



MATLAB SIMEVENT FOR TRAFFIC QUEUE MODEL

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ABSTRACT

The use of MATLAB (SimEvent) for network performance measure determination is encouraged by the novel precision that comes with artificial intelligence techniques. However, most efforts in this direction have been undervalued due to distribution assumptions. Therefore, a comparative analysis with an analytical method is studied in this work, with service rate distribution determined, using a distributive StatAssist tool. Kendall's model adopted was M/M/1 for a single server queueing system and was confirmed by the service rate distributive pattern as 1.0 second per customer. Estimating the network measures showed analytical and simulation models hourly average queue length of 3,751 vehicles, with 1hr and 11 minutes waiting time. The total daily queueing length is 8419 vehicles, with 8819secs total waiting time. The utilization factor of 0.984 and the model is found to be 0.9825/1.025/1. From the optimum determination of the analytical model (AM) and simulation model (SM) weekly performance measures carried out, the AM produced the following average waiting time 3751, 125, 56, 35, 110, 19, and 17, from Monday through Sunday. In contrast, the SM produced an average waiting time of 3681, 3007, 2789, 2567, 2854, 2467, and 1976 respectively. Due to the continuous waiting line output, the SM has proven realistic. Therefore, the Simulation model coupled with distributive StatAssist tool is recommended for queueing studies. A comparative study of simulators is recommended for further studies.

1.0 Introduction

Life is full of trade-offs. People must choose how to spend scarce money and time. Time-saving and convenience are commonly mentioned by consumers as among the most important motivations for purchasing a service. However, waiting to be served may neutralize potential benefits and negatively affect attitudes toward the quality of service, brand, or product (Anyin and Etika, 2022; Anyin, 2022; Delgado, 2016). Customers identify waiting in line as frustrating, stressful, and expensive (Anyin and Etika, 2022). Vehicular queue length and queuing duration are an important basis for traffic management departments to establish and implement traffic control measures. The study of vehicular queue length and queuing duration has important practical significance and value in operational research (Li et al., 2019; Anyin et al., 2023; Adeke et al., 2018).

With the development of artificial intelligence-based models in scientific research, models like MatLab and other commercial simulation tools used for qualitative and quantitative analysis have progressed into qualitative-based management decisions referred to as operational research. As recommended by Anyin and Etika (2022), a simulation model is

needed for a more detailed evaluation of any case study in the field. The use of Matlab Simulink for queue model is not new. However, most efforts in this direction have been undervalued due to service rate distribution assumptions. Thus, this study attempts to suggest a better approach to queueing performance characteristics determination using MATLAB SimEvent.

The basic knowledge of queueing performance characteristics which includes, waiting time and queueing length, can be gained more in Anyin and Etika (2022). The basic queueing theory may be divided into two mathematical studies: one deals with specific type distributions from which mathematical formulas are derived, while the other deals with classical empirical or hypothesized distributions which are determined through analysis. Fundamentally, queueing analysis is used to determine the difference between a queued road segment and how long it would have taken if there were no queueing or congestion (Tarabia, 2008, Lakshmi and Sivakumar, 2013).

The Goodness of Fit (GoF) test is used to test if sample data fits a distribution from a certain population (therefore, a population with a normal distribution or one with a Weibull distribution). In other words, it tells you if your sample data represents the data you would expect to find in the actual population. The Goodness of fit tests commonly used in statistics are the chi-square, Kolmogorov-Smirnov, Anderson-Darling, and Shipiro-Wilk (Feine *et al.*, 2018).

The chi-square test is the most commonly used goodness of fit test and it is one among many you will find among advanced placement (AP) statistics or elementary statistics. The chi-square can be used for discrete distributions like the binomial and Poisson distribution, while the Kolmogorov Smirnov and AndersonDarling goodness of fit tests can only be used for continuous and discrete distribution (Garfield *et al.*, 2008, Piccolino, 1996). Chi-Square has two potential disadvantages and they are; (a) the test can only be used for data put into classes (bins). If you have nonbonded data you will need to make a frequency table or histogram before performing the test. (b) It requires a sufficient sample size for the chi-square approximation to be valid (Feine *et al.*, 2018; Piccolino, 1996). There are two types of chi-square tests, the first is the chi-square independence test, which compares two sets of data to see if there is a relationship. The second is the chi-square Goodness of fit is to fit one categorical variable to a distribution. Both tests use the chi-square statistic and distribution (Feine *et al.*, 2018, Garfield *et al.*, 2008).

