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Original Article

Spectrum Sensing in Cognitive Radio Using Multiple Antenna by Eliminating Phase Noise

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***Abstract** - Efficient spectrum sensing is crucial in Cognitive Radio Networks (CRNs) to identify and utilize unoccupied frequency bands, unobtrusively for primary users. By providing spatial diversity, the use of multiple antennas can enhance spectrum sensing performance. The proposed work makes use of multiple antenna spectrum sensing with a Deep Q Network (DQN) model to ascertain the existence of an estimated signal. The presence of phase noise reduces the efficiency of spectrum sensing compared to other widely used methods. To overcome this, the proposed work adopts Jelly Fish Optimization (JFO), Single Candidate Optimization (SCO) and Sand cat swarm optimization algorithms with Multiple Antenna Spectrum Sensing DQN (MASSDQN) to decrease the phase noise and enhance the spectrum sensing. The experimental outcome demonstrates the superior performance of the sand cat swarm optimization technique in multiple antenna spectrum sensing and optimize the phase noise for the secondary users to harness the spectrum effectively.*

***Keywords** - MASSDQN, Spectrum Sensing, Phase Noise, Cognitive Radio Network, Single Candidate Swarm Optimization.*

1. Introduction

The underutilization of the Radio Frequency (RF) spectrum is largely a result of the traditional fixed spectrum allocation policies. As a result, many spectrum bands end up being vacant for extended periods of time. Cognitive Radio (CR) is a viable method for increasing spectrum utilization and addressing the issue of spectrum scarcity. CR's basic concept is to make underutilized or vacant spectrum bands, which are primarily reserved for Prime Users (PUs), available to Secondary Users (SUs). In order to do this, SUs must use spectrum sensing to determine whether PUs are presently using a specific spectrum band. The best bands for cognitive transmission can be selected by the SUs if they determine that the spectrum is empty. The usage of a multiple antenna approach may improve CR systems' spectrum sensing performance, offering more precise detection capabilities and mitigating the limitations of conventional methods.

Multiple antenna techniques [1, 2] are commonly used in communication systems and have been shown to work well in a number of different situations. In dynamic spectrum sharing, Secondary Users (SUs) equipped with multiple antennas have achieved reliable signal transmission and efficient spectrum sensing. By leveraging the spatial domain observations provided by multiple antennas, Cognitive Radios (CRs) can greatly enhance the accuracy of spectrum sensing [3]. Phase noise is the short-term random changes in a signal's phase. These changes are usually caused by flaws in oscillators or other RF parts. Phase noise in spectrum sensing can make spectrum sensing methods much less effective, especially in cognitive radio systems and systems with more than one Antenna. Phase noise breaks up the coherence between different antenna signals in systems with more than one Antenna, like Multiple Input Multiple Output (MIMO). This phase distortion between antennas affects spatial diversity and multiplexing gains, making spectrum sensing less effective in these systems.

The proposed work explores the usage of multiple antennas for spectrum sensing with various optimization algorithms like jellyfish, single candidate, and sand cat to reduce the presence of phase noise and detect the unusable spectrum. The optimal detector structure for this scenario has been simulated to reduce the phase noise and enhance the spectrum sensing using various algorithms, and effective accuracy has been obtained.

2. Literature Review

Adding more antennas to systems has improved their ability to sense the spectrum. By using spatial diversity, several antennas can improve signal detection, make fading less likely, and lessen the effects of noise and interference. Furthermore, integrated spatial and temporal sensing is made possible by multiple-antenna approaches, which may result in more effective spectrum use. Zhang et al. [2] explored a spectrum sensing approach based on Matched Filter Detection (MFD) and addressed a scenario in which the transmit power of the Primary User (PU) varies over time. This fluctuating transmit power introduces challenges for reliable spectrum sensing, as many traditional techniques assume a constant signal strength from the PU. By accounting for variations in the PU's transmit power, their study aimed to enhance the detection accuracy and robustness of the sensing process in dynamic environments. Lucas dos Santos Costa et al [4] coupled impairments on the performance of two blind methods under frequency-selective fading channels in centralized Cooperative Spectrum Sensing CSS with data fusion and Decision Fusion (DF) for varying the CRs and antennas. An auto-encoder for spectrum sensing was created by Xie et al. [5]. It does not require a significant quantity of data labeled for training, but it exhibits detection performance that is comparable to supervised algorithms under Gaussian and Laplace noise, unlike the previously stated systems. DL-based techniques have also become more prominent in the spectrum sensing field in multiantenna receiving scenarios. For the CR IoT with several sensing antennae, Wang et al. [6] suggested a sensing algorithm based on numerous high-order cumulants. It can successfully balance computation and detection performance while mitigating the negative effects of noise uncertainty. The spectrum sensing problem for noncircular signals in CR networks with multiple receive antennas is examined by An-Zhi Chen et al. [7], with particular attention paid to the situation in which the antennas encounter varying noise power levels. For these networks, Noncircular Covariance (NCC) is a potent spectrum sensing method that leverages the advantages of the NC signal. By comparing complementary covariance matrices and the standard covariance of the received signals among the null and alternative hypotheses, PUs can be found. Keunhong and Yusung [8] developed a Deep Spectrum Sensing Method for Multiple Antennas (DS2MA) reception by using the auto and cross-correlation functions of received signals. DS2MA may be able to learn to identify the presence of a Principal User (PU) with the help of the rich information matrix and a simple Convolutional Neural Network (CNN) structure. DS2MA can greatly enhance detection performance by combining cross-correlation functions. Research in [9-11] highlights the importance of using several antennas in SUs for SS in situations when data on noise power levels, sensing channels, and/or PU signal may not be available. It is important to keep in mind that correlation of signals frequently occurs in receivers with multiple antennas, for instance, because of the close proximity of the antennas.

Furthermore, one may anticipate that performance will suffer in a particular communication setting when geographical diversity declines and correlation rises. Transmitted signals are destroyed by phase noise from both the transmitter and the receiver. In multiple-antenna systems, phase noise [12-17] can lead to random fluctuations in received signal amplitude. The receiver's non-coherent mixing of the received signals is the main source of this. Phase noise is a big problem in cognitive radio spectrum sensing because more and more people are using multiantenna systems and advanced sensing methods. Cooperative sensing, hardware upgrades, and sophisticated signal processing methods like DQN-based optimization are all effective mitigation tactics. In order to guarantee dependable spectrum access without interfering with key users, phase noise must be understood and compensated for.

