

MODELING AND PERFORMANCE ANALYSIS OF CONTENTION RESOLUTION OF A COGNITIVE RADIO NETWORK

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Abstract:

Challenges associated with contention handling in cognitive radio environment includes spectrum underutilization, interference, and fairness in spectrum utilization. The proposed model provided leverages on M/G/1/K queuing model, providing a theoretical foundation for optimizing contention resolution. Through the First-come First-serve (FCFS) algorithm, the model ensures equitable access to the spectrum, prioritizing the first arriving users. To validate the efficacy of the proposed model, Matlab and Minitab software were employed for simulation and statistical analysis. The simulation results not only demonstrate the model's effectiveness in mitigating contention issues but also provide insights into system performance under various scenarios. This research contributes to the advancement of cognitive radio networks by offering a robust contention resolution model supported by empirical evidence from Matlab and Minitab simulations. The integration of these software tools enhances the reliability and practicality of the proposed solutions, making them valuable for designing efficient and fair cognitive radio communication systems. Above all, the model and process will contribute in helping Nigerian Communication Commission (NCC) and other Dynamic Spectrum Usage functionaries in analyzing and optimizing the contention resolution process for the effective utilization of available spectrum resources in dynamic cognitive radio environment.

Keywords: Spectrum Sensing, Spectrum management, First Come First Serve Algorithm and M/G/1/k Model.

1. INTRODUCTION

Cognitive Radio Networks (CRNs) have emerged as a promising solution to address the growing demand for wireless communication services while efficiently utilizing the limited and crowded radio frequency spectrum, Mitola, (2009). In the dynamic and unpredictable nature of the radio environment, contention arises when multiple cognitive radio devices seek to access the same frequency bands simultaneously. Contention resolution becomes a critical aspect of ensuring fair and efficient spectrum utilization in cognitive radio networks, Akbar, et al (2010). Contending devices must contend with each

other to access available spectrum resources, and effective contention resolution models play a pivotal role in optimizing network performance. These models aim to manage the competition among cognitive radio nodes, dynamically allocating spectrum access based on priority, fairness, and overall network efficiency, Ramani & Sharma (2017). Helen & Susan, W, (2015).

The complexity of contention resolution in cognitive radio networks is magnified by the need to coexist with primary users and adapt to the changing radio frequency environment. Traditional contention resolution mechanisms, such as Carrier Sense Multiple Access (CSMA), may not fully address the unique

challenges posed by the dynamic and cognitive nature of these networks, Rahman & Karmakar (2018), Akyildiz, et al., (2011, Uddin, & Al-Dubai, (2013),.

This introduction explores the significance of contention resolution models within the context of cognitive radio networks, highlighting the need for adaptive and intelligent mechanisms to address contention challenges. By delving into the principles, algorithms, and advancements in contention resolution, we aim to gain insights into how these models contribute to the efficient and reliable operation of cognitive radio networks in diverse and dynamic communication scenarios, Mahmoodi, et al.,(2009, Digham, et al., (2007)..

Contending for spectrum access (sensing) in cognitive radio networks involves intricate decision-making processes, as devices must dynamically adapt to changing environmental conditions, avoid interference with primary users, and adhere to regulatory constraints. Contention resolution models play a crucial role in orchestrating these decisions, ensuring that cognitive radio devices cooperate effectively to share the spectrum efficiently Yucek and Arslan (2009), Khan, et al.,(2015), Zang, et al. (2009),.

The challenges associated with contention resolution in cognitive radio networks are manifold. Devices must contend not only with each other but also with the uncertainties introduced by varying propagation conditions, interference levels, and the presence of dynamic primary users. Traditional contention resolution mechanisms may struggle to cope with these complexities, necessitating the development of novel models that harness the cognitive capabilities of the devices.

Moreover, contention resolution in cognitive radio networks is closely tied to the concept of spectrum sensing, where devices must accurately detect and assess the occupancy status of the spectrum. The integration of sensing information into contention resolution models adds a layer of intelligence, allowing devices to make more informed decisions about when and where to contend for spectrum access.

