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Evaluation And Selection Of Optimal Mimic Algorithms For Enhanced Information Exchange System

Vinivarshini R G[1], Srinithi K[2], Deeksha K[3] , Janarthanan N[4], Mythili S[5]

[1]UG Student, Dept. of Electronics and Communication Engineering. Bannari Amman Institute of Technology, India
[2]UG Student, Dept. of Electronics and Communication Engineering. Bannari Amman Institute of Technology, India
[3]UG Student, Dept. of Electronics and Communication Engineering. Bannari Amman Institute of Technology, India
[4]UG Student, Dept. of Information Technology. Bannari Amman Institute of Technology, India
[5]Assistant Professor, Dept. of Electronics and Communication Engineering. Bannari Amman Institute of Technology, India

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Abstract - *Efficient information exchange is crucial in modern communication networks, requiring robust optimization techniques for enhanced performance. This study evaluates and compares three bio-inspired metaheuristic algorithms—Particle Swarm Optimization (PSO), Gray Wolf Optimization (GWO), and Firefly Algorithm (FA)—in optimizing key parameters of information exchange systems. PSO offers fast convergence but may struggle with global exploration, GWO balances exploration and exploitation through hierarchical hunting strategies, and FA excels in multimodal optimization but may converge slowly in certain cases. The research aims to determine the most suitable algorithm for optimizing switching, efficiency, scalability, and robustness. A comprehensive performance analysis is conducted based on key metrics, with validation through simulations. The findings provide insights into the strengths and limitations of each algorithm, aiding in the selection of the optimal approach for real-world applications. These bio-mimic algorithms are analyzed and here in this study contribute to advancing bio-mimic inspired optimization techniques in enhancing information exchange systems.*

Key Words: Algorithms, Optimization, Information Exchange System, Bio-mimic, Metaheuristic Algorithms.

1.INTRODUCTION

The rapid expansion of modern communication networks has led to an increasing demand for efficient, adaptive, and scalable information exchange systems. These systems must handle dynamic conditions, high data loads, and interference, all while ensuring low latency, minimal packet loss, and optimal throughput. Traditional optimization techniques, such as deterministic algorithms and rule-based heuristics, often struggle with these challenges due to their inflexibility, high computational complexity, and lack of adaptability to changing environments. As a result, researchers have turned to bio-inspired metaheuristic algorithms, which are well-suited for solving complex multi-parameter optimization problems in dynamic and uncertain conditions.

In this context, bio-inspired metaheuristic algorithms have gained significant attention due to their ability to efficiently solve complex multi-parameter optimization problems. Among these, Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Firefly Algorithm (FA) are widely used due to their adaptability and effectiveness. This study focuses on, Analyzing the efficiency, scalability, and robustness of each algorithm, Comparing their convergence speed, solution accuracy, and resource utilization, and Identifying the most suitable optimization technique for enhancing information exchange systems. By systematically comparing PSO, GWO, and FA, this research provides practical recommendations for selecting the most appropriate algorithm based on specific demands..

1.1 Problem Statement

As complexity grows, ensuring high efficiency, scalability, and robustness in information exchange becomes increasingly difficult. Key challenges includes, Dynamic conditions like varying signal strengths, interference, congestion, and fluctuating traffic loads.Given these challenges, there is a critical need to evaluate and compare bio-inspired optimization techniques for their effectiveness in real-time information exchange optimization. The core problem can be stated as: How do bio-inspired optimization algorithms (PSO, GWO, FA) compare in optimizing information exchange, and which algorithm provides the best trade-off between efficiency, scalability, and robustness in dynamic environments?

1.2 Background and Motivation

Information exchange systems must dynamically adapt to changing conditions, such as varying traffic loads, interference, mobility, and environmental noise. These complexities make optimization a challenging and computationally intensive task. Traditional optimization approaches, including linear programming, rule-based decision-making, and deterministic algorithms, often struggle with scalability, adaptability, and real-time decision-making. To address these limitations, researchers have turned to bio-inspired metaheuristic algorithms.

