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Enhancing the Performance of Low-Priority IoT Nodes Through Connection Drop Mitigation in Cognitive Radio-Based IoT Networks

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Abstract

Cognitive Radio-based Internet of Things (CR-IoT) is an emerging paradigm that combines the strengths of CR and the IoT to address spectrum scarcity and enhance IoT connectivity. This paper introduces a new Priority-Based Channel Allocation (PBCA) scheme with integrated queueing and dynamic retrial mechanisms for CR-IoT applications. The scheme effectively mitigates connection drops for low priority IoT (IoT-LP) data traffic in the network, where heterogeneous real-time and non-real time nodes opportunistically share licensed spectrum with primary users (PUs). Unlike conventional approaches that often sacrifice low-priority traffic under heavy load, the proposed scheme ensures fair and reliable access while preserving priority for delay-sensitive traffic. Spectrum handoff, connection request queueing, and a new retrial process are jointly employed to enhance quality of service. The system is modeled using a multi-dimensional continuous-time Markov chain and validated through extensive simulations. Results show that the proposed PBCA scheme eliminates connection drops for IoT-LP nodes, increases total channel utilization by up to 4.65%, and reduces connection handoff probability by 50.05% compared with the baseline Random DSA scheme.

Keywords: IoT, DSA, Integrated Queueing, Dynamic Retrial Mechanism, Connection Drop Mitigation.

1 Introduction

Over the past few years, the number of Internet-connected devices has surged, paving the way for the Internet of Things (IoT). IoT refers to a paradigm connecting a vast array of objects equipped with sensors and actuators, enabling them to collect, analyze, and share data with each other the over the Internet [1]-[4]. IoT applications span domains from smart homes (improving convenience and energy management) and healthcare (remote patient monitoring and personalized treatment) to industrial automation (enhancing efficiency and reducing costs), environmental monitoring (tracking and mitigating issues like pollution and climate change), and even military uses (e.g., border surveillance) [5],[6]. These diverse applications each have unique data transfer requirements and quality of service (QoS) considerations. Consequently, IoT systems must support heterogeneous data flows and maintain appropriate QoS for each data type [7]. However, the exponential growth of IoT services and devices has introduced significant communication challenges given the limited availability of spectrum resources [8]. The skyrocketing number of IoT devices with their collective spectrum demands, now far exceeds the available spectrum, impeding efficient heterogeneous data transmission. This scarcity leads to issues such as congestion, collisions, poor channel utilization and degraded network performance, and compromised QoS. To address these challenges, cognitive radio (CR) has emerged as a promising solution for the spectrum scarcity problem. CR technology enables opportunistic use of underutilized licensed spectrum, making it a key enabler for IoT connectivity [8]-[12]. As asserted in [11], IoT would be insignificant without the CR capability. In CR-based IoT (CR-IoT) networks, certain spectrum bands are licensed to primary users (PUs) who have exclusive usage rights for their wireless applications. Many of these licensed bands remain underutilized, with usage varying by location and time [12]. Therefore, secondary users (i.e., IoT nodes) or CR-enabled IoT devices can access the licensed bands temporarily and opportunistically without interfering with PUs. They achieve this by employing spectrum sensing, dynamic spectrum access, spectrum mobility (handoff/handover) and spectrum sharing techniques to identify and utilize vacant channels while ensuring that PU communications are not disrupted [10],[11].

Advancements in IoT communications have produced a multitude of new services and applications. Some traffic types such as real-time healthcare monitoring, disaster management, banking, and security are more critical or time-sensitive than others. In dense networks or under heavy traffic with dynamic channel access, certain CR-IoT connections should thus be given high priority to ensure their connections are not blocked or forcibly terminated (events that would degrade network performance). Meanwhile, delay-tolerant CR-IoT connections can be assigned lower priority. In other words, different traffic classes demand different priority levels based on their distinct characteristics and QoS requirements [11].

This paper proposes a new Priority-Based Channel Access (PBCA) scheme that uses integrated queueing and dynamic retrial mechanisms to mitigate connection drops for low-priority IoT nodes (IoT-LPs) in CR-IoT networks, where heterogeneous IoT nodes dynamically share spectrum with PUs. In the proposed scheme, IoT nodes relaying delay-sensitive traffic (e.g., VoIP) are given high priority, whereas those with delay-tolerant traffic (e.g., non-real-time data) are assigned low-priority. The PBCA scheme aims to improve spectrum utilization, reduce connection handoffs and mitigate connection drops for IoT-LP nodes. Unlike prior approaches that often sacrifice low-priority traffic under heavy load, this scheme ensures fair and reliable access for low-priority connections while still preferential treatment for high-priority traffic.

Main contributions of this work include: (1) development and analytical modeling of a PBCA framework that classifies IoT nodes into two priority levels based on QoS requirements; (2) analysis of the impact of varying PU and low-priority IoT traffic loads on system performance in comparison to a baseline PBCA scheme (classical Random DSA); (3) demonstration that the proposed scheme mitigates connection drops for low priority IoT nodes; (4) showing that it significantly increases low priority IoT channel utilization by up to 1.98 times under high PU traffic load; and (5) showing that it reduces handoff probability by up to 2.05 times. The system is modeled by using a multi-dimensional continuous-time Markov chain (CTMC), and the analytical results are validated through comprehensive simulations. Numerical results further confirm that the proposed scheme improves channel utilization and reduces handoff probability compared to the baseline PBCA scheme.

The remainder of the paper is organized as follows: Section 2 reviews state of the art work on CR-IoT, QoS support for IoT nodes and CTMC-based performance analysis. Section 3 describes the proposed PBCA scheme and the network model. Section 4 details the developed multi-dimensional CTMC model for performance evaluation. Section 5 presents and discusses the analytical and simulation results, and the final section concludes the paper.

2 Related Works

Over the past decade, numerous studies have investigated the performance of CR-IoT networks. In [12], Amjad et al. propose a priority-based IoT nodes connection admission and channel allocation scheme with dynamic channel reservation for CR-IoT networks. The objective is to reduce the blocking probability of higher-priority secondary user (SU) connection requests while maintaining sufficient channel utilization. The arrival rates of SU connections in each priority class are estimated by using a Markov chain model, and channels for each priority class are reserved based on this analysis. The priority-based scheme is evaluated against greedy non-priority and fair proportion schemes in terms of the SU connection blocking probability, SU connection dropping probability, channel utilization, and throughput. Results show that the proposed priority scheme outperforms the greedy non-priority and fair proportion schemes on these metrics. However, as this work adopts a channel reservation scheme for high-priority IoT nodes, it can lead to a reduction in overall channel utilization due to the unused channels reserved for high-priority IoT nodes.

In [13], Abd et al. introduce a spectrum efficient CR network (SE-CRN) that employs a hybrid underlay-interweave (UI) mode of CRNs for IoT nodes under cooperative communication in order to investigate the channel availability and service completion probability. In this model, two types of IoT nodes, with low and high priority levels, are considered. SE-CRN scheme comprises two algorithms: spectrum efficient dynamic spectrum access (SE-DSA) and spectrum efficient dynamic channel reservation (SE-DCR). SE-DSA dynamically assigns available channels to PUs and IoT nodes based on their priority levels. SE-DCR dynamically keeps a number of channels reserved to support interruption of ongoing services. For the performance analysis, the system is modeled via a CTMC to analyze various QoS parameters. The scheme utilized in SE-CRN is evaluated under varying network traffic loads and channel failure rates, and the results show that spectrum utilization efficiency is enhanced compared to conventional approaches.

In [14], Faisal et al. propose a reliable, intelligent and smart CR-IoT Medium Access Control (MAC) protocol that consumes less computational time and requires less transmission energy while achieving higher throughput compared to the benchmark CR-MAC protocols. The work demonstrates new applications of CR technology for IoT and offers efficient solutions to real world CR challenges to make IoT more affordable and applicable. Throughput, IoT nodes transmission probability and energy consumption are chosen as performance metrics in this work. The results indicate that the average energy consumed by the CR-IoT MAC protocol is lower and the throughput is higher in comparison to the benchmark CR-MAC protocols.

In [15], Ali et al. propose a spectrum allocation framework that jointly considers the QoS providing for heterogeneous secondary real-time (RT) and non-real rime (NRT) users, the spectrum sensing, spectrum access decision, channel allocation, and connection admission control in distributed cooperative CR networks. In this work, higher priority is given to the RT users with QoS requirements in terms of the connection dropping and blocking probabilities, and a number of the identified available channels are assigned to the optimum number of the RT SUs that can be accepted into the network, while the remaining available channels are allocated adaptively to the optimum number of the NRT SUs considering the spectrum sensing and channel utilization. The results show that the distributed cooperative CRNs efficiently utilize the unused spectrum and guarantee the QoS requirements of both the RT and NRT SUs. However, the study did not consider any queueing mechanism or dynamic retrial policy, resulting in connection drops for RT users.

In [16], a spectrum reservation technique that considers the heterogeneity of IoT nodes and employs a channel reservation scheme to improve the performance of low-priority IoT nodes is proposed. The authors model the system using a multi-dimensional Markov chain and evaluate performance metrics including spectrum utilization, connection blocking probability and connection handoff probability. While the approach benefits low-priority nodes, its channel management scheme underutilize spectrum due to the unused channels reserved for high priority users.

In [17], Abd et al. propose a novel channel allocation scheme for CR enabled social IoTs (CR-SIoTs) with multi-priority and heterogeneous users. This work offers a heuristic approach to utilize IoT nodes' heterogeneous priorities, addresses IoT nodes' dropping systematically, and follows an efficient channel access scheme. A Markov chain model is used to drive performance metrics such as capacity, spectrum utilization, blocking probability and handoff probability. The findings indicate an improvement in capacity, spectrum utilization, connection handoff and connection blocking probabilities. However, the CR-SIoTs channel access mechanism relies on spectrum reservation for PUs, which in turn results in spectrum underutilization due to the reserved unused channels for PUs.

