Memory Matters: Bumblebee Behavioral Models for Vehicle-to-Vehicle Communications

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***Abstract*—Vehicles forming connected communication networks are routinely challenged with the complex decision problem of either staying with the same wireless channel or moving to a different wireless channel when experiencing highly variable channel quality conditions. In order to obtain a practical solution to this problem, we refer to bumblebee behavioral models, which possess evolved decision-making mechanisms to adaptively solve similar problems while foraging in environments containing multiple floral resources (channels). In order to enable vehicles to adapt to these time-varying channel conditions, we propose in this paper a bumblebee-inspired decision-making algorithm in which channel quality information is stored and updated in vehicle memory. This information is used to estimate qualities of channel options and then weighed against switch costs to determine optimal channel selection. We incorporated our algorithm into a VDSA-based VANET model, while the GEMV^2 Vehicle-to-Vehicle (V2V) propagation simulator was used to test its performance under different memory parameters and against existing models. Our results show that a memory system based on the averaging of stored channel information dramatically increased channel selection performance over a memoryless system in both urban and highway scenarios by 52% and 20%, respectively.**

***Index Terms*—Connected Vehicles, Bumblebees, Dynamic Spectrum Access (DSA), Foraging Theory**

I. Connected Vehicles Meet Spectrum Scarcity

The United States Federal Communication Commission (FCC) allocated six channels in the 5.9 GHz band for vehicular communications [1]. However, it is anticipated that these dedicated channels will not be sufficient for handling all connected vehicle communications in the future due to the increasing number of connected vehicles operating in densely populated cities [2]. One potential solution to this spectrum scarcity issue is to leverage underutilized wireless spectrum elsewhere, such as in the digital television spectrum band, using an approach called *Vehicular Dynamic Spectrum Access* (VDSA) [3], [4]. The fundamental idea behind DSA is to use unoccupied channels without interfering with the licensed users, *i.e.,* primary users (PUs), of the frequency bands. This result can be achieved via spectrum sensing techniques [4]. However, such channel sensing approaches possess two significant technical challenges that need to be accounted for in connected vehicles environments, namely:

- In a highway scenario, there exists a highly dynamic vehicular environment caused by varying network topology whereas in an urban scenario channel conditions change rapidly, which significantly impacts network reliability and efficiency. In particular, the time-varying propagation characteristics of the connected vehicles environment, such as Doppler Effect, multipath fading channels, and transmission errors on the control messaging need to be considered [5], [6].
- The limited capability for information sharing, *i.e.,* latency caused due to processing operations in the radio and, as well as limited spectrum availability makes network organization challenging. These constraints may potentially affect the adaptation process to the current network conditions although information sharing may increase environmental awareness [7].

Therefore, the technical challenges resulting from severe dynamic characteristics of the vehicular networking environment makes it difficult to employ DSA via conventional approaches such as spectrum pooling, CORVUS, DIMSUMnet [8]–[11]. This is especially true when channel sensing parameters such as the noise floor, propagation fading, and interference are time-varying [8].

In this paper, we explore how a VDSA framework for distributed Vehicle-to-Vehicle (V2V) networks can be based on adaptive behavioral responses of animals that must survive under similar complex and highly varying resource conditions in their natural habitat [12]. In V2V networks, we have a similar environment where the channel energy changes in a highly time-varying manner, and the vehicles need to find better channels for packet transmission. In particular, we focus on bumblebee foragers since they have evolved cognitive abilities that enable them to make adaptive behavioral decisions under such conditions based on individually acquired information [13]–[15]. Using the bumblebee model, an efficient channel sensing and selection system has been developed that can rapidly and adaptively respond to changes in multichannel environments of a vehicular communication band. The key components of this system are: i) channel memory, which enables more accurate estimates of available channel quality to determine the optimum point to switch to better quality channel, and ii) the mapping of stored information on channel quality using 'Mean' strategy (*i.e.* past information on each channel gained through sampling is averaged and then used to make the decision on the channel with the best quality).

The rest of this paper is organized as follows: In Section II, we explain why the bumblebee is an ideal model for channel access optimization in vehicular communication networks. In Section III, we explain the similarities between decision problems in vehicular and bumblebee resource environments. In Section IV, we outline the the bumblebee decision-making process. In Section V, we describe our bumblebee-inspired algorithm for channel access in a memoryless system, which is then expanded to include memory in Section VI. In Section VII, we discuss the results of simulation employing the algorithm, followed by concluding remarks in Section VIII.

II. Why Bumblebees?

There have been several practical approaches proposed in the open literature that leverage distributed optimization techniques employed by natural model systems, such as ant colonies, honeybees, and other insects, which perform swarm optimization of available resources [16]. However, these techniques require that each node within the network is dependent on the social interaction with all other nodes within the network, which is not the case in applications such as connected vehicle networks.

We propose the bumblebee as a more suitable social insect model for studying distribution optimization of channel resources. Unlike ants and honeybees, individual bumblebee foragers acquire information on their own and independently solve optimization problems within the distributed network [12], [17]. Thus, bumblebees do not depend on a centralized information system, which can be highly ineffective and unreliable in environments that rapidly change over time and space. For vehicular networks, this description corresponds to rapidly changing environments, where centralized information may be inaccurate or too slow to reflect local changing conditions. Furthermore, vehicles may lose connectivity to a centralized database or other neighboring vehicles under some conditions (*e.g.* highway, rural area). In such a scenario, any optimization mechanism relying on this form of communication is highly inefficient and poses a major safety concern.

