: OPTIMAL DETECTION TECHNIQUE FOR PRIMARY USER EMULATOR IN COGNITIVE RADIO NETWORK

Grace Olaleru¹
Department of Electrical and Electronics
Engineering, Federal University of
Technology, Minna,
Minna, Nigeria.

Umar Suleiman Dauda⁴
Department of Electrical and Electronics
Engineering, Federal University of
Technology, Minna,
Minna, Nigeria.

Henry Ohize²
Department of Electrical and Electronics
Engineering, Federal University of
Technology, Minna,
Minna, Nigeria.

Abubakar Saddiq Mohammed³
Department of Telecommunications
Engineering, Federal University of
Technology, Minna,
Minna, Nigeria.

Abstract—The primary user emulation attack (PUEA) is one of the most common attacks affecting the physical layer of the cognitive radio network (CRN). In this attack, a malicious user or a selfish user mimics the signal characteristics of the primary user (PU) to deceive the legitimate secondary user (SU) causing it to leave the available channel while the real PU is absent hence, detecting this attacker is vital in building a real CRN. In this paper, the PUEA is detected based on the Time difference of Arrival (TDOA) localization technique using the particle swarm optimization (PSO), novel bat algorithm (NBA), and the modified particle swarm optimization (MPSO) to minimize the localization error from the TDOA measurement and comparison is made among the three algorithms in term of the localization accuracy, convergence rate, computation time via simulation using the MATLAB simulation tool by running the monte Carlo 1000 times. The performance of the techniques was evaluated using the mean square error (MSE) and cumulative distribution function (CDF) and the MPSO algorithm out-performed the PSO and the NBA

Keywords— Cognitive Radio Network, Primary User Emulation Attack, Time Difference of Arrival (TDOA), Modified Particle Swarm Optimization (MPSO), Novel Bat Algorithm (NBA), Particle Swarm Optimization (PSO).

I. INTRODUCTION

The cognitive radio (CR) technology helps in alleviating the spectrum scarcity problem faced by wireless networks by allowing for the opportunistic use of the spectrum holes in the licensed band by the unlicensed users thus, enhancing better spectrum utilization [1-3]. However, this promising technology is faced with some security challenges one of which is the primary user emulation attack (PUEA) where a malicious or selfish user mimics the primary user (PU) signal characteristics to deceive the secondary users (SUs) to leave the channel while the real PU is absent [4]. This attacker aims at causing a denial of service to the legitimate SUs, degradation of the quality of service, bandwidth wastage, and possibly degrade the practical implementation of the CR technology [5] therefore, this attacker must be detected and eliminated from the CR network.

In this paper, we developed an optimal technique for detecting and localizing the PUEA in the IEEE 802.22 networks. The IEEE 802.22 is the first worldwide effort to define a standardized air interface based on the CR techniques to allow the utilization of the white spaces in the TV channel and exploit them to

provide wireless broadband access to rural areas on an interference-free basis [6, 7]. The technique is capable of detecting the PUEA at any location within the CRN communication range. The system model comprises the PU network which is a TV tower with two TV receivers at fixed positions, an SU network that comprises the CR base station, and a set of randomly distributed SUs at fixed positions. The PUEA is detected and localized based on the TDOA localization technique. Each SU makes spectrum sensing and sends its recorded measurements to the CR base station, which collects the measurements, and applies the cross-correlation method to extract the TDOA values. The MPSO, PSO, and NBA algorithms are then used to minimize the cost function error provided from the TDOA measurements and provide an accurate estimation of the unknown transmitter position which can be a PU (TV tower) or an attacker with reduced computation time and localization inaccuracy.