2. MATERIALS AND METHODOLOGY

Developing a contention resolution model in a cognitive radio network involves considering various materials and methods as we shall discuss. Here are key elements:

Hardware Components: Describe the physical components used in the study. Which include details about the cognitive radios, antennas, signal processing equipment, and any other relevant hardware as indicated in diagram below.

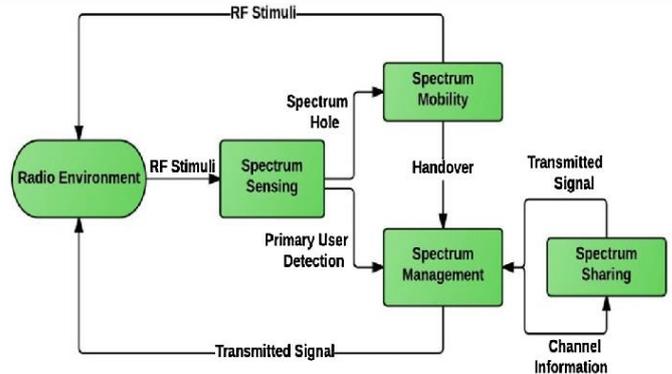


Figure 1: Design of Hardware Components used Contention Model

Software Tools: The software tools for simulation platforms are MATLAB and MINITAB used for implementing the contention resolution model. Cognitive radio often involves complex algorithms and simulations.

Datasets: The datasets are provided according to the displayed graph for testing and validating the contention resolution model in table 1 and 2.

Methods:

Algorithm: Algorithms is provided as a detailed explanation of the contention resolution in the model.

Experimental Design: Speculative assumption was conducted because of absent of equipment and outline the speculative variables.

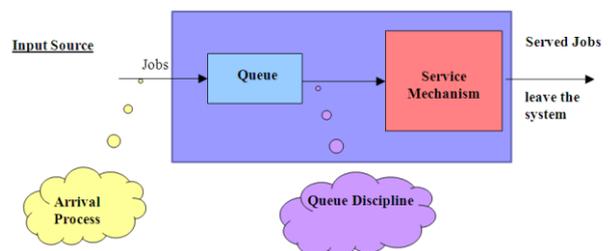


Figure 2: Queuing Model for transmission of Contention Using First Come First Serve (FCFS)

In a cognitive radio network, the contention resolution process often involves deciding which node or device gets access to a particular spectrum channel when node is contending for the same channel as indicated in

Figure 2. Queuing theory is employed to model and analyze contention resolution as one common approach is the First Come First Serve (FCFS) algorithm. FCFS is a simple queuing discipline where the node that arrives first is served first. Here's a simplified representation of a contention resolution algorithm using FCFS in a cognitive radio network environment:

First Come First Serve (FCFS) Contention Resolution Algorithm for Transmission:

Step 1: Initialization: Maintain a queue to store the nodes that is contending for spectrum access.

Step 2: Contending Node Arrival: When a cognitive radio node wants to access the spectrum, it joins the end of the queue.

Step 3: Channel Sensing: If the channel is sensed to be idle, the node at the front of the queue gains access to the spectrum or The node is removed from the queue and begins transmission.

Step 4: Channel Busy: If the channel is sensed to be busy

The contending node remains in the queue or the node at the front of the queue will gain access once the channel becomes idle.

Step 5: Transmission Completion: Upon completing its transmission, the node releases the channel, making it available for the next contending node.

Step 6: Repeat: Steps 2-5 are repeated for each contending node in the queue.

End: 7. The process continues as long as there are contending nodes.

3 RESULTS AND DISCUSSION

We Consider the imbedded Markov Chain of system states at these time instants $t_i = 1, \dots$ when the i th SU leaves from the system after transmitting. At a time instant t_i , the system state n_i will be the number of SUs left behind in the system when the i th SU leaves. Note that n_i will range between 0 and $K - 1$ since the departure of the job cannot leave the system completely full, i.e. with system state K .

