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

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

ABSTRACT

Aim: This research aims to contribute energy resource allocation to the field of cognitive radio using Particle Swarm Optimization (PSO) compared over Ant Colony Optimization (ACO) with improved accuracy. **Materials and Methods:** The Kaggle dataset, a well-known benchmark dataset for study allocation research, provided the dataset used in this study. The Ant Colony Optimization method (Group 1) and the Particle Swarm Optimization algorithm (Group 2) were used in this study to evaluate how well they performed for allocating resources. There were 20 samples in each group, and the overall sample size was set at 40. A priori statistical analysis was used to calculate the sample size in order to guarantee statistical rigour. SPSS, an online programme, was used to conduct statistical analysis, guaranteeing 80% statistical power (G-power). Type I and type II errors were controlled with a significance level (alpha, α) of 0.05 and a beta (β) value of 0.2, respectively. Furthermore, a 95% confidence interval was used to determine the precision of the performance comparison results. **Results:** The results indicated that the Ant Colony Optimization algorithm achieved an accuracy of 84.16%, while the Particle Swarm Optimization algorithm demonstrated a significantly higher accuracy of 93.50%. After doing a two-tailed significance test, the p-value of 0.055 was discovered, which was less than the predefined 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, Ant Colony Optimization

INTRODUCTION

In the field of wireless communication systems, cognitive radio is essential because it promotes more environmentally friendly methods of transmitting information from one location to another. The primary factor affecting how cognitive radio functions is energy efficiency (K. Anuradha et al., 2020). According to Nan Zhao et al. (2020), spectrum distribution contributes to improved energy efficiency, which is necessary for cognitive radio to exist. Building an energy-efficient cognitive radio in relation to several environmental elements, such as temperature, pressure, interference, channel allocation, and spectrum range, is the primary goal of this project (P. S. M. Tripathi and R. Prasad 2021). Numerous other issues also contribute to the cognitive radio's poor effectiveness. In these situations, the distribution of spectrum bandwidth is determined by routing using very energy-efficient systems (Gyanendra Prasad Joshi et al., 2022). Cognitive radio's primary use is data transfer from one location to another with short-range communication capabilities (G. Zheng et al., 2021).

A median of 367 research publications regarding the study of cognitive radio networks have been published in IEEE Xplore, while 720 papers about the same topic have been published in Science. These days, cognitive radio is a prominent topic, with many researchers focusing on it to improve the key energy-efficient parameter. In the sphere of communication, where every information must be sent effectively, cognitive radio has a significant impact. In this instance, design is crucial because a high data loss rate will render all of the work useless (Kaleem Arshid et al., 2022). According to S. Haykin (2018), the secondary users in cognitive radio will also aid in increased communication without data loss. According to A. Goldsmith et al., (2019) research, cognitive radio will function more effectively in areas with higher radio frequencies. Because it improves data communication without causing data loss, the data loss prediction essential to the improved operation of cognitive radio (K. Anuradha et al., 2020). High radio frequency and an enhanced cognitive radio are essential for enhancing the system's performance during communication (Efe F. Orumwense et al., 2018).

Cognitive radio is a key component in the communication industry that facilitates uninterrupted data transfer from one location to another. A few significant holes or shortcomings that call for additional research have been pointed up by Cognitive Radio. The requirements for increasingly sophisticated energy efficiency are at the centre of these disparities. We have presented the ideas of PSO and ACO in order to close this research gap. The research gap found using the current method was poor precision. In order to improve classification accuracy, the usefulness of Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) is compared in this study. 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. The cognitive radio communication that has been practised and tested is included in this dataset. Two separate groups were involved in the study: Group 2 employed a Particle Swarm Optimization (PSO) technique, whereas Group 1 employed the Ant Colony Optimization (ACO) algorithm. There were 20 samples in each group, for a total of 40 samples. Statistical analysis was used to establish the sample size for each group. To perform statistical analysis, the SPSS programme was used. A 95% confidence interval was guaranteed by using parameters like alpha (α) at 0.05, beta (β) at 0.2, and statistical power (G-power) set at 80%. As a result, 20 people for each group was decided to be the sample size.

