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From Field Data to Analytical Queueing Model

A Two-Periode Assessment of M/M/2 Service Capacity at a Gas Station

[1]Annie Purwani*, [1]Laode Rivaldi, [1]Magfira Samsi, [1]Nazla Khaira Adz Dzurr, [1]Muhammad Panca Nugraha
Corresponding Author: * annie.purwani@uad.ac.id
[1] Universitas Ahmad Dahlan, Yogyakarta, Indonesia

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Abstract

Queueing systems at gas stations (SPBU) exhibit variable arrival and service characteristics; thus, selecting an appropriate queueing model requires aligning assumptions with empirical conditions. This study aims to identify the probability distribution characteristics of inter-arrival times and service times and to evaluate their fit with the assumptions of the M/M/2 queueing model at the Tugu 44.552.15 gas station. Data were collected through customer-level observations during two sessions—July 10, 2026, and August 12, 2026—between 12:00 and 15:00. Arrival and service time data were processed to derive inter-arrival and service times, which were then analyzed using distribution fitting in the Arena Input Analyzer. Several probability distributions were compared based on squared error and goodness-of-fit test results. The analysis revealed that the exponential distribution lacked statistical support to represent either inter-arrival times or service times. This pattern was consistently observed across both sessions. Thus, the system's empirical characteristics during the observation period do not support the Markovian assumptions underlying the M/M/2 model. These findings suggest that the M/M/2 model relies on relatively restrictive assumptions for representing the observed system, implying that empirical-based approaches—such as discrete-event simulation—may be suitable for further analysis.

Keywords: *gas station, goodness-of-fit, inter-arrival time, M/M/2, queueing system, service time.*

Introduction

Queues are one of the common problems found in service systems when there's an imbalance between the number of customers coming in and the facility's ability to provide service. This situation can make customers wait before getting service and eventually affects the system's efficiency [1]-[3]. Queueing theory provides a framework for analyzing arrival and service processes and evaluating system performance through measures such as server utilization, the average number of customers in the system, and customer waiting times [4].

Public fuel filling stations (SPBU) are examples of service systems characterized by queuing [5]. At these stations, arriving vehicles often have to wait to receive refueling services from the available facilities or servers. These performance measures provide a basis for assessing whether the existing service capacity is adequate to accommodate customer demand and for identifying potential congestion within the service system. If the vehicle arrival rate exceeds service capacity, vehicle queues and increased waiting times can occur. Numerous previous studies have addressed the imbalance between customer arrivals and service facilities at gas stations by applying queuing theory [2], [5]-[10].

Several previous studies on gas-station queuing systems have predominantly employed analytical queueing models, such as M/M/1, M/M/2, and M/M/s, to evaluate system performance and identify appropriate service configurations [11], [12]. The initial step in using the analytical method is to identify the actual system [4]. This step aims to ensure the selection of an appropriate model to represent service conditions. In a multi-channel, single-phase system, multiple servers can provide service to customers in parallel. The findings from this identification process are then used to construct an M/M/s model to evaluate system performance and generate alternatives regarding the number of pumps to be used.

The first and second "M" letters in the M/M/s model indicate that arrival and service characteristics are assumed to follow specific distributions, while the letter "s" represents the number of servers providing service to customers in parallel [4]. Required data include arrival times, service start times, service completion times, inter-arrival times, and waiting times [3], [4]. These data are used to model a system where customers arrive randomly and subsequently receive service from one of the available servers.

Before a queuing model is implemented, the characteristics of arrival and service data must be considered to ensure the model accurately represents the system's conditions. In analytical queuing methods, arrival and service data patterns must follow an exponential distribution [4], [7], [10], [11]. These two characteristics describe customer arrival patterns and the system's capacity to serve customers; therefore, the probability distributions of both datasets must first be determined. Selecting an appropriate distribution helps establish whether the data characteristics support the assumptions required for a specific queuing model.

Although identifying the characteristics of arrival interval and service patterns is crucial, some previous studies [2], particularly those concerning gas station queues, have not strictly adhered to this step. One researcher did not explicitly mention this step, despite clearly stating the use of the M/M/s analytical method in their methodology. Another researcher [6], [13] also stated they used the M/M/s method and performed this step (finding that the arrival and service data did not follow an exponential distribution) yet still applied the model's formulas to evaluate the queue.

A literature review revealed a research gap regarding the need for an empirical evaluation of the M/M/2 model's probabilistic assumptions before its application to a real-world service system, as well as the need to examine the consistency of distribution characteristics. Consequently, this study aims to identify inter-arrival and service time characteristics, determine the best-fitting distribution, statistically test its goodness-of-fit, evaluate its alignment with M/M/2 assumptions, and assess the consistency of distribution results across two observation sessions.

