

Maximization of Throughput in Cognitive Radio using non-persistent CSMA combined with Reinforcement Learning

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Abstract: The Cognitive Radio project aims to develop radios that can sense the existing spectrum and identify and use free frequency bands. Primary users using time division multiple access (TDMA) are licensed users who are assigned with certain channels, and secondary users using carrier sense multiple access (CSMA) are unlicensed users who are allowed to use the channels assigned to a primary user when it is free. This paper introduces a novel spectrum sharing protocol for secondary users combining multichannel non-persistent carrier sense multiple accesses (CSMA) and reinforcement learning. Simulation results show that the throughput performance improves when reinforcement learning is applied in conjunction with non-persistent CSMA.

Keywords: Cognitive Radio; multichannel CSMA; channel assignment; Reinforcement learning.

I. INTRODUCTION

The rapid developments of emerging wireless applications require efficient utilization of physical spectrum of wireless communication. Investigations on spectrum utilization indicate that not all the spectrum is used in space or time [2]. To cater for the increasing demand for wireless bandwidth, cognitive radio networks (CRNs) have been proposed as a potential way [3]. The purpose of this cognitive communications is to investigate the spectrum utilization issues associated with primary and secondary user (SU) systems sharing common spectrum [4, 5]. The primary user (PU) is the licensed user and has top priority to use the specified spectrum licensed to them. CR permits SU, an unlicensed user, to explore and exploit idle spectrum without causing harmful interferences to PU [6]. A cognitive radio [7, 8, 9] is defined as: 'a radio that is aware of and can sense its environment, learn from its environment and adjust its operation according to some objective function'. In cognitive radio networks, every user can access the spectrum if the spectrum is not occupied. This offers more spectrum opportunities and increases the spectrum utilization.

Much of the recent research on cognitive radio resource allocation assumes that cognitive users exchange information about the spectrum utilization state and negotiate on the spectrum allocation. The ability to incorporate learning distinguishes cognitive radio from other wireless communication techniques, and this learning enables the performance of wireless communication systems to be improved. However, the interference between primary users and secondary users is a crucial issue that may have a negative effect for both types of users, thereby limiting the spectrum sharing. The basic interaction characteristics of CR and primary user are modeled by two traditional schemes. Specifically, these are Contention-free time division multiple access (TDMA) [9] and contention-based non-persistent carrier sense multiple access (CSMA) [10].

Contention-free time division multiple accesses (TDMA) [11] is used to characterize the primary user who has the primary right and have purchased license to access channel whenever they have information to send.

Contention-based non-persistent CSMA is used to describe the behavior of a SU having the ability to sense and access a free channel. The CSMA system is distributed without a centralized controller and does not provide priority control i.e. all CSMA users are equal.

CSMA is a multiple access scheme where individual users make their own decisions on how and when to access a channel. A number of protocols of CSMA, which differ in their retransmission strategies when a channel is sensed busy, are proposed in literature namely; p-persistent CSMA, 1-persistent CSMA and non-persistent CSMA protocol.

In p-persistent CSMA, the parameter p is chosen so as to reduce the level of interferences while keeping the idle periods between any two consecutive non overlapping transmissions as small as possible. The 1-persistent CSMA protocol, which is special case when $p = 1$, is devised in order to achieve acceptable throughput by never letting the channel go idle if some ready terminal is available. In this system, if channel is sensed busy, secondary user waits until the channel goes idle and only transmits the packet with probability one. On the other hand the non-persistent CSMA protocol is designed to maximize channel utilization and achieve optimum throughput by never letting the channel become idle. It limits the interference among packets by always rescheduling a packet which finds a channel busy upon arrival. It has been observed that the non-persistent CSMA scheme increases the performance of the throughput of secondary users as compared to the earlier used scheme [12].

TDMA combined with multichannel non-persistent CSMA system allows the users to transmit on different channel at the same time thus reducing the probability of conflict. Further in this system, the throughput characteristic of TDMA and non-persistent CSMA differs in a single channel.

Earlier in [13], the authors have proposed 1-persistent CSMA scheme combined with reinforcement learning for secondary users in a radio scenario based on radio network with primary users using TDMA/FDMA. RL is a machine learning approach where an agent learns from trial-and-error interactions with an unknown environment [14]. In this context, in [15], the reinforcement learning (RL) is applied to SU which avoids unnecessary interaction amongst primary and secondary user.

