Turkish Journal of Computer and Mathematics Education Vol.12 No.10 (2021), 3476-3482

Research Article

Efficient Channel Allocation for Cognitive Radio Internet of Things

Leena K[1], Hiremath S G[2]

[1]Research Scholar, Department of Electronics and Communication Engineering, East West Institute of Technology, Bangalore, Karnataka, India.
[2]Professor and HoD, Department of Electronics and Communication Engineering, East West Institute of Technology, Bangalore, Karnataka, India.
Email: leenarenjith@gmail.com

Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 28 April 2021

Abstract: Recently, multiple wireless technology has arisen to provide effective and flexible IoT networking. Cognitive radio (CR) technology that facilitates software-defined radio is one of the key technology that gives IoT connectivity to a multitude of linked IoT devices in an opportunistic way. Unlicensed bandwidth has congested latest creation and study in the area of networking technology. The effect is unchecked and unregulated intrusion in the Internet of Things with low-powered wireless sensors (IoT). On the other hand, these technologies allowed low-energy IoT architecture at low cost, low energy usage and efficient spectrum use. Cognitive radio (CR) network, a low-cost approach for effective spectrum use, discusses the issue of spectrum use. Unlicensed users use underused bandwidth in CR networks. Due to its opportunistic existence, these networks' output relies on the observed spectrum pattern of the primary consumer. In these networks, frequency detection and usage must be accurately modelled. In this article, we propose the main Cognitive Radio Internet of Things (CR IoT) user identity mechanism using Markov's secret model. We implemented two algorithms: one for free channel identification and one for successful channel allocation. Simulation results suggest that CR-IoT surpassed traditional networking systems.

Key words- Hidden Markov Model, Allocation of resources, Evaluation of results, Cognitive Radio Networks.

1. Introduction

Commercial, science and medical bands (ISM) and mobile cellular bands are congested by wireless spectrum and the market for data traffic is continually growing. Static control of the spectrum by regulators, where spectrum is allowed over a long term span over broad geographical areas, cannot assign adequate spectrum to satisfy demand. Smart radio devices with Cognitive Radio (CR) technologies can feel their surroundings and likely access the usable radio spectrum. CR will complement carrier aggregation technologies for mobile networks and shape disparate bands together for large channels, but enable greater spectrum use. SDRs support the design of software rather than hardware [4]. Recent advancement in SDR technologies has allowed a range of soft and scalable radio functions that can be used in potential 5G networks and beyond, with substantially lowers costs. This means that a lot of the frequency is utilized on and off and is hence congested in some areas of the continuum. Artificial and actual spectrum deficiencies [5, 6] make effective usage of the spectrum significant.

Inefficiency of spectrum can be overcome by the implementation of an Opportunity Spectrum Access System (OSA), often known as a method for dynamical spectrum access (DSA). OSA is called a key function of CR, which can be detected, learned and adapted to wireless devices. CRSN aims to boost IoT network efficiency and user specifications. However, sensor systems use overhead energy to conduct spectrum sensing and spectrum sharings[7] to obtain QoS and strong application performance requirements[8][9]. This programme includes distributed channel control, which takes undisclosed network knowledge into consideration. Such prototypes were introduced in [10] and in [11,12] for single cognitive consumers. However, given the multi-user situation, it triggers a network collision. Consumers are selfish because of interference and other CR-IoT. The user needs [13,14] to wait for a new channel while the channel is busy and the capacity is wasted when another channel is available.

Evolutionary computing methods such as optimising particle swarming, reinforcement learning, game theory models have been implemented in order to obtain a rational distribution of capital [15], [16] and [17]. However, these model frameworks are built in terms of secondary, single-channel and homogenous users and[18] an evolutionary computing model with a multi-channel framework and a mobile interface based on game theory has been proposed. But Nash's alignment is not presented and channel overhead switches arise due to conflict as mobility speed is enhanced. Additionally, current models have discussed concerns of interference in the same area and relatively little analysis is performed while the system is communicated under two neighbouring primary cell overlaps. Moreover, user mobility is very restricted in the CR-IoT application, as in the case of CR-WSN but needs less latency with strong energy efficiency; user mobility is very quick in CR-VANET; user mobility in CR-D2D is complex in nature. In the present scheme, certain heterogeneous criteria in the CR-IOT spectrum allocation model are not taken into account.

