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## Article

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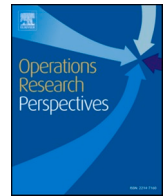
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# Fleet sizing of trucks for an inter-facility material handling system using closed queueing networks

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## ABSTRACT

Material handling systems (MHS) are integral to logistics functions by providing various supports such as handling, moving, and storing materials in manufacturing and service organisations. This study considers determining the optimal size of a homogeneous fleet of trucks to be outsourced (or subcontracted) from a third-party logistics provider to be used daily to cyclically transport different types of raw materials from designated storage yards to intermediate buffer locations to be fed as inputs to a production facility for processing. Within this context, the problem is modelled as a closed queueing network (CQN) combined with mixed-integer nonlinear programming (MINLP) to determine the optimal fleet size. This study proposes an analytical method based on sequential quadratic programming (SQP) methodology coupled with a mean value analysis (MVA) algorithm to solve this NP-Hard problem. Furthermore, a discrete event simulation (DES) model is developed to validate the optimisation of non-dominant solutions. The proposed analytical approach, along with the simulation, are implemented in a real case study of a steel manufacturing setup. Analytical model results are validated using the simulation results, which are proved to be very accurate, with deviations ranges within  $\pm 7\%$ .

## 1. Introduction

Modern-day supply chains are complex networks of entities based in various geographical locations that are designed to fulfil customer expectations. Irrespective of its complexity or magnitude, making a product or service involves synchronising several logistical activities such as sourcing, transporting, storing, transforming, and distributing. Within these complex systems, material handling plays a critical role in smoothing operations during the various processes and activities. However, material handling is not often recognised as a process that adds value to a product's explicit form but as an enabler in creating a "time and place" utility for the product [1]. In a nutshell, material handling is often seen as a combination of subsystems that consist of material handling equipment (MHE), type of operation, and adopted design methodology. Organisations usually pick the lowest cost option to design their MHS [2]. Material handling systems (MHS) are defined as interacting and independent MHEs that are treated as a single mass [3].

Material handling activities account for 15% to 70% of total manufacturing cost, depending on the type of products [4]. Similarly, 55% of warehouse operational cost consists of material handling

activities [5]. According to Eurostat [6], 10.8 million people employed in the warehouse-transport-storage sector account for EUR 556.0 million in the European Union (EU).

Transportation modes, such as trucks and other equipment, are critical material handling components in a manufacturing organisation from an operations management perspective. As these manufacturing organisations are often focusing on their core business, this has led to the emergence of third-party logistics service providers to support the primary activity through providing supporting logistics services such as transportation, material handling, and warehousing [7]. The decision on the level of involvement of logistics service providers depends on two theories: resource-based view and transaction cost economics [8]. When negotiating a contractual agreement with third-party logistics service providers, the type of MHEs, fleet size, fleet composition, fleet expansion and shrinking flexibility, and time horizon are critical strategic-level decisions [9].

The most critical decisions concerning designing an MHS revolve around the MHE. The goal of an MHS is first to select the correct type of MHE and second to manage the material handling operations in ways in which they do not interrupt the core functions at the lowest possible cost

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[10,1,11,3].

Numerous studies regarding the selection of MHE present a wide range of methodologies. Bouh and Riopel [12] classify the solution approaches in selecting MHEs as follows: optimization models, expert systems, hybrid systems, multi-criteria decision methods, and systematic framework approaches. Besides choosing the right MHE for handling operations, two more essential categories are associated with MHS efficiency: cost and service level. Vehicle fleet sizing (optimal number of MHE) and fleet management (scheduling, allocation, routing, tracking) are critical factors of any given MHS's cost and service level measures [2].

Moreover, significant design decisions for an MHS can be categorised into two parts, design and operational features, and many other factors need to be considered depending on specific industry needs [13]. Fig. 1 shows the factors needed to consider under design and operational features in designing an MHS for an organisation. The fleet size is a critical design factor that consequently affects the operational features of scheduling and maintenance operations. Similarly, the fleet size will have an impact on the determination of other design features.

Once an organization selects the appropriate MHS, it needs to assess the performance to measure system productivity. Assessing MHS performance proved to be a challenging task for industry practitioners for various reasons [14]. For instance, inherent variability factors such as irregular time-varying manufacturing environments, human involvement, demand-supply fluctuations, machine breakdown, changes in product mix, and machine capabilities may complicate assessing and optimizing MHS performance [15].

Queueing networks have been used extensively to model complex systems such as manufacturing, healthcare, telecommunications, computing, internet networks, and material handling systems. The wide use of queueing networks is due to their capability to capture the stochastic features of these systems. Different types of queueing networks based on features such as population (open, closed and mixed), blocking mechanism (blocking after service, blocking before service, repetitive blocking), and probability distribution (product form, non-product form) have been used for modelling, analysing and optimising discrete material handling systems [16]. Generally, queues and queueing networks are useful modelling constructs that can be mathematically tractable when assumptions are made to simplify them. However, most assumptions may not precisely describe the actual system properties and features. Therefore, most studies focus on developing heuristics and approximations to determine non-dominated performance measures to solve these queueing network models [17,16]. Simulation tools are also used in such situations to validate the proposed methodologies'

accuracy.

This paper focuses on determining the optimal fleet of trucks needed to operate efficiently and effectively in order to transfer the forward flows within the various stages of the supply chain under study using closed queueing networks.

The rest of the paper is structured as follows. Section 2 contains the literature review related to the problem presented in this study. Section 3 contains the methodology, modelling approach, mathematical notations, and model development. Moreover, subsections in Section 3 describe the algorithms, optimisation models, and analytical and simulation approaches. Section 4 presents the actual case study representing a regional steel manufacturing setup where the analytical model is tested and then validated using a discrete-event simulation approach. Moreover, Extensive sensitivity analyses are conducted, leading to managerial insights and recommendations. Finally, Section 5 provides possible future extensions of the presented work and a conclusion.

## 2. Literature review

This section provides the three streams of literature: i) studies on queueing network models for the analysis of general MHS applications, including the type of network used and identification of models' evaluation methods, ii) MHS fleet sizing problems which used analytical, simulation, and hybrid models (except queueing models) and iii) queueing network models of MHS fleet sizing problems.

### 2.1. Queueing network models of the MHS

Material logistics must fulfil the material requirement of its domain by coordinating the MHS to minimise the waiting time, double handling, blocking, and congestion while increasing the throughput and resource utilisation [18]. Several studies have used queueing network models to analyse MHS in various domains such as warehouses, distribution centres, manufacturing facilities, and mining fields. Studies related to MHS in warehouses and storage facilities primarily focused on estimating order cycle time, throughput and equipment utilisation rates concerning the operations or as a valuable insight for the design conceptualisation of the facility. Heragu et al. [19] and Marchet et al. [20] used an open queueing network (OQN) to estimate the performance measures, such as throughput, cycle time and utilisation of an automated vehicle system/retrieval system (AVS/RS) in a warehousing facility. The authors used the customer orders' as the network's customer and the parametric decomposition method to solve the model.

Multiple authors have used a semi-open queueing network (SOQN)

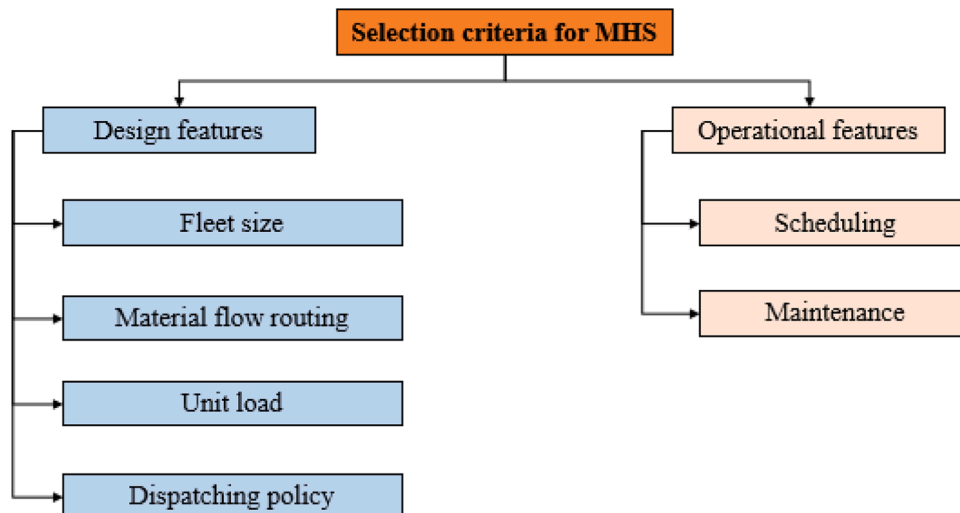


Fig. 1. Decision structure for MHS selection.

to model an AVS/RS, coupled customer orders' with warehouse handling equipment where customer orders' are modelled as a QON and handling equipment is modelled as CQN with infinite buffer capacities [21,22,23]. Roy et al. [24] developed SOQN with a finite buffer with the possibility of vehicle blocking phenomenon and extended it to study the multi-tiered layouts models [25] to estimate system performance and determine the design decision trade-offs. Ekren et al. [21] used the aggregation method to solve the model using the matrix geometric method (MGM) algorithm. Roy et al. [22–25] used the decomposition method to solve the model where CQN was solved using the convolution algorithm, and OQN was solved using Pollaczek–Khinchin mean queue length and a Laplace–Stieltjes transform formulas.

