

Double Threshold Spectrum Sensing Methods in Spectrum-Scarce Vehicular Communications

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Abstract – as vehicular communication becomes a widespread phenomenon, there will be an increase in spectrum scarcity. Cognitive radio provides an effective solution but requires a robust sensing mechanism that entails a large overhead; this additional sensing data could be detrimental to a system already lacking in bandwidth. This paper proposes novel ways of limiting sensing overhead by improving upon current methods which use cooperative mechanisms and adjustable double thresholds (DTHs). Based on a sliding variable, the proposed thresholds can react to changes in the environment, providing the required primary user detection and false alarm probabilities while limiting the number of vehicles reporting sensing data. Three new DTHs have been proposed: detection-based DTH, decision-based DTH, and independent-threshold DTH. Each has unique properties that make it suited for different environments. Simulations were run on all proposed thresholds to test their validity and endurance under environmental changes. The results indicate that the double thresholds would greatly benefit high-contention, dense vehicular networks.

Index Terms—Cognitive Radio, Cooperative Spectrum Sensing, Dynamic Double Threshold, Exponential Distribution

I. INTRODUCTION

DUE to recent advances in intelligent transport systems (ITSs), interest in vehicular communications research has increased. With the ability to ‘extend the horizon’ of drivers and on-board computers comes the opportunity to improve road safety and organisation [1], reducing congestion, road traffic accidents, travelling time and fuel consumption. However, as ITSs are deployed, spectrum scarcity is becoming a serious challenge, with negative implications for vehicular safety applications.

Vehicular ad-hoc networks (VANETs) generally use the IEEE 802.11p Wireless Access in Vehicular Environments (WAVE) standard to realise communication between vehicles [3]. This standard employs the carrier sense multiple access/collision avoidance (CSMA/CA) protocol, meaning messages can be subject to collisions and losses when there is channel congestion. In an existing study on spectrum scarcity [4], it was shown that, at high traffic levels, there was not enough bandwidth to maintain a reasonable quality of service. This is particularly concerning because safety-related packet loss or delay could cause road traffic accidents. Some researchers have suggested that non-safety use of the control channel (CCH) should be limited during peak hours of traffic [5], [6], although this restricts the commercial and coordination prospects for ITSs. In response to this problem, the U.S Federal Communications Commission (FCC) has allowed secondary

use of the broadcast television spectrum through cognitive radio (CR) [7].

CR uses opportunistic spectrum overlay to gain ITS bandwidth. It actively seeks out additional spectrum through dynamic channel access. Underutilised portions of spectrum are reused, with the constraint that spectrum access by an unlicensed secondary user (SU) does not interfere with the licensed primary user (PU). Spectrum overlay, where ‘white spaces’ in the PU spectrum are used [8], is generally preferred over underlay, as SUs using underlay are required to keep their power below a threshold, so must spread their signals over large bandwidths [9].

A condition of using spectrum overlay is that a robust sensing mechanism is required to ensure no PU interference occurs. Changes in PU presence must be detected quickly, which requires regular reports from vehicles in the network on the state of the PU spectrum [10]. To improve the reliability of detection, cooperative spectrum sensing (CSS), where multiple vehicles sense the spectrum and combine their information, can be employed. However, using CSS requires a significant overhead. There is therefore a trade-off between the ‘cognitive gains’ of additional bandwidth and the bandwidth lost due to spectrum sensing overhead, especially in vehicle-dense environments where the channel is highly utilised [11]. This is particularly important because the channel through which sensing data is sent, the CCH, experiences the most congestion and carries safety messages.

Many cognitive CSS methods for CR have been explored previously; authors in [12] and [13] have proposed double-threshold (DTH) methods for improving detection and false alarm reliability. Furthermore, authors in [14], [15] and [16] have explored the use of cognitive radio in small cell networks, with the aims of reducing power consumption, optimizing sensing time, increasing user fairness and limiting interference using hybrid spectrum sensing. However, in these papers, the primary aim is not to reduce sensing overhead, which is addressed as an aside. The key novel contributions of this paper, therefore, are:

- The design of original DTH-CSS models, built with the primary aim of use within non-distributed, dense vehicular environments.
- The determination of sensing threshold values that explicitly aim to minimise sensing data overhead.
- The use of expectations of PU presence to build time-variant expressions to build double thresholds, used in conjunction with equations built using the probability of

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detection and false alarm (DEC-DTH).

- The determination of an equation for a threshold model that minimises the probability of falsely detecting the PU, leading to reduced sensing data and more access to the cognitive spectrum (previous papers have attempted to keep the probability of false alarm below a threshold rather than minimising it).
- The use of two thresholds, each based on independent equations, in a DTH-CSS scheme to achieve optimum probability of detection and false alarm simultaneously.

In section II, the background and theory will be explained, followed by the system model and proposed method in section III. Section IV will cover the results and discussion, and section V will conclude the findings.

II. BACKGROUND AND THEORY

A. Vehicular Network Standards

75 MHz of dedicated spectrum, from 5.850-5.925 GHz, has been assigned for ITS purposes by the FCC [10]. This is divided into seven 10MHz channels: six service channels (SCH) for general purpose messages, and one control channel, which carries safety, coordination and control messages [17]. The channel switches between intervals of the CCH and SCH intermittently, each with durations of 50 ms [4].