In [18], Ram et al. present a prioritized spectrum access scheme to address the QoS requirements of heterogeneous traffic in cognitive smart grid communication systems. In their scheme, Smart Grid (SG) traffic is divided into two priority classes (high and low) based on QoS requirements. It is modeled with a multidimensional Markov chain and its performance is evaluated in terms of connection blocking probability, the connection dropping probability, the interference probability and the connection completion rate for both high and the low-class smart grid traffics. The authors report that the priority-based scheme is capable of increasing the QoS of high-priority traffic and that prioritized system is preferable over the non-prioritized system where all traffic types are treated equally in terms of SG data delivery.

In [19], a priority-aware spectrum management framework for vehicular IoT, integrating interweave, underlay, and coexistence modes to optimize spectrum utilization, energy efficiency, and throughput while minimizing blocking and interruption probabilities is proposed. The algorithm manages resources efficiently and gives proper attention to each device based on its priority, so all IoT nodes, from high to low priority, receive continuous and reliable service. But it does not address the broader problem of connection drops for low-priority IoT nodes across general CR-IoT environments.

In [20], an energy-efficient smart gateway framework with QoS-aware resource allocation, focusing on optimizing energy consumption while meeting QoS requirements is presented. While relevant, this framework primarily targets energy consumption and does not tackle the fairness issues between priority classes in CR environments.

A supermodular game model to allocate resources in energy-harvesting CR-IoT networks is employed in [21]. It is mathematically rigorous and captures competitive interactions among nodes, yet it does not explicitly incorporate queueing or retrial mechanisms to reduce connection drops. Similarly, [22] proposed a multi-objective spectrum assignment framework for heterogeneous CR-IoT networks, providing valuable insights into the effects of non-uniform channel availability and nodes diversity. Nevertheless, the framework emphasizes heterogeneity and multi-objective trade-offs without explicitly safeguarding low-priority nodes under high spectrum contention.

And finally, [23] analyzes a QoS-aware resource allocation strategy for IoT nodes and provides insights into fairness and throughput. However, the work does not consider CR networks nor explicitly aims to eliminate connection drops for low-priority nodes.

Differing from the above related papers, the main differences and advances of our work are as follows: (1) Priority-Based Channel Access (PBCA) with Queuing and Retrial: We develop a new PBCA scheme with an integrated queueing mechanism and dynamic retrial policy in which IoT nodes are classified into two-level priority according to QoS requirements under a realistic wireless networking scenario. The proposed scheme is mathematically modeled and its performance is evaluated comprehensively. Notably, very few existing works in literature have addressed channel access management in IoT networks with both queueing and retrial mechanisms for non-real-time low priority IoT nodes. (2) Impact of Traffic Load and Primary Users: We provide an in-depth evaluation of the effects of PUs and low-priority IoT nodes' offered load on the connection performance of IoT nodes under the PBCA scheme in comparison to a similar baseline PBCA (Random DSA). This analysis highlights how the integrated queuing/retrial affects system performance versus a baseline without these features. (3) Elimination of Low-Priority Call Drops: The proposed PBCA scheme effectively eliminates call drops for low-priority IoT nodes by buffering their connection requests in a queue and employing retrial rather than dropping them outright. This ensures that low-priority traffic is eventually served, improving fairness and reliability for non-real-time IoT applications. (4) Enhanced Utilization and Throughput: The PBCA strategy improves total channel utilization and overall network throughput by making better use of available channels through queuing, while also reducing call handoff probabilities. In other words, the network can carry more successful transmissions with fewer interruptions, compared to conventional schemes that lack queuing and retrial for secondary users (i.e., IoT-LPs).

3 The CR-IoT Network Model with The Proposed PBCA Scheme

3.1 The CR-IoT Network Model

In the proposed network model, a centralized CR-IoT network is considered, where licensed PUs and unlicensed IoT nodes coexist in the same area under two priority classes. The PUs have exclusive spectrum licenses and thus highest priority to access the channel, while the IoT nodes act as cognitive radio devices (CR-IoT nodes) that opportunistically use the licensed spectrum when it is free. To support differentiated QoS requirements, IoT nodes are categorized into high-priority (IoT-HP) and low-priority (IoT-LP) classes. This two-level priority structure for secondary users (the IoT nodes) is akin to models in literature where secondary traffic is divided into classes with preemptive priority for higher classes.

The network model developed is composed of PUs, IoT-HP nodes, IoT-LP nodes, a Primary Base Station (PBS), and an IoT Gateway (IoT-GW) (Figure 1). The PUs are licensed users and authorized entities to access the channel and have higher priority to use the channel than both IoT nodes. Coordination between the IoT-GW and IoT nodes is maintained via a common control channel. Whenever a PU or IoT node requests access, the IoT-GW consults the dynamic channel allocation table (DCAT) to determine channel availability and makes an assignment decision based on priority. The PBS, on the other hand, manages only the PUs and assigns an idle channel to a new PU without awareness of IoT node usage on that channel (this oblivious assignment may force an IoT node off the channel). In essence, PUs always get immediate access to any channel they need, and the IoT-GW ensures that IoT nodes only use channels when such use will not disrupt PUs. By opportunistically sharing the licensed spectrum in this controlled way, the model aims to improve spectrum utilization while protecting the PUs' primary rights.

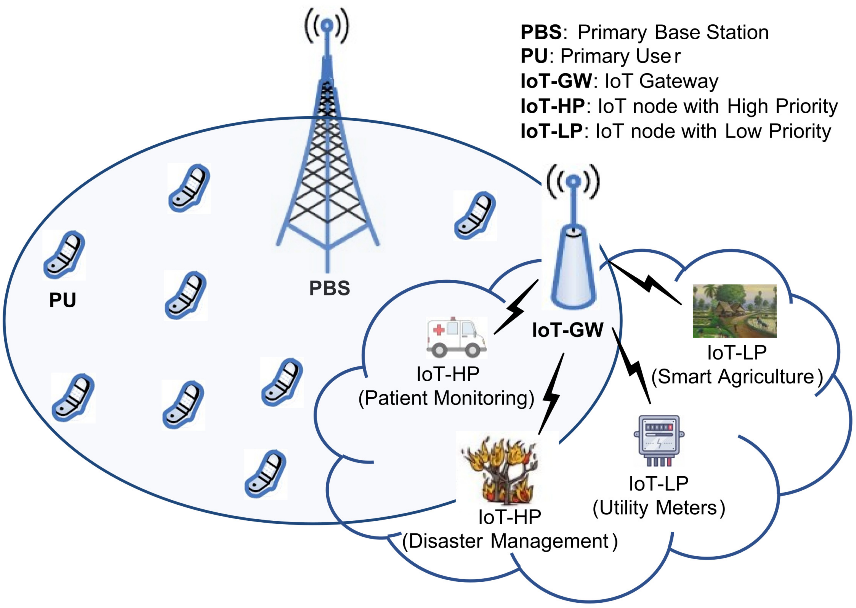


Figure 1: Proposed Cognitive Radio-based IoT Network Model

3.2 The Proposed PBCA Scheme with Integrated Queueing and Dynamic Retrial Mechanism

The structure of the proposed PBCA scheme with first-in-first-out (FIFO) queue for IoT-LP nodes is presented in Figure 2. There are a total of N homogeneous channels with equal bandwidth available.

All PUs have supreme priority over any IoT node (of either priority) for occupying a channel. The PU connections are independent of the IoT nodes' connections, and for a PU connection, only one channel is allocated. The PBS allocates an available channel to a newly arrived PU connection request, and a PU connection assignment is based simply on the number of PU connections that are currently ongoing in the network. As the PBS is oblivious of current IoT nodes' connections, any IoT node connection that interferes with a new PU connection must be managed in one of the following ways: (1) to be transferred to another vacant channel, (2) to be moved to a channel occupied by an IoT-LP node connection if it has higher priority, or (3) to be dropped if it is IoT-HP or to be sent to the queue if it is IoT-LP.

It is worth noting that the present analysis assumes homogeneous channels, Poisson-distributed traffic arrivals, and stationary node positions for tractability of the CTMC model. However, in real-world CR-IoT deployments, spectrum bands may exhibit heterogeneous characteristics such as variable bandwidth and fading conditions, traffic arrivals can follow bursty or self-similar patterns, and IoT nodes may be mobile. These factors are expected to influence queueing dynamics and spectrum access performance. Extending the proposed PBCA framework to incorporate heterogeneous channel conditions, burst traffic models, and node mobility therefore constitutes an important direction for future research.

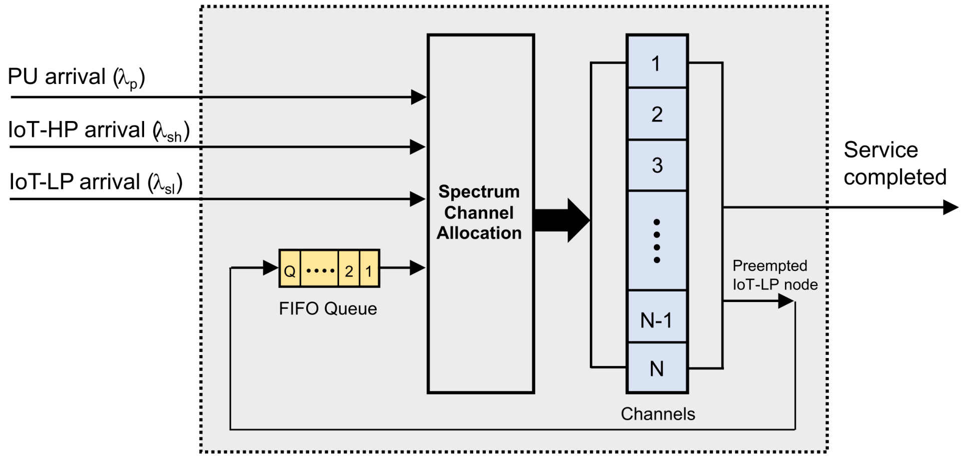


Figure 2: Structure of the proposed PBCA scheme with FIFO queue for IoT-LP

In this PBCA scheme, an IoT node's connection may go through several possible states depending on spectrum availability and preemption events. We distinguish five states for an IoT node's service:

1. *No-Block/Drop/Queueing state*: The IoT node obtains a channel upon arrival and its connection proceeds to completion without interruption. This occurs when channels are available (or can be made available) for the IoT node at connection request and no PU preemption happens during its session.

