On the Sensing Time and Achievable Throughput in Sensor-Enabled Cognitive Radio Networks

Deepak G. C. and Keivan Navaie
School of Electrical and Electronics Engineering, University of Leeds, UK
Email: {eldgc, k.navaie}@leeds.ac.uk

***Abstract*—In cognitive radio networks, the accuracy of the spectrum sensing is vital to protect the primary network and is often a function of channel sensing duration. The choice of the sensing duration, on the other hand, directly affects the achievable throughput of the secondary system. In this paper, we propose a spectrum sensing method based on cognitive monitoring network (CMoN) which is a network of sensors deployed in the network coverage area which carries out collaborative spectrum sensing. Consequently, the achievable throughput can be maximized irrespective of the sensing duration. In this technique, the secondary users do not need to be equipped with spectrum sensors and the availability of the spectrum is assessed from the CMoN through a signaling protocol. Here we further propose a two-tier decision fusion mechanism at the base station and show that through the proposed method a significant improvement in the network throughput is achieved. Numerical results also confirm that the proposed method outperforms the conventional spectrum sensing in terms of achievable throughput.**

I. Introduction

In Cognitive Radio Networks (CRN), unlicensed users, also known as Secondary Users (SU), are allowed to access the licensed bands under the condition that licensed users, also known as Primary Users (PU), are protected from the harmful interferences [1]. The CRN adopts *opportunistic spectrum access* (OSA), where SUs opportunistically operate on the channel which is originally allocated to the PUs. In this case, the SUs make sure the status of the primary channels is accurately sensed. Therefore, in OSA based CRN the accuracy of the sensing strategy is exceptionally critical. Hereafter for brevity we simply refer to OSA based CRN as CRN.

Spectrum sensing accuracy is often modeled through probability of detection, p_d, and probability of false alarm p_f [2]. Probability of detection is the probability that spectrum sensing concludes that the radio spectrum is active while it is in fact active. Probability of false alarm, on the other hand, is the probability that the spectrum sensing senses the radio spectrum as active while its actual status is idle. The lower the value of p_d, the higher is the chance of collision between PU and SU transmission; thus higher is the reduction in the system throughput. Having a higher p_f results in underutilization of the available primary spectrum by the SUs.

In the conventional CR system, SU also senses the spectrum and operates on frame basis, where each frame is divided into the sensing and actual data transmission duration. The optimum choice of sensing duration determines the performance of CR system [3]. If the sensing duration is chosen to be small, there will be small number of samples to be observed by the spectrum sensor. As a result, the accuracy of the spectrum sensing is compromised. If the sensing duration is chosen to be large, the actual data transmission duration becomes lower which results in a lower achievable throughput.

Moreover, fundamental characteristics of multi user wireless mobile environments, e.g., multi path fading, user mobility and hidden terminal problem might potentially result in inaccurate sensing [4]. In such environment, conventional sensing mechanisms may not be able to sense the availability of the spectrum with an acceptable level of accuracy which is required to protect the primary users. Therefore, the quality of service (QoS) requirements to the end users may not be guaranteed.

The sensor network aided CR was initially described in [5] to use in nomadic cognitive radios in urban and sub-urban areas. This work has prominently described CR reconfiguration management framework. The major differences between traditional sensor and cognitive sensor node is that there is cognitive radio transceiver in later case as shown in Fig. 3 of [6]. The issue on sensor based CRN, which is referred in this paper as cognitive monitoring network (CMoN), is the energy efficiency and it has been under immense investigation within CRN research community.

Many studies have revealed the sensing mechanism of CR system associated with energy saving. There are various algorithms for energy saving in sensor-based cognitive radio has been studied such as Optimal Scheduling, Combined Sleeping and Censoring Scheme etc. For details, see, e.g., [7],[8] and references therein. Therefore, many studies deal with the design framework for total energy consumption in sensor enabled CRN, but hardly discuss about the throughput gain and spectrum efficiency when additional sensor network is implemented as a monitoring network. This paper enlighten the throughput achievement due to monitoring nodes on the secondary network.

