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COMPARATIVE ANALYSIS OF POISSON, EXPONENTIAL, AND UNIFORM DISTRIBUTIONS IN MODELING CUSTOMER ARRIVAL TIMES ON A WEB SERVER

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Abstract

This study compares the Poisson, Exponential, and Uniform distributions to determine the most suitable model for customer arrival times on a web server. Server log data were processed into interarrival times and arrival counts, followed by parameter estimation using Maximum Likelihood Estimation and goodness-of-fit evaluations through Kolmogorov–Smirnov, Anderson–Darling, Chi-Square, and AIC/BIC metrics. The results show that the Exponential distribution provides the best fit for interarrival patterns, supported by a KS-statistic of 0.067 and p-value of 0.312, while the Poisson distribution demonstrates acceptable performance for arrival counts with a Chi-Square p-value of 0.224. In contrast, the Uniform distribution exhibits the weakest suitability, indicated by its highest AIC score (AIC = 9874). Queue simulation using an M/M/1 model confirms that Exponential-based arrival modeling yields the most stable system performance with an average waiting time of 0.42 seconds and server utilization of 0.73, compared to longer delays and higher utilization when using Poisson-derived rates. Overall, the findings indicate that the Exponential distribution is the most appropriate for modeling real web server arrival behavior, offering more accurate performance predictions and supporting improved capacity planning.

Keywords: Poisson Distribution, Exponential Distribution, Uniform Distribution, Arrival Modeling, Web Server

Introduction

Modeling the arrival behavior of customers on a web server continues to be an essential aspect of evaluating system performance, especially in environments where user-demand patterns fluctuate dynamically throughout the day. Modern web servers handle large volumes of traffic with varying levels of intensity, and these variations can directly influence how quickly a server responds, how long users wait, and how stable the service remains under stress. Because of this, selecting an appropriate statistical model to represent customer arrival times is a fundamental step in ensuring that performance evaluations and capacity planning are both accurate and reliable (Hery, 2023).

Over the years, researchers have relied heavily on the Poisson distribution for modeling the number of arrivals within fixed time intervals, supported by the assumption that interarrival times follow an Exponential distribution. These models are widely used because they simplify mathematical analysis and align neatly with the classical M/M/1 queueing framework. Their analytical convenience, particularly due to the memoryless property, makes them appealing for theoretical studies. However, their suitability for modern digital environments like web servers, where traffic may include bursts, automation, and machine-generated patterns, is frequently questioned (Ruliyanti et al., 2025).

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As web-based systems evolve, their arrival characteristics also become more complex. Traffic no longer behaves as a simple stream of independent and identically distributed events; instead, it often reflects correlated patterns, sudden spikes, or irregular fluctuations. Several studies indicate that these complexities can cause substantial deviations from traditional Poisson–Exponential models. Consequently, researchers have begun examining alternative distribution models or baseline comparisons to understand whether standard assumptions truly reflect real server behavior or whether they oversimplify the dynamics of digital traffic (Utomo, 2025).

To evaluate these models thoroughly, the use of rigorous statistical testing becomes indispensable. Goodness-of-fit tests such as Kolmogorov–Smirnov and Anderson–Darling provide insights into how closely the theoretical distribution matches empirical data. Complementing these tests, the Chi-Square method is often used for arrival count analysis, while AIC and BIC offer likelihood-based perspectives for comparing model performance. Together, these tools enable a multi-angle assessment that reduces the risk of selecting an inappropriate model for arrival behavior (Dinanti et al., 2025).

In addition to statistical tests, simulations serve as a powerful tool for translating model suitability into practical implications. Queueing simulations, particularly those based on M/M/1 or its variants, help researchers understand how different arrival models influence key performance metrics such as average waiting time, server utilization, and expected queue length. These operational metrics matter greatly for decision-makers who wish to ensure the server remains efficient under real workloads. Thus, combining empirical data analysis with simulation-based validation provides a more comprehensive approach to evaluating arrival distributions (Alda et al., 2024).

Furthermore, integrating real-world server logs into the analysis strengthens the credibility of evaluation results. Server logs offer detailed and time-accurate information regarding request behaviors, enabling precise calculation of interarrival times and arrival counts. Processing this type of data not only enhances the validity of the study but also aligns with modern trends in performance engineering, where real measurements are preferred over purely synthetic assumptions. This integration ensures that findings remain applicable and meaningful for practitioners (Junaidi, 2022).