3. Preliminary Basics

3.1. Signal Model

A cognitive Radio-5G network comprises one Primary User (PU) with a transmitting antenna and numerous Secondary Users (SU) with multiple receiving antennas. The Secondary User detects the existence of the Primary User with N (N≥1) received signals. For each Secondary User (SU), the challenge of spectrum sensing can be framed as a binary hypothesis test.

$$\left.\begin{array}{c} H_0: r(n) = \varphi(n) \\ \boldsymbol{H_1: r(n) = h(n)t(n) + \varphi(n)} \end{array}\right\} \quad (1)$$

Where H_0 indicates PU is absent,
H_1 indicates the PU is present, respectively.
r(n) indicates the SU received signal,
t(n) represents the PU transmitted signal,
h(n) represents the SU and PU channel,
ϕ (n) represents additive noise, n = 0, 1, . . , N − 1,
N is the number of received samples

$$r(n) = [r_1(n), r_2(n), \ldots, r_M(n)]^T \in C^{MX1} \quad (2)$$

$$\mathrm{h(n)} = [\mathrm{h1(n), h2(n), \ldots, hM(n)}]^{\mathrm{T}} \in \mathrm{C}^{\mathrm{MX1}} \quad (3)$$

$$\varphi(n) = [\varphi_1(n), \varphi_2(n), \ldots, \varphi_M(n)]^T \in C^{MX1} \quad (4)$$

Where $r_i(n)$ indicates the i^{th} Antenna received signal, $h_i(n)$ is the channel response between the i^{th} Antenna and the transmitter, and $\varphi_i(n)$ represents the ϕ^{th} antenna noise.

3.2. Noise Model

3.2.1. Phase Noise

Phase noise is the noise resulting from swift, transient, random variations in the phase of a signal. These unpredictable phase changes occur because of time-domain instabilities, known as phase jitter. This noise can degrade the performance of the radio by impacting various aspects of signal processing. In situations when great precision and dependability are needed, phase noise is an important consideration in the design and implementation of cognitive radio systems. In frequency division multiplexing systems, spectral regrowth brought on by phase noise may exacerbate adjacent channel interference. A stochastic process denoted by is added to the signal in the following manner to introduce phase noise.

$$V(t) = A\cos(2\pi f_0 t + \varphi(t)) \tag{5}$$

3.3. Channel Model

3.3.1. Ideal Channel

In an ideal channel, where there are no impairments like multipath fading, interference, or noise (except for phase noise), Phase noise is still a significant factor since it directly impacts the transmission and reception integrity of signals. Phase noise can impair communication systems' performance even in such a perfect situation.

3.3.2. Rayleigh Channel

In a Rayleigh fading channel, where the signal undergoes multiple reflections and scattering, leading to random amplitude variations, phase noise adds another layer of complexity to the communication system.

Phase noise and Rayleigh fading together may seriously hinder the functionality of wireless communication devices, such as cognitive radios. When both Rayleigh fading and phase noise are present, the received signal y(t) is given as

$$y(t) = h(t).s(t)e^{j\theta_{pn}t} + n(t) \tag{6}$$

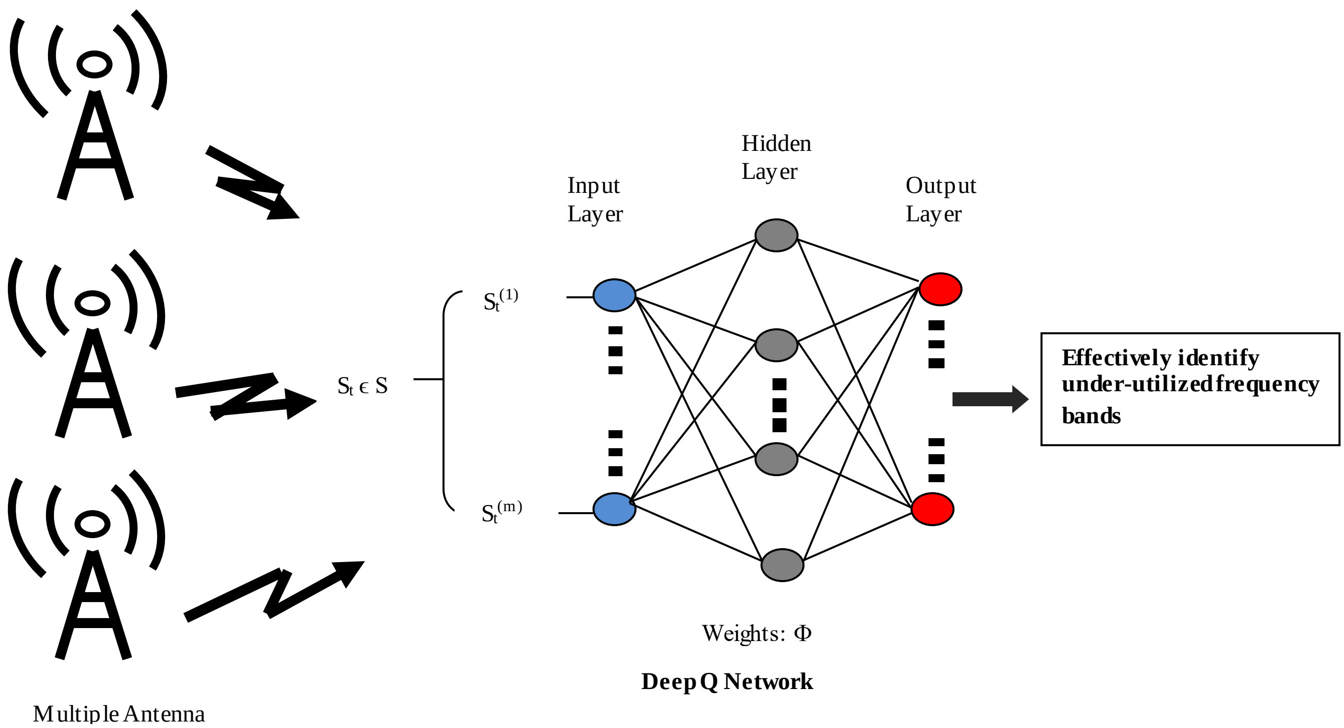


Fig. 1 Block diagram of MASSDQN

4. Proposed MASSDQN

4.1. Multiple-Antenna Spectrum Sensing Methods based on Deep Q Networks

A Deep Q Network (DQN) [18-20] is a new approach to spectrum sensing in cognitive Radio-5G networks utilizing deep reinforcement learning and multiantennas. The considered approach seeks to enhance available spectrum detection by increasing the capability of the cognitive radio to effectively identify underutilized frequency bands through MASSDQN. The use of multiple antennas provides spatial diversity, which can be used to improve the detection efficiency in the presence of fading and interference. The multiple antennas gather signal information from various locations in space, providing a better understanding of the spectrum environment. A DQN is a type of deep reinforcement learning algorithm combining deep neural networks and Q-learning. The DQN learns to make spectrum availability decisions based on Time to predict the expected reward of sensing various spectrum bands and improve its sensing approach accordingly. The combination of spatial diversity with sophisticated learning algorithms makes this approach a robust solution to spectrum management issues under dynamic and complex wireless scenarios. The block diagram of MASSDQN is represented in Figure 1.

