This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSE.2018.2877646, IEEE Transactions on Network Science and Engineering

Quality of Service Provisioning for Heterogeneou -s Services in Cognitive Radio-enabled Internet of Things

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Abstract—

The Internet of Things (IoT) is a network of interconnected objects, in which every object in the world seeks to communicate and exchange information actively. This exponential growth of interconnected objects increases the demand for wireless spectrum. However, providing wireless channel access to every communicating object while ensuring its guaranteed quality of service (QoS) requirements is challenging and has not yet been explored, especially for IoT-enabled mission-critical applications and services. Meanwhile, Cognitive Radio-enabled Internet of Things (CR-IoT) is an emerging field that is considered the future of IoT. The combination of CR technology and IoT can better handle the increasing demands of various applications such as manufacturing, logistics, retail, environment, public safety, healthcare, food, and drugs. However, due to the limited and dynamic resource availability, CR-IoT cannot accommodate all types of users. In this paper, we first examine the availability of a licensed channel on the basis of its primary users' activities (e.g., traffic patterns). Second, we propose a priority-based secondary user (SU) call admission and channel allocation scheme, which is further based on a priority-based dynamic channel reservation scheme. The objective of our study is to reduce the blocking probability of higher-priority SU calls while maintaining a sufficient level of channel utilization. The arrival rates of SU calls of all priority classes are estimated using a Markov chain model, and further channels for each priority class are reserved based on this analysis. We compare the performance of the proposed scheme with the greedy non-priority and fair proportion schemes in terms of the SU call-blocking probability, SU call-dropping probability, channel utilization, and throughput. Numerical results show that the proposed priority scheme outperforms the greedy non-priority and fair proportion schemes.

Index Terms—Internet of Things, cellular cognitive radio networks, multimedia applications, next generation communication systems, resource allocation.

1 Introduction

In recent years, Internet of Things (IoT) has emerged as a new computing paradigm, in which heterogeneous devices with interesting services and applications are connecting to each other at an unprecedented rate [1]. These applications include patient monitoring, real-time health status, remote personnel monitoring, cardiac monitors, surveillance cameras, disaster management, response planning, resource management and distribution, real-time traffic monitoring, smartphones, utility meters, kitchen appliances, televisions, cars, thermostats, industry monitoring, noise monitoring, air pollution, waterways, banking, security, and almost anything imaginable [2], [3]. According to Gartner research findings, by 2020 approximately 63 million of IoT devices will

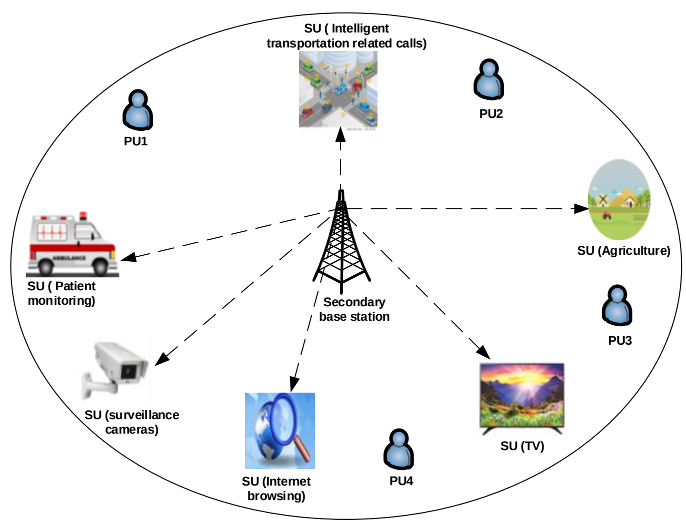

Fig. 1: Cognitive radio-enabled cellular IoT architecture. Multiple CR-empowered IoT users with heterogeneous applications accessing the primary channels opportunistically.

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Manuscript received April 15, 2018; revised Sep. 07, 2018 and Oct. 17, 2018.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSE.2018.2877646, IEEE Transactions on Network Science and Engineering

connect to the enterprise networks per second [4]. McKinsey predicted that IoT has great potential for creating a large economic impact of $2.7 - 6.2$ trillion dollars annually by 2025 [5]. Thus, in accordance with these statistics, it is expected that in the next decade Cisco will make approximately 14.4 trillion dollars profits from IoT projects worldwide [6]. Similarly, GSMA predicted approximately 1.3 trillion dollars profit for mobile network operators from the IoT industry [3]. However, accommodating exponentially increasing new applications and services over limited available spectrum band poses new communications challenges [7].

Due to recent advancements in cognitive radio networks (CRN) and IoT, it has been visualized that the junction of cognitive radio (CR) and IoT will become the vital need of future communications. IoT devices would be equipped with CR technology to enable them to think, learn, and make decisions via awareness of both physical and social environments. Additional specifications include the perception action cycle, intelligent decision making, semantic derivation, on-demand service provisioning, knowledge discovery, and massive data analytics. According to Khan and Rehmani, all versions of IoT (e.g., Internet-oriented, semantic-oriented, and things-oriented) are insignificant without the CR facility [8], [9]. Hence, CR technology has emerged as a key enabling technology for IoT. Since the beginning of spectrum regulation, static and fixed spectrum allocation schemes have been adopted to allocate wireless spectrum bands. However, statistics prove that most of the allotted wireless resources remain unused most of the time all around the world [10]. Therefore, if the free slot/white space of already-allocated spectrum bands can be used opportunistically, the spectrum scarcity issue can be resolved, and new emerging IoT services and applications can be accommodated [11]. CR technology has emerged as a promising technique that identifies and utilizes spectrum opportunities opportunistically. In CR-enabled IoT networks, two types of spectrum users exist: 1) primary users (PUs) or legitimate users, who actually own the spectrum bands and have exclusive rights to use them for specific wireless applications, and 2) secondary users (SUs) or CR-empowered IoT users, who identify spectrum opportunities and utilize them.

Why do we need differentiated priority for multi-class traffic? The recent trends in IoT communication systems have introduced a variety of *IoT services and applications*. Hence, it is a challenging task to allocate the wireless spectrum to the enormous number of CR-IoT users [8], [9]. However, among a variety of IoT services and applications, a few classes of traffic (e.g., traffic related to disaster management, response planning, banking, healthcare, and security) are more important than others. However, if all the SU calls are considered equal in priority under a heavy traffic load and dynamic channel availability, then a high blocking rate of more important SU calls occurs, resulting in low performance for CR-IoT networks. Therefore, the priorities of all the traffic classes are not considered to be equal due to their corresponding traffic profile and quality of service (QoS) requirements. Moreover, important traffic classes should be given higher-priority than other traffic classes. Hence, it is preferable to block the low-priority traffic calls rather than high-priority traffic calls under dynamic resource availability and high-traffic-load scenarios.

What are the challenges to enable differentiated priority in multi-class CR-IoT networks? With a high traffic load of diverse IoT services and applications, because the number of available resources is limited in CR-IoT networks (e.g., licensed channels), there are two challenges to enable differentiated priority for SUs' multi-class traffic: 1) First, how to design an efficient call admission control scheme that ensures low-blocking probability to high-priority traffic? 2) How to combine the priority-differentiated admission control with a channel allocation scheme without sacrificing the channel utilization?

Our contributions. To tackle the aforementioned challenges, we introduce a priority-based call admission and channel allocation scheme using traffic-aware dynamic channel reservation to lower the higher-priority SU call-blocking probability with efficient channel utilization. To ensure guaranteed SU transmissions, we estimated licensed channels using two important factors: 1) PU idle probability during SU transmission and 2) receipt of ACK at the transmitter SU. The SU calls are classified into multi-priority classes. We allocate channels from the pool of available channels to a particular prioritized SU based on the call arrival rate of specific types of SU requests, which changes with the variation in arriving requests. The number of allocated channels from the pool of available channels for each priority class is computed based on the traffic arrival rate estimation, which is based on queuing analysis and the Markov chain model. Our main contributions are summarized below.

- First, we propose a priority-based traffic-aware dynamic channel reservation scheme using queuing analysis and estimation of SU arrival rates of all priority classes.
- Second, we propose a priority-based SU call admission and channel allocation scheme, which is further based on a dynamic channel reservation scheme for lowering the higher-priority SUs call-blocking probabilities while maintaining a sufficient level of channel utilization.
- Third, we analyze the performance of the proposed scheme and compared it with other proposed greedy non-priority and fair proportion schemes. The performance of the proposed schemes is evaluated in terms of the SU call-dropping probability, SU call-blocking probability, channel utilization, and throughput.

