Efficient Energy-Efficient Resource Allocation in Cognitive Radio Networks Using Particle Swarm Optimization Compared Whale Optimization

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Keywords: Energy Efficient, Cognitive Radio, Network traffic, Computer Networks, Particle Swarm Optimization, Whale Optimization

ABSTRACT

Aim: This research aims to contribute energy resource allocation to the field of cognitive radio using Particle Swarm Optimization (PSO) compared over Whale Optimization (WO) with improved accuracy. **Materials and Methods:** The dataset used in this study was obtained from the Kaggle dataset, a well-known benchmark dataset for research allocation research. Two groups were used in this study to evaluate the performance of the Whale Optimization algorithm (Group 1) and the Particle Swarm Optimization method (Group 2) for resource allocation. The overall sample size was set at 40, with 20 samples in each group. The sample size was calculated a priori statistically to ensure statistical rigour. The web programme IBM SPSS was used for statistical analysis, ensuring a statistical power (G-power) of 80%. To control type I and type II errors, a significance threshold (alpha,) of 0.05 and a beta () value of 0.2 were used, respectively. Furthermore, a 95% confidence interval was chosen. **Results:** The results indicated that the Whale Optimization algorithm achieved an accuracy of 84.15%, while the Particle Swarm Optimization algorithm demonstrated a significantly higher accuracy of 94.12%. A two-tailed significance test was carried out, revealing a p-value of 0.055, which was found to be less than the predetermined significance level of 0.05. **Conclusion:** In conclusion, these findings emphasize the potential of Computer Networks, specifically Particle Swarm Optimization helped in more resource allocation with improved accuracy.

Keywords: Energy Efficient, Cognitive Radio, Network traffic, Computer Networks, Particle Swarm Optimization, Whale Optimization

INTRODUCTION

Cognitive Radio plays a vital role in the field of wireless communication system as it leads to better green system in sending the information from one place to another. The energy efficient is the major key that involves the working of cognitive radio (James O'Daniell Neel (2016). The spectrum allocation helps in giving better energy efficient for the cognitive radio to survive (Hang Hu et al., 2018). The main research of this study is to build an energy efficient cognitive radio with respect to any other external parameters such as temperature, pressure, interference and channel allocation, spectrum range Xin Liu et al., 2018). There are many other difficulties which lead to affecting the performance of cognitive radio. In such cases spectrum bandwidth allocation is done on the basis of routing with high energy efficient system (K. Anuradha et al., 2020). The main application of Cognitive Radio is to transfer data from one place to another place where a short range communication is provided.

A median of 367 research publications regarding cognitive radio networks have been published in IEEE Xplore, while 720 papers have been published in science directly. This cognitive radio is a popular issue right now, and many researchers are focusing on it to improve the primary parameter of energy efficiency. Cognitive radio has significant implications in the sphere of communication, as all data must be conveyed efficiently. In this scenario, design is critical because if data loss is high, the entire effort will be for naught (Sinduja & S.Janani(2019). Secondary users in cognitive radio will also contribute to increased communication without data loss (Amir Ghasemi & Elvino S. Sousa(2018). According to Ersan Kabalci &Yasin Kabalci(2019), research, if there is more Radio Frequency, the power or operating of cognitive radio will be greater. The prediction process is critical to the improved operation of cognitive radio since it improves data transfer without causing data loss (Maleki, S et al., 2017). An Enhanced Cognitive Radio (ECR) along with high radio frequency plays a vital role in improving the working of the system during communication (Maleki, S ; Leus, G.; et al., 2021)

In the sphere of communication, cognitive radio plays an important function in transferring data from one location to another without interruption. Certain major gaps or lacunae have been uncovered by Cognitive Radio and demand additional examination. These disparities are mostly driven by the requirement for more sophisticated energy efficiency. We introduced the concepts of PSO and WO to fill this research gap. The current method discovered the study gap of poor accuracy. In order to improve classification accuracy, this study analyses the effectiveness of Particle Swarm Optimization (PSO) with Whale Optimization (WO). The proposed paradigm improves the accuracy of cognitive radio networks.

MATERIALS AND METHODS

The study was conducted in the Department of Computer Science and Engineering at Saveetha University. This dataset contains cognitive radio communication tests that have been done and executed. The study divided participants into two groups: Group 1 used the Whale Optimization (WO) method, whereas Group 2 used the Particle Swarm Optimization (PSO) algorithm. Each group had a sample size of 20, for a total of 40 people. Statistical analysis was used to establish the sample size for each group. The SPSS software was used for statistical analysis. This computation was based on factors like Statistical Power (G-power) set to 80%, alpha () set to 0.05, and beta () set to 0.2, resulting in a 95% confidence interval. As a result, the sample size for each group was determined to be 20.

