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ORIGINAL ARTICLE

Congestion Control in Finite-Capacity Time-Dependent Queuing Systems Using Blocking Probability and Capacity-Based Arrival Regulation

Pushpa Itan[1]*, **Vikash Siwach**[1]

1 Department of Mathematics and Statistics, Chaudhary Charan Singh Haryana Agricultural University, Hisar, India

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* **Corresponding author**.

pushpaitan@gmail.com

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Abstract

Objectives: To develop effective congestion-control mechanisms for finite-capacity time-dependent queuing systems operating under fluctuating arrival and service rates. **Method:** A transient $M(t)/M(t)/C/K$ + Control queuing framework is developed and integrated with two arrival-rate control strategies. The first strategy regulates arrivals using the blocking probability, while the second incorporates queue length and system capacity of the queuing system. The governing differential equations are solved numerically using the Fourth-Order Runge–Kutta (RK4) method and validated using real sugar mill data. **Findings:** Numerical results show that both control mechanisms significantly reduce queue length, waiting time, and congestion compared with the uncontrolled system. The queue-length and capacity-based control model demonstrates superior performance under congested conditions, whereas the blocking-probability-based model effectively controls congestion while maintaining system accessibility and utilization. **Novelty:** The study introduces and compares two dynamic arrival-rate control mechanisms within a transient queuing framework, enabling congestion management under time-varying operating conditions. Unlike conventional steady-state approaches, the proposed methodology captures the dynamic behavior of finite-capacity systems and incorporates congestion-aware arrival regulation.

Keywords: Congestion control; arrival-rate control; transient analysis; blocking probability; time-dependent finite-capacity queue; sugar mill operations

1 Introduction

Queuing systems with time-dependent arrival and service rates are frequently encountered in transportation, banking, hospitals, and communication networks, where demand varies significantly over time[(1)]. Furthermore, relatively few studies have investigated dynamic arrival-rate control mechanisms that simultaneously account for blocking probability and queue occupancy for congestion management in finite-capacity, time-dependent queuing systems. This limitation motivates the present study.

Despite the extensive literature on admission-control policies and finite-capacity queuing systems, several important research gaps remain. Most existing studies have focused on F-policy mechanisms, or controllable arrival rates under steady-state conditions [2], [3]. Although these approaches improve system performance, they generally assume constant arrival and service rates and therefore do not accurately represent practical systems in which demand varies continuously over time. Furthermore, previous studies have primarily concentrated on performance evaluation or threshold-based control and have not developed dynamic arrival-control mechanisms that continuously adapt to the instantaneous congestion level in transient finite-capacity queuing systems. Consequently, there remains a need for adaptive control strategies that can reduce congestion under time-varying operating conditions.

To address this gap, the present study develops two dynamic arrival-rate control models for a transient $M(t)/M(t)/C/K$ + Control queuing system. The first model regulates the effective arrival rate using the transient blocking probability, whereas the second model incorporates queue length and available system capacity to continuously adjust customer admissions. The transient governing equations are solved numerically using the Fourth-Order Runge–Kutta (RK4) method, and the proposed methodology is validated using real sugar mill transportation data. Compared with the existing $M(t)/M(t)/C/K$ + Control model, the proposed models provide more realistic congestion management by responding continuously to changes in system conditions, resulting in lower queue lengths, shorter waiting times, and reduced blocking probability. Therefore, the main contribution of this study is the integration of transient queuing analysis with dynamic state-dependent arrival control for finite-capacity systems, providing an effective and practical framework for congestion management in transportation, manufacturing, and other time-varying service systems.

