Abstract—Recent rules from FCC and OFCOM foresee the utilization of spectrum database as the main solution to provide accurate spectrum information about TV white spaces for secondary users in cognitive vehicular networks. Spectrum database provides maximum protection to licensed users, however, its implementation is not straightforward in vehicular environments, due to the significant query overhead generated by mobile vehicles in congested urban scenarios. For this reason, in this paper we investigate possible solutions to integrate cooperative sensing and spectrum database querying, with the goal to minimize the primary users detection overhead while guaranteeing maximum protection for these primary users. We propose both theoretical and practical contributions in this field. First, we introduce a topological study to determine the optimal ratio between cooperation and spectrum database querying (referred to as ModeI, ModeII, cooperative Sensing-only devices according to FCC terminology) in order to minimize the network utilization for white space detection. We investigate various system parameters such as spectrum database query frequency, broadcast frequency (for cooperative sensing) and vehicles’ velocity, and study their impact on system performance. Then, we propose a distributed (bio-inspired) protocol for network deployment that enables multi-interfaces vehicles to dynamically decide the detection mode to use, in order to minimize the database load, while providing high enough protection for licensed users.

I. INTRODUCTION

Frequency differentiation constitutes one of the most promising approaches to provide adequate bandwidth for vehicular applications on large-scale urban scenarios. The IEEE 1609.4 protocol [1] has been recently proposed to enable multi-channel operations on the DSRC spectrum band, by allocating safety- and not-safety applications on different 10MHz channels. At the same time, several recent works [2] [3] have shown the inadequacy of DSRC spectrum in meeting the QoS requirements of critical vehicular applications (like the safety ones) on large-scale urban scenarios, and have suggested the utilization of Cognitive Radio (CR) technology [4] to increase the available bandwidth for the vehicular network. In this field, TV-white spectrum constitutes the best candidate to support vehicular communication, for its propagation characteristics, and also for the availability of recent standards (e.g. the IEEE 802.22 standard) and national spectrum agency regulations. (e.g. FCC [5] and OFCOM [6]) that define the opportunistic utilization of these frequencies. However, the big challenge is to guarantee accurate detection of TV white spaces in order to protect the activity of licensed users (also referred to as Primary Users (PU) in the literature. Recent proposals from national spectrum agencies like FCC and OFCOM foresee the presence of a centralized spectrum database, that must be queried by CR devices to get information about TV white spectrum availability at their locations [5] [6]. While guaranteeing maximum protection to licensed users, the utilization of spectrum database poses some additional complexities in vehicular networks environments. First, since it is likely that not all the vehicles will be equipped with Internet connection, strategies for spectrum information dissemination among vehicles should be considered. Second, the traffic load to the database might constitute a system bottleneck, as a consequence of (i) the high number of network devices, e.g. during peak hours of vehicular traffic, and (ii) the mobility factor, which might cause a vehicle to frequently re-check the database while traveling [7]. On the opposite, mobility and high network density have been shown to produce gains on the performance of cooperative sensing techniques [8] [9].

In this paper, we investigate the possibility of integrating spectrum database with cooperative sensing strategies on cognitive vehicular networks, in order to guarantee maximum protection of PU users while minimizing the communication overhead involved by the TV white space detection process. To this aim, we provide a three-step approach in this paper. First, we model the operations of each class of devices foreseen by recent FCC directives, i.e. Model devices, ModeII devices, and Sensing-only devices (enhanced through cooperation). We analyze the impact of class-specific parameters such as database querying frequency for ModeII devices, or sensing interval for cooperative devices- on the PU detection process. We also analyze the communication overhead required for TV white space detection on both the cellular data network (for querying the database), and on the IEEE 802.11p network (for enabling Model-ModeII communication and for cooperative sensing strategies). Second, we formulate the problem of determining the optimal ratio of ModeI, ModeII and Sensing-only devices based on current traffic density, so that (i) system-based thresholds of PU detection accuracy and responsiveness are guaranteed, while (ii) communication overhead is minimized. To this aim, three different cost functions are investigated. Third, we propose a distributed protocol to enable multi-interfaces vehicles to dynamically select their role (Model, ModeII or Sensing-only) in the cognitive network in order
to minimize database access load. The proposed approach is based on a swarm-intelligence model (i.e. the division of labor model in ant colonies), and is provided to mitigate congestion problems to the database, while guaranteeing high detection of spectrum resources.

