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A Spectrum Sensing and Allocation Model for Primary User Detection and Interference Mitigation in Television Whitespaces

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Abstract: Television White Space (TVWS) emerges as an encouraging solution to address the challenge of a restricted wireless communication spectrum. It denotes the frequency range spanning from 54-790 MHz and researchers have increasingly explored its propagation characteristics in recent years. Nonetheless, a notable hindrance to its effective utilization lies in the interference between primary and secondary users, as well as interference among secondary users themselves. Approaches involving spectrum sensing and resource allocation have been extensively employed independently to tackle these issues, yet they have not been integrated or utilized in combination. Hence, in this study, we formulated an architectural model that combines spectrum sensing and allocation components. This integrated model aims to detect the presence of primary users while simultaneously minimizing interference among secondary users. The spectrum sensing component utilized an energy detection model to identify primary users, mitigating interference with secondary users. Meanwhile, the spectrum allocation component employed the Particle Swarm Optimization (PSO) algorithm to determine the optimal distribution of channels among secondary users. We implemented the architectural model in a simulated TVWS network using MATLAB R2020a. Its performance was then evaluated and compared with that of matched filter and Artificial Bee Colony (ABC) algorithms, which were utilized for spectrum sensing and allocation, respectively. Based on the simulation findings, when the Signal-to-Noise Ratio (SNR) was configured at -10 dB, the detection probability for the energy detection model reached 98.23%, surpassing the matched filter's detection probability of 92.55%. With a false alarm probability of 0.51, the energy detection model exhibited a misdetection probability of 0.13%, outperforming the matched filter which had a higher misdetection probability of 2.61%. In scenarios with 10 channels and 100 secondary users, the particle swarm optimization algorithm attained a maximum throughput of 279.9 Mbps, slightly outperforming the artificial bee colony algorithm, which achieved 278.7 Mbps. In scenarios with 30 channels and 200 secondary users, the particle swarm optimization algorithm achieved throughputs of 1.575 Gbps, whereas the artificial bee colony algorithm achieved a comparable throughput of 1.571 Gbps. In the scenario where the number of channels was set to 50 and users to 300, the particle swarm optimization algorithm achieved a throughput of 3.879 Gbps, slightly surpassing the artificial bee colony algorithm, which achieved 3.864 Gbps. While the designed components consistently outperformed the matched filter and artificial bee colony algorithms across all cases, it's important to note that the model faced limitations. Specifically, it was unable to detect more than one primary user or allocate spectrum for a new incoming secondary user.

Keywords: Television Whitespace, Spectrum Sensing, Spectrum Allocation, Interference, Primary User, Secondary User

Introduction

The demand for effective utilization of bandwidth in wireless communication has increased significantly in recent times. According to a Cisco report, last updated in March 2020, It was estimated that around 5.3 billion people worldwide would be using the internet by the year 2023 (CFC, 2021; Notcker *et al*., 2023). Furthermore, it is estimated that by 2023, there will be approximately 8.7 billion personal devices capable of mobile connectivity (CFC, 2021; Notcker *et al*., 2023). As a result, there is a severe shortage of accessible radio frequencies due to this growing demand.

In response to the swift surge in wireless data consumption and to keep pace with technological progress, scientists and researchers have been actively exploring viable solutions (Notcker *et al*., 2023). TVWS stands out among the technologies discovered and being investigated in the realm of wireless communication, offering a possible remedy to lessen the impact of the spectrum shortage issue (Notcker *et al*., 2023; Mohamad and Berhad, 2018; Oluwafemi *et al*., 2021; Pineda and Hernandez, 2019; Luo *et al*., 2022). It is also referred to as spectrum holes or free space, representing unused or underutilized portions of the radio frequency spectrum that can be employed by unauthorized users for various wireless communication purposes (Ujam *et al*., 2018).

Several coexistence techniques have been devised to tackle the need for effective utilization of available space by both authorized and unauthorized users (Notcker *et al*., 2023). These methods aim to enable the harmonious sharing of spectrum resources between authorized users and unauthorized users, ensuring optimal usage for all parties involved (Adekar and Kureshi, 2019; Orumwense and Abo-Al-Ez, 2020). Nevertheless, this coexistence often results in interference problems (Ranjan *et al*., 2020).

Interference remains a substantial threat to wireless communications, leading to substantial financial implications for operators and adversely affecting the overall quality of service provided (Notcker *et al*., 2023; Politis *et al*., 2018). It poses a noteworthy challenge, impeding the efficient utilization of unused sections within TV bands and subsequently diminishing the quality of service in TVWS networks (Adekar and Kureshi, 2019; Ranjan *et al*., 2020; Politis *et al*., 2018). Indeed, effectively managing interference is essential within TVWS networks to ensure the safety of primary users while simultaneously improving the quality standards for cognitive users (Adekar and Kureshi, 2019; Ranjan *et al*., 2020; Politis *et al*., 2018).

