School of Engineering and Applied Science (SEAS), Ahmedabad University

B.Tech(ICT) Semester V: Wireless Communication (CSP 311)

- Group No : 24
- Name (Roll No) :

  Manav Darji (1741056)

  Charmil Gandhi (1741059)

  Meet Modi (1741071)

  Jay Shah (1741084)

  Shantanu Sheth (1741088)

- Project Title:

  1) Base Article: [1] Hard Fusion Based Spectrum Sensing over Mobile Fading Channels in Cognitive Vehicular Networks

  2) Security in Hard Fusion Based Spectrum Sensing over Temporal Mobile and Detection of SSDF attack

1 Introduction

1.1 Background

- Vehicular wireless system, bandwidth allocation to the users for communication is very necessary. For solving this spectrum allocation problem, cognitive radio's have been used in large extent. Cognitive radio are used for sensing the information at the primary user (basestation), Also, the users (Secondary Users) which performs this sensing operation reports this data to the fusion center (FC) which leads to one hypothesis which can be used by other users.
- Spatial and temporal resuage of empty frequency bands is one of the unique characteristics of cognitive radio [2]. There are various techniques for detection of licensed users, but all of them have different drawbacks. Mobility remains the main constraint for energy detection and improving the performance due to the fading properties of fading channels. In vehicular environments, wireless channel can be characterized by temporally correlated Rayleigh fading. Probabilities such as misdetection, detection and false alarm should be calculated (Receiver operating characteristics-Pd vs Pf). This kind of information is useful in generating different results in different scenarios.

- Our article refers to calculation of detection technique energy for spectrum sensing. It explains the analytical and simulational results for local and global probabilities in cooperative sensing. In co-operative spetrum sensing, in the reporting channel, based on energy detected by various SVUs, the fusion centre decides the result (in terms of binary hypothesis Ho and H1), whether the primary user is present or not. Considering the channel to be time varying, different inference can be obtained, which takes the mobility of the SVU into consideration [3].

1.2 Motivation

There are various such scenarios where the vehicles are not able to communicate with each other or with something else due to unavailability of proper information of frequency bands. This sensing is performed by cognitive radio. Also, for the analysis of such channel, time and mobility is the major constraint which affects the channel and performance most. We have tried to change the channel to time-varying in our analysis. Also, the security in such the sensing channel is a broad issue can cause the result to change. Various methods/algorithms have been found to detect and solve such issues. These algorithms vary for different scenarios and have no fixed solution. We have tried some techniques to implement the detection of SSDF attacks on the channel [4].

1.3 Contributions

- We have tried to reproduce the results for Local and Global probability of Miss-detection for different values of SNR and by varying the number of secondary users (SVUs). We then tried to implement the Auto-Regressive (AR) Model which is used to describe the time varying process. We took mobility of the secondary user into consideration and then tried to change the channel vector and compared the results with the previous model [5].
- We tried to create a scenario in which the secondary users have sent wrong/false data to the fusion center in the past and based on their history, we tried to obtain their trust values (denotes Whether a particular user can be trusted or not). It finds the diversity among the data sent by different users, which can help in differentiating the users which are honest and those which are under attack (sending false data).

Symbol	Description
P_{di}	Local Probability of detection
P_{f_i}	Local Probability of false alarm
P_m	Local Probability of mis-detection
Q_f	Global Local Probability of miss-detection
Q_e	Global Local Probability of error
Q_m	Global Local Probability of miss-detection
N	Number of SVUs

2 Performance Analysis of Base Article

2.1 System Model/Network Model

We have considered a vehicular network where cognitive and licensed users exist together within the same region similar to one shown in the figure 1. Cognitive network is an infrastructure where every cell has a certain number of associated SVUs and a fusion center or base station.Each SVU access the vacant PU channel and each SVU send it's information to FC and FC sends a combined decision back to that cell. Each SVU follows Poisson Distribution. All the vehicles move independent of each other. Hence, all sensing channels between SVU's and PU's are independent of each other.