2. Literature Survey

Kennedy and Eberhart's (1995) [1] paper introduces Particle Swarm Optimization (PSO), inspired by social animal behavior. It details PSO's development and testing, demonstrating its application to nonlinear function optimization and neural network training. The authors explore PSO's relation to artificial life and genetic algorithms. This work establishes PSO as a simple yet powerful optimization technique, laying the foundation for its widespread use.

Mirjalili et al. (2014) [2] introduced the Grey Wolf Optimizer (GWO), a meta-heuristic algorithm inspired by the social hierarchy and hunting behavior of grey wolves. GWO models the leadership structure using alpha, beta, delta, and omega wolves, and simulates hunting through search, encirclement, and attack phases. The algorithm's performance was evaluated using 29 benchmark functions, demonstrating competitive results compared to PSO, GSA, DE, EP, and ES. GWO's applicability to real-world problems was further validated by solving three engineering design challenges and an optical engineering application, proving its effectiveness in complex search spaces. The paper highlights GWO's potential as a robust optimization tool.

Shi and Yang (2013) [3] build upon the foundation of nature-inspired metaheuristics, specifically the Firefly Algorithm (FA), itself derived from the principles of Particle Swarm Optimization (PSO). Recognizing the prevalence of population-based algorithms, the authors introduce a chaos-enhanced FA with automatic parameter tuning, generating two new FA variants. The paper focuses on evaluating these algorithms through comparative performance analyses and their application to a benchmark engineering design problem. By comparing the results with those obtained from other methods, the authors aim to demonstrate the efficacy of their proposed enhancements, highlighting the potential for improved optimization performance through the integration of chaotic dynamics and adaptive parameter control within the FA framework.

Eberhart and Shi (2001) [4] explored Particle Swarm Optimization (PSO) development and applications, prioritizing parameter optimization for enhanced convergence. They discussed the algorithm's mechanics, focusing on dynamic adjustments of inertia weight and cognitive-social components. The paper highlighted PSO's utility in resource and frequency allocation, providing a practical understanding of its implementation. This work offers a foundational perspective on PSO's adaptable nature and its effectiveness in solving real-world optimization problems.

Ou, Yin, and Mo (2023) [5] address GWO's limitations, like slow convergence, by proposing an improved version. They employ a clone selection algorithm to enhance GWO's performance in complex optimization. Their work explores GWO with deep learning for autonomous systems and focuses on robot path planning, aiming to achieve faster convergence and better solutions.

Jiang and Zhou (2023) [11] demonstrate how biomimicry optimizes computer vision object detection. They applied the Artificial Bee Colony (ABC) algorithm, inspired by bee foraging, to improve detection accuracy and speed. ABC optimizes the search for optimal object boundaries, mimicking bees' efficient resource location. This biomimetic approach addresses limitations like long training times by leveraging nature's proven optimization strategies, resulting in faster, more accurate object detection.

3. OBJECTIVE

The primary objective of "Evaluation and Selection of Optimal Mimic Algorithms for Enhanced Information Exchange System" is to evaluate and select the most suitable bio-inspired optimization algorithm for enhancing the efficiency, scalability, and robustness of information exchange systems. To achieve this, the research focuses on analyzing the performance of three metaheuristic algorithms—Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Firefly Algorithm (FA)—in optimizing key parameters that influence the effectiveness of communication systems.

Table -1: Swarm Intelligence Optimization Algorithms

Algorithms	Reason
Particle Swarm Optimization (PSO) Algorithm	Shows how biological phenomena can help understand computation problems in artificial intelligence
Gray Wolf Optimization (GWO) Algorithm	Finds optimal solutions by balancing exploration and exploitation, guided by leader wolves.
Firefly Algorithm (FA)	Works by guiding less bright fireflies toward brighter ones, balancing exploration and exploitation to find solutions.

These algorithms are assessed in terms of their ability to handle dynamic conditions, optimize throughput, reduce latency, and maintain stability under varying load conditions.

