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ROLE OF SUPPLY CHAIN AGILITY ON SERVICE DELIVERY IN HUMANITARIAN-RELATED TRANSPORT OPERATIONS: A QUEUING MODEL APPROACH

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Abstract:

The objective of this study was to examine the role of supply chain agility on service delivery in humanitarian-based transport operations using the queuing model approach. The study was conducted at Tanzania Port Authority (TPA) as a busiest port serving about 90% of the international sea trade. The study utilized secondary data that were obtained from official database of TPA, World Bank and National Bureau of Statistics (NBS). The study adopted simulation-based data under the M/M/1 queuing model and used the Poisson distribution to determine the customer's arrival rate while the exponential distribution was used to determine the service waiting time. RStudio programming software was used to analyze data and give output results. The results indicate that the mean arrival rate is 0.75; traffic intensity is 0.75; the probability of customers in the queuing system is 0.25; and the average amount spent in line is 0.75. The Poisson distribution indicated that the probability of service delivery reached the highest at 3 customers per minute while the Interval Exponential Distribution indicated that when inter-arrival time went longer, the probability also went lower. The study concluded that supply chain agility increases service delivery in performing humanitarian operations. The study has presented a new and original approach in linking these ideas in supply chain perspective in Tanzania. The results from this study imply that agility in supply chain enhances responsiveness in service delivery of humanitarian-related products.

Keywords:

Supply Chain Agility, Service Delivery, Transport Operations

1. Introduction

Supply chain agility is the situation whereby activities along the supply chain are performed quickly to meet customer satisfaction. On the other side, humanitarian-based transport operations are logistics dealing with disaster-oriented operations such as the supply of food, water, medicines, equipment, and other supplies necessary to save the lives of the people. Therefore, the aspect of agility which involves the people and the operating equipment can influence improving service delivery in humanitarian-based transport operations thus mitigating the consequences of the disasters to the people. The issue of managing transport logistics, particularly the supply chain agility among supply chain participants, has become crucial nowadays following the increasing competition in international trade, therefore necessitating business organizations to improve efficiency in the transport sector. In moving humanitarian-based products from upstream to downstream points, several members of the supply chain are involved such as transporters, clearing and forwarding agents, distributors, suppliers, customers etc whereby each one depends on another. In this case, the issue of increasing speed in service delivery becomes necessary as supported by Bauyrzhan et al (2022) who argue that agility in supply chain facilitates movement of goods from upstream towards downstream points hence ensuring optimal delivery of goods to ending customers. Agility allows flexibility and timely decisions of supply chain thus helping to reduce transfer waiting time as well as speeding up loading and offloading operations. In other words, such a mechanism enables activities to be coordinated and operated smoothly thus increasing efficiency in supply chain (Ceder, 2016).

However, despite the importance of agility in supply chain service delivery as advocated by scholars, the story is different in developing countries due to a lack of sufficient research information on how agility contributes to increased service delivery in humanitarian-based transport services. In Tanzania, the Logistics Risk Report (2026) reported that import operations faces challenges such as port congestion, high cost and shortage of equipment which consequently exacerbate problems of delay to in-transit goods. The report added that the logistics risk in Tanzania has reached to 28.6% thus threatening supply chain partners involved in business activities in Tanzania. Similar challenges in the supply chain industry were also observed in developed countries, particularly in the USA where the report of the Council of Supply Chain Management Professionals (CSCMP) (2022) revealed challenges in the sector such as congested transportation networks which in totality cause disruption in supply chain and increase the business logistics costs by 8% of the country's GDP. The aspect of agility in supply chain operations, particularly in humanitarian operations, is critical and, thus needs special attention.

