From Channel Selection to Strategy Selection: Enhancing VANETs Using Socially-Inspired Foraging and Deference Strategies

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***Abstract*—Dynamic spectrum access (DSA) has been hailed as a possible panacea for the "spectrum crunch," drawing significant attention from researchers and industry alike. Here, we describe a novel system architecture for vehicular ad-hoc networks (VANETs) that relies on the DSA framework. In our system, nodes continuously and independently choose one of three strategies for channel selection. Two of these strategies are biosocially inspired, based on resource sharing behaviors known to have been prevalent in human societies over the course of their natural evolution. We view the strategy selection problem as an evolutionary game, proving that the only evolutionarily stable strategy is one in which all nodes utilize the same strategy that depends on the social characteristics of the nodes and the current channel conditions. Within our system, a specialized road side unit (RSU) continuously computes the game-theoretically optimal evolutionarily stable strategy and broadcasts this recommendation to all VANET nodes. Through `ns-3` simulation experiments across a range of social characteristics and channel condition scenarios, we demonstrate that a significant and robust improvement in utility (from 3% to 136%) is achieved when a large fraction of VANET nodes adopt the RSU's recommendation. The approach represents a bold departure from previous research which sought to track and micromanage channel resources from a short-term perspective, to one that provides VANET nodes with long-term recommendations for channel access *strategy*, both optimized for throughput and robust against attempts at circumvention by deviant users.**

***Index Terms*—Bio-social networking, cognitive radio, dynamic spectrum access, evolutionary game theory, VANET.**

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I. Introduction

INTELLIGENT transportation systems promise to deliver new safety and efficiency applications including pedestrian and vehicular safety, reduced fuel consumption, and reduced pollution. The design focus of new systems typically prioritizes one of several broad areas: safety, efficiency, convenience, and infotainment applications [1].

Vehicular Ad-hoc Networks (VANETs) are a key technology enabling intelligent transportation systems (Vegni *et al.* provide a good recent survey [2]). In VANETs, vehicles communicate directly with each other and with road-side infrastructure. VANETs are critical communication environments due to the fast mobility of vehicles. The Dedicated Short Range Communications (DSRC) licensed spectrum helps address some of the communication needs of VANETS. Using DSRC spectrum resources in a manner that scales with VANET size, however, requires robust resource sharing protocols.

Dynamic Spectrum Access (DSA) is a new resource sharing paradigm in wireless networking, in which radio spectrum frequencies are assigned dynamically to users in order to combat spectrum scarcity. Cognitive Radio (CR) is a framework of enabling technologies which facilitate the implementation of self-configuring DSA networks [3] that allow spectrum sensing, management and sharing. The sensing technologies developed to coordinate PU-SU interactions [4] can be adapted within the CR paradigm to enable more harmonious SU-SU co-existence, and ensure more effective resource sharing.

Here we will develop a bio-socially inspired approach to DSA, with the objective of enhancing the throughput of infotainment applications in VANETs. The impact of this is ensured by the multi-channel structure of the DSRC in the IEEE Wireless Access to Vehicular Environment (WAVE) standard: by improving infotainment throughput, greater residual bandwidth becomes available for safety traffic. Generally speaking, bio-socially inspired algorithms leverage knowledge about social and biological communities to design resource management solutions in a variety of domains. Here we apply prior findings on observed behaviors and structures of resource sharing and co-use in human societies [5] to design a new and highly effective DSA scheme for VANETs. In keeping with the bio-social paradigm in what follows, we will use the phrase "consuming a resource" and "transmitting in a channel" interchangeably.

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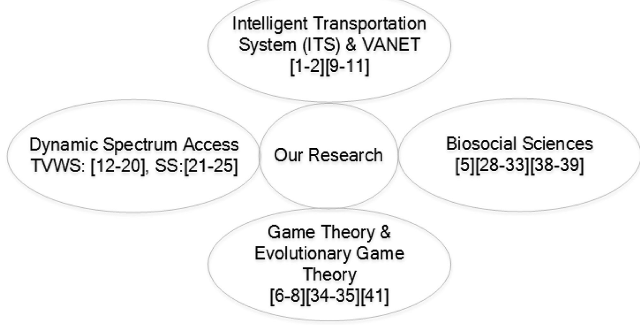

Fig. 1. A map of previous work and related areas of inquiry.

Likewise, the phrase "foraging" will signify passively listening to traffic for the purpose of collecting channel state information, without transmitting.

This work considers 3 models of resource sharing behaviors:

- **Always Consume User (ACU):** A user who always consumes, choosing the resource to consume blindly at random.
- **Forage-Consume User (FCU):** A user who only sometimes consumes, and otherwise forages, using information gathered during foraging to choose where next to consume.
- **Social Forage-Consume User (SFU):** An FCU who sometimes "defers" to other SFUs, that is, refrains from consuming so as to allow other SFUs more exclusive access to the resource they are consuming.

To quantify the merit of our proposed behaviors, we will use both simulations and formal analysis using evolutionary game theoretic techniques. Game theory is a mathematical formalism that can model strategic interactions among agents, which has been used in a wide range of domains, including wireless spectrum sharing and sensing [6] [7]. We will rely on the sub-discipline of evolutionary game theory (EGT), which is specialized to strategic aspects of evolution in terms of individual fitness within a community [8]. Fig. 1 depicts the relationships between our method and several closely related approaches in previous literature.

The remainder of this paper is organized as follows: Prior work is discussed in Section II. Section III introduces the proposed approach followed by Section IV in which we introduce the system model, and how the three proposed bio-socially inspired strategies are applied in the context of VANETs. Simulation results are discussed in Section V. The formal analysis comparing the three strategies (two of which are bio-socially inspired) is presented in section VI. Finally, Section VII provides a discussion of the implications, and an outlines of future research directions.

II. Prior Work

Different aspects of VANETs have been the subject of active and ongoing research. Several recent surveys consider VANETs from the specialized perspectives of routing [9], security [10], new technologies [11], and cloud-based approaches for VANET [12] [13]. Pagadarai *et al.* [14] were among the first to explore the potential application of DSA into vehicular communications, while Khabbas *et al.* [15] considered the application of DSA in Vehicle to Infrastructure (V2I) systems.

Some researchers have explored the possibility of using other bands, such as TV White Spaces (TVWS) [16]–[18]. Lim *et al.* use both TVWS and DSRC bands [17] by using TVWS for Emergency Safety Messages and DSRC for data and control messages. TVWS have also been utilized in the context of VANETs for route selection [19], minimizing channel switching overhead due to mobility [20], media streaming [21] and for VANET data offloading [22] [14]. With the introduction of the LTE-Direct capability in LTE Release 13 standard (and beyond), LTE-Advanced and 5G become potentially viable options to be utilized in support of ITS safety and infotainment applications [23]. Given the availability of the 5.9 GHz DSRC band [24]), several researchers have begun to explore the potential of this band to support infotainment ITS applications [25] [26] [27] in innovative and practical ways. In this paper, we too limit consideration to the DSRC band and to its use for infotainment services.

In this work, we present new DSA strategies for the band, and demonstrate their efficacy by conducting experiment using WAVE modems (IEEE 802.11p standard). In these experiments, WAVE modems act as a conceptual proxy for other communications modems including LTE-Advanced and 5G. While we expect to reach analogous conclusions (with respect to relative performance enhancement of our DSA schemes) when we repeat these experiments using LTE-Advanced and 5G modems in the future, the current set of experiments are limited to WAVE modems.

The notion of "foraging" is of course closely related to spectrum sensing, which is in turn a central aspect of DSA and the subject of a lot of prior research (see the survey by Abeywardana *et al.* [28]). In the VANET context, Kremo *et al.* developed cooperative spectrum sensing mechanisms for TVWS [29]. Doost-Mohammady *et al.* developed a system using spectrum sensing base station for database-assisted cognitive vehicular networks [30]. Tradeoffs between local (vehicular) and global (database-assisted) spectrum sensing are considered by the work of Al-Ali *et al.* [31]. *Along those lines, in this paper, we are less concerned with accurate sensing, and more concerned with understanding when sensed information (that is assumed to be accurate) can be profitably leveraged towards higher throughput, and when it cannot.* Huang *et al.* explored the potential of spectrum sensing to increase safety traffic throughput [32]; we are considering an analogous problem here for infotainment traffic.

Many researchers have designed and evaluated services that assist users in finding a good band. *In contrast, in this paper, we propose a cloud-based solution that assists users in choosing a good channel selection strategy*. Examples of previous approaches include that of Rawat *et al.* who proposed a cloud-based solution in which each vehicle downloads spectrum availability information on one fixed-channel device while actual vehicular communications take place on a second tunable-channel device [33]. Similarly, Luo *et al.* develop a database-assisted white space system incorporating technical and economic features [34]. In their system, white space information is updated

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TABLE I
COMPARISON WITH RELEVANT LITERATURE

Authors	Contribution
Aygun *et al.* [38]	Minimize the total cost of SU channel switching by applying bumblebee behavior to inform channel selection
Wisniewska *et al.* [49]	Enhance SU utility by applying contention sensing, evaluated using stochastic agent-based social simulation.
Wisniewska *et al.* [50]	Describe evolutionary pressures in CR societies, towards strategies that make use of emerging SU capabilities such as foraging, contention sensing, and sociality.
Shattal *et al.* [47]	Enhance spectrum utilization for IEEE WLAN 802.11g using evolutionary schemes, validated using `ns-3` experiments.
Shattal *et al.* [48]	Establish an evolutionary game theory framework for SU-SU interactions and use this to formalize evolutionary schemes, validated using experiments on a WLAN hardware testbed.
This work	Design a VANET system to maximize infotainment throughput through dynamic strategy selection and sensing/social capability engagement by VANET nodes, evaluated using `ns-3` IEEE WAVE simulations and evolutionary game-theoretic analysis.

periodically by spectrum licensees, and users send location-based queries to obtain current regional white space listings.