These algorithms are based on solving the unconstrained optimization minimization localization problem. It also adapts to CRN network expansion and solves this complex localization problem and finds the optimal solution. Lastly, the localization accuracy and the convergence rate of the three algorithms are compared to find the optimal technique for PUEA detection. This paper aims at contributing the following:

- Localization of the PUE in the IEEE 802.22 CRN based on the TDOA localization technique.
- Minimization of the localization error from the TDOA measurement using the PSO, NBA, and MPSO algorithms.
- Reduction of the computational complexity and the spectrum sensing time using the MPSO algorithm.
- Defense against the PUEA by comparing the position of the PUE with the known SUs positions to know which SU is performing the emulation so it can be eliminated for the network.
- Comparison to know the optimal schemes between the PSO, NBA, and the MPSO algorithms in terms of their localization accuracy, convergence speed, and computational time.

The rest of this paper is organized as follows: a brief review of the related works is presented in section II, followed by the Problem formulation and system model in section III, in section IV we presented the mathematical model for detecting the PUEA, followed by a discussion of the optimization algorithms used for minimizing the localization error in section V, section VI summarizes the detection procedure for the PUEA detection and the performance metrics used for evaluation, in section VII,

the results and discussion of the results are presented and finally, the conclusion is drawn in section VIII.

II. REVIEW OF RELATED WORKS

The localization of unknown transmitters has been intensely discussed in the research field. The localization techniques can be classified into two major categories [8] these are the range-free and range-based techniques. The range-free techniques have the advantage of less complexity, effective cost, and less computational time however, they are less accurate. On the other hand, the range-based techniques are more complex, takes longer time to compute, more costly but are highly accurate [9].

In detecting the PUE in CRNs, localization accuracy is very keen. Therefore, most researchers have employed the rangebased techniques for detecting the PUE in CRNs. The rangebased techniques rely on angle and distance as the main parameters for localizing a node [10]. These techniques include [9, 11, 12], the received signal strength (RSS), time of arrival (TOA), angle of arrival (AOA), and time difference of arrival (TDOA). In the RSS technique, the received signal (RS) is measured and then by using an appropriate path loss, these measurements are transformed into distances. The RSS method is easy to implement as it does not require additional hardware [13], however, it can only be effective when the network size is small that is, less than 2 km. Also, they are susceptible to high errors due to indoor/outdoor environments. Furthermore, it requires hundreds to thousands of cooperating stations and the cooperation among a large number of users is unpredictable [14]. In the AOA technique, the position is calculated by estimating the angle of arrival of a signal at the receiver without having prior knowledge of the distance separating the transmitter from the receiver [10]. This method is dramatically affected by the multipath effect and it also requires antenna arrays at the receiver. The TOA method localizes the attacker with the aid of velocity and time that radio signal transverses between the transmitted and received times of a signal [13, 15]. The TOA technique is very accurate however, synchronization is required at both the source and the receivers this implies a high hardware cost. Besides, line of sight (LoS) is assumed between the source and the receivers [16]. The TDOA is a modification of the TOA, it makes use of the difference in time of arrival of a signal at multiple receivers [17, 18]. TDOA takes advantage of the crosscorrelation to measure the difference in the TOA of a transmitted signal at two or more pairs of nodes. It requires a minimum of three nodes to locate a transmitter in a two-dimensional (2-D) space [19]. The three nodes give 2 TDoA measurements. The TDOA localization technique has the highest form of accuracy in localizing a source signal [20]. As compared to the TOA, the TDOA is less expensive because time synchronization is not required at the source. Furthermore, it can be used to localize a source signal over a long communication range such as in the IEEE 802.22 network [6, 17]. However, the TDoA measurements are corrupted with Gaussian error due to the environmental considerations thus the estimation of the PUE in CRNs becomes an optimization problem [21].