The proposed work focuses on detecting the existence of spectrum using MASSDQN and is optimized with Particle Swarm Optimization (PSO), Jelly Fish Optimization, Single Candidate optimization, and Sand Cat Swarm Optimization to validate its accuracy as it identifies poorly utilized Frequency bands by cancelling phase noise.

4.2. MASSDQN with Jelly Fish Optimization

The Multiple-Antenna Spectrum Sensing Deep Q Network (MASSDQN) using Jellyfish Optimization (JFO) is an advanced framework that leverages the unique power of both deep reinforcement learning and bio-inspired optimization for enhanced spectrumsensing in cognitive radio networks.

DQN is designed to identify the optimal action that enhances the anticipated collective reward over time. The Q-value Function approximated by the DQN is given by

$$Q(s_{t,}a_t;\theta) = r_t + \gamma \max_{a^{l}} Q(s_{t+1},a^{l'};\theta) \qquad (7)$$

s(t) is the present state.
A (t) is the action for selecting a frequency band.
r(t) is the reward for action taken a(t)
γ is the discount factor.
θ is the parameter (weights) of the neural network.

The JFO algorithm is employed to optimize the parameters of the DQN, such as the learning rate α, discount factor γ or other aspects like antenna selection strategies. JFO is used to optimize the DQN's hyperparameters θ by minimizing the loss function.

$$L(\theta) = E\left[(r_t + \gamma \max_{a^l} Q(s_{t+1}, a^l; \theta^-) - Q(s_t, a_t; \theta))^2 \right] (8)$$

Where θ is the target network parameters.

The JFO algorithm iteratively adjusts θ to find the optimal set of parameters that minimizes this loss, thus improving the decision-making process of the DQN. Besides tuning the DQN's hyperparameters, JFO can also optimize antenna selection strategies. The selection of antennas significantly impacts the quality of the received signal and, consequently, the performance of spectrum sensing.

JFO searches for the optimal combination of antennas that Maximizes the Accuracy of Spectrum Sensing. MASSDQN provides a powerful mechanism to optimize DQN parameters and antenna selection, leading to better performance in complex environments, Enhanced Spectrum Sensing and adaptive learning.

4.2.1. Pseudo Code for MASSDQN with JFO

// Initialize CRN environment, DQN
with weight θ, if the weight of the target network $\theta^- = \theta$,
Replay memory D and Jellyfish Optimization parameters.
// FOR each time step t do
// Take action a_t, observe reward r_t and next state s_{t+1}, store transition in replay memory D
// Compute target:
// Perform gradient descent on loss:
// Update $\theta^- = \theta$ periodically
// IF (Jellyfish Optimization condition met) THEN
// Apply JFO to optimize DQN hyperparameters
// Jellyfish Optimization update rule:
// Update jellyfish positions X_{at}:
// Select new global best solution X_a_g
// END IF
// Update state $s_t = s_{t+1}$
// END FOR

4.3. MASSDQN with Single Candidate optimization

By integrating a Deep Q-Network (DQN) with Multiple-Antenna Spectrum Sensing (MASSDQN) and employing Single Candidate Optimization (SCO), the system can learn to detect spectrum holes effectively while maintaining computational efficiency.

In a system with multiple antennas, the action space can become large, making it computationally expensive to evaluate all possible actions. Single Candidate optimization addresses this by selecting only one candidate action per Antenna based on the present state and policy, significantly reducing the complexity of the problem.
The Q-value update with Single Candidate optimization is modified as,

$$Q(s_t, \bar{a}_t; \theta) \leftarrow Q(s_t, \bar{a}_t; \theta) + \alpha[r_t + \gamma Q(s_{t+1}, \bar{a}_{t+1}; \theta^-) \\ - \tau \log \pi(\bar{a}_{t+1}|s_{t+1}) - Q(s_t, \bar{a}_t; \theta) \qquad (9)$$

Where $\bar{a}_t$ is the selected single candidate action at time t, τ is the temperature parameter controlling the exploration-exploitation trade-off.

4.3.1. Pseudocode for MASSDQN with SCO

// Initialize DQN parameters Q, target network, π - initialize_policy()
// Initialize policy, e.g., softmax over Q-values
α = learning_rate
γ = discount_factor
τ = temperature_parameter
//Main training loop
For each episode in range(total_episodes):
s = reset_environment()
// Reset environment and get initial state
// Select a single candidate action using the current policy
// Perform the action in the environment and obtain a reward
// Compute the target Q-value
// Apply a gradient descent on Q-network
// Update policy π based on the new Q-values
// Update target network if required with Q-network's weights
// Move to the next state
// Exit loop on reaching terminal state

4.4. MASSDQN with Particle Swarm Optimization

The Multiple-Antenna Spectrum Sensing Deep Q Network (MASSDQN) enhances detection precision through the utilization of spatial diversity. It has the ability to learn the best sensing policies by interacting with the environment. Together with Particle Swarm Optimization (PSO), the Multiple Antenna Spectrum Sensing DQN (MASSDQN) framework supports faster convergence speed and improved detection performance through neural network weight optimization and exploration techniques. PSO optimizes the DQN's weights to improve the learning efficiency given by

$$v_i^{t+1} = w.v_i^t + c_1.r_1(pBest_i - x_i^t) + c_2r_2(gBest - x_i^t) \quad (10)$$

Where w represents inertia weight,
c_1, c_2 indicate cognitive and social coefficients,
r_1, r_2 indicate random numbers

4.4.1. Pseudocode for MASSDQN with PSO

#Initialize swarm of particles by randomly initialize position (DQN hyperparameters)
and velocity
#Initialize personal_best_position, Evaluate fitness
#Identify global_best_position = particle with highest fitness
#For iteration = 1 to max_iterations:
Update velocity, Update position, Evaluate fitness
Train final DQN model using global_best_position hyperparameters, Function
Run_DQN(hyperparams):
#Initialize DQN with given hyperparameters
Reset environment, For every process: Observe state from multiple Antennas
Select action using ε-greedy policy
Perform action & obtain reward
Store transition in replay buffer
#Sample minibatch and train DQN
#Track average sensing accuracy over episodes
#Return sensing accuracy as fitness
#End

4.5. MASSDQN with Sandcat Swarm Optimization

Combining Multiple-Antenna Spectrum Sensing with Deep Q Network (DQN) and Sand Cat Swarm Optimization (SCSO) involves using the SCSO algorithm to optimize the learning process of DQN, enhancing the decision-making for spectrum sensing. This approach can effectively address the challenges of exploration-exploitation trade-offs and enhance the sensing accuracy in cognitive radio networks. The DQN is used to model the decision-making process for spectrum sensing, and the SCSO optimizes the DQN's parameters, like weights, biases, and exploration rates. The main goal is to make the detection of available spectrum as accurate as possible by sensing it and using it efficiently without getting in the way of primary users.