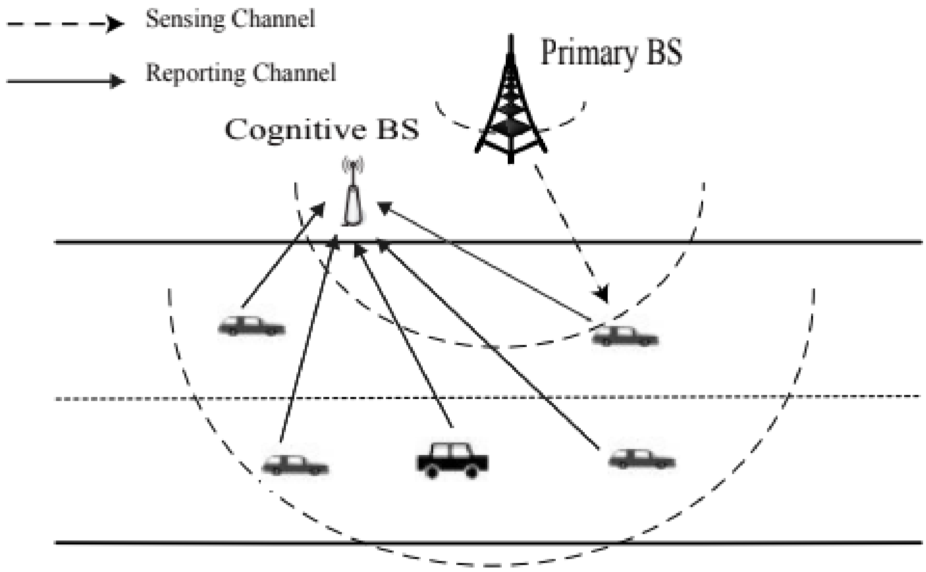


Figure 1: System Model

2.2 Sensing Model

Binary Hypothesis Detection is used in Spectrum Sensing, with H_0 and $H1_1$ as two hypotheses which are associated with absence and presence of PU respectively.

Let N be the number of SVUs and L be number of Sampling observations. Two hypothesis associated can be expressed as :

$$x_i(k) = \begin{cases} n_i(k) & \mathcal{H}_0 \\ h_i(k)s(k) + n_i(k) & \mathcal{H}_1 \end{cases},$$

In above equation, $x_i(k)$ is the received signal by i^{th} SVU, s(k) can be expressed as the signal received from PU, $h_i(k)$ is the channel coefficient between SVU and PU and $n_i(k)$ is the complex additive white gaussian noise (AWGN) which has mean equal to zero and variance σ_n^2. All s(k), $h_i(k)$ and $n_i(k)$ are independent of one another [6].

Every SVU will make a binary decision $u_i = q(x_i) \in +1, -1$ with P_{fi}(Probability of false alarm) and P_{mi}(Probability of miss detection) and then, these decisions are sent to Fusion Center (FC) via Rayleigh Fading Channel. Observation from i^{th} SVU at Fusion Center can be expressed as :

$$z_i = g_i u_i + w_i,$$

In above equation, w_i is zero mean gaussian random variable with δ_i^2 as variance and g_i as fading gain of channel from SVU to Fusion Center [7].

2.3 Local Sensing with Energy Detection

Energy Detection is commonly used spectrum sensing technique for local sensing. Also, energy detection is the most suitable option for vehicular networks because of its low latency tolerance and environment with high mobility.

Energy Statistic associated with i^{th} SVU is denoted by e_i:

$$e_i = \sum_{k=0}^{L-1} |x_i(k)|^2$$

In above equation, L represents Number of samples within a sensing interval. e_i represents the sum of squares of L gaussian random variables. $\frac{e_i}{\sigma_n^2}$ follows central chi square distribution with L degrees of freedom and parameter η_i

Decision Rule at each SVU can be expresses as :

$$u_i = \begin{cases} +1, & \text{if } \mathrm{e}_i \geq \lambda \\ -1, & \text{if } \mathrm{e}_i < \lambda \end{cases}$$

In above equation, +1 denotes that PU Signal is detected, and -1 denotes that PU signal is not detected.When L is sufficiently large, the energy statistic can be described by a Gaussian distribution under both hypotheses H 0 and H 1 [24].

