ERGODIC CAPACITY OPTIMIZATION OF UNDERLAY COGNITIVE RADIO NETWORKS UNDER INTERFERENCE TEMPERATURE CONSTRAINTS

***Iroegbu, C.[1], and Ugboaja, S. G.[2]**

[1]Department of Electrical/Electronic Engineering, Michael Okpara University of Agriculture, Umudike
[2]Department of Computer Science, Michael Okpara University of Agriculture, Umudike

*Corresponding Author: iroegbu.chibuisi@mouau.edu.ng

ABSTRACT

The rapid growth of wireless systems has increased spectrum demand, making radio resources increasingly scarce. Cognitive Radio (CR) provides a solution by enabling secondary users (SUs) to share spectrum with licensed primary users (PUs) while limiting harmful interference. This study investigates ergodic capacity optimization of underlay cognitive radio networks under interference temperature constraints. The system consists of one primary user and three secondary users, resulting in both inter-network and intra-network interference. Under the maximum interference-temperature constraint, the capacity per user increases from approximately 0.07 bpcu at −20 dB to about 6.2 bpcu at 20 dB. Under the average IT constraint, capacity also increases with SNR, while the greater flexibility in power allocation provides improved performance over the maximum IT constraint, particularly at low and moderate SNR. The sum-capacity comparison further confirms the advantage of average IT-based operation. Most importantly, at 19 dB SNR, the proposed ergodic interference-alignment approach achieves reported capacity improvements of 22.64% and 23.67% over the conventional time-division scheme under maximum and average IT constraints, respectively. The corresponding spectral-efficiency gains are 3.0094 bps/Hz and 3.1741 bps/Hz, giving an additional 0.1647 bps/Hz, or approximately 5.47%, for the average IT constraint. These results confirm that adaptive interference management and flexible power allocation can significantly improve spectral efficiency and secondary-user capacity while maintaining the required protection of the primary user.

Keywords: Cognitive Radio (CR), Interference, Secondary users, Capacity, Primary Users

1.0 INTRODUCTION

Interference is a major challenge in wireless networks, limiting achievable capacity under conventional interference management techniques. Interference alignment provides an effective approach for improving network capacity by enabling efficient use of limited time and frequency resources. In an underlay cognitive radio network, secondary users (SUs) can share spectrum with primary users (PUs) only when the interference at the PU receiver remains below the interference temperature (IT) limit. This restriction reduces SU transmit power and consequently lowers achievable capacity. With multiple SUs, mutual interference further degrades performance, making interference mitigation essential for improving the overall sum capacity of cognitive radio networks (Maso, *et al* 2020).
The imbalance between spectrum scarcity and inefficient spectrum utilization led to the development of Cognitive Radio (CR) technology as a solution for improving spectrum efficiency. A cognitive radio network is an intelligent wireless system that senses its environment, identifies available spectrum opportunities, and

dynamically adjusts its transmission parameters to enhance communication performance. Through spectrum sensing, spectrum sharing, and adaptive power control, cognitive radio networks improve spectrum utilization and increase network capacity. However, a key challenge is achieving a balance between maximizing secondary user capacity and protecting primary users from harmful interference. To address this issue, Interference Temperature (IT) constraints are employed to regulate the interference generated by secondary users while enabling efficient spectrum sharing (Maamari, *et al* 2021).

Capacity improvement in cognitive radio networks can be achieved through effective interference management, optimized power allocation, and efficient spectrum access techniques. Under maximum IT constraints, secondary users operate within strict instantaneous interference limits, ensuring strong protection for primary users but potentially reducing capacity. In contrast, average IT constraints provide greater flexibility in power allocation, allowing higher spectral efficiency and improved achievable capacity. Compared with the Time-Division (TD) scheme, which reduces spectrum utilization by allocating separate transmission periods to users, IT-based spectrum sharing enables simultaneous transmission under controlled interference conditions, resulting in better capacity performance, (Rezki and Alouini, 2012b).