2. *Drop state*: When a newly arrived PU is assigned a channel already being used by an IoT-HP, the IoT-HP utilizing that channel must vacate the channel promptly. If there is not any free channel or a channel being used by an IoT-LP then the IoT-HP service is forcibly terminated, and its connection is dropped.

3. *Queueing state*: When a newly arrived PU is assigned a channel already being used by an IoT-LP, the IoT-LP utilizing that channel must vacate the channel promptly. If there is not any free channel, then the IoT-LP service is interrupted and its connection is queued to be served at a later time.

4. *Handoff state*: This is a channel-switching state. When a newly arrived PU is allocated to a channel occupied by an IoT-HP, the IoT-HP vacates the occupied channel and switches to an

empty channel or a channel already being used by an IoT-LP if there is any available channel to resume its transmission. Else a newly arrived PU is allocated to a channel occupied by an IoT-LP, the IoT-LP vacates the occupied channel and switches to an empty channel if available to resume its transmission.

5. *Block state*: When all the channels are currently in use by either PUs or IoT nodes with the same priority then a channel cannot be allocated for the incoming IoT node arrival; therefore, its connection is blocked.

These states reflect a preemptive priority queueing system in the CR-IoT network. PUs preempt any secondary (IoT nodes) transmission, IoT-HPs have preemptive priority over IoT-LPs, and IoT-LPs have no preemptive rights. Notably, our scheme does not simply drop low-priority sessions upon preemption; instead, IoT-LPs get queued for retrial, improving their chances of eventual service at the cost of additional delay. Such an approach aligns with priority-based spectrum management techniques that strive to give continuous service to even low-priority nodes (through waiting or alternative access) rather than outright denial. Queueing and retrials for IoT nodes have been shown to significantly enhance overall throughput and resource utilization in CR-IoT networks by reducing wasted opportunities.

Figure 3 presents the flowchart of the proposed PBCA algorithm executed at the IoT-GW. This algorithm outlines how incoming connection requests (either PUs or IoT nodes of high/low priority) are handled. Starting from the top, the IoT-GW continuously listens for new connection requests. When a request arrives, the algorithm branches based on the type of user (PU, IoT-HP, or IoT-LP) and then follows the rules described below to allocate a channel if possible. The flowchart shows decision blocks for checking channel availability and priority conditions, and action blocks where spectrum handoff, queueing, or dropping is performed accordingly. By following this procedure, the IoT-GW dynamically allocates channels in a way that prioritizes PUs and IoT-HP nodes while still serving IoT-LP nodes whenever capacity allows. The PBCA algorithm can be summarized step-by-step as follows for each type of new arrival:

- When a PU connection request arrives: The PBS will assign the PU to a channel that is not currently occupied by another PU. The IoT-GW then updates the Dynamic Channel Allocation Table (DCAT) to mark that channel as occupied by a PU. If the chosen channel was idle, no IoT node is affected. However, if the channel was in use by an IoT node, that IoT node is preempted immediately. If the preempted node was an IoT-LP, the IoT-GW attempts to find another idle channel to which this IoT-LP can be moved (spectrum handoff) so it can continue its service. If an idle channel is available, the IoT-LP is transferred to that channel and the DCAT is updated accordingly. If no idle channel exists, the IoT-LP's connection is queued (moved into the waiting queue) as described above, to be resumed later when a channel becomes idle. On the other hand, if the preempted node was an IoT-HP, the IoT-GW first looks for an idle channel to save the IoT-HP (if found, the IoT-HP is handed off there). If no idle channel is open, the IoT-GW then checks if any channel is currently occupied by an IoT-LP since IoT-HP can preempt IoT-LP. If an IoT-LP is on some channel, that IoT-LP is sent to queue and the IoT-HP immediately takes over that channel to continue its transmission. This effectively sacrifices a low-priority service to accommodate the more urgent high-priority one. If neither an idle channel nor an IoT-LP-occupied channel is available, meaning all channels are taken by PUs or other IoT-HPs, then the IoT-HP session gets dropped. The PU gets the channel and the displaced IoT-HP has nowhere to go, leading to termination of that IoT-HP connection (Drop state). Throughout this process, PUs experience no blocking and always get a channel promptly, as is required for licensed users, while IoT nodes may face handoffs, queueing, or drops depending on channel availability. This behavior ensures PUs' QoS is fully protected even if disrupting IoT traffic, reflecting the paramount priority of PUs in any CR system.

- When an IoT-HP connection request arrives: The IoT-GW searches for an idle channel first. If an idle channel is available, it is assigned to the newly arrived IoT-HP. If no idle channel is found, the IoT-GW then looks for an ongoing IoT-LP connection. If an IoT-LP channel exists, the newly arrived IoT-HP connection request is assigned to this IoT-LP channel, resulting in an IoT-LP connection to be queued in order to be served at a later time.

- When an IoT-LP connection request arrives: The IoT-GW searches for an idle channel. If an idle channel is available, it is assigned to the newly arrived IoT-LP. If no idle channel is found, an IoT-LP connection block occurs.

Overall, the PBCA scheme ensures that PUs always have immediate access, IoT-HP connections get preferential treatment in obtaining or retaining a channel, and IoT-LP connections are served on a best-effort basis. This kind of prioritized dynamic spectrum access is crucial for IoT scenarios with heterogeneous QoS needs. It not only improves spectrum utilization and network throughput by letting secondary nodes use channels opportunistically but also meets QoS targets by minimizing connection drops of high-priority traffic and allowing low-priority traffic to eventually get through via delayed retries. The integration of a queueing and retrial mechanism reduces the interruption cost for low-priority sessions. This trades some additional delay for a substantial decrease in the probability of total service denial for IoT-LP nodes, leading to better fairness and efficiency: IoT-HP traffic experiences little to no blocking, and IoT-LP traffic, while it may wait longer, has a chance to resume later instead of being discarded immediately. Such a design aligns with contemporary research that emphasizes adaptive spectrum management to meet diverse CR-IoT application requirements, optimizing metrics like utilization, connection blocking probability, connection dropping probability and connection handoff probability for different priority classes.

In summary, the proposed PBCA scheme leverages CR principles (i.e., dynamic spectrum sensing and access) with a priority-aware allocation algorithm to support mission-critical IoT nodes alongside regular IoT nodes in a shared spectrum. The IoT-GW acts as an intelligent broker, assigning channels in real-time based on data traffic priority and channel availability, performing spectrum handoffs for ongoing connections when needed, and maintaining a queue for deferred service of low-priority tasks. This ensures that all nodes from PUs to IoT-HP nodes to IoT-LP nodes receive service that is as continuous and reliable as possible given the spectrum constraints, thereby enhancing the overall network performance and spectrum utilization in the IoT-enabled CR network.

4 Performance Analysis of the Proposed PBCA scheme

The performance analysis of the proposed PBCA scheme with integrated queuing and dynamic retrial policy was conducted by using a multi-dimensional CTMC in order to evaluate the channel utilization, connection blocking probability, connection dropping probability, and connection handoff probability. Connection requests of PUs, IoT-HPs, and IoT-LPs occur independently as Poisson processes with arrival rates λ_p, λ_{sh}, and λ_{sl}, respectively. Additionally, the service rates for PUs, IoT-HPs, and IoT-LPs follow an exponential distribution with rates μ_p, μ_{sh}, and μ_{sl}, respectively. Markov chain model of the proposed PBCA scheme used in the developed CR-IoT network model for three channels and a queue of size 3 is illustrated in Figure 4. Each state in the Markov chain is represented by the quadruplet (i, j, k, l), where i represents the number channels occupied by the PUs, j represents the number of channels occupied by the IoT-HPs, k represents the number of channels occupied by the IoT-LPs, l represents the number of dropped IoT-LP connections waiting in the queue and $0 \leq i + j + k \leq N,\ 0 \leq l \leq N$. Therefore, the state space S of the Markov chain is defined as follows;

