RESEARCH ARTICLE OPEN ACCESS

Comparative Analysis of Swarm Intelligence Algorithms: A Focus on Convergence Speed and Performance

Ms. Utkarsha Jiwane
Ph.D. Scholar, SSES Amt's, Science College, Department of Computer Science
Nagpur, India.

ABSTRACT
Complex optimization issues have been successfully resolved by swarm intelligence algorithms. Optimization methods based on swarm intelligence are growing in popularity as a means of resolving present real world problems. Inspired by the coordinated behaviors of social insects and other animal societies, Swarm Intelligence (SI) has proven to be highly effective at solving challenging optimization problems. A preprocessing technique called feature selection chooses the most important attribute from datasets in order to minimize their dimensionality for improving model's performance. In this research we present various performance and numerical comparative analysis of several widely used biologically inspired swarm algorithms including Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Firefly Algorithm (FA), Artificial Bee Colony (ABC), Cuckoo Search Algorithm (CS), Bat Algorithm (BAT) and Grey Wolf Optimizer (GWO) on SVM classifiers. Since each algorithm has its own strength and weakness. In the research, algorithm is surveyed and applied moreover to demonstrate performance of different algorithms. These algorithms are among the most important tools for finding optimal solutions to optimization problems. The research focus on analyzing and comparing the effectiveness of these algorithms in finding optimal solutions particularly focusing on their speed of convergence along with performance and computational efficiency.
Keywords— Artificial Intelligence, Machine Learning, Swarm Intelligence, Optimization Problem, Convergence Speed, Performance

I. INTRODUCTION

Swarm Intelligence is an artificial intelligence discipline inspired by swarm behavior observed in nature. It refers to the intelligent cooperative behaviors exhibited by a group of simple individuals. Swarm Intelligence is an artificial intelligence discipline inspired by swarm behavior observed in nature. It refers to the intelligent cooperative behaviors exhibited by a group of simple individuals. Although each individual's behavior may be simple their collective cooperation enables the group to exhibit complex global behavior that solves complex tasks. SI draws inspiration from biological systems particularly by the coordinated behaviors of social insects such as ant colonies, animal herding, bee hives, bird flocks and fish schools [1]. A collection of population based nature-inspired swarm algorithms gives reliable and inexpensive solutions to challenging issues [2]. Indirect interactions known as stigmergy which involve communication through the environment. Swarm intelligence algorithms are applied to a range of domains including optimization. Furthermore, computational modeling of swarms has been extended to diverse fields and domain [4][5]. SI has been a significant popular for the development of numerous optimization algorithms in many engineering applications. SI based optimization techniques are generally superior algorithms in solving complex optimizing problem [6]. Optimization techniques can be classified in several ways based on their algorithms. In engineering applications heuristic and metaheuristic techniques are particularly valuable due to their ability to handle randomness [7]**.** The SI algorithms effectively explore vast solution spaces and resolve challenging issues in a variety of fields. SI based algorithms are valued for their scalability, flexibility and capacity to identify the optimize solution in complex and dynamic environment. In this research we focus on SI most widely used algorithms like ACO, PSO, FA, ABC, CS, BAT and GWO along with SVM classifier for analysis and comparison of effectiveness of these algorithms in finding optimal solutions particularly focusing on convergence rates, solution accuracy and computational efficiency [8]. By minimizing dimensionality and concentrating on the most relevant data feature selection is essential to enhancing the performance in swarm intelligence models.

Nature Inspired Swarm Intelligence Algorithms

Ant Colony Optimization

The social behavior of ant colonies serves as an inspiration for ACO. Ants have been seen to work together to identify the shortest path between their food source and their nest [9]. Ants naturally lay a chemical called pheromone along their routes which helps other ants search for the shortest path from their colony to a food source. Other ants use the pheromone trails that ant leaves behind to help them ae decision and direct them towards the most effective paths. The original purpose of ACO development was to address discrete optimization problems.

Particle Swarm Optimization

The PSO algorithm resembles how birds forage. A flock of birds in the sky in real life follows to specific regulations while continuously changing their positions and routes with this information they reach their ideal positions by modifying their speed and direction and applying their collective knowledge. Similar to this in PSO every particle stands in for a bird that is constantly updating its velocity and position. Each particle in PSO iterates through the search space in an attempt to locate the optimal solution. In order to converge towards the ideal solution particles update their locations and velocities through continuous iterations [4] [10].