Material and Methods

This study employs a quantitative approach based on field observations (at the Pertamina Tugu 44.552.15 gas station) to identify customer arrival characteristics, service processes, and queue system performance at a facility featuring two service lanes. Observations were conducted at the customer level, allowing for the individual recording of each arrival and service event.

The actual system consists of two service lanes, each with a single server. Arriving customers select one of the service lanes and wait in the corresponding queue. Service is administered based on the First-In-First-Out (FIFO) principle within each lane. Primary data were collected through direct observation of each customer arriving and receiving service. The study recorded events at the individual customer level (n), allowing for the tracking of arrival time (A_i), the arrival time of the preceding customer (A_{i-1}), lane selection (Q_i), service start time (S_i), and service completion time (C_i) for each customer. The inter-arrival time (IAT_i) the i-th customer was calculated as the difference between that customer's arrival time and the arrival time of the preceding customer. Since the first customer had no preceding arrival time within the observation period, the total number of inter-arrival time observations was (n-1). Service time (ST_i) was defined as the difference between the service completion time and the service start time. Meanwhile, waiting time (WT_i) was calculated by subtracting the arrival time from the service start time. The total time a customer spent in the system (T_i) was calculated as C_i minus A_i.

The observational data were then transformed into inter-arrival time (IAT_i), waktu pelayanan (ST_i), and waiting time (WT_i). The next step involved identifying the probability distribution that best matched the empirical characteristics of the inter-arrival and service times. Arena software's Input Analyzer tool was used for this stage. Suitability was assessed using goodness-of-fit tests, where a higher p-value indicated a better fit, along with the least-squares error value and a visual comparison between the histogram and the distribution curve.

If the data characteristics supported the model assumptions, the system was subsequently analyzed using an (M/M/2) queuing model. This model was selected because gas station 44.552.15 operates with two servers. The model's key parameters include the customer arrival rate (λ), the service rate of each server (μ), and the number of servers (c). The customer arrival rate was derived from the reciprocal of the average inter-arrival time, while the service rate for each server was derived from the reciprocal of the average service time.

The steps for analyzing the arrival and service interval distributions (Fig. 1) are as follows:

1. Determination of location and object of observation. Selecting the research site, the Pertamina Tugu 44.552.15 gas station, which utilizes a multi-channel, single-phase queuing system (featuring two service points/fueling dispensers).
2. Preparation for data collection. Establishing the observation schedule and duration, and preparing a stopwatch or digital clock along with data recording sheets (tables) to accurately log the timing for each vehicle or customer.
3. Data collection and processing. Recording the time each customer/vehicle arrives and joins the queue, the time service begins (including identifying which server (Server 1 or 2) is handling the task), and the time service concludes. Subsequently, calculating the duration of service (μ), the difference between the service completion time and the service start time, and the inter-arrival time (λ), the time difference between a customer's arrival and that of the preceding customer.
4. Identification of the appropriate probability distribution. Analyzing the calculated inter-arrival times and service times using Arena's Input Analyzer.

5. Analysis of M/M/2 characteristics. Assessing the suitability of the collected data to determine whether an analytical method can be applied.
6. Conclusion. The conclusion section directly addresses the research problem statement.