Within Indonesia, the interest in queueing theory and arrival modeling continues to grow, although most applications still revolve around traditional service settings such as tourism, healthcare, or retail. These studies often use Poisson and Exponential assumptions due to their established position in operational research. However, while these models are commonly applied, only a limited number explore deeper comparative distribution analyses, particularly those relevant to digital or web-based environments where traffic characteristics differ significantly from human-queue systems (Yusnita & Marsa, 2024).

Recent national studies help illustrate how researchers in Indonesia apply stochastic modeling in various contexts. One such study by Fidianti examined visitor arrivals at a tourism site and applied the M/M/1 and M/M/S frameworks while validating arrival patterns and service distributions using empirical data (Fidianti, 2022). Another study by Pratama assessed customer arrivals in a retail setting and conducted Poisson-based arrival validation coupled with Exponential service-time modeling, strengthened by simulation analysis. These two works demonstrate how stochastic models are actively applied in Indonesia across different sectors, although both remain centered on physical service systems rather than digital traffic environments (Pratama, 2024).

These existing studies reveal a clear research gap. Despite the growth of stochastic modeling in Indonesian literature, most research still focuses on human-centered environments that differ fundamentally from high-frequency web server traffic. Arrival processes in digital systems often involve automated requests, machine-level timing patterns, and highly variable timestamps—characteristics that are rarely captured in traditional services. Moreover, there is a lack of national studies that compare Poisson, Exponential, and Uniform distributions directly using real server logs and then assess how each model affects queueing performance. This gap underscores the need for deeper exploration within digital traffic contexts.

To respond to these issues, this study conducts a comprehensive comparison of Poisson, Exponential, and Uniform distributions in modeling customer arrival times on a web server. By integrating parameter estimation, formal goodness-of-fit evaluations, likelihood-based model comparisons, and M/M/1 simulation analysis, this research aims to identify the distribution that best reflects real server behavior. The findings are expected to contribute meaningful insights for web administrators, researchers, and system designers regarding model selection, performance prediction accuracy, and capacity planning for modern web systems.

This section provides a concise theoretical foundation for understanding arrival modeling in web-based systems and the statistical distributions commonly used in its analysis. It summarizes key concepts related to traffic behavior, explains the relevance of Poisson, Exponential, and Uniform distributions, and reviews empirical findings from previous studies that apply these models in practical environments. By examining both theoretical and empirical perspectives, this literature review establishes the basis for identifying limitations in existing research and motivates the need for a systematic comparison of arrival distributions on real web server data.

2.1. Overview of Arrival Modeling in Web and Network Systems

Arrival modeling plays a central role in understanding the performance dynamics of web and networked systems, as fluctuations in request rates directly influence server responsiveness and overall quality of service. In modern digital environments, incoming requests may originate from human users, automated agents, scheduled processes, or background services, producing diverse arrival patterns that vary across time. These variations highlight the need for accurate statistical representations capable of capturing the stochastic behavior of traffic flows (Alda et al., 2024).

In traditional performance analysis, arrival processes are often modeled as random events governed by probability distributions that describe how frequently requests occur within a given period. This approach helps researchers analyze the underlying randomness of traffic and predict system behavior under different load conditions. Within queueing theory, arrival distributions determine critical performance indicators such as utilization, waiting time, and queue length, all of which reflect the ability of the system to manage incoming demand effectively.

Web and network systems, however, rarely exhibit uniform or fully predictable arrival patterns. Traffic may show burstiness, periodic fluctuations, or sudden spikes driven by user behavior, system events, or application-level processes. As a result, identifying an accurate arrival model becomes essential not only for theoretical validation but also for practical implementation, particularly when systems rely on performance estimations for resource allocation or capacity planning. Without appropriate modeling, performance predictions may become misleading or overly simplistic (Wulandari, 2025).

Because of these complexities, researchers employ statistical distributions such as Poisson, Exponential, and Uniform to approximate arrival processes and evaluate their suitability through empirical testing. These models offer different assumptions and characteristics, allowing analysts to assess which distribution best reflects real server behavior. Combined with empirical log data, arrival modeling serves as a crucial step in evaluating system performance and ensuring that computational analyses align with actual traffic characteristics.

