SPECTRUM SENSING BY CORRELATION MODULATION FORMAT IDENTIFIER AND IMPROVED ENERGY DETECTION USING NOISE ESTIMATION BASED DYNAMIC THRESHOLD

Abstract

Cognitive Radio (CR) technologies have recently been created to address spectrum underutilization issues and help in efficient data transmission. Spectrum sensing is a critical phase in cognitive applications in which the cognitive user identifies the presence of PU in one channel and switches to another to continue transmission. Despite the availability of several methodologies in the literature, their implementation in Industrial Wireless Sensor and Actuator Networks (IWSANs) is restricted due to complexity and accuracy limits. IWSANs demand less complex detection techniques Without compromising efficiency and determinism. As a result, in this research, we present a spectrum sensing technique for the Indus trial, Scientific, and Medical (ISM) band in which autocorrelation features as well as received signal noise are employed to determine the existence the presence of Primary User (PU) in the channel. Our idea is based on the fact that the presence of PU in the channel is
Specified by the presence of modulation format. The studies included four modulation techniques: Orthogonal Frequency Division Multiplexing (OFDM), Amplitude Shift Keying (ASK), Quadrature Phase Shift Keying (QPSK), and Gaussian Frequency Shift Keying (GFSK). An Improved Energy Detection (IED)
Approach is presented for signals with different modulation formats and low Signal to Noise Ratio (SNR), where the dynamic threshold is determined based on noise power estimation. In an Integrated Development Environment (IDE),

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simulations were run with IQ imbalance, DC and frequency offsets, and Gaussian noise. The findings show that the suggested approach has a high chance of detection over a range of SNRs. This also proves the suitability of the approach for implementation in IWSANs.

I. INTRODUCTION

The process of connecting wireless devices utilising cutting-edge technology and equipment is known as wireless communication. This type of communication is possible because of the Radio Frequency (RF) band, which allows data and voice conversations to be transmitted between devices. According to Cooper's Law, the amount of data transferred doubles every two and a half years, limiting RF spectrum and forcing the reuse of frequency spectrum. As a result of static spectrum allocation, certain frequency spectrums are assigned for specific applications. The problem with this method is that it leaves little space for emergency services. Furthermore, spectrum-allocated applications underutilize it, resulting in a huge number of spectrum gaps.

In such a circumstance, there arises a need for effective spectrum use strategies, without jeopardising the prominence of certain applications while also considering emergency applications. In this context, Mitola [1] suggested Cognitive Radio (CR) with Software Defined Radio (SDR), in which certain applications or Primary Users (PUs) have precedence in accessing radio spectrum, while SUs retrieve the spectrum as needed. Whenever the PU's access the spectrum, secondary users move to another channel, resolving the issues of PU spectrum underutilization and SU space constraints. Sensing, switching, and adaptation are the three main features of CR. The technique by which the system identifies the precense of PU signals in the spectrum is known as spectrum sensing. When the spectrum is determined to be filled by PU, switching refers to the procedure of changing to another channel.

The capacity of the system to respond to noise interference and channel changes is referred to as adaptation. Sensing of empty and occupied spectrums is thus the first and most important stage in the CR network's effective operation. It's a difficult undertaking, and the existing spectrum sensing technologies are divided into two groups: narrow band sensing and wideband sensing. Narrow-band sensing includes covariance-based detection, energy detection, matched filter discussion, cyclo-stationary detection and machine learning-based sensing, whereas wideband sensing includes compressive sensing and Nyquist based sensing. An overall research reveals the lack of approaches capable of detecting PU signals in a CR-based industrial setting. As a result, we're looking for a single detection method that can identify the existence of PU signals and has a wide range of capabilities.