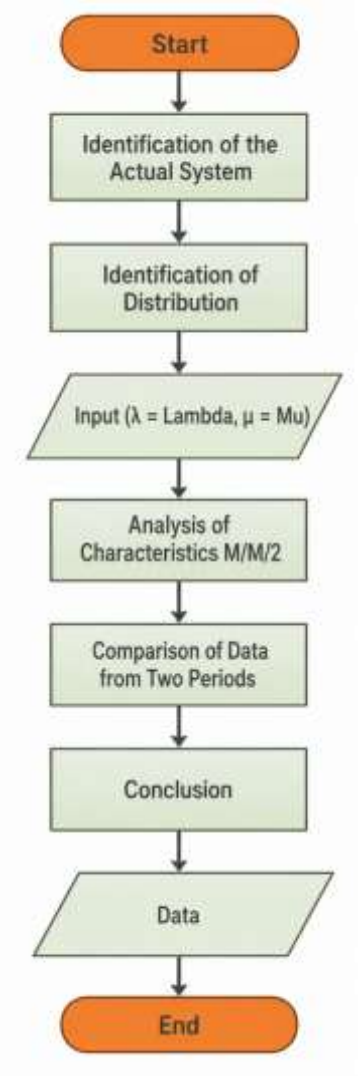


Fig. 1. Data collection flowchart

Results

A. The Characteristics Of The Queuing System

Based on the results of data collection and processing done using Microsoft Excel and Arena Input Analyzer, various information was obtained about the characteristics of the queuing system at SPBU 44.552.15 Tugu during the first data collection on Friday, July 10, 2026, and the second data collection on Wednesday, August 12, 2026. The analysis was conducted to understand the pattern of customer arrivals, the service patterns provided by the operators, and the performance of the queuing system based on several server number alternatives. Furthermore, the queuing system's performance was analyzed using three main indicators. Server utilization rate was used to determine how much of the two servers' capacity was used in serving customers. The average number of customers in the system

was used to know the average number of customers in the system, whether waiting or receiving service. Meanwhile, the waiting time for customers in the system is used to find out how long it takes for a customer from entering the system until they finish receiving service. These three indicators can give an idea about the efficiency level and operational condition of the queue system. Queueing theory generally uses utilization, the number of customers in the system, and waiting time as indicators to evaluate the performance of service facilities.

This analysis result is used to evaluate the effectiveness of the service system currently in place using the most suitable number of servers to optimize customer service. Based on the observations, at Pertamina gas station 44.552.15 Tugu, they use a Multi-Channel Single Phase model, which is a queuing system with more than one service facility (server) but only goes through one service stage. In this system, there are two operators who serve customers simultaneously at the fuel lanes. Customers who arrive will enter the queue and be served in the order they arrive, following a First In First Out (FIFO) discipline.

During the observation process on the first day, data from 150 customers was collected, and on the second day, data from 177 customers who refueled was obtained. Based on calculations using Microsoft Excel, the average arrival rate (λ) and average service rate (μ) for each data collection period were determined, as shown in Table 1. These values indicate that the customer arrival rate is higher than the server's service capacity, which could potentially lead to growing queues. In practice, the gas station uses two servers to share the service load, which is expected to reduce waiting time and prevent queue buildup. Next, the effectiveness of the two servers is analyzed using Arena Input Analyzer and POM-QM to determine the most optimal service alternative. Data Distribution Analysis Using Arena Input Analysis of Arrival Distribution

Table 1. Excel calculation results

Day One (July 10, 2026)		Day Two (August 12, 2026)	
Lambda (λ)	1.269	Lambda (λ)	47.75
Miu (μ)	0.867	Miu (μ)	69.42

Based on the data processing results using Arena Input Analyzer (Table 2), the most suitable distribution for customer arrival intervals is the Beta distribution with the equation 34.5 + 26 * BETA(1.12, 1.09). The processing results show a p-value of 0.142 and a square error of 0.006259. That p-value is greater than 0.05, so the Beta distribution is acceptable. Additionally, the square error of the Beta distribution is smaller compared to the Uniform distribution, which has a square error of 0.006356.

Table 2. Output Analyzer Arena First Day Data (July 10, 2026)

Distribution	P Value	Square Error	Expression
Exponensial	<0.005	0.017093	34.5 + EXPO(13.
Poisson	<0.005	0.010117	POIS (47.7)
Beta	0.142	0.006259	34.5 + 26 * BETA (1.12, 1.09)
Uniform	0.48	0.006356	UNIF(34.5, 60.5)

Based on these results, the Beta distribution is chosen because it meets the p-value criteria and has a smaller square error compared to other distributions that meet the criteria. Therefore, the Beta distribution can be used to represent the pattern of customer arrival intervals on the first day's data.

Based on the data processing results using Arena Input Analyzer (Table 3), the distribution that fits best for customer arrival intervals is the Uniform distribution with the equation UNIF(34.5, 60.5). The Uniform distribution has a p-value of 0.48 and a square error of 0.006025. Meanwhile, the Beta distribution has a smaller square error of 0.005766, but its p-value of 0.0246 is less than 0.05, so it does not meet the acceptance criteria.

Table 3. Output Analayzer Arena for the Second Day (August 12, 2026)

Distribution	P Value	Square Error	Expression
Exponensial	<0.005	0.017723	34.5 + EXPO(13.5)
Poisson	<0.005	0.010676	POIS(48)
Uniform	0.48	0.006025	UNIF(34.5, 60.5)
Beta	0.0246	0.005766	34.5 + 26 * BETA(1.13, 1.04)

Therefore, the Uniform distribution was chosen because it has a p-value greater than 0.05 and can be considered suitable to represent the pattern of customer arrival intervals on the second day. The choice of distribution is not only based on the smallest square error but also takes the p-value into account as a distribution acceptance criterion.