To fix mobility overhead concerns, this work offers a reliable estimate of the probability of canal accessibility using an evolutionary computation approach and models effective multichannel CR-IoT spectrum access model.

2. Literature Survey

This section carries out a thorough review of the numerous current approaches to increase access to and usage of CR-IOT spectrum. In addition, it discusses the state-of-the-art study void for achieving an optimal spectrum resource distribution model for CR-IoT.

Opportunistic spectrum access model for CR-IOT: In [2] attention was given to optimising the network usefulness by jointly tracking sensor node sample rates and the channel access under energy usage, channel bandwidth and interruption constraints. In view of fluctuating energy harvest rates and the expense of channel transmission, we formulate network utility maximisation as a nonlinear programming mixer problem and solve it efficiently and effectively by means of dual disintegration. A joint channel access and sample rate management framework, called JASC, will be presented, taking into consideration the real-time effects and the energy collection rates of the channel. A QoS-based priority model is built in this mechanism, firstly to resolve data classification. Channel efficiency and the impact of the channel transition are then built into a priority scheduling system for packets.

Interference problem in allocating resource in CR-IOT: In [24] the power regulation and sequential interference cancellation mechanism were proposed for the issue of interference. However, these models allow for very smaller number of D2D cellular network correspondence. This decreases the total ability of the network. In [25], admission control and resource allocation (i.e., power) was used to increase the device sum rate and reduce interruption. The key objective of the new paradigm of resource distribution was to cope with interferences in the same cell[26],[27]. However, D2D users can reuse the multi-cell spectrum resource that induces interference. Game theory (GT) is used to achieve an optimised resource distribution for the D2D enabled cellular network [28], [29]. [20], [21] and [32] employed games where D2D subscribers compete and gain optimum resources depending on their utility function. In [30] the D2D cooperative association proposed where D2D pairs are used as a relay for cellular user packets correspondence. In [24] we have implemented D2D power controlling and resource allocation model using vertex colouring to solve the optimization problems for optimising relation efficiency. The model consolidates the user equipment for allocating money, and then each category is refined by swapping user equipment and introducing new ones. This aims to increase the degree of resource sharing and signal consistency. The two-stage resource distribution model discussed in [25] attempts to optimise the effectiveness of both subscriber and resource service provider. The resource distribution scheme, using a binary log-linear study model, was introduced in [26]. The model ensures that the convergence is ideal in the single cell setting. In addition, it achieves almost ideal amounts in a multi-cell setting.

Opportunistic spectrum access employing evolutionary computing model for CR-IOT: In [22], Channel sensing strengthening learning was presented in a cluster dependent cooperative network of wireless sensors. The strategy is established by Markov's decision to reduce sensing. The result indicates that primary consumer identification and energy costs are higher than current greedy quest methods. The aim of users is to evaluate the sensing order of their sources. First they specified a simplified interference metric to resolve the overlap of the canal sensor order and set two optimization goals: to minimize aggregate interface for each current user set and minimize the predicted aggregate interface for all possible users The approach and channel price adaptation should be carried out asynchronously, so that vehicle consumers can acquire awareness of the channel price before making real decisions on entry. In[29] an online learning system for optimising energy transfer of the CRSN by regularising packet lengths was implemented based on a bio-inspired algorithm[28], such as Particle Swarm Optimization (PSO). [16] illustrated parity between various users and energy usage were important concerns for the potential configuration of the contact network. There are two operating paradigms for cognitive radio: opportunistic access to spectrum and sensor dependent spectrum sharing. The formulated robust max-minute allocation of resources are mixed-integer and non-convex programming with limitless inequality constraints. The transmission power and subchannel allocation scheme is based on an accurate one-dimensional search algorithm. In [17] an uncooperative medium-sized access control game was introduced for wireless networks and new completely distributed multi access carrier meaning (CSMA) algorithms were introduced which prove to be optimal in that long-term throughputs converged to the best solution for the problem of utility maximisation over the maximum ability spectrum. The most critical aspect of its solution is to incorporate new price functions in the utilities of agents such that the suggested game understands the ordinary potential feature without a price anarchy.