Subhapriya SP and Thiagarajan M [4] introduced a $M/M/1/K$ queuing model that integrates loss and delay characteristics with server vacation mechanisms and controllable arrival rates to enhance system efficiency. Therasal SN and Thiagarajan M [5] considered a finite-capacity system in which arrival rates were controlled by faster and slower Poisson input streams, while service followed an exponential distribution under FCFS (first come first served) discipline. Subhapriya SP and Thiagarajan M [6] introduced a model with a controllable arrival rate. Kumar and Sharma [7] studied the transient behavior of a Markovian queuing system with multiple heterogeneous servers and customer impatience. Tang [8] investigated the transient behavior of a finite-capacity single-server queue with bulk arrivals in IoT-based edge computing systems and derived analytical solutions using an ODE-based recursive technique. Siqueira [9] analyzed $M(t)/M(t)/c(t)/K$ and non-stationary hypercube models to examine the impact of time-varying arrival and service rates on system performance. Zeifman *et al.* [10] analyzed transient and steady-state characteristics of queuing systems modeled by inhomogeneous birth–death processes. Vytovtov *et al.* [11] analyzed the transient behavior of a multi-channel and $M/M/1/K$ queuing system with piecewise-constant arrival and service rates using a translation matrix approach to solve the equations. Kumar [12] analyzed a multi-server Markovian queue with reneging under finite-capacity and finite-population assumptions using a Runge–Kutta numerical approach. The comparison between the uncontrolled and controlled models shows that introducing the accepted arrival rate substantially reduces congestion-related performance measures. In particular, the probability of a full system, the expected queue length, and the waiting time are all consistently lower under the controlled model. Therefore, the accepted-arrival formulation provides a more effective and realistic representation of queue behavior under time-dependent demand. Satin *et al.* [13] developed a non-stationary Markovian queuing model with impatient customers using forward Kolmogorov differential equations.

Tamuli and Das [14] studied about $M/M/1/$N trasient queue with reverse balking and reneging. El-Hadidy and Fakharany [15] developed an iterative algorithm to obtain the transient probabilities of a feedback $M/M/1/N$ queue with balking and retention. El-Hadidy [16] produced a probabilistic dynamical system to detect COVID-19-infected individuals using a Markovian feedback queuing framework. El-Hadidy [17] proposed a quality control approach for selecting an appropriate queue from a set of K-independent $M/M/C/N$ queuing systems. Klimenok and Dudina [18] analyzed a retrial tandem queue with a threshold-based control strategy for repeated attempts. Itan and Siwach [19] investigated optimization-based arrival-rate control for stochastic and time-dependent queuing systems.

2 Methodology

This study develops two congestion-control mechanisms for transient $M(t)/M(t)/C/K$ queuing systems. The proposed models dynamically adjust the effective arrival rate according to blocking probability and queue length information. Their performance is evaluated using real-world sugar mill transportation data.

2.1 *M(t)/M(t)/C/K* Queuing Model

The $M(t)/M(t)/C/K$ [2] model is a generalized form of the classical multi-server queuing system with time-varying parameters and finite system capacity.

Model Description

The system is characterized by the following assumptions:

1. Customers arrive according to a non-homogeneous Poisson process with rate $\lambda(t)$
2. Service times are exponentially distributed with time-dependent service rate $\mu(t)$
3. The number of servers are C
4. The system has a finite capacity K, including both waiting and service positions
5. If the system reaches capacity K, newly arriving customers are blocked or lost

2.2 Proposed Model: *M(t)/M(t)/C/K* + Control

To overcome the limitations of the classical model, a control mechanism is introduced that dynamically regulates the arrival rate based on the system state.

Model Description

The proposed model modifies the arrival process by introducing a state-dependent control function**.** The main features are:

- Arrival rate is controlled dynamically, denoted by $\lambda_c(t) = \lambda(t) - \alpha(t)$, where $\alpha(t)$ is control function.
- Service rate μ(t) may be time-dependent or constant
- Number of servers C is considered fixed.
- System capacity remains finite K
- Control mechanism prevents system overload

Model Structure

The system is modeled as a finite-capacity+control and time-dependent queue of the form: $M(t)/M(t)/C/K+$ Control, where both arrival and service rates are functions of time.

2.3 State Representation

Let $P_n(t)$denote the probability that there are n customers in the system at time t. The state space is defined as: $n = 0, 1, 2, \ldots, K$

2.3.1. Model 1: Blocking-Probability-Based Control

The controlled arrival rate is defined as

The arrival rate is controlled using the probability of system saturation.

$$\lambda_c(t) = \lambda(t)\left((1 - P_K(t))^{\gamma}\right) \qquad \gamma \geq 0$$

$P_K(t)$ is the probability of *n* customers at time *t* in the system. This provides strong control when the system approaches full capacity.

2.3.2. Queue-Length and capacity Based Control model2

The arrival rate is adjusted based on the current queue length and capacity.

$$\lambda_c(t) = \lambda(t)\left(1 - \left(\frac{L_q(t)}{K}\right)^{\beta}\right) \qquad \beta \geq 0$$

This control ensures smooth reduction in arrivals as congestion increases. The model reduces arrivals whenever blocking probability increases.

