Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Energy Efficient Spectrum Sensing Through Cellular Automata In Cognitive Radio For 5g Networks

Dr. Resmi G Nair[1] , Dr. Sangeetha. Y[2]

[1]professor, Department Of Csesngist Group Of Institutions. North Paravur, Ernakulam reshmignair@sngist.org
[2]HOD, Dept. Of Computer Science & Engineering Rajadhani Institute of Engineering & Technology Trivandrum, Kerala hodcs@rietedu.in

As the use of wireless networks continues to expand, so does the need for bandwidth, putting a strain on an already limited supply of infrastructure. When applied to heterogeneous wireless networks, cognitive radio's changing and reactive spectrum sharing provides an efficient answer to bandwidth scarcity. Future wireless networks will require new technologies like 5G & Cognitive Radio (CR) to handle an increase of mobile data. In the future, 5G will be the standard for all forms of communication. As ultra-high-definition video with the Internet of Things become increasingly important in the next generation of mobile broadband, 5G plans to provide more capacity and a faster network speed of 10Gbps. Cost, battery life, and latency for 5G gear will all improve over that of 4G gear. The proliferation of sectors including the media, agriculture, information technology, and manufacturing could all benefit from 5G infrastructures. The primary goal of CR is to permit significantly increased spectrum efficiency by automatically adapting to supply the best possible communications channel. For decades, the Spectrum Sensing approach has been in need of energy detectors & matching filters. However, energy detectors struggle under fluctuating SNRs, cyclo-stationary detectors are overly complex, and main user (PU) signal expertise is required for matching filters. As a fresh approach to 5G Communications, we present a Cellular Automata-based cooperative Spectrum sensing methodology. Our simulation and evaluation using the NS-2 simulator of the proposed system's performance on 5G networks found it to be efficient regarding of energy consumption, false negatives, and coverage area.

Keywords-Cognitive Networks, Cooperative Spectrum Sensing,5G Networks.

1.Introduction.

The lack of available spectrum presents the greatest difficulty and problem for future wireless communication applications. When coupled with rising demands for wireless traffic and vast machine-type communication, this difficulty becomes enormous [1]. Increased demands on complete reliability and user-experience have emerged alongside the emergence of mobile and wireless communication technologies, as well as have issues with high rates of data and highly dense crowds of users. Figure 1 depicts the emergence of new types of problems brought on by emerging application domains, such as extremely low latency, extremely low energy, extremely low cost, and an enormous number of devices. The mobile network has moved its attention to 5G [2] because of the exponential surge in mobile data traffic. In order to take advantage of the spectrum above 6GHz, 5G networks employ millimeter wave access technologies.

Cognitive Radio is a technology used to improve the spectrum efficiency of a network as a whole and cut down on the time-domain spectrum waste. Spectrum efficiency is typically low in widely used networks [2, 3]. Primary users & secondary users make up the users inside a cognitive radio-based network. Users can be classified as either licensed or unlicensed. Cognitive users are not guaranteed exclusive use to the spectrum, but licensed users are free to transmit data in licensed spectrum at will. When the primary user is not present, the cognitive user is free to make use of the unoccupied licensed spectrum [4]. This improves the networks' ability to make efficient use of their spectrum resources. An efficient approach of spectrum sensing can improve resource utilization efficiency and lessen the burden on main users. Consequently, spectrum sensing is a crucial component of cognitive radio. The state of the channel during a certain sensing interval is not guaranteed to remain constant [5-9].Primary & secondary users of the Basic CRN are depicted in figure 1.

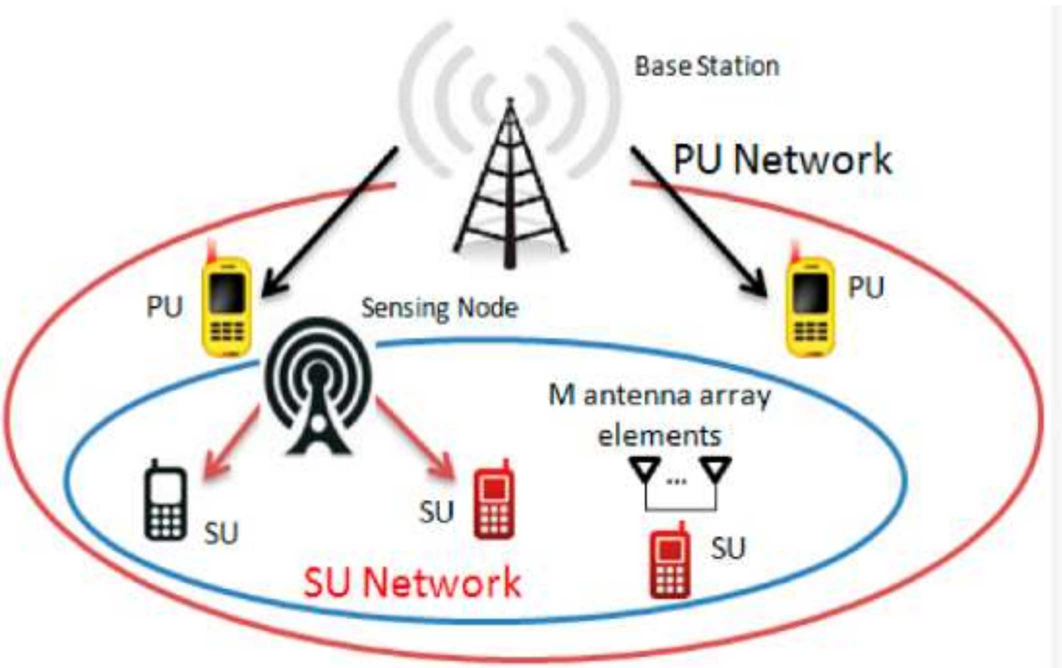

Figure1. The Fundamental Cognitive Radio System [10]

Cognitive radio systems rely on three key characteristics: the ability to learn and change, the ability to think and be aware, and the ability to react. By dynamically reusing the frequency bands, CR technology has been identified as a key solution to the spectrum crunch and minimum utilization issues [12], and it appears to be a foolproof way to meet the difficulties and demands of 5G communication [13]. There has been a lot of focus on the CR technology in the telecommunications and computer systems. Sun et al.'s [14] research examined and compared a wide range of spectrum sensing techniques and weighed their relative merits and drawbacks. Tanabe et al. [15] conducted a comprehensive review of the literature on CR networks and addressed various algorithms for allocating network resources. Recent progress in radio allocation of resources in CR networks is summarized by Ahmad et al. [16], who also discuss the different resource allocation schemes with an eye towards optimizing energy efficiency, quality of service (QoS) assurance, throughput, disruption avoidance, as well as handoff minimization. Spectrum characteristics, spectrum hiring, and CR reconfiguration were the focus of another study [17] by Masonta et al. that shed light on the spectrum decisions made in CR networks. Overlapping game models of cooperation and competition in CR systems were studied [18], as well as the methods used to gain access to the spectrum over them. When discussing the dynamic the use of spectrum method, Tehrani et al. [19] looked at how diverse networking architectures, features, use cases, and obstacles were handled in previous spectrum sharing systems.