Tappia et al. [26] and Tappia et al. [27] modelled a shuttle-based storage and retrieval system (SBS/RS) in a multi-tiered warehouse using a multi-class SOQN to estimate the expected queue length and expected throughput of the system. Tappia et al. [26,27] used the decomposition approach to reduce the original network into a single chain with two single-server and the algorithm based on MGM to solve it. Ekren and Akpunar [28] studied the performance of an SBS/RS in an e-commerce warehouse facility, where most unit loads were small, using an OQN to estimate the average cycle time for an order completion process.

Several recent studies have used queueing network models to study the robotic mobile fulfilment system (RMFS) in warehousing facilities. Several authors [29–33] used a SOQN to model RMFSs to estimate system performance considering different operational considerations. Duan et al. [29] and Yang et al. [32] studied layouts' impact on the order throughput time and used a decomposition approach coupled with MGM and an approximate mean value analysis (AMVA) algorithm to solve the model. Otten et al. [31] considered the back-ordering phenomenon in the model, and Zou et al. [33] included the battery swapping/re-charging strategy. Wang et al. [34] modelled an RMFS using an OQN to study network performance.

Seyedhoseini et al. [35] modelled outbound and inbound trucks in a cross-dock using M/M/C queues to estimate truck waiting time. Motaghedi-Larijani and Aminnayeri [36,37] used a non-stationary queueing model to study the efficiency of a cross docks layout plan.

MHS in manufacturing facilities plays a critical role in smoothing material transfer operations between facilities. Work-in-progress is one of the key indicators of the efficiency of MHS in a manufacturing facility. Several authors [38–46] used queueing network models to analyse the automated material handling system (AMHS) in a semiconductor wafer fabrication facility and calculate the work-in-progress (WIP). In addition, Zhou et al. [47,48] and Zhou and Chen [49] modelled a conveyor-based automated material handling system (AMHS) using queueing network models to study the performance of continuous flow transporters (CFT) in a semiconductor manufacturing facility.

Smith and Kerbache [17] and Bedell and Smith [50] showed that state dependant M/G/C/C queues are robust tools that can be used to model MHS and use the network to study system performance considering different network topologies. Smith and Kerbache [17] modelled a manufacturing system as an open queueing network with finite buffer capacities and used the generalised expansion method (GEM) algorithm to determine the optimal network performance measures for given layout arrangements.

Queueing network models have been used to model MHS in flexible flow shops (FFS) to determine system performance considering, random lot size [51], non-equivalent automated guided vehicles (AGV) [52] and blocking phenomenon [53]. In 2017, an MHS with AGVs was modelled as an OQN with a finite buffer in a manufacturing environment to estimate system performance [38].

Open and semi-open queueing networks are used prevalently instead of the CQN to model MHS applications in various domains. The lack of use of CQN is mainly because CQN models are more complex and challenging to solve compared to OQN.

## 2.2. Fleet sizing problem of MHS

MHS fleet sizing problems have been approached using a variety of methodologies. Zuin et al. [2] categorised the methods and algorithms used for fleet sizing problems into the following groups: simulation model, analytical model, and hybrid model. This section briefly describes the different methodologies employed in studies for MHS fleet sizing problems other than queueing network models. In some hybrid models, queueing models and queueing theory are used as a part of other main approaches.

### 2.2.1. Simulation models in fleet sizing problem

This section briefly describes MHS fleet sizing problems that used simulation as a stand-alone methodology. Gobal and Kasilingam [54] and Kasilingam and Gobal [55] used a SIMAN-based simulation model to determine the size of an AGV fleet for a manufacturing facility. Fleet size estimation was based on aggregating the waiting times of vehicles, machines, and parts. Asef-Vaziri et al. [56] used a computer simulation to estimate the throughput and equipment utilisation in a container terminal against the capacity of AGVs and AS/RS. Finally, Chang et al. [57] proposed an approach called Simulation Sequential Metamodelling (SSM) to determine the fleet size of an AMHS for a semiconductor wafer fabrication facility. Razani et al. [58] used binary mathematical programming to determine the optimal wagon size for rail freight transportation considering the maximisation of operators' and owners' benefits. The authors proposed a simulation method to solve the mathematical model for both scenarios. Simulation models often consume much higher time and cost to develop and present the visual and/or numerical results. In order to interpret the results correctly, a user must have insight and a tacit understanding of the model. However, simulation models are used to validate analytical models of stochastic problems.

### 2.2.2. Analytical models in fleet sizing problem

Sinriech and Tanchoco [59] developed a multi-criteria optimization model to determine the optimal number of AGVs based on cost and throughput performance. Egbelu [60] used a hybrid algorithm to select the optimal size of unit load, vehicle, and a fleet of AGVs in a manufacturing facility. Ilić [61] used a quantitative approach to present an AGV fleet sizing problem in a discrete manufacturing system based on the cycle time. Rajotia et al. [62] used analytical and simulation models to determine the optimal fleet size of AGVs in a flexible manufacturing system (FMS), considering vehicle blocking, empty trips, and vehicle waiting time. Arifin and Egbelu [63] employed a regression analysis technique to determine the optimal number of AGVs in a manufacturing setup. Hung and Liu [64] and Johnson [65] used analytical methods to select the optimal fleet size considering multi-loads and empty trips. Hall et al. [66] developed a genetic algorithm (GA) to determine the optimal fleet size of AGVs to maximise the throughput and compare system performance considering fleet decomposition scenarios. Vis et al. [67] developed a methodology using the minimum flow algorithm to determine the optimal fleet size of AGVs for transportation between the quay and stacking areas in a semi-automated container terminal. Vis et al. [68] expanded their previous study to consider time-window constraints for container handling between a quay and a yard using a linear integer programming model. Asef-Vaziri and Laporte [69] used exact formulations to estimate an optimal fleet size by considering the AGV dispatching policies to minimise the empty and loaded trips. Vivaldini et al. [70] studied the fleet sizing problem of a warehousing facility considering the time-window constraint using the shortest job first and meta-heuristics tabu search algorithms for task assignment. Alinaghian et al. [71] presented the fleet sizing and green vehicle routing problem for a multi-depot with a time-dependence restriction. The authors used an Improved Adaptive Large Neighbourhood Search (IALNS) algorithm to solve this NP-hard problem.

### 2.2.3. Hybrid models in fleet sizing problem

Shen and Kobza [72] used queueing theory to estimate the empty vehicle travel time of a fleet of AGVs considering dispatching policies. They formulated a dispatching rule-based algorithm (DRBA) to determine the optimal fleet size. Koo et al. [73] used a queueing network model to estimate the waiting time for parts in a manufacturing facility that uses AGVs to pick up and deliver from/to multiple locations. The authors adopted a vehicle appointment policy based on assigning the nearest empty vehicle to determine the minimum number of AGVs needed for the operation. In 2003, Talbot [43] combined the Markov chain theory, linear optimisation, and an inventory re-ordering policy to determine the optimal fleet size of AGVs based on service level and product waiting time. Raman [74] presented a study on the integrated optimisation of layout planning and MHS in a manufacturing facility. The author used queueing theory to estimate manufacturing variability and, through the presented optimisation approach, showed that a facility can improve its WIP level, travel time, utilisation, and number of MHE.

### 2.3. Queueing network models of MHS fleet sizing problems

This section describes the most similar studies presented in MHS fleet sizing problems using queueing network models as the principal methodology. Choobineh et al. [75] modelled a fleet of AGVs using a multi-class CQN. They formulated a linear programming model to determine the optimal fleet size of an MHS in a manufacturing or distribution facility. The authors' used fleet size as a continuous variable in the problem formulation. Then rounded up or down according to stated criteria. For instance, if the fleet size is  $> x + 0.1$ , it is rounded up to  $x + 1$ , and if not, otherwise. Our study has modelled the optimisation problem as an MINLP and fleet size as an integer to get accurate solutions. Yuan and Gong [76] modelled an order fulfilment system run by a fleet of robots as an OQN to estimate the system performance. They also analysed how order cycle time changes when the number and velocity of robots changes and found the threshold of the fleet size that diminishes order cycle time improvement. Smith [77] modelled an MHS using a CQN. The author formulated a mixed-integer programming model to optimise the buffer allocation and network population that maximises the system throughput. Munoz and Lee [78] modelled a sugarcane harvesting system using two independent queueing systems to represent the queues on both the mill and harvest fronts. The authors used node diagrams and balance equations to solve model and integer programming to determine the minimum number of trucks needed to ensure uninterrupted mill operation and minimum cut-to-crush cycle time. Yuan and Gong [76] and Smith [77] determined the fleet size for maximising the system's throughput. In our study, the fleet size is determined comparing a given throughput level and embedded in the subjected constraints. Moreover, this study considers a CQN with shared nodes amongst multi-class customers, making the problem more complex, challenging to model, and closer to more realistic situations. In our problem formulation, we have considered the desired throughput level

with a time-frame constraint which was not in the consideration in the studies mentioned above.