Governing differential equation can be written as

$$P_n(t) = P_r(N(t) = n) \quad n = 0, 1, 2 \quad \ldots K$$

$P_n(t)$ is the probability of n customer at time t in the system.

Where

$$\lambda_c(t) = \lambda(t) - \alpha(t)$$

For $n = 0$

$$\frac{dP_0(t)}{dt} = -P_0(t)(\lambda(t) - \alpha(t)) + P_1(t)\mu(t) \tag{1}$$

For $1 \leq n < C$

$$\frac{dP_n(t)}{dt} = -(\lambda_c(t) + n\mu(t))P_n(t) + \lambda_c(t)P_{n-1}(t) + (n+1)\mu(t)P_{n+1}(t) \tag{2}$$

For $1 \leq n \leq K-1$

$$\frac{dP_n(t)}{dt} = -(\lambda_c(t) + C\mu(t))P_n(t) + \lambda_c(t)P_{n-1}(t) + C\mu(t)P_{n+1}(t) \tag{3}$$

For $n = K$

$$\frac{dP_K(t)}{dt} = -P_K(t)C\mu(t) + P_{K-1}(t)\lambda_c(t) \tag{4}$$

2.4 Numerical Solution Procedure

The transient differential equations (1-4) are solved using the Fourth-Order Runge–Kutta (RK4) method.

Algorithm
Step 1: Initialize $\lambda(t), \mu(t)$, C and K.
Step 2: Set initial state probabilities.$P_0(0) = 1$.
Step 3: Compute controlled arrival rate.
Step 4: Solve state probability equations using RK4.
Step 5: Compute performance measures.
Step 6: Repeat for all time intervals.
Step 7: Plot performance measures using MATLAB

Table 1. Symbols and formulae for estimation of queuing characterstics

Symbol	Meaning	Formulae
$L_s(t)$	Expected number of customers receiving service	$\sum_{n=0}^{C} np_n(t) + \sum_{n=C+1}^{k} Cp_n(t)$
$L_q(t)$	Expected queue length	$\sum_{n=C}^{k} (n-C)p_n(t)$
$L(t)$	Expected number of customers in system	$L_s(t) + L_q(t)$
$W_q(t)$	Expected waiting time in queue	$\frac{L_q(t)}{(\lambda(t)-\alpha(t))}$
$W(t)$	Expected waiting time in system	$W_s(t) + W_q(t)$
$\overline{L_q}(t_1, t_2)$	Average queue length for non empty queues	$\frac{\int_{t_1}^{t_2} \sum_{n=c}^{K} (n-c)p_n(t)dt}{(t_2-t_1)}$
$\overline{W_q}(t_1, t_2)$	Average waiting time	$\frac{\overline{L_q}(t_1,t_2)}{\lambda(t)(1-P_K(t)}$
$\overline{L}(t_1, t_2)$	Average number of vehcles in system	$\overline{L_q}((t_1,t_2)) + \overline{L_s}((t_1,t_2))$
$\overline{L_s}((t_1, t_2))$	Average number of customer receiving service	$\frac{\int_{t_1}^{t_2} L_s(t)dt}{(t_2-t_1)}$
$\overline{P_0}(t_1, t_2)$	Average idle time	$\frac{\int_{t_1}^{t_2} P_0(t)dt}{(t_2-t_1)}$

2.5 Case Study: Sugar Mill Transportation System

The proposed control models were evaluated using operational data collected from a sugar mill transportation system. In this system, vehicles carrying sugarcane arrive at the mill for unloading and processing. Due to fluctuations in harvesting schedules, transportation availability, and operational conditions, both arrival and service rates vary significantly over time, making the system inherently time-dependent.

The unloading facility was modeled as a finite-capacity $M(t)/M(t)/C/K$ queuing system, where (K) represents the maximum number of vehicles that can be accommodated within the system, including those receiving service and those waiting in the queue. Since the available waiting space is limited, arrivals occurring when the system reaches capacity are blocked. Therefore, system capacity (K) plays a critical role in determining congestion levels and overall system performance.