In contrast to the individual-based bumblebee system, honeybees rely on the 'scout-recruit' method where one individual (scout) communicates resource quality information to many individuals (recruits) [18]. If the quality of the resource decreases, then the recruits are informed of a better food source by the scout when they return to the hive. The scouting process and the need for worker bees to return to the hive in order to be informed about a better food source is associated with time costs not present in the bumblebee system (where individuals sample resource alternatives and then specialize on the best one).

Thus, the honeybee system is not an efficient resource exploitation mechanism when resources vary rapidly and are unpredictable over time and space. Similarly, ant colony behavior is based on tracking pheromones deposited by 'primer' ants [19]. Although ant colonies are very efficient for routing scheduling and organization, this mechanism also cannot deal with the highly time-varying vehicular networking environment [20].

As an alternative to colony behavior, reinforcement learning [21], [22] mechanisms have been presented in the existing literature. Genetic algorithms provide a reliable optimization technique but at the expense of a large computational latency with respect to converging to the optimum value [23]. Particle swarm optimization is a computationally efficient optimization technique since it jointly solves the fitness function based on a multi-objective formulation [24]. However, it is highly dependent on the initial information about the swarm structure, which is not realistic for connected vehicle networks.

Bumblebee foraging behavior utilizes individual decision mechanisms, which can include information about the behavior of others (*e.g.*, scent marks) but does not depend on it. 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.

III. Translation Between Two Worlds

Matching the terminology between bumblebee foraging and vehicular communications is the first step in transiting bumblebee behavior to the vehicular optimization problem (see Table I). In-band interference is an unwanted phenomenon in the channel bandwidth. The equivalent of this phenomenon for bees is the presence of other bees as competitors on a particular species of flower. Out-of-band interference is a form of interference produced by co-channels that is similar to the bee competitor's effects on nectar level estimations of alternative floral species.

Channel energy levels is a key feature with respect to channel access and is similar to nectar levels of the flowers for the foraging bees. However, there is an inverse relationship between these two features. In vehicular communications, it is desired to access the channel with as low an energy level as possible since a low energy level means there is no other user in the channel, which also means low noise levels and interference effects. On the other hand, bumblebees desire to access the flower with the highest nectar (energy) levels possible since it means there are only a few other bees competing for the same floral species, thereby increasing their rate of nectar return to the colony.

Figure 1: Example of artificial mixed floral environment used to investigate memory-based decision-making in bumblebees [14]. Each color represents a species (channel).

Table I: Several Definitions in Connected Vehicular Communications and Their Equivalent Definitions in Bumblebees

Vehicles	Bumblebees
In-band Interference	Bees foraging on the same floral species
Out-of-Band Interference	Bees foraging on alternative floral species
Minimum Channel Energy Level	Maximum Nectar Level Per Floral Species
Computation/Process Time	Handling/Searching Time
Latency vs. Reliability	Sampling Frequency vs. Choice Accuracy
Switching Cost/ Time between channels	Switching Cost/Time between Floral Species
Channel activity over time	Floral Species occupancy over time
Channel-user distribution	Bee distribution across floral species

Computation/process time of the algorithms used by connected vehicles corresponds to the flower handling and search time of bees. Many algorithms have been proposed for connected vehicles that provide the perfect channel access scheme [25], [26].

However, if the algorithm gives the result across a longer time interval than the coherence time, the environment conditions change and the output of the algorithm is no longer appropriate. Latency for safety-related applications is set at 100 ms [27], with higher computation/processing times potentially leading to larger delays in the vehicular communication. Similarly, if bumblebees sample the available species across a varying floral environment too infrequently, they may be delayed in switching to a more rewarding floral species should it become available. In other words, the tradeoff between latency and reliability is mirrored with respect to the bumblebees in terms of sampling frequency and choice accuracy.

Switching cost/time between channels should be considered although switching operations provide the access to the channel with higher quality. Similarly, bumblebees switch to the floral species with the highest nectar returns in order to gain more energy. However, they can also incur a significant time cost when switching from one floral species to another.

Channel activity over time helps to understand channel behavior as well as the design of a prediction mechanism. Similarly, bees alter foraging decisions based on the number of bees within and across floral species, often showing an *Ideal Free Distribution* [28]. We detail specific components of the bumblebee system leveraged model to create a vehicular channel selection algorithm below.

IV. Foraging Theory

Bumblebees provide a robust biological framework for building and implementing cognitive algorithms for DSA in vehicular networks. Bumblebees are social insects that form colonies comprised of a single queen and up to several hundred workers [17]. A small subset of these workers are called "foragers", and they have the sole task of finding and collecting food for the colony in the form of floral nectar and pollen rewards. Foragers routinely encounter a wide array of flowers with reward levels that rapidly change over time and space (see Figure 1). Foragers are not pre-programmed with information on the reward level associated with different flowers. Rather, they learn and remember the reward level and sensory cues (color, odor, shape) associated with each flower species and then decide which ones to visit. Importantly, bumblebee foragers do not depend on "scout" bees, such as honeybees or pheromone trails left by others such as ants. Consequently, each individual has the capacity to learn, remember, and track changes in floral rewards on its own. This system has evolved to enable maximal reward intake to the colony across complex and highly variable floral conditions.