This paper focuses on analyzing the throughput performance of multichannel non-persistent CSMA combined with reinforcement learning in radio scenario. Although cognitive radios have spectrum awareness, reinforcement learning improves system performance and the probability of a user to successfully communicate with others is increased. It is because a cognitive radio will always start to sense the best available channels according to the experience gained through learning. Thus reinforcement learning uses the past record of a particular channel and it intelligently assigns a channel with the best chance of successful packet transmission, in turn increasing the throughput of the system.

II. SYSTEM MODEL

Fig 1 shows the two packet-based communication systems operating in a common coverage area [16]. Each system consists of several users transmitting to a single common receiver.

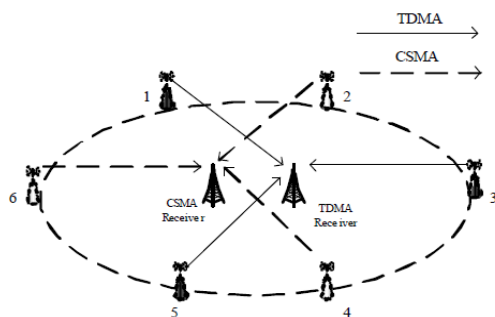


Fig.1

In the first sub-network, users 1, 3 and 5 transmit information to a receiver using TDMA. In the second sub-network, users 2, 4 and 6 transmit information to another receiver using CSMA. During transmission, TDMA users have top priority to transmit data packets using their designated time slots on a specific channel, and they do not perceive the existence of secondary users. As a secondary user in CR model, each user contains a reinforcement learning engine that acquires its transmission experiences as a reward value to adjust the next transmission. In the above scenario, the probability of successful transmission will depend on the probability of collision.

For analysing of interaction amongst primary and secondary users, let us assume that

- The receivers are co-located and all users are at the same distance from the receivers.
- All nodes are within hearing range and the scenario is non-capture.
- The delay is very small compared to the packet transmission time.
- Both systems use one or more common frequency channels.
- All packets are of a common length.
- The channels are noiseless and the only source of interference is packet overlap (collisions).
- Packet transmission time is a constant t .
- The propagation delay 'a' is normalized to 0.05 relative to the transmission time t .
- Symbol bit rate: $256 * 10^3$ bits per second

The transmission procedure of non-persistent CSMA is modified as:

- 1) A user with ready packet senses all channels first. If more than one channel is sensed idle, then user will randomly choose one from those that are sensed idle.
- 2) If channels are sensed busy there will be random delay for retransmission according to random back off interval I_n [17], the authors have considered the various values of the offered traffic ratio (p), which is the proportion of CSMA users in the system, to show the throughput performance of the multichannel system. For analysis of the system, the total offered traffic range is varied from 0.1 Erlangs to 100 Erlangs and the CSMA traffic ratio is taken to be 0, 0.5 and 0.9. In this paper, reinforcement learning is used with non-persistent CSMA users to improve the throughput of the CSMA system at various traffic loads.

III. SIMULATION METHODOLOGY

In this paper, an event based simulation based on Monte Carlo Method [18] is used to examine the performance of CSMA with reinforcement learning by applying large number of random trials to compute statistical results. In order to generate a sufficient number of trials, we set the number of packets, N , to be transmitted by a TDMA user to be equal to 1000 and 5000, and the simulation terminates after N packets have been successfully transmitted. We set the number of overall transmitters M to be equal to 100. According to the offered traffic ratio p , CSMA users have pM transmitters and TDMA users have $(1-p)M$ transmitters in the TD-CSMA system. In the CSMA transmission, if a packet suffers a collision, the transmitter schedules the retransmission of the packet according to a random back off time which is equal to the random inter-arrival time. With the TDMA transmission, all transmitters are assigned a time slot one by one with a fixed order. The transmissions are synchronized and are forced to start only at the beginning of a predefined slot [19]. If a packet suffers a collision, the retransmission will start at a predefined slot in the next round. The throughput S is expressed in terms of a (the ratio of propagation delay to packet transmission time) and G (offered traffic rate) [18] as

$$S = \frac{G e^{-aG}}{G(1+2a) + e^{-aG}}$$

According to Kleinrock and Tobagi's derivation [20], the average channel utilization is simply given by

$$S = \frac{U}{B + I}$$

where U denotes the time during a cycle that the channel is used without conflict and B + I is a busy period plus a following idle period. The probability that a transmission period is successful is simply the probability that no terminal transmits during the first 'a' seconds of the period.

