Novel evaluation framework for sensing spread spectrum in cognitive radio

Kursheed Bellary[1], Vijayashree Rajendrakumar Budyal[2]
[1]Department of Electronics and Communication, Sri Venkateshwara College of Engineering, Bengaluru, India
[2]Department of Information Science and Engineering, Sai Vidya Institute of Technology, Bengaluru, India

Article Info

ABSTRACT

The cognitive radio network is designed to cater to the optimization demands of restricted spectrum availability. A review of existing literature on spectrum sensing shows that there is still a broader scope for its improvement. Therefore, this paper introduces an efficient computational framework capable of evaluating the effectiveness of the spread spectrum concept in the context of cognitive radio network in a more scalable and granular way. The proposed method introduces a dual hypothesis using a different set of dependable parameters to emphasize the detection of optimal energy for a low signal quality state over the noise. The proposed evaluation framework is benchmarked using a statistical analysis method not present in any existing approaches toward spread spectrum sensing. The simulated outcome of the study exhibits that the proposed system offers a significantly better probability of detection than the current system using a simplified evaluation scheme with multiple test parameters.

Corresponding Author:

Kursheed Bellary
Department of Electronics and Communication, Sri Venkateshwara College of Engineering
Bengaluru, India
Email: bkursheedofficial@gmail.com

1. INTRODUCTION

The mobile communication standards have evolved by the technological inclusions like global system for mobile communication (GSM), wideband code division multiple access (WCDMA), long-term evolution (LTE), worldwide interoperability for microwave access (WiMAX), and multiple-input multiple-output (MIMO) and mm-waves as 2G, 3G, 4G, and 5G, respectively [1], [2]. Typically, the 5G operates between 30 to 300 GHz bandwidth to exploit unused spectrum to cater to the need of the future generation applications based on cyber-physical systems or the internet of things to provide adequate data transfer rate [3]. The typical use-cases of 5G networks exploit both macro and microcell to establish global connectivity where the macro-cells use licensed bands. In contrast, the micro-cells utilize the un-licensed band [4], [5]. The traditional spectrum allocation provides fairness but not the higher throughput because its allocation takes place uniformly irrespective of the requirement by the user equipment (UEs) [6], [7]. However, the future generation applications, smart and intelligent ubiquitous applications, require a very flexible and dynamic, and on-demand allocation of the spectrum to meet the quality-of-service (QoS) and quality-of-experience (QoE) [8]. The collaborative support of the internet-of-things (IoT) system, along with evolved mobile communication standards like 4G and 5G, provides a platform to build new and innovative applications in various filed of the life, including smart transportation [9], smart home [10], smart grid [11], smart factories [12], smart healthcare system [13], smart city [14] and many such applications. However, the efficiency of these applications in the real-time scenario largely depends upon the adequate network and communication resources, especially power

and spectrum, to meet the high data transfer goal. Moreover, the resource is limited as the participation of the devices is large, so such methods or techniques to exploit the optimal usage of the available spectrum frequency are desirable. With this goal, a research process of spectrum sensing has been started. One such milestone research is IEEE-802.22 for wireless regional area network (RAN) to exploit the capability of cognitive radio technique to detect the unused spectrum and allocate it to the broadcasting of television services which is quite helpful in the rural region for the broadband connectivity [15]. The spectrums with larger capacities are regulated by the government bodies and the big internet service providers. They get the allocation of this spectrum through an auction process. Their base stations and the registered user equipment are designated primary users (PU), also called licensed users. However, in many of the use cases of IoT, the specific applications have their base stations to provide connectivity to the devices in their circle of influence; however, to meet the network performance demand and desired quality of service in case of high scalability, additional spectrum or the spectrum which are reserved for the PU can be allocated to the secondary users in the small cell without creating any interference to the PU. In order to enhance the perform of 5G networks, it is essential that all the devices connected in this network would truly utilize the resources allocated on the basis of available spectrum. Therefore, spectrum sensing offers a unique characteristic to identify the free spectrum, which is popularly known as white space or spectrum holes [16]. Hence, the spectrum sensing problem is formulated as a practical detection problem [17], [18], which has received less attention in perspective of 5G networks in current times. The collaborative efforts of sharing sensing information among the secondary users minimize the challenge of the detection problem [19]. Therefore, there is a need to carry out a study towards optimization to solve this detection problem in order to fully utilize the services supported by 5G.

At present, there are recent studies being carried out towards targeting the improvement in multiple access technology connecting with spectrum sensing methods. Studies carried out by Cheng et al. [20] have used deep learning mechanism using orthogonal frequency division multiplexing (OFDM) while usage of cooperative spectrum sensing is also witnessed to address the issues in 5G as noticed in work of [21], [22]. Wasilewska et al. [23] have discussed about usage of federated learning approaches for 5G networks. Reviewing the methodology used in this study briefs out the significance of using machine learning more towards improving spectrum sensing for 5G networks. However, adoption of learning approach could not be considered as a cost-effective approach as there are inclusion of excessive resource dependencies which will eventually affect the performance of service. However, this studies also offers a potential insights in the form of learning outcomes viz. i) If the signals disseminated in transmission in 5G can be extensively analyzed with respect of their features, better modelling scope is offered towards improving 5G performance; ii) The existing RFC 8822 meant for adoption in 5G deployment presents discussion about a wireline networks among the gateways, where there is no much discussion about utilizing the spectrum sensing on the practical grounds; iii) Extraction of signal on the basis of energy detection is one of the simplest and effective way to discretize the signal from each other, and better allocation strategy can be formulated during subcarrier assignments in multiple-access technique of 5G; and iv) Adoption of cognitive radio further improves the granularity of the signal in 5G which could make the system to undertake better decision during data transmission for massive number of users. Hence, all these learning outcomes suggest that there is a need to design a computational model which can utilize spectrum sensing that can contribute towards better transmission performance in 5G.

This section discusses about some of the standard approaches that has been carried out towards enhanced spectrum sensing for improving 5G networks. The recent study carried out by [24] have presented a rapid prototyping scheme for analyzing spread spectrum and its accessibility in dynamic form. A simplified computational modelling is presented exposed to various radio environment for offering higher signal quality in primary users. An investigation of factors that deteriorates detection performance due to the existence of a dynamic primary user in the channel is carried out by [25]. In this study, the authors have optimized both the sensing time and sensing period transmission period (duty cycle) under random arrivals of multiple primary users. Iqbal et al. [26] has presented solution to resist blind spot problems in massive device-to-device communication in 5G for increasing its coverage using a unique selection of relay node. Choi et al. [27] has generalized discrete Fourier spread on OFDM to address the inherent issue in using OFDM in 5G. Badawy et al. [28] focus on the quickest change detection problem for spectrum sensing in the cognitive radio network. Loulou et al. [29] have addressed the cyclic prefix problems in OFDM using spectrum improvement scheme towards meeting power demands of transmitters. A lookup table is constructed which can resists all sophisticated operation with higher resource dependencies and could be applicable for devices running under IoT environment. Hajihoseini and Ghorashi [30] has introduced a distributed diffusion-oriented scheme to improvise convergence rate in spectrum sensing and reliability factor against communication link failure.