Table 1 summarises the works most closely related to this study. The table also establishes scientific contributions and the gaps expected to be filled by this study.

## 3. Methodology

### 3.1. Inter-facility material transportation by homogenous trucks as a CQN

CQN are robust tools for modelling complex environments because they have a fixed Work-in-Process which reduces the complexity of the modelling problem, and the closed network is often more robust in computing the performance measures of a factory system.

A homogeneous fleet of trucks transports different types of raw materials from designated storage yards to intermediate buffer locations to be fed as inputs to a production facility for processing on a daily basis. These transformations are performed based on the daily demands and production scheduling and according to the bill of materials and specific blending needed for different types of finished products. For a typical raw material forward flow, a truck undergoes through many sub-processes such as inspection at the gate, weighted as an empty truck, loaded with a type of raw material, weighed as a loaded truck, security check at the production facility, unloading preparation, and finally unloaded. Then, the truck returns to the source yard for another trip. This cycle is continuously repeated throughout the day until the corresponding raw materials demands are fully satisfied. Each raw material encompasses different physical attributes and specific job routings.

We assumed that trucks are network customers to model this as a CQN. All process service stations (e.g., gate, loading dock, weighbridge, unloading dock) were treated as multi-class single server queues with infinite capacity and referred to as activity nodes. Trucks were categorized into different classes according to the products (raw material) they carry. Fig. 2 depicts a CQN with multi-class products. In this case, class (k) and class (k + 1) flow through the system. Nodes (i) in the network represent the activities required to process system customers. We considered two types of activity nodes. The first type is a resource node, where trucks are serviced by a queue modelled as a M/M/1 queue with Poisson arrivals at a rate ( $\lambda$ ), a single server with exponential service time  $t(i)$ , and an infinite queueing capacity. The second type is the movement between resource nodes, referred to as a circulation node. The trucks are serviced by a queue modelled as M/M/ $\infty$  with Poisson arrivals, an infinite number of servers with exponential service times, and infinite queueing capacity. Each product flows from its origin (supply node) to its destination (demand node) and transits through the network according to the corresponding routing (black and blue) and has dedicated demand (throughput).

First-come, first-served (FCFS) is the queue discipline followed in all service stations of the system. Each service station resource/machine is assumed to be reliable with zero probability of failure or breakdown. For the system depicted in Fig. 2, we introduced the following notations for

**Table 1**  
The studies on queueing network models of MHS fleet sizing problems.

Reference	Queueing network	Class	Optimisation model	Optimisation decision/s	Optimisation criteria	Shared workstations
Choobineh et al. [75]	CQN	Multi-class	Linear programming	Fleet size	Desired throughput	Yes
Yuan and Gong [76]	ONQ	Single	Non-linear programming	Fleet size	Maximise throughput	No
Smith [77]	CQN	Multi-class	Integer programming	Fleet size	Maximise throughput	No
Munoz and Lee [78]	Independent queueing system	Single	Mixed integer programming	Fleet size	Desired throughput	No
This study	CQN	Multi-class	Mixed integer non-linear programming	Fleet size and allocation	Desired throughput within a time frame	Yes



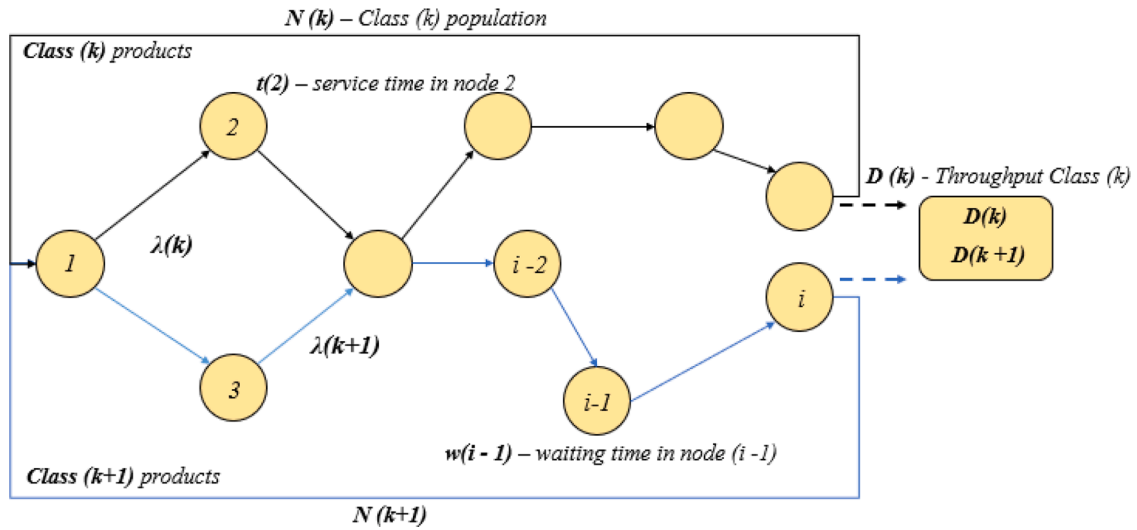


Fig. 2. A multi-class closed queueing network.

model development and mathematical formulation.

### 3.2. Notations

#### 3.2.1. Indices

$i$	index for trucks	$i = 1, \dots, t$
$j$	index for service stations	$j = 1, \dots, s$
$k$	index for product classes	$k = 1, \dots, p$

#### 3.2.2. Parameters

$t$	Available number of trucks
$s$	Number of service stations
$p$	Number of product classes
$N$	Number of trucks used in the system
$N^k$	Number of trucks for product class $k$
$T_j$	Mean service time in service station $j$
$Y_j$	Mean response time in service station $j$
$Y_j^k$	Mean response time for product class $k$ in service station $j$
$V_j^k$	Mean number of visits for product class $k$ to service station $j$
$D^k$	Demand for product class $k$
$CT^k$	Cycle time (sojourn) time for product class $k$
$F^k$	Weight of full truck load of product class $k$
$L_j$	Mean queue length in service station $j$
$L_j^k$	Mean queue length for product class $k$ at service station $j$
$\mu_j$	Mean service rate at service station $j$
$\mu_j^k$	Mean service rate for product class $k$ at service station $j$
$Y_j^k(N)$	Mean response time for product class $k$ at service station $j$ with $N$ number of trucks
$L_j^k(N)$	Mean queue length for product class $k$ at service station $j$ with $N$ number of trucks
$\Theta^k(N)$	Throughput of product class $k$ with $N$ number of trucks
$\rho_j^k(N)$	Utilisation rate of service station $j$ for class $k$ with $N$ number of trucks
$Z_i^k$	Number of trips by truck $i$ used to transport product class $k$
$\beta$	Upper bound of the number of trucks to be used in a single shift
$T$	Duration of the time window

### 3.3. The mean value analysis (MVA) algorithm

Performance measures such as cycle time for each type of transfer, utilisation of resources at task stations, and waiting time at each station are paramount for decision making in the inter-facility transportation process. The MVA algorithm is a computationally attractive method for calculating the mean length of the queue and the mean waiting time in the queue, as developed in the MVA theorem by Reiser and Lavenberg

[79]. Subsequently, other mean performance measures can be calculated from these parameters. The MVA algorithm is often used in closed queueing network performance measurements because of its efficiency, and it precludes the calculation of a normalisation constant  $G(N, k)$  [80].