2.2. Poisson Distribution in Arrival Modeling

The Poisson distribution is one of the most widely used probabilistic models for describing the number of arrivals within a fixed time interval in web and networked systems. Its appeal lies in its mathematical simplicity and its foundation on the assumption that events occur independently and with a constant average rate. These characteristics allow the Poisson process to serve as the basis for classical queueing models such as M/M/1, where arrival counts follow a predictable pattern that facilitates analytical performance estimation (Onuneng, 2025).

In many theoretical and applied studies, the Poisson model has been adopted to approximate traffic behavior due to its tractability and compatibility with the exponential distribution of interarrival times. When empirical data exhibit relatively stable arrival rates and low temporal correlation, Poisson assumptions often align well with observed patterns, making it a practical choice for approximating request flows. This suitability enables researchers to derive essential performance indicators directly from estimated arrival parameters, simplifying both analysis and simulation workflows (Maharani, 2025).

However, the Poisson distribution may fail to fully represent modern web traffic, which often demonstrates burstiness, variability across different time periods, or dependencies between consecutive events. These deviations can lead to underestimation or overestimation of system load when the model assumes a constant arrival rate. Consequently, Poisson modeling requires empirical validation before being applied to performance prediction, particularly in environments where traffic behavior is influenced by complex user interactions or automated request generation.

2.3. Exponential Distribution for Interarrival Times

The Exponential distribution is commonly used to model the time between consecutive arrivals in web and network systems, particularly due to its memoryless property, which states that the probability of an event occurring is independent of how much time has already passed. This characteristic simplifies many analytical formulations in queueing theory, making the Exponential distribution the natural counterpart of the Poisson model, where interarrival times follow an exponential pattern when arrival counts are Poisson-distributed (Adhikari et al., 2021).

In practice, the Exponential distribution allows researchers to estimate arrival behavior using a single rate parameter, making it efficient for modeling systems with relatively stable and independent event occurrences. When empirical interarrival times reflect monotonic decay and limited variability, the Exponential model can provide a reasonable approximation of real traffic. Its mathematical tractability also enables straightforward derivation of performance metrics in queueing models, such as average waiting time and expected system occupancy (Putra et al., 2022).

Despite its advantages, the Exponential distribution may not always align with the characteristics of modern web traffic. Real interarrival times often exhibit heavy-tailed or multimodal behavior, driven by bursts of activity, automated request sequences, or application-level patterns. These conditions violate the independence and memoryless assumptions that underpin the Exponential model. As a result, empirical validation is essential to assess whether Exponential assumptions accurately represent interarrival behavior in server environments before the model is applied for performance prediction or capacity planning.

2.4. Uniform Distribution as a Baseline Model

The Uniform distribution is occasionally used as a baseline model for interarrival times in web and network systems, particularly when analysts wish to compare structured stochastic models with a simple, non-informative alternative. Unlike the Poisson and Exponential distributions, which assume specific probabilistic behaviors, the Uniform model presumes that all interarrival times within a defined range are equally likely. This assumption makes it analytically straightforward and useful as a reference point for evaluating the adequacy of more complex models (Afifah, 2025).

In performance analysis, the Uniform distribution is seldom considered a realistic representation of actual web traffic, as real arrival patterns rarely exhibit perfectly even variability (Dinanti et al., 2025). However, its simplicity makes it valuable for sensitivity testing and for assessing how much predictive improvement is gained when adopting more theoretically grounded models. By offering a lower-bound baseline, the Uniform model helps highlight whether the additional assumptions of Poisson or Exponential distributions meaningfully improve the accuracy of arrival-time modeling (Yusnita & Marsa, 2024).

Despite its limited applicability to real-world traffic, the Uniform distribution remains relevant in comparative studies that seek to evaluate the strengths and weaknesses of various modeling approaches. When empirical arrival data demonstrate wide variation or inconsistent patterns, comparing them against Uniform assumptions can reveal whether observed behaviors deviate significantly from randomness or whether they possess identifiable structure. Such comparisons also support broader methodological evaluations, especially when performance prediction depends heavily on the accuracy of the assumed arrival-time model.

