Experimental Test-Bed For Bumblebee-Inspired Channel Selection in an Ad-hoc Network

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***Abstract*—In this paper, we design a test-bed for a bumblebee inspired channel selection algorithm employed on a wireless ad-hoc network. Vehicles in connected ad-hoc networks are routinely challenged with the complex decision-making problem of either staying with the same channel or moving to a different channel under highly time-varying channel quality conditions. In order to enable vehicles to adapt to these time-varying channel conditions, we designed a bumblebee-inspired decision-making algorithm. The proposed algorithm uses temporal channel quality information for optimal channel selection. Channel energy values are used for making switching decisions by taking switching costs into consideration. We implemented a test-bed inside a controlled laboratory environment using ADALM-Pluto Software-defined radios (SDRs) to evaluate the proposed approach. The test-bed can be configured to emulate a vehicular network environment. Furthermore, in this work we show the novelty of our bumblebee algorithm for optimal channel selection in a steady environment. We compared the performance of our Bumblebee algorithm with a random channel selection algorithm, and noticed an increase of 158.33% in the throughput of the network with our algorithm.**

***Keywords*—Bumblebees, Vehicular Communication, SDR, VANET, Channel Selection**

I. Introduction

Vehicular Ad-Hoc Networks (VANETs) has been extensively studied for road safety and reducing traffic. VANET systems can help prevent accidents by communicating safety messages through wireless networks. To help with the deployment of VANET technologies on the road, the United States Federal Communication Commission (FCC) has allocated six channels in the 5.9 GHz band for vehicular communication [1]. However, these dedicated channels will potentially not be sufficient to handle all connected vehicle traffic in the future [2]. To solve this spectrum scarcity issue one can leverage underutilized wireless spectrum elsewhere by employing opportunistic spectrum usage enabled by Cognitive Radio (CR) technology [3]. CR-enabled vehicles have the ability to use additional spectrum opportunities outside the FCC-specified channels. In this paper, we have implemented an ad-hoc prototyping network test-bed consisting of ADALM-Pluto software-defined radios (SDRs) using two channel selection schemes. We demonstrate the efficiency of our proposed Bumblebee algorithm [4] in an indoor environment. The bumblebee channel selection algorithm employed in our VANET test-bed uses energy detection (ED) for the spectrum sensing due to its low implementation complexity [5]. A random channel selection algorithm is also utilized in our test-bed to serve as a benchmark and the performance of both the schemes are compared in terms of throughput.

There have been several approaches proposed in the open literature that leveraged distributed optimization techniques based on models found in natural systems such as ant colonies, honeybees, and other insects, all of which perform swarm optimization of the available resources [6]. However, these techniques require each node within the network to be dependent on the social interactions with all other nodes within the network, which is not the case in applications such as connected vehicle networks. Other biologically inspired approaches include the popular Genetic Algorithms (GA) [7], which belongs to the field of evolutionary computation and has been studied to solve multi-objective optimization problem. However, GA algorithms yield accurate results over a longer period time relative to the coherence time, making them susceptible to a rapidly changing environment and outdated information. Distributed optimization techniques such as Artificial Bee Colony (ABC) optimization [8], Evolutionary Optimization [9], Particle Swarm Optimization (PSO) [10] have also been used for optimal channel selection. These optimization techniques require each vehicle within the network to share information with all other vehicles within the network for optimal channel selection. In a highly dynamic vehicular environment with varying network topology, it is challenging to maintain efficient communications between vehicles.

The proposed Bumblebee-based channel selection algorithm does not depend on the social interactions between the vehicles and can optimize the channel selection performance in a distributed manner [11]. In this paper, we look at a Dynamic Spectrum Access (DSA) technique for distributed ad-hoc networks based on bumblebee foragers [4] since they have evolved cognitive abilities that enable them to adaptively solve similar problems while foraging in environments containing multiple floral resources (channels). In [12], we have shown the potential utility of a bumblebee-inspired channel selection algorithm within a Vehicular Dynamic Spectrum Access (VDSA) framework using GEMV^2 [13] in MATLAB.