Based on the data processed using Arena Input Analyzer (Table 4), the distribution that best fits the service time is the Beta distribution with the equation 49.5 + 41 * BETA(1.05, 1.13). The results show a p-value of 0.234 and a squared error of 0.005062. This p-value is higher than 0.05, so the Beta distribution is acceptable.

Table 4. Service Distribution Analysis - First Day Data (July 10, 2026)

Distribution	P Value	Square Error	Expression
Exponensial	<0.005	0.010076	49.5 + EXPO (19.8)
Poisson	<0.005	0.017555	POIS (69.3)
Uniform	0.424	0.005121	UNIF (49.5, 90.5)
Beta	0.234	0.005062	49.5 + 41 * BETA (1.05, 1.13)

The Uniform distribution also has a p-value of 0.424, which meets the acceptance criteria. However, the Beta distribution has a smaller squared error, 0.005062 compared to Uniform's 0.005121. Therefore, the Beta distribution is chosen because it meets the p-value criteria and has a lower error rate in representing the service time data.

Based on the results of data processing using the Arena Input Analyzer (Table 5), the most suitable distribution for the service time is the Beta distribution with the equation 49.5 + 41 * BETA(1.16, 1.2). The Beta distribution has a p-value of 0.0608 and a square error of 0.005732. The p-value is greater than 0.05 so that the Beta distribution is acceptable.

The Uniform Distribution also met the criteria with a p-value of 0.111. However, the Beta distribution square error of 0.005732 is smaller than Uniform's of 0.005762. Thus, the Beta distribution was chosen because it has a p-value that meets the criteria and a smaller square error.

Table 5. Service Distribution Analysis - Second Day Data (August 12, 2026)

Distribution	P Value	Square Error	Expression
Exponensial	<0.005	0.011789	49.5 + EXPO(20.4)
Poisson	<0.005	0.017202	POIS(69.9)
Uniform	0.111	0.005762	UNIF(49.5, 90.5)
Beta	0.0608	0.005732	49.5 + 41 * BETA(1.16, 1.2)

B. Comparison Analysis of the Two Data Sets

Based on the results of processing using the Arena Input Analyzer, there is a difference in distribution between the data of the first day and the second day. At the arrival interval, the first-day data uses the Beta distribution, while the second-day data uses the Uniform distribution. These differences show that the pattern of customer arrival intervals in both observation periods has different characteristics. On the first day of data, the Beta distribution had a p-value of 0.142 and a square error of 0.006259, while on the second day of the data the Uniform distribution had a p-value of 0.48 and a square error of 0.006025.

During the service period, both sets of data used a Beta distribution. The data from the first day had a p-value of 0.234 and a square error of 0.005062, while the data from the second day had a p-value of 0.0608 and a square error of 0.005732. Both distributions have p-values greater than 0.05, so they are acceptable. Overall, the analysis results show that the Beta distribution was used for the service data on both the first and second days, while the arrival interval distribution differed between the two observation periods. These results indicate differences in customer arrival patterns, while the service time pattern for both periods follows the same distribution.

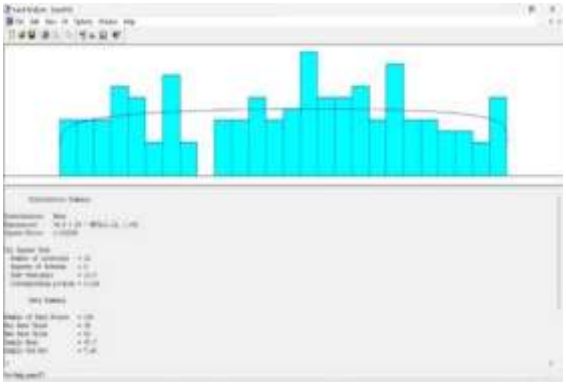


Fig. 2. Inter Arival Time



Fig. 3. Servis Time

Discussion

Distribution fitting results indicate that the inter-arrival time and service time characteristics lack statistical support for an exponential distribution. This pattern was observed during both sessions (July 10, 2026, and August 12, 2026), suggesting that the deviation from the exponential assumption was not limited to a single observation period. While certain candidate distributions demonstrated a better relative fit based on squared error, a good relative fit does not automatically imply statistical acceptability. Distribution fitting should therefore consider goodness-of-fit criteria together with measures of relative fitting error rather than relying on a single indicator [14],[15]. Accordingly, interpreting the results requires distinguishing between the distribution with the best relative fit and the distribution supported by goodness-of-fit test results. These findings have direct implications for the use of the M/M/2 queuing model. The M/M/2 model assumes a Poisson arrival process and exponentially distributed service times; consequently, the observed mismatch in the distributions of inter-arrival and service times means the model's Markovian assumptions lack empirical support [4], [16]. Empirical studies of service systems have similarly shown that actual service-time distributions