The sensor enabled CRN presented in this paper logically separates the whole cognitive radio system as monitoring sensor network and communication network. Each monitoring sensor node is embedded with CR functionality. In the proposed model, the delay associated with sensing in the primary network is sufficiently reduced to maintain the QoS requirement in the secondary networks. Moreover, the throughput and spectrum efficiency are significantly improved. Although the cost associated with establishing CMoN around the primary user coverage gets higher, the improved throughput, QoS, and spectrum efficiency will justify the initial cost considering the fact that the proposed method is a long-term solution.

In conventional CRN, the choice of sensing duration is very limited because this has direct implications on actual communication duration within a frame. In the proposed model, the sensing duration can be adjusted without affecting the transmission duration within a frame because they are designed to be independent entities. This provides a great degree of freedom on the system design.

The rest of the paper is organized as follows: In Section II, the system model is presented. Sensing accuracy and achievable throughput are then investigated in Sections III and IV, respectively. Section V presents the numerical analysis followed by conclusions in Section VI.

II. System Model

In this paper, the secondary system utilizes Orthogonal Frequency Division Multiplexing (OFDM), where the allocated radio spectrum is divided into N, B_s Hz sub-channels, indexed by $i = 1, \ldots, N$. Depending on the PU activity, SUs may have access to M accessible sub-channels, where $0 \leq M \leq N$.

The state of each sub-channel depends on the traffic pattern of PU, also described as primary user activity on sub-channel i. It means the channel state may transit from active state (ON) to idle state (OFF) and vice-versa. Moreover, it is assumed that during α_i fraction of time, channel i remains idle and β_i fraction of time, channel i remains active and $\alpha_i + \beta_i = 1, \quad \forall i$. Here, α_i and β_i are independent and exponentially distributed. Then, the probability of channel i to be busy (p_{on}) is $\beta_i/(\beta_i + \alpha_i)$ and to be idle (p_{off}) is $\alpha_i/(\beta_i + \alpha_i)$.

The system under consideration presented in Fig. 1 in which a primary base station (PBS) provides service within a network coverage area. All base stations are equipped with an omnidirectional antenna. The sensor nodes are distributed uniformly in the coverage area and they monitor the primary spectrum and provides the status of each sub-channel within the radius r_{sen}. In this system, some sensor nodes are considered as cluster heads (CH) which has sensing radius of $r_{ch} > r_{sen}$, wherein all located sensors transmit the sensing information to the CH. The sensing nodes collectively form a monitoring network whose jobs are to sense, schedule and cooperate among the sensor nodes.

The job of CHs is to collect sub-channel information from sensor nodes within a cluster and cooperate among other CHs to calculate a more accurate state of available primary sub-channels. Finally, the information is pushed to Decision Fusion Center (DFC) installed as Secondary Base Station (SBS), which stores the information about primary sub-channels.

Whenever the secondary user has to communicate utilizing available primary channel, it sends request as a query to SBS along with the ID of CH where the location of secondary user is associated with. As a result, SBS finds the cluster where secondary user is located and based on this information, SBS finds the available primary sub-channel on that particular geographic location and time. The implication is that the secondary users might often get higher bandwidth utilization comparing to the conventional spectrum sensing thereby exploiting the true sense of cognitive radio. In general sense, DFC (or SBS) acts as knowledge-base entity which keeps record of primary sub-channel information such as traffic activities, transmission power, channel gain, bandwidth, etc.