Let a_i be the number of arrivals (from the Poisson arrival process) in the i th service time. The equations for the corresponding Markov Chain can then be written as

$$\left. \begin{aligned} n_{i+1} &= \min\{a_{i+1}, K-1\} && \text{for } n_i = 0 \\ &= \min\{n_i - 1 + a_{i+1}, K-1\} && \text{for } n_i = 1, \dots, (K-1) \end{aligned} \right\} \quad (1)$$

The transition probabilities of the imbedded Markov Chain at equilibrium are defined to be

$$p_{d,jk} = P\{n_{i+1} = j\}; \quad 0 \leq j, k \leq K-1 \quad (2)$$

Let α_k be the probability of k SU arrivals to the queue during a service time.

$$\alpha_k = \int_{t=0}^{\infty} \frac{(\lambda t)^k}{k!} e^{-\lambda t} b(t) dt \quad (3)$$

where the pdf of the service time is given as $b(t)$.

The transition probability $p_{d,jk}$ for the two cases $j = 0$ and $j = 1, \dots, K-1$ will be found separately using the values of α_k found in (3). The expressions for these are given in (4) and (5), respectively, based on the observation that the final state k cannot exceed $K-1$.

$$p_{d,jk} = \begin{cases} \alpha_k; & 0 \leq k \leq K-2 \\ \sum_{m=K-1}^{\infty} \alpha_m & k = K-1 \end{cases} \quad j = 0 \quad (4)$$

$$p_{d,jk} = \begin{cases} \alpha_{k-j+1}; & j-1 \leq k \leq K-2 \\ \sum_{m=K-j}^{\infty} \alpha_m & k = K-1 \end{cases} \quad j = 0 \quad (5)$$

The equilibrium state probabilities $p_{d,k}$ $k=0,1,\dots,K-1$ at the departure instants may be calculated Using the transition probabilities of (4) and (5), along with the normalization condition as follows.

$$p_{d,k} = \sum_{j=0}^{K-1} p_{d,j} p_{d,jk} \quad k = 0, 1, \dots, K-1$$

$$\sum_{k=0}^{K-1} p_{d,k} = 1 \quad (\text{Normalization condition})$$

The transition probabilities $p_{d,jk}$ of (4) and (5) may now be substituted in (5) and (6), giving a set of linear equations that may be solved to get the corresponding state probabilities. Note that only K independent equations are needed, as there are only K unknowns (i.e. $p_{d,k}$ $k=0,1,\dots,K-1$) to be found. This set of $K-1$ equations is summarized in (8).

$$\begin{cases} p_{d,k} = p_{d,0}\alpha_k + \sum_{j=1}^{K+1} p_{d,j}\alpha_{k-j+1} & k = 0,1,\dots,K-1 \\ \sum_{k=0}^{K-1} p_{d,k} = 1 \end{cases}$$

Alternatively, one can solve first for the normalized variables ($p_{d,k}/p_{d,0}$) using

$$\frac{p_{d,k+1}}{p_{d,0}} = \frac{1}{\alpha_0} \left[\frac{p_{d,k}}{p_{d,0}} + \sum_{j=1}^k \frac{p_{d,j}}{p_{d,0}} \alpha_{k-j+1} - \alpha_k \right] \quad k = ($$

and then solve for $p_{d,0}$ using the normalisation condition to get

$$p_{d,0} = \frac{1}{\sum_{k=0}^{K-1} \frac{p_{d,k}}{p_{d,0}}} \quad (10)$$

We use this and the values obtained earlier for ($p_{d,k}/p_{d,0}$), to obtain the actual state probabilities $p_{d,k}$ $k=1,\dots,K-1$ at the SU transmission instants.