Spectrum sensing and allocation approaches stand as common methods employed to tackle the issue of interference within TVWS networks (Mwaimu *et al*., 2022; Bani and Kulkarni, 2022). Certainly, spectrum sensing involves scanning TV bands to identify available channels suitable for use by cognitive users, aiming to prevent interference between licensed and unlicensed users (Kantikar and Yelalwar, 2018; Koçkaya and Develi, 2020). On the other hand, spectrum allocation approaches are employed to reduce the potential for interference among users in the secondary role, thus enhancing their network capacities within the network (Politis *et al*., 2018; Mwaimu *et al*., 2022; Bani and Kulkarni, 2022). Indeed, existing literature often segregates the use of these approaches, focusing on implementing spectrum sensing and spectrum allocation as separate methods rather than integrating them comprehensively (Ujam *et al*., 2018; Orumwense and Abo-Al-Ez, 2020; Politis *et al*., 2018; Mwaimu *et al*., 2022; Bani and Kulkarni, 2022; Kantikar and Yelalwar, 2018; Koçkaya and Develi, 2020; Brito *et al*., 2021; Agarwal *et al*., 2022; Liang *et al*., 2019).

Therefore, there exists a necessity for further research aimed at integrating spectrum sensing and allocation techniques. This integration would serve the dual purpose of mitigating interference among cognitive users and detecting primary users, ultimately enhancing the quality of service for cognitive users while ensuring non-interference with primary users. This holistic approach could significantly contribute to improving the effectiveness and efficiency of spectrum utilization in TV White Space (TVWS) networks. The following are our contributions:

i. Evolve the architecture of a system model for a secondary transceiver in the TVWS network
ii. Design the spectrum sensing component of the model in (*i*) for detecting a primary user signal
iii. Design an optimal spectrum allocation component of the model in (*i*) to reduce interference among secondary users
iv. Implement and incorporate the designed model in multiple transceivers within a simulated TVWS network
v. Evaluate the performance of the model within the simulated TVWS network

Ayoub *et al*. (2022) employed a detector employing an adaptive threshold-matched filter and a collaborative matched filter to detect and identify available spectrum within the TV bands. These detection methods were utilized to sense and recognize usable frequency channels in the TV White Space (TVWS) network. The authors utilized MATLAB R2020a software to simulate the suggested detectors. According to their simulation results, with an SNR of -2 dB, the detection probability was calculated to be 0.929, indicating a high likelihood of correctly identifying the available spectrum. Simultaneously, the miss detection probability was found to be 0.071, signifying a relatively low rate of failing to detect the occupied spectrum when the false alarm rate was set at 0.04.

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Patil *et al*. (2020) detailed a technique for identifying the existence of the primary signal within the channel. This method relies on analyzing the periodic statistical properties and spectral correlation of the received signal, a concept known as "cyclostationary". In accordance with the results obtained from their simulations, the likelihood of detection for SNR values ranging from -10 to 10 dB is recorded as 0.22, 0.532, 0.699, 0.657, 0.807, 0.815, 0.867, 0.951, 0.98 and 1, respectively. Concurrently, the misdetection probabilities were calculated as 0.47, 0.33, 0.29, 0.24, 0.21, 0.09, 0.09, 0.03, 0.02, and 0 for varying false alarm Probability (Pfa) values of 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9.

Dannana *et al*. (2019) utilized a matched filter detection approach to identify the primary user signal. According to their findings, at a false alarm Probability (Pfa) of 10^-2, this algorithm achieved likelihood of detection values of 0.38 for an SNR of -20 dB and 0.9 for an SNR of -15 dB. These findings indicate the efficiency of the matched filter discovery method in correctly identifying the primary user signal at varying levels of signal-to-noise ratios and false alarm probabilities.

Ranjan *et al*. (2020) delved into numerous challenging aspects of interference within the Cognitive Radio Network (CRN). Their exploration aimed to mitigate these challenges, consequently enhancing network performance and facilitating the provision of service excellent to both users. This comprehensive approach sought to address interference issues, ensuring optimal network operation and improved service delivery for all users within the cognitive radio environment.

Initially, the authors employed an interference index as a crucial parameter to reduce Co-Channel Interference (CCI) among secondary nodes within the cognitive radio network. By mitigating CCI, this approach indirectly influenced and lessened the occurrence of Adjacent Channel Interference (ACI) among the nodes operating in adjacent frequency channels. By incorporating the index of interference into the distributed greedy algorithm that is currently in use and setting limits to interference towards Primary Users (PUs) within a tolerance of less than 10 dBm, the researchers managed to optimize the capacity of the Cognitive Radio Network (CRN). As a result of these enhancements, the average capacity of the CRN increased significantly, experiencing a notable 60% improvement.

