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Adaptive Resource Allocation with Traffic Peak Duration Prediction and Admission Control for Cognitive Wi-Fi Networks ☆

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Abstract

Cognitive radio network (CRN) architecture can be efficiently utilized to support different QoS requirements under variable traffic and channel conditions. Generally, deterministic radio resource allocation algorithms could significantly increase the channel utilization as well as the network QoS. In this paper, we propose an advanced cognitive network resource allocation algorithm for IEEE 802.11 cognitive Wi-Fi networks. By making use of the status of the transmission channels and the traffic conditions, the proposed algorithm effectively allocates secondary radio resources to improve the overall radio resource utilization and the QoS of the CSMA/CA-based networks. To improve the accuracy and efficiency of the proposed algorithm, a Markov chain model based technique that estimates the achievable network throughput is employed. Furthermore, an autoregressive moving average (ARMA) based model is used to predict the traffic peaks when allocating the channels. OMNeT++ based simulation models are then developed to analyze the performance of the proposed algorithm. It is

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shown that our predictive resource allocation technique offers higher throughput and QoS compared to existing resource allocation techniques.

Keywords: ARMA, Cognitive radio networks, Quality-of-service, Resource allocation, Wi-Fi

1. Introduction

The growing need of radio spectrum for 5G networks demands the development of new resource allocation techniques to efficiently utilize and share the limited radio resources available for different classes of wireless networks [2]. CRN techniques offer promising solutions to efficiently share the available radio resources among different wireless networks. In traditional CRNs, channels are borrowed by the secondary networks up on sensing the vacant channels of the primary networks. It is shown that channel sensing techniques could be less effective in borrowing additional radio resources compared to cognitive media access control (MAC) layer-based resource allocation techniques[3]. The latter is more effective due to the deterministic nature of radio resource allocation where higher network QoS can be maintained by appropriately scheduling borrowed channels among the contending secondary networks.

QoS provisioning in traditional sensing-based CR networks is well studied in literature. QoS for different services can be maintained by using appropriate priority levels in the contention period [4, 5, 6, 7, 8]. In such networks, traffic sources are classified either as real-time or as non real-time traffic, where real-time traffic sources have stricter QoS bounds. The work of [9] and [10] achieve QoS provisioning by managing the interference between primary users (PUs) and secondary users (SUs). In such cases, the SUs are allocated with optimum channel bandwidth and transmission power, which will maintain their QoS levels without generating excessive interference to the PUs. The studies in [11] and [12] maintain QoS by using reservation schemes, which can either reserve channels or time slots of a channel. The objective is to keep the blocking and packet dropping probabilities below a specified threshold value. However, none of these approaches are able to provide QoS to the end users in a deterministic manner. They do not consider real time QoS statistics of the network when selecting channels or power levels for the SUs.

The FCC regulations introduced in 2010 allowed the use of Geo-Location Database (GDB) as the primary means of determining white space availability [13]. The GDB is a database that stores, by geographic locations, the permissible frequencies and operating parameters for CR devices to fulfill regulatory requirements [14]. With a database, part of the complexity associated with the sensing and the computation is transferred to the core network, reducing complexity and power demand of the end user devices [15]. Also unlike the channel sensing approach, in a GDB based network, all the channel information is known *a priori*. This could allow efficient management of channels to guarantee that the bandwidth and the QoS requirements are met at the cognitive devices.

A GDB-assisted CR network architecture is proposed in [16], where a new entity called WhiteNet Local Database (WLD) is introduced to act as a local spectrum manager. The main tasks of the WLD are to provide spectrum information retrieved from the GDB to its member access points (APs) and to resolve contentions among these APs. Spectrum is assigned to APs such that the interference is kept minimum while the system utility is maximized. Another channel allocation algorithm for TV White Spaces is proposed in [17] where channels are assigned in such a way that the total interference is minimized.

The IEEE 802.11 standard is based on the CSMA/CA protocol where transmitting nodes compete for the channel to transmit data [18]. In a contention-based network, the normalized offered load increases when the packet arrival rate increases or when the transmission channel capacity decreases due to low signal-to-noise ratio (SNR). As the normalized load increases, the contention levels also increase, thereby degrading the network QoS. In such situations, the network QoS can be improved by allocating extra bandwidth to the network. Allocating extra transmission bandwidth will reduce the effective normalized load of the network which could result in increased QoS values. The allocated extra bandwidth can be removed from the secondary network once the traffic level is reduced [3, 19]. Hence, it is necessary to develop advanced resource allocation techniques for CRNs to effectively share the secondary channels to improve the overall QoS of secondary networks.

The quality of a wireless channel is determined by the SNR, which is time variant. This results in a time varying data throughput and QoS levels on a channel. To tackle the issue of varying SNR levels, the IEEE 802.11 specifications mandate multiple transmission rates at the physical layer, which use different modulation and coding schemes [20]. Rate adaptation, which exploits such multi-rate capability, selects the best transmission rate dynamically based on the channel quality. Also, a CSMA/CA-based network cannot exploit the full potential of the transmission capacity at a higher normalized traffic load. These networks exhibit a saturation throughput when the normalized offered traffic load exceeds a certain threshold. Here, the network throughput remains fairly constant due to inefficiencies of the CSMA/CA protocol resulting from the contention processes. These saturation throughput levels can be approximated by mathematical models [21, 22]. As the network load increases, the channel utilization and the network QoS decreases after the network reaches its saturation throughput. In such situations, secondary channels can be allocated for the duration of the peak traffic to reduce the effective normalized load, potentially leading to higher network QoS.

In this paper, we introduce a two-tier CRN resource allocation technique, which is capable of considering many factors such as traffic levels and channel conditions of the networks when allocating channels. The proposed algorithm is a substantial extension of our previous works in [3] and [19]. In [3], a priori channel information obtained from the GDB is used to improve the channel utilization and the network QoS. Also, it is assumed that the CM has perfect knowledge of the traffic peak durations of the networks. In [19], real-time QoS statistics of the networks are utilized to allocate channels to the CRNs in a proactive manner to improve the QoS levels. In both approaches, the dynamic channel conditions are not considered but instead the channel capacities are always assumed constant.

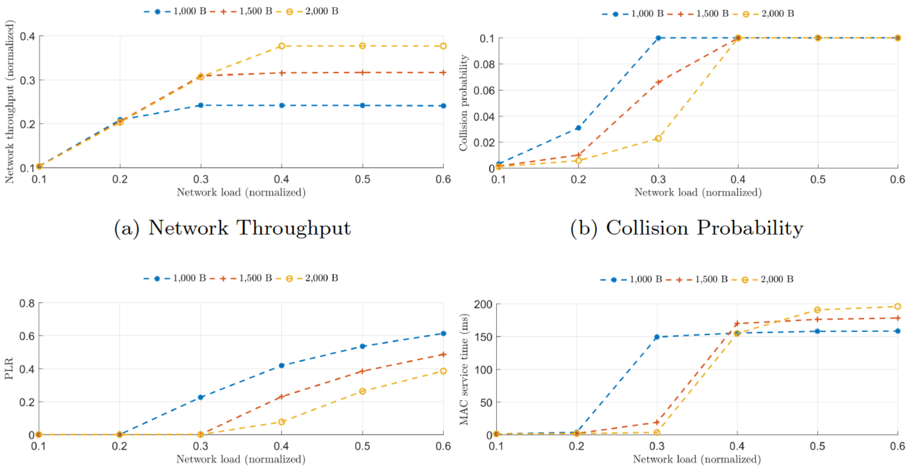
The algorithm proposed in this work employs the GDB approach to efficiently allocate secondary channels to the competing 802.11 networks with varying transmission channel and traffic conditions. The proposed algorithm outperforms existing solutions in time varying noise and interference conditions by accurately estimating the saturation channel capacities and traffic peak durations. The proposed scheme optimally allocates secondary channels to competing networks to reduce the effect of peak traffic conditions. Also, the proposed admission control mechanism improves the effectiveness of the resource allocation and maintains the stability of the networks by identifying target secondary networks.

