Fleet Sizing of Heterogeneous Fleet of Trucks in a Material Handling System Using Anylogic Simulation Modelling

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Abstract
The focus of manufacturing organisations on their core competencies has placed third-party logistics service providers (3PL) in an ideal position to deal with supportive activities such as material handling, transportation, and storage using their expertise and economies of scale. This study considers the problem of determining the optimal fleet size of heterogeneous trucks to be outsourced from a 3PL to fulfil the demand of various raw materials requirements by a production facility while achieving a minimum total cost of these daily operations. Trucks are deployed in an inter-facility material transportation system with different raw materials from designated storage areas to be transported to specified buffer locations per the production requirements. In a typical material forward flow, a truck undergoes many sub-processes with stochastic service times that vary with the type of material it carries and the type of the truck. Each material encompasses different physical attributes and specific job routings. Within this context, the inter-facility transportation process is modelled as a closed queueing network (CQN), and a mathematical model is developed to determine the optimal number of heterogeneous trucks to be outsourced from a 3PL while fulfilling the production requirements. A Discrete event simulation model, using Anylogic simulation software, is employed for solving the model to determine the optimal fleet size of trucks and their specific heterogeneous composition. Moreover, the simulation model is used to determine the main performance measures of the system, such as sub-process response times, queue lengths, cycle times, resource utilisations and bottlenecks, to assist in the decision-making process.

Keywords
Material handling system, fleet sizing, heterogeneous fleet, Simulation, queueing theory

1.Introduction

Material handling systems (MHS) are integral components in logistics functions by providing various supports such as handling, moving, and storing materials in manufacturing and service organisations. MHS is defined as a machine or set of machines responsible for material transfer over a short distance within a production facility, warehouse, or plant according to a designated requirement (Sahu et al. 2017). Material handling activities account for 15% to 70% of total manufacturing cost, depending on the type of products (Soufi et al. 2021). 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 (Kay 2012). Generally, organisations pick the available minimum cost option to execute their material handling activities (Zuin et al. 2018).

The most critical decisions relate to designing an MHS pivot around material handling equipment (MHE). Selecting the correct type of MHE and integrating it with organization operations are critical to the common goal of achieving low material handling costs (Rajagopalan and Heragu 1997; Cho and Egbelu 2005; Stephens 2020). Decisions regarding MHSs can be categorized into two factions: design- and operational-related features. Figure 1 explains both features and their sub-categories (Raman et al. 2009). Many other factors that depend on specific industry needs should be considered when selecting an appropriate MHE.

Generally, MHE can be categorized into subgroups based on its operation, technology, and application. The following categories were identified in past scientific articles: manual systems, hoists, industrial trucks, pipe systems, robotic systems, automated guided vehicles (AGVs), unit load conveyors, and bulk load conveyors (Bouh and Riopel 2016). Moreover, Smith (2013) classified MHE into three major groups: conveyors, cranes and hoists, and transporters. Conveyors convey the materials in a fixed path. Cranes and hoists are used to transfer material over a limited area. Transporters are used to carry material over a wide area.

Growing competition and customer expectations have made manufacturing organisations to focus on their core competency while outsourcing the supportive services such as transportation, warehousing, material handling to third-party logistics service providers (Giusti et al. 2019). Signing 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.