Satria and Mustika (2018) applied an updated Ant Colony Optimization (ACO) scheme to tackle the challenge of channel distribution and reduce interference among cognitive users in CRNs. The solution they suggested depended on adjusting the pheromone intensity along the paths, mimicking how ants choose channels, to decide the optimal channel allocation for secondary users. According to the outcomes of their findings, the ACO algorithm converged to a global optimum throughput of 40.56518 bits per second (bps) after the 13th iteration. This indicated the effectiveness of their approach in achieving an optimal channel allocation solution, maximizing throughput while minimizing interference among cognitive users.

Feng and Weilian (2018) used the Firefly algorithm to reduce interference among unlicensed users and increase their throughputs. They used a two-tiered binary method to depict each individual firework display. Simulation results indicated that compared to Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), the proposed Firefly algorithm demonstrated faster convergence and yielded a higher system utility, achieving 91.23 Mbps as opposed to 87.41 Mbps and 76.91 Mbps, respectively.

Agarwal *et al*. (2022) used a heightened artificial bee colony scheme to allocate various channels to unauthorized Users. According to their outcomes, the proposed method demonstrated an 11.48% increase in efficiency compared to the binary artificial bee algorithm in effectively utilizing the available spectrum. However, the performance of the proposed scheme began to degrade as the colony size exceeded 40, indicating a decrease in effectiveness with larger colony sizes. This performance degradation as the colony grows larger suggests limitations or scalability issues that could impact the algorithm's efficiency in handling larger-scale cognitive radio networks.

Materials and Methods

System Model

Figure 1 depicts the architectural model that comprises the spectrum sensing and allocation components. The spectrum sensing component intends to scan the UHF band IV with frequency ranges from 470-582 according to Nigeria National Broadcasting Commission in order to observe free channels and identify the presence of primary user signal which in this study Ogun TV signal was considered. The spectrum allocation component seeks to find the best possible distribution of free channels for unauthorized users in order to mitigate interference among themselves.

TVWS Network Model Showing Interference Scenario

Figure 2 conveys the network diagram considered in this study, with assumptions that M stands for accessible channels in such a way as $1 \leq m \leq m$ and K stands for unauthorized users in such manner as $1 \leq k \leq k$. 2. Presumably, the TV receiver is tuned to channel j and its operational frequency is f_o. Furthermore, it is assumed that the primary user is located in a protection region where the transmission power from secondary users cannot interfere with it (Notcker *et al*., 2023). Secondary users are assumed to communicate via an access point in an ad hoc network topology. Unauthorized users are assigned channels in a matrix format through a random allocation process, where an amount to the channel allotment matrix with a certain dimension $K \times M$ and is represented as $A = \{a_{k,m} \in (0,1)\}$ (Notcker *et al*., 2023). If $a_{k,m} = 1$, expresses the occupation of user k within channel m, if not $a_{k,m} = 0$ (Notcker *et al*., 2023; Mishra *et al*., 2019a).

Energy Detection-Spectrum Sensing Component for Primary User Identification

Sensing of spectrum enables cognitive users to find the spectrum holes and protect licensed users against interference (Chaudhari, 2018). The mathematical description of spectrum sensing is given by the Eq. (1) (Koçkaya and Develi, 2020):

$$r[n] = \begin{cases} z[n] & H_0 \\ s[n] + z[n] & H_1 \end{cases} \tag{1}$$

where, $r(n)$ is the received signal at SU, $s(n)$ is the authorized user signal and $z(n)$ is the Additive White Gaussian Noise (AWGN), H_1 and H_0 are the two hypotheses that stand for the presence and lack of an authorized user signal, respectively (Notcker *et al*., 2023).

The energy detection approach was adopted in this study as a spectrum sensing component to identify the existence of licensed user signal due to its simplicity (Pineda and Hernandez, 2019; Dannana *et al*., 2019; Feng and Weilian, 2018; Mishra *et al*., 2019b; Chaudhari, 2018; Wan *et al*., 2019; Rabie Mohamed *et al*., 2021). It calculates the test statistics of the received signal as shown in Eq. (2) and compares it with the detection threshold which is determined by Eq. (3) to determine whether a major user signal is present or not (Anumandla *et al*., 2021; Ramírez *et al*., 2018; Lorincz *et al*., 2021; Arjoune *et al*, 2018):

$$T(r) = \sum_{n=1}^{N} |r(n)|^2 \tag{2}$$

$$\lambda = \sigma_w{}^2 \left(Q^{-1}(P_{fa})(\sqrt{2N} + N) \right) \tag{3}$$

where, $T(r)$ is the test statistics of the received signal, N represents detection samples, P_{fa} denotes false alarm probability, $\sigma^2{}_w$ denotes noise variance of AWGN, and $r(n)$ represents the received signal. $Q(.)$ and Q^{-1} (.) are the Q-function and its inverse respectively (Luo *et al*., 2022). The Q-function serves as the tail distribution function for the standard normal distribution, as defined in the following Eq. (4) (Arjoune *et al*., 2018):