The rest of the article is organized as follows. In Section 2, we discuss the existing state of the art. Then, we present the system model including the traffic and primary channel selection models in Section 3. In Section 4, we describe the proposed priority-based dynamic channel reservation scheme, which further based on queuing analysis and SU call arrival rate estimation. In Section 5, we present the proposed priority-based SU call admission and channel allocation scheme that is based on a priority-based dynamic channel reservation method. In Section 6, we present the performance evaluation. Finally, we propose some applications of our proposed scheme and conclude the paper in Sections 7 and 8, respectively.

2 Related Work

Among a variety of IoT services and applications, a few classes are critical and more important than others. Therefore, these important traffic classes should be given higher-priority than other traffic classes while allocating channel resources. Hence, it is preferable to block the low-priority traffic calls rather than high-priority traffic calls under dynamic resource availability and high-traffic-load scenarios. Hence, the issue of dynamic spectrum allocation and call admission control for heterogeneous IoT services and applications in accordance with their traffic profiles in cellular CR-IoT networks is an important research topic. In the following, we discuss the existing state of the art on dynamic channel allocation and call admission control techniques in CR-IoT, and conventional CRNs in brief.

In [12], the authors proposed an "energy-centered and QoS-aware service selection algorithm (WQSA)" for IoT applications. In the WQSA scheme, QoS satisfaction for IoT applications is ensured by using a lexicographic optimization technique. Moreover, to reduce energy consumption, the best service is selected from the set of services based on QoS attributes, such as the user's preference and energy profile. Similarly, a unifying architecture for energy-efficient scheduling and optimization for IoT-based smart cities was presented in [13]. The authors proposed a new energy-harvesting-based framework for increasing the lifetime of IoT-based low-power devices. In [14], another wireless energy harvesting scheme was proposed for CR-IoT. In the proposed scheme, CR-IoT devices sense the licensed spectrum before using it and also harvest the wireless energy transmitted by the nearby access point (AP). The main objective of the study was to optimize the energy efficiency on the basis of parameters, such as PU interference, energy causality, data rate fairness, and buffer occupancy of IoT devices. In [15], Debroy et al. proposed a multi-hop routing technique called "SpEED-IoT: Spectrum aware Energy-Efficient multi-hop multi-channel routing scheme for D2D communication in IoT mesh network." The proposed scheme finds the best routing path, optimizes transmission power, and selects the best available channel for each hop by using the radio environment map. In order to improve the throughput and to optimize the energy for CR-IoT, Qureshi et al. used the concept of reliable channel selection [16]. The reliability of licensed channels is measured, and channels are ranked based on free/used time tracking method proposed in [17].

In [18], Zhu et al. proposed a Q-learning algorithm by using deep learning technique for improving the throughput of cooperative CR-IoT networks. The authors used the "Markov decision process (MDP)" model to formulate the packet transmission strategy from various CR-IoT devices under multi-channel CR environment. Another solution to increase the end-to-end throughput for multi-hop CR-IoT was proposed in [19]. In the proposed scheme, a concurrent transmission model was introduced, in which a link channel allocation problem was formulated with the help of a genetic algorithm. Similarly, in [20], Salameh et al. proposed a probabilistic channel allocation scheme to maximize packet transmission rate for CR-IoT networks under reactive and proactive jamming attacks. The proposed scheme selects the secure licensed channel for delay-sensitive IoT device based on the channel fading conditions and information on PU activities. In order to improve QoS degradation for IoT networks an autonomic QoS-aware middleware was introduced in [21]. In [22], an adaptive and QoS-aware architecture was introduced for wireless sensors networks based IoT by using a modular approach. This architecture helps in implementing QoS models for various IoT applications by using historical data captured in physical network. In [23], C. S. Shih et al. proposed a QoS-aware meta-routing protocol for cyber physical system-based IoT applications. The proposed routing scheme determines the best routing paths for IoT applications based on QoS parameters, such as reliability and timeliness. Moreover, node mobility and link failure parameters were also considered to ensure the better quality of transmissions. In order to optimize energy cost, a "discontinuous reception/transmission (DRX/DTX)" scheme for IoT applications was proposed in [24]. This scheme studied various sleeping patterns for IoT devices to save energy while ensuring QoS in terms of the packet delay, bit rate, and packet loss rate.

Several prior research efforts [25], [26], [27], [28], [29], [30], [31], [32], [33] deal with different schemes for call admission control (CAC) and channel allocation while guaranteeing QoS to SUs. An auction-based SU admission control and channel allocation scheme for CRN-based hotspots has been studied in [25]. Spectral resources for different SUs have been allocated according to their advertised pricing policy. In [26], Alshamrani et al. studied the channel assignment and CAC scheme for two different types of SUs: 1) non real-time, and 2) real-time. In the proposed scheme, firstly, the licensed channels are sensed based on the statistical information and then detected idle channels are assigned to both types of SUs for maintaining QoS between them in terms of call dropping and call blocking probabilities. In [27], He et al. proposed a channel assignment method with prime objective to maximize the overall user satisfaction by considering various types of SU's applications and services. In [28], Tran et al. introduced an auction theory-based spectrum allocation scheme for delay-sensitive SUs. Li et al. investigated the impact of dynamic channel availability on smooth video delivery under the CRN environment [29]. The authors primarily focused on channel allocation optimization while minimizing playback frozen probability. Moreover, they used the receiving buffer state information for analyzing the video quality. In [30], a spectrum access regulatory framework was proposed to regulate wireless spectrum access among SUs based on time slotted medium access control (MAC) structure and dynamic IDs. Huang et al. proposed a CAC scheme with soft-QoS based spectrum handoff for CRNs [31]. The proposed scheme mainly focuses on improving spectrum utilization and balancing the trade-off between SUs call-blocking and call-dropping probabilities. Similarly, Jiang et al. also proposed a CAC scheme for CRNs called "guard channels and restricted channels ($GC\&RC$)" in [32]. In the $GC\&RC$ scheme, licensed channels are classified into three categories, such as guard, restricted, and shared. Moreover, another CAC scheme for CRNs was introduced in [33]. In this scheme, a random access method called "VX (virtual-xmit-if-busy)" was used for channel allocation. Moreover, the SU collision probability, and channel capacity parameters were observed by the PU.

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TABLE 1: Key notations.

N	Number of total licensed channels
K	Number of available channels for SUs use
M	Number of secondary users
κ	Number of traffic patterns
$\Gamma_S,\ \Gamma_T$	SU sensing and transmission time
$o_t,\ \theta_t$	SU action and observation at time t about PU channel status
$\sigma_{(t+\Gamma_S^{o^S})}$	PU idle probability after SU performed Sensing S
$\sigma_{(t+\Gamma_T^{o^T})}$	PU idle probability after SU performed transmission T
λ_p	Call arriving rate of priority-class p
λ_T	Total SUs call arriving rate of all priority-classes
$\frac{1}{\omega_p}$	SU call holding time
$Y_p(t)$	Reserved channels for priority class p
$R_p(t)$	Number of accessible channels for p^{th} priority class from Ψ
K_p	Number of total accessible channels for p^{th} priority class from total K channels
η_p	Blocking probability of priority class p
$\overline{\Delta t^p}$	Average inter arrival time between two successive calls of p priority class traffic
ε	SUs transition rate
$\pi_{o_t^s}$	Steady state probability

To the best of our knowledge, there is no algorithm that jointly considers QoS provisioning of heterogeneous multimedia applications and services in accordance with their traffic profiles (e.g., priorities), spectrum sensing that is based on PU activities (e.g., traffic patterns), spectrum access decision, channel allocation, and CAC in cellular CR-IoT networks. Moreover, the objective of our study is to reduce the blocking probability of higher-priority SU calls while maintaining a sufficient level of channel utilization.

3 System Model

In this section, we first present our network and traffic models, and then discuss our PU-traffic-pattern-based primary channel selection model.

Network Model. Spectrum sensing is an essential function in CR-IoT networks to utilize licensed channels by avoiding interference with the PUs. Traditionally, the SUs sense and utilize the PU channels by assuming a predefined idle time distribution [34], [35]. However, in practice, the idle time distribution of licensed channels is PU-traffic-specific [36], [41]. For example, two different channels with different PU traffic patterns (i.e., PU activities) may have the same channel occupancy probabilities, but they still may have different idle/busy frequencies. Therefore, spectrum opportunity identification based on PU activities is an efficient way to exploit the licensed spectrum.