For example, Oloruntoba and Kovács (2015) reported that supply chain partners involved in humanitarian-related operations should be responsive and flexible in dealing with disaster oriented operations. Despite the criticality of managing humanitarian logistics and the need for agility in the supply chain, most organizations have failed to respond effectively to major disasters due to insufficient resources and capabilities (Altay et al. 2018). Whilst there is a rich body of literature on humanitarian supply chain agility (Kabra and Ramesh 2016; Altay et al. 2018; Ivanov 2020), research on assessing the role of agility in performing humanitarian-related supply chain activities is very limited. Most studies have addressed issues of humanitarian logistics in a general perspective and mainly focusing on determining supply chain operations performance. These studies overlooked to utilize a theory-driven approach of a queuing model to assess the role of agility in dealing with humanitarian-based supply chain operations (Gunasekaran et al. 2018). The need for further research on the aspect of agility in humanitarian-related logistics was also underscored by other researchers including Rameshwar et al, (2020) who stated that theoretical explanations regarding the factors of agility are still largely underdeveloped thus there is a need for a theory-driven empirical study which focuses on agility. Following the insufficient research information on the role of agility in humanitarian-related activities, especially in developing countries, this study has tried to fill the gap in knowledge by examining the role of agility on Service Delivery in Humanitarian-Based Transport Operations using the queuing model approach. This was identified as a clear research gap in humanitarian supply chain literature following its crucial impact in saving the lives of the people facing disasters in their locations. Thus, based on the preceding discussion, this study develops the guiding research question as follows:

RQ1: What is the role of Supply Chain Agility on Service Delivery in Humanitarian-Related Transport Operations?

Addressing the role of Supply Chain Agility on Service Delivery in Humanitarian-Related Transport Operations by using a queuing model enables members within the supply chain to manage the arrival of relief products at delivery points as well as increase service rate in the movement of materials from the point of origin to the destination points. Such a mechanism will cause the movement of relief products from the upstream points (producers) to match with the downstream operations (ending customers), which at the end will speed up transport operations as well as ensure timely delivery of relief products to the beneficiaries.

2. Literature Review

2.1 Mathematical formulation of agility in Queuing System

The queuing model has parameters as follows: the service rate, this is the time used by the server to serve a customer needing a service at a given time of period (utilization) whereby the higher the service rate indicate that the customer is being served effectively; customer waiting time is the time used by the customer in waiting to get a service whereby a long waiting time indicate bottlenecks in service delivery; the average number of customers in the system is another parameter whereby a large number of customers in the system imply high demand in service delivery; the average number of customers in line indicate the magnitude of customers waiting to get services whereby a large number of customers in the queue imply ineffectiveness in service delivery; the response rate is the time spent by the server to serve the arriving customers and arrival rate indicate total number of customers who arrive to get services in a given time. In queuing system perspective, the proportionate between arrival rate and service rate indicate optimization in service delivery of customers while high arrival rate and lower service rate create unnecessary queues of customers waiting for services which may lead to customer dissatisfaction.

Ghosh and Feodorowicz (2008) argue that the objective of any supply chain is to optimize service delivery by delivering a product or service to the ultimate customer at minimal cost and at the required time". A mathematical model of the arrival and departure of trucks carrying in transit goods at delivery points establishes a better arrangement mechanism for managing cargo logistics. For example, a transport hub can establish a system which gives priority to first in arriving customers to be served and get out first; such a system will establish a streamlined and coordinated operating system of which by increasing service points and deployment of other resources it will increase service rate (utilization) of transport hub and thus leading to efficiency in service delivery of disaster-natured products (Borodavkin & Kapitonov, 2021). In such mathematical models, the lower and upper boundaries of the onset of temporary events are set. A similar event can also be applied in train transportation by establishing the arrival or departure of a train at a junction whereby optimization criterion is the minimum weighted total transfer time at transport hubs. An alternative criterion is considered to be the minimization of the travel time from one point to another with the presence of a transfer or the weighted sum of the travel time from a set of initial points in the network to another set of points. One of the technical possibilities for enhancing agility is to harmonize transport time schedules, which make it possible to reduce the time for transfer between main and regional delivery points (Borodavkin & Kapitonov, 2021). According to Tirachini and Cats (2020), when there is proper assigning of time schedules between supply chain partners to arriving careers it helps to minimize the waiting time of transit vehicles. The reduction of transfer time in transport operation leads to fast arrival and loading of vehicles at the destination points.

2.2 Transportation of Humanitarian-related Products in Developing Countries

There are four major modes of transport namely road, rail, sea and air transport (Ibarra-Rojas et al., 2015). Logistics management is the packaging, transportation, handling, and storage of goods so that the products are properly managed and delivered to ending customers on time. In other words, it covers all the processes carried out from the purchase of goods from suppliers and their distribution to ending customers (Deaton & Deaton, 2020). In-transit goods, including humanitarian-related products, face several challenges in their course of movement to ending customers; for example, one of the critical points is the delivery point or port destination where most of the operations are carried out. Scholars have reported challenges causing port congestion, such as insufficient infrastructure, labour shortage, and customs delay (Escola 2005; Akyoo 2007). To mitigate such challenges in performing port operations, the aspect of supply chain agility can be a solution in speeding up operations, thus leading to improved service delivery. Supply chain agility is an important component of a system that includes organizations and people involved in the supply chain operations, whereby any disruptions of the flow, particularly humanitarian-related products, can be catastrophic to the targeted ending customers consequently leading to death, starvation, rising food inflation, malnutrition and other calamities (FAO et al., 2018).