Although previous studies have established that interference temperature (IT) constraints and interference alignment can improve spectrum utilization in cognitive radio networks, there remains a gap in jointly optimizing interference management and capacity under different IT constraints. Maximum IT constraints provide strong protection to primary users but may unnecessarily restrict secondary-user transmit power, while average IT constraints offer greater flexibility but require effective interference control. Existing approaches also give limited attention to the combined effect of multiple secondary-user interference, adaptive power allocation, and interference alignment on overall network sum capacity. Furthermore, conventional Time-Division (TD) schemes limit simultaneous spectrum utilization. Therefore, there is a need for an improved interference-management framework that integrates ergodic interference alignment with IT-based power control to enhance the sum capacity of multiple-SU cognitive radio networks while maintaining acceptable interference levels at the primary receiver. This study addresses this gap by evaluating maximum and average IT constraints and comparing their capacity performance with the conventional TD scheme.

Therefore, this study focuses on ergodic capacity optimization of underlay cognitive radio networks under interference temperature constraints.

2.0 REVIEW OF RELATED WORKS

The rapid advancement of wireless communication technologies has increased the demand for higher data rates and efficient spectrum utilization. However, fixed spectrum allocation has led to underutilization of licensed bands and spectrum scarcity. Cognitive Radio (CR) technology addresses this challenge by enabling secondary users (SUs) to access available spectrum opportunities while protecting primary users (PUs) from harmful interference. Current research focuses on enhancing cognitive radio network capacity through improved spectrum sensing, interference management, power control, and adaptive resource allocation techniques.

Mitola and Maguire (1999) introduced cognitive radio as an intelligent communication system capable of sensing its environment and adapting transmission parameters based on available spectrum opportunities. Their work established the foundation for dynamic spectrum access and improved spectrum utilization.

Zhang *et al*. (2010) investigated dynamic resource allocation in cognitive radio networks using interference temperature constraints. Their findings demonstrated that efficient power allocation, frequency management, and interference control are essential for maximizing capacity while protecting primary users.

Goldsmith and Maric (2019) analyzed the capacity limits of cognitive radio networks using interweave, underlay, and overlay spectrum-sharing techniques. Their study showed that effective use of channel information and spectrum-sharing strategies can improve spectral efficiency and network capacity.
Biglieri *et al.* (2021) examined capacity limitations and transmission techniques in cognitive radio networks. They emphasized the importance of interference management, channel knowledge, and intelligent spectrum-sharing mechanisms for achieving higher capacity while maintaining acceptable interference levels.
Hossain *et al.* (2019) reviewed the development and future trends of cognitive radio networks, highlighting spectrum sharing, cooperative communication, and dynamic resource allocation as key approaches for improving capacity. Their study emphasized the importance of efficient spectrum management and interference reduction for achieving higher network throughput.
Kim *et al.* (2016) examined the applications and advancements of cognitive radio technology, showing that efficient spectrum management enables secondary users to access unused spectrum without affecting primary users, thereby improving bandwidth utilization and network capacity.
Tachwali *et al.* (2016) studied resource allocation challenges in cognitive radio networks and identified efficient power, channel, and resource allocation as essential factors for enhancing secondary user throughput while satisfying interference constraints.
Zhou *et al.* (2018) investigated the integration of Non-Orthogonal Multiple Access (NOMA) with cognitive radio networks and demonstrated its potential to improve spectral efficiency and capacity through simultaneous user transmission. However, effective interference management remains a major challenge.
Haykin (2005) highlighted cognitive radio as a solution to spectrum underutilization by emphasizing key functions such as spectrum sensing, spectrum management, and adaptive transmission. The study showed that intelligent spectrum decision-making can enhance network capacity.
Alkhayyat *et al*. (2025) explored the application of artificial intelligence techniques, such as fuzzy logic, genetic algorithms, and neural networks, in cognitive radio networks. Their findings showed that intelligent algorithms can enhance spectrum sensing, resource allocation, and adaptive decision-making, resulting in improved network capacity and efficiency.

Recent studies have focused on applying deep learning techniques to cognitive radio networks to improve spectrum management and capacity optimization. Researchers have investigated deep learning-based approaches for spectrum sensing, spectrum sharing, resource allocation, and interference control.
Although significant improvements have been achieved, challenges still exist in balancing high secondary-user capacity with reliable protection of primary users. Strict interference constraints, channel uncertainty, and inefficient resource allocation can limit achievable capacity. Therefore, further investigation into adaptive interference temperature management, intelligent power allocation, and advanced learning-based optimization techniques remains necessary to achieve higher capacity in future cognitive radio networks.

