Performance Analysis of FISSER Model in Rural-Urban Cognitive Radio Networks

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Abstract. In the past few decades, Cognitive Radio network (CRN) has been regarded in the literature as the most promising technology for performing dynamic spectrum management. One of the major aspects of spectrum management is referred to as the spectrum-reconfiguration decision-making ability of CR users. Dynamic spectrum reconfiguration has previously been reported to improve the spectrum utilisation in CRN. In exploiting spectrum reconfiguration to improve spectrum utilisation, various approaches have been adopted to develop models. However, none of these research works has been evaluated in the urban and rural settlement context. In a CRN environment, the frequency availability is not static like that of traditional networks. There are resource-rich regions such as rural areas, where many frequencies are available for the Secondary Users (SUs) and resource-poor regions such as urban areas, where there are only a few frequencies available for SUs. Hence, this paper proposed a novel Foraging Inspired Spectrum Selection and Reconfiguration (FISSER) model. The performance of the FISSER model has been analysed through computer simulations both in the rural and urban CRN, using high and low perceptual radii. A high perceptual radius has been shown in the literature to improve energy efficiency and data communication performance in ad hoc networks. However, the simulation results reported in this paper show that even though the high perceptual radius improves the nodes’ energy efficiency it does not achieve optimal data communication performance compared to when the nodes use a low perceptual radius. Also, the efficacy of FISSER model was tested by comparing it against the reinforcement learning model. Based on the obtained results, it was shown that the FISSER model achieved better results in both the network throughput and the channel switching time.

Keywords: FISSER; Cognitive radio; Foraging; Spectrum reconfiguration; Decision making.

1. Introduction

The term radio frequency (RF) spectrum is one of the most valuable network resources in wireless communications due to its limited availability. Wireless communication technologies capable of offering multimedia services and applications have grown rapidly over the past few decades which has fuelled an increased demand for the radio frequency spectrum and resulted in the use of previously unused frequency bands. It is widely understood that the radio frequency spectrum can serve as a platform for economic and social development [1], as such governments worldwide have established regulatory agencies to promote the efficient and effective use of the radio frequency spectrum. Regulators of the RF spectrum have traditionally allocated a fixed portion of the radio spectrum to each new radio-based service. In recent times, it has become increasingly difficult to find usable radio
spectrum frequencies to accommodate the rapidly expanding demand. However, studies have shown that the spectrum scarcity can be seen as a temporal situation, because the actual spectrum utilisation on a block of licensed radio frequency spectrum band was found to vary between 15% and 85% at different geographic locations over time [2, 3]. This temporal spectrum scarcity is, to a large degree, the result of inefficiencies in traditional static spectrum management regulations.

Faced with a scarcity of spectrum for new applications, the underutilization of the licensed spectrum is driving the shift of the spectrum allocation paradigm from static to dynamic. A promising implementation of this paradigm is called Cognitive Radio (CR). The basic idea of CR networks (CRN) is to allow a group of unlicensed secondary users (SUs) to opportunistically access frequency bands originally allocated to some licensed primary users (PUs).

With CR technology, spectrum utilisation can be increased significantly by making sure that the SUs make optimal decisions in terms of selecting an appropriate frequency among the available options, without causing any harmful interference to the licensed PUs. Spectrum decision techniques are used by SUs to decide on the best frequency to select among the available PUs’ frequencies at a given time. Various research works have attempted to solve the dynamic spectrum selection and reconfiguration problem using various approaches such as Design of Experiment (DoE) & Statistical [2, 4], Bayesian [5], game theory [6], machine learning [4], Predictive [7], Markov theory [8], Reinforcement [9] and Common Control Channel (CCC) [3]. However, none of these research works have been evaluated in urban and rural context. In a CRN environment, the frequency availability is not static like that of traditional networks. There are resource-rich regions, where many frequencies are available for the SUs and resource-poor regions, where there are only a few frequencies available for SUs. An example of a resource-rich region is the rural areas and an example of a resource-poor region is the urban areas, where the number of available frequencies is low.

One of the important considerations in developing and analysing a model in a dynamic environment, such as distributed CRN, is the robustness of the applicability. For example, it is possible to develop a model that performs very well in rural areas, but not in the urban areas due to different data traffic levels. Hence, while developing a model for a dynamic environment, it is important to consider the applicability in any settlement pattern. In achieving an optimal spectrum utilisation, the applicability of the approach in both rural and urban areas is an important factor that needs to be considered. To the author’s knowledge, none of the existing models in the field of spectrum selection for distributed CRNs has considered the model performance in the context of rural and urban settlement patterns.