3 Results and Discussion

3.1 Time-Dependent Arrival and Service Rates

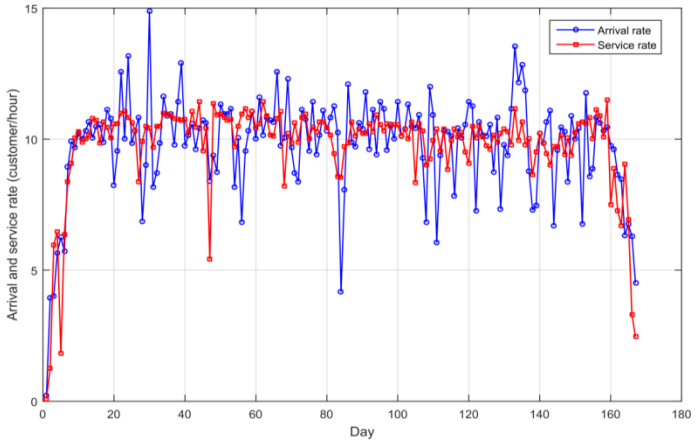


Fig 1. Arrival and service rates of the customers in the Sugar Mill System

Figure 1 represents the time-dependent behavior of the arrival rate $\lambda(t)$ and service rate $\mu(t)$ over the 166 days of the sugar mill system. The horizontal axis represents time in days, while the vertical axis represents the corresponding arrival and service rates as number of customer.

From Figure 1, it is clear that both the arrival and service rates vary over the time horizon, indicating the system's highly transient nature. In the initial days, arrival and service rates are relatively low because the system's activity is low when starting up, and at that time, both rates are zero since no customers are arriving. As time passes, both rates increase rapidly and stabilize at moderate to high levels, reflecting the sugar mill's active operational phase during the crushing season. Several peaks in the arrival rate curve indicate a large number of VEHICLES arrive in the system.

3.2 Comparative Transient congestion control (g based) Analysis

3.2.1. Comparison between model1 for different values of g and existing model

Figure 2 represents the transient behavior of the expected queue length for different values of the control parameter γ = 1, 5, 10, 20 and 50 over a time horizon measured in days. The horizontal axis represents time in days, and the vertical axis represents the expected number of customers in the queue. Figure 2 also compares the controlled and uncontrolled behavior in terms of queue length. For different values of γ, the graph has a different nature: a high value of γ implies greater extension, while lower values imply less control. The fluctuations in the graph are due to the time-dependent behavior of arrivals and service. During the early period, the queue length rises rapidly due to increasing customer arrivals and temporary congestion buildup.

Figure 3 shows the waiting time for the controlled and uncontrolled models with different parameter values of γ. Figure 3 clearly demonstrates the control parameter γ significantly influences the waiting time performance of the queuing system. For greater values of γ, smaller waiting time means customers experience a lower waiting time in the queue, and for small values, experience a longer waiting time. All curves for the controlled model remain below the uncontrolled model.

Figure 4 illustrates the transient behavior of the idle probability $P_0(t)$ for different values of the parameter γ: 1, 5, 10, 20, and 50. Over a time horizon measured in days. The graphical results for the parameter γ provide a detailed understanding of the transient performance of the queuing system in terms of expected queue length $L_q(t)$, expected waiting time$W_q(t)$, and idle

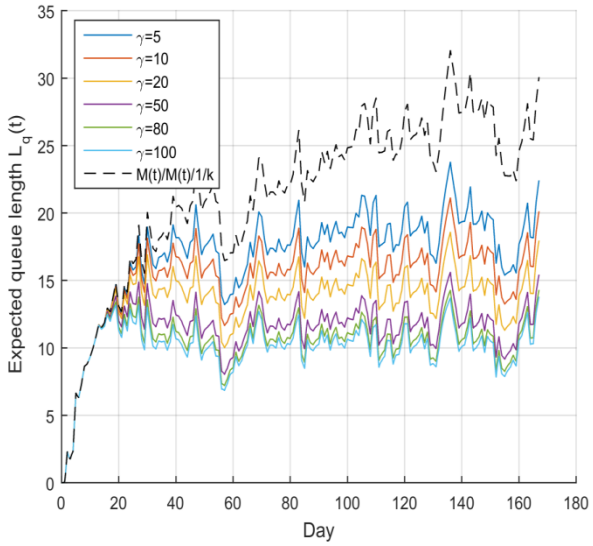


Fig 2. Comparison of queue length between existing model and control model1.

