IoT Driven Queueing System: Analyzing Customer Behavior for Optimal Service Management

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Abstract

The integration of Internet of Things (IoT) technology in queueing systems has transformed customer service management by enabling real-time data collection, analysis, and decision-making. IoT-driven solutions facilitate efficient queue management, reduce wait times, and enhance customer satisfaction through predictive analytics and automated service adjustments. This paper synthesizes existing research on IoT-based queueing systems, focusing on customer behavior analysis and service management strategies. By leveraging IoT data analytics, businesses can implement optimal service management strategies such as service time optimization, intelligent staff allocation, and dynamic queue adjustments. Additionally, IoT-based queueing models help businesses predict congestion and improve service efficiency. This study also explores the role of artificial intelligence (AI) and machine learning (ML) in enhancing IoT-enabled queueing systems. Key challenges, including security, privacy concerns, and system scalability,

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are identified as critical areas for future research. The paper provides a comprehensive overview of advancements in IoT-driven queueing systems and their impact on customer behavior and service management, offering insights for researchers and industry practitioners.

Keywords: Queueing systems, IOT, customer behaviour.

1 Introduction

Queueing systems are extensively used to analyze the behaviors of people involved in several applications. A proper understanding will enhance the system's performance for better business governance and controls. In the early days, researchers have shown their interest in analyzing the queueing system behavior by taking one of the important features of real-life queueing. The importance of the customer's arrival is understandable in many practical queueing systems. In service management, understanding the customer's behavior and availability is one of the key factors concerning serving the customers effectively. IoT is now populated in all sectors and it generates volumes of data, and its potential usage is unimaginable. In most supermarkets, ATMs, fast food centers, and restaurants, internet facilities connected with mobiles and laptops are equipped with the server facility. In these places, the customer's arrival can be very volatile. The service capacity is maintained by the corresponding managers or the service providers. Optimal service can be provided with minimal resources. The functionality of this ample amount of queueing systems is based on analyzing the customer's behavior. The behavior of the individual customer's availability poses a remarkable support towards service management. When a queue is established, the order in which clients are selected to receive service is referred to as the queue discipline. Commonly used queue disciplines are mentioned in Figure 1.

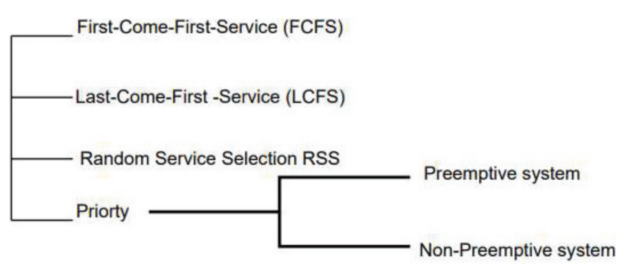


Figure 1 Queue discipline.

This research divulges one of the most important topics on queueing systems, understanding the customer's behavior to analyze their optimal service strategies. IoT technology plays a crucial role in enhancing queueing systems by enabling efficient traffic management and congestion control through innovative algorithms and adaptive strategies. The integration of IoT sensors and machine learning algorithms in traffic control systems allows for real-time data collection, analysis, and decision-making, leading to improved throughput, reduced delays, and minimized packet loss [1, 2]. [3] focused on the single server M/M/1 fuzzy queueing model having fuzzified exponentially distributed inter-arrival time and service time service time with fuzzy catastrophe. The research focus is to analyze customer behavior in a queueing system for better service allocation. This means that the server in the analyzed system has to adapt its behavior to what to expect from its customers. Any insights regarding customer behavior are likely to improve the service.

The integration of IoT in queueing systems allows for the analysis of customer behavior to optimize service management effectively. By incorporating the Internet of Behavior principles, logistics companies can track and analyze behavioral patterns to enhance Customer Relationship Management (CRM) [4]. Additionally, intelligent queue management systems based on IoT networks can proactively manage customer flow, ensuring better service quality and satisfaction [5]. Strategic customer behavior in service systems is a dynamic trend in queueing theory, emphasizing the importance of understanding and influencing customer decisions through mechanisms like pricing structures and information control [6]. Furthermore, the Internet of Behaviors (IoB) model emphasizes human behavior in engineering intelligent systems, showcasing successful implementations in real-life scenarios like crowd monitoring and queue management systems, demonstrating the potential for continuous learning and adaptation based on human behavior patterns [7].

2 Understanding IoT in Queueing Systems

The scope of the IoT has to be first ascertained, which includes various definitions and components. The development of various products and their integration with physical components has evolved as the Internet of Components (IoC). On the other hand, incorporating a view of IoT, the term Internet of Products (IoP) is depicted by incorporating some value-added services such as customizations, personalization (if IoT has associations with humans and services), etc., and their progression. In a network view of things in IoC and IoP, IoT is more complex since it envisions a service that offers a new range of services through human intervention that leverages its properties more effectively via remote monitoring and control of things.

In our daily lives, there are multiple applications of IoT and its variants, namely IoC and IoP, visible such as security systems, grocery list monitoring, and city transport management. Despite the variety and scope of these IoT applications, an IoT-presented transformation of widely discussed research areas like queueing systems will offer new capabilities in formulating service strategies that are laced with valuable insights of widespread. In this exploration, the primary focus of the system is the footfall in the shopping area, offices, service centers, etc., and the key statistical feature of the systems based on customer populations entering the physical space and their treatment times process in formulating service policies that involve providing access to the requesting customers.