The Kolmogorov-Smirnov test is a test used for the normalization of statistical data. The advantage of this test is that its distribution is not built on assumptions (Feine *et al.*, 2018). A sample can be compared to a distribution using a one-sample Kolmogorov Smirnov (K-S) test or a two-sample K-S test. This test is easily taken using software because critical values need to be calculated for each distribution and finding the table for critical values is not an easy task (Feine *et al.*, 2018). Depending on the choice fit test, EasyFit calculates the goodness of fit statistics for each of the fitted distributions. EasyFit is a data analysis and simulation application that allows users to fit probability distributions to sample data, select the best model, and apply the analyzed results to make informed decisions. Easyfit gives room automatically rather than manually to fit a large number of distributions to your data and select the best model in a bit of seconds (Moura *et al.*, 2010, Feine *et al.*, 2018).

A model in a general sense, is a small physical or mathematical abstraction of an object or a system. This has found application in many fields of research such as communication, transportation engineering, mathematics, chemistry, and a host of others (Schlecht, 2022). We have different types of models, but this research is going to be limited to queueing models.

1.1 Queueing Theory

The queueing process was first expressed by Erlang in 1913 to treat congestion problems associated with telephone call exchange at the beginning of the 20th century (Fomundam and Herrmann, 2007) The term, "queue" as defined by Anyin and Etika (2022) as a waiting line especially of persons or vehicles (customers) in a file or line waiting for services where one or more customers are called upon at a time to be served based on available service units known as servers. Service pattern – series called ' "service discipline" where identical servers are accessed through two or more channels rendering the same services; and queueing rule refers to queue discipline which includes; First-In-First-Out (FIFO), Last-In-FirstOut (LIFO) (Anyin et al., 2024). There are different types of models with diverse functionalities, they are as follows; M/M/I, M/G/I, M/M/C, M/M/, G/M/I, G/G/I, G/G/, G/M/C, G/G/C, D/D/I, M/D/I, M/D/C, and M/D/. Where M/M/I stands for Poisson arrival distribution and exponential service distribution. I represents several servers which is one. G represents general arrivals and general servers. C represents constant service rate, represents infinity server, D for arrival represents deterministic distributive arrival and for service, it represents deterministic service rate (Fomundam and Herrmann, 2007; Meisling 1958; Priya et al., 2021).

1.2 Simulation Models

SimEvents is a MATLAB event-based toolkit that provides a discrete-event simulation engine and component library containing predefined blocks with different system functionalities such as entity generators, ROS and FIFO, Signal Scope, path combiner, set attribute, etc., used for modeling in Simulink. One can model event-driven communication between components to analyze and optimize end-to-end latencies, throughput, packet loss, and other performance characteristics. Libraries of predefined blocks, such as queues, servers, and switches, enable you to accurately represent your system and customize routing, processing delays, prioritization, and other operations. With SimEvents one can design distributed control systems, hardware architectures, and sensor and communication networks for aerospace, automotive, and electronics applications. One can also simulate event-driven processes, such as the execution of a mission plan or the stages of a manufacturing process, to determine resource requirements and identify bottlenecks (Vilaplana et al., 2014; Inacio and Antunes, 2008, Seo et al., 2019).

2 Material and Method

A simulation model was implemented in the determination of traffic network performance measures. This study was performed on the Kugbo checkpoint Abuja-Keffi Highway. Kugbo is the name of a town in Abuja, located along Abuja-Keffi Highway. It occupies about 121km². Abuja-Keffi Highway is a road linking Keffi, Karu, Maraba, New-Karu, and Nyanya, to Abuja, with an average travel demand of 42400vehs a day (Anyin and Etika 2022). Figure 1 shows a Google map of the Kugbo checkpoint spotted in red ink. Abuja is a city in the central part of Nigeria and the Federal Capital of Nigeria. It is about 1250m (about 4100 ft) above sea level,

occupying 713 km² of land area. The city’s average monthly temperature is in the range of 210-350 C (690 – 770 F). The coordinates of Abuja is Latitude 904’20.1504’’N and Latitude 7029’28.6872’’E. The data collected was processed and is presented in Table I.