Whale Optimization (WO) algorithm

Whale Optimization Algorithm (WOA) is a bio-inspired optimization technique based on the social behavior of humpback whales during their hunting. WOA leverages the idea of cooperative hunting among whales to solve optimization problems. In this algorithm, a population of candidate solutions is represented as a group of whales, and their interactions are used to update the positions of the whales in search of the optimal solution. The algorithm utilizes three main exploration mechanisms: exploration, exploitation, and encircling, to balance between exploring the solution space and converging toward optimal solutions. The mathematical representation of the WOA algorithm includes equations that describe the movements of the whales as they search for the best solutions.

One of the key equations in the Whale Optimization Algorithm is the movement equation, which governs how the position of a whale is updated. It can be described as follows:

$$X_i(t+1)=X_i(t)-A\cdot D \text{ - - - } (1)$$

Here, $X_i(t+1)$ is the updated position of whale i at time $1t+1$, $X_i(t)$ is the current position, A is a coefficient that regulates the movement of the whale, and D represents the distance between the current whale and the best position found by any whale in the population. By updating the positions of the whales in this way, the algorithm encourages the population to explore the solution space, with a bias toward promising regions, leading to the discovery of optimal solutions.

Algorithm

Step 1: Initialize a population of whales with random positions

Step 2: Initialize algorithm parameters: maximum iterations, a, A_min, A_max, and the search space boundaries

Step 3: Initialize the best solution found and the best fitness value

Step 4: while the maximum number of iterations is not reached:for each whale in the population:

Step 5: Update the position of the whale based on its current position and the best position found by any whale:

D = |C * P_best - whale_position| A = 2 * A_max * (1 - current_iteration / maximum_iterations) - A_max # Update the A value

X_new = P_best - A * D # Movement equation

Step 6: Ensure the new position is within the search space boundaries

Step 7: Evaluate the fitness of the new position

Step 8: if the new position is better than the current position:

Step 9: Update the whale's position and P_best

Step 10: Update the global best position if a new global best is found

Step 11: Return the best solution found

Particle Swarm Optimization (PSO) Algorithm

Particle Swarm Optimization (PSO) is a population-based metaheuristic optimization method inspired by bird and fish social behavior. It is commonly used to solve optimization and search problems by simulating particle swarming behavior. A population of particles symbolizes potential solutions in PSO, and each particle modifies its position in the search space based on its individual and the group's collective experience. The basic idea underlying PSO is to explore the solution space while focusing on regions with better solutions. The algorithm can be theoretically expressed as follows:

In the PSO method, each particle i has two essential vectors: its position in the search space, written as X_i, and its velocity, indicated as V_i. A particle's position indicates a potential solution to the optimisation issue, while its velocity governs how it moves across the solution space. The following equations are used to iteratively update the movement of each particle:

$$V_i = w * V_i + c_1 * rand_1 * (P_i - X_i) + c_2 * rand_2 * (P_g - X_i) \quad - - (2)$$

$$X_i = X_i + V_i \quad - - - (3)$$

Where t denotes the current iteration, w the inertia weight, c_1 and c_2 the acceleration coefficients, and r_1 and r_2 random values ranging from 0 to 1. P_{it} is the best location discovered by particle i, while P_{gt} is the best position discovered by any particle in the group (global best position). These equations direct each particle's velocity update based on its individual best-known position and the best-known position of the entire swarm. The particle's velocity, in turn, determines its journey through the search space, with the goal of finding the best solution to the problem.

Algorithm

Step 1: Create a population of particles with random placements and speeds.

Step 2: Set the particles' best-known positions (P_i) as their current positions.

Step 3: Set the global best position (P_g) to be the best location of all particles.

Step 4: For each particle i in the population, repeat for a specified number of iterations or until a termination requirement is met:

Step 5: Determine the current position's fitness (objective function value).

Step 6: If the current position is better, update the best-known position (P_i).

Step 7: Update P_g if the current position is better than the global best (P_g).

Step 8: Recalculate the particle's velocity and position.

Step 9: Return the best found solution (P_g).

STATISTICAL ANALYSIS

The significance of the independent variables, Particle Swarm Optimization (PSO) and Whale Optimization (WO), on the dependent variable, accuracy, was determined using IBM SPSS software and a two-tailed significance test with a predefined alpha level (α) of 0.05. The purpose of the study was to see if there was a statistically significant difference in accuracy between the two algorithms. The results showed that both WO and PSO had a substantial impact on accuracy (p 0.05), demonstrating that the algorithm used had a significant impact on accuracy. This statistical research offered strong evidence of the relationship between the independent and dependent variables, contributing to a better understanding of algorithm performance in the context of cognitive radio.