In this study, we consider an infrastructural CR-IoT network with one secondary base station (SBS) and M SUs. As shown in Figure 1, each SU generates different applications, which are categorized into P different priority classes. Each SU requests channel allocation from the SBS for its transmission. The SBS decides either to assign the channel or block the requesting SU based on its priority class and total number of channel accessible by that specific priority class SU. The SBS also detects the K idle channels from the total available licensed channels N, and orders the K available idle channels (i.e., $1 \leq K \leq N$) based on PU idle probability at the time of SU transmission. The Key notations and symbols are presented in Table I.

SUs' Traffic Model. We assume that there are two major categories of radio users: 1) PUs and 2) SUs or CR-empowered IoT users, which are further classified into P different priority classes based on their applications. We make the following assumptions:

A.1: PUs always have the highest priority to use the licensed channels and can occupy licensed channels being used by any SU.

A.2: Each SU can allocate a maximum of one channel at a time for its service.

A.3: The arrivals of each priority class p $(1 \leq p \leq P)$ SU call requests follow the Poisson process with λ_p rate, where the priority class 1 SU calls have the highest priority, and SU calls of priority class P have the lowest priority in terms of their running applications.

A.4: The call holding time of each priority class is assumed to follow an exponential distribution with expectation of $\frac{1}{\omega_p}$.

Assumptions A.1–A.3 are standard technological assumptions in CR-IoT networks [17], [37], [38]. A.4 is widely used to model the service rate in communication networks [39], [40]. In this study, we assume that an SBS knows the licensed channel traffic patterns, which are computed based on Bayesian nonparametric traffic clustering approaches given in [36], [42].

Primary Channel Selection-Based on PU Traffic Patterns. We discuss our licensed channel selection criteria, which is based on the PU traffic patterns. Suppose t is the time required for a PU to switch its state from busy to idle. The probability of interference with the PU when the SU senses the licensed channel at time t under traffic pattern κ is given by [42] as follows:

$$\rho_t^S = \frac{1 - F_x(t + \Gamma_S)}{1 - F_x(t)}. \tag{1}$$

Similarly, ρ_t^T represents the probability of PU interference during the SU transmissions at time t under traffic pattern κ, which is as below:

$$\rho_t^T = \frac{1 - F_x(t + \Gamma_T)}{1 - F_x(t)}, \tag{2}$$

where $F_X(.)$ is a cumulative distribution function of the PU idle time, and Γ_S and Γ_T are the SU sensing and transmission times, respectively. Let γ_0 and γ_1 represent the probabilities of receiving Negative ACKnowledgment (NACK) due to channel conditions (e.g., fading, multipath loss, etc.) and receiving NACK due to the PU collision, respectively. Let θ_t represent the SU action space, such as $\theta_t \in \{1 : transmit,\ 0 : sense\}$. The sensing observation denoted by $o_t^S \in \{idle,\ busy\}$, and similarly $o_t^T \in \{ACK,\ NACK\}$, represents the transmission observation. Let σ_t denote the conditional probability that a PU is idle at time t, given action-observation o_t based on the history for a traffic pattern κ. The licensed channel's idle

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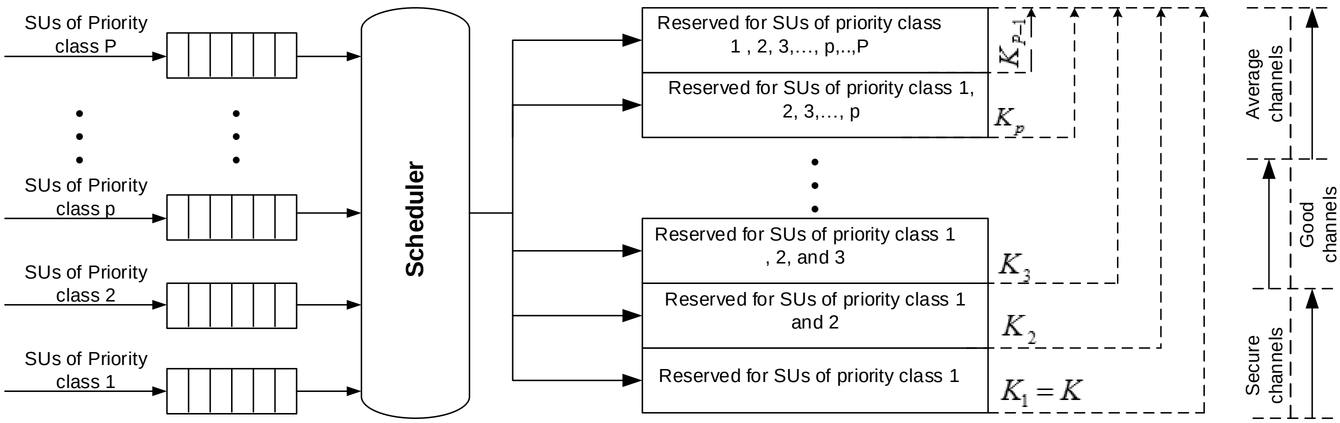

Fig. 2: System model for traffic-aware dynamic channel reservation for CR-enabled IoT network.

probability $\sigma_{(t+\Gamma^{o^S}_S)}$ and transmission probability $\sigma_{(t+\Gamma^{o^T}_T)}$ at $\theta_t = 0$ given in [35] are updated using observation o_t, which is obtained from θ_t as follows:

$$\sigma_{(t+\Gamma^{o^S}_S)} = \begin{cases} \frac{\sigma_t \rho_t^S (1-P_f)}{\sigma_t \rho_t^S (1-P_f)+(1-\sigma_t \rho_t^S)(1-P_d)}, & \text{if } o^S = idle; \\ \frac{\sigma_t \rho_t^S P_f}{\sigma_t \rho_t^S P_f+(1-\sigma_t \rho_t^S) P_d}, & \text{if } o^S = busy, \end{cases} \tag{3}$$

$$\sigma_{(t+\Gamma^{o^T}_T)} = \begin{cases} \frac{\sigma_t \rho_t^T (1-\gamma_0)}{\sigma_t \rho_t^T (1-\gamma_0)+(1-\sigma_t \rho_t^T)(1-\gamma_1)}, & \text{if } o^T = ACK; \\ \frac{\sigma_t \rho_t^T \gamma_0}{\sigma_t \rho_t^T \gamma_0+(1-\sigma_t \rho_t^T)\gamma_1}, & \text{if } o^T = NACK. \end{cases} \tag{4}$$

PU detection cannot be guaranteed 100% through sensing. Therefore, sensing error is included in (3). P_d and P_f are the detection and the false alarm probabilities, respectively. Similarly, successful SU transmission is based on the fact that the channel must remain idle for the duration of transmission and ACK is received at the SU transmitter, which is dependent on γ_0 and γ_1, respectively.

4 Priority-Based Dynamic Channel Reservation Scheme

In this section, we propose a priority-based dynamic channel reservation scheme that is based on queuing analysis and the SU calls arrival rate estimation.

Priority-based dynamic channel reservation scheme. The radio resource management module in CR-IoT networks ensures efficient utilization of licensed channels while guaranteeing the required QoS to various type of SUs in accordance with their traffic profiles. Therefore, in a non-QoS adaptive CR-IoT network environment, where spectrum channels are time and PU activity dependent, it is crucial to give the higher-priority to more important classes of traffic calls. Thus, we exploit a QoS-provisioning-based dynamic channel reservation scheme for QoS adaptive CR-IoT networks for reducing the call-blocking probability of higher-priority CR-IoT calls and ensuring efficient utilization of licensed channels.

In this scheme, the number of total licensed channels available to accept the SU traffic call of any priority-class p changes with the variation in call arrival rates; this concept is shown in Figure 2. We consider P different SU traffic priority-classes, where λ_p represents the arrival rate of calls with priority class p. The total arrival rate of all SU traffic calls is as follows:

$$\lambda_T = \sum_{i=1}^{P} \lambda_i. \tag{5}$$

N represents the number of total licensed channels in the vicinity of the SBS from which K channels are available to an SBS at time t for SU reservation. The number of reserved channels for priority class p is computed as follows:

$$Y_p(t) = \frac{\lambda_p}{\lambda_T} \times K, \ p = 1, ..., P. \tag{6}$$

Hence, K can be alternatively represented as follows:

$$K = \sum_{i=1}^{P} Y_i(t). \tag{7}$$

Consequently, the total number of accessible channels for the p^{th} priority class from K vacant channels is calculated as below:

$$K_p = \lfloor \sum_{i=p}^{P} Y_i(t) \rfloor, \tag{8}$$

In the proposed scheme, if the priority of the SU traffic is high, then it is allocated a greater number of licensed channels to minimize its call-blocking probability. However, a traffic call of any priority class p is only accepted if reserved channels for that class are not already occupied. Moreover, we use a queuing analysis model to compute the SU call-blocking probability with the help of traffic arrival estimation of SUs.