The proportion of mobile data traffic generated by smart devices using at least 3G connectivity is projected to rise from 79% of all mobile data traffic in 2018 to 97.6% in 2023. This is much more than the percentage of smart devices plus connections (76.8% by 2022) since smart devices, on average, produce significantly more traffic than non-smart devices. Thus, 5th generation cellular networks are planned to satisfy increasing necessities for example high-speed wireless broadband, less latency, increased competence, little utilization of energy, as well as support for many different devices, all of which are beyond the scope of the present 4G/IMT-Advanced standards. IoE apps (sensors, metres, etc.) will be the primary force behind the development of 5G, in contrast to 4G, which has been driven by the proliferation of devices and dynamic information access.

Fixed wireless broadband access for homes will be a primary use of 5G in urban and densely populated areas. [21] In other words, 5G is equipped to address societal issues because it provides a communication environment that is programmable, secure, privacy-preserving, ubiquitous, and adaptable. Power consumption is decreased together with per-bit expenses thanks to 5G technology [22]. To accommodate the ever-increasing volume of mobile data transfers, researchers are hard at work on next-generation 5G mobile networks. In order to enhance bandwidth, scientists are investigating the usage of underutilized frequencies between 50 and 500 GHz [23], even if spectrum deficit might be dealt with by dynamic spectrum allocation. With 5G, channels will be assigned based on knowledge about the user's location, the services they need, the devices they're using, and their biometric authentication. Spectrum management & frequency licensing problems may finally be solvable with this technology. Major 5G rollouts are not anticipated until 2023 or later [20]. On the other hand, 5G cannot ensure constant network and service availability and functionality. It's possible that 4G and 5G won't ever be as dependable as 2G or wired options. Although 5G does not represent a single technological advancement, when combined with cognitive radio, it may lead to a significant boost in performance. Figure 2 depicts the foundation of 5G capabilities.

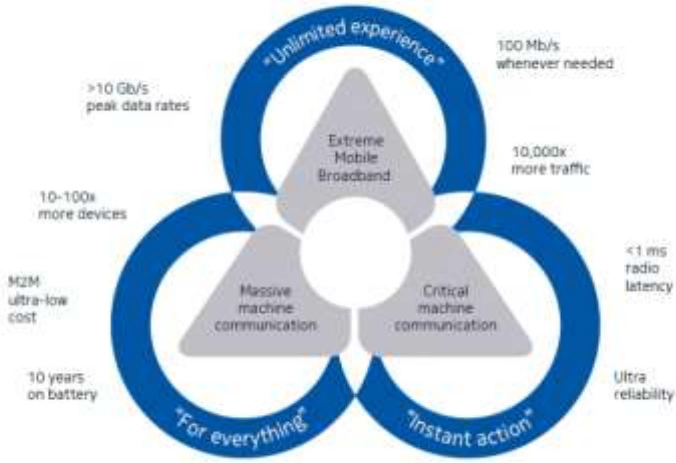

Figure 2. Capabilities Associated with 5th Generation Mobile Networks in General

Here is how the rest of the paper is laid out. The latest methods for implementing cooperative spectrum sensing, CRN, and 5G communications are discussed in detail in Section2's Literature Survey. The suggested cellular automata-based approach and its distributed implementation are discussed in Section 3.The simulation environment, parameters, and implementation are covered in Section 4, and the paper concludes up in Section 5.

2. Literature Survey:

Governments strictly monitor and license electromagnetic radio frequency spectrum. Spectrum underutilization is greatly exacerbated by the fixed allocation technique when a designated spectrum is not in use. [24]. As a result, today's most pressing issue is not a lack of spectrum, but rather insufficient use of the spectrum we do have. Some frequency bands are completely empty much of the time even in revenue-rich urban regions, and other bandwidth bands are only partly utilized. In order to provide universal wireless high-speed access, CR looks into this undiscovered radio spectrum to open it up to a previously unreachable user.

To solve the issue of spectrum shortage facing future wireless networks, dynamic spectrum allocation is employed. Spectrum utilization is enhanced when a radio node is capable of full duplex operation, where it uses the same radio frequency for both reception and transmission. Improvements in spectrum utilization efficiency, end-to-end and feedback latency, connection ability, Security at the physical layer and wireless simulation are all benefits of full duplex functioning in wireless systems, which also permits simultaneous sensing and transmission. Three-dimensional (3D) beam formation, massive multiple-input multiple-output (MIMO), and millimeter wave communication are other methods to increase the ability of future wireless networks. Visible Light Communication will be used to improve the ability, effectiveness, & safety of 5G [22] because it can handle data transmission rates from low (like position tracking) to high (like video transfer). In CR, the concept of beam shaping in smart antennas is crucial to maximizing spectral efficiency. Mobile broadband consumers are the primary emphasis of 4G and 3G networks technologies, which offer increased system capability & data transfer speed. Upcoming 5G technology will be propelled not only by applications like video, but also by the need for larger data speeds and more system capacity.

Any future wireless network worth its weight will allow wireless connection to any and all nodes and entities that could profit from connectivity. Therefore, the 5G network is more than just an upgrade to "traditional" mobile broadband. Support for IoT-related "machine to machine communication" and "machine-centric communications" is a primary focus for 5G networks. According to data gathered across North America, their most valuable clients are now robots. Devices like digital billboards, in-car entertainment centers, and smart water meters are examples [25]. Some of the spectrum provided to a licensed user in a cellular network is generally underutilized, hence adopting CR can help alleviate spectrum congestion [26]. Secondary systems are able to use the primary system's allocated spectrum resources more flexibly and dynamically thanks to CR [27]. To avoid interfering with the primary user, the resultant user looks for "spectrum holes" or "spectrum white spaces" in time, frequency, and/or physical place. Spectrum sensing [28, 29] and geo location [30] plus access to a spectrum utilization database are both viable methods for discovering white spaces. Figure 3 depicts CR's spectrum management system. Through CR methods, unlicensed systems can coexist alongside licensed ones, sharing spectrum bands in a way that minimizes or eliminates interference. 5G cellular networks are distinguished by active reuse of frequencies, extremely dense network bases and mobile device deployments, and the combination of many forms of communication to serve large volumes of data traffic. Various interference control and interference coordination methods are used to control network performance [26].

