On The Capacity Bounds For Bumblebee-Inspired Connected Vehicle Networks Via Queuing Theory

Kuldeep Gill[†], Kevin N. Heath[*], Robert J. Gegear[*], Elizabeth F. Ryder[*], and Alexander M. Wyglinski[†]
[†]Department of Electrical and Computer Engineering, Worcester Polytechnic Institute, Worcester, MA
[*]Department of Biology & Biotechnology, Worcester Polytechnic Institute, Worcester, MA
{ksgill, knheath, rgegear, ryder, alexw}@wpi.edu

***Abstract*—The bumblebee has recently been proposed as a model to optimize channel allocation in connected vehicle networks where the quality of each channel varies unpredictably over time and space. A fundamental mathematical challenge that must be overcome before implementing the bumblebee model is determining the theoretical upper bound of spectrum optimization that can be achieved under such stochastic channel conditions. In this paper, we leverage the concept of queuing theory in order to conduct the performance bound analysis of bumblebee-inspired distributed optimization operation in vehicle-to-vehicle (V2V) environments. We initially established the maximum switching costs associated with urban and highway environment, and then used GEMV^2 and SUMO to compute the performance bounds for several metrics in a time-variant urban environment, including P_m (the probability of all channels being busy) and mean response time. We discuss the implications of these results for future development of bumblebee-inspired vehicular communication systems.**

***Keywords*—Bumblebees, Distributed Optimization, Foraging Theory, Queuing Theory**

I. Introduction

There have been several approaches proposed in the open literature that leverage 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 available resources [1]. 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, [2] which belongs to the field of evolutionary computation and has been studied to solve multi-objective optimization problem. However, GA algorithms yield results across a longer time interval than the coherence time, making them susceptible to rapidly changing environment and outdated information. Recently, bumblebee behavior has been investigated as a mechanism for optimizing network resources in complex distributed architectures [3, 4]. Unlike other natural processes, many of which depend on highly correlated social interaction and decision-making, the bumblebee behavioral model is well-suited for applications where decision-making is performed independently. Consequently, bumblebee behavioral models applied to network resource optimization problems, especially vehicular networks in rapidly changing wireless spectrum environments, are very attractive option.

Focusing on vehicular ad-hoc networks (VANETs), there has been extensive research on the application of optimization techniques based on natural models. For example, in [5], artificial bee colony (ABC) optimization algorithm has been applied to VANETs in order to overcome connectivity and signal fading issues. The authors in [6] employed modified GA algorithms to optimize white space utilization in VANETs. The optimization of routing protocol performance based on both particle swarm optimization (PSO) and ant-colony optimization (ACO) in VANET is discussed in [7]. However, quantitative analyses on the bounds of these approaches have been noticeably absent. Most of the research into bio-inspired optimization techniques has been presented with a problem-specific approach. To the best of the authors' knowledge, no one has yet investigated quantitative performance bounds at the vehicular level.

In this paper, we leverage the concept of queuing theory in order to conduct the performance bound analysis of bumblebee-inspired distributed optimization operation in vehicle-to-vehicle (V2V) environments. The work is based on the techniques presented in [8], where the authors assume the channel is quasi-static whereas in this work we conduct the performance analysis on a time-variant channel and further explore correlated effects between channels.

The rest of this paper is organized as follows: In Section II we describe the bumblebee-inspired optimization technique. In Section III, we compute bounds for vehicular wireless channels based on our proposed Queuing Theory Model. In Section IV the GEMV^2 simulation test-bed is described in detail and results are generated. Concluding remarks and future work is provided in Section V.

II. Bumblebee-Inspired Distributed Optimization

Unlike ants and honeybees, individual bumblebee foragers can acquire information on their own and independently solve optimization problems within a distributed network. Consequently, bumblebees do not need to depend on a centralized information system, which can be highly ineffective and unreliable in environments that rapidly change over time and space [9]. For vehicular networks, this description corresponds to rapidly changing urban environments, where centralized information may be inaccurate or too slow to reflect local