By understanding the concepts of PSO, GWO, and FA, the research aims to provide practical insights into their deployment in real-world applications. The goal is to contribute to the development of more efficient and intelligent information exchange mechanisms that can adapt to the growing demands of modern digital communication.

4. METHODOLOGY

This study follows a structured methodology to evaluate and compare bio-inspired optimization algorithms for enhancing information exchange systems. The approach includes dataset construction, algorithm implementation, simulation-based evaluation, and comparative analysis to determine the most efficient technique. By systematically assessing Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Firefly Algorithm (FA) under realistic conditions, the study aims to identify the most suitable optimization strategy

4.1 Bio Metaheuristic Algorithms

Bio-heuristic algorithms are nature-inspired optimization techniques designed to solve complex problems by mimicking biological processes. They use adaptive search strategies to explore and exploit solutions efficiently, making them suitable for optimizing performance in dynamic environments.

This study evaluates Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Firefly Algorithm (FA) for optimizing information exchange systems. PSO, inspired by swarm intelligence, updates particle positions based on personal and global best solutions, ensuring fast convergence but sometimes leading to premature stagnation. GWO, modelled after the hunting strategies of grey wolves, balances exploration and exploitation effectively, making it suitable for complex search spaces. FA, based on the flashing behaviour of fireflies, is effective for multimodal optimization but may converge more slowly than PSO and GWO.

5. ALGORITHMS

Algorithms are step-by-step procedures or rules designed to solve specific problems efficiently. They can be categorized into various types, such as optimization algorithms, search algorithms, and machine learning algorithms. Here we use Bio-inspired algorithms, like PSO, GWO, and FA, mimic natural behaviors to find optimal solutions in complex environments.

5.1 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population-based metaheuristic optimization algorithm inspired by the social behavior of birds flocking or fish schooling. Developed by Kennedy and Eberhart in 1995, PSO is widely used for solving complex optimization problems.

In PSO, potential solutions to the optimization problem are represented as particles in a swarm, and each particle adjusts its position in the search space based on its own experience and the experience of its neighbors. Each particle has a position and a velocity, which are updated iteratively. The particles are influenced by two key components: their own best-known position (personal best) and the best-known position found by the entire swarm (global best). These factors guide the particle's movement through the solution space, balancing exploration (searching new areas) and exploitation (refining solutions).

The position and velocity of each particle are updated using the following formulas:

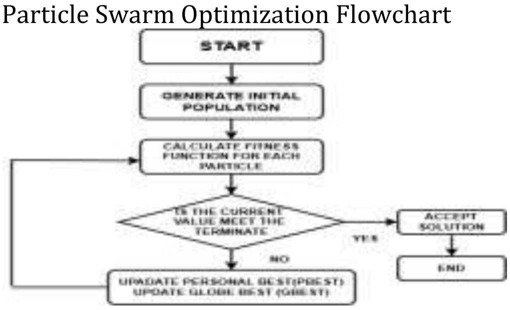
Velocity Update:
$$vi(t+1)=w\cdot vi(t)+c1\cdot r1\cdot(pbest,i-xi(t))+c2\cdot r2\cdot(gbest-xi(t))$$

Where: $vi(t+1)$ is the velocity of particle i at time step t+1, $vi(t)$ is the velocity of particle i at time step t, w is the inertia weight, c1 and c2 are acceleration constants, r1 and r2 are random numbers between 0 and 1. pbest,i is the personal best position of particle i, gbest is the global best position in the swarm, $xi(t)$ is the current position of particle i.

Position Update:
$$xi(t+1)=xi(t)+vi(t+1)xi(t+1))$$

Where: $xi(t+1)$ is the new position of particle i at time step t+1, $xi(t)$ is the current position of particle i.
The personal best position, pbest,i , and the global best position, gbest , are updated based on the fitness of the particle positions. The fitness function depends on the specific optimization problem being solved. PSO is a simple and powerful algorithm that can handle complex, high-dimensional, and nonlinear optimization problems. Despite its advantages, PSO can struggle with finding the global optimum in highly complex or noisy environments, but this can be mitigated through adjustments such as inertia weight and with other algorithms.