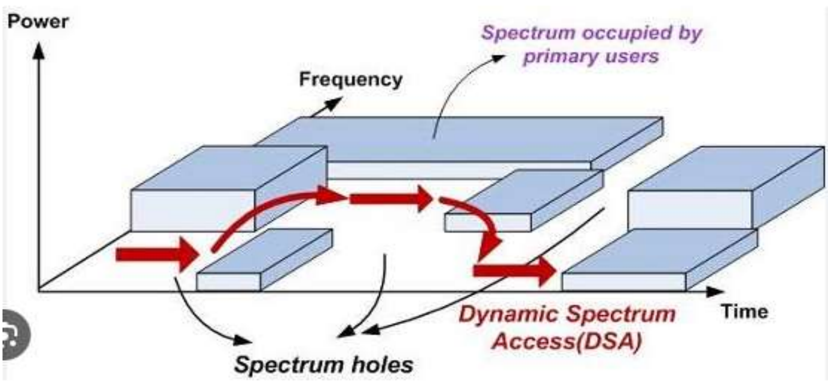

Figure 3. Bandwidth Management in the CRN

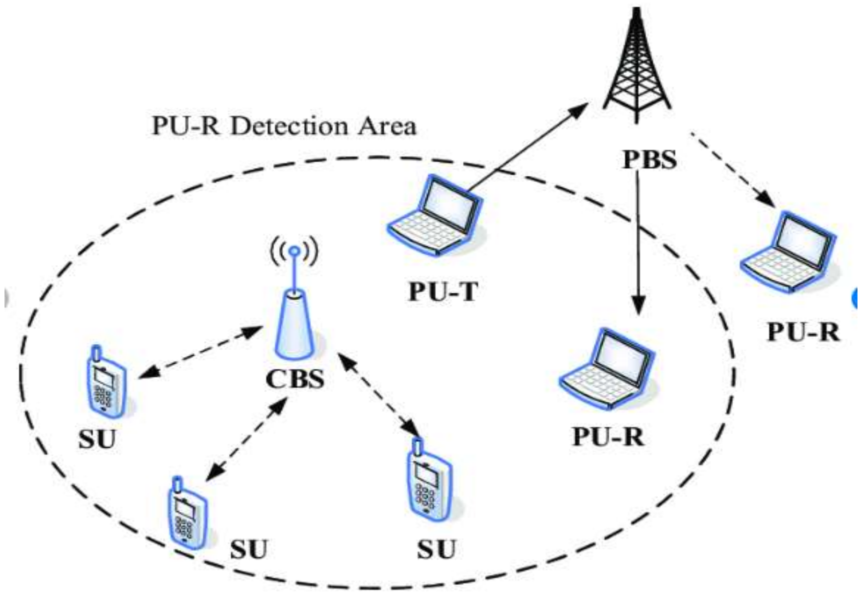

Figure 4. CRN Framework Design

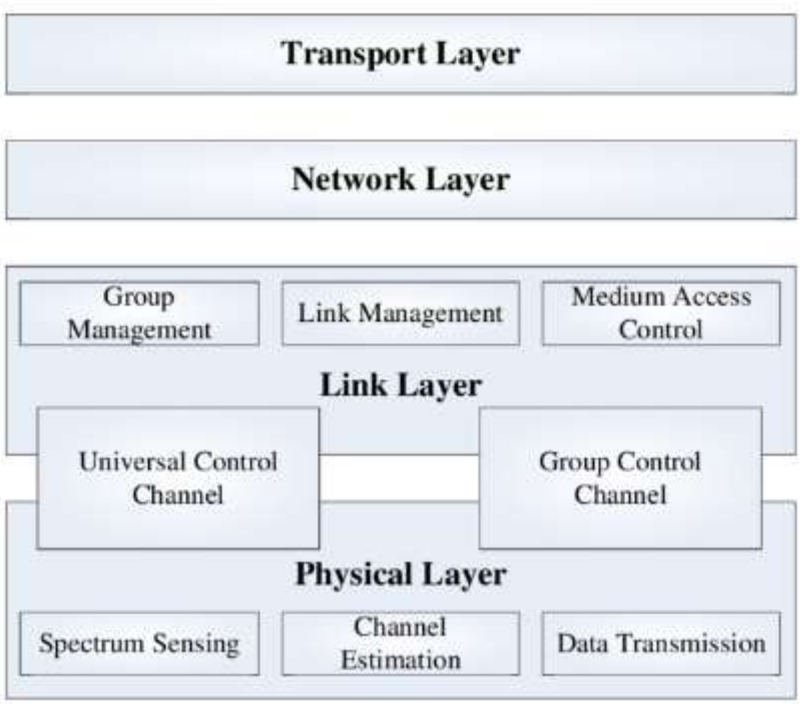

Figure 5. Structure of the CRN and Its Major Components

Figures 4 and 5 detail the several layers that make up the CR architecture. The physical layer manages the many algorithms used for sensing the spectrum. Radio environment description and power regulation fall under the purview of the link layer. The network layer is responsible for spectrum-aware routing, whereas the transport layer is in charge of spectrum handoff. Quality of service (QoS) and user utility are topics addressed at the application layer. Surendra and coworkers developed a new detection approach using DNN for spectral sensing. In this paper, we present "DLSenseNet," a deep learning (DL)-based example of spectrum sensing that makes use of the structure data from modulated signals received in the field.

In order to reduce the mistake rate and improve false alarm detection for CR customers, An enhanced convolution neural network (CNN) performance has been achieved. The proposed DNN- based spectral analyzer [31] has a major drawback in that it necessitates substantial training.Wang and Using SVM, CNN, and reinforcement learning algorithms, Liu [32] compared and contrasted the two types of learning methodologies for cooperative spectrum sensing. The challenges of real-time implementation of machine learning algorithms for spectrum sensing applications were also studied by Sundous and Halawani [34]. Multiple supervised and unsupervised reinforcing models were compared in this study for feature extraction using energy detection, cyclostationary, and signal processing [35].

"KNN learning models," "decision trees," and "artificial neural networks" are all employed in the identification of signals, as stated by Sabre et al. (2020). According to [36], the effectiveness of the classifiers was measured to determine which of the three methods for detecting spectrum was optimal. Cheng et al. [37] developed a stacked automatic encoder-based spectrum detection technique (SAE-SS) to address these serious problems. When it comes to sorting through incoming signals, its architecture excels at isolating the most important details while ignoring the more superficial ones. Furthermore, it is more resistant to time-delay noise than previous sensing systems. The proposed approach will never necessitate prior information or unique features of current users [38]. In addition, it does not rely on any external feature extraction methods.

Raw signal samples were prepared with a stacked auto encoder (SAE) in the time domains by Cheng et al. (2019), and then the PU transmission status was determined with a logistic regression classifier. With its exceptional capacity to learn crucial elements of signals, the SAE surpasses existing DL spectrum detection algorithms [39]. Using the K-nearest neighbor machine learning technique, Saha and Kun [40] detail a dependable spectrum intelligence scheme that can identify interference. During the training phase, the fusion centre takes into account the varying needs of CR users around the world and delivers a single, universally accepted answer. Each CR user in the classification phase does a similarity check between their current sensing statement and preexisting sensing classes, from which distance vectors are derived [41]. The K-nearest neighbor method is used to find the set of quantitative factors that will be used to calculate the posterior probability. A new selection combining approach, which factors in the trustworthiness of each CR user, is used to this pool of local decisions at the fusion centre. The proposed KNN classifier suffers from a flaw that renders it ineffective for many users [32].

