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Maximizing Cognitive Radio Networks Throughput Using Limited Historical Behavior of Primary Users

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ABSTRACT Cognitive radios (CRs) mainly aim to reuse the spectrum holes in order to efficiently utilize the available scarce radio spectrum. However, current CRs techniques have a throughput limitation problem which ultimately limits telecommunication applications horizons nowadays. Moreover, achieving high throughput will overcome the bottleneck of CRs application limitations to the reporting and browsing applications only. To tackle this emerging throughput limitation issue in the CRs, this paper proposes the online greedy throughput maximization (OGTM) algorithm which overcomes the throughput limitations. OGTM allows the sensing cycle frame to have a variable length according to the assumed decision validity interval. Then, OGTM varies the decision validity interval of secondary users (SUs) based on the primary users (PUs) historical behavior. As a proof of concept, we developed a simulator in order to evaluate the performance of the proposed OGTM technique. The simulation results show that SUs benefit from the limited PU historical behavior learning, which resultantly increases the throughput up to 95% and at the same time decreases the miss detection probability by 50%.

INDEX TERMS Behavior learning, cognitive radios, primary users, secondary users, miss detection, ogtm, throughput limitation.

I. INTRODUCTION

Cognitive Radios (CRs) are capable of changing their parameters such as operating frequency and power in order to benefit from the opportunistic spectrum access to licensed channels [1]. Such opportunistic spectrum access allows new telecommunication applications to share the overbooked under-utilized spectrum with the existing applications and hence increases the spectrum utilization efficiency.

In order to detect and utilize the under-utilized spectrum holes, CRs perform sensing cycles. The CR sensing cycle is composed of three intervals; the spectrum sensing interval to detect the spectrum holes, the detected spectrum holes for reporting and CRs cooperation interval seeking the refined spectrum decisions, and the payload data transmission interval [2]. A further illustration of these three intervals is discussed in the next paragraphs.

In the spectrum sensing interval, all secondary users (SUs) sense the targeted primary users (PUs) channels searching for spectrum holes. The sensing criterion is assumed to be an energy detection because it is a simple method which does not require any a priori information about PUs [3]. However, this individual spectrum sensing process has a degraded performance because of the shared channel effects, such as hidden PU terminal problem, SU shadowing and multipath fading between PUs and SUs. In other words, the individual spectrum sensing needs to be more reliable through cooperation.

In the cooperation interval, each SU sends its spectrum holes information towards a centralized coordinator named as group master or data fusion center (FC), which process the final decision making. The received local sensing results processing at FC is based on a fusion rule, such as AND rule, OR rule, the linear combination rule, and the majority rule. The final decision making output is then transmitted to all SUs to start the payload data transmission.

In the payload data transmission interval, each SU selects a spectrum hole and transmits a single data packet within the hole. If no spectrum hole detected, the SU would keep the data packet in its buffer for the next sensing cycle.

Sending more than one packet will increase the throughput. However, sending more than one packet will also increase the sensing cycle frame size that leads to increased collision probability with the PUs.

According to [4] and [5], throughput is one of the key limitations which prevent the full realization of CR algorithms. Moreover, in the CRs, among the major limitations such as energy consumption, processing resources, cost, and quality of service limitations, the throughput limitation is a key hurdle which prevents a wide range of telecommunication applications nowadays. These applications can be summarized in four categories (1) reporting, (2) browsing, (3) live streaming and (4) downloading (including non-live streaming) [6]. Furthermore, the CR, by definition, does not guarantee the quality of services (i.e., no live streaming is supported). Alternatively, achieving high throughput is important because it is the key parameter in order to support the downloading applications. Then achieving high throughput will overcome the bottleneck of CR application limitations to the reporting and browsing applications only.

By focusing on the throughput limitations in the CRs, this paper proposes an online greedy algorithm to increase the CR system throughput while maintaining the PU protected. The proposed algorithm learns from the PU behavior in a given window of sensing cycles to determine whether to increase the transmission rate or not. The proposed algorithm must be lightweight in the processing capacity, in order to be compatible with the CR limited processing capacity. Our simulation results show that the proposed algorithm achieves a maximum throughput of 95% of the available spectrum holes while increasing the PU protection by at least 50%. Moreover, the majority of interferences probabilities on PU is within the PU connection establishment interval, where such interferences have lesser importance.

