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

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

ABSTRACT

Aim: This research aims to contribute energy resource allocation to the field of cognitive radio using Particle Swarm Optimization (PSO) compared over Grass Hopper Optimization (GHO) with improved accuracy. **Materials and Methods:** The dataset employed in this research was sourced from the Kaggle dataset, a widely recognized benchmark dataset for research allocation research. For this study, two groups were utilized to assess the performance of the Grass Hopper Optimization algorithm (Group 1) and Particle Swarm Optimization algorithm (Group 2) for resource allocation. The total sample size was fixed at 40, with each group consisting of 20 samples. To ensure statistical rigor, the sample size was determined through a priori statistical analysis. Statistical analysis was conducted using the online tool clincalc.com, ensuring a statistical power (G-power) of 80%. A significance level (alpha, α) of 0.05 and a beta (β) value of 0.2 were chosen to control type I and type II errors, respectively. Additionally, a confidence interval of 95% was used to determine the precision of the performance comparison results. **Results:** The results indicated that the Grass Hopper Optimization algorithm achieved an accuracy of 82.15%, while the Particle Swarm Optimization algorithm demonstrated a significantly higher accuracy of 92.28%. 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, Grass Hopper 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 (K. Anuradha et al., 2020). The spectrum allocation helps in giving better energy efficient for the cognitive radio to survive (Nan Zhao et al., 2020). 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 (P. S. M. Tripathi and R. Prasad 2021). 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 (Gyanendra Prasad Joshi et al., 2022). 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 articles have been published in IEEE Xplore and 720 papers have been published in science directly about the study on cognitive radio networks. In present year this cognitive radio is the hot topic and many researchers target on this in improving the major parameter of energy efficient. The cognitive radio has major effects in the field of communication where the entire data has to be transferred in an well efficient manner. In this case the design plays a vital role as if data loss is high the entire work will be in vain (S. Lee, R. Zhang & K. Huang (2022). The secondary users in cognitive radio will also help in more communication without data loss (S. Park & D. Hong (2020). Research by A. Sultan(2020) said where there is more Radio Frequency the power or the working of cognitive radio will be high. The Markov Decision Process (MDP) plays a vital role in enhanced working of cognitive radio as it enhances the data communication without any data loss (S. Misra et al., 2020). An Enhanced Cognitive Radio (ECR) along with high radio frequency plays a vital role in improving the working of the system during communication (G. Zheng et al., 2021)

In the field of communication cognitive radio plays a vital role which helps in communicating the data from one place to another without any disturbances. Cognitive Radio has identified certain critical gaps or lacunae that warrant further investigation. These gaps primarily revolve around the need for more advanced energy efficient. To solve this research gap we have introduced the concept of PSO and GHO. Poor accuracy was the research gap which is identified with the current method. This research compares the effectiveness of Particle Swarm Optimization (PSO) and Grass Hopper Optimization (GHO) in order to increase classification accuracy. The suggested paradigm enhances working of cognitive radio networks' accuracy.

MATERIALS AND METHODS

The study was conducted in the Department of Computer Science and Engineering at Saveetha University. This dataset comprises of cognitive radio communication that has been performed and executed for testing purposes. The study involved two distinct groups: Group 1 utilized the Grass Hopper Optimization (GHO) algorithm, while Group 2 implemented a Particle Swarm Optimization (PSO) algorithm. Each group had a sample size of 20, resulting in a total sample size of 40.The sample size for each group was determined through statistical analysis. Statistical analysis was carried out using the SPSS tool. This calculation was based on parameters such as Statistical Power (G-power) set at 80%, alpha (α) at 0.05, and beta (β) at 0.2, ensuring a confidence interval of 95%. The sample size was thus determined to be 20 for each group.