II. PROPOSED MODULATION CLASSIFIER

For working with discrete signals, the Equation (1) is considered. The signal length is set to 200 samples and the sampling frequency is set at 40 MHz for the purposes of this experiment [2]. This equation is used to discriminate between ASK, QPSK, GFSK, and OFDM for different combinations of α and d. Various combinations of (α, d) are tested, and the results of this expression for various values of d are shown in Figure 1 and Figure 2.

$$R_A^{\alpha}(d) = \frac{1}{N}\sum_{n=0}^{N-1} A[n]A^*[n-d]e^{-\frac{jr\pi\alpha n}{N}} \quad (1)$$

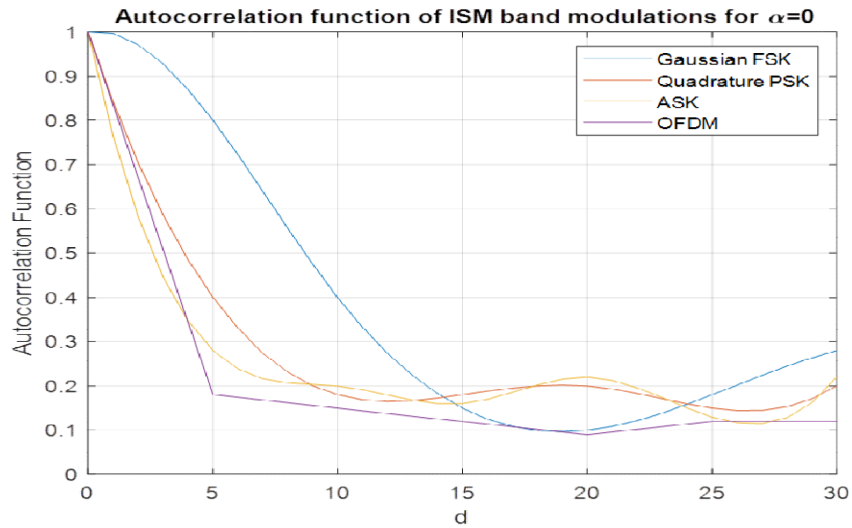

Figure 1: Autocorrelation Function of ISM Band Modulations for Different Values of d and α=0

Where t is the time period, α is the cyclic frequency and $R_A^{\alpha}(d)$ corresponds to DFT coefficients, A is the signsl received by CR user and n represents different modulation.When d values are less than 15, the modulation forms may be distinguished as depicted in Figure 1. There is a risk of misclassification after d=15. When n=32, all modulation methods follow a similar trend, as seen in Figure 2. It should be highlighted that the modulation scheme may be easily identified using d values for $\alpha = 0$. Choosing one d value to categorise four distinct modulation schemes, on the other hand, may impair accuracy. As a result, we used four distinct combinations of $(\alpha, d)$to identify modulation format: (0, 2), (0, 3), (0, 4) and (32, 0).

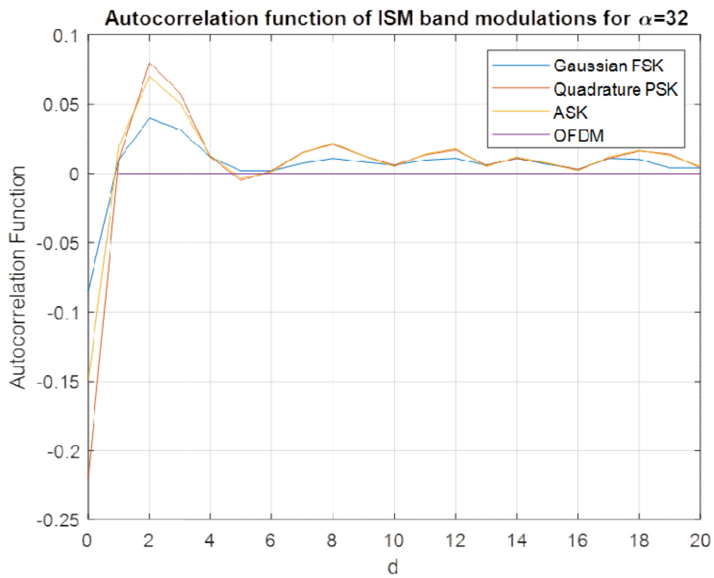

Figure 2: Autocorrelation Function of ISM Band Modulations for Different Values of d and α = 32

Because OFDM signals have a large bandwidth, autocorrelation is smaller. As a result, $R_A^0[2]$ differentiates between OFDM and all other types of signals. $R_A^0[3]$ also distinguishes ASK from other modulation schemes. However, because $R_A^0[4]$ does not discriminate between QPSK and GFSK, it is a source of worry. As a result, another $R_A^{32}[0]$characteristic is evaluated. Figure 3 depicts a plot of several cyclo-stationary features.

