – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 36 small trucks

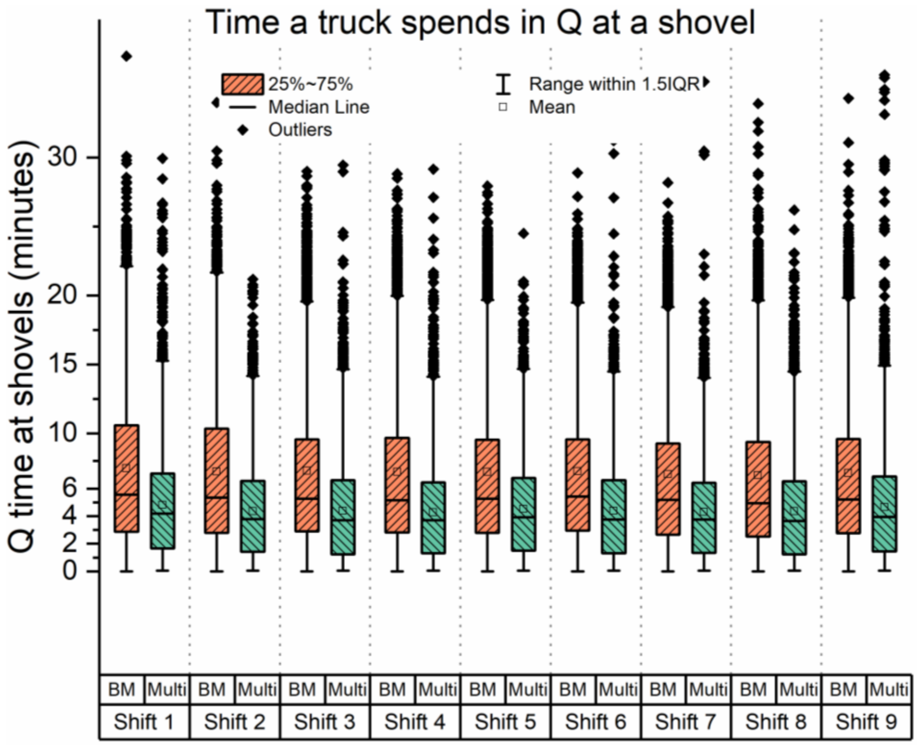

Figure 4.69: Queue time at shovels – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 36 small trucks

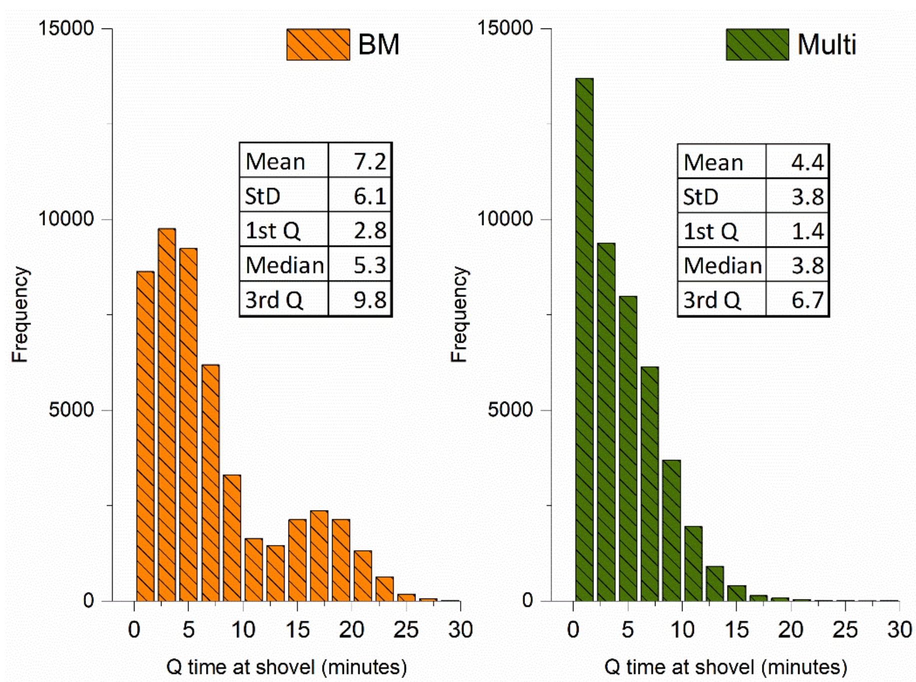

Figure 4.70: Histogram for time a truck spent in queue at shovels – MOGP (green bars) versus BM (orange bars) – fleet of 36 small trucks

4.5.4.4. Fleet of 31 small trucks with MOGP and 36 small trucks with BM

The least possible number of small trucks required to meet all the production requirement of the case study with the BM truck-dispatching model was scenario 9 with 36 small trucks. However, by replacing the BM truck-dispatching model with the MOGP truck-dispatching model, we were able to meet the production requirement of the operation with fleet of 31 small trucks (scenario 5). Although using both scenarios the production requirement of the operation was met, using MOGP truck-dispatching model resulted in using of a fleet with 17% less number of trucks than BM truck-dispatching model. This consequently improved number of trucks in queue at shovels (Figure 4.73) and time each truck spent in queue at shovels (Figure 4.74 and Figure 4.75). Another advantage of implementing MOGP model instead of BM model was that the deviation from the hourly feed rated reduced for both processing plants (Figure 4.71 and Figure 4.72).

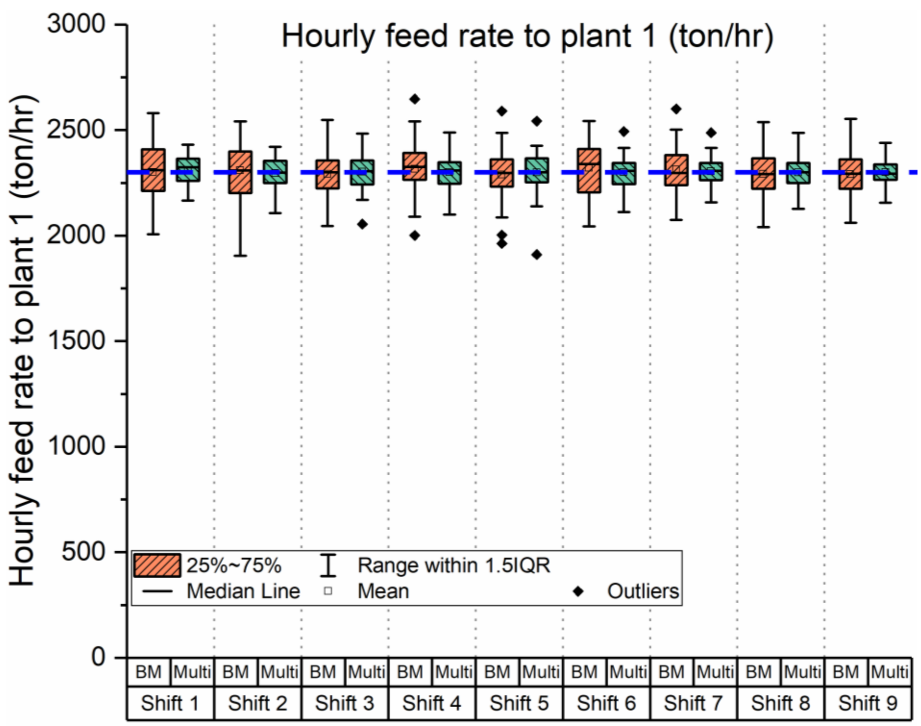

Figure 4.71: Hourly feed rate for plant 1 – optimum fleet of small trucks for MOGP (green boxes) versus optimum fleet of small trucks for BM (orange boxes)

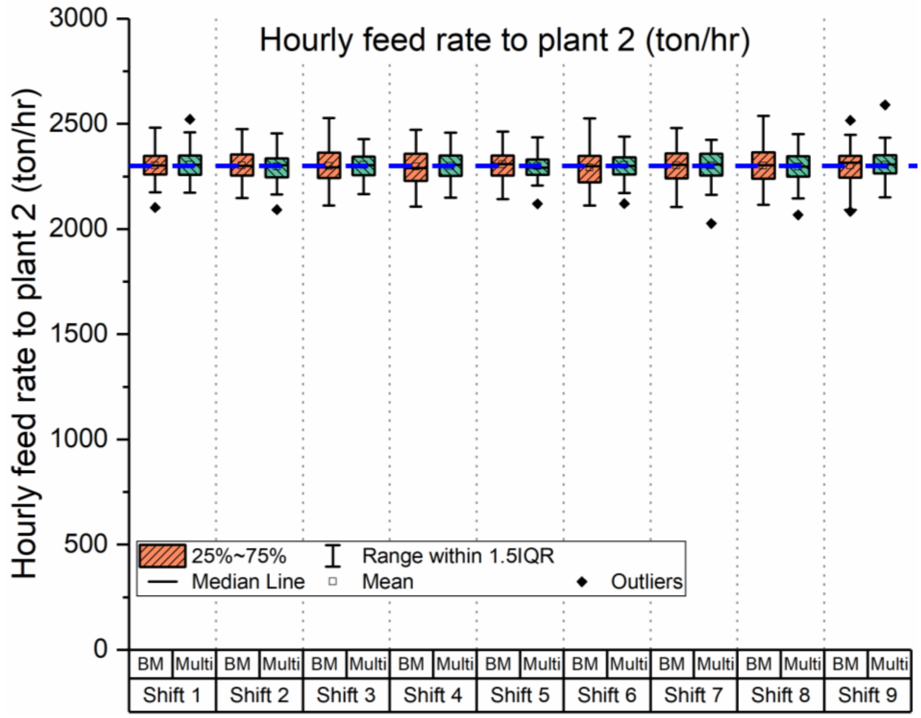

Figure 4.72: Hourly feed rate for plant 2 – optimum fleet of small trucks for MOGP (green boxes) versus optimum fleet of small trucks for BM (orange boxes)

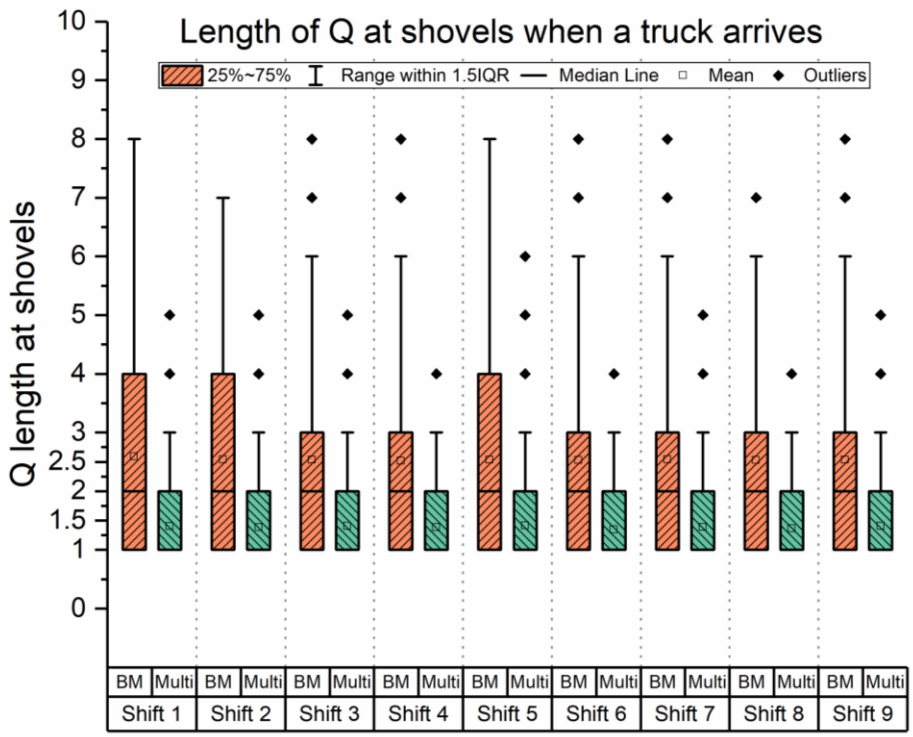

Figure 4.73: Length of queue at shovels – optimum fleet of small trucks for MOGP (green boxes) versus optimum fleet of small trucks for BM (orange boxes)

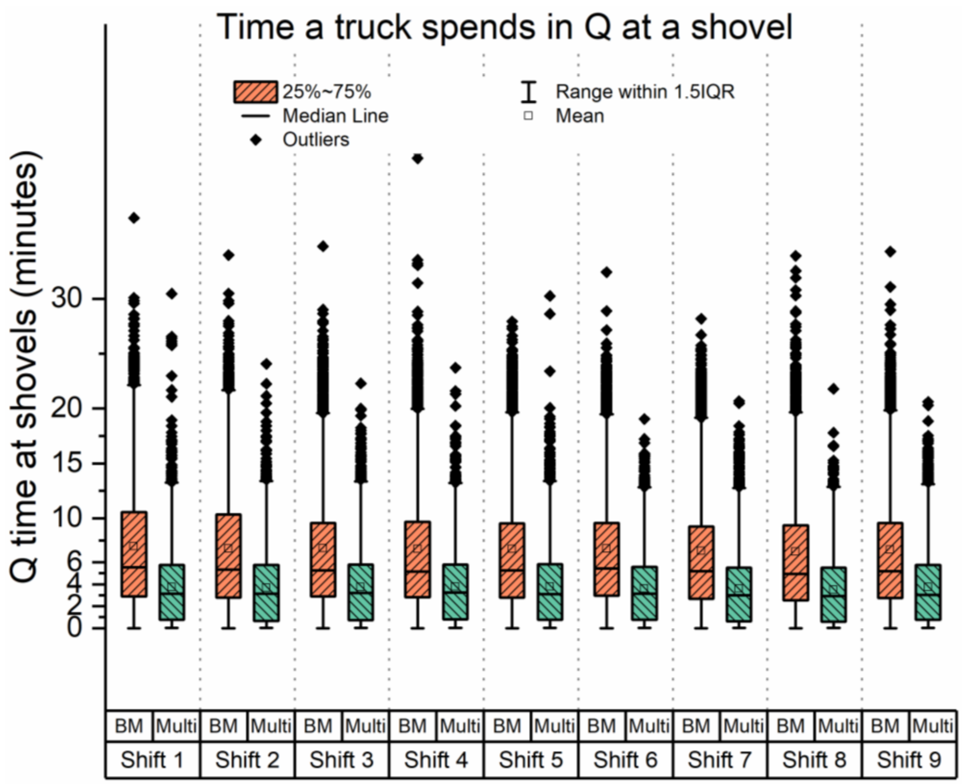

Figure 4.74: Queue time at shovels – optimum fleet of small trucks for MOGP (green boxes) versus optimum fleet of small trucks for BM (orange boxes)

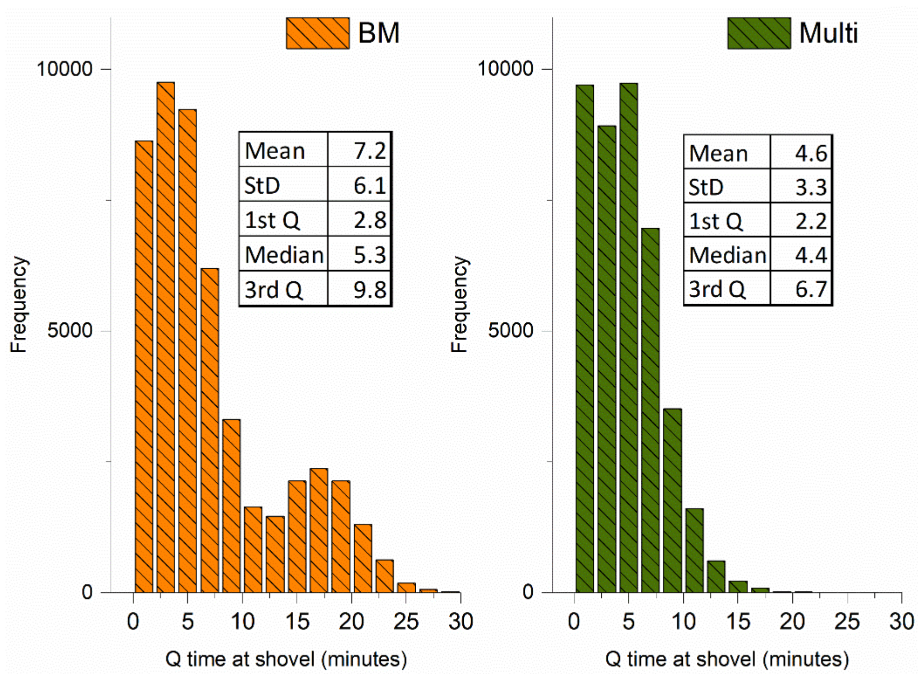

Figure 4.75: Histogram for time a truck spent in queue at shovels – optimum fleet of small trucks for MOGP (green bars) versus optimum fleet of small trucks for BM (orange bars)

4.5.4.5. Fleet of 17 large trucks

The first scenario among all the evaluated scenarios with the large trucks that met the production requirement in the case study was scenario 12 with 17 large trucks in its fleet and MOGP mathematical model as its truck-dispatching decision maker tool. Using fleet of 17 large trucks, the BM model met the total production requirement for each shift of the operation (Figure 4.76). However, it was not able to meet the shift by shift (Figure 4.78) and hourly (Figure 4.80) feed requirement for processing plant 1 and shift by shift (Figure 4.79) and hourly (Figure 4.81) feed requirement for processing plant 2. In contrast, the operation met all the production requirements when the BM model was replaced by the MOGP model. It met the production requirement (Figure 4.77), shift by shift (Figure 4.78) and hourly (Figure 4.80) feed requirement for processing plant 1 and shift by shift (Figure 4.79) and hourly (Figure 4.81) feed requirement for processing plant 2. For both the models, if there is any lineup in front of a shovel when a truck reaches there, there is only one truck waiting in queue (Figure 4.82) and truck needs to spend around 1.5 minutes in the queue (Figure 4.83). However, most of the time a truck reaches to a shovel when using MOGP model, there is no lineup in front of it (Figure 4.84).

