Channelized Blocking Probability Estimation Model for Infrastructure Based Mobile Cognitive Radio

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Abstract

Infrastructure based Cognitive Radio (CR) relies upon a fixed Base Station (BS) where the Secondary User (SU) may be directly connected or through relay chain. For operation in licensed band, either SUs or BS has to remain aware of the current occupancy status of primary channels. In existing literatures, usage histories of the channels are also used by researchers for prediction of future occupancy. Hence, CR operator software has to estimate the blocking probability when an SU places service request. Blocking probability can be estimated by last clock hour (e.g. from 10 am to 11am) occupancy, as in classical teletraffic theory and this estimation has been further improved through prediction models. Both the methods depend on hourly occupancy statistics. Researchers of present paper counts an hour as composed of immediately preceding 60 minutes (e.g. from 10:09 am to 11:08 am if SU place service request at 11:08 am instant). In the present work, minute wise collected occupancy data was calculated for 7 days for 50 cells with different channel capacities. Channelized blocking probability has been calculated based on immediate past 60 minutes occupancy. Instantaneous blocking probability has also been calculated based on current minute occupancy for all available channels as reference. A comprehensive prediction model is employed in the proposed work to compute the instantaneous blocking probability both on immediate minute occupancy basis and its preceding 60 minutes basis from time of request by SU. Validation through actual data establishes that Channelized Blocking Probability estimation model has lower error value compared to estimation through prediction models of other researchers. It was also observed that hourly basis prediction model has constant blocking probability value during clock hour, whereas, minute wise Grade of Service (GoS) prediction model addresses the local peak demand and hence leads to a stringent GoS estimation.

Keywords: Channelized Blocking Probability, Cognitive Radio (CR), Grade of Service (GoS), Instantaneous Blocking Probability

1. Introduction

Cognitive Radio (CR) secondary user accesses unallocated spectrum/channels in licensed bands. CR responses to observe and exploit interim spectrum hole in specific period of time without causing interference to the licensed users. In order to find probability of availability of vacant channels in the licensed band, prediction of traffic pattern of primary user is necessary to assess the number of vacant channels in the system. The authors^{1,2} have established that a sufficient number of quasi-permanently vacant channels are available which can be deployed as Cognitive Control Channel (CCC) for out-of-band sig-

naling. In addition, dynamically available channels are also available for traffic allocation to SU³ with required Quality of Service (QoS)⁴.

A technique has been proposed that enables secondary users to evaluate channel availability in cognitive radio networks when SUs coexist with PUs⁵. The call arrival of PUs is monitored by the SUs. The author has compared the simulation results with the SARIMA model. However, this method does not mention about scanning frequency and channel updation method.

An infrastructure-based CR network architecture integrated in a PU network operating in licensed spectrum band has been discussed⁶, where, the CR network has a centralized network entity such as a base station and associated CR nodes. The simulations are done to parameterize the primary user traffic.

The different traffic prediction techniques has introduced and have discussed the process of evaluating channel availability through predicting traffic pattern of PUs for cognitive radios in an infrastructure CR network^{7,8}. SUs can predict or estimate the call arrival rate and call holding time of primary users that use this channel. Then, SUs are able to evaluate the probability that the channel would be available for a given time period according to the prediction and/or estimation results. By comparing the evaluated probability with some threshold, secondary users can decide whether to use this channel. This model does not explicitly state the need of infrastructure. The spectrum sensing and prediction need high computing capability and more power and thus hard to implement in practice.

Cognitive Radio based spectrum access by opportunistic approach is based on the traffic pattern prediction for evaluating the channel availability and the call arrival rate⁹. It was analyzed and simulated for validation using NS2 simulator. The results obtained from the software were used to evaluate the probability of the channel availability of a frequency band within a time period. The proposed work made comparison with the Normal Spectrum Utilization (NSU), Fuzzy Logic System (FLS) and with Traffic Pattern Prediction and proved that spectrum utilization is more using Traffic Pattern Prediction method. The analysis was not exclusively meant for CR rather increasing efficiency in primary bands themselves.