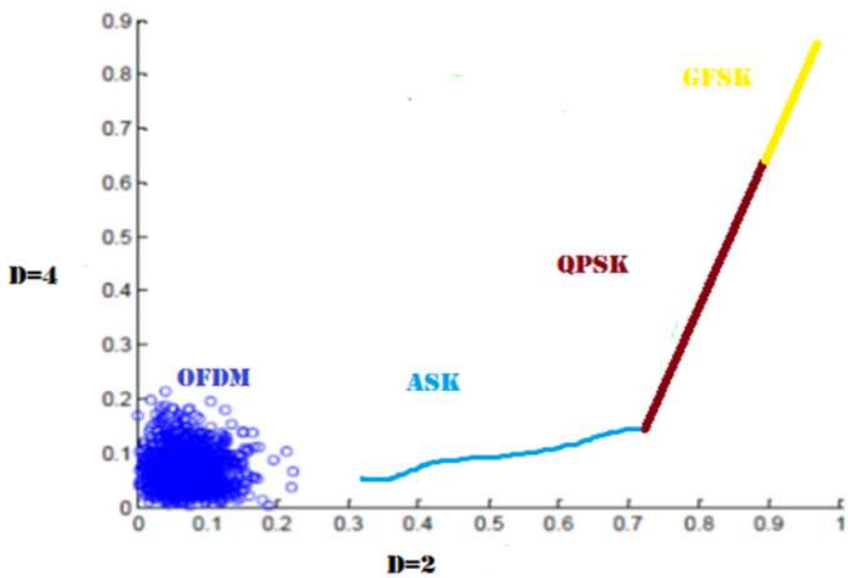

Figure 3: Plot of $R_A^0[2]$ versus $R_A^0[4]$

The results revealed that $R_A^0[2]$ successfully differentiates OFDM from all other signals.$R_A^0[3]$ distinguishes ASK from other modulation schemes in the same way. Finding differences between QPSK and GFSK is easy with $R_A^0[4]$ and $R_A^{32}[0]$. To detect the existence of a PU signal, the acquired autocorrelation values are fed as input into a Support Vector Machine (SVM) classifier.

III. SUPPORT VECTOR MACHINE CLASSIFIER

The classifier SVM may be used for classification since our goal is not to detect the modulation format, but for determining the existence of PU by detecting the presence of modulation in a signal [2]. Instead of using probabilities, the SVM helps to classify signals based on the presence or lack of PUs. SVM is fed the obtained values of $R_A^0[2]$, $R_A^0[3]$, $R_A^0[4]$, and $R_A^{32}[0]$. The range of values that correspond to different modulation formats is known from the plot values in Figure 2 and Figure 3. The range of values is presented in Table 1.

Table 1: Range Values for Classification

Correlation Value	Range	Correlation Value	Range	PU Presence
$R_A^0[2]$	0-0.25	$R_A^0[4]$	0-0.25	Yes
$R_A^0[2]$	0.7-0.9	$R_A^0[4]$	0.1-0.65	Yes
$R_A^0[2]$	0.91-1	$R_A^0[4]$	0.66-0.9	Yes
$R_A^0[4]$	0-0.25	$R_A^{32}[0]$	0-0.225	Yes
$R_A^0[4]$	0.2-0.65	$R_A^{32}[0]$	0.025-0.225	Yes
$R_A^0[4]$	0.65-0.85	$R_A^{32}[0]$	0	Yes

Figure 4 illustrates the block diagram of the proposed method. The programme correctly identifies PU existence and absence based on matching range values. The method by which SVM detects the existence of PU is described below. The data from Table 1 is first transformed to an n dimensional data space. A hyper-plane created by Equation (2) divides the linear data into two equal half spaces.

$$g(X) = W^T X + b = 0 \tag{2}$$

The following equation is a linear discriminant, with X, W, and b standing for feature vector, weight vector, and bias value, respectively. Parameters W and b determine the hyper-orientation plane's and location. Data is used to train such that

$$W^T X + b > 0 \; for\ PU\ Presence \quad \text{and} \quad W^T X + b < 0 \; for\ PU\ Absence \tag{3}$$

It is critical to note that such a teaching method may result in larger gaps between courses.