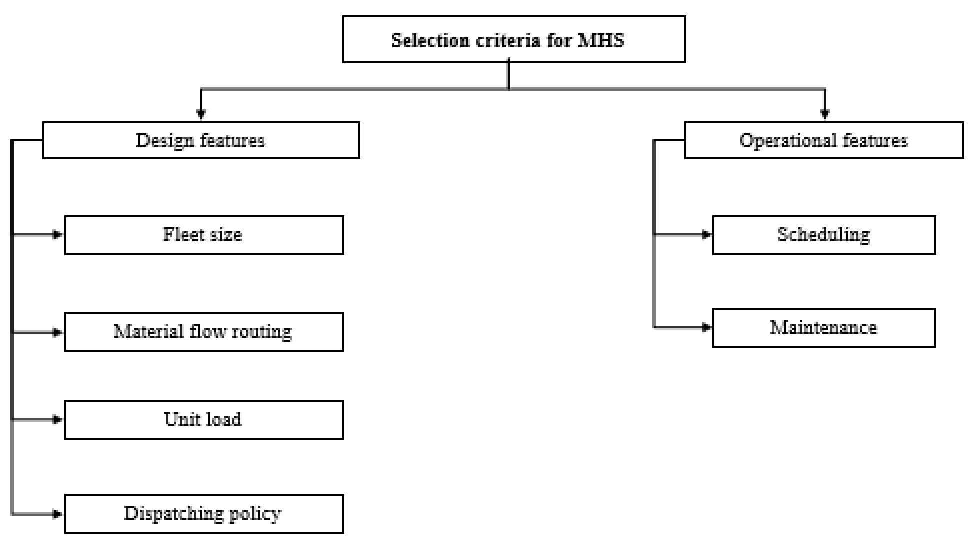

Figure 1. Decision structure for MHS selection

1.1 Objectives of the study

This study considers the problem of transporting different types of materials from dedicated storage to specified intermediate locations as per the production requirement. The study's objective is to determine the optimal fleet size and fleet composition of trucks to be outsourced from an available heterogeneous fleet based on minimising the total cost. Factors such as different attributes of materials, service times and cost variability based on the type of the trucks make this problem challenging. Moreover, this study provides a basis for the decision-making process to streamline the inter-facility material transfer operations.

2. Literature review

Queueing networks are used as a modelling tool to analyse complex systems such as telecommunication, manufacturing, computer, and material handling systems. The ability to encompass the stochastic features made queueing networks an apt tool to represent complex real-world applications. However, as these network models are often mathematically intractable, most studies focus on developing heuristics and approximations to solve the models (Smith and Kerbache 2012; Smith 2013).

Methods and algorithms in fleet sizing problems related to material handling processes can be categorized into simulation, analytical, and hybrid models (Zuin et al. 2018). Gobal and Kasilingam (1991) and Kasilingam and Gobal (1996) determined the optimal fleet size of an automated guided vehicle (AGVs) required for a manufacturing facility using SIMAN based simulation model. Sinriech and Tanchoco (1992) presented a multi-criteria optimization model based on cost and system throughput to determine the optimal fleet size of AGVs. Egbelu (1993) developed a hybrid algorithm to determine the optimal fleet size of AGVs and load size in a manufacturing facility. Huang and Kumar (1994) proposed a model based on the queueing theory to determine the optimal fleet size of load-haul-dump machines in a mine. Ilić (1994) proposed a quantitative approach to determine the optimal fleet size of AGVs based on the cycle time calculations in a manufacturing facility.

Rajotia et al. (1998) proposed an analytical model to determine the optimal fleet size of AGVs in a flexible manufacturing system and validated the result with the simulation model. Arifin and Egbelu (2000) used the regression technique to find the right fleet size of AGVs. Hall et al. (2001) developed a genetic algorithm (GA) to determine the optimal fleet size while maximizing the system throughput. Vis et al. (2001) studied a transfer between the quay and stacking area of a semi-automated container terminal using a minimum flow algorithm to determine the optimal fleet size of the trucks. Koo et al. (2004) study the problem of parts delivery and pick-up in a manufacturing facility, considering waiting time using queueing theory to determine the minimum required vehicles for the continuous operation.

Choobineh et al. (2012)studied requirement of the vehicle for a distribution facility. The authors modelled the facility as a closed queueing network and formulated a linear integer programming model to find the optimal fleet size of the vehicle. Smith (2016) modelled an MHS using a closed queueing network to determine the optimal vehicle fleet size that maximize the system throughput. Munoz and Lee (2021) modelled the mill and harvest front in a sugarcane harvesting system using queueing networks to determine the number of minimum trucks for an un-interrupted operations.

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

Table 1. Closest related studies and gap analysis

Reference	Products	Fleet	Optimization decision/s	Optimization criteria	Shared workstations
Choobineh et al. (2012)	Multiple	Homogeneous	Fleet size	Desired throughput	Yes
Smith (2016)	Multiple	Homogeneous	Fleet size	Maximum throughput	No
Munoz and Lee (2021)	Single	Homogeneous	Fleet size	Desired throughput	No
This study	Multiple	Heterogeneous	Fleet size, composition, and allocation	Minimum cost & desired throughput within a time frame	Yes

3. Methodology

This section explains the employed methodology in this study.