The organization of the remaining sections is as follows. Section II describes the state-of-the-art on existing CR approaches. Section III presents motivation behind the proposed OGTM algorithm. The description of the system model is presented in Section IV. The proposed OGTM algorithm is presented in Section V. Details of simulation setup, and performance analysis are given in Section VI. Finally, Section VII draws conclusions.

II. STATE-OF-THE-ART

Nowadays, Cognitive Radio (CR) systems have achieved significant attention from the research community. Researchers have proposed several techniques in order to make the best use of CR systems to optimally use the scarce radio spectrum. For instance, Pratibha *et al.* [7] proposed a technique to optimize the sensing intervals in order to balance between spectrum access and energy harvesting. Furthermore, the Pandit and Singh [8] proposed a technique to improve the throughput of the CR user while reducing the interference with the primary users. Besides, Pandit and Singh [9] studied the impact of perfect and imperfect sensing on the performance of throughput and energy efficiency in CR systems. Moreover, the opportunities available for operating CR systems within the radio frequency spectrum are characterized in [10]. Similarly, Suseela and Sivakumar [11] studied the impact on CR throughput using channel optimization techniques. They optimized channel using particle swarm optimization technique and tree seed algorithm in CR systems.

Since CRs mainly focuses to increase system throughput, therefore several techniques were proposed in the past in order to achieve the maximum CRs throughput. The most prominent of the available techniques achieve maximum throughput by decreasing either the spectrum sensing interval or the cooperation interval as proposed in [12]–[17]. The main approaches to increase the throughput in CRs can be divided into three categories: (1) either reduce the sensing interval through reducing the sensed channels or the sensing period per channel. (2) by reducing the cooperation interval through minimizing the needed reporting packets before reaching the final decision, and (3) by increasing the transmission interval by increasing the transmitted packet size or the number of packets.

A. REDUCING THE SENSING INTERVAL

In order to reduce the sensing interval, [12] divides the sensing interval into coarse and fine intervals. In the coarse sensing interval, if a clear decision is reached, then SUs start the cooperation interval. Otherwise, the SUs initiates the fine sensing interval before starting the cooperation interval. Ergul and Akan [13] propose only a coarse channel sensing interval. In the case of no clear decision, they assume using any other fine sensing algorithm in the literature to perform the final decision. At very low SNR below -3 dB, this coarse channel sensing performs well. However, it has a near PU detection problem.

In [14], each channel sensing slot is reassigned for multiple channels sensing in order to reduce the sensing interval. In contrast, they ignore that reducing the number of samples per channel leads to degraded performance of PU detection. While Ali *et al.* [15] assume sensing only a subset of the channels by each SU and count on the cooperation algorithm for the needed information about other channels.

B. REDUCING THE COOPERATION INTERVAL

In order to reduce the cooperation interval, three major algorithms available in the literature include sequential detection (SD), ordered transmission (OT), and implicit cooperation (ImCo). In SD, SUs sequentially sends their individual decisions to FC only if no clear final decision is reached from the previously collected decisions [16], [17]. In other words, FC performs aggregation after each decision reception, then decides either to continue or to stop and declare the final decision. SD is not scalable because it requires a delay proportional to the needed number of SU to reach the final decision. In addition, SD requires the advanced FC capability to perform aggregation after each new reception from SUs.

In contrast to SD where the next transmitting SU is chosen randomly, OT sort the SUs by their probability of detection (PD) or signal to noise ratio (SNR) [17]. In OT, SUs sends their individual decisions in an order according to aforementioned criterion. OT has the SD problems and a SU sorting problem. In ImCo, the cooperation interval is reduced by preventing some SU from sending their reports [10]. A criterion is made to determine which SUs has no useful information in order to silence them before reporting. The authors also proposed slotted ImCo for the small fixed cooperation interval.

C. INCREASING THE TRANSMISSION INTERVAL

To the best of the author's knowledge, there is no research available in the literature which study the effect of transmission interval in different situations. However, the majority of the research work focuses on decreasing the collision probability with PUs in order to increase the successfully transmitted ratio.

III. MOTIVATION

Existing CR algorithms do not consider system throughput as a primary criteria while improving the system performance. Resultantly, existing CR algorithms have poor performance in terms of system throughput. Moreover, in literature, the primary metrics being used to evaluate the performance of CR algorithms include delay, energy efficiency, scalability, and node required resources [18], [19]. Among these metrics, the metric that affects the overall system throughput is the decision making delay. It is either due to the spectrum sensing interval (i.e., sequentially sensing N channels with N_S samples for each) or reporting interval (i.e., sequentially reporting M decisions with possible retransmissions). Furthermore, increasing N or M up to a certain limit leads to a higher delay than the decision validity interval.

