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Research Article

Analysis of Factors that Influence Automobile Workshop Queue Performance Using Design of Experiments

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Abstract

Probability and simulation techniques have been applied to analyse automobile workshop queue performance, but no study has been conducted to identify factors that affect automobile workshop queue performance. It is necessary to identify the factors that influence queue performance to design automobile workshop queue system. This study uses the design of experiments method to investigate the factors that influence queue performance. The number of servers, server area, number of phases, number of workers, and arrival rate are among the numerical factors evaluated. There are two categorical factors to consider: layout type and worker experience. Their effect on queue performance, including queue cost, service time, average customer waiting time, and number of customers, is examined. Additionally, this study seeks to discover appropriate experimental designs. There are three different experimental designs used. The first design is a split plot 2^{7-1}_{VI} that considers arrival rate as a categorical factor. The second design is a robust design that considers arrival rate as a source of variation. The third design is a full split plot design that considers arrival rate as a numeric factor. According to this study, a full split plot design offers higher accuracy in identifying factors influencing queue performance. The queue performance is significantly affected by the number of servers, phases, workers, arrival rate, and layout. This study paves the way for future studies to determine the optimal point of queue performance.

Keywords: Queue; Design of experiments; Automobile workshop; Categorical; Numerical

1. Introduction

Implementing a queue system is a common practice in many services. When a customer enters the service facility, the queue begins. Server performance measurement evaluates a server's ability to effectively meet the needs of customers (Nguyen & Phung-Duc, 2022). A queue system is a method or procedure for organizing and managing a line of people or entities waiting for service or accessing a specific facility, service, or process. This research focuses on the automobile workshop queue system. A conventional automobile workshop queue system, as depicted in Figure 1, incorporates multiple servers, each of which performs automobile repair. A mechanic attends to each server. The entire task is completed in a single phase. Automobile service encompasses a variety of tasks, such as vehicle maintenance, retrieval of spare parts, and quality inspection. The mechanic will attend to the automobiles that come to the workshop as soon as they arrive. The mechanic inspects the components to determine which ones need to be repaired or replaced. Subsequently, the mechanic then fills out the spare parts request form and submits it to the authorized spare parts department. The replacement component will be given to the mechanic and installed in the automobile. The mechanic examines the automobile thoroughly to determine its optimal working condition (Raghuwanshi & Goyal, 2015).

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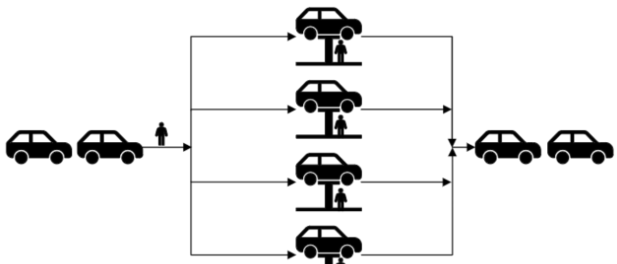


Fig. 1. Conventional automobile workshop queue system or type A layout

The presence of lines at automobile workshop facilities has a negative impact on customer satisfaction. Customers will be dissatisfied if the queue is too long. In addition, queues incur costs, such as customer waiting costs and capacity costs. The customer waiting costs are related to the costs incurred to accommodate the queue, which may include providing space, queue facilities, etc. Capacity costs are associated with the provision of a queue system and include worker, equipment, and resource costs. As the number of customers waiting increases, so do the costs of queue. To optimize the queue performance and reduce related costs, many efforts have been undertaken to integrate several factors, including service time, number of servers, and arrival rate (Vijay Prasad et al., 2020).

Analysis of automobile workshop queue performance is typically conducted with a queue theory-based method. The average arrival rate and average service time or service rate are the only two factors utilized by queue theory. These two factors are used to predict a variety of responses, including the average number of materials or people being served, the average number of materials or people in the system, the average time that people or materials are in queue, system utilization, the probability of zero units in the system, the probability of n units in the system, the number of customers in the system, and the probability that an arrival must wait. As the arrival rate is an uncontrollable factor, the average arrival rate is utilized to predict queue performance. Queue theory makes numerous assumptions to characterize the queue system; therefore, calculations will be erroneous if the assumptions are not met. Queue theory ignores other factors that influence queue performance (Yaduvanshi et al., 2019). Priority-based queue theory approaches are also utilized to estimate queue performance. The analysis is conducted using identical factors, specifically the arrival rate and service rate (Aziziankohan et al., 2017).

The performance of the automobile workshop queue system is also analyzed using the layout arrangement (Premono et al., 2020) and server area (Almomani & Almutairi, 2020). Break-even is the criterion that determines which layout is selected. Arrival rate, service rate, and other factors that could potentially influence the queue performance are not considered in the analysis.

Gender and age of workers are identified as factors that influence queue performance (Siregar, 2020). This must be investigated further, as the age of workers is equivalent to their level of experience, which impacts the queue performance.

Also utilized to estimate queue performance is the number of servers. Experiments are conducted utilizing both single and multiple servers. The findings of the analysis indicate that the implementation of multi-servers in the queue system enhances its performance through the reduction of customer queueing, acceleration of service time, and minimization of queue costs. Typically utilized as a factor, Service time is regarded as a response in this study (Bannikov et al., 2018).

Motivated by previous literature, it is necessary to identify factors that impact the automobile workshop queue performance simultaneously. Analysis is carried out simultaneously to determine the factors that have dominant impacts. The design of experiments is used to determine whether these factors have a significant impact on the queue performance. This research also identifies the design of the experiment model with the highest accuracy for identifying the factors that influence the queue performance.

2. Literature Review

2.1 Factors used for queue performance analysis.

The Markov chain is the basic way to evaluate queue performance. The Markov chain is a stochastic model that is built using a probabilistic technique. The probability of each object in the queue is highly dependent on the state attained in the previous event. This approach uses only the probability value of each event (Litvak, 2022).

Evaluation of queue performance is carried out using the birth-and-death process approach. The term birth refers to the arrival of a new customer. The term death refers to the departure of a served customer. The birth-and-death process is a special type of markov chain. The birth-and-death process uses only two factors, the average service rate, which is assumed to have an exponential distribution, and the average arrival rate, which is assumed to have a poisson distribution. The birth and death process approach derives several queue models, such as M/M/S, M/M/1, M/M/s/K, and M/M/1/K. This approach estimates the characteristics of the queue system (Pang et al., 2022).

Analyzing queue systems also employs the queue network methodology. At a specific point or stage, customers are in and out. A connection exists between this point or phase and another. At this point, customers have the option to proceed to an alternative point or exit the queue system. Modeling and simulation are nearly analogous to this approach. It is presumed that the distributions of the arrival rate and service rate are free (Moka et al., 2023).