Fig -1: Particle Swarm Optimization Flowchart



5.2 Grey Wolf Optimization (GWO)

The Grey Wolf Optimizer (GWO) is a nature-inspired optimization algorithm developed by Mirjalili et al. in 2014. It is based on the social hunting behavior and leadership hierarchy of grey wolves (Canis lupus), which are known for their coordinated hunting strategies.

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In GWO, the search agents, known as wolves, work collaboratively to find the optimal solution by mimicking the leadership and hunting behavior of wolves in the wild.
In the algorithm, the wolves are divided into different categories based on their rank in the pack: alpha, beta, delta, and omega wolves. The alpha wolf is the leader, representing the best solution found so far. The beta and delta wolves support the alpha by contributing their knowledge, while the omega wolves explore and help maintain diversity in the search space.

The GWO algorithm performs optimization by iteratively updating the positions of the wolves in the search space. The position updates are guided by the positions of the alpha, beta, and delta wolves, enabling the swarm to explore the solution space in a balanced manner between exploration (finding new areas) and exploitation (refining the best solution).

The positions of the wolves are updated using the following formulas:

Position Update:
$Xi(t+1)=Xi(t)+A\cdot D$

where Xi(t+1) is the updated position of the i-th wolf, A is a coefficient that controls the exploration-exploitation trade-off, D is the distance between the current position and the position of the alpha, beta, or delta wolves.

Distance and Coefficient Calculation:

A and C Coefficients:
$A=2a\cdot r1-a,\ \ C=2\cdot r2$

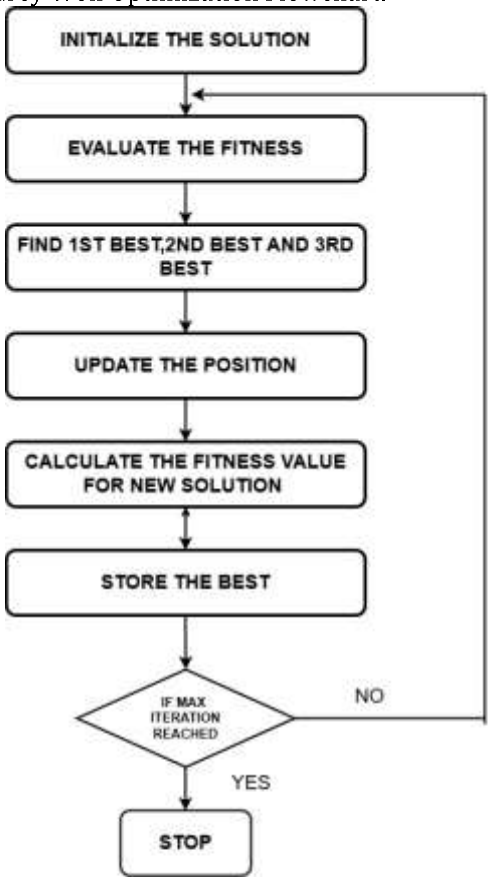
Where a is a linearly decreasing coefficient. r1 and r2 are random vectors in the range [0, 1].

Distance Calculation:
$D=|C\cdot Xbest-Xi|$

Where Xbest is the position of the alpha, beta, or delta wolf, Xi is the position of the current wolf.

The update mechanism in GWO allows wolves to explore the search space effectively while focusing their search towards the best solutions discovered by the pack. The method uses a balance between exploration and exploitation to converge towards an optimal solution.GWO is considered efficient in solving continuous and discrete optimization problems, offering advantages such as fewer parameters, easy implementation, and flexibility for various applications. However, it can suffer from premature convergence in complex problem landscapes. GWO with other algorithms or introducing more diverse exploration strategies can improve its performance.

Fig-2: Grey Wolf Optimization Flowchart.