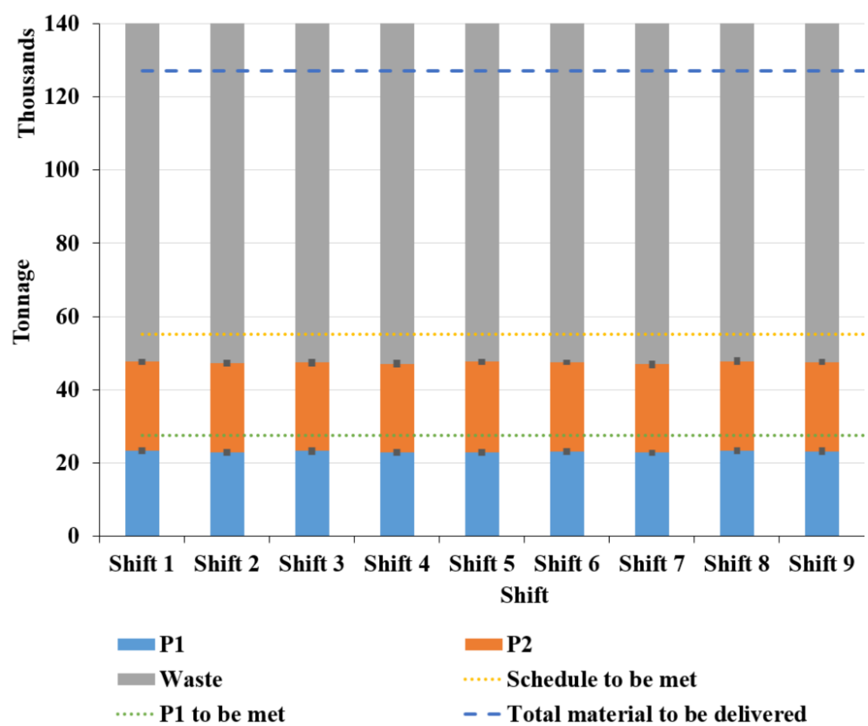

Figure 4.76: Shift by shift production – fleet of 17 large trucks – BM

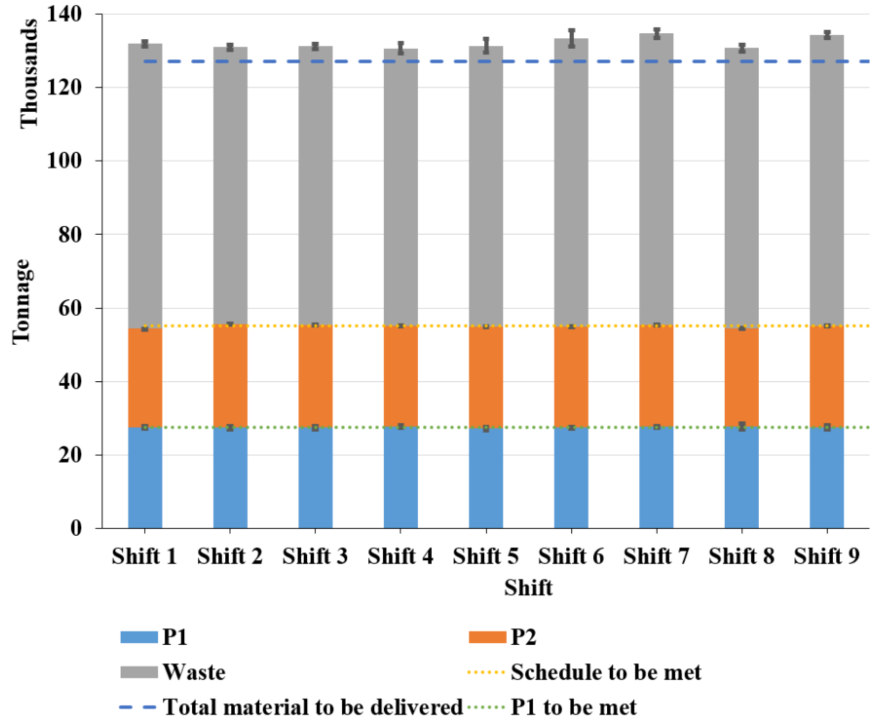

Figure 4.77: Shift by shift production – fleet of 17 large trucks – MOGP

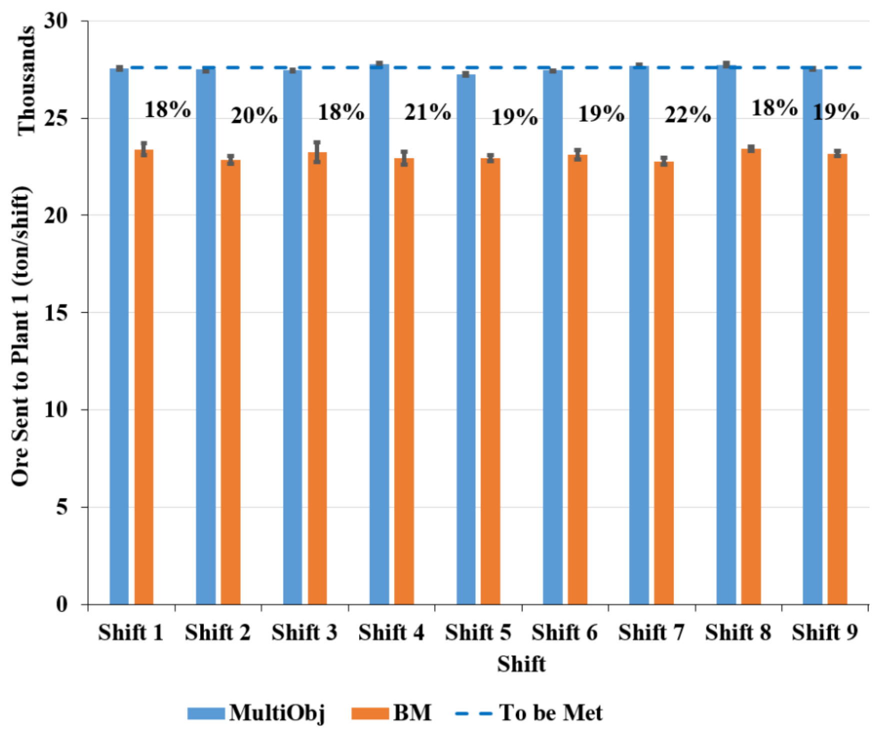

Figure 4.78: Ore sent to plant 1 – MOGP (blue bars) versus BM (orange bars) – shift by shift resolution – fleet of 17 large trucks

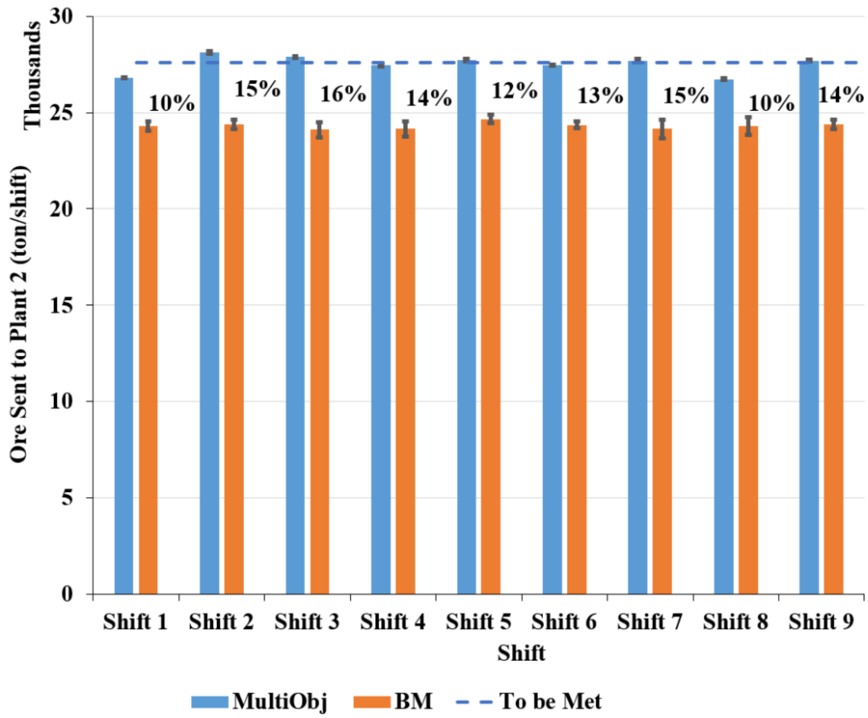

Figure 4.79: Ore sent to plant 2 – MOGP (blue bars) versus BM (orange bars) – shift by shift resolution – fleet of 17 large trucks

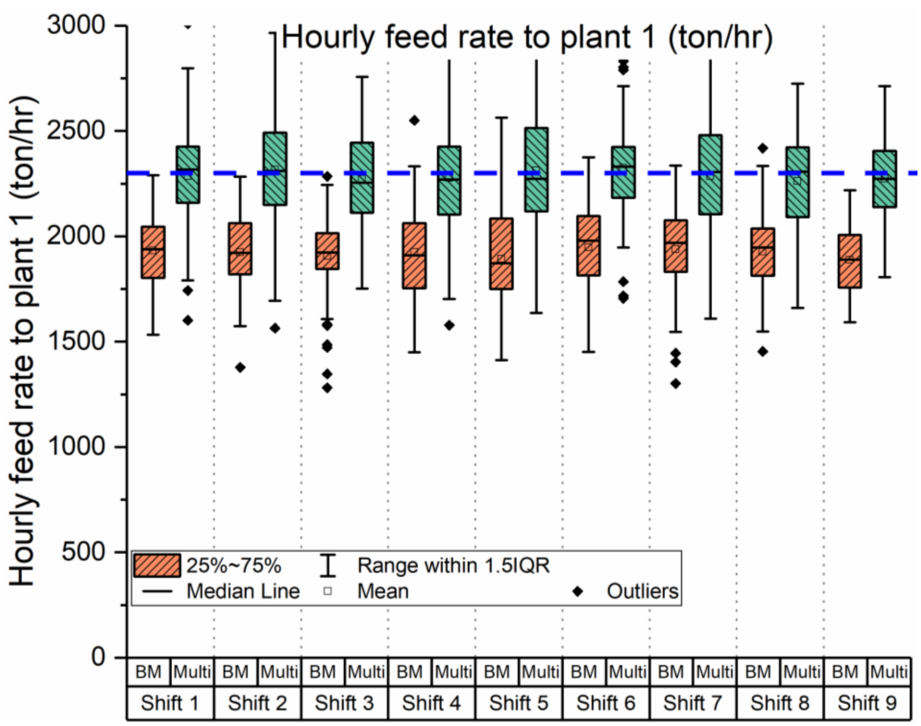

Figure 4.80: Hourly feed rate for plant 1 – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 17 large trucks

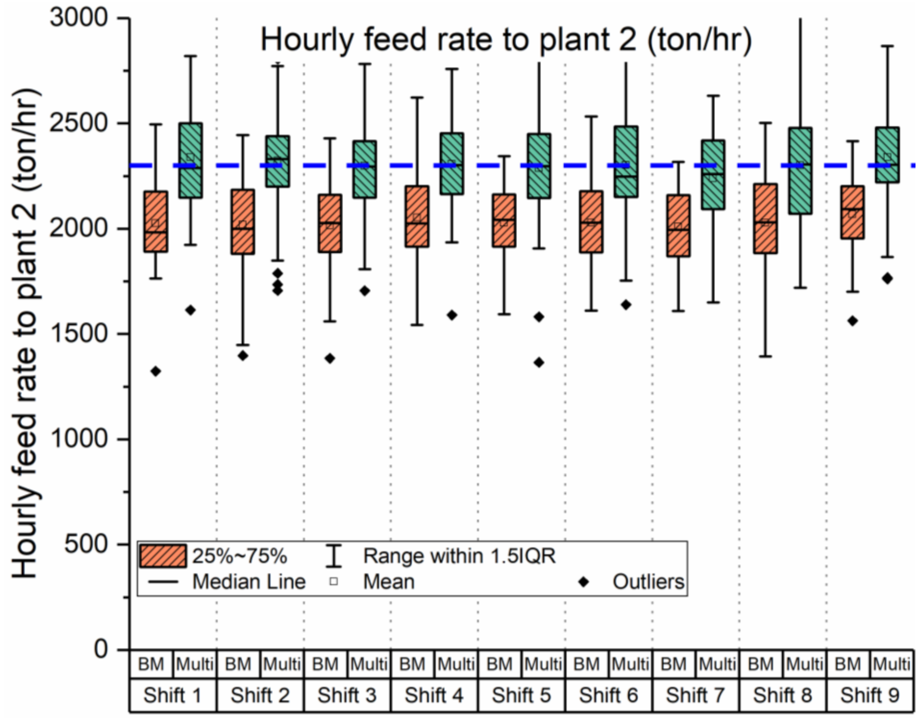

Figure 4.81: Hourly feed rate for plant 2 – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 17 large trucks

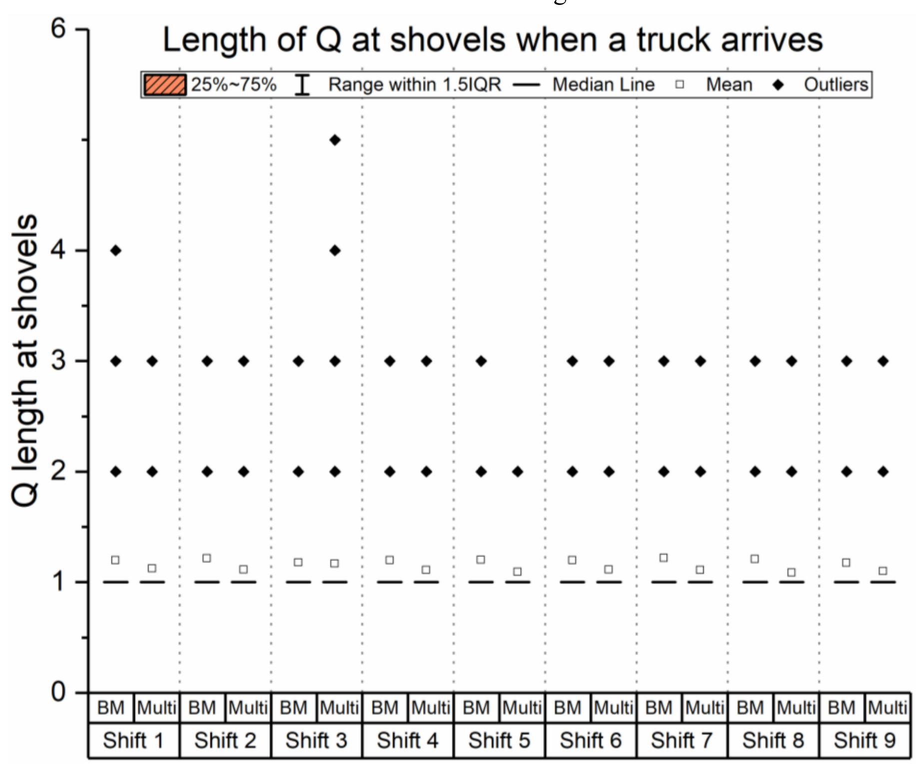

Figure 4.82: Length of queue at shovels – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 17 large trucks

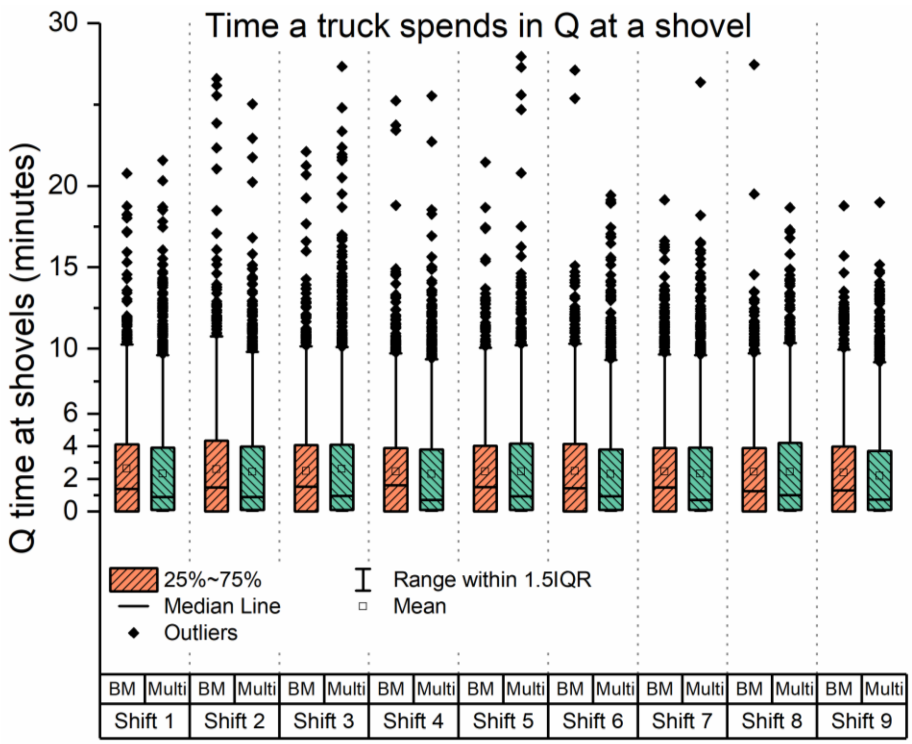

Figure 4.83: Queue time at shovels – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 17 large trucks

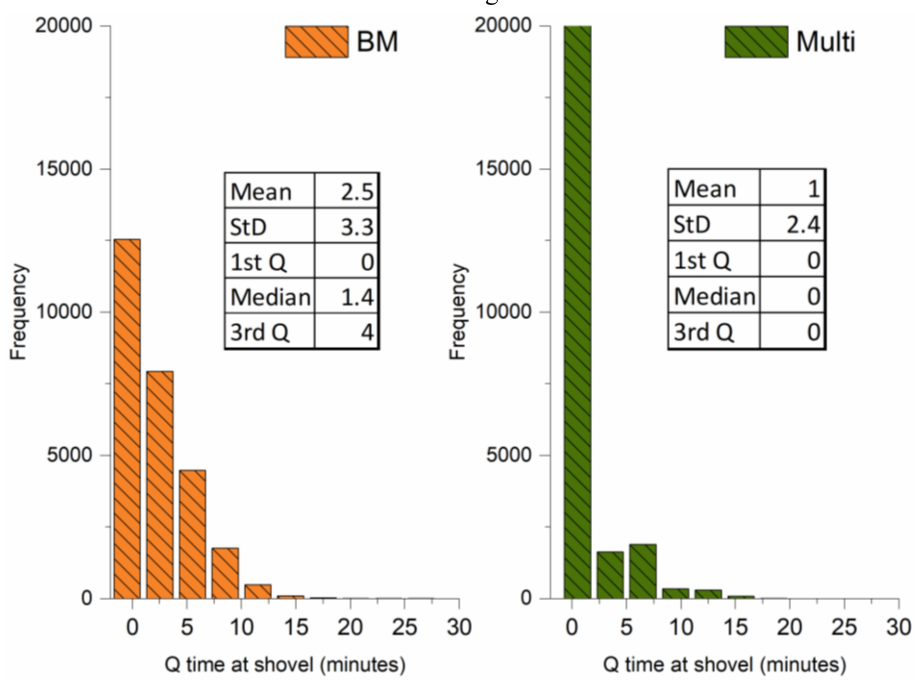

Figure 4.84: Histogram for time a truck spent in queue at shovels – MOGP (green bars) versus BM (orange bars) – shift by shift resolution – fleet of 17 large trucks

4.5.4.6. Fleet of 21 large trucks

Fleet of 21 large trucks (scenario 16) is the smallest fleet of large trucks that the operation of the case study was able to meet all the production requirement using the BM truck-dispatching model including ore + waste (Figure 4.85), shift by shift ore required to be sent to plant 1 (Figure 4.87), hourly plant 1 feed rate requirement (Figure 4.88), shift by shift ore required to be sent to plant 2 (Figure 4.89), and hourly plant 2 feed rate requirement (Figure 4.90). MOGP truck-dispatching models meets all the production requirement using a fleet of 21 large trucks (scenario 16) as well. As depicted by Figure 4.86, Figure 4.87, Figure 4.88, Figure 4.89, and Figure 4.90, it met total production requirement, shift by shift plants' input requirement, and hourly plants' feed rate requirement. when using MOGP model instead of BM model, queue lengths at shovels are shorter (Figure 4.91) that results in shorter queue time at shovels for trucks (Figure 4.92), and consequently less deviation in plants feed rates (Figure 4.89 and Figure 4.90).