Several authors have previously proposed solutions with a bio-social component. Fei *et al.*, for example, introduce the benefits of leveraging social centrality among users with common interests to enhance DSA in VANETs [35]. Sociality also plays a role in Frigau *et al.* proposal for an adaptive multi-channel social relay strategy [36] that optimizes the transmission of service updates. A social approach for SS is proposed in [37]. Perhaps closest to our own work is the that of Aygun *et al.*, who developed novel bio-social DSA schemes for VANETs based on the social foraging and consumption behavior of bumblebees [38].

Social behaviors were utilized in a variety of engineering applications. The work of Chen *et al.* [39] applied social behaviors and social interactions including conformity, imitation, and experience sharing in support of transportation applications. Furthermore, users' preferential weights were utilized by Emrich *et al.* [40] to provide recommendations for the points of interest for users with similar profiles. In the Internet of Things (IoT) domain, the work of Mirri *et al.* [41] applied social tendencies such as altruistic behaviors to assist in the identification of objects, through users collaborations to offer services for visually impaired users. In the domain of security, Zheng *et al.* [42] utilized a hybrid social approach to enhance users' privacy, by regulating the publishing of user's sensitive data based on both the user's profile and behavior. In the computing domain, Song *et al.* [43] proposed a distributed storage model that utilizes selfishness and rationality among contributing nodes to support resource selection mechanism and replica placement.

In this paper, we consider schemes based on more complex processes–reflecting cognitive and social phenomena observed in human societies–that give rise to a range of resource-sharing behaviors [44]–[46] and extend existing evolutionary game theory frameworks [47], [48], applying them to the problem of serving infotainment requirements in VANETs under the synchronization interval timing constraints.

Previous research has considered social interactions among SUs in cognitive radio communities under different assumptions about SU's channel sensing capabilities [49], albeit without consideration of network implementation issues. Others have explored social behaviors, including group structures that incentivize SU deference, and starvation avoidance mechanisms based on "hunger" accumulation [50]. We extend these established models further here, by rendering them for application in vehicular networks, and evaluating our proposed implementation using evolutionary game theoretic analysis and ns-3 network simulation. Our work applies channel sensing and social deference within a process of strategic evolution in the VANET domain.

The application of bio-social strategies to VANETs is not without precedent. Aygun and others apply bumblebee organizational structures towards enhancing DSA in VANETs [38]. However, the focus of their work is channel selection–which is achieved by maximizing the adaptability of individual vehicles to access better channels, and minimizing accumulated cost associated with channel switching. Following their model, we too consider a system of SUs that are able to switch from channel to channel based on the channels condition and user demand. However, we consider a system is which users decide on a strategy first, and then access channels stochastically based on the chosen strategy's prescription. Table I, summarizes the contribution of this work in comparison with recent relevant work in literature.

III. APPROACH

We begin with two observations: (1) Each user does not compete against one other user for a channel, but rather simultaneously against all other users and over all channels; (2) If users gradually change strategies over time by mimicking the strategies of peers who are achieving greater utility, then the system can be considered to be evolving. These two observations naturally point to an evolutionary game. *Playing the field games* consider the behavior of a large population of strategically interacting players [51], each of whom plays against the whole community (or a subset thereof). While pair-wise games require complete knowledge of the utilities (prior to the game), playing the field games involve the accumulation of empirical information on relative advantages of pure strategies (see Nash [52]). An Evolutionary Stable Strategy (ESS) is defined to be any strategy which, once adopted by a community, cannot be displaced by any different "invading" strategy. The ESS may be viewed a Nash equilibrium since players who unilaterally deviate from the ESS see no gain. Having recognized that our DSA problem in VANETs can be cast as a game against the field, the ESS of our game will turn out to be critical to our understanding of the VANET's performance.

In the proposed architecture (see Fig. 2), a community of vehicles moves along a network of roads that are covered by a set of fixed Road Side Units (RSUs), each of which is connected to

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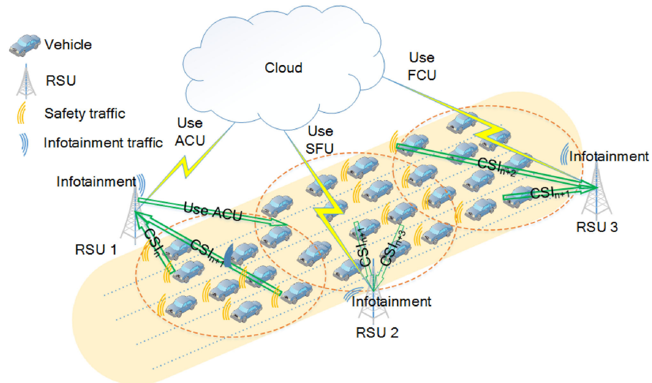
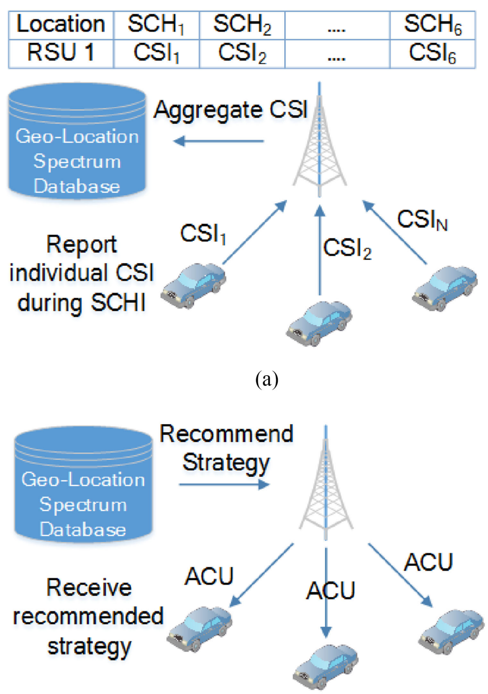


Fig. 2. Strategic DSA for VANET.



(a)

(b)

Fig. 3. System interactions for strategic DSA.

a back-end cloud-based service. VANET nodes are responsible for periodically reporting their local Channel State Information (CSI) and sending it to their local RSU, stamped with the current time. Interference level, noise level, and capacity are examples of potential CSI. In this work, the CSI is simply each node's measurement of its own recent throughput in its current channel; we take this as a proxy for the channel's residual capacity. Each RSU receives this CSI information from VANET nodes, and continuously updates a geo-indexed spectrum availability database, effectively producing a live channel-by-channel residual capacity heatmap (see Fig. 3). Each RSU periodically examines this live data, and then via a game-theoretic analysis computes a strategy recommendation, which it sends to all VANET nodes within its broadcast radius. It is important to note that the RSU's recommendation is *not* for specific users

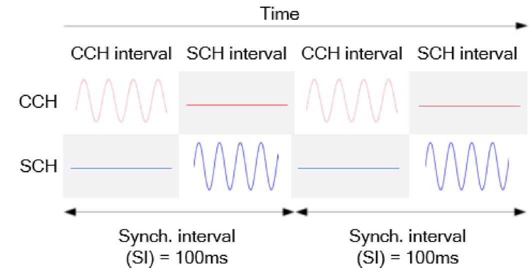


Fig. 4. Synchronization interval in alternating mode in IEEE 1609.4.

to use specific channels[1]—rather the RSU simply recommends that all users (uniformly) follow a particular strategy.

IV. System Model

Our proposed system supports N VANET nodes, each of which sends/receives infotainment data at a combined rate of R bits/s. The system is designed over the DSRC 5.9 GHz band in alternating mode (see WAVE standard [53] for details). In this mode, flexible alternating access is provided to support $n = 6$ service channels (SCHs) and 1 control channel (CCH). VANET nodes synchronize their transmission across a 100 ms synchronization interval which is, in turn, divided into SCH (α ms), CCH (β ms) and guard subintervals (see Fig. 4, $\alpha + \beta \approx$ 100ms). The node send/receives infotainment data (over IP) to the RSU during the SCH interval, as well as receiving any strategy recommendations broadcast by the RSU. During the CCH interval, the user broadcasts Basic Safety Messages (BSMs), WAVE short messages, and WAVE Service Announcements (WSAs). The last of these is used by vehicles to announce their SCH during the next SCH interval (SCHI). Each SCH has a residual capacity of C_i bit/s ($i = 1, 2, ..., n$); and nodes' recent measurements of their throughput in channel i collectively serve as a proxy for C_i. The normalized residual channel capacity of channel i is defined as $\overline{\mathrm{C_i}} = C_i / \sum_j C_j$. For system evaluation, we use throughput γ as a metric for infotainment traffic, and Packet Delivery Ratio (PDR) as the metric for BSM broadcast messages. Fig. 5 provides an interaction diagram for the key entities in our system; the sequence of interactions is as follows.

1) A User enters a coverage area handled by a given RSU.
2) The RSU sends the most recently computed ESS as a strategy recommendation to the user, who then starts accessing the bands using the recommended strategy.
3) During the Service Channel Interval, the user sends/receives infotainment traffic to/from the RSU.
4) During the Control Channel Interval, the user sends BSMs.
5) The User reports sensed CSI along with its corresponding time stamp to the RSU.
6) Reported CSI and selected channel access strategies are stored in a geo-location spectrum database for strategy analysis.