3. Research Gap

The ultimate study indicates that cognitive radio plays an important role in enhancing the global Internet efficiency of an application relevant to the heterogeneous wireless networking world of the future century. The use of evolutionary measurement technology helped to enhance the estimation of channel-state details for effective spectrum sensing. The ultimate result indicates that very small spectrum sensing is performed for CR-IoT in view of complex mobility. A better optimization technique is required to enhance accurate channel state prediction for successful channel access. In comparison, the current paradigm fails from having an equal and effective spectrum access model that takes into account the CR-IoT multi-channel environment. The usage of evolutionary machine technology will help overcome issues of spectrum allocation. The nature of Nash equilibrium (i.e. optimum distribution of resources) is not presented by the current evolutionary continuum allocation paradigm focused on machine and channel overhead swapping exists when the speed of mobility is enhanced. It is essential to develop an effective dispersed opportunity spectrum access model for CR-IoT that uses spatial distribution and the temporal channel knowledge pattern to address research challenges. In addition, utilising powerful evolutionary computing strategies to continue using more spectrum productivity under the heterogeneous multi-channel mobile CR-IoT environment. In addition, present an efficient allocated resource model which addresses the problem of interference among contending devices in the overlapping region of the adjacent cellular network.

4. System Model

An IoT network that, which operates according to the Carrier Sense Multiple Access/Collision Avoidance scheme, which may coexist with other PU networks, such as the CR-oT in Figure 1 (e.g. hazardous areas monitoring systems using CSMA/CA), is classified as a ruralized CAPE-based network. The non-overlapping orthogonal system of channels gives the PUs permission to use their transmission. The ultimate objective is to present all PUs of equal bands with the same Fourier bandwidth for each channel (in Hz). Often, the spectrum of apertures can persistently scan the available spectrum to discover potential sources of the spectrum. In light of the continuum being as shown in Figure 2 (a). Each set of channels, shown in part (b) of this figure, is displayed as a "tone block." It is made up of two ranges: (or regions): (1) the idle blocks, (2) the busier blocks, and (3) performance. A lot of the CR-I transmissions will use different frequencies have plenty of idle channels for GBs between them, and others will be almost exclusively assigned. GBs are the last and remaining channels in the block designated for PRs, whether they're unutilized. It should be noted that potential CR-transmitted bytes would be reutilized in order to reuse existing GBs We assume that all CR-I control channels are available. While a dedicated channels are predefined in the CR-I network, not all of them must be devoted. Many CRN-designed controls exist (e.g. [5], [21], [29], [30]).For our purposes, processes, we will use either spectro-dynamic or localized dynamic cluster-hopping[28].

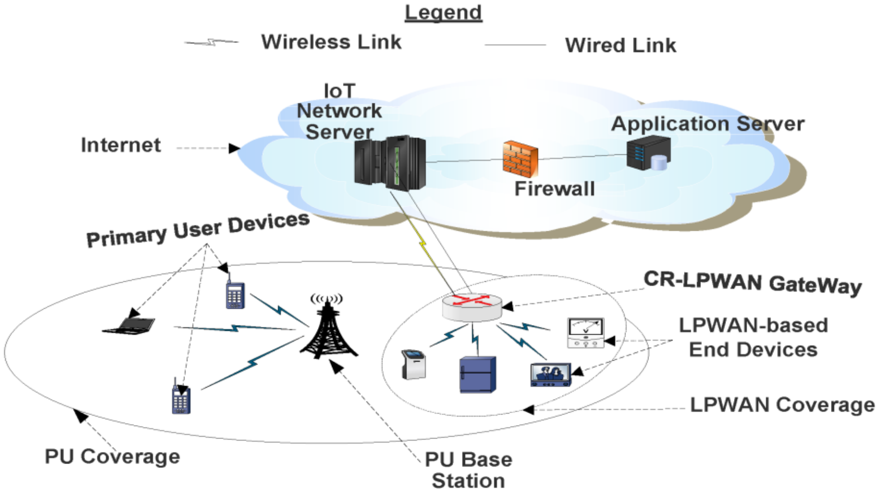

Fig.1. An example between the coexistence of PU and CR-IoT networks.

