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# OPERATIONAL EFFICIENCY ASSESSMENT OF URBAN PEDESTRIAN INFRASTRUCTURE: QUEUEING SYSTEM ANALYSIS OF ATAL FOOTBRIDGE

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## ABSTRACT

This study focuses on analyzing the queueing system at the Atal Bridge, Ahmedabad to understand and improve its operational efficiency. The bridge's functioning is divided into two main parts: the ticket window and the bridge visit. Primary data, including arrival rates and service times, were collected through direct observation. The collected data was analyzed to determine its distribution, which was used to construct a suitable queueing model. Using this queueing model, a numerical analysis was performed to identify the causes of crowding and delays in the system. Moreover, the performance measures of weekdays (Monday to Friday) and weekends (Saturday and Sunday) were compared in the analysis to highlight differences in crowd patterns and system efficiency. The results of this analysis provide valuable insights into how the system can be improved to reduce waiting times and enhance the overall visitor experience. This research highlights the practical application of queueing theory in managing pedestrian flow and improving the efficiency of public infrastructure like the Atal Bridge.

**Keywords:** Atal Bridge, Queueing Model, Operational Efficiency

## 1. INTRODUCTION

The Atal Footbridge is a pedestrian bridge located in Ahmedabad; the Bridge spans the Sabarmati River and connects the eastern and western parts of the city. The Atal Footbridge is a popular attraction among tourists and locals alike, offering stunning views of the Sabarmati River and the surrounding areas. Many people visit the bridge, especially in the evenings, due to the LED show on the bridge, which draws large crowds Gujarat Tourism (n.d.). Understanding the inflow of people on the Atal Footbridge is critical for optimizing its operation, which may lead to a better pedestrian experience and higher quality of service. This study utilises queueing models and their operating characteristics to analyse the evening pedestrian flow at the ticket centre and bridge viewing area.

One of the fundamental aspects of queueing theory is the modelling of arrival and service processes. Arrival processes describe how customers or entities enter the system, while service processes determine how these entities are served and ultimately exit the system. By mathematically representing these processes, queueing models can be developed to analyze the behaviour and performance of queues under different scenarios and assumptions.

In the system, overcrowding is not a continual problem but becomes a significant challenge during peak hours when the arrival rate exceeds the service rate. During these times, the density of the population increases, leading to delays and dissatisfaction among visitors. This study focuses on the Atal bridge in Ahmedabad, specifically analyzing its queueing system during peak hours (evening) to address these challenges. By using an appropriate queueing model that matches the bridge's functioning, the study aims to provide actionable insights for improving the system. Before constructing the model, the distribution of the collected data was analyzed to avoid pre-assumptions of model to ensure accurate outcomes. The numerical analysis conducted for both weekdays (Monday to Friday) and weekends (Saturday and Sunday) reveals distinct operational patterns between these periods. In conclusion, appropriate insight is given to reduce overcrowding and enhance the overall efficiency and visitors experience at the Atal Bridge.

## 2. LITERATURE REVIEW

Gumus et al. (2017) studied the queue of blue meadows restaurant to determine its operating characteristics and to reduce waiting lines for customers. For that they collected data of peak and off-peak period time of restaurant. Arrival and service time data distribution was tested by goodness of fit test with 95% of confidence interval level. M\M\C queueing model was used to determine waiting time, customer in system, utilization rate etc. for restaurant queue.

Mehri et al. (2006) constructed a queueing model on airport queue with some valid assumptions. The multiple-channel queueing model with Poisson arrival and exponential service times is used in this airport for travelers with reservations. They also analyzed total cost of model by using service cost and waiting line cost. Moreover, they used linear programming to resolve the waiting line.

Kabamba (2019) constructed mathematical model in their research work, "Modeling and analysis of queuing system in banks" a case study analysis of one of the Congo banks. The queueing characteristics of the bank were analyzed using a Multi-server queueing model. In which they used TORA optimization software for analyzing data and also the performance measure of queueing systems were evaluated. Using analyzed result some recommendations were given to improve the system.

Simaiakis and Balakrishnan (2016) presented an analytical model of the aircraft departure process at an airport, in which they used transient analysis at departure point of airport for D/E/1 queueing model. Moreover, the model estimates the expected taxi-out time, queueing delay, congestion level of airport, departure throughput etc. A new method for estimating the unimpeded taxi-out time distributions was proposed, and techniques to estimate both the distribution of inter-departure times and the throughput distribution were proposed. In conclusion they compared the result with actual data to check the efficiency of the model.