3.1 Inter-facility material transportation by heterogeneous trucks as a CQN

A heterogeneous fleet of trucks transports different raw materials from designated storage yards to intermediate locations those act as feeders to a production facility. These material transfers occur on a daily basis according to the production plant requirement. For a typical raw material forward flow, a truck undergoes through many sub-processes such as inspection at the entry, weighted as an empty truck, loaded with a type of raw material, weighed as a loaded truck, and finally unloaded. Then, the truck returns to the storage area for another trip. This process is repeated throughout the day until the corresponding raw materials demands are fully satisfied.

Trucks are network customers to model this as a CQN. All sub-processes (service stations) (e.g., gate, loading dock, weighbridge, unloading dock) were treated as multi-class single server queues with infinite capacity. Movement between service stations is considered multi-class, infinite capacity queues with infinite servers. It is assumed that service times follow an exponential probability distribution.

Trucks are served on a first-come, first-served (FCFS) basis in all service stations of the system. Each service station is assumed to be reliable with zero probability of failure or breakdown.
A truck's carrying capacity, cost, and service time varies according to the truck's type. A truck carries only one type of material/product during a single period.

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	$k = 1,\dots, p$
m	index for type of trucks	$m = 1,\dots, r$

- ✓ 3.2.2. Parameters

t	Available number of trucks
s	Number of service stations
p	Number of product classes
r	Number of truck types
N_m^k	Number of type *m* trucks for product class *k*
N_m	Number of type *m* truck used in a single time period
CT_m^k	Cycle time for product class *k* for truck type *m*
F_m^k	Full truckload for product class *k* for truck type *m*
$Y_{,j,m}^k$	Service time for product class *k* for truck type *m* service station *j*
D^k	Demand for product class *k*
T	Duration of single time period
C_m	Cost of type *m* truck for single time period
Z	Total cost

Total cost, service time and cycle time calculation

$$N_m = \sum_{k=1}^{p} N_m^k \quad (1)$$

$$Z = \sum_{m=1}^{r} N_m C_m \quad (2)$$

$$CT_m^k = \sum_{j=1}^{s} Y_{m,j}^k \quad (3)$$

3.3 Optimisation model

This optimisation model is to determine the optimal truck allocation that minimises the total cost (Z) while fulfilling the demand for each product during the given period. Eq.1 provides the total number of trucks used by each product class. Cost is the product of the number of each truck type into the cost of truck type.

The decision variable and the surrogate variables are as follows:

$$X_{i,m}^{k} = \{if\ type\ m\ truck\ i\ \ assigned\ to\ product\ class\ k\ \ is\ 1, \qquad Otherwise\ 0$$

CT_m^k := Cycle time for product class *k* for truck type *m*.
N_m^k:= Number of type *m* trucks assigned to product class *k*.

Objective function

$$\text{Minimize } Z = \sum_{i=i}^{m} \quad N_m\, C_m \tag{4}$$

Constraints

$$\sum_{m=1}^{r} \quad \sum_{k=1}^{p} \quad x_{i,m}^{k} \qquad\qquad \forall\ i \tag{5}$$

$$\sum_{m=1}^{r} \quad (\frac{T}{CT_m^k} . F_m^k . N_m^k) \ \geq\ D^k \qquad \forall\ k \tag{6}$$

$$N_m^k \in\ Z^+, CT_m^k \in\ R^+ and\ X_{i,m}^k\ is\ binary \tag{7}$$

Eq.5 fulfils the condition that each truck of any type can be assigned to only one type of product or unassigned. Eq.6 satisfy the demand constraint for each product type. The equations ensures that all demand values are met during the given period. eq. 7 ensures that $N_m^k$is a positive integer, $CT_m^k$is positive real, $and\ X_{i,m}^k$ is binary.

3.4 Simulation model

A discrete event simulation model is developed to analyse and optimise the inter-facility transportation process. initially, a process map was developed with all the material flows. Then the relevant data such as frequency of flow, service times gathered and recorded. These material flow information is inputted in the building of the simulation model. Then the model was checked for its stability and then validated the outputs with the existing operations outputs to ensure its accuracy.

For the optimisation experiments, decision variables, objective function, and constraints were fed to the model. Anylogic optimisation engine uses OptQuest tool to determine the solution through the use of metaheuristics algorithms (The Anylogic n.d.).

4. Case study

This study considers a case study based on a steel production facility that has raw material storages a few kilometres away from its intermediate processing facility. These three types of raw materials (A, B, & C) from its dedicated storage need to deliver to the intermediate plant on a daily basis. This study considers one shift time period (12 hours) for all calculations.Figure 2 shows the facility layout and the material flow path.Figure 3 explains the sub-processes for a typical material flow from the storage to the intermediate plant.