Let threshold be λ.

2.4 Probability of False Alarm

Probability of false alarm (P_f) can be represented in terms of ratio of incomplete and complete gamma function.

$$P_f = Pr(e_i \geq \lambda | H_0) = \frac{\Gamma(u, \frac{\lambda}{2})}{\Gamma(u)}$$

where $\Gamma(u, \frac{\lambda}{2}) = \int_x^\infty t^{(u-1)} e^{-t} dt$ and $\Gamma(u) = \int_0^\infty t^{(u-1)} e^{-t} dt$

Thus P_f can be given as :

$$P_f = \frac{\int_x^\infty t^{(u-1)} e^{-t} dt}{\int_0^\infty t^{(u-1)} e^{-t} dt}$$

where u is time-bandwidth product.

Thus Probability of false alarm can be given as :

$$P_f = Pr(e_i \geq \lambda | H_0) = Q\left(\frac{\lambda - L\sigma^2}{\sqrt{L}\sigma^2}\right)$$

2.5 Probability Of Detection

Probability of detection can be given as u^th order Marcum-Q function with parameters γ and λ where γ represents SNR and λ represents threshold value.

$$P_d = Q_u(\sqrt{2\gamma}, \sqrt{\lambda})$$

u^{th} order Marcum-Q function can be expressed as :

$$Q_m(a,b) = \frac{1}{2\pi j} \oint_r \frac{e^{g(z)}}{z^m(1-z)} dz$$

where $g(z) = \frac{a^2}{2}[\frac{1}{z} - 1] + \frac{b^2(z-1)}{2}$

Here, a = $\sqrt{2\gamma}$ and b = $\sqrt{\lambda}$
Thus :

$$g(z) = \frac{\sqrt{2\gamma}^2}{2}[\frac{1}{z} - 1] + \frac{\sqrt{\lambda}^2(z-1)}{2}$$
$$g(z) = \gamma(\frac{1}{z} - 1) + \frac{\lambda}{2}(z-1)$$

Thus, Probability of detection can be expressed as :

$$P_d = \frac{1}{2\pi j} \oint_\Omega \frac{e^{(\frac{1}{z}-1)\gamma + \frac{\lambda}{2}(z-1)}}{z^u(1-z)} dz$$

$$P_d = \frac{e^{-\frac{\lambda}{2}}}{2\pi j} \oint_\Omega \frac{e^{(\frac{1}{z}-1)\gamma + \frac{\lambda}{2}(z-1)}}{z^u(1-z)} dz$$

where ω is circular contour of radius r $\in$[0,1]
$Thus$,P$_d$ can be given as :

$$P_d = Q\left(\frac{(L+\eta_i)_n^2 - \lambda}{\sqrt{(L+2\eta)^2}} \right)$$

2.6 Probability of Miss-Detection

Probability of miss-detection(P_m) can be given as : 1 - P_d

2.7 Cooperative Sensing

In Cooperative Sensing, multiple SVUs at different locations are utilized and then their independent sensing messages are combined into one unified decision which tells us about the existence of PU. To combine these independent sensing messages, we use hard fusion.
As mentioned earlier, Observation from i^{th} SVU at Fusion Center can be expressed as :

$$z_i = g_i u_i + w_i,$$

Let v_i denote the decoded version of z_i for i^{th} SVU at Fusion Center and the decoding rule can expressed as :

$$v_i = \begin{cases} 1, & \text{if } z_i \geq \lambda \\ 0, & \text{if } z_i < \lambda \end{cases}$$

