NETWORK SELECTION IN COGNITIVE RADIO USING GAME THEORY

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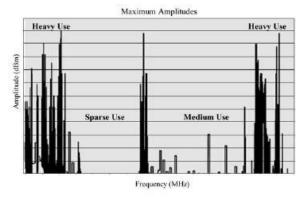
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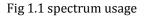
ABSTRACT: The energy detection in Cognitive Radio Networks is simple with short sensing time, though its performance is poor under low Signal to Noise (SNR) conditions. In this work, propose game-theoretic approach to model the cooperative spectrum sensing in cognitive radio environment with cognitive secondary users (SU) capable of energy harvesting. An evolutionary game model is considered in the first scenario, where distributed SUs are allowed to choose between two strategies, cooperate to sense the spectrum or deny to be a free rider. The sensed data is sent to fusion centre (FC) to have a final decision about the existence of the primary user. NS2 simulation tool used to analyse a performance of proposed system. Simulation results show the behaviour of the proposed game model improves the performance in terms of energy, delay and throughput

INTRODUCTION

Cognitive radio is the key enabling technology that permits next generation communication networks, also referred to as dynamic spectrum access (DSA) networks, to utilize the spectrum more efficiently in an opportunistic fashion without interfering with the primary users. It is defined as a radio which will change its transmitter parameters consisting with the interactions with the environment during which it operates. It differs from conventional radio devices therein that a cognitive radio can equip users with cognitive capability and re configurability. Cognitive capability refers to the power to sense and gather information from the surrounding environment, like information about transmission frequency, bandwidth, power, modulation, etc. With this capability, secondary users can identify the best available spectrum. Re configurability refers to the power to rapidly adapt the operational parameters consistent with the sensed information so as to realize the optimal performance. By exploiting the spectrum in an opportunistic fashion, cognitive radio enables secondary users to sense which portion of the spectrum are available, select the best available channel, coordinate spectrum access with other users, and vacate the channel when a primary user reclaims the spectrum usage right.







RELATED WORK

Yi-Feng Huang et al^[1] proposed by 3GPP to enable cellular data transmission in unlicensed band. The primary challenge of LTE-U is to successfully coexist with the incumbent systems (e.g., WiFi networks) within the unlicensed bands, while still maintaining the quality-ofservice (QoS) for LTE-A users.

Ogeen H. Toma et al^[2]provided an in depth and detailed analysis of a broad range of primary channel statistics under Imperfect Spectrum Sensing (ISS) and finds a set or group of closed-form expressions for the calculated statistics under ISS as a function of the original primary channel statistics, probability of error, and therefore the employed sensing period.

Grigorios Kakkavas et al^[3]contributed towards the alleviation of the restrictions in SDR deployments by developing and evaluating a resource allocation approach for cognitive radios implemented with SDR technology over two testbeds of the ORCA federation.

Yuyang Peng et al^[4]explored the potential of an improvement of OFDM-IM by reusing inactive subcarriers to transmit signals for a secondary system.

Victor C. M. Leung et al^[5]proposed a cognitive solution that A/A communications are considered as secondary users which sense idle primary A/G communication channels and transmit data on these channels wherever possible, which brings two major issues: spectrum sensing and sharing between A/A and A/G communications.

Zhaofeng Liu et al^[6]presented a pre-coding (PC) orthogonal frequency division multiplexing-aided differential chaos shift keying (OFDM-DCSK) scheme over non-contiguous (NC) spectrum bands for cognitive radio (CR) systems.

Rohit B. Chaurasiya et al^[7]presented implementation friendly VLSI-algorithms for maximumeigenvalue-detection (MED), energy with minimumeigenvalue (EME), and mean-to-square extremeeigenvalue (MSEE) based blind spectrum sensing algorithms.

Yuan Luo et al^[8]proposed a two-step adaptive compressive spectrum sensing (TS-ACSS) method to estimate the sparsity order.

Tilahun M. Getu et al^[9]proposed an efficient tensor-based detector (TBD) for a multiple-input multipleoutput (MIMO) CR networks over multi-path fading channels.