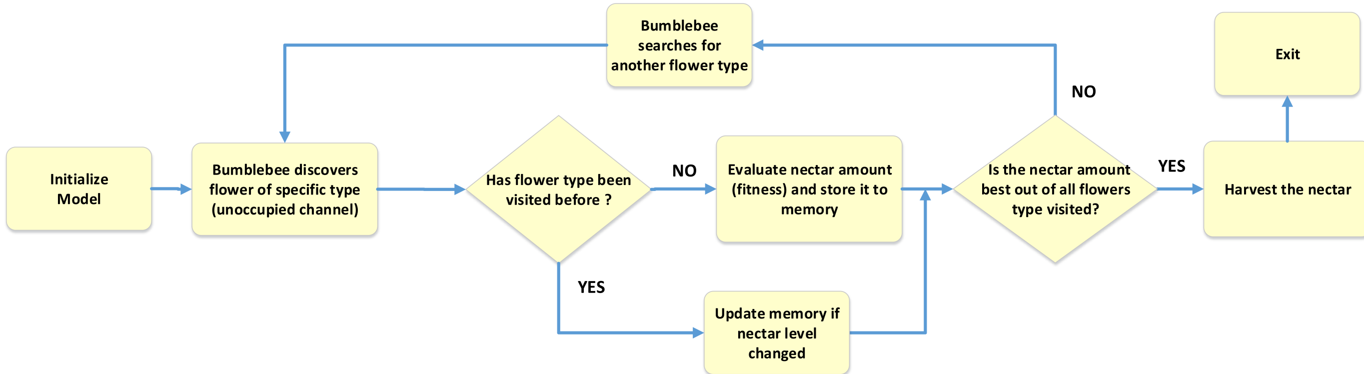

Figure 1: Flowchart describing the bumblebee based distributed optimization algorithm

changing conditions. Furthermore, a vehicle in a rural area may lose connectivity with a centralized database or other neighboring vehicles. In such a scenario, any optimization mechanism relying on this form of communication may potentially not work properly.

In a honey bee colony, the scout bee finds a food source, and then returns to the hive to perform a dance to communicate information on the food source to recruit bees [10]. If the nectar level decreases at the food source, the worker bees are informed of a better food source when they all return to the hive and decode the dance. The scouting process and the need for worker bees to return to the hive in order to be informed about a better food source can incur a significant delay penalty with respect to accessing a better food source. Thus, the honeybee food selection process would be inefficient when the quality of each flower type changes rapidly and unpredictably over time. Similarly, ant colony behavior is based on the tracking of pheromones that primer ants have deposited [11]. Although ant colonies are very efficient with respect to routing, scheduling, and organization, this mechanism also cannot deal with highly time-varying environments.

As an alternative to colony behavior, reinforcement learning (RL) mechanisms have been presented in the existing literature[12, 13]. Genetic algorithms provide a reliable optimization technique but at the expense of a large computational latency with respect to the convergence to the optimum value [14]. Partial swarm optimization is a very fast optimization technique since it jointly solves the fitness function based on a multi-objective formulation [15]. However, it is highly dependent on the initial information about the swarm structure, which is not realistic for connected vehicle networks.

Bumblebee foraging behavior is mainly based on individual decision mechanisms, hence it is well-suited for applications where decision-making is performed independently. 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. Figure 1 illustrates the bumblebee-inspired distributed optimization algorithm and the steps involved in the process. In the first step, the bumblebee discovers a flower of a specific type (channel) and depending on whether the flower type has been visited before or not the following decision is made: If the flower type is new, we calculate its nectar amount and store it in memory. Otherwise, we update the previous memory regarding the flower-type if the nectar level has changed. Subsequently we compare the nectar level of the current flower-type with the existing nectar rewards in the memory and based on the nectar value we harvest the nectar and exit algorithm or we move onto new flower type.

A time-varying stochastic channel also poses the same problems in vehicular environment as a nectar distribution in flowers where bumblebees forage. Table I shows the translation between bumblebee foraging and how it is applied to vehicular communication. Because of the strong analogy between the two systems, we expect utilizing bumblebee-inspired algorithms for autonomous vehicle channel selection to be highly efficient. However, before utilizing the bumblebee model for optimization, we need to first establish the bounds expected for efficiency through utilizing queuing theory.

III. Proposed Queuing Theory Based Bound

Queuing theory has often been used to model multiple access schemes or transmission delay in communication systems and determining the performance bounds for vehicular communication system [8, 16]. Previous work has been conducted with respect to the application of queuing analysis to cognitive radio systems [17–19]. The authors in [16] proposed a priority virtual queue interface at each unlicensed user in order to abstract the multimedia user's interactions and proposed a channel selection strategy. The queuing model introduced in [17] analyzes the performance of a cognitive radio link subject to recurrent failures and interruptions. The authors also incorporated network models with single or multiple channels. From the perspective of unlicensed users, the activity of incumbent users can be regarded as a server breakdown. Queuing models with server interruptions have been widely studied in the literature. In [8] queuing theory was used to analyze the performance of VDSA in vacant UHF TV channels from 470–698 MHz (channels 14 through 51) where they carried out the measurement campaign along I-90 highway in Massachusetts to collect the data for the analysis.