GEMV^2 is a geometry-based, efficient propagation model for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. We stored the channel energy values in memory and switching decisions were taken after weighing against the channel switch cost. Channel energy information is frequently updated in memory through periodic sampling, which provide vehicles with a more accurate estimate of the degree to which channels differ in their quality for a given vehicular environment. Our results showed that a large increase in channel selection performance was obtained for sparse highway and urban traffic by utilizing our bumblebee-based algorithm enabled with memory. For this work, we implement a memoryless bumblebee-based channel selection algorithm in an ad-hoc network using ADALM-Pluto SDR [14] hardware. In memoryless bumblebee algorithm, the channel information is not stored in the memory instead decisions are made for particular time instant while considering switching costs.

The rest of this paper is organized as follows: In Section II we describe the bumblebee algorithm in detail. In Section III we describe the implementation of bumblebee and random channel selection algorithm for ad-hoc network test-bed. We also look at the configuration of the ad-hoc network test-bed in details. In Section IV, measurements for the packet delivery ratio (PDR) of the bumblebee algorithm is gathered and compared with the random channel selection algorithm. Finally, we conclude the paper with Section V, where we discuss the future work of our research.

II. Channel Selection Using The Bumblebee Algorithm

Bumblebee foraging behavior is mainly based on individual decision mechanisms, hence making it well-suited for applications where decision-making is performed independently [15]. Since there is no need to access any centralized system or wait for information from others, the decision and adaptation to change can occur as rapidly as their highly efficient neural processing system allows. A time-varying stochastic channel also poses the same threat in a wireless environment as a nectar distribution in flowers where bumblebees forage. Due to the similarities between the two systems, we found out that by utilizing bumblebee-inspired algorithms for optimal channel selection in a time-varying noisy environment, its performance was observed to be highly efficient [4].

Algorithm 1 describes the Bumblebee channel selection algorithm in detail. The bumblebee algorithm is initiated by sampling the channels in the list and then mapping the energy values to the reward $r(t)$, which is a linear function of the energy value E. The best channel is selected based on the reward $r(t)$ and it is assigned to the node N. The channel reward function $r(t)$ is given by:

$$r(t) = \min\{\hat{E}\} \tag{1}$$

where $\min\{\hat{E}\}$ is the minimum energy value of the channels used in DSA at that time interval. A more complex channel reward function can be used based on the radio characteristics and the channel environment. However, we have used a simple channel reward mapping to reduce the processing delay caused during the channel selection algorithm. T is the total simulation time, C is the set consisting of all channels used in the ad-hoc network test-bed, s is the the switching cost, and N is the total number of Pluto SDR units. The test-bed is initiated by sampling the spectrum space for t_s duration and then assigning the channel to our radios based on the channel selection strategy. In this work, we have kept the sampling time $t_s = 300\ ms$ fixed for both bumblebee and random channel selection. For the bumblebee-based channel selection, the radio nodes select the best channel out of available options for each cycle using channel energy values. In the case of the random channel selection algorithm, the nodes randomly select a channel and start the packet transmission. Both schemes are employed on similar radio networks for the T time duration and their packet delivery ratio performance is compared. Eq. (2) describes the memoryless bumblebee algorithm:

$$\begin{array}{c}\text{Switching}\\ \text{Decision}\end{array} = \begin{cases} r_c \leq (r_n - s_n), & \text{“Switch”} \\ \text{otherwise ,} & \text{“Stay”} \end{cases} \tag{2}$$

where r_c is the current channel reward, r_n is the new channel reward, and s_n is the switch cost for the new channel during the sampling time interval. The switching cost s in this work is assumed in terms of channel energy values in order to reduce the test-bed implementation complexity. The switching cost will vary depending on the cognitive radio characteristics and channel environment.