The rest of the paper is structured as follows. Section II reviews existing studies on cognitive vehicular networks, by focusing on spectrum database approaches. Section III introduces the system model. In Section IV we formulate the optimization problem, and provide numerical results. In Section V we describe and evaluate the distributed allocation protocol. Conclusions follow in Section VI.

II. RELATED WORKS

In these last years, most of research works on TV white space detection for CR systems has been focused on spectrum sensing techniques [4]. However, the recent directives from OFCOM and FCC have also posed the attention on spectrum database issues [7] [10] [11], [12] [13]. In [10], the authors discuss some implementation details of geo-location database, and conclude that this approach can provide higher utilization of TV white spectrum resources than sensing-only techniques. CR network architecture based on spectrum database are proposed in [11], [12]. In [11], the authors describe SenseLess, an integrated service that includes a database of incumbents and a model of propagation to detect TV white spaces. Cognitive vehicular networks pose additional complexities to database implementation (for instance, the need to perform frequent queries to the database as a consequence of the vehicles' mobility), but also present some unique characteristics that can be leveraged by cooperative sensing schemes, as discussed in [8] [9]. In [14], the authors perform measurements from a vehicle traveling along an interstate highway near Boston, USA, and show the availability of vacant TV channels that might be used by CR vehicles. To this purpose, a learning-based channel selection scheme is proposed in [15] that takes into account the frequency of routes performed by each vehicle. Similarly, the authors of [7] attempt to reduce the communication overhead involved by spectrum queries through a vector-based representation of TV white space. However, none of these cited works combines the FCC regulations with the concerns of vehicular networks. For our goals, the most similar work is [13], where the authors determine the optimal base-stations density in order to minimize the connection cost. Conversely to [13], we do not rely on the presence of a fixed infrastructure, and we attempt to determine the optimal balance among sensing techniques and database load in order to guarantee maximum protection of PUs, while minimizing the overhead for TV white space detection.

III. SYSTEM MODEL

We consider an highway scenario like the one depicted in Figure 1. Here, the road scenario is divided into segments of equal length S. Spectrum database provided by spectrum agencies are accessible over all the scenario through a cellular infrastructure, and provide 100% accurate information about TV white channels on each segment. We model the street as a 1-dimensional line, where vehicles are distributed according to a Poisson process with density parameter \( \delta \). Let \( S \) be the segment length. Thus, the probability of having \( n \) vehicles on a segment \( S \) (i.e. \( P(n, S) \)) can be expressed as follows:

\[
P(n, S) = \frac{e^{-\delta S} \cdot (\delta \cdot S)^n}{n!}
\]

On each segment, vehicles move with equal speed \( v \). Following the recent regulations of FCC [5], we consider three classes of vehicles:

- **Model II device.** Vehicles can access the spectrum database through an Internet connection provided by the cellular (3G/4G) data networks. We denote with \( T_s \) the interval among consecutive queries to the database.

- **Model device.** Vehicles do not query the spectrum database directly, but leverage the presence of Model II device in their range to get information about TV white channels at their locations. Inter-vehicular unicast communication is performed through an IEEE 802.11p connection on a DSRC service channel (details below).

- **Sensing-only.** Vehicles rely on local spectrum activity to detect the presence of PU activity on TV channels. In this paper, we consider cooperative sensing strategies. i.e. each vehicle senses the TV spectrum every \( T_f \) seconds, and broadcasts a BEACON message to communicate the results of the sensing process to its neighbors. Inter-vehicular broadcast communication is performed through an IEEE 802.11p connection on the DSRC control channel (details below).