A research work towards blind spectrum sense considering the context of multiple antenna communication systems is presented by Bouallegue et al. [31]. Adoption of spread spectrum-based solution

was also witnessed in Omar and Ma [32] where a unique usage of multiplexing technique is observed in order to increase efficiency of spectrum. A research work towards analyzing the performance of energy detectors in dynamic scenarios where a primary user (PU) switches from active to inactive at random time instances is considered by [33]. The use of a deep learning mechanism for spectrum sensing is found in the work of [34]. A deep learning-based long short-term memory (LSTM) scheme was used to implicitly learn all the essential features in the time series spectrum data. According to Huang *et al.* [35], a non-cooperative spectrum sensing algorithm exploits statistical historical sensing data to improve the preciseness in spectrum sensing. The historical sensing data were transformed into prior knowledge to reduce the uncertainty and obtain higher detection accuracy. In this line of research, the work carried out by Golvaei and Fakharzadeh [36] presented a soft-decision algorithm for wideband cooperative spectrum sensing by taking into account the spatial diversity of spectrum sensors. Guimaraes and Lim [37] used a sliding window-based detection technique for spectrum sensing in radar bands. The authors have devised a spectrum sensing technique in which the conventional single detection event carried out during a sensing interval is replaced by multiple short-time intermediate detections made in a sliding-window fashion, thus exploiting the signal's sparsity to be detected. After the sliding window reaches the end of the sensing interval, the multiple intermediate sensing results are combined to yield the global decision upon the occupation of the sensed band. Alhamad *et al.* [38] presented a cooperative spectrum sensing scheme based on two random access reporting protocols: slotted ALOHA and reserved-ALOHA protocols. The authors designed a reporting channel scheme based on random-access protocols, including slotted ALOHA and reservation ALOHA, to measure the performance of the probability of detection and probability of false alarm. In this approach, the sensing results are reported after the sensing phase; the reporting collisions may also cause a spectrum sensing energy waste and decrease cooperative spectrum sensing energy efficiency. He and Jiang [39] investigated the performance of cooperative spectrum sensing using the stochastic geometry tools in random cognitive radio networks. In this study, a generalized likelihood ratio detector is derived from coping with the diversity of received signal-to-noise ratio among secondary users. This approach categorizes the combination of local sensing reports at the fusion center as soft and hard decision fusion schemes. The Secondary users forward their local decisions to the fusion center to make a global decision to infer the absence or presence of the primary user. The homogeneous Poisson point process is adopted to confront the various signal-to-noise ratios based on the generalized likelihood ratio test detector. Biswas *et al.* [40] anticipated a scheme for optimal hybrid spectrum sharing under bandwidth constraints of control channels and multiple hard decisions to maximize the throughput of the cognitive radio network (CRN). This study considers a time allocation for a single frequency resource-based scenario. The authors in [41] introduce a convolutional neural network-based deep learning algorithm for primary user activity detection in spectrum sensing. The idea is to employ the data-driven deep learning approach, which requires neither a signal-noise probability model nor the primary user activity pattern model. In this, a sensing matrix is constructed that considers the spatial and spectral correlations of the channels. Renfors *et al.* [42] have improved upon the OFDM-based technique to reduce the power consumption and noise using discrete Fourier transform spread signal model on OFDM. A reinforcement learning algorithm was also used by [43] to determine the sensing order of channels and cooperative sensing partner selection. In this work, the secondary users use the time-varying probability of detection of neighbors and select the ones with a higher probability of detection for cooperation.

After reviewing the existing approaches, the following research gap has been observed and are currently stated in the form of research problem: i) Existing schemes requires more sample collection to reconstruct the signal while modelling (especially where machine learning has been used viz [20], [23], [34], [39], [41]); ii) The studies have been individually carried out over a constrained research approach, where the outcome is not applicable for dynamic environment situation [36], [37]; iii) OFDM has been identified as one the common target for improvement using different variant of spread spectrum (especially using discrete Fourier transform spread e.g. [27]), however, there is not much discussion about selection of robust signal under variable rate of traffic or cell density; iv) There is a consideration that PU is located in the same cell as that of secondary user SU without considering the probability that it is also characterized by interference, as well as the fading characteristics of the PUs-SU links that is not addressed [38], [40]; v) Mostly limited to theoretical analysis without much effective benchmarking; vi) Existing models involve more operating cost and may associate with computational overhead [42]; vii) None of the existing studies are found to address problems when the communicating environment is associated with artifacts e.g. fading, shadowing, higher computational cost, and collisions. that may lead to spectrum sensing energy waste.

Hence, based on the above-mentioned research gap, it can be said that proposed system is associated with a core problem which is related to developing a computational framework that encapsulates maximum parameters of using spread spectrum towards improving the signal dissemination in 5G network in presence of dynamic traffic situation. The next section outlines the solution presented towards addressing above mentioned research gap and problems.

2. PROPOSED METHOD

The proposed system is implemented using an analytical research methodology that mainly emphasizes the dual hypothesis formulation to evaluate the spectrum sensing mechanism in cognitive radio. Inspired from the recent study of researchers in [24], the proposed system constructs an evaluation platform capable of selecting the best form of signal in 5G mainly concentrating on utilization of spread spectrum and sharing using energy detection attribute. The generated signal is stored in the form of a matrix, where each element in matrix is further subjected to statistical performance parameters. This operation is responsible for gauging the optimal signal being generated by presented spread spectrum in 5G that can be further suitable in multiple access operation in 5G network services. The core idea is to generate optimal form of signal with extensive test environment where the signal can be assessed comprehensively. Figure 1 highlights various dependable attributes of hypothesis formulation followed by three energy detection schemes.

