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Analysis of Diesel Fuel Refilling Queue Efficiency Using Queueing Theory at the Hawai Sentani Gas Station, Jayapura Regency

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ABSTRACT

The diesel-fuel line at SPBU Hawai Sentani, Jayapura Regency, reportedly experiences heavy queuing, although its operating characteristics had not been quantitatively established. This study evaluates the existing single-server queue and an analytical two-server scenario. Vehicle arrivals were recorded on seven observation days August 5–10 and 12, 2026 during the 07:00–17:00 WIT operating period. August 11 was not observed for an undocumented reason. A total of 2,680 arrivals produced an average arrival rate of 38.29 vehicles per hour. Based on 10 timed observations, mean service time was 1.35 minutes (SD = 0.158), corresponding to a service rate of 44.44 vehicles per hour. The existing system was modeled as M/M/1, while the two-server configuration was evaluated analytically as M/M/2. Because the observed service-time coefficient of variation was only 11.7%, substantially below the 100% implied by an exponential distribution, an M/G/1 Pollaczek–Khinchine calculation using empirical variance was included as a cross-check. Under M/M/1, utilization was 0.8616, average queue length was 5.36 vehicles, and average waiting time was 8.41 minutes. Under M/M/2, per-server utilization was 43.08%, P0 was 0.398, average queue length was 0.196 vehicles, waiting time was 0.31 minutes, and the Erlang-C probability of waiting was 0.259. The M/G/1 model predicted a 4.25-minute wait, approximately half the M/M/1 estimate. Sensitivity analysis showed waiting time increasing sharply as arrivals approached service capacity. Limitations include the small service-time sample, absence of hourly arrival data, untested distributional assumptions, and unresolved discrepancies between modeled averages and reported multi-hour waits. Thus, the two-server scenario conditionally predicts shorter waits but does not establish that adding a service line is the optimal investment. Decisions also require analysis of costs, available land, staffing, fuel supply, operational disruptions, and direct field validation.

Keywords: *Queueing Theory, Waiting Time, Utilization, Diesel Fuel, Gas Station*

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INTRODUCTION

Diesel fuel is an important fuel type for public transportation, logistics vehicles, and other operational vehicles in Sentani, Jayapura Regency. When the rate of vehicle arrivals temporarily exceeds the effective service capacity, queues may develop and increase customer waiting time [1], [2]. At a fuel station, however, waiting time is not determined only by the number of arriving vehicles. It can also be affected by vehicle type, refueling volume, verification and payment procedures, dispenser availability, operator availability, vehicle maneuvering, and fuel supply conditions.

The specific problem motivating this study is that diesel customers at this station reportedly experience queues lasting several hours, in some accounts extending until the following day. These reports come from station personnel and diesel-fuel users interviewed during data collection rather than from independent records, photographs, traffic-authority documentation, or a logged count of queue length and duration; no such supporting documentation was available for this study. This is stated here as an evidentiary limitation, not as a reason to discount the reports: the gap between these accounts and the modeled average wait of 8.41 minutes is treated throughout this manuscript as the central research problem.

SPBU Hawai (station code SPBU 84.993.02) operates four vehicle lanes in total, serving cars, motorcycles, and diesel-fuel vehicles, including trucks and public transport, through separate lines. This study analyzes only the diesel-fuel line, which is modeled as a single service point in the M/M/1 model. This means the M/M/1 server in this study represents the diesel dispenser and its operator as a combined service point, not the station's overall four-lane capacity; the gasoline and motorcycle lines are outside the scope of this analysis. The population of interest is therefore restricted to vehicles queueing specifically for diesel fuel: this includes trucks, public transport, and other diesel-powered vehicles, but excludes gasoline-fueled cars and motorcycles served at other lanes. The exact number of diesel dispensers and nozzles feeding this single queue, whether one or more attendants operate it, and whether subsidized-diesel volume limits or purchaser verification apply to some or all of these vehicles are not documented in the field notes available for this study and should be confirmed by the authors, since they affect whether "one server" is a reasonable simplification of the physical system [3], [4], [5].

Queueing theory provides a quantitative framework for evaluating arrival rates, service rates, utilization, queue length, and waiting time. Recent fuel-station studies continue to apply M/M/1 and multi-server queueing models to evaluate service performance, while some studies emphasize the importance of testing whether Poisson/exponential assumptions adequately represent actual fuel-station data. For example, a 2025 study applied a multi-channel single-phase model to fuel-station service and reported that performance varied by time period, illustrating the importance of peak-period analysis. Another 2025 study on a single-server fuel queue used sensitivity analysis to examine how changes in arrival and service rates affect queue performance. A 2026 study at SPBU Uluwatu further illustrates the value of comparing queueing distributions rather than automatically assuming an M/M/1 structure.