We assume each vehicle to be equipped with three radio interfaces: a Software Defined Radio (SDR) platform (used to communicate over detected TV white spaces), a 3G/4G-enabled and an IEEE 1609.4/802.11p radio device. On this latter, multi-channel operations are enabled by the IEEE 1609.4 protocol [1] to guarantee interpretability among different vehicular applications. According to this protocol, vehicles must periodically switch between a Service Channel (SCH) interval, during which they can be tuned to any of the 6 service channels of the DSRC band, and a Control Channel (CCH) interval, during which they must be tuned to a common control channel to exchange safety-related and broadcast data. In our study, frequency differentiation is introduced to concurrently support unicast- and broadcast- communications, assuming that Model-Model II communication will be performed during SCH intervals, while BEACON message for cooperative sensing
will be transmitted on the CCH. To measure the reactivity of vehicles in detecting the available TV spectrum resources at their locations, we introduce the Spatial Vulnerability Index (SVI), defined as follows:

\[ SVI = \min \left\{ \frac{\text{space\_covered}}{S}, 1 \right\} \]  

(2)

where \( S \) is the segment length, and \( \text{space\_covered} \) is the distance covered by the vehicle from the segment start to the location where (i) TV spectrum information are available for Model-ModeII devices, or (ii) the accuracy of cooperative sensing becomes higher than a requested accuracy on PU detection (\( P_{\text{thr}} \)). If the vehicle traverses the entire segment without acquiring sensing information for the current segment, then the \( SVI \) is set to 1. Intuitively, the lower is the SVI metric, the faster is the detection of spectrum resources from vehicles, and thus the higher is the exploitation of white space from the secondary network.

IV. PROBLEM FORMULATION AND OPTIMIZATION FRAMEWORK

Let \( \alpha, \beta \) and \( \gamma \) be the ratio of ModeI, ModeII and Sensing-only devices in our scenario, with \( \alpha + \beta + \gamma = 1 \). Moreover, let \( SVI_{\text{thr}} \), the minimum value of the SVI that must be guaranteed by the cognitive vehicular network. The goal of this analysis is to determine the optimal configuration of \( \alpha, \beta, \gamma \), so that \( SVI_{\text{thr}} \) is met by the current vehicular network deployment:

\[ SVI(\alpha, \beta, \gamma) < SVI_{\text{thr}} \]  

(3)

while a given cost function \( C \) is minimized. The cost function is related to the communication overhead generated by vehicles to detect the TV white space at each segment. To this purpose, let \( L_\alpha, L_\beta, L_\gamma \) the traffic load (in Kb/s) generated respectively by ModeI, ModeII and Sensing-only devices on the current segment, and \( C_{3G} \) and \( C_{\text{WIFI}} \) be the maximum capacity offered by the 3G and the 802.11p links, respectively. Moreover, we denote with \( R \):

\[ R = \left\{ \frac{L_\alpha}{C_{3G}}, \frac{L_\beta}{C_{\text{WIFI}}}, \frac{L_\gamma}{C_{\text{WIFI}}} \right\} \]  

(4)

the vector expressing the current utilization of wireless resources in our system. Since ModeII and Sensing-only devices utilize different DSRC frequencies, they are accounted separately in Equation 4. We consider three different formulations of cost function \( C \) in this paper:

- **Minimum Database Load.** In this case, our goal is to deploy the cognitive network in order to minimize the total load on the database, which might likely constitute the bottleneck of the system:

\[ C_1 : \minimize \left( \frac{L_\alpha}{C_{3G}} \right) \]  

(5)

- **Minimum Resources Utilization.** In this case, our goal is to deploy the cognitive network in order to minimize the utilization of wireless resources, considered as a whole:

\[ C_2 : \minimize \left( \frac{L_\alpha + L_\beta + L_\gamma}{C_{3G} + C_{\text{WIFI}}} \right) \]  

(6)