The study contribution of proposed system is as follows: i) The proposed scheme constructs a CRN module that facilitates dual hypothesis assessment on the basis of multiple attributes of signal and channel, ii) The proposed scheme designs a model which assists in spectrum sharing using energy detection for better identification of sustainable signal in 5G networks, iii) The proposed scheme adopts usage of multiple fine-tuned standard statistical parameter which can assess the performance of signal quality, which offers a higher degree of flexibility in assessing robust signal.
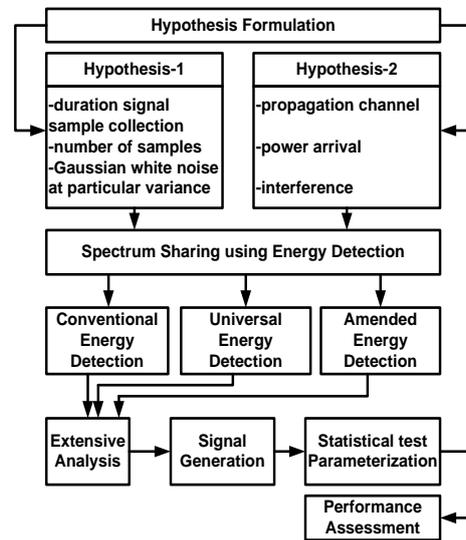
Figure 1. Schematic architecture of the proposed system

3. METHOD

The proposed system formulates a hypothesis for the modeling purpose that considers samples of signals to be carried out either individually by cognitive user (CU) or secondary user (SU) or in a collaborative process. It considers N to be the cumulative number of signals and η to be sample signal for CU and SU; then, the system defines that each primary user (PU) or secondary user (SU) will take η samples to fulfill the objective of localizing PU. This phenomenon will represent a joint operation consisting of an N receiving antenna within a single CU or SU or N number of CU or SU that include at least one antenna. The total of $N \times \eta$ samples of the signal is then transited to a dedicated processing unit, where the fusion of the movement is carried out. In this case, this assumption's scope is considered valid if there are N number of sensing capacity for at least one of the PU or SU nodes for all η samples of the signal. Impractical cases of signal fusion follow this. On the other hand, if the η sample of signal is aggregated and forwarded for fusing operation, there are certainly specific practical issues. Therefore, the proposed system formulates a hypothesis to map the stage of cognition for PU or SU to be modeled. The proposed system formulates two hypotheses. The first hypothesis is formulated with a different set of attributes, e.g., sample collection duration d, the number of samples N, and white noise Φ such that (1).

$$F(d) = [F_n(d_n)]^t \tag{1}$$

In (1), $F(d)$ represents the matrix with $N \times 1$, where the variable N represents a sample of signals that are observed at d instantaneous duration, while the Gaussian white noise can be represented in the form of

$G(d)$ for all values of duration d from 1, 2, … N. Therefore, according to the first hypothesis, the condition stated in expression as (2).

$$F(d) = G(d) \tag{2}$$

The next part is to formulate the second hypothesis considering the channel for data propagation to compute the power on arrival in the form of interference. The channel of propagation at a specific duration is represented as $\lambda \epsilon \lambda^{Nx1}$, which computes the interference between the PU and N collaborative of CU or SU. Considering μ to represent complex Gaussian of circular order to a sample duration d (1, 2, …., N) responsible for identifying the signal source with 0 as a mean value and one as a variance. This will eventually mean satisfying the following condition in (3):

$$H[\mu^2(d)] = B_D^2 \neq 0 \tag{3}$$

hence, a matrix ψ is formed to retain all the monitored sensed value in the matrix dimension with all elements F with $N \times \eta$ dimension of the matrix. However, in the situation where the samples of the signal are found to be extremely large and infinite, then an attribute θ is computed as in (4):

$$\theta = 1/\eta \, (\alpha . \alpha^K) \tag{4}$$

In the expression (4), the variable θ represents a matrix of covariance with a sample signal that is found to converge to $\theta = H[\alpha . \alpha^K]$ such that $F \leftarrow N$ sample by N, with either CU or SU. Hence, an eigenvector of θ will represent the primary signal. Ultimately, the proposed system makes use of the second hypothesis so that (5):

$$F(d) = \lambda(d) . \mu(d) + G(d) \tag{5}$$

3.1. Energy based spectrum sharing

The proposed system emphasizes the energy used for spectrum sensing by the PU when CRN is deployed over 5G, and there are multiple dependable parameters for this purpose. The majority of the existing framework considers assigning a particular set of channel capacity associated with the PU. On the other hand, the opportunistic usage of channel capacity is facilitated with SU only. The proposed algorithm, in this case, targets to minimize the outliers to compensate the demands of PU, SU, and designated service providers. Considering H and H_1 as identified energy and energy associated with the PU, respectively. The generated signal considers π as the noise, while the problem is related to determining the noise during the generation of the movement as (6):

$$H = H_1 + \pi \tag{6}$$

The expression (6) is valid in the presence of PU. Otherwise, it is redefined as $H = \pi$. In this implementation framework, the signal H is generated, and an arbitrary test input corresponding to different methods is used, including viz. i) conventional mechanism of detecting energy (M_1), ii) universal mechanism of detecting energy (M_2), and iii) amended mechanism for detecting energy (M_3). Finally, the algorithm evaluates the probability of detection of energy in contrast to outliers. The algorithm 1 developed using dynamic thresholding to determine the energy.

The algorithm 1 is meant for the M_1 scheme, which takes the sample number η along with signal to noise ratio and probability of an outlier value of o. The next part of the implementation is associated with the computation of the probability of detection Prob(*det*) and probability of outliers Prob(*out*) concerning each power factor with a unit percentile of persistent increment of Prob(*off*). This algorithm implementation is followed by enhancing the M_2 detection scheme, which is further enhanced for altering the threshold-based detection mechanism. In the M_1 scheme, the study considers a predefined cut-off value to compare the signal H. If the value of signal H is more than the cut-off value *co*, then it declares the localization of PU; otherwise, it considers the absence of PU. On the other hand, the M_2 scheme works on a similar methodology to M_1, except that the system finds the square of the value of the signal amplitude $/H/^z$ where $z = 1, 2, … N$. The proposed system formulates the M_3 scheme to control the outliers. This is carried out because there is a declination of the computed signal H below the cut-off range *co* in the presence of impulsive dynamic changes owing to varying environmental conditions. This approach of M_3 is used for finetuning the amplitude of the signal H as it organizes the heuristic records of the average outcome of priorly identified energy. In this process, when the value of the signal H is more than the cut-off value, the PU is considered to be present. In the case of the higher value of the average signal, i.e., H_{avg} compared to cut-off, the study finds the presence of PU otherwise vice-

versa. As the study can successfully reduce the extent of an outlier in the M_3 scheme, it can ensure better detection of energy that considers the average value of priorly estimated signal H value. It also assesses the last value to undertake the decision on the presence of PUs. The proposed system considers a static cut-off value for the revised detection version compared to techniques, i.e., M_1, M_2, and M_3, that consider variable cut-off energy. This is done based on noise variance v that changes concerning the initial value of signal H. It is to be noted that there are zero dependencies on the apriorism heuristics associated with the signal connected to the PU for energy detection. However, it is also associated with the computational complexity of calculating the probability of detection, i.e., Prob(*det*). This performance is entirely dependent on the uncertainty of noise power. It cannot distinguish the primary signals of CRU or identify the signals of the spread spectrum. However, the suitability of this mechanism is higher for a cooperative signal, while additional gains in optimal cooperation carry out the mitigation of performance issues.