Queue systems are also evaluated using stochastic scheduling. This methodology assumes that the workload to be performed is determined at random by the customer requests that are queued. Minimizing costs and flowtime are the primary objectives. Additionally, arrival rate and service time parameters are incorporated into this method to estimate the attributes of the queue system (Huang et al., 2022).

Queue systems are also examined using priority models. Priority is given to customers who have a greater priority for service. This is implemented to provide service to customers who require assistance immediately, thereby preventing them from exiting the queue system. The analysis is conducted using two key factors: arrival rate and service time. The objectives of this analysis are to estimate service utilization, the average amount of time customers spend in the system, and the number of customers present in the system (Walraevens et al., 2022).

The simulation approach uses random numbers to estimate the characteristics of the queue system by considering several factors such as arrival rate, service time, queue behavior, arrival process, system capacity, and calling population. These factors are used to estimate the number of customers in the queue system, the average customer waiting time, and server utilization (Blanchet, 2022).

All the previously described approaches utilize only a subset of factors, including arrival rate and service time, and disregard other factors that could potentially impact the queue performance. In addition, as shown in Table 1, queue system analyses are conducted utilizing a variety of techniques and other factors.

Table 1
Previous research

Methods	Factors	Responses	Objectives	Sources
Multi-priority strategy	Average arrival rate, Arrival service rate	Mean waiting time	To minimize customer waiting time	(Okonkwo et al., 2019)
Reservation and customer arrival schedule management are managed through mobile application-based information systems	Average arrival rate, Arrival service rate	Number of customers or queue length	To minimize the number of queues and increase the number of customers	(Windarto et al., 2021)
Dynamic programming	Admission control and service rate			(Yom-Tov & Chan, 2021)
CNN-based vehicle detection model	Arrival rate			(Umair et al., 2021)
Moment's estimator	Average arrival rate, Arrival service rate	Queue length, waiting time, queue cost	To minimize queue length, average customer waiting time and queue cost	(Ravner & Sakuma, 2021)
Layout preparation	Distance between layout	Travel times and distances	To reduce movement time and distance between departments.	(Kommula et al., 2015)
Fractional programming	Number of workers	Customer delay and abandonment costs, operating costs, and costs for changing staffing levels	To minimize queue costs	(Xiao et al., 2022)
Meta-heuristic algorithm	Distance, inventory control in the main blood center, product shortage, and queueing systems	Customer delay and abandonment costs, operating cost		(Aghsami et al., 2023)
Fuzzy environment	Number of servers	Customer delay and abandonment costs, operating cost		(Panta et al., 2021)
Queue theory and discrete simulation	Arrival rate, service rate	The cost of service and the cost associated with waiting for service		(Burodo et al., 2021)
Decomposition-based solution technique	Average arrival rate, Arrival service rate	Server utilization, projected throughput time, and predicted queue lengths	To increase service utilization and minimize queue lengths	(Van Ommeren et al., 2020)
Server movements	Server movements such as delivery, pickup, and dual transactions	Number of customers	To minimize the number of customers	(Li et al., 2020)
Non-convex nonlinear program	Interarrival-time distributions	Mean waiting time	To minimize the average customer waiting time	(Chen & Whitt, 2022)
Non-linear mathematical modelling approach	Number of servers	Waiting times, number of customers in queue and servers' utilization rates	To minimize waiting time, increase service utilization, and minimize the number of customers	(Franco et al., 2022)
Fluid deterministic model technique	Number of servers, arrival rate	Number of customers, waiting times, and service time	To minimize the number of customers and waiting time	(Zychlinski, 2023)
Moment estimator	Service time, arrival rate			(Ravner & Wang, 2023)
Simulation, and queue theory	Service time, arrival rate			(Irisbekova, 2021)
Queue theory, swot analysis	Service time, arrival rate			(Bannikov et al., 2018)
Markovian queue model	Service time, arrival rate			(Kothandaraman & Kandaiyan, 2023)
Queue theory	Service time, arrival rate			(Vasanthi & Santhi, 2022)
Queue management	Service time, arrival rate	Customer satisfaction coefficients	To maximize customer satisfaction	(Kondrashova, 2021)
Real-time system	Service time, arrival rate	Queue length	To minimize the number of customers	(Okaishi et al., 2021)
Anova, and queue theory	Service time, arrival rate	Waiting time for customers, and service time	To minimize service time and customer waiting time	(Anne et al., 2021)
Discrete-event simulation model "AS-IS"	Business process reengineering	Number of customers, average waiting time, service time, queue cost, number of leavers	To minimize all responses	(Revina & Trifonova, 2021)
Queue theory and probability	Service time, arrival rate	Traffic intensity, expected number of customers at a steady rate, expected queue length, expected waiting time, total customers waiting, and mean number of customers in the system		(Michael K. et al., 2023; State et al., 2022)
Critical path method	Activity	Car maintenance and repair times	To minimize service time	(Marit et al., 2020)

Table 1 shows that the queue system analyses use several factors, such as the number of servers, the number of workers, the server area, the arrival rate, and the layout type, but the analyses are not carried out simultaneously so that the factors that have a dominant influence on queue performance cannot be identified. Analysis of the factors that have a dominant influence on queue performance is very important because it helps management in designing the queue system by considering the dominant factors to improve its performance.

2.2 Design of experiments

Researchers have utilized design of experiments (DoE) to enhance the performance of queue systems. Among the parameters considered are the number of servers, cashiers, and interarrival rate. The relevant responses are queue length and sales rate (Galankashi et al., 2016). DoE is a procedure for optimizing manufacturing processes, but DoE can also be utilized in non-manufacturing environments. DoE can be applied to several service sectors such as healthcare, retail, logistics, education, marketing, after-sales service, and hospitality. Screening, factorial designs, taguchi, response surface technique, and split plot are among the experiments conducted. Several studies indicate that DoE has been utilized successfully in the service industry to identify factors affecting queue performance (Antony et al., 2020).

A queue system is part of supply chain management. Its performance is influenced by several factors. DoE can identify several factors that simultaneously have a dominant impact on queue performances, such as the number of errors, service time, and distance between departments that can minimize failure (Glistau et al., 2017).

The DoE approach is also integrated with the queue theory approach. For example, queue on the internet of robotic things system is optimized using a queue network-based performance model by considering factors that have impact on queue performance determined by the DoE approach (Feitosa et al., 2021).

Additionally, DoE is utilized to optimize hospital queue systems. Several factors are examined using DoE, including the quantity of beds, receptionists, nurses, and cardiologists, as well as community workers. Factors that have a significant influence on the queue performance are used to design a queue simulation system (Bahari et al., 2021).

Using the DoE method, the car queue system at gas station is also evaluated. DoE identifies factors that affect queue performance significantly. Utilizing a response surface methodology, optimization is conducted in consideration of these factors. The utilized model is a second-order equation. The existence of quadratic and interaction is demonstrated by the second order equation. DoE has the benefit of simultaneously identifying factors by minimizing correlation between factors, thereby improving the accuracy of estimation (Asadzadeh et al., 2021).