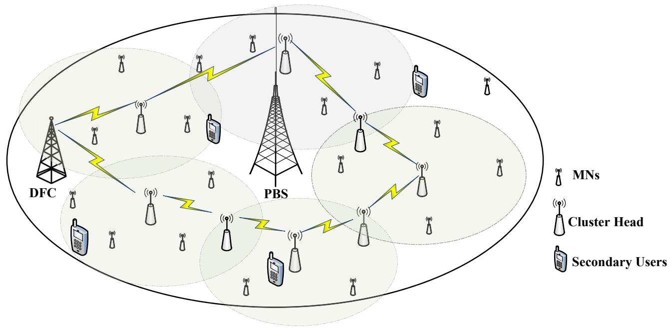

Fig. 1. CMoN System Model.

There are only two possible states of primary sub-channel, either to be in busy state or in idle state. In the proposed model, each cognitive monitoring sensor node perform spectrum sensing with the help of well defined energy detection method. For every $i = 1, \ldots, N$ primary sub-channel measured at any random location at time t, the received primary signal at sensing node is given as:

$$y_i(t) = \begin{cases} w_i(t), & : H_0, \\ h_i(t)x_i(t) + w_i(t), & : H_1. \end{cases} \tag{1}$$

The received signal will either be just noise component or the combination of both primary signal and noise. Here, $h_i(t)$ is the sub-channel gain for channel i and $w_i(t)$ is considered as noise which is independent Gaussian random variable with zero mean and variance σ_n^2. The hypothesis H_0 indicates the absence of primary signal, therefore $y_i(t)$ contains only AWGN, whereas hypothesis H_1 represents the presence of primary signal which is affected by AWGN.

When the primary users are communicating with the primary base station, transmitted signal is also being received by the sensors in CMoN which are located within the transmission range of the PU. The CMoN periodically senses the available sub-channel i and calculate the test statistics such as energy level, and the hypothesis test is performed based on this sensed parameters. Here, the energy averaging concept has been considered because of its simplicity and tractability as well as it does not need a priori channel information. For the performance of energy detection method, see e.g. [8] and [9]. For each sub-channel i, we consider that there are $m = 1, \ldots, M$ samples to be detected to get the test statistics $\mathrm{E}_i(y)$. For any random sensing node k, the probability of error while accepting H_1 when actually the channel was free is modeled as false alarm probability, $p_{f,i}^{(k)}$. Similarly, the probability of error while accepting H_0 when actually the channel was occupied is modeled as miss detection probability and is defined as, $p_{m,i}^{(k)} = 1 - p_{d,i}^{(k)}$ for channel i. Under different set of assumptions, these parameters have been obtained in the related literature, here we adopt results provided by [9]:

$$\begin{aligned} p_{d,i}^{(k)} &= \Pr\{\mathrm{E}_i(x) \geq \lambda_{th}|H_0\}, \\ &= \mathrm{Q}\left(\frac{\lambda_{th} - 2t_s W(\gamma_i+1)\sigma_n^2}{\sqrt{4t_s W}(\gamma_i+1)\sigma_n^2)}\right), \end{aligned} \quad (2)$$

and probability of false alarm, $p_{f,i}^{(k)}$, is then calculated as:

$$p_{f,i}^{(k)} = \Pr\{\mathrm{E}_i(x) \leq \lambda_{th}|H_1\} = \mathrm{Q}\left(\frac{\lambda_{th} - 2t_s W\sigma_n^2}{\sqrt{4t_s W}\sigma_n^2)}\right) \quad (3)$$

where $Q(z) := (1/\sqrt{2\pi}) \int_z^{+\infty} e^{-(\tau^2/2)} d\tau$.

It is found from (2) and (3) that the probability of detection varies according to primary user activity (α_i, β_i), channel bandwidth (W) as well as sensing duration $t_{s,i}$ of sub-channel i. The λ_{th} is the energy threshold, which is a system defined parameter. The parameter γ_i is received SNR of primary sub-channel i and it can be calculated as $\gamma_i = \frac{\mathrm{E}[|y_i(n)|^2]}{\mathrm{E}[|w_i(n)|^2]}$.

