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# Optimizing Fuel Distribution: A Queuing Theory Analysis and Strategy for Industrial Truck Queue Management at Batu Licin Terminal

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**ABSTRACT**
This study addresses chronic operational inefficiencies at the Batu Licin Fuel Terminal (TBBM), PT Multi Trading Pratama, characterized by prolonged industrial fuel truck queues. Applying a sequential explanatory mixed-methods design, the research collected quantitative data from 120 service events and qualitative insights from operational staff. Analysis using the M/M/c queuing model revealed system instability ($\rho$=1.37), an average queue length (Lq) of 8.41 trucks, and an average waiting time (Wq) of 68.9 minutes during peak hours. Root causes identified through thematic analysis include schedule non-compliance, high service time variability, and inefficient pre-loading procedures. Simulation of optimization scenarios demonstrated that adding a third loading arm (server) was the most effective intervention, stabilizing the system ($\rho$=0.91) and reducing waiting time by 89.8%. This research contributes to operational management literature by providing empirical evidence for applying Queuing Theory in the downstream energy sector and offers actionable, prioritized recommendations for terminal managers to enhance throughput, reduce costs, and improve customer satisfaction.



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## 1. Introduction

Efficient downstream supply chain operations are critical for maintaining energy security and supporting vital industries. Fuel terminals (TBBM) function as pivotal nodes in this chain, where distribution efficiency directly impacts logistics costs and service reliability (Krajewski et al., 2019). PT Multi Trading Pratama's Batu Licin Terminal serves a vast industrial clientele in Eastern Indonesia. However, its operational performance is hampered by persistent and significant truck queues during peak hours, leading to extended waiting times, customer dissatisfaction, and increased idle costs. Paradoxically, these queues occur despite seemingly adequate physical infrastructure and an existing scheduling system. This indicates a potential mismatch between planned capacity and real-time demand dynamics, representing a classic operational bottleneck (Jacobs & Chase, 2021).

A systematic, data-driven approach is required to diagnose and remedy this issue. Queuing Theory, a cornerstone of operations research, offers robust analytical tools for modeling, analyzing, and optimizing such service systems (Hillier & Lieberman, 2015). This study leverages this theory to address the following research problems: (1) What is the performance of the current truck queuing system at Batu Licin TBBM based on Queuing Theory parameters? (2) What are the primary operational factors causing long queues and wait times? (3) What optimization strategies can be recommended to improve the system's efficiency?

By answering these questions, this research aims to provide both theoretical insights into applying Queuing Theory in energy logistics and practical, evidence-based solutions for PT Multi Trading Pratama to enhance its operational competitiveness.

## 2. Literature Review

### Queuing Theory in Logistics and Service Operations

Queuing Theory mathematically analyzes systems where "customers" arrive at a "service facility" (Taha, 2017). Its application in logistics, particularly at ports and fuel terminals, is well-documented. For instance, Singh & Kumar (2019) used the M/M/c model to optimize truck queues at a port, concluding that server (berth) addition was the most effective solution for high-traffic periods. Similarly, studies at fuel stations (e.g., Wahyuni & Rizki, 2021) utilize queuing models to determine optimal pump numbers. These studies consistently identify core inefficiencies: demand-capacity imbalance, high service time variability, and suboptimal server count.

### The M/M/c Queuing Model

The Kendall notation A/B/c describes queuing systems. The M/M/c model, applicable to this case, assumes: (A) Markovian (Poisson) arrival process with rate $\lambda$, (B) Markovian (Exponential) service time with rate $\mu$ per server, and (c) identical, parallel servers. Key performance metrics include system utilization ($\rho = \lambda/c\mu$), probability of zero units in system ($P_0$), average number in queue ($L_q$), and average waiting time in queue ($W_q = L_q/\lambda$). System stability requires $\rho < 1$ (Stevenson, 2021).

## 3. Research Methods

This applied research employed a sequential explanatory mixed-methods design (Creswell & Creswell, 2018). Data collection occurred at Batu Licin TBBM in December 2025.

a. Quantitative Phase: Primary data (arrival and service times) were collected via structured observation during peak hours (09:00-15:00 WITA) over five weekdays, yielding 120 service event samples. Anderson-Darling goodness-of-fit tests confirmed data followed Exponential distributions ($p > 0.05$), validating the M/M/c model's assumptions.

Performance parameters were calculated using standard M/M/2 formulas (c=2 observed servers).

b. Qualitative Phase: Semi-structured interviews were conducted with one operations supervisor and two loading arm operators. Thematic analysis (Braun & Clarke, 2006) of transcripts identified root causes of inefficiency.
c. Triangulation & Simulation: Findings from both phases were integrated. Three optimization scenarios were simulated using the same model: Scenario A (increase $\mu$ by 15%), Scenario B (add a server, c=3), and Scenario C (combine $\mu$ increase by 10% and $\lambda$ reduction by 10%).