Figure 1: (a) Google Map picturing Kugbo Checkpoint (b) Traffic Situation in Kugbo Checkpoint.

Table I: Vehicular Hourly Arrival Rate for November 2017 Kugbo Checkpoint (Anyin and Etika 2022).

S/N	Mon	Tue	Wed	Thu	Fri	Sat	Sun
7	3794	3541	2727	2726	2852	2541	2704
8	8419	6214	5822	5310	5850	4472	3888
9	6314	5925	5602	5450	5692	4916	3855
10	3764	4499	4499	4420	4977	3851	3631
11	2449	2999	2999	2663	3530	2826	2639
12	3716	2149	2149	2171	1892	2119	1969
13	3252	3716	3716	3569	2502	3716	2718
14	2375	3252	3252	3250	3130	3252	2866
15	1937	2071	2071	2071	3721	2071	2071
16	1250	1250	1250	1250	1250	1250	2732
17	2256	1638	1638	1638	1638	1638	3343
18	2917	2344	2344	2344	2344	2344	2344
Total	42443	39598	38069	36862	39378	34996	34760

2.1 Data Collection

The data used in this study was adopted from Anyin and Etika (2022). The estimated average hourly travel demand measured in the vehicle (vehs) per time revealed that Monday had the highest travel demand as seen in Table I.

2.1.1 Data distribution

Data distribution was carried out using Easyfit to test the fitness of the distribution. This was done on inter-arrival and service time data. The arrival rate is supposed to follow a definite distribution pattern which is used to analyze its customer’s flow into the system. From the pieces of literature, it is seen that arrivals come either in batches or in singles, and are determined using the Easyfit toolkit to detect the distribution pattern it follows. In discrete random variables, there is no chi-square in this case Kolmogorov-Smirnov test is used to fit the distribution.

There are various distribution series that embrace diverse distribution patterns from Frechet, Cauchy, Exponential, Constant, Deterministic, Infinity, Poisson, and a host of others. The advantage of having a known distribution span from the analytical model to the simulation model, though its reflection on AM is not as obvious as SM. Kolmogorov-Smirnov was chosen because of its wide range of precision decisions and tolerance. The Analytical

Model (AM) and Simulation Model (SM) have different input formats; while AM requires arrival and service rates; inputs for SM are average Inter-arrival time and average service time. The performance of the entity generator and server blocks is determined by the distribution.

2.1.2 Simulation model

The model used is a MATLAB R2013a software event predictive engine, called SimEvents. The SimEvents model was built using built-in blocks found in the Simulink library. Blocks used for this model and their functions are as follows;

Event-based random number – this block is used for setting interarrival time for random events to conform to the selected arrival distribution type which could be exponential (as specified by this study), uniform, and constant.

Time-based entity generator – the block generates discrete entities representing stochastic arrivals based on the specified intergeneration time from the Event-Based Random Number block. Intergeneration time is the time lapse between consecutive arrivals in the model. In this model, an exponential distribution type is specified with estimated mean interarrival time as the intergeneration time for each queue type or case based on demands. The initial seed value of each run is set using 5-digit odd numbers to aid the repeatability of the random process when re-entered.

Set attributes block – it is used for assigning unique attributes or characteristics to discrete arrivals for the sake of identification or classification and priority specifications.

Path combiner - this block assembles entities with different attributes assumed to present the entry buffer area in the system before sorting into various queues using priority block. The precedence is set as equiprobable since all arrivals have equal chances of entering the system before taking a decision.

Priority block – in this block, the combined entities from the path combiner are sorted out based on set attributes which distinguishes each entity accordingly; the priority option does the categorized sorting.