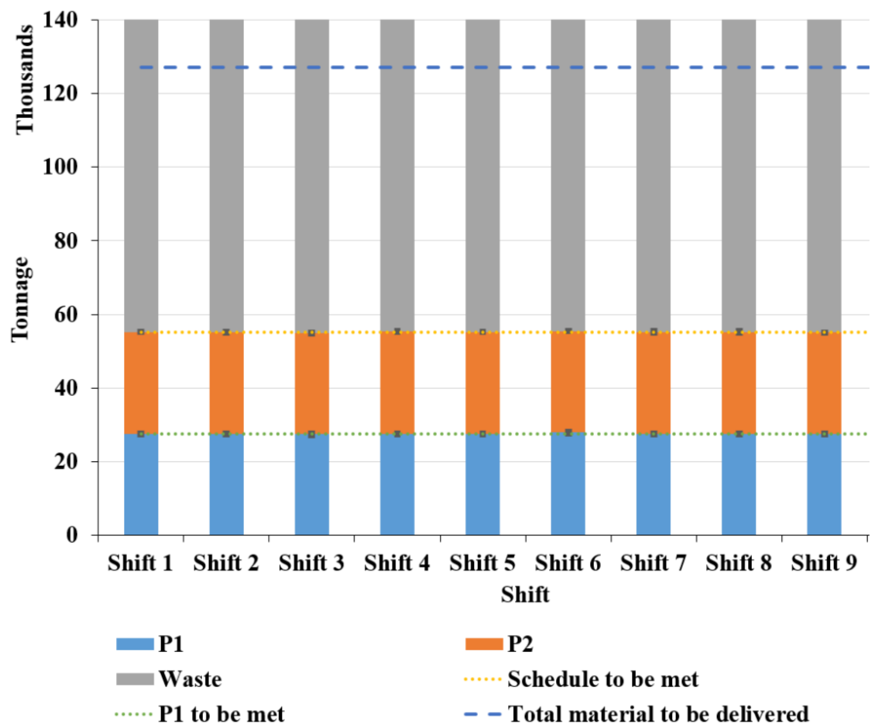

Figure 4.85: Shift by shift production – fleet of 21 large trucks – BM

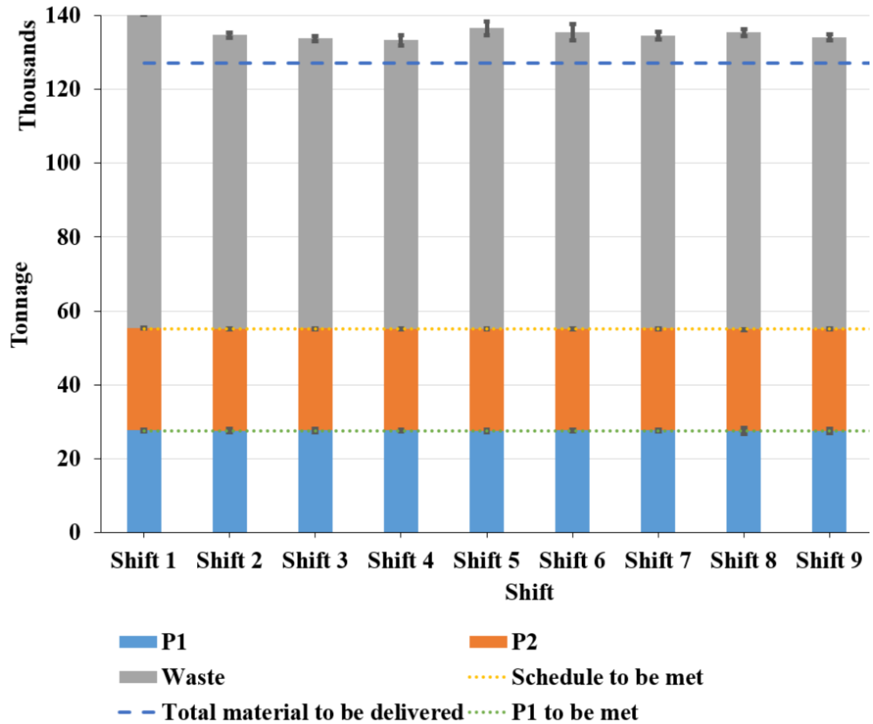

Figure 4.86: Shift by shift production – fleet of 21 large trucks – MOGP

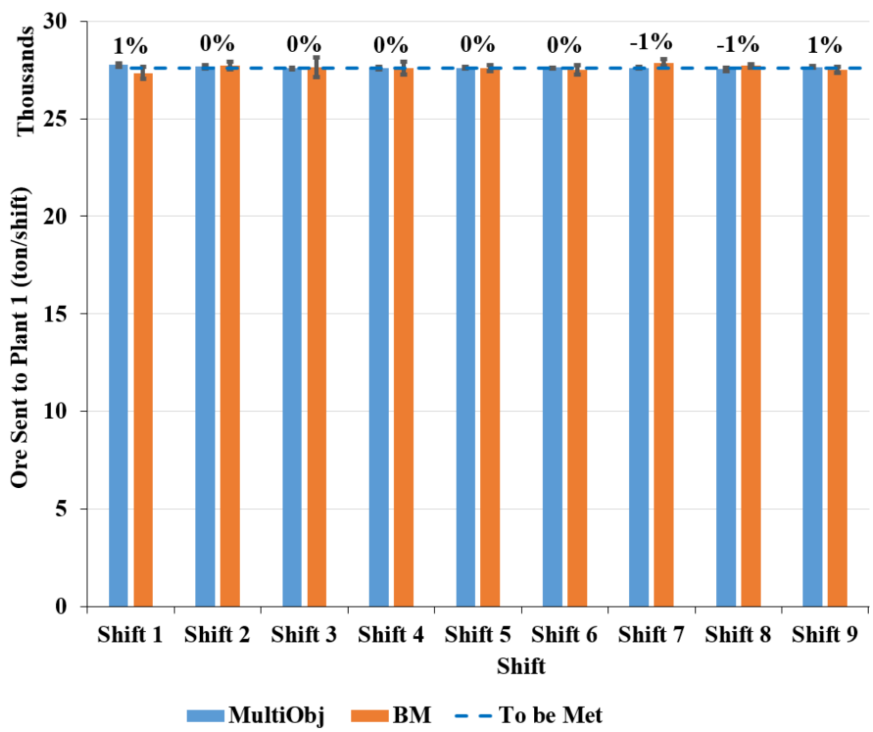

Figure 4.87: Ore sent to plant 1 – MOGP (blue bars) versus BM (orange bars) – shift by shift resolution – fleet of 21 large trucks

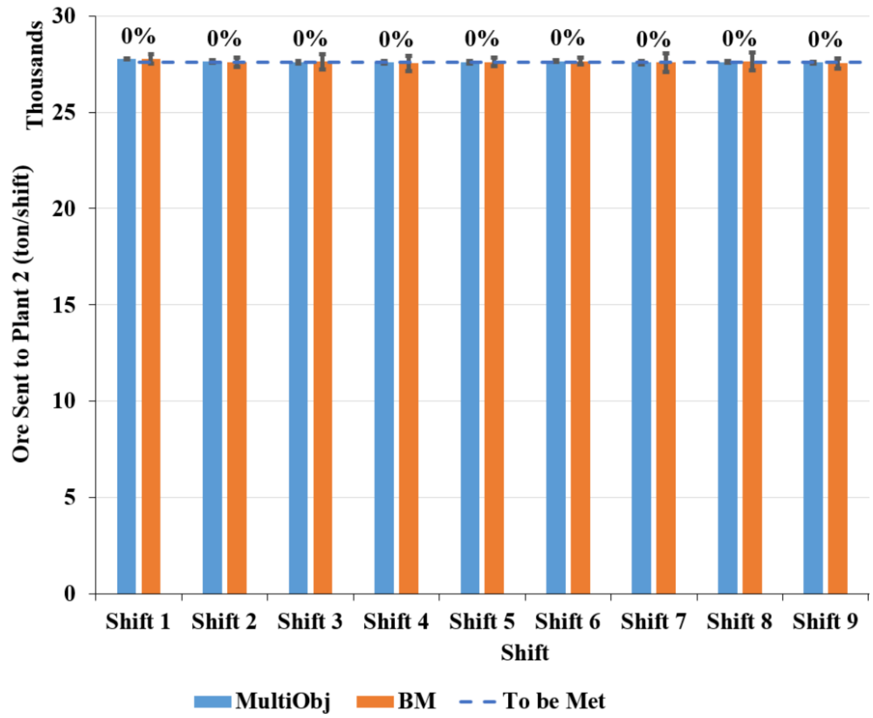

Figure 4.88: Ore sent to plant 2 – MOGP (blue bars) versus BM (orange bars) – shift by shift resolution – fleet of 21 large trucks

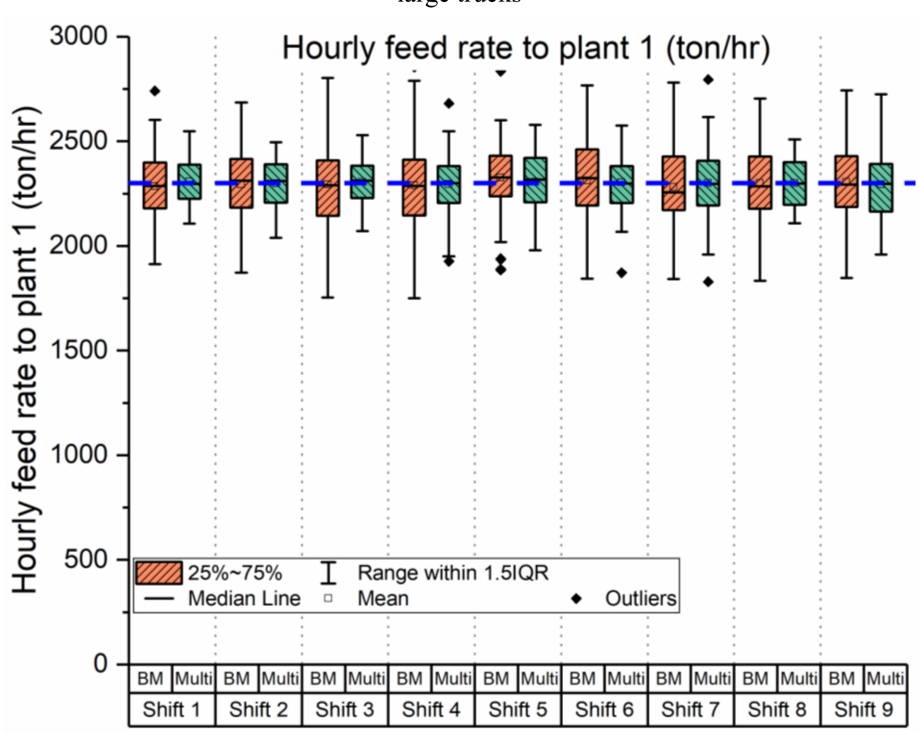

Figure 4.89: Hourly feed rate for plant 1 – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 21 large trucks

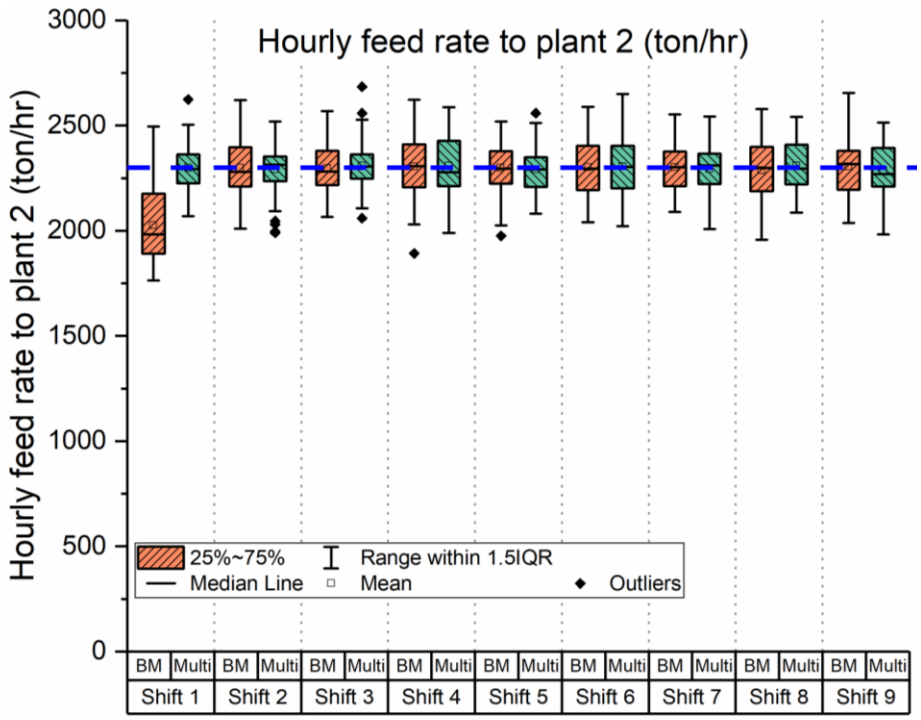

Figure 4.90: Hourly feed rate for plant 2 – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 21 large trucks

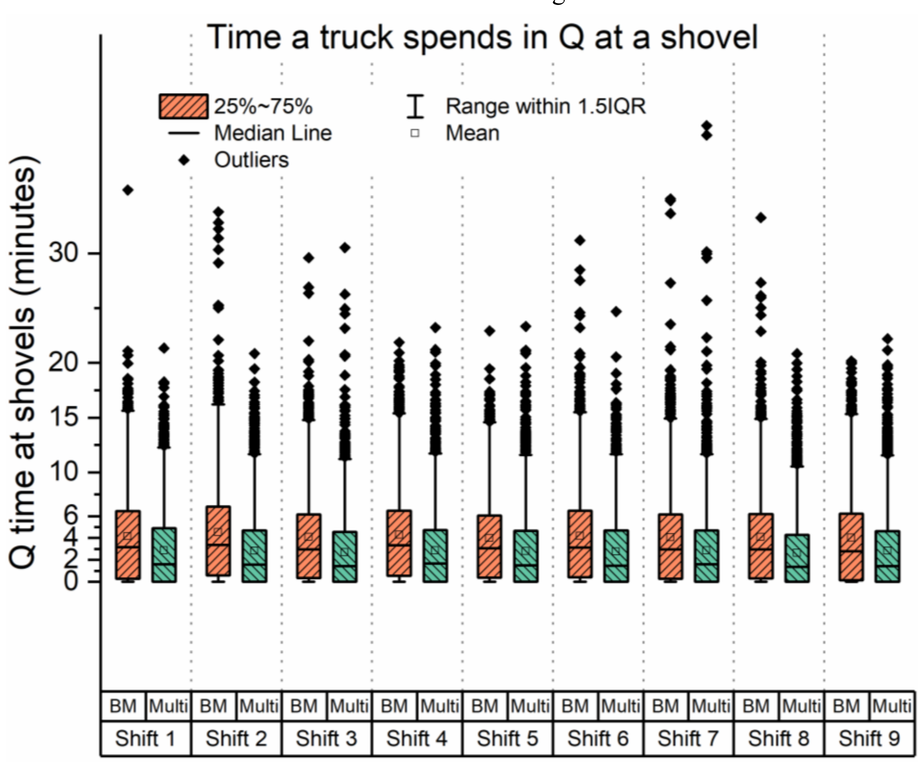

Figure 4.91: Length of queue at shovels – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 21 large trucks

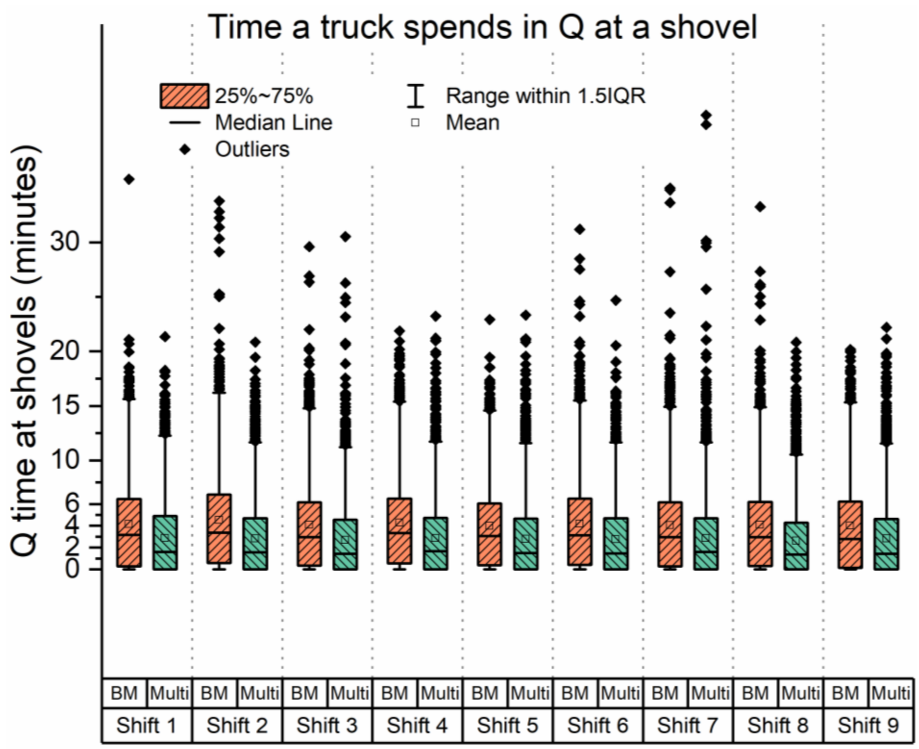

Figure 4.92: Queue time at shovels – MOGP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 21 large trucks

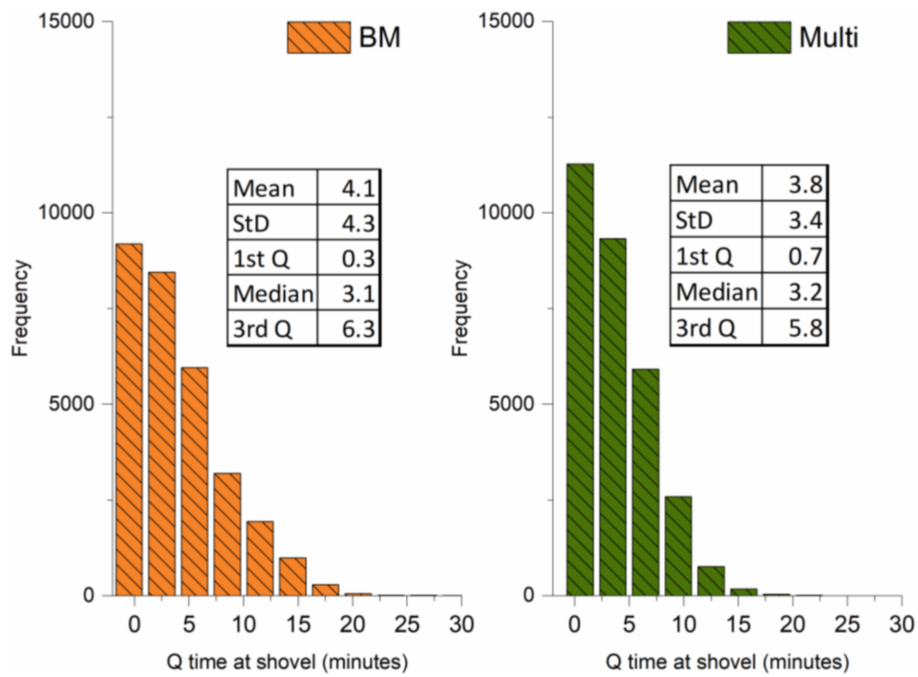

Figure 4.93: Histogram for time a truck spent in queue at shovels – MOGP (green bars) versus BM (orange bars) – fleet of 21 large trucks

4.5.4.7. Fleet of 17 large trucks with MOGP and 21 large trucks with BM

The least possible number of large trucks required to meet all the production requirement of the case study with the BM truck-dispatching model was scenario 16 with 21 large trucks. However, by replacing the BM truck-dispatching model with the MOGP truck-dispatching model, we were able to meet the production requirement of the operation with fleet of 17 large trucks (scenario 12). Although using both scenarios the production requirement of the operation was met, using MOGP truck-dispatching model resulted in using of a fleet with 19% less number of trucks than BM truck-dispatching model. This consequently improved number of trucks in queue at shovels (Figure 4.96) and time each truck spent in queue at shovels (Figure 4.97 and Figure 4.98). However, by implementing 17 large trucks instead of 21 large trucks, the deviation from the hourly feed rated increased for both processing plants (Figure 4.94 and Figure 4.95) due to having less number of trucks in the operation to consistently feed the plants.