Let E[x] represent the expectation :

$$E[v_i|H_j] = P(v_i = 1|H_j).1 + P(v_i = 0|H_j).0$$

$$E[v_i|H_j] = P(z_i \geq 0|H_j)$$

Let D[x] represent the variance :

$$D[v_i|H_j] = E[v_i^2|H_j] - E[v_i|H_j]^2$$

$$D[v_i|H_j] = P(z_i \geq 0|H_j) - P((z_i \geq 0|H_j))^2$$

v_i is directly dependent on $P(z_i \geq 0|H_j)$ which is similar to probability of miss-detection and probability of false alarm in Local Sensing. Under the hypothesis H_0 and H_1, u_i follows the distribution with parameters P_{fi} and P_{di} :

$$P(u_i|H_0) = \begin{cases} P_{fi}, & \text{if } u_i = +1 \\ 1 - P_{fi}, & \text{if } u_i = -1 \end{cases}$$

$$P(u_i|H_1) = \begin{cases} P_{di}, & \text{if } u_i = +1 \\ 1 - P_{di}, & \text{if } u_i = -1 \end{cases}$$

Let P_{Fi} be Probability of false alarm and can be expressed as :

$$P_{Fi} = f(z_i \geq 0|H_0) = \sum_{u_i \in \{-1,+1\}} f(z_i \geq 0|u_i)P(u_i|H_0)$$

$$P_{Fi} = f(z_i \geq 0|u_i = +1)P_{fi} + f(z_i \geq 0|u_i = -1)(1 - P_{fi})$$

Let P_{Di} be Probability of false alarm and can be expressed as :

$$P_{Di} = f(z_i \geq 0|H_1) = \sum_{u_i \in \{-1,+1\}} f(z_i \geq 0|u_i)P(u_i|H_1)$$

$$P_{D0} = f(z_i \geq 0|u_i = +1)P_{Di} + f(z_i \geq 0|u_i = -1)(1 - P_{di})$$

Local Probability of false alarm and Local Probability of Detection and Probability of Miss-detection is expressed as :

$$P_{Fi} = \frac{1}{2} + \left(P_{fi} - \frac{1}{2}\right).\sqrt{\frac{\gamma_i}{2 + \gamma_i}}$$

$$P_{Di} = \frac{1}{2} + \left(P_{di} - \frac{1}{2}\right).\sqrt{\frac{\gamma_i}{2 + \gamma_i}}$$

$$P_{Mi} = 1 - P_{Di} = \frac{1}{2} + \left(P_{mi} - \frac{1}{2}\right).\sqrt{\frac{\gamma_i}{2 + \gamma_i}}$$

2.8 Global Probability of false alarm and Miss-Detection

We are assuming that each and every reporting channel donot interfere with one another. The fusion center decodes z_i and gets v_i. Counting Rule is used to calculate the global statistic :

$$\Lambda = \sum_{i=1}^{N} v_i.$$

At Fusion Center, the decision rule can be expressed as :

$$v_0 = \begin{cases} 1 & if \quad \Lambda \geq T \\ 0 & if \quad \Lambda < T \end{cases}.$$

Let Q_m and Q_f be the global probability of miss-detection, global probability of false alarm and global probability of error be expressed as :

$$Q_f = Q\left(\frac{T - \mu}{\sqrt{\sigma^2}}\right) = Q\left(\frac{T - \sum_{i=1}^{N} P_{Fi}}{\sqrt{\sum_{i=1}^{N} P_{Fi}(1 - P_{Fi})}}\right)$$

$$Q_m = Q\left(\frac{\mu - T}{\sqrt{\sigma^2}}\right) = Q\left(\frac{\sum_{i=1}^{N} P_{Di} - T}{\sqrt{\sum_{i=1}^{N} P_{Fi}(1 - P_{Di})}}\right)$$

$$Q_e = Q_f + Q_m = Q\left(\frac{T - \sum_{i=1}^{N} P_{Fi}}{\sqrt{\sum_{i=1}^{N} P_{Fi}(1 - P_{Fi})}}\right) + Q\left(\frac{\sum_{i=1}^{N} P_{Di} - T}{\sqrt{\sum_{i=1}^{N} P_{Fi}(1 - P_{Di})}}\right)$$

3 Performance Analysis of New contributions

3.1 Analysis for time varying channel

Mobility is the biggest concern for vehicular wireless channel. Earlier for calculating the channel vector, we used the random rayleigh fading channel and obtained the results and comparisions for probability of miss-detection. But in real life scenarios, due to temporal correlation, the sensing channel changes which results in changes in the detection at the SU. So, time varying channel should be introduced for sensing the spectrum information. For implementing this, we have used the Auto-Regressive model (AR Model) to describe our time varying channel [5]. (AR model is used for representing any time varying process in nature). AR Model uses the past data of channel (at prevoius time instances) to calculate the channel vector for the current instance. And that instance of channel vector has been used for modelling to obtain the received signal and Probability of Miss-detection has been calculated for that channel.