- **Minimum Resources Utilization Difference.** In this case, our goal is to deploy the cognitive network in order to maximally balance the load over the wireless resources. Let \( \max(R) \) and \( \min(R) \) respectively the maximum and minimum values of the vector \( R \). The goal function \( C_3 \) attempts to minimize the difference among the most and least occupied wireless resource of the system, i.e.:

\[ C_3 : \minimize (\max(R) - \min(R)) \]  

(7)

In the following, we detail how \( L_\alpha, L_\beta, L_\gamma, T_s \) and \( T_f \) can be computed. \( T_s \) is the database query interval for ModeII devices and \( T_f \) is cooperative sensing broadcast interval for Sensing-only devices. The optimization framework is shown in Algorithm 1.

**Algorithm 1** The optimization framework

**Input:** \( S, \delta, SVI_{\text{thr}}, P_{\text{thr}} \).

**Output:** \( \alpha, \beta, \gamma \).

**Model Variable:**

- \( T_s \) (query interval) value given by Equation 9.
- \( T_f \) (broadcast interval) value given by Equation 18.

**Constraints:**

- \( \alpha + \beta + \gamma = 1 \).
- \( L_\alpha < C_{3G}, L_\beta < C_{\text{WIFI}}, L_\gamma < C_{\text{WIFI}} \)
- \( \beta = 0 \) if Equation 12 holds.
- \( \gamma = 0 \) if \( T_f < T_{f_{\text{min}}} \) (Equation 19).

**Goals:** \( C_1 \) (Equation 5), \( C_2 \) (Equation 6) or \( C_3 \) (Equation 7).

A. Modeling of ModeII devices

For ModeII devices, \( \text{space\_covered} \) parameter described in Equation 2 refers to the portion of segment covered by a vehicle moving with velocity \( v \) till the first query to the database is issued. Thus the following inequality holds:

\[ \frac{T_s \cdot v}{S} < SVI_{\text{thr}} \]  

(8)

Moreover, rules from FCC foresee that ModeII devices must re-check the database each time they move 100 meters farther than their previous spectrum query [5]. Combining this directive with Equation 8, we get an upper bound for the value for \( T_s \) on the current scenario as follows:

\[ T_s = \min \left( \frac{SVI_{\text{thr}} \cdot S}{v}, \frac{100}{v} \right) \]  

(9)

We then derive the load for ModeII devices (\( L_\alpha \)):

\[ L_\alpha = T_s \cdot (\text{REQ}_\alpha + \text{REP}_\alpha) \cdot n_\alpha \]  

(10)

Here, \( \text{REQ}_\alpha \) and \( \text{REP}_\alpha \) represent the size (in bytes) of the query message sent from the vehicle to the database service (including current vehicle position) and the reply message (including the list of TV channels and their availability in the current segment). The \( n_\alpha \) is the number of ModeII vehicle in the current segment. Assuming a Poisson distribution of vehicles based on Equation 1, we can approximate \( n_\alpha \) as:

\[ n_\alpha = \left\lfloor \delta \cdot S \cdot \alpha \right\rfloor \]  

(11)

where \( S \) is the segment size and \( \delta \) is the vehicles’ density.
B. Modeling of Model devices

Model devices do not query directly the database, but rely on Model device for spectrum information. For this reason, we impose the constraint that a vehicle cannot be in Model if it does not have at least one neighbor in Model. Thus a vehicle cannot be Model if the following equality holds:

\[ |R \cdot \alpha \cdot \delta| = 0 \]  

(12)

where \( R \) is the transmitting range of vehicles over IEEE 802.11p links, and \( |R \cdot \alpha \cdot \delta| \) is the average number of Mode devices in its range. We assume that the frequency of connecting to Mode device will be the same as the frequency of querying the database, i.e. \( T_s \), given by Equation 9. We then derive the load \( L_\beta \) for Model devices as follows:

\[ L_\beta = T_s \cdot (REQ_\beta + REP_\beta + 2 \cdot ACK_\beta) \cdot n_\beta \]  

(13)

Similar to Equation 10, \( REQ_\beta \) and \( REP_\beta \) represent the size (in bytes) of the request/reply messages (transmitted over the DSRC service channel), while \( ACK_\beta \) accounts for the size of ACK message introduced by the MAC IEEE 802.11p scheme for unicast transmissions. The analysis of MAC retransmissions will be considered in future work. The \( n_\beta \) factor is the number of Mode devices in the current segment, and can be approximated as \( \delta \cdot S \cdot \beta \).