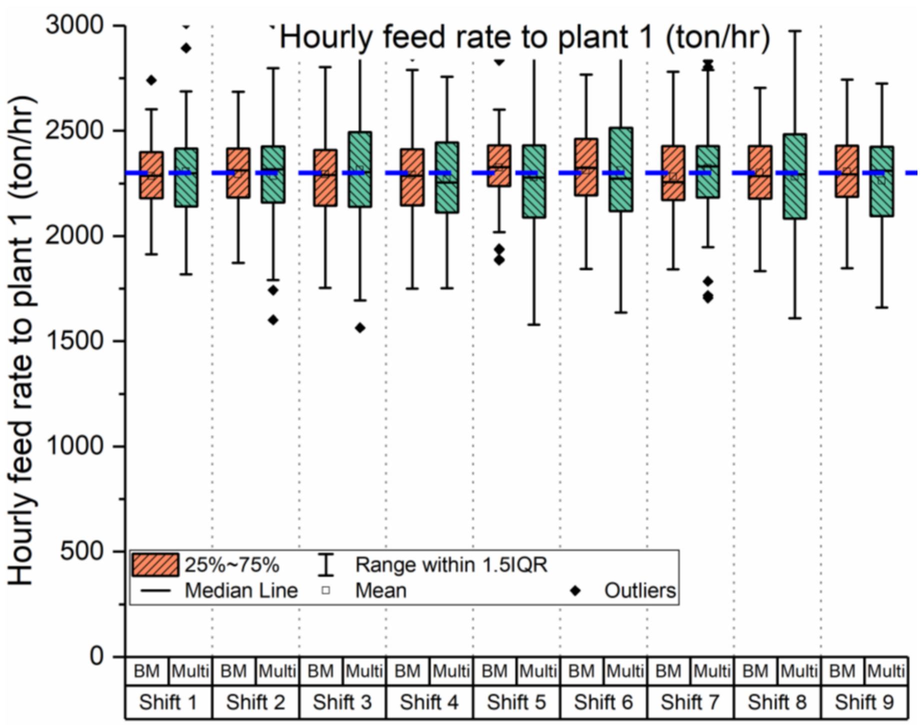

Figure 4.94: Hourly feed rate for plant 1 – optimum fleet of large trucks for MOGP (green boxes) versus optimum fleet of large trucks for BM (orange boxes)

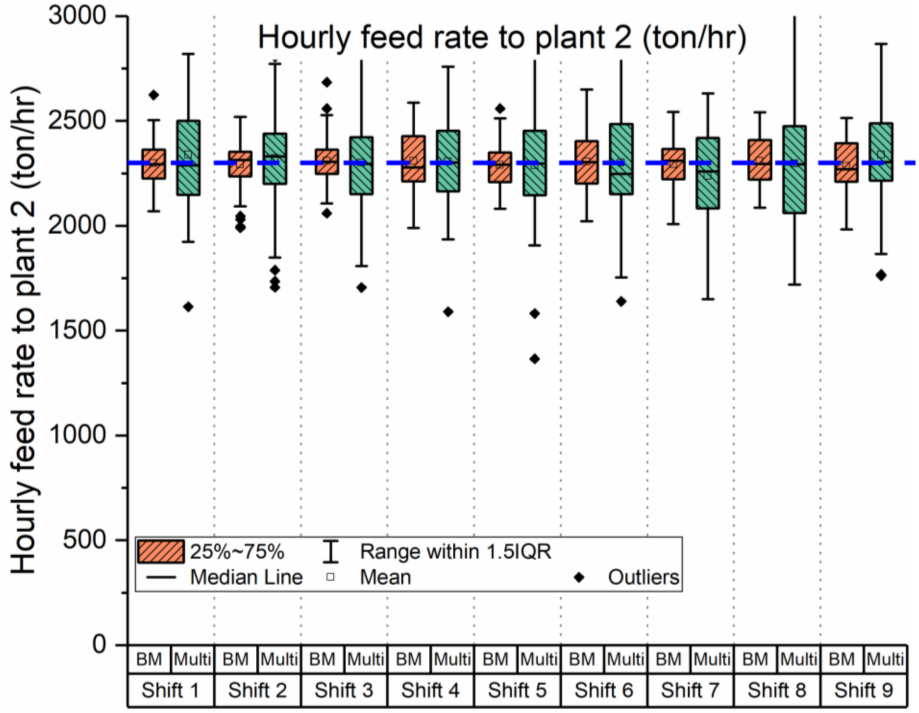

Figure 4.95: Hourly feed rate for plant 2 – optimum fleet of large trucks for MOGP (green boxes) versus optimum fleet of large trucks for BM (orange boxes)

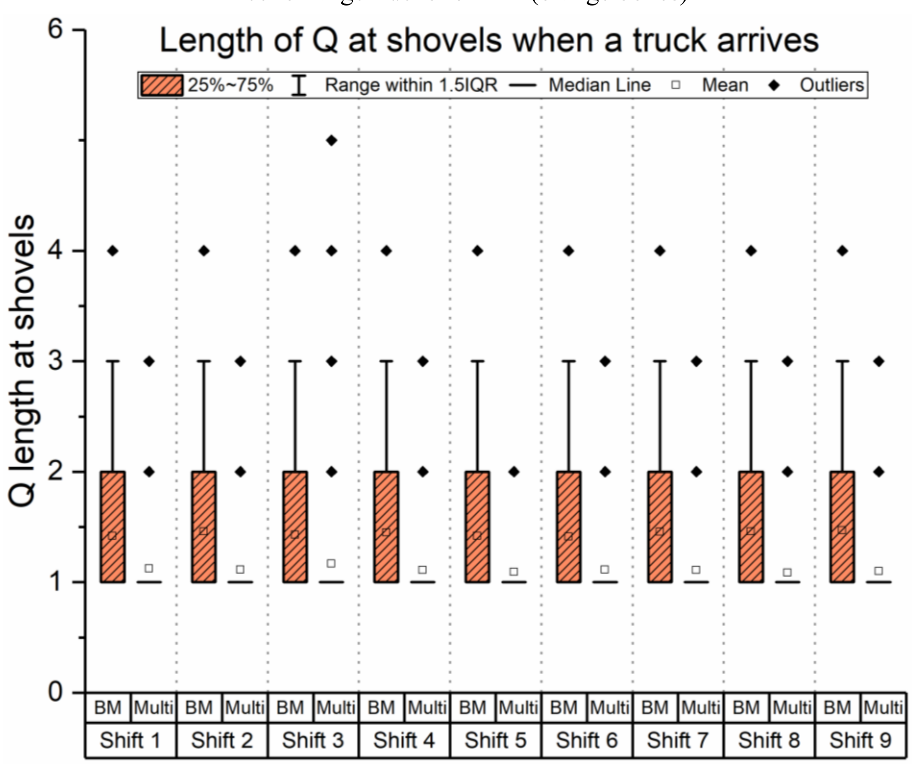

Figure 4.96: Length of queue at shovels – optimum fleet of large trucks for MOGP (green boxes) versus optimum fleet of large trucks for BM (orange boxes)

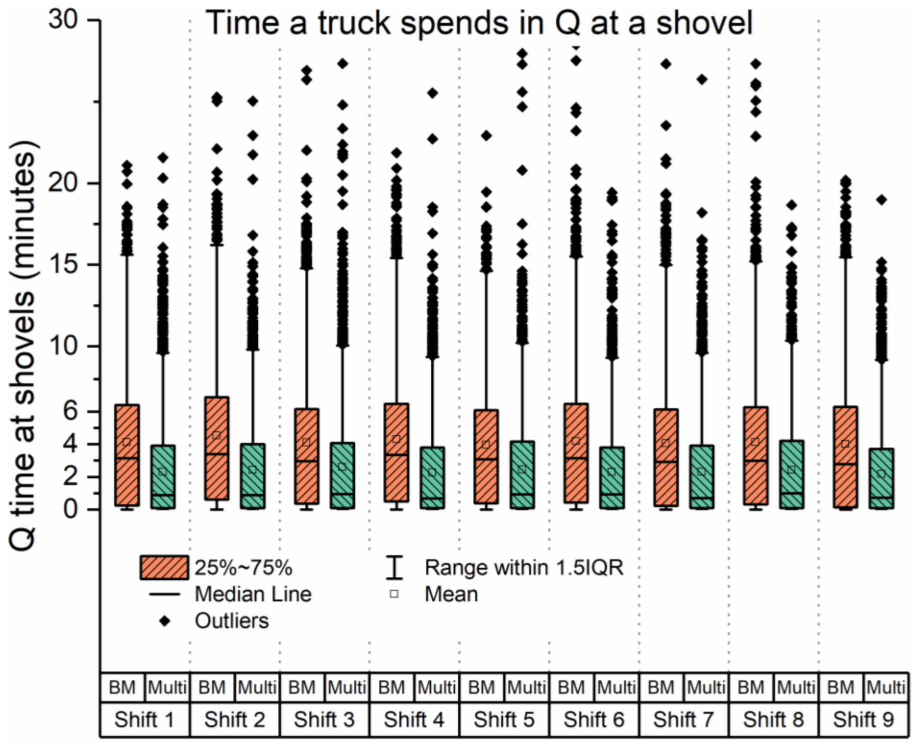

Figure 4.97: Queue time at shovels – optimum fleet of large trucks for MOGP (green boxes) versus optimum fleet of large trucks for BM (orange boxes)

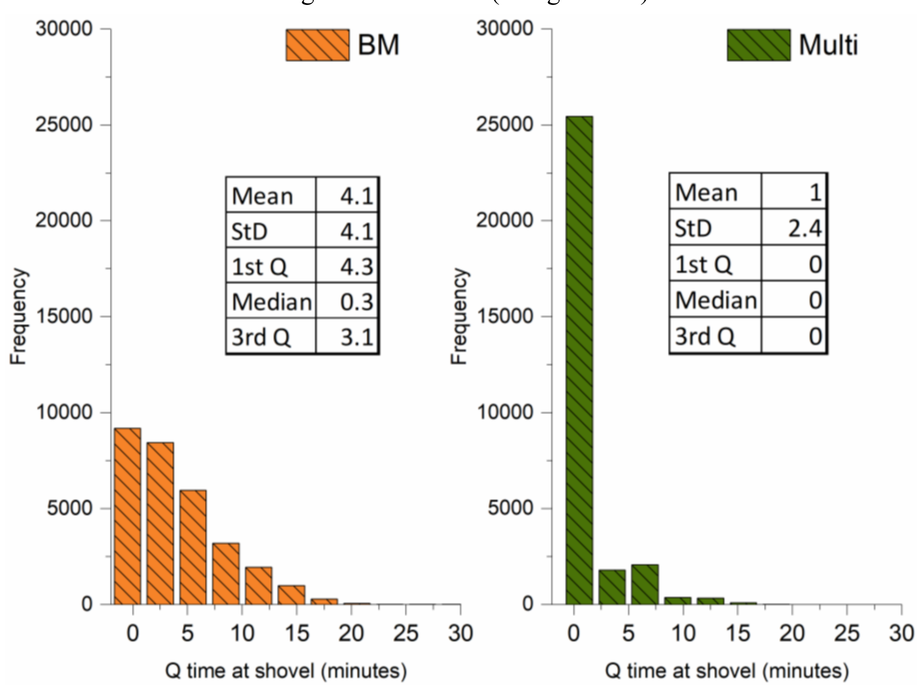

Figure 4.98: Histogram for time a truck spent in queue at shovels – optimum fleet of large trucks for MOGP (green boxes) versus optimum fleet of large trucks for BM (orange boxes)

4.5.4.8. Mixed fleet of 8 small trucks

In the category of heterogeneous scenarios, we evaluated three scenarios in higher resolution based on the flexibility of the scenarios: scenario 18 with mixed fleet of 8 small trucks as the least flexible scenario, scenario 21 with mixed fleet of 14 small trucks as a moderately flexible scenario, and scenario 26 with mixed fleet of 24 small trucks as the most flexible scenario (Table 4.10).

It is worth noting that, as all the mixed fleet scenarios meet production requirements in weekly resolution, shift by shift resolution, and hourly resolution level, we only present truck related KPIs.

In scenario 18, where the operation needs to meet the production target with 8 small trucks in the fleet, using BM model to make truck-dispatching decisions, the material handling system needs 16 large trucks to meet the production requirement. Whereas, the operation can meet the production target by adding 14 trucks (87.5% of what BM model needs) by replacing the BM model with the developed MOGP model. This consequently resulted in reduction in length of truck queue at shovels (Figure 4.99) and the time a truck spent in queue (Figure 4.100 and Figure 4.101).

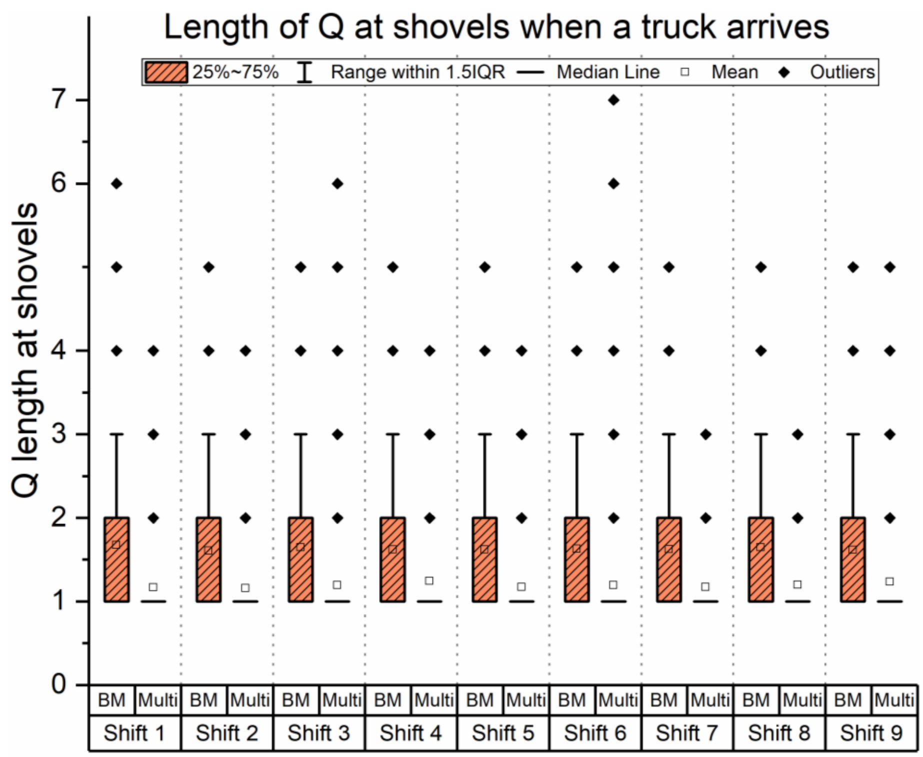

Figure 4.99: Length of queue at shovels – mixed fleet of 8 small trucks – MOGP (green boxes) versus BM (orange boxes)

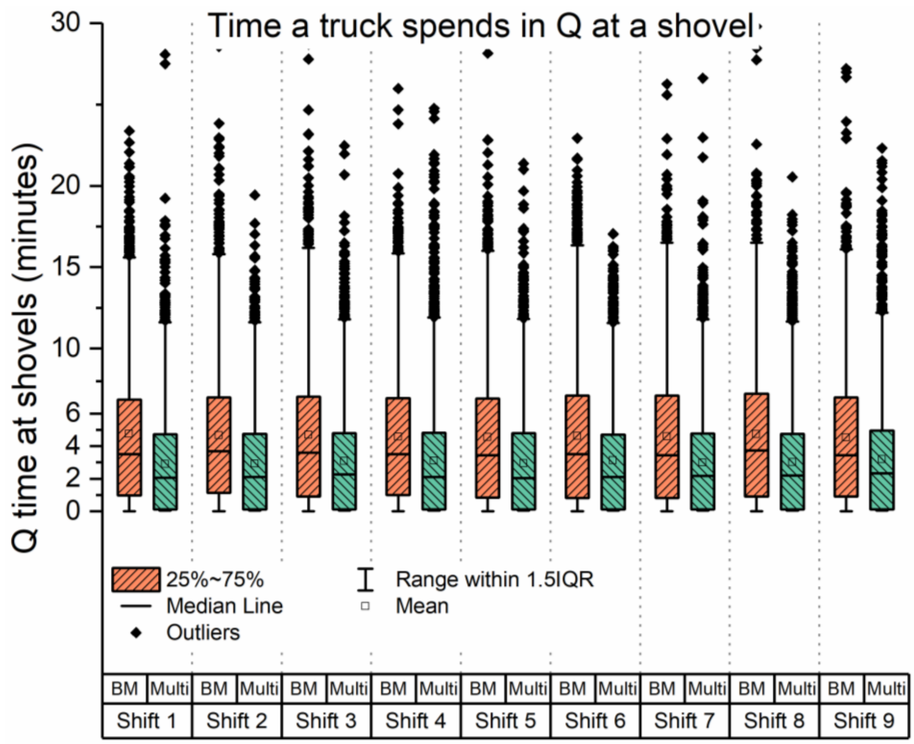

Figure 4.100: Queue time at shovels – mixed fleet of 8 small trucks – MOGP (green boxes) versus BM (orange boxes)

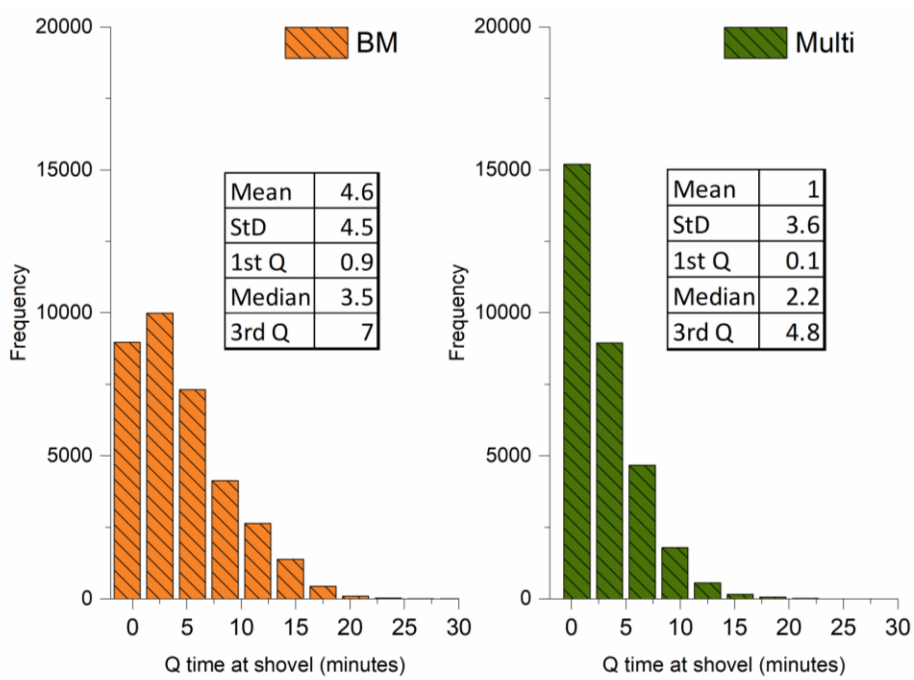

Figure 4.101: Histogram for time a truck spent in queue at shovels – mixed fleet of 8 small trucks –MOGP (green bars) versus BM (orange bars)

4.5.4.9. Mixed fleet of 14 small trucks

We evaluated a moderately flexible scenario (scenario 21) with 14 small trucks in its fleet. Although using both the truck-dispatching models the fleet met the production requirements, the MOGP model needed less trucks to do so. The MOGP model was able to meet the required production target with 11 large trucks. It is 15% less than 13 large trucks required by BM model to meet the production target. Meeting production target with less number of trucks in the fleet helped the truck fleet to face queue with an average length of one in front of shovels compared to facing a queue with an average length of two when using BM model (Figure 4.102). Figure 4.103 and Figure 4.104 show that by replacing the BM model with the MOGP model, time a truck spent in queue at shovels reduced for around two minutes.