2.1 Definition and Components of IoT

Internet of Things (IoT) refers to a wide-ranging collection of globally interconnected smart entities (gadgets, vehicles, buildings, home appliances, industry control gears, healthcare appliances, and so on) that are capable of direct or indirect interaction with globally interconnected communication and data transmission technologies (like radio frequency identifications, sensors, actuators, and other related surveillance resources and accessories) to achieve several targeted aims and objectives such as controlling, surveying, and observing global abnormalities, inter-gadget communication, decision-making, learning, data storage, and other purposes in society.

An IoT ecosystem mainly comprises metrics (IoT gadgets, IoT sensors, and device components), communication resources (GSM/CDMA components, network utilities, Ethernet ports, and RFC), application-specific gizmos like computerized surveillance cameras, automatic Google Glass, smart healthcare gadgets, RFID gadgets, automatic light and fans, smart water supply gases, and power management components, and several other gadgets.

In addition to this, an IoT zone mainly includes several application-specific technologies and useful components, protocols, standards, analysis or metrics evaluation section, censor (for converting the received signals into any application-specific model), communication and analysis tools, etc. An evolved IoT ambiance mainly comprises several sub-IoT zones, and each may include one or more sensed or looked-out application domain(s). All the zones of an IoT environment are capable of working in an interactive mode from an owned as well as operative viewpoint for the sake of dominant operations over remote distances, quality of service communicated information products, resolution of problems, etc. Finally, these zones may, in certain cases, guide the related data to an integrated IoT Zone accessible through the internet, for which various services like Google services and Torrent services are available all together at one single location. Thus, from the above brief sketch, it is clear that an IoT ecosystem provides us the flexibility and capability of achieving Interzone dominant operations for quality services at one or more application-dependent IoT-based zones in an era of globalization.

2.2 Applications of IoT in Queueing Systems

Owing to the advancements in technology, IoT is influencing daily as well as organizational activities in a very significant way. IoT can be employed to connect objects, people, and computing networks, which in turn makes it possible to analyze customer behavior and provide suitable services. Some of the applications where IoT is increasingly capturing the attention of service providers, especially in the service industry, are: IoT in healthcare to collect body parameters and report appropriate signals; IoT in customer services to provide different objects as per interests; IoT in environmental parameter sensing to take preventive measures of natural calamities such as flood, fire, pollution, etc. IoT measures in traffic congestion help to get the best possible path. Expedite movement of goods is important to facilitate and improve customer services. A queueing system is one of the important tools to manage services effectively. Because of the growing interest in the application of IoT in various queueing systems to obtain customer behavior, in the second part, the IoT application is discussed.

The main objective of these applications is to connect different types of objects via the internet as well as IP connectivity, so that a network can be formed, and communication can be carried out among both the data as well as the services. The connections, work, energy consumption, environmental issues, and efficiency in each of the above applications are possible through the operations performed through IoT. The basic motive for linking them through IoT is to have an improvement in the total efficiency of the system.

3 Behavior Analysis in Service Management

Service management is regarded as an interface for value transfer from customer to service provider. Customer demand uncertainty began to attract more study from researchers after its importance in supply chain operation was identified by Lee, So, and Tang [8]. Most studies on customer-related service management strategies mainly focused on demand variability, price elastic demand, capacity decisions under different demand patterns, and supply chains whose downstream companies have inventory. To better fulfill the customer's requirements in service management systems, researchers and practitioners need to study customer behavior. To study customer behavior, researchers assume the queueing system is the environment for customer service in most literature.

The studies in queueing systems have mainly focused on the impact of customer behavior and various queue management policies. Many queueing systems have been developed and studied in past studies with the assumption of customer behaviors. For example, studied the two-class M/M/1 queue with customer abandonment and impatient behavior and showed that the multiple customer classes provide an order of an average of 50% improvement in the performance measure. Proposed a simple heuristic to determine optimal (s, S) double-threshold policies in an M/M/1 system with impatient customers and deterministic service requirements. Explored a multiclass many-server queue with impatient customers and proved that conditional on the compound measure for each class and server, these measures evolve as independent many-server queues. Because there is no need to know the arrival time and service time, the studies mainly focus on solving the optimal customer queueing behavior problems in the queueing system using an operator or user-controlled system.

3.1 Customer Behaviour

Customer behavior analysis is a crucial aspect of IoT-driven queueing systems, as it enables businesses to understand customer preferences, behavior, and satisfaction levels. By analyzing customer behavior, businesses can identify areas for improvement and optimize their service management strategies. Customer behaviour can be classified into three types given below:

Balking: When a customer decides to avoid joining long queues, it is said to be balking.

Reneging: If a customer decides to leave the queue due to long waiting time, then this is termed as reneging.

Jockeying: If a customer moves from one queue to another in the hope of being served faster, this is called jockeying.

Figure 2 shows the customer behaviors in the queue system.