FIFO block – this block ensures that entities arriving on the queue willing to proceed to the service facility do so based on the First-In-First-Out rule.

Output switch – it is used for sorting combined entities based on assigned attributes under the ‘set attribute’ block.

N-Server block – this block allows the assignment of more than one server per queue category.

Read timer block – it measures the arrival and departure time of entities into the system, hence, two sets of it are used to estimate time spent by entities in the system (sojourn time).

Entity Sink – all departures exit the network through the entity sink block.

Signal scope – this block displays the output of the simulation process in graphical form (Adeke et al., 2019).

These block operations were operated and connected as follows. The event-based random number generator creates a sample of random numbers, according to the distribution pattern of the arrival. The numbers are travel demands and are ordered as shown in Table 1. These numbers are converted by time-based entity generators. This generator operation was measured by interarrival time, and the instantaneous event counting scope arrival was used for plotting the service rate. The start timer was sandwiched between the generator and the FIFO-queue block (there are many other protocols available) for feeding entities. The FIFO queue worked with a single server and serviced the entities that entered. Another random number-based block was connected to FIFO-queue block, which influenced its service delivery to work by the distribution pattern (exponential order). While the service was going on, the corresponding queue length and waiting time blocks measured the system network characteristics. The utilization factor also was connected to the single server for system efficiency measurement. The flow chart for this experiment is shown in Figure 2. This shows the various steps in the queuing process as represented by the Simulink Model which is characterized by different blocks and system functionalities.

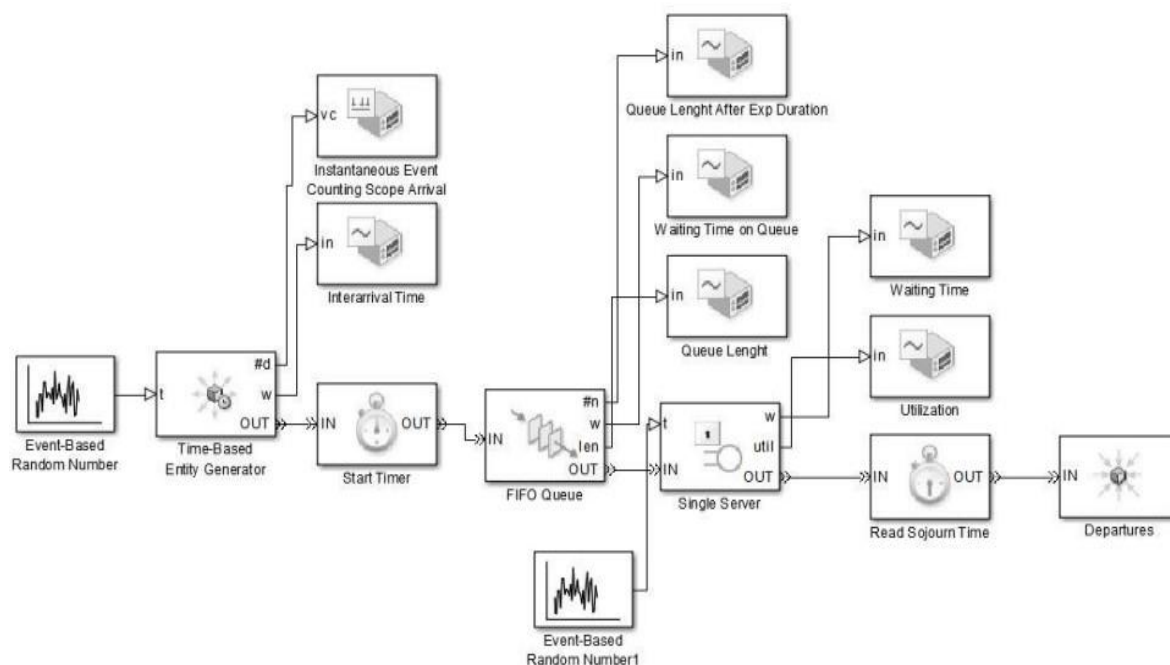


Figure 2: Flowchart of Simulation Model

This simulation model and procedure were repeated for all the scenarios. A single entity generator was used for generating identical entities; average inter-arrival time is entered in the Event-Based random number block with distribution type specified as Poisson distributed arrivals. A FIFO queuing block was used to control the service rule and finite capacity of the queue specified as maximum demand in the FIFO block. A single server block was used for the scenario. The characteristic equation is,

