e-ISSN: 3023-8943
RESEARCH ARTICLE
Vol.3 / **No.**1 / 2026 / **pp.**31-36
https://doi.org/10.69882/adba.iteb.2026015

Parametric Discrete Event Simulation for Performance Evaluation and Decision Support in Production Systems

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ABSTRACT Modern production systems operate under increasing uncertainty due to fluctuating demand, limited resources, and system disruptions such as machine failures and maintenance activities. From an economic and managerial perspective, evaluating the performance of such systems is critical for supporting operational decision-making related to capacity planning, resource utilization, and service efficiency. However, traditional analytical approaches often require restrictive assumptions and fail to capture the dynamic nature of real-world production processes. In this study, a parametric discrete event simulation model is proposed as an a computational/software-based decision support tool for the performance evaluation of a representative production service system. The model captures key operational parameters, including arrival rate, service time, failure probability, and maintenance duration, which directly influence system efficiency and economic performance. The model is evaluated through repeated simulation experiments to obtain statistically reliable performance indicators. In particular, the impacts of variations in service time and arrival rate on business-relevant performance metrics such as average waiting time, system availability, resource utilization, number of failures, and the number of serviced entities are systematically analyzed. The results demonstrate that increases in service and arrival intensities lead to performance degradation, highlighting critical trade-offs between system capacity, operational efficiency, and service quality. The proposed approach provides a practical and computationally lightweight framework for preliminary performance analysis and operational decision support in production and service-oriented systems. In addition to its applicability for early-stage economic evaluation, the model also offers educational value by enabling a clear understanding of discrete event simulation principles within an information systems context.

KEYWORDS
Discrete event simulation
Parametric modeling
Production systems
Performance analysis
Decision support systems

INTRODUCTION

Industrial systems, particularly in the production and service sectors, have become increasingly difficult to analyze due to rising levels of automation, complex workflow structures, and operational conditions characterized by uncertainty. Modern production lines incorporate numerous dynamic components, including machine failures, maintenance activities, variable demand patterns, and human-related factors. Traditional analytical methods used to evaluate and improve the performance of such systems often rely on simplifying assumptions, which may limit their ability to accurately represent real-world system behavior (Caterino *et al.* 2020; Heshmat *et al.* 2017).

In this context, simulation-based approaches provide a powerful alternative for modeling and analyzing complex systems. Simulation enables the examination of a real system or process by replicating its behavior over time. Commonly used simulation approaches in the literature include continuous simulation, Monte Carlo simulation, and discrete event simulation. Among these methods, Discrete Event Simulation (DES) is particularly well suited for production and service systems, where the system state changes only at specific event occurrences (Banks *et al.* 2013; Law *et al.* 2007).

In discrete event simulation, a system is defined through fundamental components such as events, entities, resources, and queues. When an event occurs, the system state is updated and the timing of subsequent events is determined. This structure (Figure 1) allows for the realistic modeling of situations frequently encountered in production environments, including part arrivals, service initiations and completions, machine failures, and maintenance processes (Robinson 2025).

In the existing literature, discrete event simulation is commonly implemented using specialized simulation software or programming-based solutions. Commercial tools such as Arena, Simul8, AnyLogic, and FlexSim are widely used; however, their licensing costs and learning curves may pose limitations in cer-

Manuscript received: 24 October 2025,
Revised: 13 January 2026,
Accepted: 14 January 2026.

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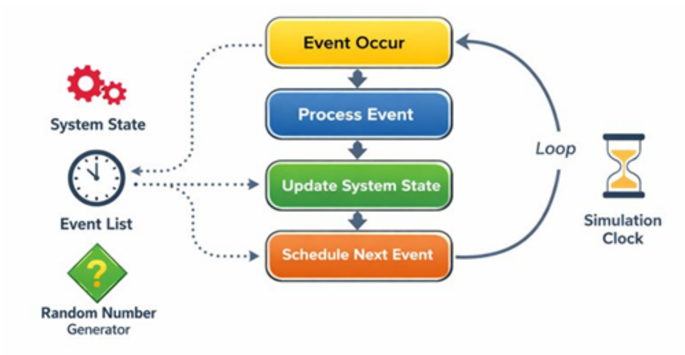

Figure 1 Basic components and event flow of discrete event simulation

tain contexts (Montgomery 2017; Forbus and Berleant 2022). As a result, there is a growing need for simpler and more flexible parametric approaches, particularly for educational purposes and preliminary feasibility analyses in industrial and business-oriented decision-making processes.