2.3 Research gap

Prior studies used simulation, queue theory, and other techniques to assess the performance of the automobile workshop queue system. Prior studies merely utilized the average arrival rate and average service time to predict and evaluate the queue performance. Other studies utilized additional factors, such as the number of workers, the number of servers, and queue discipline. Little emphasis has been placed on evaluating the factors that determine the performance of automobile workshop queue system. The factors that contribute to the performance of the automobile workshop queue system have not been thoroughly investigated yet. DoE implementation to ascertain the significance of factors affecting queue performance has also never been conducted. This study introduces several new factors, including number of phases and server area. The performance of the automobile workshop queue system includes queue cost, service time, average customer waiting time, and the number of customers. This study not only identifies factors that influence the automobile workshop queue performance but also identifies appropriate designs for the experimental model. This research is conducted at an SUV automobile maintenance business with a daily capacity of fifty cars. This research examines routine maintenance services.

3. Methodology

3.1 Factors

There are several factors to consider:

1. Number of servers (x_1) as numeric factor.
   The number of servers affects queue performance, particularly in the number of customers. If more servers are used, queue length will be smaller. Eighty percent of customers, according to company data, request routine maintenance services. Routine maintenance services employ four terminals. To ascertain the impact of the number of servers on the response, the number of servers varies between two levels, 4 and 8 workstations (Asadzadeh et al., 2021; Bahari et al., 2021; Feitosa et al., 2021; Srivastava, 2015).
2. Server Area (X_2) as numeric factor.
   Each server has a space allocated to automobile maintenance and repair. In analysis, the server area is divided at two levels, 9 square meters and 12 square meters.
3. Number of phases (x_3) as numeric factor.
   In a single phase, all stages of routine maintenance services are carried out by a worker. If the task is divided into three phases, the following activities will be included in each phase:
   The first phase consists of:

a. Inspecting the condition of the brake pads and tires.
b. Examining the oil leak, the ball joint, the tie rod, the wheel bearing, and the shock absorber leak.

The second phase consists of:

a. Examining radiator water, windshield washer fluid, windshield wiper rubber, brake fluid, and radiator water for leaks.
b. Examining exterior and interior lighting, engine and body electricity, and heat.
c. Inspecting the air conditioning unit.
d. Examining the battery's performance.

The third phase consists of engine tune-up.

4. Number of workers per phase (x_4) as numeric factor.
The impact of the number of workers per phase on response is investigated in this study. Between one and two workers are combined for each phase.
5. Arrival rate (x_5).
The arrival rate will be regarded as a categorical, variance source, and numeric factor in this study. Experiments will be conducted on the value between low and high.
6. Layout Type (z_1) as categorical factor.
Types A and B correspond to two discrete variations of layouts. The Type A model, which is depicted in Figure 1, is widely employed by most workshops. As illustrated in Figure 2, the Type B layout permits customers to remain within the car. To facilitate understanding, type A and type B factors are assigned the values -1 and 1, respectively.

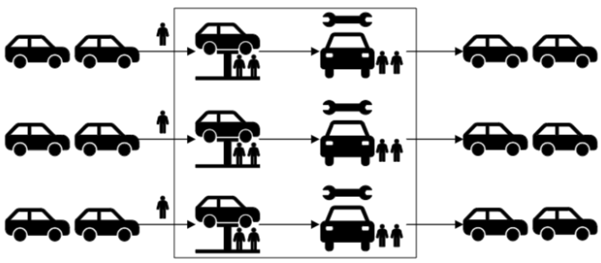


Figure 2. The type B layout

7. Worker experience (z_2) as categorical factor
Worker experience is a categorical factor with values ranging from -1 to 1. A non-certified worker with one to three years of work experience is deemed to have level -1 or low-level experience. A worker who has successfully completed training and possesses over three years of professional experience is classified as level 1 or high-level.

3.2 Responses

There are several responses that will be examined as follows:

1 Queue costs are divided into two categories: capacity costs and customer waiting costs (Vijay Prasad et al., 2020). Capacity costs include resource costs and the cost of providing equipment or equipment depreciation. Customer waiting costs include the cost of waiting space, and the opportunity cost incurred because of the customer's refusal to wait.
2 The average number of customers in the queue system per hour consists of the number of customers in the line who are expecting to receive service and the number of customers who are being served.
3 Average customer waiting time per day is the average time spent by customers to be in the queue line and to get service in one day.
4 Service time is the time it takes to repair one car. Service time is one response that needs to be considered in making service designs (Galankashi et al., 2016).

3.3 Design of experiments

1. Design of experiments for arrival rate is considered as categorical factor.

There are seven factors that are analyzed to determine the queue performance. The utilized model is as follows:

$$\mathbf{Responses} = \boldsymbol{\alpha} + \sum_{j=1}^{4} \boldsymbol{\beta}_j \mathbf{x}_j + \sum_{i=1}^{3} \boldsymbol{\beta}_{z_i} \mathbf{z}_i + \sum_{i=1}^{4} \sum_{i<j<2}^{4} \boldsymbol{\beta}_{ij} \mathbf{x}_i \mathbf{x}_j + \sum_{i=1}^{3} \sum_{j=1}^{4} \boldsymbol{\beta}_{z_{ij}} \mathbf{z}_i \mathbf{x}_j \quad (1)$$

Three categorical factors are represented by equation 1, including arrival rate, layout type, and worker experience. With generator I = ABCDEG, a split plot 2_{VI}^{7-1} design is used to calculate the model's coefficient as indicated by equation 1. The design of the experiments is depicted in Figure 3.

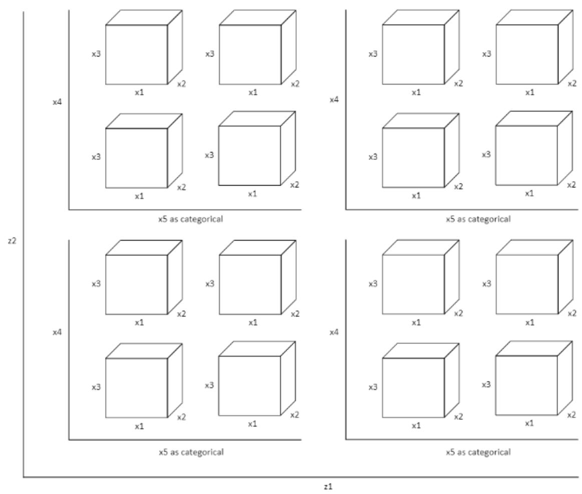


Figure 3. DoE for arrival rate as categorical and controlled factor

All factors are combined at two levels, denoted as low and high, as illustrated in Figure 3. Low magnitude (26-35 cars per day) and high magnitude (36-45 cars per day) are the two values assigned to the arrival rate category factor. One factor and the interactions of five factors, two factors and the interactions of four factors, and three factors and the interactions of three factors are all correlated. Empirically, interactions involving more than two factors are disregarded because they rarely have a significant impact on responses. This construction has an orthogonal design. The split plot 2^{7-1}_{VI} design is repeated once so that the significant factors can only be found using a half normal plot.