While searching for flowers containing the greatest reward, foragers implement a number of adaptive behavioral processes [29], [30] that are comparable to those processes needed for vehicles to function independently and effectively in a connected network environment(see Figure 2). First, foragers (vehicles) evaluate the available flower species (channels) and then select the type (channel) that yields the greatest reward (channel quality) [31]. Second, foragers (vehicles) track and respond to changes in floral reward levels (channel quality) in a flexible manner. Finally, foragers (vehicles) make floral (channel) decisions that maximize the rate of nectar delivery to the colony (constant utilization of a high quality channel by the vehicle) [32]. For example, the decision on whether or not to switch to a new flower species (channel) is based on a trade-off between the rewards gained by visiting a new type types (channel quality) and the time costs incurred when switching to that type (channel; also referred to as a "switch cost").

Although bumblebees primarily use their personal experiences to make floral decisions, they can also enhance their knowledge of floral environments by gaining information from other foragers. For example, individuals can passively acquire information about reward quality from cuticular hydrocarbon "footprints" left on flowers by previous foragers: low hydrocarbon levels signal high likelihood of reward and high hydrocarbon levels signal low likelihood of reward [33]. In this way, individual bumblebee foragers can use the experiences of others (use memory of other vehicles) in order to increase their efficiency of flower (channel) selection by minimizing the amount of time spent (cost) on empty flowers (low quality channels). By incorporating this agent-based approach in our empirical studies of forager behavior, we greatly accelerate the subsequent development and implementation of cognitive algorithms for optimal channel selection by vehicles in connected network environments.

V. Bumblebee-Based Channel Selection

To leverage the potential of bumblebee foraging behavior [34] in connected vehicle environments, we translated the evolutionarily optimized [35] memory-mediated bumblebee foraging strategies to a VDSA decision-making algorithm for connected vehicle networks [36]. One of the major challenges