The key contribution of this paper is a novel two-tier adaptive resource allocation technique for CRNs, which can operate in varying SNR and traffic conditions. Specifically,

- The proposed resource allocator employs a Markov model based estimation technique to predict the saturation throughput, which is utilized by the admission control and resource allocation processes.
- The resource allocator also uses an ARMA (1,1) based traffic prediction model to predict the traffic peak durations when allocating channels to improve channel utilization.
- The resource allocator combines the admission control decision with secondary network traffic levels and channel conditions to assign additional channels in an efficient manner.

2. Proposed Radio Resource Allocation Algorithm

In a CSMA/CA based wireless network, transmitting nodes compete for the channel before transmitting their data. The winning node transmits data while other nodes wait for their transmission opportunity in the next contention period. Network load refers to the total offered load generated by all nodes in a network, which is expressed in the number of bits per sec. As the network



(a) Network Throughput (b) Collision Probability

(c) Packet Loss Ratio (d) Packet Delay

Figure 1: Performance statistics with respect to the network load for an IEEE802.11 WiFi network with 5 hosts for packet sizes of 1,000, 1,500, and 2,000 bytes.

load increases, so do the contention levels. A sudden traffic burst in a node or several nodes can cause a surge in the network load. Performance statistics of a typical CSMA/CA network are shown in Fig. 1 for different packet sizes. When the network load is very low (e.g., normalized load is less than 0.2), the QoS performance is high. Only several nodes have packets to transmit at a given time resulting in low contention levels. All the packets generated at the nodes are transmitted immediately with minimum collision levels, leading to low packet loss ratio (PLR) and packet delay (PD) values. As the load increases to between $0.2 - 0.4$, there is a sudden decrease of QoS values. Traffic starts to accumulate in the internal queues and the number of nodes participating in the contention process increases resulting in a higher collision probability, and increased PLR and PD values. As the load keeps on increasing, the effective network throughput is reduced due to high packet losses. As the traffic levels grow (e.g., during a burst), the transition of the network QoS parameters from "good" to "worst" happens within a small duration. This transition can be used as an indication of a network in need of extra capacity/bandwidth. Allocating extra bandwidth will increase the network capacity thus reducing the relative load of the network, which results in increased QoS values.

The CRN model used in this paper utilizes the architecture developed in [3] and [19]. This CRN architecture is based on the IEEE 802.11 standard where each secondary network is controlled by an access point (AP) as shown in Fig. 2. The architecture is based on the GDB CRN architecture where the GDB contains all the information received from the primary networks about the channels and their availability depending on geographical locations. The channel manager (CM) acts as a proxy between the cognitive APs and the geolocation database. It contains channel information relevant to its control area mirrored from the GDB. The CM is also responsible for allocating channels to the APs whenever necessary, depending on real-time network statistics. The APs are connected to the CM via wired Ethernet links which provide reliable and fast communication. Let N be the total number of secondary networks controlled by the CM and $\mathcal{N} = \{1, 2, ..., N\}$ be the set of all the secondary networks. Let AP_i denote the AP of secondary network $i \in \mathcal{N}$.

APs of the competing secondary networks send channel requests as well as traffic and SNR data to the CM via the backbone network. We assume that the secondary network terminals can handle multiple channels. Transmission capacity of a network depends on the total number of allocated channels. Normally, each AP is allocated with a single primary channel. Additional channels are allocated when the normalized load in a secondary network increases.

In this work, we propose a two-tier adaptive resource allocation algorithm. The resource allocator structure presented in Fig. 3 is implemented in the CM of Fig. 2. It consists of a saturation throughput estimation engine, traffic peak duration prediction engine, an admission controller, and a channel allocator. The saturation throughput estimation engine uses the channel SNR data to predict the achievable saturation throughput as described in Sec. 2.1. Saturation throughput estimation is an integral part of the proposed algorithm. The achievable channel capacities of different networks are considered when allocating radio resources. For the algorithm to function as expected, it is essential

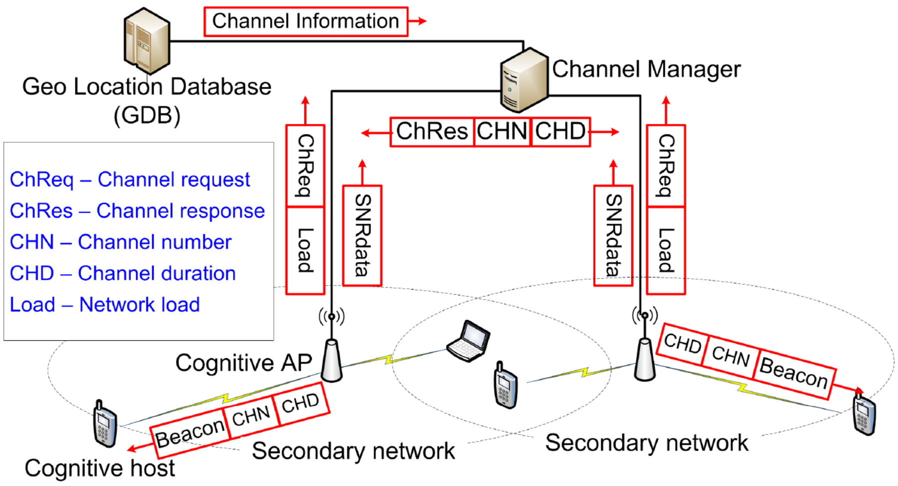


Figure 2: Cognitive radio network architecture

that we estimate the channel capacities as accurately as possible.

2.1. Saturation Throughput Estimation

In the CM, time is divided into slots of duration T_s. At the beginning of a time slot, for each requesting network, the throughput estimation engine uses a predefined packet success threshold to calculate the bit error rate (BER) required to be maintained. The BER and SNR relationship is then used to determine the best modulation and coding scheme (MCS) to be used for data transmission. After that, the prediction engine estimates the saturation throughput using a Markov model as detailed in [21, 22].

Let T_{slot} denote the slot time duration used in the IEEE 802.11 protocol. Let τ be the probability that a node transmits in a T_{slot}, which is derived using the discrete-time Markov chain model as [21, 22]:

$$\tau = \frac{2(1-2p)}{(1-2p)(W+1) + pW(1-(2p)^m)}, \tag{1}$$

where W is the minimum back-off window size ; m is the maximum back-off stage in the CSMA/CA process; p is the probability that a transmitted packet encounters a collision, which is the probability that at least one of the remaining

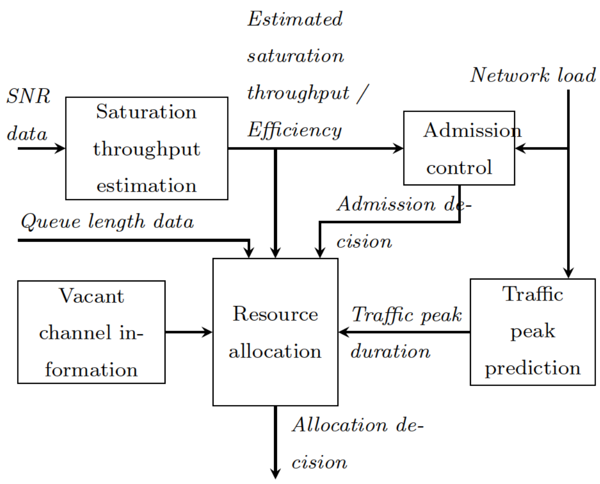


Figure 3: Operation of the proposed resource allocation algorithm with admission control

stations transmit in the T_{slot} duration given by

$$p = 1 - (1 - \tau)^{n-1}, \tag{2}$$

where n is the number of transmitting nodes in the system. Let P_{tr} be the probability that there is at least one transmission in the considered T_{slot}. Since n nodes contend on the channel and each transmits with a probability of τ, we have

$$P_{tr} = 1 - (1 - \tau)^n. \tag{3}$$

The probability P_s that a transmission is successful is same as the probability that exactly one station transmits on the channel, conditioned on the fact that at least one station transmits, i.e.,

$$P_s = \frac{n\tau(1-\tau)^{(n-1)}}{P_{tr}} = \frac{n\tau(1-\tau)^{(n-1)}}{1-(1-\tau)^n}. \tag{4}$$