Cooperative spectrum sharing across different service providers have been discussed in¹⁰, in which BS governs the radio transmission on the allocated spectrum. It discusses the operation of CR nodes and infrastructures of service providers for the spectrum sharing, the CR node sensing range decision and optimal channel selection. The author has assumed fixed blocking probability for each operator which is not possible in real time environment. The use of CR technology by Wireless Sensors has been explained by author of¹¹ in Cognitive Radio Sensor Network (CRSN). In¹¹, the authors has established that channel selection with Reinforcement Learning (RL) system in is better than random channel selection method for next generation sensors but threw no light about the lifetime of the selected channel. It is thus observed from above literature reviews that none of the authors have measured the instantaneous traffic of the primary channels. The authors have assumed that the channel occupancy is constant throughout a clock hour under observation and this hourly value has been used for prediction of blocking probability. Hence, there is ample scope to study and assess blocking probability based on minute wise observation which has been dealt in the present paper.

A radio frequency channel consist of a band of frequency, available for communication, at least, for a part of time. In ad hoc cooperative spectrum sensing, nodes do not maintain a database for decision support on the selected channels. To solve this limitation in the ad hoc cooperative spectrum sensing, CR-BS architecture is proposed. In the CR-BS architecture, a Cognitive Radio - Base Station Controller (CR-BSC) is provisioned which computes the traffic prediction based on the current and the past history of occupancy of the channels. In this architecture, SU functions as probe for occupied primary and secondary channels available in the environment with location information through GPS and transmit to CR-BS for periodic updation of channel status database. A database is prepared in CR-BSC which compiles data in minutes, filtered and accumulated in hours and in days. The reason for selection of one minute as a time unit has been explained in Section 2. The BS monitoring system of CR computes the instantaneous and hourly blocking probability for placing a secondary user call to different channels in the system considering daily traffic pattern. The CR service provider has to offer a GoS at the instant of generation of service request. In classical teletraffic theory, GoS is defined as the portion of calls that are allowed to fail due to congestion in the busy hour. The GoS and blocking probability are used as synonyms in this paper.

When an SU makes a channel request to CR-BS, CR-BS assesses the availability of each channel as a combination of current occupancy position plus expected vacant time in future from its occupancy history, which is considered in minutes. A comprehensive prediction model is employed to evaluate the instantaneous blocking probability from time of request by SU.

The proposed work calculates blocking probabilities both on immediate minute occupancy basis and its preceding 60 minutes basis at the instant of service request by SU. Blocking probability based on current minute occupancy yields random values with several local peaks like irregular ripples within an hour of observation. The basic postulate for the proposed work has been discussed in detail in Section 2. The new concept of channelized blocking probability has been defined along with the general definitions of blocking probabilities in Section 3. Collection of PU data and the channel occupancy during a day along with its analysis method for computation of instantaneous and channelized (hourly) blocking probability has been discussed in Section 4 followed by results and discussions in Section 5 and conclusions in Section 6.

2. Basic Postulates of Present Work

A cellular system uses the trucking methods to accommodate a large number of users in a limited radio spectrum. An infrastructure base CR network is shown in Figure 1 that consists of 'm' active users and 'n' outlets along with a monitoring system that records the occupancy pattern for all channels in the system at regular interval of time.



Figure 1. Access network part of infrastructure based CR network.

In the present work, data has been acquisitioned in each minute interval. The basic postulates related to the present work are as follows:

- 1. Call is offered at random to a system having few trunk servers. The calls have random holding time. If all the servers are busy at a certain time, new call requested will be cleared from the system.
- 2. Monitoring system records the occupancy status of individual servers after a fixed time interval. The interval shall be as small as possible, however, practically limited by processing efficiency of monitor server and related signaling link. It has been taken as one minute in present work, although, all traffic calculation is based on hourly basis involving Erlang's formula.

- 3. Erlang's calculation is based on Poisson's distribution which assumes that one and only one call is offered to the system in a sufficient small interval of time when lim.(Δt) 0. In the present work, the establishment time of a call in practical scenario is considered to be maximum 20 seconds. Hence, establishment conversation/data transfer and release processes for a single call do not give birth to a second call to be completed within same minute under observation.
- 4. If a call is generated at the border of a minute and continues up to a fraction of next minute, both the minutes are to be considered as occupied.
- 5. A cognitive call request cannot force release another cognitive call which is already in progress. Hence, to a new cognitive call request agent, total occupancy of the channels in licensed band are the sum of primary calls and secondary calls existing in the system.
- 6. Grade of Service (GoS)≤ 0.02 shall be considered as acceptable limit.