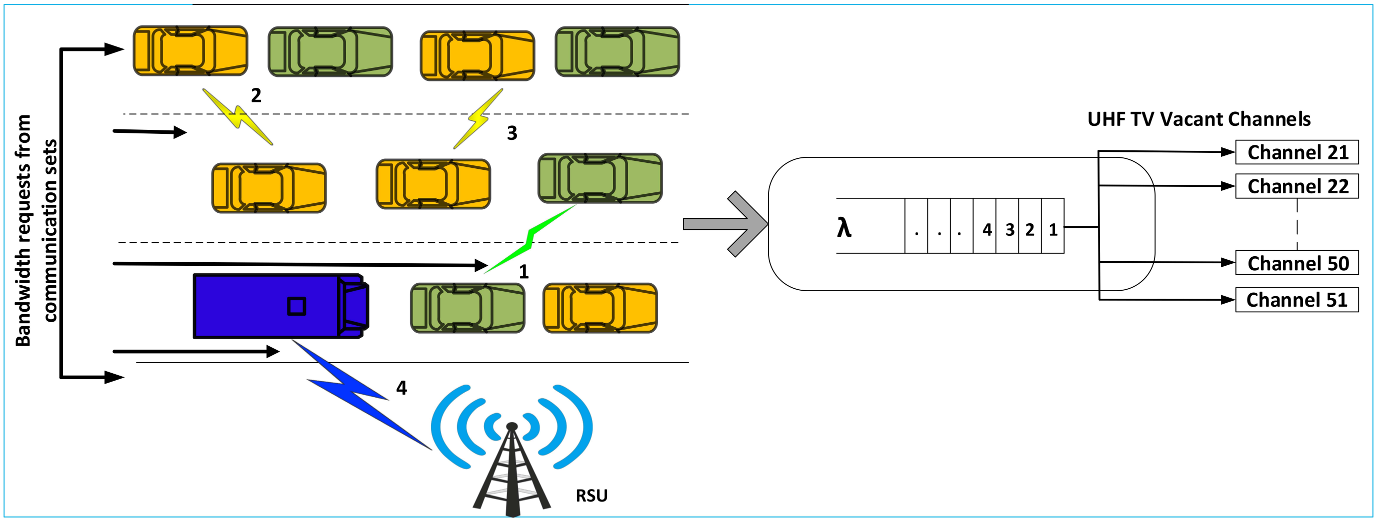

Figure 2: Packet-based Queuing Model for VDSA in vacant UHF TV channels

For the scenario being addressed in this paper, namely high-speed ground vehicles performing dynamic spectrum access across stochastic time-varying vacant TV channels, we propose a queuing model consisting of multiple server and same priority class (see Figure 2). This scenario can be formulated as an opportunistic multiple access problem [8]. We assume a transmission range of 500 m for each consumer vehicle, the same as the transmission range defined in DSRC standard [20]. In this paper, the vehicular channel connections are treated as an M/M/S queuing system due to the time-varying nature of the environment. The arrival process is assumed as Poisson with arrival rate λ and the inter-arrival times are exponentially distributed with mean $1/\lambda$. The service times of the servers are also assumed to be exponentially distributed with mean $1/\mu$. The wireless channels/servers S are assumed to be providing service independently of each other. The first-in first-out (FIFO) queuing discipline is adopted to maintain the same priority for all the vehicles.

The traffic intensity ρ which directly relates to number of vehicles N, λ, μ and number of servers S is given by:

$$\rho = \frac{N\lambda}{S\mu}. \tag{1}$$

The probability that there are no jobs in service in such a system, is given by [8]:

$$P_0 = \left[\sum_{k=0}^{S-1} \frac{(S\rho)^k}{k!} + \frac{(S\rho)^S}{S!(1-\rho)} \right]^{-1}, \tag{2}$$

And the probability that all servers are busy, also referred to as Erlang-C P_m is given by:

$$P_m = \frac{(S\rho)^S}{S!(1-\rho)} P_0. \tag{3}$$

Thus, the probability of having at least one vacant UHF-TV channel is given by 1-P_m. For M/M/S queuing model the mean waiting time T_W given by [21]:

$$T_W = \frac{\rho}{\lambda(1-\rho)} P_m. \tag{4}$$

The expected mean response time T_R, which describes the mean amount of time spent by each job in the queue, is expressed as:

$$\begin{aligned} T_R =& \frac{1}{\mu} + T_W \\ =& \frac{1}{\mu}\left(1 + \frac{P_m}{S(1-\rho)}\right) \end{aligned} \tag{5}$$