5.3 Firefly Algorithm (FA)

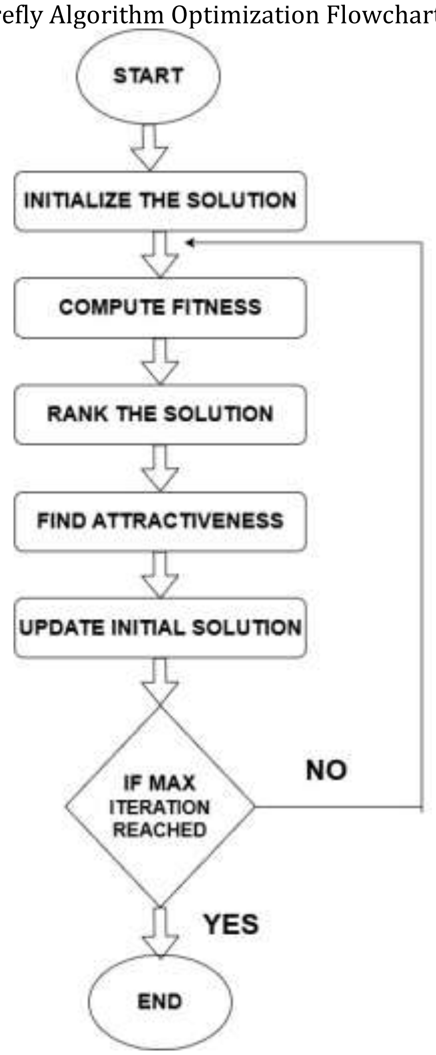
The Firefly Algorithm (FA) is a nature-inspired optimization algorithm developed by Yang in 2008, based on the flashing behavior of fireflies. The primary inspiration for FA comes from the communication and mating behavior of fireflies, which use light to attract mates or signal others. In the FA algorithm, the fireflies represent potential solutions, and their light intensity is determined by the quality of these solutions. The brighter the light, the better the solution. In FA, the fireflies are modeled as agents in a search space, and they move towards brighter fireflies, which represent better solutions. The movement of a firefly is governed by both its attraction to brighter fireflies and random fluctuations, allowing the algorithm to explore the solution space effectively. The balance between attraction and randomness helps FA avoid local optima and ensures thorough exploration and exploitation of the search space. FA operates under the assumption that the brightness of a firefly is proportional to the quality of the solution, with higher brightness indicating a better solution. The algorithm iteratively updates the position of each firefly based on its brightness and the brightness of other fireflies in the population, leading to an optimization process that converges towards the best solution.

The movement of a firefly in the FA algorithm is governed by the following equation:

$Xi(t+1)=Xi(t)+\beta \cdot e{-}\gamma \cdot r\hat{}2 \cdot (Xj(t)-Xi(t))+\alpha \cdot \epsilon$

where Xi(t+1) is the updated position of firefly i at time t+1, Xj(t) is the position of a brighter firefly j. β is the attraction parameter, determining how much the firefly is attracted to a brighter one. e−γ·r^2 is the distance-dependent light absorption, where r is the Euclidean distance between two fireflies, and γ is a constant that controls the rate of light absorption, α is the randomization parameter that introduces randomness in the movement, ϵ is a random vector that provides a random component for exploration.

Fig-3 : Firefly Algorithm Optimization Flowchart.



The firefly algorithm works in a loop where the position of each firefly is updated based on the brightness of other fireflies. The brightness of a firefly is typically calculated as a function of the objective function, and fireflies are attracted to brighter ones. This attraction mechanism ensures that fireflies move towards optimal solutions over time.

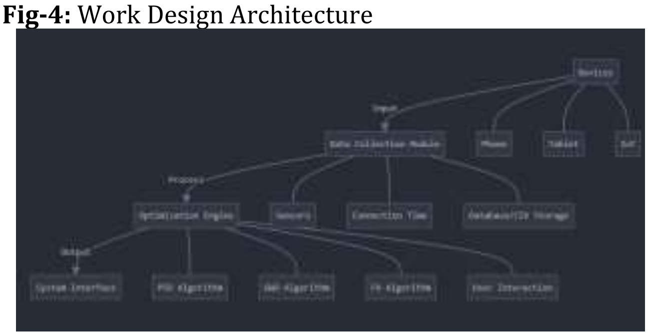
FA Parameters:
Alpha (α): Controls the randomization of the movement and allows for exploration.
Beta (β): The attraction coefficient that determines the degree of attraction between fireflies.
Gamma (γ): Controls the light absorption, which decays the intensity with distance.
Attractiveness Function: Often a function of distance, usually in the form of exponential decay with distance to simulate the effect of light intensity.