Algorithm 1. Detection of energy

```
Input: η, SNR, o
Output: Prob(det), Prob(out)
Start
    1.  Initialize: η, SNR, o
    2.  for each power factor z∈{1,2,3,4,5}
    3.      Prob(out)←∑[(out),(n−1)Δd)], (out)ᵢ=initial value of fout , n=100, Δd = increment
    4.      for each Prob(out)ₙ
    5.       for each o,
    6.          N←f₁(η)
    7.          Hz← SNR x f_rand(η)
    8.          H=Hz + N
    9.          Compute, μ₀,μ₁,σ₀,σ₁
    10.         co(P) ← μ₀(P)x Q_f(Pb(fa)n)+,μ₁(P)
    11.         H =|H|ᶻ
    12.         [H] ← 1/N_s x ∑H
    13.         Check: If [H] ≥ co(P)
    14.         Update H⃗
    15.        end
    16.     end
    17. end
    18. Prob(det)← H⃗/o
End
```

3.2. Extensive analysis

The proposed system uses a cooperative approach for SU to enhance the sensing capacity. However, there is an overhead associated with cooperative spectrum sensing concerning the channel capacity due to an increased number of nodes' participation during the data forwarding process. The SU aggregates all the sensing information in cooperative spread sensing that is forwarded to an operational block to carry out data fusion. The core goal of this model is to carry out data validation from different data fusion approaches in cooperative spectrum sensing over poor signal quality associated with applications of cognitive radio. The proposed study considers two noise variants, i.e., uniform and non-uniform noise. The proposed study work on centralized and decentralized mode where a fusion module is used in the centralized model while there is no such fusion module in the decentralized mode. In centralized mode, the fusion module aggregates sensed information from SU for identifying the white spaces for SU. In decentralized mode, each SU exchanges their sensed data to adjacent SU nodes that facilitate anyone of the SU to make a final decision. The proposed system is designed based on a different number of parameters, e.g., number of PU (transmitters), number of SU (receivers), mean signal-to-noise ratio for all SU, aggregated samples of all SU, type of PU signal along with the length of transmitted symbols using quadrature phase shift keying (QPSK), mean-variance of noise overall SU. Apart from the parameters mentioned above, there are the inclusion of other parameters too in the proposed model, i.e., the fractions of noise power and received signal variations about their means, the type of PU-SU channel according to the configurable sensing channel Rice factor K (mean and std deviation), the reference probability of false alarm (Prob(*out*)) at which the probability of detection (Prob(*det*)) is computed by varying several of the system parameters. Based on these parameters, the test statistics of several spectrum sensing techniques are generated for all Monte Carlo runs. The performance of the methods is plotted in terms of Prob(*det*) versus the respective parameters of the variations.

3.3. Signal generation

This is one of the essential modules in proposed scheme where the generated signals will mean that signals that are processed by proposed scheme and stored in the form of matrix. The core idea of this matrix

formulation is to ensure selection of superior quality of signals on varied condition of communication environment of PU and SU in cellular structure of 5G networks. The proposed system is implemented using multiple parameters associated with the SU. The *m* represents the number of SU with all even numbers between [2], [12], while the SNR is between -20 to 5 dB. The proposed system computes the fraction of variation in noise power *FracN* to be equivalent to that of variation in receiver power, i.e., $PR \times avg$. This is empirically represented as (7).

$$PR \times avg = \sigma^2{}_{avg} \times 10^{SNR/10} \tag{7}$$

In the expression (7), the variable $\sigma^2{}_{avg}$ represents the average value of noise power. The source power of transmitting node *PTx* is computed by dividing $PR \times avg$ by several PUs. The cumulative distribution function $CDF()$ associated with the arbitrary variable for each event is represented as a function $f(X)$ that is equivalent to the probability of $(X < x)$ for all real values. On this basis, the normal distribution function for PU is computed considering a logical condition where PU_{signal} is equivalent to zero. In this case, the computation of the initial component of S is calculated as (8).

$$S = Rf(A) + If(A) \tag{8}$$

In the expression, the variable A represents a set of statistical mean, standard deviation, number of PU, and several samples for each SU. The function $Rf()$ and $If()$ will stand for the real and imaginary part of a n arbitrary generator obtained from a normal distribution of A, where the standard deviation is considered to be $= 1/\sqrt{2}$. The following process is about normalizing and approximating the vector S considering transposition operation over diagonal matrix. The next task is about the computation of variation of noise (σ^2) over all the iterations as (9).

$$\sigma^2 = \sum[(B1),(B2)] \tag{9}$$

In (9), the variable $B1$ represents the product of several arbitrary values and $FracN$, while $B2$ represents $(1 - FracN)$. It should be noted that random numbers are considered equivalent to the number of SU. The study considers the computation of the received power PRx defined for all the simulation rounds as a function of the number of SU, FracP, and PRxavg. Finally, covariance is computed for the received signal along with the eigenvalue. This numerical outcome assists in evaluating the generated signals which is further assessed using extensive statistical test methods. The simulation study has been performed considering scripting of the proposed analytical models where different parameter settings are considered to realize the performance, viz. analysis of the probability of detection for both average signal to noise ratio (SNR) and secondary users (SUs/CRus). The following section discusses the result analysis.