For S channels/servers the optimal number of vehicles which can sustain the communication without breaking the connection, with each vehicle requesting data with a packet-rate λ

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

Vehicles	**Bumblebees**
Channel	Floral Species
Channel Sensing	Bumblebee Foraging
Radio Discovers New Channel	Bumblebee Discovers Flower of Specific Type
Minimum Channel Energy Level	Maximum Nectar Level Per Floral Species
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

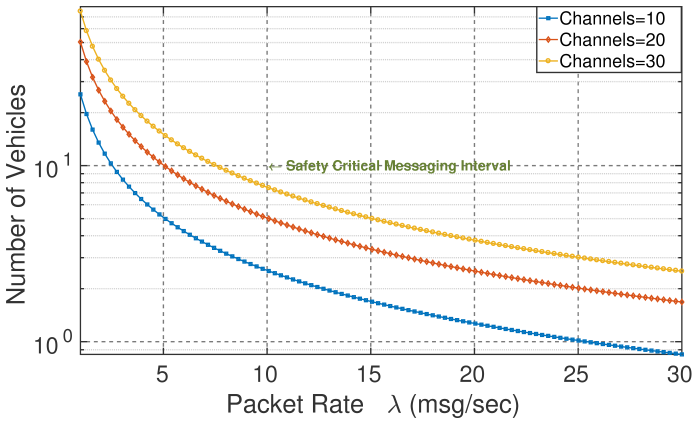

Figure 3: Total Vehicles With Optimal Communication between the vehicles.

and 1-γ of the requested packets will be served within time t is given by [22]:

$$N < \frac{\mu t S - log(\frac{P_m}{\gamma})}{\lambda t} \tag{6}$$

Eq. (6) shows that the number of vehicles N should be less than the bound to achieve optimum performance. The Figure 3 shows the relationship between the number of vehicles and packet rate with fixed number of channels.

IV. Simulation Test-bed and 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 [23]. GEMV^2 is a computationally efficient propagation model for V2V communications, which accounts for the surrounding objects. The model considers different V2V link types (LOS, non-LOS due to static objects, non-LOS due to vehicles) depending on the LOS conditions between the transmitter and the receiver to deterministically calculate large-scale signal variations. 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). Simulation of Urban Mobility (SUMO) [24] was used to generate the traffic data 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 channel sensing algorithm is performed for DTV frequency band at 700 MHz.

In Figure. 4 we compare the switching cost between highway and urban environments. The highway scenario assumes sparse traffic conditions (12 $vehicles/km^2$), while the urban scenario assumes dense traffic conditions (150 $vehicles/km^2$). We assume a random channel switching for both scenarios where vehicles decides to switch to another channel during each time-step without any switching decision. The urban scenario has a very high switching cost due to the highly stochastic nature of the environment. This highly time-variant urban scenario is similar to the bumblebee foraging environment, where the nectar reward (noise in the channel) varies rapidly, requiring the bumblebee to respond quickly. Thus, we expect that applying the bumblebee-based distributed optimization algorithm will greatly reduce switching cost by selecting the channel based on past experiences.

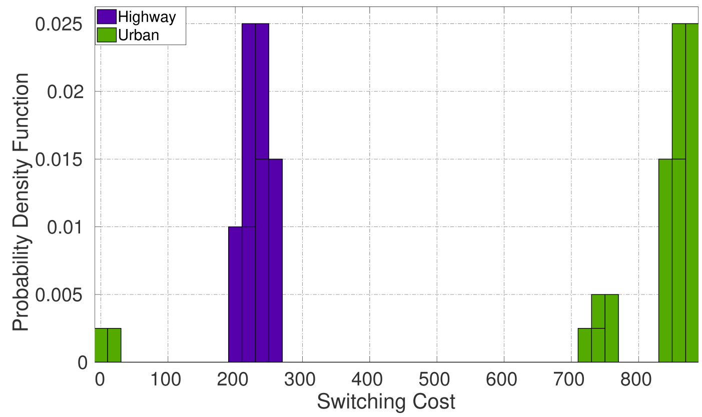

Figure 4: Comparison of Switching Cost in highway and urban environment. The high switching cost in the urban scenario implies the high amount of channel switching which results from highly time-variant channel.

