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ADAPTIVE THRESHOLDING IN CYCLOSTATIONARY SPECTRUM SENSING USING ARTIFICIAL NEURAL NETWORK UNDER NON-STATIONARY NOISE CONDITIONS

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Abstract

An efficient spectrum sensing is a primary requirement in cognitive radio networks to ensure optimal utilization of underused spectral resources without interfering with licensed users. The cyclostationary feature detection shows periodic statistical properties of modulated signals to distinguish them from noise, offering superior detection reliability at low signal-to-noise ratios. However, the performance of cyclostationary feature detection can degrade when the noise characteristics or signal-to-noise vary dynamically. This work proposes an artificial neural network assisted adaptive thresholding framework for cyclostationary feature detection based spectrum sensing to address these challenges. The artificial neural network is trained to predict optimal detection thresholds under different SNR and noise variance conditions, thereby improving detection accuracy while maintaining optimal computational complexity. Simulation results show that the proposed method achieves high detection probability, P_d under severe noise fluctuations and low SNR environments. Specifically, M-ary phase shift keying exhibits reliable performance down to –30 dB, while M-ary quadrature amplitude modulation maintains accuracy up to –20 dB. The findings indicate that artificial neural network driven adaptive thresholding can significantly enhance the adaptability and robustness of cognitive radio systems in spectrum sensing process.

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Keywords Adaptive spectrum sensing; cognitive radio; cyclostationary feature detection; artificial neural network; adaptive thresholding; noise variance.

1. Introduction

Cognitive radio (CR) technology has emerged as a promising standard to address spectrum scarcity by enabling secondary users (SUs) to opportunistically access underutilized frequency bands without interfering with licensed primary users (PUs). A crucial component of CR operation is spectrum sensing, which determines the existence or nonexistence of primary user signals. Mathematically, this can be expressed as a binary hypothesis testing problem: H_0 indicates that the primary user is absent, while H_1 denotes its presence. The received discrete-time signal *x(n)* at the secondary user can thus be represented as described in equation (1):

$$\begin{cases} H_0 : x(n) = w(n) & , n = 1,2,\ldots,N \\ H_1 : x(n) = s(n) + w(n) & , n = 1,2,\ldots,N \end{cases} \quad (1)$$

where *s(n)* and *w(n)* denote the transmitted primary user's signal and additive noise, respectively. The accuracy of a spectrum sensing algorithm is generally quantified using two key performance metrics namely probability of detection and probability of false alarm. A high P_d ensures that the cognitive radio correctly identifies active primary user's transmissions, thereby minimizing interference, while a low P_f improves spectral efficiency by avoiding unnecessary idle channels, which is represented in the following equation (2).

$$\begin{aligned} P_d &= P_r\{H_1 \mid H_1\} \\ P_f &= P_r\{H_1 \mid H_0\} \end{aligned} \quad (2)$$

Cognitive radio spectrum sensing techniques are typically classified into energy detection, matched filtering, and cyclostationary feature detection. Among these methods, energy detection is computationally simple and does not require prior signal knowledge; however, it performs poorly under noise uncertainty. Matched filtering offers the best theoretical detection performance but demands detailed prior information about primary user signals. This makes matched filter method is impractical in dynamic wireless environments. The CFD, on the other hand, leverages the periodicity inherent in modulated signals to distinguish them from stationary noise, providing robust performance even under low SNR conditions.

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Despite these advantages, conventional CFD suffers from high computational complexity and sensitivity to noise variance. The estimation of cyclic autocorrelation and spectral correlation functions involves significant processing resources, which limits its application in real-time and resource-constrained CR systems. Moreover, variations in noise power or SNR degrade the reliability of a fixed detection threshold, resulting in either missed detections or increased false alarms. To overcome these limitations, artificial neural networks (ANNs) have recently been explored for spectrum sensing applications [1]. ANNs possess strong nonlinear mapping and adaptive learning capabilities, enabling them to infer complex relationships between input features and detection outcomes. Their ability to generalize from diverse training data makes them particularly effective under non-stationary signal conditions.

The recent references [2-6] show the application of artificial neural network for the cognitive radio spectrum sensing application. The research directions and challenges about ANN based spectrum sensing are discussed in [7, 8]. For sequence prediction, a recursive neural network (RNN) is mainly used for spectrum sensing in addition with CNN was proposed in references [9-15]. Authors in [16-21] references discussed about the ANN based auto correlation function.