Considering a system at equilibrium, let $p_{a,k}$ $k=0,1,\dots,K$ be the probability that a newly arriving SU, irrespective of whether it finally joins the queue or not, finds k SUs waiting in the queue. For this system, let p_k $k=0,1,\dots,K$ be the probability that the queue has k SUs in it at an arbitrarily chosen instant of time. We will have that

$$p_k = p_{a,k} \quad k = 0, 1, \dots, K \quad (11)$$

We can also define $p_{ac,k}$ $k=0,1,\dots,K-1$ as the equilibrium probability of the system state k as seen by an arrival which does actually enter the queue. Based on the fact, that the state of the queue can change by at most ± 1 because of these arrivals and the departures from it, we can claim that

$$p_{d,k} = p_{ac,k} \quad k = 0, \dots, K-1 \quad (12)$$

Using P_B as the equilibrium probability that an arrival is blocked (because the queue is full, i.e.

$$p_k = p_{a,k} = (1 - P_B)p_{ac,k} = (1 - P_B)p_{d,k} \quad k = 0, \dots, K-1 \quad (13)$$

Note that this may also be confirmed by observing that

$$\sum_{k=0}^{K-1} p_{a,k} = 1 - P_B = \sum_{k=0}^{K-1} (1 - P_B)p_{ac,k}$$

$$\text{since } \sum_{k=0}^K p_{a,k} = 1 \text{ and } \sum_{k=0}^{K-1} p_{ac,k} = 1$$

Since the average arrival rate of SUs actually entering the queue (also the average departure rate of SUs leaving the queue) is $\lambda_c = \lambda(1 - P_B)$, the actual traffic throughput of the queue will be $\rho_c = \rho(1 - P_B)$.

This implies that the probability p_0 of finding the queue empty at an arbitrary time will be

$$p_0 = 1 - \rho_c$$

Using (13) for the case $k=0$, we can then write

$$1 - \rho(1 - P_B) = (1 - P_B)p_{d,0} \quad (14)$$

The blocking probability P_B (or p_K) can be found using (14) as

$$P_B = 1 - \frac{1}{p_{d,0} + \rho} \quad (15)$$

Using the values of $p_{d,k}$ and the results of (13) and (15), the equilibrium state distribution p_k , $k=0,1,\dots,(K-1)$ of the queue at arbitrary time instants may then be shown to be

$$p_k = \frac{1}{p_{d,0} + \rho} p_{d,k} \quad k = 0, \dots, K-1 \quad (16)$$

The equilibrium state distribution may now be used to find the mean number N in the system as

$$N = \sum_{k=0}^K kp_k = \frac{1}{p_{d,0} + \rho} \sum_{k=0}^{K-1} p_{d,k} + K \left(1 - \frac{1}{(p_{d,0} + \rho)} \right) \quad (17)$$

Note that the effective arrival rate λ_c to the queue will be given by

$$\lambda_c = \lambda(1 - P_B) = \frac{\lambda}{p_{d,0} + \rho} \quad (18)$$

Using this and Little's result, the mean total time spent in system by a SU actually entering the queue will be

$$W = \frac{N}{\lambda_c} = \frac{\sum_{k=0}^{K-1} p_{d,k} + K[(p_{d,0} + \rho) - 1]}{\lambda} \quad (19)$$

This may be used to get the mean time spent waiting in the queue W_q as

$$W_q = W - \bar{X} = \frac{1}{\lambda} \sum_{k=0}^{K-1} p_{d,k} + \frac{K}{\lambda} (p_{d,0} + \rho - 1) - \bar{X}$$

where \bar{X} is the mean service time. The second moment of the time spent waiting in queue is given by

$$\overline{W_q^2} = (K-1) \left[(K-2)(\bar{X})^2 + \overline{X^2} - \frac{K\bar{X}p_{d,0}}{\lambda} - \frac{2\bar{X}}{\lambda} \right]$$

where $\overline{X^2}$ is the second moment of the service time

Table 1 shows the analysis of results obtained from the simulation of contention resolution model of the speculation of the server transmission

Table 1: Result of Analysis in Contention Model

S/N	Arrival Time (λ)	Service Rate (μ)	Traffic Intensity (P)	Number of SUs (Lq)	Meantime in the Queue (Wq) per Secs
1	0.100	0.111	0.901	8.19	81.90
2	0.067	0.071	0.944	15.81	235.92

Implementation Requirement

Here, we employ Testing and Simulation to thoroughly test and simulate the scenario which validate the performance and reliability of the contention resolution model as shown in table 1 above.