Xu et al. (2019) proposed a passenger flow control model tailored for peak hours at subway stations. Their study introduced a multi-station coordinated passenger flow control model designed to simultaneously regulate the number of inbound and transfer passengers across multiple stations or lines. The model was formulated as a bi-level programming problem, where the upper level focused on optimizing system performance under various passenger flow control strategies. The lower level addressed a logit-based stochastic user equilibrium assignment problem, incorporating factors such as passenger flow evolution, dynamic path costs, and route choices under a given strategy. To solve this complex model, the authors developed an algorithm that integrated the method of successive averages with a genetic algorithm. This approach provided an effective framework for managing passenger flow during peak hours, offering valuable insights into optimizing transportation systems under high-demand conditions.

Priyangika and Cooray (2015) used queueing model for checkout unit of supermarket. By using queueing simulation, they tried to estimate the waiting time and length of queue. Furthermore, they used empirical data which included variables like the arrival time in the queue of checkout operating unit (server), departure time, service time, etc. The primary data of arrival rate and service rate collected though the questionnaire. The model designed for research had multiple queues and multiple-server model. In conclusion it was found that the checkout operation unit was too busy to serve the arrived costumers.

## 3. METHODOLOGY

### 3.1. DATA COLLECTION

The data collection process for this study was designed to capture the arrival and service patterns at the Atal Bridge, focusing on two key stages: the ticket collection counter and the bridge entry point.

- **Arrival rate**: Primary data of arrival has been collected though observations of two key stages of the Atal bridge: the ticket collection counter and the bridge entry point. The arrival rate is determined by the number of people arriving at service station per minute.
- **Service rate**: As per the ordinance set by the authorities, visitors are allowed to spend up to 30 minutes on the bridge. However, there is no strict enforcement of this time limit, leading to variations in the actual time spent by visitors. To determine the service time for visitors, their tickets were collected at the exit point. Each ticket contained the arrival time of the visitor, and by comparing this with the departure time recorded at the exit, the time difference was calculated and noted as the service time.

Additionally, the data collection process was categorized into two distinct periods: weekdays (Monday to Friday) and weekend (Saturday and Sunday). The observations were conducted during peak hours (6:00 PM to 8:00 PM), as this period experiences the highest footfall.

### 3.2. DATA ANALYSIS

- **Arrival rate:** To determine the distribution of arrival units, the data was first divided into half-hour intervals, resulting in a total of four intervals. To verify whether the arrival pattern follows a Poisson distribution, a Chi-Square Goodness-of-Fit Test was performed. The Chi-Square Goodness-of-Fit Test is a statistical tool used to compare observed data with a theoretical distribution, such as the Poisson distribution (in this case).

**Hypothesis**

Null hypothesis ($H_0$): The arrival pattern follow a Poisson distribution.

Alternative hypothesis ($H_1$): The arrival pattern does not follow a Poisson distribution.

The result of chi square test is mentioned below:

**Table 1**

**Table 1 Chi Square Goodness of Fit Test (Arrival Rate at Ticket Window)**

| Time | Weekdays | | | | Weekends | | | |
|---|---|---|---|---|---|---|---|---|
| | Chi-square | Degree of freedom | p value | Mean | Chi-square | Degree of freedom | p value | Mean |
| 6:00 - 6:30 | 19 | 29 | 0.921 | 4.83 | 22.5 | 29 | 0.8 | 6.9 |
| 6:30 - 7:00 | 24.2 | 29 | 0.721 | 4.93 | 17.8 | 29 | 0.948 | 7.467 |
| 7:00 - 7:30 | 11.5 | 29 | 0.998 | 5.167 | 16.6 | 29 | 0.93 | 7.434 |
| 7:30 - 8:00 | 13.7 | 29 | 0.993 | 5.233 | 16.9 | 29 | 0.964 | 7.467 |
| 8:00 - 8:30 | 27.4 | 29 | 0.552 | 5.833 | 16.6 | 29 | 0.968 | 7.3 |

Table 1 shows that for each interval the p-value is greater than or equal to 0.05. Therefore, the null hypothesis is accepted, and it can be concluded that the arrival pattern follows a Poisson distribution for all four intervals.