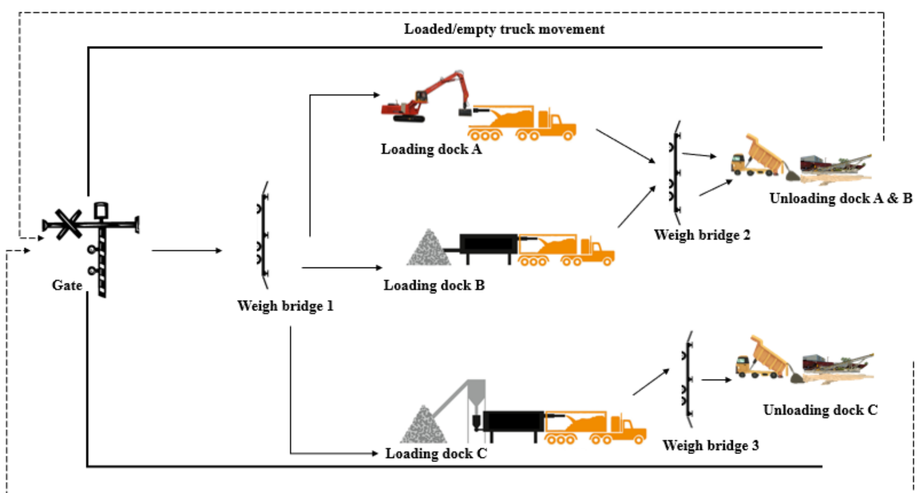

Figure 2. Storages and intermediate plants' layout and truck paths

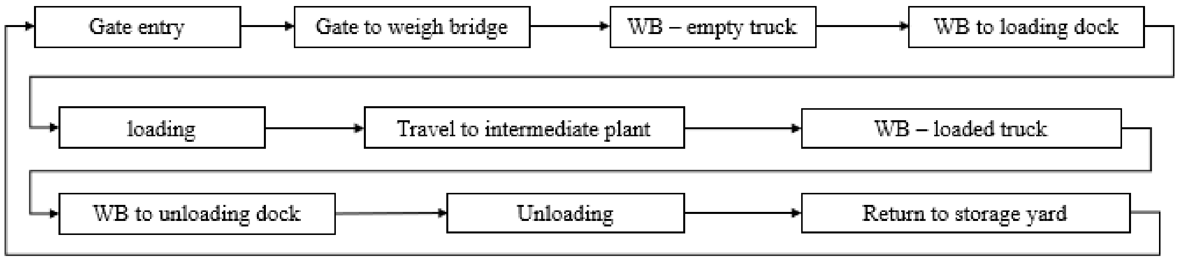

Figure 3. Process map of inter-facility material transfer

This study considers three different types of trucks, namely small, medium, and large trucks, as available fleets. Table 2 shows the service time at each station for all products, and Table 3 shows the operational cost and full truckload masses of each type of truck. Figure 4 shows the inter-facility material transfer process simulation model carried out by a fleet of heterogeneous trucks.

Table 2. Average service time for sub-processes

Process	Ave. time (min)	Process	Ave. time (min)
Gate Entry	1.5	Storage to intermediate plant	15
Moving to Weigh Bridge (WB) 1	0.5	WB 2	0.5
WB 1	1.5	WB 3	0.5
WB 1 to loading dock A	1.5	WB 2 to unloading dock A & B	1.5
WB 1 to loading dock B	1.5	WB 3 to unloading dock C	5
WB 1 to loading dock C	1.5	*Unloading A	5,6,8
*Loading – A	5,6,8	*Unloading B	1.5,2,2.5
*Loading - B	13,17,23	*Unloading C	1.5,2,2.5
*Loading - C	5,6,8	Intermediate plant to storage	12

** loading and unloading service times vary according to the type of the truck and service times are provided for small, medium and large trucks respectively.*

Table 3. Full truckload masses and cost of trucks based on the type

Truck type	Cost $ (for 12 hours)	Full truckload mass (tons)		
		A	B	C
Small	100	12	27	24
Medium	150	15	33	30
Large	250	18	40	35

Table 4 shows the different demand scenarios for each type of products that needs to deliver from storage to intermediate plant within 12 hours.