Discrete event simulation has been widely used for many years as an effective method for modeling and analyzing complex systems. Particularly in production and service systems, where the system state changes only upon the occurrence of specific events, discrete event simulation is able to represent real system behavior with a high degree of accuracy. Consequently, DES has been applied in the literature across various domains, including production planning, capacity analysis, queueing systems, and the evaluation of maintenance strategies. Negahban and Smith (2014) reviewed simulation-based approaches for the design and operation of manufacturing systems, highlighting the effectiveness of discrete event simulation for performance evaluation and system analysis. Fitouhi *et al.* (2017) evaluated the performance of a two-machine production line with a finite buffer by incorporating condition-based maintenance policies, demonstrating the impact of maintenance strategies on system blocking and starvation probabilities. Zhou and Zha (2024) developed performance evaluation and optimization models for closed-loop production lines that consider preventive maintenance and rework processes, emphasizing the role of maintenance planning in improving system efficiency. Wei *et al.* (2023) analyzed production lines subject to degradation and preventive maintenance from a reliability and performance perspective, revealing the quality-related and other possible costs on overall system performance. De Felice *et al.* (2025) investigated the role of discrete event simulation in supporting digital transformation in manufacturing, showing how simulation-based approaches contribute to the restructuring of industrial systems and decision-support processes. Kleijnen (2015) discussed the design and analysis of simulation experiments by emphasizing the use of metamodeling approaches such as polynomial regression and Kriging to compare different parameter scenarios, support optimization, and enhance decision-making under uncertainty. Similar parametric or reliability-focused approaches have also been applied to production line modeling (Koyuncuoğlu 2024; Cui *et al.* 2022; Waseem *et al.* 2024).

This study aims to examine the fundamental principles of discrete event simulation from a parametric perspective. Instead of employing a full-scale simulation platform, a conceptual discrete event simulation model is developed to represent the core dynamics of production systems. Key parameters such as arrival rate, service time, failure probability, and maintenance duration are incorporated into the model, and their impacts on system performance are systematically investigated. The proposed approach enables the analysis of widely used performance indicators, including average waiting time, system utilization, and production efficiency. Moreover, the parametric structure of the model allows decision-makers and researchers to easily generate and compare alternative operational scenarios. From an information technology and business analytics perspective, the model serves as a practical decision-support tool for evaluating operational performance under uncertainty.

METHODOLOGY AND MODEL DEFINITION

In this study, a discrete event simulation (DES) model is developed based on a single-server queueing structure similar to an M/M/1 system, extended with server failure and maintenance mechanisms. Customer arrivals are modeled as a Poisson process with arrival rate λ, while service times are assumed to follow an exponential distribution with service rate μ. Accordingly, the proposed system adopts the fundamental characteristics of a classical M/M/1 queue; however, the inclusion of server failures and maintenance durations allows for a more realistic representation of operational conditions commonly observed in production and service systems. The simulation model is implemented using the Python programming language and follows the event scheduling approach, in which the dynamic behavior of the system is represented through a chronological list of discrete events. The model explicitly considers customer arrivals, service completions, server failures, and maintenance completions as distinct event types. The system state is updated only at the occurrence of these events, in accordance with the core principles of discrete event simulation.

The proposed simulation framework operates entirely under the event scheduling paradigm, making it particularly suitable for educational and academic analyses as well as preliminary performance evaluations. Rather than continuously tracking system evolution over time, the model focuses on state transitions triggered by events, which enables efficient computation and clear interpretation of system dynamics. Within the parametric modeling framework adopted in this study, the system state is updated exclusively at specific event times. These events are defined as the arrival of entities into the system, the initiation and completion of service processes, the occurrence of server failures, and the execution of maintenance activities. This event-driven structure reflects the discrete and interrupt-driven nature of production systems, where system behavior changes only when operational events occur.