3.0 SYSTEM MODEL

A spectrum sharing model is considered as illustrated in Fig. 1 where three Secondary Users (SUs) underlay their transmissions in the same narrow-band frequency as the Primary User (PU). A user is defined as transmitter- receiver pair.

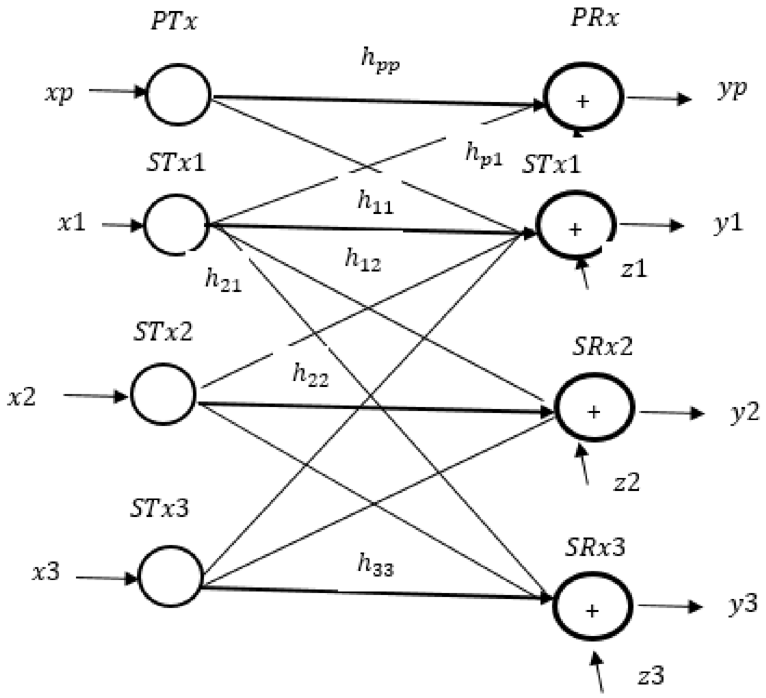

Figure 1: System Model: 3 SUs Coexisting with a Single PU

Figure 1 presents the considered underlay cognitive radio network consisting of one PU and three SUs. The three SUs share the same narrow-band frequency with the PU. The system therefore contains both SU–PU interference and SU–SU interference. The network comprises:

i. One (1) primary transmitter–receiver pair
ii. Three (3) secondary transmitters–receiver pairs
iii. Four (4) transmitting nodes
iv. Four (4) receiving nodes
v. Three (3) SU-to-PU interference links
vi. Six (6) SU-to-SU cross-interference links in the fully connected three-SU network.

The model assumes that all channel coefficients are independent and identically distributed Rayleigh random variables.

The PU is licensed to freely exploit the spectrum; whereas the SU, is allowed to share the spectrum with the PU without harming the latter 's communication. This condition is met by ensuring that the maximum received interference power, P_{Imax} at PU is below a given threshold. The interference temperature metric, IT, would be used as measure of the interference power.

The channel coefficient between transmitter j to receiver i is denoted as h_{ij}. All the channel coefficients are assumed to be independent and identically distributed random variable following Rayleigh distribution.

The following forms of interference exist;

i. Inter-network interference of two kinds: SU-PU interference and PU-SU interference
ii. SU-SU intra-network interference

The received signal at the primary receiver, y_p, is a noisy linear combination of the signals from the intended primary transmitter and unintended secondary transmitters which can be modelled as (Xu *et al*., 2013):

$$y_p = h_{pp}x_p + \sum_{k=1}^{3} h_{pk}x_k + z_p \tag{1}$$

where:
h_{pp} and h_{pk} are the channel coefficient between the PU transmitter and PU receiver and the channel coefficient between the kth SU transmitter and the PU receiver respectively;
x_p and x_k are the signals transmitted by the PU transmitter and the kth SU transmitter respectively;
z_p is an additive white Gaussian noise with zero mean and unit variance at the primary receiver.