The channel vector for k-th time instant is given as:

$$h_j(k) = \rho_j^{k-1} h_j(1) + \sqrt{1-\rho_j^2} \sum_{l=1}^{k-1} \rho_j^{k-l-1} e_j(l)$$

Parameters:

$\rho_j = J_0(\dfrac{2\pi f_c v_j}{R_s c})$ is the correlation parameter, where $J_0(.)$ is the zeroth-order bessel function of first kind.

v_j is the relative speed of j-th SVU.

R_s is the tramsmission symbol rate.

$h_j(k)$ is the channel component of j-th SVU at k-th instance.

$e_j(l) \sim CN(0, \sigma_e^2 j)$ represents time varying component of the channel [5].

We have compared the Pm vs SNR graph for time varying and time invariant channel. For any time varying channel, Pm value for a fixed SNR should be more than that for time invariant channel [Refer section 4.3 for comparision result].

3.2 System Model

In order to improve the utilization of spectrum resources Co-operative Spectrum Sensing(CSS) Approach is considered powerful tool. But one of the major drawback of CSS is that it may assume that all the secondary vehicles(SVU) are honest which means that they doesn't send any kind of

false data [4].So here the opportunity is created for the attacker to send the false data to the fusion center(FC).But to prevent the falsification of data, trust mechanism is developed. But some of the attackers can collude with each other and form a collusive clique which can avoid the detection of trust mechanism. As data can be either false or honest we have proposed a scheme from the perspective of XOR distance analysis which can detect and avoid the attack.
Fusion center gathers the information of individual sensing of SVU, data reporting and data fusion.Firstly each of the SVU sense the PU signal via sensing channel.After that each SVU send their data to the fusion center via reporting channel.

FC will have a database of all data sent from every SVU.Based on this, a simple ratio of credibility(correctly reported / Total Values) will be maintained of each SVU at the FC.As in Co-operative sprectrum sensing a single SVU cannot change a FC's decision individually. Inorder to change the FC decision, many SVU's (attacker) would have to send same type of data, where as honest SVUs will not send same type of data. There will be some diversity in it. To exploit this diversity, we use calculation of XOR distance between each and every SVU. XOR distance is used because there are only 2 classes of data that is 0 and 1 and XOR is the best tool to measure difference between these classes. Both honest and malacious SVU may have higher trust value, but what seperates them is XOR distance. Malacious SVU will have smaller XOR distance than Honest SVUs. After this operation, attacker SVU's can be identified and thier data won't be considered in fusion process.Hence, decision won't be affected.

3.3 Algorithm

- Algorithm to detect Attackers

```
for each i = 0 to n:
      for each j = 0 to n:
          xor_matrix(j) = columni (xor) column2;
      end
      for t = 0 to k
          sum(:) = sum(:) + k*xor_matrix(t)          //simultaneous row-updates
      end
      x(i) = sum(:)                                  //simultaneous row-updates
end
```

As the xor distance will be very high in magnitude,we normalize it by max element of the row. Therefore, the xor distance will be in range [0,1].
Both honest SVU and Attackers will have high credibility, therefore, we will distinguish those SVU which have higher ratio.