The targeted transmission interval is the difference between the decision validity interval and the decision making delay. However, fixed frame interval does not support the use of such intervals deference. In contrast, fixed frame interval assigns the minimum guaranteed transmission interval only for payload data transmission before starting the next frame (which reduce the system throughput).

In this paper, the primary goal is to increase the system throughput. The main idea is to achieve higher system throughput by increasing the transmission interval within the frame. This is achieved by varying the frame interval while fixing the decision making delay intervals (i.e., sensing and reporting intervals). In order to achieve high throughput, the frame variation is assumed to be depending on the variation in the decision validity interval. Since the decision validity interval is based on the historical behavior of PUs, we try to implicitly estimate the PUs activity factor. In other words, we assume that a longer period after the last PU activity means lower PUs activity factor. This ultimately leads to higher decision validity interval and consequently the transmission interval.

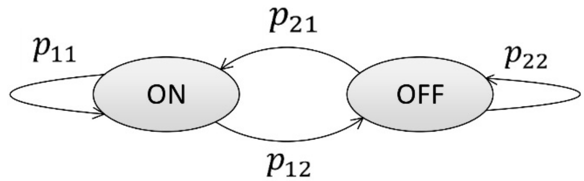

FIGURE 1. ON-OFF transition Markov model.

IV. SYSTEM MODEL

A detailed description of the system model is presented in this section. Particularly, topics such as energy detection based spectrum sensing, spectrum sensing error probability, reporting, and transmission interval are mainly covered in this section.

A. MODEL DESCRIPTION

We consider geographical collocation between primary users (PUs) and secondary users (SUs). PUs can only operate in one of N separate channels. Furthermore, PUs are assumed with connection-oriented communication (e.g., phone calls). According to the proposed Markov model shown in Figure 1, each PU state is either ON or OFF in each time slot. Moving from time slot X_i to X_{i+1} have four probabilities: p_{11} to remain in ON state, p_{12} to move from ON to OFF state, p_{22} to remain in OFF state and p_{21} to move from OFF to ON state. For connection-oriented communication, we assume $P_{11} \gg P_{12}$ and $P_{22} \gg P_{21}$. The OFF interval means that the PU is not occupying the channel, and then SUs can exploit this channel until the PU switch to ON state. Moreover, FP is defined as the percentage activity factor of PU channel utilization, i.e., the ratio of the PU time in ON state to the total time (i.e., in both ON and OFF states):

$$F_P = \frac{T_{ON}}{T_{ON} + T_{OFF}} \tag{1}$$

Each SU can switch between any of the N channels. However, SU can only operate in one channel at a time. The proposed SUs population is M nodes, uniformly distributed in the targeted area. No mobility is assumed (i.e., SUs are with static locations). Each SU has only one half-duplex transceiver, which can operate in the ISM band in addition to N PU channels, one at a time. Moreover, each SU is computation resource constrained. Furthermore, all SUs hardware is homogenous.

The reporting packets from SUs to FC cannot be in any of the N channels because of no guaranteed availability for such channels. In contrast, a common control channel (CCC) is used for this cooperation task. The CCC may be chosen overlay in the ISM band (i.e., unlicensed band) or underlay using UWB spread spectrum. The individual decisions are taken locally using energy detection [3], [20]. Among other detection methods, energy detection is mostly preferred because it has low complexity and does not need a priori information from PUs. In our proposed algorithm, the common CR synchronous sensing frame is adopted. Each frame with interval

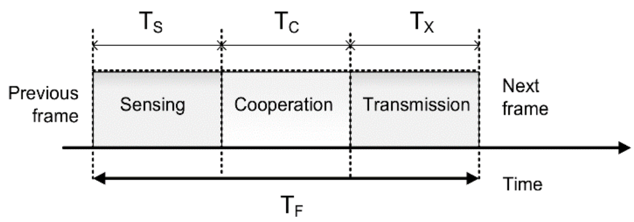

FIGURE 2. The sensing frame.