2. Robust design of experiment.

The arrival rate is uncontrollable because it is challenging to maintain customer arrivals. Variation in the arrival rate will affect the variance or standard deviation of the responses. The design model consists of inner and outer designs (Hamzaçebi, 2021; Wahid et al., 2020). Controllable factors are used in inner design. Outer design is used for arrival rate that cannot be controlled (Ashenafi & Geremew, 2020). The inner design model employed is:

$$\mathbf{Responses} = \boldsymbol{\alpha} + \sum_{i=1}^{2} \mathbf{z_i} \left(\sum_{j=1}^{4} \boldsymbol{\beta}_j \mathbf{x_j} + \sum_{i=1}^{4} \sum_{i<j<2}^{4} \boldsymbol{\beta}_{ij} \mathbf{x_i x_j} \right) \tag{2}$$

As shown in Equation 2, the arrival rate has been removed, leaving only two categorical factors and four numerical factors in the equation.

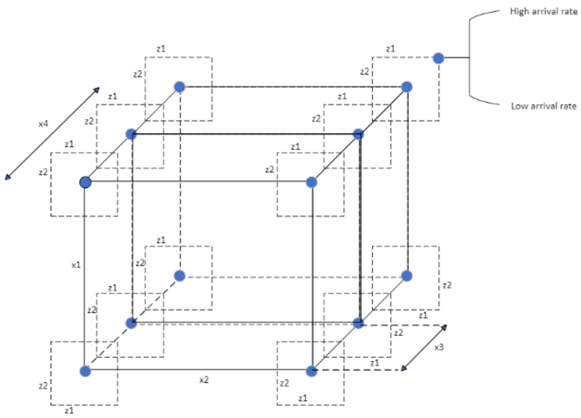


Figure 4. Robust design

A split plot $\mathbf{2^{6-1}_{V}}$ design is used for the inner design and is depicted by Figure 4. Each factor and their interaction are not mutually aliasing. Two-factor interactions are alias for three-factor interactions. This indicates that the inner design is orthogonal. The outer design is an arrival rate factor with two levels of variations. Each inner design experiment is replicated twice at both high and low arrival rates, as shown in Figure 4. The standard deviation and mean of the responses are utilized in the analysis. The robust design experiment seeks to ascertain the effect of controlled factors on responses and variances (Wahid et al., 2020).

Experiments are being carried out with a daily arrival rate of 35 cars. The arrival rate changes by +/- 5 cars during the experiment. The low arrival rate is less than -5 automobiles per day. The high arrival rate is within +5 cars/day.

3. Split plot full design.

The split plot full design consists of seven factors, as shown in Figure 5. Figure 5 shows that arrival rate is considered a controlled and numeric factor.

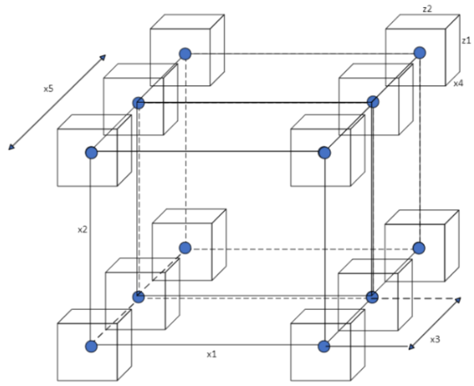


Figure 5. Full design

There are 128 experiments that must be conducted to identify the factors that influence the responses. Equation 3 represents the mathematical model employed in the analysis. As demonstrated by Equation 3, the arrival rate is explicitly accounted for and designated as a numerical factor within the mathematical model.

$$\mathbf{Responses} = \boldsymbol{\alpha} + \sum_{j=1}^{5} \boldsymbol{\beta}_j \mathbf{x_j} + \sum_{i=1}^{2} \boldsymbol{\beta}_{z_i} \mathbf{z_i} + \sum_{i=1}^{5} \sum_{i<j<2}^{5} \boldsymbol{\beta}_{ij} \mathbf{x_i x_j} + \sum_{i=1}^{2} \sum_{j=1}^{5} \boldsymbol{\beta}_{z_{ij}} \mathbf{z_i x_j} \tag{3}$$

The arrival rate is maintained at a constant level to ensure an accurate estimate. The average daily arrival rate is 50 vehicles, so the experiment is conducted with two daily arrival rates of 20 and 30 cars. This is achieved through the booking mechanism.

4. Results

4.1 Design experiment for arrival rate is considered as categorical factor.

According to Table 2, the number of servers, number of phases, and arrival rate all have a significant impact on queue cost. Table 2 reveals that the number of servers has a positive impact. The queue cost increases with the number of servers. According to previous research, increasing the number of servers reduces the total queue cost to a certain threshold, after which the total queue cost rises when the cost of providing a server exceeds the queue cost. Both the number of phases and the number of workers per phase have a detrimental effect on the queue cost. This contradicts previous research, which indicates that the number of phases and workers ought to have a positive effect on queue costs. The low R square value of 0.533 indicates a lack of fit.

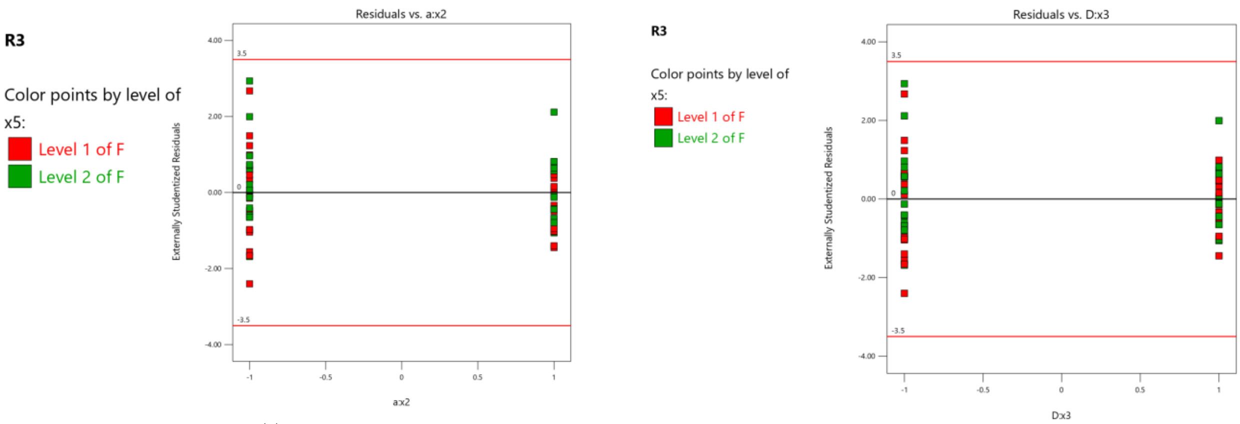
The number of phases, the number of workers, and their interactions all negatively affect service time, as shown in Table 2. Increasing the number of phases and workers reduces service time. A high R square value of 0.9458 indicates a good fit.