$$S = \{(i, j, k, l) | 0 \leq i, j, k, l \leq N,\ i + j + k \leq N\} \tag{1}$$

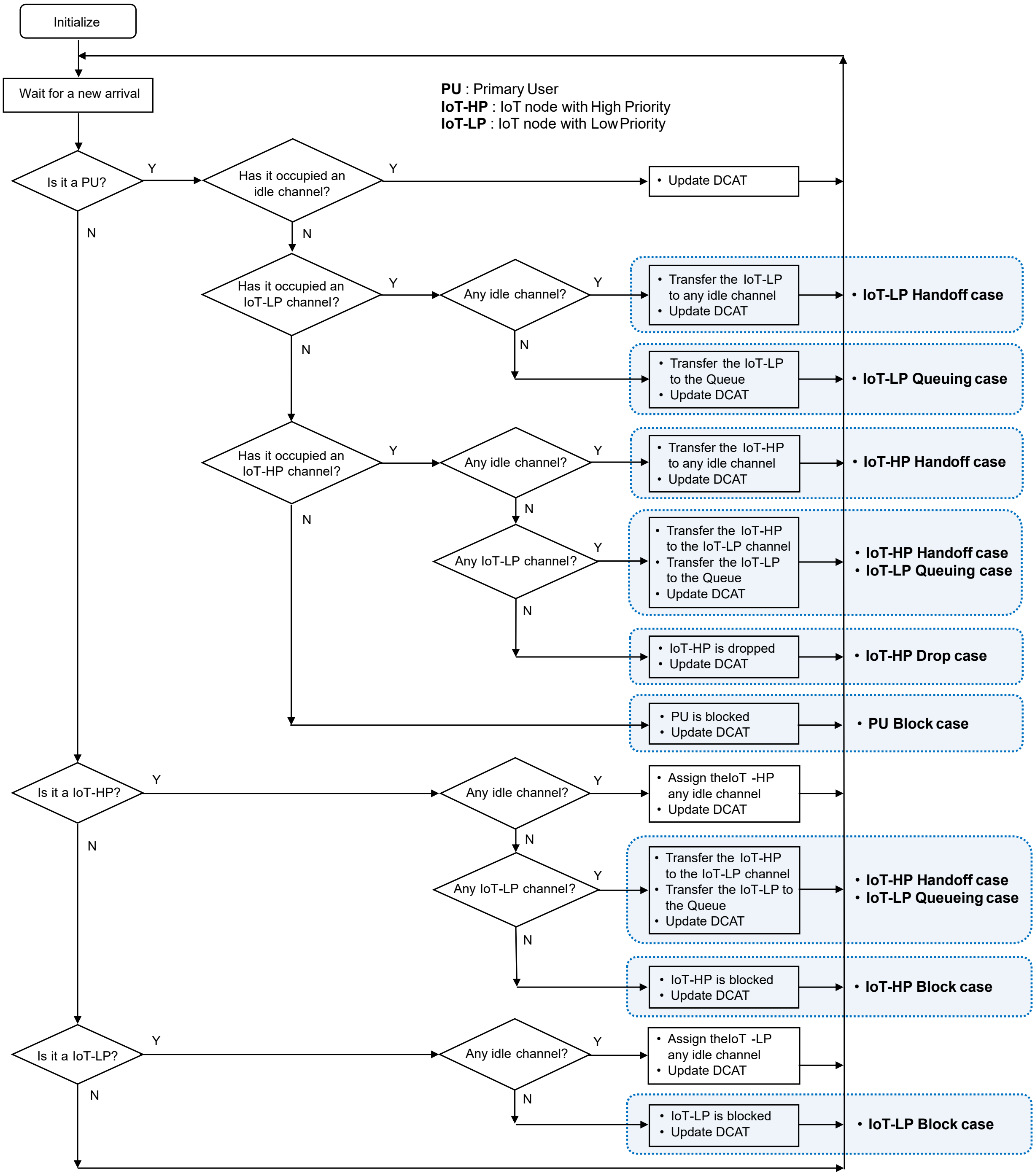


Figure 3: Flowchart of the proposed PBCA algorithm executed at the IoT Gateway

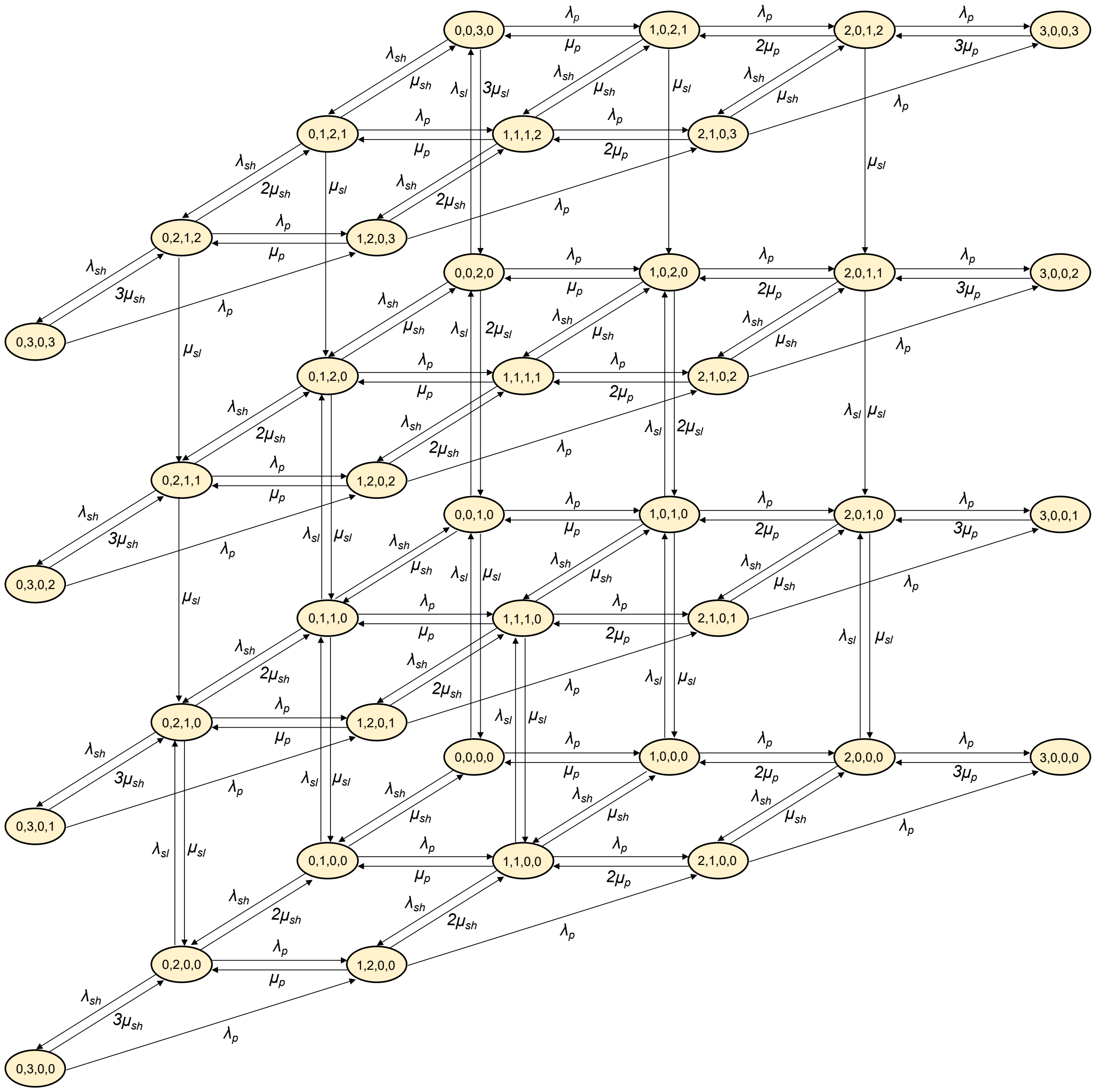


Figure 4: Multi-dimensional CTMC model of the proposed PBCA scheme, illustrated for the case of three channels and a queue size of three.

The steady-state probability distribution of the continuous-time Markov chain, denoted by $P(i, j, k, l)$ can be easily attained by utilizing the appropriate state transition rate matrix and applying the Gauss-Seidel method [24].

The balance equations for the proposed PBCA scheme incorporating both queueing and retrial policies for the CR-IoT network model are formulated as follows.

For $i = 0, j = 0, k = 0, l = 0$,

$$P(0,0,0,0)(\lambda_p + \lambda_{sh} + \lambda_{sl}) = P(1,0,0,0)\mu_p + P(0,1,0,0)\mu_{sh} + P(0,0,1,0)\mu_{sl} \tag{2}$$

For $i = N, j = 0, k = 0, l = 0$,

$$P(N,0,0,0)(N\mu_p) = P(N-1,0,0,0)\lambda_p + P(N-1,1,0,0)\lambda_p \tag{3}$$

For $i = 0, j = N, k = 0, l = 0$,

$$P(0,N,0,0)(\lambda_p + N\mu_{sh}) = P(0,N-1,0,0)\lambda_{sh} + P(0,N-1,1)(N_{sh} - N + 1)\lambda_{sh} \tag{4}$$

For $i = 0, j = 0, k = N, l = 0$,

$$P(0,0,N,0)(\lambda_p + \lambda_{sh} + N\mu_{sl}) = P(1,0,N-1,1)\mu_p + P(0,0,N-1,0)\lambda_{sl} + P(0,1,N-1,1)\mu_{sh} \quad (5)$$

For $i = 0, j = 0, 1 \leq n < N, l = 0$,

$$\begin{aligned} P(0,0,k,0)(\lambda_p + \lambda_{sh} + \lambda_{sl} + k\mu_{sl}) = {} & P(1,0,k,0)\mu_p + P(0,0,k-1,0)\lambda_{sl} \\ & + P(0,1,k,0)\mu_{sh} + P(0,0,k+1,0)(k+1)\mu_{sl} \end{aligned} \quad (6)$$

For $i = 0, j = N, k = 0, 1 \leq l < N$,

$$P(0,j,0,l)(\lambda_p + N\mu_{sh}) = P(0,N-1,1,l-1)\lambda_s h \quad (7)$$

For $i = N, j = 0, k = 0, 1 \leq l < N$,

$$P(N,0,0,l)N\mu_p = P(N-1,0,1,l-1)\lambda_p + P(N-1,1,0,1)\lambda_p \quad (8)$$

For $1 \leq i < N, j = N - i, k = 0, l = 0$,

$$P(i,j,k,l)(\lambda_p + i\mu_p + j\mu_{sh}) = P(i,j-1,k,l)\lambda_{sh} + P(i-1,j,k,l)\lambda_p + P(i-1,j+1,k,l)\lambda_p \quad (9)$$

For $1 \leq i < N, j = N - i, k = 0, 1 \leq l < N$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p + i\mu_p + j\mu_{sh}) = {} & P(i,j-1,k+1,l-1)\lambda_{sh} + P(i-1,j+1,k,l)\lambda_p \\ & + P(i-1,j,k+1,l-1)\lambda_p \end{aligned} \quad (10)$$