T_F carries the sensing, cooperation, and transmission tasks sequentially in their subintervals as shown in Figure 2. The individual decisions are taken during the spectrum sensing intervalT_S, the reporting packets are exchanged during the cooperation interval T_C, and the last duration is the payload data transmission T_X (i.e. $T_F = T_S + T_C + T_X$).

B. SPECTRUM SENSING USING ENERGY DETECTION

PUs, in general, refuse to share their detailed information with SUs. Even if SUs know the PUs information at any time, PUs reserve the right to change their transmission parameters without notifying the SUs. In such cases, energy detection is the appropriate detection algorithm due to its feature of not requiring any a priori information about the PUs. In this detection algorithm, the accumulation of the received energy for a given number of samples NS is computed. Then, using a decision strategy, each SU reaches its local decision. There are two strategies, soft decision, and hard decision. In soft decision strategy, each SU convey the accumulated energy samples into a number of bits representing the average energy level.

In contrast, the hard decision strategy conveys the accumulated energy samples into one bit representing whether the average energy level of all samples is above or below a threshold. If the average accumulated energy sample is above, the channel decision is ON (i.e., busy). Otherwise, channel decision is considered OFF (i.e., spectrum hole). In this paper, we adopt the hard decision strategy because it has less delay and requires less computational resources [21].

C. SPECTRUM SENSING ERROR PROBABILITY

From the aforementioned sections, we conclude that the PU may be ON or OFF while the SU may decide the channel to be ON or OFF with a certain error probability. The four probabilities are:

1) The probability of correctly detection a busy channel, i.e., $p(SU_{d=ON}|PU_{ON})$
2) The probability of Miss-detection (MD), p_{MD}, which is the probability of falsely deciding the channel as free given that it is busy, i.e., $p(SU_{d=OFF}|PU_{ON})$
3) The probability of false alarm (FA), p_{FA}, which is the probability of falsely deciding the channel as busy given that it is free, i.e., $p(SU_{d=ON}|PU_{OFF})$
4) The probability of correctly detection a spectrum hole, i.e., $p(SU_{d=OFF}|PU_{OFF})$

TABLE 1. Simulation parameters and settings.

PU	SU decision	Results	Effects
ON	ON	Busy channel	SU silence
ON	OFF	MD	Collisions with PUs
OFF	ON	FA	Spectrum holes underutilization
OFF	OFF	Free channel	SU transmission

A summary of the above mentioned probabilities is provided in Table 1.

The effect of MD is allowing the SUs to transmit their packets within the existence of PU, which results in a collision. Such collisions are not acceptable by PUs. The MD probability formula in energy detection is as follows [3].

$$p_{MD} = Q\left(\frac{\sqrt{N}_S\left(\beta - \left(\sigma_S^2 + \sigma_n^2\right)\right)}{\sigma_S^2 + \sigma_n^2}\right) \tag{2}$$

Where Q (.) is the normal cumulative function, σ_S^2 and σ_n^2 are the signal power and noise power respectively. On the other hand, the effect of FA is not allowing the SUs to transmit their packets within the absence of PU, which results in a channel underutilization, i.e., degrade the throughput. The FA probability formula in energy detection is as follows [3].

$$p_{FA} = Q\left(\frac{\sqrt{N}_S\left(\beta - \sigma_n^2\right)}{\sigma_n^2}\right) \tag{3}$$

D. REPORTING OR COOPERATION INTERVAL

The advantage of SUs cooperation is decreasing both the probability MD p_{MD}^{T} and probability FA p_{FA}^{T} in the aggregated decision. In cooperative sensing, each SU reports its sensing information to the FC, which fuses all reports for an accurate decision [22]. All reports transmissions are on CCC in the cooperation interval using CSMA/CA as a contention-based channel access. Unlike other SUs, the FC has advanced computational resources in order to perform the reports fusion. The FC fuses the reported individual decisions using statistical or logical algorithms. The most widely used logical fusion algorithms are AND, majority (MAJ.), and OR. Existing techniques considered OR rule is the most suitable cooperation fusion algorithm [23]. In this paper, we adopt the OR rule as it has the lowest probability MD and probability FA. In OR fusion algorithm, if at least one SU reports a decision with PU existence, then the global FC decision is the same. Then,

$$P_{MD}^{T} = (P_{MD})^{M} \tag{4}$$
$$P_{FA}^{T} = (P_{FA})^{M} \tag{5}$$

E. TRANSMISSION INTERVAL

After both the sensing and reporting intervals, each SU can use the remaining interval of the frame for sending a payload data packet. The probability of correctly using such interval is the fourth mentioned probability, i.e.,$\mathbf{p(SU_{d=OFF})/PU_{OFF}}$. However, this probability depends on both the PUs activity factor FP and fused decisions FA probability p_{FA}^{T}. SUs, by definition, do not know the PUs activity factor. Conventionally, each SU assumes that the PU activity factor is constant at a certain high value, which degrades the throughput performance.