The saturation throughput, defined as the fraction of time the channel is used to successfully transmit payload bits, is then given by

$$S = \frac{\mathbb{E}[\text{time used for successful transmission in a slot time}]}{\mathbb{E}[\text{length of a slot time}]}. \tag{5}$$

Since a successful transmission occurs in a T_{slot} with the probability $P_{tr}P_s$, the average amount of payload information successfully transmitted in a T_{slot}

duration is $P_{tr}P_sT_p$, where T_p is the packet transmission time. A T_{slot} duration can be either empty with a probability of $1-P_{tr}$ or has a successful transmission with a probability of $P_{tr}P_s$ or contains a collision with a probability of $P_{tr}(1-P_s)$. Substituting these values in (5) yields:

$$S = \frac{P_s P_{tr} T_p}{(1-P_{tr})\sigma + P_{tr}P_sT_b + P_{tr}(1-P_s)T_c}, \tag{6}$$

where σ is the duration of an empty T_{slot} duration. Let T_b be the average time the channel is sensed busy because of a successful transmission. We then have:

$$T_b = T_H + T_p + T_{SIFS} + T_\delta + T_{ACK} + T_{DIFS} + T_\delta, \tag{7}$$

where T_H is the packet header duration, T_{SIFS} is the short inter-frame space, T_δ is the propagation delay, T_{ACK} is the duration of the acknowledgement packet, and T_{DIFS} is the DCF inter-frame space. If we denote by T_c the average time the channel is sensed busy by the stations during a collision, then

$$T_c = T_H + T_p + T_{DIFS} + T_\delta. \tag{8}$$

2.2. Admission Control

After the capacity estimation by the prediction engine, admission control is carried out based on the estimated saturation throughput values and the network load values of each requesting network. This mechanism ensures that the radio resources are allocated only to the requesting secondary networks that can utilize them successfully to improve their throughput and QoS. Secondary networks severely affected by high SNR variations or traffic levels, whose stability cannot be reached by allocating extra resources, are omitted from the allocation process, which improves the effectiveness of the resource allocation process and the utilization of secondary channels.

Suppose that for AP_i ($i \in \mathcal{N}$), the saturation throughput achievable on channel j at time t is $RS_{i,j}[t]$. In a general situation, when the total number of allocated channels per network is n ($n > 1$ including the secondary channels), the combined saturation throughput $RC_i[t]$ and the effective normalized network load $ENL_i[t]$ of AP_i are given by (9) and (10) respectively:

$$RC_i[t] = \sum_{j=1}^{n} RS_{i,j}[t], \tag{9}$$

$$ENL_i[t] = \frac{L_i[t]}{nR_i[t]}, \tag{10}$$

where $R_i[t]$ is the 802.11 transmission rate based on the chosen MCS index.

Let $L_i[t]$ be the network load. In the situation where $L_i[t] \leq RC_i[t]$, i.e., $ENL_i[t] \leq E_i[t]$, where $E_i[t]$ is the normalized saturation throughput or the channel efficiency, the combined channel capacity is adequate to cater for the load of the network. Therefore allocating secondary channels to the network i will be beneficial. However, in the scenario where $L_i[t] > RC_i[t]$, i.e., $ENL_i[t] > E_i[t]$, the combined channel capacity is still not sufficient to handle the network load. Here, the backlog traffic can keep on increasing and the network will become unstable. The channel allocation will thus be less beneficial. Allocating the channels to another network that satisfies the former condition will increase the channel utilization as well as the network QoS. This observation is used to implement admission control at the CM.

At time t, for a requesting AP_i, we define admission control decision as

$$\gamma_i[t] = \begin{cases} 1, & \text{if } ENL_i[t] \leq E_i[t] \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

2.3. Weighted Queue Length based Resource Allocation with Admission Control (WQL-AC)

After saturation throughput estimation and admission control, the proposed weighted queue length based with admission control (WQL-AC) algorithm allocates resources based on the estimated saturation throughput levels, queue length data of the primary channel of the transmitting hosts in the requesting networks, and the admission control decision. The resource allocation algorithm uses a weighted queue length based approach for channel allocation which is based on the modified largest weighted delay first (M-LWDF) algorithm [23].

WQL-AC can take advantage of the SNR variations by giving some form of temporary priority to the networks with better SNR performance. Since channel throuthput levels of different networks vary in time in an asynchronous manner, the QoS of all secondary networks can be improved compared to the allocation schemes that do not take the channel conditions into account. We take a cross-layer approach here by considering the both traffic statistics and the physical channel conditions.

Suppose the number of available secondary channels at a given time instant is M. We consider a resource limited situation where $M < N$. Let $Req_i[t]$ indicate whether or not AP_i is requesting for a secondary channel at the time t, i.e.,

$$Req_i[t] = \begin{cases} 1, & \text{if network } i \text{ is requesting,} \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

Let $Q_i[t]$ be the mean primary channel traffic queue length of the cognitive hosts of network i. For each time slot, the admission controlled weighted queue length $WQ_i[t]$ for each secondary network is calculated as:

$$WQ_i[t] = Req_i[t]\gamma_i[t]Q_i[t]RC_i[t]. \tag{13}$$

Let j be the network with largest $WQ_i[t]$ value where

$$WQ_j[t] = \max\{WQ_i[t]\}, \ \forall i \in \mathcal{N}. \tag{14}$$

A vacant channel is allocated to network j and the process is repeated until all the channels are allocated or all the requesting networks are served.

2.4. Traffic Peak Duration Prediction

In real world scenarios, there is a delay associated with changing the secondary channel. When a secondary channel is needed, the APs have to connect to the CM to request a vacant channel for their communication. There is a communication delay T_{com} associated with this process. Once the AP receives the secondary channel information, it has to disseminate that information to the

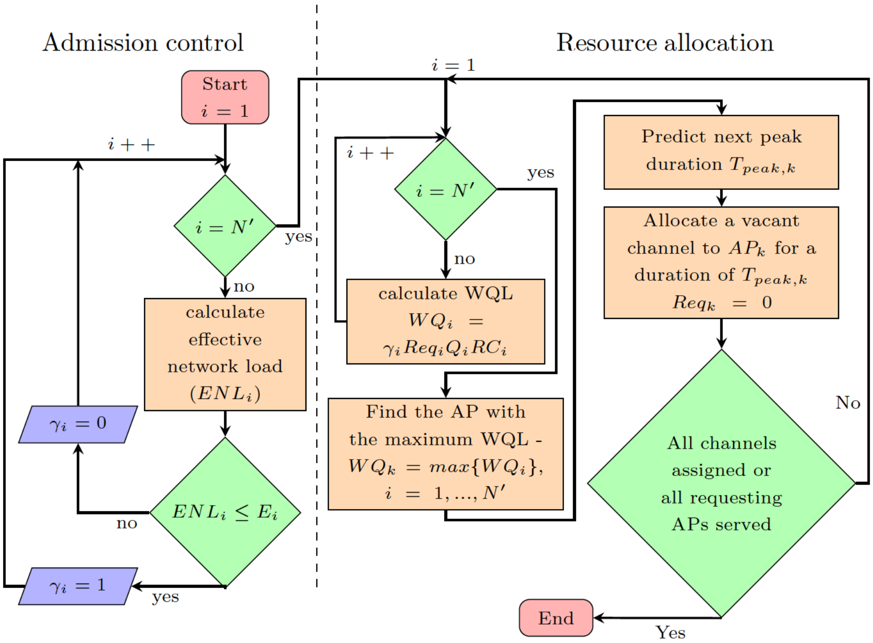


Figure 4: Flowchart of the proposed resource allocation algorithm with admission control

cognitive hosts via the Wi-Fi beacon. Typically, the Wi-Fi beacons are broadcasted periodically at every T_{beacon} seconds. Once the hosts receive the channel information, they reconfigure their physical layer to transmit on the newly assigned channel. There is a delay of T_{tune} associated with this re-configuration process [24]. The total delay associated with acquiring a secondary channel from the CM is thus:

$$T_d = T_{com} + T_{beacon} + T_{tune}. \tag{15}$$

During this period the hosts cannot transmit on the allocated secondary channel.