Queuing Analysis Using Markov Model. The SBS calculates the number of accessible channels for any priority class p based on its traffic arrival rate. The traffic queue of the SBS is modeled as $M/M/K/K$ queuing system [43], which we analyzed based the Markov chain method. The SBS blocks any traffic call of priority p when the request's queue is in the K_p state. The SU of any priority class p can hold an allocated channel only for the duration $\frac{1}{\omega_p}$. The probability that the scheduler queue is in state i is denoted by β_i and is computed as follows [45]:

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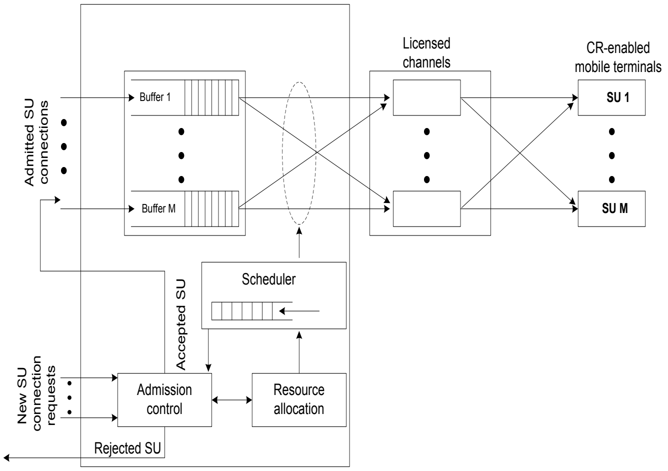

Fig. 3: Call admission control and resource allocation architecture for CR-IoT networks.

$$\begin{cases} i\beta_i\omega = \lambda_T\beta_{i-1}, & 0 \le i \le K_P, \\ i\beta_i\omega = (\lambda_T - \lambda_P)\beta_{i-1}, & K_P < i \le K_{P-1}, \\ i\beta_i\omega = (\lambda_T - \sum_{j=p}^{P}\lambda_j)\beta_{i-1}, & K_p < i \le K_{p-1}, \\ i\beta_i\omega = (\lambda_1+\lambda_2)\beta_{i-1}, & K_3 < i \le K_2, \\ i\beta_i\omega = \lambda_1\beta_{i-1}, & K_2 < i \le K_1. \end{cases} \tag{9}$$

Thus, any new highest-priority SU call will only be blocked if all the available channels (i.e., K_1) are already occupied. The call blocking probability η_1 of priority class 1 SUs can be computed by using queuing analysis as follows:

$$\eta_1 = \beta_1 = \frac{\lambda_T^{K_P}}{\omega^K K!}\beta_0 \prod_{j=1}^{P-1}\sum_{i=1}^{P-j}(\lambda_i)^{K_{(P-j)}-K_{(P-j+1)}}, \quad p=1. \tag{10}$$

Similarly, the call-blocking probability of priority classes 2 and higher is as below:

$$\eta_p = \sum_{i=K_p}^{K}\beta_i = \eta_{p-1} + \beta_0 \sum_{i=K_p}^{K_{(p-1)}-1}\frac{\lambda_T^{K_P}}{\omega^i i!}\sum_{i=1}^{p-1}(\lambda_i)^{i-(K_p)} \prod_{j=p}^{M-1}\sum_{i=1}^{j}(\lambda_1)^{(K_j)-(K_{(j+1)})}, \quad 2 \le p \le P, \tag{11}$$

where β_0 is given [45] as

$$\beta_0 = \Bigg[(1+\sum_{i=1}^{K_P}\frac{\lambda_T^i}{\omega^i i!} + \sum_{j=2}^{P}\sum_{k=K_j+1}^{K_j-1}\Bigg(\frac{\lambda_T^{K_P}\sum_{i=1}^{j-1}(\lambda_i)^{k-K_j}}{\omega^k k!} \prod_{l=j}^{P-1}\sum_{i=1}^{l}(\lambda_i)^{(K_l)-(K_{(l+1)})}\Bigg)\Bigg]^{-1}. \tag{12}$$

Interestingly, we observe that the proposed Markov chain model can be effectively applied for any number of priority classes for queuing analysis.

Arrival Rate Estimation of SU Calls. To estimate the call arrival rate, we observe the last $n+1$ calls of all priority classes and measure the inter-arrival time Δt_i^p between two successive calls, $(i-1)$ and i, of any priority class p. Hence, to calculate the average inter-arrival time denoted by $\overline{\Delta t^p}$, between two successive calls, we take n samples of each priority class and compute $\overline{\Delta t^p}$ as follows:

$$\overline{\Delta t^p} = \frac{1}{n}\sum_{i=1}^{n}\Delta t_i^p. \tag{13}$$

For unbiased estimation, we take the expectation with respect to $\overline{\Delta t^p}$, given in [44] as follows:

$$E[\overline{\Delta t^p}] = E\left[\frac{1}{n}\sum_{i=1}^{n}\Delta t_i^p\right] = \Delta t^p, \tag{14}$$

where Δt^p denotes the true value and proves that the $\overline{\Delta t^p}$ is an unbiased estimation. Thus, the average call arrival rate of priority class p, λ_p, is computed based on the last $n+1$ observations as follows:

$$\lambda_p = \frac{1}{\overline{\Delta t^p}} = \frac{1}{\frac{1}{n}\sum_{i=1}^{n}\Delta t_i^p}. \tag{15}$$

Therefore, λ_p is an unbiased estimation that helps in estimating the arrival rate of priority class p traffic calls.

Algorithm 1: Primary Channel Estimation Procedure

input : Global channel set N
output: Sorted Set of available channel K

```
Initialize channel list with K ← null
for Ch_i ← 1 to N do
    /* Estimate Ch_i using Eq.(3)*/
    if Ch_i is Idle then
        Add Ch_i to the list of available channels K
    else
        Ignore Ch_i
for Ch_i ← 1 to K do
    /* Sort Ch_i based on PU idle probability using Eq.(2)*/
```

5 SU Call Admission and Channel Allocation Schemes

This section first describes our proposed priority-based SU call admission and channel assignment scheme. It then presents the performance analysis of our proposed scheme and compared it with the proposed greedy non-priority and fair proportion schemes.

5.1 Priority-Based SU Call Admission and Channel Allocation Scheme

In the proposed priority-based SU call admission and channel allocation scheme, the SBS will admit and assign the channel to the SU based on its priority class and the corresponding number of reserve channels. To provide a certain QoS level to SU calls according to their traffic profile, we employ two mechanisms in the SBS: 1) SU resource allocation and admission control, and 2) scheduling, as depicted in Figure 3.

SUs' Resource Allocation and Admission Control. Upon arrival of a new SU call request of priority class p, the

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Algorithm 2: Priority-based Call Admission and Channel Allocation Procedure

input : Available channel set K and total priority classes P
output: Channel allocation to SU
1 **if** *Call request* SU_p^m *arrived* **then**
2   **for** $p \leftarrow 1$ **to** P **do**
3   /* Estimate λ_p by using Eq. (15)*/
4 /* Calculate K_p as follows by using Eq. (6), (7), (8), (13), (14), and (15) */
5 $K_p = \left\lfloor \frac{\sum_{j=1}^{m-1} \frac{1}{\sum_{i=1}^{n} \Delta t_i^j}}{\sum_{j=1}^{P} \frac{1}{\sum_{i=1}^{n} \Delta t_i^j}} \right\rfloor$
6 **if** $Oc_p < K_p$ **then**
7   Accept the SU_p^m and Allocate channel Ch_k
8   Update the residual channel list $Oc_p \leftarrow Oc_p + 1$
9 **else**
10   Reject SU_p^m
11 **if** *PU Detection on* Ch_k *== True* **then**
12   Stop immediately SU_p^m and find some alternative channel
13   **if** $Oc_p < K_p$ **then**
14   Reallocate channel Ch_k
15   update residual channel list $Oc_p \leftarrow Oc_p + 1$
16   **else**
17   Drop SU_p^m
18   /* Append SU_p^m into waiting queue */

resource allocation module computes the number of channels to be reserved for this priority class to ensure its QoS; then, based on the reserved resources, the admission control module decides whether to accept this new SU call request or reject it. The SBS establishes a buffer, for each admitted SU, if required. Moreover, the resource allocation module also estimates the channel availability and pools the idle detected channels. Thus, Algorithm 1 lies in the resource allocation module.