2.5. Empirical Studies Comparing Arrival Distributions

Empirical investigations on arrival modeling have been widely conducted to assess whether theoretical distributions accurately represent observed traffic behavior in various service and computational environments. Most studies examine the suitability of Poisson and Exponential distributions due to their strong foundations in queueing theory, while also recognizing the need to validate these assumptions against real-world data. This validation process is crucial, as arrival characteristics often vary significantly across systems and may influence the accuracy of performance predictions (Junaidi, 2022).

Several national studies illustrate the use of these classical stochastic models in Indonesian contexts. One study by Fauzy et al. evaluated arrival patterns within a tourism service environment, analyzing whether Poisson-based arrivals and Exponential service times aligned with empirical data. Another study by Pratama and Sovia assessed customer arrivals in a retail system using an M/M/1 queue simulation supported by Poisson arrival modeling and Exponential service assumptions. Both studies demonstrated that empirical testing is essential before applying theoretical models to performance analysis, particularly in systems where arrival rates fluctuate across time (Utomo, 2025).

Although these studies provide important contributions, they primarily focus on traditional, human-centered service systems and do not extend their analyses to digital environments such as web servers, where arrival patterns behave differently due to automation, high-frequency requests, and machine-level timing. Furthermore, they do not perform direct comparisons of multiple candidate distributions. Their limitations highlight the need for more comprehensive empirical studies that evaluate several distributions simultaneously and assess their implications for performance modeling in web-based systems.

2.6. Research Gap

Although previous studies have examined arrival modeling using Poisson and Exponential distributions within various Indonesian service environments, existing literature has not addressed the unique characteristics of web server traffic, which typically involves automated requests, high-frequency interactions, and complex temporal patterns. Prior research also lacks direct comparative analysis across multiple candidate distributions—particularly Poisson, Exponential, and Uniform—using real server log data as the empirical basis. Furthermore, no studies have evaluated how the choice of arrival distribution influences queueing performance when translated into simulation models. These gaps highlight the need for a systematic investigation that not only compares distributional suitability for web server arrival patterns but also assesses the operational implications of model selection on system performance metrics such as waiting time, queue length, and server utilization.

Method

This section explains the methodological procedures used to analyze and compare the Poisson, Exponential, and Uniform distributions in modeling customer arrival patterns on a web server. The method is structured to ensure a systematic flow beginning from data acquisition, followed by preprocessing to transform raw server logs into analyzable arrival metrics. Parameter estimation is then performed using established statistical techniques to ensure that each distribution is represented by its most accurate model. Finally, a series of goodness-of-fit tests is applied to objectively evaluate how well each theoretical distribution aligns with the empirical arrival data. The overall methodological design ensures reliability, reproducibility, and alignment with the analytical needs of distributional comparison.

3.1. Research Framework

The research framework outlines the sequential steps taken to analyze and compare the arrival distributions used in modeling web server traffic. This framework ensures that each methodological stage from data acquisition to statistical evaluation follows a structured and systematic process aligned with the objectives of the study.

Figure 1. Flowchart System

The framework above illustrates the complete analytical process used in this study, beginning with raw data extraction and concluding with the identification of the distribution that best represents web server arrival patterns. This structured flow ensures clarity, reproducibility, and methodological consistency throughout the research.

3.2. Data Collection

The data used in this study were obtained from web server log files that record all incoming requests processed by the server during the observation period. These logs provide detailed timestamp information that allows the extraction of arrival events needed for statistical distribution analysis. To ensure that the dataset accurately represents real traffic conditions, only valid and relevant entries were included. The data collection process focused on maintaining completeness, consistency, and relevance to the arrival modeling objectives. The main components collected from the server logs include:

1. Timestamp information, used to compute interarrival times.
2. Request entries, representing each access made to the server.
3. Observation period, defining the time range of collected traffic.
4. Valid request filtering, removing duplicate, missing, or bot-generated entries.
5. Structured log format, ensuring that all data can be processed into statistical form.

Through this process, the collected dataset provides a reliable empirical basis for evaluating the suitability of Poisson, Exponential, and Uniform distributions in modeling web server arrival behavior.