C. Modeling of Sensing-only devices

For Sensing-only devices, we first determine the amount of cooperation needed to guarantee that the accuracy of cooperative sensing scheme is higher than the requested threshold, i.e. \( P_{thr} \). Let \( p_{dt}, p_m \) and \( p_f \) be the probability of performing accurate PU detection, PU mis-detection and false alarm detection for each sensing sample. It is easy to see that the following relationship holds among \( p_{dt}, p_m \) and \( p_f \):

\[ p_d = 1 - p_m - p_f \]  

(14)

In our study, we consider \( p_m \) and \( p_f \) as fixed parameters of the system, and we derive the probability of PU detection \( P_d(n) \) when \( n \) sensing samples are available for the same segment. Generally speaking, deriving the curve of \( P_d(n) \) is a challenging task, since collected samples might be likely affected by correlated fading in both time and space. To make the analysis tractable, we consider the shadowing model proposed in [16], where a de-correlation distance \( \Delta \) is defined as the threshold over which two sensing samples can be considered as independent. To mitigate the impact of correlated shadowing on sensing performance, we restrict the set of cooperating vehicles to those located at higher distance than \( \Delta \). Thus, the number of cooperating vehicles of a Sensing-only device, i.e. \( n_c \), can be approximated as follows:

\[ n_c = [\delta \cdot (R - \Delta) \cdot \gamma] \]  

(15)

The majority rule is found to be the optimal fusion rule in case of independent sensing observations [17]. Under these assumptions, the \( P_d(n) \) function can be computed through the CDF of a Binomial distribution, i.e.:

\[ P_d(n) = \sum_{k=\lfloor \frac{n_c}{2} \rfloor + 1}^{n_c} \binom{n}{k} \cdot p_d^k \cdot (1 - p_d)^{n-k} \]  

(16)

It can be shown (not reported here for space reasons) that \( P_d(n) \) is a strictly monotonic function for odd/even values of \( n \). Let \( n_M \) the minimum value of \( n \) so that \( P_d(n_M) > P_{thr} \). Computing the SVI for Sensing-only devices, we have:

\[ \frac{\left\lfloor \frac{n_M}{n_c+1} \right\rfloor \cdot T_f \cdot v}{S} > SVI_{thr} \]  

(17)

Here, the numerator represents the space covered by the vehicle till \( n_M \) sampling samples are collected. From Equation 17, the upper bound on \( T_f \) can be derived as follows:

\[ T_f = \frac{S \cdot SVI_{thr}}{\left\lfloor \frac{n_M}{n_c+1} \right\rfloor \cdot v} \]  

(18)

Since consecutive samples should be not affected by correlated shadowing, a lower bound on \( T_f \) is:

\[ T_f^{min} = \frac{\Delta}{v} \]  

(19)

In case \( T_f > T_f^{min} \), no values of broadcast frequencies can guarantee to meet the requested \( SVI_{thr} \), and thus \( \gamma=0 \), i.e.
cooperative sensing is disabled. Finally, we derive the load $L_\gamma$ produced by Sensing-only devices:

$$L_\gamma = T_f \cdot \left( BEACON_\gamma \cdot n_\gamma \right)$$  \hspace{1cm} (20)$$

where $BEACON_\gamma$ is the size of the BEACON message, and $n_\gamma$ is the average number of Sensing-only devices, approximated by $[\delta \cdot S \cdot \gamma]$. In this analysis, we do not consider a lower bound on $T_f$, which however should be considered on a practical scenario.