III. Sensing Accuracy

Inaccurate sensing may cause interference on the primary users and degrade their QoS. To avoid such interference, sensing measure with acceptable accuracy level is to be designed which should be fast enough to sense and inform the users through SBS. The condition that CMoN may not correctly sense sub-channel is because of non-zero probabilities of false alarm, $p_{f,i}^{(k)}$, and miss detection $p_{m,i}^{(k)}$.

Since there are uniformly distributed cognitive sensors as a cluster member, they cooperatively detect the activity of primary sub-channels. The cluster heads (CHs) receive all the sensing data and use the logical-AND rule to fuse the received decisions. As a result, the probability of accurate sensing of sub-channel i by sensing node k in a cluster is

$$p_{c,s}^{(ch)} = 1 - \left\{\prod_{j=1}^{|cm|} p_{m,i}^{(k)} + \prod_{j=1}^{|cm|} p_{f,i}^{(k)}\right\}. \quad (4)$$

In this case, for every sub-channel i and monitor node k, the sensor nodes calculates two conditional probabilities. In first case, $p(.|H_0)$ has two possible values, either $p_{f,i}^{(k)}$ or $(1 - p_{f,i}^{(k)})$. Similarly in second case, $p(.|H_1)$ has two possibilities of $p_{d,i}^{(k)}$ or $p_{m,i}^{(k)}$. The energy detector estimates energy density which is either greater or less than the given threshold, and it indicates that either hypothesis H_1 or H_0 is true depending on the observed parameters.

A. Two Tier Decision Fusion

The proposed decision aggregation strategy is *two tier decision fusion* model. As mentioned earlier, the logical AND rule is implemented in clusters to collect decisions taken by individual cluster members so that all members must agree on channel i to declare it as a free channel. If any member observes channel i is busy, the secondary users on this clusters will not be permitted by CMoN to use channel i within that cluster. It helps to avoid the interference with primary users within the cluster. On the other hand, the cluster heads aggregate the decisions from cluster member and provide it to the SBS (i.e., DFC), where decisions are aggregated using logical OR rule.

A hard combination technique is implemented where quantized information as hard decision bits are transmitted. This reduces bandwidth consumed by decision bits because one bit is sufficient to represent the status of 1 sub-channel. For instance, if there are 10 cluster members to detect 128 sub-channel, a maximum of 1280 bits would be enough for perfect sensing of sub-channel. The sensing nodes within a cluster are relatively close to each other and therefore the chance of wrong decision occurrence at secondary user is negligible.

To execute this strategy, each CH sends its *Identity*, which is based on its location, and channel state information along with aggregated decision of the cluster. When logical OR rule is implemented on semi-processed decision from cluster members at SBS, the probability parameter of correct sensing of sub-channel i from (4) is

$$\begin{aligned} p_{cs,i}^{(sbs)} &= 1 - \prod_{k=1}^{|ch|} 1 - \left[1 - \prod_{j=1}^{|cm|} p_{m,j}^{(k)} - \prod_{j=1}^{|cm|} p_{f,j}^{(k)}\right], \\ &= 1 - \left[\prod_{j=1}^{|cm|} (1 - p_{d,j}^{(k)}) - \prod_{j=1}^{|cm|} p_{f,j}^{(k)}\right]^{|ch|}. \end{aligned} \quad (5)$$

As a matter of fact, for every sub-channel i, (5) is calculated at the SBS with the help of cooperative decision parameters obtained from cluster heads and cluster members. As it can be observed $p_{cs,i}$ not only depends on detection and false alarm probabilities but also on number of cluster heads and cluster members within the transmission range of the PBS.

IV. Achievable Throughput

As mentioned before, the sensing duration can be optimized for maximum achievable throughput for CRN when the whole frame is divided into sensing and data transmission duration. In the proposed CMoN framework, the throughput is independent of sensing duration and it further expands the boundary of the achievable throughput.