B. Double Threshold Cooperative Spectrum Sensing

CSS uses the temporal and spatial diversity provided by a highly mobile vehicular environment to accurately and quickly detect the PU [18]. In urban environments, signals encounter obstacles (buildings, for example) that cause shadowing, multi-path fading and Doppler shifts [10]. CSS significantly reduces these effects by combining sensing data from multiple vehicles. In most CSS cases, each sensor uses the same sensing technique for detection. In [10], some local sensing techniques were explored, including maximum likelihood ratio detection and soft energy detection. Due to its low computational cost and simplicity, the most commonly used technique is energy detection, which this paper will focus on.

A DTH censoring method is a way of reducing the number of vehicles transmitting sensing data. In conventional energy detection CSS, a single energy threshold (STH) determines whether the PU is present, whereas in DTH-CSS an upper and lower threshold are set. If the energy detected by the SU lies between these, the sensing data is not reported. Thus, the thresholds determine how many vehicles report. Some papers have explored different methods for choosing where the thresholds lie; authors in [12] proposed a DTH scheme to ‘achieve more reliable detection’ in CSS networks, however the aim was not to reduce sensing overhead. In [13], a user correlation and DTH based CSS was proposed, where a DTH based on correlation (among other variables) was used to reduce sensing overhead. It achieved a ‘trade-off between sensing performance and system overhead’ in dense networks, defining equations that governed a sliding DTH. However, although this paper addressed the need for a reduction in sensing reports, the core goal was to improve the probability of PU detection, and

not to reduce the number of transmitters.

This paper will show that it is possible to majorly limit the number of vehicles transmitting sensing data while maintaining a reasonable PU detection and false alarm probability by using novel energy-detection DTH-CSS schemes.

III. SYSTEM MODEL AND PROPOSED METHOD

A. System Model

Vehicular networks are unique in that many of their nodes, namely vehicles’ on-board units (OBUs), can be highly mobile. Structures for cognitive radio VANETs (CR-VANETs) proposed in literature can generally be classified as distributed or non-distributed. Although a fully distributed network in which no static architecture is needed would work well in rural areas where traffic is spread out, a non-distributed architecture involving road-side units (RSUs), which aid network formation and communication [19], is generally more practical in urban environments. The stationary RSU has memory, substantial computational capacity and short-range wireless transmission capability [20] and acts as a server to provide SUs (in this case, the OBUs) with local guidelines for accessing PU white spaces. It has the processing power and coordination needed for cooperative spectrum sensing and spectrum allocation [4]. Moreover, as spectrum scarcity is most common in vehicularly dense environments, urban areas will be the biggest benefactors of CR technology. This paper will therefore focus on densely-populated, non-distributed networks involving RSUs.

In non-distributed networks, once the sensing data is received by the fusion center (in this case, a RSU), it is merged to form a final decision about the presence of a PU. The fusion method chosen in this case is OR-rule fusion, in which only one node must detect the PU for the fusion center to decide that it is present [13].

The system model is shown in Fig. 1. It comprises one RSU, acting as the fusion center, one PU, and N SUs, each with an OBU of low computational capability which can retain spectrum sensing information and retransmitting it to the RSU.

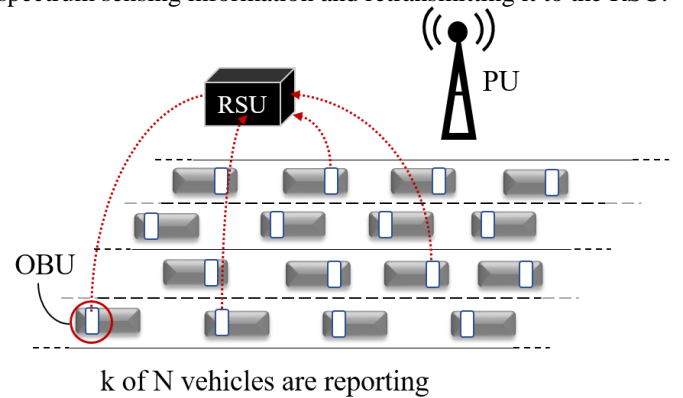


Fig. 1. Schematic of a non-distributed VANET with N vehicles

The RSU can communicate with every vehicle within its range during the 50 ms CCH interval, and is aware of the number of vehicles, N , in its range. Fig. 2 shows the system’s timing model.

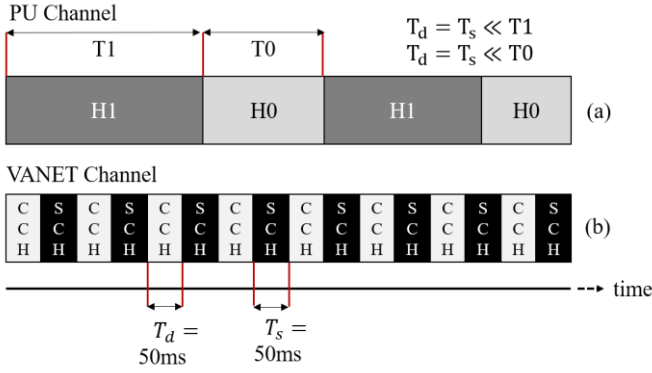


Fig. 2. Timing model of the PU channel (a) and VANET channel (b)

During the CCH interval, information can be passed between the RSU and OBUs. During the SCH interval, sensing information is collected by the OBUs and a decision about the PU state is made. This is transmitted to the RSU during the following CCH. The SCH therefore comprises the sensing duration, T_s , and the CCH the data duration, T_d . The transmission duration, $T_t = T_s + T_d$, is the amount of delay expected for the system to react to a change in the environment (for example, the PU channel changing its state or the number of vehicles changing).