In recent times, many optimization algorithms have been developed which are applied in different applications in medical, science and engineering. These algorithms are nature-inspired such as the genetic algorithm (GA), PSO, ant colony optimization (ACO), Cuckoo search algorithm (CSO), bee colony optimization (BCO), Differential Evolution (DE), Harmonic Search (HS), Simulated Annealing (SA), Bat Algorithm (BA), Firefly Algorithm (FA), to mention but a few [14]. These algorithms have also been engaged in the PUEA localization. [16]. In [22], the author proposed a detection

technique based on the TDOA localization technique using the Taylor series estimation (TSE) for minimizing the localization error from the TDOA measurements. The author provided a method for solving the synchronization problem with the TDOA localization technique nevertheless, the TSE has two major drawbacks which are: (1) the need for careful choice of initial value as this will determine the convergence of the algorithm, (2) it exhibits slow convergence, high complexity, and low position accuracy. To further improve on the location accuracy and increase the convergence rate, the author in [21] proposed a detection method based on the TDOA using the firefly algorithm (FA), the algorithm offers better accuracy and faster convergence than the TSE and could be used in the IEEE 802.22 network albeit, the localization error was quite high and it could not detect the PUEA when located close to the PU. To further reduce the localization error, and increase the convergence rate, the author [14]. The author considered various PSO approaches and compared the best seven approaches in terms of their accuracy. The approaches were very efficient in defining the attacker when located inside the CRN however, the authors failed to consider when the PUEA is close to the PU. The author in [23] proposed a detection method based on the TDOA values using the NBA, he used the algorithm to determine the detectability of the attacker when located inside and outside the CRN. The method could easily define the attacker when located inside the CRN but has a high localization error when the attacker is located outside the CRN. Hence, this paper aims at developing a detection technique capable of detecting and localizing the PUEA when located inside and outside the CRN with minimum localization error and a fast convergence rate.

III. PROBLEM FORMULATION AND SYSTEM MODEL

The system model comprises the PU network with a TV tower as the transmitter and two TV receivers, and the CR network composed of a CR BS and N static SUs at specified locations and they communicate with the CR BS as shown in Figure 1 The CR BS knows the positions of the PU and each SU. The CRN range varies from 30 km to 100 km and the PU is located outside the CRN at a distance of 30km to 150 km.

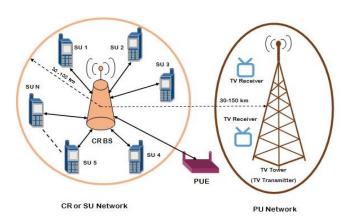


Figure 1: System model for the PUEA detection

The following users exist in the system:

- Primary User (PU): licensed user of a particular spectra band.
- **Secondary User:** the unlicensed user which seeks to take advantage of the spectrum hole(s).
- Primary User Emulator (PUE): this can either be a malicious or selfish user which aims at preventing the SUs from accessing and using the available spectrum holes. It can

receive the PU signal, mimic it, and thereafter, transmit its signal with the same signal features as that of the real PU.

The position of the emitted signal source is calculated and compared with the position of the real PU. If the location is the same, then the real PU is transmitting, otherwise, it is the PUEA. The following assumptions were made for the detection of the PUEA in the system:

- The CRN does not have any knowledge about the attacker's strategy.
- The PUEA can be located either inside or outside the SU network.
- The PU and the PUEA have similar radio behavior.
- The CR BS knows the PU and each legitimate SU's positions.

IV. THE MATHEMATICAL MODEL FOR DETECTING THE PUEA

The Time difference of arrival (TDOA) localization technique is employed for localizing the PUEA. The TDOA takes advantage of the cross-correlation technique to obtain the difference in the time of arrival of a signal at two or more pairs of nodes. In 2-D space, a minimum of three nodes is required to obtain the TDOA values. To locate the transmitter, the TDOA provides two hyperbolic curves which usually will intersect at a point which is the location of the transmitter. Figure 2 shows the basic concept of PUEA localization.