Table 2 indicates that the number of servers, phases, workers per phase, and layout type all have a significant effect on average customer waiting time. Additionally, Table 2 shows that the average customer waiting time is negatively impacted by the number of servers, number of phases, number of workers, and layout type. The average customer waiting time can be decreased by using a type B layout and by adding more phases, servers, and workers. The R square value of 0.9293 shows a good fit.

Table 2 demonstrates that the number of customers is significantly impacted by several factors. The regression coefficient for the number of servers is positive. This suggests that expanding the number of servers will increase the number of customers within the system. This contradicts previous research findings. The low R square value of 0.6792 indicates a lack of fit. The residual variance is shown to be non-uniform across Figures 6a and 6b. The factor values exhibit a correlation with the residual variance. As the value of the factor increases, the residual value diminishes. This is due to the fluctuating nature of the arrival rate, which causes response values to vary.

Table 2
Estimation of each response's coefficient when the arrival rate is categorical.

Factor	Coefficient Estimate for Each Response			
	Queue Cost	Service Time	Average Customer Waiting Time	Number of Customers
Layout type (z_1)	-	-	-0.3757	-
Servers (x_1)	1.24E+06	-	-0.1562	1.47
Phases (x_3)	-1.60E+06	-0.636	-0.6213	-0.6074
Workers (x_4)	-1.80E+05	-0.2582	-0.2594	-0.4512
Arrival rate (x_5)	1.82E+06	-	-	0.6191
x_1-x_3	1.63E+06	-	-	-
x_3-x_4	1.41E+06	0.0764	-	-
x_4-x_5	-	-	-	-0.5605
R Square	0.533	0.9458	0.9293	0.6792



(a) (b)

Fig. 6. Residual versus factor plot for average customer waiting time with categorical arrival rate.

4.2 *Robust design of experiment*

Table 3 demonstrates that the number of workers, the number of servers, the number of phases, the layout type, and their interactions have significant effects on the queue cost. The high R square value of 0.9827 indicates a good fit. The number of servers and phases has significant impacts on the variance of queue cost. According to Table 3, the number of servers has a significant negative impact, whereas the number of phases has a significant positive impact. Because the coefficients of the two factors are almost identical but have opposite signs, their effects are nullified. A low R square value of 0.3962 indicates a poor fit. This indicates that fluctuating arrival rate values have no effect on the variance of queue cost.

Table 3 reveals that the number of phases, the number of workers per phase, and their interactions all have a significant impact on service time. Service time is decreased by increasing both the number of phases and the number of workers. Increasing the number of servers and workers speeds up repair operations, resulting in a reduction in service times. Due to its high R square value of 0.9889, the model fits perfectly. Table 3 demonstrates that the number of servers and workers has a negative effect on service time deviation. The service time fluctuates slightly as the number of servers and workers increases. The high R square value of 0.9836 supports this finding.

Table 3.
Coefficient estimates for robust design.

Factor	Coefficient Estimate for Each Response							
	Queue Cost		Service Time		Average Customer Waiting Time		Number of Customers	
	Response	Deviation	Response	Deviation	Response	Deviation	Response	Deviation
Layout (z_1)	-3.55E+05	-	-	-	-0.2836	-	-0.9092	-
Servers (x_1)	-4.47E+06	-0.1745		-0.6332	-0.0801	-0.6166	-1.92	-0.5249
Phases (x_3)	8.15E+05	0.1571	-0.4588	-	-0.456	-	-1.07	-0.4351
Workers (x_4)	1.58E+06	-	-0.2017	-0.37	-0.2073	-0.3681	-	-
x_1 - x_3	1.69E+06	-	-	-	-	-	-	-
x_1 - x_4	8.25E+05	-	-	-0.2078	-	-0.1993	-	-
x_3 - x_4	9.12E+05	-	-0.0801	-	-	-	-	-
z_1 - x_1	-	-	-	-	-0.0548	-	-	-
x_3 - x_4	-	-	-	-	-0.0783	-	-	-
z_1 - x_3	-	-	-	-	-	-	0.667	-
x_1 - x_3 - x_4	4.63E+05	-	-	-	-	-	-	-
R Square	0.9827	0.3962	0.9889	0.9836	0.9945	0.9871	0.8739	0.660

The number of servers, the number of phases, the number of workers per phase, and the interaction between factors all have a negative impact on the average customer waiting time, as shown in Table 3. This indicates a reduction in the average customer waiting time if these factors are integrated at a high level. The high R square value of 0.9945 indicates that the proposed equation has a good fit.

The number of servers, the number of workers, and their interactions all have a considerable negative effect on the average customer waiting time deviation. The response deviation is diminished when the two factors are operated at high levels. The high R square value of 0.9871 indicates that the model is well-fitting.

Table 3 reveals that layout type, number of servers, number of phases, and the interaction between layout type and number of phases have a significant negative effect on the number of customers. The number of customers will decrease as more servers and phases are added. The high R square value of 0.8739 indicates a good fit.

According to Table 3, both the number of servers and the number of phases have a negative impact on the number of customer deviations. The R square value of 0.660, however, is relatively low. This indicates a poor fit. In general, the response deviation value decreases if the factors are operated at a high level, or, in other words, the effect of the arrival rate on the response can be eliminated if the factors are operated at a high level. Not all factor values can be operated at a high level under optimal conditions, making this difficult to achieve during the optimization process.

4.3 Full design

The factors that have a substantial impact on automobile workshop queue performance are listed in Table 4. Arrival rate that was excluded from the analysis model in Table 3 are now included in Table 4's analysis. The number of servers has a negative effect on queue cost. Increasing the number of servers will decrease queue costs. The number of phases, the number of workers, and the arrival rate have a substantial positive effect on queue cost. Increasing the number of phases causes a proportional increase in the number of workers, thereby causing an increase in queue cost. With an increase in the arrival rate, the costs of losing customers and the cost of providing space to accommodate lines both increases. The server area does not have a significant impact on queue cost. Increasing server or workstation space has no effect on queue costs because it has no effect on service time. The layout type also has no effect on the queue cost. Queue cost is unaffected by worker experience. Workers with one to three years of work experience go through the same training programs to develop a standard method of doing their jobs. As a result, the number of customers who leave the queue system is unaffected, and neither is the queue cost.