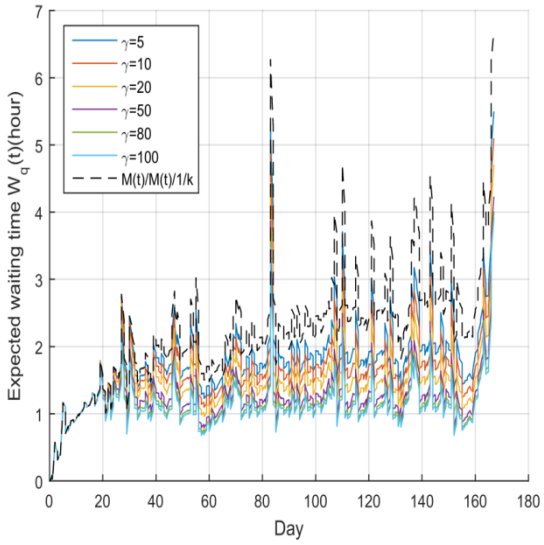


Fig 3. Comparison of waiting time between existing model and control model1.

probability $P_0(t)$. The analysis clearly demonstrates that the parameter γ significantly influences queue length, waiting time, and the probability of being idle over the planning horizon.

In the expected queue length and waiting time graph, all curves initially start from zero because the system begins when customers start arriving. As time increases, the queue length rises rapidly during the early transient phase and later fluctuates due to the stochastic and time-dependent nature of arrivals and services. For the smallest value γ=1, the queue length remains the highest among all the considered cases. The curve in Figure 2 fluctuates approximately between 16 and 29 customers and remains very close to the dashed reference curve $M(t)/M(t)/1/K$, indicating heavy congestion and larger customer accumulation. When γ, the queue length decreases moderately and fluctuates approximately between 14 and 22 customers. For an increase in $\gamma = 10$, the queue length further decreases and mostly remains between 13 and 20 customers. The cases $\gamma = 20$ and $\gamma = 50$ show a substantial improvement in system performance. In particular, $\gamma = 50$ produces the smallest queue lengths, and waiting time generally fluctuates between 9 and 14 customers, indicating strong congestion control.

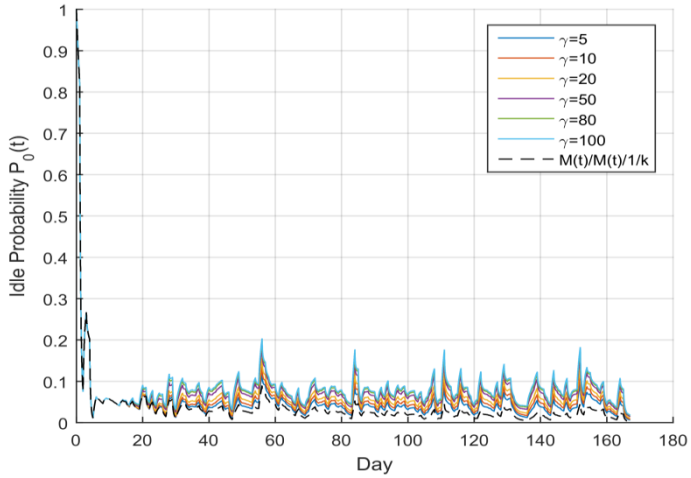


Fig 4. Comparison of idle probability between existing model and control model1.

3.3 Comparative Transient congestion control (b based) Analysis

3.3.1. Comparison between model2 with different values of b and existing model

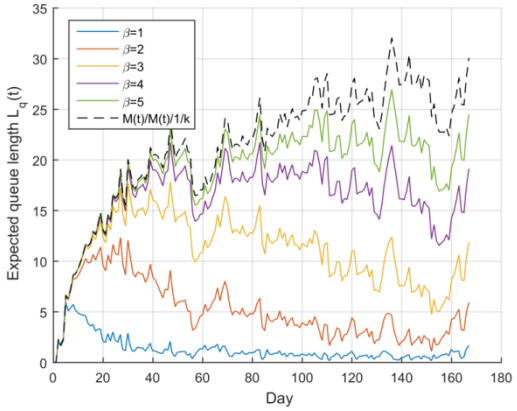


Fig 5. Comparison of queue length between existing model and control model2.