SCSO is used to optimize the DQN by adjusting its parameters, such as network weights and learning rates. The optimization improves the exploration-exploitation balance by dynamically tuning the DQN's behavior based on the swarm's position updates. The fitness of each agent (solution) in SCSO is defined based on the competence of the DQN, such as minimizing the loss function:

$$Fitness(X_i) = -\sum[r + \gamma \max_{a^l} Q(s^l, a^l) - Q(s, a)]^2 \quad (11)$$

This combined approach enhances the DQN's performance in spectrum sensing by leveraging the adaptive and intelligent behavior of SCSO, resulting in more accurate and efficient spectrum sensing.

4.5.1. Pseudocode for MASSDQ with Sand Cat Swarm Optimization

// Initialize parameters for DQN and SCSO with random weights and biases, SCSO population with random positions, fitness of each agent based on DQN performance
// while not termination_condition:
for each agent i in SCSO population:
// Exploration phase: agents explore new areas else:
// Exploitation phase: agents refine solutions around the best
// Boundary handling to keep parameters within valid ranges
// Update DQN with new parameters and evaluate fitness
// Measure performance using the loss function
// Update fitness if the new parameters perform better
//Assuming higher fitness is better (maximize reward)
// Update agent's fitness
// Update global best position based on current fitness evaluations
// DQN learning process using the optimized parameters
// Perform action & obtain reward
// Use the optimized parameters from SCSO
// Update Q-value
// Update state
// Periodically update the target network
// Decay epsilon for exploration-exploitation trade-off
// End Program

5. Results and Discussion

5.1. Dataset

A 5G and LTE synthetic dataset has been created that includes phase noise consistent with the respective Bandwidths of the signals. It contains high-level information for Case A, which corresponds to urban areas, and low-level data for Case B, which is rural area information. Subcarrier spacing ranges from 15 kHz to 30 kHz, and the synchronization is derived from a single block interval duration of 40 milliseconds. LTE signal generation is on the basis of reference channels R.2, R.6, R.8, and R.9, with emphasis on downlink transmission scenarios usually encountered in urban or indoor conditions with common levels of interference. They use a unique modulation strategy called Frequency Division Duplex (FDD). Tables 1 and 2 indicate the 5G NR & LTE parameters and Phase Noise Parameters, respectively.

Table 1. 5G NR & LTE parameters

5G NR Parameter	Value	Units	LTE Parameter	Value	Units
Bandwidth	[10, 15, 20, 25, 30, 40, 50]	MHz	Reference Channel	[“R.2”,”R.6”,”R.8”,”R.9”]	-
Subcarrier spacing	[15, 30]	kHz	Bandwidth	[10, 5, 15, 20]	MHz
SSB Block pattern SSB Period	[“case A” “case B”] [20]	 ms	Duplex Mode	FDD	-

Table 2. Phase noise parameters

Channel Parameter	Value Range	Units
SNR	[0 40]	dB
Carrier Frequency	2.5	kHz

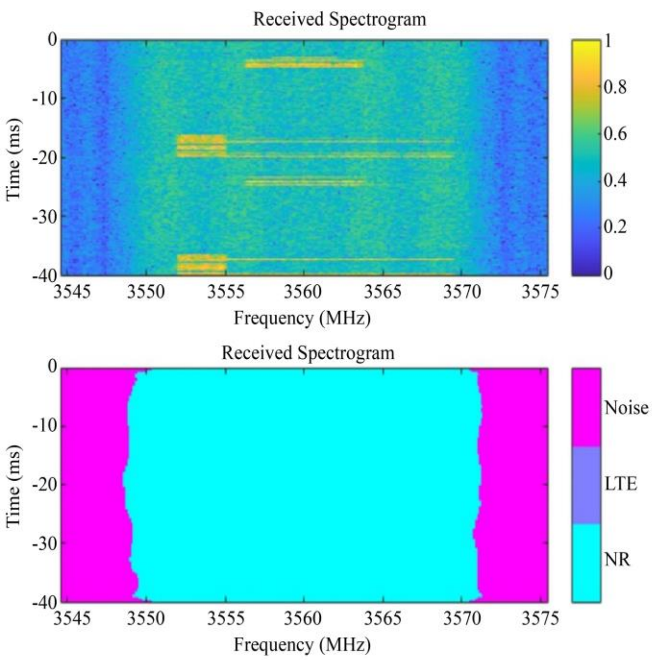


Fig. 2 Estimated signals

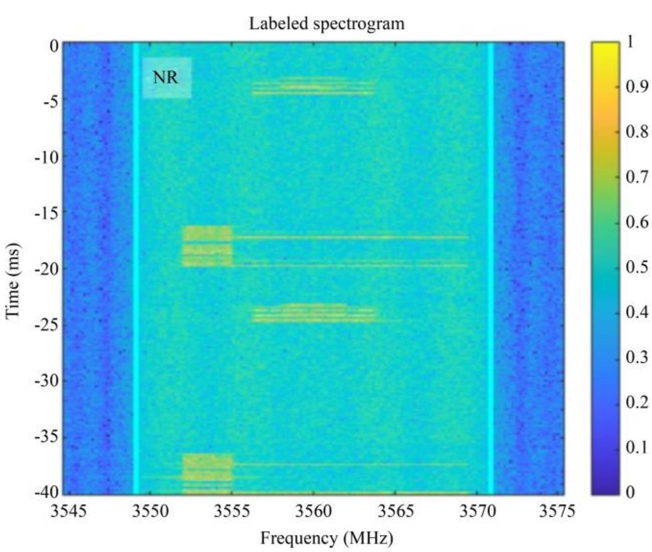


Fig. 3 Estimated NRSCO

Figure 2 shows the received spectrogram signal to estimate the presence of spectrum sensing, such as NR, LTE and Noise. The received spectrogram shows the probable presence of NR (sensed spectrum) highlighted as Yellow in colour, ranging from 0.8 to 1, for the frequency range from 3550 to 3570MHz, while the rest of the spectrum indicates phase noise. It is seen from the figure that the presence of the estimated signal for NR occupies a greater frequency range when compared with LTE and noise.

Figure 3 shows the probability of spectrum sensing for NR with respect to single cat optimization. The shades of yellow highlight the probability of sensed spectrum ranging from 0.9 to 1, for the frequency range from 3550 to 3570 MHZ.