Firefly Colony Optimization

Fireflies mutual attraction and light emission characteristics served as the inspiration for the population based stochastic search method known as FA [11]. In optimization the quality of the solution a firefly represents can be inferred from its light intensity where better solutions are represented by brighter fireflies. The intensity of the light a firefly emits its current location and a random component (spontaneous walk) all affect its travel. The attraction between firefly and brighter (i.e., superior) fireflies can be statistically manipulated to direct the search for the global optimum [12].

Artificial Bee Colony Algorithm

The ABC technique is a population based optimization technique that draws inspiration from honey bee foraging behavior. It imitates how bees identify the finest food sources by sharing information and searching for nectar which in the context of optimization means figuring out the optimum course of action. Employer bees, onlooker bees and scout bees are its three constituent parts. The employer bees are paired with food sources in the immediate are of the hive and they inform the observer bees about the nectar quality of the food sources they are using. Observing the employed bee's movements throughout the hive onlooker bees use the information the employer bees supply to select one food source to take advantage. When their food supplies are abandoned the employed bees turn into scouts and randomly look for other food sources. The location of likely optimization issue solutions is indicated by the number of food sources and the quality of the solution is shown by the amount of nectar in a food source [12].

Cuckoo Search Algorithm

The way cuckoo birds engage in brood parasitism served as the model for the CS algorithm. There are three types of brood parasitism intra-specific parasitism, cooperative breeding and nest takeover. While some species of cuckoos deposit their eggs in nests shared by other species some do so in the nests of other species. When a host bird discovers that the eggs in its nest are not its own it may confront the cuckoo or leave the nest completely. Some cuckoo species have developed to imitate the colors and patterns of the host bird's eggs in order to avoid this, which lessens the possibility that their eggs will be found and left behind. Nests with the worst fitness are abandoned and new nests are created to replace them [13].

Bat Algorithm

The BA is an optimization technique inspired by nature that was created using bat echolocation. It is a population-based metaheuristic algorithm that emulates the echolocation techniques used by bats to find prey and move through their surroundings. Bats use echolocation to locate their nests in the dark, track food and navigate obstacles. In BA the issues are resolved through frequency tuning and echolocation. Bats fly at a fixed frequency and a random place and velocity. Different wavelengths and loudness are utilized to identify the prey. Depending on the target's proximity they automatically alter the pulses' frequency and rate [14][15].

Grey Wolf Optimization Algorithms

Grey wolves live in groups that typically consist of 5-12 members organized according to a social dominance hierarchy. At the top of the hierarchy is the alpha wolf who acts as the leader of the pack. The alpha wolf is responsible for making decisions related to searching for prey, encircling, attacking and hunting. Beta wolves are positioned at the second level of the hierarchy and play a supportive role. They help implement the alpha wolf's decisions and provide feedback on these decisions from the lower-ranking wolves (delta and omega) to the alpha wolf. Beta wolves are considered potential candidates for leadership if the alpha wolf is no longer able to fulfill its role [16]. The next level consists of delta wolves who are subordinate to the alpha and beta wolves. Delta wolves are responsible for providing food to the pack and protecting its members. They assist the alpha and beta wolves during hunting and other activities. At the lowest level are the omega wolves who have the least authority and are not considered as important in the hierarchy.

II. LITERATURE REVIEW

E. Reddy et al. [17] proposed a study of specifically examines PSO and ABC algorithm. The authors compare the standard versions of these algorithms with their guided variants, which incorporate the current global best solution to enhance performance.

Hoang L et al. [18] proposed a study to evaluates the swarm intelligence algorithms based on their performance in solving complex and nonlinear optimization problems. The authors implement each algorithm on a set of benchmark optimization functions and assess their effectiveness by analyzing convergence rates, solution accuracy and computational efficiency.

J. Guerra et al. [19] uses ACO, BA, GWO, MFO algorithms and employed to optimize the parameters of the Unscented Kalman Filter (UKF) within a decentralized neural block control (DNBC) scheme. The objective is to enhance the trajectory tracking performance of 2-DOF robotic manipulator.