3. Methodology

This study has used simulation-based data whereby the M/M/1 queuing model simulation was used to analyze the data. The Tanzania Port Authority (TPA) was used as a study area because it is the country's most dominant seaport, serving about 90% of the country's international sea trade, thus becoming the busiest and loading seaport in the East and Central Africa landlocked regions (Msabaha & Jin, 2020). Data were collected from the official database of TPA, the Word Bank database, and the National Bureau of Statistics of Tanzania and also the researcher used telephone calls to interview respondents whom their numbers were accessed from the website of TPA.The study employed the Poisson distribution to give probability distribution on arrival process (which is equivalent to an exponential distribution of time between arrivals) and an Exponential Distribution of service hours using Rstudio programming software in assumption that there is one server, an exponential service time of four clients per minute, and a Poisson arrival rate of three consumers per minute. Then, the results were calculated and shown in the form of tables to give a better interpretation of the results about examining the role of supply chain agility on service delivery of humanitarian-related transport operations under the queuing model approach.

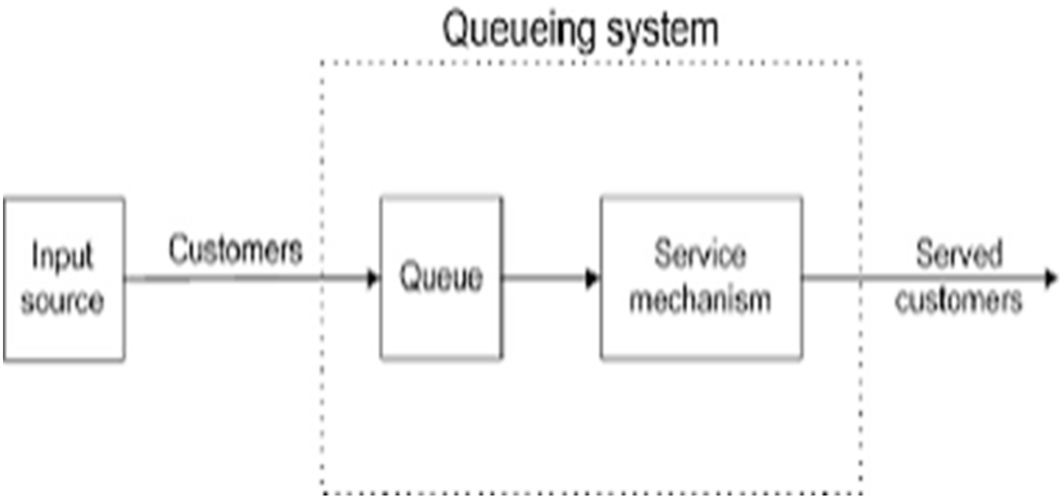

Figure 1. The Use Process of the Queuing Model

3.1. Illustration of Indexes

The queuing model has the following variables shown in Tables 1 and 2.

Table 1. Independent variables and their meanings

Variable	Meaning
λ	The mean rate of service completions
μ	The mean rate of arrival
n	How many servers there are in the system

Table 2. Dependent variables and their meanings

Variables	Meaning
$1/\lambda$	The customer arrival interval
$1/\mu$	The service time
W (or S)	The typical duration of use of the system
Wq	The average length of time in line
ρ	The traffic intensity (the utilization factor)
γ	The mean rate of arrival
Pn	The likelihood of having n customers in the system
Lq	The average number of customers waiting in line
L	The typical client count in the system

Table 2 and 3 show the independent and dependent variables of Queuing model used in this paper, all the variables are simulated in the model process.