In Figures 2(a), 2(b) and 2(c) we depict the vehicular network deployment (i.e. the configuration of $\alpha$, $\beta$ and $\gamma$) computed by the optimization framework for the goal functions $C_1$, $C_2$ and $C_3$, respectively. The model parameters used in the analysis are shown in Table I. Figures 2(a) refers to the case where the traffic on the 3G network must be minimized (according to Equation 5). We can notice that for low density scenarios ($\delta \leq 0.03$), cooperative sensing is disabled, since it does not meet the requested accuracy $P_{thr}$ and responsiveness $SVI_{thr}$. As a result, vehicles switch to Model connection as much as possible. For $\delta = 0.04$, cooperative sensing is enabled since $T_f < T_{thr}^\text{min}$, i.e. there exists values of the broadcast interval that guarantee to a vehicle to receive $n_M$ independent samplings. For higher vehicular densities (i.e. $\delta \geq 0.04$), vehicles rely on cooperative sensing only, in order to minimize the load to the database. Figure 2(b) refers to the case where the total traffic of the network must be minimized, without any distinction between network connection types (according to Equation 6). In this case, vehicles attempt to use their 3G connection to database as much as possible. Under high traffic density conditions (i.e. $\delta \geq 0.08$), the load to database becomes excessive, and cooperative sensing is enabled (since in our model broadcast communication involves less MAC overhead than ModeI unicast communication). Finally, Figure 2(c) refers to the case where the traffic on TV white space detection must be balanced among the available network resources (according to Equation 7). Like for the scenario depicted in Figure 2(a), channel detection is performed through Model and ModeII devices under low and medium traffic density conditions, while cooperative sensing is enabled for $\delta \geq 0.6$. However, conversely to previous case, all the three detection modes are used in the network deployment, proportionally with the overhead introduced on each channel for TV white space detection. Figures 3(a), 3(b) and 3(c) provide additional insight on the impact of the vehicle speed on system performance. More specifically, Figure 3(a) shows the broadcast interval value (i.e. $T_f$) of cooperative sensing, when varying the vehicle speed (on the x-axis) and for different configurations of density $\delta$ (different lines). Goal $C_1$ is used. As expected the broadcast interval ($i$) decreases with the vehicle speed (keeping fixed $\delta$), since a vehicle must sense the channel more frequently to collect the requested $n_M$ samples within the SVI threshold, and ($ii$) increases with $\delta$, since more sensing samples can be collected by vehicles at each beaconing interval. However, for goal $C_1$ the ratio of Sensing-only devices (i.e. $\gamma$) is not affected by the vehicle speed. This is shown in Figure 3(b), that depicts the values of $\gamma$ for different values of density $\delta$ and vehicle speed. It is easy to see that the utilization of cooperative sensing depends on network density, but it is not affected by vehicle speed, since vehicles can cope the effect of mobility by reducing the $T_f$ value. Finally, Figure 3(c) shows the database load (expressed as number of queries for second) as a function of the vehicle density and for different values of the vehicle speed, when goal

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**TABLE I**

**MODEL PARAMETERS**

<table>
<thead>
<tr>
<th>Segment length ($S$)</th>
<th>1000m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transmission range ($R$)</td>
<td>300m</td>
</tr>
<tr>
<td>De-correlation distance ($\Delta$)</td>
<td>50m</td>
</tr>
<tr>
<td>SV Threshold ($SVI_{thr}$)</td>
<td>0.3</td>
</tr>
<tr>
<td>Sensing accuracy Threshold ($P_{thr}$)</td>
<td>0.95</td>
</tr>
<tr>
<td>Local sensing accuracy ($p_\gamma$)</td>
<td>0.6</td>
</tr>
<tr>
<td>Packet sizes: $REQ_\alpha+REP_\alpha$</td>
<td>400B</td>
</tr>
<tr>
<td>Packet sizes: $REQ_\beta+REP_\beta+ACK_\beta$</td>
<td>420B</td>
</tr>
<tr>
<td>Packet size: $BEACON_\gamma$</td>
<td>400B</td>
</tr>
<tr>
<td>Capacity ratio $\frac{C_{WIFI}}{C_{3G}}$</td>
<td>6</td>
</tr>
</tbody>
</table>
$C_3$ is used. The load increases with vehicle speed, because of the reduced interval among queries (Equation 9). Moreover, Figure 3(c) shows that the load increases with density till the point cooperative sensing is enabled, which produces a significant reduction of spectrum requests to database.