In the Figure 5, the x-axis represents time, and the y-axis represents the expected number of customers waiting in the queue. Figure 5 shows the queue length for different β values (controlled parameter) and examines the impact on queue length as β increases. Also, Figure 5 compares the control and uncontrolled (existing) models, from Figure 5 it is clear that the queue length is progressively controlled across different values of β. As a low β, indicates high control, whereas a higher β, indicates low control. The fluctuations in this graph are due to the transient behavior of the arrival rate.

Figure 6 shows the waiting time of customers in the queue. Horizontal line represents the time, and vertical line represents the waiting time of the customers. As the waiting time is initially is very low because in starting, there is no customer after time progress the waiting time is also increase as queue builds up, and we see the effect of different controlled parameter values on the waiting time as the β values is high the waiting time is also high and the low value of β is minimum waiting time. It is observe that all parameter values of β successively reduced the waiting time.

Figure 7 illustrates the transient behavior of idle probability. For the uncontrolled or existing model, a very high idle probability means the system is very busy. In a controlled system, this probability is greater than in the existing model because, after controlling, the queue is reduced, thereby increasing this probability.

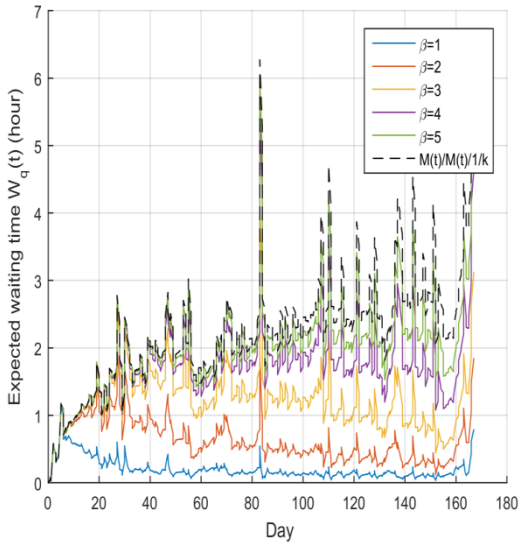


Fig 6. Comparison of waiting time between existing and control model2.

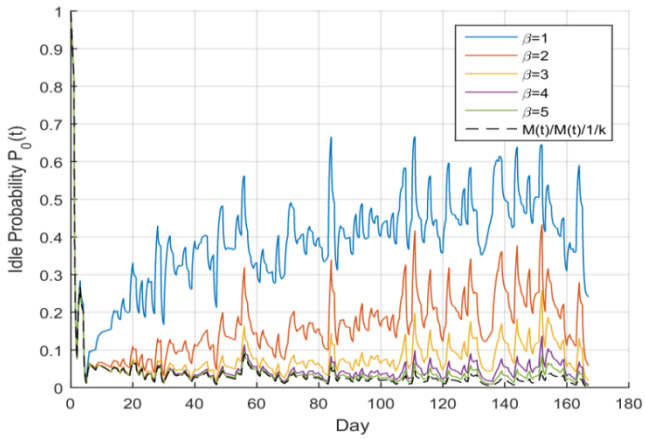


Fig 7. Comparison of idle probability between existing model and control model2

Previous studies have investigated admission-control policies for finite-capacity queuing systems using threshold mechanisms, F-policies, or controllable arrival rates. Jain and Sanga[2] analyzed an admission-control policy with retrial customers under state-dependent rates, while Therasal and Thiagarajan[3] developed a finite-capacity queue with controllable arrival rates and server breakdowns. Although these approaches improve system performance, they primarily focus on steady-state analysis, specific admission policies, or transient performance evaluation. In contrast, the proposed models continuously regulate the arrival rate according to the instantaneous blocking probability and queue occupancy, enabling proactive congestion control under time-varying operating conditions.

Overall, the proposed models advance by combining transient queuing analysis with continuous state-dependent arrival control for finite-capacity systems. Unlike conventional stationary models, threshold-based admission policies, or approximation methods, the proposed framework actively regulates customer arrivals according to the current system state, resulting in more effective congestion management and improved operational performance. The integration of dynamic control, transient numerical analysis using the Fourth-Order Runge-Kutta method, and validation with real industrial data represents the primary novelty and practical contribution of this research.