Table 4. Different demand scenarios for the analysis

Scenario #	Class A (tons)	Class B (tons)	Class C (tons)
Scenario 1	650	550	1000
Scenario 2	800	700	700
Scenario 3	1000	800	400

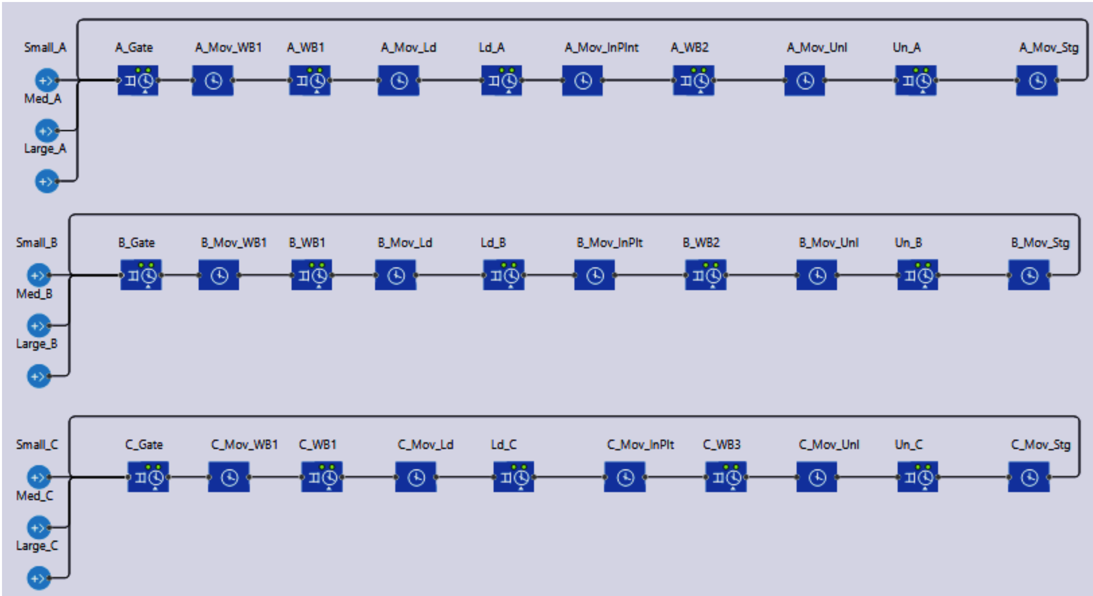

Figure 4. Simulation model of heterogeneous trucks in the inter-facility material transfer process

5. Analysis of Results

This section determines the optimal truck allocation for each product class for the scenarios shown in Table 4. Moreover, for the optimal truck allocation scenarios, network performance measures such as service station's response time and resource utilisation are calculated to assist the decision-making process.

Table 5 shows the optimal total number of trucks and the allocation of trucks to each product class for each scenario.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 algorithm toward better solutions (The AnyLogic, n.d.). Figure 5 shows the parameters, variables, function, resource pools and data analysis tools that were used in this model. For the optimisation experiments, the number of iterations was set to 5000 runs (Figure 6) for each scenario to determine the optimal solution.

Table 5. Optimal truck allocation and cost for each scenario

	A			B			C			
Scenario #	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large	Total cost $
Scenario 1	4	-	-	-	2	-	2	1	-	1050
Scenario 2	4	-	1	3	-	-	-	2	-	1250
Scenario 3	7	-	-	3	-	-	2	-	-	1200