Queueing systems serve as fundamental models for studying and optimizing the flow of entities through service systems. In real-world scenarios,

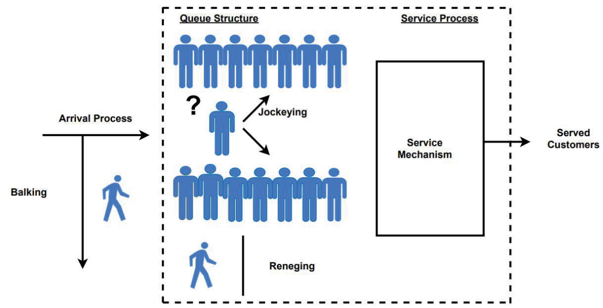


Figure 2 Customer behaviour.

service facilities often encounter discouraged arrivals and reneging behaviour from impatient customers, leading to complex dynamics that challenge efficient resource allocation and service quality. Moreover, incorporating feedback mechanisms further complicates the analysis of such systems. The study on customer behaviour was done by so many researchers. [9] analyzed a finite capacity multi-server queueing system with a retention policy of reneged customers and Bernoulli's scheduled modified vacation policy. [10] studied the warm-spare provisioning computing network with switching failure, common cause failure, vacation interruption, and synchronized reneging. [11] analyzed closed-form expressions of some important other queueing indices such as the probabilities when the servers are in different states, the proportion of customers served per unit of time, and the average rates of balking and reneging. [12] analyzed the queue model and highlighted the model's relevance for decision-makers dealing with server breakdowns, balking thresholds, and customer behavior. [13] discussed single-server congestion problems with prominent customer impatience attributes and server strategic differentiated vacation using a modified Bessel function and generating function technique. [14] discussed the Machine Interference Problem with Standby, Random Switching Failure, Vacation Interruption and Synchronized Reneging using the Successive Over-Relaxation (SoR) method.

Some factors that influenced customer behaviour in queueing systems are shown in Table 1.

3.2 Optimal Service Management

Optimal service management involves optimizing service processes to meet customer demands efficiently. IoT-driven queueing systems enable businesses to optimize their service management strategies by analyzing customer

Table 1 Factors influencing customer behavior in queueing systems

Factors	Description	References
Wait Time	The number of customers already in line, which can influence a customer's decision to join or leave the queue.	[15]
Queue Length	The number of customers already in line, which can influence a customer's decision to join or leave the queue.	[5, 16, 17]
Service Speed	The rate at which service is provided, which can affect perceptions of efficiency and customer satisfaction.	[18–21],
Customer Expectations	Preconceived notions about how long the wait will be and the quality of service, which can influence satisfaction and behavior.	[22, 23]
Perceived Fairness	The customer's perception of whether the queueing system is fair, such as first-come-first-served vs. other prioritization methods.	[24]
Queue Type	The structure of the queue (e.g., single queue vs. multiple queues), which can impact the perceived efficiency and fairness.	[13, 25]
Environment	Physical and psychological aspects of the waiting area, such as cleanliness, comfort, and ambient conditions.	[26, 27]
Social Influence	The behavior and attitudes of other customers in the queue, which can affect an individual's own behavior and perceptions.	[28]
Personal Factors	Individual differences such as patience, mood, time constraints, and personal priorities that influence waiting tolerance and satisfaction.	[29, 30, 61],
Feedback and Communication	Information provided to customers about expected wait times and reasons for delays, which can manage expectations and improve satisfaction.	[31–33, 59, 60]
Past Experiences	Previous experiences with the service or similar services, shaping expectations and tolerance for waiting.	[29, 34, 35]

behavior and preferences. There are some strategies mentioned for optimal service management in the Table 2:

Customer behavior analysis, powered by IoT technology, is a vital tool for optimizing service management in queueing systems. By leveraging real-time data, service providers can gain deep insights into customer behaviors, preferences, and pain points, enabling them to enhance service efficiency and

Table 2 Optimal service management strategies

Factors	Description	Key Points	References
Service Time Optimization	Reducing the time taken to serve each customer to enhance overall efficiency.	Reducing the time taken to serve each customer to enhance overall efficiency	[36–39]
Staff Allocation Optimization	Ensuring optimal allocation of staff to meet customer demand and reduce wait times.	Dynamic staffing, demand forecasting, employee training.	[40–42, 55]
Dynamic Behaviour	Adapting to real-time changes in customer flow and demand to maintain efficiency.	Real-time monitoring, flexible staffing, dynamic queue management.	[43–45]
Personalized Service	Tailoring services to individual customer needs and preferences to enhance satisfaction.	Personalized wait time estimates, VIP services, customer history tracking.	[45, 46]
Real-time Feedback	Collecting and acting on customer feedback in real-time to improve service quality and customer experience.	Feedback kiosks, mobile apps, real-time surveys.	[47, 48]
Discouragement and feedback	Implementing strategies to manage customer expectations and perceptions, reducing dissatisfaction and negative feedback.	Clear communication, setting realistic expectations, managing perceived wait times.	[33, 49–51, 56–59],

customer satisfaction. As IoT technology continues to evolve, its integration into queueing systems will become increasingly sophisticated, providing even more opportunities for innovation and improvement in service management.

4 IoT Service and Birth-Death Process

The Birth-Death Process is often used as a mathematical foundation to model queueing dynamics in IoT service environments. This model is ideal for IoT queueing systems where devices continuously send data (births) and the system processes them (deaths). A birth process corresponds to a new customer (or request/data packet) arriving at the system and death process corresponds to a customer being served and leaving the system. Birth-death processes allow modelling congestion, delays, blocking, and service quality, which are all critical in real-time IoT services. A continuous time Markov chain $\{X(t), t \geq 0\}$ with discrete states 0,1,... and homogeneous transition rate matrix V_{ij} is called a birth-death process if $v_{ij} = 0$ for all i and j such that $|i - j| > 1$.