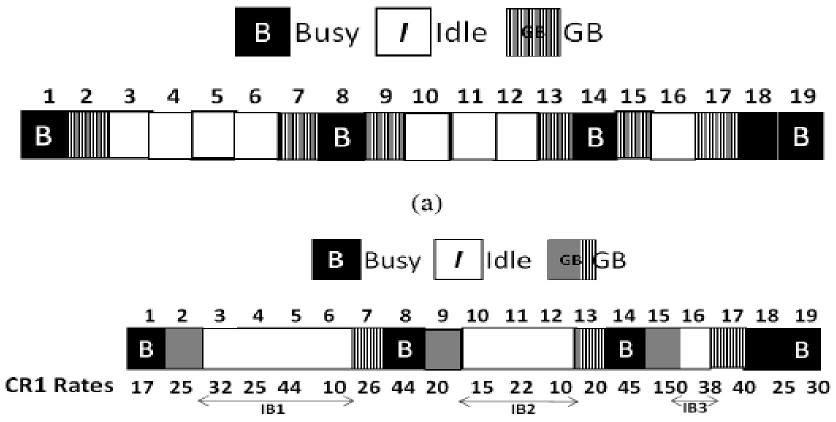

Fig.2. Illustrative example of channel vs. 19 channel block forming. (a) State of channel accessibility. (b) Creation of the idle block. [31]

5. Simulation Results

This CR-IoT has average packet latency and average throughput values. We know the CR-I depends on the free channel (PFL). Additionally, the CR-I is designed and simulated using MATLAB to relay fifty thousand packets, all of which are simulated in the field. To begin the demonstration, the simulation, the packet scheduler first makes an initial attempt to collect all the packets. We made reference to clarification in paragraph II-C and to figure 3, to demonstrate that fast-priority data performs better than delayed data. When a free channel appears, the critical data follow; if no free channel is accessible, normal data are used. if a PU is located inside a CS, no daily data is sent. If you can see in Figs. 4 and 5, the vital and normal CRIT is in data points, These CR figures are kept back.

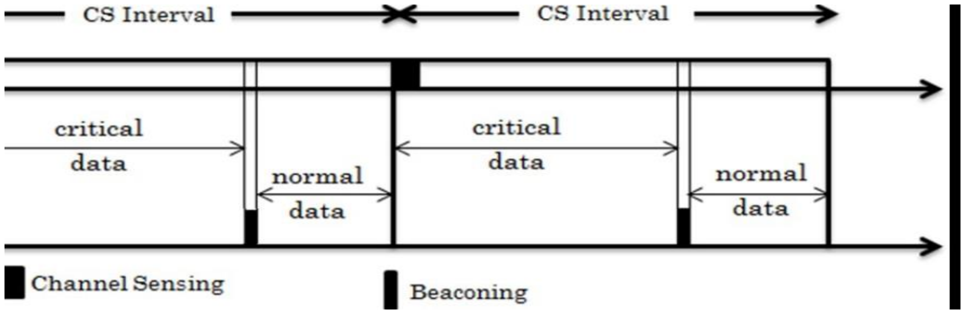

Fig. 3. Transmission of data in a CS interval [31]