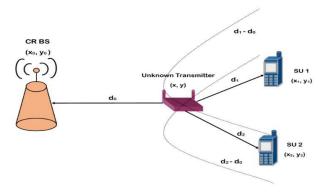


Figure 2: TDOA based detection of the PUEA

The TDOA measurement between the signals received at the *ith* SU and the CR BS is [16]:

$$\tau_i = t_i - t_0 \tag{1}$$

Where t_i , is the TOA of a signal at the *ith* SU, and t_0 is the TOA of a signal at the CR BS

Multiplying equation (1) by the speed of light (c), we have the actual range difference between the ith SU and the PUEA when the CR BS is taken as the reference node as:

$$d_{i,0} = c(t_i - t_0) = ct_i - ct_0 = d_i - d_0$$
 (2)

Equation (2) can be written as,

$$d_{i,0} = \sqrt{(x - x_i)^2 + (y - y_i)^2} - \sqrt{(x - x_0)^2 + (y - y_0)^2}$$
 (3)

The TDOA measurements are corrupted with Gaussian error due to environmental consideration as given in equation (4):

$$r_{TDOA,i} = d_{i,0} + n_{TDOA,i} \tag{4}$$

 $n_{TDOA,i}$ is an additive white Gaussian noise (AWGN) with zero mean and variance equal σ^2 given as (Ghanem 2019);

$$\sigma^2 = \sigma_i^2 + \sigma_0^2, \tag{5}$$

$$\sigma_i^2 \ge \frac{1}{8\pi^2 . B^2 . SNR_i},$$
 (6)

$$SNR_i = SNR_0 - \Delta L_p(dB), \tag{7}$$

and,

$$\Delta L_p(dB) = [44.9 - 6.55(h_t)] \log \left[\frac{d_i}{d_0} \right]$$
 (8)

Where, σ_i^2 is the variance of the measurement at the ith SU, σ_0^2 is the variance of the measurement at the CR BS, B is the bandwidth of the TV signal, SNR_i is the signal to ratio at the ith SU, SNR_0 is the signal to noise ratio at the CR BS, $\Delta L_p(dB)$ is the path loss calculated from the Hata model for suburban regions which is the path loss model for IEEE 802.22 network, and h_t is the height of the transmit antenna.

The position of the unknown transmitter is given by estimating X given \mathbf{r}_{TDOA} and it is formulated as an optimization problem that involves minimizing an objective function representing the localization precision. The objective function for localizing the unknown transmitter is given as [14];

$$f(\tilde{x}, \tilde{y}) = \sum_{i=1}^{N} \left(r_{TDOA} - \sqrt{(\tilde{x} - x_i)^2 + (\tilde{y} - y_i)^2} + \sqrt{(\tilde{x} - x_0)^2 + (\tilde{y} - y_0)^2} \right)^2$$
(9)

The estimated location of the unknown transmitter (\tilde{x}, \tilde{y}) , is the value that minimizes the objective function given in equation (9).

V. OPTIMIZATION ALGORITHMS FOR THE LOCALIZATION ERROR MINIMIZATION

The estimation of (\tilde{x}, \tilde{y}) involves using an optimization algorithm. The PSO, NBA, and MPSO algorithms were used to obtain the position of the unknown transmitter.

(a) Particle Swarm Optimization (PSO) Algorithm

PSO is a widely used optimization algorithm because it is very simple to use and efficient. It was proposed by Eberhart and Kennedy in 1995, inspired by the social behavior of swarm such as the school of fish or flocks of birds. The PSO searches the space of an objective function in equation (9) by adjusting the trajectory of the individual particles. Each particle is denoted by four vectors in the search space namely: the current position, particle's best location (p_{best}), global best (g_{best}), and velocity. The total number of birds of fish is called the swarm size. In each iteration (t+1), each jth particle updates its position and velocity according to equations (10) and (11) [24]

$$v_i^{t+1} = w * v_i^t + c_1 r_1 (p_{best_i} - x_i^t) + c_2 r_2 (g_{best_i} - x_i^t), \tag{10}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}, (11)$$

where, v_j^t is the jth particle's velocity, x_j^t is the position of the jth particle, w is the inertia weight taken as 0.9, c_1 and c_2 are the acceleration constants (that is, the cognitive coefficient and social factor respectively) that determine the attraction of the particle towards p_{best} and g_{best} respectively, $c_1 = 2$ and $c_2 = 2$, p_{bestj} and g_{bestj} are the best locations found by each particle and the whole swarm respectively, r_1 and r_2 are two random numbers between

0 and 1. The particle with the best fitness value is the location of the PUEA with minimum error.