Scheduling. The scheduler schedules the admitted SU m over its allocated channel k for the duration $\frac{1}{\omega_p}$. Moreover, when a PU arrives on any SU-allocated channel k, the scheduler immediately stops the transmission of the SU that was using channel k and finds an alternative channel from the list of its accessible channels to reschedule it. If no channel is found, the SBS puts the suspended SU into the waiting queue. The SUs appended in the waiting queue have higher-priority for being assigned a channel based on their priority class when a channel is available to the SBS. Because the PU has the highest priority, therefore, when a PU is detected, its corresponding channel will be vacated immediately, and the SBS terminates the respective SU. Algorithm 1 illustrates a concise procedure for maintaining a pool of K idle detected licensed channels. Algorithm 2 explains the procedure for the priority-based SU call admission and channel allocation method.

Algorithm 1 (Primary Channel Estimation Procedure): First, the SBS evaluates/estimates all of the licensed channels and identifies idle channels (lines 2–3). If a channel is found to be idle, it should be pooled into the set of available channels

Algorithm 3: Greedy Non-priority Based Call Admission and Channel Allocation Procedure

input : Set of available channels K
output: Channel allocation to SU
1 **for** $m \leftarrow 1$ **to** M **do**
2   **if** $!Empty(K)$ **then**
3   Allocate Ch_k to SU^m */
4   Update the residual channel list $K \leftarrow K - 1$
5   **else**
6   Reject SU^m
7 **if** *PU Detection on* Ch_k *== True* **then**
8   Stop immediately SU^m and find some alternative channel
9   **if** $!Empty(K)$ **then**
10   Reallocate channel Ch_k and update residual channel list $K \leftarrow K - 1$
11   **else**
12   /* Drop SU^m */

(lines 4–5); otherwise, it is ignored (lines 6–7). Finally, all the detected idle channels are sorted based on their corresponding PU idle probabilities (lines 8–9). Thus, the final set of K available channels is sorted, where $(1 \leq K \leq N)$.

Algorithm 2 (Priority-based Call Admission and Channel Allocation Procedure): From lines 1–4, upon the arrival of an SU call request of any priority class p, the SBS estimates the traffic arrival rate λ_p for each priority class.

At line 5 it computes K_p, the number of accessible channels by each priority class p. A call of priority class p is accepted if the number of already occupied channels, Oc_p, is less than K_p (lines 6–8); otherwise, it is rejected. After the SU is admitted the SBS reserves the buffer for the admitted SU if required and updates the occupied channel index. When the SBS detects a PU arrival on any channel used by an SU, the SBS immediately suspends the transmission of the respective SUs and looks for an alternative. If an alternative channel is found, the SBS reschedules the suspended SU; otherwise, it is dropped and appended to the waiting queue (lines 11–18).

5.2 Greedy Non-Priority SU Call Admission and Channel Allocation Scheme

In this subsection, we discuss our proposed greedy non-priority admission and channel allocation scheme. The greedy non-priority call admission and channel allocation scheme admits the SU on the basis of First-In, First-Out (FIFO). This scheme does not consider the priorities of the arriving SUs. Algorithm 3 represents the concise procedures for greedy non-priority call admission and channel allocation for SUs. However, similar to Algorithm 2, Algorithm 3 also relies on Algorithm 1 for idle channel identification.

Algorithm 3 (Greedy Non-priority-Based Call Admission and Channel Allocation Procedure): The SBS accepts the incoming SU connection requests based on the total available channel resources in a FIFO manner. If a channel is available, the SBS will admit the requesting SU m and allocate the available channel to that newly admitted SU; otherwise, the requesting SU is rejected (lines 1–6). Similar to the priority scheme,

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Algorithm 4: Fair Proportion Call Admission and Channel Allocation Procedure

input : Available channel set K and total priority classes P
output: Channel allocation to SU

1 $FP_p = \frac{K}{\sum_{i=1}^{P} i}$
2 **if** *Call request of priority class p* SU_p^m *is arrived* **then**
3   **if** $Oc_p < FP_p$ **then**
4   Accept SU_p^m
5   Allocate the available channel Ch_k to SU_p^m
6   Update the residual channel list
        $Oc_p \leftarrow Oc_p + 1$
7   **else**
8   Reject SU_p^m
9 **if** *PU Detection on* Ch_k *== True* **then**
10   Stop immediately SU_p^m and find some alternative channel
11   **if** $Oc_p < FP_p$ **then**
12   Reallocate channel Ch_k and update residual channel list $Oc_p \leftarrow Oc_p + 1$
13   **else**
14   /* Drop SU_p^m */

the SBS immediately suspends the ongoing transmission of an SU in case a PU arrival is detected on the any channel. If an alternative channel is available, the SBS reschedules the suspended SU; otherwise, it drops it (lines 7–12).

5.3 Fair Proportion-Based SU Call Admission and Channel Allocation Scheme

In this subsection, we discuss our proposed fair proportion SU admission and channel allocation scheme. The fair proportion scheme reserves an equal number of channels for each priority class p based on the total number of priority classes. Algorithm 4 also relies on Algorithm 1 for channel estimation and pooling of the available K channels.

Algorithm 4 (Fair Proportion Call Admission and Channel Allocation Procedure): First, the SBS computes an equal number of channels for all priority classes based on the fair proportion (line 1). The SBS admits the requesting SU connection based on the available channels reserved for that SU priority class. If any channel is available for requesting SUs, then the SBS admits the requesting SU call; otherwise, the SBS rejects it (lines 2–8). Similar to the other two approaches, in this approach, the SBS also immediately suspends the ongoing transmission of the SU in case a PU arrival is detected on the same channel and reschedules the suspended SU if any alternative channels are available for that SU based on its priority class; otherwise, the SBS drops it (lines 9–14).

5.4 Complexity Analysis

In this subsection, we analyze the complexity of the proposed algorithms.

Algorithm 1: The time complexity from lines 2–7 is $\sum_{i=1}^{N} C_o = C_o \times N$, and the complexity from lines 8–9 is K^2 according to the selection sort algorithm. Thus, the total time complexity of Algorithm 1 is calculated as follows:

$$\sum_{i=1}^{N} C_o + K^2 = C_o \times N + K^2, \tag{16}$$

where C_o is a constant that denotes the computing cost of instructions from lines 3–7.

Priority Scheme: In order to compute the time complexity of the proposed priority scheme, we first compute the time complexity of Algorithm 2. The time complexity of Algorithm 2 from lines 1–18 is as follows:

$$1 + (\sum_{i=1}^{P} 1) + C_1 = 1 + P + C_1, \tag{17}$$

Where, C_1 is a constant that denotes the computing cost of instructions from lines 6–18. Hence, the final time complexity of the proposed priority scheme (TC_0) is computed as follows:

$$\begin{aligned} TC_0 = (C_o \times N + K^2)(1 + P + C_1) = (C_o \times N + K^2) \\ +P(C_o \times N + K^2) + C_1(C_o \times N + K^2). \end{aligned} \tag{18}$$

We are only interested in computing the worst-case complexity. Therefore, we exclude the least significant terms and only count the most significant terms, those mainly contribute in the worst-case time complexity of the proposed priority scheme. Hence, the Big O time complexity of the proposed priority scheme is $O(K^2)$.

Greed Non-priority Scheme: The time complexity of the greedy non-priority scheme is also based on the time complexity of Algorithm 3 and Algorithm 1. The time complexity of Algorithm 3 from lines 1–12 is computed as below:

$$(\sum_{m=1}^{M} C_2) + C_3 = C_2 \times M + C_3, \tag{19}$$

where C_2 and C_3 are constants denoting the computing costs from lines 2–6 and lines 7–12, respectively. Thus, the Big O time complexity of the greedy non-priority scheme (TC_1) is given as below:

$$TC_1 = (C_o \times N + K^2) \times (C_2 \times M + C_3) \tag{20}$$

As discussed previously, for the Big O time complexity, the least significant values do not play a major role; therefore, the final time complexity of the greedy non-priority scheme is $O(K^2)$.