Similarly, the channel model for the jth SU receiver is as follows

$$y_j = h_{jp}x_p + \sum_{k=1}^{3} h_{jk}x_k + z_p \tag{2}$$

where, j = 1,2,3

3.1 Achievable Usable Capacity of SUs

The interference from the PU is assumed to be very strong so that each SU could first decode it and subtract from the received signal without incurring any decrease in its achievable rate (Rini et al., 2011). Thus, for a 3-user fully connected CR the received signal vector at j-th SU receiver is obtained from equation (2) as:

$$y_k = h_{kk}x_k + \sum_{k\neq 1}^{3} h_{ki}x_i + z_{p,}\ i = 1,2,3 \tag{3}$$

Each SU would clearly be better off if it had exclusive access to secondary transmission and faced no interference from other SUs. The interference-free capacity would be determined under two constraints, namely; maximum interference temperature limits and average interference temperature limits.

3.2 Maximum Interference Temperature Limits

In this setting, a maximum interference temperature limit is fixed. The SU is not allowed to exceed this threshold regardless of the channel condition. This is applicable to delay sensitive PU. Therefore, instantaneous channel gain of the cross link is assumed to be available at the SU transmitter. The capacity, C, is solution to the following optimization problem.

$$C = Max_{P\geq 0}^{E[\log(1+g_{ss}P)]} \tag{4}$$

Subject to

$$g_{ps}P \leq kBT_L \tag{5}$$

Where, $E[.]$ Is the expected operator
g_{ss} and g_{ps} are the channel gains of the secondary link and the cross link
The solution of this problem is simple to derive and the optimal power, $P*$, is given by

$$P^* \frac{KBT_L}{g_{ps}} \tag{6}$$

putting equation (6) in equation (4) gives

$$C = Max_{P\geq 0}^{E\left[\log\left(1+\frac{g_{ss}}{g_{ps}}\varphi\right)\right]} \quad (7)$$

where, $\psi = kBTL$is the signal to noise ratio of AWGN channel with zero mean and unit variance.
The ratio of the random variables $\frac{g_{ss}}{g_{ps}}$ is another random variable.

$$f_x(x) = \frac{1}{(1+x)^2} \quad (8)$$

Putting equation (8) into equation (7) using analytical method gives

$$C = 1.44\int_0^{\infty} \log\left(1+\varphi x\right)\frac{1}{(1+x)^2}dx \quad (9)$$

$$C = 1.44\frac{\varphi log\varphi}{\varphi-1} \quad \text{Bits per channel use (Bpcu)} \quad (10)$$

3.3. Average Interference Temperature Limits

From the spectrum-sharing point of view, an average interference temperature constraint is reasonable when the PU‘s QoS is determined by the average SNR. This is applicable for delay-insensitive service. This constraint is less stringent than the maximum IT limit. Subsequently, the ergodic capacity is obtained by solving the following optimization problem.
The optimal power, $P*$, is obtained using the Lagrangian method, given by,

$$P^* = \left(\frac{1}{\lambda g_{ps}} - \frac{1}{g_{ss}}\right)^+ \quad (11)$$

λ is the Lagrange multiplier, found by solving the constraint with equality as

$$E\left[\left(\frac{1}{\lambda g_{ps}} - \frac{1}{g_{ss}}\right)^+\right] = kBT_L \quad (12)$$

Since g_{ss} and g_{ps} are independent and identically distributed, then $\frac{g_{ss}}{g_{ps}}$ and $\frac{g_{ps}}{g_{ss}}$ have the same Pdf. Let $\frac{1}{\lambda} = \gamma$ so that equation (12) is now written as

$$\int_0^{\gamma}(\gamma - x)\frac{1}{(1+x)^2}dx = \gamma - \log(1+\gamma) = kBT_L \quad (13)$$

Thus,

$$\gamma - \log(1+\gamma) = \varphi \quad (14)$$

Putting equation (11) into equation (9) using analytical method gives

$$C = 1.44\int_{\gamma}^{\infty}(\gamma x)\frac{1}{(1+x)^2}dx \quad (15)$$

Thus,

$$C = 1.44\log\left(1+\gamma(\varphi)\right) \quad (16)$$

Where $\gamma(\varphi)$ is the solution of (14) for a given φ.