V. DISTRIBUTED PROTOCOL

In this Section, we propose a distributed protocol that allows a multi-interface vehicle to decide the spectrum detection mode to use (i.e. Model, ModeII or Sensing-only), based on current vehicular traffic conditions. The goal here is to minimize the database load (e.g. goal $C_1$ of Section IV), while protecting the operations of licensed users. Following the guidelines provided by Figure 2(a), we propose a bio-inspired distributed cognitive network deployment, based on the labour division model in social insects colonies [18]. In the original model, a colony of $N$ elements is given a set of $K$ tasks to perform. Each task $k$ is associated a stimulus with intensity $s_k$ (a real number). Moreover, each insect $j$ provides with a response threshold $\theta_{j,k}$, which reflects the tendency of the individual to perform task $k$. Based on the values of $s_k$ and $\theta_{j,k}$, a response function $T_j(k)$ can be defined as follows [18]:

$$T_j(k) = \frac{s_k^3}{s_k^n + \theta_{j,k}^n}$$  \hspace{1cm} (21)

where $n > 1$ determines the steepness of the threshold. Intuitively, for $s_k \gg \theta_{j,k}$, the individual $j$ has a high response to the stimulus, i.e. it will likely perform task $k$, while it might likely ignore it for $s_k \ll \theta_{j,k}$. In our case, the set of tasks $N$ corresponds to the three detection modes, i.e.:

$$K = \{\text{ModeII}, \text{ModeI}, \text{Sensing}\}$$  \hspace{1cm} (22)

We assume that each vehicle $j$ is able to estimate the local traffic density (e.g. $\delta_j$) and to know the detection modes used by neighbor vehicles. Practically, in 1609.4 vehicular networks, traffic density can be inferred by monitoring the period exchange of WAVE Service Advertisement (WSA) messages on the CCH. Additional bits can be added to WSA messages to flag the current detection mode used by a vehicle. For space reasons, we do not further elaborate on these assumptions. Interested readers can refer to [19] for distributed traffic estimation techniques. For each vehicle $j$ and detection mode $k$ (i.e. the task), we formulate the response function $T_j(k)$ as follows:

- **Cooperative Sensing-only devices.** In this case, the stimulus to enable cooperative sensing is expressed as a function of the local traffic density perceived by vehicle $j$, i.e. $\delta_j$. The response threshold $\theta_{\text{Sensing}}$ is defined as the density threshold beyond which cooperative sensing should be disabled. Using $n = 3$, we have:

$$T_j(\text{Sensing}) = \frac{\delta_j^3}{\delta_j^3 + \theta_{\text{Sensing}}^3}$$  \hspace{1cm} (23)

- **ModeII devices.** Conversely to previous case, vehicles should access the database under low traffic conditions. For this reason, we define the stimulus $s_{\text{ModeII}}$ as follow:

$$s_{\text{ModeII}} = \max\{\delta_j - \theta_{\text{Sensing}}, s_{\text{min}}\}$$  \hspace{1cm} (24)

where $s_{\text{min}}$ is a parameter guaranteeing a minimum ratio of ModeII devices in network deployment. The response function for vehicle $j$ is defined as follows:

$$T_j(\text{ModeII}) = \frac{s_{\text{ModeII}}^3}{s_{\text{ModeII}}^3 + \theta_{\text{ModeII}}^3}$$  \hspace{1cm} (25)

