INTERNATIONAL RESEARCH JOURNAL IN ADVANCED ENGINEERING AND TECHNOLOGY (IRJAET) E - ISSN: 2454-4752 P - ISSN : 2454-4744
VOL 2 ISSUE 2 (2016) PAGES 573-581
RECEIVED : 04/03/2016. PUBLISHED : 15/03/2016
March 15, 2016

THROUGHPUT MAXIMIZATION COGNITIVE RADIO NETWORKS USING LEVENBERG-MARQUARDT ALGORTHIM

Jayalakshmi.B, PG Scholar, Dept of CSE, Mahendra engg college, Namakkal,
Pandiyan.M, Asst prof, of CSE, Mahendra engg college, Namakkal.

Abstract:

To guarantee a high system throughput in (Cognitive Radio System) CRNs, the channel state needs to be accurately detected to reduce conflict. Identifying an ideal free channel for future data transmission is most important in CRN environment. If the arrival rate of primary user's license band is high, then availability of free channel will be low. Due to that,current channel selection and switching strategy should solve issue to increase throughput of the data transmission of cognitive radio network. Cognitive radio network combines many algorithms to adjust the system from physical layer and communication channel. Artificial Neural Networks (ANNs), evolutionary or genetic algorithms, fuzzy logic and Hidden Markov Models are used to solve above issue.To solve current wireless network problems for cognitive radios, resulting from the limited available spectrum for throughput maximization and also increases throughput via limited bandwidth available in cognitive radio networks.

Keywords – CRN, ANN, Fuzzy logic.

1. INTRODUCTION

Current research into cognitive radios hopes to improve spectral utilization by allowing users from crowded bands to bleed off into nearby empty bands. It adapts its own radio parameters accordingly. For example, consider a private wifi network. The total number of other networks available will be in 2.4 giga hertz band in which private wifi devices are working. Instead of adding an additional device to an over-used band, if a cognitive radio able to find the over usage of the allocated spectrum and lower or under usage of other spectrum blocks nearby. The cognitive radio works under available free band and efficiently utilizing the total available spectrum. Examples of spectrum blocks that may be underutilized may include empty broadcast television/radio stations, radio- astronomy blocks, radio-navigation blocks, and others. The advance of cognitive radio and spectrum sensing radios is a high priority for the FCC. The 802.22 draft standard, which is still under review, is the FCC's first foray into cognitive radio and demonstrates their commitment and active interest in this emerging technology. Despite promise of cognitive radio, there are still many technical hurdles to overcome before the technology is ready to be implemented in a real world scenario

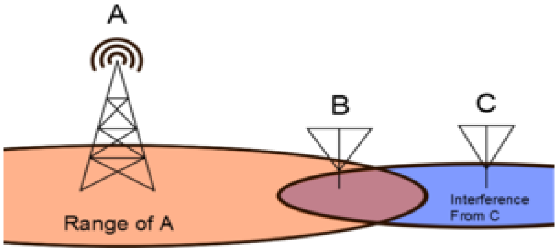


Fig. 1: An out-of-range secondary user C can interfere with primary spectrum users A and B.

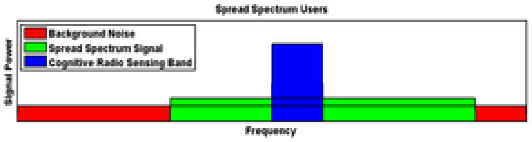


Fig. 2: It is often impossible to distinguish between background noise and a spread spectrum signal with wide bandwidth.

The geometry of the hidden primary user problem is depicted in Fig. 1. Consider primary transmitter A, primary receiver B, and secondary user C who would like to use the spectrum licensed for use by A and B. Before operating C measures the energy in the band and compares it to a threshold set by background noise so as to determine if the band is in use. In the case where the secondary user C is just out of range of the primary transmitter A it may conclude that there is no primary user in the immediate vicinity and co-opt the spectrum.

The problem arises when secondary user C begins to transmit. Although C is far away from A, the primary receiver B may be near enough to A to receive its signal. However, once C begins to transmit interference may obstruct those transmissions preventing the licensed spectrum usage between A and B. Spread spectrum primary can be an equally insidious problem. Consider the frequency utilization plot depicted in Fig. 2 which is representative of a spread spectrum user.

As in Fig. 2 a spread spectrum user may only require a very low power signal spread across a wide bandwidth. In the worst case scenario a cognitive radio system might test the spectrum in bands much smaller than the wide bandwidth used by the primary user. Unfortunately, the primary user's low power transmission is often designed to look like background noise, and may be interpreted as such by the cognitive radio. In fact the only way to distinguish a spread spectrum transmission from the background is to sample the entire bandwidth, which may be impossible for the cognitive radio, thus leading to false identification of empty spectrum.