3. Proposed System:

3.1 System Model

We take into account a situation when the spectrum hole data is being provided to Secondary Users (SUs) via a third party. This data is collected by the outside organization via wireless field sensors. We assume that low-cost, low-power sensors have been installed in the ground, and that the appropriate networks & protocols were in place to bring all of the collected information to a centralized hub. Once the information is processed, CN knows the exact coverage area and channel occupancy status for each Primary User (PU). We also assume that the output of these sensors is not guaranteed to be accurate due to fading and random shadowing. To model and test the system's efficacy, an NS-2 simulation environment was developed. It is assumed that the sensors cover an area of 500 square kilometres, laid out in a two-dimensional grid. And in the middle is the transmitter. Power levels are adjusted so that receivers can be placed both inside and outside the transmitter's range. The network relays the sensor data to a centralized location. The proposed technique processes this data at the CN, allowing for the determination of spectrum use status & coverage area. This can now be made available via broadcast or on-demand.

The path loss model, which we have used in our practical link budget design, forms the basis of our estimates. The predicted percentage of places inside a cell where the power that is received is above a certain minimum defines the cell area of coverage in a cellular system. The average obtained authority P_r at the cell boundary is used to calibrate the base station's transmitting power. Some parts of the cell will have an received energy below P_r min and some will have a received power above P_r min due to multi-path and shadowing [43]. See Fig. 4.1 for an illustration of this. Using the transmit power Pt (in dBm), we can calculate the received power Pr(in dec) at a receiver 'd' metres away use eqtn 2. from [44], which defines the propagation path loss as a function of distance from the transmitter.

$$\mathrm{PL_{dB}} = 10\mathrm{n}\log_{10}^{\mathrm{d}} + 20\log_{10}\frac{4\pi}{\lambda} + \mathrm{X_{dB}} \text{ ------[1]}$$

$$\mathrm{P_{r(dBW)}} = \mathrm{P_{t(dBW)_1}} - \mathrm{PL_{(dB)}} + \mathrm{G_{r(dB_{i})}} \text{ ------[2]}$$

The route loss exponent values 'r' and 'λ' are assumed to be 5.8 and 14, respectively [44], to account for the dense urban environment that has been taken into account. Because only in a highly populated environment will it be possible to clearly see how different methods perform As a result of their low placement, sensors in this urban environment are frequently obscured by passing automobiles and other obstacles. The fast Fourier transform (FFT) bins are averaged to achieve this, it is also possible to compute it in the frequency domain. Here, the computational gain is directly related to both the FFT range 'N' and the average instance 'T'. Increasing the FFT's size enhances its frequency resolution, making it better suited for identifying signals with a narrow bandwidth. Similarly, less average time results in a higher SNR since the noise power is diminished. It makes an approximation of the signal's presence by comparing the received energy to a threshold calculated from the noise statistics.

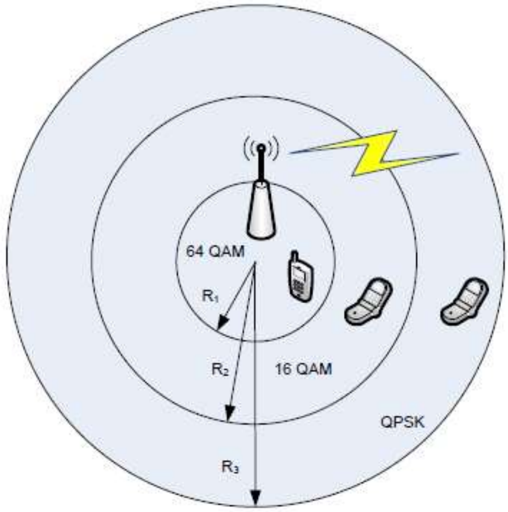

Figure 6. Experimental Range of Cellular Service

3.2 Brief Introduction to Cellular Automata (CA):

The building blocks of a cellular automaton are cells arranged in a grid. Each cell can take one of 'k' values and is updated at regular intervals in accordance with a rule ('f') that takes into account the values of neighboring cells. Two-dimensional cellular automata can have a variety of lattices and neighborhood configurations [45]. In a multi cellular automaton in which the only governing principle is the distance between cells, the value of a cell at location (i, j) therefore evolves in accordance with equation 3.

$$a_{i,j}^{t+1} = f[a_{i,j}^{t} + a_{i,j+1}^{t} + a_{i,j-1}^{t} + a_{i+1,j}^{t} + a_{i-1,j}^{t}] \text{ -----[3]}$$

The rule for cell '$a_{i,j}$' is denoted by the function '$f_{i,j}$'. If and only if both of the '$f_{i,j}$' are linear, then so is the transition function 'f' [46]. Typically, a rule table is used to provide the identical rule present in each cell; this table has an entry for each feasible neighborhood configuration of states. Each field-deployed sensor in this system is analogized to a single cell within cellular space, and the data from each sensor's single node is represented by a collection of cellular states. Each node's sensing result at a given moment is sent to the CN, where it is processed to determine the PU's presence and coverage area. The 2-dimensional grid formed by the CN's single-node results will be updated according to the cell rule, such that each cell's state is always correct in relation to its neighbors. Applying this rule frequently will result in stable cellular states. It can also be used again, up to a predetermined limit. It's also possible to apply multiple rules on it in sequence. Two common examples of 2-D CA neighborhoods are the Moore neighborhood and the Von Neumann neighborhood. The following are the rules that have been established for these communities.

3.3 New Decision Fusion Guidelines Based on CA Theory

State '1' is used to indicate that the nodes have sensed the spectrum, while state '0' indicates that they have not. State '1' is represented by white, while state '0' is represented by black. The Moore neighborhood takes into account eight neighbors, while the Von Neumann neighborhood takes into account only four. The state of a node can transition to any of the others depending on the states of its neighbors. This pattern of white & black cells represents the rule. The state of the main cell will transition to the state described by the rule if and only if the cell's and its neighbors' states fit the template. Having eight neighbors means 38 possible permutations. According to the rule's application, the rule's core node can change colours from black to white and back again.

With CRN's external sensing component, a 3-dimensional grid of sensors is set up in the field, with data from each sensor being sent back to the server. A 3-D CA with two states will result from representing this information relative to their location in the field. The transition rule determines whether a certain cell in the CA will transition from the sensed to the unsensed state. It was discovered that CA is effective at processing images. Because of this, we've come up with the two guidelines for external sensing that are presented below.

Rule set 1 : CA$_1$ [based on Moore-Neighborhood][51]

The following are some guidelines (patterns) that can be used in making decisions. If the central pixel and its surrounding cells match the mask, it will switch to the 1 state. Here, white denotes the detected state of '1' and black denotes the un sensed state of '0'. This process can be repeated an unlimited number of times, or until no further changes occur in the cellular space. Moore's guidelines for a specific neighborhood are depicted in Fig. 7. In this case, the eight surrounding cells will determine the fate of the core cell.