In this work, an adaptive thresholding approach based on artificial neural networks for cyclostationary feature detection in spectrum sensing is proposed. The ANN is trained using varying SNR and noise variance scenarios to learn an adaptive thresholding mechanism capable of adjusting to real-time environmental changes. This framework mitigates the inefficiencies of static thresholds and enhances the probability of detection, especially under low SNR conditions.

The paper is organized as follows: Section 2, details the methodology of the proposed ANN assisted adaptive thresholding for CFD based sensing. Section 3 presents the simulation setup and discusses the results obtained for MPSK and MQAM modulation schemes with three different channel settings. Finally, section 4 concludes the proposed work and suggests potential directions for future research.

2. Methodology

The cyclostationary feature detection shows the inherent periodicity of modulated signals to discriminate between the existence and nonexistence of primary users in a frequency band.

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Unlike conventional energy detection, CFD utilizes the second-order statistics of signals to capture their cyclostationary characteristics. A cyclostationary signal has the period of T_0 and it's mean and autocorrelation function exhibit periodicity in time. When the cyclic frequency $\alpha \neq 0$, the cyclic spectrum reveals components that distinguish the signal from noise, since noise lacks cyclostationary properties. This allows CFD to detect signals at very low SNRs where conventional detectors fail.

Despite its robustness, CFD involves significant computational complexity due to the estimation of autocorrelation and cyclic frequency components. Furthermore, the optimal threshold for distinguishing between signal and noise varies with environmental conditions such as SNR and noise variance, making static thresholding suboptimal.

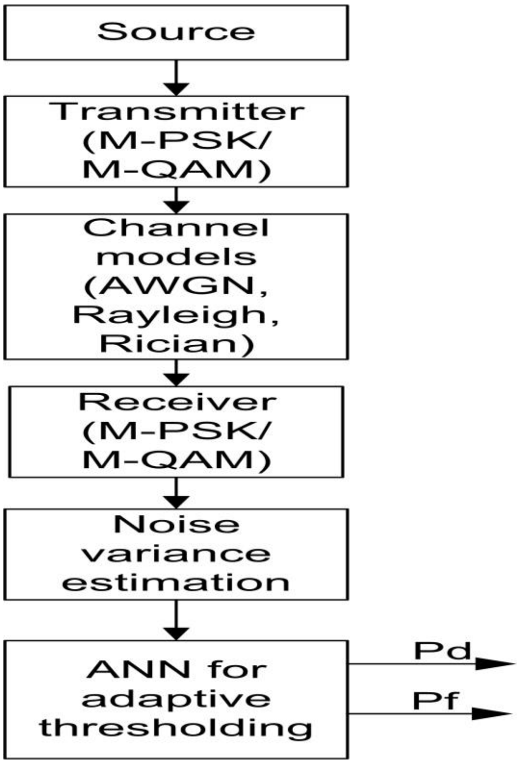

Fig. 1 Proposed ANN based adaptive thresholding model.

Artificial Neural Networks are data-driven models consisting of multiple interconnected layers namely input, hidden, and output layers that learn nonlinear mappings between input features and target outputs. In cognitive radio systems, ANNs can model the relationship between signal statistics and detection thresholds. In the proposed approach, an ANN is trained to predict the optimal CFD threshold under varying SNR and noise conditions. The

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model inputs include extracted cyclostationary features and environmental parameters such as estimated SNR and noise variance. The network outputs a predicted threshold value that adapts dynamically to the operating conditions. The feed forward ANN architecture was adopted, comprising input, hidden, and output layers. The ANN was trained using datasets corresponding to diverse SNR and noise variance conditions to enhance generalization capability [22-25].

The proposed CFD ANN hybrid model integrates cyclostationary analysis with machine learning based threshold prediction. The process begins with signal preprocessing, where received samples are normalized and cyclostationary features are extracted. These features are then fed into the ANN, which outputs an adaptive threshold. Once the threshold is determined, the CFD module performs spectrum sensing by comparing the test statistic to the ANN generated threshold. This dynamic mechanism compensates for environmental variations, improving reliability without excessive computational cost.

3. Results and Discussions

The simulation environment and the parameters used in the simulations are discussed as follows. Simulations were carried out to assess the significance and performance of the ANN assisted CFD framework under different channel and noise variance conditions. The feed forward ANN architecture was optimized with appropriate learning parameters shown in Fig.2 (a) and trained using diverse SNR datasets. The internal architecture of the feed forward ANN used in the proposed adaptive thresholding model is shown in Fig.2 (b).