The number of phases and the number of workers both have a significant negative impact on service time. The results of this analysis match those of the robust design analysis in Table 3. Increasing the number of phases and workers improves efficiency while shortening the service time. Service time is unaffected by the number of servers, server area, worker experience, layout type, or arrival rate. The number of servers has a minimal impact on the work process, hence their impact on service time is minor. The increase in workstation size from 9 to 16 square meters has no significant impact on service time. Ergonomic considerations led to the choice of a nine-square-meter workstation space, such that enlarging the area would not have a significant impact on service time. Worker experience has no impact on service time because all workers have been trained to ensure that all work is performed in accordance with standards. The layout type has no significant effect on service time because it does not result in a decrease in service duration. The arrival rate has no effect on the service time. The arrival rate has the effect of lengthening the queue or increasing the number of customers without shortening the service duration.

Table 4.

Coefficient estimates for full design.

Terms	Queue cost		Service time		Average customer waiting time		Number of customers	
Terms	Effect	F	Effect	F	Effect	F	Effect	F
Layout (z_1)	43750	1,06	-0,00	0,02	-20,06	3846.62	-0.18	4,14
Server area (x_2)	28125	0,44	-0,05	2,71	0,55	2.94	0.11	1,64
Servers (x_1)	-2068187	459,01	0,11	0,12	0,14	0.14	-4,684	1653,86
Phases (x_3)	1503125	242,46	-36,44	12201,06	-36,58	9510.48	-1,086	88,91
Workers (x_4)	1528125	250,59	-31,87	9330,99	-32,33	7431.62	-1,113	93,44
Arrival rate (x_5)	4579688	2250,70	-0,06	0,04	5,16	189.44	4,605	1599,14
Worker experience (z_2)	-70312	0,53	-0,37	1,27	0.46	1.5	0.11	0,90
Servers*Phases	1031250	114.12	-	-	-	-	-	-
Servers*Workers	1078125	124.73	-	-	-	-	-	-
Phases*Workers	1201563	154.93	-	-	-	-	-	-
R^2		97,44%		99,56%		99,45%		97,38%

The analysis results for average customer waiting time in Table 4 differ from Table 3. The number of servers has no effect on the average customer waiting time. This occurs because increasing the number of servers does not reduce service time or overall waiting time. The layout has a significant negative impact on the average customer waiting time. The Type B layout decreases the average customer waiting time. The Type B layout eliminates non-value-added activity, resulting in a shorter average customer waiting time. Both the number of phases and the number of workers have a negative impact on the average customer waiting time. An increase in the number of phases and workers reduces service time and the customer's waiting time within the queue system. The arrival rate increases the average customer waiting time. Customers will spend more time in the queue system if the arrival rate is higher, as the queue will be longer.

The number of servers negatively impacts the number of customers. Increasing the number of servers increases the number of customers serviced, which reduces the number of customers. The number of phases and the number of workers have a negative effect on the number of customers. When the number of phases and the number of workers is increased, service time decreases, and the number of customers decreases. This result differs from the findings in Table 3, which indicate that the number of workers has no significant impact on the number of customers. The arrival rate adds to an increase in the number of customers because, as the arrival rate expands, more customers will attend the queue.

The split plot 2^{7-1}_{VI} design is less accurate for determining the factors that influence the response. The results of the analysis indicate that the linear model for the queue cost and the number of customers in the queue system is inadequate. Estimates of the effect of factors on responses are obscured by the arrival rate.

The next experiment is carried out using a robust design experiment technique. Robust design experiment combines inner and outer design. The inner design is a split plot 2^{6-1}_{V} design. Because there are no correlations between single factors, the design is orthogonal. The outer design comprises a two-level arrival rate. Each experiment on the inner design is repeated twice at each level of arrival rate, for a total of four replications. The replications are averaged, and a single response is obtained, resulting in a single replicated experiment. The goal is to eliminate the impact of the arrival rate on response variances. The results show that the arrival rate causes the response value to fluctuate. Robust design can identify factors that influence the response, but the arrival rate is the main source of response variance. A robust design can eliminate the effect of arrival rate but cannot identify the influence of arrival rate on response.

The split plot full model accurately estimates the factors that influence responses. High magnitudes of R square indicate a perfect fit. The equations 4 to 7 represent the mathematical model that is generated in accordance with the full split plot design.

$$\textbf{Queue cost} = \boldsymbol{\alpha} + \mathbf{z_1}(\boldsymbol{\beta_1}\mathbf{x_1} + \boldsymbol{\beta_3}\mathbf{x_3} + \boldsymbol{\beta_4}\mathbf{x_4} + \boldsymbol{\beta_5}\mathbf{x_5} + \boldsymbol{\beta_{13}}\mathbf{x_1}\mathbf{x_3} + \boldsymbol{\beta_{14}}\mathbf{x_1}\mathbf{x_4} + \boldsymbol{\beta_{34}}\mathbf{x_3}\mathbf{x_4}) \quad (4)$$

$$\textbf{Service time} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{x_1} + \boldsymbol{\beta_3}\mathbf{x_3} + \boldsymbol{\beta_4}\mathbf{x_4} \quad (5)$$

$$\textbf{Average customer waiting time} = \boldsymbol{\alpha} + \mathbf{z_1}(\boldsymbol{\beta_1}\mathbf{x_1} + \boldsymbol{\beta_3}\mathbf{x_3} + \boldsymbol{\beta_4}\mathbf{x_4} + \boldsymbol{\beta_5}\mathbf{x_5}) \quad (6)$$

$$\textbf{Number of customers} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{x_1} + \boldsymbol{\beta_5}\mathbf{x_5} \quad (7)$$

Equation 4 can be used to find the optimum point with the steepest descent. Equation 4 and 6 indicate that determining the optimum point must be carried out on two types of layouts to obtain comprehensive results. In the absence of the layout type factor in Equations 5 and 7, optimization can be performed with a single layout type.

5. Conclusions

The split plot full model has the best accuracy in identifying factors that affect automobile queue performance. The performance is significantly impacted by several factors, including servers, workers, phases, layout, and arrival rate. Responses are unaffected by the server area. This is a result of the workspace's design prioritizing the flexibility and ergonomics of its users. Worker experience is a categorical factor that has minimal effect on responses because workers receive adequate training, ensuring that new workers and experienced workers perform at the same level. This study affects the managerial aspect in which the automobile queue system design must consider the number of servers, workers, and layout in addition to the arrival rate. Services must be divided into multiple phases to enhance the performance of the queue system. This study opens several possibilities for future research to optimize workshop queue performance using a response surface technique.