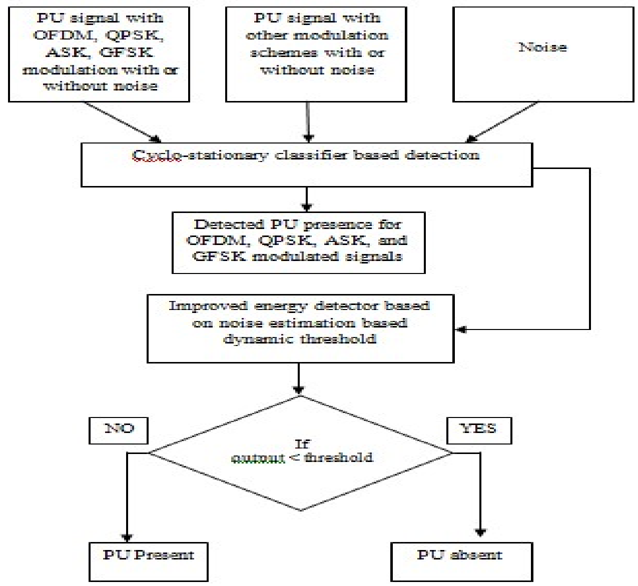

Figure 4: Block Diagram of Proposed Method

When a cyclo-stationary feature is supplied as input, a value for Equation (3) is derived from the preceding b, W values of hyper-plane. The signal is categorized as having modulation or not having modulation, which indicates the existence or absence of PU.

Due to increasing space-related classification errors, a more suitable hyper-plane is derived from Equation (3).

$$\mathrm{W^T X + b} > \gamma \tag{4}$$

Where, γ relates to the margin that has to be reduced. For the chosen margin of interest, the distance measured between data points and hyper-plane is provided in Equation (5).

$$\frac{\mathrm{W.X + b}}{||\mathrm{W}||} \geq \gamma \tag{5}$$

As a result, it's assumed that $\mathrm{WX + b} \geq 1$ for PU Presence and $\mathrm{WX + b} \leq -1$ for PU Absence.
Thus,

$$\mathrm{Y_i(WX + b)} \geq 1 \tag{6}$$

Where Yi is the output class value, and -1 and 1 are the input class values. If the b and mod values are adjusted to reduce the margin of error, the classification will be incorrect. This is accomplished by utilising a Lagrangian operator, as shown in Equation (7).

$$\mathrm{L(W,b)} = \frac{1}{2}(\mathrm{W.W}) - \sum \mathrm{\alpha_i [Y_i[WX + b] - 1]} \tag{7}$$

Where, α_i stands for Lagrangian Multiplier. As a result, the ultimate mathematical classification rule is constructed by substituting the derivatives of b and W in Equation (7) as given in Equation (8).

$$\mathrm{f(X,\alpha,b)} = \{\underline{+}1\} = \mathrm{sgn}\left(\sum_{i=1}^{n} \mathrm{Y_i \pm_i K\,(X, X_i) + b}\right) \tag{8}$$

The cyclo-stationary characteristics are denoted by K(X, Xi). Other modulation forms, however, may pass unnoticed, even if in tiny amounts. An ED has been added to this for post modulation based PU presence estimate. Normal ED, on the other hand, performs poorly at high SNR levels. As a result, an Improved Energy Detector (IED) based on noise variance estimate is presented. The block diagram for the proposed method is shown in Figure 4.