V. ONLINE GREEDY THROUGHPUT MAXIMIZATION

In this paper, we propose a PU activity factor implicit estimator based on the historical behavior of the PUs. The proposed online greedy throughput maximization (OGTM) algorithm aims to increase the SUs system throughput while keeping the PUs protected. Moreover, due to the behavior of PU connection oriented communication, the interference in establishing the connection can withstand higher collision ratio than within the connection itself. The algorithm process starts with counting the frames with no PU activity in a given channel N_i. Then, when the counter reaches the predefined window W, SUs assumes lower PU activity factor.

A. THE MARKOV MODEL ADAPTATION

In this proposed model, we are going to set the values of the general Markov model introduced in Section IV-A. However, p_{21} depends on the PU activity factor and the probability of ending the connection in the proposed connection oriented communication. Because these two probabilities are independent and identically distributed (i.i.d.) then the p_{21} probability formulation may be written as,

$$p_{21} = p_{trn} \times F_P \tag{6}$$

While $\mathbf{p_{12}}$ can be formulated as

$$p_{12} = p_{trn} \times (1 - F_P) \tag{7}$$

Where $\mathbf{p_{trn}}$ is the average probability of changing the state. From the Markov model property, the sum of outgoing probabilities in each state equals one, then

$$p_{11} + p_{12} = 1 \tag{8}$$
$$p_{22} + p_{21} = 1 \tag{9}$$

From Equation 6 to 9, the other two probabilities can be formulated as

$$p_{22} = 1 - (p_{trn} \times F_P) \tag{10}$$
$$p_{11} = 1 - (p_{trn} \times (1 - F_P)) \tag{11}$$

Which means that the four Markov model probabilities can be fully described using the constant probability $\mathbf{p_{trn}}$ and the variable activity factor F_P.

B. ACTIVITY FACTOR IMPLICIT ESTIMATION

In order to estimate the PU activity factor, one can sense the channel for a long period and calculate the activity factor according to Equation 1. However, the PU may change its activity factor at any instance, and then the calculated FP became no longer valid. On the other hand, we assume OGTM as an online greedy algorithm for FP estimation as shown in Figure 3. According to Equation 1, the activity factor estimation for the next window (given that the first window is sensed free) is 50% or less. Moreover, if both the first and second windows are free, then the activity factor estimation for the next window is 25% or less and so on.

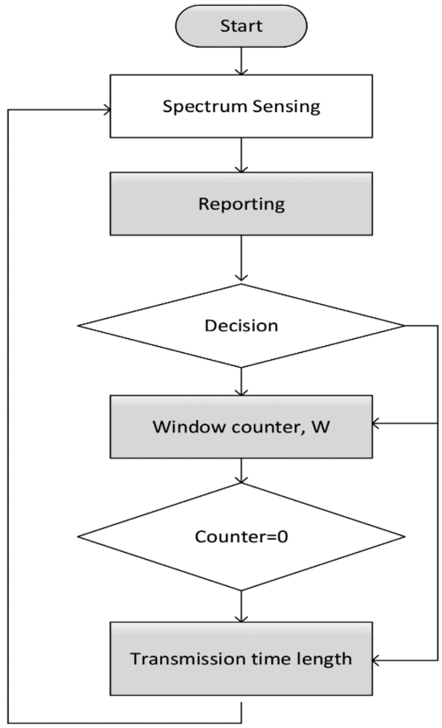

FIGURE 3. The proposed algorithm flow chart.

On the other hand, the PU re-existence indicates a long period of busy channel, as given in Equation 11. In other words, OGTM assumes high activity factor as long as the PU state is ON. However, when the PU state switched to OFF, OGTM start decreasing the PU activity factor. Then, the algorithm decides to increase the validity interval of the spectrum sensing decision. Moreover, the transmission interval increases based on the increased validity.