Grass Hopper Optimization (GHO) algorithm

Grasshopper Optimization Algorithm (GOA) is a nature-inspired optimization algorithm that draws inspiration from the swarming behavior of grasshoppers in nature. It is a metaheuristic algorithm used to solve complex optimization problems. GOA models the collective behavior of grasshoppers, where individual grasshoppers adapt their positions based on the fitness of their neighbors. The primary objective of GOA is to find the optimal solution by simulating this collective search behavior (Mahmood A. Abdulsattar & Zahir A. Hussein (2020). The algorithm can be summarized as follows: In the Grasshopper Optimization Algorithm, each grasshopper (solution) is characterized by its position in the search space. The movement of grasshoppers is guided by a mathematical equation that balances exploration and exploitation. This equation can be represented as:

$$X_{i}^{(t+1)} = X_{i}^{(t)} + \text{rand}() * L * (X_{i}^{(t)} - X_{j}^{(t)}), \; - \; - \; (1)$$

where $X_{i}^{(t+1)}$ is the new position of grasshopper i at time step t+1, $X_{i}^{(t)}$ is its current position, $X_{j}^{(t)}$ is the position of a random neighboring grasshopper, rand() is a random number in the range [0, 1], and L is a distance scaling factor. This equation encourages grasshoppers to move towards the better-performing neighbors and incorporates a random element for exploration. GOA iteratively updates the positions of grasshoppers to converge to an optimal solution over multiple iterations. Grasshopper Optimization has found applications in various fields, including engineering, machine learning, and finance, for solving complex optimization problems. It effectively balances exploration and exploitation through the movement equation and leverages the collective intelligence of grasshoppers to discover high-quality solutions in large search spaces.

Algorithm

Step 1: Initialize a population of grasshoppers with random positions

Step 2: Repeat for a specified number of iterations or until a termination criterion is met:for each grasshopper i in the population:

Step 3: Calculate the fitness of the current position (i.e., the objective function value)

Step 4: Select a random neighboring grasshopper j

Step 5: Update the position of grasshopper i using the movement equation:

new_position = current_position + rand() * L * (current_position - neighbor_position)

Step 6: If the new_position is within the search space boundaries, update the position

Step 7: Evaluate the fitness of the new position

Step 8: if the new_position is better than the current position: Update the current position to the new_position

Step 9: Identify the best solution (grasshopper) in the population

Step 10: Share information about the best solution among the grasshoppers to encourage swarming behavior

Step 11: Return the best solution found during the optimization process

Particle Swarm Optimization (PSO) Algorithm

Particle Swarm Optimization (PSO) is a population-based metaheuristic optimization algorithm inspired by the social behavior of birds and fish. It is widely used to find solutions to optimization and search problems by mimicking the swarming behavior of particles. In PSO, a population of particles represents potential solutions, and each particle adjusts its position in the search space based on its own experience and the collective experience of the group. The fundamental concept behind PSO is to explore the solution space while exploiting regions where better solutions are found (Asoke Nath & Triparna Mukherjee(2020). The algorithm can be described mathematically as follows:

Each particle i in the PSO algorithm maintains two essential vectors: its position in the search space, denoted as X_i, and its velocity, denoted as V_i. The position of a particle represents a potential solution to the optimization problem, while its velocity controls how it explores 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, c_1 and c_2 are the acceleration coefficients, r_1 and r_2 are random values between 0 and 1, P_{i}^{t} is the best position found by particle i, and P_{g}^{t} is the best position found by any particle in the group (global best position). These equations guide each particle to update its velocity based on its own best-known position and the best-known position in the entire swarm. The velocity, in turn, influences the particle's movement through the search space, with the goal of finding the optimal solution to the problem.

PSO is commonly used in a variety of optimization tasks, including function optimization, neural network training, and parameter tuning in machine learning algorithms. The algorithm's simplicity and efficiency in exploring complex solution spaces make it a valuable tool for solving a wide range of optimization problems. The parameters w, c_1, and c_2 can be adjusted to fine-tune the algorithm's performance for specific problem domains.