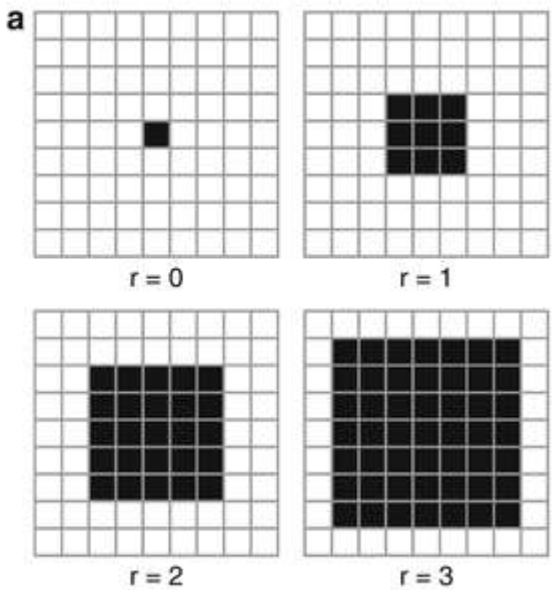

Figure 7: Rule set 1

Another way to express this rule is as follows:-R1 A detected (live) cell will continue to be such if at least three of its neighbors are also sensed (live), else it will transition to a different state. A dead (not felt) cell will become active if four or more of its neighbors are active, or it will remain in its current condition otherwise.

Rule set 2 : CA_2 [based on Von-neighborhood][51]
Four surrounding neighbors are taken into account for the core cell's transition according to the Fig. 8 presentation is based on the Von Neumann neighbor principles. All these patterns have one thing in common: the main pixel will either keep its current state or switch to another.

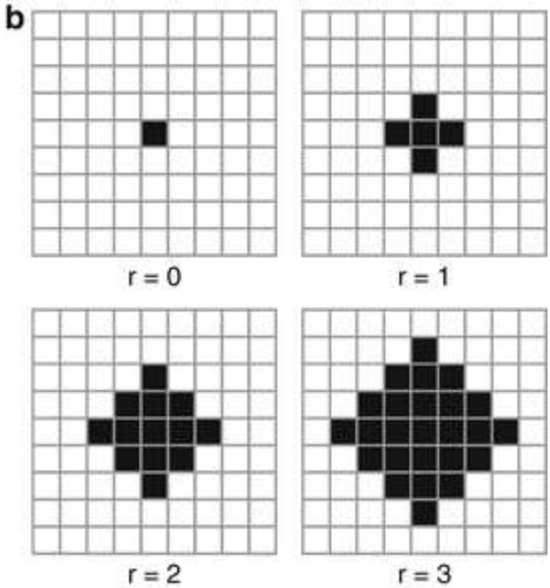

Figure 8: Rule set 2

Another way to express this rule is as follows: A detected live cell will maintain its status only if more than one of its neighbors also remain alive (-R2). A dead (not detected) cell will become active if at least two of its neighbors are also active.

3.4 Fuzzy based Information Combining

In [47], the author proposes a fuzzy-based technique to distributed sensing. By assigning a language term (such as "low," "medium," "high," etc.) to each input in fuzzy logic, the input is transformed into a linguistic variable. The set of labels for the possible linguistic interpretations of a given variable (here, x) is called the term set T(x). Fuzzy sets characterise the elements of T(x). Membership function F of a fuzzy set F in the universe of discourse U has elements in the interval [0,1]: $\mu F : U \rightarrow [0,1]$.The CN receives a two-bit decision in order to make a call, as described in [47]. There are indicators for how "low," "medium," and "high" the linguistic variable is. A fuzzy controller receives these fuzzy inputs and makes a choice using the central node's fuzzy rule base. For the sake of clarity, we will refer to this technique as Fuzzy2. In [47], it is used for a two-input case with an eight-rule base. To put it another way, when making a choice, a node will take into account the inputs of two of its neighbors. We've expanded it to include our 95-rule-base's additional four neighbors. We test its efficacy by applying it to the external sensing situation. The nodes in [48] send the collected energy to a central node, which then makes a call based on the data. For ease of reference, we will call to this procedure as Fuzzy1. Power received varies depending on how far a node is from the transmitter, how strong the fading is, and how much power is being transmitted. Within this interval, membership functions are shaped relative to the detection threshold. We have built this using a 95-rule basis and a 4-neighbor case. The scope of the rule base will grow proportionally to the number of neighbors.

3.5 Algorithm for Distributed Detection

The References [44][51] offer a distributed detection technique (DDA) to integrate the results of neighboring nodes to make a cooperative judgment. Equation 4.2 represents this choice mechanism. It does a weighted merging of the neighbor's results here. The weight is determined by the distance of the neighbor from the core node. In addition, the node performs a backwards analysis of the outcomes from the preceding time steps and emphasizes its own result. In this exterior sensing context, the rule mentioned earlier is applied with a single time step, and its effectiveness is compared to that of the suggested CA-based merging alternatives. For the execution of this approach, we considered 8 neighbors.

$$Q= [A_1 \ldots A_N][B_1 \ldots B_N]J + [C_1 \ldots C_M][D_1 \ldots D_M]j+ EF \quad \text{------}[4]$$

where 'A_N' is the sensing result from the neighboring node, 'B_N' is the weight based on distance, C_M' is the consequence of 'M' instance steps, 'D_M' is the load based on prior time steps, 'E' is the internal load, and 'F' represents the node's original outcome.

4. Results and Simulation:

In this part, we compare the results of the proposed CA-based technique to the Efficient co-operative spectrum sensing technique[ECSSA][49] & collaborative Spectral Sensing[CSS] [50] in a simulation experiment with various network sceneries. The effectiveness of the proposed CA technique is assessed using Network Simulator NS-2 dynamically simulations. It first describes the simulation configuration, then defines the resultant parameters, and lastly displays the simulation results.

Table 1. Description of Simulation Elements

S.No.	Parameter	Description
1.	Network Area	1000 x 1000 m2
2.	Cognitive Radio Nodes	500
3.	Data Packet size	2500 bytes
4.	Channels Bandwidth	2 Mbps
5.	Bandwidth of Available Spectrum	54MHz-72 MHz
6.	Standard	IEEE 802.15.6

7.	Total number of Cycle Simulations	10
8.	Type of the Traffic	Constant bit rate flow
9.	Time for simulation	1000 seconds
10.	Data Carrier Production	1 Packet/sec
11.	Distribution of Nodes	Uniform Random Distribution
12.	Filter	Gradient Filter
13.	Transmitting Power	2w
14.	Antenna	Omni Antenna
15.	Simulation Duration	500 ms

4.1 Performance Metrics

Three separate performance measures are provided in this section for examination. They are

- Energy consumption
- Coverage Area
- False Negative

(i) Energy consumption: The most significant component for the cognitive radio node contributing to the network is energy. Sensing tasks consume a certain amount of energy. The overall energy is computed as follows:

$$E = \frac{1}{Q_s}\sum_{1}^{Q_s} e[Q] \qquad (5)$$

From the above equation (5), the energy 'E' is determined based on the sampled energy vectors generated '$e[Q]$, where $(n = 1,2,3, \dots, Q_s)$'.