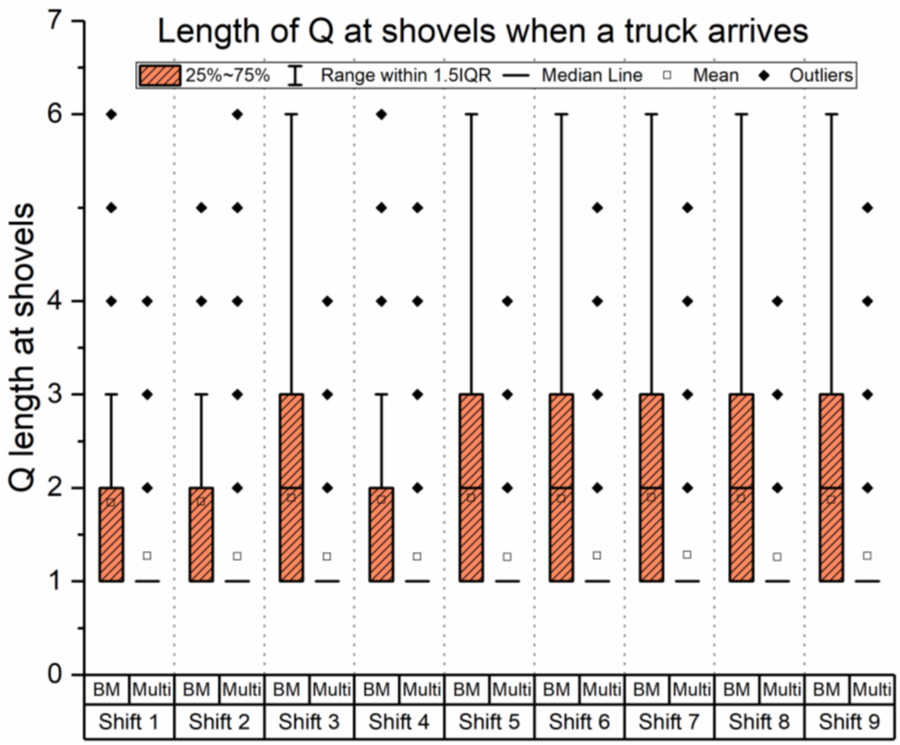

Figure 4.102: Length of queue at shovels – mixed fleet of 14 small trucks – MOGP (green boxes) versus BM (orange boxes)

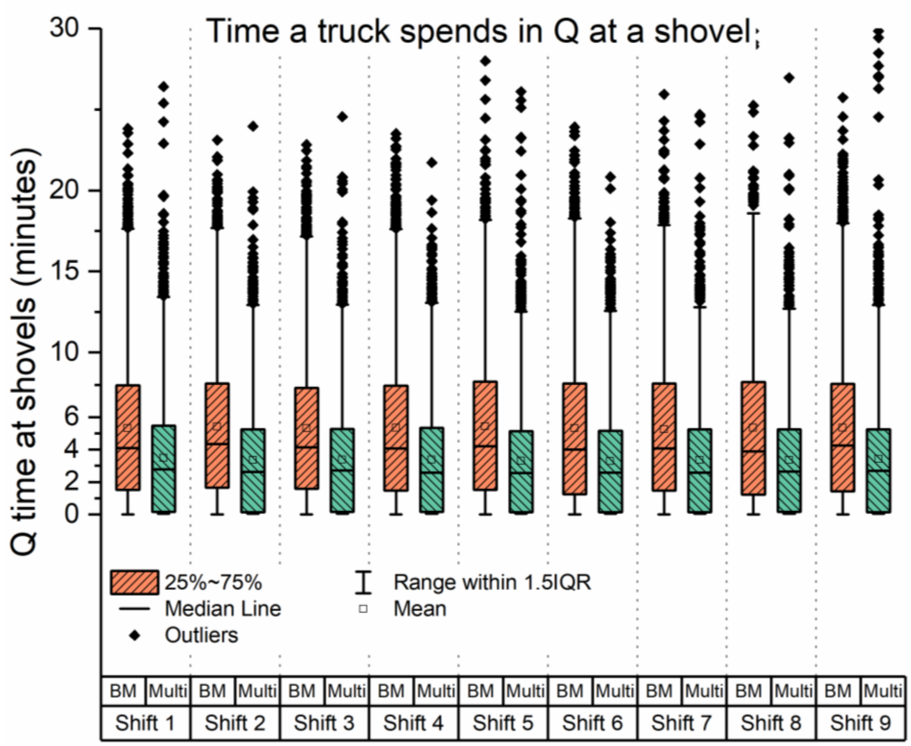

Figure 4.103: Queue time at shovels – mixed fleet of 14 small trucks – MOGP (green boxes) versus BM (orange boxes)

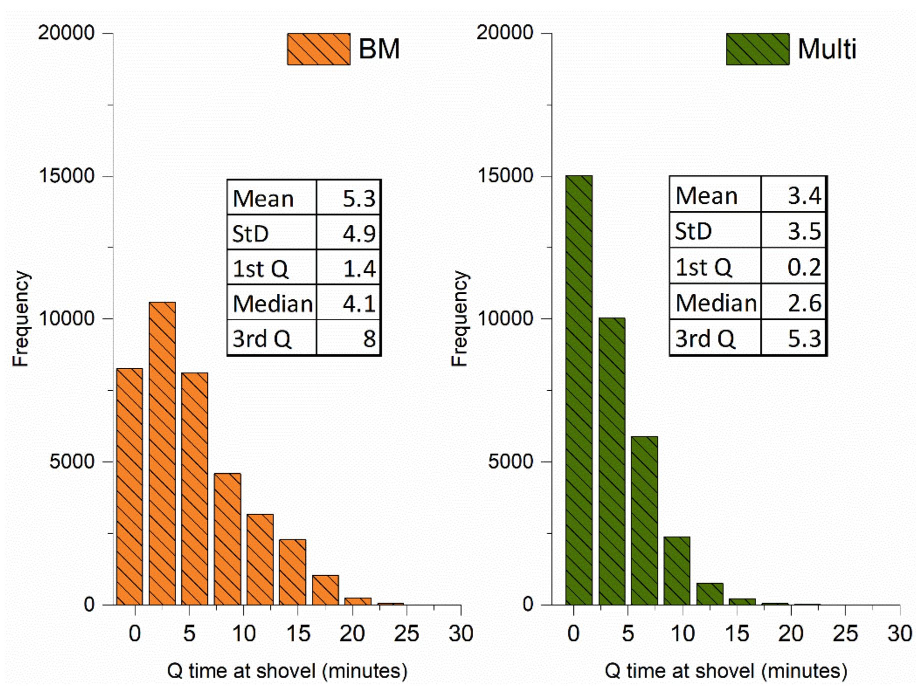

Figure 4.104: Histogram for time a truck spent in queue at shovels – mixed fleet of 14 small trucks –MOGP (green bars) versus BM (orange bars)

4.5.4.10. Mixed fleet of 24 small trucks

Data analysis on the most flexible mixed fleet scenario (scenario 26) showed that the MOGP model met the production requirement with a fleet of 24 small trucks and 2 large trucks (26 trucks in total). The same analysis also showed that the BM truck-dispatching model required a fleet of 24 small trucks and 7 large trucks (31 trucks in total) to meet the production target. This 71.4% reduction in the required number of large trucks in fleet consequently results in decrease in queue length (Figure 4.105) and queue time at shovels (Figure 4.106 and Figure 4.107).

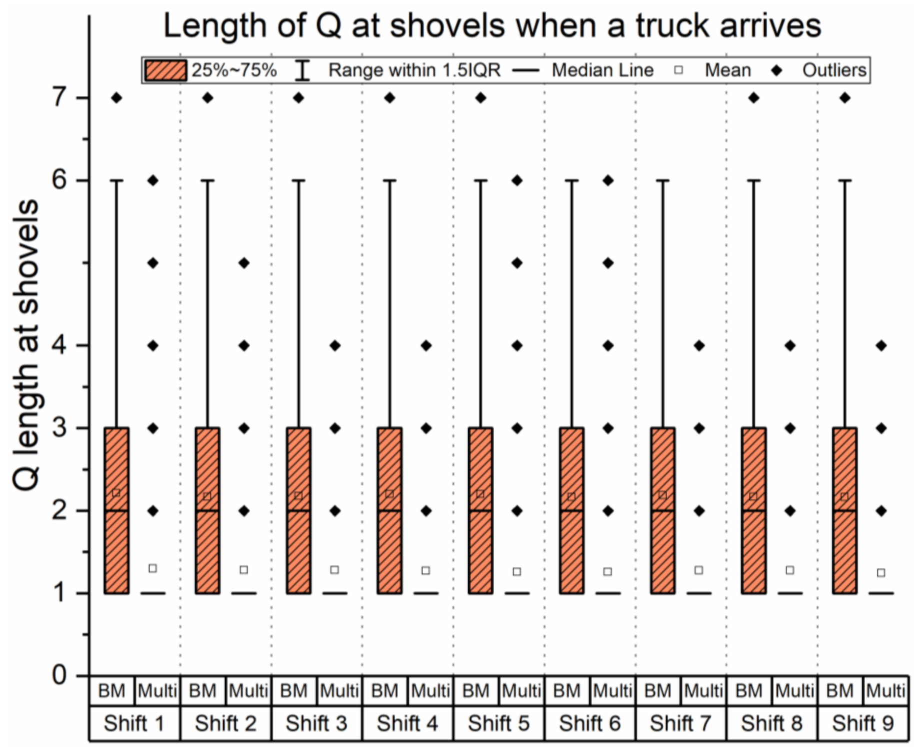

Figure 4.105: Length of queue at shovels – mixed fleet of 24 small trucks – MOGP (green boxes) versus BM (orange boxes)

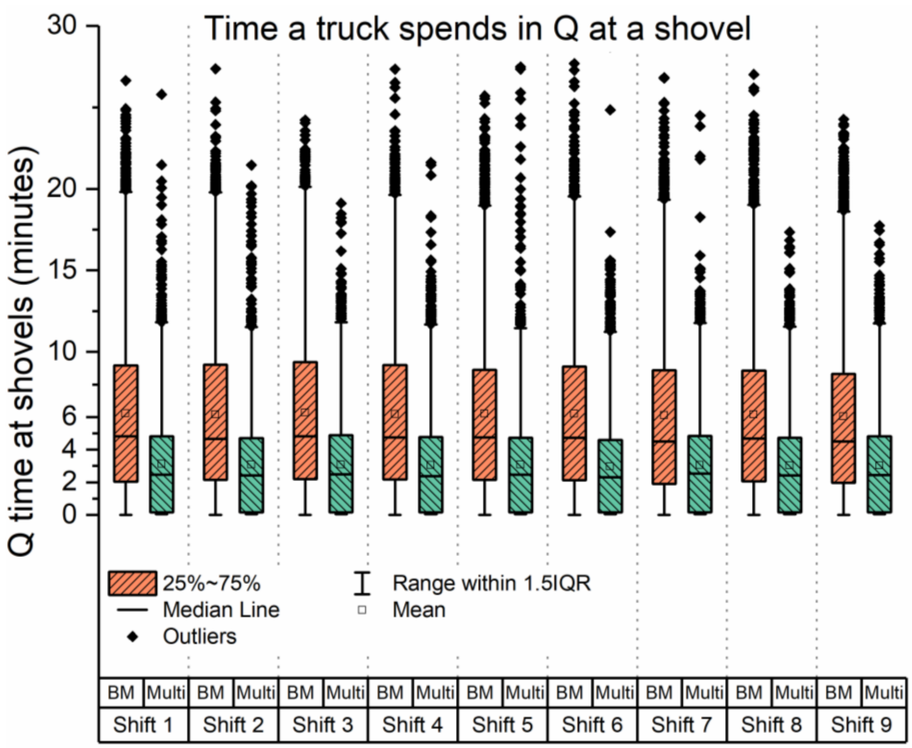

Figure 4.106: Queue time at shovels – mixed fleet of 24 small trucks – MOGP (green boxes) versus BM (orange boxes)

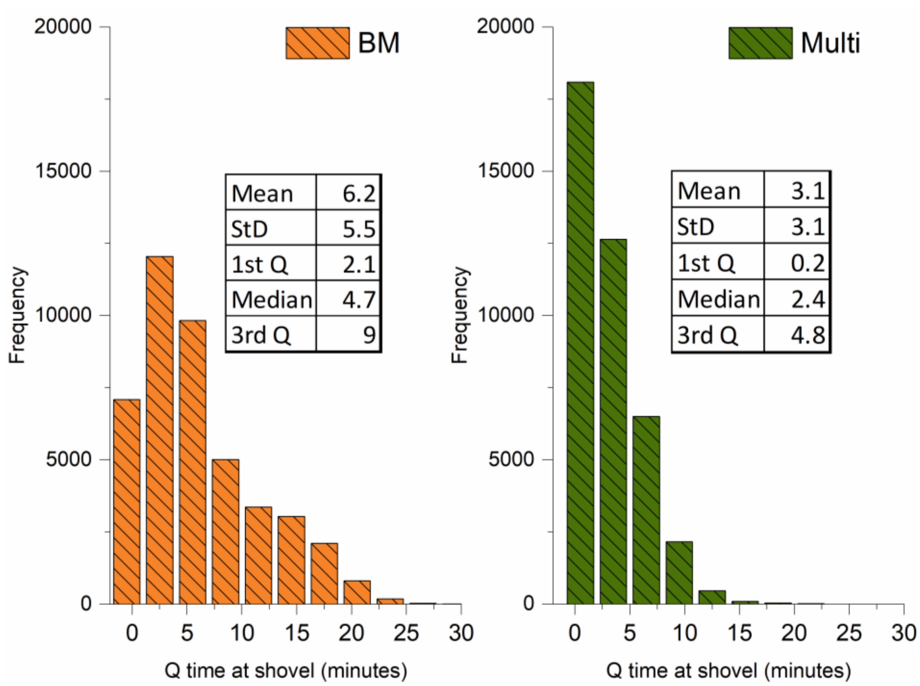

Figure 4.107: Histogram for time a truck spent in queue at shovels – mixed fleet of 24 small trucks –MOGP (green bars) versus BM (orange bars)

Statistical summary of all the scenarios are presented in Table 4.11 for the small trucks fleets, Table 4.12 for the large trucks fleets, and Table 4.13 for the mixed fleets.

Table 4.11: The results of implementing different small truck scenarios in the mining operation of the case study

Scenario	Fleet Size	Meet the production?		Average Q Length			Sum Q time (hr)			Truck Utilization (%)			Shovel Utilization (%)		
		BM	Multi	BM	Multi	%Dif	BM	Multi	%Dif	BM	Multi	%Dif	BM	Multi	%Dif
1	20	NO	NO	1.3	1.1	15	1207	1137	6	90	91	1	73	70	4
2	22	NO	NO	1.4	1.2	14	1625	1361	16	88	90	2	78	76	3
3	24	NO	NO	1.6	1.2	25	2129	1833	14	85	87	2	83	81	2
4	26	NO	NO	1.7	1.3	24	2783	2197	21	82	86	5	86	85	1
5	28	NO	NO	1.9	1.3	32	3475	2532	27	79	85	7	90	86	4
6	30	NO	NO	2.1	1.4	33	4259	2836	33	76	84	10	92	86	7
7	32	NO	YES	2.3	1.4	39	5102	3202	37	73	83	12	95	88	7
8	34	NO	YES	2.4	1.5	38	5924	3541	40	71	83	14	97	90	7
9	36	YES	YES	2.5	1.6	36	6574	3867	41	70	82	15	98	90	8

As presented in Table 4.11, a fleet of 36 small trucks is capable of meeting production requirements using either of the two truck-dispatching models. However, a fleet of 32 small trucks is sufficient if the mine uses the MOGP model. Reducing the size of the fleet by 5 trucks can result in significant capital and operational costs.

In the case study, there is a possibility to use a fleet of trucks with higher capacities. The deterministic calculations for the case study operation suggests 28 large trucks will serve the production purposes. To find the optimum number of large trucks to meet the production requirements using the developed framework, 8 under-truck scenarios (scenario 10 to scenario 17) were tested for the case study. The results of the implementation are summarized in Table 4.12.

Table 4.12: Results of implementing different large truck scenarios in the mining operation of the case study

Scenario	Fleet Size	Meet the production?		Average Q Length			Sum Q time (hr)			Truck Utilization (%)			Shovel Utilization (%)		
		BM	Multi	BM	Multi	%Dif	BM	Multi	%Dif	BM	Multi	%Dif	BM	Multi	%Dif
10	15	NO	NO	1.1	1.1	0	843	851	-1	91	91	0	73	67	8
11	16	NO	NO	1.2	1.1	8	1040	964	7	89	90	1	77	71	8
12	17	NO	YES	1.2	1.1	8	1258	1070	15	88	90	2	80	73	9
13	18	NO	YES	1.2	1.1	8	1510	1143	24	86	89	3	83	72	13
14	19	NO	YES	1.3	1.1	15	1802	1218	32	84	89	6	86	74	14
15	20	NO	YES	1.4	1.2	14	2114	1276	40	82	89	8	88	74	16
16	21	YES	YES	1.4	1.2	14	2321	1309	44	82	90	9	89	75	16
17	22	YES	YES	1.5	1.2	20	2469	1448	41	81	89	9	89	76	15

As presented in Table 4.12, a fleet of 21 large trucks can meet the production requirements using either of the two truck-dispatching models. However, a fleet of 17 large trucks is sufficient if the mine uses the MOGP model. The mining operation can meet the production target with 17 trucks if they are using the BM model, or with 17 trucks if they are using the MOGP model.

We also implemented the developed integrated framework on scenarios with different combinations of types of trucks to deal with the truck fleet size determination in the case study. Table 4.13 lists all the optimum fleets of trucks to meet the production demand when we used the heterogeneous fleet of trucks.

Table 4.13: Results of implementing different optimum mixed fleets in the mining operation of the case study

Scenario	**Fleet Size**			**Meet the production?**		**Average Q Length**			**Sum Q time (hr)**			**Truck Utilization (%)**			**Shovel Utilization (%)**		
	Small	Large															
		BM	Multi	BM	Multi	BM	Multi	%Dif	BM	Multi	%Dif	BM	Multi	%Dif	BM	Multi	%Dif
18	8	16	14	YES	YES	1.6	1.2	25	3003	1784	41	79	86	8	91	92	1
19	10	15	14	YES	YES	1.7	1.3	24	3273	2034	38	78	86	9	92	92	0
20	12	14	12	YES	YES	1.8	1.3	28	3543	2027	43	77	86	10	91	92	1
21	14	13	11	YES	YES	1.9	1.3	32	3812	2165	43	76	86	12	91	92	1
22	16	12	10	YES	YES	2	1.3	35	4118	2299	44	76	85	11	91	92	1
23	18	12	8	YES	YES	2.1	1.3	38	4695	2394	49	74	85	13	91	92	1
24	20	10	6	YES	YES	2.1	1.3	38	4684	2338	50	74	85	13	91	92	1
25	22	8	4	YES	YES	2.1	1.3	38	4683	2298	51	74	85	13	91	92	1
26	24	7	2	YES	YES	2.2	1.3	41	4984	2262	55	73	86	15	91	92	1

We started the heterogeneous fleet scenarios with scenario 18 including 8 small trucks. For each new scenario we first increased the number of small trucks by adding two extra trucks to the fleet up to 24 small trucks. Afterwards, fixing the number of the small trucks in the fleet, we calculated the required number of large trucks using the deterministic calculation method. For example, the deterministic calculation showed that the case study will meet the production demand with 37 small trucks. However, in scenario 18 we have 8 small trucks available. We need to complete the rest of the required with large trucks. It means that we need to substitute 29 trucks of 140 tonne capacity with 240-ton capacity trucks. The result of the calculation ([(29*140/240)]+1 =17) shows that without any fleet management system, the operation needs 17 large trucks to meet the production demand when 8 small trucks are available. This number is the starting point for the number of large trucks to meet the production demand using 8 small trucks. However, herein, we developed an integrated simulation and optimization framework that can add fleet management system to the operation evaluation of any surface mine. Thus, adding the value of the decision maker tools, we tested different under-truck scenarios to find the minimum fleet size that can meet the production demand within the constraints of the fleet management systems. All the heterogeneous fleets listed in Table 4.13 meet the production demand.

4.5.5. Stochastic lower stage model

Despite all the deterministic models have been presented in the literature of truck-dispatching, we know that most of the input parameters into the truck-dispatching decision-making mathematical models are associated with uncertainties. Based on our knowledge about uncertainties in the truck travel time, we developed a mixed integer linear programming model. The model is modified version of the MOGP model that we presented its deterministic implementation in previous sections. We implemented the stochastic model in scenario with 31 small trucks (optimum scenario for MOGP model) and results are presented here.

Figure 4.108 depicts that using the stochastic truck-dispatching model, the operation met the production requirement. Comparing material sent to processing plants, the shift by shift and hourly resolution data analysis show that stochastic model met the plant input requirement for plant 1 (Figure 4.109 and Figure 4.111) and plant 2 (Figure 4.110 and Figure 4.112) whereas the BM model were short for 13% in feeding plant 1 (Figure 4.109 and Figure 4.111) and 8% in feeding plant 2 (Figure 4.110 and Figure 4.112). because of the nature of the developed model, it sends trucks to the shovels with the shortest possible lineup. Thus, replacing the BM model with the developed model, the length of queue a truck faced when reached to a shovel reduced from an average of 2.2 to an average of 1.4 (Figure 4.113). This in consequence led to save trucks an average of 2.9 minutes wait time in each lineup (Figure 4.114 and Figure 4.115).