In absence of peak duration information, the secondary channels are generally allocated either for a fixed duration or for a random period, which could affect the QoS of the primary and secondary networks by increasing the number of channel switchings required to cover a traffic peak [3]. To allocate channels in a deterministic manner we introduce traffic peak duration prediction technique using an auto regressive moving average (ARMA) model. Traffic peak duration prediction allows the algorithm to minimize the number of secondary channel allocations required to support the traffic peaks. This strategy improves the channel utilization as well as the QoS values. The channel allocation delay is not a direct input to the proposed resource allocation algorithm. However, the algorithm is able to reduce the number of channel switchings by appropriately allocating channels considering the predicted traffic peak durations.

Channels are allocated to the winning secondary networks for the predicted duration of the traffic peak. The channel durations are predicted based on previous traffic data using an on-line ARMA model with lag values 1,1 to compute the 1 step ahead prediction of the traffic peak duration. ARMA(1,1) model has been used in [25] to predict Internet traffic with high accuracy.

Parameter estimation is difficult for time-varying wireless channels with heterogeneous wireless traffic. Recursive techniques can be used to estimate the parameters of the time series model as they do not require a long observation history compared to off-line estimation methods. A pseudo-linear regression recursive identification technique can handle a wide range of time series models including auto regressive (AR), moving average (MA), and ARMA. Let $y(t)$ be an observation of a random process Y at discrete time t. To predict $y(t+1)$, the time series data $y(t-1), ..., y(1)$ are collected.

Recursive parameter estimation methods have the general form of [26]

$$y(t) = \psi^T(t)\theta + \epsilon(t), \tag{16}$$

where the repressor $\psi(t)$ depends on the past data and the model structure, θ is a system parameter vector, and $\epsilon(t)$ is the prediction error of estimation. For the $ARMA(n_a, n_c)$ model where n_a and n_c respectively denote the orders of autoregressive and moving average parts, $\psi(t)$ and θ are given by

$$\psi(t) = \Big[-y(t-1), \ldots, -y(t-n_a), \quad \epsilon(t-1), \ldots, \epsilon(t-n_c)\Big]^T \tag{17}$$

$$\theta = \Big[a_1, \quad \ldots, \quad a_{na}, \quad c_1, \quad \ldots, \quad c_{nc}\Big]^T. \tag{18}$$

Here, $\epsilon(t)$ is given by

$$\epsilon(t) = y(t) - \hat{y}(t) \tag{19}$$

where $\hat{y}(t)$ is the predicted value of the process Y at the time t as

$$\hat{y}(t) = \psi^T(t)\hat{\theta}(t-1). \tag{20}$$

The parameter estimate $\hat{\theta}(t)$ is calculated by modifying the last calculated estimate $\hat{\theta}(t-1)$ as

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)\epsilon(t) \tag{21}$$

where

$$K(t) = P(t)\Psi(t) \tag{22}$$

and

$$P(t) = \frac{1}{\lambda}\left[P(t-1) - \frac{P(t-1)\Psi(t)\Psi^T(t)P(t-1)}{\lambda + \Psi^T(t)P(t-1)\Psi(t)}\right] \tag{23}$$

with forgetting factor λ. For the initial values, it is common to set $\hat{\theta}(0) = 0$ and $P(0) = \rho I$, where ρ is a sufficiently large number [25].

Fig. 4 details the channel allocation process for a network with two PHY interfaces, i.e., one primary channel and one secondary channel. Let N' be the number of requesting networks. First the achievable saturation throuthput levels of all the requesting secondary networks are estimated and the admission control decision γ_i is carried out for each requesting AP_i. After the admission control process, the requesting APs are ranked according to the weighted queue length and the vacant channels are allocated to the highest ranking APs. The channels are allocated to the winning AP_k for a duration of $T_{peak,k}$, which is the predicted peak duration of AP_k using the ARMA prediction engine. After the $T_{peak,k}$ duration, the allocated channel is removed from the AP_k.

2.5. Traffic Load Distribution between Primary and Secondary Channels

Once a network is assigned with a secondary channel, how to distribute the traffic load between primary and secondary channels is an important issue. The primary channel is always available to the network to transmit whereas the secondary channel is only available for a pre-defined time duration. In the proposed architecture, each host maintains two traffic queues, one for the primary channel and the other for the secondary channel as shown in Fig. 5. The

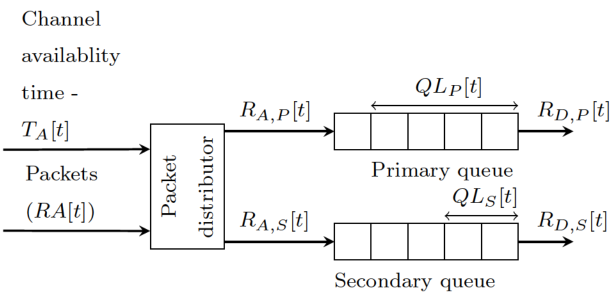


Figure 5: Proposed proportional traffic distribution mechanism for the CR-Host

task of distributing the packets between these two queues is performed at each node by considering the current primary queue length $QL_P[t]$, the secondary queue length $QL_S[t]$, the secondary channel allocation duration $T_A[t]$, the packet departure rates of primary and secondary queues $R_{D,P}[t]$ and $R_{D,S}[t]$, and the packet arrival rate $RA[t]$.

The packets are distributed to the secondary queue in a proportional manner based on the maximum $QL_{P,\max}$ and the current length of the primary queue. That is,

$$R_{A,S,prop}[t] = RA[t]\frac{QL_P[t]}{QL_{P,\max}}. \tag{24}$$

For the secondary channel, the current queue length depends on the old queue length and the departure and arrival rates as:

$$QL_S[t] = QL_S[t-1] + R_{A,S}[t]T_s - R_{D,S}[t]T_s. \tag{25}$$

Packets inserted to the secondary queue must be transmitted before the secondary channel allocation expires. Therefore,

$$QL_S[t] \leq R_{D,S}[t]T_A[t]. \tag{26}$$

From (25) and (26),

$$R_{A,S}[t] \leq \frac{R_{D,S}[t](T_s + T_A[t]) - QL_S[t-1]}{T_s}. \tag{27}$$

$R_{A,S}[t]$ is non-negative because once a packet is inserted to the queue it cannot be taken back. Therefore, the maximum value of $R_{A,S}[t]$ is

$$R_{A,S,\max}[t] = \max\left\{\frac{R_{D,S}[t](T_s + T_A[t]) - QL_S[t-1]}{T_s}, 0\right\}. \tag{28}$$

From (24) and (28),

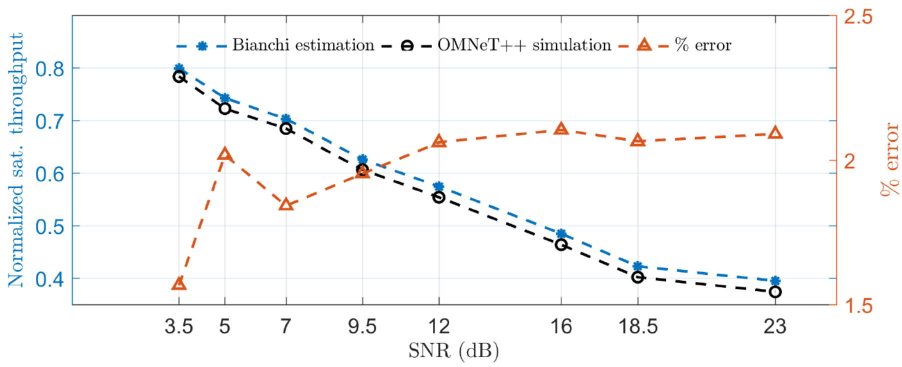
$$R_{A,S}[t] = \min\{R_{A,S,prop}[t], R_{A,S,\max}[t]\}. \tag{29}$$