TABLE 2

Result of Analysis in Contention Model using MANITAB Software to validate transmission

S/N	Threshold (T)	Arrival Time (λ)	Service Rate (μ)	Traffic Intensity (P)	Number of Sus (Lq)	Meantime in the Queue (Wq)
1.	0.39	0.10000	0.11100	0.9010	8.190	81.90
2.	0.58	0.06700	0.07100	0.9440	15.810	235.92
3.	0.78	0.05000	0.05300	0.9430	15.720	314.47
4.	0.86	0.04000	0.04200	0.9520	19.050	476.19
5.	0.75	0.03300	0.03400	0.9710	32.030	970.59
6.	0.29	0.02857	0.02941	0.9714	33.400	1157.47
7.	0.78	0.02500	0.02273	0.9750	38.087	21523.50
8.	0.83	0.02222	0.02273	0.9767	42.590	1916.79
9.	0.90	0.02000	0.02041	0.9799	47.800	2390.03
10.	0.19	0.01818	0.01852	0.9816	52.490	2887.18

where $0 \leq \text{Threshold} < 1$. That is, the threshold value lies between zero (with zero inclusive) and one (with one exclusive). With this in mind, we have randomly assigned threshold values to each level of the five variables: arrival time (λ), service rate (μ), Traffic Intensity (P), Number of Sus (Lq), and Meantime in the Queue (Wq).

We seek a **specific multiple linear regression model** whose general form assumes:

$$\hat{T} = \hat{\beta}_0 + \hat{\beta}_1\lambda + \hat{\beta}_2\mu + \hat{\beta}_3P + \hat{\beta}_4(Lq) + \hat{\beta}_5(Wq) \quad (A)$$

where: $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4, \hat{\beta}_5$ are parameter estimates of the model.

In order to develop this model, the data in the Table 4.1(b) is used in MINITAB Software (version 17) to obtain a **specific multiple linear regression model** which assumed the general form in equation (A), and which describes the Contention Model. The result of this analyses is presented below, alongside the developed model given as equation (B).

Regression Equation

$$\text{Threshold (T)} = 9.7 + 38(\lambda) - 47(\mu) - 8.6(P) - 0.0096(Lq) + 0.000000(Wq)$$

Regression analysis: Threshold (T versus arrival time, service rate, traffic intensity)

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	5	0.162128	0.032426	0.30	0.890
Arrival Time (λ)	1	0.000742	0.000742	0.01	0.938
Service Rate (μ)	1	0.001287	0.001287	0.01	0.918
Traffic Intensity (P)	1	0.002395	0.002395	0.02	0.889
Number of Sys (Lq)	1	0.003344	0.003344	0.03	0.869
Meantime in the Queue (Wq)	1	0.000001	0.000001	0.00	0.998
Error	4	0.432122	0.108031		
Total	9		0.594250		
Model Summary	S	R-sq	R-sq(adj)	R-sq(pred)	
	0.328680	27.28%	0.00%	0.00%	

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
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Constant 9.7 54.4 0.18 0.867
 Arrival Time (λ) 38 464 0.08 0.938 11982.77
 Service Rate (μ) -47 435 -0.11 0.918 13505.73
 Traffic Intensity (P) -8.6 58.0 -0.15 0.889 177.90
 Number of Sus (Lq) -0.0096 0.0544 -0.18 0.869 56.37
 Meantime in the Queue (Wq) 0.000001 0.000060 0.00 0.998 12.56

Regression Equation

Threshold(T)=9.7+ 38 (λ)- 47 (μ)- 8.6 (P)

Fits and Diagnostics for Unusual Observations

Obs	Threshold (T)	Fit	Resid	Std Resid	
1	0.390	0.390	0.000	0.01	X
7	0.780	0.779	0.001	0.64	X

X Unusual X

Since the work is speculative, it does not provide table for initial testing. The result is tested with table 1 and validated with table 2. The system is speculative without experiment being carried out because of absent of equipment within the scenario of this work. However, the above mathematical equations are used to justify and validate the work.