These five cited studies [6], [7] differ in exactly the ways relevant to the present analysis. [8], [9], [10] both apply multi-server (M/M/S or multi-channel single-phase) models but, like the original version of this manuscript, do not report a formal goodness-of-fit test for the Poisson or exponential assumptions. [11], [12], [13] is the most methodologically comparable prior work, since it applies sensitivity analysis to a single-server fuel queue in a manner similar to the sensitivity analysis added to this study; its case, however, involves a small informal fuel retailer (Pertamini) with a different demand and service profile than a full SPBU diesel line. [14], [15], [16] reports time-period-dependent performance using a multi-channel single-phase model, which is directly relevant to this study's own finding that daily-aggregated rates likely conceal peak-period behavior, but that study does not report an alternative to the exponential service assumption. [17], [18], [19], studying SPBU Uluwatu, is the only one of the five cited studies that explicitly compares more than one queueing distribution rather than assuming M/M/1 by default; this study's own addition of an M/G/1 cross-check follows that same logic, using the empirically observed service-time variance rather than an assumed distribution. None of the five studies reports a discrepancy of the kind found here between modeled average waiting time and field-reported waiting time, which is accordingly presented as this study's most distinctive contribution rather than as a shortcoming to be minimized [20], [21], [22].

Based on these considerations, this study addresses three questions: (1) what are the characteristics of the existing diesel-fuel queueing system at SPBU Hawai Sentani; (2) how does the existing system perform under the M/M/1 model; and (3) what performance change is predicted by an analytical M/M/2 scenario? A fourth question is added in this revision: (4) is the exponential service-time assumption underlying M/M/1 and M/M/2 supported by the observed data, and if not, what does an alternative model predict? The objective is to quantify existing queue performance and provide a conditional capacity alternative without claiming that the second server is automatically the optimal investment decision.

Research contribution. The contribution of this study is the quantitative evaluation of a diesel-fuel service queue in the Sentani area using observed arrival and service data, combined with a transparent comparison between the existing single-server condition and a two-server analytical scenario. The study also explicitly identifies the gap between theoretical queueing results and reported field conditions, which becomes a basis for further validation. This revision adds a service-time distribution check, an M/G/1 cross-check, an explicit sensitivity analysis, and a separation of Results from Discussion, none of which were present in the earlier draft.

MATERIAL AND METHODS

Research Design and Location

This study uses a quantitative descriptive case-study approach. The research object is the diesel-fuel service queue at SPBU Hawai Sentani, Jayapura Regency, Papua. The analysis focuses on the service point represented by one server in the existing M/M/1 model. As noted in the Introduction, the station operates four vehicle lanes in total; this study analyzes only the diesel line. The precise count of dispensers, nozzles, and operators feeding that line is not available in the field notes reviewed for this study and is flagged in Limitations as necessary information for confirming that the single-server representation is appropriate.

Population, Observation Period, and Sample

The population consists of vehicles receiving diesel-fuel service during the observation period, specifically trucks, public transport, and other diesel-powered vehicles; gasoline-fueled cars and motorcycles served at other lanes of the station are excluded. Vehicle arrivals were recorded on seven days: August 5, 6, 7, 8, 9, 10, and 12, 2026, within the 07:00-17:00 WIT operating window. These seven observation days span an eight-calendar-day period, because August 11, 2026 (a Tuesday) was not observed; the reason (equipment or observer unavailability, a station closure, or another field circumstance) is not recorded in the material available for this study and should be stated by the authors, since an unexplained gap in an otherwise dense observation schedule is relevant to assessing whether the sampled days are representative [23], [24], [25]. The observation days span three weekdays before the gap (Wednesday through Monday, including a Saturday and Sunday) and one weekday after it (Wednesday), so the sample does include weekend and weekday variation, though not a full, evenly spaced week.

The study reports 2,680 vehicle arrivals over seven days, with an average of 382.86 vehicles/day. With 10 observation hours per day, the average arrival rate is 38.29 vehicles/hour. Service-rate estimation is based on 10 observed vehicles with service times ranging from 1.1 to 1.6 minutes and an average of 1.35 minutes. Because only 10 service observations were used, this estimate is treated as a major limitation and should not be interpreted as fully representative of all vehicle types, time periods, operators, or refueling volumes.