- Algorithm To remove attackers from current Fusion Process

```
for each i in n :
     if cratio > 0.6 and x(i) < 0.4
          Label = Attacker;
          discard data from fusion decision process.
end
```

4 Numerical Results

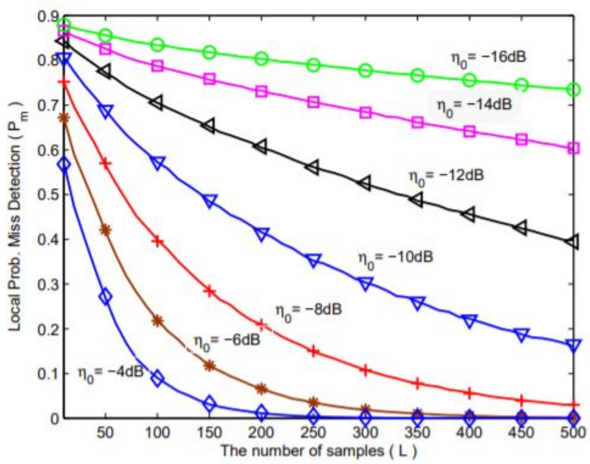
4.1 Simulation Framework

The various controlling parameters are as follows :
1) For time varying simulation:
number of samples : 60
number of monte carlo simulations = 10^5
Probability of false alarm Pf= 0.01

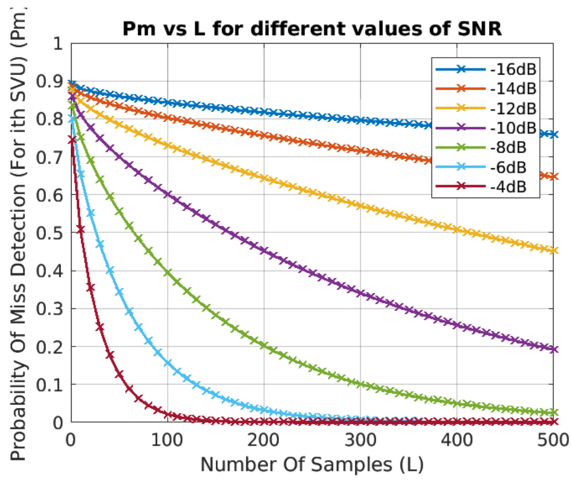
2) For SSDF attack simulation
number of SVU h = 40
No. of truth values = any random value between 2000 and 4000
No. of false values = total - truth values.