3. Simulation Results

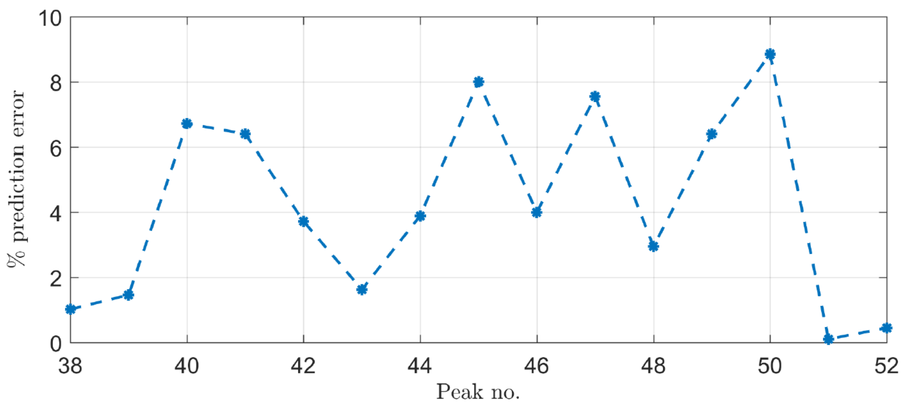
To simulate the proposed channel allocation mechanism, OMNeT++ version 4.6 and INET framework version 2.5.0. are used. Moreover, the IEEE802.11g Wi-Fi host and IEEE802.11g Access point modules in INET are modified to implement cognitive capabilities as described in [19].

3.1. Accuracy of the Saturation Throughput Estimation and Peak Duration Prediction

Fig. 6(a) compares the saturation throughput levels obtained for different channel SNR values using the estimation method in[21, 22] and OMNeT++ simulations. The Bianchi's estimation method in [22] and [23] uses a Markov chain based analytical model to estimate the saturation throughput of the IEEE 802.11 protocol. The results obtained form that model is compared with the results obtained from the standard IEEE 802.11 model available in OMNeT++/INET. The IEEE 802.11 model in OMNeT++ is discrete event based, where the model is implemented as an ordered sequence of well-defined events. The accuracy of the IEEE 802.11 models available in OMNeT++ has been verified by the results obtained from real world Wi-Fi test beds [27]. It can be seen from the figure that the estimation error is less than 2.5% for all SNR values. The ability to accurately estimate the saturation throughput levels for each secondary network enhances the accuracy of the channel allocation algorithm. Fig. 6(b) shows the peak duration prediction error for several consecutive peaks. It can be seen that the estimation error is always less than 10% with an average around 4.5%.



(a) Estimated saturation throughput levels using Bianchi's method [22] vs. saturation throughput levels obtained through simulation.



(b) % error of the ARMA(1,1) based peak duration prediction mechanism

Figure 6: Prediction accuracy of the Bianchi's method and the ARMA(1,1) model

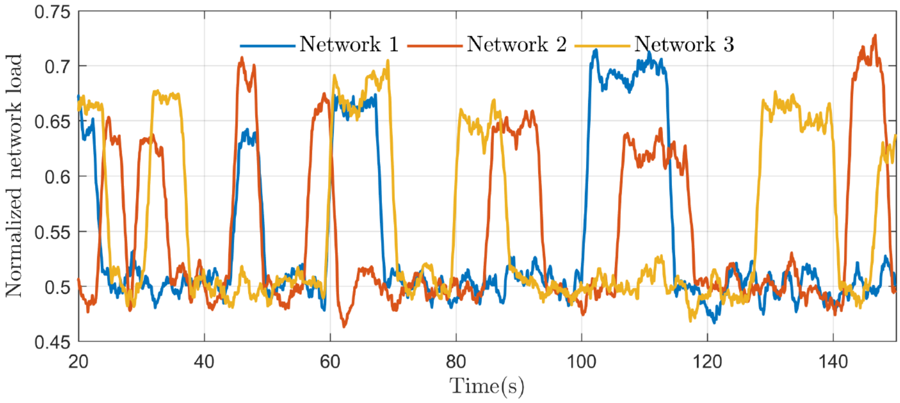
3.2. Performance Evaluation of the Channel Allocation Algorithm

Network simulation is used to evaluate network performance under varying SNR and load conditions. Table 1 summarizes the key simulation parameters of the simulation model. Different versions of the proposed algorithm are compared with two existing channel allocation algorithms. Most of the existing channel allocation algorithms proposed or investigated for cognitive radio networks use the traditional channel sensing approaches. Since there are special provisions in those protocols to accommodate channel sensing, they are not directly applicable to the GDB-based CRN architecture. The number of available resource allocation algorithms targeted at GDB-based CRNs is very limited. As such, we have selected two MAC layer-based channel allocation algorithms available in literature, which have been proposed for GDB-based CRN network architecture and compared those algorithms with our proposed algorithm, which is also introduced for the GDB-based CRN architecture. The algorithms selected are referred to as the QL (Queue Length) [19] and B-SAFE (distriButed Spectrum Allocation For whitespacE) [16]. The results generated by the QL and B-SAFE are verified by comparing with the original papers [19, 16].

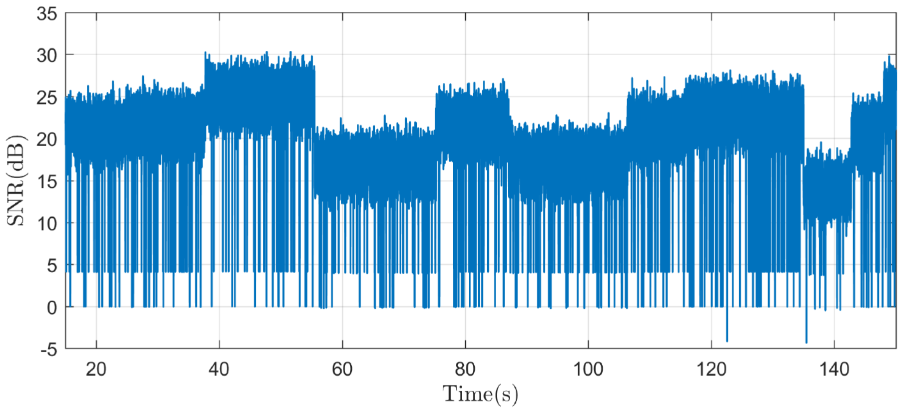
The performance data are obtained for the following resource allocation algorithms:

- **B-SAFE** [16]: The channel allocation is implemented based on the aggregated poverty line of each AP.
- **QL** [19]: The channel allocation is carried out based on the mean queue lengths of the transmitting nodes. The queue length can be used as an indication of QoS degradation. The channel allocation is performed in a proactive manner based on the mean queue length of the transmitting nodes. It only considers the traffic conditions but not the transmission channel conditions. The channels are allocated for a fixed duration of Ts = 500ms and the algorithm is executed every 500ms.
- **WQL-AC-PP** - The proposed algorithm described in Sec. 2.
- **WQL-PP** - The algorithm described in Sec. 2 without the admission control mechanism.
- **WQL-AC** - The algorithm described in Sec. 2 without the peak prediction mechanism. The channels are allocated for a fixed duration of $T_s = 500ms$ and the algorithm is executed every $500ms$.

Initially we run the simulations for three secondary networks. In each secondary network, traffic is simulated by using a base load and a peak load. The nodes normally transmit at the base load. However, traffic peaks appear occasionally, increasing the total offered load. In such situations the total load



(a) Network load for the mean base load of 0.5 normalized with respect to 54 Mbps.



(b) SNR levels of network 1.

Figure 7: Network load and SNR behavior of the secondary networks.