**Table 2**

**Table 2 Chi Square Goodness of Fit Test (Arrival Rate at Bridge Entry Point)**

| Time | Weekdays | | | | Weekends | | | |
|---|---|---|---|---|---|---|---|---|
| | Chi-square | Degree of freedom | p value | Mean | Chi-square | Degree of freedom | p value | Mean |
| 6:00 - 6:30 | 15.4 | 29 | 0.982 | 14.7 | 19 | 29 | 0.922 | 22.9 |
| 6:30 - 7:00 | 20.6 | 29 | 0.873 | 14 | 16.3 | 29 | 0.972 | 25.53 |
| 7:00 - 7:30 | 13.3 | 29 | 0.991 | 15.23 | 28.2 | 29 | 0.508 | 28.67 |
| 7:30 - 8:00 | 27.9 | 29 | 0.525 | 15.93 | 32.7 | 29 | 0.292 | 30.2 |
| 8:00 - 8:30 | 40.7 | 29 | 0.073 | 17 | 35.9 | 29 | 0.176 | 31.8 |

Table 2 shows that for each interval the p-value is greater than or equal to 0.05. which means null hypothesis is accepted, and data follows a Poisson distribution for all four intervals. Therefore, it can be concluded that the arrival pattern at a bridge entry point follows Poisson distribution.

- **Service rate**

**Table 3**

**Table 3 Service Time**

| Weekdays | | Weekends | |
|---|---|---|---|
| Mean | 33.75 | Mean | 41.85 |
| Variance | 482.5 | Variance | 469.028 |
| S.D | 21.96 | S.D | 21.65 |

Table 3 indicates some descriptive statistics for service time of weekdays and weekends collected at exit point of the bridge. The variance of service times is significantly high for both weekdays and weekends. Thus, general service time distribution is more appropriate for modeling the service process.

### 3.3. FORMULATING OF ATAL BRIDGE QUEUEING MODEL

The visitor experience at the bridge consists of two distinct and independent service stages. The first service stage is the ticket counter, and the second service stage is the actual bridge visitation. These two service stations operate independently, each with unique characteristics and functional parameters. The distinct nature of these service components requires separate examinations of their queueing behaviors and visitor management approaches.

**Node A: Ticket window**

The first stage of the system involves visitors collecting tickets from the ticket window. At this stage, individuals arrive and join a queue to obtain a ticket. The number of arrivals per minute is defined as the arrival rate, which, as previously tested using the Chi-Square Goodness-of-Fit Test, follows a Poisson distribution. The service rate is defined as the time it takes for an individual to receive a ticket once they reach the window. Since the service time is almost the same for everyone, it follows an exponential distribution. The system is assumed to have infinite capacity, meaning there is no limit to the number of individuals that can join the queue. Given the Poisson arrival process, exponential service times and multiple servers, the M/M/C queueing model is the most appropriate for this stage. Here, C represents the number of servers (ticket windows), which is 2 for weekdays and 3 for weekends.

**Node B: Bridge visit area**

After collecting the ticket, individuals proceed for the bridge visit. At the entry point of the bridge, the ticket is checked by a staff member, and visitors can proceed without any waiting time. The arrival of individuals per minute is defined as the arrival rate, and the time it takes for an individual to visit the bridge is defined as the service time. As previously tested, the arrival rate for bridge visits follows a Poisson distribution, while the service time follows a general distribution. Unlike the ticket collection stage, there is no dedicated server for bridge visits; visitors can enter and enjoy the view independently, making this a self-service system. Since there is no limit to the number of individuals who can visit the bridge simultaneously, the number of channels for this stage is effectively infinite. Therefore, the M/G/∞ queueing model is the most appropriate for this stage.

**Table 4**

| **Table 4 Notations** | |
|---|---|
| $\lambda_i$ | Arrival rate of node $i$ (per minute) |
| $\mu_i$ | Service rate of node $i$ (per minute) |
| $\rho_i$ | Utilization of node $i$ (per minute) |
| $L_i$ | Average number of visitors in node $i$ |
| $L_{qi}$ | Average number of visitors waiting in line of node $i$ |
| $W_i$ | Average time spent by visitors in system of node $i$ |
| $W_{qi}$ | Average time spent by visitors in waiting line of node $i$ |
| $P_{0i}$ | Probability that no visitor in system of node $i$ |

### 3.3.1. ASSUMPTIONS

- Arrivals and service times are independent of each other. The service time for one visitor does not affect the service time for another.
- The arrival pattern follows Poisson **distribution,** as validated by the Chi-Square Goodness-of-Fit Test, and service time is considered as exponential and general distribution for first and second node respectively.
- The system has **infinite capacity**, meaning there is no limit to the number of visitors that can wait in the queue.
- Visitors do not leave the system without being served (no balking or reneging).