Sinchan Biswas et al^[10]analyzed under two different assumptions on the available information pattern: 1) non-causal channel state information (CSI), energy state information (ESI), and infinite battery capacity and 2) the more realistic scenario of the causal CSI/ESI and finite battery.

Tianheng Xu et al^[11] proposed a sliced sensing technique, which may support 5G cognitive radio applications working in fast time-varying channels.

p-ISSN: 2395-0072

Muhammad Ejaz Ahmed et al^[12]provided different spectral access/energy harvesting opportunities in RFpowered cognitive radio networks.

Tilahun M. Getu et al^[13]presented and evaluate simple F-test-based spectrum sensing techniques that don't require the knowledge of CSI for multi-antenna cognitive radios.

Jingyu Feng et al^[14]considered as a powerful and effective approach to enhance the use of scarce spectrum resources.

Abdelmohsen Ali et al^[16] proposed a wideband spectrum sensing architecture by utilizing a one-bit quantization at the cognitive radio receiver.

Guodong Zhao et al^[17] proposed by enabling the CT to sense primary signals.

Huifang Chen et al^[18]proposed a completely unique attack-proof CSS scheme with M-ary quantized data, mainly including a malicious SU identification method and an adaptive linear combination rule.

Hesameddin Mokhtarzadeh et al^[19]presented as a threshold on probability of collision.

Zan Li et al^[20]designed objectives in future wireless communication networks.

Xin-Lin Huang et al improved spectrum utilization and supply broad wireless band for wireless services.

EXISTING SYSTEM

Energy Detector

The energy detection is favourable in an environment when power of random AWGN is available to the CRU. The energy detector is less complicated and easy to implement. To find the power of obtained signal is an elementary method of Energy Detector. If energy of obtained signal is greater than the threshold, It means PU

International Research Journal of Engineering and Technology (IRJET)

e-ISSN: 2395-0056 p-ISSN: 2395-0072

National Conference on Recent Advancements in Communication, Electronics and Signal Processing-RACES'20 Organised by: Department of ECE, Velammal Engineering College, Chennai-66

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is present otherwise spectrum is spare. It works on following two hypothesis by.

x(t) = n(t) H0 defining signal is absent (1)

x(t) = s(t) + n(t) H1 defining signal is present (2)

Volume: 07 Issue: 08 | Aug 2020

where n(t) is an AWGN, s(t) source signal and received signal is x(t). The energy of the received signal (γ) and threshold (τ) of energy detector are compared as,

 $\gamma < \tau$ for H0 signal is absent (3)

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 $\gamma > \tau$ for H1 signal is present (4)

The approximated formulae of Pd, Pfa and Pmd can be given by.

Pfa = $\Gamma(N, \tau/2)/\Gamma(u)$ (5)

 $Pd = Q(\sqrt{2\delta}, \sqrt{\tau}) (6)$

where δ is SNR, u is time bandwidth product, Γ and Γ are incomplete and complete gamma capabilities respectively. A Rayleigh fading channel is more practical apart from AWGN as given in. Thus Energy Detector is applied in Rayleigh channel also to offer a greater realistic environment. The average SNR δ a is taken into consideration here instead of δ due to one of a kind transmission paths. The Pd is given by.

 $\begin{array}{l} Pd = [\exp - (\tau/2) \ uX - 2 \ k = 0 \ 1 \ k! \ (\ \tau \ 2 \) \ k + \ (1 + \delta a \ \delta a \) \ u - 1 \\ (\exp - (\tau/2(1 + \delta a)) \ - \ \exp - (\tau/2) \ uX - 2 \ k = 0 \ 1 \ k! \ (\ \tau \ \delta a \ 2(1 + \delta a) \)] \ (7) \end{array}$

Other Spectrum Sensing techniques offer higher consequences than Energy Detector. A matched Filter maximizes the SNR and offer high processing gain whereas Cyclostationary Feature Detection not like Energy Detection can distinguish among noise and PU's signal. But both of them require priori understanding about acquired signal and dedicated receivers for every incoming signal. A conventional energy detection method is used with the proposed approach for Spectrum Sensing.