The PU channel, whose spectrum will be overlaid when the PU is absent, alternates between states H1, where the PU is present, and H0, where the PU is absent. The durations of PU presence and absence, $T1$ and $T0$ respectively, can be modelled as an exponential distribution with expectations $E[T1] = \bar{T}1$ and $E[T0] = \bar{T}0$ [21]. The expectations are assumed to be much larger than T_t , so that delays caused by OBU to RSU communication are small compared to the PU durations. The probability of the primary user's absence can then be calculated as

$$P(H0) = \frac{\bar{T}0}{\bar{T}0 + \bar{T}1}, \quad (1)$$

where $P(H1) = 1 - P(H0)$.

The PU signal energy and channel noise energy are modelled, as in [13], as

$$x_i(t) = \begin{cases} n_i(t) & H0 \\ h_i(t)s(t) + n_i(t) & H1 \end{cases} \quad (2)$$

where $x_i(t)$ is the signal received by sensor i (where each vehicle has one sensor) at time t , n is the channel noise power, h is the channel gain, and s is the PU signal. The signal-to-noise ratio, γ , at sensor i is defined by variance, as $\gamma_i = \frac{h_i^2 \sigma_s^2}{\sigma_n^2}$, where σ_s^2 is the PU signal variance and σ_n^2 is the channel noise variance. When the number of samples, $M = [T_s f_s]$, where f_s is the sampling frequency, is sufficiently large, the test statistic for each sensor at the end of the sensing period T_s is defined as

$$X_i = \sum_{M=1}^M x_i, \quad (3)$$

as proved in [22]. This can be modelled, as in [13], as the normal Gaussian distribution

$$X_i \sim \begin{cases} \mathcal{N}(\mu_0, \sigma_0^2) & H0 \\ \mathcal{N}(\mu_1, \sigma_1^2) & H1 \end{cases}, \quad (4)$$

where $\mu_0 = [M\sigma_n^2]$ and $\sigma_0^2 = [2M\sigma_n^4]$ are the mean and variance under hypothesis H0 respectively, and $\mu_1 = [M(\sigma_n^2 + \sigma_s^2)]$ and $\sigma_1^2 = [2M(\sigma_n^2 + \sigma_s^2)^2]$ are the mean and variance under hypothesis H1.

After detection, a decision is made by each OBU and the results are transmitted to the fusion center. The OR-fusion rule is then used to make a final decision, which greatly increases the probability of PU detection.

B. Detection-Based DTH Energy Detection

To decrease the number of reporting vehicles, a double threshold has been proposed. A sliding variable, τ , is used as in [13]. The system can react to changes in the environment by building an equation for τ that includes as many relevant environmental factors as possible, and by recalculating τ after each sensing period. The threshold model is shown in Fig. 3.

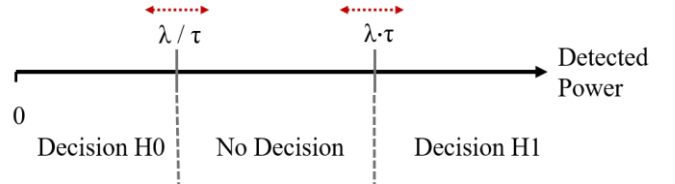


Fig. 3. Double-threshold model for energy detection with sliding tau

The variable λ is defined according to the non-cooperative probability of false alarm in an STH case, $P_{f,1th}$, as

$$\lambda = \sigma_n^2 (\sqrt{2M}Q^{-1}(P_{f,req}) + M), \quad (5)$$

where $P_{f,req}$ is the maximum allowed probability of false alarm, usually set at 0.1. If the noise variance and sampling rate are assumed constant with time, λ will also be constant, and, according to (5), greater than 1. This provides an appropriate value to build the sliding threshold on. τ will be calculated by the RSU in the OBU sensing duration T_s , and sent to the OBUs in the data duration, T_d . In the following sensing period, each OBU will make its sensing decision based on the rule

$$D_i = \begin{cases} 0 & X_i < \lambda/\tau \\ ND & \lambda/\tau < X_i < \lambda\tau \\ 1 & X_i > \lambda\tau \end{cases}, \quad (6)$$

where ND stands for 'no decision' and means that no report is made to the RSU. Out of N vehicles in the RSU range, k will report sensing information, where $0 \leq k \leq N$. The higher the number of detected values within in the 'no decision' zone, the lower the value of k and the lower the overall sensing overhead in the CCH.

The non-cooperative probabilities of PU detection and false alarm can be calculated, respectively, based on normal cumulative distribution functions, as

$$P_{d,2th} = P(X_i > \lambda\tau | H1) = 1 - \phi\left(\frac{\lambda\tau - \mu_1}{\sigma_1}\right) = Q\left(\frac{\lambda\tau - \mu_1}{\sigma_1}\right), \quad (7)$$

$$P_{f,2th} = P(X_i > \lambda\tau | H0) = 1 - \phi\left(\frac{\lambda\tau - \mu_0}{\sigma_0}\right) = Q\left(\frac{\lambda\tau - \mu_0}{\sigma_0}\right), \quad (8)$$