Unit	Initial value	Stopped value	Target value
Epoch	0	10	1000
Elapsed time	-	00:00:01	-
Performance	0.17	0.0402	0
Gradient	0.923	0.000458	1e-07
Mu	0.001	1e-08	1e+10
Validation checks	0	6	6

(a)

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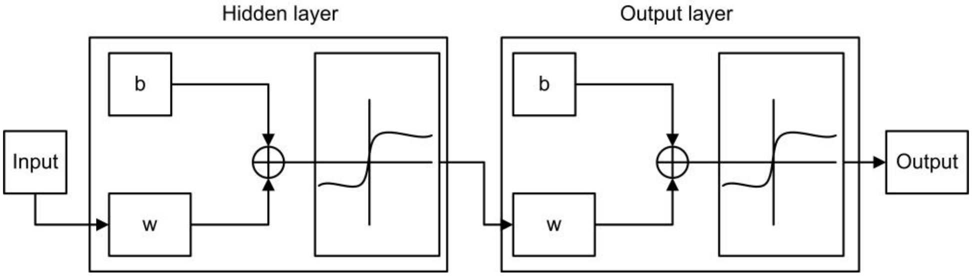
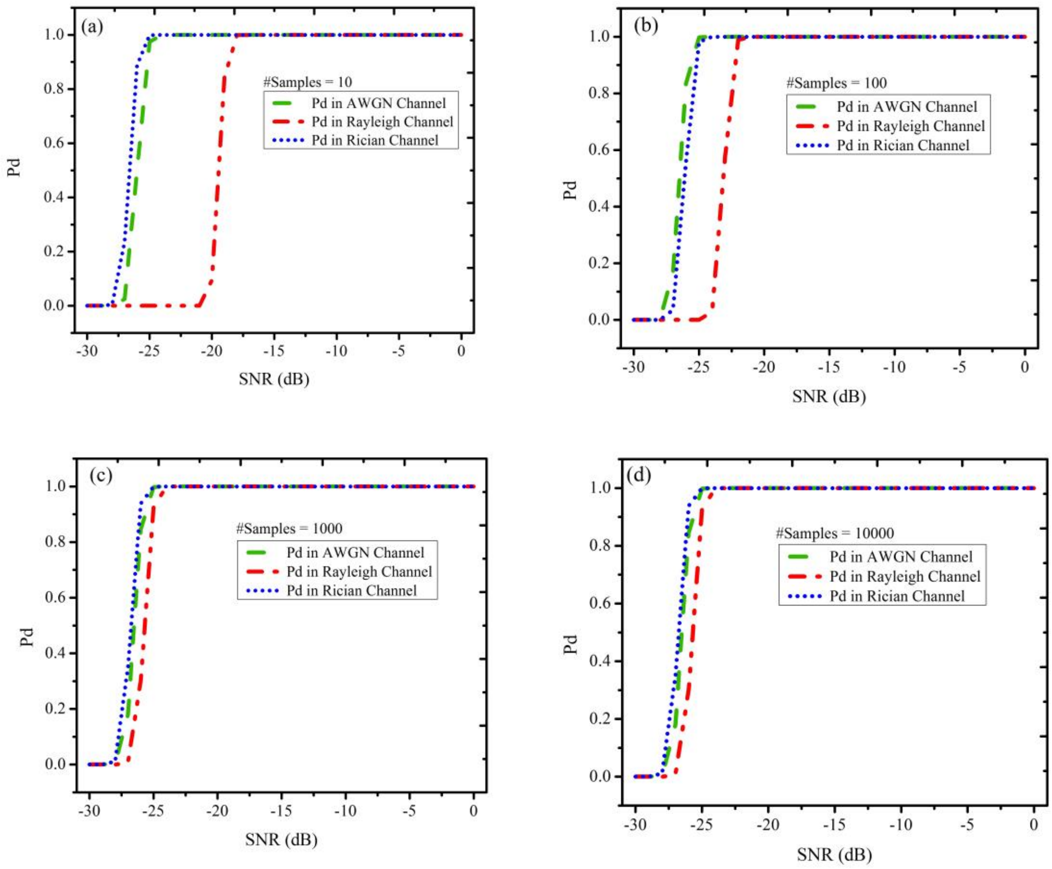


(b)

Fig. 2. Simulation setup (a). Learning parameters (b). Internal architecture of the feed-forward ANN utilized in the proposed work.