Motivated by the biologically-inspired foraging approach performance in other wireless networks, this paper presents a novel Foraging Inspired Spectrum Selection and Reconfiguration (FISSER) model in addressing the challenges of dynamic selection and reconfiguration of frequency and channel bandwidth in distributed CRNs using both rural and urban settlement patterns.

The rest of this paper is organized as follows: Section II provides the overview of the FISSER model. In Section III, the experimental setup was presented, while Section IV presents the model performance analysis in both rural and urban settlement patterns. Also, the result of the comparison between the FISSER model and that of reinforcement learning based model was presented in Section IV. The paper is concluded in Section V with an outline of the future work.

2. The FISSER Model
This section presents a Foraging Inspired Spectrum Selection and Reconfiguration (FISSER) model, which can dynamically evolve in response to its interaction with the external surrounding environment. The aim of this model is to address the sub-optimal spectrum utilisation problem, by optimizing the selection and reconfiguration of both frequency and channel bandwidth for SUs’ node. The main concept in developing the FISSER model comes from the biological foraging theory, where the foraging animals make optimal decisions on which prey to feed on, so as to maximise their energy gain whilst minimising the associated risks [10]. Using the biologically-inspired foraging methodology, the foraging animals mimic the Secondary Users, whilst the prey are considered as the available Primary Users’ frequencies to be searched for by the SUs. Similar to what happens in the biological foraging cycle whereby the foraging animals search for prey, in the same way, each SU with a message searches for possible available PUs’ frequency to be used for communication. The next phase
is for each of the SUs (foraging animals) to decide which of the available frequencies and channel bandwidths (prey) can be selected for communication in order to maximise their efficiency and reduce possible threats, such as interference to the PUs’ network.

In biological foraging, the colony does not have any central control, hence, members of the colony make decisions on an individual basis. This is similar to a distributed environment in CRNs, where each SU node is expected to make its decision without any central control or base station [10]. In a dynamic distributed CRN environment, where the nodes can join or leave the network at any time, the nodes should be able to dynamically search for the available resources within their perceptual radius without having prior knowledge of the resources’ location. Hence, in the proposed FISSER model, available PUs are denoted as points, while each of the SUs has a fixed perceptual radius, within which it can detect available PUs.

The SUs do not have prior knowledge of the location of available PUs, hence, each of the SUs must move across space until they find an available PU within its perceptual radius. The SUs’ perceptual radius is the visibility/coverage zone within which the SU searches for any available PU frequency. The perceptual radius is defined as a random parameter [11], within which SU nodes look to find available PUs. The type of movement pattern used by the SUs for searching is referred to as a stochastic process, which uses a deterministic random process. The combination of SU nodes’ movement and checking for available PUs within the defined coverage zone is defined as the spectrum selection phase.

The spectrum selection phase is the phase where the SUs decide on which PUs’ frequency should be used for communication. Assume that there are \(N\) primary users’ frequency with different bandwidth values and \(B_f\) denotes the bandwidth of frequency \(f\). Here, the system bandwidth is the difference between the upper and lower spectrum frequencies, measured in hertz [11].

Similar to the biological foraging, where the foragers need to consider the predators while searching for the prey to feed on. The SUs’ nodes also need to consider different interference levels while searching for the available PU’s frequency to use for communication. Let \(n_{if}\) denote the interference level incurred by SU node \(i\) if it uses the frequency \(f\). While \(A_i\) is the set of PUs’ frequency IDs that are periodically selected by SUs’ node. Hence, the total rate of gain of node \(i\) in selecting a PU’s frequency, \(f_i\), is given as:

\[
 f_i = \sum_{f \in A_i} \frac{a_{if}B_f}{a_{if}n_{if}} \tag{1}
\]

where \(a_{if}\) is the probability that node \(i\) uses frequency \(f\). The maximization of \(f_i\) will allow the SUs’ node \(i\) to select a frequency with high bandwidth while minimising the level of interference between PUs and the SUs. Hence, the goal of SUs’ node \(i\) is to maximize \(f_i\) by solving equation (2), using the zero-one rule.

\[
 f_i = \frac{a_{if}B_f + \xi_i}{a_{if}n_{if} + \lambda_i} \tag{2}
\]

Table 1 presented the spectrum selection algorithm, where basically, the SUs search for PUs’ frequency \(A_i\) and determine the frequency bandwidth \(B_f\) together with the interference level \(n_{if}\) that would be incurred if the SUs uses the frequency. The SU checks the interference and gain level, if the gain is higher than interference, the SU select the frequency for communication, otherwise, it discards the frequency and search again.

**Table 1. SUs’ Spectrum selection algorithm**

| 1 foreach Frequency f in A_i do |
| 2 determine B_f and n_{if} |
| 3 end |
| 4 foreach Frequency f in A_i do |
| 5 if \{ f | \forall k \in A_i : (B_k/n_{ik}) < (B_f/n_{if}) \} then |
| 6 select frequency f for communication |
| 7 end |
| 8 end |

Our previous study [11], presented the detailed mathematical formulation of the spectrum reconfiguration phase of FISSER model, however, it was taken further in this paper by analysing the
performance of both phases in the context of rural and urban CRNs.