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} exp(-\frac{t^2}{2}) \tag{4}$$

Equation 2, the presence of a principal user signal is indicated if the test statistics value is larger than the detection threshold, otherwise is absent (Luo *et al*., 2022).

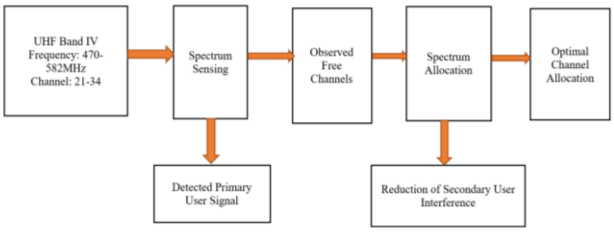

Fig. 1: Model architecture for spectrum sensing and allocation

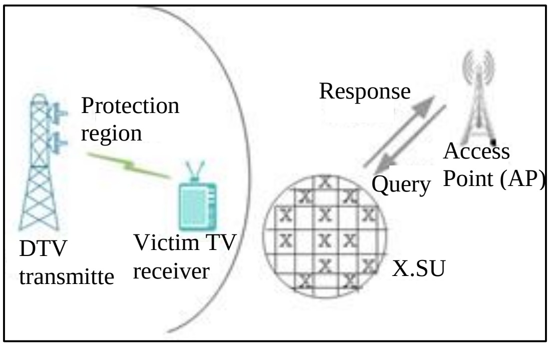

Fig. 2: Interference scenario (Mwaimu *et al*., 2022)

$$\begin{cases} T > \lambda\, H_1 \\ T < \lambda\, H_0 \end{cases} \tag{5}$$

Figure 3 illustrates the diagram showing the energy detection flow algorithm. The steps of the process are explained:

Step 1: Initialization of Input Parameters: Such as AWGN variance, False alarm probabilities, Ogun TV Centre Frequency, Ogun TV Transmit Power, Signal Noise Ratios, and Ogun TV Channel Number
Step 2: Selecting of the band: In this case, UHF (474-582 MHz) with a bandwidth of 8MHz is considered
Step 3: Take Fast Fourier Transform: In this case received signal is converted to frequency domain
Step 4: Compute Test Statistics: The energy of the received signal is computed in order to be compared with the detection threshold
Step 5: Determine Detection Threshold
Step 6: Compare the results of Steps 4 and 5
Step 7: End

Spectrum Allocation Optimization Using Particle Swarm Algorithm

Optimization of spectrum is one of the major targets of this study with the goal of lowering secondary user interference and maximizing system throughput. The spectrum allocation optimization issue can be expressed as follows:

$$U(R) = max \sum_{k=1}^{K} \sum_{m=1}^{M} a_{k,m} \times b_{k,m} \quad (6)$$

$$\text{s.t } \forall 1 \le n, k \le K, 1 \le m \le M$$

$$a_{n,m} + a_{k,m} \le 1, If\ C_{n,k,m} = 1$$

$$A = \{a_{k,m}\}_{N \times K}$$

$$C = \{c_{k,m}\}_{N \times K}$$

$$L = \{l_{k,m}\}_{N \times K}$$

where, K and M are a number of secondary users and channels respectively:

$U(R)$ = The object function aims to maximize system capacity
$a_{k,m}$ = The interference-free allocation matrix utilized for channel assignment to several users. When $a_{k,m} = 1$, shows whether user k is using channel m, if not $a_{k,m} = 0$ (Notcker *et al*., 2023)
$c_{k,m}$ = Interference constraints matrix which indicates the possibility of interference when user n and k cohabit in one channel (m)
$l_{k,m}$ = Channel availability matrix which indicates the accessibility of free spectrum for secondary users. If $l_{k,m} = 1$, user k accesses channel m without interfering with primary users, otherwise $l_{k,m} = 0$ (Notcker *et al*., 2023)
$b_{k,m}$ = A channel reward matrix that signifies the benefits user k can attain by utilizing channel m, under the presumption of the absence of interference from adjacent users