[1]Indeed, individual channel occupancies are likely to be fluctuating so rapidly as to render specific channel recommendations useless.

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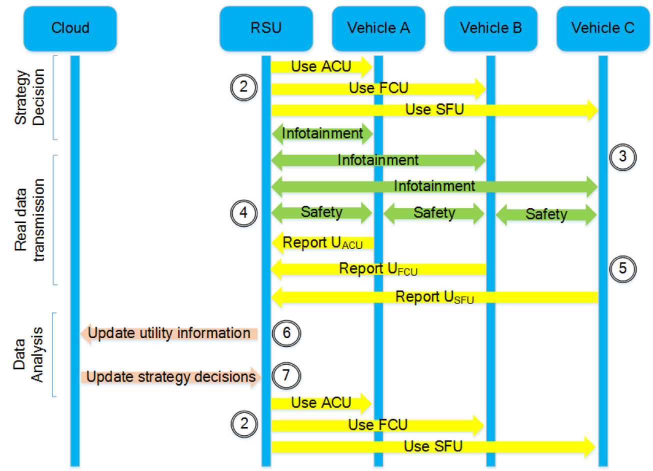

Fig. 5. Sequence of system events.

7) A cloud-based entity computes the ESS strategy based on the geo-location spectrum database entries for the given service area and time. Steps 2 through 7 repeat periodically.

By providing the ESS as its strategy recommendation to the VANET nodes, the RSU ensures that (if almost all nodes adopt its recommendation) no small group of opportunistic nodes will be able to gain unfair advantage by deviating from the recommended strategy. As we shall see in Section VI, the RSU can actually compute the ESS-based recommendation as a closed-form expression, based on the aggregated CSI data.

In this work, we consider a "menu" of three strategies (two of which are bio-socially inspired): The **Always Consume User (ACU)** is always transmitting on an SCH that is uniformly selected from all SCHs. This strategy was used previously by Xin *et al.* [54], and allows the ACU to act with a naive opportunistic view to capture utility using the set of channel resources. The ACUs strategy can be implemented cheaply since no sensing capability is needed. The channel selection process itself is fast, requiring minimal computational resources and no coordination overhead. When transmitting, an FCU chooses to transmit on channel i with probability $1/n$.

The **Forage Consume User (FCU)** engages in two different activities stochastically. With probability P_f it "forages," sensing CSI [2] while ceasing transmission, while with probability $P_c = 1 - P_f$, it "consumes" or transmits data on a SCH. When transmitting, an FCU chooses to transmit on channel i with probability $\overline{C_i}$. The FCU forgoes short-term utility benefits while in the foraging state, but may stand to gain more long-term utility by acquiring data about the channels. On the other hand, too much foraging could yield inefficient usage of spectrum resources and decreased users utility. FCU accesses channels based on channel characteristics, favoring channels with higher residual capacity.

Advancing from FCU, the **Social Forage Consume User (SFU)** incorporates sociality as an additional factor in its channel selection logic. This type of user has sensing capabilities beyond the measurement of relative capacity levels. In particular, SFUs may be biased against *not* transmitting on channels where other SFUs are transmitting. We refer to this phenomenon as **deference**. The SFU strategy model reflects well-known findings from the structure of animal societies [55] and well as those of non-human primates [56], where sociality plays a significant organizing function and helps towards species survival. To model this phenomenon concretely, we assume that while consuming, an SFU can either be in Defer state (relative frequency P_s) or Active state (relative frequency $1 - P_s$). While in Defer, a user does not transmit at all; in contrast, while in Active, the user transmits at an elevated rate $(1 + S_+)R$, making use of the additional bandwidth made available by the deference of their peers. To account for the potential costs of deference coordination among the SFUs, we will assume that each gives up S_- fraction of its utility towards coordination overhead. We take $S_- \propto c_0 N^h$ where $h \in [0, 2]$ is the penalty due to coordination overhead among SFUs to access the channel. The parameter h represents the extent of coordination, with $h = 2$ being full coordination and $h = 0$ being no coordination. Full coordination implies that SFUs must spend time and channel resources to transmit the $O(N_{SFU}^2)$ coordination packets needed to exchange data about the each SU's state (e.g., what channel they are in, and whether they are active or deferring). The value of S_- abstracts the details and (multiplicative) opportunity cost arising from this coordination overhead. More complex coordination schemes are represented by higher values of S_-. In this work, we assume that the decision to defer (or actively transmit) is determined by a Bernoulli process that specifies deference with probability P_S; this simplification limits the complexity of SU-SU interactions, while still allowing for interesting theoretical and experimental results.

The RSU aggregates and relays per-band throughput measurements from its area nodes to the cloud. The cloud service uses this data to compute the evolutionary stable strategy through simulations. The existence of such a strategy is analyzed in Section VI. Having computed the ESS, the cloud relays this optimal strategy to the RSU, which then broadcasts it onwards to its area nodes; the data flow is shown in Figures (2) and (5). The performance advantage of such a scheme is explored in Section V. Note that the recommendation only specifies the strategy type (e.g., ACU, FCU or SFU), and not node attributes (e.g., P_c, P_s, and S_+) which are assumed to be static and external to the optimization process. The dynamic optimization of node-specific parameters, and a fine-grained analysis of control traffic overhead are beyond the scope of this work and are planned for future research. Here we seek to evaluate the feasibility of the proposed bio-social strategies and their optimal dynamic selection in the VANET domain, and to understand the impact of social attributes on the performance of the infotainment traffic.

We note that the above distribution of computing responsibilities across cloud and RSU resources is just one realization of a concrete system architecture whose further optimization

[2] In this work, we do not focus on contributions toward the problem of spectrum sensing, but rather assume that an FCU has access to sufficient information about the channel at the moment of decision-making. In our analysis and simulation experiments (described in later sections), the FCU has access to basic CSI on noise and interference levels), implemented as channel sniffing spectrum sensing at the MAC layer.

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is outside the scope of this paper. Neither a cloud-only nor an RSU-only approach can be argued to enjoy an obvious dominance over the other in the current context. However, the above cloud-based rendering may be more advantageous long term, as we aspire to fuse the data of neighboring RSUs towards the design of more coordinated macro strategy selection schemes in our future work.

Research Questions

The potential of using a bio-social model to enhance spectrum access in the context of the VANETs prompts the following research questions:

1) *Can the bio-socially inspired FCU, and SFU strategies enhance spectrum access and utilization in VANETs, compared to the baseline performance of ACUs?*
2) *From the perspective of group performance outcomes, is there a uniform "best strategy" to be played, or does the best choice depend on the environmental conditions?*
3) *Is the best choice with respect to group performance outcomes "robust" against unilateral actions of users who try to deviate from it individually for selfish motives?*

We will gain experimental intuitions into the first two questions through simulation experiments in Section V. There we shall see that (1) the bio-social schemes FCU and SFU can often enhance spectrum access and utilization (compared to baseline performance of ACUs) in VANETs, but that (2) which of the three strategies performs best depends very much on the environmental conditions. Those insights will be proved in Section VI, where we will also resolve question (3) by a formal analysis showing that once a group adopts the best strategy, no user can gain any advantage by deviating from the group's chosen strategy (assuming the environment does not change significantly). In resolving these questions, we arrive at a new understanding of resource co-use dynamics, which in turn motivates the architectural design of our system for enhanced VANET communication: (I) A road-side unit continuously senses environmental conditions, computes the optimal bio-social strategy, and broadcasts this as a recommendation to all users; (II) users willingly adopt the strategy recommendation, knowing that by doing so they will get optimal utility as a group (across the space of bio-social strategies), and assurance that no (sufficiently small set of) users will be to do better by taking an alternative strategy.

V. Simulation Performance Analysis

Our experiments are carried out using `ns-3` [57] to simulate an 802.11p environment with 6 service channels and 1 control channel, all OFDM channels with a data rate of 3 Mbps (see Table III for details).The `ns-3` 802.11p model utilizes the ns-3 WiFi module for wireless signal transmissions, incorporates signal-to-noise-plus-interference ratio (SNIR) [58], and provides error rate models that agree closely with results obtained on physical hardware testbeds [59], giving us confidence in conclusions drawn from our simulation experiments. The experiments adopt non-idealized channels with a capacity of 3Mbps (a standardized parameter in IEEE 802.11p), in which the perceived capacity of the channels is affected by PHY layer conditions and any potentially non-compliant vehicles in the vicinity of our system of vehicles. In the experimental framework, channel capacity assumptions may in principle be set differently, the only formal requirement being that the system complies with the `ns-3` IEEE WAVE 802.11p standard implementation.

In this work, we applied the National Institute of Standards and Technology (NIST) error rate model [60]. When experiments required a heterogeneous spectrum environment, we set channels 1, 2, 3 to have an energy detection level of -61.1 dBm, while the channels 4, 5, 6 operate at a -91.1 dBm setting. When we needed to consider scenarios with homogeneous spectrum environment, we set all 6 channels to operate at a -91.1 dBm setting. Within the experiments, the `ns3::ConstantPositionMobilityModel` mobility model was chosen so as to exclude the effects of mobility on the variability of infotainment traffic throughput and safety traffic PDR, while allowing us to focus on quantifying the impacts of vehicle DSA strategy selection behaviors on throughput and PDR metrics.