The Firefly Algorithm has shown excellent results in solving multimodal and complex optimization problems due to its ability to handle multiple optima and its flexibility. It is particularly useful in scenarios where the search space is highly irregular and requires a balance between local exploitation and global exploration. However, as with other nature-inspired algorithms, it can sometimes suffer from slow convergence in certain problem settings. FA has been successfully applied in various domains such as image processing, engineering design, machine learning, and parameter tuning due to its simple structure, ease of implementation, and capability to escape local optima.

6.DESIGN ARCHITECTURE

Our design architecture focuses on integrating bio-inspired optimization algorithms to enhance the efficiency, scalability, and robustness of information exchange systems. The architecture is built around the selection of three key algorithms—Particle Swarm Optimization (PSO), Gray Wolf Optimization (GWO), and Firefly Algorithm (FA). These algorithms work in tandem to optimize critical parameters such as throughput, latency, and energy consumption, ensuring improved performance under varying conditions. This approach allows the system to leverage the strengths of each algorithm while mitigating their individual limitations.

Fig-4: Work Design Architecture



6.1 Machine Learning

In our system, machine learning (ML) plays a crucial role in enhancing the optimization process and improving decision-making within the information exchange system. By utilizing an Artificial Neural Network (ANN), ML helps in predicting key parameters such as throughput, latency, packet loss, and signal strength based on historical data. The network learns from past interactions, identifying patterns and trends that enable it to make accurate predictions in real-time. ML allows the system to adapt dynamically to changing conditions, such as varying loads, interference, or signal fluctuations, by continuously learning and adjusting its predictions. The integration of ML with bio-inspired optimization algorithms like PSO, GWO, and FA creates a powerful synergy, where ML provides intelligent insights and optimizations, while the optimization algorithms fine-tune system parameters based on these insights. This combination of ML and optimization algorithms ensures that the system can respond to real-world challenges more efficiently, improving overall performance, robustness, and scalability, particularly in complex, dynamic environments.

6.2 Artificial Neural Network (ANN)

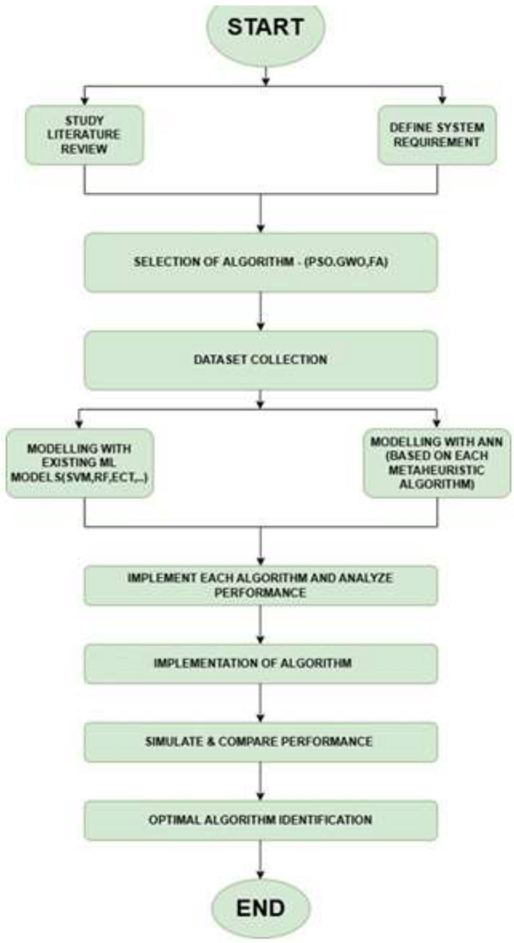
Our Artificial Neural Network (ANN) is designed to enhance the performance of the information exchange system by leveraging advanced machine learning techniques. The ANN serves as a critical component for predicting and optimizing parameters such as throughput, latency, and packet loss, based on historical data and real-time input. It utilizes a multi-layered architecture, where each layer processes different features and extracts valuable insights to make informed decisions. The network is trained using a combination of supervised learning techniques, enabling it to learn from existing data and improve its predictions over time. By integrating the ANN with the bio-inspired optimization algorithms (PSO, GWO, and FA), the system can dynamically adjust and optimize the communication network's parameters in real-time. This combination of machine learning and optimization techniques helps the system achieve higher accuracy, faster convergence, and more robust performance in complex and variable environments.