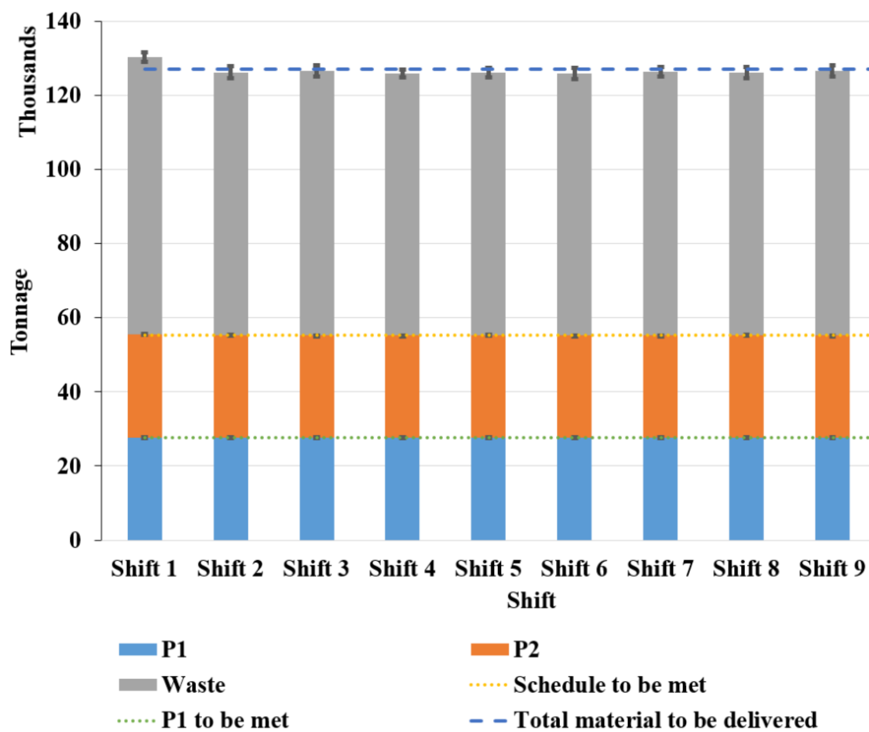

Figure 4.108: Shift by shift production – fleet of 31 small trucks – Stochastic

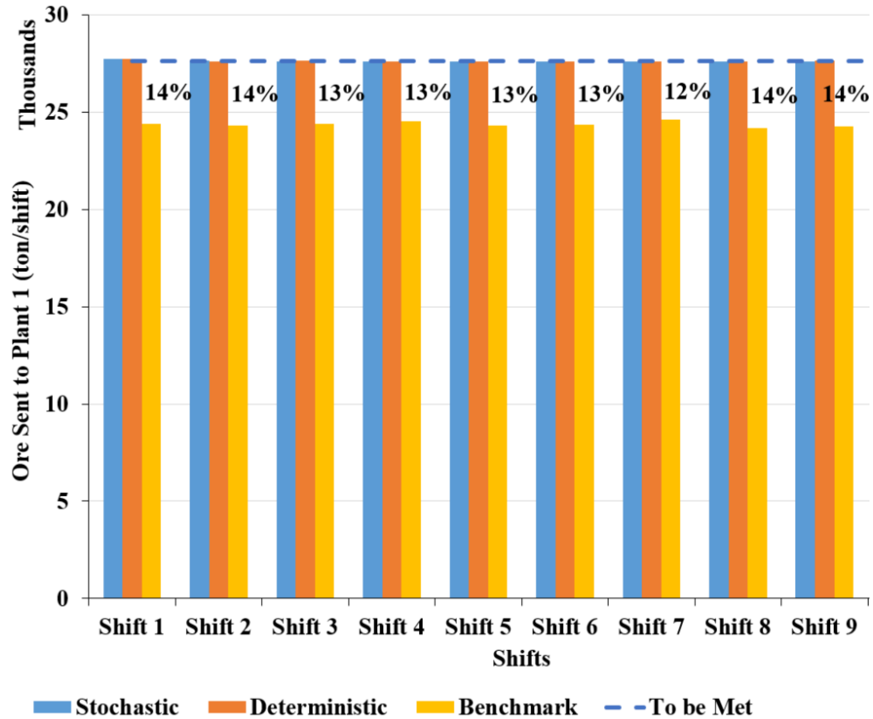

Figure 4.109: Ore sent to plant 1 – Stochastic (blue bars) – MOGP (orange bars) – BM (yellow bars) – shift by shift resolution – fleet of 31 small trucks

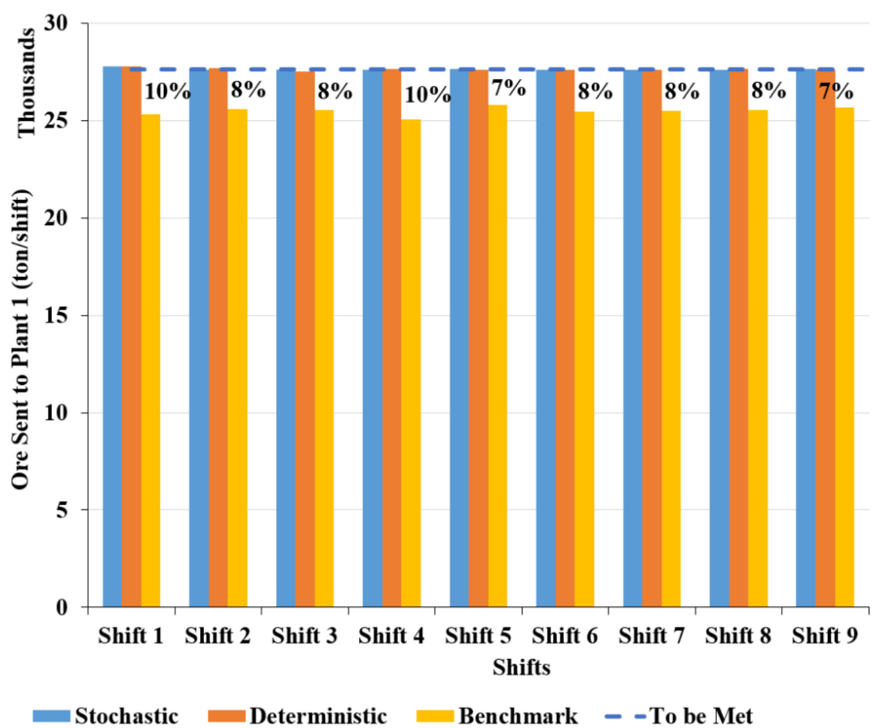

Figure 4.110: Ore sent to plant 2 – Stochastic (blue bars) – MOGP (orange bars) – BM (yellow bars) – shift by shift resolution – fleet of 31 small trucks

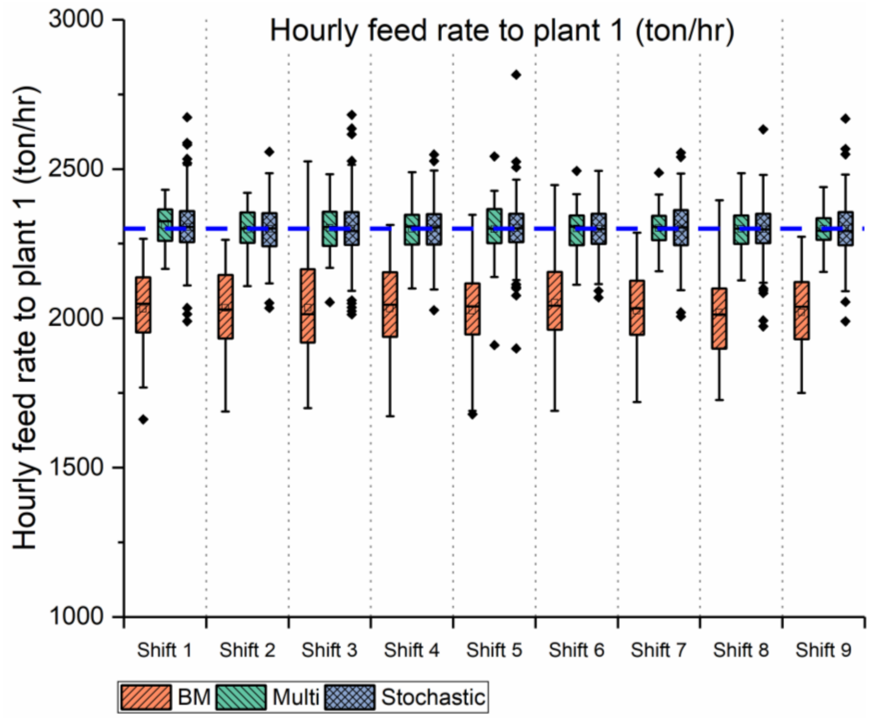

Figure 4.111: Hourly feed rate for plant 1 – Stochastic (blue boxes) – MOGP (green boxes) – BM (orange boxes) – shift by shift resolution – fleet of 31 small trucks

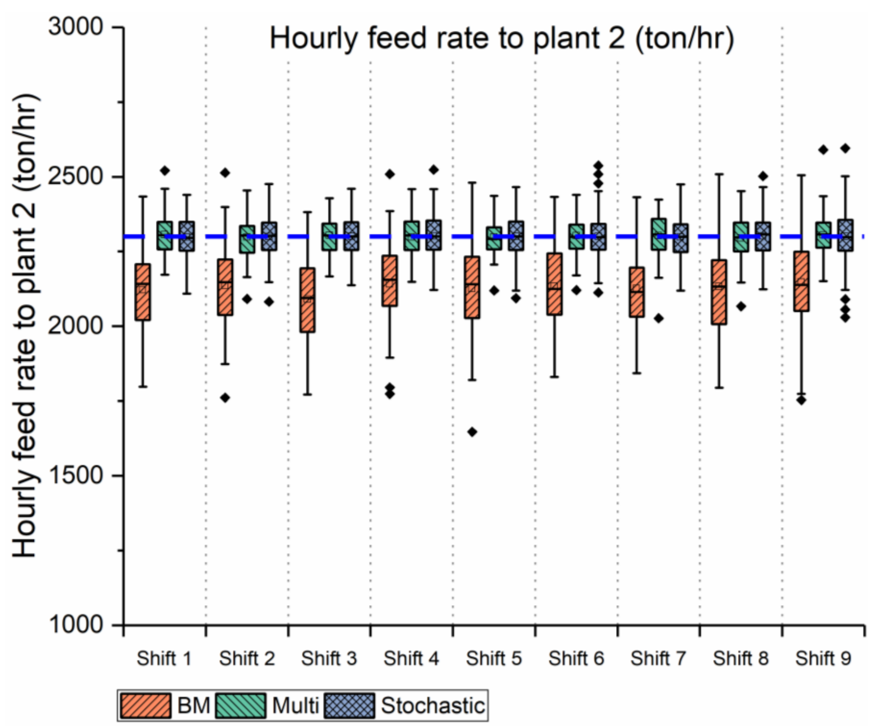

Figure 4.112: Hourly feed rate for plant 2 – Stochastic (blue boxes) – MOGP (green boxes) – BM (orange boxes) – shift by shift resolution – fleet of 31 small trucks

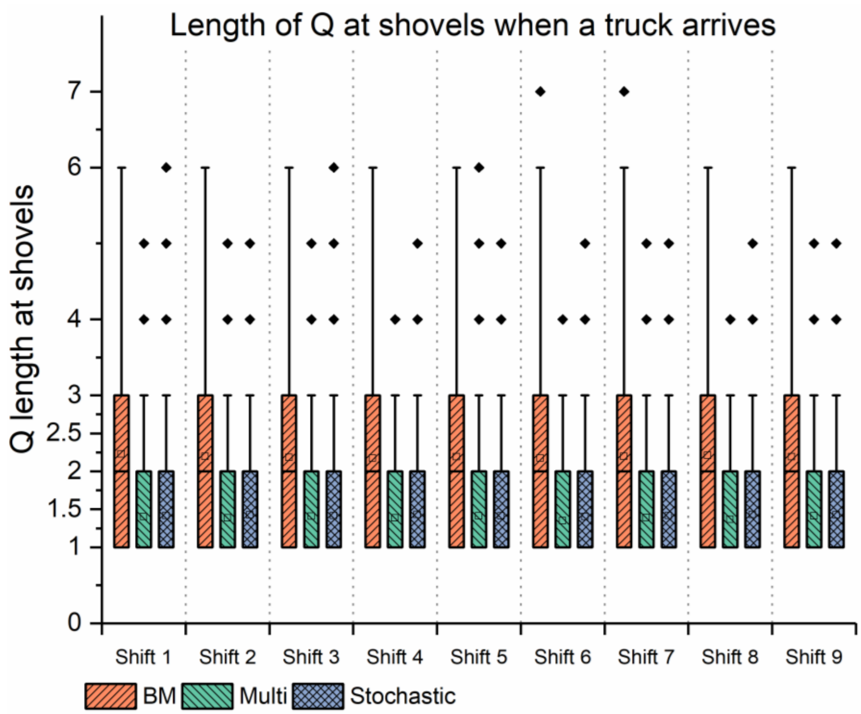

Figure 4.113: Length of queue at shovels – Stochastic (blue boxes) – MOGP (green boxes) – BM (orange boxes) – shift by shift resolution – fleet of 31 small trucks

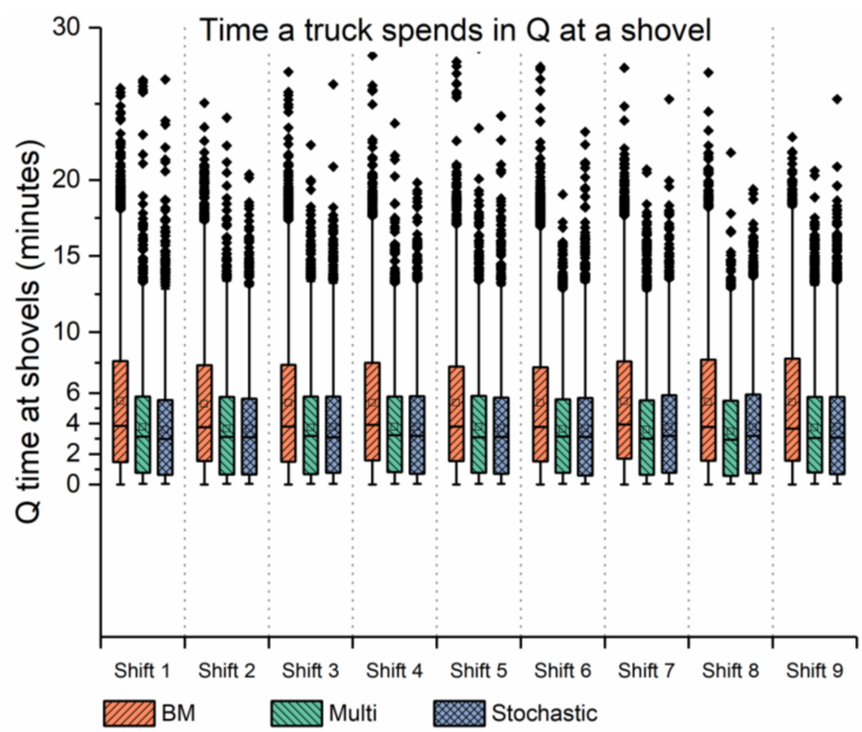

Figure 4.114: Queue time at shovels – Stochastic (blue boxes) – MOGP (green boxes) – BM (orange boxes) – shift by shift resolution – fleet of 31 small trucks

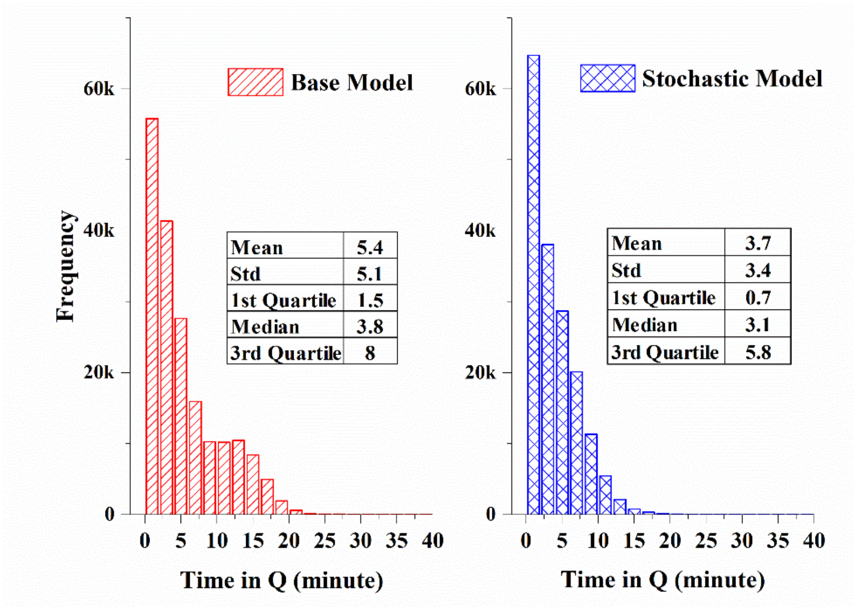

Figure 4.115: Histogram for time a truck spent in queue at shovels – Stochastic (blue bars) – BM (red bars) – fleet of 31 small trucks

4.5.6. Fuzzy logic based lower stage model

To evaluate our fuzzy approach towards the truck-dispatching problem we defined 13 scenarios with fleets of small trucks. This time instead of increasing number of trucks by two from each scenario to the next one, we added only one truck to the fleet to be used in the next scenario. The designed experiments are listed in Table 4.14.

Table 4.14: Operation Scenarios of the case study ran for evaluation of the developed truck-dispatching model

Scenario	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11	S12	S13
Fleet Size	25	26	27	28	29	30	31	32	33	34	35	36	37

For the designed experiments, we ran the integrated simulation and optimization model of the case study for a designated operation time of 10 consecutive 12-hour shifts for two times. We replaced BM truck-dispatching model with the fuzzy based decision-making model. After running the developed integrated simulation and optimization models for the case study, we plotted the production for different scenarios in Figure 4.116 to compare results.

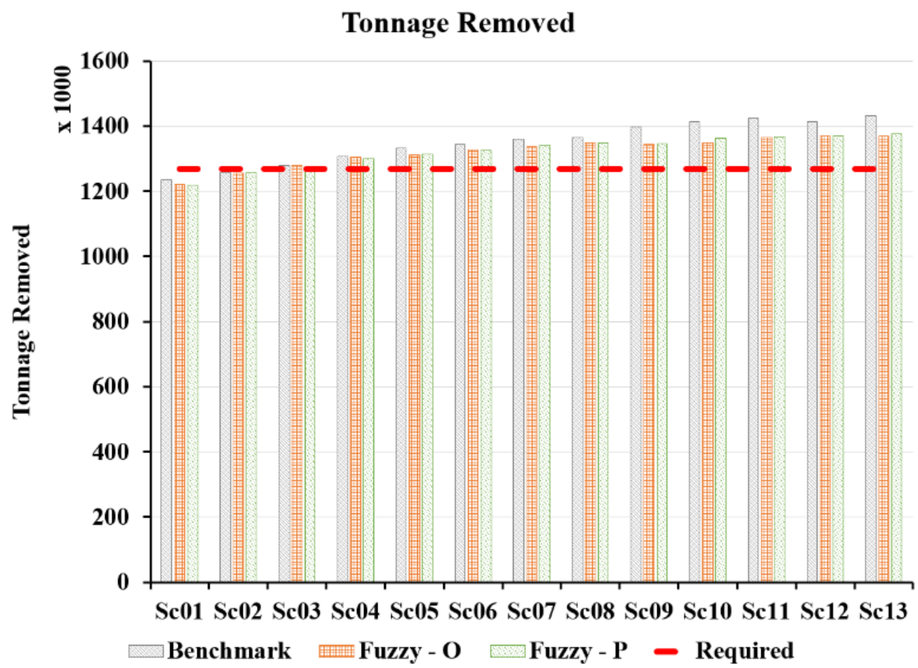

Figure 4.116: Total material removed from the pit over the simulation run time using different fleet where Fuzzy – O stands for optimistic fuzzy decisions (with degree of optimism equal to 75%) and Fuzzy – P stands for pessimistic fuzzy decisions (with degree of optimism equal to 25%).

Figure 4.116 shows that from scenario Sc03 with 27 trucks on, both approaches to solve the truck-dispatching problem result in meeting the total production (ore + waste) requirement. However, producing as much material as possible is not the only goal of a mining operation. Meeting plants' requirements (tonnage of ore sent to the plants) is another critical objective of the mining operation. Thus, the best fleet is a fleet with the minimum number of truck in it that can meet both total production requirement and ore sent to plants' requirement. Figure 4.117 represents how various scenarios with the two truck-dispatching models can meet the required ore delivery.