### 3.3.2. QUEUEING MODEL

**Node A: Ticket window ($M/M/C$)** Gross et al. (2011)

Key assumptions:

- The arrival pattern follows Poisson **distribution,** as validated by the Chi-Square Goodness-of-Fit Test.
- The service time follows exponential distribution and the system has infinite capacity for the visitors.

Using the balance equations of birth-death processes, the steady state probabilities ($p_{nA}$) of M/M/C model is given by:

$$p_{nA} = \begin{cases} \dfrac{\lambda_A{}^n}{n!\,\mu_A{}^n}\, p_{0A} & (0 \le n < c) \\ \dfrac{\lambda_A{}^n}{c^{n-c}c!\,\mu_A{}^n}\, p_{0A} & (n \ge c) \end{cases}$$

$$p_{0A} = \left( \sum_{n=0}^{c-1} \frac{\lambda_A{}^n}{n!\,\mu_A{}^n} + \sum_{n=c}^{\infty} \frac{\lambda_A{}^n}{c^{n-c}c!\,\mu_A{}^n} \right)^{-1}$$

Let $r_A = {}^{\lambda_A}/_{\mu_A}$ and $\rho_A = {}^{\lambda_A}/_{c\mu_A}$, then we have

$$p_{0A} = \left( \sum_{n=0}^{c-1} \frac{r_A{}^n}{n!} + \sum_{n=c}^{\infty} \frac{r_A{}^n}{c^{n-c}c!} \right)^{-1}$$

Consider infinite series term and rearrange it with suitable formula:

$$\sum_{n=c}^{\infty} \frac{r_A{}^n}{c^{n-c}c!} = \frac{r_A{}^c}{c!} \frac{1}{1 - {}^{r_A}/_c} \qquad ({}^{r_A}/_c = \rho_A < 1)$$

Therefore,

$$p_{0A} = \left( \sum_{n=0}^{c-1} \frac{{r_A}^n}{n!} + \frac{{r_A}^c}{c!} \frac{1}{1-\rho_A} \right)^{-1}$$

Now, the performance measures of M/M/C model by means of the following formulas:

1) $L_{qA} = \sum_{n=c+1}^{\infty}(n-c)p_{nA} = \left(\frac{{r_A}^c \rho_A}{c!(1-\rho_A)^2}\right) p_{0A}$
2) $L_A = L_{qA} + \frac{\lambda_A}{\mu_A} = r_A + \left(\frac{{r_A}^c \rho_A}{c!(1-\rho_A)^2}\right) p_{0A}$
3) $W_{qA} = \frac{L_{qA}}{\lambda_A} = \left(\frac{{r_A}^c}{c!(c\mu_A)(1-\rho_A)^2}\right) p_{0A}$
4) $W_A = \frac{1}{\mu_A} + W_{qA} = \frac{1}{\mu_A} + \left(\frac{{r_A}^c}{c!(c\mu_A)(1-\rho_A)^2}\right) p_{0A}$

**Node B: Bridge visit area ($M/G/\infty$)** Gross et al. (2011)

Key assumptions:

- The arrival pattern follows Poisson **distribution,** as validated by the Chi-Square Goodness-of-Fit Test.
- Service times are independent and identically distributed with a general distribution. Let S denote the service time, with:

  Mean service time: $E_B(S) = \frac{1}{\mu_B}$

  Variance of service time: $Var(S) = \sigma^2$
- There are always enough servers to handle all the arrivals immediately, so no queue forms.

In an M/G/∞ system, the number of customers in the system at time t, denoted by $N(t)$, follows a **Poisson distribution**. Hence, the probability of having *n* customers in the system at time *t* is given by:

$$P_B(N(t) = n) = \frac{(\lambda_B E_B[S]\,)^n}{n!} e^{-\lambda_B E_B[S]}$$

Where, $\lambda_B E_B[S]$ is the traffic intensity (average number of customers in the system) For the M/G/∞ model, the performance measures are straightforward:

1) $L_B = \lambda_B E_B[S]$
2) $W = E_B[S]$
3) $P_0 = e^{-\lambda_B E_B[S]}$
4) $L_{qB} = W_{qB} = 0$

## 4. RESULTS AND DISCUSSION

### Node A: Ticket window ($M/M/C$)

The performance measures of M/M/C queueing system can be derived using primary data on arrival and service rates through the corresponding analytical equations.