PSO has three main disadvantages in solving optimization problems. They are [14]:

- Slow convergence rate
- Low accuracy
- · Trapping in local minima.

Therefore, modifying the PSO parameters is important to increase the convergence rate, accuracy, and the ability not to trap it in the local minima.

A. (b) Modified Particle Swarm Optimization (MPSO)

In this paper, the w is modified according to equation (12) given in [25] in order to improve the performance of the PSO algorithm

$$W(t) = w_{initial} * e^{-a\left[\frac{t}{t_{max}}\right]^b}$$
 (12)

where, a = 2, b = 1.5, and $w_{initial} = 0.4$, t_{max} is the maximum iteration, and t is the current iteration.

The acceleration coefficients are modified as follows:

$$c_1 = c_{1_{\text{initial}}} + \left[\frac{c_{1_{\text{end}}} - c_{1_{\text{initial}}}}{t_{max}} \right] * t, \tag{13}$$

$$c_2 = c_{2 \text{initial}} + \left[\frac{c_{2 \text{end}} - c_{2 \text{initial}}}{t_{max}} \right] * t, \tag{14}$$

where,
$$c_{1\text{initial}} = 2.5$$
, $c_{1\text{end}} = 0.5$, $c_{2\text{initial}} = 1.25$, $c_{2\text{end}} = 2.25$

(c) Novel Bat Algorithm (NBA)

The NBA is one of the efficient optimization algorithms which can be used to minimize equation (9). It was developed to improve the performance of the Bat Algorithm. it involves integrating the Bats habitat choices and self-adaptive allowance for Doppler Effect in echoes in the fundamental event when a viewer steps forward in relation to its source. The idealized rules for the mathematical development of NBA are as follows [26]:

- The bats in the swarm will compensate for the doppler effect in echoes.
- In various habitats, bats in the swarm of NBA can forage by stochastic selection.
- Depending upon the proximity of the target/prey, all bats can adjust and adapt compensation rate.

All the N Bats denoted by their position x_i^t and with velocities v_i^t at time t, searches for food in the 2-D search space. The NBA is used is localize the unknown transmitter by using the echolocation feature of Bats and solving the cost function given in equation (9). New solutions are generated as follows:

$$f_i = f_{min} + (f_{max} - f_{min}) * \text{rand} (0,1)$$
 (15)

$$v_i^{t+1} = v_i^t + (G_{best} - x_i^t) * f_i$$
 (16)

$$x_i^{t+1} = x_i^t + v_i^{t+1} (17)$$

VI. PUEA DETECTION PROCEDURE AND METRIC PERFORMANCE EVALUATION

(a) PUEA detection Procedure

We deployed 100 SUs random in the network. The procedure for detecting the PUEA is given in figure 3.

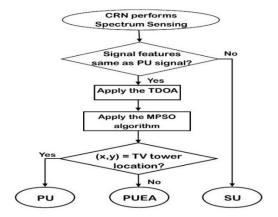


Figure 3: Flowchart for the PUEA Detection

(b) Metric Parameter for Performance Evaluation

In this paper, we evaluate the performance of the PSO, NBA, and MPSO algorithms for the PUEA detection and using the Mean Square Error (MSE) and cumulative distribution function (CDF).

(i) Mean Square Error (MSE)

The MSE is a suitable metric for evaluating the performance of a localization or positioning technique [14]. It is used to calculate the difference between the actual or expected result and the estimated or calculated result. Given that the location PUEA is estimated n times, such that we have the population of coordination calculated as $(X_1, Y_1), \ldots, (X_n, Y_n)$, then, the mean of the calculated coordinates is calculated using equation (18).