Arrivals were recorded only as daily totals; no hourly or interval-level breakdown is available in the material reviewed for this study. This is a substantive limitation, addressed directly in Section 4.1 and Limitations, because a single 10-hour average cannot reveal whether arrivals cluster into a morning and afternoon peak, which the field reports of long queues would suggest [26], [27], [28]. Future data collection should record arrivals in 15- or 30-minute intervals, or with arrival timestamps, so that peak and off-peak rates can be estimated separately and a time-inhomogeneous or time-segmented queueing model can be considered.

Data Collection

Arrival data were obtained by recording the number of vehicles entering the diesel-fuel queue. Service time was defined as the interval from the start of service until completion of the service process. Whether this interval includes verification, payment, and vehicle maneuvering and departure, in addition to the physical dispensing of fuel, is not specified in the field protocol available for this study; this should be clarified by the authors, since a narrow definition (dispensing only) would understate real service time relative to a broad definition (arrival at the pump to departure), and the discrepancy discussed is sensitive to this choice.

Supporting information was obtained through documentation and brief interviews with station personnel and diesel-fuel users [29], [30]. The number of personnel and users interviewed, the specific questions asked, whether responses were recorded and how they were analyzed, and whether station permission and participant consent were obtained are not documented in the material reviewed for this study; these should be reported by the authors in the final version, together with confirmation that no vehicle license plates or other personally identifying information were retained.

Queueing Model and Assumptions

The existing system is analyzed using the M/M/1 model, with Poisson arrivals, exponentially distributed service times, FIFO discipline, a single service channel, and steady-state operation. The M/M/2 model is used only as an analytical scenario with two identical, independent servers sharing one common FIFO queue, continuously available throughout the operating period; it is not a discrete-event or Monte Carlo simulation.

This study treats these assumptions as testable rather than given wherever the available data allow a check, following the general approach recommended for applied queueing analysis [31], [32], [33]. The exponential service-time assumption is checked directly using the coefficient of variation of the 10 observed service times; the Poisson arrival assumption is checked only partially, using the day-to-day dispersion of the seven daily totals, because interval-level arrival data are not available. The assumption that a second server would retain the same service rate of 44.44 vehicles/hour is treated explicitly as an assumption of the M/M/2 scenario, not a measured fact, since a second server could share equipment, staffing, a payment stage, or a fuel-supply constraint with the first.

Equations

Arrival rate: $\lambda = N/T$

Service rate: $\mu = 1/\bar{t}$

For M/M/1: $\rho = \lambda/\mu$; $Lq = \rho^2/(1-\rho)$; $Wq = Lq/\lambda$; $Ls = Lq + \rho$; $Ws = Wq + 1/\mu$.

For M/M/c, the probability of an empty system and the corresponding Lq, Wq, Ls, and Ws are calculated using the standard multi-server queueing equations. The M/M/2 scenario uses $c = 2$, $\lambda = 38.29$ vehicles/hour, and $\mu = 44.44$ vehicles/hour per server. The condition $\rho < 1$ is interpreted as mathematical stability, not as proof of economic efficiency.

Sensitivity Analysis

To address the concern that a single averaged lambda and mu can obscure how close the system operates to instability, this revision adds a sensitivity analysis that recomputes M/M/1 Wq while varying lambda (holding mu fixed at 44.44 vehicles/hour) and, separately, varying mu (holding lambda fixed at 38.29 vehicles/hour), each across a range of plausible values around the observed baseline. This addresses, in a bounded analytical way, the concern that the true peak-hour lambda or the true effective mu, once verification delays, dispenser downtime, and fuel-supply interruptions are accounted for, could differ materially from the 10-hour averages used elsewhere in this study.

Validation and Decision Criteria

The decision to add capacity should not be based solely on utilization. Relevant criteria include average waiting time, maximum or percentile waiting time, queue length during peak periods, service-level targets, operational feasibility, labor requirements, land availability, dispenser capacity, fuel supply, and investment and operating costs.

This study does not conduct a cost-benefit analysis, since no cost data (labor, land, dispenser installation, fuel-supply contracting) were available; this is stated as a limitation, and the managerial implications in [34], [35], [36] are accordingly framed as candidate options for further feasibility study rather than as a recommendation to implement a second line. Direct validation of the model against field-measured queue lengths and waiting times (for example, by timing a sample of real queues at different hours) was not conducted in this study and is identified as the single highest-priority next step, given the size of the discrepancy discussed in Section.

RESULTS

This section reports the observed data and the calculations that follow directly from it, without interpretation; interpretation, comparison with prior studies, and managerial implications are presented separately in Section, in response to review comments that the combined presentation in the earlier draft interspersed raw data with conclusions.