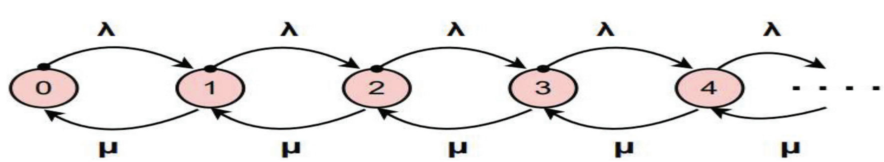
The Chapman-Kolmogorov equations are a foundational part of Markov process theory, and they are used in IoT-driven queueing systems to model how the system evolves over time. These equations describe the probability of transitioning from one state to another over a time interval by considering all intermediate states. Using the Markov property of the process, the Chapman-Kolmogorov equation gives the multi-step transition probability from state i to state j over all possible k values and is expressed by:

$$P_{ij}(t+s) = \sum_{k} P_{ik}(t) P_{kj}(s)$$

This equation describes that in order to move from state i to state j in time $t + s$, the process first moves from state i to state k in time t, and then from state k to state j in the remaining time s.

4.1 Single Server Problem with IoT

This queue model is used to model uninterrupted service of messages (transmission, reception or processing) as part of an (end-to-end) IoT interaction. It corresponds to the classical M/M/1 queue where Poisson arrivals are serviced by a single server for an exponentially distributed service time. In an IoT-driven environment, the M/M/1 model helps predict key performance metrics such as system utilization, average waiting time, queue length, and processing delays. These insights are essential for resource allocation, capacity planning, and ensuring Quality of Service (QoS) in time-sensitive IoT applications like smart healthcare, autonomous vehicles, industrial automation, and environmental monitoring.



Rate transition diagram for the M/M/1 queue.

The Differential difference equations governing the model are given by:

$$\frac{d}{dt}P_0(t) = -\lambda P_0(t) + \mu P_1(t)$$

$$\frac{d}{dt}P_n(t) = \lambda P_{n-1}(t) - (\lambda + \mu)P_n(t) + \mu P_{n+1}(t), n \geq 1$$

In steady state, as $t \to \infty$, $P_n(t) = P_n$ and therefore, $\frac{d}{dt}P_n(t) = 0$ as $t \to \infty$, then equations become;

$$\lambda P_0 = \mu P_1$$

$$(\lambda + \mu)P_n = \mu P_{n+1} + \lambda P_{n-1} \quad n \geq 1$$

The steady-state solution for M/M/1 system is

$$P_0 = (1 - \rho) \quad \left(\rho = \frac{\lambda}{\mu} < 1\right)$$

$$P_n = (1 - \rho)\rho^n \quad \left(\rho = \frac{\lambda}{\mu} < 1\right)$$

For a basic M/M/1 queue, where both arrival and service processes are memoryless (exponential inter-arrival and service times), the following metrics are used:

- Traffic Intensity

$$\rho = \frac{\lambda}{\mu}$$

- Average number of customers in the system

$$L = \frac{\rho}{1 - \rho},$$

- Average time in the system

$$W = \frac{1}{\mu - \lambda}$$

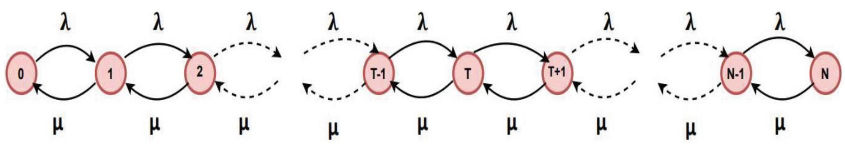
Where,

λ is the arrival rate,
μ is the service rate,
ρ is the utilization factor.

These formulas are foundational in analyzing simple IoT service systems.

4.2 Finite Capacity and IoT Queue Model

The M/M/1/N queue is a queueing model that represents systems with Poisson arrivals, exponentially distributed service times, a single server and finite capacity. It extends the classic M/M/1 model by limiting the number of customers (or jobs, packets, etc.) that the system can hold at any time. In modern IoT-driven environments, such as smart cities, connected vehicles, and intelligent transportation systems, queueing systems are essential components for managing limited resources (e.g., bandwidth, edge processors, parking spaces). The M/M/1/N queue model becomes highly relevant due to the finite capacity of such systems and the need to analyze performance under resource constraints.



Rate transition diagram for the M/M/1/N queue.

The Differential difference equations governing the model are given by:

$$\frac{d}{dt}P_0(t) = -\lambda P_0(t) + \mu P_1(t)$$

$$\frac{d}{dt}P_n(t) = \lambda P_{n-1}(t) - (\lambda + \mu)P_n(t) + \mu P_{n+1}(t), n = 1, 2, 3, \ldots, N-1$$

$$\frac{d}{dt}P_N(t) = \lambda P_{N-1}(t) - \mu P_N(t)$$

In steady state, as $t \to \infty$, $P_n(t) = P_n$ and therefore, $\frac{d}{dt}P_n(t) = 0$ as $t \to \infty$, then equations become;

$$0 = -\lambda P_0(t) + \mu P_1(t)$$

$$0 = \lambda P_{n-1}(t) - (\lambda + \mu)P_n(t) + \mu P_{n+1}(t),\ n = 1, 2, 3, \ldots, N-1$$

$$0 = \lambda P_{N-1}(t) - \mu P_N(t)$$

On solving the above equations, we get

$$P_0 = \frac{1-\rho}{1-\rho^{N+1}} \text{ Where } \rho = \frac{\lambda}{\mu}$$

$$P_n = \rho^n P_0; \quad 1 \le n \le N$$

In IoT systems with limited resources, finite capacity queues are common. Key performance metrics include:

- Blocking Probability:
$$P_B(t) = P(n, t)$$
Where $P(n, t)$ is the probability that the system has n customers at time t leading to new arrivals being blocked.
- Availability:
$$A_S(t) = 1 - P_B(t)$$
Indicates the probability that the system can accept at least one customer.
- The expected number of customers in the System:
$$L_s(t) = \sum_{i=0}^{n} i\, P(n, t)$$
- Expected waiting time in the system:
$$L_W(t) = \frac{L_s(t)}{\lambda_{eff}(t)}$$
Where $\lambda_{eff}(t)$ is the effective arrival rate, accounting for blocked arrivals.
- Effective arrival rate
$$\lambda_{eff}(t) = \lambda(1 - P_B(t))$$
Where, λ is the nominal arrival rate. $P_B(t)$ is the blocking probability at time t.

This adjusted rate reflects the actual load the system processes.

5 Benefits of IOT-Driven Queueing Systems

IoT is influencing daily as well as organizational activities in a very significant way. IoT can be employed to connect objects, people, and computing networks, which in turn makes it possible to analyze customer behavior and provide suitable services. There are some benefits of IOT- driven queueing systems:

Real-Time Monitoring: IoT devices enable the continuous tracking of queues, providing instant updates on customer volumes and service times.

This real-time visibility helps in identifying and addressing potential delays proactively. Recently, airports like Amsterdam Schiphol have implemented IoT sensors to monitor passenger flow, reducing wait times significantly, which allows them to proactively manage crowds and significantly reduce wait times at security checkpoints and other areas within the airport; this data-driven approach helps them optimize operations and improve the passenger experience.

Data-Driven Decision Making: With access to detailed analytics, businesses can make informed decisions about resource allocation, such as adjusting staff levels during peak hours or reorganizing service points to reduce congestion. According to a study, IoT analytics improved resource utilization by 25% in retail environments.

Personalized Customer Experience: IoT technology can track individual customer preferences and behavior, allowing businesses to offer personalized services. For example, Starbucks' mobile app leverages IoT data to customize promotions and notify customers of shorter queues.

Cost Efficiency: By streamlining operations and reducing idle time, IoT-driven systems can lower operational costs while maintaining high service quality. A one of the case study found that IoT-based queue management reduced operational expenses by 15% in healthcare facilities [52].

6 Conclusion and Future Scope

The integration of IoT technology in queueing systems has revolutionized the way businesses manage customer service. IoT-driven queueing systems enable businesses to analyze customer behavior, optimize service management, and improve customer satisfaction. This paper has synthesized existing research on IoT-driven queueing systems, customer behavior analysis, and optimal service management. The findings of this paper suggest that IoT-driven queueing systems can significantly reduce wait times, improve customer satisfaction, and increase operational efficiency. The integration of IoT technology enhances both operational efficiency and customer satisfaction by reducing wait times, improving resource allocation, and personalizing customer experiences. Despite challenges related to data security, implementation costs, and technical complexity, the future of IoT-based queueing systems is promising, with AI, blockchain, and AR offering new avenues for innovation. By embracing these technologies, businesses can achieve a competitive edge in service management and customer engagement.

References

[1] A. N. Sada, O. M. Olanrewaju, and Y. Surajo, "A Priority-Based Self-Adaptive Random Early Detection Algorithm in IoT Gateways," J. Basics Appl. Sci. Res., vol. 2, no. 1, pp. 18–27, 2024, doi: 10.33003 /jobasr.

[2] K. Manjunath and K. Suresh, "Adaptive Task Scheduling Procedure By Using Improvised Q-Learning Technique in Internet of Things," in 2022 International Conference on Computing, Communication, Security and Intelligent Systems (IC3SIS), IEEE, pp. 1–6, Jun. 2022. doi: 10.1109/ IC3SIS54991.2022.9885624.

[3] S. Varshney, A. Kumar, and C. Shekhar, "Parametric nonlinear programming for fuzzified queuing systems with catastrophe," Int. J. Process Manag. Benchmarking, vol. 10, no. 1, p. 69, 2020, doi: 10.1504/ijpmb. 2020.10025877.

[4] A. Agatić, E. Tijan, S. Aksentijević, and A. Pucihar, "Internet of Behavior – The Transformation of Customer Relationship Management in Logistics," in 2023 46th MIPRO ICT and Electronics Convention (MIPRO), IEEE, pp. 1411–1415, May 2023.

[5] R. Klimek, "Sensor-enabled context-aware and pro-active queue management systems in intelligent environments," Sensors (Switzerland), vol. 20, no. 20, pp. 1–29, 2020, doi: 10.3390/s20205837.

[6] A. Economou, "The Impact of Information Structure on Strategic Behavior in Queueing Systems," Queueing Theory 2 Adv. Trends, pp. 137–169, 2021, doi: 10.1002/9781119755234.ch4.