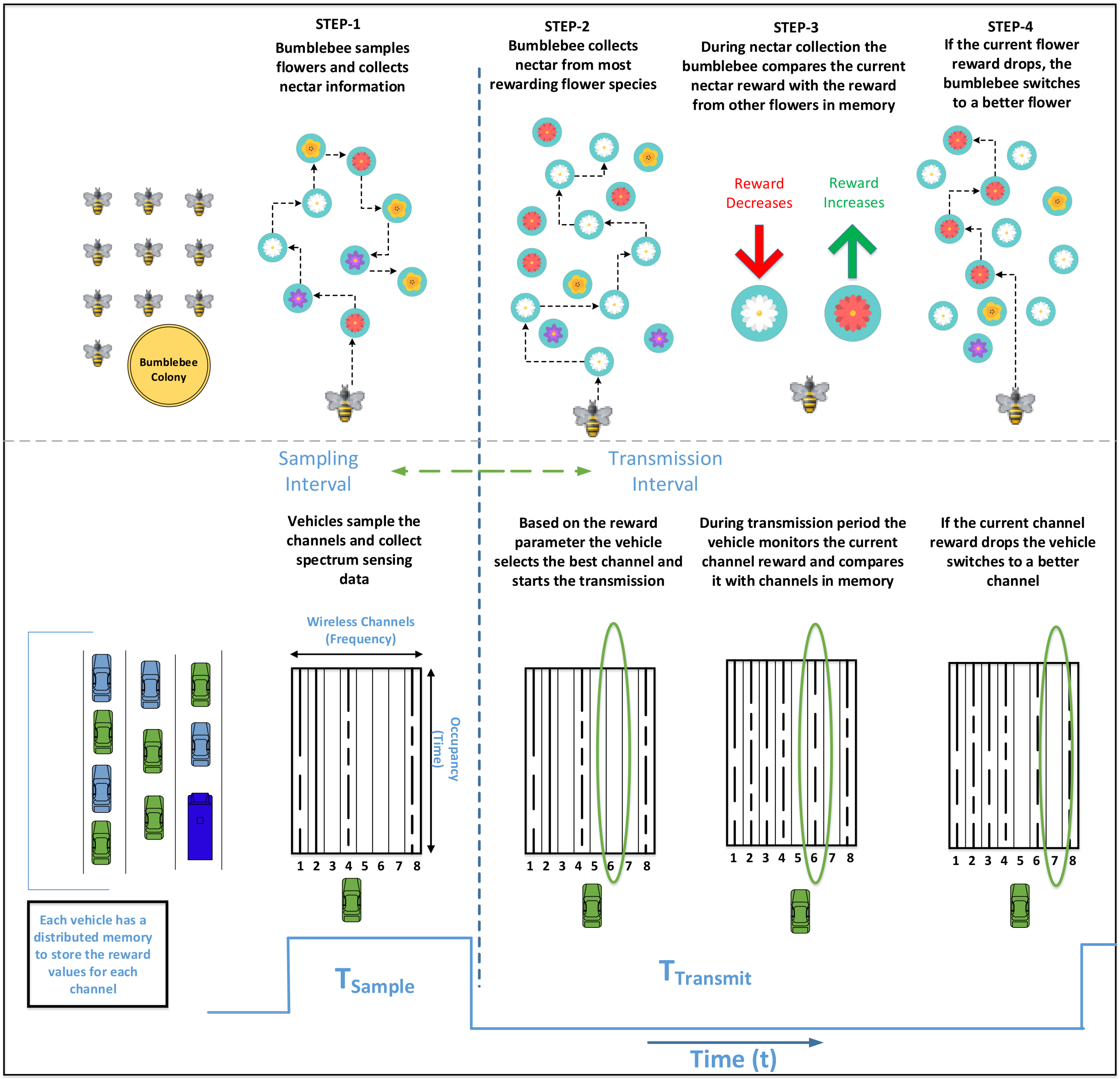

Figure 2: The memory-based channel selection algorithm from bee (top) and vehicle (bottom) perspectives. Similar to each bumblebee, each vehicle is equipped with memory to store channel (floral) reward information, which is then used to select the channel (floral species) with the highest reward quality out of those available in sampling interval. During the transmission interval, the vehicles (bumblebees) use their current channels for communication (forage on current species) while simultaneously tracking the change in the reward level. The vehicles switch to a better channel (floral species) based on their memory if the current channel level drops to a lower value. Vehicles alternate between sampling (T_{Sample}) and transmission ($T_{Transmit}$) periods to track changes in a time-varying noisy resource environment.

faced by vehicles in a connected network environment is that they must accurately estimate channel quality from power levels that significantly vary over both time and space. The incorporation of an individual memory component into the algorithm design overcomes this challenge by enabling individual vehicles to derive estimates of local channel quality, which could then be shared throughout the vehicular network. Equipping vehicles with an unlimited memory capacity would provide the most accurate estimate of channel quality. However, unlimited memory would also generate additional costs, *e.g.*, information processing speed, time lag in reacting to environmental changes. Thus, determination of an optimal decision-making strategy requires consideration of memory capacity, dynamics, and associated costs in terms of sensing and channel switching time. Bumblebees face identical constraints in choosing the optimal foraging strategy in variable floral environments.

Figure 2 illustrates the proposed bumblebee-based algorithm employing distributed memory for efficient channel selection. We initialize the algorithm by defining the number of channels in the dedicated memory of the vehicle. During the sampling interval, the vehicles sample the channels and collect the spectrum sensing data. The energy values collected are then converted into the channel rewards and stored in the memory. In the transmission interval, the vehicle selects the channel with the best reward gain and starts the transmission. During the transmission interval, the vehicle simultaneously keeps monitoring the channel reward level and performs packet transmission. If the current channel reward level drops below the channel reward values in the memory, it switches to another channel provided the switching cost is not too high. The algorithm is explained in detail in Section VI. After the transmission interval, the vehicle initiates another sampling interval where new sampling values are stored in the memory, and if a better channel is available the vehicle switches to the new channel.

In Figures 3, 4 and 5, we see the channel spectral map for different frequency bands. The channel characteristics change with the interference from incumbent or other secondary users stochastically. In order to determine whether our memory-based bumblebee algorithm can help to improve the channel selection performance, we performed a channel characterization study. Our bumblebee algorithm leverages past channel energy samples from memory in order to decide whether to stay on the current channel or switch to a different channel. We used broadband Personal Communication Service (PCS), Global System for Mobile Communications (GSM) and lower Long Term Evolution (LTE) bands ranging respectively from 1850–1990 MHz, 825–895 MHz, and 600–700 MHz using a USRP N210 [37] software-defined radio in an indoor laboratory environment. We monitored these frequency bands in order to get the real-time channel sensing data for comparimg against our traffic simulator generated data. Figures 3, 4 and 5 show the time-varying behavior of the channels and the energy values are approximately similar to the ones generated in GEMV^2 [38], which is used in this work to test our bumblebee algorithm. The bands are divided into 10 MHz bins which is bandwidth allocated to DSRC channels around 5.9 GHz center frequency by FCC.

Figure 6 shows the occupancy of the PCS band across a 30 minute period. The bands from 1950 – 1980 MHz possess relatively high occupancy around 100%, where the other bands are underutilized or completely vacant. These bands could potentially be used for the vehicular communication using DSA and their occupancy can be stored in memory in order to help avoid the occupied channels during the busy intervals (when channels are being used).

Without loss of generality, we will employ digital television (DTV) spectrum for this VDSA-based vehicular architecture, since the primary users of this band are relatively stable when compared to other wireless frequency bands. The primary users of the DTV band have a more uniform and steady

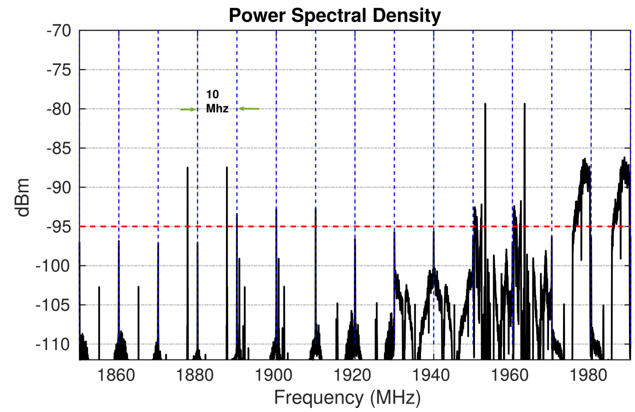

Figure 3: Fixed time snapshot of power spectral density of PCS band shows the vacant and occupied channels in that band [39].