**Table 5**

**Table 5 Performance Measures of Weekdays**

| Time | $\lambda_A$ | $\mu_A$ | $C$ | $\rho_A$ | $L_A$ | $L_{qA}$ | $W_A$ | $W_{qA}$ | $P_{0A}$ |
|---|---|---|---|---|---|---|---|---|---|
| 06:00-06:30 | 4.83 | 3 | 2 | 0.80 | 4.59 | 2.98 | 0.95 | 0.62 | 0.11 |
| 06:30-07:00 | 4.93 | 3 | 2 | 0.82 | 5.07 | 3.43 | 1.03 | 0.70 | 0.10 |
| 07:00-07:30 | 5.17 | 3 | 2 | 0.86 | 6.67 | 4.94 | 1.29 | 0.96 | 0.07 |
| 07:30-08:00 | 5.23 | 3 | 2 | 0.87 | 7.29 | 5.54 | 1.39 | 1.06 | 0.07 |
| 08:00-08:30 | 5.83 | 3 | 2 | 0.97 | 34.79 | 32.84 | 5.97 | 5.63 | 0.01 |

As indicated in Table 5, the system operates with two ticket windows on weekdays, leading to overutilization throughout the entire observation period. Notably, while the number of customers is relatively low at the beginning of the observation period, it gradually increases and peaks toward the end of the period.

**Table 6**

**Table 6 Performance Measures of Weekend**

| Time | $\lambda_A$ | $\mu_A$ | $C$ | $\rho_A$ | $L_A$ | $L_{qA}$ | $W_A$ | $W_{qA}$ | $P_{0A}$ |
|---|---|---|---|---|---|---|---|---|---|
| 06:00-06:30 | 6.9 | 3 | 3 | 0.77 | 4.25 | 1.95 | 0.62 | 0.28 | 0.07 |
| 06:30-07:00 | 7.47 | 3 | 3 | 0.83 | 5.88 | 3.39 | 0.79 | 0.45 | 0.05 |
| 07:00-07:30 | 7.43 | 3 | 3 | 0.82 | 5.75 | 3.28 | 0.77 | 0.44 | 0.05 |
| 07:30-08:00 | 7.47 | 3 | 3 | 0.83 | 5.88 | 3.39 | 0.78 | 0.45 | 0.04 |
| 08:00-08:30 | 7.3 | 3 | 3 | 0.81 | 5.29 | 2.86 | 0.72 | 0.39 | 0.05 |

Table 6 shows that the number of people in the system does not remain consistently high throughout the observation period. However, the utilization rate indicates that the system operates under overused conditions for the entire duration.

### Node B: Bridge visit area ($M/G/\infty$)

The system characteristics were analyzed using the performance equations of the M/G/∞ queuing model.

**Table 7**

**Table 7 Performance Measures of Weekdays**

| Time | $\lambda_B$ | $E_B(S)$ | $C$ | $r_B$ | $L_B$ | $W_B$ | $P_{0B}$ |
|---|---|---|---|---|---|---|---|
| 06:00-06:30 | 14.7 | 33.75 | ∞ | 496.12 | 496.12 | 33.75 | 0 |
| 06:30-07:00 | 14 | 33.75 | ∞ | 472.5 | 472.5 | 33.75 | 0 |
| 07:00-07:30 | 15.23 | 33.75 | ∞ | 514.01 | 514.01 | 33.75 | 0 |
| 07:30-08:00 | 15.93 | 33.75 | ∞ | 537.64 | 537.64 | 33.75 | 0 |
| 08:00-08:30 | 17 | 33.75 | ∞ | 573.75 | 573.75 | 33.75 | 0 |

As shown in Table 7, with a service rate of 33.75 (mean of collected data), the number of people in the system increased over a period of time.