where $Q\left(\frac{x-\mu}{\sigma}\right)$ is the tail probability of the standard normal distribution $\phi\left(\frac{x-\mu}{\sigma}\right)$, also known as the Q-function. The cooperative decision is made using the OR-fusion rule, based on the decisions of the k reporting vehicles. As a safety measure, the system has been built so that if no sensing report is made (for example, if the threshold is made so large that all vehicles find $D_i = ND$, the fusion centre will decide that the PU is present, i.e. $D_{RSU} = 1$). Assuming consistent signal-to-noise ratio throughout the environment, i.e. $\gamma_1 = \gamma_2 = \dots \gamma_N$, the DTH cooperative probability of PU detection and false alarm are calculated as

$$Q_{d,2th} = 1 - P(X_i < \lambda | H1)^N + P(k = 0) = 1 - (1 - P_{d,2th})^N + P_{nd,1}^N, \quad (9)$$

$$Q_{f,2th} = 1 - P(X_i < \lambda | H0)^N + P(k = 0) = 1 - (1 - P_{f,2th})^N + P_{nd,0}^N, \quad (10)$$

respectively, where $P_{nd,0}$ and $P_{nd,1}$ are the non-cooperative probabilities of the case $D_i = ND$ when the PU is absent and present, respectively. They are calculated as

$$P_{nd,0} = P(D = ND | H0) = Q\left(\frac{\lambda/\tau - \mu_0}{\sigma_0}\right) - Q\left(\frac{\lambda\tau - \mu_0}{\sigma_0}\right), \quad (11)$$

$$P_{nd,1} = P(D = ND | H1) = Q\left(\frac{\lambda/\tau - \mu_1}{\sigma_1}\right) - Q\left(\frac{\lambda\tau - \mu_1}{\sigma_1}\right). \quad (12)$$

Taking into consideration how $Q_{d,2th}$ and $Q_{f,2th}$ vary with respect to each other with increasing τ , as shown in the hysteresis curve in Fig. 4, a better result is found when τ is lower, corresponding to $Q_{f,0}$, where $P(k > 0)$ approaches 1 and $P_{nd,0}$ and $P_{nd,1}$ can be assumed as 0.

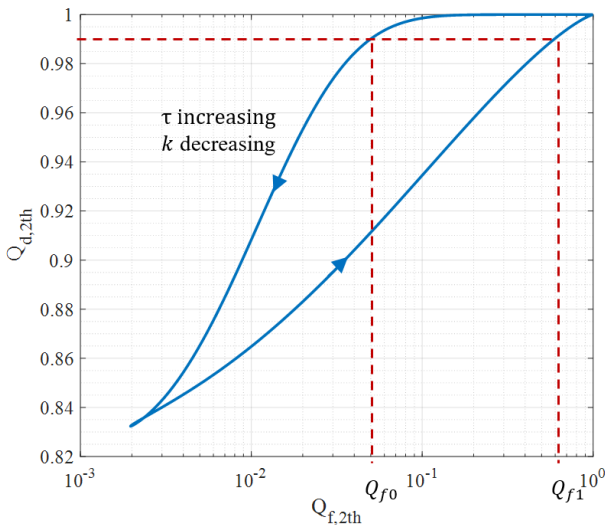


Fig. 4. Hysteresis curve of cooperative double threshold probabilities for increasing tau

Using this assumption, values of τ corresponding to the required probabilities of PU detection, $Q_{d,req}$, and false alarm, $Q_{f,req}$, are found to be

$$\tau_d = Q^{-1}\left(1 - (1 - Q_{d,req})^{\frac{1}{N}}\right)\frac{\sigma_1}{\lambda} + \frac{\mu_1}{\lambda}, \quad \tau_d \geq 1, \quad (13)$$

$$\tau_f = Q^{-1}\left(1 - (1 - Q_{f,req})^{\frac{1}{N}}\right)\frac{\sigma_0}{\lambda} + \frac{\mu_0}{\lambda}, \quad \tau_f \geq 1, \quad (14)$$

where τ_d is the maximum allowed value of τ to obtain a detection probability of at least 0.99, and τ_f is the minimum required value of τ to ensure a false alarm probability of less than or equal to 0.1. To satisfy the detection probability requirements, the value must lie between the limits $\tau_f < \tau < \tau_d$. Considering that a maximum τ is preferred to limit the number of transmitting vehicles, τ_d is the limiting factor. Hence, this method is named detection-based DTH (DET-DTH), as the thresholds are determined by the required probability of detection.

During each OBU sensing period (SCH interval), τ_d will be calculated based on the last-known value of N and γ , and transmitted in the next CCH to the OBUs, to be used in the following SCH.

C. Bi-Variable DTH-Based Energy Detection

Although part B provides a reliable method for obtaining the required detection and false alarm probability where possible, it is possible to tweak the system by using two variables, so that fewer vehicles need to report and the probability of false alarm decreases.

As equations (13) and (14) show, τ_d and τ_f will have different values depending on $Q_{d,req}$, $Q_{f,req}$ and γ , meaning that a system based on only τ_d may not always provide the required $Q_{f,2th}$. It can be noted that $Q_{d,2th}$ and $Q_{f,2th}$ benefit differently with respect to τ ; although both values eventually decrease as τ increases, the lowest possible Q_f is preferred (corresponding to a high τ , with as few vehicles reporting as possible without no vehicles reporting) whereas the highest possible Q_d is wanted, corresponding to a low τ .