In our prototyping test-bed, the wireless spectrum is sensed based on a mechanism that detects energy levels for each channel. The channel model considers all entities specific to a vehicular environment such as multipath fading, doppler shift, and scattering, which can be mathematically expressed as [16]:

$$h(\tau, t) = \sum_{k=0}^{P-1} h_k(t) e^{-j2\pi f_c \tau_k(t)} \delta[\tau - \tau_k(t)], \tag{3}$$

Algorithm 1 Memoryless Bumblebee Algorithm

procedure BumblebeeAlgorithm(r, T, C, N)
    for $t = 1\ to\ T$ **do**
        Sampling Interval :
        Compute Energy values $E \in \{C\}$
        Map to reward $r \in \{C\}$
        Select best $\{C\}$ at t for n_i
        Transmission Interval:
        Start the packet transmission
    end for
end procedure
procedure ChannelReward(E, C, T, N)
    for $t = 1\ to\ T$ **do**
        while $c = 1\ to\ C$ **do**
            $r(t, c) = min\{\hat{E}\}$
        end while
        $N \leftarrow r(t)$
    end for
end procedure

where τ is the path delay, P is total number of paths, t is time variable, $h_k(t)$ is channel envelope, δ is the channel impulse response, and f_c is the carrier frequency. Using the channel impulse response, the detection problems can be formulated as an M-ary hypothesis test. In this case, the spectrum sensing performs the following a binary hypothesis test:

$$\begin{cases} \mathbf{H}_0 : y(t) = n_r, \\ \mathbf{H}_1 : y(t) = \int_{-\infty}^{\infty} h(\tau, t) x(t-\tau) \mathrm{d}x + n_r \end{cases} \quad (4)$$

where $y(t)$ is the received signal and n_r is the noise. Once the vehicles occupy a channel that is available, such as $\mathbf{H}_0$, they need to periodically check to see whether they can potentially switch to a better channel.

III. Experimentation Hardware Test-bed

The experimental test-bed is implemented using the ADALM-Pluto SDR units with each radio connected to a desktop computer running Ubuntu 16.04. The configuration and measurements for the ad-hoc network was performed using MATLAB [17]. Figure 1 describes the layout of the laboratory where the experiment was conducted. In this experiment, we utilized six Pluto SDRs to form a wireless ad-hoc network where four radios were configured as receivers with each listening to a different channel. One node is used as a transmitter, which utilizes the bumblebee algorithm to select the optimal channel and utilize it for packet transmission. We configured another radio to be an interference node whose role was to select channels randomly. The interference node was added in order to test the performance of the bumblebee algorithm in a interference-prone environment.

Figure 2 shows the experimental setup we used in our work to evaluate the performance of bumblebee algorithm. In order to experimentally determine the channel selection performance of the bumblebee algorithm, we conducted measurements up to ten minutes for different packet sizes. Each trial was conducted three times in order to get an average estimate of packet delivery ratio (PDR) for each packet size. For the bumblebee algorithm, we first start by sampling the channels in the list and select the channel with the lowest energy at that time instant. The radio starts the packet transmission on the selected channel for 60 seconds, where it re-samples the channels and switches channels based on the switching cost. Switching channels for every sampling interval based on channel information may sound rewarding with an ideal radio. Without any channel switching delay, as well as timing or frequency correction delay, selecting a channel with least energy is the optimal choice. However, in the real-world we need to take the aforementioned delays into consideration, which can severely affect the radio performance during frequent channel switching. For example, using the ADALM-Pluto SDR takes around 300 ms for the channel switching to cause a loss of approximately 10 packets of the size 800 bytes. Additionally, it takes around 400–500 ms for the Phase-Locked Loop (PLL) implemented in MATLAB to lock onto the signal to achieve accurate timing and frequency correction. Our bumblebee