In what follows, we have tailored the algorithm for our problem using Kerbache and Smith [81]; Smith and Kerbache [17]; Smith and Kerbache [82] work. The main steps of the tailored MVA algorithm as follow:

Reiser and Lavenberg [79] proved the arrival theorem, which states that, in a closed queueing network, the stationary distribution noted by a customer arriving at a node of the network is equivalent to that of customers in the same network with one fewer customer. Based on this theorem, in a single server station “ $j$ ”, the response time is

$$Y_j(N) = T_j + T_j L_j(N-1), j \in \{1, 2, \dots, s\} \quad (1)$$

The above equation can be extended to a multi-class system, using the service rate ( $\mu$ ) instead of service time.

$$Y_j^k(N) = \frac{1}{\mu_j^k} \left( 1 + L_j^k(N-1) \right), j \in \{1, 2, \dots, s\}, k \in \{1, 2, \dots, p\} \quad (2)$$

According to Little’s law equation for product chains, the throughput of class  $k$  customers is

$$\Theta^k(N) = \frac{N}{\sum_{j=1}^s V_j^k Y_j^k}, j \in \{1, 2, \dots, s\}, k \in \{1, 2, \dots, p\} \quad (3)$$

Similarly, from Little’s law equation for queues, the mean queue length of class “ $k$ ” customers at station “ $j$ ” is

$$L_j^k(N) = \mu_j^k(N) V_j^k Y_j^k(N), j \in \{1, 2, \dots, s\}, k \in \{1, 2, \dots, p\} \quad (4)$$

Eq. (1) is the response time at service station  $j$  for a single-class network. The response time is the sum of both the waiting and service times. Eq. (2) provides the response time for a multi-class system. Finally, Eq. (3) is the throughput of the class  $k$  product, while Eq. (4) is the expected queue length of the class  $k$  product at station  $j$ .

### 3.4. Optimisation problem

Optimising the performance of a transportation network system requires taking into account many factors, such as fleet size, cost, delivery speed, and resource utilisation. Often, these factors are highly correlated and affect the overall performance of the network system. Consequently, decision-makers strive to find a non-dominated trade-off between these

factors to achieve the desired goals.

For instance, the operating cost of an inter-facility transportation network serviced by a homogenous fleet of trucks is highly dependant on the number of trucks in the system. Furthermore, if the system is modelled as a closed network with single servers at activities service stations, a large fleet size may increase waiting times and result in longer cycle times. Moreover, a confined fleet may be unable to fulfil the expected demand. Therefore, it is paramount to determine the optimal fleet size required to fulfil the demand within the given time-frame.

The primary objective of this study is to minimise the total size of the truck fleet to be used in the stated transport system. The total number of trucks should equal the aggregated sum of the trucks used by each product class in a single shift.

The decision variable and the surrogate variables are as follows:

$$x_i^k := \begin{cases} \text{if the truck } i \text{ is assigned to product class } k \text{ is } 1, \\ \text{Otherwise } 0 \end{cases}$$

$CT^k$  := Cycle time for product class  $k$ .

$N^k$  := Number of trucks assigned to product class  $k$ .

The problem objective function is as follows:

$$\text{Min } N = \sum_{i=1}^t \sum_{k=1}^p x_i^k \quad (5)$$

The constraints are as follows:

$$\sum_{k=1}^p x_i^k \geq 1 \quad \forall i \quad (6)$$

$$N^k \cdot \frac{T}{CT^k} \cdot F^k \geq D^k \quad \forall k \in \{1, 2, \dots, p\} \quad (7)$$

$$\sum_{i=1}^t \sum_{k=1}^p x_i^k \leq \beta \quad (8)$$

$$Z_i^k \cdot CT^k \leq T \quad \forall i, k \in \{1, 2, \dots, p\} \quad (9)$$

$$N^k \in \mathbb{Z}^+, CT^k \in \mathbb{R}^+ \text{ and } x_i^k \text{ are binary} \quad (10)$$

The objective function (eq. (5)) minimises the number of trucks in

the system. It is a linear function that aggregates all trucks used by different product classes. For all trucks, the constraint (eq. (6)) ensures that a truck is allocated either to one product class or left unused in a single shift. Constraint (eq. (7)) ensures that for all product classes, demand must be met. Moreover, this is a non-linear constraint ensuring that any truck used must utilise its total capacity for all trips. Constraint (eq. (8)) restricts the number of total trucks to be used owing to budgetary limitations. Constraint (eq. (9)) ensures that all trucks must respect the time limit of a single shift. Constraint (eq. (10)) ensures that  $N^k$  is a positive integer,  $CT^k$  is positive real, and  $x_i^k$  is binary.

#### 3.4.1. Computational complexity of this resulting mathematical optimisation problem

The mathematical formulation of the closed queueing network above Eq. (5) to (10) is a mixed-integer nonlinear programming problem that is NP-hard, as shown by many researchers, such as Papadimitriou and Tsitsiklis [83]. These authors considered models of closed queueing networks that have a queue discipline of non-preemptive policies. Similarly, the optimisation problem presented in our study falls in the category mentioned above, where a closed queueing network model with multiple product classes follows the first-come-first-serve policy. Consequently, one must resort to approximation solutions using numerical optimisation approaches and efficient heuristics. In this study, we used a numerical method based on the Sequential Quadratic Programming (SQP) methodology [84]. The SQP relies on performance measures determined through the MVA algorithm to determine the optimal fleet size (Fig. 3; [81]). The nonlinear optimisation problem and MVA algorithm are coded in Fortran-90 by linking the IMSL numerical library. An NNLPF subroutine in the IMSL package performs the SQP process. This subroutine solves nonlinear programming problems using the sequential equality constrained quadratic programming method [85].

All computational experiments were carried out on a PC environment Intel(R) Core i3-7100 U CPU 2.40 GHz, 4.00 GB RAM.

#### 3.5. Simulation model

A discrete event simulation (DES) model was developed to analyse the behaviour and performance of the analytical queueing network. As a

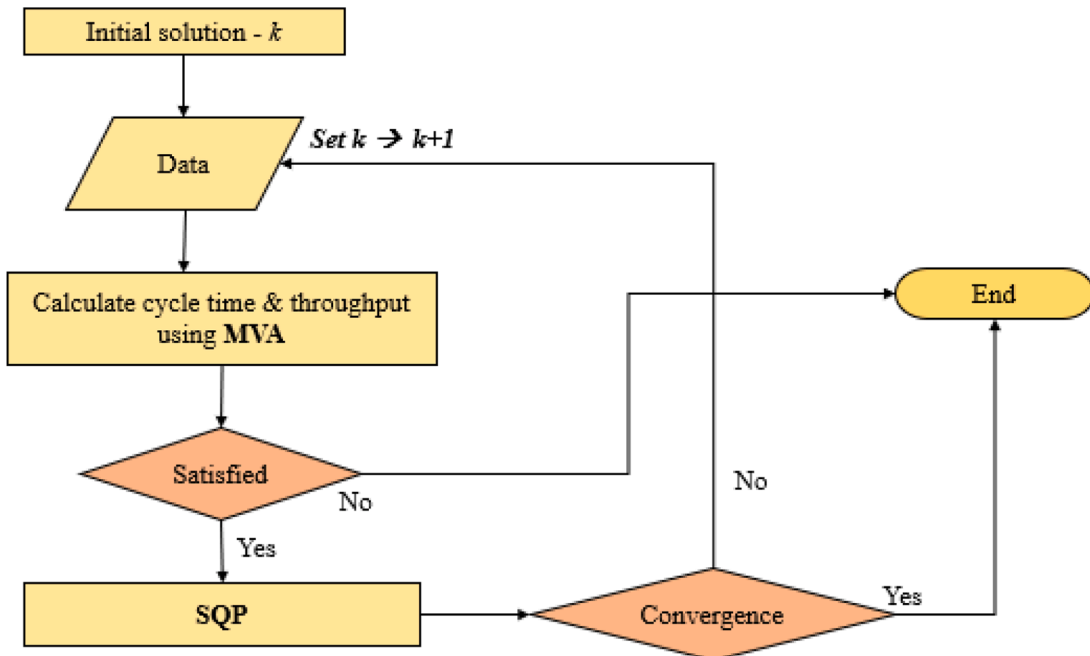


Fig. 3. Methodology flowchart for optimisation method based on SQP.

starting step, a detailed process map was developed, which indicated that all the materials flowed between and within the considered facilities. The magnitude, frequency, and processing time of each operation were estimated and inputted into the system to develop a detailed process map of all the flows. The validation process, through simulation, the existing operations and comparing the simulation outputs to the current performance measures to ensure that the model mimics the operations to its very best. Once the model is validated and stabilized, different scenario experiments are performed.

In this study, we used the Anylogic Simulation Software to build the simulation model as in Zhiwei et al. [86]. The simulation model was set up with 43,200-time units, with 1000 units (warm-up period) and 30 replications, to achieve steady-state results with a report of 95% confidence interval parameter estimates for each simulation run, as shown in Fig. 4.

#### 4. Steel manufacturing case study

To illustrate the applicability and robustness of our analytical queuing network models, we consider a real-world case study performed in collaboration with a major regional steel production company. Steel manufacturing (SM) is the sole supplier of steel requirements in the domestic market. It produces 6.4 million tons of steel rebars annually, for which raw materials are procured both locally and globally. Fig. 5 shows simple material flows representing a high level of its supply chain. This study focuses on three types of raw material (Product class A, B, and C) transfer from storage areas to billet plants. SM manufactures steel billets using the raw material in the plant and transfers them to a rolling mill to manufacture steel rebars. The finished products, such as steel rebars, are then delivered to customers.