For $i = 0, 1 \leq j < N - 1, k = N - i, l = j$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p + i\mu_p + j\mu_{sh}) = {} & P(i,j-1,k+1,l-1)\lambda_{sh} + P(i-1,j+1,k,l)\lambda_p \\ & + P(i-1,j,k+1,l-1)\lambda_p \end{aligned} \quad (11)$$

For $i = 0, 1 \leq j < N - 1, k = 0, l = 0$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p + \lambda_{sh} + \lambda_{sl} + j\mu_{sh}) = {} & P(i+1,j,k,l)\mu_p + P(i,j+1,k,l)(j+1)\mu_{sh} \\ & + P(i,j,k+1,l)\mu_{sl} + P(i,j-1,k,l)\lambda_{sh} \end{aligned} \quad (12)$$

For $i = 0, 1 \leq j < N - 1, 1 \leq k < N - 1, l = 0, j + k < N$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p + \lambda_{sh} + \lambda_{sl} + j\mu_{sh} + k\mu_{sl}) = {} & P(i+1,j,k,l)\mu_p + P(i,j,k-1,l)\lambda_{sl} \\ & + P(i,j+1,k,l)(j+1)\mu_{sh} + P(i,j,k+1,l)(k+1)\mu_{sl} \\ & + P(i,j-1,k,l)\lambda_{sh} \end{aligned} \quad (13)$$

For $i = 0, 1 \leq j < N - 1, k = N - j, l = 0$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p + \lambda_{sh} + j\mu_{sh} + k\mu_{sl}) = {} & P(i+1,j,k-1,l+1)\mu_p + P(i,j,k-1,l)\lambda_{sl} \\ & + P(i,j+1,k-1,l+1)(j+1)\mu_{sh} + P(i,j,k,l+1)k\mu_{sl} \\ & + P(i,j-1,k,l)\lambda_{sh} \end{aligned} \quad (14)$$

For $i = 0, 1 \leq j < N - 1, k = N - j, 1 \leq l < N - 1, k + l < N$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p + \lambda_{sh} + j\mu_{sh} + k\mu_{sl}) = {} & P(i+1,j,k-1,l+1)\mu_p \\ & + P(i,j+1,k-1,l+1)(j+1)\mu_{sh} \\ & + P(i,j,k,l+1)k\mu_{sl} + P(i,j-1,k+1,l-1)\lambda_{sh} \end{aligned} \quad (15)$$

For $1 \leq i < N - 1, j = 0, k = N - i, l = N - k$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p + \lambda_{sh} + i\mu_p + k\mu_{sl}) = {} & P(i+1,j,k-1,l+1)(i+1)\mu_p \\ & + P(i,j+1,k-1,l+1)\mu_{sh} + P(i-1,j,k+1,l-1)\lambda_p \end{aligned} \quad (16)$$

For $1 \le i < N-1, j=0, k=0, l=0$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p+\lambda_{sh}+\lambda_{sl}+i\mu_p) &= P(i+1,j,k,l)(i+1)\mu_p + P(i,j+1,k,l)\mu_{sh} \\ &+ P(i-1,j,k,l)\lambda_p + P(i,j,k+1,l)(k+1)\mu_{sl} \end{aligned} \tag{17}$$

For $1 \le i < N-1, j=0, 1 \le k < N-1, l=0, i+k<N$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p+\lambda_{sh}+\lambda_{sl}+i\mu_p+k\mu_{sl}) &= P(i+1,j,k,l)(i+1)\mu_p + P(i,j,k-1,l)\lambda_{sl} \\ &+ P(i,j+1,k,l)(j+1)\mu_{sh} + P(i-1,j,k,l)\lambda_p \\ &+ P(i,j,k+1,l)(k+1)\mu_{sl} \end{aligned} \tag{18}$$

For $1 \le i < N-1, j=0, k=N-i, l=0$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p+\lambda_{sh}+i\mu_p+k\mu_{sl}) &= P(i+1,j,k-1,l+1)(i+1)\mu_p + P(i,j,k-1,l)\lambda_{sl} \\ &+ P(i,j+1,k-1,l+1)(j+1)\mu_{sh} + P(i-1,j,k,l)\lambda_p \\ &+ P(i,j,k,l+1)k\mu_{sl} \end{aligned} \tag{19}$$

For $1 \le i < N-1, j=0, k=N-i, 1 \le l < N-1, k+l<N$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p+\lambda_{sh}+i\mu_p+k\mu_{sl}) &= P(i+1,j,k-1,l+1)(i+1)\mu_p \\ &+ P(i,j+1,k-1,l+1)(j+1)\mu_{sh} \\ &+ P(i-1,j,k+1,l-1)\lambda_p + P(i,j,k,l+1)k\mu_{sl} \end{aligned} \tag{20}$$

For $1 \le i < N-1, 1 \le j < N-1, k=N-i-j, l=N-k, i+j<N$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p+\lambda_{sh}+i\mu_p+j\mu_{sh}+k\mu_{sl}) &= P(i+1,j,k-1,l+1)(i+1)\mu_p \\ &+ P(i,j+1,k-1,l+1)(j+1)\mu_{sh} \\ &+ P(i-1,j,k+1,l-1)\lambda_p \\ &+ P(i,j-1,k+1,l-1)\lambda_{sh} \end{aligned} \tag{21}$$

For $1 \le i < N-1, 1 \le j < N-1, k=0, l=0, i+j<N$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p+\lambda_{sh}+\lambda_{sl}+i\mu_p+j\mu_{sh}) &= P(i+1,j,k,l)(i+1)\mu_p \\ &+ P(i,j+1,k,l)(j+1)\mu_{sh} + P(i-1,j,k,l)\lambda_p \\ &+ P(i,j,k+1,l)(k+1)\mu_{sl} + P(i,j-1,k,l)\lambda_{sh} \end{aligned} \tag{22}$$

For $1 \le i < N-1, 1 \le j < N-1, 1 \le k < N-1, 0 \le l < N-1, i+j+k+l<N$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p+\lambda_{sh}+\lambda_{sl}+i\mu_p+j\mu_{sh}+k\mu_{sl}) &= P(i+1,j,k,l)(i+1)\mu_p + P(i,j,k-1,l)\lambda_{sl} \\ &+ P(i,j+1,k,l)(j+1)\mu_{sh} + P(i-1,j,k,l)\lambda_p \\ &+ P(i,j,k+1,l)(k+1)\mu_{sl} + P(i,j-1,k,l)\lambda_{sh} \end{aligned} \tag{23}$$

For $1 \le i < N-1, 1 \le j < N-1, 1 \le k < N-1, l=0, i+j+k=N$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p+\lambda_{sh}+i\mu_p+j\mu_{sh}+k\mu_{sl}) &= P(i+1,j,k-1,l+1)(i+1)\mu_p \\ &+ P(i,j,k-1,l)\lambda_{sl} \\ &+ P(i,j+1,k-1,l+1)(j+1)\mu_{sh} \\ &+ P(i-1,j,k,l)\lambda_p + P(i,j,k,l+1)k\mu_{sl} \\ &+ P(i,j-1,k,l)\lambda_{sh} \end{aligned} \tag{24}$$

For $1 \le i < N-1, 1 \le j < N-1, 1 \le k < N-1, 0 \le l < N-1, i+j+k=N, l>0, k+l<N$,

$$\begin{aligned} P(i,j,k,l)(\lambda_p+\lambda_{sh}+i\mu_p+j\mu_{sh}+k\mu_{sl}) &= P(i+1,j,k-1,l+1)(i+1)\mu_p \\ &+ P(i,j+1,k-1,l+1)(j+1)\mu_{sh} \\ &+ P(i-1,j,k+1,l-1)\lambda_p + P(i,j,k,l+1)k\mu_{sl} \\ &+ P(i,j-1,k+1,l-1)\lambda_{sh} \end{aligned} \tag{25}$$

To evaluate the performance of IoT node connections, the steady-state probability distribution $P(i, j, k, l)$ derived from the CTMC model is employed. Key performance metrics, including channel utilization, connection blocking probability, connection dropping probability and connection handoff probability are obtained for the proposed PBCA scheme which incorporates an integrated queueing mechanism and dynamic retrial policies. These metrics are assessed for both high-priority and low-priority IoT nodes. The connection blocking probability is defined as the probability that an arriving connection request cannot be admitted into the network because all channels are already occupied by other users [24]. A new PU connection request is blocked when all the channels in the system are already occupied by other PUs. A newly arriving IoT-HP connection request is blocked if neither an idle channel nor a channel occupied by an IoT-LP is available. Similarly, an IoT-LP connection request is blocked when no idle channel exists in the network. The connection blocking probabilities of IoT-HP and IoT-LP nodes are expressed in Equations 26 and 27, respectively.

$$P_{B,IoT-HP} = \sum_{i=0}^{N} \sum_{l=0,j=N-i,k=0}^{N} P(i,j,k,l) \tag{26}$$

$$P_{B,IoT-LP} = \sum_{a=0}^{N} \sum_{i=0}^{N-a} \sum_{k=0,j=N-i-a}^{N} \sum_{l=0,i+j+k=N}^{N-a} P(i,j,k,l) \tag{27}$$

The connection dropping probability is defined as the probability that a newly arriving PU connection overlaps with an ongoing IoT node connection, resulting in the IoT node connection being terminated due to a lack of available channels. An IoT-HP connection is dropped if a PU arrival preempts a channel occupied by an IoT-HP, and the IoT-HP node is unable to find either an idle channel or a channel currently utilized by a IoT-LP. The IoT-LP connection drops are mitigated in the proposed PBCA scheme through the integrated queueing and dynamic retrial mechanism. The connection dropping probability for IoT-HP nodes expressed in Equations 28,

$$P_{D,IoT-HP} = \sum_{i=0}^{N-1} \sum_{j=1}^{N} \sum_{k=0}^{N-1} \sum_{l=0}^{N} \frac{\lambda_p}{\lambda_{sh} \left(1 - P_{B,IoT-HP}\right)} P(i,j,k,l) \tag{28}$$