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} X_i, \ \bar{y} = \frac{1}{n} \sum_{i=1}^{n} Y_i,$$
 (18)

The MSE of the estimated location is given by equation (19)

$$MSE(\bar{x}, \bar{y}) = E[(\bar{x} - x)^2 + (\bar{y} - y)^2]$$
 (19)

(ii) Cumulative Distribution Function (CDF)

The CDF depicts the probability that a real-valued random variable Z evaluated at z will have a value less than or equal to z and is given as:

$$F_Z(z) = P(Z \le z) \tag{20}$$

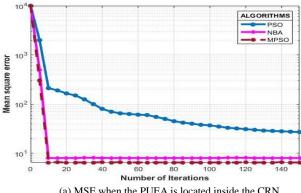
where $F_Z(z)$ is the CDF of the numerical random variable Z, and $P(Z \le z)$ is the probability distribution evaluated at a value less than or equal to z, z is the variable of the error distance in meters.

The CDF increases from 0 to 1 and it describes the performance of the PSO, NBA, and the MPSO algorithms relative to the distance error in meters.

(b) Simulation Results and Discussion

The PSO, NBA, and MPSO are used to minimize the cost function given in equation (9). To compare the accuracy of the algorithms, the MSE is calculated and the plot is shown in figure

4. In figure 4(a), it can be seen that after 10 iterations, the MSE for the PSO, MPSO, and NBA are 211m, 6.5m, and 8m respectively. This implies that the PSO is less accurate compare with the MPSO and NBA, and the MPSO is a more accurate technique. Also, after 150 iterations, the MSE for the PSO, MPSO, and NBA are 27m, 6.5m, and 7m respectively which shows that the PSO requires more iterations to be performed to give a minimum error and hence, a larger spectrum sensing time which leads to difficulty in the detection of the attacker especially when the PU does not leave its channel for a long time.



(a) MSE when the PUEA is located inside the CRN

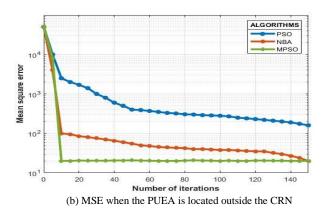
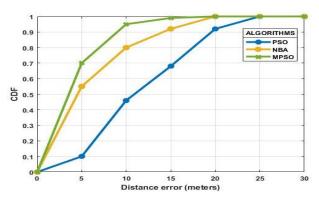


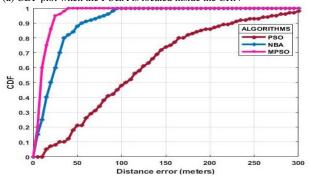
Figure 4: Graph of MSE vs. Number of Iterations

Similarly, the accuracy of the algorithms is also compared given that the PUEA is outside the CRN. As seen in figure 4b, after the 10th iteration, the MSE for the PSO, MPSO, and the NBA are 2500m, 20m, and 100m respectively. This implies that it is a bit difficult to detect the attacker when it is not inside the CRN however, with the MPSO algorithm, the attacker can be more easily defined even when the attacker is close to the PU because it gives a small localization error while the high MSE value given by the PSO and NBA implies that the attacker is more likely not to be detected when close to the PU and this may lead to a high probability of false alarm. Also, after the 150th iteration, the PSO, MPSO, and NBA gives an MSE of 160m, 20m, and 30m which has greatly reduced as compared with the MSE after the 10th iteration. This implies that the higher the number of iterations, the smaller the MSE, the larger the spectrum sensing time. Howbeit, the MPSO gives an MSE of 20m both after the 10th and the 150th iteration which implies that after the 10th iteration the MPSO gives it minimum error and hence helps save the spectrum sensing time with a better accuracy level.

Figure 5(a) shows the variation of the CDF vs Distance error (meters) for the PSO, NBA, and the MPSO algorithms when the PUEA is located inside the CRN at (7000m,1500m) with 100 cooperating SUs and 150 iterations. It is seen that the MPSO has a better performance than the PSO and the NBA. For example, at CDF equals 0.8, the distance error corresponds to 7m, 10m, and 17.5m for the MPSO, NBA, and PSO respectively. Thus, the MPSO reduces the localization error when the PUEA is located inside the CRN. In like manner, figure 5(b) shows the variation of the CDF vs Distance error (meters) for the MPSO, NBA, and PSO algorithms when the PUEA is located outside the CRN at (45000m,0m) with 100 cooperating SUs and 150 iterations. At CDF equals 0.8, the distance error for the PSO, NBA, and MPSO are 170m, 40m, and 18m respectively. This high distance error obtained shows that it is quite difficult to detect the PUEA when located outside the CRN however with the MPSO, the attacker can be easily detected when located outside the CRN with very minimal localization error.