$$\text{Utilization factor } \rho = \frac{\lambda}{\mu} \tag{1}$$

$$\text{Expected number of customers in the queue: } = \frac{\rho^2}{1-\rho} \tag{2}$$

$$\text{Expected time customers spend in the system: } = \frac{1}{m\mu(1-\rho)}$$

$$\text{Expected time customers spend in the server: } = \frac{1}{(1-\rho)} \tag{3}$$

$$\text{Expected time customers spend in the queue: } = \frac{\rho}{m\mu(1-\rho)} \tag{4}$$

Where m represents the number of servers and μ represents the service rate (Anyin and Etika 2022).

The server determines the model type, this study used the M/M/I model as explained in section 1.1. The first M is determined by the arrival rate, the second M is determined by the service rate, and the I was determined from the average service time distribution pattern.

3 Results and Discussion

This section presents the result of the study and discusses the relation of the outcome and its application and contribution to knowledge. The outcome is particularly the network performance characteristics and its corresponding comparative analysis. This, therefore begins with the arrival characteristics.

3.1 Arrival Characteristics

The arrival time distribution pattern was achieved using the data provided in Table 1, where with the aid of EasyFit the distribution pattern was determined from Kolmogorov-Smirnov Series to be Poisson distribution. The outcome of the test is provided in Table 2.

Table 2: Average arrival Poisson distribution Pattern.

Poisson [#1]					
Kolmogorov-Smirnov					
Sample Size	72				
Statistic	0.22455				
P-Value	0.00874				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.24558	0.26637	0.28482	0.20667	0.22174
Reject?	No	No	No	No	No
Anderson-Darling					
Sample Size	72				
Statistic	13.432				
Rank	3				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No

The arrival rate is supposed to follow a defined distribution pattern which was used to analyze its customer’s flow into the system. It was seen that arrivals come either in batches or in singles, and are determined using the Easyfit toolkit to detect the distribution pattern it follows.

Kolmogorov-Smirnov series was used to check the goodness of fit, and it accounted that Poisson distribution ranked first, though, from EasyFit discrete distribution, chi-square was not displayed in all the occasions but was displayed in continuous distribution. A Kolmogorov-Smirnov statistics test showed that; the arrival rate followed the Poisson distribution and is accepted as a null hypothesis with 0.22455 at 5 degrees of freedom less than 1, as shown in Table 2.

3.2 Service Characteristics

The service rate at the checkpoint was also determined using EasyFit StatAssist Application, this application enabled this study to fit data to a distribution. With the distribution pattern, the server simulation equation adopts a defined analysis equation in serving its customers. It finds use in most simulations, precisely in MathLAB where with the help of Event-Based-Random Numbers, distribution patterns are created for simulation. The service rate data is used to determine the service rate pattern.

The service time goodness of fit was analyzed using Kolmogorov-Smirnov. The best fit was exponential. A Kolmogorov-Smirnov statistics test showed that; the service time followed exponential distribution and was accepted as a null hypothesis with $= 0.05959$ at 5 degrees of freedom which is less than 0.15755 , shown in Table 3. The acceptance of exponential distribution at all levels of critical juxtaposes that the service time practicability of this study is stochastic rather than deterministic. A deterministic service rate defines the serviceability of the system to follow a constant proportion. From the graph shown in Figure 3, it is seen that the mean of the distribution has a mean service rate of $0.00167/\text{second}$, and its inverse is 1.0015 second. Which can be interpreted as the server serving the event entities at an exponential rate of one customer per second. The serviceability distribution pattern is relatively important to the Simulation Model (SM) in determining its stochastic service distributions.