Equations (10) and (16) give the interference-free capacity under maximum and average interference temperature limits which would be used to gauge the performance of the proposed interference mitigation technique. For the three SUs to underlay their transmission, a simple technique for mitigating the interference is to have transmitters take turns using the channel usually termed as time division. If the channel access time is partitioned equally between transmitters, the capacity per user, C_{su} would be given by

$$C_{su} = \frac{1}{3}E[\log(1 + g_{ss}P^*)] \tag{17}$$

Thus, putting equations (10) and (16) in equation (17) gives the corresponding capacity per user under maximum and average interference temperature limits as

$$C_{su-max} = \frac{1.44}{3}\frac{\varphi log\varphi}{\varphi - 1} \tag{18}$$

$$C_{su-av} = \frac{1.4427}{3}\log(1 + \gamma(\varphi)) \tag{19}$$

4.0 RESULTS AND DISCUSSIONS

In Figure 2, the capacity per user under maximum IT limit is plotted in bits per channel use as a function of the SNR using equation (18)

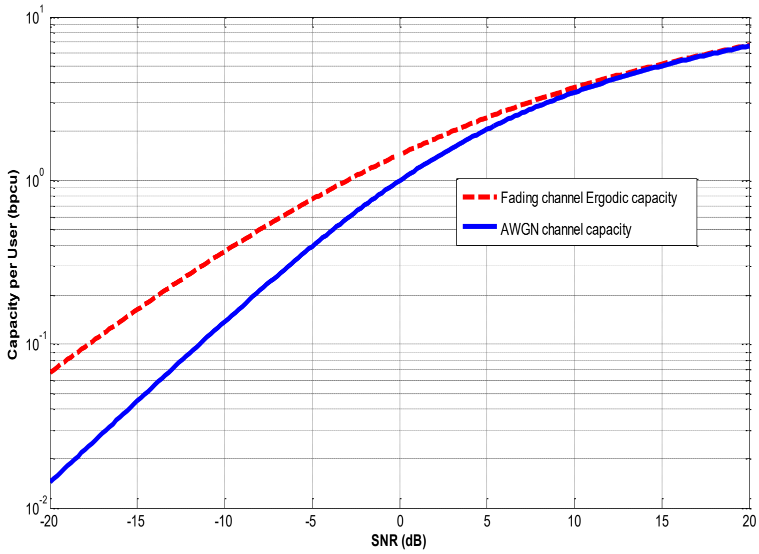

Figure 2: Capacity per User through Time Division User under Maximum IT Limit

Figure 2 shows that capacity per user increases substantially with SNR under the maximum interference-temperature constraint. At −20 dB, the fading-channel capacity is approximately 0.07 bpcu, increasing to about 1.2 bpcu at 0 dB and approximately 6.2bpcu at 20dB. This represents an overall increase of approximately 6.13 bpcu across the simulated SNR range. The rapid increase at low and moderate SNR indicates that improved signal quality significantly enhances the achievable rate. However, capacity growth becomes progressively slower at high SNR because the maximum IT constraint restricts the allowable transmit power of the secondary users.

Similarly, Figure 3, shows the capacity per user under average IT limit plotted in bits per channel use as a function of the SNR using equation (19)