2. RELATED WORK

In order to assign a channel in CRN different issues of spectrum availability has to be considered. Based on observing local interference patterns various distributed approximations and maximizing system utility with co ordinations between different CR nodes were proposed. Yuan et.al. Proposed a time spectrum model of the available band. Several efforts have been recorded in the literature that aims at combining artificial intelligence and machine learning techniques with cognitive radio technology.

Multilayer Back Propagation Neural Network is used for training in different applications. Multilayered Feedback Neural Network (MFNN) is used as an effective technique for real-time characterization of the communication performance and therefore offers some interesting learning capabilities. A distributed cognitive network access scheme is presented in , with the objective to provide the best Quality of Service

(QoS), with respect to both radio link and core network performance and user application requirements, by using Fuzzy Logic-based techniques.

Integration of SUs to improve the efficiency of spectrum access and allow the relaxation of constraints at individual SUs is discussed. Optimal multi-channel cooperative sensing algorithms, are considered to maximize the SU throughput subject to per channel detection probability constraints. Mokhnache and Boubakeur compared the performance of three backpropagation algorithms, Levenberg-Marquardt, back propagation with momentum and back propagation with momentum and adaptive learning rate to classify the transformer oil dielectric and cooling state.

Kisi and Uncuoglu compared Levenberg-Marquardt, conjugate gradient and resilient algorithm for stream-flow forecasting and determination of lateral stress in cohesion less soils. They found that Levenberg-Marquardt algorithm was faster and achieved better performance than the other algorithms in training. Esugasini et al. Compared the classification accuracy of the standard steepest descent back-propagation algorithm against the classification accuracy of the gradient descent with momentum and adaptive learning, resilient back propagation, Quasi-Newton and Levenberg-Marquardt algorithm. The simulations show that the neural network using the Levenberg-Marquardt algorithm achieved the best classification performance.

Employed three neural networks with different algorithms to the problem of intrusion detection in computer and network systems. The learning algorithms considered by the authors were the standard, the batch, and the resilient back propagation algorithm. Nouir et al. Compared the performance of the standard back propagation with and Levenberg-Marquardt algorithms to the prediction of a radio network planning.The system model consists of a primary transmitter with unknown location and transmit power, which alternates between ON and OFF states, with respect to a given frequency channel. Spatial spectrum sensing is employed to estimate the MIFTP for a secondary node during an ON period. Estimates of the primary transmitter's location and transmit power obtained in the course of spatial sensing are used by a fusion center to select a subset of the secondary nodes to make a temporal sensing decision, i.e., a decision as to whether the primary is ON or OFF.

Cognitive radios are promising technology for enabling unlicensed devices to efficiently uses the white spaces. These radios dynamically identify portions of the spectrum that are not in use by primary users, and configure the radio to operate in the appropriate white space. Prior work has shown that white spaces are fragmented and of different sizes. The availability of white spaces is temporal and depends on the geographic location of the radio. Thus, a key challenge in the design of cognitive radios is the dynamic allocation of white spaces to different radios in the network. The efficiency of the spectrum allocation determines both the network's throughput as well as the overall spectrum utilization. The problem of allocating spectrum in cognitive radio networks poses new challenges that do not arise in several wireless technologies.

Optimal multi-channel cooperative spectrum sensing strategies in cognitive radio networks determine the total sensing time and how to distribute the total sensing time to different channels in cooperative soft-decision spectrum sensing. For the slotted-time sensing mode, transformed the initial non convex mixed-integer problem into convex mixed-integer sub problems, and provided a polynomial complexity algorithm to achieve the optimal solution of the initial problem. For the continuous-time sensing mode, successfully transformed the initial non convex optimization problem into a convex bi level optimization problem. Energy Consumption is high.Efficient spectrum allocation in open spectrum systems is a challenging problem, particularly for devices with constrained communication resources such as sensor and mobile ad hoc networks. And device-centric spectrum management scheme with low communication costs, where users observe local interference patterns and act independently according to preset spectrum rules.

Five rules that tradeoff performance with implementation complexity and communication costs, and derive a lower bound on each user's allocation based on these rules. Experimental results show that our proposed rule-based approach reduces communication costs from efficient collaborative approaches by a factor of 3-4 while providing good performance.