**Table 8**

**Table 8 Performance Measures of Weekend**

| Time | $\lambda_B$ | $E_B(S)$ | $C$ | $r_B$ | $L_B$ | $W_B$ | $P_{0B}$ |
|---|---|---|---|---|---|---|---|
| 06:00-06:30 | 22.9 | 41.85 | ∞ | 958.37 | 958.37 | 41.85 | 0 |
| 06:30-07:00 | 25.53 | 41.85 | ∞ | 1068.43 | 1068.43 | 41.85 | 0 |
| 07:00-07:30 | 28.67 | 41.85 | ∞ | 1199.84 | 1199.84 | 41.85 | 0 |
| 07:30-08:00 | 30.2 | 41.85 | ∞ | 1263.87 | 1263.87 | 41.85 | 0 |
| 08:00-08:30 | 31.8 | 41.85 | ∞ | 1330.83 | 1330.83 | 41.85 | 0 |

Table 8 demonstrates that the service rate during weekends is substantially higher compared to weekdays, resulting in a significantly greater number of visitors within the system. Furthermore, these footsteps show a progressive increase over time, indicating sustained growth in system occupancy throughout the observation period.

## 5. PROPOSED SYSTEM

**Node A: Ticket window ($M/M/C$)**

- **Weekdays**

The analysis presented in Table 5 indicates that the current configuration of operational ticket windows is insufficient to maintain proper system balance. To resolve this imbalance, we examine the potential effects of incorporating an additional service window into the system.

**Figure 1**

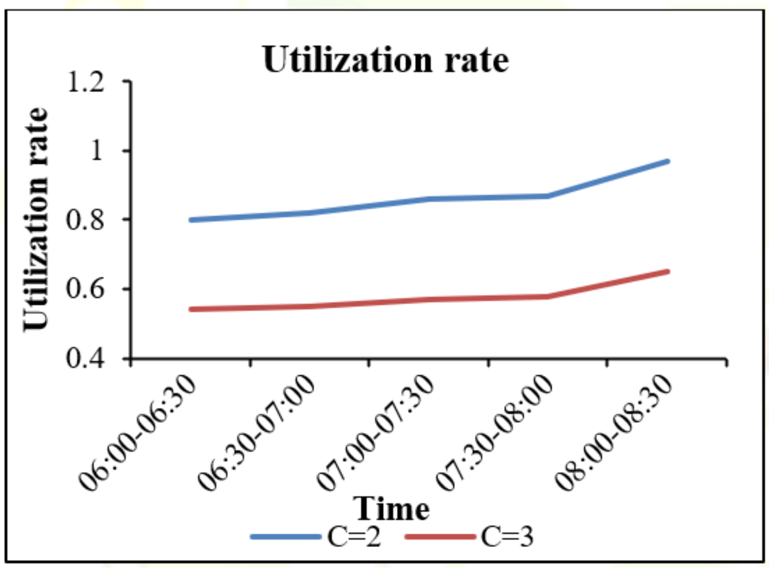


**Figure 1** Weekdays

**Figure 2**

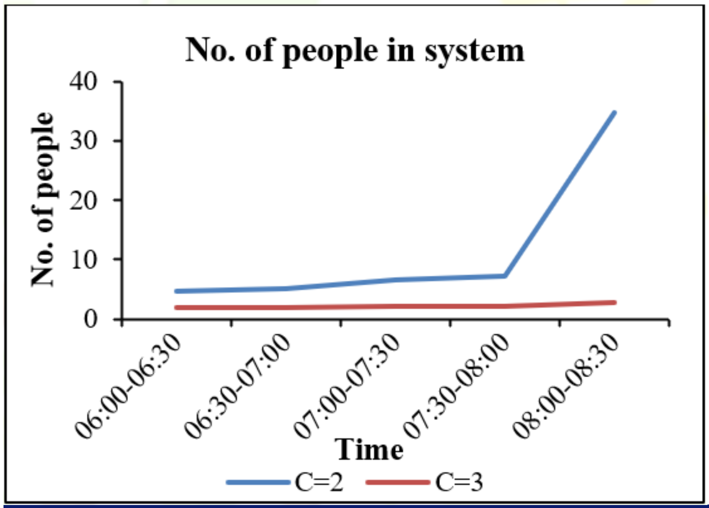


**Figure 2** Weekdays

As illustrated in Figure 1, introducing a third ticket window substantially improves system overload, leading to more efficient operations. Furthermore, Figure 2 demonstrates that this expansion reduces the number of users within the system, particularly during peak periods where congestion was previously most severe. These findings confirm that increasing service capacity effectively mitigates operational strain and improves overall system performance.