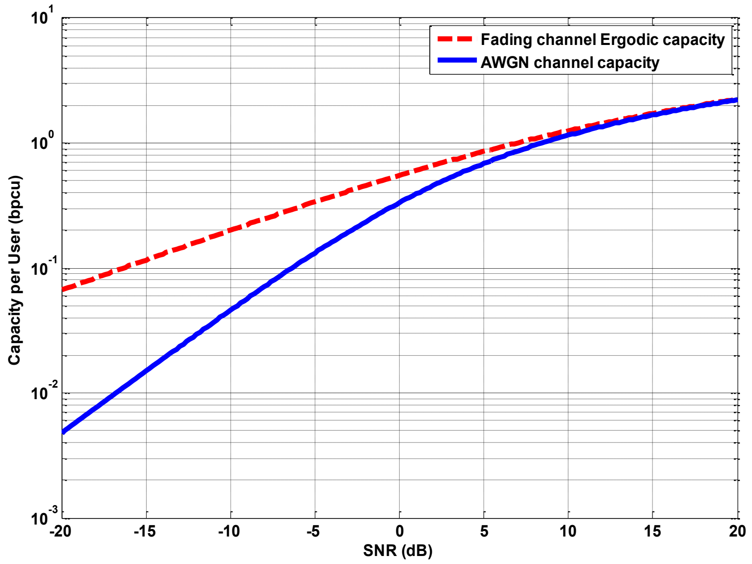

Figure 3: Capacity per User through Time Division under Average IT Limit

The capacity-per-user versus SNR curve under an average Interference Temperature (IT) limit shows that capacity improves as the SNR increases. Figure 3 demonstrates that the capacity per user under the average IT constraint increases with SNR. At −20 dB, the fading-channel capacity is approximately 0.055 bpcu, increasing to approximately 0.50bpcu at 0 dB and 2.0 bpcu at 20 dB. The improvement from −20 dB to 20 dB is therefore approximately 1.945 bpcu. The considerable separation between the fading and AWGN curves at low SNR indicates the influence of the fading/channel model and the average interference-temperature power allocation. As SNR increases, the two curves converge, indicating reduced relative influence of the low-SNR channel effects. Due to channel fading effects, the Rayleigh fading channel achieves higher capacity than the AWGN channel for the same average SNR and IT constraint conditions (Sboui *et al.,* 2013). This statement holds only at low SNR levels as indicated in Figures 2 and 3.

Comparison of the sum capacities of the SUs under maximum IT limit and average IT limit for the same SNR in done in Figure 4. The plots were obtained using equations (10) and (16).

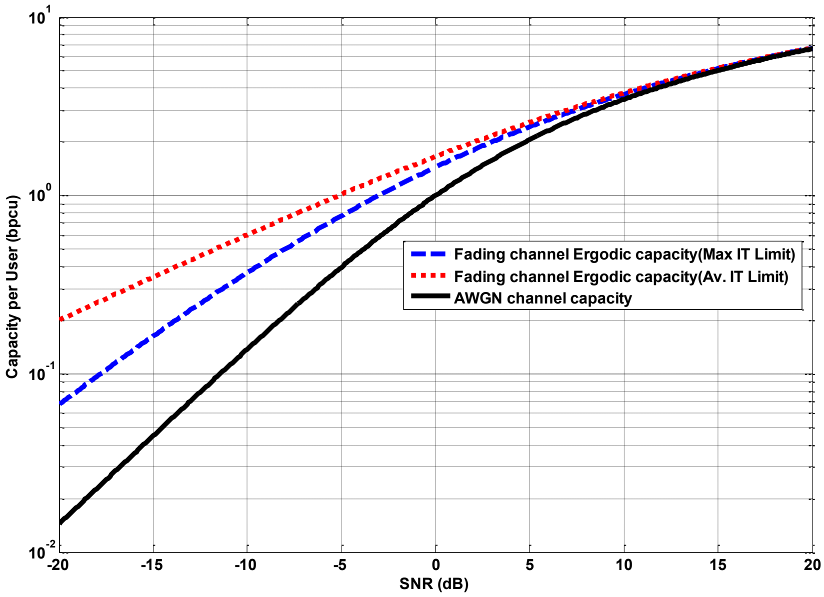

Figure 4: Sum Capacity through Time Division

Figure 4 demonstrates the capacity advantage of the average IT constraint over the maximum IT constraint. At approximately 0 dB, the average IT capacity is about 1.4 bpcu compared with approximately 1.0 bpcu for maximum IT, representing an improvement of approximately 40%. At 10 dB, the corresponding capacities are approximately 3.0 and 2.8 b pcu, giving an improvement of approximately 7.1%. At 20 dB, both methods approach approximately 6 bpcu. These results demonstrate that average IT provides greater flexibility in secondary-user power allocation, particularly in the low-to-moderate SNR region. Comparison of the achievable capacity under IT constraints with that of the time-division scheme is done in Figure 5.

The comparison of the achievable capacity under Interference Temperature (IT) constraints and the Time-Division (TD) scheme is an important performance evaluation in cognitive radio and spectrum-sharing systems. It illustrates the efficiency of simultaneous spectrum sharing under interference constraints compared with orthogonal channel access using time division.

In the IT-constrained scheme, secondary users (SUs) are allowed to transmit simultaneously with primary users (PUs), provided that the interference generated at the primary receiver remains below a specified threshold. Conversely, in the Time-Division (TD) scheme, users transmit in separate time slots, eliminating mutual interference but reducing the effective transmission time available to each user.

The comparison also gives an upper bound to the capacity which corresponds to capacity achievable by non-interfering cognitive users.