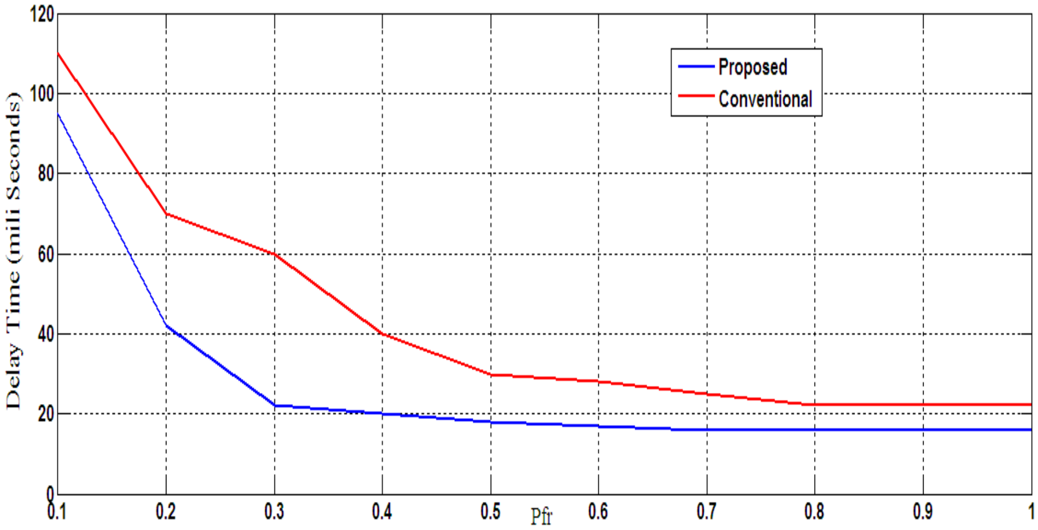

Fig. 4. Delay of the CR-IoT and conventional networks (in milliseconds) versus Pfr

In simulation and analytical modelling, IoT is contrasted to the standard model. The CR-IoT simulation correlates favourably with the study outcomes and has less time than Conventional model. Conventional model. From the Fig. 4 and 5. It is observed that, the delay is minimum when free channel (Pfr) probability is minimum. to begin with the latency is upper when Pfr values are marginal and when Pfr rises it is smaller. Likewise, in Fig. 6 and Fig. 7, CRIoT efficiency for vital and usual data is contrasted with traditional models utilising simulation and computational modelling, respectively. The CR-IoT simulation nearly fits the findings and exceeds the conventional schemes. In both estimates, if the Pfr is smaller, the incidence is low and strong when the Pfr levels are raised.

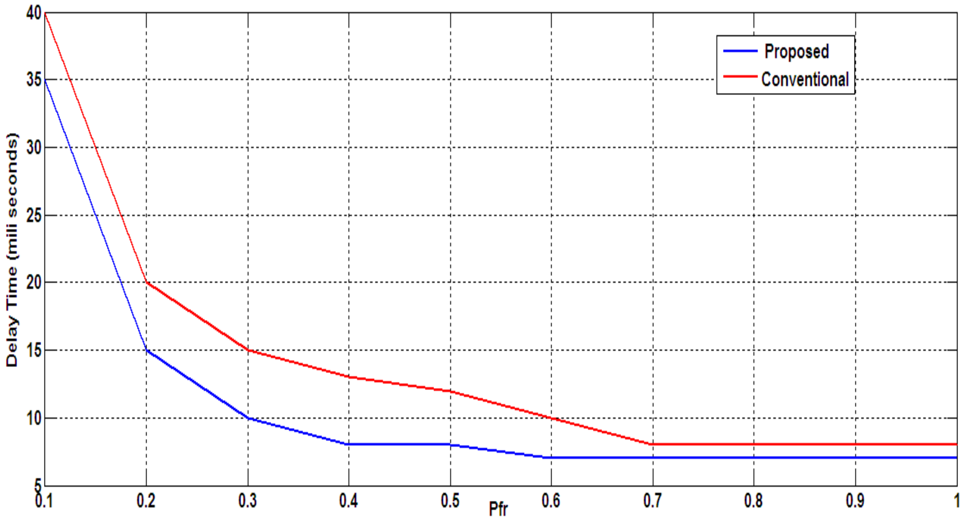

Fig. 5. Critical data delay (in milliseconds) against CR-IoT and Conventional Networks Pfr