## 4. Results and Discussion

### Current System Performance (M/M/2)

Descriptive analysis yielded: $\lambda$ = 7.32 trucks/hour, $\mu$ = 2.67 trucks/hour/server.

a. Utilization ($\rho$): 1.37. This value >1 confirms an *unstable* system where arrival rate exceeds maximum service capacity (5.34 trucks/hour).
b. Average Queue Length (Lq): 8.41 trucks.
c. Average Waiting Time (Wq): 68.9 minutes (≈1 hour 9 minutes).
d. These figures quantitatively validate the observed operational problem (Table 1).

Table 1. Current System Performance Metrics

| Metric | Symbol | Value | Interpretation |
|---|---|---|---|
| Arrival Rate | $\lambda$ | 7.32/hr | High demand during peak hours. |
| Service Rate per Server | $\mu$ | 2.67/hr | Intrinsic speed of loading process. |
| Number of Servers | c | 2 | Current loading arms. |
| System Utilization | $\rho$ | 1.37 | System is overloaded and unstable. |
| Avg. Trucks in Queue | Lq | 8.41 | Substantial queue buildup. |
| Avg. Waiting Time in Queue | Wq | 68.9 min | Excessive delay for drivers. |

### Root Cause Analysis

Triangulation with qualitative data revealed three intertwined causes:

a. Schedule Non-Compliance: Truks from the same project often arrived in convoys outside assigned time slots, creating clustered arrivals that overwhelmed capacity.
b. High Service Time Variability: Differences in product viscosity (e.g., Bio-Diesel) and delays due to incomplete documentation led to inconsistent service times.
c. Inefficient Pre-Loading Process: Mandatory document and safety checks were performed sequentially after a truck secured a loading arm, not in parallel while queuing, wasting valuable server time.

### Optimization Scenario Analysis

Simulation of three improvement scenarios provided clear comparative insights (Table 2).

Table 2. Performance Comparison of Optimization Scenarios

| Parameter | Current System | Scenario A ($\mu$↑15%) | Scenario B (c=3) | Scenario C (Combo) |
|---|---|---|---|---|
| $\lambda$ (trucks/hour) | 7.32 | 7.32 | 7.32 | 6.59 |

| | | | | |
|---|---|---|---|---|
| μ (trucks/hour/server) | 2.67 | 3.07 | 2.67 | 2.94 |
| c (servers) | 2 | 2 | 3 | 2 |
| Utilization (ρ) | 1.37 (Unstable) | 1.19 (Unstable) | 0.91 (Stable) | 1.12 (Unstable) |
| Lq (trucks) | 8.41 | 6.25 | 0.85 | 4.12 |
| Wq (minutes) | 68.9 | 51.2 | 7.0 | 37.5 |
| % Reduction in Wq | - | 25.7% | 89.8% | 45.6% |

Discussion: Scenario B (adding a third server) is unequivocally the most effective. It transforms the system from unstable to stable (ρ=0.91) and slashes waiting time by nearly 90%. While Scenarios A and C offer improvements, they fail to achieve system stability because the fundamental imbalance between demand (λ) and aggregate capacity (cμ) is not fully resolved. This finding aligns with queuing theory principles: for severely congested systems, adding capacity is often the most direct path to significant improvement (Heizer et al., 2020). The qualitative root causes explain *why* the calculated λ and μ values are unfavorable; for example, non-compliance inflates λ during peaks, and serial pre-checks suppress the effective μ.

## 5. Conclusion and Recommendation

### Conclusion

This study successfully diagnosed the truck queuing problem at Batu Licin TBBM. The application of the M/M/2 model proved the system's instability during peak hours, with excessive queue lengths and waiting times. The mixed-methods approach uncovered that beyond pure capacity issues, operational practices—schedule indiscipline, process variability, and inefficient workflows—are significant contributors. Among the tested interventions, the addition of a third loading arm (server) emerged as the most impactful solution for achieving system stability and drastically reducing waiting times.

### Recommendations

A phased implementation plan is proposed for PT Multi Trading Pratama:

a. Short-Term (Immediate):
   1. Implement a Dedicated Pre-Check Bay to conduct document and safety inspections in parallel with queueing, thereby increasing the effective service rate (μ).
   2. Enforce Strict Schedule Adherence through a clear penalty system for non-compliant customers.

b. Medium-Term (1-3 Months):
   1. Activate the Third Loading Arm (Scenario B) during peak hours. A cost-benefit analysis should weigh the investment against savings from reduced idle time and potential revenue from increased throughput.
   2. Install a Digital Queue Information System to manage driver expectations and improve transparency.

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c. Long-Term (Beyond 3 Months):
   1. Develop an Integrated Digital Scheduling Platform with real-time tracking to proactively manage arrival patterns.
   2. Standardize Operating Procedures (SOPs) for all product types to minimize service time variability.

**Limitations and Future Research**

This study is limited by its 5-day observation period and the assumptions of the M/M/c model. Future research could: (1) employ a G/G/c model for greater accuracy in modeling service time distribution, (2) conduct a detailed economic cost analysis to find the optimal server count balancing waiting and service costs, and (3) build a discrete-event simulation model to dynamically test more complex operational policies.

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