Fair Proportion Scheme: The time complexity of the fair proportion scheme is also based on Algorithm 1 and Algorithm 4. The time complexity of Algorithm 4 from lines 1–14 is a constant value C_4. However, the Big O time complexity of the fair proportion scheme (TC_2) is computed as follows:

$$TC_2 = C_4 \times (C_o \times N + K^2). \tag{21}$$

The Big O time complexity of the fair proportion scheme is $O(K^2)$. Thus, the worst-case time complexity of our proposed schemes is linear.

6 Performance Analysis

In this section, we first present our selected parameters for performance evaluation. We then present and discuss the simulation results.

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6.1 Performance Evaluation Criteria

We define the following metrics to evaluate the performance of the proposed call admission and channel allocation schemes.

Call-Blocking Probability of SUs. A call request of any particular priority class p is blocked when all the reserved channels for that particular priority class p are occupied. Thus, the call-blocking probability of priority class p $(1 \leq p \leq P)$ is given by (10) and (11).

Call-Dropping Probability of SUs. When a PU arrives with the intention of reusing its licensed channel, then the SU must vacate that licensed channel immediately and look for an alternative available channel in the list of its accessible channels to resume its service. If no channel remains in the list of its accessible channels, then the SU service will be suspended (dropped). Generally, the dropping probability is computed by dividing the total number of terminated SUs by the sum of the completed and terminated SUs [39]. The dropping probability of SUs is given as follows:

$$\omega^D = \frac{\sum_{\delta(o_t^s), i_{o_t^s}=0, o_t^s \in S} \sum_{j=1}^{K_P} (K - K_P)\lambda_j \pi_{o_t^s}}{\sum_{i=1}^{P} (1-\eta_i)\lambda_i}, \quad (22)$$

where $i_{o_t^s} \in \{idle, busy\}$ represents the sensing observation state of channel i at time t, $\pi_{o_t^s}$ is its steady state probability, and $\delta(o_t^s)$ is the conditional limitation for the given state $S(1_{o_t^s}, 2_{o_t^s}, ..., K_{o_t^s})$, which follows $K < K_P$. $K - K_P$ represents the number of dropped SUs under $K < K_P$. Thus, the call-dropping probability of priority class p is as follows:

$$\omega_p^D = \frac{\sum_{\delta(S), i_{o_t^s}=0, o_t^s \in S} \sum_{j=1}^{K_p} \phi(p)\lambda_j \pi_{o_t^s}}{(1-\eta_p)\lambda_p}, \forall p \quad (23)$$

where $\phi(p)$ is the number of dropped SUs of priority class p of state S when PUs arrive.

Total Channel Utilization. Radio spectrum is a scarce resource; therefore, its efficient utilization is an important performance parameter. In the proposed scheme, we reserve a specific number of channels for each priority class to minimize its call-blocking probability. Thus, the total channel utilization U is measured as the ratio of the total number of channels assigned to SUs to the total number of available channels, which is computed as follows:

$$U = \frac{\Lambda^S}{K}, \quad (24)$$

where Λ^S and K denote the number of total SUs admitted (i.e., assigned channels for their services) and the number of total available channels, respectively. Similarly, the channel utilization by any priority class p is measured as the ratio of the total number of channels assigned to the SUs of priority class p and the total number of channels reserved for that priority class, which is computed as below:

$$U_p = \frac{\Lambda_p^S}{K_p}, \quad (25)$$

where Λ_p^S and K_p represent the number of total SUs of priority class p assigned to the channel for their service and the number of total channels reserved for priority class p, respectively.

Throughput of SUs. In CR-IoT networks, the PU arrival affects the ongoing SU, as upon the arrival of a PU, the SU has to vacate the channel immediately and look for some other available channel from the list of its accessible channels to complete its service. Thus, the overall throughput of CR-IoT network, denoted by Ω, is measured as the average of the successful SU services per second, given below:

$$\Omega = \sum_{j=1, o_t^s \in S}^{P} \varepsilon_j \pi_{o_t^s}, \quad (26)$$

where $\pi_{o_t^s}$ and ε_j denote the steady state probability and the transition rate, respectively. Similarly, the throughput of priority class p SU, denoted by Ω_p, is measured as the total number of successful SUs of priority class p per unit time (i.e., second), given as:

$$\Omega_p = \sum_{o_t^s \in S} \varepsilon_p \pi_{o_t^s}. \quad (27)$$

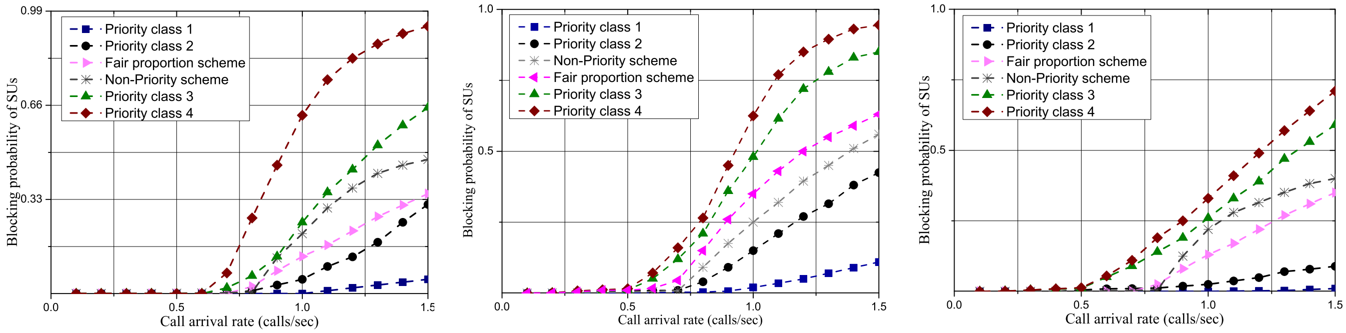
6.2 Simulation Results

This section presents the performance evaluation of the proposed priority-based SU call admission and channel allocation scheme with the greedy non-priority and fair proportion schemes. The performance of the proposed scheme is analyzed in terms of the SU call-blocking probability, the SU call-dropping probability, channel utilization, and throughput. We consider a CR-IoT-based cellular network, in which an SBS is responsible for spectrum sensing based on the knowledge of the PUs' activity, such as PUs' traffic patterns, spectrum access decision, CAC, and channel allocation. The SBS receives heterogeneous multimedia SU call requests. We divide all the SU call requests into four different classes based on their importance and criticality. Table II presents the details of the different priority classes for SU call requests. According to our traffic assumptions, presented in Section II.B, every SU call arrival process follows a Poisson distribution with an exponentially distributed call holding time, which is 120 s on average. The availability of the number of licensed channels is dependent on the PU activity.

Hence, we assume that on average 16 licensed channels are available to the SBS at any time t for SU reservation. Similar channel availability assumptions were made in various previous works in the literature (e.g., [46], [47], [48], [49]. Moreover, our channel reservation scheme is dynamic and can adapt to any number of available channels. For the SU call arrival rate estimation, we use a total of 100 samples for each priority class.

In order to fully analyze the performance of the proposed schemes from different aspects, we evaluate our performance metrics presented in Section VI.A as follows:

- First, we analyze the performance of the proposed schemes in terms of SUs' call-blocking probability and total channel utilization under three different call arrival ratios: 1) equal call arrival rates of all four priority classes, 2) high arrival rates of higher-priority class calls, and 3) high arrival rates of lower-priority class calls.



(a) Call-blocking probability for equal arrival rates

(b) Call-blocking probability for unequal arrival rates

(c) Call-blocking probability for unequal and lower call arrivals of higher-priority SUs

Fig. 4: Call-blocking probability for equal and unequal arrival rates: Priority scheme vs non-priority and fair proportion schemes.

- Second, we analyze the performance of the proposed schemes in terms of SUs' call-dropping probability and throughput under an increased rate of PUs and SUs. However, in these two cases, the arrival ratios of all priority classes are equal.

Figure 4a-c compares the SU call-blocking probability for the priority scheme with the greedy non-priority and the fair proportion schemes under three different calls arrival ratios such as (2:2:2:2), (4:3:2:1), and (1:2:3:4). Figure 4(a) demonstrates that the proposed priority scheme provides a very low SU call-blocking probability for higher-priority classes under a light and equal traffic load. Our design, which relies on the arrival rate estimation and the maximum number of available channels for priority class p (K_p), can help higher-priority SUs experience a better blocking/dropping probability. First, when a call of any priority class p arrives, the SBS estimates the call arrival rates of all the priority classes and calculates K_p. If the number of already occupied channels is less than K_p, the arrived call of priority class p is accepted. A call of priority class p is blocked or rejected if the state of the system calls is greater than or equal to K_p. Thus, K_P and K_1 denote the number of total channels available for the lowest and highest-priority classes P and 1, respectively. The priority class 1 SU calls are blocked only when all available channels K_1 are already occupied. This concept is illustrated in Figure 2.