- **Weekend**

Table 6 indicates that while weekend operations with three service channels do not experience overcrowding issues, the system still suffers from overutilization. To address this inefficiency, we evaluate the operational impact of introducing a fourth service channel.

**Figure 3**

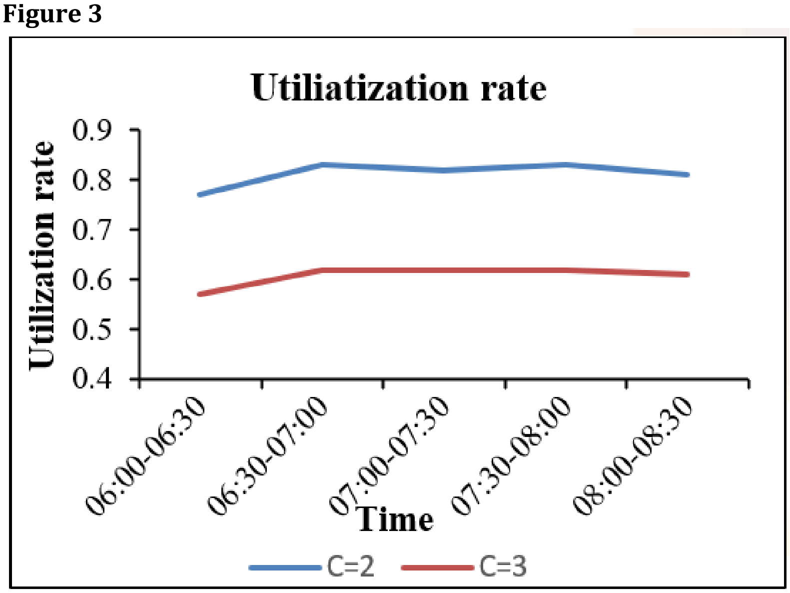


**Figure 3** Weekend

**Figure 4**

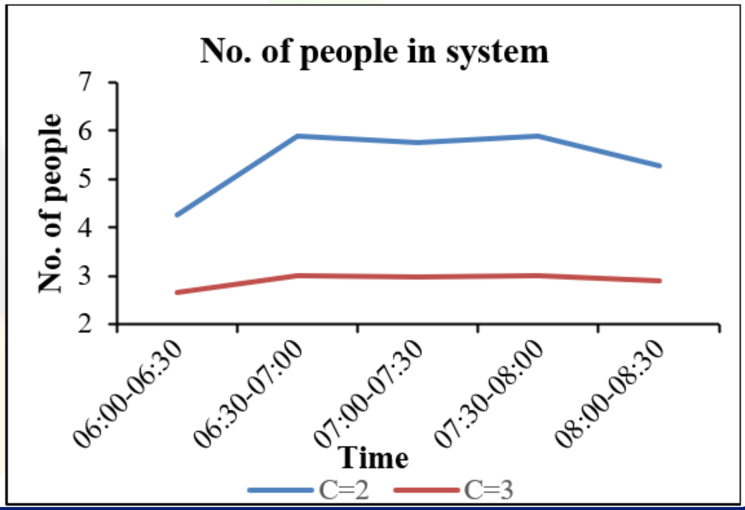


**Figure 4** Weekend

[Figure 3](#) demonstrates that the additional channel would optimize resource utilization. This modification primarily improves service efficiency by better distributing workloads across available resources, thereby reducing strain on individual channels while maintaining consistent service quality throughout operational hours.

**Node B: Bridge visit area ($M/G/\infty$)**

The analysis examines the impact of adhering to the designated 30-minute visiting time at Atal Bridge, which currently operates without strict enforcement. Collected data indicates that actual service times exceed this benchmark, averaging 33.75 minutes on weekdays and 41.8 minutes on weekends. The graphical representation illustrates how enforcing the 30-minute limit could substantially decrease the number of people within the system. Table 5.5 and 5.6 aligning actual service times with the prescribed duration, the system would experience reduced congestion and improved operational efficiency.