3.2 Computation of the variables by use of the formula

$$S = W_q + \frac{1}{\mu} \tag{1}$$

$$\gamma = \frac{\lambda}{\mu} \tag{2}$$

$$\rho = \frac{\lambda}{n\mu} \tag{3}$$

$$L_q = \lambda W_q \tag{4}$$

$$L = \lambda W \tag{5}$$

$$L = L_q + \gamma \tag{6}$$

For the 1st formula, customers' mean time spent in the system comprises their mean time spent in the queue and their predicted wait time. For the 2nd formula, γ is called the "load" of the system, representing the "estimated number of arrivals during the typical service completion time". For the 3rd formula, ϱ is referred to as the utilization factor, with λ being the arrival rate and sμ being the service capacity. If ϱ>1, the rate of arrival is greater than service capacity, the queue will approach infinity without additional mechanism. If ϱ<1, the service capacity is smaller than the rate of customer arrivals, and the probability of any particular system size no longer changes over time. The 4th and the 5th formulas are two fundamental formulas called the "Little's formulas", which can be combined to get the 6th formula. These are some specific formulas for calculating dependent variables, particularly for the model of M/M/1 queuing. For the 7th formula, with Pn known in the 6th formula, since there are no customers in the queue when 0 or 1 customer exists in the system with 1 server, Lq could be calculated in the 8th formula. After that, three other variables could be derived in the 9th, 10th, and 11th formulas (Yulu 2023).

$$P_n = \rho^n(1-\rho) \tag{7}$$

$$L_q = \frac{\lambda^2}{\mu(\mu-\lambda)} \tag{8}$$

$$L = L_q + \gamma = \frac{\rho^2+\rho-\rho^2}{(1-\rho)} = \frac{\rho}{1-\rho} = \frac{\lambda}{\mu-\lambda} \tag{9}$$

$$W_q = \frac{L_q}{\lambda} = \frac{\lambda}{\mu(\mu-\lambda)} \tag{10}$$

$$W = \frac{L}{\lambda} = \frac{1}{\mu-\lambda} \tag{11}$$

Using the M/M/1 queuing model in this study, the values of the three variables λ, μ, and n were set whereby the value of n in the M/M/1 queueing is 1. By simulation, the impact of the model was examined.

4. Results and Discussion

This paper set up a model of M/M/1 queuing by using Rstudio, which is the most basic queuing situation in life. The study utilized the queuing situation with the value of λ is 3, the value of μ is 4, and the value of n is 1 (TPA, 2022). More specifically, three customers are coming per unit of time, four customers are served per unit of time, and one waiter. After setting the values of these three arguments, the Rstudio was operated and then produced the results, as shown in Table 3.

Table 3. The results of dependent variables

Variable	p	γ	*P*0	w	Wq	L	Lq
Value	0.75	0.75	0.25	1	0.75	3	2.25

In simple terms, the results in Table 3 of the dependent variables are explained as follows. The traffic intensity is 0.75. The mean rate of arrival is 0.75. The possibility (P0, P1 …, Pn) of the n=0 customers in the queuing system is 0.25. One minute on average is spent in this system. The average amount spent in line is 0.75. There are typically 3 clients in the system. 2.25 clients on average are waiting in the queue.

3.2. Probability Distribution and Discussion

Since the results were shown, a Poisson distribution for arrival procedure, an Inter-arrival Time Exponential Distribution, and for a service process, an Exponential Distribution could be drawn.

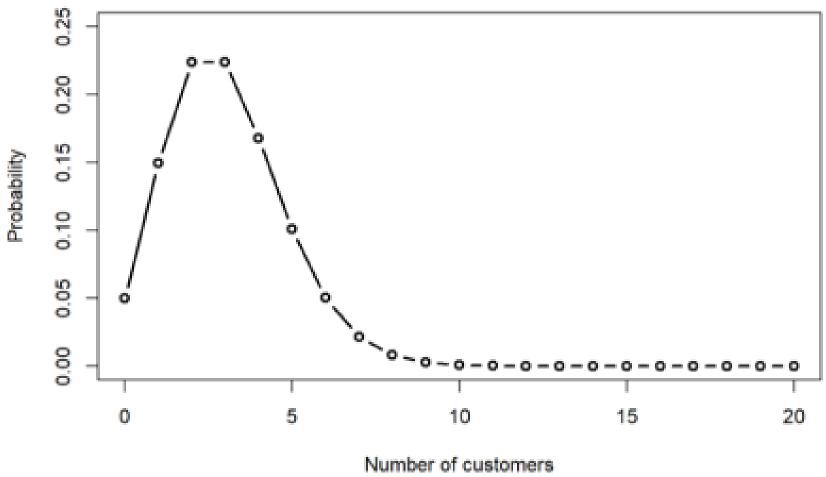

Figure 2: Poisson distribution for the Arrival Process

Results in Figure 2 indicates values of Poisson distribution graph for the arrival process whereby the x-axis represents number of customers while y-axis represents the probability. The results shows that when the number of customers is 3, the probability reaches the highest, and then the probability becomes lower. In the model of M/M/1 queuing, the greater the volume of customers in the system the lower the probability of receiving services.