7.PROCESS FLOW OF DESIGNED MODULES

The proposed working modules employed in this study is illustrated in the flowchart (Fig-5). This structured approach aims to identify the optimal algorithm for system optimization, leveraging both machine learning and metaheuristic techniques.

The initial phase involves a comprehensive literature review to survey existing research and establish a theoretical foundation. This is followed by a precise definition of system requirements, outlining the specific objectives and constraints of the optimization problem.

Fig-5: Proposed Working Modules.



Subsequently, the methodology diverges into two primary avenues: traditional machine learning and Artificial Neural Networks (ANNs). Traditional machine learning encompasses algorithms such as Support Vector Machines (SVM), Random Forests (RF), and others. The ANN approach involves the development and optimization of neural networks, utilizing metaheuristic algorithms like Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Firefly Algorithm (FA) to fine-tune parameters.
Crucial to both avenues is the acquisition of a robust dataset suitable for training and validating the chosen algorithms. Performance analysis and comparison are conducted for each implemented algorithm, including an exploration of different techniques to potentially achieve superior results.

Through simulation and further performance evaluation, the research culminates in the selection of the most effective algorithm for the defined system optimization problem. This rigorous methodology ensures a comprehensive exploration of the solution space and a data-driven selection of the optimal approach.

8. PERFORMANCE ANALYSIS

Our project focuses on the performance analysis of optimal mimic algorithms—Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Firefly Algorithm (FA). The evaluation considers key performance metrics such as throughput, latency, signal strength, and interference. By analyzing convergence speed, adaptability, and optimization accuracy, we assess each algorithm's effectiveness in dynamic environments. The study also explores different techniques to enhance performance. The results aim to identify the most efficient algorithm for real-time decision-making, ensuring high data speed, minimal interference, and improved efficiency in adaptive wireless communication systems.

Through simulation and further performance evaluation, the research culminates in the selection of the most effective algorithm for the defined system optimization problem. This rigorous methodology ensures a comprehensive exploration of the solution space and a data-driven selection of the optimal approach. In this study, we evaluated the performance of several optimization algorithms, including Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Firefly Algorithm (FFA), and their combinations. The algorithms were assessed based on their Best Fitness (Cost), Test Loss, and Test Accuracy. The results are summarized in the figure below:

- Grey Wolf Optimization (GWO): The GWO algorithm achieved the best performance in terms of Best Fitness (Cost) and demonstrated the highest Test Accuracy with a relatively low test Loss.
- Particle Swarm Optimization (PSO): The PSO algorithm showed balanced performance across all metrics, with moderate Best Fitness (Cost), Test Loss, and Test Accuracy.
- Firefly Algorithm (FFA): The FFA algorithm exhibited a higher Test Loss and lower Test Accuracy compared to the other algorithms.

Fig-6: Performance Overview.

Algorithm	Best Fitness (Cost)	Test Loss	Test Accuracy
PSO	0.4040675461292267	1.6318391561508179	92.00000166893005
Grey Wolf	0.13490326702594757	0.7888352274894714	98.00000190734863
Firefly (FFA)	0.7200154066085815	298510.71875	56.00000023841858

The graphical representations of the Best Fitness (Cost) values and Test Accuracy values for the different algorithms are provided in the following figures:

Chart -1: Accuracy Comparison. (Firefly Algorithm has higher test loss).