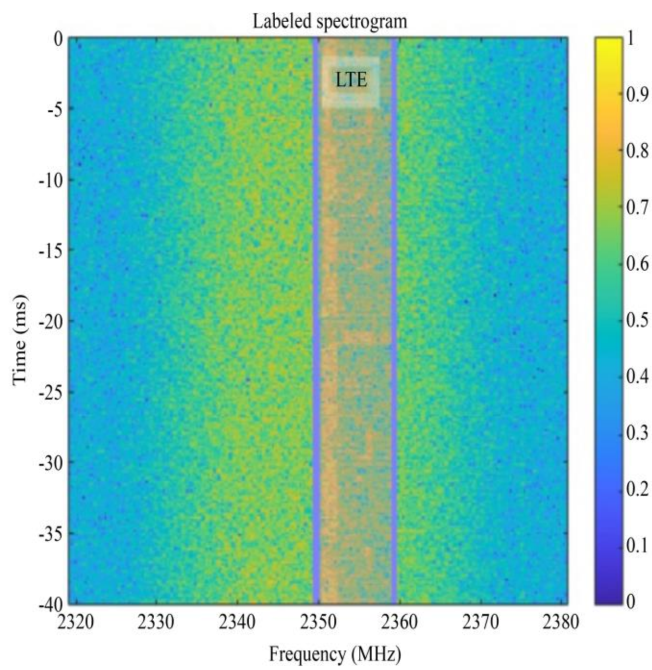


Fig. 4 Labeled spectrogram of LTE

Figure 4 shows the probability of spectrum sensing for LTE with respect to single cat optimization. The shades of yellow highlight the probability of sensed spectrum ranging from 0.8 to 0.9, for the frequency range 2350 to 2360 MHz.

Figure 5 shows the Multiple Antenna labeled spectrum sensing of NR and LTE for SCO, with a wider range of sensed spectrum for NR and a smaller Antenna range for LTE.

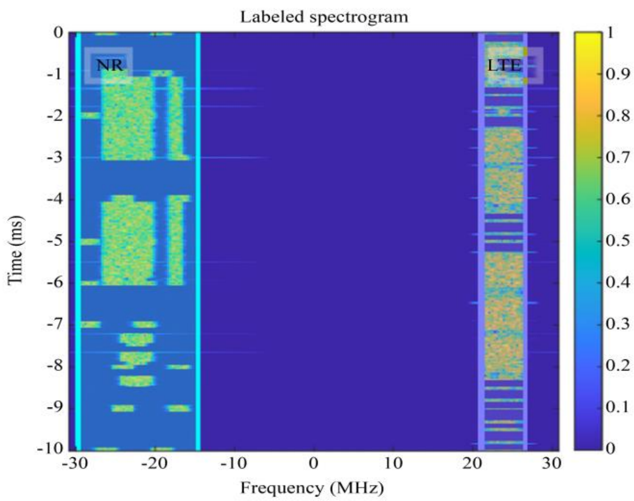


Fig. 5 Labeled spectrogram for SCO

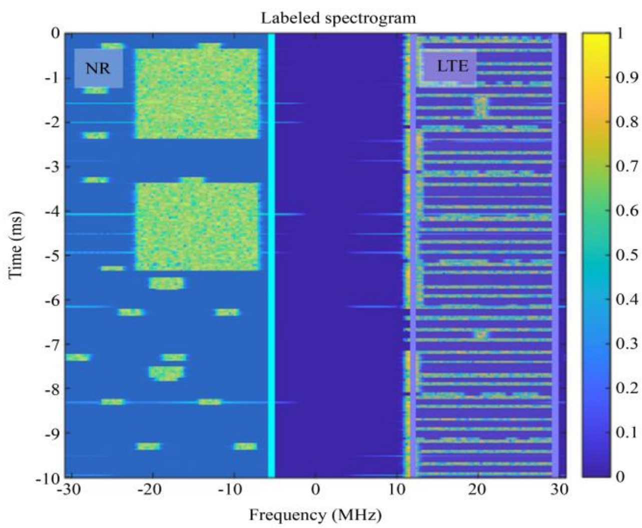


Fig. 6 Multiple antenna labeled spectrogram for SCSO

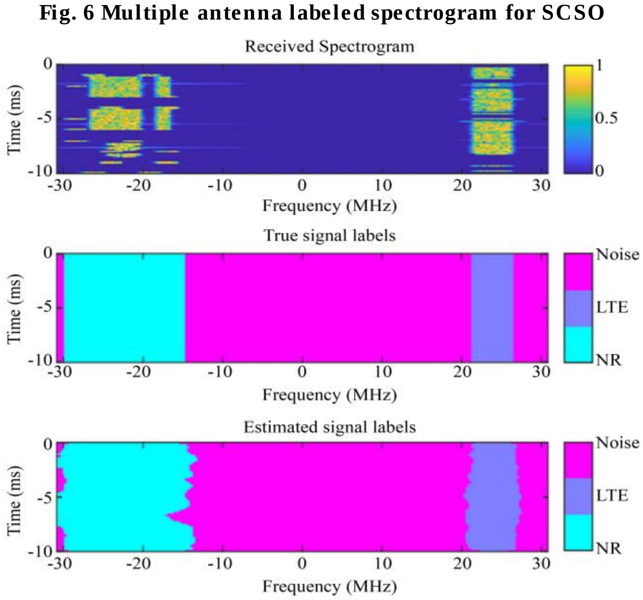


Fig. 7 MASSDQN jelly fish optimization

Figure 6 shows the Multiple Antenna Labeled Spectrogram for SCSO spectrum sensing of NR and LTE for SCSO with a wider range of sensed spectrum for NR compared with LTE.

Figure 7 shows the Multiple Antenna Labeled Spectrogram for Jelly Fish Optimization spectrum sensing of NR and LTE, with a wider range of sensed spectrum towards noise.

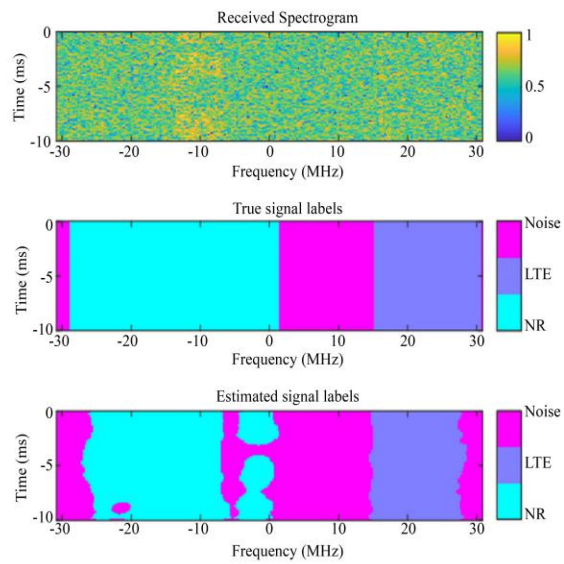


Fig. 8 MASSDQN single candidate optimization

Figure 8 shows the Multiple Antenna Labeled Spectrogram for single candidate optimatization, spectrum sensing of NR and LTE, out of which the estimated signal label of NR is higher compared with LTE and noise.