J. Sobecki et al. [20] uses ACO, PSO, ABC, BA algorithms on dataset containing historical student course data. The dataset is preprocessed to remove inconsistencies and normalized for optimal algorithm performance and the objective function is designed to minimize the prediction error for student grades while ensuring accurate course recommendations.

A. Chopra et al. [21] provides insights into how different SI algorithms perform across optimization problems. They conclude that no single algorithm outperforms all others in every scenario as the effectiveness of each method depends on the problem domain and parameter settings.

III. METHODOLOGY

Data Set and Attributes

The information was gathered from the Kaggle database. Students Adaptability Level in Online Education Data Set. Many different types of datasets from different disciplines are available in the Kaggle repository. This repository was created by Nishat Ahmed Samrin and Md. Aktaruzzaman Pramanik. The data set provided for Effectiveness of online education its attributes are mentioned below in Table 1. The dataset URL is https://www.kaggle.com/datasets/mdmahmudulhasansuzan/students-adaptability-level-in-online-education/data

Sr. No.	***Attribute***	***Description***
1	Gender	Boy, Girl
2.	Age	21-30
3.	Education Level	University, College, School
4.	Institution Level	Non Government, Government
5.	IT Student	No, Yes
6.	Location	No, Yes
7.	Load-shedding	Low, High
8.	Financial Condition	Medium, Poor
9.	Internet Type	Wifi, Mobile Data
10.	Network Type	4G,3G
11.	Class Duration	Time
12.	Self Lms	No, Yes
13.	Device	Tablet, Mobile
14.	Adaptivity Level	Moderate, Low

Table 1. Dataset Attributes

Optimization Techniques for Feature Selection

SVM based classification approach based on swarm intelligence algorithms for best feature selection, convergence speed and comparative analysis is included. Figure 1 depicts the proposed system's primary structure.

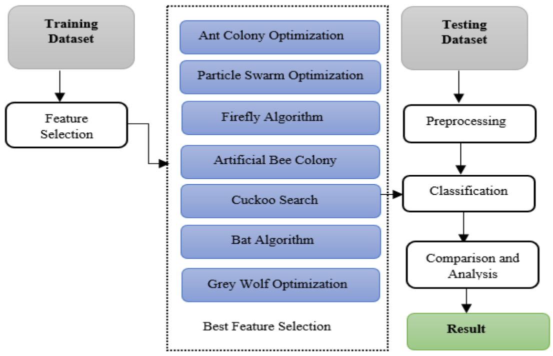

Figure 1. The Proposed Architecture [4]

1. Dataset Preparation
   - Training Dataset: The dataset is split into training and testing subsets and the training dataset is used to select the most relevant features.
   - Testing Dataset: The testing dataset is reserved for evaluating the performance of the model after feature selection and classification.
2. Feature Selection
   - Various SI optimization algorithms are applied to select the best features that contribute significantly to the predictive performance.
   - Each algorithm is used to evaluate the importance of features and select a subset that yields the best performance metrics.
3. Best Feature Selection
   - Based on the outputs of the various optimization algorithms the best feature set is identified.
   - This feature set is then used to train and test the model to ensure improved performance and computational efficiency.
4. Preprocessing
   - The testing dataset undergoes preprocessing to ensure consistency with the training data which includes data normalization or standardization, handling missing values and outliers, encoding categorical variables.
5. Classification
   - A classification model is trained using the selected features from the training dataset.
   - The model is then tested on the preprocessed testing dataset to evaluate its performance.
   - We are using SVM which is often regarded as classifiers that achieve high accuracy across various tasks. Work by constructing a hyperplane with the maximum Euclidean distance or margin from the nearest training examples. Simply by put SVM algorithm represent instances as points in space are mapped to a high dimensional plane in which the instances of different classes are differentiated by the largest possible margin from the hyperplane. In the same space new instances are mapped and their anticipated class is determined by which side of the hyperplane they fall on. Support vectors are a relatively small subset of the training data that

determines the SVM hyperplane the remaining training data has no effect on the final classifier.

6. Comparison and Analysis
- The classification results are compared after feature selection to determine the effectiveness of each algorithm.
- Performance metrics such as Accuracy, Precision, Recall, F1 Score and Execution Time are analyzed.

7. Result
- The final output includes the best feature selection method, optimal set of features and model with the highest performance.