The connection handoff probability is defined as the probability that a newly arriving PU connection request overlaps with an ongoing IoT node connection, causing the IoT node connection to be transferred to either an idle channel or a channel currently used by a IoT-LP in the network. An IoT-HP connection handoff occurs when a newly arriving PU connection request overlaps with a channel occupied by an IoT-HP, and the IoT-HP connection is transferred to either an idle channel or a channel occupied by an IoT-LP connection. Similarly, an IoT-LP connection handoff occurs when a newly arriving PU connection request overlaps with a channel occupied by an IoT-LP connection, and the IoT-LP connection is transferred to an idle channel. The connection handoff probabilities for IoT-HP and IoT-LP nodes are expressed in Equations 29 and 30, respectively.

$$\begin{aligned} P_{H,IoT-HP} = & \sum_{i=0}^{N-2} \sum_{j=1}^{N-1} \sum_{k=0}^{N-1} \sum_{l=0,i+j<N}^{N-1} \frac{\frac{j}{(N-i)}\lambda_p}{\lambda_{sh} \left(1 - P_{(B,SH)}\right)} P(i,j,k,l) \\ & + \sum_{i=0}^{N-1} \sum_{j=1}^{N-1} \sum_{k=1}^{N-1} \sum_{l=0,i+j=N}^{N-1} \frac{\frac{j}{(N-i)}\lambda_p}{\lambda_{sh} \left(1 - P_{(B,SH)}\right)} P(i,j,k,l) \end{aligned} \tag{29}$$

$$P_{\text{queue\_access}} = \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=0}^{N} \sum_{l=1,i+j+k=N}^{N} \left(i\mu_p + j\mu_{sh} + k\mu_{sl}\right) P(i,j,k,l)$$

$$P_{H,IoT-LP} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \sum_{k=1}^{N-1} \sum_{l=0,i+j+k<N}^{N-1} \frac{\frac{k}{(N-i)}\lambda_p}{\lambda_{sl} \left(1 - P_{(B,IoT-LP)}\right) + P_{\text{queue\_access}}} \tag{30}$$

Spectrum utilization is defined as the ratio of the average number of occupied channels to the total number of available channels [25]. The spectrum utilization for IoT-HP and IoT-LP nodes is defined as the ratio of the average number of channels occupied by IoT-HP to the total number of available channels, and the ratio of the average number of channels occupied by IoT-LP to the total number of available channels, respectively. The spectrum utilization for IoT-HP nodes, IoT-LP nodes and overall system are expressed in Equations 31, 32, and 33, in a given order.

$$U_{IoT-HP} = \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=0}^{N}\sum_{l=0}^{N}\frac{j}{N}P(i,j,k,l) \tag{31}$$

$$U_{IoT-LP} = \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=0}^{N}\sum_{l=0}^{N}\frac{k}{N}P(i,j,k,l) \tag{32}$$

$$U_{T} = \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=0}^{N}\sum_{l=0}^{N}\frac{i+j+k}{N}P(i,j,k,l) \tag{33}$$

5 Analytical and Simulation Results with Discussion

In this section, the performance of the proposed PBCA scheme is evaluated in comparisons with the baseline Random DSA scheme. Both schemes are analyzed under identical network scenarios and traffic loads to ensure a fair comparison. The performance of IoT-LP nodes is examined in terms of spectrum utilization, connection blocking probability, connection dropping probability and connection handoff probability across varying arrival rates of PUs and IoT-LP nodes. Furthermore, the analytical results of the proposed PBCA scheme are validated through a comprehensive Python-based discrete event simulation study. The simulation models were implemented in Python 3.10 using Monte Carlo methods, with approximately 200,000 connection-request events generated for each offered load in all networking scenarios. This extensive number of events ensures statistical robustness and yields stable averages. The strong consistency observed between the simulation and analytical model results confirms the reliability of the performance evaluation.

The parameters used in the analytical and simulation models are summarized in Table 1, defining the network configuration, traffic arrival rates, service times, and system capacities.

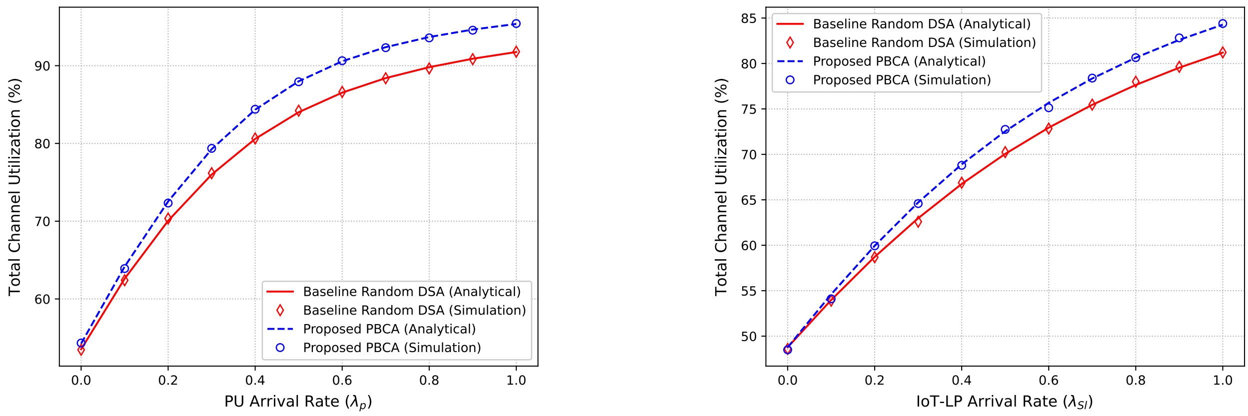
Table 1: Parameters for the analytical and the simulation studies of the proposed PBCA

Definition	**Parameter**	**Value**
Number of channels	N	8
PU	Mean arrival rate (λ_{pu})	$0.0 - -1.0 call/sec$
	Mean service rate (μ_{pu})	0.1 call/sec
IoT-HP	Mean arrival rate (λ_{sh})	0.4 call/sec
	Mean service rate (μ_{sh})	0.2 call/sec
IoT-LP	Mean arrival rate (λ_{sl})	0.0 – 1.0 call/sec
	Mean service rate (μ_{sl})	0.2 call/sec

The impact PU and IoT-LP of arrival rates on total channel utilization is illustrated in Figure 5a and Figure 5b, respectively. As shown in Figure 5a, increasing the PU arrival rate (λ_p) leads to a steady rise in total channel utilization for both schemes, which is expected since higher PU activity results in more channels being occupied. However, the results clearly demonstrate that the proposed PBCA scheme with integrated queueing and dynamic retrial significantly outperforms the baseline scheme without these mechanisms. When λ_p increases from 0 to 1, the proposed PBCA scheme achieves up to a 4.65% improvement overall channel utilization compared to the baseline.

Similarly, Figure 5b shows as the IoT-LP arrival rate (λ_{sl}) increases, the PBCA scheme with queueing and retrial consistently provides enhanced utilization over the baseline. Specifically, when λ_{sl} increases from 0 to 1, the proposed PBCA scheme yields up to 3.87% improvement in channel utilization.

Importantly, higher channel utilization directly translates into better spectrum efficiency and improved QoS for IoT nodes, as fewer connection requests are wasted and more IoT-LP connections are successfully admitted into the network without sacrificing the performance of high-priority traffic.



(a) (b)

Figure 5: Total channel utilization versus (a) PU arrival rate and (b) IoT-LP arrival rate

The impact of PUs and IoT-LP arrival rates on the channel utilization of IoT-LP nodes is illustrated in Figure 6a and Figure 6b, respectively. As shown in Figure 6(a), the channel utilization of IoT-LP nodes decreases as the PU arrival rate (λ_p) increases. This decline occurs because higher PU activity occupies more channels, leaving fewer opportunities for IoT-LP transmissions. Nevertheless, the results clearly demonstrate that the proposed PBCA scheme with integrated queueing and dynamic retrial significantly improves IoT-LP channel utilization compared to the baseline scheme. Specifically, when λ_p increases from 0 to 1, the proposed PBCA scheme achieves up to a 49.8% improvement in IoT-LP channel utilization.

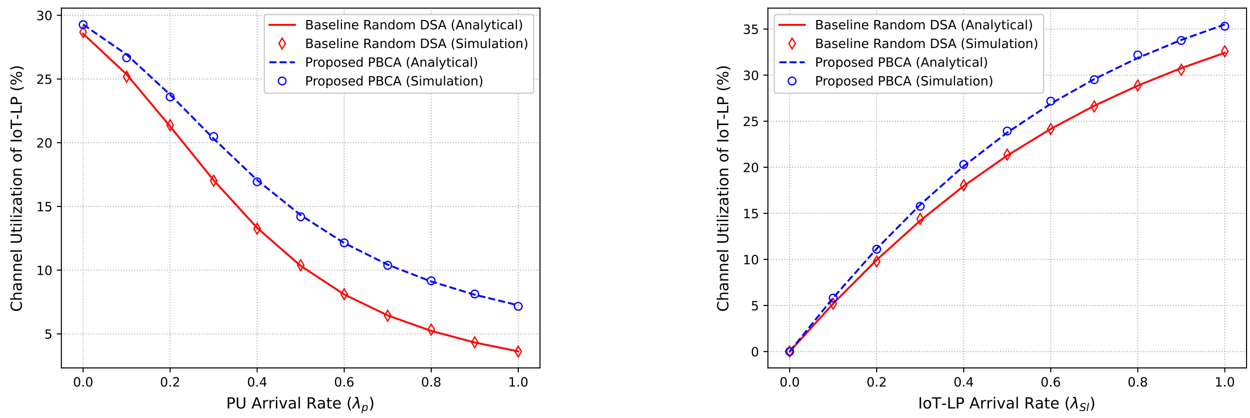
As shown in Figure 6b, increasing the IoT-LP arrival rate (λ_{sl}) also leads to improved channel utilization, with the PBCA scheme consistently outperforming the baseline. This improvement stems from the ability of queueing and retrial mechanisms to efficiently manage excess IoT-LP traffic and reduce wasted transmission opportunities.