[7] M. T. Moghaddam, H. Muccini, J. Dugdale, and M. B. Kjagaard, "Designing Internet of Behaviors Systems," Proc. – IEEE 19th Int. Conf. Softw. Archit. ICSA 2022, pp. 124–134, 2022, doi: 10.1109/ICSA5365 1.2022.00020.

[8] T. S. Chain, H. L. Lee, K. C. So, and C. S. Tang, "The Value of Information Sharing in a Two-Level Supply Chain," Management Science, vol. 46, no. 5, pp. 626–643, 1995.

[9] C. Shekhar, S. Varshney, and A. Kumar, "Matrix-geometric solution of multi-server queueing systems with Bernoulli scheduled modified vacation and retention of reneged customers: A meta-heuristic approach," Quality Technology & Quantitative Management, vol. 18, no. 1, pp. 39–66, 2021, doi: 10.1080/16843703.2020.1755088.

[10] C. Shekhar, N. Kumar, A. Gupta, A. Kumar, and S. Varshney, "Warm-spare provisioning computing network with switching failure, common

cause failure, vacation interruption, and synchronized reneging," Reliability Engineering & System Safety, vol. 199, 2020, doi: 10.1016/j.ress.2020.106910.

[11] A. A. Bouchentouf, L. Medjahri, M. Boualem, and A. Kumar, "Mathematical analysis of a Markovian multi-server feedback queue with a variant of multiple vacations, balking and reneging," Discrete and Continuous Models and Applied Computational Science, vol. 30, no. 1, pp. 21–38, 2022, doi: 10.22363/2658-4670-2022-30-1-21-38.

[12] A. Kumar, S., and C. Shekhar, "Cost Analysis of a Finite Capacity Queue with Server Failures, Balking, and Threshold-Driven Recovery Policy," International Journal of Mathematical, Engineering and Management Sciences, vol. 9, no. 5, pp. 1198–1209, 2024, doi: 10.33889/ijmems.2024.9.5.063.

[13] A. Kumar, S. Kaswan, M. Devanda, and C. Shekhar, "Transient Analysis of Queueing-Based Congestion with Differentiated Vacations and Customer's Impatience Attributes," Arabian Journal for Science and Engineering, vol. 48, no. 11, pp. 15655–15665, Nov. 2023, doi: 10.1007/s13369-023-08020-3.

[14] A. Kumar, M. Boualem, A. A. Bouchentouf, and Savita, "Optimal Analysis of Machine Interference Problem with Standby, Random Switching Failure, Vacation Interruption and Synchronized Reneging," in Applications of Advanced Optimization Techniques in Industrial Engineering, 2022. doi: 10.1201/9781003089636-10.

[15] M. J. Bitner, S. W. Brown, and M. L. Meuter, "Technology infusion in service encounters," Journal of the Academy of marketing Science, vol. 28, no. 1, pp. 138–149, 2000, doi: 10.1177/0092070300281013.

[16] M. M. Nazrul Islam and M. Sultana, "Impact of Queue on Customers: An Analysis of the Retail Shops in Bangladesh," International Conference on Business Management, vol. 2, no. 3, pp. 11–20, 2012.

[17] Y. Lu, A. Musalem, M. Olivares, and A. Schilkrut, "Measuring the effect of queues on customer purchases," Management Science, vol. 59, no. 8, pp. 1743–1763, 2013, doi: 10.1287/mnsc.1120.1686.

[18] S. K. Roy, V. Shekhar, A. Quazi, and M. Quaddus, "Consumer engagement behaviors: do service convenience and organizational characteristics matter?," Journal of Service Theory and Practice, vol. 30, no. 2, pp. 195–232, 2020, doi: 10.1108/JSTP-03-2018-0049.

[19] A Abror, D Patrisia, Y Engriani, S Evanita, Y Yasri, and S Dastgir, "Service quality, religiosity, customer satisfaction, customer engagement

and Islamic bank's customer loyalty,"Journal of Islamic Marketing, pp. 1691–1705, 2020.

[20] N. Ifeoma and E. Chigozie, "Waiting Line Management and Customers' Satisfaction of Quick Service Restaurants In," vol. 27, pp. 119–142, 2024.

[21] C. Shekhar, S. Varshney, and A. Kumar, "Standbys provisioning in machine repair problem with unreliable service and vacation interruption," in The Handbook of Reliability, Maintenance, and System Safety through Mathematical Modeling, Elsevier, pp. 101–133, 2021. doi: 10.1016/B978-0-12-819582-6.00006-X.

[22] C. M. Voorhees et al., "Service encounters, experiences and the customer journey: Defining the field and a call to expand our lens," Journal of Business Research, vol. 79, pp. 269–280, 2017, doi: 10.1016/j.jbusres.2017.04.014.

[23] C. Shekhar, A. Kumar, S. Varshney, and S. Ibrahim Ammar, "M/G/1 fault-tolerant machining system with imperfection," Journal of Industrial and Management Optimization, vol. 17, no. 1, pp. 1–28, 2021, doi: 10.3934/jimo.2019096.

[24] K. Nam, J. Baker, N. Ahmad, and J. Goo, "Determinants of writing positive and negative electronic word-of-mouth: Empirical evidence for two types of expectation confirmation," Decision Support Systems, vol. 129, p. 113168, Feb. 2020, doi: 10.1016/j.dss.2019.113168.