3. Definitions

We consider a licensed spectrum network with static wireless nodes communicating with each other using n licensed channels (j = 1 to n). A cognitive radio network is located within the licensed coverage area. The measurement setup used for detection of spectrum holes in CR is a drive test equipment which performs tests in a cellular network and collects data on a moving vehicle¹⁻³. The cognitive nodes are equipped with spectrum sensor devices that monitor and report channel states to the central node via dedicated channels. Also, the sensor outcome can be defined as a sequence of binary signal {0,1}, which represents the vacancy and occupancy of observed channels at an instant of time, t. Assuming that the duration of idle and busy time is much greater than sensing time, all the channels are sensed and the history database is updated with the most recent sensing information. Based on the collected history, the traffic patterns of different channels can be used to compute the different blocking probabilities to estimate GoS:

1. Predicted Blocking Probability (PBP): The probability computed by Autoregressive-moving-average (ARMA) model that is a mathematical model of the persistence, or autocorrelation, in a time series is called as PBP. In ARMA model, a time series is observed for total number of calls $(y_1, y_2, ..., y_T)$. To predict the total number of calls in dth day, forecast is done by minimizing the mean squared error (MSE), i.e., Min._{y'T+k} E = $((y_{T+k} - y'_{T+k})^2)$. In that case, the best forecast is the mean of y_{T+d} , conditional on the information up to T, (y_1, y_2, \dots, y_T) :

$$\alpha = y'_{T+k} = E(y_{T+k} | y_1, y_2, \dots, y_T).$$

In the present work, the BS monitoring system records the minute wise channel occupancy of licensed users for continuously 7 days. The predicted value of offered load during the 8th day is calculated by using data of total calls of a particular hour for 7 days (i.e., T = 1 to 7) using ARMA model, and has been depicted in Table 1.

Table 1. Prediction of offered load in a particular hourusing ARMA model.

Predic	tion of (Offered 7	Гraffi	c usiı	ng A	rma Mo	del for	
Channels j=1 to n								
Hour	1:00	2.00	-	-	-	22:00	23:00	00:00
Day	AM	AM				PM	PM	AM
#1	1243	1587	-	-	-	-	-	1325
#2	1453	1325	-	-	-	-	-	1243
-	-	-	-	-	-	-	-	
-	-	-	-	-	-	-	-	
-	-	-	-	-	-	-	-	
-	-	-	-	-	-	-	-	
#7	1000	1106	-	-	-	-	-	1106
#8*	1102*	1258*	-	-	-	-	-	1151*
*Predicted offered load								

Table 2. Calculation of offered load at an instant of time t=t+1 (a snapshot taken from software).



Table 4. Difference between standard deviation of IBPand CBP vs. IBP and PBP.

Trunk Servers	Std. Dev. (IBP & PBP)	Std. Dev. (IBP & CBP)	Difference
7	0.0139	0.0118	0.0021
15	0.0046	0.0040	0.0005
22	0.0017	0.0018	-0.0001
29	0.0014	0.0013	0.0001
36	0.0007	0.0007	0.0000
43	0.0003	0.0003	0.0000
50	0.0003	0.0003	0.0000

The predicted value of total calls of 8th day of a particular hour is taken for computation of blocking probability using the formula:

Table 3. Calculation of offered load considering based on immediate preceding 60 minutes data

Estimation of Offer j=1 to n	red Tra	ffic Con	sidering	Preced	ing 60 N	linutes D	ata fo	r Channel	S		
Time (In Minutes) Channel No.	1	2	-	-	t-60	-	-	t	**t+1	-	3600
#1	1	0	-	-	1	-	-	1			
#2	0	0	-	-	0	-	-	1			
-	-	-	-	-	-	-	-	-			
-	-	-	-	-	-	-	-	-			
-	-	-	-	-	-	-	-	-			
#50	1	0	-	-	1	-	-	1	İ		
**Estimation of CBP at time t+1basedon immediate past 60 minutes											

$$\frac{a^{c}}{c!}$$

PBP = $\overline{\Sigma_{i=0}^{c} \frac{a^{i}}{i!}}$ where, c= total channels in the system.