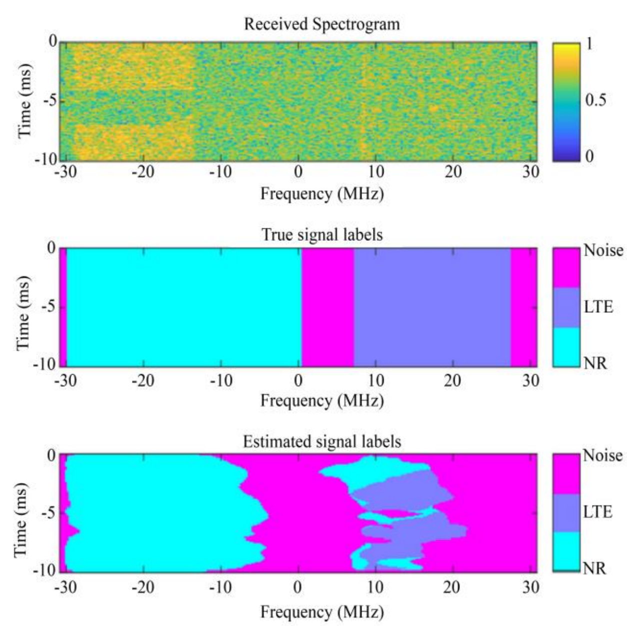


Fig. 9 MASSDQN sand cat swarm optimization

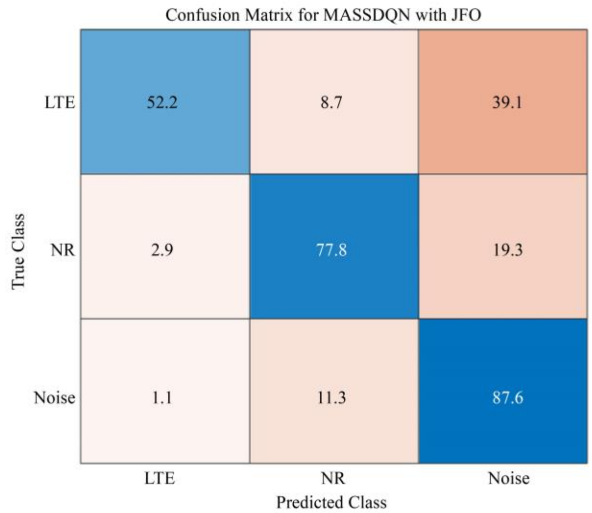


Fig. 10 Confusion matrix for MASSDQN with JFO

Figure 9 shows the Multiple Antenna Labeled Spectrogram for sandcat swarm optimatization spectrum sensing of NR and LTE, while the estimated signal label of NR shows better spectrum sensing compared with JFO and SCO.

Figure 10 shows the Confusion Matrix for MASSDQN with JFO for multiple secondary users. It is clearly absorbed that the spectrum sensing for NR is 77.8, as the detection of phase noise is 87.6 for MASSDQN with JFO. The estimated signal for the spectrum sensing with multiple antennas justifies the NR presence with a reduction in phase noise.

Figure 11 shows the Confusion Matrix for MASSDQN with SCO for multiple secondary users. It is clearly absorbed that the spectrum sensing for NR is 91.4, as the detection of phase noise is 88.6 for MASSDQN with SCO. Phase noise reduction and the anticipated signal for spectrum sensing with multiple antennas justify the inclusion of noise reduction.

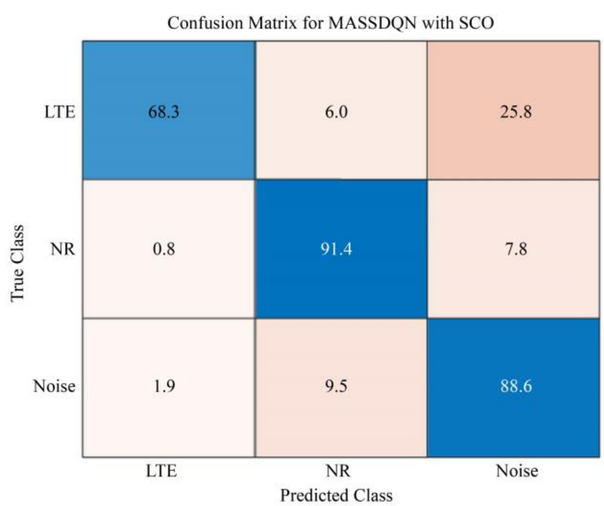


Fig. 11 Confusion matrix for MASSDQN with SCO

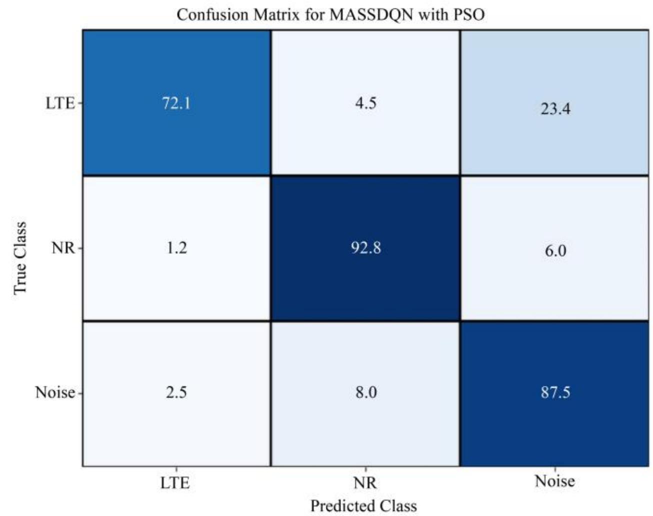


Fig. 12 Confusion matrix for MASSDQN with PSO

Figure 12 shows the Confusion Matrix for MASSDQN with PSO for multiple secondary users. It clearly shows that the spectrum sensing for NR is 92.8, as the detection of phase noise is 87.5 for MASSDQN with PSO.

Phase noise reduction and exact estimation of the anticipated signal are important for efficient spectrum sensing with multiple antennas. Adding noise reduction makes the signal clearer and improves the detection reliability.

Figure 13 shows the Confusion Matrix for MASSDQN with SCSO for multiple secondary users. It is clearly observed that the spectrum sensing for NR is 97.2, as the detection of phase noise is 88.9 for MASSDQN with SCSO.