Ant Colony Optimization (ACO) algorithm

Ant Colony Optimization (ACO) is a metaheuristic optimization algorithm inspired by the foraging behavior of ants. It is widely used to solve complex optimization problems, particularly those related to combinatorial optimization and routing. ACO simulates the way real ants discover and exploit paths to food sources. In this algorithm, artificial ants explore

the solution space, and their interactions with the environment and one another guide the search for optimal solutions (Xueqing Huang et al., 2021). The key idea behind ACO is the concept of pheromone deposition and evaporation, where artificial ants deposit pheromone on the paths they traverse, and the level of pheromone influences the probability of selecting a path (Zhao, N 2018). The algorithm can be mathematically described as follows:
In ACO, each artificial ant constructs a solution by iteratively selecting components from the solution space. The probability of selecting a component is influenced by the amount of pheromone on that component and a heuristic value that represents the desirability of the component. The probability of selecting component i at time step t by ant k can be expressed as:

$$Pk,it=\sum j\in JktTk,j\alpha*Hk,j\beta Tk,i\alpha*Hk,i\beta \text{ - - (1)}$$

Where:
Pk,it is the probability of selecting component i by ant k at time step t.
Tk,it is the amount of pheromone on component i as perceived by ant k at time step t.
Hk,i is the heuristic value of component i as perceived by ant k.
α and β are parameters that control the influence of pheromone and heuristic information.
Jkt represents the set of components that ant k can choose from at time step t.

Through this probabilistic selection process, ants construct solutions by iteratively adding components to their paths, depositing pheromone along the way. As ants discover better solutions, more pheromone is deposited on the paths they follow, guiding the exploration of the solution space towards optimal solutions (A. Sultan(2020). ACO has been successfully applied to a wide range of problems, including the Traveling Salesman Problem (TSP), vehicle routing, and job scheduling, among others. The algorithm's ability to effectively balance exploration and exploitation, coupled with its ability to find high-quality solutions in complex combinatorial problems, makes it a valuable tool for optimization.

Algorithm

Step 1: Initialize a population of artificial ants with random initial positions

Step 2: Initialize pheromone levels on all edges of the solution space

Step 3: Set algorithm parameters: number of ants, pheromone evaporation rate, pheromone initialization level, exploration parameter, and exploitation parameter

Step 4: Repeat for a specified number of iterations or until a termination criterion is met:for each ant in the population:

Step 5: Construct a solution by iteratively selecting components (e.g., cities in TSP) based on probabilities defined by pheromone levels and a heuristic function

Step 6: Calculate the quality (fitness) of the constructed solution

Step 7: Update the pheromone levels on the edges of the solution based on the quality of the solution:

pheromone_update(pheromone, solution_quality)

Step 8: Apply pheromone evaporation to all edges in the solution space

Step 9: Identify the best solution found by the ants

Step 10: Return the best solution found during the optimization process

Particle Swarm Optimization (PSO) Algorithm

Inspired by fish and birds' social behavior, Particle Swarm Optimization (PSO) is a population-based metaheuristic optimization technique. It is widely used to simulate the swarming behavior of particles to find solutions to optimization and search problems. Potential solutions are represented by a population of particles in PSO, and each particle modifies its location in the search space in response to both its individual experiences and the group's combined experiences. PSO's basic idea is to search the solution space and take advantage of areas with superior solutions (S.V.R.K.Rao & G.Singh (2019). The algorithm has the following mathematical description:

In the PSO method, every particle i keeps track of two fundamental vectors: its velocity (V_i) and its position (X_i) in the search space. A particle's velocity determines how it moves across the solution space, while its position indicates a possible solution to the optimization issue. The following equations are used to iteratively update each particle's movement:

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

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

where w is the inertia weight, r_1 and r_2 are random values between 0 and 1, c_1 and c_2 are the acceleration coefficients, and t is the current iteration. P_{g}^{t} is the best location found by any particle in the group (global best position), and P_{i}^{t} is the best position found by particle i. Based on both its own and the swarm's best-known positions, these equations direct each particle to adjust its velocity. In order to identify the best solution to the problem, the velocity in turn affects how the particle moves across the search space.