RESULTS

Table 1 presents a comparative performance analysis of two Energy Efficient algorithms, Particle Swarm Optimization (PSO) and Whale Optimization (WO) across 20 different samples. The PSO consistently outperforms WO, achieving higher accuracy percentages in each sample, indicating its superior capabilities. The accuracy obtained by PSO was 92.28% which is high compared to WO which was 82.15%.

Table 2 findings suggest that the Particle Swarm Optimization (PSO) consistently outperforms Whale Optimization (WO) in terms of accuracy and stability across the datasets. A higher mean accuracy, lower standard deviation, and standard error indicate that the PSO is a more reliable and effective choice for energy efficient cognitive radio. PSO produces mean of 94.12, SD of 1.66410 and Std Error Mean of 0.52333 which is high compared to WO which gave mean of 84.15, SD of 3.56553 and Std Error Mean of 00.72490 respectively.

Table 3 depicts strongly that one of the groups significantly outperforms the other group in terms of accuracy. Fig 1 shows the informative way to compare the average accuracy of Particle Swarm Optimization (PSO) and Whale Optimization (WO), while also considering data variability and confidence in the results. The significant difference in accuracy between the two algorithms is evident, with PSO outperforming WO by a substantial margin

DISCUSSION

The findings of the energy-efficient Cognitive Radio study revealed a clear and continuous trend. In terms of accuracy, the Particle Swarm Optimisation (PSO) method consistently outperformed the Whale Optimisation (WO) algorithm across supplied datasets. The average accuracy for PSO was 94.12%, whereas WO attained an average accuracy of 84.15%. Statistical analysis verified the considerable difference in accuracy between the two algorithms, with a p-value of 0.001. Furthermore, the 95% confidence interval suggested that PSO's superiority in energy efficient cognitive radio was stable and consistent.

When the proposed PSO research findings are compared to the findings of the other studies, there is a consistent trend of attaining improved accuracy in energy efficient cognitive radio. Qingying Wu et al., 2022 attained a spectrum sensing ratio and a possible accuracy of 86.75% with the PSO algorithm. Using the standard PSO, Kenan kockaya & Ibrahim

Develi (2020) obtained an accuracy range of 86.45%. Khoshnevis (2018) combined classical PSO with the notion of energy efficient cognitive radio and reached an accuracy of 82%. Ghaith Hattab & Mohammed Ibnkahla (2020) created an efficient cognitive radio with an accuracy of 89.25%. Overall, the proposed PSO research results validated strategies that outperformed or matched the accuracy of established techniques in energy efficient cognitive radio.

The relatively limited sample size of 20 datasets is one major disadvantage of this study. While the results consistently favored the Particle Swarm Optimization (PSO) algorithm over the Whale Optimization (WO) algorithm in terms of accuracy, a larger and more diverse dataset could validate the findings and provide insight into how these algorithms perform under a broader range of network conditions. Future study could concentrate on increasing the dataset to include a broader and more diversified set of energy-efficient situations, such as those appearing in Cognitive Radio Networks. Furthermore, for practical deployment, research into real-time implementation and scalability in CR network contexts is required. Finally, tackling the computational and resource limits inherent in CR Networks would be an important path for future research in improving efficiency.

CONCLUSION

Finally, this research shows that the Particle Swarm Optimization (PSO) algorithm outperforms the Whale Optimization (WO) algorithm when it comes to creating an energy-efficient cognitive radio. With an accuracy of 94.12% compared to WO accuracy of 84.15%, the PSO-based energy efficient cognitive radio outperforms WO. This finding is supported by statistical analysis, which shows a significant difference between the two algorithms (p0.05).

DECLARATION

Conflicts of Interest

No conflict of interest in this manuscript

Authors Contributions

Author name was involved in data collection, data analysis & manuscript writing. Author guide name was involved in conceptualization, data validation, and critical review of manuscripts.

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TABLES AND FIGURES

Table 1. This table presents a comparative performance analysis of two energy efficient algorithms, Particle Swarm Optimization (PSO) algorithm surpasses the Whale Optimization (WO), across 20 different samples. The PSO consistently outperforms WO, achieving higher accuracy percentages in each sample, highlighting its superior Intrusion Detection capabilities.