With a decrease in phase noise, the estimated signal for spectrum sensing with multiple antennas validates the presence of NR.

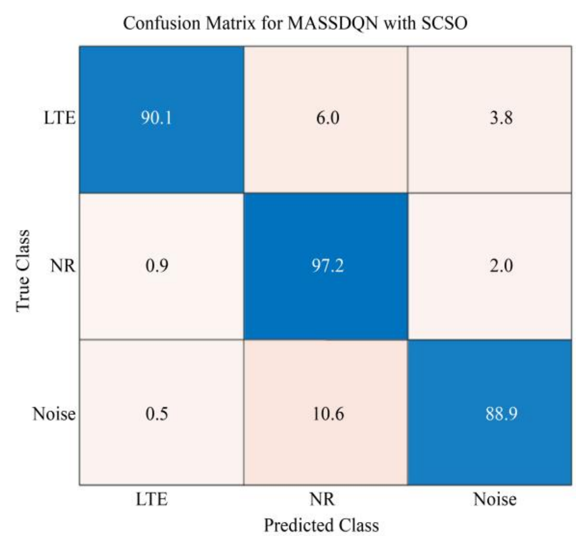
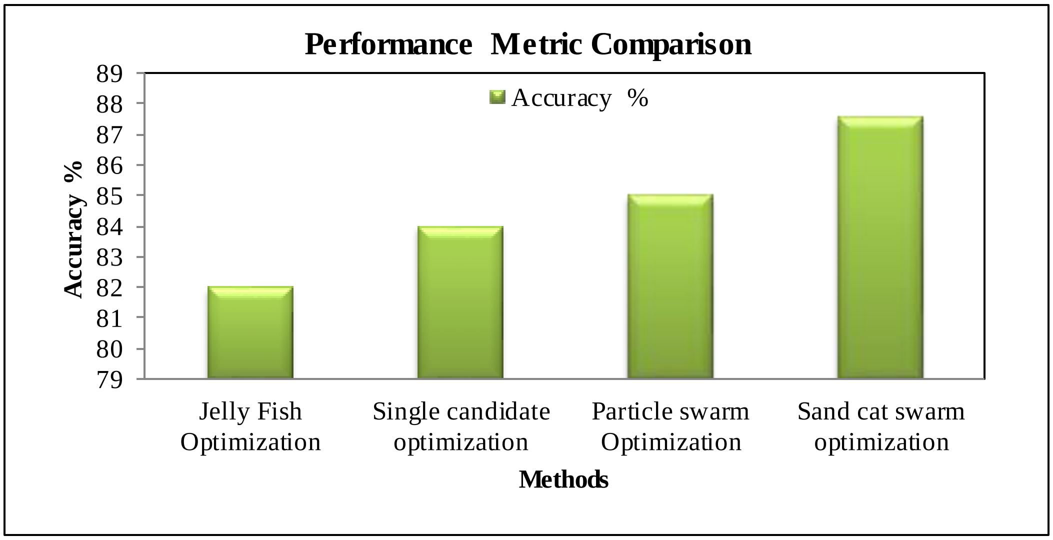
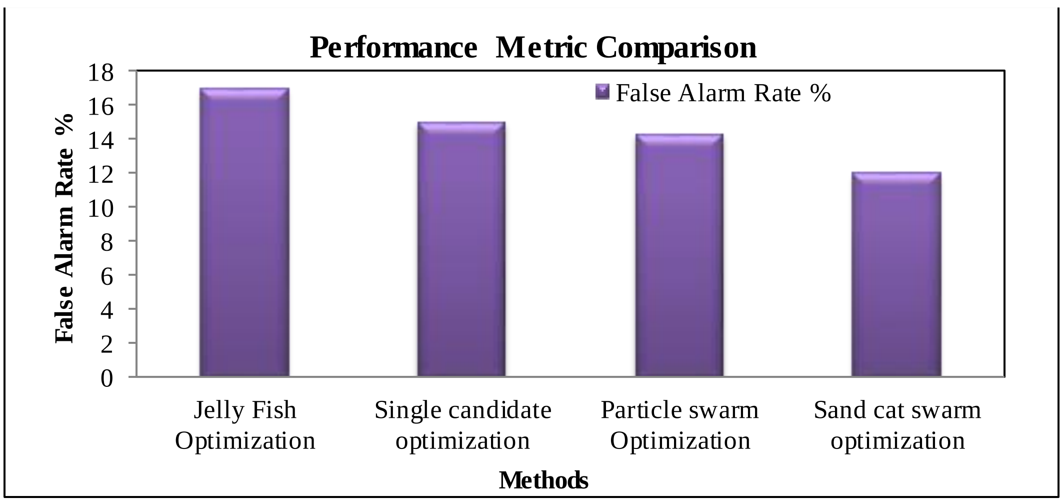


Fig. 13 Confusion matrix for MASSDQN with SCSO



(a)



(b)

Fig. 14 Optimization methods performance comparison, (a) Accuracy, and (b) False alarm rate.

Figure 14(a) shows the performance comparison with respect to accuracy and False alarm rate. The graph shows that sand cat swarm optimization achieves the highest accuracy of 87.6 % compared with particle swarm optimization 85%, single candidate optimization 84% and Jelly fish optimization 82%. Figure 14 (b) shows the false alarm rate performance comparison of four optimization methods, with sand cat swarm optimization having a lesser and effective false alarm rate than particle swarm, single candidate and jellyfish optimization methods.

Figure 15 ROC curve comparison of optimization methods. Illustrates the performance of four different optimization techniques. Among the four, Sand Cat Swarm Optimization demonstrates the highest performance with an Area Under the Curve (AUC) value of 0.91, while particle swarm optimization achieved an AUC Value of 0.89, Single Candidate Optimization follows closely with an AUC of 0.87, and Jelly Fish Optimization records a slightly lower AUC of 0.86.

Figure 16 illustrates the runtime performance of the MASSDQN framework when integrated with different optimization algorithms. Among the methods evaluated, Jelly Fish Optimization recorded an execution time of 12.5 seconds, indicating a relatively slower convergence rate. Single Candidate Optimization performed slightly better, completing its execution in 11.8 seconds.

Particle Swarm Optimization took only 10.3 seconds, while Sand Cat Swarm Optimization outperformed all others by delivering the fastest runtime of 9.6 seconds. These results highlight the impact of optimization strategy selection on the overall processing efficiency of the MASSDQN model, with Sand Cat Swarm Optimization emerging as the most time-efficient approach among the four.