Consistent with the fundamental assumptions of discrete event simulation, the system is analyzed at event instants rather than over continuous time. This approach allows for a realistic and computationally efficient modeling of discontinuous and event-based processes frequently encountered in manufacturing and service environments.

Model Components

The proposed discrete event simulation model is built upon fundamental components that are widely adopted in the simulation literature. The system consists of entities representing jobs or service requests entering the production system, resources representing machines or service providers, and queues in which entities wait for service when resources are unavailable. In addition, events define instantaneous occurrences that trigger changes in the system state. The interactions among these components enable the evaluation of key performance indicators such as waiting times and resource utilization levels.

Parametric Modeling Framework

The simulation model is formulated within a parametric framework to represent key operational characteristics commonly observed in production systems. The primary parameters considered in the model include the arrival rate (λ), average service time (Ts), service rate (μ), failure probability (Pf), and maintenance duration (Tm). This parametric structure allows systematic variation of input parameters and facilitates the comparative analysis of different operational scenarios, making the model suitable for performance evaluation and decision-support purposes.

Event Structure and Time Advancement

In the discrete event simulation framework, system time advances by jumping from one event to the next rather than progressing continuously. Time advancement in the model is achieved by scheduling the occurrence of the next imminent event. The core events considered in the simulation include entity arrivals, service initiation, service completion, server failure occurrence, and maintenance start and completion. The relationships among these events govern the dynamic behavior of the system and enable the computation of performance measures throughout the simulation horizon.

Performance Measures

The performance of the proposed discrete event simulation model is evaluated using a set of commonly adopted metrics in queueing and production system analysis. The primary performance measures considered in this study include the average waiting time of entities in the system, server utilization, the number of serviced entities, and the total number of server failures observed during the simulation horizon. These metrics provide insight into system efficiency, congestion levels, and resource reliability under different parameter configurations. By analyzing variations in these measures, the impact of arrival and service characteristics on overall system performance can be systematically assessed.

Assumptions and Limitations

The proposed simulation model is developed under a number of simplifying assumptions to maintain analytical clarity and computational efficiency. Customer arrivals are assumed to follow a Poisson process, and service times are modeled using an exponential distribution, consistent with the classical M/M/1 queueing framework. The system is assumed to operate with a single server, and entities are served according to a first-come, first-served (FCFS) discipline. Server failures occur probabilistically, and maintenance activities restore the server to an operational state after a fixed repair duration.

While these assumptions enable a clear and interpretable parametric analysis, they also impose certain limitations. The model does not consider multiple servers, priority-based service disciplines, or time-dependent arrival and service processes. Additionally, economic cost factors are not explicitly modeled. Therefore, the results should be interpreted as indicative rather than exhaustive, and the model is primarily intended for conceptual analysis, preliminary evaluation, and educational purposes.

RESULTS

In this section, the results obtained from the developed discrete event simulation model are presented based on replicated simulation experiments. The effects of service time and arrival rate parameters on key system performance measures namely average waiting time, total number of failures, and number of served customers are analyzed separately. In the conducted simulation experiments, a single-server system was modeled with stochastic arrivals and service times, incorporating server failure and repair mechanisms. The global parameters were set as follows: failure probability (Pf) = 0.05, repair time Tm = 3.0 time units, total simulation duration $SIM\_TIME = 1000$, and each scenario was replicated 200 times to obtain reliable average estimates. Thus, Monte Carlo–based simulation framework was adopted, where multiple independent replications were performed to quantify the impact of parameter variability on system performance measures. In the experimental setup, customer arrivals are modeled as a Poisson process with arrival rate λ, while service times follow an exponential distribution with mean service time (Ts). Unless otherwise stated, the arrival rate is fixed at $\lambda = 0.8$ to represent a moderately loaded system, and the effects of varying service time and arrival intensity on system performance are analyzed through multiple simulation replications.