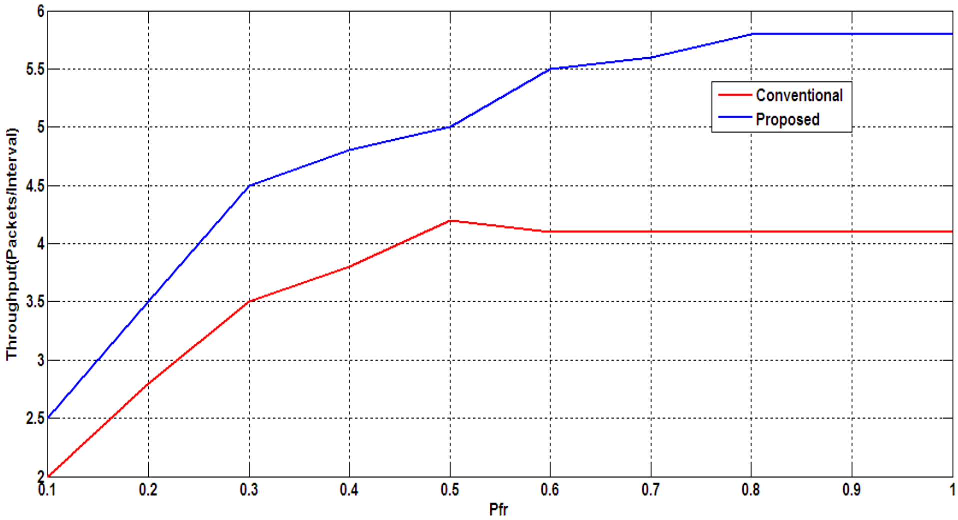

Fig. 6. Critical data (in CS interval packets) vs Pfr for CR-IoT and traditional networks

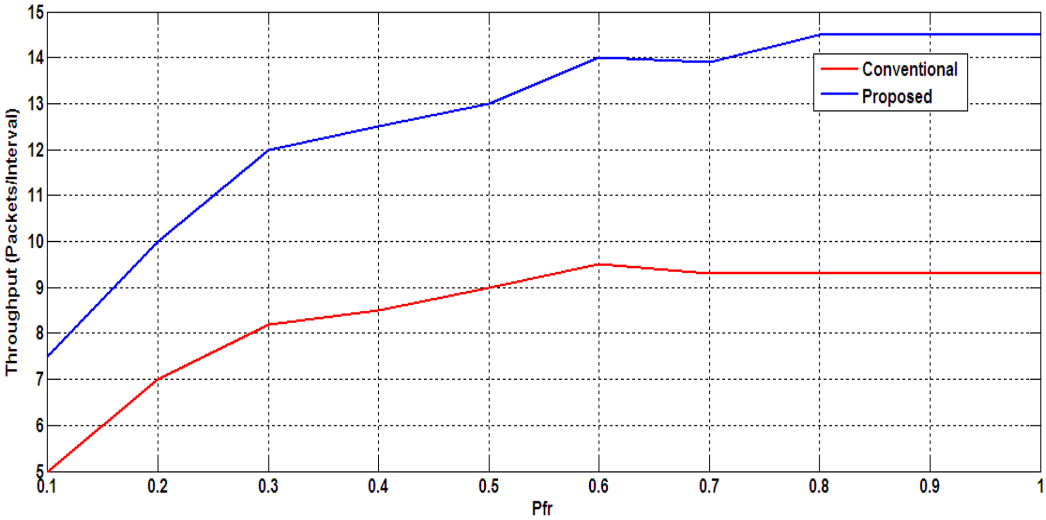

Fig. 7. Throughput of Normal Data (in packets per CS interval) versus Pfr

for the CR-IoT and Conventional Networks

CONCLUSION

In this work, we presented a simple model for speeding up critical data in CR-IoT. CR-IoT models have lower average latency than standard models; we assume (critical and normal data). Statistical and cognitive models provide similar outcomes, but utilize various strategies. We look forward in future towards widen this concept to the multi-shop and multi-cluster CR internet. In the future work the issue of transmission pause and throughput as well as multi-shop touch will be explored.