Table 1: Simulation parameters

Number of cognitive APs/secondary networks (N)	$3, 6, 9$
Number of cognitive hosts per AP	5
Number of secondary channels (M)	$2, 4, 6$
Packet size	$2,000$ Bytes
Network peak size (normalized)	uniform $(0.1, 0.2)$, uniform $(0.2, 0.3)$, uniform $(0.1, 0.3)$
Network peak inter-arrival time	exponential (10)s
Mean SNR level	uniform $(14, 25)$ dB
Operating frequency	2.4 GHz
Channel bandwidth	20 MHz
Fading model	Rician fading
No. of PHY interfaces per node	2
802.11g data rates used (Mbps)	$6, 9, 12, 18, 24, 36, 48, 54$
Channel change delay (T_d)	$0, 100, 300$ ms
Time slot duration (T_s) at CM	500 ms

of the network is the sum of the base load and the peak load. Two simulation scenarios are implemented. In the first scenario, the normalized traffic peak is distributed uniformly between $0.1 - 0.2$ for all three secondary networks. In the second scenario, the traffic peaks are distributed differently for the three networks. For network 1, the peak is uniformly distributed between $0.1 - 0.2$, for network 2 between $0.2 - 0.3$, and for network 3 between $0.1 - 0.3$. These values are summarized in Table 2. Simulation of the SNR behavior is conducted independently for these networks. Fig. 7(a) shows the simulated behavior snapshots of the network load of the three networks for a normalized base load of 0.5. Fig. 7(b) shows the SNR levels of network 1.

Fig. 8 plots the performance of network 1 for the scenario 1 as mentioned in table 2 for B-SAFE, QL, WQL-PP, and WQL-AC-PP algorithms along with

Table 2: Traffic peak distribution for the two simulation scenarios

	Scenario 1	Scenario 2
Network 1	uniform $(0.1 - 0.2)$	uniform $(0.1 - 0.2)$
Network 2	uniform $(0.1 - 0.2)$	uniform $(0.2 - 0.3)$
Network 3	uniform $(0.1 - 0.2)$	uniform $(0.1 - 0.3)$

the data when no secondary channels are allocated. The figure clearly shows the effectiveness of secondary channel allocation in dealing with the peak traffic load. In particular, at lower load levels of $0.1 - 0.2$, the QL yields higher throughput than WQL-PP or WQL-AC-PP despite the slightly higher collision levels of the QL compared to the WQL-PP and WQL-AC-PP. At lower load levels, the saturation network capacity is always sufficient to transmit all the generated packets all the time. The queue lengths are generally very low and as a result, the effect of the saturation throughput dominates the weighted queue length values. However, the saturation throughput has a small impact on representing the capacity requirements of the networks accurately in lower load conditions. In such situations, the queue length represents the capacity demand of the networks better than the weighted queue length. Therefore, QL offers higher throughput than WQL-PP and WQL-AC-PP.

However, as the load increases, the WQL-PP and the WQL-AC-PP start to outperform the QL. Here, the saturation throughput achievable on a secondary channel is not always sufficient to cater for the load demands of all secondary networks. Considering the saturation throughput when allocating channels gives better results than only relying on the queue length. The WQL-AC-PP algorithm offers the best results thanks to the admission control mechanism. Here, a requesting AP is only considered in the channel allocation process at the CM only if the allocated channel can cater for the excess traffic load demand. The admission control mechanism prevents the networks served with the secondary channels from being driven into extreme regions in the normalized load axis. Therefore, the WQL-AC-PP reduces the contention levels and improves the

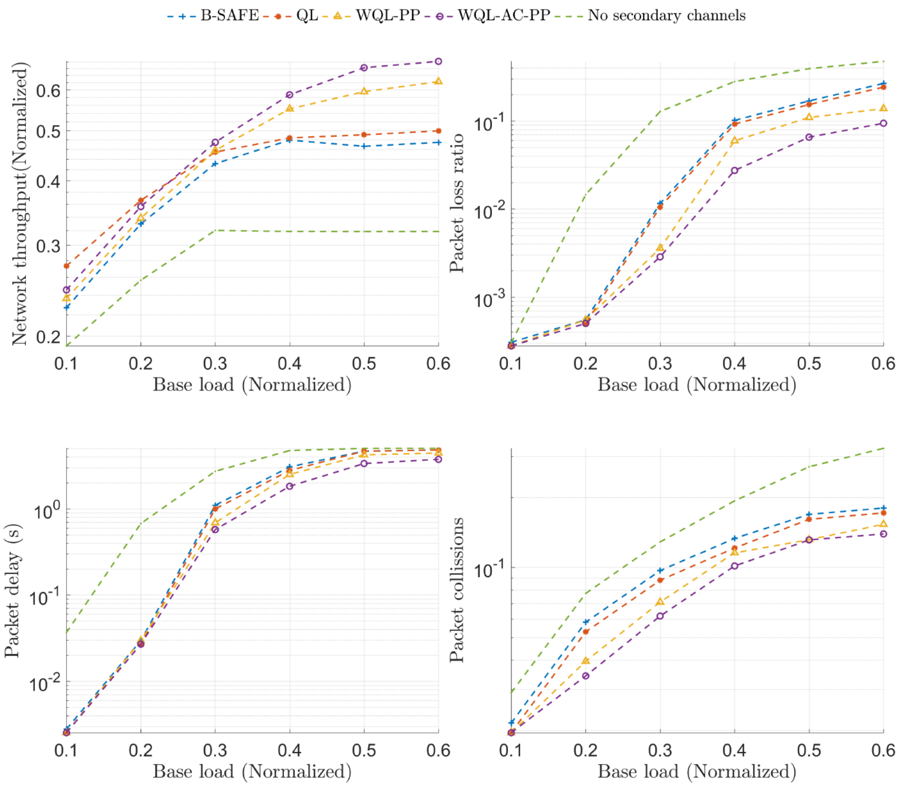


Figure 8: QoS data of network 1 for the three channel allocation mechanisms in scenario 1.

QoS and throughput. At higher load levels of $0.5 - 0.6$, the WQL-AC-PP is capable of achieving about 30% higher throughput than that of the QL algorithm. Interestingly, at all load levels, the B-SAFE algorithm yields the worst performance among the compared algorithms. The B-SAFE is not capable of considering real-time network QoS statistics and saturation channel capacities. Hence, it performs worse than the other algorithms.

When the PLR and the PD metrics are considered, as shown in Fig. 8, at lower load levels, all three mechanisms perform similarly. The network load is much lower than the saturation network capacity and all the generated packets are promptly transmitted without any delays or queue buildup, resulting in lower PLR and PD levels. As the network load grows, the contention levels

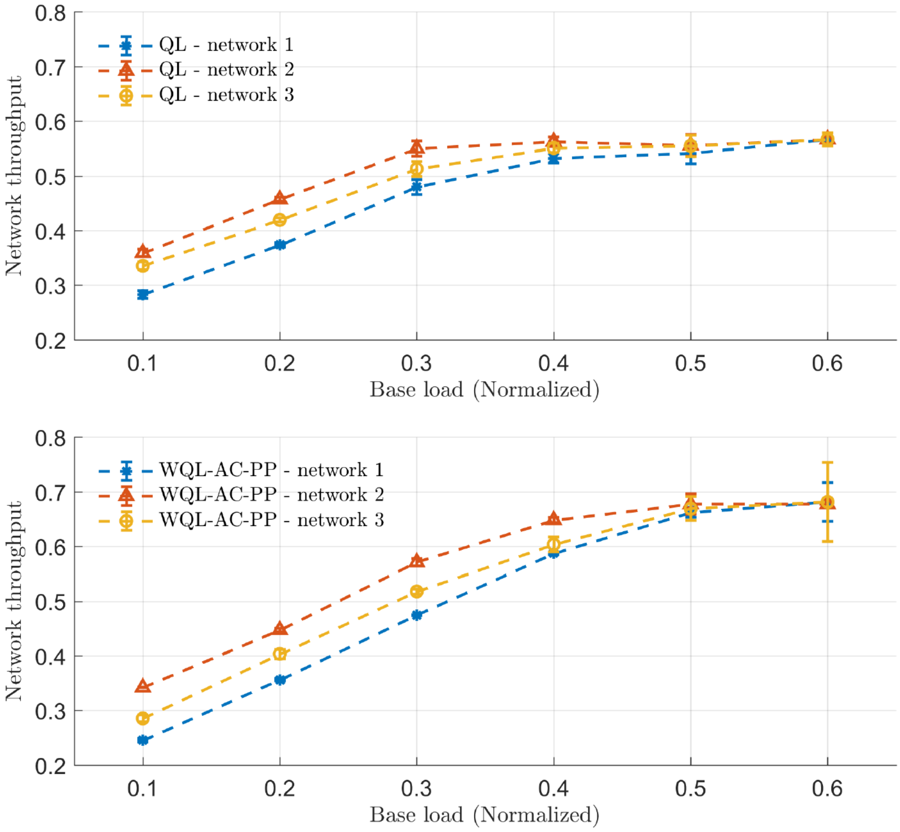


Figure 9: Performance data of the three networks for the three channel allocation mechanisms in scenario 2.