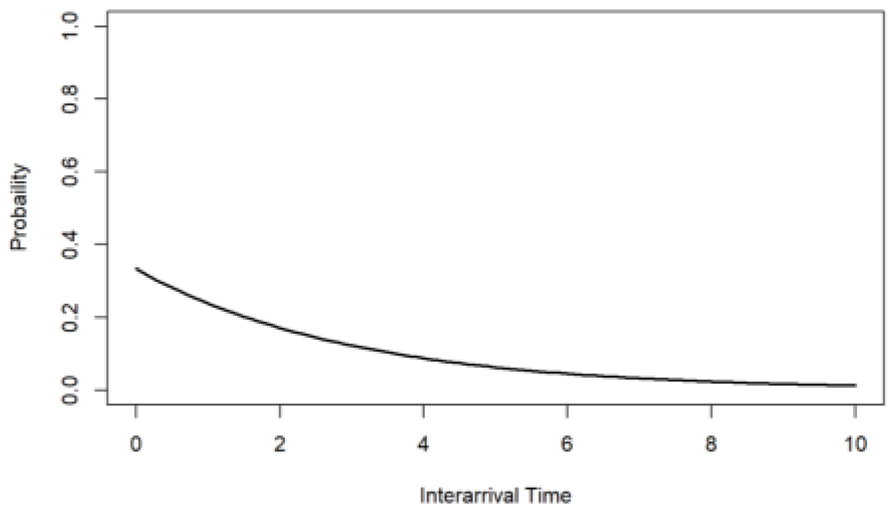

Figure 3. Time Interval Exponential Distribution

Figure 4. For a Service Process, Exponential Distribution

The results in Figure 3, show that when the inter-arrival time went longer, the probability also went lower. Similarly, in Figure 4, in the first minute, the probability decreased drastically in the view that as the service waiting time got longer, the probability was also getting closer to zero. The results mean that the longer the customer waits, the lower the probability of getting the service. The results portray the real situation in our daily lives; for example, when cargo transporters of human-related products are lining up at delivery points to dispatch their products and wait for a certain amount of time, they will not tolerate waiting and hence may decide to abandon the service and find an alternative way.

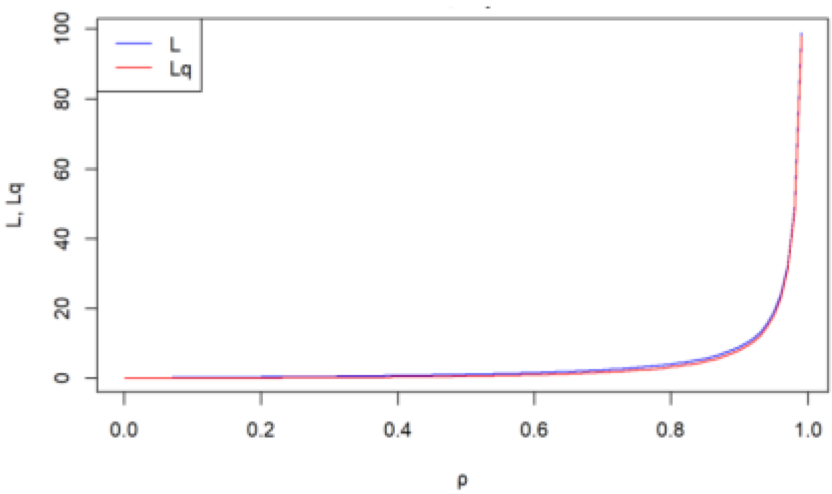

Figure 5. A Distribution Function of L and L_q

The results in Figure 5 indicates that when ϱ approaches 1 infinitely, the values of L and Lq grow faster and faster. In general, however, the value of L is always greater than Lq. This implies that there must be more clients in the system than there are clients waiting in line. It is because just one person is ever served in the model of M/M/1 queuing, this is the case.