(ii)**Coverage Area:** The area of coverage is the region where the PU's received power is sufficient to overcome background noise. Wireless network service area is often defined as the area where the signal intensity around an antenna is higher than the edge field's capacity and is measured in metres. This is also known as the area across which wireless signals are sent and received. This is computed using Equation 2.

(iii)**False Negative:** Negative sensing results from sensors placed within the average service region are considered false negatives in this analysis. The percentage inaccuracy is derived as the ratio of the number of sensors situated within the average cover region to the overall number of sensors.

4.2 SIMULATION RESULTS

This section presents the simulation results for three distinct parameters. Table 1 simulation elements are used in simulations. Using simultaneously the table and the graph, a comparative examination of three different approaches, CA, ECSSA [49], and CSS [50], is accomplished.

4.2.1 Energy Consumption

First, the energy used during the sensing phase is given, which creates the important parameters for CRN attack protection. Because sensing is a preliminary and fundamental component of any network architecture, energy expenditure is the first measure examined. Table 2 shows the energy usage for three different ways.

Table 2 Energy Consumption Simulation Results

Number of CRN nodes	Energy consumption (kJ)		
	CA	ECSSA	CSS
50	2.8	3.7	4.9
100	5.2	6.9	8.3
150	8	10	12.6
200	9.2	12.6	15.2
250	10	14.5	19
300	11.2	15	20.8
350	12	16.5	22.8
400	13.4	18.9	24.8
450	15.2	21.6	27.5
500	16	22.4	31.6

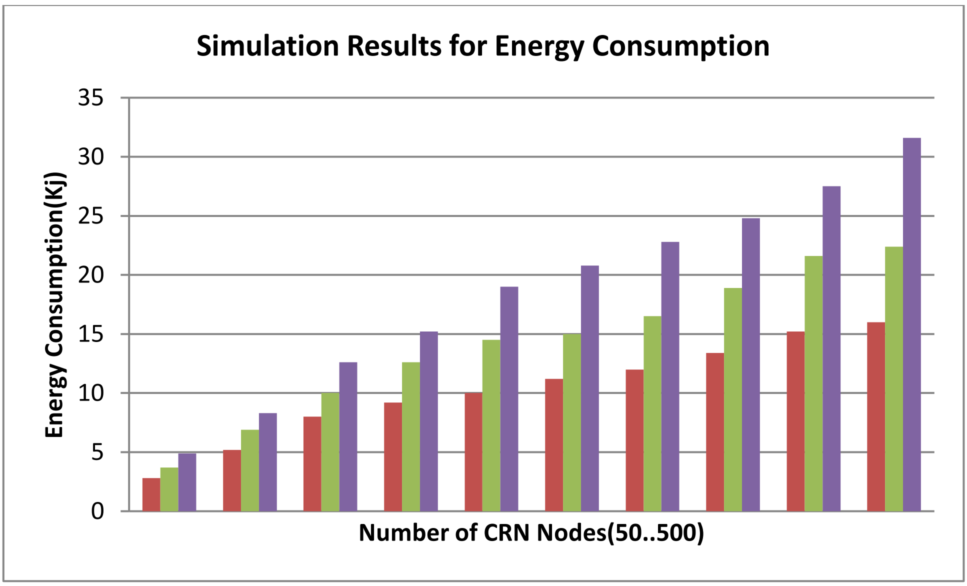

Figure 9. Energy Consumption Simulation Results

CA, ECSSA [49], and CSS [50] are graphically represented above in Figure 9. During spectrum sensing, the secondary user consumes a lot of power, yet the unlicensed user gets the spectrum that isn't being used. Quantity of CRN, including primary as well as secondary users, is plotted along the X-axis. As the number of nodes in a CRN grows, so does its energy bill, as seen in the diagram. Energy consumption does not increase proportionally due to the inclusion of secondary users in the CRN. But the total number has grown dramatically. CA was found to reduce energy usage in spectrum sensing when compared to two other approaches ([49] and [50]).

4.2.2 Coverage Area:

Second, the CR's service area is summarized. The coverage area is the most crucial aspect of the sensing technique to analyze, beside the energy consumption. The mean coverage area for each of the three schemes is shown in Table 3.

Table 3 Average Coverage Area Simulation Results

Number of CRN nodes	Average Coverage Area (m)		
	CA	ECSSA	CSS
50	12.6	10.5	8.4
100	13.7	11.3	9.5
150	14.8	12.4	10.2
200	15.9	13.4	11.4
250	17.4	15.6	12.6
300	18.3	16.5	13.8
350	22.4	17.4	14.9
400	27.9	18.4	15.4
450	32.4	20	16.7
500	38.5	21	18

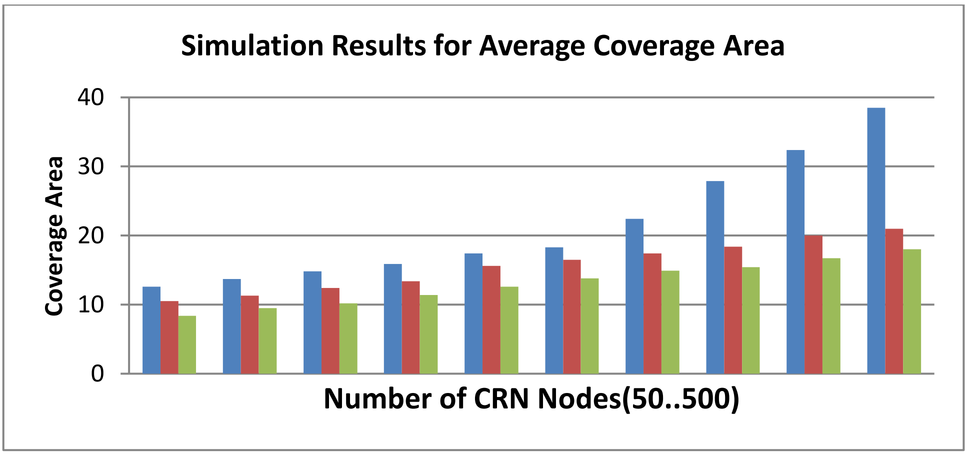

Figure 10. Coverage Area Simulation Results

For ten primary and tertiary consumer simulation runs, Figure 10 shows the mean coverage area for 500 CRN nodes. Coverage expands proportionally with the quantity of CRN nodes, hence the latter is a necessary condition for the former. When compared with the other methods, the nodes in our suggested CA strategy cover greater ground.

4.2.3 False Negative:

Finally, the effect of false negatives is assessed here. The mistake is expressed as a percentage. Ten measurements at each sensor density were averaged for the evaluation. It is also observed that the false negative rate is relatively unaffected by the number of sensors used. However, a greater density will always result in sharper images and a more defined coverage zone. The numbers from the false-negative tests are presented in table 4.