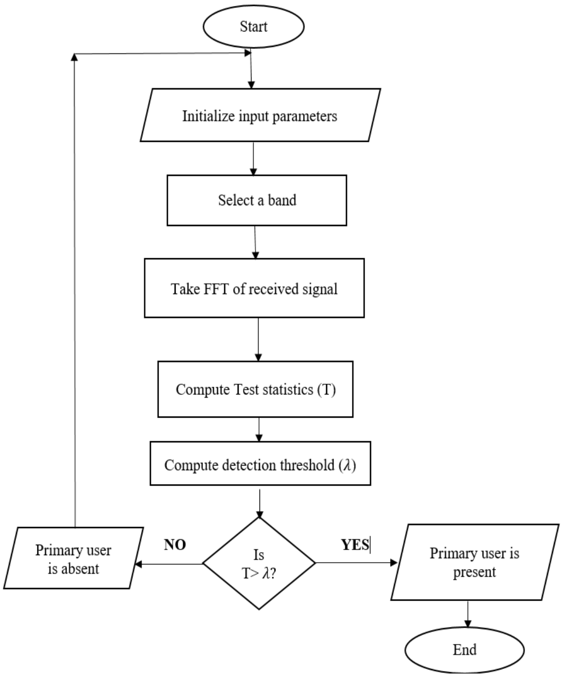

Fig. 3: Energy detection algorithm flow chart

A particle swarm optimization algorithm was adopted in this study to address the optimization problem formulated in Eq. (6). It is widely recognized in the literature for its popularity owing to several advantages. These include ease of implementation and robustness (Koçkaya and Develi, 2020; Toma *et al*., 2019; Carrick, 2018; Garg and Saluja, 2018; Wang *et al*., 2018; Gul *et al*., 2020; Zhao and Zhou, 2022; Latif *et al*., 2021).

The following are the PSO steps:

Step 1: Start
Step 2: Define fitness function $U(R)$ as in Eq. (6)
Step 3: Initialise matrices A, B, C, L, number of channels (M), number of cognitive users (K), and *PSO* parameters (c_1, c_2, and w)
Step 4: Get all particles that have the best answers for the individual matrix ($pbest_{i,j}$), latest solution matrix ($currentsol_{i,j}$), matrix of global solutions ($gbest_{i,j}$), as well as a velocity matrix ($Vel_{i,j}$) to zeros where $0 \le i \le K$ and $0 \le j \le M$
Step 5: For (t < max number of iteration) (assign a j^{th} element to L where $1 < j < L$ for all particles. Then, for all m find all (n, k) that meets $C_{n,k,m} = 1$ and observe if $a_{k,m} = a_{n,m} = 1$, next arbitrarily set one of them to 0
Step 6: Establish the particle positions by utilizing the objective function $U(R)$
Step 7: Revise the state of a particle if its present position proves superior to its prior best position. Stabilize the optimal particle by considering its past best positions
Step 8: Update the speeds of the particles and move the particles to their new places as shown in Eqs. (7-8) respectively
Step 9: Find the best solution, then stop

$$V_i^{t+1} = wV_i^t + c_1r_1(P_i^t - X_i^t) + c_2r_2(G^t - X_i^t) \quad (7)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (8)$$

Where by:

X_i^{t+1} = Updated position
X_i^t = Current position
V_i^{t+1} = Updated velocity
V_i^t = Current velocity
P_i^t = Local best
G^t = Global best
w = The weight of inertia
c_1 and c_2 = Constants of acceleration
r_1 and r_2 = Arbitrary numbers

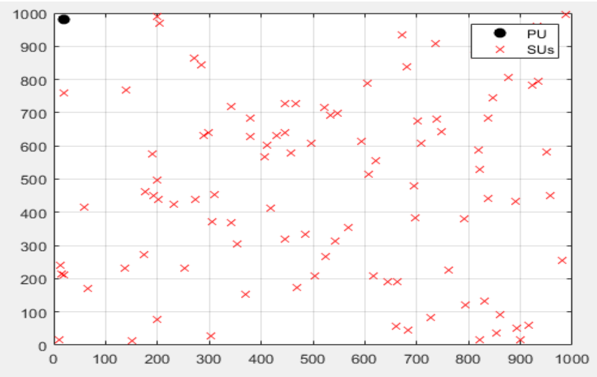

Fig. 4: Demonstration of random allocation of 10 channels to 100 secondary users within a 1000 m-by-1000 m area

TVWS Network Simulation

The simulation of the Cognitive TVWS Network was carried out in MATLAB R2020a. Fig. 4 shows the illustration of 10 channels randomly assigned to 100 secondary users and one primary user to be detected. The free-space path loss model was used to simulate the path loss, as stated in Eq. (9):

$$PL(d) = 20\log d + 20\log f - 147.55 \quad (9)$$

where, d is the distance in meters and f is the operating frequency.