Within each experiment, $162 - 210$ DSA vehicles generate infotainment traffic in conformance with the IEEE WAVE 802.11p standard in multi-channel operation mode [53]. The number of vehicles is fixed to either 162 (i.e., lightly loaded) or 210 (i.e., highly loaded), and the channels are assumed to have either homogeneous or heterogeneous capacities. We then study the performance of each strategy under each of the 4 resulting scenarios (2 settings for channel contention x 2 settings of channel capacity heterogeneity).

The nodes are distributed on a grid of 5 lanes, with 4 m spacing between neighboring nodes, both across neighboring lanes and within each lane lane. The RSU is fixed at position $(0, 0)$ of the grid with transmission range of 500 m. Each vehicle transmits on a channel that is dynamically updated in a continuous stochastic manner, as prescribed by the vehicle's chosen bio-social channel selection strategy. Each vehicle must choose between three channel selection strategies: ACU, FCU and SFU (the latter two being bio-socially inspired). To compare the efficacy of the different strategy choices, we consider 3 homogeneous systems where 100% of the population use the same strategy; we also consider 3 heterogeneous populations where 80% of the vehicles employ one strategy, while the remaining 20% of the population is deviant, with 10% adopting each of the remaining two strategies. There are thus 6 distinct simulation scenarios in each experiment (3 homogeneous and corresponding to each, a heterogeneous system). By measuring the performance of each homogeneous strategy in various settings, we can determine which is dominant across a range of environmental conditions. By comparing the performance of nodes in each homogeneous strategy with the performance achieved by deviant nodes in the corresponding heterogeneous system, we can measure the evolutionary stability of the homogeneous system.

To establish the relative efficacy of each strategy in different regimes of vehicular DSA, we consider a system whose social and channel condition parameters are listed in Table II. To quantify the behavior of this system through simulation, we carry out experiments in which the parameters are varied as described in Table III. The experiments are carried out as a series of `ns-3` simulations under a range of settings for parameters directly related to the strategies utilized by the vehicles. This variation

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TABLE II
SYSTEM PARAMETERS

	Symbol	Parameter	Value/Range
Constants	n	Number of service channels	$6SCHs$
	N	Number of vehicles	$162, 210$
	C_i^{max}	Maximum service channel capacity	$10Mbps$
Input Parameters	C_i	Service channel capacity	varies in $[0, C_i^{max}]$
	α	Service channel interval	varies in $[0-100]ms$
	P_c	Probability of consume	varies in $[0,1]$
	P_s	Probability of Sociality	varies in $[0,1]$
	S_+	enhancement due to sociality	varies in $[0,1]$
	S_-	Overhead of sociality	varies in $[0,1]$
Calculated Parameters	$\overline{C_i}$	Relative service channel capacity	$C_i/\sum_j C_j$
	β	Control channel interval	$100ms-\alpha$
	G_s	Sociality gain	$(1-S_-).(1+S_+)$
Output Parameters	$\gamma(.)$	Fraction of attained vehicle throughput	[0,1]

TABLE III
SIMULATION PARAMETERS

Parameter	Value
Number of Channels (n)	6 SCHs, 1 CCH
Number of vehicles (N)	162, 210
Vehicle transmission rate (R)	10 kbps (once every 100ms)
Channel Capacity (C_i)	OFDM 3Mbps
P_c, P_s, S_+, S_-	Varies based on the experiment
Number of packets	IP: 1, 6, 14, BSM: 10
Transmission Range	500m
WLAN Standard	IEEE 802.11p
Simulation Time	10 seconds
Number of replications	10
Propagation Loss Model (PLM)	Log Distance Model [60]
Exponent of the PLM	3 (default) [60]
Reference distance for the PLM	$1m$ (default) [60]
Reference loss for the PLM	$46.7dB$ (default) [60]
Mobility Model	Constant Position Mobility Model
Energy Detection Threshold	-61.1 dBm, -91.1dBm (default) [60]
Power Transmission Level	16.0206 dBm [61]
Error Rate Model Signal to Noise + Interference	NIST validated experimentally [60]

impacts the MAC layer properties of the vehicles, including their transmission rate, willingness to transmit and defer, and channel switching properties. Other aspects related to the physical and link layers (e.g. BER, SNR and channel interference) are addressed by the PHY layer implementation of the simulator. Parameters related to these aspects are fixed as shown in Table III. Further optimization of these parameters is the subject of ongoing research.

A. Simulation Results and Discussion

In this section, we address research questions (1) and (2) from the previous section.

Can the FCU channel selection strategy outperform all other strategies in some circumstances? We hypothesize that scenarios which favor FCUs are marked by heterogeneous channel characteristics, or when the cost of sociality is high $P_s(1-S_-)$ relative to its benefit. To test this hypothesis, we configured our simulation to consist of $n = 6$ channels with normalized residual capacities $\overline{C_i} = (\frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{2}{9}, \frac{2}{9}, \frac{2}{9})$. In such a system, FCUs and SFUs have probability of $\frac{1}{3}$ to access "good" channels 1,2, and 3 (-61.1 dBm) and probability of $\frac{2}{3}$ to access "bad" channels 4, 5, and 6 (-91.1 dBm). Within this environment, we placed $N = 162$ vehicles, 80% of which adopted the FCU channel selection strategy, while the remaining 20% utilized the ACU and SFU strategies evenly. This is compared with populations that totally employed FCU strategy. Each vehicle sent 6 IP packets per $\alpha = 10..50$ ms, yielding transmission rates $R = 60$ KBytes/sec $= 480$ Kbps. For FCUs and SFUs, the probability of foraging was set at 2% ($P_c = 0.98$). SFUs deferred to peers 30% of the time ($P_s = 0.3$) but then transmitted at rate elevated 5% above normal when in active state ($S_+ = 0.05$). To implement this social structure, SFUs were charged 60% overhead to account for group coordination costs ($S_- = 0.6$). Fig. 6(a) shows the throughput achieved in each of the three homogeneous and heterogeneous scenarios. As shown in Fig. 6(b), FCUs obtain 82.6%–136.8% improvement in throughput over ACUs and SFUs. Even though FCUs spend time not consuming ($P_c < 1$), they are able to compensate for this loss and outperform ACUs because they can choose better channels for transmission as a result of their sensing capabilities. FCUs also outperform SFUs in this scenario because SFU defer too readily, and the cost of their deference and coordination is high.

Can the SFU channel selection strategy outperform all other strategies in some circumstances? We hypothesize that the SFU strategy outperforms the other strategies in highly loaded network scenarios. In these scenarios, channels are not able to accommodate all the demand and there will be an emergent need for social deference. In order to test this hypothesis, we configured the simulation to consist of $n = 6$ channels with normalized residual capacities $\overline{C_i} = (\frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{2}{9}, \frac{2}{9}, \frac{2}{9})$. In such a system, FCUs and SFUs have probability of $\frac{1}{3}$ to access "good" channels 1, 2, and 3 (-61.1 dBm) and probability of $\frac{2}{3}$ to access "bad" channels 4, 5, and 6 (-91.1 dBm). Within this environment, we placed $N = 210$ vehicles, 80% of which adopted the SFU channel selection strategy, while the remaining 20% utilized the ACU and FCU strategies evenly. This is compared with populations that totally employed SFU strategy. Each vehicle sent 14 IP packets per $\alpha = 10..50$ ms, yielding transmission rates $R = 140$ KBytes/sec $= 1120$ Kbps. For FCUs and SFUs, the probability of foraging was set at 1% ($P_c = 0.99$). SFUs deferred to peers 80% of the time ($P_s = 0.8$) but then transmitted at rate elevated 40% above normal when in active state ($S_+ = 0.4$). To implement this social structure, SFUs