4.   RESULTS AND DISCUSSION

This section discusses the discussion associated with hypothesis formulation followed by the study outcome from simulation. The proposed system considers ten statistical test parametrizations to formulate the model's dual hypothesis. Following are the parameters briefing:

a. Maximum eigen value detection (MED): This parameter performs analysis of the eigen value of the covariance matrix of signal for PU using arbitrary matrix theory. It reduces the probability of detection with maximization of correlation level. Accordingly, the extra deviation is compensated using a cut-off score to enhance the score accuracy. Hence, better suitability related to sensing is ascertained in the presence of noise.

b. Generalized likelihood ratio (GLR): This parameter assumes that signals generated from PU occupy a dimensional subspace lower than that of the observed one to represent non-white noise in the spectrum. The noise variance is also used here to offer a better outcome than the conventional system. These parameters also have a pitfall of generalized probability ratio test for spread spectrum for higher computational complexity. This is because of the higher inclusion of resources to compute the signal covariance and Eigen matrix decomposition. However, it is quite beneficial for access mechanism of opportunistic form associated with spectrum owing to short interval time for sensing the anticipated probability of detection and probability of outlier detection.

c. Maximum-minimum eigenvalue detection (MMED): This parameter is based on the fact that the spread spectrum method using eigenvalue decomposition can be tailored to achieve enhanced outcomes despite low signal quality SNR. This is feasible considering the highest and lowest value of the eigenvalue.

d. Energy detection (ED): This parameter is discussed in the prior section in detail and is generally considered an optimal scheme for identifying the PU considering use of single antenna s as a constraint. The noise

distribution and signal process are carried out considering random variables of Gaussian form is quite an identical form and independently with predefined information about noise or power variance.

e. Arithmetic to geometric mean (AGM): This parameter is used for the spread spectrum method based on the ratio of maximized eigenvalue and minimal eigenvalue. Usually, either a mean or the largest of the average eigenvalue is considered. An approximation of the probability density function associated with the gamma matching method is used. This parameter evaluates a variable φ which is an array element product function. At the same time, it is supportive of handling faded context with anticipation of the reduced value of the probability of detection and outliers.

f. Hadamard ratio (HR): A defective calibration system may result in non-uniformity in the variance of noise associated with the antenna, which is possible in the parameters discussed above. Hence, this parameter HR is responsible for managing the calibrated error using a detection scheme based on HR for the spread spectrum. An appropriate approximation is utilized for modeling the objective function of the probability of detection and outliers.

g. Volume-based (VD): The conventional usage of volume detection was designed for real-value observation without any benchmarked values or environment associated with it. It is noticed that the volume-based detector showcases a better outcome in contrast to the Hadamard ratio and arithmetic to geometric mean parameter concerning the identical and independent presence of noise in the probability of detection and outliers.

h. Gershgorin radii centers ratio (GRCR): This parameter is responsible for computing the covariance matrix associated with single or multiple transmitting nodes. Apart from this, this parameter is less robust towards non-uniform noise and does not support much over the dynamic context of the transmission state. However, it is found to be cooperative towards the use case of multi-antenna in a spread spectrum environment.

i. Gini index detection (GID): This parameter is developed mainly by targeting incorporating a statistical dispersion attribute; however, the proposed scheme uses it for the cooperative spread spectrum method using Gini Index. These performance parameters showcase the robustness associated with the noise of dynamic conditions and unequal power of the signal.

j. Rician, rice factor-based detection (RFD): The improved version of the Rician fading channel consisting of multiple values of rice factors K associated with a multi-rate spectrum. Although it is known that a wideband spread spectrum offers better performance concerning the Nyquist sampling rate compared to other systems, a spread spectrum using multi-rate is found to offer higher probability of detection and lower computational complexity.

Tables 1 and 2 highlights the mathematical expression deployed for hypothesis testing for adopted statistical performance parameters as well as numerical outcomes obtained respectively. Table 1 highlights the inclusion of most significant parameters that is adopted for both primary and secondary hypothesis testing. Table 2 showcases the numerical results obtained when both primary and secondary hypothesis is subjected to assigned test-bed for evaluation of proposed model.

Table 1. Hypothesis formulation

#	Param	1st Hypothesis	2nd Hypothesis
1	MED	$\dfrac{\lambda_{h0}}{\sigma_2}$	$\dfrac{\lambda_{h1}}{\sigma_2}$
2	GLR	$\dfrac{\lambda_{h0}}{\sum_{i=2}^{m}(\lambda_{h0})i}$	$\dfrac{\lambda_{h1}}{\sum_{i=2}^{m}(\lambda_{h1})i}$
3	MMED	$\dfrac{\lambda_{h0}}{\lambda_{h0}\ \forall\ m}$	$=\dfrac{\lambda_{h1}}{\lambda_{h1}\ \forall\ m}$
4	ED	$=\dfrac{\sum|\lambda_{h0}|^2\ \forall\ m}{(\sigma_2)\ \forall\ m}$	$\dfrac{\sum|\lambda_{h1}|^2\ \forall\ m}{(\sigma_2)\ \forall\ m}$
5	AGM	$\sum\dfrac{\lambda_{h0}}{\varphi(\lambda_{h0})^{1/m}}$	$\sum\dfrac{\lambda_{h1}}{\varphi(\lambda_{h1})^{1/m}}$
6	HR	$\dfrac{\mathbb{R}|RH_0|}{\varphi(D(RH_0))}$	$\dfrac{\mathbb{R}|RH_1|}{\varphi(D(RH_1))}$
7	VD	$\mathbb{R}\left(log\left(\left|\dfrac{1}{D(DH_0)}\times RH_0\right|\right)\right)$	$\mathbb{R}\left(log\left(\left|\dfrac{1}{D(DH_1)}\times RH_1\right|\right)\right)$
8	GRCR	$=\dfrac{\sum(\sum(\mathring{r}|\mathring{r}(RH_0)|)-D(RH_0))}{\sum(D(RH_0))}$	$=\dfrac{\sum(\sum(\mathring{r}|\mathring{r}(RH_1)|)-D(RH_1))}{\sum(D(RH_1))}$
9	GID	$=\dfrac{\sum|RH_0|}{\sum_{i=1,j=1}^{m^2m^2}(\left|\left(RH_{0i}-RH_{0j}\right)\right|)}$	$\dfrac{\sum|RH_1|}{\sum_{i=1,j=1}^{m^2m^2}\left(\left|\left(RH_{1i}-RH_{1j}\right)\right|\right)}$
10	RFD	$\dfrac{\sum|RH_0|}{\sum\left(|RH_0|-\frac{1}{2}\sum_{i=1}^{m}(RH_{0i})\right)}$	$\dfrac{\sum|RH_1|}{\sum\left(|RH_1|-\frac{1}{2}\sum_{i=1}^{m}(RH_{1i})\right)}$

Table 2. Numerical outcome obtained

#	Param	1st Hypothesis	2nd Hypothesis
1	MED	0.0977	3.8865
2	GLR	0.0283	0.2765
3	MMED	52.3458	239.4252
4	ED	1.0133×10^3	2.1822×10^6
5	AGM	0.9973	2.0562
6	HR	2.4172×10^{-4}	0.0184
7	VD	0.0042	1.1822
8	GRCR	0.0020	0.1181
9	GID	2.3392×10^{-6}	2.4575×10^{-4}
10	RFD	8.1796×10^{-4}	0.0765

It should be noted that above mentioned 10 statistical performance parameters is used for final assessment of quality of generated signal. The contribution of this adoption is that existing schemes of improving 5G network communication based on spread spectrum deals with single form of signal where its performance for signal quality of detection is tested in singular form. However, such evaluation method may not be suitable as different application over any computing device used over 5G network will have potential affect towards the data transmission as well as resource usage pattern. Hence, singular form of performance parameter will never be able to judge the overall quality of the signal.