increase and not all the packets from higher layers can be transmitted, which results in a backlog of traffic. As a result, the PD and PLR levels are increased. Again, WQL-PP and WQL-AC-PP perform better than the QL algorithm because the former can allocate the secondary channels to the competing networks, which can utilize the channels efficiently. Increased channel utilization results in lower PLR and PD levels compared to the QL. WQL-PP and WQL-AC-PP perform better because they take in to account the SNR levels of the networks and the resulting network capacity when allocating channels. The proposed admission control mechanism can filter out the requesting networks whose effective loads are too high to be satisfied by allocating an extra secondary channel. The admission control mechanism allows the secondary channels to be utilized more effectively resulting in better QoS performance in the networks served. At higher load levels of $0.5 - 0.6$, the WQL-AC-PP algorithm gives about 55% lower PLR values and 25% lower PD values than those of the QL algorithm. Again, the B-SAFE algorithm performs even worse than the QL because the B-SAFE is not capable of considering real-time QoS data of the networks, where as QL performs channel allocation based on the network load levels.

Fig. 9 shows the throughput statistics for scenario 2 for all three networks. The peak traffic load in network 2 has a higher average value than that of the other two networks. Again, at lower load levels of $0.1 - 0.2$ the QL performs better due to the reasons described above. However, as the network load increases, the WQL-AC-PP algorithm deals with the peak traffic efficiently and offers a higher throughput. The WQL-AC-PP achieves higher performance thanks to its ability to consider channel conditions when allocating channels and the admission control mechanism, which filters out unstable networks from the channel allocation process. It can be seen from the figure that the throughput by the QL mechanism saturates at higher load levels. In this case, the WQL-AC-PP algorithm yields about 20% higher throughput than that of the QL for all three networks.

To evaluate the effect of the peak duration prediction mechanism on the overall performance, we compare the WQL-AC-PP with the WQL-AC for traffic distribution scenario 1 with different T_d values. The results are presented in Fig. 10. It can be seen that the channel switching delay has a small effect on the WQL-AC-PP algorithm. The WQL-AC-PP algorithm can predict the next peak duration and assign the channels accordingly, resulting in a very few number of channel switchings. On the other hand, the WQL-AC allocates channels in a slotted manner, causing many possible channel switchings to cover a traffic peak. The higher rate of channel switching reduces the channel utilization and as a result, the throughput and the QoS values are compromised. Also, it can be seen that when $T_d = 0$, i.e., when there is no channel switching delay, the WQL-AC performs marginally better than the WQL-AC-PP algorithm. This

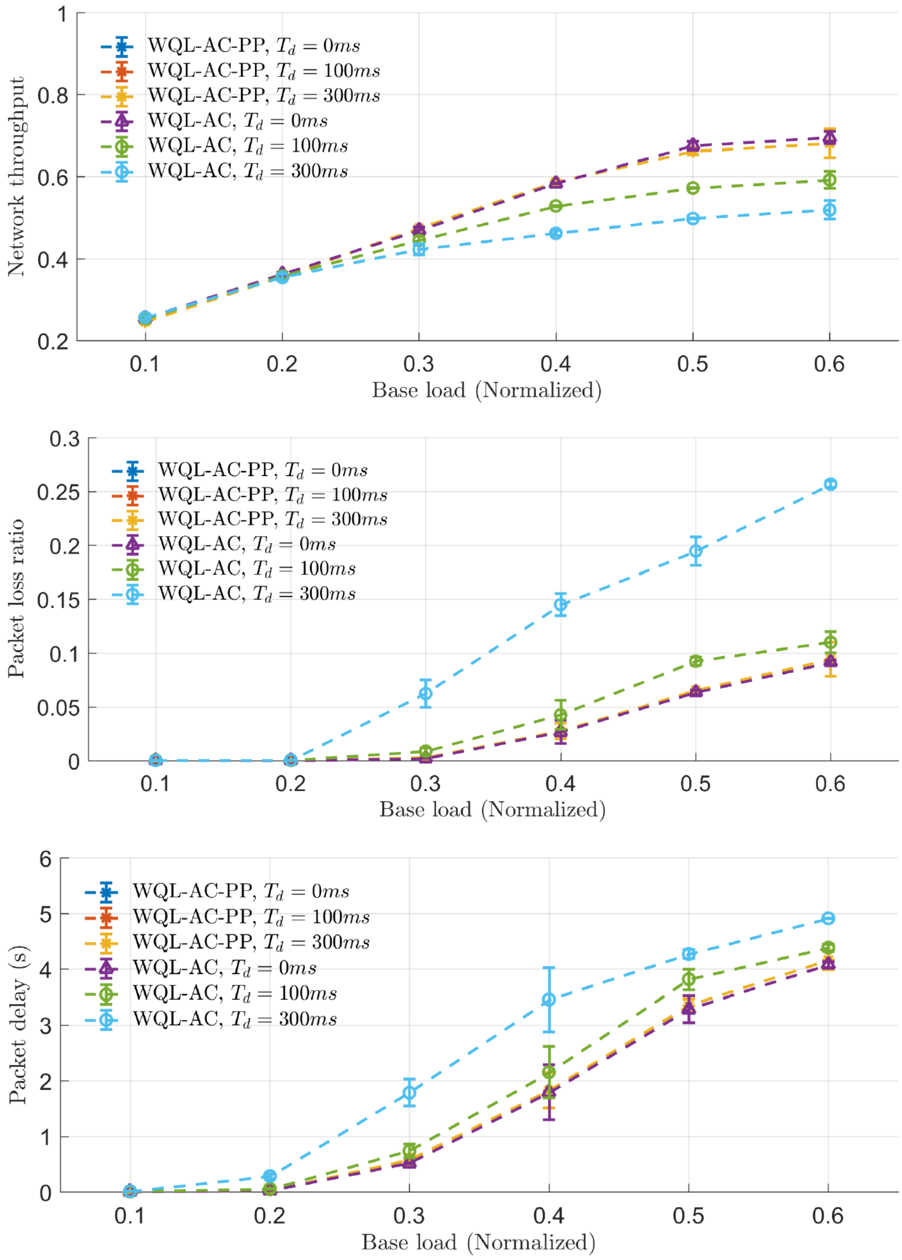


Figure 10: Performance data of WQL-AC-PP, WQL-AC, and QL for different channel switching delay values.

is because the slotted nature of the WQL-AC allows it to capture the state of the secondary networks better than the WQL-AC-PP whose allocation period is much longer. But with the introduction of the channel switching delay, performance of the WQL-AC degrades due to the lower channel utilization caused by the frequent channel switchings. Also it can be seen that the QoS levels decrease as the channel switching delay increases. Increased channel switching delay results in a lower channel utilization, which contributes to packet queue build-up and increased contention levels. As a result, the QoS levels are decreased. The channel allocation delay is not a direct input to the WQL-AC-PP algorithm. However, the algorithm is able to reduce the number of channel switchings by appropriately allocating channels considering the predicted traffic peak duration.