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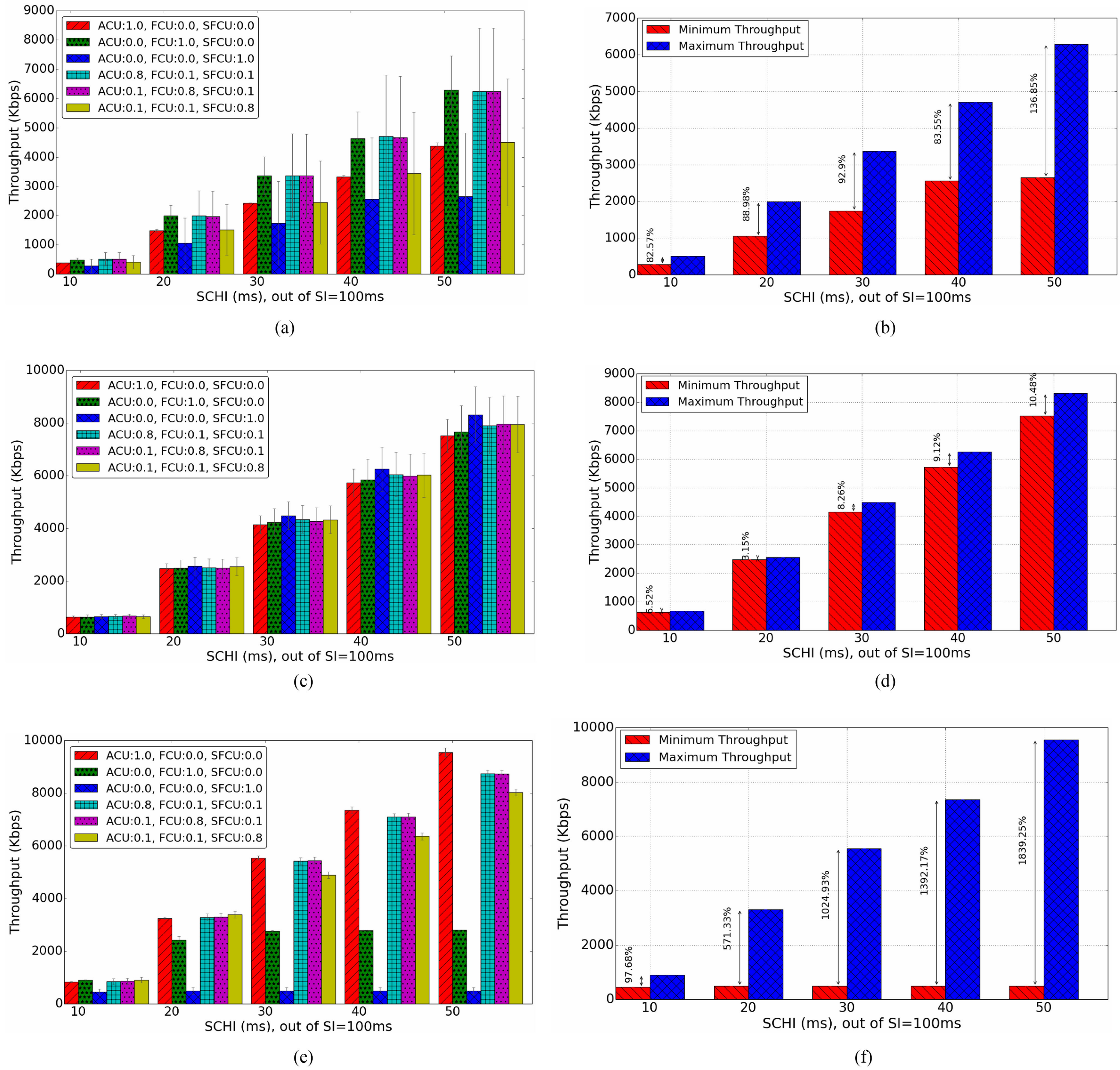

Fig. 6. Simulation Results for proposed strategies under various channels' conditions and nodes' properties. (a) FCU strategy outperforms, utility increases with SCHI Heterogeneous channel capacity, Lightly loaded P_c : 0.98, P_s : 0.3, S_+ : 0.05, S_- : 0.6. (b) Improvement on throughput corresponding to Figure (a) Heterogeneous channel capacity, Lightly loaded P_c : 0.98, P_s : 0.3, S_+ : 0.05, S_- : 0.6. (c) SFU strategy outperforms, utility increases with SCHI Heterogeneous channel capacity, Highly loaded P_c : 0.99, P_s : 0.8, S_+ : 0.4, S_- : 0.04. (d) Improvement on throughput corresponding to Figure (c) Heterogeneous channel capacity, Highly loaded P_c : 0.99, P_s : 0.8, S_+ : 0.4, S_- : 0.04. (e) ACU strategy outperforms, utility increases with SCHI Heterogeneous channel capacity, Lightly loaded P_c : 0.6, P_s : 0.4, S_+ : 0.05, S_- : 0.3. (f) Improvement on throughput corresponding to Figure (e) Heterogeneous channel capacity, Lightly loaded P_c : 0.6, P_s : 0.4, S_+ : 0.05, S_- : 0.3.

were charged 4% overhead to account for group coordination costs ($S_- = .04$). Fig. 6(c) shows the throughput achieved in each of the three homogeneous and heterogeneous scenarios. As shown in Fig. 6(d), SFUs obtain 3.1%–10.5% improvement in throughput over ACUs and FCUs. In such scenarios, nodes with social behavior will be able to gain more utility by coordinating so that only P_s fraction of them are deferring, while only $1 - P_s$ fraction are actively transmitting, albeit at an elevated rate. This results in decreased contention over the channels and helps users to access better channels more frequently in order to improve their utility. Under such network conditions, ACUs and FCUs fail to achieve better utility since these nodes do not defer to others, and therefore, experience higher contention on channels. Notice that as the number of vehicles and their load increases, the SFU strategy gains more utility compared to other strategies as shown in Fig. 6(c).

Under what conditions does ACU outperform the bio-social FCU and SFU strategies? We hypothesize that the ACU

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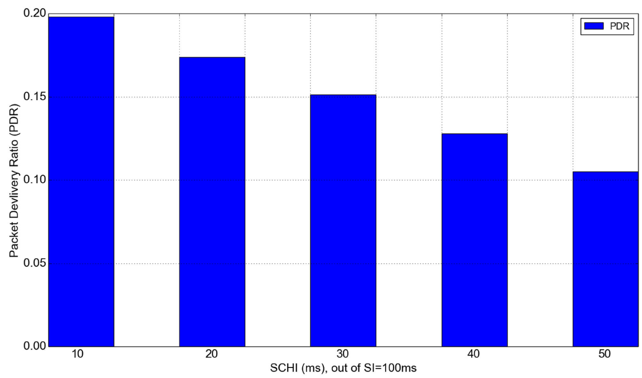

Fig. 7. PDR for BSM Traffic.

strategy outperforms the other strategies in lightly loaded network scenarios where channel conditions are homogeneous. In these scenarios, channels are able to accommodate all the demand and there is no need for foraging and social behaviors. In order to test this hypothesis, we configured the simulation to consist of $n = 6$ channels with normalized residual capacities $\overline{C_i} = (\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6})$. In such a system, FCUs and SFUs have probability of $\frac{1}{6}$ to access all 6 channels configured with (-91.1 dBm) energy detection threshold. Within this environment, we placed $N = 162$ vehicles, 80% of which adopted the ACU channel selection strategy, while the remaining 20% utilized the FCU and SFU strategies evenly. This is compared with populations that totally employed ACU strategy. Each vehicle sent 1 IP packets per $\alpha = 10..50$ ms, yielding transmission rates $R = 10$ KBytes/sec $= 80$ Kbps. For FCUs and SFUs, the probability of foraging was set at 40% ($P_c = 0.6$). SFUs deferred to peers 40% of the time ($P_s = 0.4$) but then transmitted at rate elevated 5% above normal when in active state ($S_+ = 0.05$). To implement this social structure, SFUs were charged 30% overhead to account for group coordination costs ($S_- = .3$). Fig. 6(e) shows the throughput achieved in each of the three homogeneous and heterogeneous scenarios. As shown in Fig. 6(f), ACUs obtain 97.7% to 1839.2% higher throughput than FCUs and SFUs. Thus, FCUs and SFUs receive less throughput than the baseline strategy (i.e., ACU) in scenarios with light infotainment traffic. In such settings, the foraging behavior employed by FCUs and SFUs offers little benefit, since the time spent in foraging and sensing decreases the utility of the nodes and provides little useful information; similarly, the social deference of SFUs leads P_s fraction of the nodes to defer transmissions, which is unnecessary given the traffic conditions, and only lowers throughput.

In all the simulations above, in addition to evaluating throughput for infotainment traffic, we also measured the packet delivery ratios for safety traffic. The ACU, FCU, and SFU strategies only concern the transmission for infotainment IP packets, and do not affect the transmission of safety traffic such as BSM messages. Fig. 7 shows the PDR for safety traffic in networks corresponding to experiments of Fig. 6(e) and (f) where the efficacy of the ACU strategy was being evaluated. The figure shows the PDR for BSM broadcasts in a scenario with 162 nodes transmitting 10 BSMs per CCH interval. The figure clearly shows that as SCH interval increases, the CCH interval decreases, yielding a decreased delivery ratio of the BSM packets.

These results demonstrate the interplay between infotainment and safety traffic. As the SCH interval increases, the throughput for infotainment traffic increases and the PDR for safety traffic decreases; the reverse is true as well, and hence the trade off. This work does not address the optimal design of the SCHI and CCHI values. However, it shows the feasibility of employing the proposed bio-socially inspired strategies in the realm of vehicular networks that utilize DSA in support of infotainment applications.

We have arrived at an experimentally derived intuition concerning questions (1) and (2): it appears that the bio-socially inspired FCU, and SFU strategies can indeed sometimes enhance spectrum access and utilization in VANETs (compared to the baseline performance of ACUs), but the best strategy choice depends on the environmental conditions. The FCU and SFU strategies have two distinct behaviors. FCUs tend to immediately benefit from the knowledge about the underlying channel conditions and try to access better channels more frequently (i.e., with higher probability). SFUs provide the users with the ability to grant their share of the bandwidth to other fellow nodes in the SFU group (i.e., altruistic behavior), and prefer to let others transmit on channels when the channels are crowded in favor of obtaining more utility from a group perspective. We say that FCUs tend to have a short-term view and selfish behavior, while SFUs which have a long-term view and altruistic behavior. Experimentally, we observe that both strategies benefit (relative to ACUs), under suitable channel and traffic conditions. These experimental intuitions will be proven in the next section.

VI. Analytical Performance Analysis

Here will will prove the experimental intuitions of the previous section concerning research questions (1) and (2), as well as address research question (3).

A. Preliminaries

We distinguish the concept of a *mixed strategy* from that of a *heterogeneous population*. A node that employs a *mixed strategy* switches between pure strategies over time at random; it might act like an ACU 10% of the time, like an FCU 60% of the time, and like an SFU 30% of the time. We will not consider mixed strategies in this paper. A *heterogeneous population* on the other hand, is a population in which each SU employ a "pure" strategy (an ACU, or an FCU, or an SFU, and uses the corresponding strategy 100% of the time); different nodes in the population, however, may use different strategies. In this paper, a *homogeneous population* will be one in which all the nodes use the same *pure* strategy.