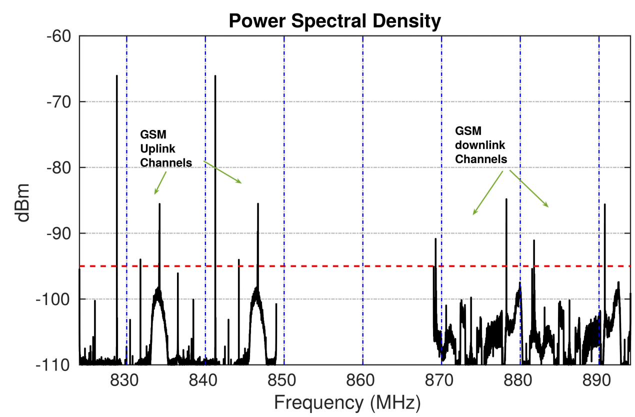

Figure 4: Fixed Time Snapshot of Power spectral density of GSM band shows the vacant and occupied channels in that band [39].

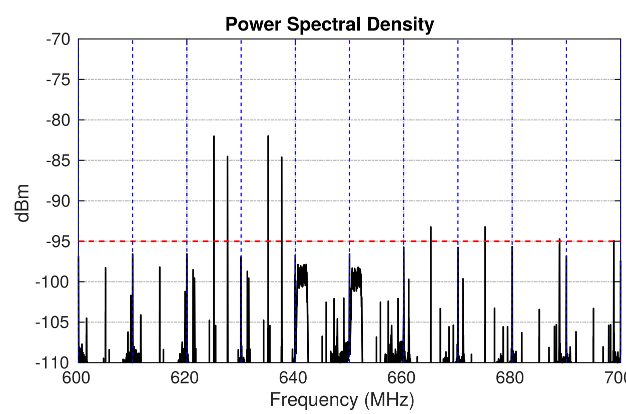

Figure 5: Fixed Time Snapshot of Power spectral density of lower LTE band shows the vacant channels in the band [39].

usage of frequency bands [4]. The vehicles within the vicinity are designed to individually detect the available channels for unlicensed users.

Wireless spectrum is sensed based on a mechanism that detects energy levels for each channel [40]. The channel model considers all entities specific to a vehicular environment such as multipath fading, Doppler shift, and scattering, which can

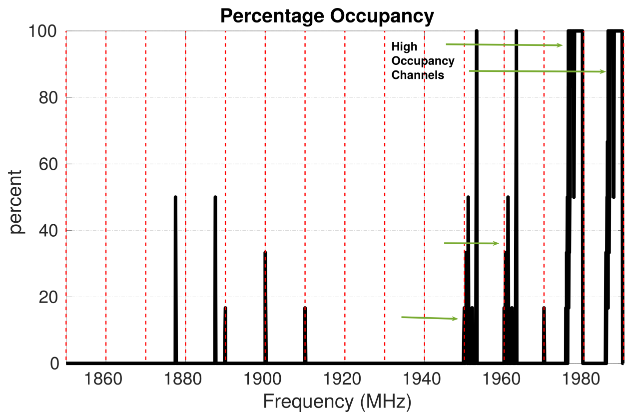

Figure 6: Percentage Occupancy of the PCS band during 30 minutes period from 1850–1990 MHz bandwidth [39].

be mathematically expressed as [41]:

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

where τ is the path delay, 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 M-ary hypothesis test. In this case, the spectrum sensing performs the following a binary hypothesis test:

$$\begin{cases} \mathbf{H}_0 : y(t) = n_r, \\ \mathbf{H}_1 : y(t) = \int_{-\infty}^{\infty} h(\tau,t)x(t-\tau)\mathrm{d}x + n_r \end{cases} \tag{2}$$

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.

The key parameter associated with a channel switching decision is the switching cost, which determines whether the vehicles should continue to use the same channel or search for another. For example, if vehicle switches from channel A to channel B for better reward and it does not take into consideration the switching cost, the vehicle will actually have less throughput due to the switching lag time. Also, the channel that the vehicle switched to might only be slightly better than the previous channel. To remedy this issue, we take switching cost into consideration for maximizing the channel reward of the vehicles. Note that we cannot use a fixed value for switching cost since a fixed switch cost does not work for a highly dynamic connected vehicle environment. For example, the noise level may be low while the vehicle drives across a highway during a time step, and then suddenly it drives into an urban area possessing a high noise floor during the next time step. In this example, switching to another channel may not be the best decision since all of the channels could potentially be affected.

This issue can be resolved by employing our bumblebee–based algorithm, which is suitable for highly time-variant channel environments. For the bumblebee algorithm, we first derive the channel reward function $r(t)$ using the energy values of the channels. The channel reward function $r(t)$ is given by:

$$r(t) = |\min(\hat{E})| - |\hat{E}| \tag{3}$$

where $|\min(\hat{E})|$ is the noise floor of the vehicular radio and $|\hat{E}|$ is the energy value of the channels used in DSA. Thus, the higher the channel reward, the better the channel quality. The channel reward function can be made more sophisticated in order to depend on the radio characteristics and the environment. Eq. (4) describes the memoryless bumblebee algorithm:

$$\begin{matrix}\text{Switching} \\ \text{Decision}\end{matrix} = \begin{cases} r_c \leq (r_n - s_n), & \text{“Switch”} \\ \text{otherwise ,} & \text{“Stay”} \end{cases} \tag{4}$$

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. The switching cost s in this work is assumed in terms of channel reward (% of reward value r_c) in order to reduce the simulation complexity. The switching cost will vary depending on the cognitive radio characteristics and channel environment.