The probability of detection (P_d) is directly influenced by the number of samples considered. As shown in Fig. 3, increasing the number of samples improves detection accuracy across all channel models namely AWGN, Rayleigh, and Rician though the improvement saturates beyond a certain point.



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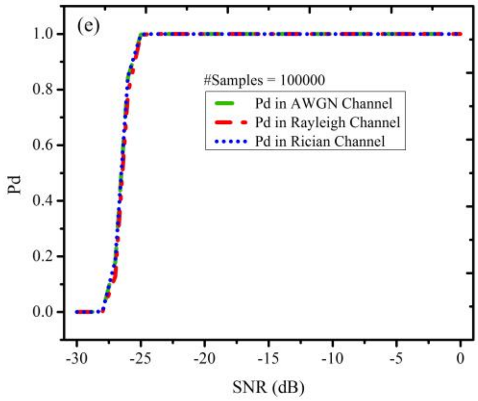
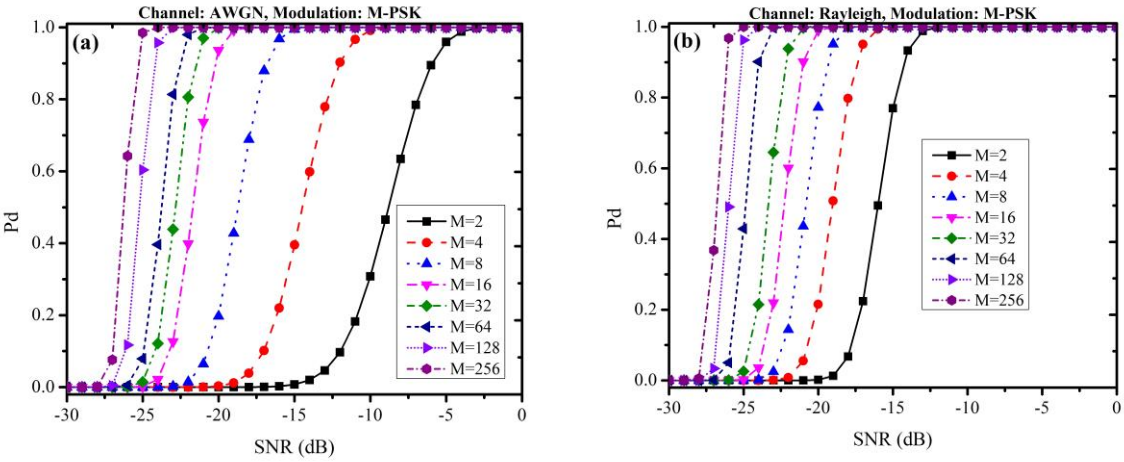


Fig. 3. Effect of number of samples in measuring probability of detection versus SNR in different channels.

The performance of the ANN CFD model was analyzed using MPSK and MQAM modulation schemes under AWGN, Rayleigh, and Rician channels. For MPSK, 90% detection accuracy was achieved between –5 dB and –25.5 dB (AWGN), –14 dB to –27 dB (Rayleigh), and up to –30 dB (Rician). For MQAM, detection accuracy of 90% was maintained from –2 dB to –22.7 dB (AWGN), –4.8 dB to –30 dB (Rayleigh), and –2.4 dB to –30 dB (Rician).



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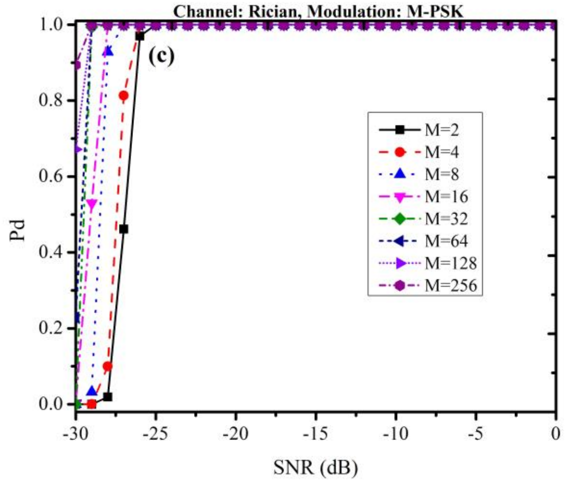

Fig.4: The MPSK modulation based measurement of probability of detection under (a). AWGN channel (b). Rayleigh fading channel and (c). Rician channel.