A. Applying Reinforcement Learning to SU

In order to avoid collisions among the primary and secondary users, we apply the RL to make SU aware of the radio environment and intelligently assign a channel with the best chance of successful packet transmission by considering the previous experiences on the channels. The RL assures that each secondary user is assigned an optimum channel through maximization of an average reward over the long-term [17]. Fig 2 depicts the transmission methodology for SU with reinforcement learning when sharing the same spectrum with primary users. We consider weight matrix associated with each channel $W_i(k, m)$ being the channel weight of user k on the channel m at the time t and the user updates the weight according to the rule

$$W_{t+1}(k, m) = W_t(k, m) + f_{km}$$

where W_{t+1} , W_t , and f represent the new weight, the old weight, and the reward factor, respectively. Without reinforcement learning we consider f_{km} to be 0 for both the successful transmission and the collision. In case of reinforcement learning we consider f_{km} to be 1 for successful transmission and to be 0 for collision.

The throughput equation can be modified as

$$S = \frac{\text{(Successful transmitted packets / Symbol bit rate)}}{\text{Simulation Time}}$$

The channel capacity is found by maximizing S with respect to G. S/G represents merely the probability of a successful transmission and G/S is the average number of times a packet must be transmitted until success. During a transmission of k^{th} secondary user, the user will use the information of the experienced transmissions by comparing the weight vectors of each channel, and will make a channel selection decision by choosing the idle channel with the highest value of weight.

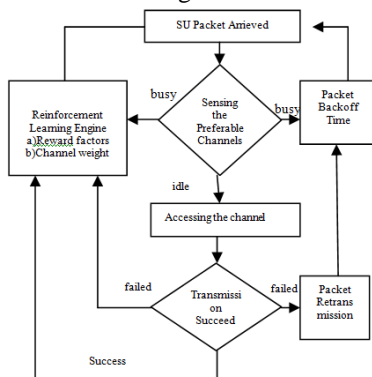


Fig. 2 Methodology for applying Reinforcement Learning to secondary users

B. Simulation Results

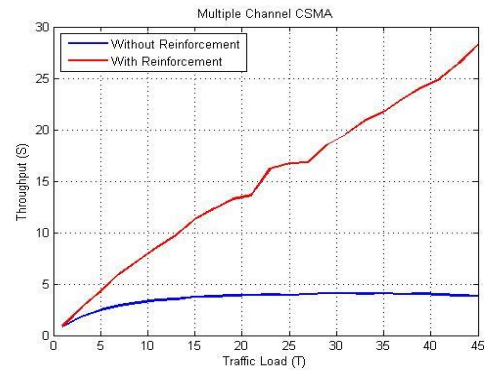


Fig. 3 : Effect of Reinforcement Learning on Throughput of non-persistent CSMA system with 5 channels and 1000packets

In fig.3, the performances of secondary users, with and without reinforcement learning has been compared for the system with 5 channels and 1000 TDMA packets. It can be seen that the throughput of secondary users show better performance with RL. This is because by applying RL, the secondary users avoid collisions with primary users and other secondary users, thus providing them with a greater throughput improvement. For example, from the figure, it is clearly seen that at a traffic load of 25 Erlangs, the throughput achieved is around 4 without RL whereas with RL the throughput achieved is around 17. Thus, RL improves the throughput performance significantly. It is also observed that as the traffic load is increased the throughput performance with RL increases while it approaches a constant in the case when no RL is used.