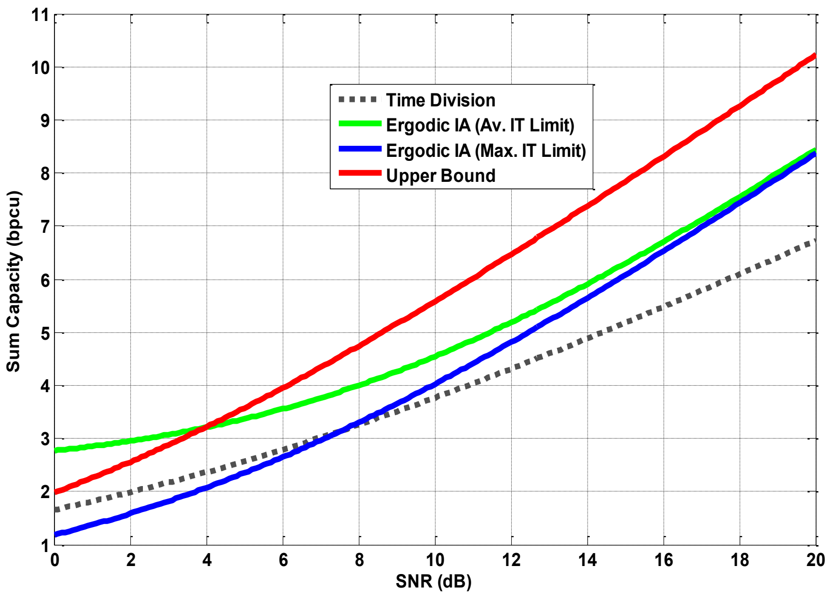

Figure 5: Sum Capacity Comparison

Figure 5 provides the clearest evidence of the capacity improvement produced by the proposed interference-management approach. The figure compares: Time Division (TD), Ergodic under average IT, Ergodic under maximum IT Upper-bound capacity. The SNR range is approximately 0–20 dB.
At 19 dB SNR. The spectral-efficiency gains 3.0094 bps/Hz under the maximum IT constraint, and 3.1741 bps/Hz under the average IT constraint.

The difference is: $13.1741 - 3.0094 = 0.1647 \text{ bps/Hz}$

The percentage advantage of average IT over maximum IT is: $\frac{3.1741-3.0094}{3.0094} \times 100 = 5.4\%$

Thus, at 19 dB, the average IT constraint produces approximately 5.47% greater spectral-efficiency gain than the maximum IT constraint. Also at 19 dB, there was 22.64% TD improvement for maximum IT and 23.67% for average IT.
Spectral efficiency gain was achieved through exploiting the long delay necessary for the ergodic alignment. By utilizing the waiting time slot to send delay sensitive bits in time division scheme, 3.0094 bps/Hz and 3.1741 bps/Hz gains in spectral efficiency was achieved under maximum and average IT limits over a full time-division scheme at SNR of 19 dB.

5.0 CONCLUSION

This research investigated capacity improvement in cognitive radio networks through efficient spectrum utilization and interference management techniques. The increasing demand for wireless services has created spectrum scarcity, despite the underutilization of many licensed frequency bands. Cognitive radio addresses this challenge by allowing secondary users (SUs) to access available spectrum while protecting primary users (PUs) from harmful interference.

The study examined the effect of Interference Temperature (IT) constraints on cognitive radio capacity. Results showed that maximum IT constraints provide strong protection for primary users but limit secondary user capacity due to strict power restrictions. In contrast, average IT constraints enable adaptive power allocation, allowing secondary users to exploit favorable channel conditions and achieve higher spectral efficiency and throughput.

This study demonstrated that effective interference management can improve the capacity and spectral efficiency of underlay cognitive radio networks. The results showed that both maximum and average interference-temperature constraints provide increasing capacity as SNR improves, but the average IT constraint generally achieves better performance because it allows more flexible power allocation.

The proposed interference-alignment approach also outperformed the conventional Time-Division scheme by allowing simultaneous spectrum access while controlling interference to the primary user. At 19 dB SNR, capacity improvement over the Time-Division scheme was 22.64% under maximum IT and 23.67% under average IT**.** The corresponding spectral-efficiency gains were 3.0094 bps/Hz and 3.1741 bps/Hz**,** respectively. Overall, the study concludes that average IT-based spectrum sharing combined with ergodic interference alignment provides improved capacity, spectral efficiency, and spectrum utilization, while maintaining appropriate protection of the primary user.

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