(a) CDF plot when the PUEA is located inside the CRN



b) CDF plot when the PUEA is located outside the CRN

Figure 5: Graph of CDF vs. Distance error (meters)

VII. CONCLUSION

The CR technology will help in alleviating the spectrum scarcity problem as it provides for the opportunistic use of the spectrum holes or white spaces in the licensed band by the unlicensed user and thereby enabling the reliable connection of more wireless devices to the radio spectrum. However, the CRN is faced with many security threats one of which is the PUEA which aims at causing a denial of service to the SUs. In this paper, we focused on detecting this attacker by using the TDOA localization technique, we also used the PSO, NBA, and MPSO algorithms to minimize the localization error and compared the accuracy and convergence rate of the three algorithms. Simulation results show that the MPSO is more accurate and shows faster convergence than the PSO and NBA thus, it is an optimal technique for detecting a static PUEA located both inside and outside the CRN.

REFERENCES

A. Jayapalan, P. Savarinathan, J. C. Reddy, and J. D. [1] Baskar, "Detection and Defense of PUEA in Cognitive Radio Network," Arabian Journal for Science and Engineering, vol. 46, no. 4, pp. 4039-4048, 2021.

- [2] Y. Arjoune and N. Kaabouch, "A Comprehensive Survey on Spectrum Sensing in Cognitive Radio Networks: Recent Advances, New Challenges, and Future Research Directions," (in eng), *Sensors (Basel)*, Review vol. 19, no. 1, p. 126, Jan 2 2019, doi: 10.3390/s19010126.
- [3] I. Omer, K. Hamid, and M. Mohamed, "Overview on Cognitive Radio Network Review," *International Journal of Engineering Sciences Paradigms and Researches*, vol. 33, no. 20, pp. 7-13, 2016.
- [4] B. Naqvi, I. Rashid, F. Riaz, and B. Aslam, "Primary user emulation attack and their mitigation strategies: A survey," in 2013 2nd National Conference on Information Assurance (NCIA), 2013: IEEE, pp. 95-100.
- [5] I. Gupta and O. Sahu, "An Overview of Primary User Emulation Attack in Cognitive Radio Networks," in 2018 Second International Conference on Computing Methodologies and Communication (ICCMC), 2018: IEEE, pp. 27-31.
- [6] W. R. Ghanem, R. Essam, and M. Dessouky, "Proposed particle swarm optimization approaches for detection and localization of the primary user emulation attack in cognitive radio networks," in 2018 35th National Radio Science Conference (NRSC), 2018: IEEE, pp. 309-318.
- [7] D. Dansana and P. K. Behera, "A Study of Recent Security Attacks on Cognitive Radio Ad Hoc Networks (CRAHNs)," in *Soft Computing Techniques and Applications*: Springer, 2021, pp. 351-359.
- [8] S. Adebo, E. Onwuka, A. Usman, and A. Onumanyi, "A hybrid localization scheme for detection of primary user emulator in cognitive radio networks," *International Journal of Computing and Digital Systems*, vol. 8, no. 03, pp. 217-227, 2019.
- [9] A. Mesmoudi, M. Feham, and N. Labraoui, "Wireless sensor networks localization algorithms: a comprehensive survey," *arXiv* preprint *arXiv*:1312.4082, 2013.
- [10] S. A. Adebo et. al, "A Hybrid Localization Scheme for Detection of Primary User Emulator in Cognitive Radio Networks," *International Journal of Computing* and Digital Systems, vol. 8, no. 3, pp. 217-227, 2019, doi: 10.12785/ijcds/080302.
- [11] K.-C. Chen, Y.-J. Peng, N. Prasad, Y.-C. Liang, and S. Sun, "Cognitive radio network architecture: part II-trusted network layer structure," in *Proceedings of the 2nd international conference on Ubiquitous information management and communication*, 2008: ACM, pp. 120-124.
- [12] G. Mao, B. Fidan, and B. D. Anderson, "Wireless sensor network localization techniques," *Computer networks*, vol. 51, no. 10, pp. 2529-2553, 2007.
- [13] S. Singh, R. Shakya, and Y. Singh, "Localization techniques in wireless sensor networks," *International Journal of Computer Science and Information Technologies*, vol. 6, no. 1, pp. 844-850, 2015.