IV. RESULT AND DISCUSSION

The experiment was carried out using a laptop running Windows 10 with an Intel i5 8th Gen processor and 8 GB of RAM. Python was used for the coding. 30% of the dataset was used for testing while 70% was used for training. As indicated in Table 1, the dataset has 14 attributes in total and we utilized a dataset containing 100 educational records obtained from Kaggle titled “Students Adaptability Level in Online Education”. The evaluation of the proposed ACO, PSO, FA, ABC, CS, BAT and GWO algorithms was carried out using SVM classifiers available in the Scikit-learn library. The constants (free parameters) used in all the optimization algorithms are shown in Table 2.

ACO	***PSO***	***FA***	***ABC***	***CS***	***BAT***	***GWO***
num_ants = 30 num_iterations = 100 alpha = 1.0 beta = 1.0 evaporation_rate = 0.5 pheromone_init = 1.0	num_particles = 30 max_iterations = 100 w = 0.5 c1 = 1 c2 = 1	num_fireflies = 30 num_iterations = 100 alpha = 0.2 beta_min = 0.2 gamma = 1.0	num_bees = 30 num_iterations = 100 limit = 10	num_nests = 30 num_iterations = 100 pa = 0.25	num_bats = 30 num_iterations = 100 A = 0.5 r = 0.5 Q_min = 0 Q_max = 2	num_wolves = 30 num_iterations = 100

Table 2. Algorithms with Free Parameters for the Experiments

First, a trial run was conducted to select a suitable classifier. We used SVM because it works exceptionally well with high dimensional data (e.g., datasets with many features) because it finds the optimal hyperplane that separates data points into classes in higher-dimensional feature spaces. The margin-based approach and kernel functions make SVM resistant to outliers and noise especially when using a soft-margin classifier. Other classifier like Random Forest and Decision Trees struggle with overfitting in high dimensional data if not tuned properly and Random Forest is fairly robust to noise and it take more execution time and Decision Trees alone are highly sensitive. KNN performance drops with high-dimensional data due to the "curse of dimensionality and Very sensitive to noise as it relies directly on distance calculations between neighbors. Naive Bayes **a**ssumes independence among features which is rarely the case in high-dimensional spaces and Performance deteriorates significantly in noisy datasets where feature independence assumptions are violated. The experiment was executed with 100 iterations on the dataset and the results are summarized in Table 3.

Algorithm	***Accuracy***	***Execution Time***
Ant Colony Optimization	0.9890	65.80 seconds
Particle Swarm Optimization	0.9972	51.74 seconds
Firefly Algorithm	0.9945	18.42 seconds
Artificial Bee Colony	0.9890	123.31 seconds
Cuckoo Search	0.9917	50.95 seconds
Bat Algorithm	0.9751	37.28 seconds
Grey Wolf Optimization	0.9945	11.97 seconds

Table 3. Algorithms with Accuracy and Execution Time

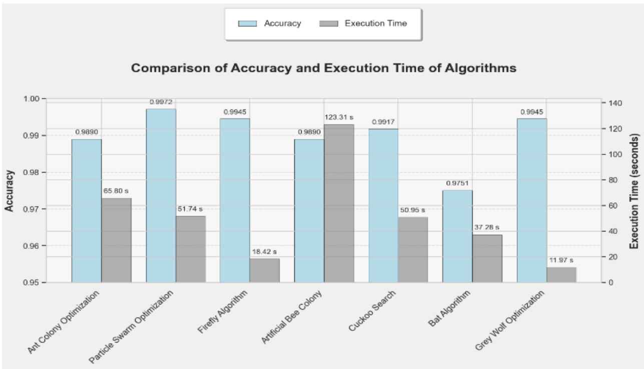

Figure 2. Comparison of Accuracy and Execution Time of Algorithms

V. CONCLUSION

According to Figure 2 a comparative analysis of SI algorithms including ACO, PSO, FA, ABC, CS, BAT and GWO is presented. From Table 3 it can be observed that PSO has the highest accuracy followed by the FA and GWO. This highlights the effectiveness of these algorithms in achieving optimal solutions with precision. GWO demonstrated the shortest execution time making it the most efficient algorithm in terms of computational speed. For real time applications or situations with limited computational resources it is highly useful. GWO emerges as a balanced choice offering both high accuracy and low execution time.

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