VI. Memory Based Switching Decision

Our proposed mechanism includes an individual memory structure to store the energy levels of the channel during each energy detection period. In this paper, we have assumed that energy detection scheme employed is ideal to simplify the simulation process. In a system without memory, individuals would always respond instantaneously to changing channel conditions [36]. However, instantaneous responses may not always be the most beneficial behavior due to the associated switching costs and potential inaccuracies in the estimation of the channel energy levels. With the help of memory, we can reduce the computation load and eliminate inefficiencies of instantaneous switching which causes low packet-delivery ratio (PDR) and large latency in the vehicular communication system. Algorithm 1 describes the memory based bumblebee algorithm in detail.

The parameter M defines the memory length and it depends on the sampling rate of the cognitive radio, and N is the total number of samples collected in sampling interval t_s. In this work, we have kept the sampling time $t_s = 200ms$ fixed in all scenarios. It will be an interesting problem to see how varying the sampling and transmission times will affect the channel rewards of our bumblebee algorithm, but this is outside the scope of this paper. For the network simulation, we have set the memory length M to $5N$, $10N$, $15N$ and $20N$, where N is the sample size. T is the total simulation time, r is the reward values of the channel, C is the set consisting of all channels used in the simulation, s gives the switching cost, and finally V is the total number of vehicles. We initialize our bumblebee model by assigning random channels to the vehicles and setting the memory length to l. We then perform the computation for each time-step, the discrete time-steps simulates the real-time variation where the channel energies vary with time. As we explained earlier in Section V there are two modes in the algorithm: sampling and transmission. We start the iteration with a sampling interval and then we compute the energy values, map it to reward r, and select best channel for each vehicle v_i.

Algorithm 1 Memory Based Bumblebee Algorithm

procedure BUMBLEBEEALGORITHM(M, r, T, C, V,s)
    Initialize:
    $v_i \in rand\{C\}$
    $M = l$
    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 v_i
        Transmission Interval:
        Start the packet transmission
        Monitor $v_i \in \{C\}$ for $v_i \in V$
        if $r_i < (r_{new} - s)$ **then**
            Switch to the new Channel
        else
            Stay on the same channel
        end if
    end for
end procedure

procedure CHANNELREWARD(E, C, T, V)
    for $t = 1$ to T **do**
        while $c = 1$ to C **do**
            $r(t, c) = |min(\hat{E})| - |\hat{E}|$
        end while
        $V \leftarrow r(t)$
    end for
end procedure

In the transmission interval, we start using the channel and simultaneously monitor our current channel reward values. If the current channel reward value drops lower than the channel values in the memory, we switch to the new channel if the switching cost is lower or else we stay on the same channel. With the parameter r_{new} being the reward value for the new channel, we consider all the channels in the memory when making the switching decision. For each time-step iteration, we have a sampling and transmission interval. During the sampling interval, we sample all the channels again and add new values to the memory. Depending on the memory length, we flush out the old values and keep inserting the new values in a First-in-First-Out (FIFO) manner.

VII. Experiment Results

We have analyzed the performance of a DSA-based VANET using the adaptive behavioral response mechanism in the GEMV^2 Vehicle-to-Vehicle (V2V) propagation simulator via MATLAB. GEMV^2 is a computationally efficient propagation model for V2V communications, which accounts for the surrounding objects in the environment. The model considers different V2V link types (*e.g.*, LOS, non-LOS due to static objects, non-LOS due to vehicles) depending on the LOS conditions between the transmitter and the receiver in order to deterministically calculate large-scale signal variations [42], [43]. Additionally, GEMV^2 determines small-scale signal variations stochastically using a simple geometry-based model that takes into account the surrounding static and mobile objects (specifically, their number and size). We use Simulation of Urban Mobility (SUMO) [44] to generate the car traffic data on the roads since it allows generation of different scenarios such as different environments (*e.g.,* urban, suburban, highway) and traffic densities (*e.g.,* high-density, low-density, changing density). The experimental traffic data is created in SUMO around the city of Worcester, MA, USA and used as an input to GEMV^2. The examples of traffic simulator figures generated by GEMV^2 for downtown Porto, Portugal and Pittsburgh, PA, USA are available in [38]. The channel sensing algorithm is performed across the DTV frequency band at 700 MHz.

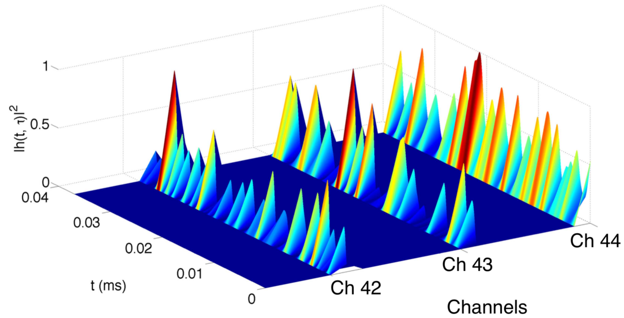

Figure 7: Normalized squared magnitude of the channel impulse response Eq. (1): t refers to the time variation on a channel. Three representative channels are visualized to indicate the environment changes over time.