- [14] W. R. Ghanem, R. E. Mohamed, M. Shokair, and M. I. Dessouky, "Particle Swarm Optimization Approaches for Primary User Emulation Attack Detection and Localization in Cognitive Radio Networks," *arXiv* preprint arXiv:1902.01944, 2019.
- [15] S. Leelavathy and S. Sophia, "Providing localization using triangulation method in wireless sensor networks," *International journal of innovative technology and exploring engineering*, vol. 4, pp. 47-49, 2014.
- [16] H. C. So, "Source Localization: Algorithms and Analysis," in *Handbook of Position Location*, 2011, pp. 25-66.
- [17] O. León, J. Hernández-Serrano, and M. Soriano, "Cooperative detection of primary user emulation attacks in CRNs," *Computer networks*, vol. 56, no. 14, pp. 3374-3384, 2012.
- [18] P. Patil, P. Patil, M. K. Paradeshi, and P. Budhgaon, "Detection of Primary User Emulation (PUE) Attack in Cognitive Radio Network," *International Journal of Engineering Science*, vol. 5845, 2017.
- [19] W. R. Ghanem, M. Shokair, and M. Desouky, "Defense against selfish PUEA in cognitive radio networks based on hash message authentication code," *International Journal of Electronics and Information Engineering*, vol. 4, no. 1, pp. 12-21, 2016.
- [20] Z. El Mrabet, Y. Arjoune, H. El Ghazi, B. Abou Al Majd, and N. Kaabouch, "Primary User Emulation Attacks: A Detection Technique Based on Kalman Filter," *Journal of Sensor and Actuator Networks*, vol. 7, no. 3, p. 26, 2018.
- [21] W. R. Ghanem, M. Shokair, and M. I. Desouky, "An improved primary user emulation attack detection in cognitive radio networks based on firefly optimization algorithm," in 2016 33rd National Radio Science Conference (NRSC), 2016: IEEE, pp. 178-187.
- [22] O. León, J. Hernández-Serrano, and M. Soriano, "Cooperative Detection of PUE Attacks in CRNs," in *Cognitive Communication and Cooperative HetNet Coexistence*: Springer, 2014, pp. 287-316.
- [23] A. Rehman and D. Prakash, "Detection of PUE attack in CRN with reduced error in location estimation using novel bat algorithm," *International Journal of Wireless Networks and Broadband Technologies (IJWNBT)*, vol. 6, no. 2, pp. 1-25, 2017.
- [24] Y. Shi and R. Eberhart, "A modified particle swarm optimizer," in 1998 IEEE international conference on evolutionary computation proceedings. IEEE world congress on computational intelligence (Cat. No. 98TH8360), 1998: IEEE, pp. 69-73.
- [25] A. Nickabadi, M. M. Ebadzadeh, and R. Safabakhsh, "A novel particle swarm optimization algorithm with adaptive inertia weight," *Applied soft computing*, vol. 11, no. 4, pp. 3658-3670, 2011.
- [26] N. A. Kumar, G. S. Rao, and B. Lavanya, "Novel BAT Algorithm for Position Estimation of A GPS Receiver Located in Coastal Region of Southern India," *Procedia computer science*, vol. 143, pp. 860-867, 2018.