References

1. ITU Radio Regulations, International Telecommunication Union, Genève, 2008. https://www.itu.int/pub/R-REG-RR
2. J. Mitola and G. Q. Maguire, "Cognitive radios: making software radios more personal", IEEE Personal. Communications., vol. 6, no. 4,, pp. 13-18, August 1999. https://pdfs.semanticscholar.org/fb5d/1bb23724d9a5a5eae036a2e3cf291cac2c1b.pdf
3. S. Haykin, "Cognitive radio: brain-empowered wireless communications", IEEE Journal on Selected Areas in Communications, vol. 23, no. 2, pp. 201-220, February 2005. https://pages.jh.edu/bcooper8/sigma_files/JF/COGNITIVE/Cognitive%20Radio%20brain-empowered%20wireless%20comms.pdf
4. I. F. Akyildiz, W. Y. Lee, M. C. Vuran and S. Mohanty, "Next generation / dynamic spectrum access / cognitive radio wireless networks: A Survey", Computer Network, vol. 5, no.13,pp. 2127-2159, September 2006. https://sites.cs.ucsb.edu/~ravenben/classes/papers/al06.pdf
5. I. F. Akyildiz, W.-Y. Lee, K. R. Chowdhury: "CRAHNs: Cognitive radio ad hoc networks", Ad Hoc Networks, Elsevier, vol. 7, no. 5, pp. 810-836, July 2013. https://www.researchgate.net/publication/222412073_CRAHNs_Cognitive_radio_ad_hoc_networks
6. Pratas, N., Prasad, N. R., Rodrigues, A., & Prasad, R. "Cooperative spectrum sensing: State of the art review." In Wireless Communication,Vehicular Technology, Information Theory and Aerospace &Electronic Systems Technology (Wireless VITAE), 2nd International Conference on IEEE. pp. 1-6. February 2017. doi: 10.1109/wirelessvitae.2011.5940902
7. K. Seshukumar, R. Saravanan and M. S. Suraj., "Spectrum sensing review in cognitive radio," 2013 International Conference on Emerging Trends in VLSI, Embedded System, Nano Electronics and Telecommunication System (ICEVENT), Tiruvannamalai, 2013, pp. 1-4, doi: 10.1109/ICEVENT.2013.6496549.
8. H. Urkowitz, "Energy detection of unknown deterministic signals," in Proceedings of the IEEE, vol. 55, no. 4, pp. 523-531, April 1967, doi: 10.1109/PROC.1967.5573.
9. T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," in IEEE Communications Surveys & Tutorials, vol. 11, no. 1, pp. 116-130, First Quarter 2009, doi: 10.1109/SURV.2009.090109.
10. F. F. Digham, M. Alouini and M. K. Simon, "On the Energy Detection of Unknown Signals Over Fading Channels," in IEEE Transactions on Communications, vol. 55, no. 1, pp. 21-24, Jan. 2007, doi: 10.1109/TCOMM.2006.887483.
11. M.N. Morshed, S. Khatun, L.M. Kamarudin, A. Zakaria, N. Azmi, "Distributed cognitive radio detection using waspmote sensor for windows based PC/Laptop", 2nd International Conference on Electronic Design (ICED), Penang, Malaysia, 19 – 21 August 2018. doi: 10.1109/ICED.2014.7015816
12. A. Palaios, J. Riihijärvi, P. Mähönen, P. Van Wesemael, M. Desmet and A. Dejonghe, "Performance evaluation of single-chip spectrum sensing platform for portable spectrum measurements," 2013 IEEE 14th International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM), Madrid, 2013, pp. 1-6, doi: 10.1109/WoWMoM.2013.6583460
13. J. Zhu, Z. Xu, F. Wang, B. Huang and B. Zhang, "Double Threshold Energy Detection of Cooperative Spectrum Sensing in Cognitive Radio," 2008 3rd International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CrownCom 2008), Singapore, 2008, pp. 1-5, doi: 10.1109/CROWNCOM.2008.4562451.
14. B. G. Kurien, "Collaborative and Passive Channel Gain Estimation in Fading Environments," in IEEE Transactions on Cognitive Communications and Networking, vol. 5, no. 4, pp. 863-872, Dec. 2019, doi: 10.1109/TCCN.2019.2922315.
15. M. Grissa, A. A. Yavuz and B. Hamdaoui, "Location Privacy in Cognitive Radios With Multi-Server Private Information Retrieval," in IEEE Transactions on Cognitive Communications and Networking, vol. 5, no. 4, pp. 949-962, Dec. 2019, doi: 10.1109/TCCN.2019.2922300.

16. D. Cabric, A. Tkachenko and R. W. Brodersen, "Spectrum Sensing Measurements of Pilot, Energy, and Collaborative Detection," MILCOM 2006 - 2006 IEEE Military Communications conference, Washington, DC, 2006, pp. 1-7, doi: 10.1109/MILCOM.2006.301994.

17. Z. Ning et al., "Deep Reinforcement Learning for Intelligent Internet of Vehicles: An Energy-Efficient Computational Offloading Scheme," in IEEE Transactions on Cognitive Communications and Networking, vol. 5, no. 4, pp. 1060-1072, Dec. 2019, doi: 10.1109/TCCN.2019.2930521.

18. J. Zhu, Z. Xu, F. Wang, B. Huang and B. Zhang, "Double Threshold Energy Detection of Cooperative Spectrum Sensing in Cognitive Radio," 2008 3rd International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CrownCom 2008), Singapore, 2008, pp. 1-5, doi: 10.1109/CROWNCOM.2008.4562451.

