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

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

ABSTRACT

Aim: This research aims to contribute energy resource allocation to the field of cognitive radio using Particle Swarm Optimization (PSO) compared over Butterfly Optimization (BO) with improved accuracy. **Materials and Methods:** The dataset used in this study was taken from the Kaggle dataset, a well-known benchmark dataset for study allocation research. In this work, the performance of the Particle Swarm Optimization algorithm (Group 2) and the Ant Colony Optimization method (Group 1) for resource allocation was assessed. Each group contained 20 samples, and the total sample size was 40. To ensure statistical rigour, the sample size was determined using a priori statistical analysis. The statistical analysis was carried out using the web programme SPSS, which ensured 80% statistical power (G-power). A significance level (alpha, α) of 0.05 and a beta (β) value of 0.2 were used to control type I and type II errors, respectively. Furthermore, a 95% confidence interval was used to determine the precision of the performance comparison results. **Results:** The results indicated that the Butterfly Optimization algorithm achieved an accuracy of 88.50%, while the Particle Swarm Optimization algorithm demonstrated a significantly higher accuracy of 93.25%. After doing a two-tailed significance test, the p-value of 0.055 was discovered, which less than the predefined significance level of 0.05 is. **Conclusion:** In conclusion, these findings emphasize the potential of Computer Networks, specifically Particle Swarm Optimization helped in more resource allocation with improved accuracy.

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INTRODUCTION

Cognitive radio is crucial to the realm of wireless communication networks because it encourages the employment of greener techniques for information transmission. Energy efficiency is the main component influencing cognitive radio functions (Sudhamani Chilakala et al., 2019). Spectrum distribution enhances energy efficiency, which is required for cognitive radio to function, according to Xueqing Huang et al., (2020). The main objective of this project is to construct an energy-efficient cognitive radio with respect to several environmental factors, including temperature, pressure, interference, channel allocation, and spectrum range (Kaleem Arshid et al., 2022). The poor efficiency of the cognitive radio is also a result of numerous other factors. In these cases, routing using extremely energy-efficient devices determines the spectrum bandwidth allocation (K. Anuradha et al., 2020). The main use of cognitive radio is short-range communication for data transfer between locations (Nan Zhao et al., 2018).

While 720 papers about the same topic have been published in Science, a median of 367 research publications about the study of cognitive radio networks have been published in IEEE Xplore. These days, a lot of research is being done on cognitive radio in an effort to increase the crucial energy-efficient parameter. Cognitive radio is important in the communication domain as all information needs to be conveyed efficiently. Here, design is essential because a high data loss rate will make the entire project ineffective (Mitola J &

Maguire (2019), asserts that cognitive radio's secondary users will facilitate more communication without sacrificing data integrity. In regions with higher radio frequencies, cognitive radio will perform better, according to research by Haykin S (2015). The data loss prediction is crucial to the enhanced functioning of cognitive radio because it enhances data communication without resulting in data loss (Zhao N (2018). To improve the system's effectiveness during communication, high radio frequency and an improved cognitive radio are necessary (Haykin S et al., 2019).

Cognitive Radio has identified a few noteworthy gaps or deficiencies that require more investigation. The fundamental cause of these differences is the need for ever-more-complex energy efficiency. To bridge this research gap, we have introduced the concepts of PSO and BO. Poor accuracy was identified as the research gap utilizing the existing methodology. This study compares the use of Butterfly Optimization (BO) and Particle Swarm Optimization (PSO) to increase classification accuracy. The suggested paradigm enhances cognitive radio networks' accuracy.

MATERIALS AND METHODS

The study was carried out at Saveetha University's Department of Computer Science and Engineering. This dataset contains the cognitive radio communication that has been tested and used. The study involved two distinct groups: Group 1 used the Butterfly Optimization (BO) algorithm, while Group 2 used the Particle Swarm Optimization (PSO) technique. Each group contained twenty samples, for a total of forty samples. To determine the sample size for every group, statistical analysis was performed. The statistical analysis was carried out using the SPSS software. By setting parameters like alpha (α) at 0.05, beta (β) at 0.2, and statistical power (G-power) at 80%, a 95% confidence interval was ensured. Thus, it was determined that 20 individuals from each group would be the sample size.