4.2 Reproduced Figures

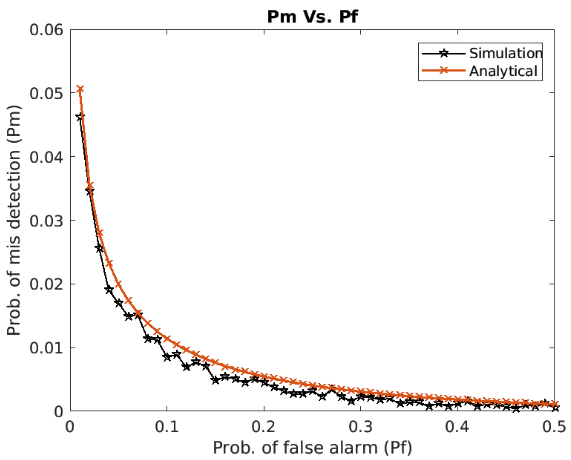
- Reproduced Figure-1



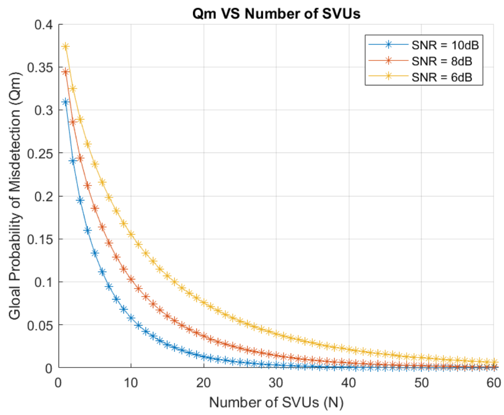
(a) 1B



(b) 1R



(a) P_m Versus P_f

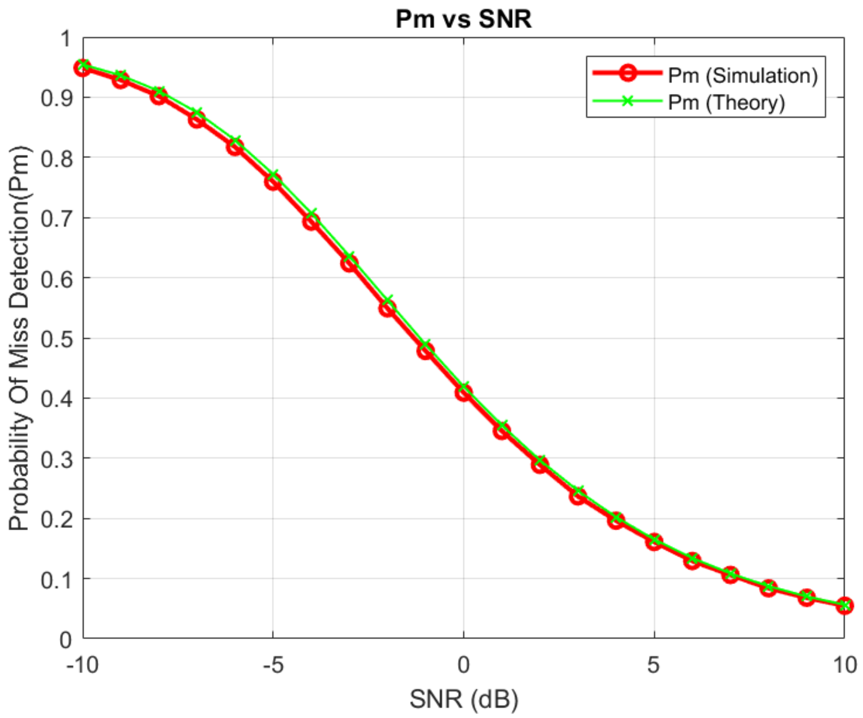


(b) Q_m versus N

- Pm vs L: For different SNR's, the local probability of Misdetection (Pm) has been calculated on basis of number of samples (L) in a particular sensing interval. This denotes the value of Pm for ith SVU (i.e. local probability). As the number of samples (L) increases, the value of Pm decreases gradually. Also, with increase in SNR values, Pm decreases.

- Pm vs Pf Curve: Graph of Probability of Misdetection vs Probability of false alarm has been shown in the given figure and comparision has been made between analytical and simulational results. For different values of Pf, and fixed value of SNR = -8db, Pm has been plotted. With the increase in Pf value, Pm gradually decreases.

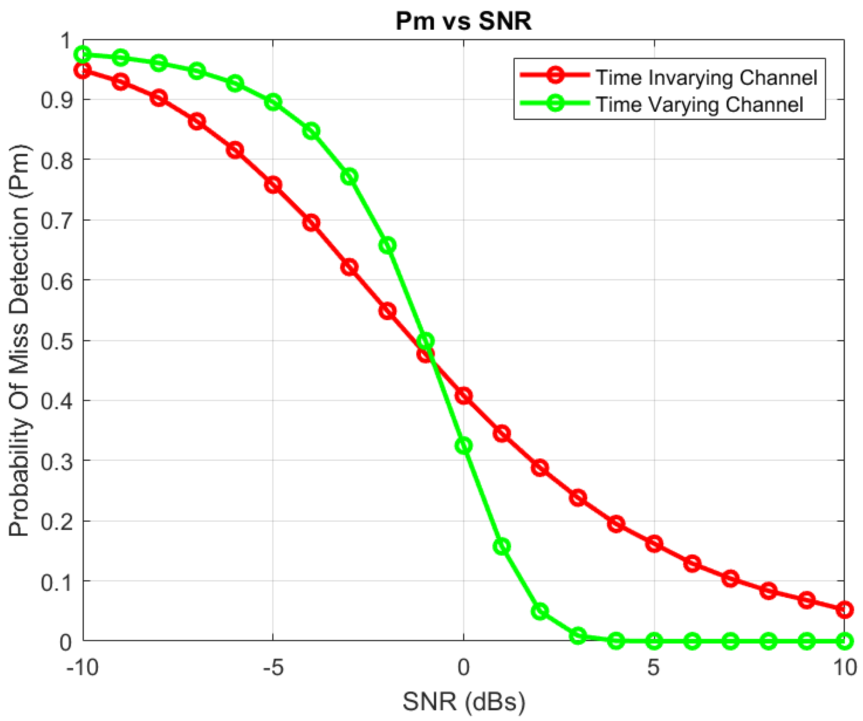
- Qm vs N: This graph shows comparision of Global probability of misdetection (Qm) vs Number of SVU's for different values of SNRdb. It can be clearly seen that with the increase of number of sencondary users, the value of Qm decreases as the vehicles involving in the decision process at the fusion centre are more. Also, for high value of SNR, the value of Qm is low as compared to value of Qm for low SNR (in dBs).