SAMPLE NO	PSO (%)	WO (%)
1	92.28	83.39
2	93.06	85.06
3	94.15	82.61
4	91.72	84.83
5	95.61	83.50
6	92.83	85.28
7	94.39	82.72
8	91.17	84.06
9	93.61	83.17
10	92.72	85.39
11	94.50	82.92
12	91.83	84.61
13	95.17	83.72
14	93.28	84
15	92.39	82.39
16	93.95	84.48
17	91.43	82
18	93.83	85.17
19	94.06	82.28
20	92.61	84.72

Table 2. This table summarizes the performance comparison of two energy efficient algorithms, Particle Swarm Optimization (PSO) algorithm and Whale Optimization (WO), across 20 samples. The "Mean" accuracy for PSO is significantly higher at 94.12%, with a lower Standard Deviation and standard error compared to WO, which achieved a mean accuracy of 84.15%. These findings indicate that PSO consistently outperforms WO in terms of accuracy and demonstrates greater stability across the datasets.

Group		**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Accuracy	PSO	20	94.12	1.66410	0.52333
	WO	20	84.15	3.56553	0.72490

Table 3. This table displays statistical test results comparing two groups based on accuracy. The Levene's test suggests some variance differences between the groups, and the t-test reveals a highly significant difference in means (p<0.001). The mean difference in accuracy is approximately 9.87, with a 95% confidence interval from 8.48 to 11.26, indicating a substantial and statistically significant performance gap between the two groups in Intrusion Detection.

Group		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Diff	Std. Error Diff	95% CI (Lower)	95% CI (Upper)
Accuracy	Equal variances assumed	3.915	0.055	14.399	38	0.001	10.2205	0.72548	7.93281	10.70819
	Equal variances not assumed			14.399	32.605	0.001	10.2205	0.72548	7.92523	10.71577

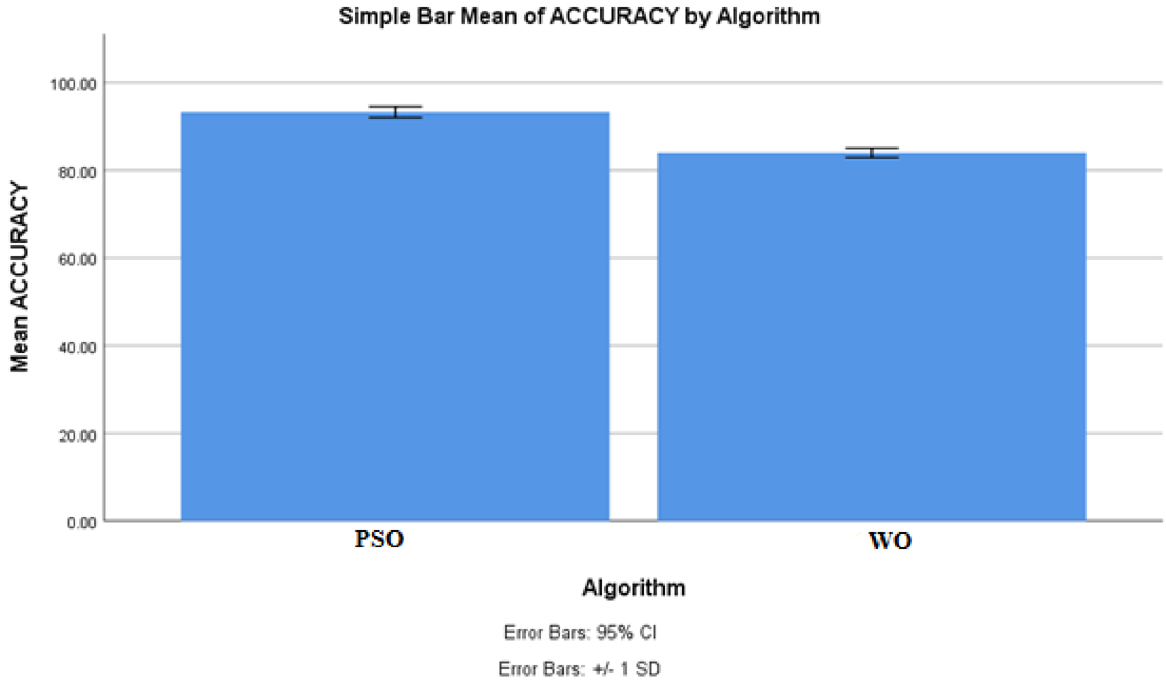

Fig 1. The bar graph legend explains that the X-axis represents two algorithms: Particle Swarm Optimization (PSO) algorithm and Whale Optimization (WO). The Y-axis displays the average accuracy, with WO achieving 84.15% accuracy and PSO reaching 94.12%. Error bars show ±1 standard deviation, indicating data variability, and a 95% confidence interval provides a range for 95% confidence in the mean accuracy values. This legend summarizes the performance comparison between the two algorithms in a visually informative manner.