To assess the validity of the proposed discrete-event simulation (DES) framework, an analytical comparison was conducted by disabling machine failures (Pf = 0). Under this condition, the system reduces to a classical M/M/1 queue, where interarrival and service times follow exponential distributions and a single server is continuously available. Table 1 presents a comparison between the average waiting times obtained from the DES model and the corresponding theoretical values derived from the M/M/1 formulation for selected arrival rates (λ) and a fixed average service time (Ts = 1). The theoretical waiting time was computed using the well-known expression $W = \frac{1}{\mu-\lambda}$, where $\mu = \frac{1}{Ts}$.

The results demonstrate a strong agreement between simulation and analytical outcomes, with relative errors remaining below 2% across all tested scenarios. These small discrepancies are primarily attributed to stochastic variability and finite simulation horizon effects. Overall, the close correspondence confirms the correctness of the event scheduling logic, time advancement mechanism, and performance metric calculations employed in the DES model.This validation establishes a reliable baseline for the subsequent analyses, where machine failures and repair processes are introduced and the system behavior deviates from classical queueing assumptions.

Figure 2 illustrates the effect of increasing average service time on the average waiting time in the system. The results reveal a nonlinear and accelerating increase in waiting time as the service time grows. When the average service time is Ts = 1, the average waiting time is approximately 15.20 time units. This value increases to 353.26 time units at Ts = 5 and further rises to 441.11 time units when Ts reaches 10. These findings indicate that longer service times significantly reduce service capacity, leading to rapid queue accumulation and system congestion.

Figure 3 presents the relationship between average service time and the total number of failures. The results indicate a decreasing trend in the number of failures as the service time increases. Specifically, the average number of failures is 39.24 for Ts = 1, decreases to 13.05 at Ts = 5, and further drops to 9.03 at Ts = 10. This behavior can be attributed to the reduction in the number of service initiations under longer service times, which in turn lowers the likelihood of failure occurrences.

Figure 4 shows the effect of service time on the number of served customers. The results demonstrate a significant decline in system throughput as service time increases. While an average

Table 1 Comparison of simulation and analytical outcomes

λ	Ts	DES Avg. wait time	M/M/1 Theory	Error (%)
0.2	1.0	1.2273	1.2500	1.82
0.4	1.0	1.6557	1.6667	0.66
0.6	1.0	2.5090	2.5000	0.36
0.7	1.0	3.3675	3.3333	1.03

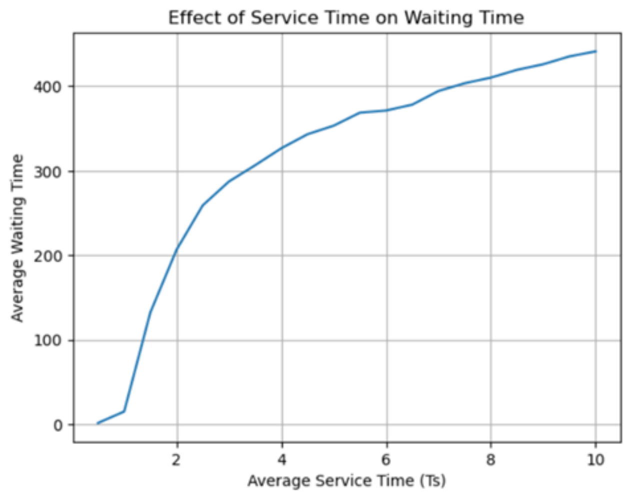

Figure 2 Effect of service time on average waiting time

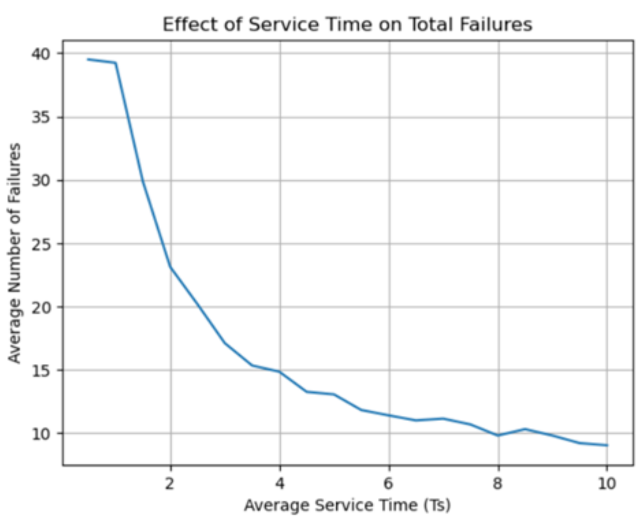

Figure 3 Effect of service time on total number of failures

of 785.8 customers are served when Ts = 1, this number decreases sharply to 257.2 at Ts = 5. At Ts = 10, the system serves only 186.9 customers on average. These results clearly indicate that service time is a critical determinant of productivity and operational efficiency in production and service systems.