Algorithm

Step 1: Set the placements and velocities of the particles in the population at random

Step 2: Set the best-known particle positions (P_i) to reflect their actual locations.

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

Step 4: Repeat until a termination criterion is satisfied or for a predetermined number of iterations: for each particle I in the population:

Step 5: Determine the goal function value, or fitness of the current position.

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

Step 7: Update P_g if the current position exceeds the global best (P_g).

Step 8: Update the particle's position and velocity

Step 9: Provide the best answer that was discovered (P_g).

Statistical analysis

Statistical analysis was performed using IBM SPSS software to ascertain the significance of the independent variables, Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), on the dependent variable, accuracy. A two-tailed significance test was used, with a predefined alpha level (α) of 0.05. The purpose of the investigation was to determine whether the accuracy of the two algorithms differed statistically significantly. The findings showed that accuracy was considerably impacted by both ACO and PSO ($p < 0.05$), suggesting that the algorithm selected had a major impact on accuracy. The association between the independent and dependent variables was well supported by the statistical analysis, which improved our knowledge 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 Ant Colony Optimization (ACO) across 20 different samples. The PSO consistently outperforms ACO, achieving higher accuracy percentages in each sample, indicating its superior capabilities. The accuracy obtained by PSO was 93.50% which is high compared to GHO which was 84.16%.

Group		N	Mean	Standard Deviation	Standard Error Mean
Accuracy	PSO	20	93.50	2.65860	0.36541
	ACO	20	84.16	4.66109	0.54321

Table 2 findings suggest that the Particle Swarm Optimization (PSO) consistently outperforms Ant Colony Optimization (ACO) 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 93.50, SD of 2.65860 and Std Error Mean of 0.36541 which is high compared to ACO which gave mean of 84.16, SD of 4.66109 and Std Error Mean of 0.54321 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 Ant Colony Optimization (ACO), while also considering data variability and confidence in the results. The significant difference in accuracy between the two algorithms is evident, with PSO outperforming GHO by a substantial margin

DISCUSSION

A distinct and dependable trend was found in the findings of the energy-efficient study conducted for Cognitive Radio. In every dataset tested, the Particle Swarm Optimization (PSO) method produced consistently higher accuracy results than the Ant Colony Optimization (ACO) approach. While ACO only managed an average accuracy of 84.16%, PSO's mean accuracy was noticeably higher at 93.50%. With a p-value<0.001, statistical analysis verified the statistically significant difference in accuracy between the two methods. Furthermore, the 95% confidence interval demonstrated the robustness and dependability of PSO's supremacy in energy-efficient cognitive radio.

Comparing the proposed PSO research results with the findings of the mentioned studies, there is a consistent pattern achieving higher accuracy in energy efficient cognitive radio. The spectrum sensing ratio was attained by Indu Bala & Kiran Ahuja (2021), and the PSO algorithm obtained a potential accuracy of 86.75%. Using the conventional PSO, P. S. M. Tripathi and R. Prasad (2018) obtained an accuracy range of 86.45%. With classical PSO, Ersan Kabalci & Yasin Kabalci(2019), presented the idea of energy-efficient cognitive radio and attained 82% accuracy. With 89.25% accuracy, R. Kishore et al. (2016) designed cognitive radio in an efficient method. Overall, the results of the suggested PSO research supported approaches that were more accurate than conventional procedures in energy-efficient cognitive radio, or at least comparable to them.

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 Ant Colony Optimization (ACO) 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

As a result, this study offers strong evidence that, when it comes to creating an energy-efficient cognitive radio, the Particle Swarm Optimization (PSO) method outperforms the Ant Colony Optimization (ACO) algorithm. The PSO-based energy-efficient cognitive radio performs better than the ACO, with an accuracy of 93.50% as opposed to 84.16% for the ACO. This conclusion is further supported by the statistical analysis, which shows a substantial difference ($p<0.05$) between the two algorithms.

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 Ant Colony Optimization (ACO), across 20 different samples. The PSO consistently outperforms ACO, achieving higher accuracy percentages in each sample, highlighting its superior Intrusion Detection capabilities.