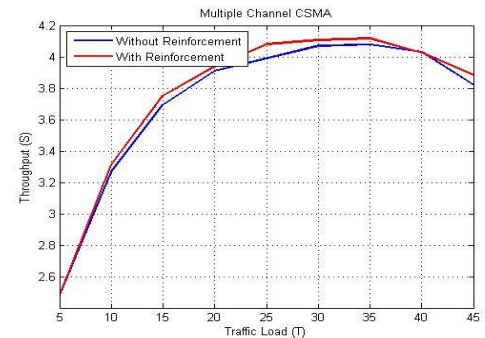


Fig. 4. Effect of Reinforcement Learning on Throughput of non-persistent CSMA system with 5 channels and 5000packets

Fig.4 depicts the performance of CSMA users in TD-CSMA system with increased total numbers of TDMA packets to be transmitted to 5000 and the same number of channels as in figure 3. Comparing the curves in figure 3 and 4, it is seen that the performance of CSMA users deteriorates significantly in the case where RL is used. In the case, when RL is not used the performance is almost similar for smaller traffic load. However as the traffic load is increased the throughput attains a constant value when the number of TDMA packets to be transmitted is 1000 but it decreases when the number of TDMA packets to be transmitted is 5000. This is intuitive since the primary users have the priority to use the channels and can transmit

the packets without considering CSMA users, thereby reducing the probability of CSMA users packets transmission. From figure 4, it is clearly seen that throughput of CSMA users increased up to traffic load of 30 Erlangs and after that it starts descending. More interestingly it is seen that there is not significant improvement in the throughput performance with RL or without RL when the number of TDMA packets to be transmitted is increased.

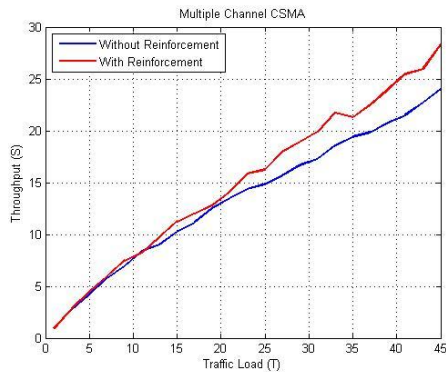


Fig. 5. Effect of Reinforcement Learning on Throughput of non-persistent CSMA system with 40 channels and 5000 packets

Fig.5 shows the simulation result when the number of channels is increased from 5 to 40 and TDMA packets to be transmitted is same as that shown in figure 4. It is seen that, in both the cases i.e. when RL is used and when it is not, the probability of CSMA users to transmit their packets increases thereby improving the throughput. For example, it is seen from figure 4 and 5 that in case of without RL at the traffic load of 25 Erlangs the throughput is around 15 when the number of channels is 40 while it is around 4 when the number of channels is 5. From figure 5, it is also seen that in case of without RL as the traffic load is increased the throughput increases. Applying RL further improves the throughput performance of CSMA users, for example, at 25 Erlangs throughput increases from around 15 to around 17 and at 35 Erlangs throughput increases from around 19 to around 22 as compared to the case when RL is not used. Thus it can be concluded that as the number of channels is increased the throughput increases.

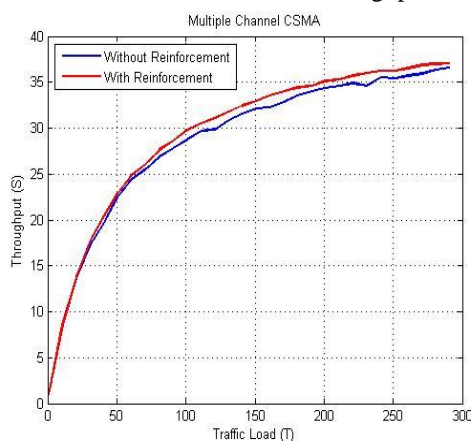


Fig. 6. Effect of Reinforcement Learning on Throughput of non-persistent CSMA system with 40 channels and 5000 packets and increased traffic load.

In fig.6, the throughput variations are compared for the TD-CSMA system with 40 channels and 5000 TDMA packets when the offered traffic load is increased. It is seen that for smaller value of the offered load there is significant increase in the throughput. However as the offered traffic load is increased beyond 250 Erlangs the throughput becomes almost insensitive to the offered traffic load. This is because it is likely that increased traffic provides a high blocking probability from primary users and also the collision between TDMA and CSMA packets causes additional retransmissions for CSMA users. Further, RL has only a minor effect on the throughput performance of the CSMA users which also attains a constant value at the increased traffic load.