The highest possible τ that maintains $Q_{d,req}$ is τ_d , as in the DET-DTH case. However, considering (10), an optimum false alarm probability will be found at the minimum point of the $Q_{f,2th}$ - τ curve, between where $P_{nd,0}^N$ starts increasing (as this will yield a false decision $D_{RSU} = 1$), and where $1 - (1 - P_{f,2th})^N$ falls to its minimum. Although the most accurate way of calculating this point would be to set the derivative of the cooperative false alarm probability, $Q'_{f,2th}$, to zero, the complexity of this equation would make it impossible to solve without using a numerical method, which would take more computational capacity. Therefore, a prediction of this point has been made by considering the two points where $P_{nd,0}$ and $1 - (1 - P_{f,2th})^N$ approach zero. In each case, the desired probability of false alarm is set to 0.01, resulting in values of

$$\tau_{Qf} = \frac{\sigma_0}{\lambda} Q^{-1}\left(1 - 0.99^{\frac{1}{N}}\right) + \frac{\mu_0}{\lambda}, \quad (15)$$

$$\tau_{nd,0} = \frac{\lambda}{\sigma_0 Q^{-1}\left(0.01^{\frac{1}{N}}\right) + \mu_0}. \quad (16)$$

The mean of these two values gives an accurate estimate for the point at which the minimum false alarm probability occurs. This results in a new value, τ_{f2} , defined as

$$\tau_{f2} = \frac{1}{2} \left(\frac{\sigma_0}{\lambda} Q^{-1} \left(1 - 0.99 \frac{1}{N} \right) + \frac{\mu_0}{\lambda} + \frac{\lambda}{\sigma_0 Q^{-1} \left(0.01 \frac{1}{N} \right) + \mu_0} \right). \quad (17)$$

This provides the possibility of greatly reducing the false alarm probability while simultaneously decreasing the number of reporting vehicles. This value is the highest possible τ_f , as, although τ could be increased even further to when it reaches 0.1 for the second time, as seen in the hysteresis curve in Fig. 4, increasing it by this much would adversely affect the detection probability, making this a safer choice.

1) Decision-Variant DTH

Generally, the discrepancies between the τ that provides the optimum Q_d and that which corresponds to the optimum Q_f can be considered as a trade-off problem, and an all-encompassing equation for τ can be found. This not only limits how low the false alarm probability can be but means that the value of τ is lower than it needs to be, resulting in more vehicles transmitting sensing data.

Integrating τ_{f1} or τ_{f2} into the system will solve this problem. A simple integration method to adopt is that, once the RSU has decided that the PU is present, τ_d is used, and vice versa. This behavior can be described as:

$$\tau(t + T_t) = \tau_d, \quad D_{RSU}(t) = 1, \quad (18)$$

$$\tau(t + T_t) = \tau_{fx}, \quad D_{RSU}(t) = 0, \quad (19)$$

where $D_{RSU}(t)$ is the cooperative decision made at the RSU at time t , and x is either 1 or 2, depending on whether (14) or (17) is used to calculate τ_f . Thus, a more tailored τ can be used. However, this method is problematic because, when the PU transitions the system is not ready to react, as the thresholds are set for the opposite PU case. To address this problem, a time-variant method has been developed.

Considering the system with respect to time, it is possible to change the method of calculating τ depending on how likely it is that the PU's state will transition. Because the durations of PU presence and absence, $T1$ and $T0$ respectively, can be modelled with an exponential distribution, the probability of transition can be calculated, based on the exponential cumulative distribution function, as

$$P_{trans,01}(t) = 1 - \exp\left(-\frac{t-t_0}{T_0}\right), \quad (20)$$

$$P_{trans,00}(t) = \exp\left(-\frac{t-t_0}{T_0}\right), \quad (21)$$

where t is time since the system initialized, $D_{RSU}(t_0) = 0$, and $D_{RSU}(t_0 - T_t) = 1$ i.e. the probability 'timer' only resets if the transition from $D = 1$ to $D = 0$ occurs. These probabilities can then be used to slide the value of τ_f closer to that of τ_d as the probability of a transition from $D = 0$ to $D = 1$ increases. A time-variant τ_{fx} is then defined as

$$\tau_{fx}(t) = \tau_{fx} P_{trans,00}(t) + \tau_d P_{trans,01}(t), \quad (22)$$

where the number of vehicles, N , and γ can also change with time. To keep the probability of detection at a reasonable value, the time-variant method will only be used on the thresholds while $D = 0$. This is because the probability of detection determines the likelihood of PU interference. The final decision-variant bi-variable system is therefore defined as

$$\tau(t + T_t) = \tau_d, \quad D_{RSU}(t) = 1, \quad (23)$$

$$\tau(t + T_t) = \tau_{fx}(t), \quad D_{RSU}(t) = 0. \quad (24)$$

The result is a system that has memory and can accurately track the PU presence while keeping the sensing overhead low. Because the chosen τ is based on the most recent D_{RSU} , this method is called decision-variant DTH (DEC-DTH).

2) Independent-Threshold DTH

Although the method outlined in *C.1* has the advantage that the RSU needs to send only two values, λ and τ , to the OBUs in each CCH interval, a somewhat simpler solution can be found by sending two separate values of τ . Instead of changing τ based on the most recent cooperative decision, separate upper and lower thresholds based on τ_d and τ_{fx} respectively can be defined:

$$D_i = \begin{cases} 0 & X_i < \lambda/\tau_{fx} \\ \text{ND} & \lambda/\tau_{fx} < X_i < \lambda\tau_d \\ 1 & X_i > \lambda\tau_d \end{cases}. \quad (25)$$

In this case, the two thresholds can change independently of each other, making it an independent-threshold DTH (IT-DTH). This will require more CCH bandwidth, but should make the system much more robust, as it will never have to transition between τ_d and τ_{fx} .