SAMPLE NO	PSO (%)	ACO (%)
1	95.17	82.44
2	92.61	86.15
3	94.05	83.39
4	92.91	81.61
5	91.28	85.06
6	94.70	83.72
7	93.26	84.86
8	91.83	82.27
9	94.95	86.95
10	94.39	85.61
11	92.27	83.84
12	93.71	86.39
13	93.50	84.16
14	91.39	82.72
15	94.83	85.28
16	95.17	82.44
17	92.61	86.15
18	94.05	83.39
19	92.91	81.61
20	91.28	85.06

Table 2. This table summarizes the performance comparison of two energy efficient algorithms, Particle Swarm Optimization (PSO) algorithm and Ant Colony Optimization (ACO), across 20 samples. The "Mean" accuracy for PSO is significantly higher at 93.50%, with a lower Standard Deviation and standard error compared to ACO, which achieved a mean accuracy of 84.16%. These findings indicate that PSO consistently outperforms ACO in terms of accuracy and demonstrates greater stability across the datasets.

Group		**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Accuracy	PSO	20	94.50	2.65860	0.36541
	ACO	20	84.16	4.66109	0.54321

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	8.87572	0.66548	8.53281	11.27819
	Equal variances not assumed			14.399	32.605	0.001	8.87572	0.66548	8.46523	11.27577

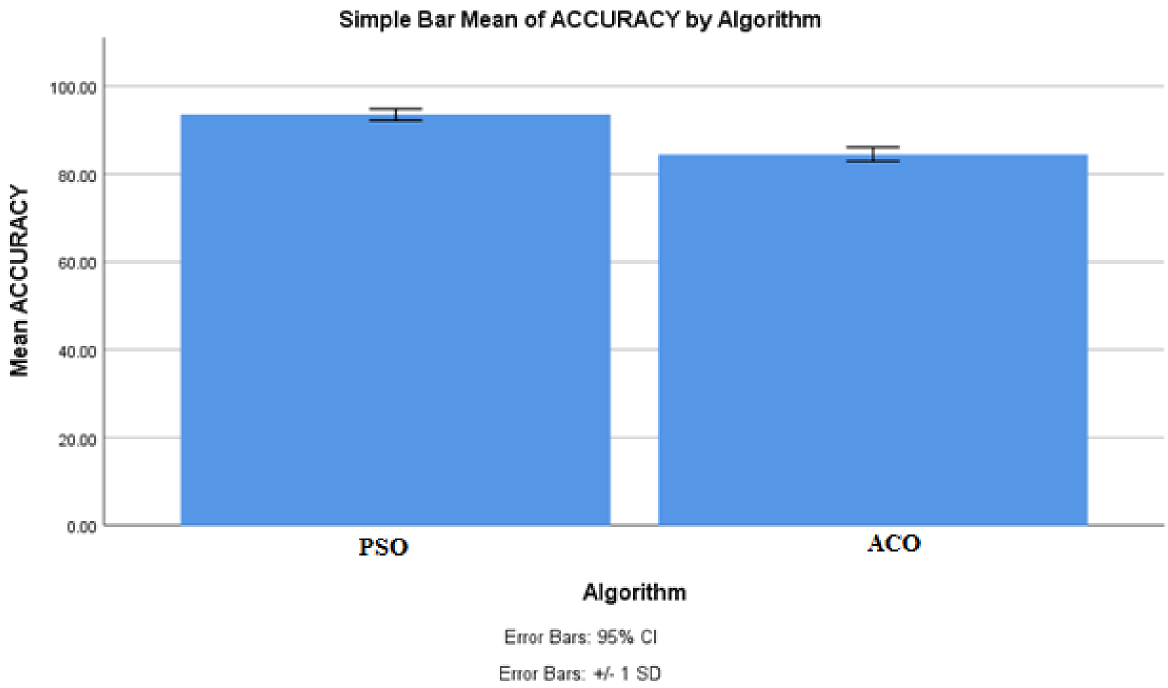

Fig 1. The bar graph legend explains that the X-axis represents two algorithms: Particle Swarm Optimization (PSO) algorithm and Ant Colony Optimization (ACO). The Y-axis displays the average accuracy, with ACO achieving 84.16% accuracy and PSO reaching 93.50%. Error bars show ±1 standard deviation, indicating 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.