PROPOSED SYSTEM

System Model

There exist K SUs and a single FC in EHCRN who are allowed to access the PU licensed spectrum. We assume that the PU spectrum is divided into M sub bands, and each SU can use any of the M sub bands when the PU is absent. At each time slot, SUs ought to sense the M sub bands to classify every one of the sub bands as either occupied or vacant. Due to the limited hardware for every SU, we assume that each SU can most effective perform one of the tasks, i.e. energy harvesting, sensing or transmitting at the same time. In the proposed model, the FC transfers RF energy and communicates with the SUs using different time slots. Regarding RF energy harvesting, two techniques exist, energy harvesting from a committed source and energy harvesting from ambient RF sources. In this project, we assume that the K SUs are tuned to most effective harvest the RF energy broadcasted by the dedicated source, i.e., the FC in a certain band. The dedicated source RF energy harvesting can be optimized concerning the antenna design, directivity and the quantity of energy committed to the users primarily based on the distance. This is why we trusted this version in our paper. However, we are able to accommodate the assumption of harvesting the RF energy of the PU to our game models without loss of generality.

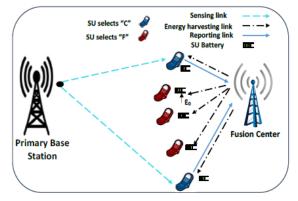


Fig 4.1 The proposed evolutionary game version for EH-CRNs.

That the K SUs are divided into two groups, GC and GF, where GC is the group of SUs who are willing to cooperate in sensing the PU spectrum and send the sensing reports to the FC, and GF is the group of SUs who

decide to be free riders and overhear the sensing results broadcasted through the FC through a common signaling channel. By this way all SUs inside the network have the equal chance or probability of false alarm PF

Each member of GC follows the time frame structure that is divided into three phases. In Phase I, the SUs harvest the ambient RF energy broadcasted by FC all through the time Th1 = $\rho\alpha T$, where T is the overall frame time, and $0 \le \rho$; $\alpha \le 1$ is weighting factor. In Phase II, the members of GC sense the M sub bands and report the sensing information to the FC throughout the time Ts = (1 $-\rho$)T, in order to take the final decision through applying soft combining rules and then the FC announce sensing consequences and results via the common signaling channel. Then in Phase III, the SUs transmit their data and information over vacant channels during the time Tt1 = $\rho(1 - \alpha)T$. Meanwhile, the members of GF refuse to take part in cooperative spectrum sensing. Consequently, they can benefit from greater time for energy harvesting and data transmission. The members of GF follow the time frame structure. They harvest the ambient RF energy broadcasted by using FC and transmit their data during time slots Th2 = α T and Tt2 = (1 - α)T, respectively, usage of the vacant sub bands which are identified in the preceding time slot. If nobody joins group GC, the throughput of all SUs will be zero and the FC stops energy broadcasting.

CONCLUSION

In this project, studied the behavior of SUs with energy harvesting skills in cooperative spectrum sensing with egocentric but rational SUs. We made use of the powerful and effective game theory models to predict this behavior in two scenarios. In the primary scenario, we considered an evolutionary game, in which SUs are the players and each SU can determine to cooperate or no longer without intervention from the FC. Simulation results display that the evolutionary game model has a better performance than the full cooperation model, in terms of total residual energy and the total throughput. However, the proposed evolutionary game model can reach steady and consistent state with low cooperation probability as selfish SUs are not willing to provide their resources such energy and time and it is far a challenge to motivate and inspire them. To address this problem, we introduce a scenario, wherein the FC can intervene in the cooperation process to allocate payments to the SUs in return of their participation in the sensing operation. The stackelberg game fits flawlessly in modeling the interaction between the FC and the SUs. Simulation results show that the proposed CSS scheme with the stackelberg game model can obtain comparable detection performance to that of the evolutionary game model.

e-ISSN: 2395-0056

p-ISSN: 2395-0072

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