Nomenclature

R = Response
$\boldsymbol{\alpha}$ = Intercept
$\boldsymbol{\beta_j}$ = Coefficient for numeric factors
$\boldsymbol{\beta_{z_i}}$ = Coefficient for categorical factors
$\boldsymbol{\beta_{ij}}$ = Coefficient for numeric factor interaction
$\boldsymbol{\beta_{z_i j}}$ = Coefficient for numeric and categorical factor interaction
$\boldsymbol{\epsilon}$ = Error
$\mathbf{z_i}$ = Categorical factor
x_i and x_j = Numeric factors

References

Aghsami, A., Abazari, S. R., Bakhshi, A., Yazdani, M. A., Jolai, S., & Jolai, F. (2023). A meta-heuristic optimization for a novel mathematical model for minimizing costs and maximizing donor satisfaction in blood supply chains with finite capacity queueing systems. *Healthcare Analytics*, *3*, 100136. https://doi.org/https://doi.org/10.1016/j.health.2023.100136

Almomani, H., & Almutairi, N. (2020). Vehicles Maintenance Workshops Layout and its Management to Reduce Noise Pollution and Improve Maintenance Quality. *Journal of Environmental Treatment Techniques*, *8*(4), 1352–1356.

Anne, M., Sy, P. C., Malabuyoc, F. L. S., Sobrevilla, M. D. M., & Estember, R. D. (2021). A Queuing Theory Approach to Improve Service Quality of Banking Systems : A Case Study of a Bank in Laguna , Philippines. *Proceedings of the International Conference on Industrial Engineering and Operations Management*, 2703–2714.

Antony, J., Viles, E., Torres, A. F., Paula, T. I. de, Fernandes, M. M., & Cudney, E. A. (2020). Design of experiments in the service industry: a critical literature review and future research directions. *The TQM Journal*, *32*(6), 1159–1175. https://doi.org/10.1108/TQM-02-2020-0026

Asadzadeh, S., Akhavan, B., & Akhavan, B. (2021). Multi-objective optimization of Gas Station performance using response surface methodology. *International Journal of Quality and Reliability Management*, *38*(2), 465–483. https://doi.org/10.1108/IJQRM-06-2019-0181

Ashenafi, A. M., & Geremew, S. (2020). A combined simulation-based taguchi robust design approach for improved parameter design. *Industrial Engineering and Management Systems*, *19*(3), 644–656. https://doi.org/10.7232/iems.2020.19.3.644

Aziziankohan, A., Jolai, F., Khalilzadeh, M., Soltani, R., & Tavakkoli-Moghaddam, R. (2017). Green supply chain management using the queuing theory to handle congestion and reduce energy consumption and emissions from supply chain transportation fleet. *Journal of Industrial Engineering and Management*, *10*(2Special Issue), 213–236. https://doi.org/10.3926/jiem.2170

Bahari, A., Asadi, F., & Moody, B. (2021). Simulation Modeling for Evaluation of the Patients ’ Queue System Performance at Emergency. *Research Square*, *1*(1), 1–22.

Bannikov, D., Sirina, N., & Smolyaninov, A. (2018). Model of The Maintenance And Repair System In Service. *Transport Problems*, *13*(3), 1–10. https://doi.org/10.20858/tp.2018.13.3.1

Blanchet, J. H. (2022). Some open problems in exact simulation of stochastic differential equations. *Queueing Systems*, *100*(3), 509–511. https://doi.org/10.1007/s11134-022-09835-x

Burodo, M. S., Mikailu, I., & Yusuf, G. (2021). An Empirical Analysis of the Queuing Theory and its Application to Customer Satisfaction in a Small and Medium Enterprises (SMEs): A Study of Danjalele Enterprise , Funtua , Kastina State. *International Journal of Novel Research in Healthcare and Nursing*, *8*(3), 89–99.

Chen, Y., & Whitt, W. (2022). Applying optimization theory to study extremal GI/GI/1 transient mean waiting times. *Queueing Systems*, *101*(3), 197–220. https://doi.org/10.1007/s11134-021-09725-8

Feitosa, L., Gonçalves, G., Nguyen, T. A., Lee, J. W., & Silva, F. A. (2021). Performance evaluation of message routing strategies in the internet of robotic things using the d/m/c/k/fcfs queuing network. *Electronics (Switzerland)*, *10*(21), 1–22. https://doi.org/10.3390/electronics10212626

Franco, C., Herazo-Padilla, N., & Castañeda, J. A. (2022). A queueing Network approach for capacity planning and patient Scheduling: A case study for the COVID-19 vaccination process in Colombia. *Vaccine*, *40*(49), 7073–7086. https://doi.org/https://doi.org/10.1016/j.vaccine.2022.09.079

Galankashi, M. R., Fallahiarezoudar, E., Moazzami, A., Yusof, N. M., & Helmi, S. A. (2016). Performance evaluation of a petrol station queuing system: A simulation-based design of experiments study. *Advances in Engineering Software*, *92*, 15–26.

https://doi.org/https://doi.org/10.1016/j.advengsoft.2015.10.004

Glistau, E., Isaias, N., & Machado, C. (2017). Full-Factorial Design of Experiments in Logistics Systems. *MultiScience - XXXI. MicroCAD International Multidisciplinary Scientific Conference University of Miskolc, Hungary, April*, 1–9. https://doi.org/10.26649/musci.2017.042

Hamzaçebi, C. (2021). Taguchi Method as a Robust Design Tool. In *Quality Control - Intelligent Manufacturing, Robust Design and Charts*. IntechOpen. https://doi.org/10.5772/intechopen.94908

Huang, J., Mandelbaum, A., & Momčilović, P. (2022). Appointment-driven service systems with many servers. *Queueing Systems*, *100*(3), 529–531. https://doi.org/10.1007/s11134-022-09782-7

Irisbekova, M. (2021). Improving methodology of automobile operating companies activities simulation modeling. *E3S Web of Conferences*, *05024*(05024), 1–8.

Kommula, V. P., Mapfaira, H., Gandure, J., Mashaba, K., Monageng, R., & Samuel, O. (2015). Improving Productivity of a Machine Workshop through Facilities Planning. *International Journal of Mining, Metallurgy & Mechanical Engineering (IJMMME) Volume*, *3*(3), 187–192.