Vehicle Arrivals

Table 1. Daily Diesel-Vehicle Arrivals

Day	Date	Vehicles
1	05/08/2026 (Wednesday)	380
2	06/08/2026 (Thursday)	365
3	07/08/2026 (Friday)	402
4	08/08/2026 (Saturday)	395
5	09/08/2026 (Sunday)	410
6	10/08/2026 (Monday)	388
7	12/08/2026 (Wednesday)	340
	Total	2,680
	Mean/day	382.86
	SD/day (new)	23.95
	CV (new)	6.25%
	Index of dispersion, variance/mean (new)	1.50

The seven-day dataset contains 2,680 observed vehicle arrivals. The resulting average is 382.86 vehicles/day. With an observation period of 10 hours/day, the estimated average arrival rate is lambda = 2,680/(7x10) = 38.29 vehicles/hour.

The day-to-day standard deviation is 23.95 vehicles (CV = 6.25%), and the ratio of variance to mean (573.48/382.86 = 1.50) is somewhat above the value of 1.0 expected under a Poisson daily-count process, a pattern usually called overdispersion. With only seven days, this is a weak and preliminary diagnostic, not a formal goodness-of-fit test, and it says nothing about whether arrivals are Poisson within a given hour, which is the assumption that actually matters for the M/M/1 and M/M/2 calculations below. A proper test of the within-day Poisson assumption requires interval-level arrival counts, which were not collected in this study.

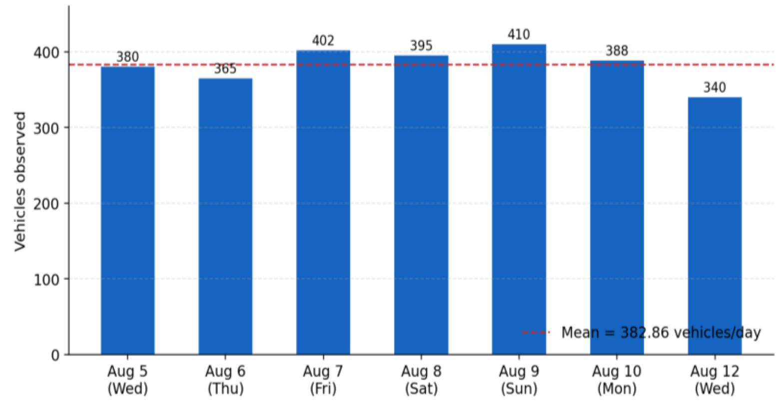

Figure 1. Daily Diesel-Vehicle Arrivals

Service Time

Table 2. Observed Diesel Service Times

No.	Service time (minutes)
1	1.2
2	1.5
3	1.1
4	1.3
5	1.4
6	1.6
7	1.2
8	1.3
9	1.5
10	1.4
Mean	1.35
Median (new)	1.35
SD (new)	0.158
Min / Max (new)	1.1 / 1.6
CV (new)	11.71%
95% CI for mean (new)	1.237-1.463 min

The average observed service time is 1.35 minutes per vehicle. The corresponding estimated service rate is mu = 60/1.35 = 44.44 vehicles/hour.

The observed coefficient of variation of service time is 11.71%. Under the exponential-service assumption used by M/M/1 and M/M/2, the coefficient of variation should be approximately 100% (for an exponential distribution, the standard deviation equals the mean). An observed CV an order of magnitude below this expected value is a clear indication, even with only 10 observations, that service times are far less variable than the exponential assumption implies, consistent with a service process dominated by a fairly fixed procedure (for example a similar refueling volume and a consistent pump flow rate) rather than a highly variable one. With n = 10, a formal distributional test (for example Kolmogorov-Smirnov or Anderson-Darling) would have very low power, so this is reported as a directional diagnostic rather than a definitive rejection of the exponential model; it is nonetheless sufficient to justify the M/G/1 cross-check in Section 3.3 and to caution against relying on the M/M/1 and M/M/2 results as more than one plausible scenario.