Let P_{off} be the total offered packets during the allocation period and let P_{tx} be the total transmitted packets on both channels during the allocation period. To analyze the effectiveness of the channel allocation algorithms under consideration, we define a new parameter called the allocation efficiency factor η_{eff} as:

$$\eta_{\text{eff}} = \frac{P_{\text{tx}}}{P_{\text{off}}}. \tag{30}$$

Fig. 11 shows the values of η_{eff} by the four allocation mechanisms for the simulation scenario 1. A higher value of η_{eff} denotes the ability to successfully transmit a higher portion of the offered traffic when a secondary channel is allocated. This results in less backlogged traffic, lower contention levels, and improved QoS of the network. It can be seen that the QL performs better than the B-SAFE as the load increases thanks to the ability of QL to allocate channels based on the network load levels. The WQL-PP can improve the allocation effectiveness over the B-SAFE and the QL. The allocation can be further enhanced by implementing an admission control as in the WQL-AC-PP because the admission control guarantees that only the networks with a combined saturation throughput sufficient to transmit all the generated traffic are considered in the resource allocation process.

To evaluate the scalability of the proposed algorithm, we compare the WQL-

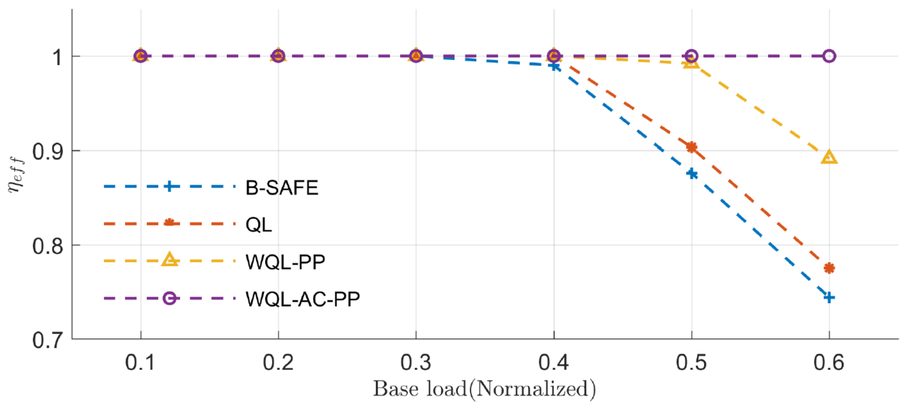


Figure 11: Allocation effectiveness in scenario 1.

AC-PP and the QL algorithms for scenario 1 by varying the number of CRNs and available secondary channels. The normalized base network load is set at 0.4. As seen in Fig. 12, the throughput of the WQL-AC-PP improves slightly as the number of vacant channels increases and decreases slightly as the number of networks increases. However, these variations are marginal compared to the performance of the QL mechanism. Again, the WQL-AC-PP is capable of offering relatively constant throughput compared to the QL thanks to the integrated admission control mechanism.

3.3. Performance of the Traffic Distribution Techniques for the Two Queues.

We compare our proposed proportional load distribution mechanism with an equal load distribution mechanism when allocating traffic load to the secondary channel. Fig. 13 shows that the PLR and PD values are similar in the low load conditions. However, as the load increases, the proposed proportional algorithm offers lower PLR and PD, thus exploiting the secondary channel more efficiently. The proportional load distribution mechanism is capable of distributing the traffic between the primary channel and the allocated secondary channel in an efficient manner by considering the secondary channel allocation duration, primary and secondary queue lengths, and packet arrival and departure rates. This also helps to effectively vacate the secondary channel when the allocation

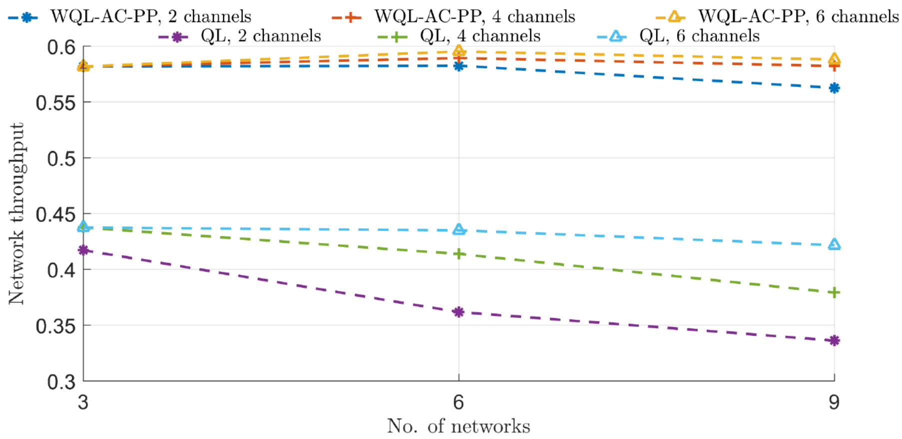


Figure 12: Network throughput of WQL-AC-PP and QL for different numbers of vacant channels and numbers of networks.

460 duration expires.

4. Conclusion

Cognitive radio networks are a promising solution to deal with the growing demand for radio spectrum. QoS provisioning and maximizing the utilization of the secondary channels are important issues when allocating channels. This paper presents an advanced channel allocation algorithm that maximizes the utilization of the secondary channels while improving the QoS under varying SNR and traffic conditions in cognitive Wi-Fi networks. To further enhance the performance of the algorithm, an admission control and traffic prediction mechanisms are also incorporated. The proposed channel allocation mechanism is compared with existing queue length-based allocation mechanisms. Simulation results demonstrate the clear advantages of the proposed cross-layer cognitive resource allocation algorithm.

For the proper operation of the algorithm, the CRN should be able to continuously measure and assess the network traffic volumes and channel conditions. Such information should be continuously transferred to the CM, incurring additional transmission overhead. However, this overhead is outweighed

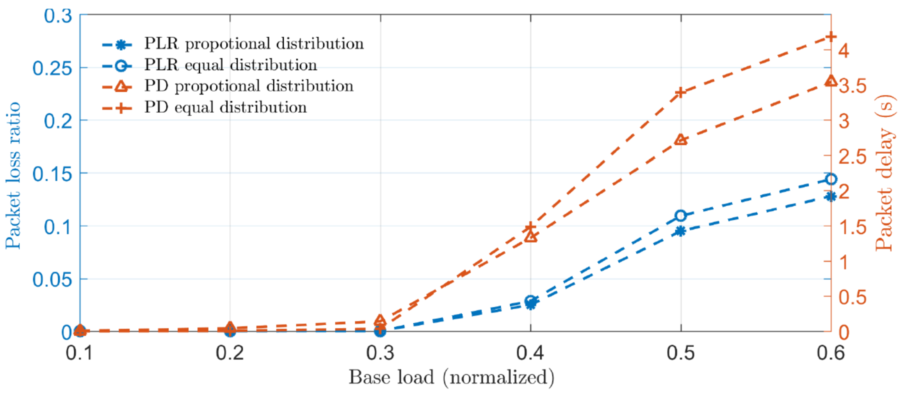


Figure 13: Traffic distribution between the two packet queues.

by the performance improvement gained. It is essential that continuous traffic and SNR measurement is reliably implemented, and the measurement data are reliably transferred to the CM for processing. This is not generally done at standard wireless networks but in cognitive networks traffic measurements, and situational information is implemented as a general feature. The proposed resource allocation algorithm is targeted at cognitive Wi-Fi networks. Saturation throughput estimation is a critical feature of the algorithm. The algorithm can be extended to other network types with different MAC protocols. However, it is important to employ proper methods to accurately estimate the actual capacities of the channels to improve the accuracy of the resource allocation algorithm. Additional tasks proposed in the CRN algorithm are not part of the existing standards. Hence, it is necessary to introduce a convergence layer on top of the existing standard when implementing a cognitive Wi-Fi network.

5. Further Research Directions

The proposed architecture assumes the information sourced from the GDB is 100% accurate. It would be useful to find out the effect of the accuracy of the information on the system performance. Also, obtaining the primary network information for the GDB should be studied. It would be also interesting to find out how to fine tune the proposed algorithm to support multiple traffic classes such as VoIP with different QoS requirements. In addition, a study on energy efficiency of the proposed algorithm compared to that of a sensing-based algorithm would be useful for implementation purposes.

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Biography

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