- **Model devices.** The utilization of Model detection should be limited to the presence of ModeII devices in the vehicle’s transmitting range. To reflect this constraint, we define the stimulus $s_{\text{Model}}$ as the ratio of ModeII device over the total number of neighbors of vehicle $j$, and use a constant threshold $\theta_{\text{Model}}$ to preserve a minimal ratio of ModeII devices. The response function for vehicle $j$ is defined accordingly to Equation 21:

$$T_j(\text{Model}) = \frac{s_{\text{Model}}^3}{s_{\text{Model}}^3 + \theta_{\text{Model}}^3}$$  \hspace{1cm} (26)

Based on the response functions, the probability $P(j,k)$ that a vehicle $j$ will perform task $k$ (i.e. use detection mode $k$) can be computed as follow:

$$P(j,k) = \frac{T(k)}{\sum_{i \in N} T(i)}$$  \hspace{1cm} (27)

We assume that at the start of each segment, each vehicle $j$ will re-compute the $P(j,k)$ values, and then decide accordingly its detection mode. In the following, we evaluate the performance of our distributed cognitive network deployment algorithm through NS-2 simulations. To this aim, we model a 3-lane circular highway scenarios of 10 Km length, with $S=1000$ m. Each vehicle moves at uniform speed between 20 and 30 m/s. The number of vehicles is kept constant during the simulation. Each vehicle adapts its querying interval based on Equation 8, while it uses a fixed broadcast interval for cooperative sensing ($T_f=2s$). Referring to the parameters introduced in Section IV, we use the following settings in the simulation: $\Delta=50m$, $R=300$ m, $n_{M}=40$. Moreover, based on the results shown in Figure 2(a), we set the threshold values as follows: $\theta_{\text{Model}}=0.01$, $\theta_{\text{ModeII}}=0.01$, $\theta_{\text{Sensing}}=0.04$. Figure 4(a) shows the average device distribution as a function of the number of vehicles in the scenario. Here, ModeII device connections are used to alleviate the load to the database in low traffic conditions, while cooperative sensing is progressively enabled by increasing the traffic density. Also, we highlight that the device distribution can be arbitrary controlled through the tuning of the device thresholds $\theta_k$. Figure 4(b) confirms the effectiveness of our approach in reducing the database load while guaranteeing fast detection of spectrum resources. On the y-axis, we show the average per-vehicle rate of spectrum queries (per second) as a function of the number of vehicles, for the cases where cooperative Sensing is completely disabled $^2$, or cooperative Sensing is enabled $^3$ according to

$^2$Referred to as Sensing OFF in Figures 4(b) and 4(c).

$^3$Referred to as Sensing ON in Figures 4(b) and 4(c).
the probabilistic mechanism of Equation 21. Moreover, in the same Figure we show (on the y2-axis) the SVI metric for the two configurations. As expected, the Sensing OFF configuration optimizes the detection responsiveness, but at the cost of introducing a significant overhead on the 3G connection. Conversely, the Sensing ON configuration progressively reduces the load to the database, while approaching the performance of the database-only configuration in terms of SVI for increasing traffic load conditions. This is also confirmed by Figure 4(c), where we depict the total database load (expressed as number of queries per second) for the two configurations, in a dynamic vehicular environment. Here, we consider an initial scenario with 100 vehicles in the simulation, and a new vehicle is added to the simulation every 10 seconds till time 5000. From time 8000, a vehicle is removed from the scenario every 10 seconds, till simulation end. Figure 4(c) confirms the ability of the bio-inspired distributed algorithm to adapt to dynamic traffic environments, by minimizing the load to database.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, we have investigated the problem of TV white space detection on cognitive vehicular networks. Following the recent directives from national spectrum agencies (i.e. FCC and OFCOM), we have analyzed the joint utilization of cooperative sensing and spectrum database to guarantee maximum protection of licensed users, while minimizing the resources utilized by vehicles for white space detection. To this aim, we have proposed both theoretical and practical contributions. Future works include: the modeling of MAC 802.11p contention and its impact on Model and cooperative sensing operations, the extension of the theoretical framework to a multi-lane scenario with different speed distributions, the evaluation of the distributed protocol on simulated large-scale urban environments.

REFERENCES