As shown in Fig. 5, the raw materials come from different sources and are transported to the dedicated facilities in the storage yard. Inter-facility transportation ensures that the material requirements of the billet plant are satisfied by the storage yard. At the start of the day, the Billet plant provides the daily materials requirement to the storage yard logistics manager, who, in turn, mobilises the fleet of trucks to be assigned to transfer the various types of raw materials.

The internal transfer is carried out by a homogenous fleet of trucks from a third-party logistics (3PL) provider. Obviously, the task of the logistics manager is to order the optimal number of trucks for the day to ensure the minimum optimal total operational cost while fulfilling the plant requirements. Additional complexities arise in this process because the plant uses a different bill of materials (BOM) in the manufacturing process, which requires different combinations of raw materials. Each raw material has different density properties, leading to different weights on the full truckload, as shown in Table 2.

Fig. A.9 in the Appendix illustrates the layout of the SM facility, and Table 3 shows the node labelling and the details of the nodes. All service activities and circulations are indexed as nodes. Several nodes are dedicated to processing a single class of product, while the other nodes are jointly used by all or a combination of product classes. For instance,

all classes of products use nodes 1 and 2, whereas node 4 is used only by product class A. Fig. 6 shows SMs inter-facility material transfer operations modelled as a multi-class CQN. Fig. 7 shows the process flow mapping for internal material transfer operations. Each process has a specific operational processing time and uses a set of resources. The process may have different operation times depending on the product class. For instance, product class A loading requires an average of 8 min, while product class B loading requires 19 min. Table 4 shows the average processing service time for each process with respect to product class and type of the service station.

The product class routes (paths) are shown as per below.

Path class A: 1→2→3→4→5→6→7→8→9→10→11→12→1

Path class B: 1→2→13→14→15→6→16→17→18→10→11→19→1

Path class C: 1→2→13→20→15→6→16→17→21→22→23→19→1

The type of node indicates the number of trucks that can be handled at once. Specific processes (M/M/1 nodes) can serve one truck at a time, while other processes (M/M/∞ nodes) can accommodate an infinite number of trucks at a given time. The use of M/G/C/C models was not felt necessary since the capacities of the circulation aisles were deemed adequate.

As shown in Table 5, the following scenarios are different production BOMs used by the SM to produce steel billets. Each BOM requires 2000 tons of raw-material combinations in a single shift (12 h), which must be delivered from the storage yard to the billet plant. SM obtains trucks from a third party to transport the materials based on a cost that is proportional to the number of trucks to be used.

##### 4.1. Analyses and comparisons of results

This section presents analyses and results of the proposed optimisation method based on the SQP and the performance evaluation method based on the MVA algorithm. Figs. 6 and 8 provides the SMs inter-facility material transfer operations modelled as a multi-class CQN and simulation model. The optimisation results for the scenarios, as shown in Table 5, are determined through the proposed analytical method and validated against the simulation model results. Similarly, network performance measures such as queue response time, server utilisation rate, and cycle time for scenarios, as shown in Table 5, were calculated using the analytical method and validated through simulation model results.

##### 4.1.1. Optimal trucks allocation and computation times

Table 6 shows the optimal total number of trucks and the allocation of trucks to each product class for each scenario. Analytical model solutions were validated using the results of the simulation model. The developed Anylogic simulation model uses successive iterations and metaheuristic approaches to determine the optimal solutions. The OptQuest Optimization Engine was primarily used in the Anylogic optimisation tool, which can incorporate metaheuristics to guide its search

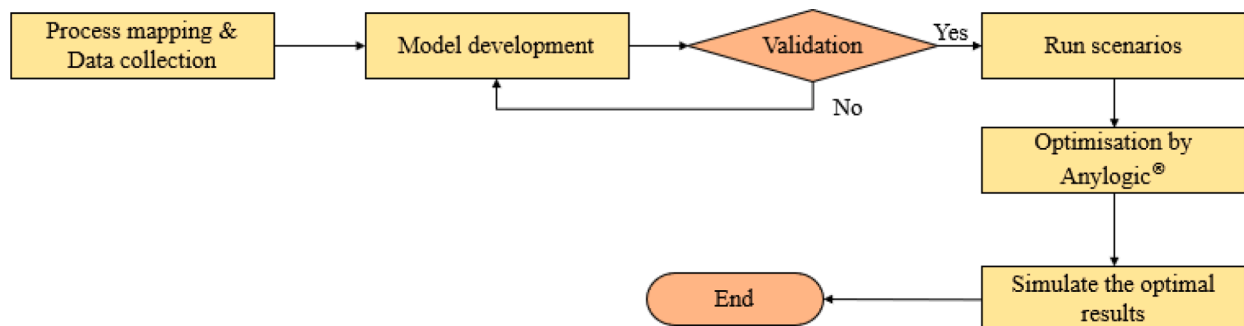


Fig. 4. Flow chart of simulation model development and experiments.



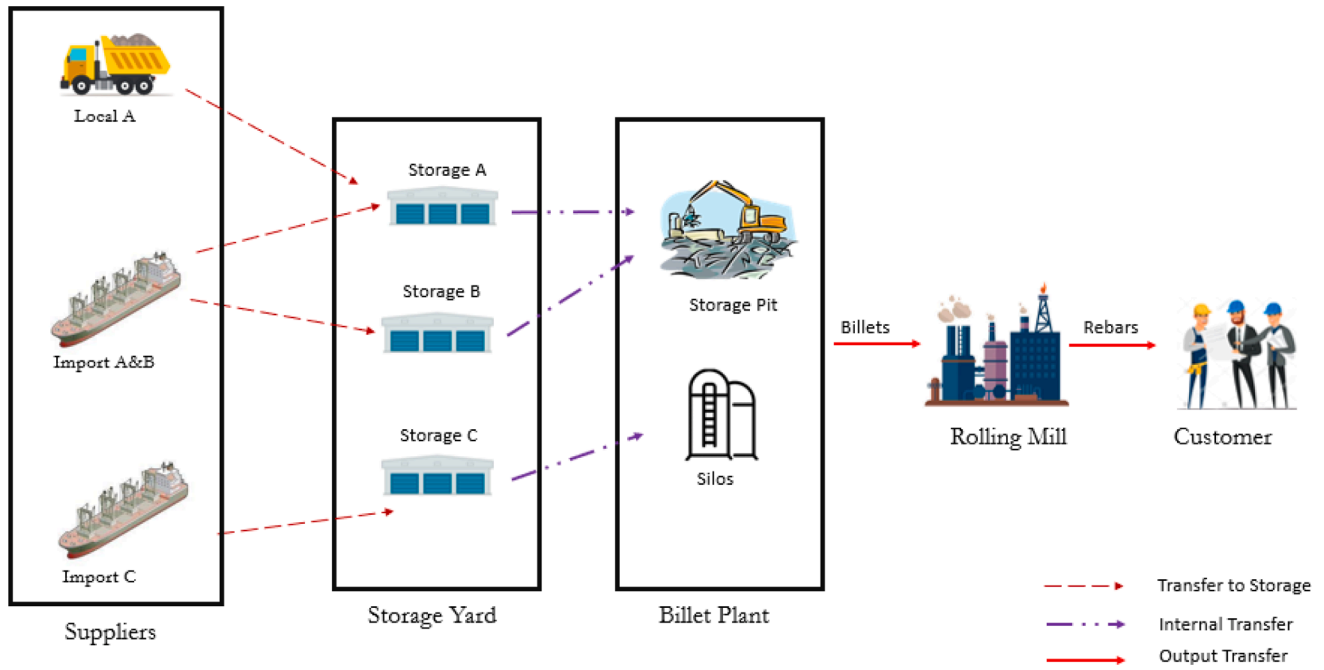


Fig. 5. High-level supply chain of SM.

Table 2

Full truckload weights.

Product class	Mass of a truckload (tons)
A	15
B	33
C	30

Table 3

Node labelling and details.

Node #	Detail	Node #	Detail
1	Gate	13	Proceeding to loading dock – B,C
2	Weigh bridge (WB) – tare weight	14	Loading operation - B
3	Proceeding to loading dock - A	15	Proceeding to WB – B,C
4	Loading operation - A	16	Travel – yard to plant – B,C
5	Proceeding to WB	17	Plant WB – B,C
6	WB – gross weight	18	Proceeding to unloading dock - B
7	Travel – yard to plant - A	19	Plant to yard – B,C
8	Plant WB - A	20	Loading operation - C
9	Proceeding to unloading dock - A	21	Proceeding to unloading dock - C
10	Unloading preparation – A,B	22	Unloading preparation - C
11	Unloading operation - A, B	23	Unloading operation - C
12	Travel – plant to yard - A	-	-

algorithm toward better solutions [87].

In this study, the number of iterations was set to 5000 for each scenario to determine the optimal solution. As shown in Table 6, the computation times show the superiority of the analytical model compared to the simulation model. For a given scenario, the simulation model requires a higher computation time compared to that of analytical model. Simulation model consumes similar computation time for all the scenarios due to the fact of same number of iterations used for all cases.