Table 3: Average Service Time Goodness of Fit Result

Goodness of Fit - Details [hide]					
Exponential [#13]					
Kolmogorov-Smirnov					
Sample Size	72				
Statistic	0.05959				
P-Value	0.94684				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.12413	0.14183	0.15755	0.17618	0.18903
Reject?	No	No	No	No	No
Anderson-Darling					
Sample Size	72				
Statistic	4.2152				
Rank	45				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	Yes	Yes	Yes	Yes	Yes

Service characteristics

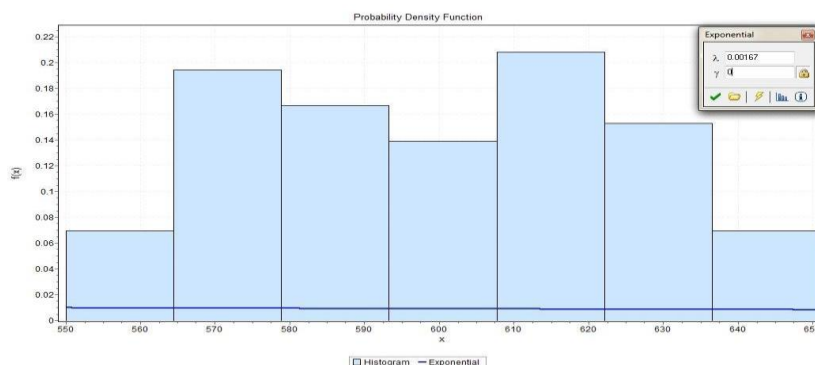


Figure 3: Average service time exponential distribution pattern.

3.1 Queueing Model Determination

From the number of servers observed from the field, it is discovered that the system has one server, the choice of model is a single server denoted by M/M/1 where, M represents the arrival rate pattern following Poisson distribution, M, the service times of all customers are independent and identically distributed random variables (I.I.D) and exponentially distributed. Two types of queueing models can be used in this research, single (M/M/1) and dual (M/M/2), so far only M/M/1 has been used, which is determined as 0.9825/1.029/1.

3.3.1 Determination of queue system performance measures

The average arrival rate for all days is estimated and used respectively across the days shown in Table 4. From Table 1, Monday has the highest hourly travel demand, this corresponds to the queueing outcome found in Table 4. These queueing studies provide insight into how queue data are determined graphically. This study is limited to comparative and efficient investigation of SimEvent-Simulinks and EasyFit coupling.

Table 4: Performance measures of Analytical and Simulation Model.

Days	Traffic Intensity (unit) AM	Traffic Intensity (unit) SM	Average waiting Time(Sec) AM	Queue Length (Veh) AM	Average waiting Time(Sec) SM	Queue Length (Veh) SM
Monday	0.9835	0.9839	3818	3751	3712	3681
Tuesday	0.9180	0.9380	137	125	3121	3007
Wednesday	0.8825	0.8950	64	56	2806	2789
Thursday	0.8546	0.8820	41	35	2654	2567
Friday	0.9129	0.9350	121	110	2987	2854
Saturday	0.8113	0.8350	23	19	2574	2467
Sunday	0.8056	0.8280	21	17	2187	1976

3.4 Optimum Performance of Analytical and Simulation Model

3.4.1 System performance measure

The waiting time and queue length of customers are determined using Little's relation and SimEvent-Simulinks, following the mathematical relations provided by Anyin and Etika (2022). The various performance measures for all days were estimated in an Excel spreadsheet for Kugbo checkpoint.

From Table 4, the traffic intensity of both the analytical and simulation models are approximately the same, but the waiting time and queue length are different because the analytical model follows constant proportion and the simulation model follows a discrete-time process by using the service rate distribution pattern. The service rate for all days is assumed to be the same and the arrival rate follows a constant proportion in the analytical model, while in the simulation model, the service time cannot be assumed to be the same, because of the provision for distribution input and the fact that arrival is dynamic because of the provision of Event-Based-Random-Number block which provides distribution to the system.

3.4.2 Waiting time of SM and AM

From Table 4, it is practically impossible to have only Mondays very busy, because the analytical model could not estimate the waiting time of other days in the week, but the simulation model could. This could be seen from the unrealistic assumptions that govern the

analytical approach over the simulation approach and its negligence of distribution pattern. Therefore, the graphical distribution of the waiting time of the simulation model is chosen and shown in Figure 4a.