Spectrum Sensing Simulation Parameters

Several parameters were used to simulate the energy detection algorithm such as AWGN variance which is set to 1 dB, Ogun TV Centre Frequency is set to 503.23 MHz, Ogun TV Transmit Power set to 35 KW, Ogun TV Channel number set to 25, bandwidth of TV channel is set to 8 MHz, SNR to -25 to 0 dB, false alarm probabilities to 0.1-1, as summarized in Table 1.

Spectrum Allocation Setup Parameters for Simulation

The parameters employed in the simulation for PSO are summarized in Table 2. The number of secondary users is set to 100, 200, and 300, while the number of channels is set to 10, 30, and 50.8 MHz television bandwidth as assigned by Nigeria National Broadcasting Commission to Ogun State. The Ogun TV center frequency and transmit power are set to 503.25 MHz and 35 KW as seen in Oluwafemi *et al*. (2021). The maximum transmitting power for secondary users is set to 4 W (30 dBm) as indicated by the Nigeria Communication Commission.

Table 1: Experimental parameters for the energy detection algorithm

Parameters	Values
AWGN variance	1 dB
Ogun TV center frequency	503.23 MHz
Ogun TV transmits power	35 KW
Ogun TV channel number	25
Signal-to-noise ratios	-25 to 0 dB
False alarm probability	0-1
Number of iterations	1000
FFT samples	1024
Bandwidth of TV channel	8 MHz

Table 2: Parameters of the particle swarm optimization algorithm experiment

Parameters	Values
Bandwidth of TV channel	8 MHz
Ogun TV center frequency	503.23 MHz
Ogun TV transmits power	35 KW
Ogun TV channel number	25
Number of Ogun state TVWS Channels	10, 30, 50
Maximum transmit power of secondary users	30 dBm (1 W)
Number of secondary users	100, 200, 300
Acceleration constants ($c_1 = c_2$)	2
Inertia weight (w)	1
Maximum iteration	1000
Population size	50
Number of primary users (Ogun TV transmitter)	1

Results and Discussion

This section presents the simulation results for the created architectural model that combines spectrum allocation with sensing. MATLAB R2020a was used to implement the model on a simulated TVWS network. The spectrum sensing component designed based on energy detection was compared with the matched filter algorithm whereas the spectrum allocation component based on PSO was compared by the ABC algorithm. The metrics used to assess the effectiveness of the spectrum sensing component include the likelihood of detection, false alarm likelihood, Signal Noise Ratio (SNR), and misdetection likelihood while sum throughput is used for the spectrum allocation component of the model.

Signal to Noise Ratio

To evaluate the effectiveness of the energy detection algorithm, we run several simulations by varying SNR. Fig. 5 shows the results of our analysis, where in all cases, the energy detector outperforms the matched filter algorithm. For instance, when the value of SNR was set to -25 dB, the likelihood of detection for the energy detector was 0.2146 while for the matched filter was 0.061. When SNR was set to -20 dB, the detection likelihood for the energy detector was 0.2737 while for the matched filter was 0.0983. At SNR equals -15, -10, -5, and 0 dB, the values of energy detection and matched filter detection were 0.5485, 0.9823, 1,1, 0.2676,0.9255, and 1,1 respectively. Table 3 summarizes these results. From our observations, the energy detector performs better as the values of SNR increase while as the values of SNR decrease, its performance degrades.

Table 3: Detection probability with different values of SNR

SNR (dB)	Probability of detection Matched filter detection	Developed energy detection
-25	0.0610	0.2146
-20	0.0983	0.2737
-15	0.2676	0.5485
-10	0.9255	0.9823
-5	1.0000	1.0000
0	1.0000	1.0000