IV. CONCLUSION

The Reinforcement learning enables secondary users to intelligently share the spectrum with primary users by considering their transmission, and choosing the channels with more successful transmission probability which increases throughput of secondary users. SU with RL maximizes channel utilization and achieve optimum throughput. From the simulation results it can be concluded that if the number of TDMA packets to be transmitted is increased for a fixed number of channels then the probability of successful packets transmission of CSMA users packet decends. Therefore the RL gives better results when number of channels is more and the traffic load is less. Furthermore, if the total offered traffic is increased the throughput performance of the CSMA users achieves a constant value which characterizes the basic idea of CR that the secondary user must give preference when the primary user wishes to transmit packets.

REFERENCES

- [1]. C.M. Cordeiro K.Challapali, and D. Birru. Ieee 802.22: An introduction to the first wireless standard based on cognitive radios. Journal of communications, 1, April 2006
- [2]. Chen, J.Park, and J. H. Reed. Defense against primary user emulation attacks in cognitive radio networks IEEE Journal on Selected Areas in Communications, 26(1):25– 37,2008
- [3]. Parliamentary Office of Science and Technology: Radio Spectrum Management, 2007, POSTNOTE
- [4]. C. M. Cordeiro, K. Challapali, and D. Birru. Ieee 802.22: An introduction to the first wireless standard based on cognitive radios. Journal of communications, 1, April 2006
- [5]. Cognitive radio technology: a study for Ofcom. Summary Report, QinetiQ Ltd, Febreary 2007
- [6]. Fette, B.: "Cognitive radio technology" (Newnes, 2006)
- [7]. FETTE B. (ED.): "Cognitive radio technology", Communication Engineering Series" (Newnes, 2006), p. 622
- [8]. ERKIP E., AAZHANG B.: "A comparative study of multiple accessing schemes", IEEE, 1998, 1, pp. 614–619
- [9]. PAHLAVAN K., LEVESQUE A.H.: "Wireless information networks", 'Wiley Series in Telecommunications and Signal Processing' (Wiley, 1995), p. 572
- [10]. Dasilva, L., Mackenzie, A.: "Cognitive networks: tutorial" (CrownCom Orlando, Florida, USA, 2007)
- [11]. ABRAMSON N.: 'The throughput of packet broadcasting channels', IEEE Trans. Commun., 1977, COM-25, (1), pp. 117–127
- [12]. KLEINROCK L., TOBAGI F.A.: 'Packet switching in radio channels. Part 1 – carrier sense multipleaccess modes and their throughput-delay characteristics', IEEE Trans. Commun., 1975, COM-23, (12), pp. 1400–1416.
- [13]. Haibin Li, David Grace, Paul D. Mitchell, "Collision Reduction in Cognitive Radio using Multichannel 1-persistent CSMA combined

with Reinforcement Learning”Department of electronics, The university of York.2010

- [14]. Sutton, R.S., Barto, A.G.: “Reinforcement learning: an introduction” (The MIT Press, 1998)
- [15]. L.P.Kaelbling,M.L.Littman,andA.w.Morre,Reinforcement Learning: A Survey. Journal of Artificial Intelligence Research,1996.4(1996);p,337-285.
- [16]. LEUNG K.K., MASSEY W.A., WHITT W.: “Traffic models for wireless communication networks”, IEEE Commun. Select. Areas, 1994, 12, (8), pp. 1353–1364
- [17]. H.Li, D. Grace, P.Mitchell, Throughput Analysis of Non-persistent CSMA combined with TDMA and its implication for Cognitive Radio, Journal on IET Communications, 2010, accepted for publication.
- [18]. KALOS M.H., WHITLOCK P.A.:“Monte Carlo methods” (Wiley, 1986), p. 208
- [19]. R. G. Gallager, “A perspective on multi-access channels”, IEEE Transactions on Information Theory, vol. 31, pp. 124-142, 1985.
- [20]. T.Jiang,D.Grace, Y.Liu, Performance of Cognitive Radio Reinforcement Spectrum Sharing Using Difference Weighing Factors, Communications and Networking in China. Third International Conferences on ChinCom.2008.