In contrast, the PU burst traffic contains some gaps within the same connection. However, assuming decreased activity factor after each single free spectrum hole may lead to higher collision probability. Then, we propose increasing the transmission interval only after a certain number of frames denoted by W. Figure 3 illustrates the OGTM algorithm flow chart.

Figure 4 shows five sensing frames in order to illustrate the algorithm i.e.,

1) The first and second frames found the PU channel free then, the transmission interval is doubled at the third frame (i.e., for $W = 2$)
2) As the third frame found the PU channel free, then the fourth frame has the same length (i.e., $2T_{Xmin}$)
3) Due to the collision, the fifth frame transmission interval length is reset to T_{Xmin}.

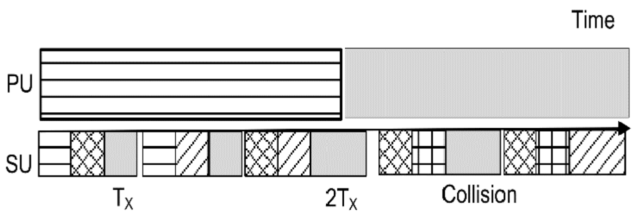

FIGURE 4. Five sensing frames versus the PU activity.

VI. SIMULATION SETUP AND RESULTS

We build a custom-made simulation code using MATLAB R2016b to evaluate the proposed algorithm performance. The proposed system composed of one primary channel with 2 PUs communicating with each other. Moreover, 10 SUs sensing the primary channel and cooperate on CCC using CSMA/CA. All factors that may affect the channel is considered (e.g., shadowing, Rayleigh fading and hidden node problem).

A. PERFORMANCE METRICS

The proposed performance metrics are:

- Performance probabilities (i.e., MD, FA) as percentages.
- The percentage overhead caused by the sensing and reporting intervals compared to the entire SUs activities.
- The throughput percentage compared to the entire simulation interval.

In each PU activity factor FP scenario, the performance metrics are computed for the proposed algorithm OGTM and a system with fixed transmission interval at both the minimum and maximum transmission interval allocated for OGTM. The chosen metrics in the chosen scenarios are meant to illustrate the OGTM advantages over the fixed transmission interval algorithms.

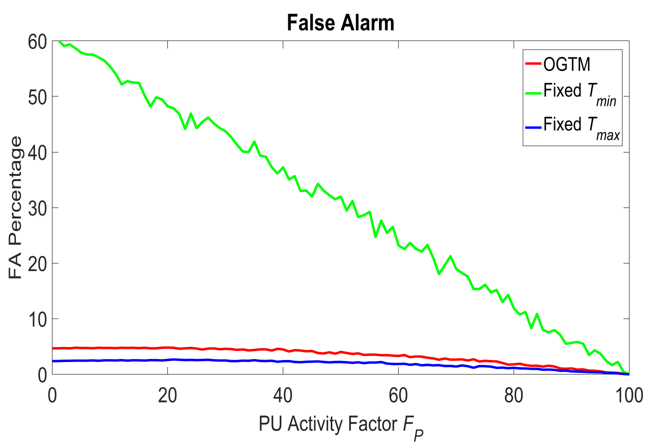

FIGURE 5. The FA percentage versus the PU activity factor.

B. RELATED PROBABILITIES

According to Equation 5 and 3, the probabilities of MD and FA are computed in the aforementioned scenarios. Figure 5 Shows that the OGTM has low FA performance nearly equal to the fixed transmission interval algorithm at high transmission interval assignment. In contrast, at low transmission interval assignment, the fixed interval has high recurrence ratio with high probability to false sense the background noise as PU existence. However, as the PU activity factor increases the SUs become more aware of distinguishing between the background noise and PU existence. Hence, the FA percentage decreases as the activity factor increases.

On the other hand, Figure 6 shows the MD performance. The PU half activity factor means the highest PU ON OFF transition probability. However, increasing such transitions leads to sense PU as OFF during the sensing interval, then the PU change its state to ON within the reporting or transmission intervals. For a low transmission interval, Figure 6 shows small MD probability. In contrast, higher transmission intervals show MD up to 1.5%. The proposed OGTM represents a superposition between the two above mentioned intervals. OGTM not only reduce the MD probability to 50%. Nevertheless, it also limits the majority of those MDs at the beginning of PU connections where MD represents lesser importance.