[25] A. Kumar, A. Kumar, and C. Shekhar, "Transformation-Based Stationary Analysis of Single Server Feedback Fluid Queue: An Enhanced Approach," in 2023 3rd International Conference on Advancement in Electronics & Communication Engineering (AECE), IEEE, Nov. 2023, pp. 580–583. doi: 10.1109/AECE59614.2023.10428397.

[26] A. H. Abdou, H. S. Shehata, H. M. E. Mahmoud, A. I. Albakhit, and M. Y. Almakhayitah, "The Effect of Environmentally Sustainable Practices on Customer Citizenship Behavior in Eco-Friendly Hotels: Does the Green Perceived Value Matter?," Sustainability, vol. 14, no. 12, 2022, doi: 10.3390/su14127167.

[27] L. T. Tuan (Tuan Luu), "Activating tourists' citizenship behavior for the environment: the roles of CSR and frontline employees' citizenship behavior for the environment," Journal of Sustainable Tourism, vol. 26, no. 7, pp. 1178–1203, Jul. 2018, doi: 10.1080/09669582.2017.1330337.

[28] J. van Doorn et al., "Customer engagement behavior: Theoretical foundations and research directions," Journal of service research, vol. 13, no. 3, pp. 253–266, 2010, doi: 10.1177/1094670510375599.

[29] L. C. Harris and M. M. H. Goode, “The four levels of loyalty and the pivotal role of trust: A study of online service dynamics,” Journal of retailing, vol. 80, no. 2, pp. 139–158, 2004, doi: 10.1016/j.jretai.2004.04.002.
[30] C. Shekhar, S. Varshney, and A. Kumar, “Optimal and Sensitivity Analysis of Vacation Queueing System with F-Policy and Vacation Interruption,” Arabian Journal for Science and Engineering, vol. 45, no. 8, pp. 7091–7107, Aug. 2020, doi: 10.1007/s13369-020-04690-5.
[31] X. Xu and Y. Li, “The antecedents of customer satisfaction and dissatisfaction toward various types of hotels: A text mining approach,” International journal of hospitality management, vol. 55, pp. 57–69, May 2016, doi: 10.1016/j.ijhm.2016.03.003.
[32] C. Shekhar, A. Kumar, and S. Varshney, “Modified Bessel series solution of the single server queueing model with feedback,” International Journal of Computing Science and Mathematics, vol. 10, no. 3, pp. 313–326, 2019, doi: 10.1504/ijcsm.2019.10022402.
[33] C. Shekhar, A. Gupta, N. Kumar, A. Kumar, and S. Varshney, “Transient solution of multiple vacation queue with discouragement and feedback,” Scientia Iranica, vol. 29, no. 5 E, pp. 2567–2577, 2022, doi: 10.24200/sci.2020.52933.2955.
[34] C. Shekhar, A. Kumar, and S. Varshney, “Load sharing redundant repairable systems with switching and reboot delay,” Reliability Engineering & System Safety, vol. 193, p. 106656, Jan. 2020, doi: 10.1016/j.ress.2019.106656.
[35] C. Shekhar, A. A. Raina, A. Kumar, and J. Iqbal, “A survey on queues in machining system: Progress from 2010 to 2017,” Yugoslav Journal of Operations Research, vol. 27, no. 4, pp. 391–413, 2017, doi: 10.2298/YJOR161117006R.
[36] A. Yakubu and U. Najim, “An Application of Queuing Theory to ATM Service Optimization: A Case Study,” Mathematical Theory and Modeling, vol. 4, no. 6, pp. 11–24, 2014.
[37] M. Sani Burodo, S. Suleiman, and Y. Shaba, “Queuing Theory and ATM Service Optimization: Empirical Evidence from First Bank Plc, Kaura Namoda Branch, Zamfara State,” American Journal of Operations Management and Information Systems, vol. 4, no. 3, p. 80, 2019, doi: 10.11648/j.ajomis.20190403.12.
[38] C. Shekhar, S. Varshney, and A. Kumar, “Optimal control of a service system with emergency vacation using bat algorithm,” Journal of

computational and applied mathematics, vol. 364, p. 112332, Jan. 2020, doi: 10.1016/j.cam.2019.06.048.

[39] C. Shekhar, A. Kumar, S. Varshney, and S. I. Ammar, "Fault-tolerant redundant repairable system with different failures and delays," Engineering Computations, vol. 37, no. 3, pp. 1043–1071, Nov. 2019, doi: 10.1108/EC-01-2019-0003.

[40] A. R. Andersen, B. F. Nielsen, L. B. Reinhardt, and T. R. Stidsen, "Staff optimization for time-dependent acute patient flow," European Journal of Operational Research, vol. 272, no. 1, pp. 94–105, 2019, doi: 10.101 6/j.ejor.2018.06.015.

[41] K. Ghanes et al., "Simulation-based optimization of staffing levels in an emergency department," Simulation, vol. 91, no. 10, pp. 942–953, 2015, doi: 10.1177/0037549715606808.

[42] C. W. Chan, M. Huang, and V. Sarhangian, "Dynamic Server Assignment in Multiclass Queues with Shifts, with Applications to Nurse Staffing in Emergency Departments," Operations Research, vol. 69, no. 6, pp. 1936–1959, 2021, doi: 10.1287/opre.2020.2050.

[43] A. U. K. Wagoum, A. Tordeux, and W. Liao, "Understanding human queuing behaviour at exits?: an empirical study," Royal Society open science," 2017.