These enhancements in IoT-LP channel utilization not only increase spectrum efficiency but also promote fairness across traffic classes, ensuring that low-priority nodes benefit from more reliable access without compromising the service quality of high-priority traffic.

Figure 7 illustrates the impact of PU and IoT-LP arrival rates on the blocking probability of IoT-LP connection requests. As shown in Figure 7a, the blocking probability of IoT-LP nodes increases with the PU arrival rate (λ_p) in both the baseline Random DSA and the proposed PBCA scheme. This trend arises because higher PU activity occupies more channels, leaving fewer available for IoT-LP connections and thereby increasing the likelihood of blocked requests.

It can also be observed that the blocking probability of IoT-LP nodes is higher under the proposed PBCA scheme than under the baseline Random DSA. This increase is attributed to the greater channel utilization achieved by PBCA, which reduces idle spectrum opportunities. However, this trade-off is beneficial: while more IoT-LP requests may be blocked, the PBCA scheme keeps the blocking probability within acceptable Grade of Service (GoS) limits while simultaneously improving overall channel utilization and preventing connection drops for IoT-LP nodes.

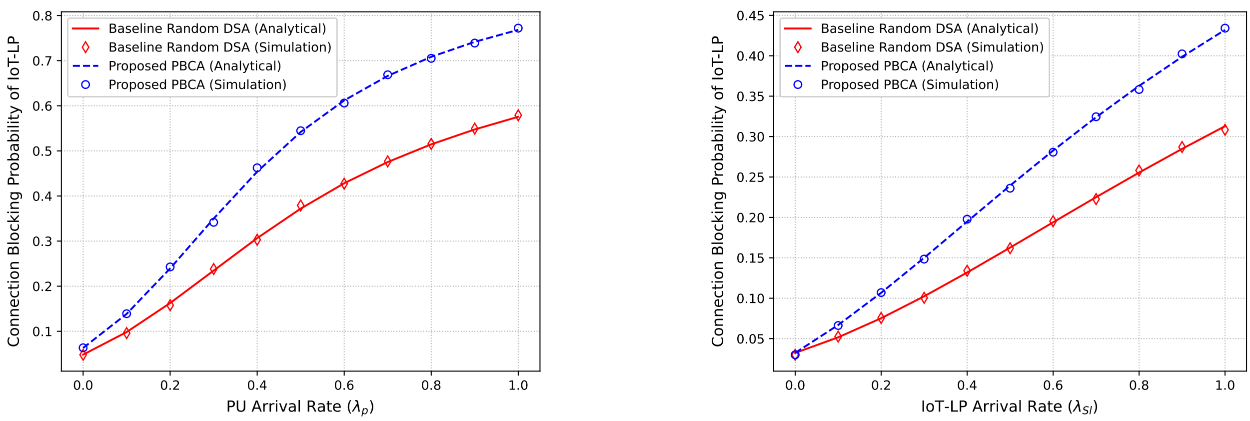
Numerically, when $\lambda_p = 1.0$, the blocking probability of IoT-LP connections reaches approximately 0.68 in the PBCA compared to 0.55 in the baseline scheme, indicating about a 23% relative increase.



(a) (b)

Figure 6: Channel utilization of IoT-LP nodes versus (a) PU arrival rate and (b) IoT-LP arrival rate

Similarly, in Figure 7b, when $\lambda_{sl} = 1.0$, the blocking probability under the PBCA rises to nearly 0.42, while the baseline scheme remains around 0.31, corresponding to a relative increase of 35%. Importantly, this outcome highlights a QoS balancing mechanism in PBCA: by tolerating slightly higher blocking probabilities, the scheme ensures more efficient spectrum use and eliminates the more detrimental issue of connection drops for low-priority traffic.

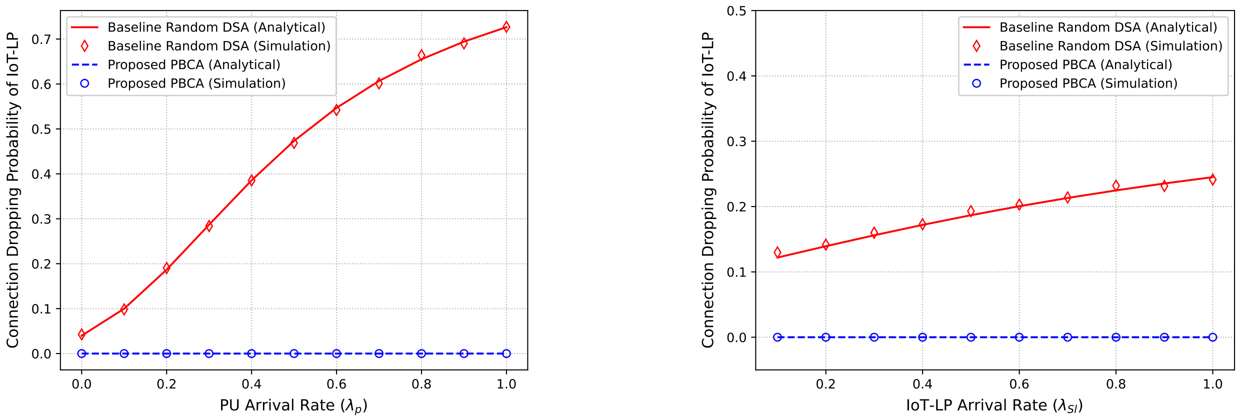


(a) (b)

Figure 7: Connection blocking probability of IoT-LP nodes versus (a) PU arrival rate and (b) IoT-LP arrival rate

Figure 8 presents the connection dropping probabilities of IoT-LP nodes as functions of the PU arrival rate (λ_p) and the IoT-LP arrival rate (λ_{sl}). As shown in both Figure 8a and Figure 8b, the baseline Random DSA scheme exhibits steadily increasing connection dropping probabilities as either arrival rate grows. This behavior results from the absence of buffering or retrial mechanisms, which causes ongoing IoT-LP connections to be forcibly terminated whenever new PU or IoT-LP requests exceed the available spectrum resources.

In sharp contrast, the proposed PBCA scheme with integrated queueing and dynamic retrial completely mitigates IoT-LP connection drops across the entire range of arrival rates. The analytical and simulation results for PBCA remain consistently at zero, highlighting the scheme's ability to protect IoT-LP connections even under heavy traffic conditions. When $\lambda_p = 1.0$, the baseline scheme shows a connection dropping probability of approximately 0.72, while PBCA maintains 0.0, representing a 100% elimination of IoT-LP drops. Similarly, when $\lambda_{sl} = 1.0$, the baseline scheme reaches about 0.25, whereas PBCA again achieves zero connection dropping. This outcome underscores the critical advantage of PBCA: by integrating queueing and retrial, the scheme not only improves spectrum efficiency but also provides reliable QoS support for low-priority traffic, ensuring that IoT-LP nodes are no longer penalized with forced terminations under high load scenarios.



(a) (b)

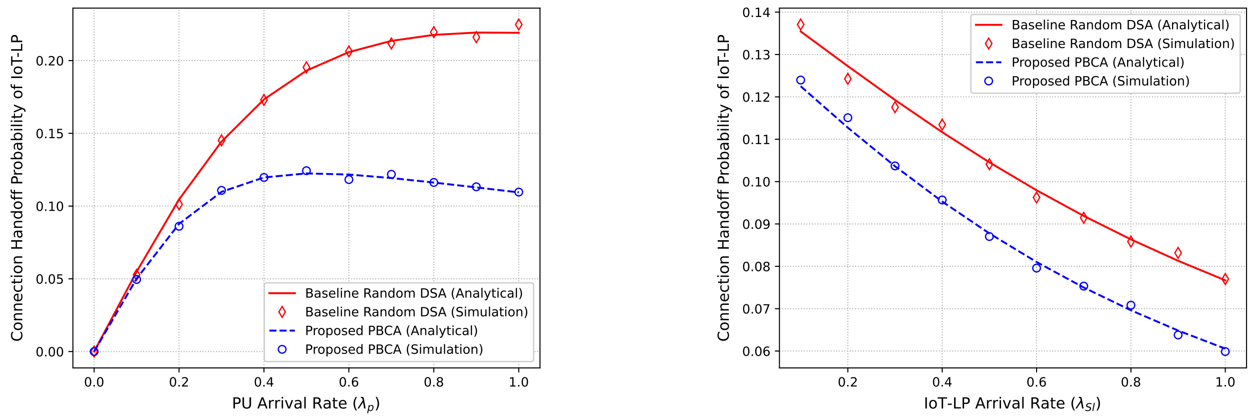
Figure 8: Connection dropping probabilities of IoT-LP nodes versus (a) PU arrival rate and (b) IoT-LP arrival rate

Figure 9 shows the connection handoff probabilities of IoT-LP nodes as functions of the PU arrival rate (λ_p) and IoT-LP arrival rate (λ_{sl}). As seen in Figure 9a, increasing λ_p raises the handoff probabilities for both schemes, since more PU activity forces IoT-LP nodes to vacate their channels more frequently. However, the gap between the two schemes widens as λ_p increases, with the proposed PBCA consistently achieving lower handoff probabilities than the baseline Random DSA. When λ_p increases from 0 to 1, the PBCA scheme reduces IoT-LP handoff probability by up to 50.06% compared with the baseline.