Figure 5 illustrates the impact of arrival rate (λ) on the average waiting time. At low arrival rates, waiting times remain minimal; however, as the arrival rate approaches the system's service capacity, waiting time increases dramatically. When λ = 0.1, the

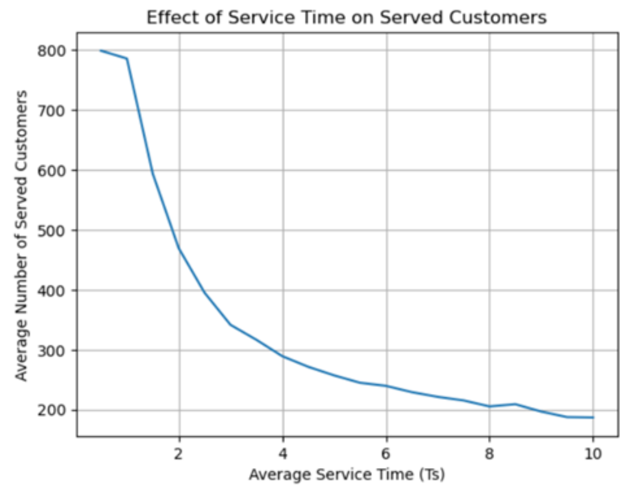

Figure 4 Effect of service time on number of served customers

average waiting time is 1.33 time units, increasing to 2.98 at λ = 0.5. A sharp escalation is observed at higher arrival rates, with waiting times reaching 15.49 at λ = 0.8 and 216.18 at λ = 1.5. These results indicate that the system enters a congestion regime as it approaches saturation.

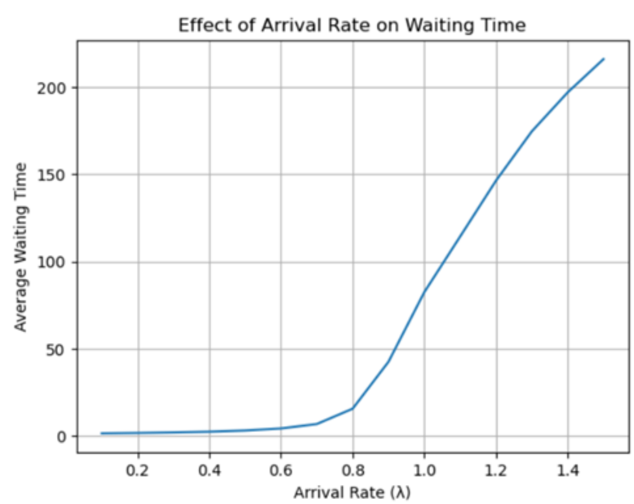

Figure 5 Effect of arrival rate on average waiting time

Figure 6 depicts the relationship between arrival rate and the total number of failures. The results show that the number of failures increases with arrival rate but eventually reaches a saturation level. While the average number of failures is 4.89 at λ = 0.1, it rises to 39.15 at $\lambda = 0.8$. For arrival rates greater than or equal to 0.9, the number of failures stabilizes around 42, suggesting that the system operates continuously under high load and reaches its failure occurrence limit.