- P_m Analytical Simulation: The comparision of Simulational and Analytical Results for Pm (Prob. of Misdetection) vs. SNR (Signal to Noise Ratio) has been done. For Simulational Results, the received energy has been compared with a given threshold (in terms of gamma inverse function), which gives corresponding value of Pm.

4.3 New Results

- Comparision of Time Invariant and Time Varying Channel.
  []This comparision is not correct for value of SNR > 0]



For SNR ≤ 0, the trend is correct, as the Pm value for time varying channel is less than Pm value of time invariant channel for same value of SNR.

5 Conclusions

- In the sensing channel, with increase in number of secondary vehicles (SVUs), number of samples and SNR Value, the Probability of miss-detection decreases. Also, while comparing the channels, the value of Pm in case of time varying channel is more as compared to that of time invarying channel. This change is observed due to mobility of vehicles, which in turn decreases the performance of the channel.
- Security is a big concern in co-operative spectrum sensing as secondary vehicle users can easily falsify data. Some ways for incorporating security are clustering, XOR distance analysis, trust or reputation based mechanisms can be used for labelling or differentiating the attackers. We have tried to implement XOR distance based security method for above case.

6 Contribution of team members

6.1 Technical contribution of all team members

Tasks	Manav Darji	Charmil Gandhi	Meet Modi	Jay Shah	Shantanu Sheth
Understanding Base Article	Yes	Yes	Yes	Yes	Yes
Analytical Results	Yes	No	Yes	Yes	Yes
Simulation Results	Yes	Yes	Yes	No	No
Derivations	No	Yes	No	Yes	Yes
Innovation	Yes	Yes	Yes	Yes	Yes

6.2 Non-Technical contribution of all team members

Tasks	Manav Darji	Charmil Gandhi	Meet Modi	Jay Shah	Shantanu Sheth
Project Report Writing	Yes	Yes	Yes	Yes	Yes

9*

References

[1] L. H. Xiaomin Qian, "Hard Fusion Based Spectrum Sensing over Mobile Fading Channels in Cognitive Vehicular Networks," *Sensors*, vol. 18, no. 6, 2018.

[2] J. Mitola, "SNR walls for signal detection," *IEEE J. Sel. Topics Signal Process.*, vol. 2, no. 6, pp. 13–18, 1999.

[3] H. W. Ali A, "Advances on Spectrum Sensing for Cognitive Radio Networks: Theory and Applications." *IEEE Commun. Surv. Tutor. 2017.*, vol. 19, no. 6, 2017.

[4] M. Z. Jingyu Feng, "Securing Cooperative Spectrum Sensing Against Collusive SSDF Attack using XOR Distance Analysis in Cognitive Radio Networks," *Sensors*, vol. 19.

[5] L. Gahane, "An Improved Energy Detector for Mobile Cognitive Users Over Generalized Fading Channels," *IEEE Transactions on Communications.*, vol. 66, pp. 534 – 545, 2018.

[6] Ho-Van, "Bit error rate of underlay decode-and-forward cognitive networks with best relay selection." *IEEE/KICS J. Commun. Netw.*, pp. 162–171, 2015.

[7] J. Tsitsiklis, "Decentralized detection." *Adv. Stat. Signal Process.*, pp. 297–344, 1993.