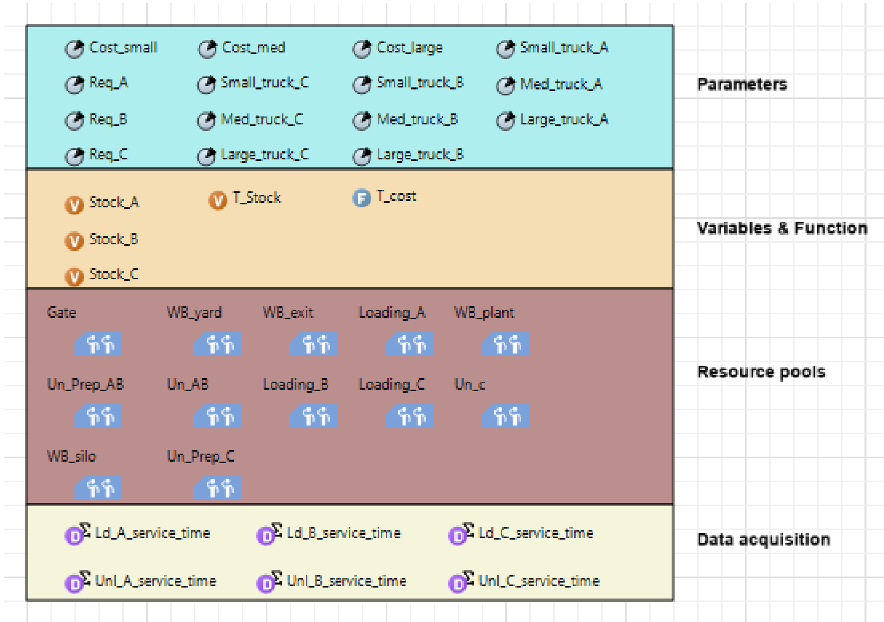

Figure 5. Building blocks of simulation model

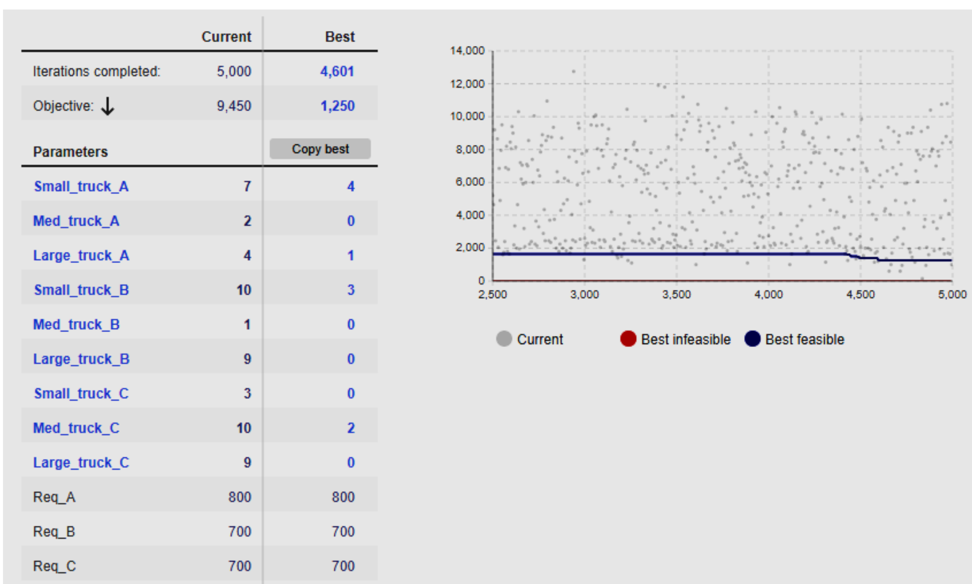

Figure 6. Simulation optimisation window for scenario 2

5.1 Network performance measures

Waiting time and resource utilisation rate are key performance indicators for a given queueing network. The sum of waiting and service times is known as response times for a service station. Higher response time at the service station will increase cycle time for a given operation. Utilisation rates are indications of the occupancy and usage of service stations. Utilisation rates closer to 1.0 (100%) indicate congestion or bottleneck. In the meantime, meagre utilisation rates indicate a poor use of the resources and high idle times.

Figure 7andFigure 8 provide the summarised graphical output of the selected service station's response times and utilisation rates for scenarios 1 & 2.Figure 8 provides the graphs under steady-state behaviour, whereas Figure

7includes transient state data in the graphical output. The simulation model is observed for 10,000-time units, and the first 500 time units are excluded under steady-state behaviour.