The proposed scheme is shown to outperform state-of-the-art solutions in several multi-technology and multi-application scenarios, while at the same time achieving similar performance to application-specific omniscient schemes that we introduce in this paper as a benchmark.

The system Implemented energy detection sensing scheme. The detection probability dramatically increases as the number of relay secondary user increases, strategies achieve better performance than a non-cooperative (or non-relay) spectrum sensing method and an existing cooperative detection method. Derived Expressions: False alarm probability and the detection probability. Cooperation is in combining the results of various users which may have different sensitivities and sensing times.Energy detectors that might diminish their simplicity in implementation.

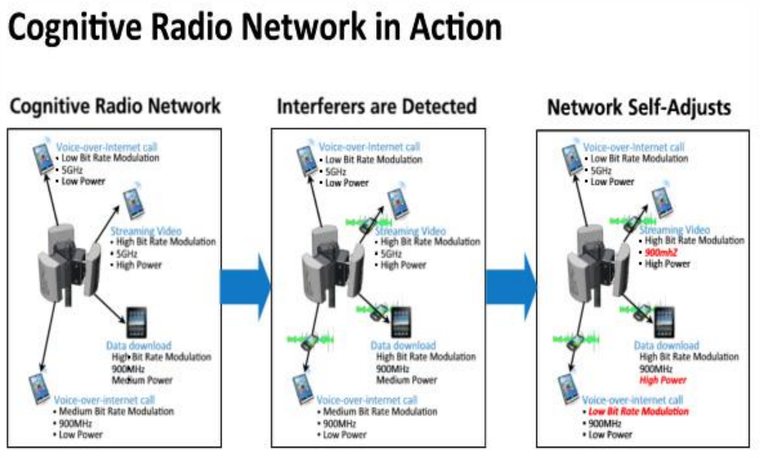
3. SYSTEM MODEL

Cognitive (or smart) radio networks like xG’s xMaxsystem are an innovative approach to wireless engineering in which radios are designed with an unprecedented level of intelligence and agility. This advanced technology enables radio devices to use spectrum (i.e., radio frequencies) in entirely new and sophisticated ways. Cognitive radios have the ability to monitor, sense, and detect the conditions of their operating environment, and dynamically reconfigure their own characteristics to best match those conditions.

Using complex calculations, xMax cognitive radios can identify potential impairments to communications quality, like interference, path loss, shadowing and multipath fading. They can then adjust their transmitting parameters, such as power output, frequency, and modulation to ensure an optimized communications experience for users.

Conventional, or “dumb” radios, have been designed with the assumption that they were operating in a spectrum band that was free of interference. As a result, there was no requirement to endow these radios with the ability to dynamically change parameters, channels or spectrum bands in response to interference. Not surprisingly, these radios required pristine, dedicated (i.e., licensed) spectrum to operate. By contrast, xMax cognitive radios have been engineered from the ground up to function in challenging conditions. Unlike their traditional counterparts, they can view their environment in great detail to identify spectrum that is not being used, and quickly tune to that frequency to transmit and/or receive signals.They also have the ability to instantly find other spectrum if interference is detected on the frequencies being used.

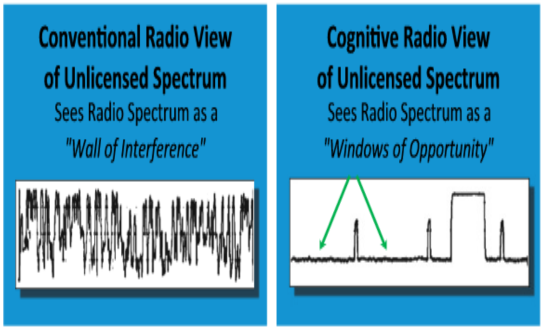
The following graphic shows how a cognitive radio network operates in relation to its environment:



Copyright xG Technology, Inc. 2012. All rights reserved.

In the case of xMax, it samples, detects and determines if interference has reached unacceptable levels up to 33 times a second.The following image illustrates how xMax cognitive radios operate differently from conventional radios. It shows screen captures of spectrum analyzer readings taken from an xMax network tower in Ft Lauderdale, FL. The frequencies being measured are in the unlicensed 900 MHz ISM band. Because this spectrum is unlicensed (i.e., free of charge for anyone to use) it is used by hundreds, if not thousands of radios in the local area for applications like cordless phones, baby monitors, commercial video security systems, etc.