Kondrashova, E. (2021). Optimization of Controlled Queueing Systems : the Case of Car Wash Services TransSiberia 2020 Conference. *Transportation Research Procedia*, *54*(2020), 662–671. https://doi.org/10.1016/j.trpro.2021.02.119

Kothandaraman, D., & Kandaiyan, I. (2023). SS symmetry Analysis of a Heterogeneous Queuing Model with Intermittently Obtainable Servers under a Hybrid. *Symmetry*, *15*, 1–18. https://doi.org/https://doi.org/10.3390/sym15071304

Li, K., Pan, Y., Liu, B., & Cheng, B. (2020). The setting and optimization of quick queue with customer loss. *Journal of Industrial and Management Optimization*, *16*(3), 1539–1553. https://doi.org/10.3934/JIMO.2019016

Litvak, N. (2022). New ways of solving large Markov chains. *Queueing Systems*, *100*(3), 217–219. https://doi.org/10.1007/s11134-022-09821-3

Marit, I. Y., Nursanti, E., & Vitasari, P. (2020). Critical Path Method to Accelerate Automotive Maintenance Duration. *International Journal of Scientific & Technology Research*, *9*(03), 6777–6782. https://doi.org/DOI:10.1088/1757-899X/885/1/012059

Michael K., A., Saheed A., A., & Awaw K., A. (2023). Congestion Problem during Covid-19 in the University College Hospital , Ibadan , Oyo State , Nigeria : An Application of Queuing Theory. *International Journal of Mathematics and Statistics Studies*, *11*(June), 61–66. https://doi.org/https://doi.org/10.37745/ijmss.13/vol11n16166

Moka, S. B., Nazarathy, Y., & Scheinhardt, W. (2023). Diffusion parameters of flows in stable multi-class queueing networks. *Queueing Systems*, *103*(3), 313–346. https://doi.org/10.1007/s11134-022-09869-1

Nguyen, H. Q., & Phung-Duc, T. (2022). Strategic customer behavior and optimal policies in a passenger–taxi double-ended queueing system with multiple access points and nonzero matching times. *Queueing Systems*, *102*(3), 481–508. https://doi.org/10.1007/s11134-022-09786-3

Okaishi, W. Al, Zaarane, A., Slimani, I., & Atouf, I. (2021). A Vehicular Queue Length Measurement System In Real-Time Based On Ssd Network. *Sciendo*, *22*(1), 29–37. https://doi.org/10.2478/ttj-2021-0003

Okonkwo, U. C., Okokpujie, I. P., Odo, B. N., & Fayomi, O. S. I. (2019). Workshop Queue System Modification Through Multi Priority Strategy. *Journal of Physics: Conference Series*, *1378*(2). https://doi.org/10.1088/1742-6596/1378/2/022030

Pang, G., Sarantsev, A., & Suhov, Y. (2022). Birth and death processes in interactive random environments. *Queueing Systems*, *102*(1), 269–307. https://doi.org/10.1007/s11134-022-09855-7

Panta, A. P., Ghimire, R. P., Panthi, D., & Pant, S. R. (2021). Optimization of M / M / s / N Queueing Model with Reneging in a Fuzzy Environment. *American Journal of Operations Research*, *11*, 121–140. https://doi.org/10.4236/ajor.2021.113008

Premono, A., Victor, M., & Sutrisno, H. H. (2020). An experimental study of a car maintenance workshop layout optimization. *AIP Conference Proceedings*, *May*, 1–8. https://doi.org/10.1063/5.0000585

Raghuwanshi, P., & Goyal, A. (2015). Evaluation and Improvement of Plant Inventory and Layout Design in Automobile Service Industries. *International Journal of Innovative Research in Science, Engineering and Technology*, *4*(9), 8178–8185. https://doi.org/10.15680/IJIRSET.2015.0409023

Ravner, L., & Sakuma, Y. (2021). Strategic arrivals to a queue with service rate uncertainty. *Queueing Systems*, *97*(3), 303–341. https://doi.org/10.1007/s11134-020-09683-7

Ravner, L., & Wang, J. (2023). Estimating customer delay and tardiness sensitivity from periodic queue length observations. *Queueing Systems*, *103*(3), 241–274. https://doi.org/10.1007/s11134-022-09867-3

Revina, I. V, & Trifonova, E. N. (2021). Car Service Optimization Based on Simulation. *Journal of Physics: Conference Series*, *1791*, 1–11. https://doi.org/10.1088/1742-6596/1791/1/012084

Siregar, N. (2020). Queue System in Automobile Service Sectors. *International Journal of Advanced Science and Technology*, *29*(5), 13365–13378.

Srivastava, S. (2015). Queuing theory in workshop. *International Journal of Science, Technology & Management*, *04*(01), 88–95.

State, K., Adeniran, A., & Burodo, M. S. (2022). Application of Queuing Theory and Management of Waiting Time Using Multiple Server Model : Empirical Evidence From Ahmadu Bello. *International Journal of Scientific and Management Research*, *5*(4), 159–174. https://doi.org/http://doi.org/10.37502/IJSMR.2022.5412

Umair, M., Farooq, M. U., Raza, R. H., Chen, Q., & Abdulhai, B. (2021). Efficient Video-based Vehicle Queue Length Estimation using Computer Vision and Deep Learning for an Urban Traffic Scenario. *MDPI*, *9*, 1–19.

Van Ommeren, J.-K., Baer, N., Mishra, N., & Roy, D. (2020). Batch service systems with heterogeneous servers. *Queueing Systems*, *95*(3), 251–269. https://doi.org/10.1007/s11134-020-09654-y

Vasanthi, J., & Santhi, S. (2022). Application of Queueing Theory for the Improvement of Railway Services. *International Journal of Mechanical Engineering*, *7*(2), 1479–1483.

Vijay Prasad, S., Donthi, R., & Challa, M. K. (2020). The sensitivity analysis of service and waiting costs of a multi-server queuing model. *IOP Conference Series: Materials Science and Engineering*, *993*(1). https://doi.org/10.1088/1757-899X/993/1/012107

Wahid, Z., Ming, T. T., & Ahmad, K. (2020). Use of Taguchi Robust Design to Optimize Rubber Glove Process. *Journal of Physics: Conference Series*, *1489*(1). https://doi.org/10.1088/1742-6596/1489/1/012034

Walraevens, J., Van Giel, T., De Vuyst, S., & Wittevrongel, S. (2022). Asymptotics of waiting time distributions in the accumulating priority queue. *Queueing Systems*, *101*(3), 221–244. https://doi.org/10.1007/s11134-022-09839-7

Windarto, Y., Hersant, R., & Putro, E. (2021). Developing Home Service System; Business Process Reengineering for Motorcycle Workshop. *Indonesian Journal of Information Systems*, *3*(2), 94–104. https://doi.org/10.24002/ijis.v3i2.4144

Xiao, L., Xu, S. H., Yao, D. D., & Zhang, H. (2022). Optimal staffing for ticket queues. *Queueing Systems*, *102*(1), 309–351. https://doi.org/10.1007/s11134-022-09854-8

Yaduvanshi, D., Sharma, A., & More, P. V. (2019). Application of Queuing Theory to Optimize Waiting- Time in Hospital Operations. *Operation and Supply Chain Management*, *12*(3), 165–174.

Yom-Tov, G. B., & Chan, C. W. (2021). Balancing admission control, speedup, and waiting in service systems. *Queueing Systems*, *97*(1), 163–219. https://doi.org/10.1007/s11134-021-09685-z

Zychlinski, N. (2023). Applications of fluid models in service operations management. *Queueing Systems*, *103*(1), 161–185. https://doi.org/10.1007/s11134-022-09868-2