By solving (2) and (3) for threshold value of SNR (λ_{th}), detection probability can be obtained for the target value of false alarm probability for specific SNR and sampling frequency. Therefore, for sub-channel i, $\bar{p}_{d,i}$ is the target probability of detection and $\bar{p}_{f,i}$ is the target probability of false alarm which are related to false alarm probability and detection probability respectively as shown below:

$$p_{d,i} = \mathrm{Q}\left(\frac{1}{\gamma_i+1}\left(\mathrm{Q}^{-1}(\bar{p}_{f,i}) + \gamma_i\sqrt{t_s W}\right)\right), \quad (6)$$

$$p_{f,i} = \mathrm{Q}\left(\mathrm{Q}^{-1}(\bar{p}_{d,i})(\gamma_i+1) + \gamma_i\sqrt{t_s W}\right). \quad (7)$$

Here, the only varying factor is t_s considering that t_s is very small duration compared to the frame duration T. There are large volume of research outcomes to study the throughput in terms of t_s and T, see, e.g., [3].

Let us consider that the sub-channel gain between SUs is g_{ss} and between PU to SU is g_{ps}, also the P_s and P_p are

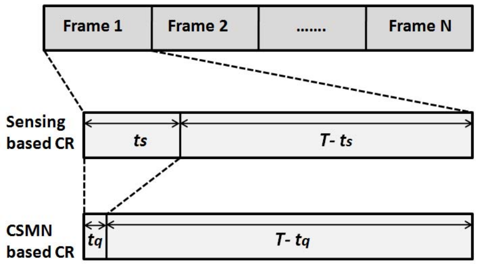

Fig. 2. Frame Structure with Periodic Sensing and Query Time.

secondary and primary transmission power respectively. From the secondary users point of view, let $R_i^{(ab)}$ is the expected throughput for a particular channel of interest i under the condition of $(a\ b)$. Here, $a, b \in \{0, 1\}$ represents the decision taken and actual status of the sub-channel i, where 0 and 1 represents idle and busy states respectively. Therefore,

$$R_i^{(00)} = \log_2\left(1 + \frac{g_{ss,i}p_{s,i}}{N_0}\right), \tag{8}$$

$$R_i^{(01)} = \log_2\left(1 + \frac{g_{ss,i}p_{s,i}}{g_{ps,i}P_{p,i} + N_0}\right). \tag{9}$$

Then, the average throughput will be given by considering all possible a and b such that SUs are allowed to send packet.

$$\bar{C}_{i,avg} = \frac{T - t_s}{T} p_{cs,i} \mathrm{E}[p_{off}R_i^{(00)} + p_{on}R_i^{(01)}], \tag{10}$$

where $p_{cs,i}$ is the probability that the MoN correctly senses the status of sub-channel i. As mentioned in the beginning, the concept of proposed CMoN model is to minimize the sensing duration by keeping average throughput at its maximum achievable rate. In the proposed framework, within each frame duration T, sensing duration is further decreased to channel query time t_q, which is defined as the short frame duration into which SUs send query to monitoring sensors and receive the response as the status of sub-channel i. The transition from t_s (in conventional CRN) to t_q (in proposed CMoN based CRN), and its implication on the available data transition duration is shown in Fig. 2.

A. Maximum Achievable Throughput

When t_q is smaller than the coherence time of the channel, the channel gain and transmission power of PUs and SUs remains constant. In such scenario, it is reasonable to assume that $\mathrm{E}[p_{off}R_i^{(00)} + p_{on}R_i^{(01)}]$ does not vary within one frame duration. Thus, further analysis is performed only on the remaining parts $\frac{T-t_s}{T}p_{cs,i}$. Therefore, putting (5), (6), and (7) on the average throughput, the objective function is obtained as following:

$$C_{i,avg} = \frac{T - t_s}{T}\left\{\mathrm{Q}\left(\frac{1}{\gamma+1}\mathrm{Q}^{-1}(\bar{p}_f) + \frac{\gamma}{\gamma+1}\sqrt{t_sW}\right) - \mathrm{Q}\left((\gamma+1)\mathrm{Q}^{-1}(\bar{p}_d) + \gamma\sqrt{t_sW}\right)\right\}. \tag{11}$$