4.1. Outcome accomplished

The scripting of the proposed study is carried out in MATLAB over a standard 64-bit machine with a windows platform. A uniform testbed is maintained for all the parameters to assess the performance. Figure 2 highlights the comparative analysis of the proposed system Prop-RFD with the existing system with increasing iteration of 1,000 to record the outcomes of the probability of detection. The proposed scheme offers a higher probability of detection with the lower SNR ranges between -20 to 0. Figure 3 highlights the comparative analysis of the probability of detection concerning the number of SU. The outcome showcases that both the AGM and MMED scheme offer degraded performance, whereas the proposed system and HR nearly perform similarly. However, from the scale of probability, the proposed method is significantly better than the existing system.
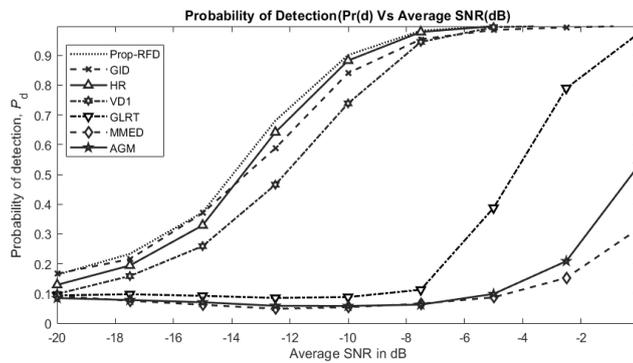
Figure 2. Comparative analysis of probability of detection
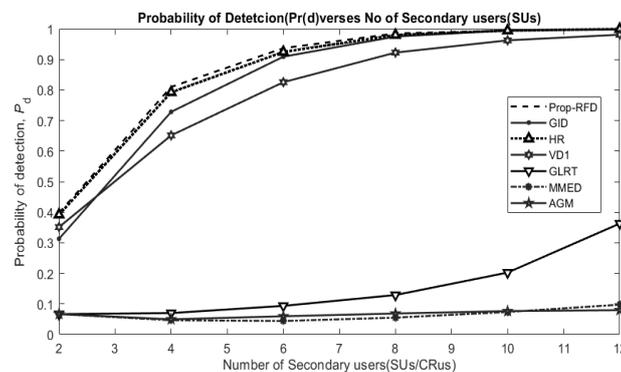
Figure 3. Comparative analysis of probability of detection w.r.t. SU

Novel evaluation framework for sensing spread spectrum in cognitive radio (Kursheed Bellary)

4.2. Discussion

From the outcome observed in Figures 2 and 3, it can be seen that Rician based detection method has offered higher probability of detection score with increasing value of SNR. However, it does not make any conclusive remark that Rician-based detection method could be the best method applicable for all environment. It should be noted that analysis of proposed scheme is carried out towards dual hypothesis testing in presence of peak traffic condition, where Rician-based detection as well as GID approach is found to have nearly similar performance towards detection. The proposed scheme has basically implemented an evaluation platform in cognitive radio network in order to investigate the better utilization degree of spectrum. By detecting the probability in Figures 2 and 3, the proposed scheme investigates sensing capability of spectrum band towards primary user over license band. Adoption of multiple statistical technique in proposed system is basically meant for overcoming the issue in 5G network towards making a decision of optimal signal. The proposed evaluation platform basically introduces a simplified and flexible filtering operation that can be applied to multiple subcarriers in 5G. This offers reduction of choosing the signals with artifacts while a transmitter can be designed with such extensive performance detection scheme for analyzing probability of detection. If the probability of detection is high, the performance of cognitive radio in 5G can be claimed appropriate or vice versa.

5.   CONCLUSION

This paper addresses both high and low SNR settings and evaluates various cooperative sensing systems using statistical analysis of detection probability. The MED approach examines the eigenvalue of the signal covariance matrix and uses thresholding to correct errors. The GLR is the second approach used. It uses the eigenvector of the covariance matrix and other factors such as noise variance dimension. However, it has a more considerable computing complexity. Maximum-minimum eigenvalue detection is a configurable algorithm that outperforms both the ED and the MED in low SNR situations. Of course, the ED is the most popular, as it can work alone or in tandem, and it does not require any prior heuristic information about the signal. The method AGM considers an approximation of the PDF for the gamma matching, and it deems different means of the minimum and maximum eigenvalues. The AGM is suitable for the faded channels if the expectation is low for detection probability and warning. The Hadamard ratio, volume base, GRCR, and GID index method also are evaluated. Eventually, the Rician fading channel may support the proposed approach with different values of the K (Rice factor) for a multi-rate spectrum estimated as RFD. Though the wideband SS using Nyquist sampling rates provides better performance than other SS, the multi-rate SS, like the proposed RFD, exhibits better Prob(det) and Prob(out) in lower computational complexity.

REFERENCES

[1]   D. P. Mishra, K. K. Rout, and S. R. Salkuti, "Compact MIMO antenna using dual-band for fifth-generation mobile communication system," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 24, no. 2, pp. 921–929, Nov. 2021, doi: 10.11591/ijeecs.v24.i2.pp921-929.

[2]   B. Kursheed, and V. R. Budyal, "Survey: 5G wireless communication using cognitive radio," *Indian Journal of Computer Science and Engineering*, vol. 11, no. 5, pp. 658–669, Oct. 2020, doi: 10.21817/indjcse/2020/v11i5/201105231.

[3]   S. Sasikala and S. Sakthivel, "Adaption of 5G networks in industrial sector with improved bandwidth utilization," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 6, pp. 6433–6444, Jun. 2021, doi: 10.1007/s12652-020-02252-z.

[4]   N. Shabbir *et al.*, "Vision towards 5G: Comparison of radio propagation models for licensed and unlicensed indoor femtocell sensor networks," *Physical Communication*, vol. 47, Aug. 2021, doi: 10.1016/j.phycom.2021.101371.