The blocking-probability-based control strategy (Model 1) regulates arrivals according to the probability that the system reaches full capacity. When the blocking probability is small, the effective arrival rate remains close to the original arrival rate, allowing customers to enter the system with minimal restrictions. However, as the blocking probability increases during peak demand, the arrival rate is progressively reduced. This adaptive mechanism prevents additional customers from entering an already congested system, thereby reducing blocking probability, limiting queue growth, and improving overall system stability. Consequently, fewer customers experience excessive waiting, and the probability of the system operating near saturation is considerably reduced.

The queue-length-and-capacity-based control strategy (Model2) responds directly to the current queue length relative to the maximum system capacity. During periods of low congestion, when the queue length is much smaller than the system capacity, the controlled arrival rate remains close to the original arrival rate. As the queue length approaches the system capacity, the arrival rate is gradually reduced according to the proposed control function. This gradual reduction prevents rapid queue growth before the system becomes fully congested. Compared with the blocking-probability-based strategy, Model 2 reacts earlier because queue length serves as an immediate indicator of congestion rather than waiting until blocking becomes significant.

The comparison between the two control strategies indicates that both models effectively reduce congestion compared with the uncontrolled system. However, their operating principles are fundamentally different. Model1 primarily controls customer admissions after the probability of system saturation increases, whereas Model2 continuously adjusts arrivals according to the queue length throughout the operating period. Consequently, Model2 generally achieves lower queue lengths and shorter waiting times because congestion is controlled before the system reaches its maximum capacity.

The practical application of the proposed models to the sugar mill unloading system demonstrates their effectiveness in real operational environments. During the crushing season, truck arrivals vary considerably because of harvesting schedules, transportation delays, and operational uncertainties. Without arrival regulation, these fluctuations lead to long truck queues and increased unloading delays. The proposed arrival-control strategies reduce these operational bottlenecks by regulating truck arrivals according to the current congestion level. As a result, unloading operations become more balanced, vehicle waiting times are reduced, and the available unloading facilities are utilized more efficiently.

Therefore, the proposed methodology offers an effective and computationally efficient framework for congestion management in time-dependent queuing systems and can be extended to other applications such as manufacturing systems, transportation terminals, healthcare services, warehouses, and logistics operations.

4 Conclusion

This study developed two arrival-rate control mechanisms for transient finite-capacity queuing systems. It demonstrated that both approaches improve system performance by reducing congestion and waiting times. The blocking-probability-based model provides efficient congestion regulation, while the queue-length and-capacity-based model offers stronger control when the system approaches capacity. The proposed methodology provides a practical framework for congestion management in time-dependent service and production systems.

In model 1 for$\gamma = 1$, the idle probability remains the lowest among all cases, fluctuating approximately between 0.01 and 0.08, indicating that the system is busy for nearly 92% to 99% of the time. This indicates a heavily loaded system with a high queue length. As the value of γ increases, the idle probability gradually rises. For $\gamma = 5$ and $\gamma = 10$, the idle probability fluctuates roughly between 0.02 and 0.12, showing moderate improvement in server relaxation. The cases $\gamma = 20$ and $\gamma = 50$ exhibit the highest idle probabilities. In particular, $\gamma = 50$ ranges approximately from 0.03 to 0.18, indicating that the server remains idle for 3% to 18% of the time similary model2 also reduced waiting time and queue length also.

The novelty of this study lies in the integration of two dynamic arrival-rate control mechanisms within a transient $M(t)/M(t)/C/K$ + Control queuing framework. Unlike conventional steady-state congestion-control approaches, the proposed methodology captures the system's time-dependent behavior and regulates the arrival rate on real-time congestion conditions, thereby providing a more realistic and effective congestion-control strategy for finite-capacity service systems.

No conflict of interest

References

1) Dudin A, et al. Algorithmic Analysis of Queueing System with Varying Arrival and Service Rates in a Markovian Random Environment. *Computation*. 2025;13(7):154. https://doi.org/10.3390/computation13070154.
2) Jain M, Sanga SS. Admission control for finite capacity queueing model with general retrial times and state-dependent rates. *Journal of Industrial & Management Optimization*. 2020;18(2):861–889. https://doi.org/10.3934/jimo.2019073.
3) Therasal SN, Thiagarajan M. Poisson input and exponential service time finite capacity interdependent queueing model with breakdown and controllable arrival rates. *Indian Journal of Science and Technology*. 2024;17(12):1167–1179. https://doi.org/10.17485/IJST/v17i12.2852.