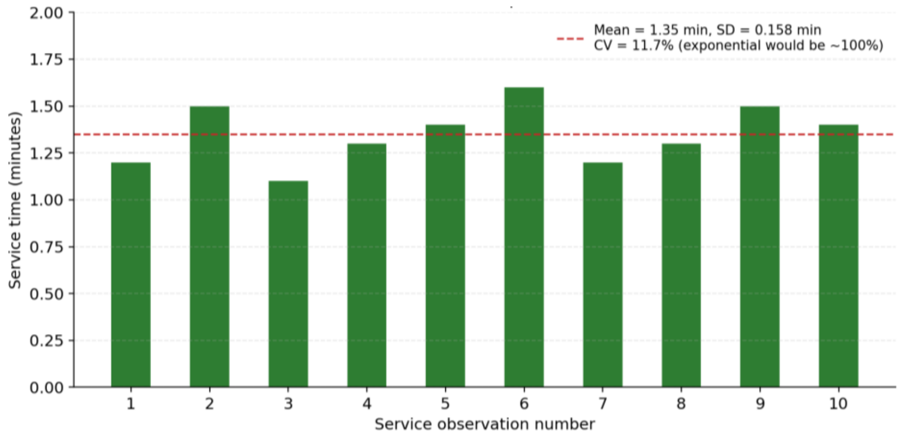

Figure 2. Observed Diesel Service Times, n = 10, with mean, SD, and CV annotated

Existing M/M/1 Performance

Table 3. M/M/1 Operating Characteristics

Parameter	Symbol	Value	Interpretation / Formula
Arrival rate	lambda	38.29 vehicles/hour	N/T
Service rate	mu	44.44 vehicles/hour	1/mean(S)
Utilization	rho	0.8616 (86.16%)	lambda/mu
Probability system empty (new)	P0	0.1384 (13.84%)	1 - rho
Probability an arrival waits (new)	P(wait)	0.8616 (86.16%)	= rho for c = 1
Average queue length	Lq	5.36 vehicles	rho^2/(1-rho)
Average waiting time	Wq	8.41 minutes	Lq/lambda
Average number in system	Ls	6.23 vehicles	Lq + rho
Average time in system	Ws	9.76 minutes	Wq + 1/mu

The M/M/1 calculation gives a utilization of 86.16%, indicating a highly utilized service point under the model assumptions. Because rho is below one, the queue is mathematically stable in steady state.

M/G/1 Cross-Check

Table 4. M/G/1 Scenario Using the Empirical Service-Time Variance

Parameter	M/M/1 (exponential)	M/G/1 (empirical variance)
Average wait, Wq	8.41 minutes	4.25 minutes
Average queue length, Lq	5.36 vehicles	2.71 vehicles
Average number in system, Ls	6.23 vehicles	3.58 vehicles
Average time in system, Ws	9.76 minutes	5.60 minutes

Using the empirically observed service-time variance rather than the exponential assumption roughly halves the predicted average wait, from 8.41 to 4.25 minutes. This result is reported here as a fact about the calculation; its implications for interpreting the model-field discrepancy are discussed.

Analytical M/M/2 Scenario

Table 5. M/M/1 versus M/M/2 Analytical Scenario

Parameter	M/M/1	M/M/2 (analytical scenario)
Number of servers	1	2
Utilization	86.16%	43.08% per server

Parameter	M/M/1	M/M/2 (analytical scenario)
Probability system empty, P0 (new)	0.1384	0.3979
Probability an arrival waits (new)	0.8616 (=rho)	0.2593 (Erlang C)
Average queue length, Lq	5.36	0.196
Average waiting time, Wq	8.41 min	0.31 min
Average number in system, Ls	6.23	1.058
Average time in system, Ws	9.76 min	1.66 min

Under the two-server analytical scenario, the predicted average waiting time decreases from 8.41 minutes to 0.31 minutes, the average queue length decreases from 5.36 to 0.196 vehicles, and the probability that an arriving vehicle must wait at all falls from 86.16% (M/M/1) to about 25.93% (Erlang C, M/M/2). These values are model predictions conditional on the M/M/2 assumptions stated in Methods (identical, independent, continuously available servers sharing one FIFO queue). They are not described as a statistically significant decrease, since no statistical significance test or uncertainty analysis was conducted.