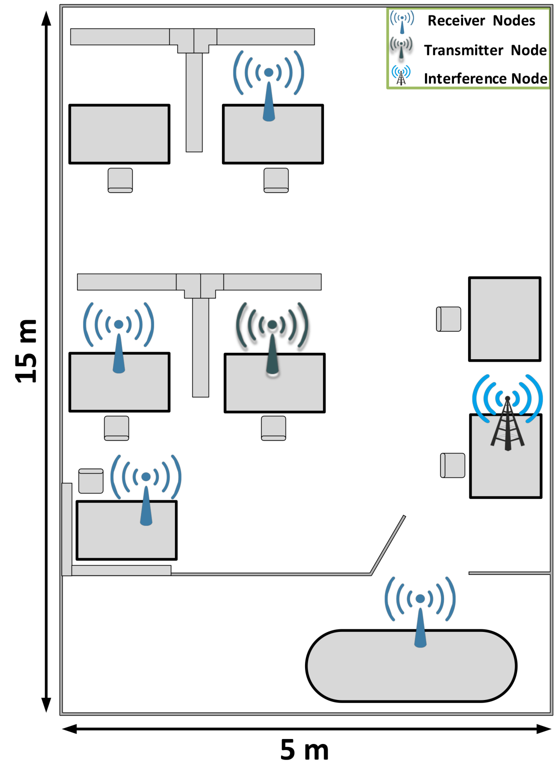

Figure 1: Layout of the laboratory where the experiment is conducted. The layout shows the location of each individual radio node.

channel selection algorithm takes this switching cost into consideration before making a decision to switch to another channel. In this work, we implemented the switching cost in a very simplistic manner in order to reduce the processing time and overhead delay for making switching decision.

We ran the same experiment for random channel selection where the transmitter selects a random channel from a list and starts packet transmission. Random channel selection does not sample the spectral environment, which results in high collisions with the interference node and incurring a high packet loss. In Section IV, we can observe a large difference in the PDR whilst comparing the two schemes. The severe packet loss is caused due to the interference node and frequent channel switching.

IV. Measurement and Results

To evaluate the performance of our channel selection algorithm, we first computed the channel sensing performance of the energy detection. In this work, we used an adaptive threshold for the energy detection scheme in order to efficiently determine the channel utilization. A fixed threshold can be used in a static environment for accurate primary user (PU) detection but in a time-varying noise environment it can lead to a high rate of false alarm and missed detection probabilities. We compute the mean energy of all the channels in each time interval and then add a random factor K to compute the final threshold. Consequently, the threshold changes dynamically with the environment and we can get an accurate estimate of the primary user. Figure 3 shows the probability of detection

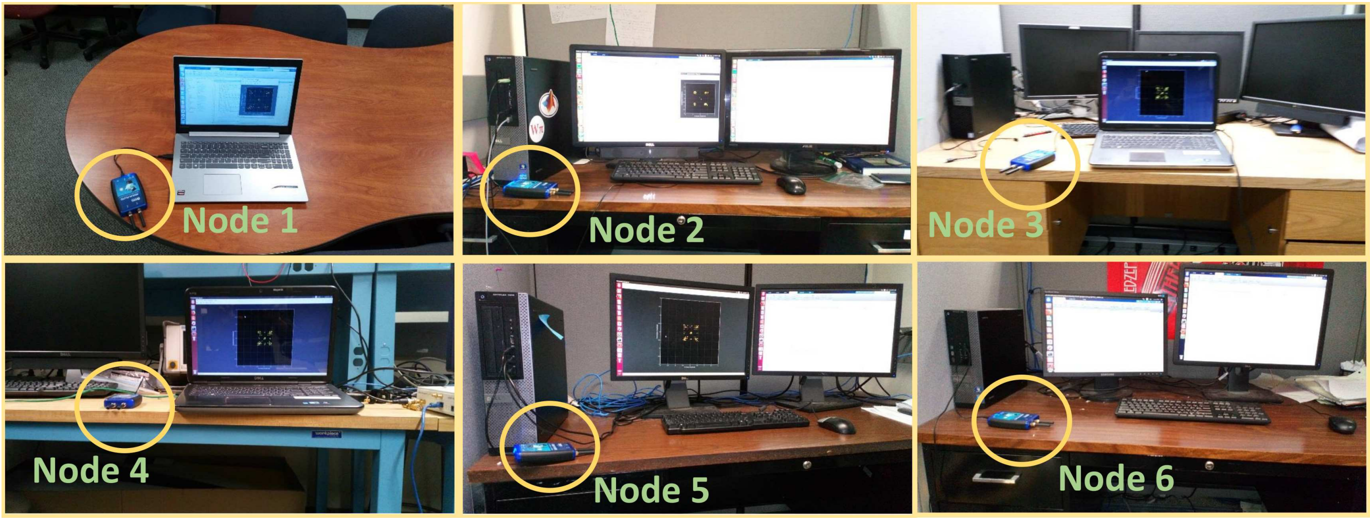

Figure 2: The experimental test-bed consisting of six Pluto-SDRs forming an Ad-Hoc network. The experiment is conducted in a controlled laboratory environment.