2. Instantaneous Blocking Probability (IBP): The blocking probability provided by the system at an instant of time, t+1, is called as IBP. The IBP is on every minute basis. In this case, the offered load, a, is defined as,

 $\sum_{a=j=1}^{n} a_{j}$ = number of channels busy during the minute of observation, where, $a_{j} = 1$, if channel is busy & $a_{j} = 0$ if channel is free, and j=1 ton channels. The table for calculation of offered load at an instant of time, t, is shown in Table 2.

The instantaneous blocking probability at time t, is defined as:

$$\frac{a^{c}}{c!}$$

 $IBP = \sum_{i=0}^{c} \frac{\alpha}{i!}$ for c= n, where, c= total channels in the system.

3. *Channelized Blocking Probability (CBP):* The blocking probability provided by the system at an instant of time t+1 considering the traffic of the preceding 60 minutes is called as CBP. The offered load in this case is defined as,

$$\sum_{j=1}^{n}\sum_{t=60}^{t}a_{t}$$

a = j = 1 t - 60, where, $a_j = 1$, if channel is busy $\&^{a_j} = 0$ if channel is free, and j=1 to n channels.

The channelized blocking probability, as shown in Table 3 is defined as:

$$\frac{\frac{a^{c}}{c!}}{\sum_{i=1}^{c} \frac{a^{c}}{c!}}$$

CBP = $\sum_{i=0}^{\infty} \overline{i!} \sum_{i=0}^{\infty} \overline{i!}$ where c= 60*n = total channels in the system.

4. Error estimation: In the present paper, the error is estimated by the computation of standard deviation between IBP and PBP, and IBP and CBP. The standard deviation of the sample is the degree to which individual data within the sample differ from the sample mean. A high standard deviation shows that the data is widely spread (less reliable) and a low standard deviation shows that the data are clustered closely around the mean (more reliable). Since PBP is fixed for a clock hour, the error between IBP and PBP is given by:

$$\sqrt{\boldsymbol{\Sigma}_{i=1}^p[\![(\boldsymbol{x}]\!]_i - \boldsymbol{x}'\big)^2}$$

 $e_{pbp} = p$ where, x= value of IBP, x'= predicted value of PBP with i= 1 to 60, p= 60 in present case.

As CBP varies minute wise, the error between IBP and CBP is given by:

$$\frac{\sqrt{\sum_{i=1}^{p} \left[\left(\mathbf{x} \right]_{i} - \mathbf{x}_{i}^{\prime} \right)^{2}}}{n}$$
 wh

 $e_{cbp} =$ **p** where, $x_i^2 =$ estimated value of CBP. The present paper proves that $e_{pbp}^2 - e_{cbp}^2 \ge 0$.

4. Procedure and Analysis Method

4.1 Axioms to Prove

The proposed work shall prove the following axioms:

- 1. Erlang theory is effective for Poisson's distribution theorem with ≥ 20 channels for GoS to achieve.
- 2. The GoS improves linearly with total number of channels in the system.
- 3. The CBP is a better estimation method than PBP.

4.2 Data Preparation

In infrastructure based CR network, the SU transceiver has built-in GPS facility for location id. Also, they continuously monitor the signal levels and channel occupancy information for all licensed users, as shown in Figure 1. The CR receiver gets channel occupancy and other related information from SUs. As the CR database is not available in present telecommunication system, the first step is to set up a Database Engine, for data collection and updation. The main function of BS monitoring system is to maintain database of total number of channels licensed to PU along with its traffic load, signal strength, SINR etc. Thus, it maintains a channel status table in which the traffic pattern of each channel is observed. It also prepares a table on daily basis that contains total count of calls handled in a particular day for 24 hours. The above data is filtered for duplicates by the BS monitoring system. All channels are sensed and the channel history database is updated with the most recent sensing information.

To establish minute wise GoS, the real time minute wise channel occupancy data captured by the CR-BS monitoring system is presented minute wise for calculation of GoS achievable to SU at a random point of time, t, where, the future minute traffic at time (t+1) is not known to the system.

In the present analysis, minute wise collected occupancy data was calculated for 7 days on each minute basis for 50 cells of with different traffic channel capacities ranging from 7 to 50 at different RF standards (like 1 RF = 7 channels, 2 RFs= 15 channels, etc.) for GSM system.

When the CR system places a call for certain time duration, the database stored in CR-BS monitoring system helps to compute the number of busy channels at that instant of time and the software computes the instantaneous blocking probability along with the channelized blocking probability using the Erlang B formula.