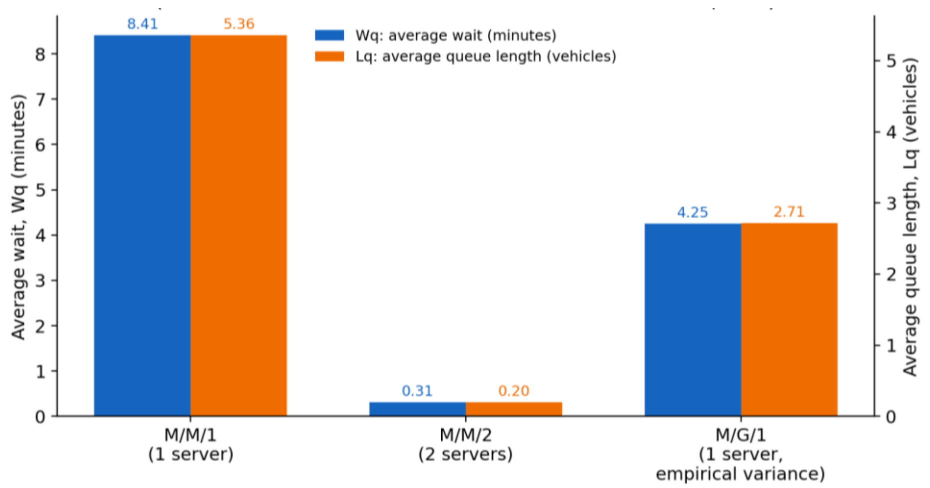

Figure 3. Comparison of Wq and Lq across the M/M/1, M/M/2, and M/G/1

Sensitivity Analysis

Table 6. M/M/1 Wq under Varying Lambda and Mu

Lambda (veh/hr), mu fixed at 44.44	rho	Wq (min)
34	0.7650	4.39
36	0.8100	5.76
38.29 (observed)	0.8615	8.40
40	0.9000	12.15
42	0.9450	23.20
Mu (veh/hr), lambda fixed at 38.29	**rho**	**Wq (min)**
40	0.9572	33.59
42	0.9117	14.74
44.44 (observed)	0.8616	8.41
46	0.8324	6.48
48	0.7977	4.93

A 10% increase in the arrival rate, from 38.29 to 42 vehicles/hour, raises the predicted average wait from about 8.4 to about 23.2 minutes, nearly a threefold increase, because the system is operating close to the region where rho approaches 1. Equally, a modest reduction in effective service rate, from 44.44 to 40 vehicles/hour (about 10%), raises predicted Wq from 8.41 to about 33.6 minutes. Effective service rate could fall below the measured 44.44 vehicles/hour if verification, payment, or maneuvering time is added to the narrow service-time definition used in Table 2, or during periods of equipment slowdown; this sensitivity is reported here as a factual result of the model and interpreted further.

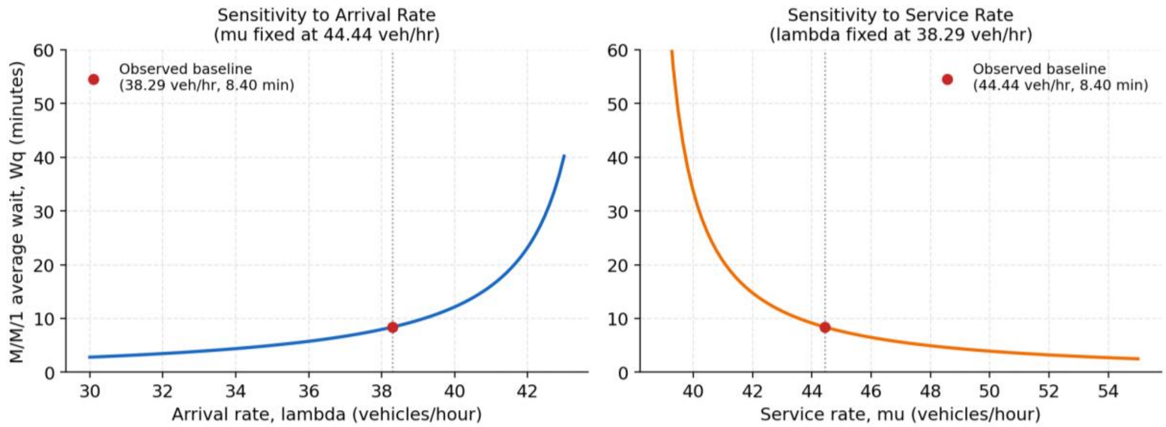

Figure 4. M/M/1 Average Wait as a Function of Lambda and Mu

DISCUSSION

Utilization Is Not, by Itself, a Verdict of Inefficiency

The M/M/1 calculation gives a utilization of 86.16%. High utilization should not by itself be labeled "inefficient." Efficiency requires comparison with service targets and the costs and benefits of additional capacity. No universal utilization threshold (for example, 80%) applies to every service system; the appropriate threshold depends on the cost of customer waiting relative to the cost of idle capacity, and on any explicit service-level target the station operator adopts. No such target is defined in the material available for this study, so this manuscript does not conclude that the existing system is inefficient; it reports only that it is highly utilized and, per Table 6, close enough to rho = 1 that modest increases in demand or reductions in effective service rate produce disproportionate increases in predicted waiting time.

The Model-Field Discrepancy

The central problem this study identifies, and the one this Discussion opens with, is the gap between the M/M/1 average wait of 8.41 minutes (and even the lower M/G/1 estimate of 4.25 minutes) and field reports of queues lasting several hours or extending until the following day [37], [38]. This is a large discrepancy, roughly forty-fold relative to the M/M/1 average, and it cannot be dismissed as ordinary variation around a mean. Under the fitted M/M/1 model, an hour-long wait is an extreme event, not a routine one; frequent multi-hour waits would be difficult to reconcile with a genuinely stationary M/M/1 process operating at the parameters estimated here.