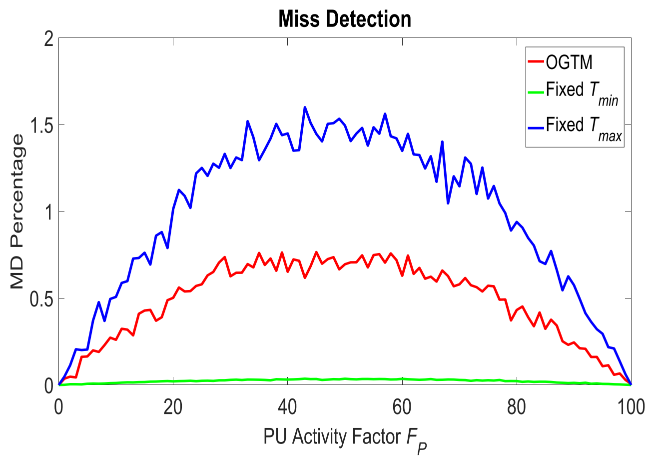

FIGURE 6. The MD percentage at different PU activity factor.

C. OVERHEAD PERCENTAGE

One of the main important factors in CR is the overhead percentage among SUs. We call the sensing and reporting intervals as the sensing cycle overhead because they consume energy and delay without transmission of payload data. Moreover, reducing such intervals will result in increasing the system efficiency and throughput. Figure 7 shows the overhead percentage versus the PU activity factor. OGTM has an average overhead, while the fixed high transmission interval shows lower overhead compared to OGTM. However, this drawback can be ignored compared to the other advantages.

D. THROUGHPUT PERCENTAGE

Figure 8 shows the throughput percentage as a function of PU activity factor. OGTM shows a competitive performance compared to the high fixed transmission interval with 95%

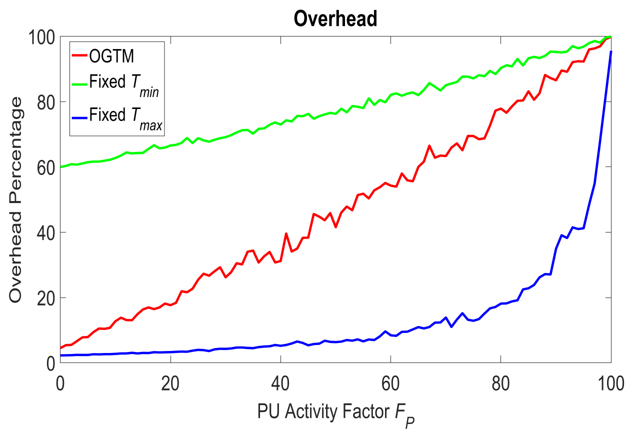

FIGURE 7. Increasing SUs overhead due to increased activity factor.

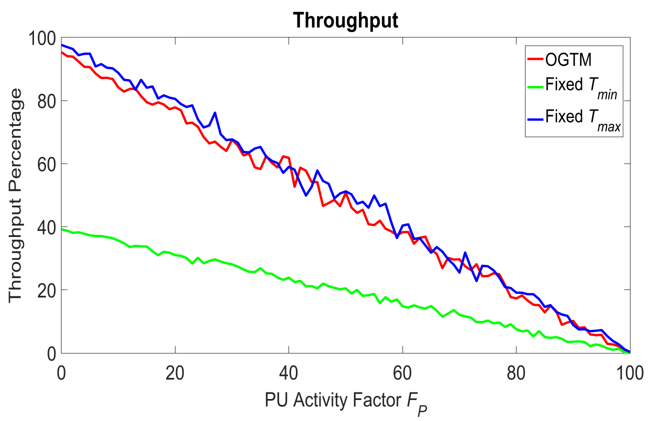

FIGURE 8. Competitive throughput performance for OGTM.

throughput at no PU existence. Moreover, OGTM has a lesser collision ratio with PU, which leads to increased successful packet reception.

VII. CONCLUSIONS

In this paper, we have introduced the online greedy throughput maximization algorithm for CR. OGTM is proposed to overcome the throughput limitations in CRs. OGTM allow the sensing cycle frame to have a variable length according to the assumed decision validity interval. OGTM increases the decision validity interval based on the PU historical behavior. Our simulations have proven that SUs benefit from the limited PU historical behavior learning to increase the throughput up to 95%. Furthermore, OGTM decreases the MD probability by 50% and limit most of the collision probabilities to be within the PU connection establishment phase, where the PUs can tolerate such collisions through retransmission.

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