3.5 System Utilization Factor

It is essential to understand the network system’s occupancy or working period within the experimental duration, as it affects other performance parameters. This is the percentage of time the system functioned out of the available period (12 hours). The analytical and simulation model utilization factors were determined following non-priority system operation based on the FIFO rule. Results obtained from M/M/1 analytical and simulation models are denoted as AM and SM respectively. The Utilization factor for AM and SM is as shown in Figure 4b.

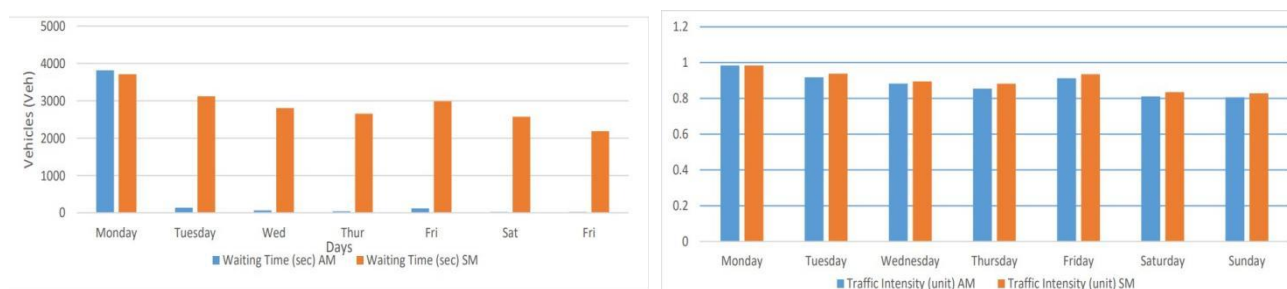


Figure 4: This consists of (a) The waiting time of the analytical and simulation models. (b) The Utilization factor of the AN and SM.

From the system utilization factors plot evaluated in Figure 4b. the SM and AM have approximately the same values of 0.9839 and 0.9835 units respectively, this connotes that both models are valid and in agreement with Anyin and Etika (2022). = 0.28482. It is seen that the mean of the distribution which happened to become the mean 10 minutes arrival is 589.49 veh. This value was adopted for further determination of the secondary parameters. It finds its application in engineering operational management, to provide a hedge to mitigate future hitches. From Figure 5 shown below, the simulation model outputs the following network performance measure characteristics, the average waiting lines of 3682vehs and waiting time 3751sec.



Figure 5: The waiting time of the simulation Model (SM).

4 Conclusion

In this work, an M/M/1 model queueing system with customer interjection and jockeying neglected was extensively studied using MATLAB SimEvents. This model was chosen using a distributive StatAssist tool by analyzing the arrival and service distribution pattern. Thus, the queueing model was confirmed to be single server, by service rate distributive pattern of 1.0

second per customer. The optimum performances of both AM and SM were achieved. It was found that; The arrival rate followed Poisson distribution and the service rate followed exponential distribution in the Kolmogorov Smirnov series. The model determined was a single server queue model, 0.9825/1.029/1, From the simulation model and analytical model, the system performance measures show the days that customers suffer more queues to be Mondays, which gave an average queue length of 3682 vehicles and 3751 seconds waiting time. The utilization factors for AM and SM are the same 0.9835, Thus validate the SM. From the optimum determination of AM and SM performance measures carried out, the AM produced the following average waiting time 3751, 125, 56, 35, 110, 19, and 17, while the SM produced average waiting time of 3681, 3007, 2789, 2567, 2854, 2467, and 1976, for Mondays through Sundays respectively. Looking at the SM waiting line which is more empirical because of the distributive nature of the simulation, while for analytical model used for the analysis of the queueing system yielded unrealistic results due to unrealistic assumptions of having an average constant service rate throughout the process. The difference in performance outputs from analytical and simulation models is attributed to the fact that; the simulation model carries out discrete time analysis of the system. A comparative study of other simulation models such as Genetic Algorithm, Python, Netsim, and others on the Queueing Model is recommended.

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