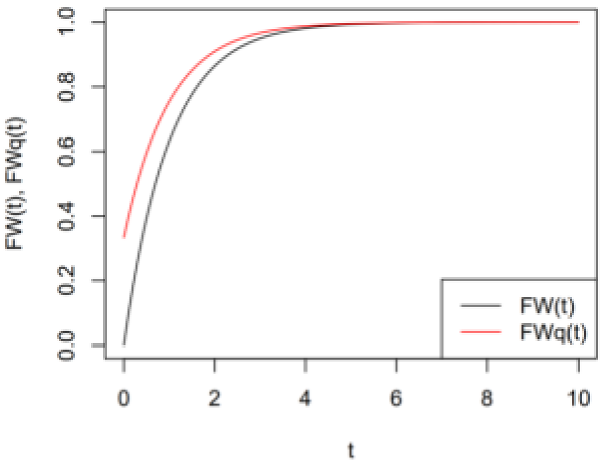

Figure 6. A Distribution Function of W and Wq-Based on the Model of M/M/1

In Figure 6, Fw means the likelihood of a client using the system, and FWq means the probability of a customer waiting in the queue. The results indicate that when the customers have waited at least 4 units of time, the values of Fw and FWq are equal. Both have the same probability of 1.

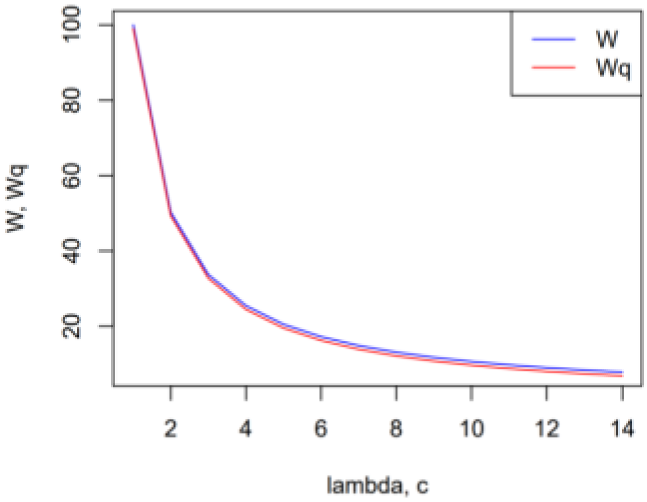

Figure 7. A Distribution Function of W and Wq-Based on the M/M/c Queuing Model

The results in Figure 7 shows that the arrival rate changes in line with the number of servers available in the system. For example, it shows that as the values of λ and c increase, the values of W and Wq decrease. In other words, the mean time spent in the system and the mean time spent in the queue rapidly decrease as the mean rate of service completions and the number of servers in the system increase. Based on the obtained results in relation to use of queueing model, it indicates that the model is more relevant in relation with agility and increase of service delivery in humanitarian-related transport supply chain operations. In this view, when transport supply chain partners including destination points (seaports) deploy resources in terms of human resources, funds, and equipment it means agility will be ensured. Agility means to be flexible and do things on time, for example, during peak hours when congestion is high, an organization can use its idle resources from other sections to empower the overwhelmed one hence increasing service level to a great extent. Port congestion has been reported as a major challenge in many developing countries which consequently leads to delays in the supply of materials including products needed for people affected by disasters. Products such as food, medicines, and items for shelter are examples of humanitarian-related products that need to be delivered fast to the beneficiaries facing disasters. Agility ensures timely delivery of materials to delivery service points due to synergy in operations; operators will be able to plan their transport logistics among supply chain members such as shippers, distributors, warehouse operators, clearing and forwarding agents, port authorities, and end customers. The matching or alignment of time schedules among supply chain partners also enhances the effective utilization of transport hubs in the supply chain of products (Borodavkin & Kapitonov, 2021). This means that by increasing the number of servers in the system the mean time spent in the queue (congestion) will decrease hence making delivery of humanitarian-related products to consumers (beneficiaries) in developing countries to be guaranteed.

5. Conclusion

This study concludes that agility in service delivery in humanitarian-related transport operations decreases the mean time spent in the system and the mean time spent in the queue during transport operations. This means that when the number of servers in the system increases, the mean time spent in the system and the mean time spent in the queue decreases in other words, supply chain agility has a possibility of increasing the service rate at the delivery points thus ensuring fast arrival of humanitarian-related products to the ending beneficiaries.

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