INTERNATIONAL RESEARCH JOURNAL IN ADVANCED ENGINEERING AND TECHNOLOGY (IRJAET) E - ISSN: 2454-4752 P - ISSN : 2454-4744
VOL 2 ISSUE 2 (2016) PAGES 573-581
RECEIVED : 04/03/2016. PUBLISHED : 15/03/2016
March 15, 2016

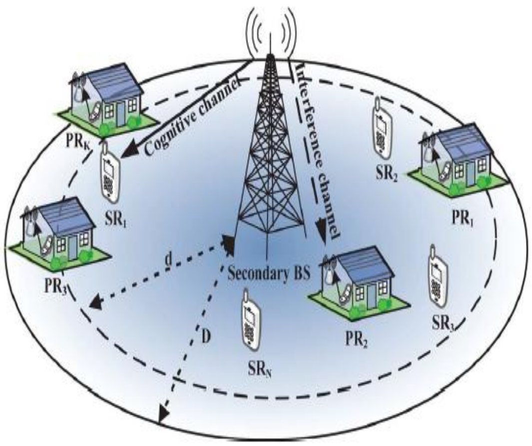


This spectrum analyzer reading shows how conventional radios see congested radio spectrum with heavy interference, and essentially unusable.

Cognitive radios can view the same radio spectrum in deeper detail, allowing them to identify unused gaps to transmit signals.

xMax divides the 900 MHz spectrum block shown into 18 channels—giving it 18 opportunities (windows) every 33 milliseconds to find available spectrum. In short, the xMax cognitive radio network sees windows of opportunity where other radios see walls of interference. To reduce “thrashing” and unnecessary channel switching due to temporary and very short-lived interference phenomenon, or degraded network conditions (that do not cause a noticeable impact to performance or quality), actual channel and handovers decisions are made by trending multiple samples and measurements. The system only switches from its current channel when extreme levels of interference exceed its built-in interference mitigation capabilities. This enables xMax to use frequencies and find available bandwidth where other radios can only see static, yet its real-world tuned algorithms reduce signaling overhead and optimize throughput and quality.

Assume that a CR network consists of a single ST, i.e., macro BS, which transmits signals to multiple SRs. The CR network shares a spectrum owned by an indoor primary network. The primary network also consists of multiple PRs, i.e., primary indoor access points (APs). The SRs and PRs are indexed by n •¸ N = {1, . . . , N} and k •¸ K = {1, . . . , K}, respectively. The SRs and PRs are uniformly distributed in a cell of radius d and a cell of radius D(d . D), respectively, as shown in Fig. 3. The downlink transmissions of the CR network are considered and assumed to occur in the uplink transmission of the primary network.



There are many advantages for sharing the spectrum of the uplink transmissions of an indoor network. First, since the primary network is assumed to be an indoor one, the mutual interference between the primary and secondary networks will be scaled down because of the penetration losses. Secondly, as the PRs, are all fixed in position, this offers an opportunity to easily detect them by the ST. Hence, the STs can detect the pilot channel broadcast from indoor PRs and decide how many PRs with which they are surrounded [31]. The ST can then rely on channel reciprocity and estimate the channel coefficient of the interference channel using injected pilots in the uplink channel of the PRs.

Finally, it is also possible that the interference channel status information (ICSI) is sent from all PRs along with their identities and collected by a certain central unit. In fact, using a separate wireline control channel that broadcasts the interference measured over a broadband connection is a very practical solution. Before the secondary network can utilize the spectrum, it must register itself with the central unit first to be updated regarding the ICSI.

However, the PRs do not necessarily need to identify each registered ST. The ICSI can inform the STs regarding the status of the worst aggregate interference that a PR suffers. The STs can also use ICSI as an alternative way to estimate the channel status to that PR and regulate their transmit power accordantly. In this work, we assume that there is only one registered CR network with a single secondary cell.

Forming a random network

First we accept the number of nodes and place all the nodes on “work panel” randomly. Here we use a separate panel for placing these nodes. This panel will be added to the “main window” (Frame). Each device actual position will be taken into an array. This array will be used to identify the neighbors within its range.

Implementation of Artificial Neural Network

An artificial neural network (ANN) is an effective data modeling scheme used to model and learn both linear and non-linear input/output interactions by training. According to the application, a NN has to be configured such that the application of a set of inputs produces the desired set of outputs which can be achieved by properly adjusting the weights „w‟ among all neuron pairs. The propagation is typically tempered by a constant or bias value, b. This bias value is controlled by the user, so that a known input vector may produce the desired output value. This process is called learning or training. Learning can be categorized as supervised and unsupervised learning. In supervised learning, the NN is fed with teaching patterns and trained by allowing it to change its weights according to some learning rule. In unsupervised learning the NN discovers features of the input data in a statistical manner by developing its own ways of classifying the input irritants.