In (11), the terms that are independent to sensing time are $K_1 = \frac{1}{\gamma+1}\mathrm{Q}^{-1}(\bar{p}_f)$ and $K_2 = (\gamma+1)\mathrm{Q}^{-1}(\bar{p}_d)$. Therefore,

$$C_{i,avg} = \frac{T - t_s}{T}\left\{\mathrm{Q}\left(K_1 + \frac{\gamma}{\gamma+1}\sqrt{t_sW}\right) - \mathrm{Q}\left(K_2 + \gamma\sqrt{t_sW}\right)\right\}. \tag{12}$$

To optimize the achievable throughput, the first derivative of the objective function at $t_s \to t_q$ will provide the estimate of its maximum achievable functional value because the objective function has the negative curvature. Note that $\mathrm{Q}'(x) := -(1/\sqrt{2\pi})e^{-(x^2/2)}$ and therefore,

$$C_{i,avg} = M_1 + M_2 + \frac{\gamma}{2\sqrt{2\pi}\,(\gamma+1)}e^{-k_1^2/2}\sqrt{\frac{w}{t_s}} - \frac{\gamma}{2\sqrt{2\pi}}e^{-k_2^2/2}\sqrt{\frac{w}{t_s}}. \tag{13}$$

The expression for $C_{i,avg}$ is obtained by considering the summation term of t_s to be zero because CMoN-based model has provision of query time t_q to assess the status of the sub-channel i. This approximation is justifiable since $t_q \ll t_s \ll T$. The only variation parameter is t_s.Therefore finally,

$$C_{i,avg} = M_1 + M_2 + M_3\frac{\sqrt{w}}{\sqrt{t_s}} - M_4\frac{\sqrt{w}}{\sqrt{t_s}}, \forall\ i. \tag{14}$$

where, $M_1 = -\frac{1}{T}\mathrm{Q}(k_1)$, $M_2 = -\frac{1}{T}\mathrm{Q}(k_2)$ are independent of sampling time and sensing duration. Thus, these two terms have ignorable contribution to the achievable throughput. The last two terms associated to sensing duration are $M_3 = \frac{\gamma}{2\sqrt{2\pi}(\gamma+1)}e^{-k_1^2/2}$, and $M_4 = \frac{\gamma}{2\sqrt{2\pi}}e^{-k_2^2/2}$. Therefore, the condition $t_q \ll t_s$ proves that $C_{i,max}(t_q) \gg C_{i,max}(t_s)$.

V. Numerical Analysis and Discussion

The sensing accuracy is a very important parameter in CR for the overall system performance. Therefore the concept of $p_{cs,i}$ has been defined which addresses many possible scenario in spectrum sensing in CRN. Furthermore, the cluster-based monitoring network presented to analyze the multi-user cooperative cognitive radio. The design parameter is presented in Fig. 3, which shows the $p_{cs,i}$ for various cluster members to cluster heads ratio to monitor the network area. This is a basic design framework of monitoring network for two tier decision modules. This analysis is done under $p_{d,i} = 94\%$ and $p_{f,i} = 4\%$. By increasing the number of cluster members, the accuracy of detection for each sub-channel is decreased which is mainly because of the AND rule implemented in cluster level. Fig. 3 also indicates higher detection accuracy by selecting large number of cluster heads which ultimately means creating the small cluster size for monitoring network.