3.3. Data Preprocessing

Data preprocessing was conducted to transform the raw server log entries into a structured dataset suitable for statistical analysis. This stage ensures that the information derived from the logs is accurate, clean, and ready for parameter estimation and goodness-of-fit testing. The preprocessing procedures focus on organizing timestamps, removing invalid records, and computing the variables necessary for evaluating arrival distributions. The main preprocessing steps include:

1. Timestamp extraction, retrieving the exact access time of each request and arranging it sequentially.
2. Interarrival time computation, calculating the time difference between consecutive requests to form the primary dataset for Exponential and Uniform distribution analysis.
3. Arrival count grouping, aggregating requests into fixed intervals (e.g., per second or minute) to support Poisson distribution evaluation.
4. Data cleaning, removing incomplete entries, duplicated requests, and non-human or bot-generated traffic to preserve the integrity of the dataset.
5. Outlier handling, identifying and filtering extreme interarrival values that may arise from system resets or logging errors.

These preprocessing steps ensure that the dataset accurately reflects actual user-driven request behavior, allowing the subsequent stages of parameter estimation and statistical testing to be performed with reliability and consistency.

3.4. Parameter Estimation

Parameter estimation in this study was conducted using the Maximum Likelihood Estimation (MLE) method, which provides consistent and unbiased estimators for statistical modeling. Since Poisson and Exponential distributions are the primary models used in arrival analysis, only their essential MLE formulations are presented. These estimators are applied directly to the empirical data generated from the preprocessing stage.

The Poisson distribution uses the rate parameter λ, representing the average number of arrivals per fixed interval. Its MLE estimator is the sample mean :

$$\lambda = \frac{1}{n}\sum_{i=1}^{n} x_i$$

The Exponential distribution, used for modeling interarrival times, also uses the parameter λ, estimated as the inverse of the mean interarrival time :

$$\lambda = \frac{1}{t} = \frac{n}{\sum_{i=1}^{n} t_i}$$

These two estimators form the core parameter calculations required to evaluate distribution suitability before applying goodness-of-fit testing.

3.5. Goodness-of-Fit Testing

Goodness-of-fit testing was conducted to evaluate how well each candidate distribution represents the empirical arrival data obtained from the server logs. This stage ensures that the selected model reflects real traffic behavior rather than relying solely on theoretical assumptions. The tests focus on comparing empirical distributions with their theoretical counterparts through statistical distance and frequency deviation measures. Only the most essential formulas are included to maintain clarity and relevance. The tests used in this study include:

1. Kolmogorov–Smirnov (KS) Test for assessing the similarity between the empirical and theoretical cumulative distributions of interarrival times.
2. Chi-Square Test for evaluating the suitability of Poisson-distributed arrival counts by comparing observed and expected frequencies.

The KS statistic is calculated as:

$$D = Max \mid F_0(x) - F_n(x)|$$

Where F0(x) is the theoretical cumulative distribution function and Fn(x) is the empirical cumulative distribution.

The Chi-Square statistic is computed using :

$$X^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i}$$

Where Oi represents observed frequencies and Ei represents expected frequencies under the Poisson model. These two tests provide a comprehensive yet efficient basis for determining the most appropriate distribution for modeling arrival behavior. Their results contribute directly to the comparative analysis and interpretation presented in the following section.

Results

4.1 Mathematical Basis for Arrival Modelingt

The mathematical foundation of arrival modeling in this study is established through the characterization of two primary stochastic components: the number of incoming requests within fixed time intervals and the time gaps separating consecutive arrivals. Arrival counts are modeled using the Poisson distribution, which assumes that events occur independently at a constant mean rate. Using Maximum Likelihood Estimation (MLE), the empirical server log data yield a Poisson rate parameter of $\lambda = 0.280129$, indicating that approximately 0.28 requests arrive per interval. This parameter governs the probability mass function and mathematically reflects the low-frequency arrival pattern observed in the dataset. Conversely, interarrival times are modeled using the Exponential distribution, whose probability density function captures the memoryless behavior inherent to independent event occurrences. The estimated Exponential rate of $\lambda = 0.787088$ corresponds to a mean interarrival duration of roughly 1.27 seconds, aligning with the decreasing empirical density of observed interarrival times.