TABLE 2: Priority classes

Priority class 1	patient monitoring, real-time health status, cardiac monitors, surveillance cameras, disaster management, response planning, real-time traffic monitoring, industry monitoring, banking, and defense-related calls traffic
Priority class 2	noise monitoring, air pollution, waterways, resource management and distribution, intelligent path optimization, water quality, leakage, usage, distribution, and waste management related calls traffic
Priority class 3	structural fatigue monitoring and other maintenance, temperature, humidity control, activity monitoring for energy usage management, heating, ventilation, and air Conditioning related calls traffic
Priority class 4	smart kitchen, smart laundry, Internet browsing, television and other home and personal appliances related calls traffic

The greedy non-priority scheme results in a high call-blocking probability for the higher-priority class calls. Moreover, the greedy non-priority scheme does not guarantee QoS in terms of the call-blocking probability. Similarly, the call-blocking probability for higher-priority SU calls is also high in the fair proportion scheme due to its static channel allocation mechanism. However, the fair proportion scheme provides a certain QoS level to all the priority classes by reserving a fix and an equal number of channels for all priority classes. Similarly, Figure 4(b) demonstrates the higher-priority SU calls blocking probability values in a special scenario when a greater number of higher-priority calls arrive. The proposed priority scheme only blocks a slightly greater number of calls of the lower-priority class to reduce the call-blocking probability of the higher-priority class. However, the greedy non-priority and fair proportion schemes result in a very high call-blocking probability for the higher-priority SU calls.

Figure 4(c) presents the higher-priority SU call-blocking probability values in a particular scenario when a fewer number of higher-priority SU calls arrive. In this special scenario, there are a slightly greater number of licensed channels available for lower-priority SU calls. Therefore, the proposed priority scheme only blocks a very few number of lower-priority SU calls, and consequently, the lower-priority SUs experience better blocking probability values. Under such scenario, the greedy non-priority and fair proportion schemes result in high call-blocking probabilities for the higher-priority SU calls.

Figure 5(a) compares the proposed priority, greedy non-priority, and fair proportion schemes in terms of call-dropping probability for the higher-priority SUs under an increased rate of PUs. The arrival ratios of all priority classes are equal. This figure shows that the priority class 1 has a better call-dropping performance, and the dropping probability of the priority class 4 is the highest. This is because all four priority classes can access a different number of channels, so that priority class 1 can access the highest number of channels, and priority class 4 can access only the fewest number of channels. When PUs interrupt the priority class 1 SUs, the SUs try to find alternative channels to reschedule their affected connections. If they fail to find alternative channels, then the dropping probability of SUs of

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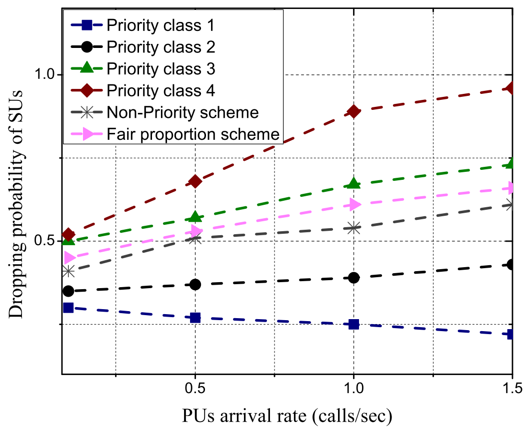
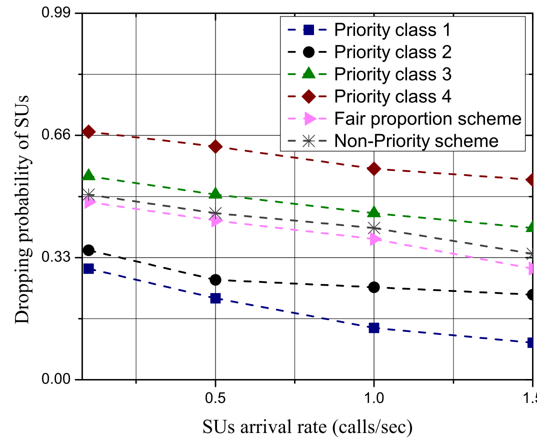


(a) Call-dropping probability under an increased rate of PUs



(b) Call-dropping probability under an increased rate of SUs

Fig. 5: Call-dropping probability: Priority scheme vs non-priority and fair proportion schemes.

priority class 1 also increases, as shown in Figure 5(a). However, they have more options to reschedule their affected connections than the priority class 4 SUs, which have very limited options to reschedule their affected connections. Consequently, the dropping probability of priority class 4 SUs is higher than that of priority class 1.

The greedy non-priority and fair proportion schemes result in high call-dropping probabilities for the higher-priority SU calls due to their greedy and fixed natures, respectively. Similarly, Figure 5(b) shows the comparison in terms of the call-dropping probability of all three schemes under an increased rate of SUs with equal call arrival ratios for all priority classes. The figure shows that with an increased rate of SUs, their call-dropping probability decreases. This is because the high arrival rate of SUs leads to a low rate of accepted calls due to the limited number of accessible channels for each priority class. We defined the SU call-dropping probability as the number of dropped SU calls divided by the number of accepted SU calls. The SUs' dropping probability decreases as the number of accepted SU calls increases. We found that priority class 1 has the lowest call-dropping probability, and priority class 4 has the highest call-dropping probability. This is because each priority class has its own number of accessible channels. Priority class 1 has a higher number of accessible channels, while priority class 4 has a lower number of accessible channels. The priority class 1 SUs achieve the best performance in terms of the call-dropping probability under increased rates of both PUs and SUs, which guarantees a better QoS.

Figure 6a-b shows the total throughput of all three schemes under an increased rate of PUs and SUs, respectively. Similarly, Figure 7a-b shows the throughput of individual priority classes for the priority scheme under the same environment. The higher the arrival rate of the PUs, the higher the probability that the licensed channel is busy. Therefore, a higher SU call-dropping probability and fewer fully completed SU services result in a lower SU throughput. Figure 6(a) shows that with an increase in the PU arrival rate, the total throughput of the SUs decreases. Figure 6(b) shows that with an increase in SU call arrivals, the SU throughput increases under conditions of constant PU arrivals. This is due to the fact that a greater number of arrivals causes a greater number of SU call admissions and, consequently, a higher probability of successful SU call completions.

Figure 7a-b presents the throughput of each individual SU priority class under an increased rate of PUs and SUs for the priority scheme. Figure 7(a) shows that an increased rate of PUs, the call-blocking probability of all priority classes is affected; however, due to the higher-priority of class 1, the SUs belongings to priority class 1 have more opportunities to access the available channels and to be rescheduled to complete their services. As the priority class 1 SUs have permission to access almost all of the available channels, their throughput is not effected much. However, priority class 4 has lower priority and can access only very few channels. Moreover, if their calls are dropped, they have very few opportunities to gain access to the channel again. Therefore, their throughput seriously affected. Similarly, Figure 7(b) shows that with the increased rate of SUs, priority class 1 achieves a higher throughput, and lower-priority classes achieve a lower throughput.