4) Subhapriya SP, Thiagarajan M. M/M/1/K loss and delay interdependent queueing model with vacation and controllable arrival rates. *Indian Journal of Science and Technology*. 2024. https://doi.org/10.17485/IJST/v17i6.1691.
5) Subhapriya SP, Thiagarajan M. M/M/1 Interdependent Queuing Model with Vacation and Controllable Arrival Rates. *Indian Journal of Science and Technology*. 2024;17(14):1497–1506. https://doi.org/10.17485/IJST/v17i14.251.
6) Rahim KH, Thiagarajan M. M/M (a, b)/1 Model of Interdependent Queueing With Controllable Arrival Rates. *Indian Journal of Science and Technology*. 2023;16(37):3100–3109. https://doi.org/10.17485/IJST/v16i37.1259.
7) Kumar R, Sharma S. Transient analysis of a Markovian queuing model with multiple-heterogeneous servers and customers' impatience. *OPSEARCH*. 2021;58(3):540–556. https://doi.org/10.1007/s12597-020-00495-0.
8) Tang S. Transient Analysis of a Finite Queueing System with Bulk Arrivals in IoT-Based Edge Computing Systems. *IoT*. 2022;3:435–449. https://doi.org/10.3390/iot3040023.
9) Siqueira RM. M(t)/M(t)/m(t)/C(t) and non-stationary hypercube models. *GEPROS Gestão da Produção, Operações e Sistemas*. 2022;17(1):112–146. https://doi.org/10.15675/gepros.v17i1.2864.
10) Zeifman A, Satin Y, Usov I, Sztrik J. Computation of Transient and Steady-State Characteristics of Queueing Systems with Different Types of Customer. *Computation*. 2025;13(6):150. https://doi.org/10.3390/computation13060150.
11) Vytovtov KA, Barabanova EA, Vishnevsky VM. Modeling and analysis of multi-channel queuing system transient behavior for piecewise-constant rates;vol. 13766. Springer Nature Switzerland AG. 2022. https://doi.org/10.1007/978-3-031-23207-7_31.
12) Kumar B. Transient analysis of M/M/C queuing model with reneging, finite capacity and population. *International Journal of Mathematics in Operational Research*. 2022;21(1):1–25. https://doi.org/10.1504/IJMOR.2022.120339.
13) Satin Y, Zeifman A, Sipin A, Ammar SI, Sztrik J. On probability characteristics for a class of queueing models with impatient customers. *Mathematics*. 2020;8(4):594. https://doi.org/10.3390/math8040594.
14) Vytovtov K, Barabanova E, Vishnevsky V. The analytical method of transient behavior of the M/M/1/n queuing system for piece-wise constant information flows;vol. 13144. Springer. 2021. https://doi.org/10.1007/978-3-030-92507-9_15.
15) Tamuli A, Das D. Transient analysis and cost optimization in single server Markovian queuing system with reverse balking and reneging. *Sankhyā B: The Indian Journal of Statistics*. 2025;87(2):367–399. https://doi.org/10.1007/s13571-025-00368-w.
16) El-Hadidy MAA, Fakharany M. A transient analysis algorithm to control the quality and performance of the queuing system. *Journal of the Egyptian Mathematical Society*. 2021;29(1):683–700. https://doi.org/10.1080/16843703.2021.1932053.
17) El-Hadidy MAA. Developing a detection model for a COVID-19 infected person based on a probabilistic dynamical system. *Mathematical Methods in the Applied Sciences*. 2021. https://doi.org/10.1002/mma.7443.
18) El-Hadidy MAA. Quality control for a detected an appropriate queue from K-independent M/M/C/N queueing models. *Quality and Reliability Engineering International*. 2020;36(8):2669–2683. https://doi.org/10.1002/qre.2728.
19) Itan P, Siwach V. Optimal Control of Arrival Rates in a Queueing Model with Stochastic and Time Dependent Demand. *Indian Journal of Science and Technology*. 2026;19(8):568–573. https://doi.org/10.17485/IJST/v19i8.82.