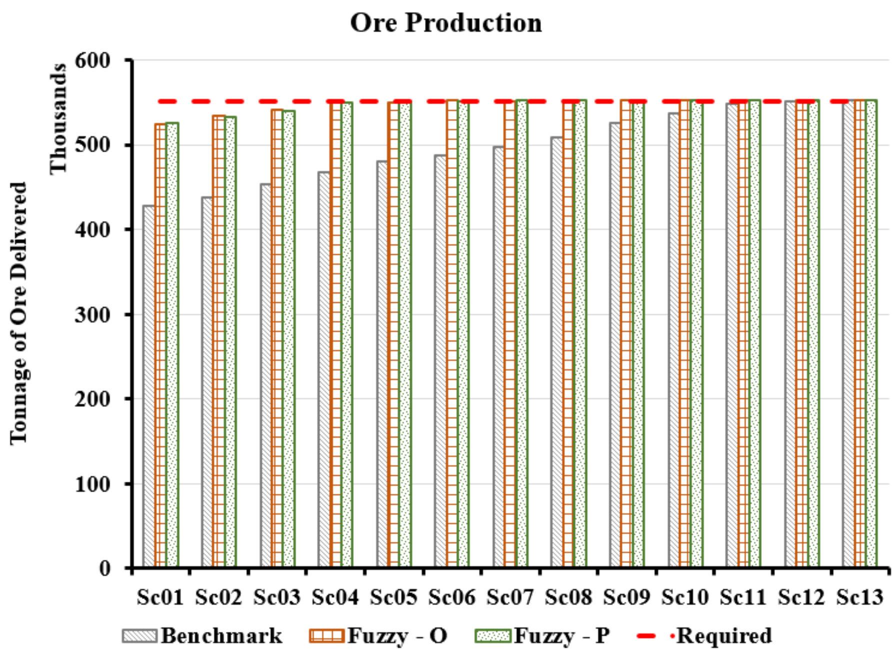

Figure 4.117: Cumulative tonnage of ore delivered to the processing plants during the simulation run time using each scenario

Although using both benchmark model and the FLP model the production requirement is met in scenario Sc03 with 28 trucks, the plants are fed in their full capacity in scenario Sc04 with 29 trucks when implementing FLP model and in scenario Sc12 with 36 trucks when using benchmark truck-dispatching model. Thus, the optimum fleet required to meet the schedule is a fleet of 36 trucks when using benchmark truck-dispatching model and a fleet of 29 trucks when using FLP truck-dispatching model. Apart from the production, other important Key Performance Indicators (KPI) have critical role in mining operations. For the two fleets explained above, we compare KPI of the operation when using the FLP model versus the time using BM model.

4.5.6.1. Fleet of 28 trucks – Sc04

In Figure 4.118 and Figure 4.119 the graphs show hourly feed rate of the processing plants 1 and 2 respectively, when a fleet of 28 trucks operates in the mine. Figure 4.118 shows that with the fleet of 28 trucks, the operation is not able to meet the hourly feed rate requirement for the plant 1 by implementing benchmark truck-dispatching model. The graph in Figure 4.118 shows that using the BM truck-dispatching model with the fleet of 28 trucks, the operation can meet an average of 1885.2±71 ton/hr (82%) of plant 1 required feed rate. However, the same graph reveals that by implementing the FLP truck-dispatching model with the same truck fleet, the material handling system is capable of meeting 2285.2± 94 (99.3%) of the required feed rate for plant 1. It means an improvement of 17.3% in the tonnage per hour of ore delivered to plant 1 during the simulated operation time. The analysis shows a slightly different result when investigating plant 2 (Figure 4.119).

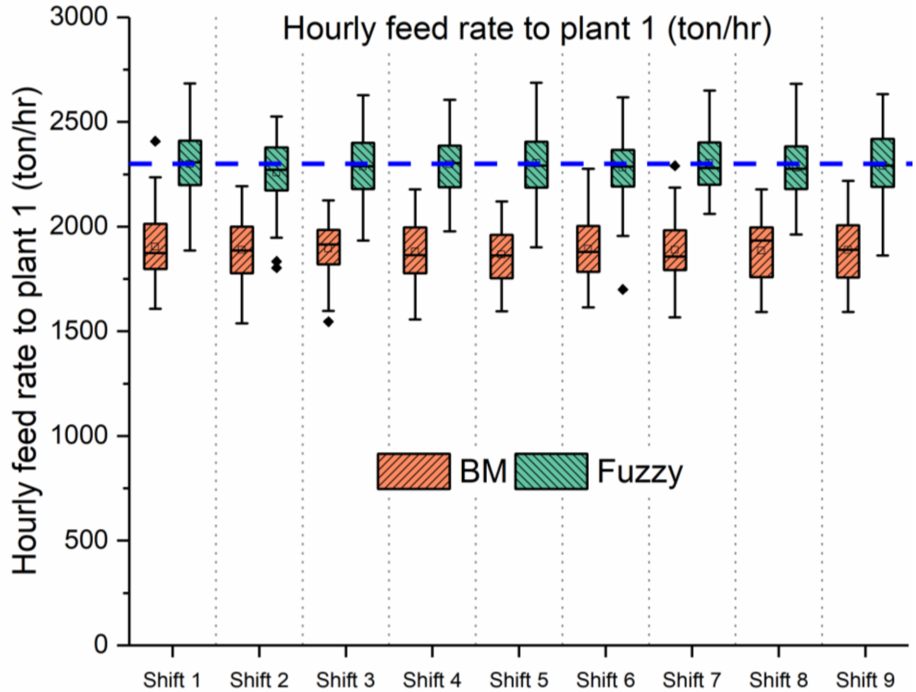

Figure 4.118: Hourly feed rate for plant 1 – FLP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 28 small trucks

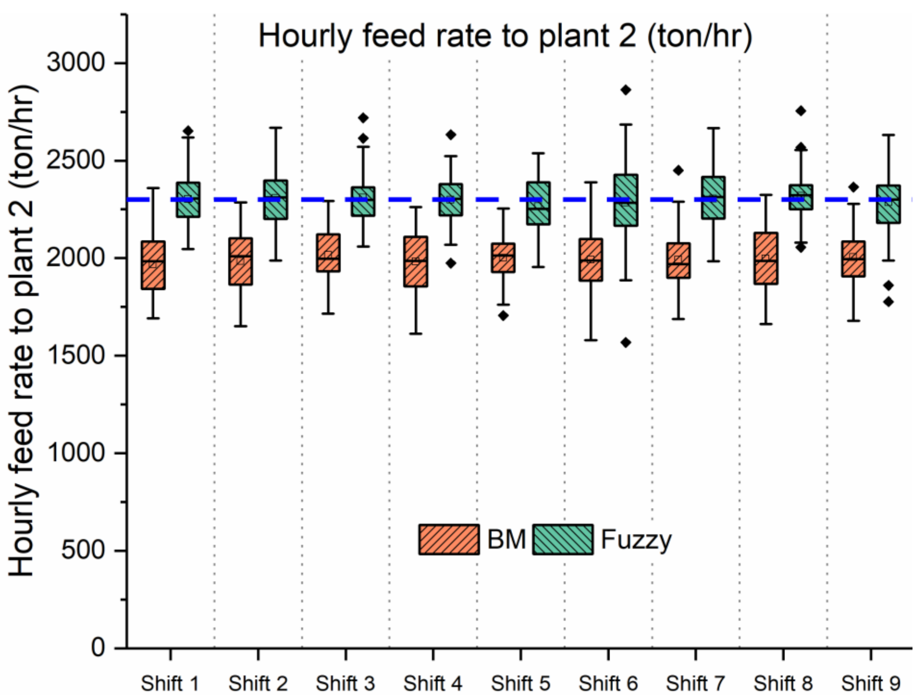

Figure 4.119: Hourly feed rate for plant 2 – FLP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 28 small trucks

Both truck-dispatching models feed plant 2 slightly more than plant 1. In the case of using benchmark truck-dispatching model, the graph shows a feed rate of 1990.4±70 ton/hr to the plant 2, a 6% more feed rate in comparison to the feed rate of plant 1. However, it still fails to meet the 2300 ton/hr feed rate requirement of the plant by 13.5%. By replacing the benchmark truck-dispatching model with the FLP model, Figure 4.119 shows that the operation meets 99.8% of plant 2 hourly feed rate requirement by delivering 2295.8±77 ton/hr.

The benchmark truck-dispatching model and the FLP truck-dispatching model meet head grade requirement for both processing plants as presented in Figure 4.120. The reason is that both are using the same upper stage model. The threshold of 60% head grade is met for both plants using the benchmark and the developed truck-dispatching models.

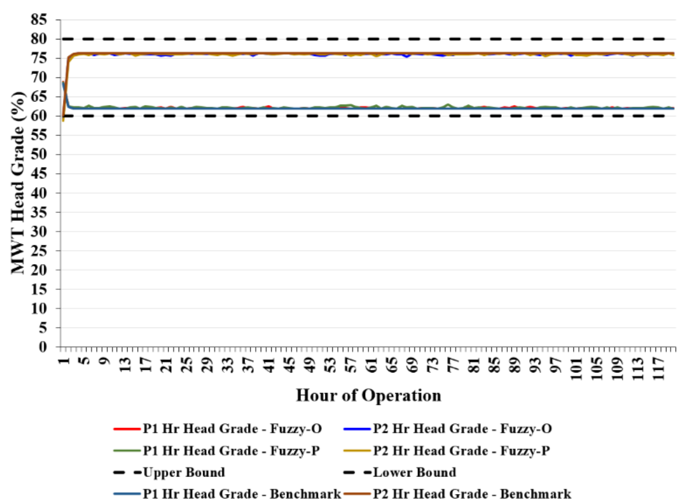

Figure 4.120: Plants' hourly head grade requirements and hourly head grade delivered by each of the truck-dispatching models implementing fleet of 28 trucks

Shovel 1 and Shovel 2 operate at ore mining faces. The rest of the shovel fleet dig waste mining faces. Table 4.15 represents shovel utilization for each active shovel in the operation and the utilization of combined shovel fleet for both benchmark and FLP truck-dispatching models.

Table 4.15: Shovel fleet utilization (%) for a fleet of 28 trucks – comparison between benchmark model and the FLP model

	Benchmark		Fuzzy - P			Fuzzy - O		
Shovel	Mean	StD	Mean	StD	Diff	Mean	StD	Diff
Shovel 1	82.7	1.1	95.8	1.9	13.1	95.3	2.1	15.2
Shovel 2	78.9	1.2	95.2	2	16.3	95.5	1.4	21.0
Shovel 3	93.6	1.4	80.6	1.3	-13.0	80.9	1.2	-13.6
Shovel 4	92.5	1.4	82	1.6	-10.5	83	2	-10.3
Shovel 5	99.8	5.9	94.4	1.8	-5.4	94.3	1.8	-5.5
Entire fleet	89.5	2.2	89.6	1.72	0.1	89.8	1.7	0.3

Information represented by Table 4.15 shows that, although, both truck-dispatching models utilize the shovel fleet almost the same, the benchmark model utilizes the waste shovels more than the ore shovels. However, according to the same table, the developed FLP truck-dispatching model utilizes the ore shovels more than the waste shovels. Instead of producing more waste material than required to meet the production schedule, the developed FLP model makes truck-dispatching decisions in a way that meet the plants' input requirement. Concurrent with keeping the shovels in the required utilization, the developed truck-dispatching model helps trucks to spend shorter time in the queue of shovels (Figure 4.122 and Figure 4.122).

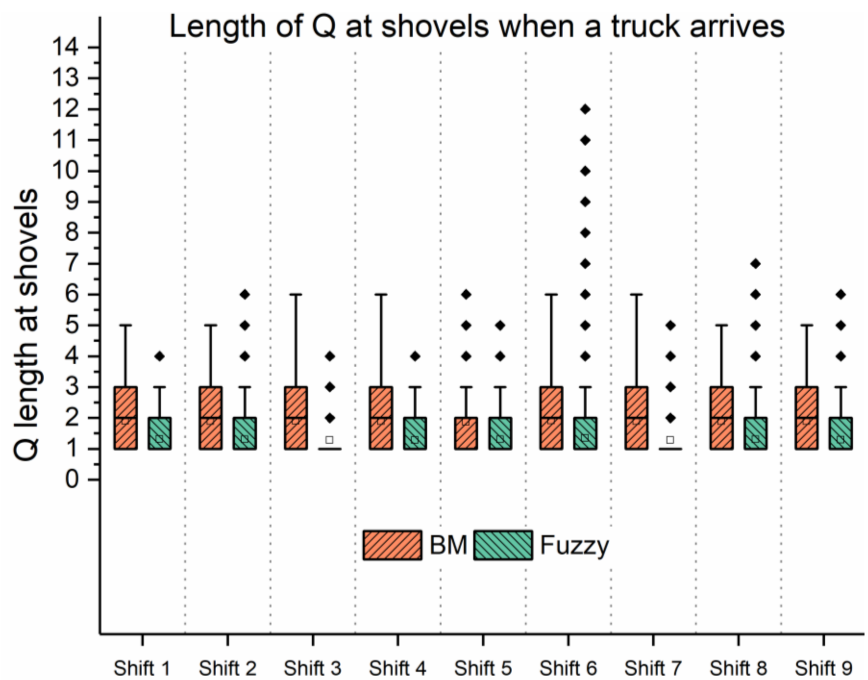

Figure 4.121: Length of queue at shovels – FLP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 28 small trucks

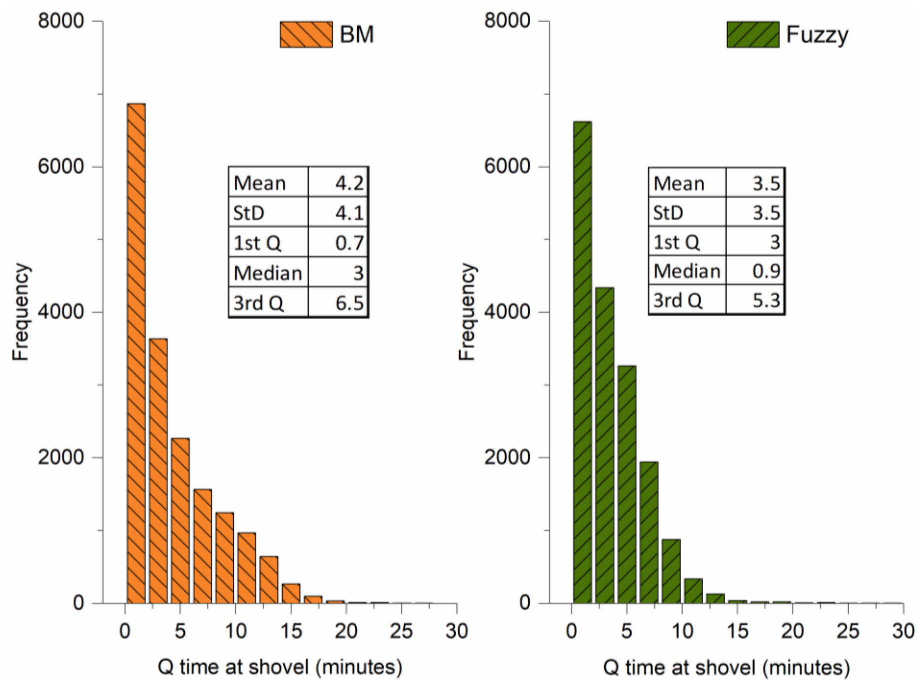

Figure 4.122: Histogram for time a truck spent in queue at shovels – 28 small trucks – FLP (green bars) versus BM (orange bars)

Figure 4.122 and Figure 4.122 show that trucks in the fleet spent less time in queues in different loading points when the truck-dispatching decisions are made by the developed FLP model. This consequently helps the operation to be capable of meeting the processing plants feed rate requirements.

To sum up, implementing the fleet of 28 trucks, the operation can meet the production requirement if the truck-dispatching decisions are made using the developed FLP model instead of benchmark model.

4.5.6.2. Fleet of 36 trucks – Sc12

Although the operation is capable of meeting production requirement with 28 trucks using the FLP model, the BM model is capable of meeting that using a fleet of 36 trucks. Thus, we evaluate the operation implementing 36 trucks and compare results of using FLP model versus BM model.

With a fleet of 36 trucks, as presented in Figure 4.123, both the benchmark truck-dispatching model and the FLP truck-dispatching model meet the plant 1 (P1) feed requirement with a standard deviation of 85 ton/hr and 50 ton/hr, respectively. Similar results are obtained for plant 2 as shown in Figure 4.124. The benchmark model is meeting the hourly feed rate requirement of the plant with a deviation of 55 ton/hr, whereas, the developed FLP model can meet the feed rate requirement of plant 2 with a standard deviation of 64 ton/hr. Another noteworthy result is that, both truck-dispatching models meet the head grade requirement of the active processing plants in the operation because both of them are using the same upper stage model (Figure 4.125).

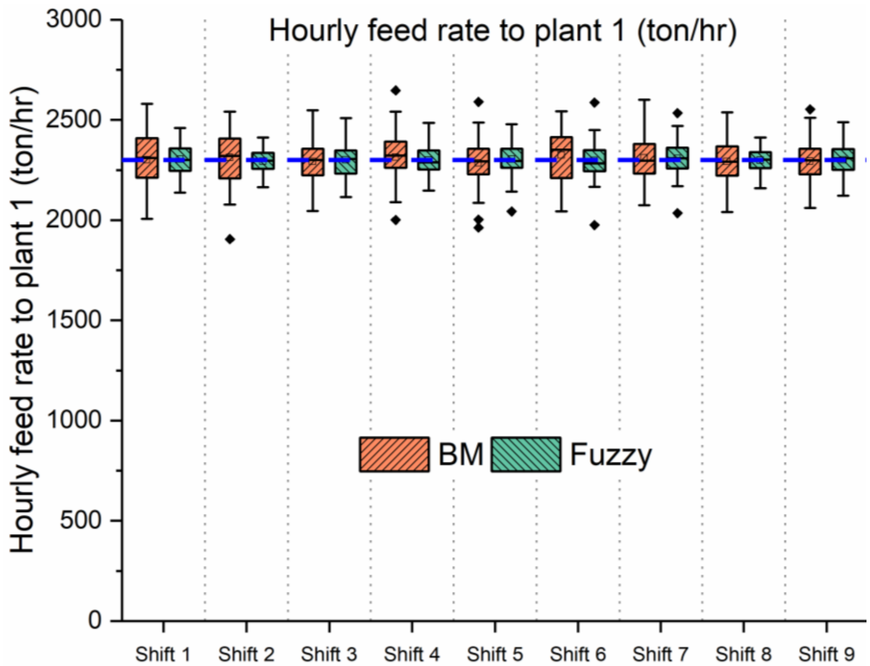

Figure 4.123: Hourly feed rate for plant 2 – FLP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 36 small trucks

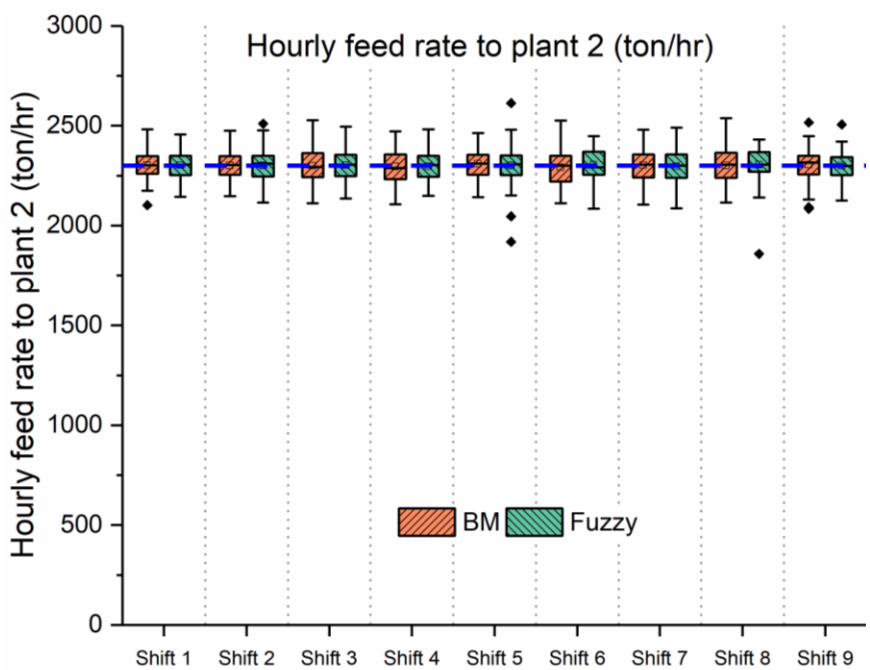

Figure 4.124: Hourly feed rate for plant 2 – FLP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 36 small trucks

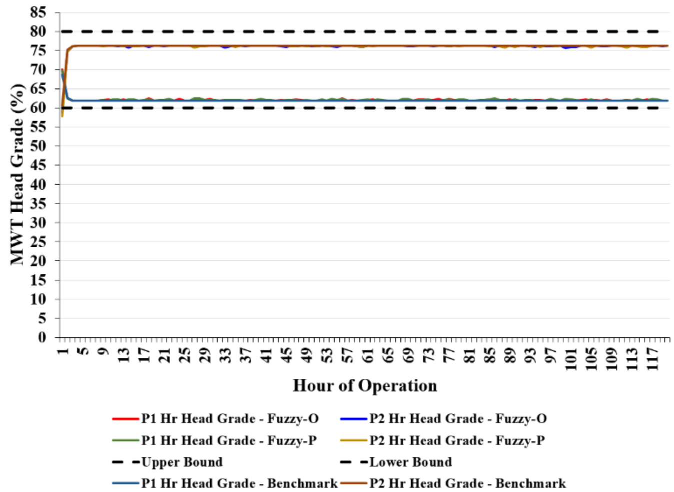

Figure 4.125: Plants' hourly head grade requirements and hourly head grade delivered by each of the truck-dispatching models implementing fleet of 36 trucks

Although using a fleet of 36 trucks both truck-dispatching models can meet the production requirement in the same way, they utilize trucks and shovels fleets in different way. Using benchmark truck-dispatching model, as presented by Table 4.16, the shovel fleet attains an average utilization of 98%, which is 4% more than the average utilization of shovel fleet when the benchmark truck-dispatching model is replaced by the FLP truck-dispatching model.