IV. DYNAMIC THRESHOLD SELECTION IN ENERGY DETECTION BASED ON NOISE VARIANCE ESTIMATION

The basic principle behind simple energy detection is to calculate the square of the Fourier transform for each sample received and then average these samples across the amount of samples. The average is then compared to a threshold, and if it falls below it, the PU signal is said to be missing. If it's above, PU will very certainly be present. However, noise in the transmission may make it impossible for the ED to perceive the channel. As a result, previous knowledge of noise is required for efficient ED performance, which is calculated using eigenvalues of the covariance matrix of the received signal. The received signal's matrix format may be written as,

$$X = \begin{bmatrix} X_{1,1} & X_{1,2} \dots\dots\dots & X_{1,N} \\ X_{2,1} & X_{2,2} \dots\dots\dots & X_{2,N} \\ X_{M,1} & X_{M,2} \dots\dots\dots & X_{M,N} \end{bmatrix} \tag{9}$$

Where, X denotes the received signal and M×N denotes the matrix's order. After modulation identification, the received signal might be either mixed with noise or pure noise. The following is a mathematical description of both of these kinds.

$$H_0 \to X(n) = N(n) \; and \; H_1 \to X(n) = Y(n) + N(n) \tag{10}$$

Where, H_0 denotes a signal with only noise and H_1 denotes a signal with both information and noise. Y(n) is the signal component and N(n) denotes the noise component in an Additive White Gaussian Noise(AWGN) noise model. The transferred signal takes up a portion of the bandwidth determined by the covariance matrix, with noise filling the rest. On the other side, the eigenvalues of the covariance matrix, deviate from the signal power components following the MarcenkoPastur distribution. Noise power eigenvalues and signal power eigenvalues have now been separated from the rest of the eigenvalues. The ultimate noise variance is estimated using MarcenkoPastur densities for both types of eigenvalues [2]. Based on the expected noise variance, the dynamic threshold is calculated using the following formula.

$$\lambda_D = \widehat{\sigma_N^2}(Q^{-1}(P_{fa})\sqrt{2N} + N)) \quad (11)$$

Where $\widehat{\sigma_N^2}$ indicates signal to noise ratio. The inverse of the Q function is Q^{-1}, N stands for sample numbers, and P_{fa} stands for the false alarm target probability. Even at low SNRs, such a dynamic threshold setting allows for good signal detection. Furthermore, as mentioned in the next section, a combination of modulation classifier and dynamic threshold based PU identification is effective in terms of different performance characteristics.

V. IMPLEMENTATION AND SIMULATION RESULTS

All of the tests were run on an Intel i3 core CPU using the MATLAB software. The tests were carried out on a total of 200 samples. The enhanced energy detection method identifies additional signals even at low SNR values, and the modulation classifier detects PU existence for four distinct modulations: QPSK, ASK, GPSK, and OFDM. Under Gaussian noise, as well as DC and frequency offsets, the suggested technique has been evaluated. The I/Q imbalance is also taken into account. Figure 5 depicts the suggested method's performance in the presence of Gaussian noise.

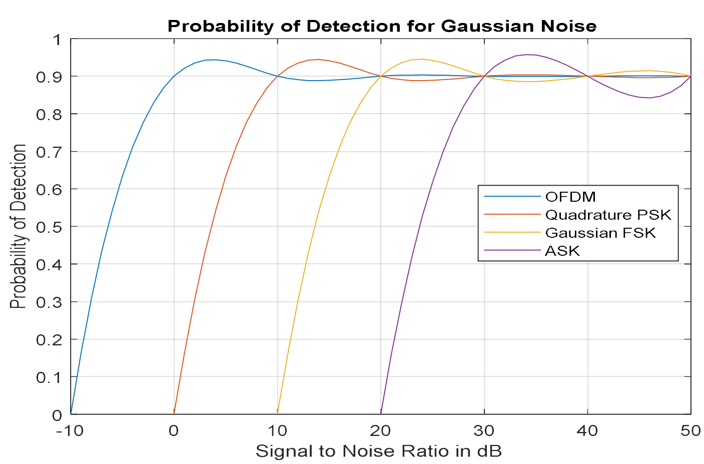

Figure 5: Probability of Detection under Gaussian Noise

Plainly, for SNRs underneath 17dB, the likelihood of PU identification is high. This is a result of the straightforwardness utilized in cyclo-fixed arrangement based discovery technique and commotion power assessment utilized in energy recognition. It is important that identification likelihood is higher for GFSK and lower for OFDM, inferable from the innate qualities of OFDM and GFSK. Nonetheless, over these SNRs recognition likelihood is low. This can be ascribed to various balance strategies utilized. Only four modulation schemes in the ISM band were evaluated since we wanted to decrease the complexity of the detection process. Be that as it may, when more adjustment methods are considered, higher outcomes can be obtained as more autocorrelation related provisions other than the ones picked could likewise become an integral factor. In general, one might say that, as intricacy builds, location likelihood likewise increments. Figure 6 and Figure 7 shows the likelihood of location of the proposed technique under stage I/Q irregularity.