Table 4 False Negatives Simulation Results

Number of CRN nodes	False Negatives (%)		
	CA	ECSSA	CSS
50	1.6	1.1	0.4
100	1.8	1.6	1.2
150	2.6	2.1	1.6
200	2.9	2.3	1.9
250	3.1	2.8	2.1
300	3.6	3.1	2.4
350	4.2	3.4	2.8
400	4.6	3.9	3.4
450	5.1	4.1	3.5
500	5.3	4.9	3.8

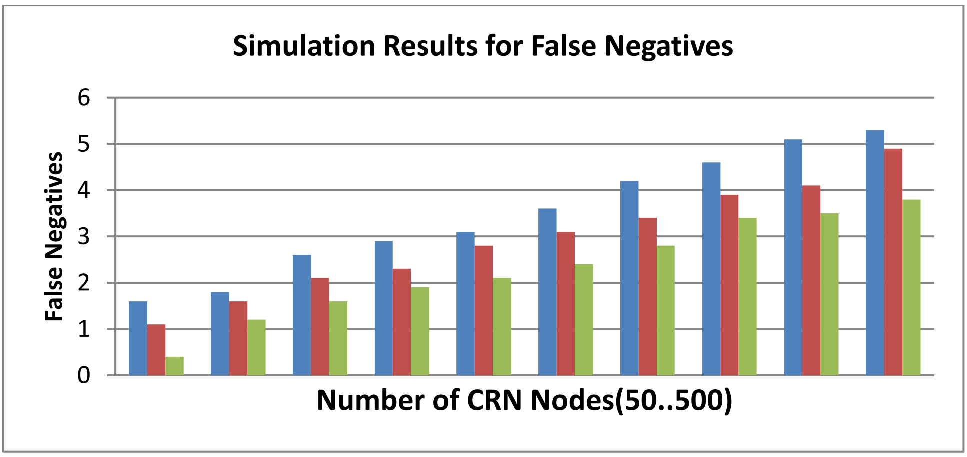

Figure 11. False Negatives Simulation Results

Figure 11 displays the estimated number of false negatives for 500 CRN nodes taken into account across multiple simulated time intervals. The resolution of the covered area will always improve as the concentration increases. It's possible that the neighborhood's small size is contributing to CA's high rate of false negatives. False negative rates for others are below 5%.

5. Conclusion:

This Work considers and implements a Cellular Automata scenario for 5G networks, an external sensing scenario that makes use of wireless sensor networks for cognitive radio. Since the total number of deployed SUs is not capped, it makes sense to free them from the burden of tasks like spectrum sensing, data consolidation, and PU availability decision making. As a result, significant energy savings will be generated on the SU side. This means that the battery life of cellular SUs in 5G networks may improve. We propose two rules inside a CA-based approach, and we compare their performance to that of other, existing distributed sensing algorithms like ECSSA and CSS. Three metrics are used to assess the efficiency of each algorithm. When a CN is responsible for monitoring a greater area, the transmitter's coverage is crucial. The coverage area provided by CA-based methods is practical. Coverage areas are uniquely well-formed by CA. Our CA algorithm outperforms the competition in terms of both energy efficiency and false negative rates. It is also demonstrated that, of the three algorithms, the CA-based technique is extremely computationally effective and, thus, the most energy-efficient. Cognitive networks in 5G communications can benefit from our work being expanded to include a larger set of parameters and more advanced distributed sensing techniques.

References:

[1] J.G. Andrews et al., "What will 5G Be?," IEEE J. Sel. Areas Commn,vol.32, no.6,pp.1065-1082, June 2014.

[2] Jose F Monserrat, Genevieve Mange, Volker Braun, Hugo Tullberg, Gerd Zimmermann and Ömer Bulakci, "METIS research advances towards the 5G mobile and wireless system definition", Monserrat et al. EURASIP Journal on Wireless Communications and Networking (2015) 2015:53 DOI 10.1186/s13638-015-0302-9.

[3] X.Chen, H.H Chen et al., "Cooperative communications for cognitive radio networks-from theory to applications", IEEE commn. Survey Tuorial,vol.16., no. 3,pp1180-1192, third quarter 2014

[4] K. Rajendra Prasad, Santoshachandra Rao Karanam, D. Ganesh, Kazi Kutubuddin Sayyad Liyakat, Vamsidhar Talasila, P. Purushotham, "AI in public-private partnership for IT infrastructure development",The Journal of High Technology Management Research,Volume 35, Issue 1,2024,100496,https://doi.org/10.1016/j.hitech.2024.100496

[5] Davanam, G.;; Singh, N.; Gunjan, V.K.; Roy, S.; Rahebi, J.; Farzamnia, A.; Saad, I. Multi-Controller Model for Improving the Performance of IoT Networks. Energies **2022**, 15, 8738.

[6] M. B. Mukesh Krishnan and D. Ganesh, "Hybrid Machine Learning Approaches for Predicting and Diagnosing Major Depressive Disorder" International Journal of Advanced Computer Science and Applications(IJACSA), 15(3), 2024. http://dx.doi.org/10.14569/IJACSA.2024.0150363

[7] Turukmane, A. V. ., Tangudu, N. ., Sreedhar, B. ., Ganesh, D. ., Reddy, P. S. S. ., & Batta, U. . (2023). An Effective Routing Algorithm for Load balancing in Unstructured Peer-to-Peer Networks. International Journal of Intelligent Systems and Applications in Engineering, 12(7s), 87–97.

[8] S.Attapattu, H. Jiang, Energy Detection for Spectrum Sensing in Cognitive Radio, Springer Press, BerlinGermany, 2014
[9] X.L. Huang, F. Hu, H.H. Chen, “Intelligent cooperative spectrum sensing via hierarchial Dirichlet process in cognitive radio networks,”IEEE J.Sel. Areas Commn, vol.33, no. 5, pp771-787, May 2015
[10] Davanam, Ganesh, T. Pavan Kumar, and M. Sunil Kumar. "Novel Defense Framework for Cross-layer Attacks in Cognitive Radio Networks." International Conference on Intelligent and Smart Computing in Data Analytics: ISCDA 2020. Springer Singapore, 2021.
[11] Kumar, T. P., & Kumar, M. S. (2021). Optimised Levenshtein centroid cross-layer defence for multi-hop cognitive radio networks. IET Communications, 15(2), 245-256.
[12] T. Pavan Kumar, and M. Sunil Kumar. "Efficient energy management for reducing cross layer attacks in cognitive radio networks." Journal of Green Engineering 11 (2021): 1412-1426.
[13] P. Rawat, K. D. Singh, and J. M. Bonnin, ``Cognitive radio for M2M and Internet of Things: A survey," Comput. Commun., vol. 94, pp. 129, Nov. 2016.
[14] H. Sun, A. Nallanathan, C.-X. Wang, and Y. Chen, ``Wideband spectrum sensing for cognitive radio networks: A survey," IEEE Wireless Commun., vol. 20, no. 2, pp. 7481, Apr. 2013.
[15] M. E. Tanab and W. Hamouda, ``Resource allocation for underlay cognitive radio networks: A survey," IEEE Commun. Surveys Tuts., vol. 19, no. 2, pp. 12491276, 2nd Quart., 2017.
[16] A. Ahmad, S. Ahmad, M. H. Rehmani, and N. Ul Hassan, ``A survey on radio resource allocation in cognitive radio sensor networks," IEEE Communication Surveys Tuts., vol. 17, no. 2, pp. 888917, 2nd Quart., 2015.
[17] M. T. Masonta, M. Mzyece, and N. Ntlatlapa, ``Spectrum decision in cognitive radio networks: A survey," IEEE Commun. Surveys Tuts., vol. 15, no. 3, pp. 10881107, 3rd Quart., 2013.
[18] W. Liang, S. X. Ng, and L. Hanzo, ``Cooperative overlay spectrum access in cognitive radio networks," IEEE Commun. Surveys Tuts., vol. 19, no. 3, pp. 19241944, 3rd Quart., 2017.
[19] R. H. Tehrani, S. Vahid, D. Triantafyllopoulou, H. Lee, and K. Moessner, ``Licensed spectrum sharing schemes for mobile operators: A survey and outlook," IEEE Commun. Surveys Tuts., vol. 18, no. 4, pp. 25912623, 4th Quart., 2016.
[20] Cisco Visual Networking Index: Global Mobile Data Traffic Forecast, 2015–2020, February 3, 2016
[21] https://en.wikipedia.org/wiki/5G
[22] 5G: Challenges, Research Priorities, and Recommendations, NetWorld2020 ETP European Technology Platform for Communications Networks and Services, August 2014
[23] Ganesh, D., and T. Pavan Kumar. "A survey on advances in security threats and its counter measures in cognitive radio networks." Int J Eng Technol 7.2.8 (2018): 372-378.