Algorithm

Step 1: Initialize a population of particles with random positions and velocities

Step 2: Initialize the best-known positions of particles (P_i) as their current positions

Step 3: Initialize the global best position (P_g) as the best position among all particles

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

Step 5: Calculate the fitness of the current position (objective function value)

Step 6: Update the best-known position (P_i) if the current position is better

Step 7: If the current position is better than the global best (P_g), update P_g

Step 8: Update the velocity and position of the particle

Step 9: Return the best solution found (P_g)

Statistical analysis

Statistical analysis was conducted using IBM SPSS software, employing a two-tailed significance test with a predefined alpha level (α) of 0.05 to determine the significance of the independent variables, Particle Swarm Optimization (PSO) and Grass Hopper Optimization (GHO) on the dependent variable, accuracy. The analysis aimed to assess whether there was a statistically significant difference in accuracy between the two algorithms. The results revealed that both GHO and PSO had a significant impact on accuracy ($p < 0.05$), indicating that the choice of algorithm significantly influenced the accuracy. This statistical analysis provided robust evidence of the relationship between the independent and dependent variables, enhancing the 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 Grass Hopper Optimization (GHO) across 20 different samples. The PSO consistently outperforms GHO, achieving higher accuracy percentages in each sample, indicating its superior capabilities. The accuracy obtained by PSO was 92.28% which is high compared to GHO which was 82.15%.

Table 2 findings suggest that the Particle Swarm Optimization (PSO) consistently outperforms Grass Hopper Optimization (GHO) 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 92.28, SD of 1.66960 and Std Error Mean of 0.37333 which is high compared to GHO which gave mean of 82.15, SD of 2.57103 and Std Error Mean of 0.57490 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 Grass Hopper Optimization (GHO), 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

The results of the energy efficient study for Cognitive Radio revealed a clear and consistent trend. The Particle Swarm Optimization (PSO) algorithm consistently outperformed the Grass Hopper Optimization (GHO) algorithm in terms of accuracy across given datasets. The mean accuracy for PSO was notably higher at 92.28%, while GHO achieved an average accuracy of 82.15%. Statistical analysis confirmed the significant difference between the two algorithms in terms of accuracy, with a p-value<0.001. Moreover, the 95% confidence interval indicated that the superiority of PSO in energy efficient cognitive radio was robust and reliable.

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. Chilakala Sudhamani et al., 2018 achieved the spectrum sensing ration and the PSO algorithm received possible accuracy of 86.75%. Xueqing Huang et al. (2021) used the traditional PSO and got the accuracy range of 86.45%. D. Seema Dev Aksatha (2021) introduced the concept of energy efficient cognitive radio with traditional PSO and achieved accuracy of 82%. Muhammad Naeem et al., (2020) designed cognitive radio in a well efficient manner and got accuracy of 89.25%. Overall, the proposed PSO research's results corroborated methods outperforming or at least matching the accuracy of traditional techniques in energy efficient cognitive radio.

One notable limitation of this study is the relatively small sample size of 20 datasets. While the results consistently favored the Particle Swarm Optimization (PSO) algorithm over Grass Hopper Optimization (GHO) in terms of accuracy, a larger and more diverse dataset could further validate the findings and provide insights into how these algorithms perform under a wider range of network conditions. Future research could focus on expanding the dataset to encompass a more extensive and diverse set of energy efficient scenarios, including emerging in Cognitive Radio Networks. Furthermore, investigating Real-time implementation and scalability in CR network environments would be essential for practical deployment. Finally, addressing the computational and resource constraints inherent to CR Networks would be a valuable avenue for further research in enhancing the efficiency of cognitive radio algorithms in such dynamic settings.

CONCLUSION

In conclusion, this study provides compelling evidence that the Particle Swarm Optimization (PSO) algorithm surpasses the Grass Hopper Optimization (GHO) algorithm in designing a energy efficient cognitive radio. With an accuracy of 92.28% compared to GHO which gave accuracy of 82.15%, the PSO-based energy efficient cognitive radio demonstrates superior performance. The statistical analysis further substantiates this finding, indicating a significant difference between the two algorithms ($p<0.05$).