4.3 Analysis Method

The data was chosen at busy hours for 50 channels and minute wise occupancy for 300 minutes calls is practically taken for calculation purpose. A study was carried out for computing instantaneous blocking probability and channelized blocking probability for various trunk servers ranging from 7 to 50 channels. The different value of CBP in progressive minutes was predicted from the software. A comparison graph of CBP versus number of vacant channels is shown in Figure 2 for various trunk servers. It is thus evident from figure2 that Erlang theory is effective for Poisson's distribution theorem with \geq 20 channels for GoS to achieve (axiom (i)).



Figure 2. Channelized Blocking Probability (CBP) vs. normalized total number of vacant channels.

The mean and standard deviation of IBP was calculated during the busy hour for various trunk servers and is shown in Figure 3. The Figure 3 clearly indicates that as number of trunk server increases, the difference between mean and standard deviation of IBP also increases. The relative difference of standard deviation also decreases, which indicates that as number of channels ≥ 22 , IBP approaches PBP. Thus, the GoS improves linearly with total number of channels in the system at a given per channel availability, (axiom (ii)).



Figure 3. Mean and standard deviation of Instantaneous Blocking Probability (IBP) vs. total number of channels in the system.

Figure 4 is plotted for comparison of CBP and PBP for consecutive four hours. It is evident from Figure 4 that the standard deviation of PBP is fixed with respect to IBP but the standard deviation of CBP matches with that of IBP during the busy hour which shows that the CBP is better than PBP. The CBP is much more prominent during the peak hours where random variation of instantaneous values is more (axiom (iii)).



Figure 4. IBP, CBP and PBP vs. time in minutes in the system with c= 22 trunk servers.

Also, it is evident from Table 4 that as the number of trunk server increases, error between IBP and CBP is less than that of error between IBP and PBP. Thus, the estimation of CBP is a better method than the estimation of PBP.

5. Results and Discussions

In the present work, study has been done for the channel occupancy pattern for varying channels during day peri-

ods and it has been established that channel occupancy is well below 50% of the total available channels during most part of a day. This shows that, cells with \ge 22 channel capacities have blocking probability of \le 2%. The paper establishes that CBP is much more relevant during the peak hours where random variations of instantaneous values are more. Also, it has been established that the mean value of blocking probability increases as standard deviation increases which shows more uncertainty in prediction of GoS. It has been established that the CBP is definitely closer to IBP compared to PBP as depicted in Figure 5.

No. Inst. Particular Entrance No. No. Desc. Desc. No.	a x
A for A constructions A mark for a construction A mark for a construction A mar	¥
Copenset S Fort S Mapment S Name S Page 1 Page 2 Page	¥
A17 • 6 & ** Estimation of IDP at an instant of time tr1, in present example, t= 21:36pm	¥
	0
CALCULATION OF OFFERED TRAFFIC AT AN INSTANT OF TIME t+1 FOR CHANNELS = 1 to n	
TIME (IN MINUTES) V	
CHANNEL NO. 1 2	
#2 1. INITIALIZE 4. IEP 1 1	
#3 START 1 S.PROCESS SU call offered on 17/01/2016 at 20:16 pm has:	
#4 (a) Total number of channels = 22	
#5 3. PRESS CTRL. & PAUSE 6. CBP (b) Number of channels occupied = 13	
1 #6 (c) Instantaneous Blocking Probability = 0.00302 (d) Channelius Blocking Probability = 0.01307	_1
1 #7 1 1 1 0 1 (c) Characterized Diocharg Probability = 0.01233	
** Estimation of the at an instant of time t+1, in present example, t+21.30pff	
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4.5.6 ama_/dp_/bp_result_/9_/	2
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Figure 5. Computation of IBP, CBP and PBP at an instant of time t=t+1 (a snapshot taken from software).

6. Conclusion

It is very much necessary to study the individual channel occupancy history and current state of occupancy of each channel before handing over of SU call to a specified channel for a defined duration. Validation through actual data establishes that Channelized Blocking Probability estimation model has lower error value compared to estimation through prediction models of other researchers. A software for estimation of CBP with sample database has been prepared in MS excel with embedded Visual Basic Access and can be obtained from authors for verification of results.The software can also be upgraded to allocate a channel to a SU.

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