(P_d) vs SNR for the ED scheme for different K values. In this paper, we set the K value to 6 dB as that lead to the best detection probabilities. Lower K values increases detection but they also leads to increase in false alarm probabilities.

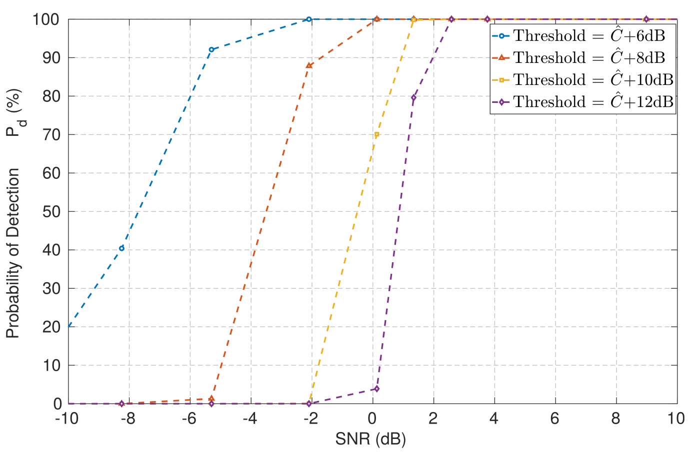

Figure 3: P_d vs SNR for threshold factor K = 6, 8, 10, 12. As we increase K, the sensing performance degrades due to large misdetections in the network.

We also tested the interference caused due to increase in the number of nodes and how it affects the packet failure rate. Two radios were configured in order to transmit and receive packets continuously on single channel. The transmit power was kept fixed at 8 dBm while the receiver gain was changed to generate different Signal-to-Noise Ratio (SNR) data. Initially, only the transmitter and receiver nodes were used to get the benchmark packet failure rate (PFR) performance in the absence of any interference. An experiment was then performed with four and six nodes, where we observed that as the number of nodes are increased the performance degrades in the network. The effect is more severe at low SNR values, where the large amount of data packets are lost. Figure 4 shows the plot for PFR vs SNR as the number of nodes are increased from $N = 2$ to 6.

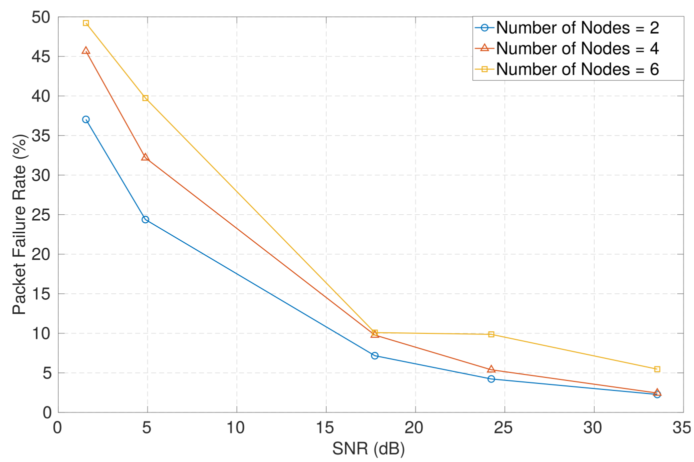

Figure 4: Packet Failure Rate in an Ad-hoc network as the nodes are increased from $N = 2$ to 6 for varying SNR.

Figure 5 describes the behavior of the bumblebee algorithm in the presence of the interference node. The radio node avoids the interference node to avoid the packet collisions based on the switching cost. If the cost is high for the channel switching, then the bumblebee algorithm will stay on the same channel. During the experimental run, channel 5 was being continuously used by the ISM band users, which means it was never utilized by the radio node. Channel 2 was the most rewarding during our simulation run, which was verified with the spectrum analyzer and is evident by the bumblebee algorithm's channel selection.