[44] M. Johnstone and D. Creighton, "A Dynamic Architecture for Increased Passenger Queue Model Fidelity," In Proceedings of the 2009 Winter Simulation Conference (WSC), pp. 3129–3139, 2009.

[45] A. Einstein, "Study on Behavioral Patterns in Queuing?: Agent Based Modeling and Experimental Approach," Doctoral thesis, University of Lugano, 2011.

[46] Z. Liu, C. Long, X. Lu, Z. Hu, J. Zhang, and Y. Wang, "Which Channel to Ask My Question?: Personalized Customer Service Request Stream Routing Using Deep Reinforcement Learning," IEEE Access, vol. 7, pp. 107744–107756, 2019, doi: 10.1109/ACCESS.2019.2932047.

[47] B. Chang, B. Kizilkaya, L. Li, G. Zhao, Z. Chen, and M. A. Imran, "Effective Age of Information in Real-Time Wireless Feedback Control Systems," Science China Information Sciences, vol. 64, pp. 1–14, 2021.

[48] K. Kang, J. Oh, and S. H. Son, "Chronos?: Feedback Control of a Real Database System Performance," In 28th IEEE International real-time systems symposium (RTSS 2007), IEEE, pp. 267–276, 2007.

[49] A. Kumar, Savita, and C. Shekhar, "Optimizing Resource Allocation in M/M/1/N Queues with Feedback, Discouraged Arrivals, and Reneging

for Enhanced Service Delivery," Journal of Reliability and Statistical Studies, vol. 17, no. 1, pp. 1–16, 2024.

[50] A. Kumar, "Single server multiple vacation queue with discouragement solve by confluent hypergeometric function," Journal of Ambient Intelligence and Humanized Computing, vol. 14, no. 5, pp. 6411–6422, 2020.

[51] A. Kumar, Savita, and C. Shekhar, "Optimizing Resource Allocation in M/M/1/N Queues with Feedback, Discouraged Arrivals, and Reneging for Enhanced Service Delivery," Journal of Reliability and Statistical Studies, vol. 17, no. 1, pp. 1–16, 2024, doi: 10.13052/jrss0974-8024.1711.

[52] P. W. Ma'arif, M. R., Priyanto, A., Setiawan, C. B., and Cahyo, "The Design of Cost Efficient Health Monitoring System based on Internet of Things and Big Data," In 2018 International Conference on Information and Communication Technology Convergence (ICTC), pp. 12–17, 2018.

[53] Kumar, A. Parametric optimization of repairable systems in IoT: addressing detection delays, imperfect coverage, and fuzzy parameters. Life Cycle Reliability and Safety Engineering, 1–12, 2025.

[54] Kumar, A., and Shekhar, C. Bayesian Modeling of Repairable Systems With Imperfect Coverage and Delayed Detection Dynamics. Quality and Reliability Engineering International. 2025.

[55] Kumar, A., Prikshit, P., and Gonder, S. S. C. Queueing System Optimization and Computational Analysis: A Comprehensive Investigation into Research Evaluation. In 2024 4th International Conference on Advancement in Electronics & Communication Engineering (AECE) (pp. 391–396). IEEE.

[56] Kumar, A., and Singh, S. Optimizing Service Performance in Single Working Vacation: Queueing Theory Perspective. In 2024 4th International Conference on Advancement in Electronics & Communication Engineering (AECE) (pp. 386–390). IEEE, 2024.

[57] Preeti, S. Sharma and V. Garg, "Exploring Research Evaluation in Social Science: A Statistical Approach," 2024 4th International Conference on Advancement in Electronics & Communication Engineering (AECE), GHAZIABAD, India, 2024, pp. 76–80, doi: 10.1109/AECE62803.2024.10911492.

[58] Preeti, N. Sharma and V. Garg, "Forecasting the Future: Exploring Advanced Trends in Digital Education," 2024 4th International Conference on Advancement in Electronics & Communication Engineering

(AECE), Ghaziabad, India, 2024, pp. 81–86, doi: 10.1109/AECE62803.2024.10911732.

[59] Preeti, V. Garg and V. Garg, "Quantifying Influence: Insights into Data Science Applications in Comparative Politics," 2024 4th International Conference on Advancement in Electronics & Communication Engineering (AECE), Ghaziabad, India, 2024, pp. 92–97, doi: 10.1109/AECE62803.2024.10911544.

[60] Preeti, A. K. Jha and V. Garg, "Trends and Patterns in the Application of Fuzzy Theory within Political Science," 2024 4th International Conference on Advancement in Electronics & Communication Engineering (AECE), Ghaziabad, India, 2024, pp. 123–127, doi: 10.1109/AECE62803.2024.10911754.

[61] Preeti, Dixit and V. Garg, "Analyzing the Development of Data Envelopment Analysis Research," 2024 4th International Conference on Advancement in Electronics & Communication Engineering (AECE), Ghaziabad, India, 2024, pp. 330–334, doi: 10.1109/AECE62803.2024.10911300.

[62] Shivani, S., Ram, M., Goyal, N., and Kumar, A. Analysis of series–parallel system's sensitivity in context of components failures. RAIRO-Operations Research, 57(4), 2131–2149, 2023.

[63] Goyal, N., and Ram, M. Exploiting performance analysis of redundant system (KM+ 1S)-Incorporating fault coverage and reboot delay. RAIRO-Operations Research, 56(3), 1187–1202, 2022.

Biography

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