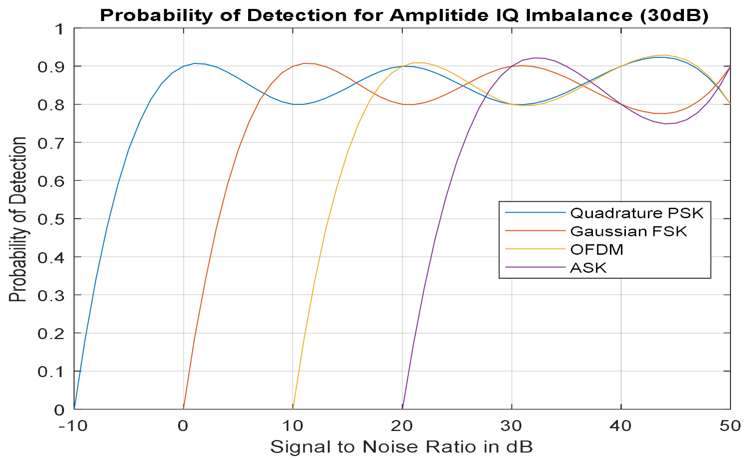

Figure 6: Probability of Detection under Amplitude IQ Imbalance (30dB)

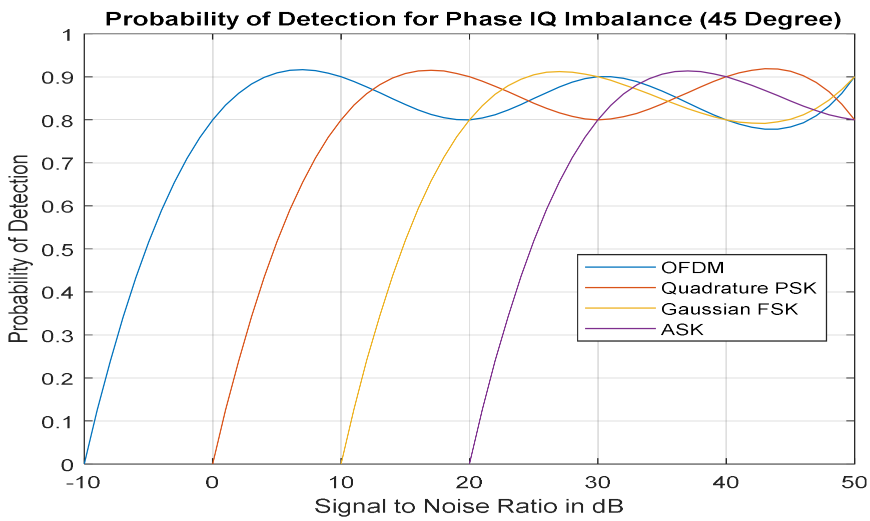

Figure 7: Probability of Detection under Phase IQ Imbalance (45 Degree)

On the CR platform, IQ imbalance commonly degrades the performance of transmitters and receivers. This is due to the direct transfer of RF to baseband. When frequencies are translated directly, there is no intermediary frequency step, resulting in IQ imbalance and DC offset. Because we aren't concerned with demodulation, the effect of IQ imbalance is less evident. Receiver mismatches can also create IQ disparities. At high SNRs, amplitude IQ anomalies are more confused than phase IQ imbalances, as seen in Figures 6 and 7. Furthermore, for IQ imbalances, the likelihood of detection follows the same performance pattern as the Gaussian plots. The proposed technique, on the other hand, is unaffected by IQ imbalance, highlighting the method's merits. It also states that when implementing the algorithm on a Field Programmable Gate Array (FPGA) or any other user-defined platform, IQ imbalances are not essential for taking it in account. The suggested approach performance under frequency offset is shown in Figure 8.