Figure 8a-b presents a comparison of SU channel utilization for all three schemes under an equal call arrival ratio for all priority classes and a higher call arrival ratio of higher-priority classes (e.g., [2:2:2:2] and [4:3:2:1]). These figures show that the proposed priority scheme performs well and improves the channel utilization significantly. Moreover, it significantly reduces higher-priority class SUs' call-blocking and call-dropping probabilities with the help of the dynamic channel reservation method. The priority scheme increases the number of reserved channels for the higher-priority class if the arrival rate of that class increases. However, if the call arrival rate of the higher-priority class SU calls is low compared to that of the lower-priority classes of SU calls, then the priority scheme reserves fewer channels for the higher-priority class of SUs and maintains efficient channel utilization. It is clear from the figures that the greedy non-priority scheme is outperformed, because it admits and assigns available channels to the first incoming SU of any priority class; therefore, this scheme does not guarantee QoS. The performance of the fair proportion scheme is better under equal call arrival ratios, but it does not perform well

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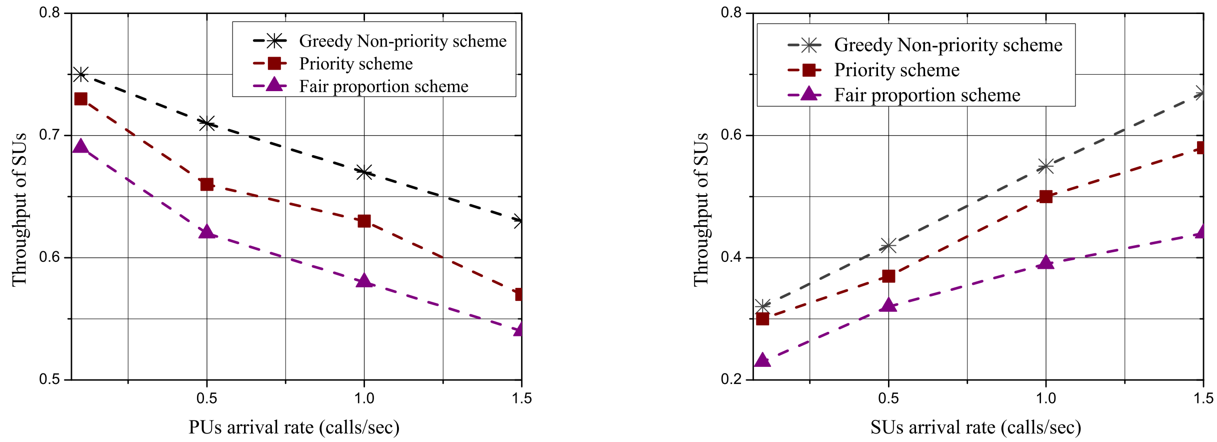
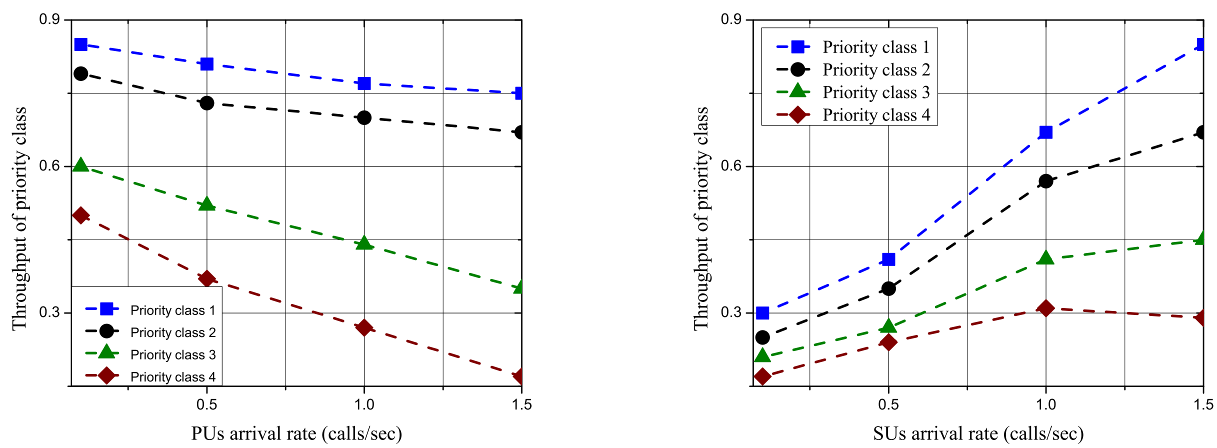


(a) Throughput of SU under an increased rate of PUs (b) Throughput of SU under an increased rate of SUs

Fig. 6: Throughput of priority, non-priority, and fair proportion schemes.



(a) Throughput of SU under an increased rate of PUs (b) Throughput of SU under an increased rate of SUs

Fig. 7: Throughput of individual SU priority classes for the priority scheme.

under different call arrival ratios of different priority classes, and it also causes channel underutilization due to its fixed and static channel reservation method.

7 Applications

Among the variety of wireless multimedia applications, a few traffic classes are more important than others. However, if all the traffic classes are considered equal in priority under a heavy traffic load and dynamic channel availability, then there is a high blocking rate of more important traffic calls, resulting in low-performance CR-IoT networks. Therefore, the priority of all of the traffic classes is not as equal due to their corresponding traffic profile and QoS requirements. Thus, the proposed priority-based call admission and channel allocation scheme can be directly applied in future for real implementation of the SBS that will provide heterogeneous wireless applications and services to cellular CR-IoT networks. Similarly, the proposed study can also be successfully applied to other emerging communication systems where resources are allocated to multiple traffic classes based on their traffic profiles. A few of the promising application areas are as follows.

CR-IoT-Based Smart Vehicular Networks: This is an emerging communication paradigm that is promising for providing various types of multimedia applications and services for safe driving, mobile health, and entertainment. Hence, the CR-IoT paradigm is of great significance for smart vehicular networks.

CR-IoT-Based Smart Grid: This term represents the next-generation power grid, which is considered a promising technology for providing a multi-class of applications and services, such as fault diagnosis, remote home and industry monitoring, equipment and remote customer site monitoring, and automatic meter reading. Thus, there is a vital need for CR-IoT in the smart grid.

CR-IoT-Based Smart Cities: The CR-IoT-based smart city is an urban development paradigm that integrates CR-IoT with information and communication technology systems. The key objective of the CR-IoT-based smart city is to provide e-services, such as smart traffic management, intelligent energy management, home automation, mobile healthcare, medical aids, elderly assistance, smart gym, smart parks, and smart parking systems and playgrounds to all of its inhabitants for their improved quality of life in an

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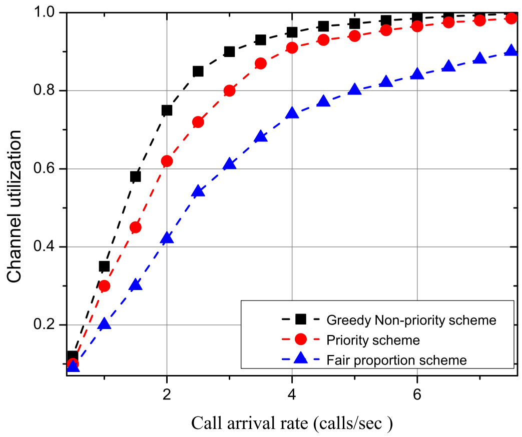
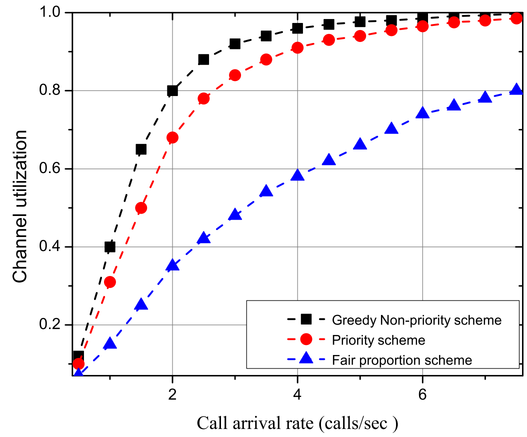


(a) SU channels utilization for (1:1:1:1)



(b) SU channels utilization for (3:4:2:1)

Fig. 8: SU channel utilization.

eco-friendly style. However, in order to provide this facility, continuous connectivity is necessary, which is provided through CR-IoT. Moreover, CR-IoT technology plays a key role in user interaction and data gathering in smart cities.

8 Conclusion

This paper introduced a linear time traffic-aware priority-based call admission and channel allocation scheme for cognitive radio-enabled Internet of Things (CR-IoT) by using the dynamic channel reservation method. First, we estimate the availability of each licensed channel based on its PU activity (e.g., traffic patterns) for optimized and guaranteed CR-IoT transmissions. Second, for minimizing the call-blocking probability of higher-priority traffic and efficient channel utilization, we divided the entire IoT traffic into different priority classes based on their QoS requirements in terms of priority and reserved a dynamic number of licensed channels for each priority class on the basis of its real-time traffic estimation. Finally, all three proposed schemes are evaluated in terms of the call-blocking probability, call-dropping probability, channel utilization, and throughput. Simulation results show that the proposed priority scheme outperforms the proposed greedy non-priority and fair proportion schemes.

Acknowledgment

This research was supported by National Research Foundation (NRF) of Korea Grant funded by the Korean Government (MSIP) (No. 2017R1E1A1A01073742).

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSE.2018.2877646, IEEE Transactions on Network Science and Engineering

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSE.2018.2877646, IEEE Transactions on Network Science and Engineering

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