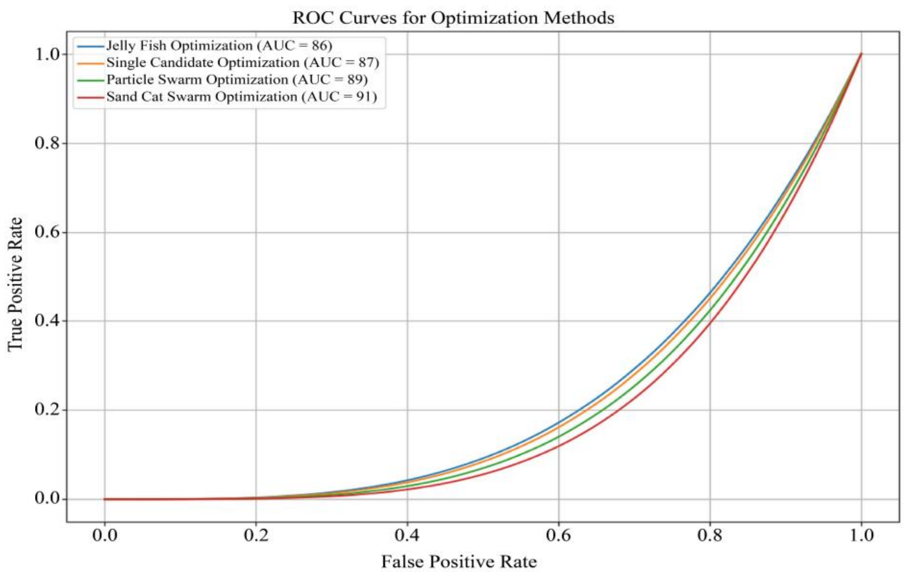


Fig. 15 ROC curve comparison of optimization methods

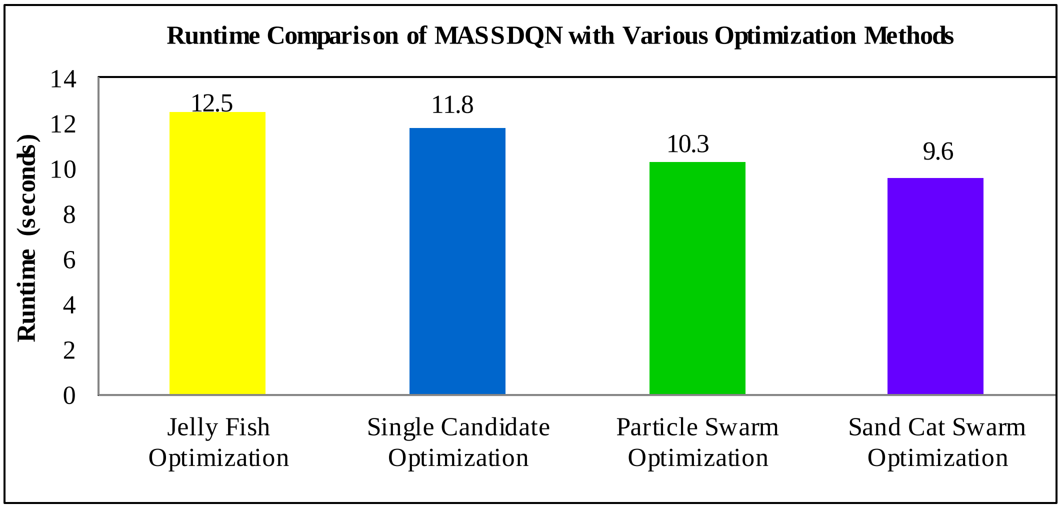


Fig. 16 Runtime comparison

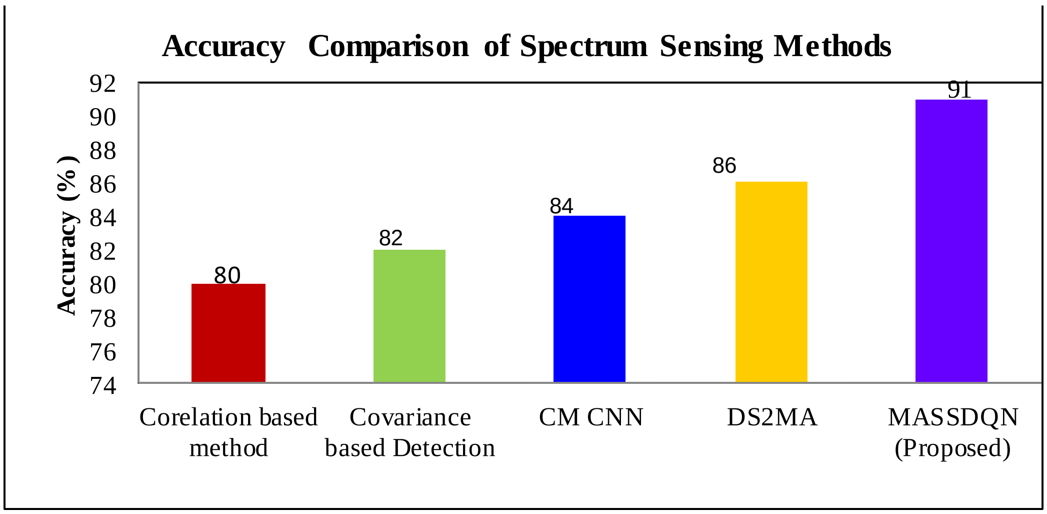


Fig. 17 Accuracy comparison of spectrum sensing methods

Figure 17 presents a comparative analysis of various spectrum sensing methods in terms of their accuracy. The Correlation-based method achieved the lowest accuracy at 80%, indicating limited effectiveness in identifying spectrum occupancy. A slight improvement is observed with Covariance-based Detection, which reached an accuracy of 82%. The performance further increases with CM-CNN, which attained 84%, followed by DS2MA with 86%, reflecting better feature extraction and learning capabilities. The proposed MASSNET-DQN method stands out by achieving the highest accuracy of 91%, demonstrating its superior ability to detect spectrum usage accurately.

6. Conclusion

The proposed work uses multiple antenna spectrum sensing with a DQN network to detect the presence of an estimated signal in LTE and 5G Networks. In cognitive radio, phase noise decreases the effectiveness of spectrum sensing. The proposed work utilizes four optimization algorithms, Jellyfish Optimization (JFO), Single Candidate Optimization (SCO), Particle Swarm Optimization (PSO) and Sand cat swarm optimization algorithms with multiple antenna spectrum sensing DQN to reduce the phase noise and enhance the spectrum sensing.

The simulated results show that sand cat optimization has better performance in phase noise reduction compared with jellyfish optimization, single candidate optimization and Particle swarm optimization. The future work may focus on reducing the effect of Additive white Gaussian noise and colored noise using multiple antenna spectrum sensing with DQN.

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