Figure 9b presents the handoff probability trends with varying IoT-LP arrival rates. In both schemes, the probability decreases as λ_{sl} increases. This occurs because higher IoT-LP arrival rates also increase connection blocking events, which in turn reduce active connections and hence lower the number of potential handoff events. Nevertheless, the PBCA scheme achieves consistently better performance than the baseline. Specifically, when λ_{sl} increases from 0 to 1, the PBCA scheme reduces IoT-LP handoff probability by up to 17.29%. When $\lambda_p = 1.0$, the baseline scheme's handoff probability stabilizes around 0.21, while the PBCA maintains approximately 0.11, reflecting the 50% reduction. Likewise, for $\lambda_{sl} = 1.0$, the baseline probability falls to about 0.078, whereas the PBCA achieves 0.064, reflecting a relative improvement of 17.29%. These results highlight that the proposed PBCA not only improves spectrum efficiency but also ensures more stable and reliable service continuity for IoT-LP nodes, a critical factor for QoS in heterogeneous IoT networks.

The comprehensive analytical and simulation results clearly demonstrate that the proposed PBCA scheme with integrated queueing and dynamic retrial mechanisms provides significant advantages over the baseline Random DSA approach. Across all evaluated metrics, including spectrum utilization, connection blocking, connection dropping, and connection handoff probabilities, the PBCA consistently outperforms conventional schemes by striking an effective balance between efficiency and fairness. In particular, the results show up to 4.65% higher total channel utilization, 49.8% improved IoT-LP channel utilization, complete elimination of IoT-LP connection drops, and reductions in connection handoff probability of up to 50.05%. These gains are achieved without violating GoS requirements, ensuring robust QoS support for heterogeneous IoT traffic. Unlike conventional approaches that sacrifice low-priority traffic under congestion, the PBCA guarantees reliable access for IoT-LP nodes while maintaining service continuity for high-priority traffic. This dual advantage, i.e., eliminating IoT-LP connection drops while enhancing utilization, represents a novel contribution to CR-IoT research, positioning the PBCA scheme as a scalable and spectrum-efficient solution for next-generation IoT networks operating under spectrum scarcity.

The PBCA offers very important trade-off between delay and reliability. By allowing interrupted or dropped IoT-LP requests to queue and retry, PBCA completely eliminates connection drops (Figure



(a) (b)

Figure 9: Connection handoff probabilities of IoT-LP nodes versus (a) PU arrival rate and (b) IoT-LP arrival rate

8), significantly enhancing reliability. However, this comes at the cost of additional waiting delays for IoT-LP traffics, as queued requests must wait for upcoming spectrum availability. This trade-off can be interpreted as a shift in the failure mode: rather than facing outright service denial, IoT-LP sessions experience controlled waiting times. For many delay-tolerant applications (e.g., smart metering, environmental monitoring), this is a favorable exchange, as reliability is paramount. Conversely, in case of time-sensitive IoT-LP applications, delay must be carefully bounded. In such cases, PBCA could be configured with deadline-aware queueing policies, bounded queue sizes, or retrial pacing to limit latency while preserving its reliability gains. Thus, PBCA provides a flexible framework in which delay and reliability can be tuned according to application-specific QoS requirements.

6 Conclusions

This paper has proposed, modeled, and analyzed a new Priority-Based Channel Allocation (PBCA) scheme incorporating queueing and retrial mechanisms for low priority (non-real-time) IoT traffic in CRIoT networks. By classifying IoT nodes into two priority levels according to their traffic characteristics, the scheme enables priority-based spectrum allocation and handoff policies while preventing service termination of low-priority connections through buffering and retrial.

The performance of the proposed scheme was evaluated using a multi-dimensional continuous-time Markov chain (CTMC) model and validated through discrete-event simulations. Comparative analyses with a classical Random DSA scheme without queueing show that the proposed approach achieves substantial gains: total channel utilization improved by up to 4.65% and handoff probabilities reduced by 50.05%, while completely eliminating connection drops for low-priority IoT nodes.

These findings highlight the dual contribution of PBCA: enhancing spectrum efficiency and throughput while ensuring fairness and reliable QoS support for heterogeneous IoT traffic. As future work, the development of a prioritized dynamic spectrum access framework under imperfect channel conditions will be considered to further adapt the proposed scheme to realistic deployment scenarios.

Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

References

[1] Alex, K.; Carol, S. S.; Jeretta, H. N.; Joanna, P. (2022). Internet of Things (IoT): From awareness to continued use, *International Journal of Information Management*, 62, 2022.

[2] Kassab, M.; Joanna, D.; Phillip, L. (2020). A systematic literature review on Internet of things in education: benefits and challenges, *Journal of computer Assisted learning*, 36, 115-127, 2020.

[3] Deniz, T.; Selcuk, Y. (2020). A Long-range context-aware platform design for rural monitoring with IoT In precision agriculture, *International Journal of Computers Communications & Control*, 15(2), 2020.

[4] Luigi, A.; Antonio I.; Giacomo M. (2010). The Internet of Things: A survey, *Computer Networks*, 54(15), 2787-2805, 2010.

[5] Munam, A. S.; Sijing, Z.; Carsten, M. (2013). Cognitive radio networks for Internet of Things: Applications, challenges and future, *19th International Conference on Automation and Computing*, 102(46), 1-6, 2013.

[6] Bandyopadhyay, D.; Sen, J. (2011). Internet of Things: Applications and Challenges in Technology and Standardization, *Wireless Personal Communications*, 58, 49–69, 2011.

[7] Manisha, S.; Gaurav, B. (2018). Quality of Service (QoS) in Internet of Things, *3rd International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU)*, 1-6, 2018.

[8] Priyanka, R.; Kamal, D. S.; Jean, M. B. (2016). Cognitive radio for M2M and Internet of Things: A survey, *Computer Communications*, 94(1), 1–29, 2016.

[9] Sridhara K.; Chandra, A.; Tripathi, P.S.M. (2008). Spectrum Challenges and Solutions by Cognitive Radio: An Overview, *Wireless Personal Communications*, 45, 281-291, 2008.

[10] Zhonggui, M.; Hongbo, W. (2012). Dynamic Spectrum Allocation with Maximum Efficiency and Fairness in Interactive Cognitive Radio Networks, *Wireless Personal Communications*, 64, 439-455, 2012.

[11] Athar, A. K.; Mubashir, H. R.; Abderrezak, R. (2016). When Cognitive Radio meets the Internet of Things?, *2016 International Wireless Communications and Mobile Computing Conference (IWCMC)*, 469-474, 2016.

[12] Amjad, A.; Li, F.; Ali, K. B.; Shaker, E. S.; Syed, H. A.; Muddesar, I.; Gunasekaran, R. (2020). Quality of Service Provisioning for Heterogeneous Services in Cognitive Radio-Enabled Internet of Things, *IEEE Transactions on Network Science and Engineering*, 7(1), 328-342, 2020.

[13] Abd, U. K.; Ghulam, A.; Ziaul, H. A.; Muhammad, W.; Ahmad, K. H. (2020). Spectrum utilization efficiency in the cognitive radio enabled 5G-based IoT, *Journal of Network and Computer Applications*, 164, 2020.

[14] Faisal, F. Q.; Rahat, I.; A.; Muhammad, N. A. (2017). Energy efficient wireless communication technique based on Cognitive Radio for Internet of Things, *Journal of Network and Computer Applications*, 89, 14-25, 2017.

[15] Ali, S.; Abbas, K.; Nirwan, A. (2019). Energy Efficient Resource Allocation in EH-Enabled CR Networks for IoT, *IEEE Internet of Things Journal*, 6(2), 3186-3193, 2019.

[16] Ahmed, T. E. T; Aslan, H. (2020). Enhancing the performance of low priority SUs using reserved channels in CRN, *EEE Wireless Communications Letters*, 9(4), 513–517, 2020.

[17] Abd, U.K.; Muhammad, T.; Hyundong, S.; Musheer, A.; Ammar M.; Abdukodir A. K. (2023). Toward Spectrum Efficiency and Reliability for Heterogeneous Users in CR-Enabled Social Internet of Things, *IEEE Access*, 11, 145706-145722, 2023.

[18] Ram, N. Y.; Rajiv, M.; Sourabh, B. (2017). Spectrum access in cognitive smart-grid communication system with prioritized traffic, *Ad Hoc Networks*, 65, 38–54, 2017.

[19] Iqbal, A.; Khurshaid, T.; Qadri, Y. A.; Nauman, A.; Kim, S. W. (2025). Priority-Aware Spectrum Management for QoS Optimization in Vehicular IoT, *Sensors*, 25(11), 3342, 2025.

[20] Gunjan, B.; Anita, S. (2025). Energy-efficient smart gateway framework with QoS-aware resource allocation in IoT ecosystem, *Next Energy*, 9, 2025.

[21] Jun, W.; Weibin, J.; Changchun, C.; Ruiquan, L.; Riqing, C.; Hongjun, W. (2024). A novel resource allocation method based on supermodular game in EH-CR-IoT networks, *Ad Hoc Networks*, 152, 2024.

[22] Umer, F.; Najam, U. H. (2024). Multi-objective spectrum assignment in heterogeneous cognitive radio networks for internet of things, *International Journal of Communication Systems*, 37(7), 2024.

[23] AlQahtani, S. A. (2023). Performance Analysis of a Quality of Service-Aware Resource Allocation for Internet of Things, *Wireless Personal Communications*, 129, 1961–1982, 2023.

[24] Stewart, W. J. (1994). *Introduction to the Numerical Solution of Markov Chains*, Princeton University Press, 1998.

[25] Moshe, Z. (2023). *Introduction to queueing theory and stochastic teletraffic modelss*, arXiv preprint arXiv:1307.2968, 2023.

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