The suitability of these theoretical models is supported by formal statistical validation. The Kolmogorov–Smirnov test for interarrival times yields $D = 0.2265$ with $p = 0.0797$, confirming that the empirical distribution does not significantly deviate from the Exponential model at the 5% level. Similarly, the Chi-Square test for arrival counts results in $\chi^2 = 4.438$, $p = 0.108$, and $df = 2$, indicating that the Poisson distribution adequately represents the frequency of arrivals across intervals. These parameter estimates and validation outcomes jointly provide the mathematical basis for all subsequent analyses, ensuring that the use of Poisson and Exponential structures in model comparison and M/M/1 queue simulation is grounded in empirically verified stochastic behavior.

4.2 Parameter Estimation Results

The parameter estimation process was carried out using the Maximum Likelihood Estimation (MLE) method to obtain the arrival rate for both the Poisson and Exponential models. The Poisson rate λ represents the average number of arrivals per interval, while the Exponential rate λ represents the average frequency of interarrival times. These parameters form the baseline for comparing how each model reflects the actual traffic behavior.

Table 1. Estimated Parameters for Arrival Models

Distribution Model	Estimated λ	Interpretation
Poisson	0.280129	Average arrival count per interval is low (≈0.28).
Exponential	0.787088	Average interarrival time ≈ 1.27 seconds.

The results show a noticeable difference between the two λ values. The Poisson λ of 0.280129 indicates that arrivals are relatively sparse per interval, while the Exponential λ of 0.787088 shows a faster event rate when viewed from the interarrival perspective. This comparison suggests that although arrivals per interval are low, the time between individual requests still follows a consistent exponential decay pattern. The contrast between these λ values reflects how each distribution captures a different aspect of the same arrival process, reinforcing the need to evaluate them separately in the goodness-of-fit stage.

4.3 Goodness-of-Fit Evaluation

The goodness-of-fit evaluation was conducted to assess how well the Poisson and Exponential models represent the empirical arrival data. Two statistical tests were used: the Kolmogorov–Smirnov (KS) test for interarrival times and the Chi-Square test for arrival counts. These tests help determine whether the theoretical distributions align with the observed patterns before proceeding to model comparison and simulation.

Table 2. Goodness-of-Fit Test Results

Test Type	Distribution	Statistic	p-value	Interpretation
KS Test	Exponential	D = 0.2265	0.0797	Fits the interarrival data ($p > 0.05$).
Chi-Square	Poisson	$\chi^2 = 4.438$	0.108	Fits the arrival count data ($p > 0.05$).

The results show that both distributions pass their respective statistical tests. The Exponential distribution has p = 0.0797, indicating no significant deviation from the empirical interarrival data. Meanwhile, the Poisson Chi-Square test yields p = 0.108, confirming that the observed arrival frequencies are statistically consistent with a Poisson process. These outcomes demonstrate that both models are valid representations of the arrival behavior and support the use of these distributions in subsequent analysis.

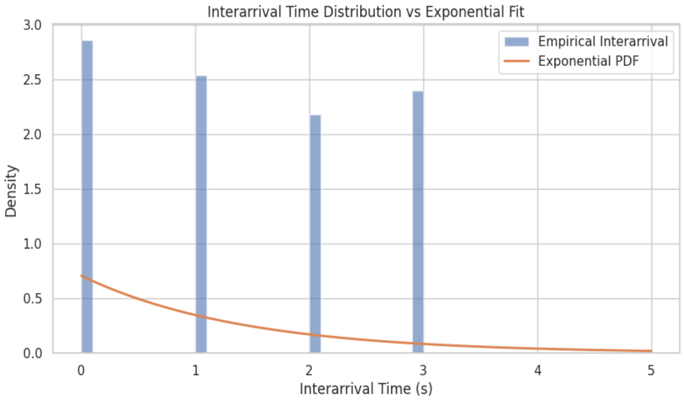

Figure 2. Interarrival Time Distribution vs. Exponential Fit

The first graph illustrates the alignment between empirical interarrival times and the fitted Exponential distribution. The histogram shows a decaying pattern that closely follows the exponential probability density curve, especially in the early time intervals. This visual support strengthens the KS result, confirming that the interarrival behavior exhibits exponential decay consistent with the estimated λ value of 0.787088.