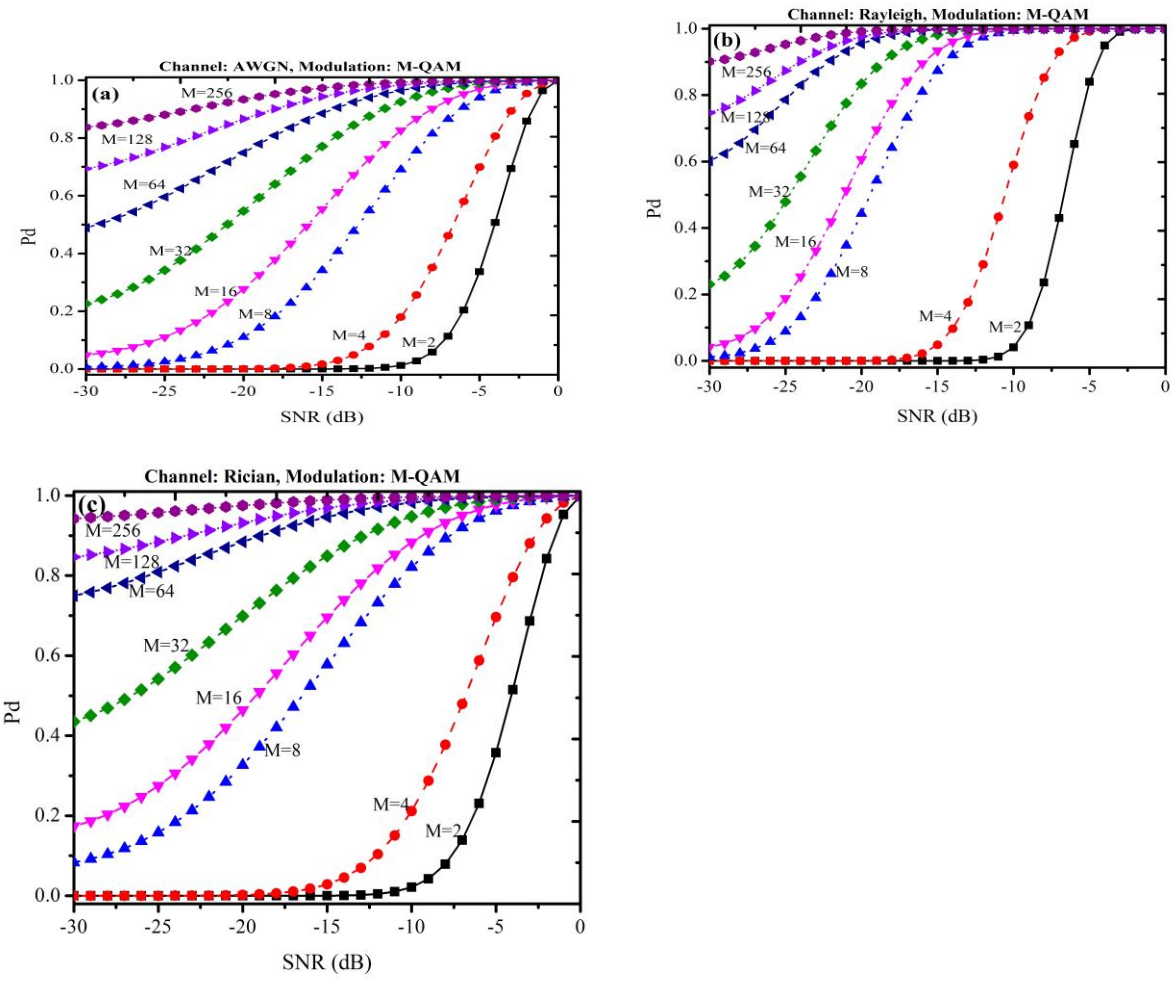

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Fig.5: The P_d measurement for MQAM modulation scheme under (a). AWGN channel (b). Rayleigh fading channel and (c). Rician channel.

Considering the selected channel conditions and modulation schemes, spectrum sensing using MQAM demonstrates superior performance compared to MPSK based methods. The key advantage of the cyclostationary feature detection approach lies in its ability to identify the presence of primary signals even under low SNR environments. Using the proposed ANN assisted CFD model, a probability of detection of 90% has been adopted as the reference benchmark for evaluation. From Fig. 4 and Fig. 5, it is observed that MQAM based sensing maintains reliable detection performance down to –30 dB SNR, whereas the MPSK configuration achieves 90% detection up to approximately –27.7 dB. The complete set of 100% P_d values across varying SNR levels is summarized in Table 1.