Notably, the M/G/1 cross-check in Table 4, which uses the empirically observed (low) service-time variance instead of the exponential assumption, predicts an even shorter average wait than M/M/1, not a longer one. This means that correcting for the apparent overstatement of service-time variability in the M/M/1 model moves the theoretical prediction further from, not closer to, the reported field experience [39], [40]. The discrepancy is therefore unlikely to be explained by the exponential-service assumption being wrong in the direction of understating variability; if anything, that assumption already overstates predicted waiting relative to a lower-variance alternative. This strengthens, rather than weakens, the case that the multi-hour field reports reflect factors outside the basic queueing model altogether.

Possible operational explanations include fuel stock constraints, rationing or purchasing restrictions, verification and payment delays, dispenser downtime, supply delivery delays, large differences in refueling volume, vehicle maneuvering, and queues formed before the observation window [41], [42]. These factors should be measured or documented separately. The sensitivity analysis in Table 6 offers one concrete, testable link to these explanations: if fuel stockouts, delivery delays, or dispenser downtime periodically reduce the effective service rate well below the measured 44.44 vehicles/hour, or if arrivals surge well above 38.29 vehicles/hour during specific hours, predicted waiting time rises sharply and non-linearly, which is at least qualitatively consistent with occasional very long waits coexisting with a much shorter 10-hour average. This remains a plausible mechanism rather than a demonstrated explanation, since the interval-level data needed to test it directly were not collected in this study. The discrepancy is treated as a limitation and the top priority for further validation, not as a result to be explained away [8], [10].

Would a Second Server Really Double Capacity?

The M/M/2 scenario indicates that additional capacity has the potential to reduce queueing under idealized assumptions. However, the study does not establish that a permanent second lane is optimal. The M/M/2 calculation assumes the second server is identical to, and fully independent of, the first: independently staffed, independently supplied with fuel, and not sharing a payment or verification stage or a single-entry lane. If, in practice, a second diesel line would share the station's fuel storage and delivery schedule, a single attendant working both lines, or a single vehicle-entry lane feeding both, its effective contribution to capacity could be well below the assumed 44.44 vehicles/hour, and the true benefit would fall somewhere between the M/M/1 and idealized M/M/2 predictions in Table 5. It is also worth asking whether the binding constraint on queue length is really pump service rate rather than physical space: if the station's internal maneuvering area or the road-side turning movements needed to reach the diesel line are limited, adding a pump might not relieve congestion if vehicles still cannot physically queue, maneuver, or exit any faster. Neither of these possibilities can be evaluated with the data available in this study and both should be investigated before any capacity decision is made [6], [7].

Adding a server may not double effective capacity if servers share a pump, attendant, payment stage, entrance lane, or fuel-supply constraint. A second server reduces utilization to 43.08% per server and may create expensive off-peak excess capacity. A permanent second line sized for the observed 10-hour average would likely sit underused outside identified peak periods, a real economic cost that a purely queueing-theoretic comparison of Wq and Lq does not capture. This is a reason to consider a flexible, peak-only activation policy rather than a permanent second line, pending the interval-level peak data this study lacks.

Managerial Implications

Before implementation, management should evaluate land availability, dispenser/nozzle capacity, operator requirements, fuel supply, investment cost, and the possibility of excess capacity during non-peak periods. A flexible approach, such as activating an additional server during verified peak periods, may be considered if operational and economic analysis supports it.

Non-capital alternatives may also be evaluated, including peak-period queue management, additional queue-control personnel, improved verification/payment procedures, and information systems that provide estimated waiting times. An information system can improve customer information, but it does not by itself increase physical service capacity or reduce arrival demand. Scheduling subsidized-diesel purchasers outside peak hours is another non-capital option raised by the general pattern of results here; it is not modeled quantitatively in this study, and it raises fairness and enforcement questions (whether all diesel users can equally comply with an off-peak schedule, and how compliance would be monitored) that are outside the scope of a queueing analysis and would need separate policy evaluation.

None of the options in this subsection has been evaluated against a defined objective function or cost basis in this study; only two configurations (c = 1 and c = 2, both under identical-server assumptions) were compared, so no configuration, capital or non-capital, is described as optimal here.