#### 4.1.2. Utilisation rate

Server utilisation rates are key performance indicators of queueing networks. Utilisation rates range between 0% and 100%. Higher utilisation rates are indications of congestion at service stations, and they are often used to determine the bottlenecks of a system. Similarly, lower utilisation rates indicate the under-utilisation of service stations in the system.

Table 7 presents the utilisation rate comparison of selected nodes for each of the four scenarios. Node 4 (loading – class A), Node 10 (unloading preparation – classes A and B), node 14 (loading – class B), and node 23 (unloading – class C) are selected for comparison, as these nodes play a critical role in this transport system. The last column of Table 7 indicates the differences between the analytical and simulation model outputs.

Each difference is calculated as follows and expressed as a percentage:

$$\text{Difference } (\Delta) = (\text{Ana. model value} - \text{Sim. model value})$$

As shown in Table 7, the values of this percentage difference with respect to the analytical model output lie within  $\pm 6\%$  in all instances. Therefore, it is evident that the proposed analytical model approach can produce effective outputs that are reasonably accurate in determining the utilisation rates. Moreover, Table 7 shows that node 10 has the highest utilisation rate in all scenarios except Scenario 2, where node 14 has the highest utilisation rate. For node 10, except in Scenario 1, the utilisation rate is approximately 0.75. It is evident that node 10 becomes rapidly congested with an increase in trucks in the network. Node 10 is clearly the system's bottleneck in Scenarios 2,3, and 4. Similarly, node 14 becomes congested in Scenarios 2 and 3. In summary, node 10, the unloading preparation station for class A and B products, and node 14, the loading dock for class B, are the bottlenecks of the system. These flagged results are valuable for decision managers to mitigate potential system saturation challenges by implementing continuous process improvements.

#### 4.1.3. Queue response time

Waiting time is a crucial performance measure in a queueing network. Table 8 shows the analytical and simulated queue response time comparisons for the selected nodes for each scenario per product

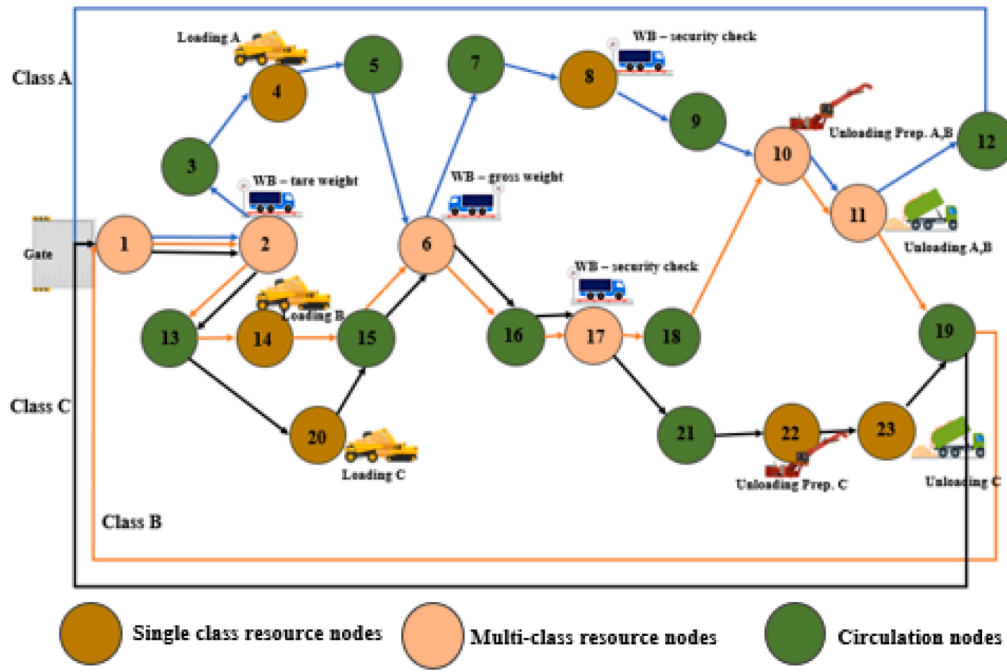


Fig. 6. CQN of SMs inter-facility material transfer operations.

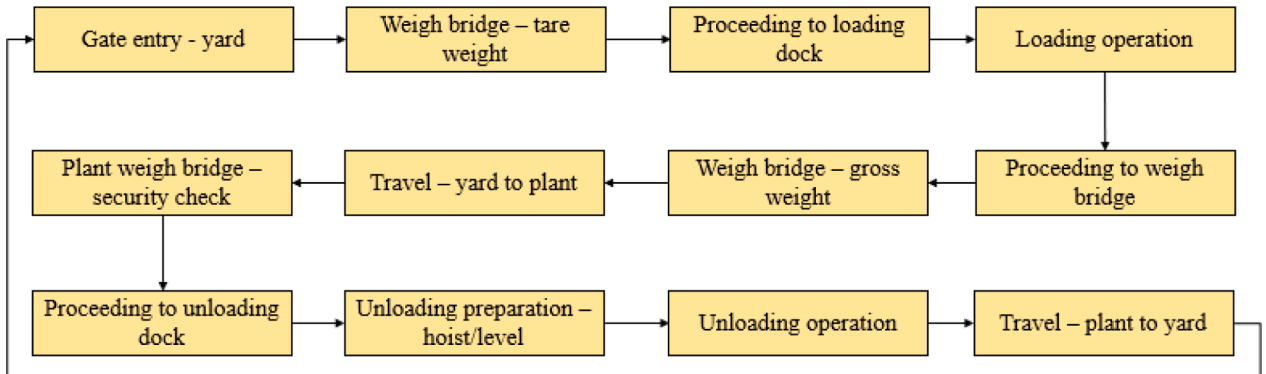


Fig. 7. Process mapping flow chart for inter-facility material transfer.

class. Table 8 shows that across all instances, the percentage differences between the analytical and simulation approaches with respect to the analytical approach lie within  $\pm 7\%$ .

$$\text{Difference } (\Delta) = \frac{(\text{Ana. model value} - \text{sim. model value})}{\text{Ana. model value}} * 100\%$$

For instance, the outputs from both analytical and simulation methods for the queue response times for selected nodes in Scenario 1 were compared for all classes. Moreover, a set of selected node queue response times for a selected single class was compared for Scenarios 2, 3, and 4.

Clearly, the analytical model provides robust results for the queue-response time measures in each case. Moreover, the percentage deviations of the queue response times for circulation nodes, such as node 7 (moving to billet plant pit), node 13 (moving to storage B and C), node 15 (moving to WB), node 16 (moving to silo), and node 19 (moving to the yard), are within a range of  $\pm 3.5\%$ .

#### 4.1.4. Cycle time

The cycle time is also considered one of the key performance indicators of a queueing network. Table 9 shows the output obtained from the analytical and simulation methods and their deviation percentages.

The deviation percentage was calculated as follows.

$$\text{Difference } (\Delta) = \frac{(\text{Ana. model value} - \text{sim. model value})}{\text{Ana. model value}} * 100\%$$

In conclusion, the proposed analytical model is a robust and effective approach for the optimisation and performance evaluation of this type of problem.

#### 4.2. Robustness of the methodology

This section briefly explains the robustness of the proposed methodology for optimising and analysing CQN models for MHS applications. The validation is done through the corresponding simulation experiment. Choobineh (2012) presented a CQN coupled with a linear programming model that registered 87% accuracy in determining the optimal fleet size of AGVs in a manufacturing environment. Our methodology demonstrates 100% accuracy on the optimal fleet size (Table 6) determination in the SMs case study. Moreover, the outputs of performance measures such as queue response time, utilisation, and cycle times are found to be within acceptable limits all the time. Table 10 summarises the performance measures' absolute deviation of similar studies and this study.

**Table 4**  
Node types and average service times.

Process	Ave. time (min)	Type of node	Process	Ave. time (min)	Type of node
Gate entry - yard	1.5	M/M/1	Travel – yard to plant – B,C	14	M/M/∞
WB – tare weight	1.5	M/M/1	Plant WB – A	0.45	M/M/1
Proc. to loading dock – A	1.5	M/M/∞	Plant WB – B,C	0.45	M/M/1
Proc. to loading dock – B,C	1.5	M/M/∞	Proc. to unloading dock – A,B	1.5	M/M/∞
Loading – A	8	M/M/1	Proc. to unloading dock – C	5	M/M/∞
Loading – B	19	M/M/1	Unloading preparation	8	M/M/1
Loading – C	8	M/M/1	Unloading – A	7	M/M/1
Proceeding to WB – A	2.5	M/M/∞	Unloading – B	2.5	M/M/1
Proceeding to WB – B,C	1.5	M/M/∞	Unloading – C	2.5	M/M/1
WB – gross weight	0.45	M/M/1	Travel – plant to yard – A,B	12	M/M/∞
Travel – yard to plant – A	18	M/M/∞	Travel – plant to yard – B	12	M/M/∞

**Table 5**  
Identified BOM scenarios.

Scenario #	Class A (tons)	Class B (tons)	Class C (tons)
Scenario 1	350	550	1100
Scenario 2	500	700	800
Scenario 3	650	800	550
Scenario 4	800	800	400

### 4.3. Sensitivity analysis

This section briefly discusses how the optimal solution changes with changes in the model parameters. Sensitivity analysis is an integral tool for decision-making risk management over the short, medium, and long term.