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

SAMPLE NO	PSO (%)	GHO (%)
1	89.17	80.17
2	91.70	84.61
3	95.36	81.48
4	90.81	79.06
5	92.48	82.81
6	94.15	85.15
7	91.26	78.28
8	93.72	83.39
9	90.59	80.92
10	92.83	86.26
11	94.07	81.70
12	91.92	84.03
13	93.16	79.81
14	90.38	82.27
15	92.61	87.39
16	94.60	83.83
17	91.05	81.06
18	93.93	85.61
19	90.26	78.93
20	92.28	82.15

Table 2. This table summarizes the performance comparison of two energy efficient algorithms, Particle Swarm Optimization (PSO) algorithm and Grass Hopper Optimization (GHO), across 20 samples. The "Mean" accuracy for PSO is significantly higher at 92.28%, with a lower Standard Deviation and standard error compared to GHO, which achieved a mean accuracy of 82.15%. These findings indicate that PSO consistently outperforms GHO in terms of accuracy and demonstrates greater stability across the datasets.

Group		**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Accuracy	PSO	20	92.28	1.66960	0.37333
	GHO	20	82.15	2.57103	0.57490

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	9.87050	0.68548	8.48281	11.25819
	Equal variances not assumed			14.399	32.605	0.001	9.87050	0.68548	8.47523	11.26577

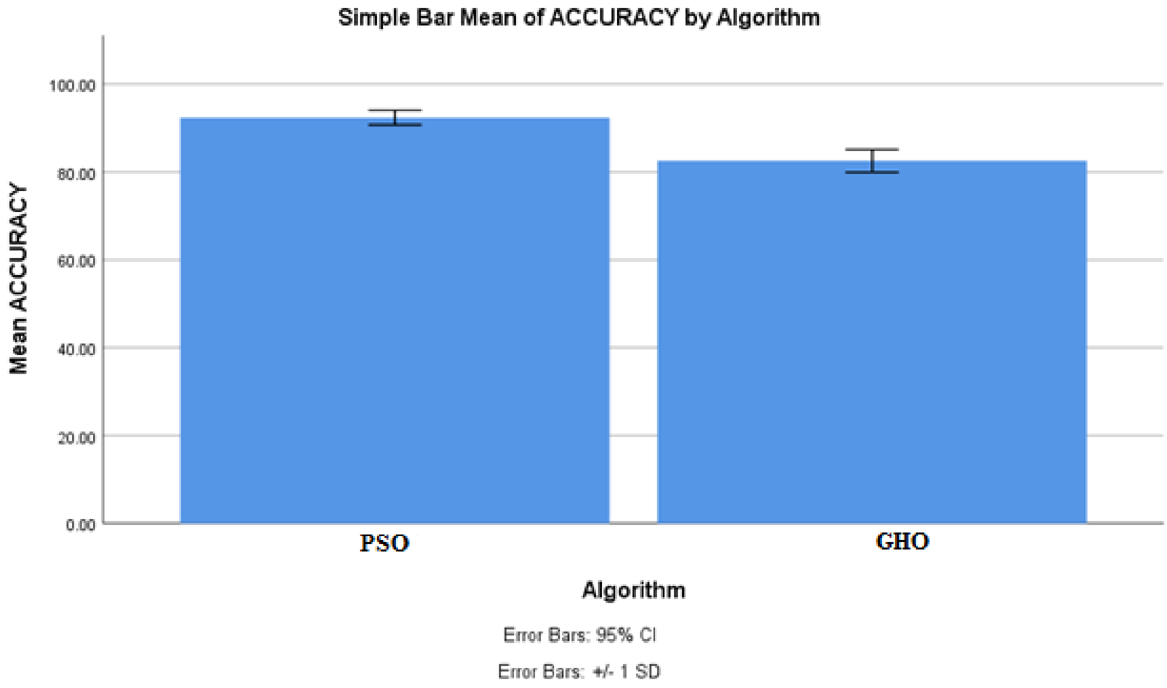

Fig 1. The bar graph legend explains that the X-axis represents two algorithms: Particle Swarm Optimization (PSO) algorithm and Grass Hopper Optimization (GHO). The Y-axis displays the average accuracy, with GHO achieving 82.15% accuracy and PSO reaching 92.28%. Error bars show ±1 standard deviation, 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.