may depart substantially from the exponential form assumed in simple Markovian models [16], [17]. Thus, even though the system under observation features two service facilities, this characteristic does not automatically mean the system can be represented by the M/M/2 model. These results indicate that the M/M/2 model is a relatively restrictive representation when applied to actual systems without first validating its distributional assumptions. More general queueing formulations can accommodate non-exponential inter-arrival and service-time distributions when empirical characteristics do not support conventional Markovian assumptions [18]. In other words, the limitation lies not in the queuing theory approach in general, but in the suitability of a simple Markovian model for the empirical characteristics of the system being observed.

The consistency of results across two observation sessions reinforces the indication that the M/M/2 model is ill-suited to represent the system studied during that period. However, these findings do not imply that all gas station service systems inherently possess non-Markovian characteristics, as the scope of the observation was limited. The study's primary implication is that selecting a queuing model for a real-world system requires considering not only the number of servers but also the probabilistic characteristics of arrivals and service [2], [7], [8], [17], [18]. For future research, approaches that preserve the system's empirical characteristics, such as discrete-event simulation, could be considered as alternatives to achieve a more realistic system representation [9], [11], [14], [15], [19].

Conclusion

This study evaluated the suitability of the M/M/2 queueing model for service operations at SPBU 44.552.15 Tugu using observations from two periods. The results showed that inter-arrival times followed Beta and Uniform distributions, while service times followed Beta distributions in both sessions. Neither inter-arrival nor service times provided statistical support for the exponential distribution required by the M/M/2 model. Therefore, the model's Markovian assumptions were not empirically satisfied during the observed periods. Queueing model selection should consequently be preceded by distributional validation. Future studies should consider longer observations, discrete-event simulation, or non-Markovian models to represent system behavior more realistically overall.

Limitation and Suggestions

This study was limited to two observation sessions; consequently, it did not fully capture the variations in arrival and service characteristics under different operational conditions, nor did it allow for the generalization of results to other gas station systems. The research focused on evaluating the validity of the M/M/2 model assumptions and did not develop alternative models to represent the system's empirical characteristics. Future research is advised to extend the observation period and develop discrete-event simulation or non-Markovian queuing models based on empirical data to achieve a more realistic representation of the system.

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Conflict of Interest

The authors declare no conflict of interest.

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Authors



Annie Purwani is a full-time lecturer at Universitas Ahmad Dahlan, Yogyakarta. She is currently focusing on improving the stochastic operations research practicum module. Her research interests lie in industrial engineering and supply chain management in general, with a specific focus on circular supply chains. (email: annie.purwani@uad.ac.id).



Laode Rivaldi is an undergraduate student at Universitas Ahmad Dahlan, Yogyakarta. He is currently studying Industrial Engineering and is interested in industrial engineering, operations research, and supply chain management. His academic interests include data analysis, production systems, process optimization, and the application of quantitative methods for industrial system optimization. (email: 2400019083@webmail.uad.ac.id).



Magfirah Samsi is an undergraduate student at Universitas Ahmad Dahlan, Yogyakarta. She is currently studying Industrial Engineering and has an interest in industrial engineering, operations research, and supply chain management. Her a cademic interests include data analysis, quantitative methods, process optimization, and data-driven decision-making in industrial systems. (email: 2400019072@webmail.uad.ac.id).



Nazla Khaira Adz Dzurr is an undergraduate student at Universitas Ahmad Dahlan, Yogyakarta. She is currently studying Industrial Engineering and has an interest in industrial engineering, operations research, and supply chain management. Her academic interests include production systems, data analysis, and the application of quantitative methods to solve industrial problems. (email: 2400019090@webmail.uad.ac.id).



Muhammad Panca Nugraha is an undergraduate student at Universitas Ahmad Dahlan, Yogyakarta. He is actively involved in various competitions, seminars, training programs, and frequently serves as a speaker in academic and professional activities. His interests lie in industrial engineering, particularly in production systems and product design. He has a strong passion for innovation and continuously seeks to develop creative and applicable solutions in the field of industrial engineering. (email: 2315019134@webmail.uad.ac.id).