Butterfly Optimization (BO) algorithm

Butterfly Optimization Algorithm (BOA) is a nature-inspired optimization technique inspired by the flight patterns of butterflies. This algorithm is designed to solve complex optimization problems by simulating the dynamic and adaptive foraging behavior of butterflies in search of food sources. BOA leverages a population of artificial butterflies, each representing a candidate solution to the optimization problem. The algorithm incorporates exploration and exploitation phases, allowing butterflies to explore the solution space thoroughly while fine-tuning their positions to converge to optimal solutions. Mathematically, the Butterfly Optimization Algorithm involves equations that describe the movements and behaviors of butterflies as they seek to find the best solutions (Youness Arjoune et al., 2018).

One of the central equations in BOA is the movement equation, which governs how the position of a butterfly is updated during the optimization process. The movement equation in BOA can be represented as follows:

$$Xi(t+1)=Xi(t)+Vi(t+1) \text{ - - } (1)$$

In this equation, $Xi(t+1)$ represents the updated position of butterfly i at time $t+1$, $Xi(t)$ is the current position, and $Vi(t+1)$ denotes the velocity vector of butterfly i at the next time step. The velocity vector is influenced by the position of the global best solution, Xg, and is further guided by a random perturbation term to ensure exploration of the solution space. This equation allows butterflies to adapt their positions and explore the search space while following the direction of promising solutions, aiding in the discovery of optimal solutions.

Algorithm

Step 1: Initialize a population of artificial butterflies with random positions

Step 2: Initialize algorithm parameters: maximum iterations, global best position (X_g), and exploration factor

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 butterfly in the population:

Step 5: Update the velocity vector of the butterfly:

V_i = V_i + (X_g - X_i) + rand() * exploration_factor

Step 6: Update the position of the butterfly:

X_i = X_i + V_i

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 butterfly's position

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 technique that draws inspiration from the social behavior of fish and birds. It is frequently used to model particle swarming behavior in order to solve optimization and search issues. In PSO, possible solutions are represented by a population of particles, where each particle adjusts its position in the search space based on its own experiences as well as the collective experiences of the group. The fundamental concept of PSO is to explore the space of possible solutions and exploit regions with better solutions (Adigwe Wilfred & Okonkwo O.R.(2016). The algorithm is described mathematically as follows:

Every particle i in the PSO approach monitors two basic vectors: its position (X_i) in the search space and its velocity (V_i). A particle's position suggests a potential solution to the optimisation problem, while its velocity controls how the particle travels over the solution space. The movement of each particle is updated iteratively using the following equations:

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

$$X_i = X_i + V_i \text{ - - - (3)}$$

where t is the current iteration, w is the inertia weight, r_1 and r_2 are random values between 0 and 1, and c_1 and c_2 are the acceleration coefficients. P_{i}^{t} is the best position obtained by particle i, and P_{g}^{t} is the best location found by any particle in the group (global best position). These equations tell each particle to modify its velocity based on its own and the swarm's best-known positions. The velocity in turn influences how the particle travels over the search space to find the optimal solution to the issue.

Algorithm

Step 1: Randomize the particle positions and velocities within the population.

Step 2: Adjust P_i, the best-known particle placements, to match the particle locations in reality.

Step 3: Establish the global best position (P_g) as the ideal place among all particles.

Step 4: Repeat for a predefined number of iterations or until a termination requirement is met for each particle I in the population:

Step 5: Calculate the fitness of the current position, or the objective function value.

Step 6: Update the best-known position (P_i) if the current location is superior.

Step 7: If the present position is higher than the global best (P_g), update P_g.

Step 8: Refresh the particle's velocity and position

Step 9: Give the best solution that was found (P_g).