[5]   A. Pratap, R. Gupta, V. S. S. Nadendla, and S. K. Das, "Bandwidth-constrained task throughput maximization in IoT-enabled 5G networks," *Pervasive and Mobile Computing*, vol. 69, Nov. 2020, doi: 10.1016/j.pmcj.2020.101281.

[6]   T. Akhtar, C. Tselios, and I. Politis, "Radio resource management: approaches and implementations from 4G to 5G and beyond," *Wireless Networks*, vol. 27, no. 1, pp. 693–734, Jan. 2021, doi: 10.1007/s11276-020-02479-w.

[7]   M. Bacco *et al.*, "IoT applications and services in space information networks," *IEEE Wireless Communications*, vol. 26, no. 2, pp. 31–37, Apr. 2019, doi: 10.1109/MWC.2019.1800297.

[8]   P. T. Sivagurunathan, P. Ramakrishnan, and N. Sathishkumar, "Recent paradigms for efficient spectrum sensing in cognitive radio networks: Issues and challenges," *Journal of Physics: Conference Series*, vol. 1717, Jan. 2021, doi: 10.1088/1742-6596/1717/1/012057.

[9]   J. Zhang, Y. Wang, S. Li, and S. Shi, "An architecture for IoT-enabled smart transportation security system: A geospatial approach," *IEEE Internet of Things Journal*, vol. 8, no. 8, pp. 6205–6213, Apr. 2021, doi: 10.1109/JIOT.2020.3041386.

[10]   D. Shin, K. Yun, J. Kim, P. V. Astillo, J.-N. Kim, and I. You, "A security protocol for route optimization in DMM-based smart home IoT networks," *IEEE Access*, vol. 7, pp. 142531–142550, 2019, doi: 10.1109/ACCESS.2019.2943929.

[11]   H. Hui, Y. Ding, Q. Shi, F. Li, Y. Song, and J. Yan, "5G network-based internet of things for demand response in smart grid: A survey on application potential," *Applied Energy*, vol. 257, Jan. 2020, doi: 10.1016/j.apenergy.2019.113972.

[12]   D.-W. Lee, K. Cho, and S.-H. Lee, "Analysis on smart factory in IoT environment," *Journal of Internet of Things and Convergence*, vol. 5, no. 2, pp. 1–5, 2019.

[13]   A. Ahad, M. Tahir, and K.-L. A. Yau, "5G-based smart healthcare network: Architecture, taxonomy, challenges and future research directions," *IEEE Access*, vol. 7, pp. 100747–100762, 2019, doi: 10.1109/ACCESS.2019.2930628.

[14] F. Sartipi, "Influence of 5G and IoT in construction and demolition waste recycling – conceptual smart city design," *Journal of Construction Materials*, vol. 1, no. 4, Jul. 2020, doi: 10.36756/JCM.v1.4.1.

[15] L. W. Abdullah, Q. H. Kareem, and A. H. Sallomi, "A quad-port multiple-input-multiple-output system for underlay or interweave cognitive radio," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 29, no. 3, pp. 1480–1495, Mar. 2023, doi: 10.11591/ijeecs.v29.i3.pp1480-1495.

[16] B. T. Hashim, H. T. Ziboon, and S. M. Abdulsatar, "Covariance absolute values spectrum sensing method based on two adaptive thresholds," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 30, no. 2, pp. 1029–1037, May 2023, doi: 10.11591/ijeecs.v30.i2.pp1029-1037.

[17] A. M. A. AL-Hussain and M. K. Mahmood Al Azawi, "Spectrum sensing of wideband signals based on cyclostationary and compressive sensing," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 20, no. 3, pp. 1361–1368, Dec. 2020, doi: 10.11591/ijeecs.v20.i3.pp1361-1368.

[18] O. S. Okediran, F. K. Ojo, J. A. Ojo, O. F. Oseni, and O. O. Obanisola, "Enhancement of spectrum sensing technique with energy harvesting for cognitive radio network," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 28, no. 2, pp. 810–819, Nov. 2022, doi: 10.11591/ijeecs.v28.i2.pp810-819.

[19] J. Unnikrishnan and V. V. Veeravalli, "Cooperative spectrum sensing and detection for cognitive radio," in *IEEE GLOBECOM 2007-2007 IEEE Global Telecommunications Conference*, Nov. 2007, pp. 2972–2976, doi: 10.1109/GLOCOM.2007.563.

[20] Q. Cheng, Z. Shi, D. N. Nguyen, and E. Dutkiewicz, "Deep learning network based spectrum sensing methods for OFDM systems," *Prepr. arXiv.1807.09414*, Jul. 2018.

[21] S. Dikmese, K. Lamichhane, and M. Renfors, "Novel filter bank-based cooperative spectrum sensing under practical challenges for beyond 5G cognitive radios," *EURASIP Journal on Wireless Communications and Networking*, vol. 2021, no. 1, Dec. 2021, doi: 10.1186/s13638-020-01889-w.

[22] Y. Zhao, C. Wang, M. Hu, H. Wu, F. Lin, and Z. Liu, "A cooperative wideband spectrum sensing framework in the frequency domain for resource allocation with 5G-NR," *Measurement*, vol. 191, Mar. 2022, doi: 10.1016/j.measurement.2022.110756.

[23] M. Wasilewska, H. Bogucka, and A. Kliks, "Federated learning for 5G radio spectrum sensing," *Sensors*, vol. 22, no. 1, Dec. 2021, doi: 10.3390/s22010198.

[24] K. W. Barlee, R. W. Stewart, L. H. Crockett, and N. C. MacEwen, "Rapid prototyping and validation of FS-FBMC dynamic spectrum radio with simulink and ZynqSDR," *IEEE Open Journal of the Communications Society*, vol. 2, pp. 113–131, 2021, doi: 10.1109/OJCOMS.2020.3039928.

[25] T. Duzenli and O. Akay, "Effect of non-Gaussian noise and primary user traffic on detection performance in cognitive radio," in *2018 26th Signal Processing and Communications Applications Conference (SIU)*, May 2018, pp. 1–4, doi: 10.1109/SIU.2018.8404307.

[26] A. Iqbal *et al.*, "cDERSA: Cognitive D2D enabled relay selection algorithm to mitigate blind-spots in 5G cellular networks," *IEEE Access*, vol. 9, pp. 89972–89988, 2021, doi: 10.1109/ACCESS.2021.3090965.

[27] J. Choi, J. Kim, J. H. Cho, and J. S. Lehnert, "Widely-linear nyquist criteria for DFT-spread OFDM of constellation-rotated PAM symbols," *IEEE Transactions on Communications*, vol. 69, no. 5, pp. 2909–2922, May 2021, doi: 10.1109/TCOMM.2021.3056106.