19. A. Tkachenko, D. Cabric, and R. W. Brodersen, (2017), “Cyclostationary feature detector experiments using reconfigurable BEE2,” in Proceedings of . IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, Dublin, Ireland, Apr, pp: 216-219. doi: 10.1109/DYSPAN.2007.36

20. C. Liu, J. Wang, X. Liu and Y. Liang, "Deep CM-CNN for Spectrum Sensing in Cognitive Radio," in IEEE Journal on Selected Areas in Communications, vol. 37, no. 10, pp. 2306-2321, Oct. 2019, doi: 10.1109/JSAC.2019.2933892.

21. R. Tandra and A. Sahai, “Fundamental limits on detection in low SNR under noise uncertainty,” in Proceedings of IEEE International Conference Wireless Networks, Communication and Mobile Computing, vol. 1, Maui, HI, June 2015 , pp: 464–469. doi: 10.1109/WIRLES.2005.1549453

22. C. Liu, J. Wang, X. Liu and Y. Liang, "Deep CM-CNN for Spectrum Sensing in Cognitive Radio," in IEEE Journal on Selected Areas in Communications, vol. 37, no. 10, pp. 2306-2321, Oct. 2019, doi: 10.1109/JSAC.2019.2933892.

23. N. Muchandi and R. Khanai, "Cognitive radio spectrum sensing: A survey," 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), Chennai, 2016, pp. 3233-3237, doi: 10.1109/ICEEOT.2016.7755301.

24. V.D Gowda, S. B. Sridhara, K. B. Naveen, M. Ramesha, and G. N. Pai, “Internet of things: Internet revolution, impact, technology road map and features,” Advances in Mathematical Science Journal., vol. 9, no. 7, pp. 4405–4414, 2020, doi: 10.37418/amsj.9.7.11.

25. P. Ramesh Naidu, N. Guruprasad, and V. Dankan Gowda, “Design and implementation of cryptcloud system for securing files in cloud,” Advances in Mathematical Science Journal, vol. 9, no. 7, pp. 4485–4493, 2020, doi: 10.37418/amsj.9.7.17.

26. M. Ramesha, Dankan Gowda V, Sridhara S.B, Naveena Pai G, “FPGA Implementation of Low Power High Speed BTED Algorithm for 8 Bit Error Correction in Cryptography System,” International Journal of Emerging Trends Engineering Researh., vol. 8, no. 7, pp. 3893–3897, 2020, doi: 10.30534/ijeter/2020/158872020.

27. M. Penna, Danka. V. Gowda, J. J. Jijesh, and Shivashankar, “Design and implementation of automatic medicine dispensing machine,” in RTEICT 2017 - 2nd IEEE International Conference on Recent Trends in Electronics, Information and Communication Technology, Proceedings, 2017, vol. 2018-Janua, pp. 1962–1966, doi: 10.1109/RTEICT.2017.8256941.

28. V. Amrutha and K. V. Karthikeyan, "Spectrum sensing methodologies in cognitive radio networks: A survey," 2017 International Conference on Innovations in Electrical, Electronics, Instrumentation and Media Technology (ICEEIMT), Coimbatore, 2017, pp. 306-310, doi: 10.1109/ICIEEIMT.2017.8116855.

29. M. Di Renzo, L. Imbriglio, F. Graziosi and F. Santucci, "Cooperative Spectrum Sensing over Correlated Log-Normal Sensing and Reporting Channels," GLOBECOM 2009 - 2009 IEEE Global Telecommunications Conference, Honolulu, HI, 2009, pp. 1-8, doi: 10.1109/GLOCOM.2009.5425665.

30. A. W. Min and K. G. Shin, "An Optimal Sensing Framework Based on Spatial RSS-profile in Cognitive Radio Networks," 2009 6th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks, Rome, 2009, pp. 1-9, doi: 10.1109/SAHCN.2009.5168908.

31. Fazlullah Khan and Ateeq ur Rehman, " Efficient Resource Allocation for Real time Traffic in Cognitive Radio Internet of Things," 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart-Data(SmartData),2019,pp.1143-1147, doi.org/10.1109/iThings/GreenCom/CPSCom/SmartData.2019.00193