Comparison with Prior Fuel-Station Queueing Studies

As discussed in the Introduction, the five fuel-station studies cited here (references 1-5) collectively illustrate three practices this revision has tried to adopt: explicit peak-period analysis (Setiawannie, 2025), sensitivity analysis (Restuasih et al., 2025), and comparison across candidate distributions rather than defaulting to M/M/1 (Razando et al., 2026). None of the five reports a comparably large gap between modeled and field-reported waiting time, which may reflect a genuine difference in field conditions at this station, a difference in how field experience was documented across studies, or simply that this gap is rarely investigated once a queueing model produces internally consistent output. This study's explicit foregrounding of that gap, rather than its resolution, is offered as its main point of contrast with this literature.

Limitations

1. The observation period covers seven days within an eight-calendar-day window (one day, August 11, was not observed for an undocumented reason), which is short relative to the likely week-to-week and seasonal variability of fuel-station demand.
2. Arrivals were recorded only as daily totals; no hourly or sub-daily breakdown is available, so the 10-hour average used throughout this study may conceal substantial peak-period variation, which is precisely the condition under which the sensitivity results in Table 6 predict sharply elevated waiting.

3. The service-rate estimate rests on only 10 timed observations. Its coefficient of variation (11.71%) is far below the 100% implied by the exponential assumption, which motivated the M/G/1 cross-check in this study, but 10 observations remain too few to support a formal distributional test or a precise variance estimate.
4. Neither the Poisson arrival assumption nor the exponential service assumption was tested against interval-level data in this study; the diagnostics reported in Sections 3.1 and 3.3 are preliminary and directional, not confirmatory.
5. The physical configuration of the diesel service point (number of dispensers and nozzles, number of attendants, whether subsidized-volume verification applies) is not documented in the material available for this study, which limits confidence in the single-server representation used for M/M/1 and in the identical-independent-server assumption used for M/M/2.
6. No cost, land, staffing, or fuel-supply feasibility analysis was conducted for the second-server scenario, so no capacity recommendation in this study should be read as a final operational decision.
7. The discrepancy between the theoretical average waiting time and reports of multi-hour waiting has not been resolved and requires direct field validation (for example, timed observation of actual queues at different hours across several weeks) as the top-priority next step.
8. Interview methodology (sample, questions, recording, consent, and confidentiality procedures) is not documented in the material available for this study and should be reported by the authors.

CONCLUSION

The M/M/1 and M/M/2 results reported in this study are conditional predictions, valid only under their stated assumptions: Poisson arrivals, exponentially distributed service times, FIFO discipline, steady-state (stationary) demand, independence between successive arrivals and services, and, for the M/M/2 scenario, two identical, continuously available, independent servers sharing a common queue. None of these assumptions was fully tested against interval-level field data in this study. The existing diesel-fuel service system at SPBU Hawai Sentani has an estimated arrival rate of 38.29 vehicles/hour and a service rate of 44.44 vehicles/hour based on the available observations. Under the M/M/1 assumptions, the utilization is 86.16%, the average queue length is 5.36 vehicles, and the theoretical average waiting time is 8.41 minutes. The system is mathematically stable because rho < 1, but utilization alone is insufficient to conclude that the system is inefficient, since no service-level target was defined against which to judge it.

The observed service-time coefficient of variation (11.71%) is far below the value implied by the exponential assumption, and an M/G/1 cross-check using the empirical variance predicts a substantially shorter average wait (4.25 minutes) than M/M/1. This does not resolve the study's central open question: field reports describe waits lasting hours, far beyond either the M/M/1 or the M/G/1 average, and this gap remains unexplained by the data collected here. The M/M/2 calculation is an analytical two-server scenario, not a simulation. With two identical servers and the same assumed service rate per server, the model predicts utilization of 43.08% per server, an average queue length of 0.196 vehicles, and an average waiting time of 0.31 minutes, with an Erlang-C probability of waiting of about 25.93%. These results indicate potential queue reduction under the model assumptions, but they do not prove that adding a second lane is the optimal operational or economic solution: only two configurations were compared, no cost or feasibility analysis was performed, and the second server's assumed independence from the first has not been verified. A defensible conclusion, bounded by the evidence available, is therefore that the two-server analytical scenario predicts substantially lower average waiting under idealized assumptions, and that the coefficient-of-variation evidence favors a lower-variance service model than the exponential assumption uses, but that field validation of both the base M/M/1 model and the magnitude of the reported multi-hour waits remains necessary before any capacity or investment decision is made. The conflict between the model's average results and the reported peak-period field experience is the central limitation of this study, not a peripheral caveat.
The discrepancy between the theoretical waiting time and reports of multi-hour waiting is a key finding that requires further validation. Future studies should collect larger time-stamped datasets, separate peak and non-peak periods, distinguish vehicle types and refueling volumes, test arrival and service distributions formally, document operational disruptions, and conduct a cost-service analysis before recommending permanent capacity expansion.

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