Levenberg–Marquardt Algorithm

The LM algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of nonlinear real valued functions. It is fast and has stable convergence. In the artificial neural-networks field, this algorithm is used for training networks. The LM algorithm can be thought of as a combination of the steepest descent method and the Gauss–Newton algorithm which inherits the speed advantage of the Gauss–Newton algorithm and the stability of the steepest descent method.

Performance Evaluation

The proposed channel prediction model can be used to detect the spectrum hole in CRN. The maximum throughput value obtained represents the superior performance of L-M algorithm. The simulations are carried out in Java to verify the performance of the prediction model by Artificial Intelligence (AI) based neural networks through L-M algorithm. It is observed that the throughput performance increases with the increase in time slots and also with increase in number of channels. The extensive simulated results show that, such a solution is better than HMM.

CONCLUSION

This project has investigated the spectral and energy efficiencyin interference-tolerant CR networks. The initial analysis hasstudied the spectral-energy efficiency trade-off for a link-level CR network under transmit power and interference constraints.In the low SNR regime, transmitting a signal with average power constraint provides better energy efficiency than transmittinga signal with peak power constraint. In addition to that, the interference channel has no impact on $(E_b/N_0)_{\min}$required for reliable communications.

In the high SNR regime, however,transmitting signals with either power constraint gives the sameenergy efficiency. Project has also proposed a CR-based cellular network inwhich a secondary network shares a spectrum belonging to an indoor system. This project has also demonstrated that withCR technology, cellular operators can share their spectrum opportunistically with each other to increase the performance of their network. One way to do so is to share a spectrum in the uplink phase of an indoor system. This is indeed an opportunity to make the implementation of the CR-based cellularnetwork more feasible in the near future without the necessity of modification at the end user’s handset. An exampleof a practical application of CR and its integration with existing technology is the use of carrier aggregation applied with CR toallow greater spectrum accessibility whilst remaining efficient by using the underutilized spectrum.

The challenge is howto practically estimate the interference channels by the STs.Relying on channel reciprocity or broadcasting ICSIs can give some insight to solving this issue. The spectral and energy efficiency of the proposed networkhave been analysed. By adopting the extreme value theory,we have derived the spectral efficiency of the system-level CR network under optimal power allocation. In this project has studiedthe impact of multi-user diversity gain in both the primary and secondary receivers on the spectral and energy efficiency.The spectral efficiency of the CR network is relatively large when the number of primary receivers is small. The spectralefficiency, however, diminishes rapidly with the increase in the number of primary receivers. This degradation can be compensatedby relaxing the interference threshold or by increasing thenumber of SRs that are within a short distance from the ST.

REFERENCES

1. X. Ge et al., “Spectrum and energy efficiency evaluation of two-tier femtocell networks with partially open channels,” IEEE Trans. Veh. Technol., vol. 63, no. 3, pp. 1306–1319, Mar. 2014.
2. X. Hong, J. Wang, C.-X. Wang, and J. Shi, “Cognitive radio in 5G: A perspective on energy-spectral efficiency trade-off,” IEEE Commun. Mag., vol. 52, no. 7, pp. 46–53, Jul. 2014.
3. X. Hong, Y. Jie, C.-X. Wang, J. Shi, and X. Ge, “Energy-spectral efficiency trade-off in virtual MIMO cellular systems,” IEEE J. Sel. Areas Commun., vol. 31, no. 10, pp. 2128–2140, Oct. 2013
4. Ku,C.-X.Wang,andJ.S.Thompson,“Spectral-energyefficiencytradeoff in relay-aided cellular networks,” IEEE Trans. Wireless Commun., vol. 12, no. 10, pp. 4970–4982, Oct. 2013.
5. Y.Pei,Y.C.Liang,K.C.Teh,K.H.Li,”Sensing-throughput tradeoff for cognitive radio networks: A multiple channel scenario”, Personal ,Indoor and Mobile Radio Communications , 2009 IEEE 20th International Symposium ,sept,2009.
6. R.Muta,R.Kohno,” Throughput analysis for cooperative sensing in Cognitive radio networks”, Personal , Indoor and Mobile Radio Communications , 2009 IEEE 20th International Symposium ,sept,2009.
7. Q.Zhao,S.Geirhofer,L.Tong, and B.Sadler, “Opportunistic spectrum access via periodic channel sensing,” in IEEE Trans.Signal Process.,vol.56,pp. 785-796,Feb.2008.