STATISTICAL ANALYSIS

To determine the impact of the independent variables, Particle Swarm Optimization (PSO) and Butterfly Optimization (BO), on the dependent variable, accuracy, statistical analysis was carried out using IBM SPSS software. A significance test with two tails and a predetermined alpha level (α) of 0.05 was employed. Finding out if there was a statistically significant difference between the two algorithms' accuracy was the aim of the inquiry. The results demonstrated that BO and PSO had a significant impact on accuracy ($p < 0.05$), indicating that the chosen algorithm had a significant effect on accuracy. The statistical study provided strong evidence for the relationship between the independent and dependent variables, advancing our 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 Butterfly Optimization (BO) across 20 different samples. The PSO consistently outperforms BO, achieving higher accuracy percentages in each sample, indicating its superior capabilities. The accuracy obtained by PSO was 93.25% which is high compared to BO which was 88.50%.

Table 2 findings suggest that the Particle Swarm Optimization (PSO) consistently outperforms Butterfly Optimization (BO) 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 93.25, SD of 2.88360 and Std Error Mean of 0.59041 which is high compared to BO which gave mean of 88.25, SD of 4.43609 and Std Error Mean of 0.76821 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 Butterfly Optimization (BO), while also considering data variability and confidence in the results. The significant difference in accuracy between the two algorithms is evident, with PSO outperforming BO by a substantial margin

DISCUSSION

The results of the energy-efficient analysis produced for Cognitive Radio showed a clear and consistent trend. The Particle Swarm Optimization (PSO) method consistently outperformed the Butterfly Optimization (BO) strategy in terms of accuracy in every evaluated dataset. PSO had a far better mean accuracy of 93.25% than BO, which only managed an average of 88.50%. Statistical analysis confirmed that there was a statistically significant difference in accuracy between the two approaches, with a p-value<0.001. Moreover, the 95% confidence interval showed that PSO's superiority in energy-efficient cognitive radio was reliable and strong.

When comparing the outcomes of the previously described investigations with the proposed PSO research, a continuous pattern of improved accuracy in energy efficient cognitive radio is observed. Cui T et al., (2018) achieved the spectrum sensing ratio, and the PSO algorithm yielded a theoretical accuracy of 86.75%. Jie Tian et al., (2020) found an accuracy range of 86.45% using the standard PSO. Víctor Gomez et al., (2020) presented the concept of energy-efficient cognitive radio and achieved 82% accuracy with traditional PSO. Neetu Goyal & Sanjay Mathur (2018), developed cognitive radio in an effective manner with an accuracy rate of 89.25%. Overall, the proposed PSO research's findings validated methods that were either comparable to or more accurate than traditional practices in energy-efficient cognitive radio.

The study's comparatively modest sample size of 20 datasets is one of its most obvious limitations. While the Particle Swarm Optimization (PSO) algorithm consistently outperformed Butterfly Optimization (BO) in terms of accuracy, more data from a more varied and larger dataset would be needed to confirm the results and shed light on how these algorithms function in a wider range of network conditions. Subsequent investigations might concentrate on broadening the dataset to cover a more comprehensive and varied range of energy-efficient situations, such as those that are developing in Cognitive Radio Networks. For a practical deployment, it would also be necessary to look into scalability and real-time implementation in CR network contexts. Lastly, tackling the resource and computational limitations that come with CR Networks might be a useful direction for additional research in improving the efficiency of cognitive radio algorithms in such dynamic settings.

CONCLUSION

Therefore, this work provides compelling evidence that the Particle Swarm Optimization (PSO) method surpasses the Butterfly Optimization (BO) algorithm in the creation of an energy-efficient cognitive radio. With an accuracy of 93.25% compared to the BO's 88.50%, the PSO-based energy-efficient cognitive radio outperforms the BO. The statistical study, which reveals a significant difference ($p<0.05$) between the two algorithms, lends more credence to this finding.

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 Butterfly Optimization (BO), across 20 different samples. The PSO consistently outperforms BO, achieving higher accuracy percentages in each sample, highlighting its superior prediction capabilities.