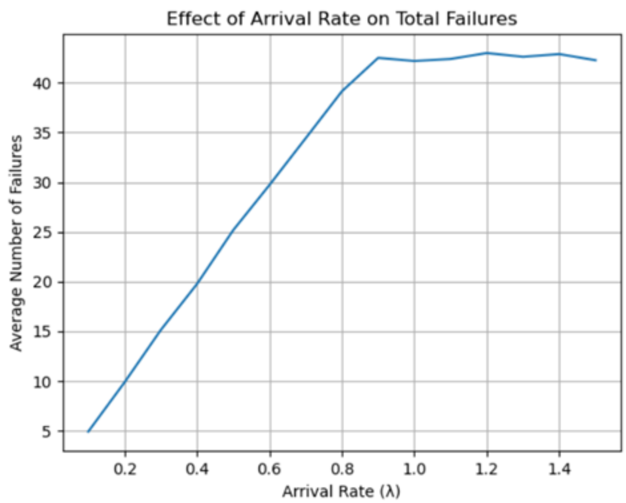

Figure 6 Effect of arrival rate on total number of failures

Figure 7 presents the effect of arrival rate on the number of served customers. As the arrival rate increases, the number of served customers also rises; however, this increase becomes limited beyond a certain threshold. When $\lambda = 0.1$, the system serves an average of 98.4 customers, whereas this number increases to 784.2 at $\lambda = 0.8$. For $\lambda \geq 1.0$, the number of served customers stabilizes in the range of 845–851, indicating that the system has reached its maximum service capacity and additional arrivals do not lead to further throughput gains.

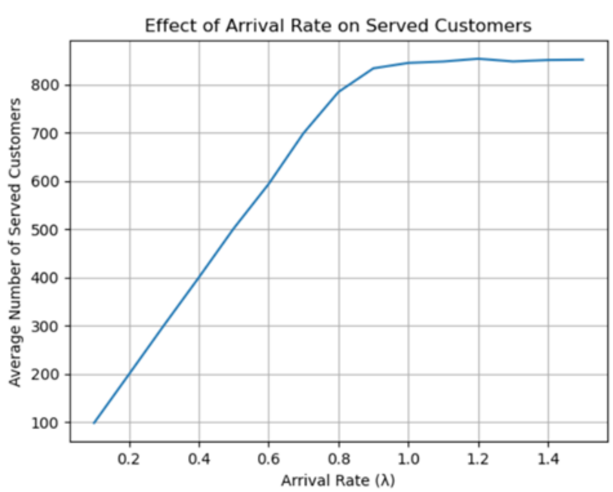

Figure 7 Effect of arrival rate on number of served customers

CONCLUSION

This study presented a parametric discrete event simulation model for analyzing the performance of a single-server production system subject to stochastic arrivals, service times, and failure–repair mechanisms. Without relying on full-scale commercial simulation software, the proposed approach demonstrated how key operational parameters can be systematically evaluated through replicated simulation experiments. The effects of arrival rate and service time variations on system performance were analyzed through a probabilistic sensitivity analysis based on repeated simulation runs. The results clearly showed that service time and arrival rate are dominant factors influencing system performance. Increases in average service time led to a rapid and nonlinear growth in average waiting time, accompanied by a significant reduction in system throughput. Conversely, longer service times resulted in fewer system failures due to a reduced number of service initiations. Similarly, increasing the arrival rate caused waiting times to rise sharply as the system approached saturation, while the number of served customers eventually reached a capacity limit, beyond which additional arrivals no longer improved throughput. The failure behavior under high arrival rates also exhibited a saturation effect, indicating sustained high system utilization.

From a practical perspective, these findings highlight the importance of capacity planning, service time optimization, and workload control in production and service systems. The proposed parametric model provides decision-makers with a simple yet effective tool for exploring "what-if" scenarios and understanding the trade-offs between efficiency, reliability, and congestion under uncertainty. In an economic and business context, such insights can support cost-effective operational planning and risk-aware system design.

Future studies may extend the proposed discrete event simulation framework to more complex system configurations, such as multi-machine production lines, parallel server structures, and batch processing mechanisms. In addition, incorporating human–machine interactions, operator-dependent service times, and learning effects would further enhance the realism and applicability of the model. Such extensions would allow the analysis of more intricate operational dynamics and broaden the relevance of the proposed approach to real-world manufacturing and service systems.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

Not applicable.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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How to cite this article: Sevin, A., Rafiq, M., Munoz-Pacheco, J. M., and Yaman, G. Parametric Discrete Event Simulation for Performance Evaluation and Decision Support in Production Systems. *Information Technologies in Economics and Business*, 3(1), 31-36, 2026.