Our aim is to discover conditions under which each proposed strategy is expected to be evolutionarily stable. Such knowledge allows us to predict the strategy that users will employ in the community to enhance their individual utility. At each moment, each SU within the system is free to choose its strategy, and so different SUs may be concurrently experiencing different utilities. An EGT framework enables us to analyze such a varied

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population and make provable assertions that the number of SUs who are not using the majority strategy (i.e., the "mutants") is small. If all users adopt the same strategy and no mutants arise, the system has evolved to reach a stable strategy (ESS). Most importantly, EGT provides a way to determine whether such stability will arise and what the final stable strategy will be, *in advance*, from a description of the system *now*.

We follow the analysis presented in [62] for a formal definition of ESS. A strategy σ^* is an ESS, if mutants that adopt another strategy σ leave fewer offsprings in the post-entry population x_ϵ where:

$$x_\epsilon = (1-\epsilon)\sigma^* + \epsilon\sigma \tag{1}$$

assuming that the proportion of mutants ϵ is sufficiently small ($0 < \epsilon < \overline{\epsilon}$). Hence, for σ^* to be ESS, then:

$$U(\sigma^*, x_\epsilon) > U(\sigma, x_\epsilon) \tag{2}$$

where $U(\sigma^*, x_\epsilon)$ is the payoff (i.e., utility) of players that play σ^* and $U(\sigma, x_\epsilon)$ is the payoff of the mutants that play σ in the post-entry population x_ϵ.

B. Mathematical Model

Consider a heterogeneous system $\mathcal{S}$ in which there are k_1 ACUs, k_2 FCUs, k_3 SFUs, In $\mathcal{S}$, there is just one channel of capacity C and ACUs and FCUs transmit at a rate of r_1 while $SFUs$ transmit at a rate of r_2. Such a system will be specified by a 5-tuple:

$$\mathcal{S} = (k_1, k_2, k_3, r_1, r_2) \tag{3}$$

When SUs engage ACU or FCU strategies, they transmit at r_1 bits/sec; when they adopt the SFU strategy, they use a higher rate $r_2 > r_1$. This is done to prevent non-SFUs from unfairly benefiting from the deference behavior of SFUs. The channel is thus subject to $N_{ACU} + N_{FCU}$ SUs transmitting at a rate of r_1 and N_{SFU} SUs transmitting at a rate of r_2. The actual throughput achieved is a function of channel conditions, channel capacity and interference among ACUs, FCUs and SFUs.

The fractional throughput of each SU in $\mathcal{S}$ will be written

$$X_\gamma(\mathcal{S}) := \gamma(C, k_1 + k_2, r_1, k_3, r_2) \tag{4}$$

where the functional form of γ will be described below.

Now, when we consider a system $\mathcal{S}^*$

$$\mathcal{S}^* = (n_{ACU}, n_{FCU}, n_{SFU}, R, (1+S_+)R) \tag{5}$$

having access $M \geqslant 1$ channels of capacities $C_1, \ldots C_M$. In what follows, $\mathcal{S}^*$ will always consist of a set of SUs who each follow a pure strategy. We will, however, sometimes subject system to the possibility that some fraction of its players could "mutate" or "defect" or "switch" to different (possibly mixed) strategy.

Assuming $\mathcal{S}^*$ is in steady state, the expected number of ACUs, FCUs and SFUs in channel i is given by

$$O^i_{ACU} := \frac{N_{ACU}}{M} \tag{6}$$

$$O^i_{FCU} := \overline{\mathrm{C_i}} N_{FCU} \tag{7}$$

$$O^i_{SFU} := \overline{\mathrm{C_i}}(1-P_S) N_{SFU} \tag{8}$$

The total demand for channel i is computable as

$$D_i(\mathcal{S}^*) = (O^i_{ACU} + O^i_{FCU}) * R + O^i_{SFU} * (1+S_+)R \tag{9}$$

and the fractional throughput of users in channel i is:

$$X^i_\gamma(\mathcal{S}^*) := \gamma(C_i, O^i_{ACU} + O^i_{FCU}, R, O^i_{SFU}, (1+S_+)R) \tag{10}$$

The function γ aggregates key physical and MAC layer factors, abstracting their impact on throughput in a system with specified numbers of each SU type and transmission rate settings. We use throughput reported by the SUs as a proxy measurement for channel conditions. This data is used to drive periodic (long term) strategy selection decisions, as well as more frequent (short-term) channel selection decisions within each SUs currently chosen strategy. While the precise form of γ is intractable, we will take

$$X^i_\gamma(\mathcal{S}^*) = \begin{cases} 1 & \text{if } D_i(\mathcal{S}^*) < \rho C_i \\ \frac{1}{\exp^{D_i(\mathcal{S}^*) - \rho C_i}} & \text{if } D_i(\mathcal{S}^*) \geq \rho C_i \end{cases} \tag{11}$$

Here ρ is a fitting parameter chosen so that γ mirrors experimental measurements. The theoretical maximum throughput in the channel is derived from Shannon's formula:

$$R_{th} = B \cdot \left(1 + \frac{G_z P_z}{\sum_{y=1}^{k} G_{zy} P_y + W}\right) \tag{12}$$

Here k is the number of co-consumers in the channel i, which is the sum of O^i_{ACU}, O^i_{FCU} and O^i_{SFU} in equations (6), (7) and (8), respectively. The transmission power of each SU z (resp. y) is denoted P_z (resp. P_y); B is the channel bandwidth; G_z is the channel gain for transmissions by z, G_{zy} represents the channel gain for the transmission between z and y, and W is the power level of the ambient white Gaussian noise. The `ns-3` simulation carried out in Section (V) reflects the physical parameters shown in Table II (e.g., gain, transmission power, etc.) that contribute to the overall level of channel interference, and consequently throughput. Again, $X^i_\gamma(\mathcal{S}^*)$ is a decimal number between 0 and 1, representing the fraction of the channel's theoretical throughput R_{th} that is actually available for use. This fraction, in turn, depends on the demands D_i of users and the channel capacity C_i).

In what follows we define $U(\mathcal{S}^*; s, x_\epsilon)$ as the utility received by users employing strategy s in a multi-band system $\mathcal{S}^*$ of a mixed population that utilize employing strategies different from s. For convenience, $U(\mathcal{S}^*; s, x_\epsilon)$ is denoted as $U_s(\mathcal{S}^*)$. The stability of the strategy, when it exists, is guaranteed only when the number of users deviating from strategy s is sufficiently small.

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In system $(\mathcal{S}^*)$, the utility achieved by each ACU, FCU, and SFU respectively is:

$$U_{ACU}(\mathcal{S}^*) = \nu \frac{1}{M} \sum_{i=1}^{M} R \cdot X_\gamma^i(\mathcal{S}^*) \tag{13}$$

$$U_{FCU}(\mathcal{S}^*) = \nu P_c \sum_{i=1}^{M} \overline{\mathrm{C}_\mathrm{i}} R \cdot X_\gamma^i(\mathcal{S}^*) \tag{14}$$

$$U_{SFU}(\mathcal{S}^*) = \nu P_c \sum_{i=1}^{M} \overline{\mathrm{C}_\mathrm{i}} R \cdot G_s \cdot X_\gamma^i(\mathcal{S}^*) \tag{15}$$

where $\nu = \frac{\alpha}{\alpha+\beta}$ is the service channel duty cycle, and $G_s = (1+S_+)\cdot(1-S_-)$ is the sociality gain.

C. Existence of ESS—the general framework

In this section, we describe the conditions in which a homogeneous system of SUs is an ESS—that is, invasion by any competing mixed strategy will fail, provided the invading population is sufficiently small. Towards this, we will first state a general formulation of conditions for an ESS in the Lemma below. This lemma will be specialized and applied to homogeneous systems of ACUs, FCUs, and SFUs in the next section. The next definition will be helpful in the results that follow.

Definition 1: Let $\mathcal{S}^*$ be the system in (5), and $\sigma^* = (p^*, q^*, k^*)$ and $\sigma = (p, q, k)$ are mixed strategies where ACU, FCU, SFU are used with probabilities p^*, q^*, k^*, for σ^* and p, q, k, for σ, respectively; where $(p^*+q^*+k^*=1)$ and $(p+q+k=1)$. Define

$$\begin{aligned} A(\mathcal{S}^*, \sigma^*, \sigma) = \; & p^*(p^*-p)\cdot U_{ACU}(\mathcal{S}^*) \\ & + q^*(q^*-q)\cdot U_{FCU}(\mathcal{S}^*) \\ & + k^*(k^*-k)\cdot U_{SFU}(\mathcal{S}^*) \end{aligned}$$

$$\begin{aligned} B(\mathcal{S}^*, \sigma^*, \sigma) = \; & (p^*-p)^2\cdot U_{ACU}(\mathcal{S}^*) \\ & + (q^*-q)^2\cdot U_{FCU}(\mathcal{S}^*) \\ & + (k^*-k)^2\cdot U_{SFU}(\mathcal{S}^*) \end{aligned}$$