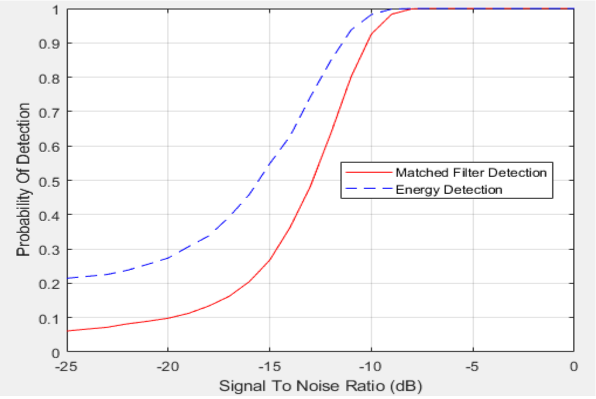

Fig. 5: Signal-to-noise ratio Vs detection probability

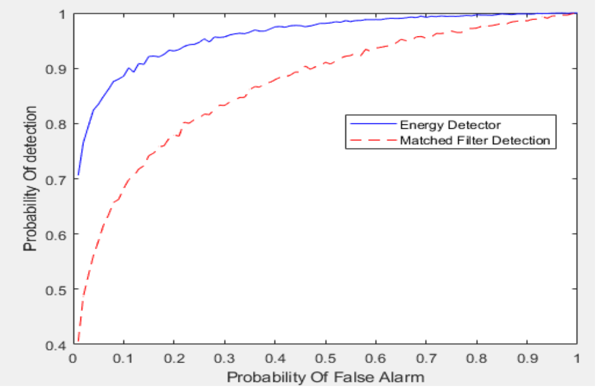

Fig. 6: False alarm probability Vs detection probability

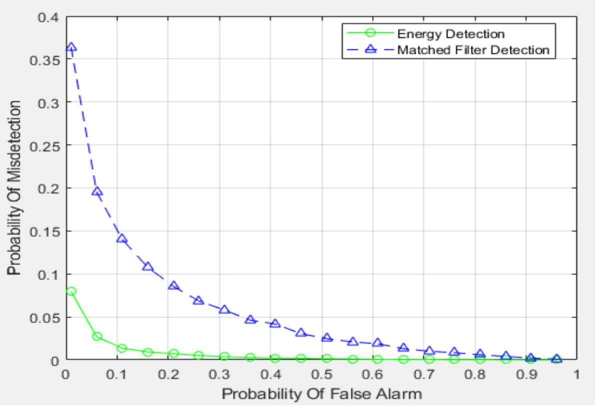

Fig. 7: False alarm probability Vs misdetection probability

Table 4: Likelihood of detection with fluctuation in the likelihood of false alarms

False alarm probability	Probability of detection Matched filter algorithm	Developed energy detection algorithm
0.1	0.6738	0.8841
0.2	0.7802	0.9345
0.3	0.8369	0.9590
0.4	0.8748	0.9685
0.5	0.9073	0.9808
0.6	0.9348	0.9873
0.7	0.9575	0.9932
0.8	0.9739	0.9960
0.9	0.9864	1.0000
1.0	1.0000	1.0000

Table 5: Probabilities of misdetection with variations in false alarm probability

False Alarm Probability	Misdetection probability Developed Energy Detection %	Matched Filter Detection %
0.01	7.6400	36.310
0.21	0.7400	8.723
0.36	0.2825	4.535
0.51	0.1300	2.610

Detection Probability

In this experiment, we tested the ability of an energy detector to get the signal of the authorized user when the user is present. Figure 6 shows the results of our experiments and it entails that as false alarm probability increases the model performs better and gives more accuracy in detecting the primary user than a matched filter. For instance, when the false alarm probability was set from 0.1 to 1 the values of detection probability for the energy detection algorithm were 0.8841, 0.9345,0.959, 0.9685, 0.9808, 0.9873, 0.9932, 0.996, 1 and 1 respectively. While at the same values of false alarm probabilities, the values of detection probability for the matched filter were 0.6738, 0.7802, 0.8369, 0.8748, 0.9073, 0.9348, 0.9575, 0.9737, 0.9864 and 1 respectively. However, when the value of false alarm probability is one, all algorithms achieve one hundred percent accuracy. Table 4 summarizes the results of the experiments.

Misdetection Probability

The developed energy detector model was also tested on its ability to miss the signal when the signal is present. In all scenarios, it performs better than matched filter as indicated in Fig. 7. For instance, when false alarm probabilities were set to 0.01, 0.21, 0.36, and 0.51, the misdetection probabilities of energy detection were 7.641, 0.74, 0.2825 and 0.13% respectively, while at the same values of false alarm probabilities, the misdetection probabilities for matched filter were 36.31, 8.723, 4.535 and 2.61% respectively. This shows that the energy detection model has less miss detection percentage than a matched filter. Table 5 summarizes the results of the experiment.

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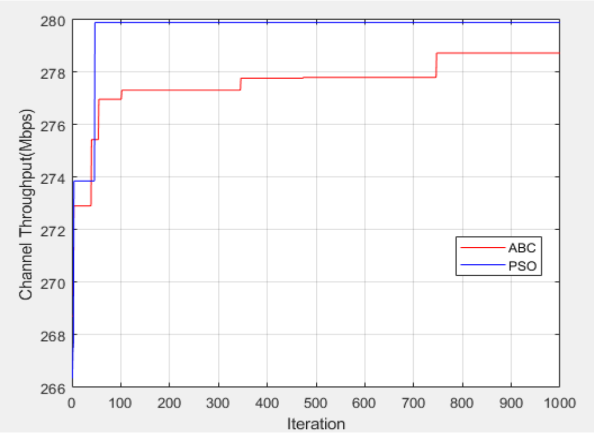