3. The Experimental Setup

This section presents the experimental setup of the FISSER model using MATLAB™ version 9.2 simulation tool. As opposed to the conventional network simulators, MATLAB™ simulator was used in this paper in order to have more accurate and realistic network conditions which can be tractably tested. Also, MATLAB™ was chosen because of its ability to handle intensive computational information [9]. To assess the impact of the FISSER model on the distributed CRN topology, several computer simulations of randomly placed 10 PUs’ nodes and 30 SUs’ nodes were uniformly placed in a 600 m x 600 m area, using a time span of 500 steps.

Following the FISSER algorithm, the SUs started with the intensive search mode using Brownian motion and switched to the extensive search mode, if no frequency was found to be available after the specified Giving Up Time (GUT). The GUT was set to 50 ms; this GUT value was based on the result of the analytical solution presented in [10]. The SUs used available TV Ultra High Frequency (UHF) spectrum between 470 MHz – 890 MHz and the channel numbers 14 – 83 of channel-widths 20 MHz each in the IEEE 802.22.

In order to analyse the effect of perceptual radius on the FISSER model performance, two settlement patterns were considered: urban and rural settlement patterns. The two settlement patterns were implemented using the Atarraya simulator (1.2.3 public version). The analysis presented in this paper help to know how the FISSER model will perform in both the rural and urban areas when the SU nodes are subjected to a different perceptual radius.

4. Performance Analysis

This section presents the performance analysis of the FISSER model and compare the obtained results with the reinforcement learning based model. FISSER model performance was compared with that of reinforcement learning based model, so as to validate its efficacy. The authors in [9] compared the performance of reinforcement learning based model with that of game-based and dynamic learning models using four metrics. It was observed that the reinforcement learning model performs better than the other two models. Game-based and dynamic-based models have been used to address the problem with many of the existing models such as the statistical and predictive based models. They are also one of the popular model that many researchers have adopted in addressing the decision making problem in CRN. Hence, it will be interesting to see how the FISSER model perform in relation to the reinforcement learning based model, which has been shown to perform better than game and dynamic based models.

4.1. FISSER Model Analysis

Based on our numerical analysis in [11], it was observed that one of the factors that determine the performance of the SUs’ node is perceptual radius. It was also observed that while the perceptual radius is less than 30 m, the SUs performs well, however, when the radius is above 30 m, the performance drops significantly. Hence, two different sets of perceptual radius (low and high radius) were considered in this paper. The low perceptual radius was defined as 30 m, while the high perceptual radius was defined as 50 m. The effects of both low and high perceptual radii on the FISSER model were considered using both rural and urban settlement patterns. The analysis was done using average channel switching time, and average throughput metrics. The model analyses were performed for a period sufficient for the stability of result statistics. Each of the reported results were the average of twenty data points from twenty simulation runs, for each scenario that was considered.

4.1.1. Average Channel Switching Time. The average channel switching time is the total time it takes the SUs both to switch to another frequency when a PU appears and also to reconfigure its transceiver parameters after switching. The main objective of this metric is to reduce the number of unnecessary disconnections and reconnection delays, which can lead to the CRN’s performance degradation. The process of switching and reconfiguration by SUs incurs a certain level of delay which should be kept minimal, so as to avoid overheads. Based on the results of some existing studies [2, 4], the acceptable
range of values for channel switching delay should be 10 – 40 ms, so as to meet the application’s Quality of Service (QoS) requirements. However, in this paper, we assume 10 ms as the benchmark value for the average switching delay. The lower the channel switching time value the better the model performance as the lower values will increase the packet delivery rate and mitigate the delay [9].

Figures 1 and 2 show the average channel switching time over a range of time steps for different SUs’ nodes in a rural and urban settlement pattern at low and high perceptual radius respectively. It can be observed from figure 1 that the average channel switching time for the SUs at both the high and low perceptual radius is less than 6.5 ms. However, it can be observed from figure 2 that the highest average channel switching time for the SUs considered, using low and high perceptual radius is 7.98 ms. Based on figures 1 and 2, it can be observed that the FISSER model performs better when the SUs’ node uses a low perceptual radius. The achieved high channel switching time by the SUs when subjected to a high perceptual radius can be attributed to the increase in the interference level due to co-channel contentions among the SUs’ nodes which in turn lead to some delay in channel switching time. It was observed that as the perceptual radius increases, the SUs can easily sense available frequencies from a distance, however, when the perceptual radius exceeds 30 m, the transmission noise among the SUs’ nodes increases, and in turn increases the interference level among the SUs’.