For a comprehensive analysis, we consider the influence of changes in the following two design parameters on the optimal solutions discussed previously. The first design parameter is the truck capacity, and

the second parameter is the service time of a bottleneck node. The analysis was performed as follows:

#### 4.3.1. Changes in truck capacity

Let us assume that the truck capacities are changed by  $\pm 20\%$ , thus leading to both reduced and increased capacity cases. Obviously, the truck capacity changes will result in a change in the full truckload weights for each class. The new full truckload weights for each class led to the analysis of six cases, as shown in Table 11.

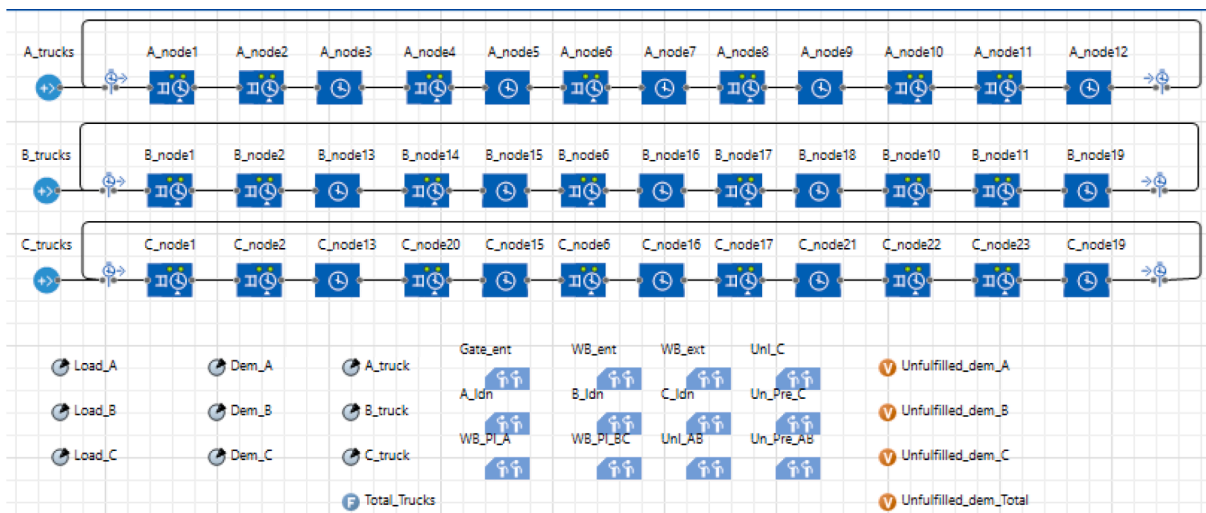
Table 12 presents the optimal solutions for Scenarios 1 and 2 for the reduced and increased truck capacity parameters. Logically, increasing the truck capacity should reduce the number of trucks required to meet daily demand and vice versa. A 20% decrease in capacity resulted in an increase of 22.22% and 10% in the total number of required trucks in Scenarios 1 and 2, respectively, while a 20% increase reduced the requirement by 22.22% and 30% for Scenarios 1 and 2, respectively. Again, the simulation model outputs validate the analytical model's optimal solutions.

#### 4.2.2. Changes in the service times for the bottleneck node 10

We assume that there is an improvement in the service time of node 10. Previously, this node was identified as one of the bottleneck nodes in the system, as both product classes A and B use it for an average service time of 8 min. Table 13 shows the impact of the improved service time at node 10 on the optimal solution and utilisation rate under Scenarios 3 and 4. In what follows, we set the new service time for node 10 to 4 min (50% improvement). The improvement in the service time at node 10 resulted in a decrease in the optimal fleet size from 10 trucks to 9 trucks in Scenario 3 and from 12 trucks to 10 trucks in Scenario 4. Similarly, as expected, the improved service time reduced the utilisation rate at node 10 in both scenarios. The analytical results were validated using the simulation model.

### 4.4. Managerial insights

Table 6 summarises the optimal truck allocation for all scenarios assuming that the plant receives 2000 tons of raw materials from the yards. However, the number of trucks required in each scenario and the truck allocations are different. Therefore, logistics decision-makers must consider the physical attributes of different products, the composition of different products, and the service times of various processing stations present in multi-class product transportation systems. Similarly, specific scenarios require fewer trucks than others which implies that those BOMs and production blending incurs lower logistics costs. Table 9



**Fig. 8.** The simulation model of SM's inter-facility material transfer operation.

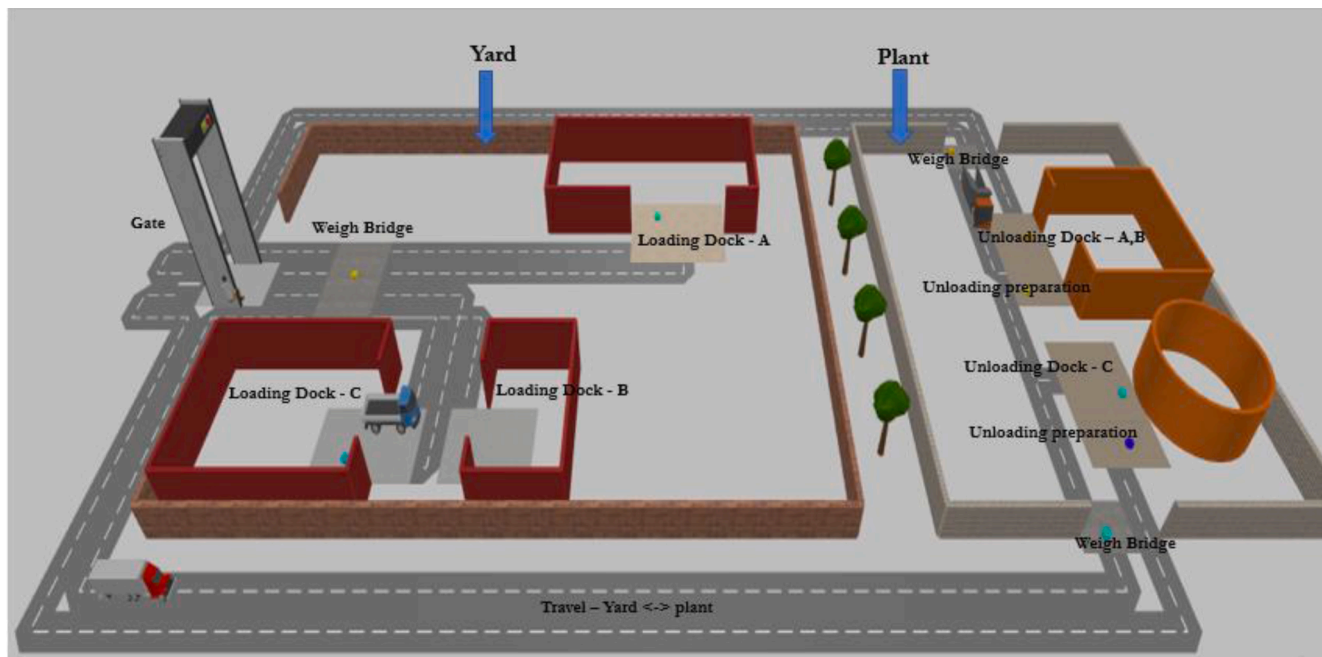


Fig. A.9. Facility layout of SM.

Table 6

Validation of optimal truck allocation and computation time comparison.

Scenario #	Analytical model		Total # of trucks	Simulation model		Total # of trucks
	Optimal allocation Class (A,B,C)	Computation time (s)		Optimal allocation Class (A,B,C)	Computation time (s)	
Scenario 1	3,2,4	3	9	3,2,4	23	9
Scenario 2	4,3,3	3	10	4,3,3	24	10
Scenario 3	5,3,2	3	10	5,3,2	24	10
Scenario 4	7,3,2	3	12	7,3,2	25	12

Table 7

Utilisation rates comparison between analytical and simulation model.