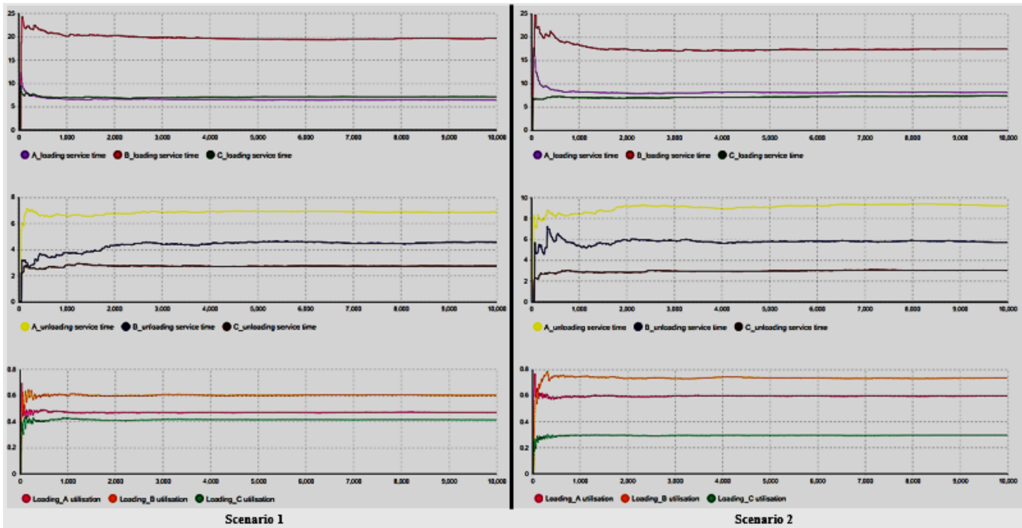

Figure 7. Service time and utilisation rates (including transient state)

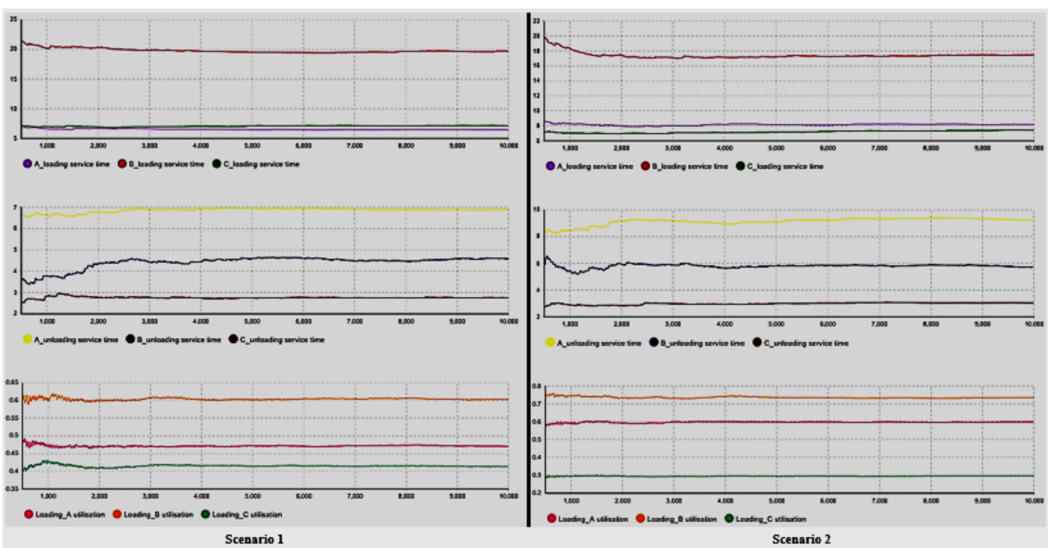

Figure 8. Service time and utilisation rates (steady-state behaviour)

6. conclusion

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 processing.Within this context, the problem is modelled as a closed queueing network (CQN). A Discrete event simulation model using Anylogic simulation software, is employed for solving the model to find the optimal number of trucks and composition of the trucks. Moreover, the simulation model is used to determine the performance measures of the system such as response times, cycle times, resource utilisations and bottlenecks to assist in the decision-making process.

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Laoucine Kerbache is currently serving as a Full Professor and a founding faculty member of the Engineering Management and Decision Sciences Division at Hamad Bin Khalifa University in Doha, Qatar. Further, he has been Full Professor of Operations and Supply Chain Management at HEC Paris in France for the last twenty-two years. During this tenure period, beside managing many international academic programs, he has also served as Associate Dean of the HEC Paris PhD Program (5 years) and then as Dean and CEO at HEC Paris Qatar (4 years). For over thirty years of academic, research, and consulting activities, he has been very active in his areas of expertise, Operations and Supply Chain Management. He has published over 120 papers in international journals and has been guest speakers at numerous international events. He holds a PhD, an MSc, and a BSc in Industrial Engineering and Operations Research (IEOR) from the Mechanical and Industrial Engineering Department, University of Massachusetts, Amherst, USA. Further, he has an "Habilitation to Direct Research (HDR)" from the University of Nantes (France) and a certification from the "International Teachers Program" from IMD Lausanne (Switzerland).

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