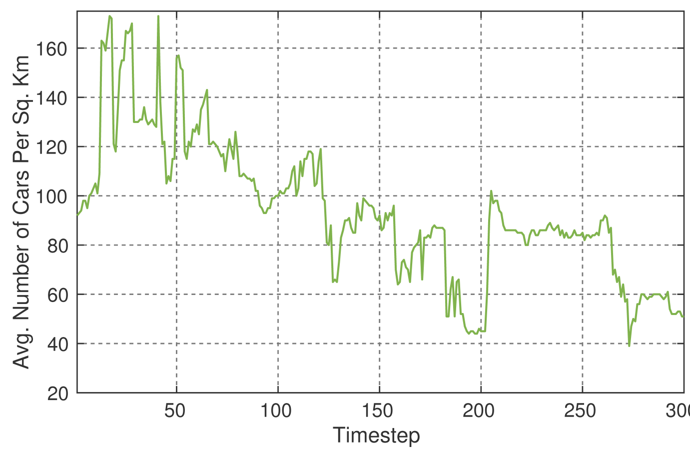

Figure 5: Average number of cars per square kilometer simulated in GEMV^2 in Worcester, MA.

Figure 5 shows the average number of cars per square kilometer simulated in GEMV^2 using SUMO. To estimate the bounds in a dense urban environment an average of 100 vehicles are used entering and leaving the downtown Worcester area. The figure shows how the vehicles change each time-step around the area and later gradually exit the area. In Figure 6, the probability P_m of all servers being busy is shown around the Worcester area. The figure is generated using 10 servers and two different packet rates λ are used. For $\lambda = 10$ we have excellent P_m depending on the number of vehicles. But as the packet rate is increased, the performance of system starts degrading. Finally, the mean response time is

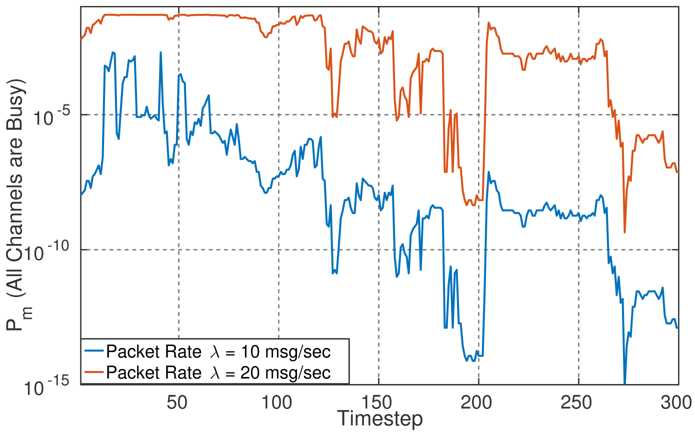

Figure 6: The Probability (P_m) of all channel being busy observed by the vehicles during the discrete timestep emulating the real-world environment.

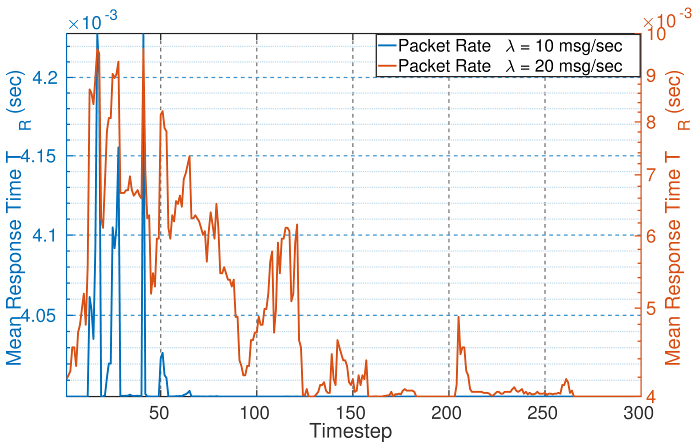

Figure 7: The predicted Mean Response Time (T_R) for vehicles performing VDSA in a simulated real-time environment.

provided in Figure 7 for both packet rates and as expected we see the increase in mean response time for higher packet rate.

V. Conclusion and Future Work

In this work, we explore bumblebee-inspired distributed optimization and compute the quantitative performance bound using queuing theory. We showed that switching cost varies in urban and highway scenarios and how we can apply the bumblebee algorithm to optimize the channel switching. Since an urban scenario is similar to bumblebee foraging environment, bumblebee-distributed optimization can be applied to optimize the channel switching. Finally, we computed the performance bounds for metrics such as P_m which is the probability of all channels being busy and mean response time in a time-variant urban environment using GEMV^2 and SUMO.

In the future we will use the bumblebee distributed optimization on top of the GEMV^2 with memory to see how the past experience can help in improving channel selection.

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