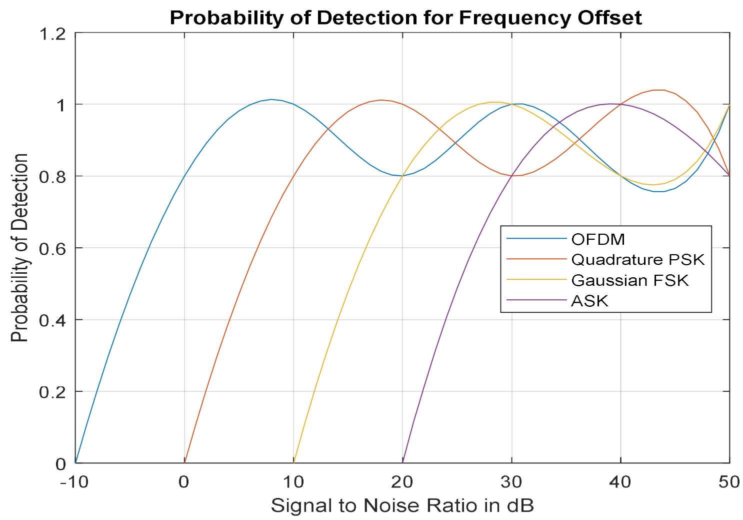

Figure 8: Probability of detection under Frequency Offset

In spectrum sensing, the frequency offset is also unimportant since receivers are used to a change in broadcast radiofrequency. While interference from other users degrades the performance of CR algorithms, it has no effect on the suggested methods for SNRs less than 17 dB. Due to spurious radiation and fringe reception of channels, the likelihood of detection after certain SNRs is low under frequency offset. Frequency offset has insignificant impact and should not be taken into account while designing a system. The algorithm's performance under DC offset is shown in Figure 9.

The likelihood of detection curve shows significant changes when the DC offset is taken into consideration. There are substantial differences in the DC and non-DC probability of detection curves in OFDM. Due to the sensitivity of OFDM to carrier offset, the receiver must estimate and compensate carrier frequency, which affects all subcarriers. By deriving, Symbol Error Rate (SER) designers can determine whether or not to use DC correction. However, our studies show that DC compensation is necessary for real-time implementation of the recommended approach. Although QPSK has a minor impact on DC offset, it has a moderate effect on GFSK. The suggested technique improves the performance of sensing spectrum, notably for modulation signals in the ISM band, according to the overall study. When DC offset is taken into account, performance is also affected. This means that while building a classifier-based detection technique, the DC offset level must be considered.