IV. RESULTS AND DISCUSSION

To test the validity of the equations and models developed and to compare their performance, simulations were run in MATLAB. Unless stated otherwise, the parameters used were as shown in Table I.

TABLE I
PARAMETERS USED IN SIMULATIONS

Parameter	Notation	Value
Sensing Duration	T_s	50ms
Data Duration	T_d	50ms
T1 Expected Value	\bar{T}_1	2000ms
T0 Expected Value	\bar{T}_0	2000ms
SNR	γ	-1dB
Required Probability of PU Detection	$Q_{d,req}$	0.99
Required Probability of PU False Alarm	$Q_{f,req}$	0.1
Number of Vehicles	N	100
Probability of Primary User Presence	$P0$	0.5
Number of Samples	M	500

DET-DTH, DEC-DTH and IT-DTH methods were compared using a non-timing model, and a timing model.

A. Static Model

Firstly, a model was built that simulated the system without considering how the PU would change with time or how the sensing system would react to this. This provided the opportunity to test how the theoretical, probability-based

equations compared to simulated ones. A Monte-Carlo simulation with 1000 iterations was used to generate the simulated results.

DET-DTH, DEC-DTH using τ_{f1} and DEC-DTH using τ_{f2} were tested. A distinction between DEC-DTH and IT-DTH cannot be made in these simulations, as they do not consider time; both are modelled as DEC-DTH. The results can be seen in Fig. 5, where the probability of detection has been omitted as it is the same for every case, reaching 0.99 when 5 or more vehicles enter the environment. The simulation results closely follow the theoretical predictions.

The DET-DTH method performs well in vehicle-dense environments, with a low overhead (see Fig. 5-b) and adequate Q_f after 20 vehicles enter the environment (see Fig. 5-a). Nevertheless, this method is not viable in this environment with fewer than 20 vehicles, as, although $Q_{d,req}$ is met after 5 vehicles, $Q_{f,req}$ is too high until 20 vehicles are present. This may not be a problem if spectrum sensing is not required below this number of vehicles, due to low traffic making the CR-spectrum unneeded.

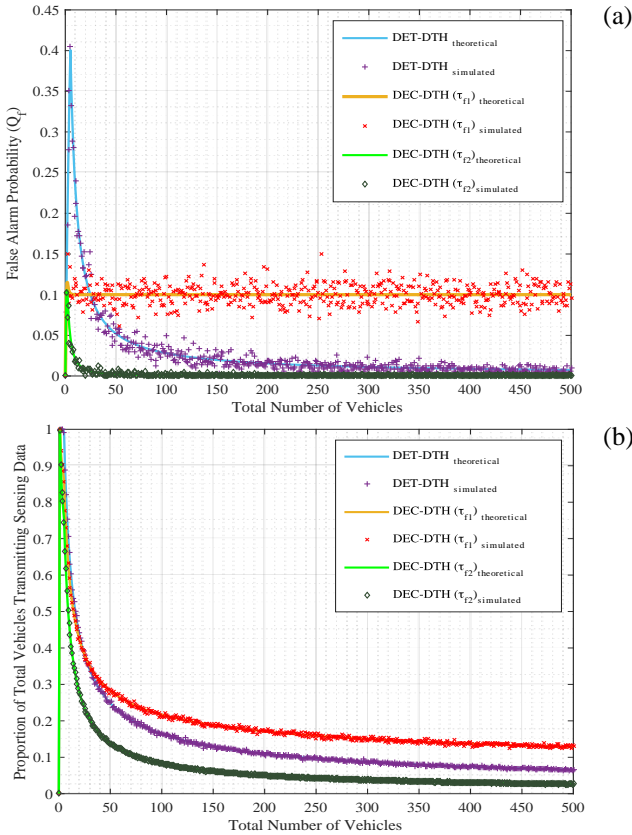


Fig 5. Comparison of three DTH methods with increasing number of vehicles

The next method, using DEC-DTH with τ_{f1} (calculated by reversing the equation for the probability of false alarm) holds Q_f at approximately 0.1, independently of how many vehicles are present. However, the simulation results show that the true value may stray from this, and Q_f can reach values up to 0.15. To compensate for this, $Q_{f,req}$ could be set to 0.05 rather than 0.1, which would decrease the likelihood of Q_d reaching higher than 0.1.

As Fig. 5-a also shows, using DEC-DTH with τ_{f2} determining the thresholds makes it possible to keep the

average false alarm probability below $Q_{f,req}$ for almost any number of vehicles. Fig. 5-b shows that the average percentage of vehicles required to report sensing data decreases as the total number of vehicles increases, and is lowest for the DEC-DTH method using τ_{f2} , making this the method of choice for keeping k and Q_f low while simultaneously keeping Q_d high. This result can be explained by considering that, whenever the PU is absent (in this simulation this is in 50% of cases), τ_{f2} , which is nearly always larger than τ_{f1} and τ_d , is used to limit the number of vehicles reporting.