Lemma 1: Let $\mathcal{S}^*$ be the system in (5), and suppose that the majority $1-\epsilon$ of SUs employ $\sigma^* = (p^*, q^*, k^*)$ where ACU, FCU, SFU are used with probabilities p^*, q^*, k^*, respectively. When a small ϵ fraction of SUs contemplate a defection to a mixed strategy $\sigma = (p, q, k)$ where ACU, FCU, SFU are used with probabilities p, q, k, respectively, then for ϵ sufficiently small, the defection fails to be rational. In particular, $\mathcal{S}^*$ is evolutionarily stable as long as

$$\epsilon < \frac{A(\mathcal{S}^*, \sigma^*, \sigma)}{B(\mathcal{S}^*, \sigma^*, \sigma)} \tag{16}$$

Proof: Since $\epsilon \approx 0$ the payoff for a defecting player is:

$$U_\sigma(\mathcal{S}^*) = p\cdot U_{ACU}(\mathcal{S}^*) + q\cdot U_{FCU}(\mathcal{S}^*) + k\cdot U_{SFU}(\mathcal{S}^*) \tag{17}$$

The existence of an ESS in an EGT game requires the inequality condition of (2) to hold. Suppose $\sigma^* = (p^*, q^*, k^*)$ is the strategy employed in $\mathcal{S}^*$ and $\sigma = (p, q, k)$ is the strategy of the defectors. The utility achieved by the defectors is

$$\begin{aligned} U_\sigma = \; & p[p^* - \epsilon(p^*-p)]\cdot U_{ACU}(\mathcal{S}^*) \\ & + q[q^* - \epsilon(q^*-q)]\cdot U_{FCU}(\mathcal{S}^*) \\ & + k[k^* - \epsilon(k^*-k)]\cdot U_{SFU}(\mathcal{S}^*) \end{aligned} \tag{18}$$

while the non-defectors achieve

$$\begin{aligned} U_{\sigma^*} = \; & p^*[p^* - \epsilon(p^*-p)]\cdot U_{ACU}(\mathcal{S}^*) \\ & + q^*[q^* - \epsilon(q^*-q)]\cdot U_{FCU}(\mathcal{S}^*) \\ & + k^*[k^* - \epsilon(k^*-k)]\cdot U_{SFU}(\mathcal{S}^*) \end{aligned} \tag{19}$$

It is easy to check that $U_{\sigma^*} > U_\sigma$ if and only if $\epsilon < A/B$. ■

D. Existence of ESS—Applied to VANETs

Since we have three pure strategies and one mixed strategy we need the following five propositions to study the existence of ESS:

Proposition 1: If $\mathcal{S}^*$ is a homogeneous system of ACUs, a defection to strategy $\sigma = (p, q, k)$ by an ϵ fraction of players fails to be rational if ϵ is less than

$$\frac{(1-p)\cdot U_{ACU}(\mathcal{S}^*)}{(1-p)^2\cdot U_{ACU}(\mathcal{S}^*) + q^2\cdot U_{FCU}(\mathcal{S}^*) + k^2\cdot U_{SFU}(\mathcal{S}^*)}$$

Proof: Using Lemma 1, we specialize Definition 1 to the situation $\sigma^* = (1, 0, 0)$ to obtain

$$A(\mathcal{S}^*, \sigma^*, \sigma) = (1-p)\cdot U_{ACU}(\mathcal{S}^*) \tag{20}$$

$$B(\mathcal{S}^*, \sigma^*, \sigma) = (1-p)^2\cdot U_{ACU}(\mathcal{S}^*) \tag{21}$$

$$+ q^2\cdot U_{FCU}(\mathcal{S}^*) + k^2\cdot U_{SFU}(\mathcal{S}^*) \tag{22}$$

The proposition is proved. ■

As $U_{ACU}(\mathcal{S}^*)$ decreases, we see that the bound on ϵ in Proposition 1 approaches 0, making it more likely that users will defect away from the homogeneous ACU society. Conversely, as $U_{ACU}(\mathcal{S}^*)$ increases relative to $U_{FCU}(\mathcal{S}^*)$ and $U_{SFU}(\mathcal{S}^*)$, we see that the bound on ϵ approaches 1, making it so users will be unable to defect away from the homogeneous ACU society without group coordination.

Proposition 2: If $\mathcal{S}^*$ is a homogeneous system of FCUs, a defection to strategy $\sigma = (p, q, k)$ by an ϵ fraction of players fails to be rational if ϵ is less than

$$\frac{(1-q)\cdot U_{FCU}(\mathcal{S}^*)}{p^2\cdot U_{ACU}(\mathcal{S}^*) + (1-q)^2\cdot U_{FCU}(\mathcal{S}^*) + k^2\cdot U_{SFU}(\mathcal{S}^*)}$$

Proof: Using Lemma 1, we specialize Definition 1 to the situation $\sigma^* = (0, 1, 0)$ to obtain

$$A(\mathcal{S}^*, \sigma^*, \sigma) = (1-q)\cdot U_{FCU}(\mathcal{S}^*) \tag{23}$$

$$\begin{aligned} B(\mathcal{S}^*, \sigma^*, \sigma) = \; & p^2\cdot U_{ACU}(\mathcal{S}^*) \\ & + (1-q)^2\cdot U_{FCU}(\mathcal{S}^*) + k^2\cdot U_{SFU}(\mathcal{S}^*) \end{aligned} \tag{24}$$

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The proposition is proved. ■

As $U_{FCU}(\mathcal{S}^*)$ decreases, we see that the bound on ϵ in Proposition 2 approaches 0, making it more likely that users will defect away from the homogeneous FCU society. Conversely, as $U_{FCU}(\mathcal{S}^*)$ increases relative to $U_{ACU}(\mathcal{S}^*)$ and $U_{SFU}(\mathcal{S}^*)$, we see that the bound on ϵ approaches 1, making it so users will be unable to defect away from the homogeneous FCU society without group coordination.

Proposition 3: If $\mathcal{S}^*$ is a homogeneous system of SFUs, a defection to strategy $\sigma = (p, q, k)$ by an ϵ fraction of players fails to be rational if ϵ is less than

$$\frac{(1-k) \cdot U_{SFU}(\mathcal{S}^*)}{p^2 \cdot U_{ACU}(\mathcal{S}^*) + q^2 \cdot U_{FCU}(\mathcal{S}^*) + (1-k)^2 \cdot U_{SFU}(\mathcal{S}^*)}$$

Proof: Using Lemma 1, we specialize Definition 1 to the situation $\sigma^* = (0, 0, 1)$ to obtain

$$A(\mathcal{S}^*, \sigma^*, \sigma) = (1-k) \cdot U_{SFU}(\mathcal{S}^*) \tag{25}$$

$$B(\mathcal{S}^*, \sigma^*, \sigma) = p^2 \cdot U_{ACU}(\mathcal{S}^*) + q^2 \cdot U_{FCU}(\mathcal{S}^*) + (1-k)^2 \cdot U_{SFU}(\mathcal{S}^*) \tag{26}$$

The proposition is proved. ■

As $U_{SFU}(\mathcal{S}^*)$ decreases, we see that the bound on ϵ in Proposition 2 approaches 0, making it more likely that users will defect away from the homogeneous SFU society. Conversely, as $U_{SFU}(\mathcal{S}^*)$ increases relative to $U_{ACU}(\mathcal{S}^*)$ and $U_{FCU}(\mathcal{S}^*)$, we see that the bound on ϵ approaches 1, making it so users will be unable to defect away from the homogeneous SFU society without group coordination.

Proposition 4: If $\mathcal{S}^*$ is a system in which

$$U_{ACU}(\mathcal{S}^*) = U_{FCU}(\mathcal{S}^*) = U_{SFU}(\mathcal{S}^*)$$

then no evolutionary stable strategy exists in $\mathcal{S}^*$.

Proof: If all utilities of all strategies are equal then players may switch and mix strategies without penalty, and because the strict inequality in (2) cannot be made to hold for any strategy, no strategy is evolutionarily stable. ■

Proposition 5: If $\mathcal{S}^*$ is a system in which $U_{ACU}(\mathcal{S}^*)$, $U_{FCU}(\mathcal{S}^*)$ and $U_{SFU}(\mathcal{S}^*)$ are pairwise distinct, and σ is evolutionary stable strategy $\mathcal{S}^*$, then σ is a pure strategy.

Proof: Suppose σ is the ESS. The payoff for this strategy is

$$U_\sigma(\mathcal{S}^*) = p \cdot U_{ACU}(\mathcal{S}^*) + q \cdot U_{FCU}(\mathcal{S}^*) + k \cdot U_{SFU}(\mathcal{S}^*)$$

This function is convex combination, and so is maximized by placing all the probability mass on the unique strategy which has the highest utility. Thus, precisely one of the values p, q, k is equal to 1. ■

Corollary 1: If $\mathcal{S}^*$ is a system in which $U_{ACU}(\mathcal{S}^*)$, $U_{FCU}(\mathcal{S}^*)$ and $U_{SFU}(\mathcal{S}^*)$ are pairwise distinct, and σ is evolutionary stable strategy $\mathcal{S}^*$, then

$$\sigma = \begin{cases} ACU & \text{if } U_{ACU}(\mathcal{S}^*) > U_{FCU}(\mathcal{S}^*), U_{SFU}(\mathcal{S}^*) \\ FCU & \text{if } U_{FCU}(\mathcal{S}^*) > U_{ACU}(\mathcal{S}^*), U_{SFU}(\mathcal{S}^*) \\ SFU & \text{if } U_{SFU}(\mathcal{S}^*) > U_{ACU}(\mathcal{S}^*), U_{FCU}(\mathcal{S}^*) \end{cases} \tag{27}$$

E. Finding an ESS

Theorem 1: For a system $\mathcal{S}^*$ where $X^i_\gamma(S^*) \approx 1$, ACU is a winning strategy iff: $P_c < \min(1, \frac{1}{G_s})$.