**Figure 5**

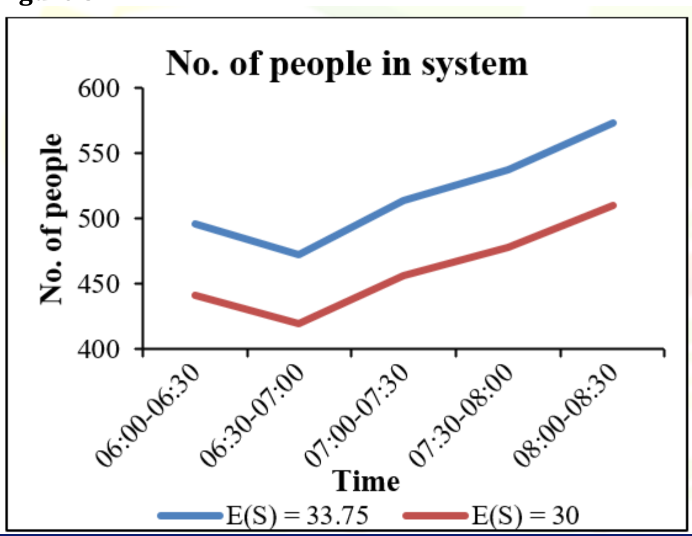


**Figure 5** Weekdays

**Figure 6**

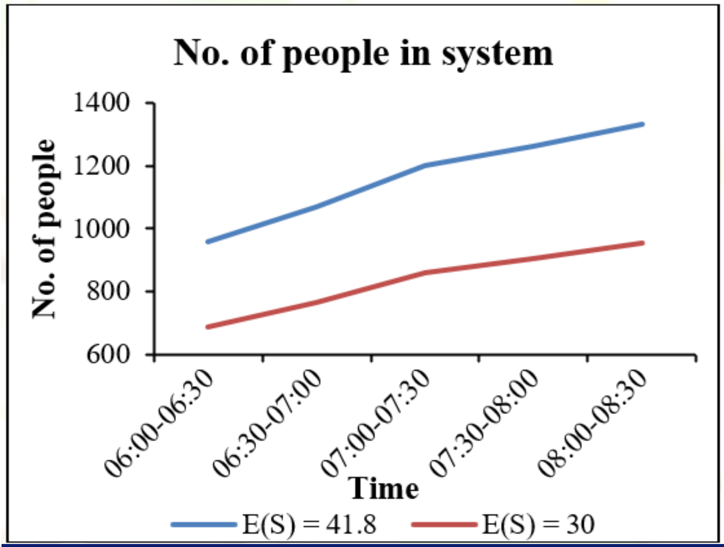


**Figure 6** Weekend

## 6. CONCLUSION

As a popular public destination, managing overcrowding is crucial to ensure positive visitor experiences. This study analyzes system occupancy and resource utilization patterns to identify operational improvements. Furthermore, evaluation of collected data patterns helps us to understand the system very efficiently. The findings are categorized into two key areas:

### 1) Ticket window management

The evaluation reveals that both weekdays and weekends experience system strain due to overcrowding and overutilization of resources. To address this:

- **Additional service channel:** Introducing extra ticket window throughout operational hours would significantly improve efficiency. However, if infrastructure costs are prohibitive, promoting online ticketing serves as a viable alternative.
- **Encouraging digital adoption:** While online ticketing is available, public adoption remains low. Implementing discounts for digital tickets could incentivize usage, reducing physical queue pressure and enhancing overall system performance.

### 2) Bridge Visit Management

Unlike the ticket system, the bridge operates as an infinite-server model, eliminating formal queues. However, controlling visitor density at key points remains essential for satisfaction. Recommendations include:

- **Time limit enforcement:** To prevent prolonged stays beyond the designated 30-minute window, measures such as exit-point checks, automated scanners, and time-based penalties should be introduced.

## 7. KEY RECOMMENDATIONS

- **Expand ticket centre capacity** to reduce queues and improve service efficiency.

- **Promote e-tickets** by offering discounts or bundled benefits (e.g., free entry to nearby attractions).
- **Enforce a strict time limit** for bridge visits with penalties for overstaying.
- **Relocate food stalls outside the bridge** area to minimize unnecessary crowding and optimize visiting time.

By implementing these targeted interventions, expanding ticket service capacity (physically or digitally) and refining bridge visitation protocols the facility can achieve better crowd control, optimized resource use and enhanced visitor satisfaction. These solutions balance cost-efficiency with practical enforcement, making them feasible for immediate and long-term improvements.

## CONFLICT OF INTERESTS

None.

## ACKNOWLEDGMENTS

None.

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