Comparing the proposed methods and considering overhead and PU detection accuracy, DEC-DTH with τ_{f2} seems the best choice for dense vehicular environments. DET-DTH performs better than DEC-DTH with τ_{f1} for environments with more than 20 vehicles. However, a benefit of the DEC-DTH method with τ_{f1} is that, by changing the value of $Q_{f,req}$ entered into the equation for τ_{f1} , the user has greater control over where they want the false alarm probability to lie, as its value is almost constant for any number of vehicles in the environment, even for low numbers. This could be beneficial if a stable, predictable system is required. As the main aim of the paper is to keep overhead low, DEC-DTH using τ_{f1} will not be considered further.

Although the equations and models made were set up to react to changes in environment such as number of vehicles and PU-signal power, they did not consider the transition of the PU from present to absent, or vice versa. This was therefore explored in a timing model.

B. Timing Model

For the next stage of simulations, the MATLAB simulation environment was extended to implement the timing specifications outlined in the system model (see Section III-A). Values of N and γ of 100 and -1 dB were chosen, respectively, and kept constant for the sake of clarity. The simulation was run for 1 minute.

Three proposed methods – DET-DTH, DEC-DTH using $\tau_{f2}(t)$, and IT-DTH using τ_{f2} – were simulated. Fig. 6 shows how each DTH behaved. Only the test statistics (which represent the predicted received PU signal strength for the 100 vehicles at each time interval) that lie above threshold 1 and below threshold 2 in the graphs can determine the final decision of the PU presence.

Table II shows the data gathered at the end of the simulations for each method.

TABLE II
TIMING SIMULATION RESULTS

DTH Method	Average Q_d	Average Q_f	Average k (out of $N = 100$)
DET	0.9895	0.028	16.696
DEC using $\tau_{f2}(t)$	0.982	0.015	12.160
IT using τ_{f2}	0.997	0.016	7.105

The DET-DTH results, seen in Table II, match what is expected from the time-invariant model. This is because the number of vehicles is above 20, and its value of τ is independent of the state of the PU, resulting in time-constant thresholds, as seen in Fig. 6-a.

Conversely, the threshold values of DEC-DTH using $\tau_{f2}(t)$, can be seen in Fig. 6-b to be time-varying, changing with the PU's state. Table II shows a low k for this method, which can be explained by considering the figure, where it is possible to see the wider $\tau_{f2}(t)$ threshold trapping more vehicles within the thresholds than in the DET-DTH case. The high detection probability is due to $\tau_{f2}(t)$ becoming closer to τ_d with time, making the system more prepared to detect the return of the PU. A problem with this method arises when a spurious reading, for example if none of the PU's signals are as high as expected, occurs. This will cause the system to believe the PU is absent, reset the timer and change the thresholds accordingly, making it even more difficult to realize the mistake, and causing misinterpretations to go unfixed for longer. However, this method is appealing because of the very low number of transmitters required and the low probability of false alarm.

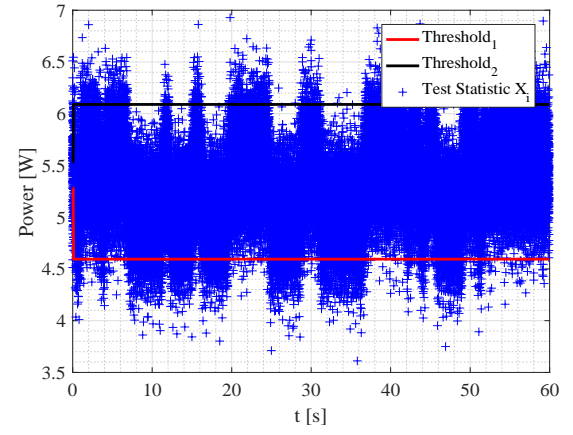
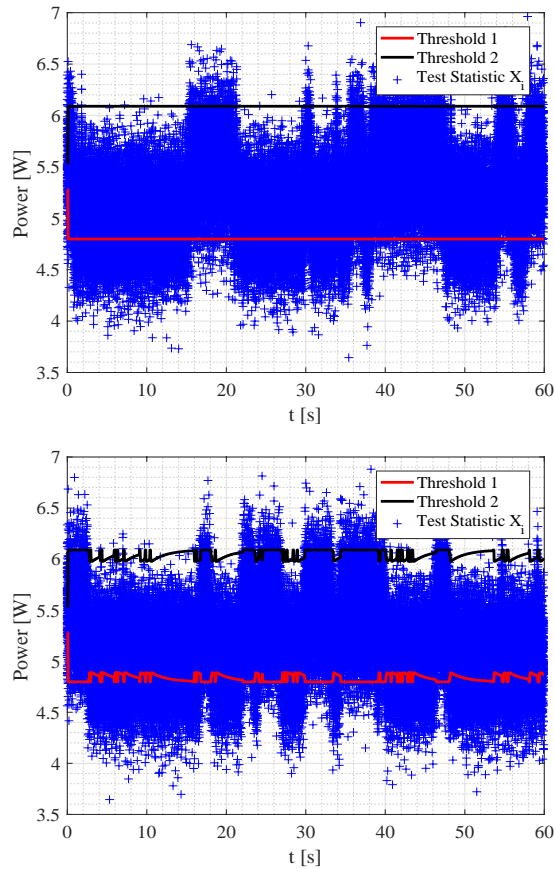


Fig. 6. Timing model for (a) DET-DTH (b) DEC-DTH using $\tau_{f2}(t)$ and (c) IT-DTH using τ_{f2}

The best performing method, however, was the IT-DTH. By utilizing two independent thresholds, it out-performed the other methods, tailoring its upper threshold, above which the PU signal is likely to lie, to provide a probability of detection greater than 0.99, and the lower threshold to let through the lowest number of detected noise test statistics as possible, without blocking all vehicles from transmitting. This results in non-time-variant threshold values, like in DET-DTH, as seen in Fig. 6-c. Although the difference between DET-DTH and IT-DTH may seem subtle when comparing Fig. 6-a and Fig. 6-b, Table II shows that, on average, over double the number of vehicles transmit in DET-DTH compared to IT-DTH.