Finally, we computed the PDR for the ad-hoc network using the bumblebee and random channel selection scheme. For each packet size, we performed the experiment for 10 minutes and ran it three times to get the mean PDR performance. As the packet size was increased from 800 bytes to 1600 bytes we saw a decrease in PDR for both bumblebee and random channel selection. The performance of random channel selection is severely affected by the interference node and

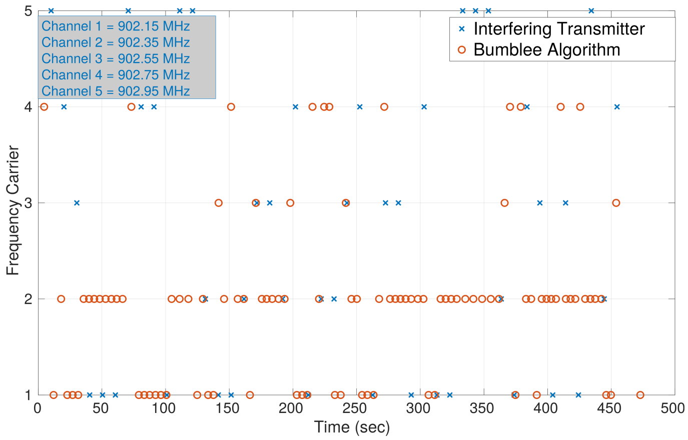

Figure 5: Bumblebee algorithm switching from one channel to another avoiding the interference node. During the entire experiment, radio running bumblebee algorithm stays on channel 2, reducing switching cost.

frequent channel switching which causes additional packet loss. The bumblebee algorithm on the other hand takes switching cost into consideration and avoid switching channels if the reward is not worth switching. Due to the relatively stationary laboratory environment, the bumblebee algorithm used 902.55 MHz around 60% of the time which reduced the frequent switching and lead to a significant gain in bumblebee performance.

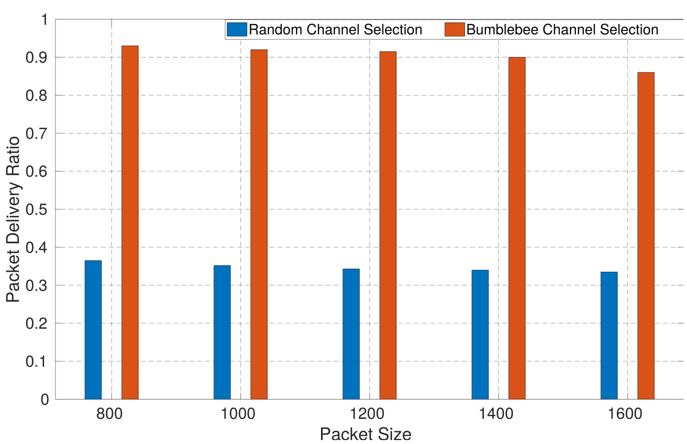

Figure 6: PDR for bumblebee and random channel selection for different packet size. Due to frequent channel switchings and large packet collisions with the interference node, the random channel selection has a high packet loss. The variation of PDR for each packet size was around 1%–2% in both bumblebee and random channel selection.

V. Summary and Future Research Directions

In this paper, we conducted an experimental study for the bumblebee-inspired channel selection in an ad-hoc network using ADALM-Pluto SDR units. We found that our bumblebee-based channel selection scheme has a relatively decent PDR performance when compared to the random channel selection algorithm. This was partially due to the reduce channel switching and selecting the best channel for transmission in regular periodic intervals.

For future work, channel information will be stored in the memory and utilized in the channel selection process. Storing the channel information can help reduce channel sampling time as well as help in assigning the appropriate dwell time for the channels. The authors will perform more detailed experiments to compute accurate switching cost that can make our decision-making more efficient. Finally, we would like to deploy the SDR units in a vehicular environment for on-road experiments to test the performance of our bumblebee algorithm in a real-world scenario for optimal channel selection.

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