[28] A. Badawy, A. El Shafie, and T. Khattab, "On the performance of quickest detection spectrum sensing: The case of cumulative sum," *IEEE Communications Letters*, vol. 24, no. 4, pp. 739–743, Apr. 2020, doi: 10.1109/LCOMM.2020.2970014.

[29] A. Loulou *et al.*, "Multiplierless filtered-OFDM transmitter for narrowband IoT devices," *IEEE Internet of Things Journal*, vol. 7, no. 2, pp. 846–862, Feb. 2020, doi: 10.1109/JIOT.2019.2945186.

[30] A. Hajihoseini and S. A. Ghorashi, "Distributed spectrum sensing for cognitive radio sensor networks using diffusion adaptation," *IEEE Sensors Letters*, vol. 1, no. 5, pp. 1–4, Oct. 2017, doi: 10.1109/LSENS.2017.2734561.

[31] K. Bouallegue, I. Dayoub, M. Gharbi, and K. Hassan, "Blind spectrum sensing using extreme eigenvalues for cognitive radio networks," *IEEE Communications Letters*, vol. 22, no. 7, pp. 1386–1389, Jul. 2018, doi: 10.1109/LCOMM.2017.2776147.

[32] M. S. Omar and X. Ma, "Spectrum design for orthogonal chirp division multiplexing transmissions," *IEEE Wireless Communications Letters*, vol. 9, no. 11, pp. 1990–1994, Nov. 2020, doi: 10.1109/LWC.2020.3010774.

[33] S. MacDonald, D. C. Popescu, and O. Popescu, "Analyzing the performance of spectrum sensing in cognitive radio systems with dynamic PU activity," *IEEE Communications Letters*, vol. 21, no. 9, pp. 2037–2040, Sep. 2017, doi: 10.1109/LCOMM.2017.2705126.

[34] B. Soni, D. K. Patel, and M. Lopez-Benitez, "Long short-term memory based spectrum sensing scheme for cognitive radio using primary activity statistics," *IEEE Access*, vol. 8, pp. 97437–97451, 2020, doi: 10.1109/ACCESS.2020.2995633.

[35] X.-L. Huang, Y. Xu, J. Wu, and W. Zhang, "Noncooperative spectrum sensing with historical sensing data mining in cognitive radio," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 10, pp. 8863–8871, Oct. 2017, doi: 10.1109/TVT.2017.2698206.

[36] M. Golvaei and M. Fakharzadeh, "A fast soft decision algorithm for cooperative spectrum sensing," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 68, no. 1, pp. 241–245, Jan. 2021, doi: 10.1109/TCSII.2020.3010587.

[37] D. A. Guimaraes and C. H. Lim, "Sliding-window-based detection for spectrum sensing in radar bands," *IEEE Communications Letters*, vol. 22, no. 7, pp. 1418–1421, Jul. 2018, doi: 10.1109/LCOMM.2018.2834932.

[38] R. Alhamad, H. Wang, and Y.-D. Yao, "Cooperative spectrum sensing with random access reporting channels in cognitive radio networks," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 8, pp. 7249–7261, Aug. 2017, doi: 10.1109/TVT.2017.2657485.

[39] H. He and H. Jiang, "Deep learning based energy efficiency optimization for distributed cooperative spectrum sensing," *IEEE Wireless Communications*, vol. 26, no. 3, pp. 32–39, Jun. 2019, doi: 10.1109/MWC.2019.1800397.

[40] N. Biswas, G. Das, and P. Ray, "Optimal hybrid spectrum sensing under control channel usage constraint," *IEEE Transactions on Signal Processing*, vol. 66, no. 14, pp. 3875–3890, Jul. 2018, doi: 10.1109/TSP.2018.2838575.

[41] Z. Xie, H. Liu, Z. Li, and Y. He, "A convolutional neural network based approach towards real-time hard hat detection," in *2018 IEEE International Conference on Progress in Informatics and Computing (PIC)*, Dec. 2018, pp. 430–434, doi: 10.1109/PIC.2018.8706269.

[42] M. Renfors, I. P. Nasarre, T. Levanen, K. Pajukoski, and M. Valkama, "Phase noise resilient three-level continuous-phase modulation for DFT-spread OFDM," *IEEE Open Journal of the Communications Society*, vol. 3, pp. 282–300, 2022, doi: 10.1109/OJCOMS.2022.3148781.

[43] Z. Ning, Q. Song, Y. Yu, Y. Lv, X. Wang, and X. Kong, "Energy-aware cooperative and distributed channel estimation schemes for wireless sensor networks," *International Journal of Communication Systems*, vol. 30, no. 5, Mar. 2017, doi: 10.1002/dac.3074.

BIOGRAPHIES OF AUTHORS

Kursheed Bellary research scholar at Sri Venkateshwara College of Engineering, Bengaluru. She holds M.Tech. degree in the field of Computer Networks from Visveswaraya Technological University, Belagavi. Experienced as Academician from 16.9+ years. Area of interest includes wireless communication, multimedia communication, cognitive radio, and microcontrollers. She published 4+ papers in various reputed International Journals, 4+ papers in various international conference. She received 3Lakhs funds from Government of Karnataka Vision Group on Science and Technology for the project "RFID based vehicle antitheft and automatic toll collection system. And received fund from KSTA and KSCST three times. She can be contacted at email: bkursheedofficial@gmail.com.

Vijayashree Rajendrakumar Budyal research guide working at Department of Information Science and Engineering, Sai Vidya Institute of Technology, Bengaluru. She holds Ph.D. degree in the field of wireless communication and networking from Visveswaraya Technological University, Belagavi. Experienced as Academician from 25+ years. Area of interest includes wireless communication, wireless sensor networks, multimedia communication, mobile ad hoc networks, distributed mobile computing, fuzzy logic and neural networks. Published 10+ papers in various reputed International Journals,19+ papers in various International Conference. Best research paper award for "ANFIS and agent-based bandwidth and delay aware anycast routing in mobile ad hoc networks", by Government of Karnataka Vision Group on Science and Technology Department of Information Technology, Biotechnology and Science and Technology VGST, 2013-2014. She received 3Lakhs funds from Government of Karnataka Vision Group on Science and Technology for the project RFID based vehicle antitheft and automatic toll collection system. And received fund from KSTA listed in marquis who is who in the world, U. S. A, 32nd edition 2015. She can be contacted at email: vijayashreerb@gmail.com.