To fully test the two highest performing systems - the DEC-DTH with $\tau_{f2}(t)$ and IT-DTH with τ_{f2} - simulations were run with time-variable N and γ . Table III shows the results.

TABLE III
SECOND TIMING SIMULATION RESULTS

Model	DTH Method	Average Q_d	Average Q_f	Average k
Increasing N	DEC using $\tau_{f2}(t)$	0.982	0.004	16.639
	IT using τ_{f2}	0.996	0.019	11.205
Increasing γ	DEC using $\tau_{f2}(t)$	0.988	0.123	13.429
	IT using τ_{f2}	1.000	0.000	6.731

Row one of Table III shows the results of both systems when 10 vehicles were added every second, starting with 1 and ending with 601. Both performed well, showing that they can react well to changing N . However, in terms of k and Q_d , IT-DTH performed better.

γ was then increased from 0.1 to 0.31. Fig. 7 and row two of Table III show the results.

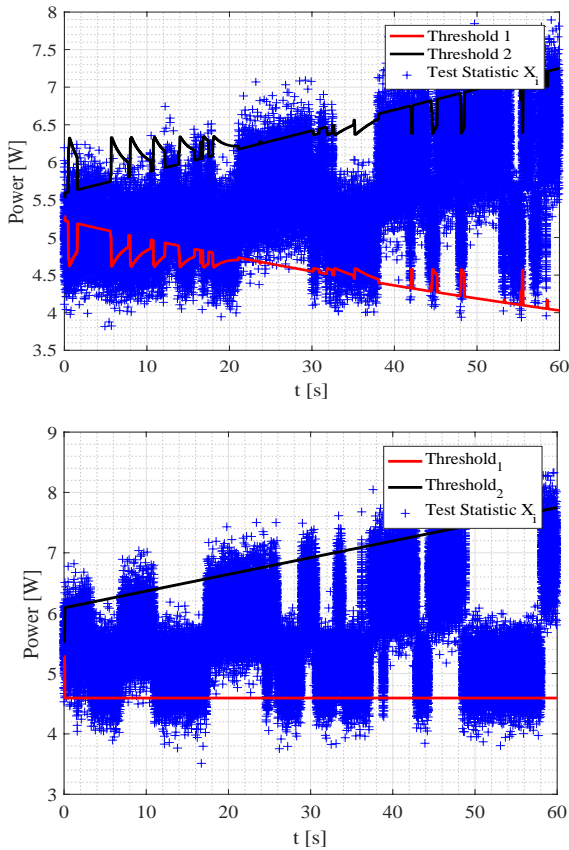


Fig. 7. Increasing γ for (a) DEC-DTH using $\tau_{f2}(t)$ and (b) IT-DTH using τ_{f2}

As can be seen in Fig. 7-a, DEC-DTH begins to break down at large γ ; because the noise signal does not change with γ , while the PU-signal strength increases as γ increases, the difference between $\tau_{f2}(t)$ and τ_d is too great for large γ . Although the detection probability remains high, the false alarm probability suffers, as seen in the results, where the average Q_f is above the threshold. However, the IT-DTH system, seen in Fig. 7-b, performs very well, as the independent upper threshold can follow the PU signal and the lower threshold can follow the noise signal (constant in this case), resulting in a very promising performance, with, in this simulation, perfect Q_d and Q_f , and very low k .

Although the IT-DTH method yields better results in terms of both detection accuracy and the restriction of vehicle-to-RSU transmission, it calls for more information to be sent through the CCH from the RSU to the OBU, as both τ_{f2} and τ_d must be sent in every T_d interval. However, its model requires no memory, whereas the timing mechanism in the DEC-DTH requires at least a counter, and knowledge of the PU expected on and off time. Which method is preferable between these two would depend on the computational abilities of the RSU and OBUs, and how much the additional τ needed for the IT-DTH adds to network contention.

Comparing the three proposed methods, DET-DTH would work best in a situation where it is most important that no PU interference occurs, and there are over 20 vehicles present. The benefits are that it is a very simple model that requires few calculations, so would be easy to implement. DEC-DTH, comparatively, would be useful when the number of vehicles is

(a) lower than 20, although the complexity would be increased. However, the IT-DTH method out-performs all other methods in terms of detection probability and probability of false alarm and will work in an environment with any number of vehicles.

Further work should be done to implement these methods outside of simulations in field tests. For example, N mobile software-defined radios simulating vehicles and one software-defined radio acting as a RSU could be set up, controlled by software using the proposed thresholds and timing models. This could then ideally be extended so that the radios and software were integrated into vehicles. Unfortunately, this was not possible for this paper due to lack of time and resources, as the author graduated university recently after completing this work.

(b)

V. CONCLUSION

Various solutions have been proposed to solve a problem that could become very important as spectrum scarcity in vehicular environments increases. Three promising cooperative double-threshold methods have been developed, which can adjust to considerable environmental changes while maintaining a high sensing standard. These methods would have the most impact in densely populated networks and could be very beneficial in saving bandwidth in already-saturated networks.

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