Proof: Corollary 1 mandates that $U_{ACU}(\mathcal{S}^*) > U_{FCU}(\mathcal{S}^*)$ and $U_{ACU}(\mathcal{S}^*) > U_{SFU}(\mathcal{S}^*)$, which implies:

$$\frac{1}{M}\sum_{i=1}^{M} X^i_\gamma(\mathcal{S}^*) > P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot X^i_\gamma(\mathcal{S}^*) \tag{28}$$

$$\frac{1}{M}\sum_{i=1}^{M} X^i_\gamma(\mathcal{S}^*) > P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot G_s \cdot X^i_\gamma(\mathcal{S}^*) \tag{29}$$

Substituting $X^i_\gamma(S^*) = 1$ and $\sum_{i=1}^{M} \overline{\mathrm{C_i}} = 1$, we get

$$P_c < 1 \tag{30}$$

$$P_c \cdot G_s < 1 \tag{31}$$

The theorem is proved. ■

Theorem 2: For a system $\mathcal{S}^*$, where

$$\forall i, j : 1 \ldots M,\ C_i = C_j$$

ACU is a winning strategy iff: $P_c < \min(1, \frac{1}{G_s})$.

Proof: Since $C_i = C_j$ for all i, j it follows that

$$\overline{\mathrm{C_i}} = \overline{\mathrm{C_j}} = 1/M$$

Substituting into inequalities (28) and (29), we get

$$P_c < 1 \tag{32}$$

$$P_c \cdot G_s < 1 \tag{33}$$

The theorem is proved. ■

Reflections on Theorems (1) and (2): The antecedent in Theorem (1) means that all channels are able to accommodate the demand, and thus, from the nodes' perspective, their demand is fulfilled regardless of their channel choices. ACUs benefit directly from this condition as they randomly access the channels. SFUs and FCUs detect this condition using their foraging capability, but to gain this knowledge, they sacrifice some of their channel access time by foraging some fraction ($P_f = 1 - P_c$) of the time. This hinders their ability to gain utility relative to ACUs. On the other hand, SFUs can recapture some of this loss by the advantage derived from social behavior (G_s). As long as the effects of foraging and social gain are less than 1, however, SFUs cannot outperform ACUs under this condition. The antecedent in Theorem (2), states that the utilities of all channels are equal but not necessarily 1. This happens when the different channels provide similar throughput; this uniformity implies that the utility lost to time spent foraging was in vain since it yielded no information about the channel environment. This leads to the same conclusion as that of Theorem (1).

Connections to previous `ns-3` experiments: The conclusion from Theorem (2) is also observed in our `ns-3` experimental results as can be seen in Table Fig. 6 (e)-(f). These figures are based on scenarios in which the different channels have similar conditions.

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Theorem 3: For a system $\mathcal{S}^*$, FCU is a winning strategy iff:

$$P_c > \frac{1}{M} \frac{\sum_{i=1}^{M} X_\gamma^i(\mathcal{S}^*)}{\sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot X_\gamma^i(\mathcal{S}^*)} \tag{34}$$

and

$$G_s < 1 \tag{35}$$

Proof: Corollary 1 mandates that $U_{FCU}(\mathcal{S}^*) > U_{ACU}(\mathcal{S}^*)$ and $U_{FCU}(\mathcal{S}^*) > U_{SFU}(\mathcal{S}^*)$, which implies:

$$P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot X_\gamma^i(\mathcal{S}^*) > \frac{1}{M} \sum_{i=1}^{M} X_\gamma^i(\mathcal{S}^*) \tag{36}$$

$$P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot X_\gamma^i(\mathcal{S}^*) > P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot G_s \cdot X_\gamma^i(\mathcal{S}^*) \tag{37}$$

Rearranging terms of the two inequalities, the theorem is proved. ∎

Reflections on Theorem 3: The antecedent in Theorem (3) assert a lower-bound on the probability of consuming that is the ratio of the ACU and FCU utilities, and indicate that the social gain is smaller than 1. We know already from Theorems (1) and (2), that ACUs outperform all strategies when channels have uniform conditions. In non-uniform settings, FCUs and SFUs have the tendency to access channels with better throughput, based on the values of $\overline{C_i}$. In non-uniform channel settings, the weighted average in the denominator is greater than the unweighted average in the numerator, and so the ratio of ACU to FCU utilities decreases below 1; the lower bound on P_c then drops correspondingly, and (for appropriately chosen $P_c < 1$) foraging wins. The second antecedent upper-bounds the sociality gain (G_s) to be less than 1. This condition restricts the SFUs from compensating for their social coordination overhead and ensures that FCUs outperform SFUs.

Connections to previous `ns-3` experiments: The conclusion from Theorem (3) is also observed in our `ns-3` experimental results as can be seen in Fig. 6(a)-(b). These figures are based on scenarios in which the channels have non-uniform conditions and the sociality overhead (S_{-}) limits (G_s) and curtails SFU utilities.

Theorem 4: For a system $\mathcal{S}^*$, SFU is a winning strategy iff:

$$P_c > \frac{1}{M} \frac{\sum_{i=1}^{M} X_\gamma^i(\mathcal{S}^*)}{\sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot G_s \cdot X_\gamma^i(\mathcal{S}^*)} \tag{38}$$

and

$$G_s > 1 \tag{39}$$

Proof: Corollary 1 mandates that $U_{FCU}(\mathcal{S}^*) > U_{ACU}(\mathcal{S}^*)$ and $U_{FCU}(\mathcal{S}^*) > U_{SFU}(\mathcal{S}^*)$, which implies:

$$P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot G_s \cdot X_\gamma^i(\mathcal{S}^*) > \frac{1}{M} \sum_{i=1}^{M} X_\gamma^i(\mathcal{S}^*) \tag{40}$$

$$P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot G_s \cdot X_\gamma^i(\mathcal{S}^*) > P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot X_\gamma^i(\mathcal{S}^*) \tag{41}$$

Rearranging terms of the two inequalities, the theorem is proved. ∎

Reflections on Theorem 4: The antecedent in Theorem (4) assert a lower-bound the probability of consume that is the ratio of the ACU and SFU utilities, and prescribe a sociality gain greater than 1. We know already from Theorems (1) and (2), that ACUs outperform all strategies when channels have uniform conditions. In non-uniform settings, FCUs and SFUs have the tendency to access channels with better throughput, based on the values of $\overline{C_i}$. In non-uniform channel settings, the weighted average in the denominator is greater than the unweighted average in the numerator, and so the ratio of ACU to FCU utilities decreases below 1; the lower bound on P_c then drops correspondingly, and (for appropriately chosen $P_c < 1$) foraging wins. The second antecedent lower-bounds the sociality gain (G_s) to be greater than 1. This condition allows the SFUs to benefit from their social coordination and ensures that SFUs outperform FCUs.

Reflections on the `ns-3` experiments: The conclusion from Theorem (4) is also observed in our `ns-3` experimental results as can be seen in Fig. 6(c)-(d). These figures are based on scenarios in which the channels have non-uniform conditions and the sociality overhead (S_{-}) is low enough such that SFUs are able to acquire greater utility (G_s) than their non-social foraging counterparts.

Together the EGT analysis and `ns-3` simulation experiments confirm that the proposed system of vehicles converges to ESS, that is, a stable strategy that is immune to deviations by numbers of mutants. If the number of mutants in the community is large, the dynamics of collective strategies choices become open-ended, and no guarantee of system stability can be made.

VII. Conclusion and Future Work

The advent of large-scale VANETs heralds the emergent problems of device co-existence and the potential of device sociality in the ecosystem of the radio spectrum. In this work, we describe an approach to dynamic selection of channel selection strategy, to optimize distributed spectrum access and enhance the throughput of infotainment traffic in VANETs. Specifically, we considered two bio-socially inspired strategies for VANETS, based on resource foraging and social deference; we compared them to a baseline strategy driven by continuous blind consumption. We found (see Section VI) that one of these three strategies is always dominant, and while the winning strategy depends on channel conditions, it is stable against defections by small numbers of deviating nodes. The intuitions for these theoretical results, and the empirical evaluation of their merits were obtained through extensive simulation experiments (see Section V)—where we saw that the optimal strategy enjoys utility gains of 3%–136% relative to baseline.

Taken together, these results together point to a new way of thinking about resource allocation problem: one where optimal and stable channel selection *strategies* are computed and uniformly recommended, rather than the current view where individual channels are micromanaged and allocated by a central authority. This new model is envisioned at the core of a VANET communications system, where a road-side unit aggregates and relays per-band throughput measurements from its area nodes to the cloud. The cloud service then uses the data to compute the

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evolutionary stable strategy based on the collected data. Having computed the optimal stable strategy, the cloud relays it to the RSU, which then broadcasts it onwards to its area nodes.

The present work considers recommendations of strategy type (i.e., ACU, FCU or SFU) only, and not node attributes (i.e., P_c, P_s, S_+). The dynamic optimization of node-specific parameters and a fine-grained analysis of control traffic overhead are planned for future research. We plan to extend these analytic and simulation findings to more realistic models of vehicular mobility in our future work. We also plan to conduct experiments to compare our WAVE-based results here against the performance of achieved by systems built using different types of wireless modems, including LTE-Advanced and 5G.

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