Table 4.16: Shovel fleet utilization for fleet of 36 trucks – comparison between benchmark model and the FLP model

	Benchmark		**Fuzzy - P**			**Fuzzy - O**		
Shovel	Mean	StD	Mean	StD	Diff	Mean	StD	Diff
Shovel 1	82.7	1.1	96.5	3.4	0.4	95.7	3.4	-0.4
Shovel 2	78.9	1.2	95.4	3.4	-0.5	95.6	3.5	-0.3
Shovel 3	93.6	1.4	89.1	2.5	-10	89.3	2.2	-9.9
Shovel 4	92.5	1.4	89.6	2.7	-9.2	89.7	2.1	-9.2
Shovel 5	99.8	5.9	99.7	2.1	-0.3	99.7	2.2	-0.3
Entire fleet	89.5	2.2	96.5	3.4	0.4	94	2.68	-4.1

Implementing FLP, the truck fleet wasted an average of 4% less time in queue at shovels than using BM truck-dispatching model (Figure 4.127). This means that the FLP model dispatches trucks to their destination in a way that they encounter shorter line ups at the next destinations (Figure 4.126). This advantage is a result of accounting for future queue time in the model formulation.

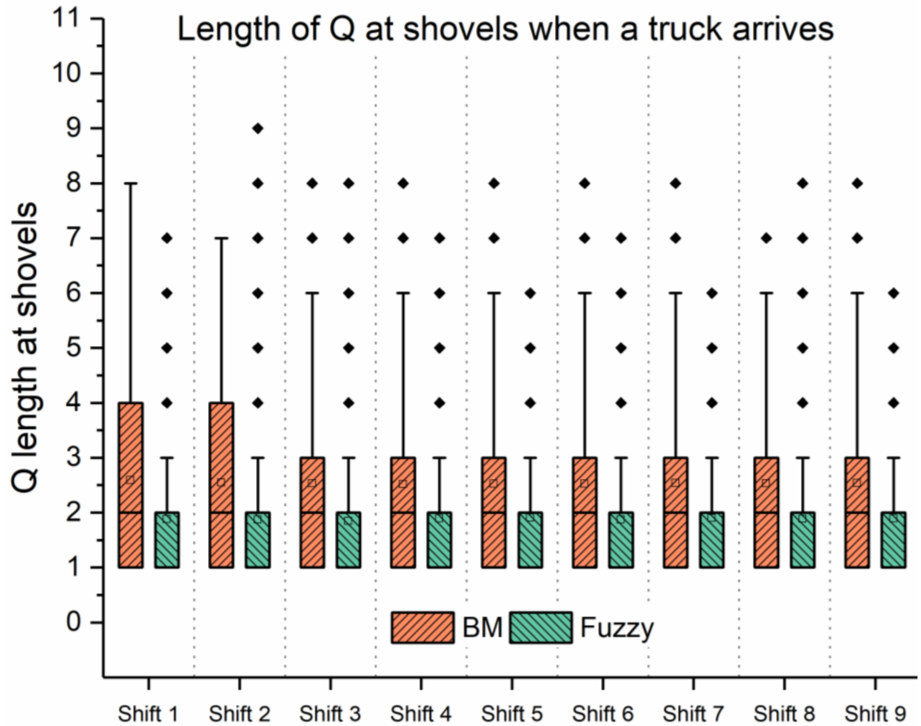

Figure 4.126: Length of queue at shovels – FLP (green boxes) versus BM (orange boxes) – shift by shift resolution – fleet of 36 small trucks

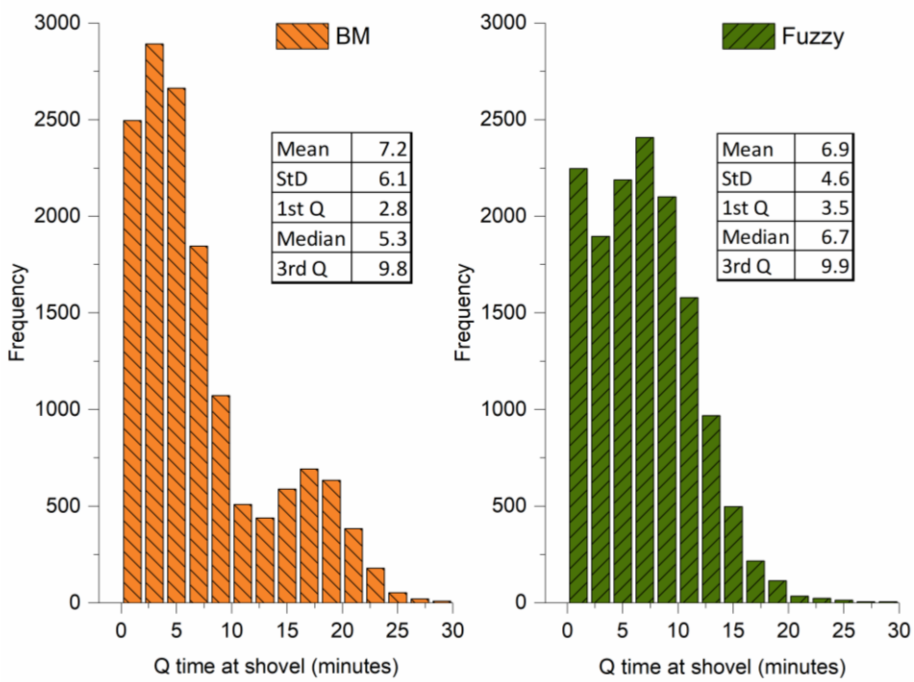

Figure 4.127: Histogram for time a truck spent in queue at shovels – 36 small trucks – FLP (green bars) versus BM (orange bars)

Although both truck-dispatching models serve the production purposes with the fleet of 36 trucks, using the FLP model material handling fleet (both shovel and truck fleets) are utilized in way that is more efficient. Shovel fleet can serve larger fleet and the truck fleet is wasting less cumulative time in the queues.

4.6. Summary and conclusions

This chapter covered the verification of the integrated simulation and optimization framework. It also covered the verification of the MOGP truck-dispatching model, stochastic truck-dispatching model, and fuzzy linear programming truck-dispatching model through a comparison with the backbone algorithm of Modular Mining DISPATCH®[11] developed by White and Olson [12].

After the introduction, we presented the production schedule, designed pit, and active haulage road network of Year 11 from a case study of a surface ore mining operation. Because historical data was not available, we used a separate historical database from the surface mine operation to model the operation’s characteristics in the simulation model.

To verify the integrated simulation and optimization framework, we studied the behavior of scenarios under a changing number of trucks in small truck, large truck, and mixed truck fleet systems. The results were as expected given the total available time and the integrated simulation and optimization framework.

After verifying the integrated simulation and optimization framework, we used the concept of match factor to calculate the number of small and large trucks required to meet the production schedule. Based on the determined fleet size, we designed different scenarios within the range of under-truck systems for fleets of small trucks and fleets of large trucks. To design scenarios for the mixed fleets, we fixed the number of small trucks in the fleet and then by running a simulation with a different number of large trucks we defined the best possible combination of trucks for the operation. We defined 26 scenarios from small truck fleets, large truck fleets and mixed truck fleets.

We ran the integrated simulation and optimization framework four times for each scenario: the first run was with the BM truck-dispatching model, the second with the MOGP truck-dispatching model, the third with the Stochastic truck-dispatching model, and the fourth with the FLP truck-dispatching model. Results of implementing the last three truck-dispatching models were compared to results of implementing the BM model. The comparisons were presented in this chapter.

Among all the scenarios for small truck and large truck fleets, to evaluate the MOGP truck-dispatching model, scenarios that met the plants' capacity were investigated with higher resolution and considering more KPI. The results show that for all the scenarios listed in

Table 4.8,

Table 4.9, and Table 4.10, the MOGP truck-dispatching model required a smaller number of trucks to meet the production target compared to the BM truck-dispatching models in the same scenarios.

After presenting the results of comparing the MOGP model with the BM model, the chapter covered the comparison between the results of implementing the stochastic model with the BM model in the scenario where the stochastic model met the production requirement. Then the chapter covered the comparison of implementing the FLP truck-dispatching model with the BM model for all the scenarios where the truck fleet contained small trucks. After that, we described the optimum scenarios in higher resolution.

CHAPTER 5: SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

5.1. Summary of the research

The simulation of surface mining operations is increasingly seen as an important way to determine the viability of future, evaluate "what if" scenarios, and test new technologies in mining operations for current and future mining projects. In recent years, many researchers have published results of simulation models in surface mining operations. The proposed models have the following limitations: 1) they treat stochastic variables as deterministic ones in materials handling systems; 2) they do not adequately link mining systems with mineral processing plants; 3) they are unable to integrate fleet management systems (FMSs) with materials handling systems; and 4) they lack flexibility to use different truck-dispatching algorithms in developed simulation systems. These limitations affect the evaluation of mining operation performance: they lead to either overestimations or underestimations.

In addition to a simulation, the optimization of mining systems has always been considered an important part of surface mining operations. There are two main sub-problems in FMSs that researchers have focused on most: 1) production optimization and truck allocation, or the upper stage; and 2) truck-dispatching and truck assignment, or the lower stage. Although several models have been proposed for the first sub-problem over the last 50 years, a few studies have been published that cover the lower stage sub-problem. In summary, the proposed models in literature for the lower stage or truck-dispatching sub-problem decision-making have the following limitations: 1) they neglect important objectives such as meeting the goal of the upper stage; 2) they ignore the importance of one side of the fleet (either the shovels or trucks) when making optimal decisions; and 3) they treat stochastic variables as deterministic ones. These limitations in modeling result in decisions that are far from optimal.

This research has two major objectives. The first is to develop an integrated simulation and optimization framework to simulate the surface mining operations that can overcome the above-mentioned drawbacks of the available simulation models and can be used to evaluate truck-dispatching models. The second is to develop an efficient truck-dispatching decision-making model that can be implemented in any mine FMS.

An integrated simulation and optimization framework was presented in this research to fulfill the first objective. The integrated framework has three major components: 1) simulation model; 2) optimization models; and 3) data file. The simulation model consists of two sub-models of the mining operation and processing plant. The mining operation's simulation sub-model mimics loading, haulage, and dumping of mined material using trucks. Alongside the mining operation sub-model, the processing plants' feeding sub-model simulates the operation of the hoppers and conveyors that deliver material to the processing plants. Although the integrated framework is capable of accepting several optimization models, in this research we focused on adding only FMS optimization models. Thus, two optimization models were integrated into the framework. The first makes decisions about the upper stage dispatching sub-problem and the second makes decisions about the lower stage sub-problem. As the optimization models were developed using external optimization software not in the simulation software, the integrated simulation and optimization framework is flexible in that it can accept different decision-making models for the upper stage or lower stage sub-problem in the FMS. Another important component of the integrated simulation and optimization framework is the datafile. The datafile is a Microsoft Excel workbook that contains different sheets, each of which contains a specific set of data required to run the integrated framework. The integrated model was used in a surface mine case study in this research.

For the second part of this research, we developed, implemented, and verified three mathematical formulations to solve the lower stage, truck assignment, or truck-dispatching sub-problem in surface mining FMSs. The three models include: a) multiple objective goal programming (MOGP) model, b) a stochastic mixed integer programing model, and c) fuzzy linear programming. All the developed decision-making models consider minimizing shovel idle time, truck wait time, and the deviation of the production from the desired target with respect to truck capacity, the shovel dig rate, and plant feed rate requirements.

To evaluate the performance of the developed truck-dispatching models we needed a benchmark model. Modular Mining DISPATCH®[11] is popular in most of the currently active mining operations. Its truck-dispatching algorithm, was publicly available at [12], so we decided to use it as the benchmark model to verify the truck-dispatching models developed in this study. The optimization models from the benchmark upper and lower stage models and the three models developed in this research were coded using IBM CPLEX [128] optimization software and integrated into the simulation model.

A case study in an iron ore mine was carried out using the developed models. The size of the fleet required to meet the target production was determined using the match factor concept for two possible types of trucks: small (140 ton) and large (240 ton). Based on the results of deterministic calculations, we defined nine scenarios for small trucks, eight for large trucks and nine for fleets of both types of trucks. We developed 26 scenarios to evaluate the performance of the truck-dispatching models. The integrated simulation and optimization framework was run for each scenario and each truck-dispatching model. We compared the results to the results we obtained when implementing the benchmark model. Chapter 3 presented the detailed procedure of developing the integrated simulation and optimization framework and the truck-dispatching models. Chapter 4 presented the detailed results of the verification study, scenario development, and performance evaluations of the models in a case study.

5.2. Conclusions

The literature review conducted in this research identified limitations in the current body of knowledge in both the simulation of mining systems and truck-dispatching optimization. The literature showed that there has never been a previous attempt to integrate the simulation of mining operations, simulation of processing plants, and mining FMSs in one model. Regarding the truck-dispatching decision-making models, the literature showed that although a few studies have been conducted to develop truck-dispatching models, there has never been a previous attempt to develop models that simultaneously consider uncertainties in the variables, the optimization of truck wait time, the optimization of shovel idle time, and the optimization of deviation from the desired production target. This research pioneers the efforts to employ discrete event simulation models and mathematical programming models in an integrated framework to mimic the surface mining operation in a way that more closely resembles reality. The research also pioneers the efforts to use mathematical programming models in the form of multiple objective goal programming, stochastic mixed integer linear programming, and fuzzy mixed integer linear programming to contribute to the body of knowledge and provide novel understanding in the field of truck-dispatching in surface mines. The research objectives outlined in Chapter 1 have been achieved within the scope of the research. The following conclusions were drawn from the implementation of the developed integrated simulation and optimization framework and three truck-dispatching models:

1. The integrated simulation and optimization framework mimics the operation of surface mines including processing plants' feeding and FMS.

2. The integration of the mining operation with the processing plants' feeding system is implemented by developing two simulation sub-models in a single model where output from one sub-model is inputted to the other sub-model.

3. The simulation model of the mining operation and the processing operation feeding system is integrated into the mining FMS by separately being linked to the FMS's upper stage decision-making model and its lower stage decision-making model.

4. Apart from the developed integrated simulation and optimization framework, the truck-dispatching models we developed in this research can be used to help make decisions about the future destinations of the trucks in the material handling fleet.

5. The MOGP truck-dispatching model simultaneously takes into account all three important objectives of any truck-dispatching problem (shovel fleet, truck fleet, and production schedule).

The framework was implemented in an iron ore open pit mine case study. To do a comparative analysis on the goodness of the developed truck-dispatching models, we chose the backbone algorithm of Modular Mining DISPATCH® [11] to run as the case study's fleet management system. By replacing the truck-dispatching model of the backbone algorithm of the Modular Mining DISPATCH® [11] FMS with the truck-dispatching models we developed in this study, we reached the following conclusions:

1. Using a fleet of small trucks, the MOGP truck-dispatching model needs 14% fewer trucks to meet the production requirement.

2. Using a fleet of large trucks, the MOGP truck-dispatching model needs 19% fewer trucks to meet the production requirement.

3. Using a fleet of mixed trucks, the MOGP truck-dispatching model always needs fewer trucks to meet the production requirement.

4. With the same fleet of trucks, the MOGP truck-dispatching model needs to utilize shovels less often than the BM model to meet the production schedule. This makes it possible to use the same fleet of shovels to serve a larger fleet of trucks in case production needs to be increased.

5. By including the length of the queue at the shovels in the MOGP truck-dispatching model's decision-making procedure, with the same fleet of trucks the MOGP truck-dispatching model can dispatch trucks to destinations with a shorter queue length, thus reducing the none productive time for trucks.
6. Comparing to the benchmark truck-dispatching model, the MOGP model meets the plants feed rate requirement with smaller fleet of trucks.
7. Implementing stochastic programming and fuzzy linear programming techniques, the truck-dispatching models developed in this study account for the uncertainty of the parameters.

5.3. Contribution of the research

This research has resulted in an integrated simulation and optimization framework that mimics surface mining operations and integrates mining operations with processing plant operations and the FMS. The research also led to three truck-dispatching decision-making models to be used in mining FMSs. The developed models use multiple objective goal programming, stochastic programming, and fuzzy linear programming techniques to make decisions about the next destination of trucks in surface mining operations. The major contributions of this research are:

1. It applied simulation modeling as well as mathematical programming approaches to develop an integrated framework to mimic the surface mining operation.
2. It implemented mathematical programming models in the form of multiple objective goal programming, stochastic mixed integer linear programming, and fuzzy mixed integer linear programming to contribute to the body of knowledge and provide novel understanding in the field of truck-dispatching in surface mines.
3. It led to an integrated simulation and optimization framework to mimic surface mining operations where a simulation model of a processing plant's feeding system is combined with the simulation model of the mine's material handling system. This helps to account for how the processing plant's feed rate capacity affects the mining operation.
4. The developed integrated framework integrates the mining system's simulation model with the mining FMS that makes semi-dynamic and dynamic operational decisions.
5. The MOGP truck-dispatching model developed in this research simultaneously tries to minimize the shovel fleet's idle time, the truck fleet's wait time, and the deviation from the

target flow rate of each path. In this way, the research contributes by involving the two main goals of any truck-dispatching models (minimizing truck wait time and minimizing shovel idle time) in a single model and adds the objective of minimizing deviation from the target flow rate to the same model.

6. This research has also contributed by capturing the uncertainties of parameters and accounting for their effects on the decisions with developing the stochastic truck-dispatching model and the FLP truck-dispatching model.

5.4. Recommendations for future works

Although this research has provided new ways to evaluate mining operations and solve the truck-dispatching problem in surface mines, the author sees a need for ongoing investigations into the application of operations research techniques in mining operation evaluation and truck dispatching problem. The following recommendations could improve and add to the body of knowledge:

- The integrated simulation and optimization framework assumes that trucks travel without any interaction. However, in real-world operations, it is possible that trucks will interact with either road intersections or trucks with different relative velocities. As these truck interactions are on the level of micro-simulation, the integrated framework can be expanded by adding a micro-simulation sub-model that mimics these interactions in detail.

- The integrated framework also assumes that trucks and shovels are working all the time without any breakdowns. However, in real-world mining operations, trucks and shovels break down and are not available all the time. For further research, a fleet break-down sub-model for each type of equipment can be added to the integrated simulation and optimization framework.

- The integrated framework does not model drilling and blasting operations. To make more practical decisions we recommend adding one simulation sub-model to mimic a drilling and blasting operation.

- The solution time for the MOGP truck-dispatching model needs improvement. We recommend implementing heuristic algorithms to reduce the solution time for the MOGP model in future research.

- As the developed stochastic and fuzzy linear programming models in this research are the first of their kind in truck-dispatching decision-making models that account for uncertainty of parameters, the author sees a lot of room for further improvement in developing the models as well as choosing the right methodologies to solve the models.

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