Table 1. Comparison of proposed work with published literature for artificial neural network based spectrum sensing methods.

Ref.	Method	Types of modulations	Types of Channels	No. of samples	Probability of detection under different SNR
[26]	Artificial neural network for Energy detection	BPSK, AM, FM	NA	200	99.99% -6 dB
[27]	Artificial neural network for Energy detection	BPSK, QPSK	AWGN, Rayleigh	2000	99.99% @ -4.5dB
[28]	Artificial neural network for Hybrid detection	QAM	AWGN	1000	82.45% @-24dB
[29]	Artificial neural network for CFD	NA	NA	NA	99.99% @ -10 dB 91.7% @ -15 dB 80.8% @ -20 dB
[30]	Artificial neural network for CFD	NA	NA	NA	100% @ -10 dB 89% @ -15 dB

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					0% @ -20 dB
[31]	Artificial neural network for CFD	NA	NA	NA	99.98% @ -5 dB 98.02% @ -10 dB 98.03% @ -15 dB 98.01% @ -20 dB
This work: adaptive thresholding with artificial neural network for CFD		256-PSK	AWGN	2000	99.97 % @ -24.22 dB
		256-PSK	Rayleigh	2000	99.98% @ -25.05 dB
		256-PSK	Rician	2000	99.99% @ -30.12 dB
		256-QAM	AWGN	2000	99.96% @ -10.12 dB
		256-QAM	Rayleigh	2000	99.97% @ -20.03 dB
		256-QAM	Rician	2000	99.96% @ -14.9 dB
Note: NA-Not available					

Earlier studies have explored artificial neural network based energy detection methods [26, 27]. In the reference [26], a 100% detection probability was obtained at –6 dB SNR with 200 signal samples for modulation formats including amplitude modulation (AM), frequency modulation (FM), and binary phase shift keying (BPSK). Similarly, in the reference [27], AWGN and Rayleigh channels were analyzed with quadrature PSK and binary PSK schemes using 2000 number of samples, achieving full detection at –4.5 dB SNR. Hybrid ANN-driven sensing approaches were further investigated in the reference [28] with QAM over AWGN channels, where 82.5% Pd was achieved at –24 dB SNR using 1000 samples.

The work in [29] evaluated an ANN-based CFD system, reporting P_d values of 100%, 92%, and 81% at SNR levels of –10 dB, –15 dB, and –20 dB, respectively, under a single-stage CFD setup. Although hybrid configurations were also discussed, the single-stage architecture was found more suitable for fair comparison, as followed in the present study. A comparable single stage artificial neural network based cyclostationary feature detection approach in [30] yielded a probability of detection results of nearly 100%, 89%, and 0% at –10 dB, –15 dB, and –20 dB SNR levels, respectively. Another study [31] presented an ANN–CFD model

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achieving P_d values of approximately 100% at –5 dB and nearly 98% at starting from –10 dB to –20 dB.

In the proposed artificial neural network based cyclostationary feature detection implementation, P_d values were determined for multiple SNR conditions using a dynamic thresholding mechanism that adapts to varying noise variance and SNR levels. By selecting an appropriate threshold, the system achieved improved detection accuracy. For the 256-PSK modulation, P_d reached 100% at –24 dB in the additive white Gaussian noise channel with 2000 samples, –25.05 dB in the Rayleigh channel, and –30.12 dB in the Rician channel. Similarly, for the 256-QAM scheme, 100% P_d was achieved at SNR values of approximately –10 dB, –20 dB, and –15 dB under additive white Gaussian noise channel, Rayleigh channel, and Rician channel respectively. The corresponding P_d variations for both MPSK and MQAM across different channel models are shown in Fig. 4 and Fig. 5.

4. Conclusion

This study introduced an ANN based adaptive thresholding mechanism for cyclostationary spectrum sensing in cognitive radio systems under varying SNR and noise conditions. By combining the robust statistical nature of CFD with the adaptive learning ability of ANNs, the proposed model effectively addressed the limitations of static thresholding. Simulation results confirmed that the method achieves high Pd even in low SNR environments, with MPSK performing well down to –30 dB and MQAM up to –20 dB under AWGN, Rayleigh, and Rician channels. The proposed methodology enhances probability of detection accuracy and adaptability while maintaining computational efficiency. In the future research, there will be an integration of hybrid deep learning models and advanced preprocessing techniques to further optimize sensing performance.

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