Figure 3 Graph showing Traffic Intensity versus Service Rate and Arrival Time (mins)

The graph in Figure 3 below depicts traffic intensity showing that both service rate and arrival time are decreasing as the throughput is less than 1 (< 1).

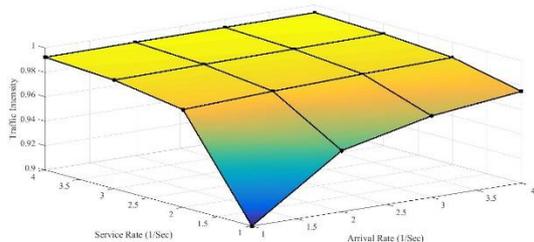


Figure 3: traffic intensity showing that both service rate and arrival time (mins)

The graphs above are plotted using MATLAB from the implementation of our contention resolution model.

Considering Figure 4, Mean time spent in the queue, Arrival time and service rate. While figure 5 shows a comparative analysis of Lq vs Arrival rate and Lq vs service rate. Arrival time (Lq) reduces as the server rate increases and remain almost constant about 0.053 mins while Arrival Time (Lq) reduces steadily with increase in arrival rate and almost constant 0.052 mins. We can deduce that at lower arrival rate and service rate of less than or equal to 0.053 mins, there is no

significance difference in the mean time spent by the server unit in the queue.

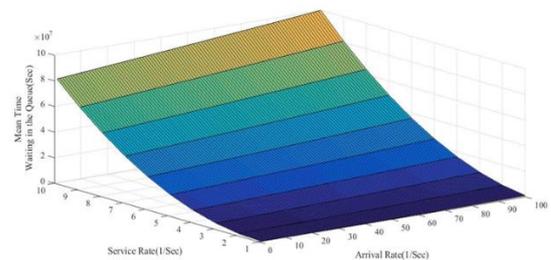


Figure 4: Mean time spent in the queue vrs Arrival time and service rate (mins)

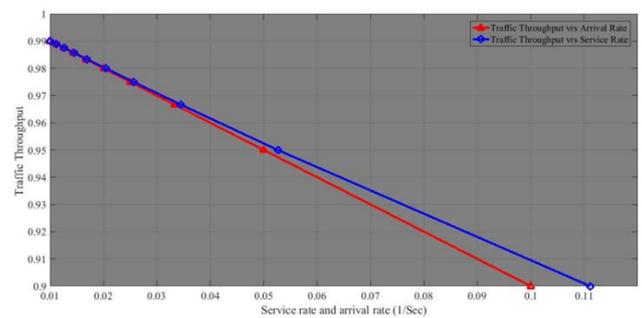


Figure 5: Traffic Throughput versus Service and Arrival Rate (mins)

Traffic Throughput decrease with an increase in service rate and arrival rate, meaning that the server is highly utilized for slower service rate and arrival rate. This show that the server is less congested and optimally used without contention and the traffic throughput is less than 1 for all conditions.

4 CONCLUSIONS

Queuing theory can be a valuable tool in solving sensing and contention resolution challenges in cognitive radio networks. In a cognitive radio, secondary users oppurtunically access the available spectrum, which often leads to contention for some resources. Sensing and contention are critical aspects of efficiently managing spectrum access in such networks. Employing MDP-based models for contention resolution in CRNs empowers cognitive radios to make informed, adaptive decisions in a dynamic spectrum environment. This approach optimizes spectrum usage, reduces contention, and improves the overall efficiency and reliability of communication in cognitive radio networks.