The resulting channel characteristic is shown in Figure 7. Vehicles switch between channels in order to find the channel with maximum reward of a given time instant. The adaptive behavioral response mechanism is needed in order to decide whether the channel is worth switching to despite the switching cost. The individual memory will provide a solid decision on the channel switching. For example, a vehicle chooses to be on Channel 42 (641 MHz), given the absence of incumbent

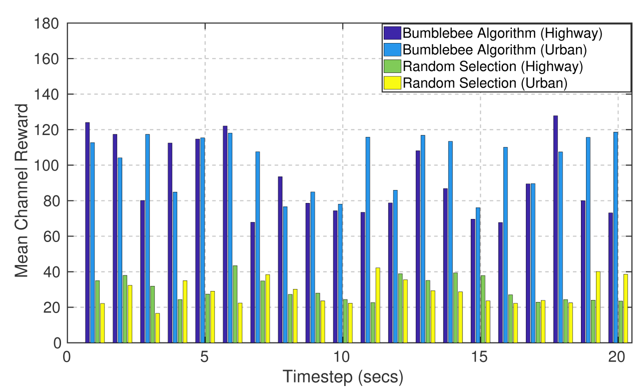

Figure 8: Mean Channel Reward $r(\bar{t})$ comparison for bumblebee model and random channel selection in urban and highway scenario. Vehicles employing the bumblebee algorithm tend to choose the channel with best reward and hence maximize the overall channel reward.

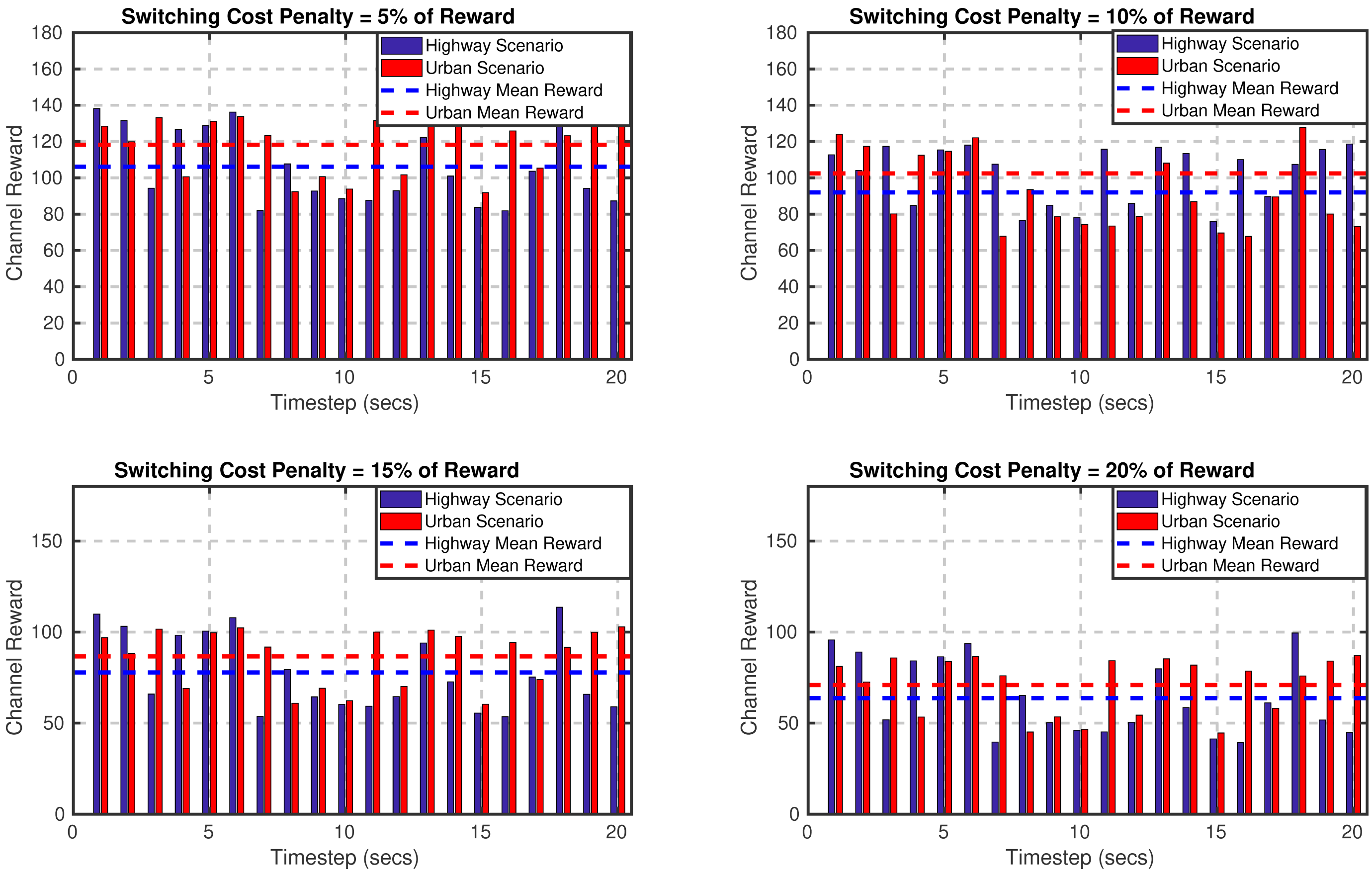

Figure 9: Mean Channel Reward for memoryless bumblebee model for different values of switching cost. The switching cost is computed in terms of channel reward to make it more generalize and independent of cognitive radio characteristics. We start with a switching cost of 5% of the channel reward and then we gradually increase it by 5% for each of the subplots. We can see a gradual decrease in the channel reward for higher switching cost.

users by accessing the past channel values stored in the memory since Channel 42 has consistent reward based on the past channel values. Therefore, the unwanted switching cost, which is caused by instantaneous decisions, will be avoided.