Scenario #	Node #	Analytical model Utilization rate	Simulation model Utilization rate	difference ( $\Delta$ )
Scenario 1	Node 4	0.342	0.387	-4.5%
	Node 10	0.564	0.623	-6.0%
	Node 14	0.526	0.559	-3.3%
	Node 23	0.150	0.167	-1.7%
Scenario 2	Node 4	0.420	0.471	-5.1%
	Node 10	0.737	0.766	-2.9%
	Node 14	0.755	0.767	-1.2%
	Node 23	0.119	0.125	-0.6%
Scenario 3	Node 4	0.494	0.541	-4.7%
	Node 10	0.798	0.843	-4.5%
	Node 14	0.724	0.758	-3.4%
	Node 23	0.083	0.078	0.5%
Scenario 4	Node 4	0.607	0.661	-5.4%
	Node 10	0.885	0.942	-5.8%
	Node 14	0.661	0.694	-3.3%
	Node 23	0.083	0.087	-0.4%

shows the cycle time for each product class and each scenario and that the total number of trucks and cycle time are positively correlated. It is clear that although the number of total trips increases when the fleet size increases, the average number of trips made by each truck decreases. This diminishing marginal average also implies that after a certain number of trucks, the throughput will only increase marginally, and the cycle time will increase drastically. Therefore, in the event of a more significant expansion of the production plant's capacity, the material transfer process needs to re-configure the number of servers in the

bottleneck stations or break down those processes into a few sub-processes to fulfil the extra demand. In addition, from the sensitivity analysis, we notice that increasing or decreasing the design parameters does not proportionately influence the optimal fleet size. Therefore, parameter changes must be analysed separately to determine the corresponding optimal configurations.

In summary, these measures provide solid inputs for sound decision making (e.g., bottleneck nodes, imbalance load nodes, idle resources). Moreover, top management needs to consider all possible scenarios to evaluate and design an organisation's fleet. All managerial levels need to provide inputs and findings to optimise the entire system. For instance, decisions and activities for determining the right fleet size, coordinated planning and scheduling, as well as monitoring and controlling need to be integrated to achieve superior performance.

## 5. Conclusion and future extensions

Manufacturing organisations' focus on their core competency has placed third party logistics service providers to deliver supportive activities such as material handling, transportation, and storage using their expertise and economies of scale. Signing leasing contract with a third-party logistics service provider for a right fleet size that ensures smooth transfer of materials between facilities is a challenging decision-making problem faced by manufacturing companies attempting to minimise transportation and handling costs. This study considers the fleet sizing problem of homogeneous trucks to be outsourced (or subcontracted) from a third-party logistics provider to be used daily to transport different types of raw materials from designated storage yards to intermediate buffer locations to be fed as inputs to a production facility for

**Table 8**  
Queue response times comparison between analytical and simulation model.

Class	Scenario #	Node #	Analytical model Queue response time (min)	Simulation model Queue response time (min)	difference ( $\Delta$ )%
Class A	Scenario 1	Node 2	1.806	1.858	-2.90%
		Node 4	10.164	9.600	5.55%
		Node 7	18.182	17.561	3.41%
		Node 10	13.200	12.611	4.46%
Class B	Scenario 1	Node 10	12.520	13.280	-6.07%
		Node 13	1.500	1.466	2.24%
		Node 15	1.500	1.514	-0.94%
		Node 19	12.005	11.540	3.87%
Class C	Scenario 1	Node 2	1.806	1.911	-5.78%
		Node 15	1.500	1.532	-2.13%
		Node 16	14.006	13.784	1.58%
		Node 23	2.823	2.630	6.83%
Class A	Scenario 2	Node 2	1.841	1.720	6.55%
		Node 4	11.372	12.082	-6.25%
		Node 7	18.182	17.667	2.83%
		Node 10	17.164	16.090	6.26%
Class B	Scenario 3	Node 10	17.890	16.836	5.89%
		Node 13	1.500	1.447	3.52%
		Node 15	1.500	1.444	3.74%
		Node 19	12.005	11.685	2.67%
Class C	Scenario 4	Node 2	1.844	1.723	6.56%
		Node 15	1.500	1.449	3.42%
		Node 16	14.006	13.504	3.58%
		Node 23	2.609	2.505	3.98%

processing. These transformations are performed based on the daily demands and production scheduling and according to the bill of materials and specific blending needed for different types of finished products. The inherent variability and uncertainty associated with demand and other functional characteristics of the raw materials make this problem extremely challenging. Within this context, the problem is modelled as a closed queueing network (CQN) combined with a mixed-integer nonlinear programming (MINLP) problem to determine the

**Table 9**  
Analytical and simulation model's cycle time for each product class.

Scenario #	Cycle time (min)			Cycle time (min)			Cycle time (min)		
	A			B			C		
	Ana.(min)	Sim.(min)	Diff.	Ana.(min)	Sim.(min)	Diff.	Ana.(min)	Sim.(min)	Diff.
Scenario 1	70.09	67.24	4.07%	72.37	75.30	-4.05%	66.85	65.07	2.65%
Scenario 2	76.27	72.86	4.47%	75.63	78.93	-4.36%	63.22	64.72	-2.37%
Scenario 3	81.06	77.20	4.76%	78.85	82.00	-4.00%	59.96	62.35	-4.00%
Scenario 4	92.33	88.01	4.68%	86.34	83.04	3.83%	60.03	63.64	-6.00%

optimal fleet size. Determining the optimal fixed population of the closed queueing network (in this case, the size of the trucks fleet) in which multi-class customers (in this case, the different types of raw materials) are transported within the closed queueing network from sources to sinks, using different routings, to be processed into different types of finished products according to the daily demands and the production facility capacities is an NP-hard problem. This study proposes an effectiveness and robustness analytical method based on a sequential quadratic programming (SQP) methodology coupled with a mean value analysis (MVA) algorithm to solve the problem.

The proposed analytical approach, along with the simulation, are implemented in a real case study of a steel manufacturing setup through two stages. The first stage consisted in validating, through simulation, the existing operations and comparing the simulation outputs to the current performance measures. The second stage consisted in modelling the system under study, as a CQN and then running the optimization model. The results are then validated by simulation. The optimization approach yielded superior performance measures than those currently used by the steel company and showed, if implemented, they would lead to substantial operational cost savings. Finally, an extensive sensitivity analyses are performed, and their results led to some interesting managerial insights.

As extensions, we plan to consider a heterogeneous fleet of trucks with different cost parameters with the objective of minimising the total operating costs. Similarly, this upstream of the supply chain will be extended to include the transformation of billets into various finished products, as well as the physical distribution of these products to local and international customers. The resulting large-scale problem can be modelled and solved as an open queueing network. Furthermore, this research can be extended to include stochastic features such as fluctuating demand, machine breakdowns, repairs, and maintenance to mimic more realistic operational conditions.

**Table 10**  
Performance index comparison between similar studies.

References	Queue waiting time		Utilisation		Cycle time	
	Ave. dev.%	Dev. range%	Ave. dev.%	Dev. Range%	Ave. dev.%	Dev. Range%
[25]	> 8%	4% - 12%	> 1%	-	> 4%	-
[33]	9.60%	2% - 16%	5%	2% - 8%	7%	3% - 9%
This paper	> 7%	1% - 8%	> 4%	1% - 6%	> 5%	3% - 6%

**Table 11**  
New truckload mass for each product class.

Class	Original full truck load mass (tons)	-20% reduced cap. (tons)	20% increased cap. (tons)
A	15	12	18
B	33	26.4	39.6
C	30	24	36



**Table 12**

Changes in optimal truck allocation with respect to changes in truckload mass.

Scenario # (original optimal allocation)	Change% truck capacity	Analytical method New optimal allocation (A, B,C)	Total # of trucks	Simulation method New optimal allocation (A, B,C)	Total # of trucks	Difference (%)
Scenario 1 (3,2,4)	−20%	3,3,5	11	3,3,5	11	22.22%
	+20%	2,2,3	7	2,2,3	7	−22.22%
Scenario 2 (4,3,3)	−20%	5,3,3	11	5,3,3	11	10.00%
	+20%	3,2,2	7	3,2,2	7	−30.00%

**Table 13**

Impact of service time improvement in node 10 on fleet size and allocation.

Scenario # (original optimal allocation)	Improved node 10 service time	Analytical method New optimal allocation (A,B,C)	Utilization rate (original & new)	Simulation method New optimal allocation (A,B,C)	Utilization rate (original & new)
Scenario 3 (5,3,2)	4 min	4,3,2	0.798	4,3,2	0.843
			0.423		0.435
Scenario 4 (7,3,2)	4 min	5,3,2	0.885	5,3,2	0.942
			0.505		0.511

**CRedit authorship contribution statement**

Mohamed Amjath: Conceptualisation, Methodology, Simulation model, Writing – original draft.

Laoucine Kerbache: Conceptualisation, Methodology, Algorithm coding, Writing – review & editing, Supervision.

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**Declaration of Competing Interests**

The authors declare that they have no competing interest.

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**Appendix A**

Facility layout of SM organisation with the storages, processing plants and service stations.

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