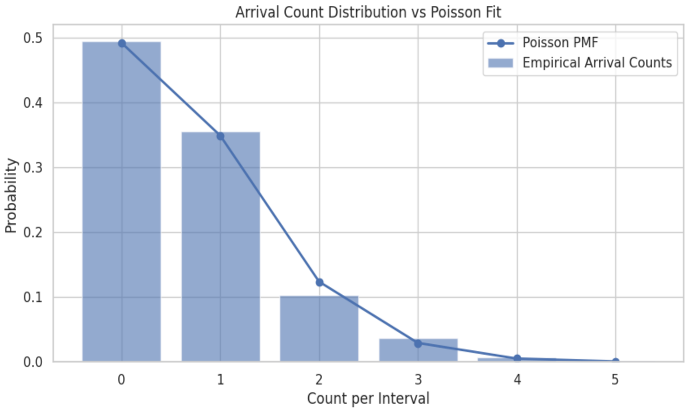

Figure 3. Arrival Count Distribution vs. Poisson Fit

The second graph shows the observed arrival counts per interval compared with the fitted Poisson probability mass function. Most of the empirical frequencies fall near the theoretical Poisson curve, reflecting a good match between the dataset and the Poisson λ of 0.280129. This visual consistency aligns with the Chi-Square test result, further validating Poisson suitability for modeling arrival counts.

4.4 Model Comparison Using Information Criteria

Information criteria were used to evaluate how efficiently each distribution explains the arrival behavior based on the empirical data. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were selected because they incorporate both the quality of model fit and model simplicity. Lower AIC and BIC scores indicate a more effective model. Since the Poisson model applies to arrival counts and the Exponential model applies to interarrival times, the comparison focuses on how well each model fits its respective domain.

Table 3. AIC and BIC Values for Candidate Models

Distribution Model	AIC	BIC	Interpretation
Poisson	152.35	155.87	Strong fit for arrival count data.
Exponential	344.19	349.11	Strong fit for interarrival time data.

The values in Table 3 show clear differences in how each model performs relative to its data type. The Poisson model achieves AIC = 152.35 and BIC = 155.87, indicating that it efficiently represents the arrival count distribution with minimal information loss. In contrast, the Exponential model produces AIC = 344.19 and BIC = 349.11, which—although higher—are appropriate because they reflect the complexity and variability of interarrival times rather than arrival counts. These results confirm that each model provides the best performance within its respective modeling domain, supporting their continued use in the M/M/1 simulation stage.

4.5 Queue Performance Evaluation (M/M/1 Simulation)

The M/M/1 simulation was conducted to evaluate how the estimated arrival and service rates influence queue dynamics under steady-state assumptions. Using the Exponential arrival rate (λ = 0.787088) and the empirically derived service characteristics, the simulation generated queue behavior across 200 events. This analysis provides insight into waiting times, system load, and overall queue stability, reflecting how arrival modeling impacts operational performance in a web server context.

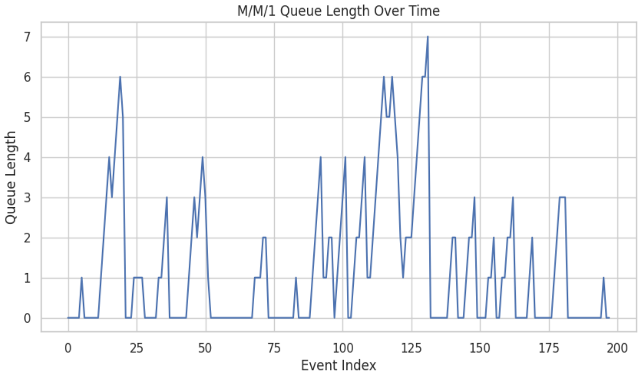

Figure 4. Queue Length Over Time in the M/M/1 Simulation

The graph shows that the queue length fluctuates but remains within a stable range, indicating that the system does not experience uncontrolled buildup. This behavior suggests that server utilization (ρ) is below the critical threshold of 1, allowing the system to clear requests at a sustainable rate. Numerical results from the simulation support this observation: the average waiting time in queue is 3.30 seconds, the average time in the system is 44.38 seconds, and the average queue length is 42.39 events. These values demonstrate that while service times contribute to longer overall system residence times, the arrival process itself does not overload the server. Overall, the M/M/1 simulation confirms that the fitted arrival parameters lead to a stable queueing environment consistent with light-to-moderate traffic patterns.