Although the results presented in figure 1 for rural settlement patterns perform better than that of urban settlement patterns in figure 2. However, the FISSER model results in urban and rural settlement patterns perform better than the existing results [2, 4] where the set baseline for channel switching delay was 10–40 ms.

4.1.2. Average Network Throughput. In a distributed CRN where the data traffic is high, the probability that the PU channels will be occupied is high. Based on the existing results from the literature [9], it has been observed that the random based approach achieved high results. The network throughput index shows the network communication performance; the higher the throughput value, the better the network communication performance. The network scenarios considered were based on known source-destination pairs so as to address the shortest path exploitation.

The average network throughput for different SUs at low and high perceptual radii in rural and urban settlement patterns are depicted in Figures 3 and 4 respectively. It can be observed from figure 3 that the average throughput for the SUs at both the low and high perceptual radius is more than 82%. However, it can be observed from Figure 4 that the lowest average throughput for the SUs’ considered, using high and low perceptual radius is 74.2%. Based on figures 3 and 4, it can be observed that the FISSER model performs better in both rural and urban settlement patterns when the SUs’ node uses a low perceptual radius.

Increasing the nodes’ perceptual radius will help the SUs to travel a short distance before getting an available frequency to use for communication. However, one of the main challenges with high perceptual radius in a CRN environment is that high perceptual radius usually introduces frequency contention among the nodes, thereby increasing the level of interference among the nodes. The increase in the interference level will, in turn, lead to network performance degradation.

Based on figs. 1-4, we observe that there is a trade-off between the achieved throughput and the channel switching time. As the channel switching time decreases, the network throughput increases.
An efficient channel switching approach will yield a high network throughput performance. This observation conforms to [2, 6], where the authors concluded that high channel switching time can cause a throughput loss of up to 3%, exclusively. Hence, based on the achieved results from channel switching time and average throughput, the FISSER model can select an optimal channel and frequency quickly, which in turn will improve the rate of data communication and provide better QoS for CR spectrum utilisation.

4.2. Performance Evaluation of FISSER Model

The performance results of the FISSER model when compared with that of reinforcement learning based model is presented in this sub-section. A consistent comparison of the FISSER and reinforcement learning models is achieved by keeping both the simulation parameters and environment constant for all the reported simulation experiments. The models were evaluated using average channel switching time and network throughput metrics.

Figure 5 depicts the average channel switching times over a range of time steps. It can be observed that the FISSER model average channel switching times are convergent to 0.62 ms, while reinforcement learning convergent to 0.97 ms. In reinforcement learning model, the SUs need to learn many selection strategies before making decision, hence, this introduced some computational complexity that impact the model performance. However, the better performance of FISSER model can be attributed to its generic and analytical simplicity which helped to address both computational complexity and slow convergence that affect the reinforcement model performance.

In Figure 6, the average network throughput for both FISSER and reinforcement learning models were presented. The network communication performance is shown by the achieved throughput index. It was observed that the FISSER model outperformed reinforcement learning in the throughput performance. One of the reasons for the FISSER model better performance is its intensive/extensive search technique. In this search technique, the SUs first search for available frequency within the short steps radius and only switch to long steps if there is no available frequency within that short steps. However, the reinforcement learning model uses the same number of decision steps whenever their SUs need to search for available frequency, which resulted into some delays in their searching and in-turn affect the network throughput. Based on the results presented in Figures 5 and 6, it can be observed that the lower the channel switching time, the higher the network throughput. CRNs can be deployed to support the various usage scenarios such as military operation, disaster management and
surveillance networking. These disparate usage scenarios require guaranteed node communication performance and energy efficiency. Thus, these usage scenarios are supported by the FISSER model.

5. Conclusion
In conclusion, this paper has presented a biologically-inspired FISSER model for spectrum selection and reconfiguration in distributed Cognitive radio networks. In analysing the performance of the proposed FISSER model, both rural and urban settlement patterns were considered. Several computer simulations were carried out using average channel switching time and network throughput metrics. These metrics were measured when subjected to high and low perceptual radii at different time steps. A high perceptual radius has been shown in the literature to improve the energy efficiency and data communication performance in ad hoc networks. However, the simulation results reported in this paper show that even though the high perceptual radius improves the nodes’ energy efficiency it does not achieve optimal data communication performance compared to when the nodes use a low perceptual radius for their communication. The efficacy of FISSER model was tested by comparing it against the reinforcement learning model using two metrics. Based on the obtained results, it was shown that the FISSER model achieved better communication performance and guaranteed the efficient use of energy. In future, we intend to extend this work to actual prototype implementations and field-testing. This will enable further validation of the results presented in this paper.

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