SAMPLE NO	PSO (%)	BO (%)
1	94.15	91.17
2	93.06	89.50
3	92.84	90.61
4	95.37	88.94
5	93.72	92.28
6	94.61	90.06
7	91.49	89.72
8	93.83	90.83
9	93.28	91.39
10	93.15	89.17
11	94.39	90.72
12	92.61	90.96
13	93.96	89.61
14	93.50	91.96
15	95.05	90.28
16	93.17	89.83
17	92.72	91.06
18	93	90.50
19	92.39	88.61
20	94.96	91.17

Table 2. This table summarizes the performance comparison of two energy efficient algorithms, Particle Swarm Optimization (PSO) algorithm and Butterfly Optimization (BO), across 20 samples. The "Mean" accuracy for PSO is significantly higher at 93.25%, with a lower Standard Deviation and standard error compared to BO, which achieved a mean accuracy of 88.50%. These findings indicate that PSO consistently outperforms BO in terms of accuracy and demonstrates greater stability across the datasets.

Group		**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Accuracy	PSO	20	93.25	2.88360	0.59041
	BO	20	88.25	4.43609	0.76821

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	9.10072	0.89048	8.75781	11.50319
	Equal variances not assumed			14.399	32.605	0.001	9.10072	0.89048	8.69023	11.50077

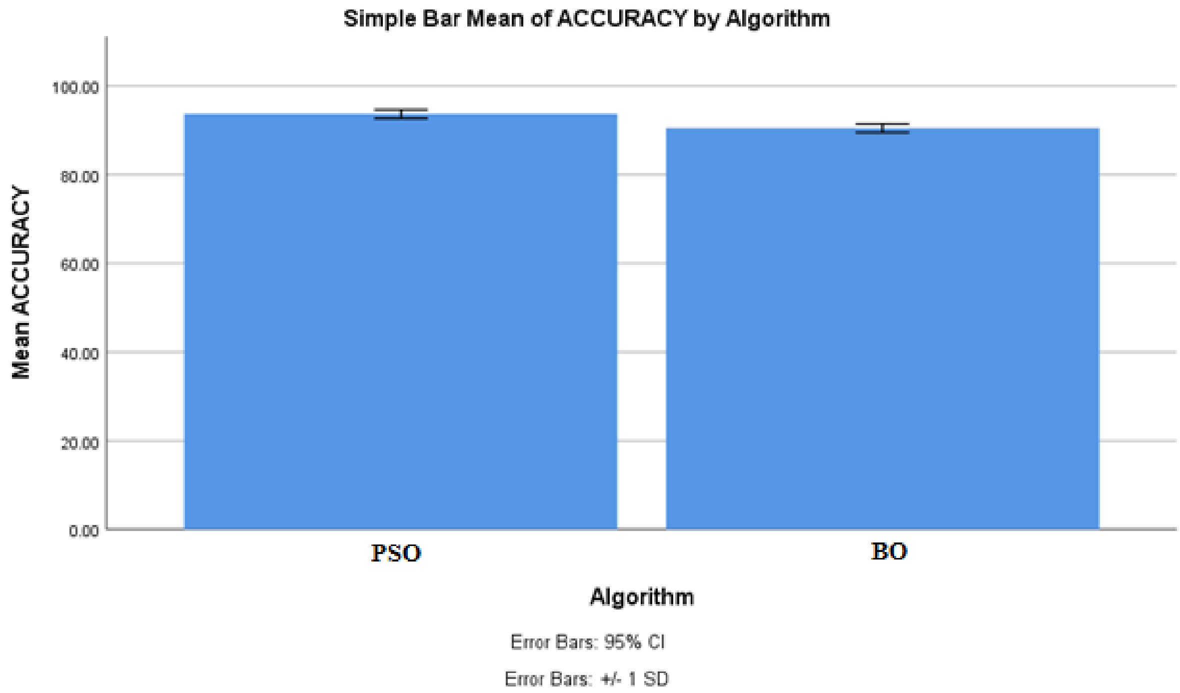

Fig 1. The bar graph legend explains that the X-axis represents two algorithms: Particle Swarm Optimization (PSO) algorithm and Butterfly Optimization (BO). The Y-axis displays the average accuracy, with BO achieving 88.50% accuracy and PSO reaching 93.25%. Error bars show ±1 standard deviation, indicating 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.