[24] Gary Tian, “The future of Cognitive Radio, Streching the spectrum”, Michigan Technology University, Engineering Research 2009
[25] 4G Americas 5G Spectrum Recommendations August 2015
[26] Interference Coordination for 5G Cellular Networks, By Lu Yang, Wei Zhang, Springer
[27] Joachim Sachs, Ivana Marić, Andrea Goldsmith, “Cognitive Cellular Systems within the TV Spectrum”, proceedings of 2010 IEEE DySPAN.
[28] T. Yucek, H. Arslan, “A survey of spectrum sensing algorithms for cognitive radio applications,” IEEE Communications Surveys & Tutorials, vol. 11, no. 1, pp. 116–130, 2009.
[29] R. Tandra, S.M. Mishra, A. Sahai, “What is a Spectrum Hole and What Does it Take to Recognize One?” Proc. of the IEEE, no. 97, no. 5. pp.824–848, 2009.

[30] Federal Communications Commission, “In the Matter of Unlicensed Operation in the TV Broadcast Bands: Second Report and Order and Memorandum Opinion and Order,” document 08-260, Nov. 14, 2008.
[31] Burada, S., Manjunathswamy, B.E. & Kumar, M.S. Deep ensemble model for skin cancer classification with improved feature set. Multimed Tools Appl (2024). https://doi.org/10.1007/s11042-024-19039-5
[32] Girinath, S., et al. "Real-Time Identification of Medicinal Plants Using Deep Learning Techniques." 2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies. IEEE, 2024.
[33] Kumar, M. Sunil, et al. "Use of Blockchain for Fake Product Detection." 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT). Vol. 5. IEEE, 2024.
[34] Sreedhar, B., et al. "Moving Vehicle Registration Plate Detection Using Machine Learning." 2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies. IEEE, 2024.
[35] Burada, Sreedhar, Manjunathswamy Byranahalli Eraiah, and M. Sunil Kumar. "Optimal hybrid classifier with fine-tuned hyper parameter and improved fuzzy C means segmentation: skin cancer detection." International Journal of Ad Hoc and Ubiquitous Computing 45.1 (2024): 52-64.
[36] M. Sunil Kumar. "AI technologies, tools, and industrial use cases", book Toward Artificial General Intelligence, De Gruyter 2024. https://doi.org/10.1515/9783111323749-002
[37] Venkata Ramana Saddi, Dynamic Scheduling Algorithms for Serverless Computing Solutions in the Cloud", 2024 International Conference on E-mobility, Power Control and Smart Systems (ICEMPS), DOI: 10.1109/ICEMPS60684.2024.10559356. 2024
[38] Venkata Ramana Saddi," Reducing loss for Brain tumour detection and classification in MRI using deep learning techniques",Communications on Applied Nonlinear Analysis,Vol 31 No. 6s, PP.330-341.(2024)
[39] Venkata Ramana Saddi, "Exploring the Quality of Service Impacts of Cloud Computing over Wireless Networks", 2024 International Conference on E-mobility, Power Control and Smart Systems (ICEMPS), DOI: 10.1109/ICEMPS60684.2024.10559341, 2024.
[40] H. A. Shah and I. Koo, “Reliable machine learning based spec- trum sensing in cognitive radio networks,” Hindawi Wireless Communications and Mobile Computing, vol. 2018, pp. 1–17, 2018.
[41] H. Urkowitz, “Energy detection of unknown deterministic sig- nals,” Proceedings of the IEEE, vol. 55, no. 4, pp. 523–531, 1967.
[42] Rappaport, T. S., A. Annamalai, R. Buehrer, and W. H. Tranter (2002). Wireless communications: past events and a future perspective. IEEE Communications Magazine, 40(5), 148–161.
[43] Goldsmith, A., Wireless communications. Cambridge university press, 2005.
[44] Harrold, T., P. Faris, and M. Beach, Distributed spectrum detection algorithms for cognitive radio. In Cognitive Radio and Software Defined Radios: Technologies and Techniques, 2008 IET Seminar on. IET, 2008.
[45] Packard, N. H. and S. Wolfram (1985). Two-dimensional cellular automata. Journal of Statistical physics, 38(5-6), 901–946.
[46] Cattell, K., S. Zhang, M. Serra, and J. C. Muzio (1999). 2-by-n hybrid cellular automata with regular configuration: theory and application. IEEE Transactions on Computers, 48(3), 285–295.
[47] Matinmikko, M., T. Rauma, M. Mustonen, I. Harjula, H. Sarvanko, and A. Mammela (2009). Application of fuzzy logic to cognitive radio systems. IEICE transactions on communications, 92(12), 3572–3580.

[48] Taghavi, E. M., B. Abolhassani, et al. (2011). A two step secure spectrum sensing algorithm using fuzzy logic for cognitive radio networks. Int'l J. of Communications, Network and System Sciences, 4(08), 507–513.
[49] Han,W., J. Li, Z. Tian, and Y. Zhang (2010b). Efficient cooperative spectrum sensing with minimum overhead in cognitive radio. IEEE Transactions on Wireless Communications,9(10), 3006–3011.
[50] Sun, H. (2011). Collaborative spectrum sensing in cognitive radio networks. Ph.D.thesis, The University of Edinburgh.
[51] Jacob, Jaison & Jose, Babita & Mathew, Jimson. (2016). Fusion Rule for Cooperative Spectrum Sensing in Cognitive Radio. Circuits, Systems, and Signal Processing. 35. 10.1007/s00034-015-0208-0.