REFERENCES

- Akbar, I. A., Anpalagan, A., & Reaz, M. B. I. (2010). Cognitive Radio Networking: A Survey. *IEEE Communications Surveys & Tutorials*, 12(1), 116–130. doi: 10.1109/SURV.2010.042610.00039
- Akyildiz, I. F., Lee, W.-Y., Vuran, M. C., & Mohanty, S. (2011). Dynamic Spectrum Access in Cognitive Radio Networks: A Comprehensive Survey. *IEEE Communications Magazine*, 46(4), 116–130. doi: 10.1109/MCOM.2011.5740360
- Akyildiz, I. F., Lo, B. F., & Balakrishnan, R. (2011). MAC Protocols for Cognitive Radio Networks: A Survey. *IEEE Communications Surveys & Tutorials*, 13(1), 116–130. doi: 10.1109/SURV.2011.040110.00026
- Digham, A., Alouini, M.-S., & Simon, M. K. (2007). A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications: Challenges and Solutions. *IEEE Communications Surveys & Tutorials*, 11(1), 116–130. doi: 10.1109/SURV.2009.090109
- Haykin, S. (2009). Spectrum Sensing in Cognitive Radio Networks: Requirements, Challenges and Design Trade-Offs. *IEEE Signal Processing Magazine*, 26(5), 116–130. doi: 10.1109/MSP.2009.933462
- Helen, T. & Susan, W. (2015). Cognitive radio networks for tactical wireless communications, Defence Research and Development Canada Scientific Report DRDC-RDDC-2014-R185 December, Canada.
- Khan, S. U., Qazi, I. A., & Ahmed, A. (2015). Cooperative Sensing Based Dynamic Spectrum Access in Cognitive Radio Networks: A Survey. *Journal of Network and Computer Applications*, 50, 1–19. doi: 10.1016/j.jnca.2014.10.005
- Mahmoodi, N. H., Arslan, H., & Tafazolli, R. (2009). A Survey on Spectrum Sensing Algorithms for Cognitive Radio. *IEEE Communications Surveys & Tutorials*, 11(1), 116–130. doi: 10.1109/SURV.2009.090109
- Mitola, J. (2009). Cognitive Radio Architecture Evolution, *Proceedings of the IEEE*, 97 (4), 627–641.
- Pandit, S. & Singh, G. (2017). Spectrum Sharing in Cognitive Radio Networks. Springer; Cham, Switzerland: Spectrum Sensing in Cognitive Radio Networks: *Potential Challenges and Future Perspective*; 35–75
- Rahman, M. M., & Karmakar, G. C. (2018). Hybrid Contention Resolution Model for Spectrum Sharing in Cognitive Radio Networks. *IEEE Transactions on Cognitive Communications and Networking*, 4(1), 50–62.
- Ramachandran, K. N., Oliveira, L. C. de B., & Alencar, M. S. (2012). Adaptive Channel Allocation in Cognitive Radio Networks. *IEEE Transactions on Mobile Computing*, 11(8), 1167–1179. doi: 10.1109/TMC.2011.142
- Ramani, V. & Sharma, S. K. (2017). Cognitive radios: a survey on spectrum sensing, security and spectrum handoff, *China Communications*, (14), (11), 185–208.
- Uddin, M. S. and Al-Dubai, A. (2013), A Comprehensive Survey of MAC protocols in Cognitive Radio Networks. *IEEE Communications Surveys & Tutorials*, 15(3), 1135–1159. doi: 10.1109/SURV.2012.110112.00114
- Yucek, A. & H. Arslan (2009), "urvey of Spectrum Sensing Algorithms for Cognitive Radio Applications". *IEEE Communications Surveys & Tutorials*, 11(1), 116–130. doi: 10.1109/SURV.2009.090109
- Zang, Y. Zheng, H & Zheng, B. (2009). Dynamic Spectrum Access in Cognitive Radio Networks: A Survey. *IEEE Signal Processing Magazine*, 26(5), 86–95. doi: 10.1109/MSP.2009.932688
- Zhang, S., Wang, X., & So, H. C. (2010). An Efficient MAC Protocol for Cognitive Radio Sensor Networks. *IEEE Transactions on Industrial Informatics*, 6(1), 116–130. doi: 10.1109/TII.2009.2035160.