Fig. 8: Sum throughput when SUs = 100, Channels = 10

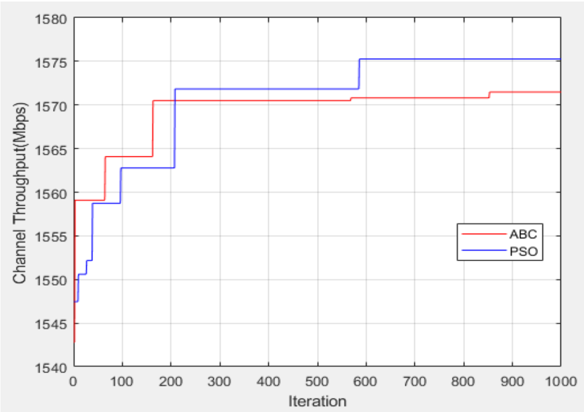

Fig. 9: Sum throughput when SUs = 200, Channels = 30

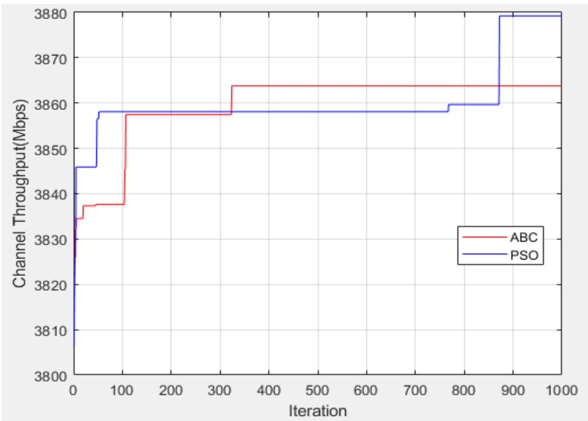

Fig. 10: Sum throughput when SUs = 300, Channels = 50

Sum Throughput

To analyze the effectiveness of the model in allocating channels to secondary users and reducing interference, different scenarios have been considered and simulated in MATLAB R2020a. We also made the assumption that there is no incoming new secondary user during the allocation of available users. In the first scenario, ten number of channels and one hundred users were considered. Figure 8 indicates the simulation results obtained where the maximum throughput for PSO was 279.9 Mbps while for ABC was 278.7 Mbps. From the experiment, PSO outperforms ABC in most iterations and enhances channel throughput. These results prove the reduction of interference as supported by the Shannon channel capacity theorem revealing that when interference is reduced the channel capacity increases. In the second scenario, thirty channels and two hundred secondary users were considered. Figure 9 shows the results of the simulation, where the PSO attains the maximum throughput of 1.575 Gbps while ABC achieved 1.571 Gbps. From the experiments, we observed that below two hundred iterations ABC performs better than PSO, but above two hundred iterations, PSO outperforms ABC. In the third scenario, we considered fifty channels and three hundred users. Figure 10 indicates the results obtained, where by PSO achieves maximum throughput of 3.879 Gbps while ABC achieved 3.864 Gbps. From the experiment, the PSO seems to perform better when the number of iterations is beyond nine hundred otherwise its performance degrades below it compared to ABC.

Conclusion

Due to the rapid deployment of a huge number of users in TV bands, accurate detection of authorized users and minimization of interference among unauthorized users are crucial, highlighting the significance of spectrum sensing and allocation.

To achieve this objective, we devised an architectural model that seamlessly combines spectrum sensing and allocation. The spectrum sensing component, employing an energy detector, was implemented to discern the presence of authorized users, mitigating interference with unauthorized users. Simultaneously, the spectrum allocation component, utilizing particle swarm optimization, was employed to minimize interference among unauthorized users.

Numerous simulation experiments were carried out in the MATLAB R2020a environment. Across all scenarios studied, the designed energy detection outperforms the matched filter, as well as PSO to ABC. However, the designed model was limited to detecting only one primary user and was not capable of allocating channels for a new incoming secondary user. Additionally, as part of future work, we propose extending the designed components to a real-world proof of concept. This extension aims to evaluate their effectiveness in actual scenarios, providing a more practical assessment beyond simulation environments. Moreover, when there is sufficient data, it is also recommended to employ machine learning techniques in order to improve detection accuracy, enhance allocation of channels for secondary users in real networks, and reduce computation complexity as the number of users increases.

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Author's Contributions

Joachim Notcker: Conducted all experiments, coordinated the data analysis, and contributed to the writing of the manuscript.

Emmanuel Adetiba: Suggested the title of the work and reviewed the manuscript for clarity and accuracy.

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Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and that no ethical issues are involved.

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