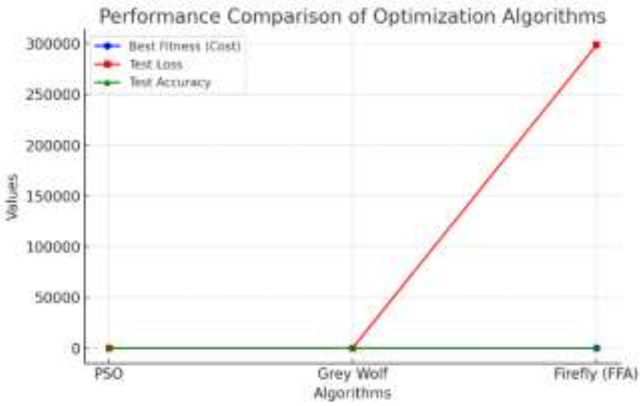


Chart-2: Comparison of Algorithms (PSO& GWO with lesser test loss).

From the results obtained, it is evident that GWO achieved the highest accuracy (98%) making it a strong candidate for optimal selection. PSO, while slightly lower in accuracy (92%) suggesting instability despite good learning capabilities. FFA alone performed poorly, with only 56% accuracy and an extremely high loss, making it unsuitable for optimal decision-making.

Regarding computational efficiency, PSO was the fastest, followed by GWO, while FFA was the slowest due to its complex nature. Overall, GWO is the best-performing algorithm, providing a balance between accuracy, computational efficiency, making it the most suitable choice for enhanced information exchange system. However, PSO remains an alternative where minimizing switching rate is a higher priority.

9. DISCUSSION

In this study, we evaluated the performance of various optimization algorithms, including Particle Swarm

Optimization (PSO), Grey Wolf Optimization (GWO), Firefly Algorithm (FFA), and their combinations, on a specific problem. The objective was to compare their effectiveness in achieving the best fitness (cost), minimizing test loss, and maximizing test accuracy. The performance metrics for each algorithm were recorded and analyzed. From the results, it is evident that the Grey Wolf algorithm achieved the best performance in terms of Best Fitness (Cost) and demonstrated the highest Test Accuracy with a relatively low. On the other hand, the combination of GWO and FFA exhibited the highest Best Fitness (Cost) value, indicating a less favorable performance. However, when excluding this combination, the remaining algorithms showcased varying degrees of success and the PSO algorithm achieved a balanced performance across all metrics.

10. RESULTS

From the results, it is evident that the Grey Wolf algorithm achieved the best performance in terms of Best Fitness (Cost) and demonstrated the highest Test Accuracy with a relatively low Test Loss. On the other hand, the combination of GWO and FFA exhibited the highest Best Fitness (Cost) value, indicating a less favorable performance. However, when excluding this combination, the remaining algorithms showcased varying degrees of success. The PSO algorithm achieved a balanced performance across all metrics. Additionally, further experimentation with parameter tuning and other optimization techniques could yield even better results.

11. CONCLUSION

In this paper, aimed to develop a novel optimization algorithm, combining Particle Swarm Optimization, Firefly algorithm and Grey Wolf Optimization, for complex engineering design problems. Our key findings demonstrated that the proposed algorithm outperformed standard PSO, FA and GWO algorithms in terms of convergence speed and solution accuracy. These results have significant implications for solving real-world engineering optimization challenges. These algorithms proved to be effective in handling constrained optimization problems, offering a more robust solution compared to its components. This research contributes to the field of metaheuristic optimization by providing a new and effective approach.

Future work could explore the application of this algorithm to other optimization problems, such as feature selection in machine learning. Further investigation into adaptive parameter tuning for the algorithm could also provide valuable insights. Ultimately, this research provides a foundation for developing more efficient and effective optimization algorithms for various applications.

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