The proposed channel monitoring solution outperforms the conventional CRN in terms of throughput performance, see Fig. 4. The throughput is normalized because the constant term $\left(R = \mathrm{E}[p_{off}R_i^{(00)} + p_{on}R_i^{(01)}]\right)$ for a frame duration

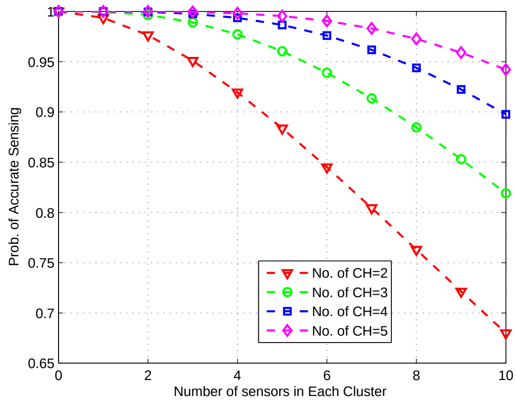

Fig. 3. Probability of accurate sensing *vs.* number of sensors in each cluster.

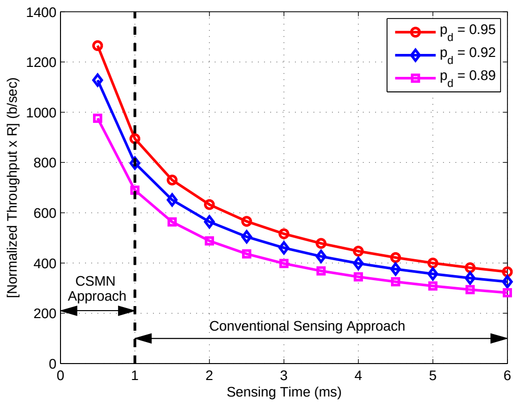

Fig. 4. Maximum achievable throughput *vs.* sensing duration (p_d varies).

is not taken into consideration for the analysis purpose. The numerical study is performed under received SNR at sub-channel i to be approximately 1dB and false alarm probability to be 4%. The narrow-band channel bandwidth is considered as 1 MHz for 100 ms frame duration.

The primary reason behind the throughput achievement is that there is very low channel query time in proposed method in comparison to the relatively long sensing duration in conventional CRN. Eventually, it offloads many computations, such as channel sensing and processing, to the sensor network from the SUs. This results the primary channels are properly used and secondary users collision probability is very low and the throughput performance is better. As shown in Fig. 4, the lower sensing duration is actually query time ($\leq$ 1ms) in proposed method where better network performance is expected than when SUs perform both jobs ($t_s \geq$ 6ms). The Fig. 5 is obtained keeping p_d at 94% while changing the expected p_f. As it can be observed in both cases that the proposed method performs better in terms of network throughput by approximately $(900 * R)bps$ when sensing duration, t_s, is bounded withing very small channel query time, t_q, for SU.

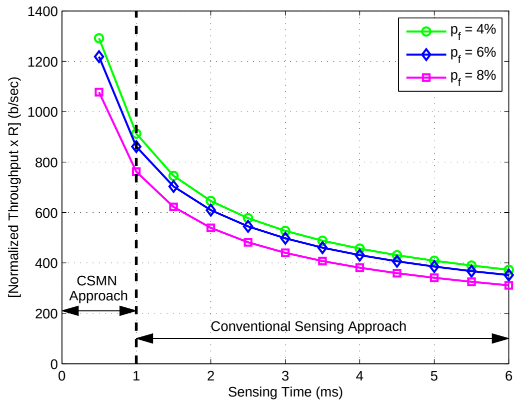

Fig. 5. Maximum achievable throughput *vs.* sensing duration (p_f varies).

VI. Conclusion

In this paper, the sensor enabled cognitive radio network has been studied where the sensing duration and network throughput are known to be independent each other. The CMoN, which has important task of channel monitoring, has been studied in detail. We also formulated the measurement of correct sensing the primary channel as well as two tier decision fusion method at the SBS to improve the network throughput and delay. The numerical study has shown that the proposed CMoN scheme achieves much better SU throughput because the query time in the proposed method is significantly smaller than conventional 'sensing within the frame' approach where frames are shared for sensing and communication.

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