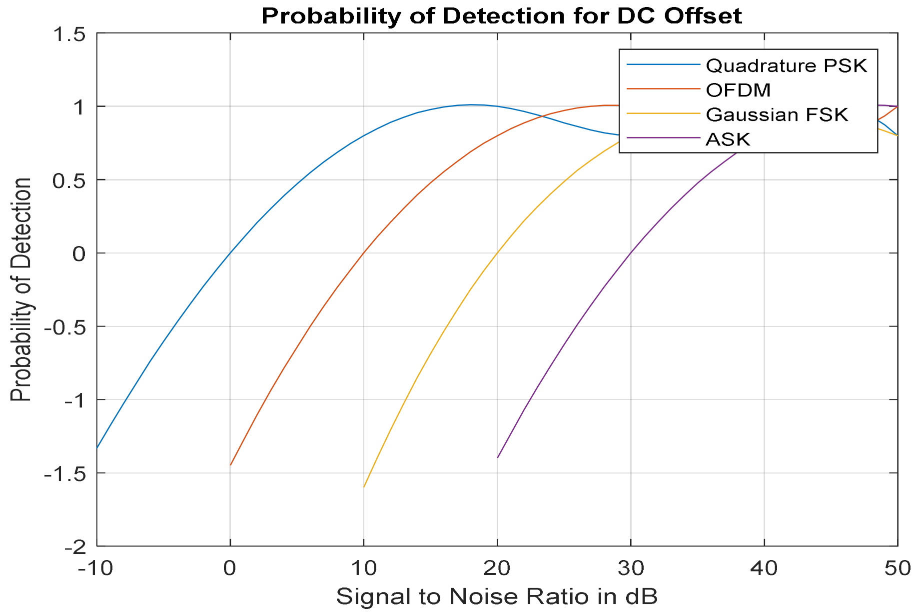

Figure 9: Probability of Detection under DC Offset

In terms of false-alarm percentage (Pf) and probability of detection, Tables 2 and 3 shows the performance of various sample length signals modulated by OFDM, QPSK, ASK, and GFSK (Pd). The suggested model's performance for a wide variety of sample lengths is demonstrated using varied sample lengths. The number of false alarms is reduced, while the probability of detection rises. The network is found to be scalable since the sensing time is superior across the entire sample length range. As a result, the proposed method for spectrum sensing in CRNs appears to be a good choice.

Table 2: Comparison of the Proposed Method for Different Sample Length Modulation Signals

Modulation Type	**64 sample length**			**128 sample length**		
	P_f	**P_d**	**Sensing time (ms)**	**P_f**	**P_d**	**Sensing time (ms)**
OFDM	0.055	0.945	0.05	0.0430	0.957	0.12
QPSK	0.052	0.948	0.021	0.0340	0.966	0.25
ASK	0.068	0.9 32	0.010	0.0490	0.951	0.16
Proposed GFSK	**0.049**	**0.951**	**0.02**	**0.0400**	**0.960**	**0.08**

Table 3: Comparison of the Proposed Method for Different Sample Length Modulation Signals

Modulation Type	256 sample length			512 sample length		
	P_f	P_d	Sensing time (ms)	P_f	P_d	Sensing time (ms)
OFDM	0.022	0.978	0.15	0.011	0.989	0.18
QPSK	0.031	0.969	0.34	0.015	0.985	0.49
ASK	0.038	0.962	2.4	0.027	0.973	2.9
Proposed GFSK	0.033	0.967	1.3	0.009	0.991	1.7

In order to further quantify the effectiveness of the suggested technique, a non-parametric statistical trial with Wilcoxon signed-rank test is done during the evaluation. It is carried out based on the sensing times discovered, which are presented in Table 2 and 3. Table 4 shows the results of the Wilcoxon signed-rank test. The significant level for the test has been determined to be 0.05, which is a good range for spectrum sensing applications.

Table 4: Wilcoxon Signed-Rank Test between 64 Sample Length and Other Range of Sample Lengths

64 sample length versus	p-value
128 sample length	0.0571
256 sample length	0.0286
512 sample length	0.0286

VI. SUMMARY

In order to use communication-related applications, CR methods need to be specified. Determinism relies heavily on spectrum sensing and handoff process in the spectrum. Apart from the fact that various sensors are present that complement both design and accuracy it should be established. As a result, improved energy sensing detector as well as a spectrum sensing approach based on cyclo-stationary exchange signals have been proposed in this work. This approach is related to the idea that each signal in the PU will have a corresponding variable format, so identifying the presence of a variable format ensures the presence of a PU signal. Four exchange schemes used in the ISM band, namely QPSK, GFSK, ASK, and OFDM, were evaluated based on autocorrelation factors. In addition, when using other formats, the presence of PU is detected using an enhanced power detector that uses a strong limit to distinguish between sound and signal using sound measurements.

This method is able to identify the presence of PUs. MATLAB was used for simulation. To determine the effectiveness of the proposed method, the acquisition possibilities were used as a determining parameter. Under various SNRs, IQ imbalances, frequency, and DC ablation are also considered more than noise. The outcome shows that the proposed approach works superior than other approaches. This approach can be further enhanced by developing cyclo-stationary features to reduce complexity, allowing for effective detection of the presence of PU in all types of variables. Inequality, frequency and DC removal are also considered more than noise. For 64, 128, 256, and 512 sample lengths, the proposed technique produces probability of detection of 95.1 percent, 96 percent, 96.1 percent, and 99.1 percent, respectively, which is higher than the existing methods.

REFERENCES

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[2] Appala Raju. Uppala, C. Venkata Narasimhulu, K.Satya Prasad "Spectrum Sensing By Correlation Modulation Format Identifier and Improved Energy Detection Using Noise Estimation Based Dynamic Threshold" to Ad Hoc & Sensor Wireless Networks,Vol.50, no. 1-4, pp.215-237,2021.