In Figure 8, we compare the memoryless bumblebee algorithm with random channel selection. In random channel selection, vehicles select the random channels on each time-step and stay on the channel until the connection is lost, whereas with the bumblebee algorithm we compare the current channel reward with other channels and switch if it is beneficial after taking into account the switching cost. For a highway scenario, with sparse traffic conditions, 12 $vehicles/km^2$ is simulated, whereas for urban traffic conditions we consider 150 $vehicles/km^2$. The number of randomly moving vehicles increase at each time step from 0 to 800 vehicles for the urban scenario, whereas for the highway scenario the vehicles increases from 0 to 180. The mean distance between the vehicles is around 100 m, with a minimum and maximum velocities of 8 km/h and 110 km/h respectively for both urban and highway scenarios. We see a significant increase in the mean channel reward for both urban and highway scenarios at each timestep. For highly time-varying channel environments, the energy will vary instantaneously, and without memory to store past reward values, the vehicles cannot efficiently make a switching decision.

For a memoryless model, any channel switching is based on the current time-step data, and for highly time-variant channel environment it does not perform efficiently. In Figure 9, we compare the channel reward for various switching costs using the memoryless Bumblebee model. It is evident from the plots as the penalty increases the channel rewards start to decrease. As discussed earlier, the switching cost depend on the environment and the cognitive radio characteristics, and the channel reward will vary with the switching costs. For example, a better cognitive radio will be able to switch to new channel faster and hence it will have low switching cost.

In Figure 10, we compare our memory-based bumblebee algorithm using two different memory strategies applied to both urban and highway scenarios. In the "Max" memory strategy, we select the best channel reward from the past samples (depending on the memory length N) in the memory and compare it with the current channel reward to make our switching decision. If the new channel has a better reward after taking switching costs into consideration, then we switch to the new channel. Using the "Max" strategy we see a 40% improvement in urban environment as we increase the memory length from $M = 0$ (memoryless) to $M = 20N$. For the highway scenario, the overall increase is small. In "Mean"

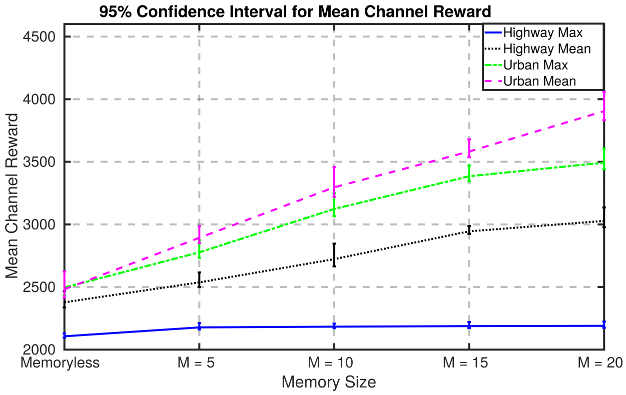

Figure 10: Mean Channel Reward for highway and urban scenario for different memory size with 95% Confidence Intervals. The channel reward increases by using higher memory size for both urban and highway scenarios for the "Mean" strategy. Using the "Max" method the performance increase is only significant for the urban scenario. In comparison to memoryless system we see an increase of about 52% in $M = 20N$ memory size for urban scenario for "Mean" strategy. The Memory length parameter N is discussed in detail in Section VI

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strategy, we take the average of all the channel rewards in memory and compare our current channel reward with the mean values. If the reward is larger after subtracting the switching cost s, then we switch to the channel otherwise we stay on the current channel. By averaging out the channel rewards, we can better estimate the channel quality over time and the "Mean" strategy outperforms "Max" strategy (by approximately 50% for highway scenario and 9% for urban). If we increase the memory length from $M = 0$ to $M = 20N$ using the "Mean" scheme, we see an overall increase of 52% for urban and 37% for highway scenario. These results show by utilizing memory we can improve the channel selection performance drastically and use the channels efficiently.

VIII. Summary and Future Research Directions

In this work, we explore the potential utility of a bumblebee-inspired memory-based decision mechanism within a VDSA framework. Channel reward levels stored in memory are weighed against switch costs to decide whether to stay on the current channel or move to a different channel. Channel reward 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 show 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. In this work, two simple memory structures using block sampling of the environment and than averaging energy values or selecting the maximum value were designed for channel selection. For future work, more nuanced memory structures will be provided in order to increase the channel selection performance even more. We will also make our channel reward function more practical so that it can be used for actual testing of the algorithm during over-the-air transmission on actual software-defined radio (SDR) experimental test-bed. Finally, we will also be using adaptive sampling rates to further reduce the load on V2V vehicular system.

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