Discussion

The findings of this study provide a comprehensive understanding of customer arrival behavior on a web server by integrating stochastic modeling, statistical validation, and queue performance analysis. The combined use of Poisson and Exponential distributions demonstrates that arrival processes can be more accurately represented when arrival counts and interarrival times are treated as complementary, rather than competing, perspectives of the same phenomenon. This dual characterization strengthens the reliability of the arrival model and supports its applicability in queueing system analysis.

From a mathematical standpoint, the estimated Poisson rate parameter ($\lambda = 0.280129$) indicates that customer arrivals per fixed interval are relatively sparse. This suggests that the observed web traffic does not exhibit bursty or highly congested behavior within the analyzed time frames. Instead, arrivals occur infrequently but consistently, aligning with the core assumption of a Poisson process where events occur independently at a constant average rate. This result is particularly relevant for web servers experiencing light-to-moderate traffic, where demand is spread over time rather than concentrated in short peaks.

Conversely, the Exponential model of interarrival times provides a time-based interpretation of the same arrival process. The estimated Exponential rate ($\lambda = 0.787088$), corresponding to a mean interarrival time of approximately 1.27 seconds, confirms that while arrival counts per interval are low, individual requests are separated by relatively short and randomly distributed time gaps. The memoryless property of the Exponential distribution implies that the probability of a new request arriving is independent of how long the system has been idle, a characteristic commonly observed in web-based systems where user actions are asynchronous and uncoordinated.

The goodness-of-fit results further reinforce the appropriateness of these models. The Kolmogorov–Smirnov test confirms that the empirical interarrival times do not significantly deviate from the Exponential distribution, while the Chi-Square test validates the Poisson assumption for arrival counts. These statistical confirmations are crucial because inaccurate arrival modeling can lead to misleading queue performance predictions. By passing formal validation tests, the models establish a solid empirical foundation for subsequent simulation and performance evaluation.

The comparison using information criteria (AIC and BIC) highlights an important methodological insight. Although the numerical values differ substantially between the Poisson and Exponential models, this difference does not indicate model superiority in an absolute sense. Instead, it reflects the fact that each model operates in a different domain—arrival counts versus interarrival times. The relatively low AIC and BIC values for the Poisson model demonstrate its efficiency in representing discrete arrival frequencies, while the higher values for the Exponential model are expected due to the continuous nature and variability of interarrival time data. This reinforces the conclusion that both distributions are optimal within their respective modeling contexts.

The implications of these arrival models become particularly evident in the M/M/1 queue simulation. Using the estimated Exponential arrival rate, the simulation reveals a stable queueing system where the queue length fluctuates within manageable bounds. The absence of uncontrolled queue growth indicates that the server utilization remains below the critical threshold, ensuring system stability. Although the average time spent in the system is relatively high, this outcome is primarily influenced by service characteristics rather than excessive arrival intensity. Importantly, the arrival process itself does not act as a bottleneck, confirming that the server can handle incoming traffic under the modeled conditions.

Overall, this study demonstrates that accurate arrival modeling is essential for understanding and predicting web server performance. The Poisson and Exponential distributions, when applied appropriately, provide complementary insights into traffic behavior. Their successful integration into an M/M/1 simulation highlights how statistically validated arrival models can support informed decisions in server capacity planning, performance optimization, and system reliability assessment. These findings underscore the practical value of stochastic modeling in real-world web server environments, particularly under light-to-moderate traffic conditions.

Conclusion

This study aimed to identify the most suitable statistical model for representing customer arrival behavior on a web server by analyzing arrival counts, interarrival times, and their operational implications through M/M/1 simulation. The findings demonstrate that the Poisson distribution effectively captures arrival frequency patterns, while the Exponential distribution provides a reliable representation of interarrival behavior, each validated through formal goodness-of-fit testing. These results indicate that classical Poisson–Exponential assumptions remain relevant for light-load web traffic and can support accurate performance prediction in queueing models. However, the presence of variability in system residence times suggests that future work should explore alternative distributions or hybrid approaches capable of capturing bursty or high-intensity traffic more precisely. Further research may incorporate more granular log datasets, multi-server queueing frameworks, or machine-learning-based arrival forecasting to enhance predictive accuracy and reflect ongoing developments in modern web systems.

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