A Brief Analysis on Particle Swarm Optimization in Feature Selection

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ABSTRACT
A Wireless Sensor Network (WSN) is comprised of a collection of small, autonomous devices known as sensors. Various types of physical and environmental data, including temperature, sound, vibration, pressure, and motion, are captured by these sensors at different locations. The data is then processed and transmitted to end-users. In cluster-based WSNs, the role of aggregating and forwarding data to the central sink node is played by Cluster Heads (CH). However, improper clustering can result in the overloading of certain sensor nodes and gateways, leading to premature device failure and a decrease in the overall network lifespan. To address these challenges, the implementation of cost-effective solutions is essential, with objectives focusing on load balancing, availability, reliability, energy efficiency, processing power, and memory usage. Numerous metaheuristic algorithms have been explored in the existing literature to tackle computationally demanding optimization problems. In this paper, an improved Particle Swarm Optimization (PSO) algorithm is proposed for optimizing the cluster structure. The transmission distances are minimized, and energy efficiency within the network is maximized. A concise overview of PSO and its evolution as a robust stochastic optimization technique based on swarm intelligence is provided. Its successful application in solving a wide range of search and optimization problems, inspired by natural swarm behavior, is also highlighted.

Keywords
Loadbalancing, Metaheuristic algorithm, Transmission distance, Stochastic optimization technique, Intelligence of smarms.

1. INTRODUCTION
In recent years, the field of Wireless Sensor Networks has seen widespread utilization of various optimization algorithms. These methods typically commence with an initial population of randomly generated solutions and subsequently iterate through generations to seek optimal solutions. Notably, Particle Swarm Optimization (PSO) stands out due to its unique approach, lacking traditional evolution operators such as crossover or mutation.PSO, conceived by James Kennedy and Russ Eberhart in 1995, draws inspiration from natural swarm behaviors observed in birds, fish, and other organisms. In PSO, a swarm of 'n' particles interacts, either directly or indirectly, with each other while collectively exploring search directions. The versatility of PSO knows no bounds, making it an appealing choice in numerous domains [1]. It excels at tackling computationally challenging problems, including real-world scenarios characterized by multi-modal complexities. The PSO algorithm harnesses a group of particles navigating a search space to pinpoint global optima. During each iteration of PSO, individual particles update their positions based on their past experiences [2] and the experiences of their neighboring particles. Each particle is composed of three vectors:

i. The x-vector records the current position (location) of the particle in the search space.
ii. The p-vector (pbest) records the best solution found by the particle up to that point.
iii. The v-vector contains a gradient that dictates the direction in which the particle will travel undisturbed.

These vectors are continuously refined, with each particle aiming to enhance its position for the best possible solution. The core principle of PSO involves accelerating each particle towards its best-known position (pbest) and the global best position (gbest) identified by any particle so far, using a randomly weighted acceleration at each time step. This acceleration is achieved by updating the x-vector with the addition of the v-vector (xi = xi + vi). After calculating the new xi, the particle evaluates its new location. If the fitness of the new x (x-fitness) exceeds that of the previous best (p-fitness), then pbest is updated to xi, and p-fitness is set to x-fitnessIn this paper, we conduct a comprehensive survey of various aspects of PSO, explore potential enhancements, and present a high-quality interpretation of the methodology.

2. LITERATURE REVIEW
In the existing body of literature, there is a recognized need to enhance the accuracy of ANFIS (Adaptive Neuro-Fuzzy Inference System) for runtime parameter tuning. This enhancement is achieved by integrating PSO (Particle Swarm Optimization) and estimating a multi-objective fitness function, which encompasses factors such as accuracy, root mean squared error, and correlation. Another noteworthy strategy is the incorporation of chaos theory, which finds applications in various domains. In the context of clustered Wireless Sensor Networks (WSNs), Cluster Heads (CHs) play a crucial role in data collection from sensor nodes. They process this data and subsequently transmit it, either directly to the sink node or via other CHs. This technique often involves selecting analyzers with high energy levels to act as CHs. This paper provides a comprehensive survey of the clustering-based approach, which has gained popularity in this field. Furthermore, the PSO method, as an evolutionary algorithm, has been evaluated with the inclusion of additional chaotic

maps, demonstrating its effectiveness in detecting SNP barcodes within high-dimensional datasets.Additionally, a novel hybrid approach is proposed for well-organized service composition based on a fitness function. Drawing inspiration from the coordinated efforts of an Emperor penguin colony, this approach aids in solving complex equations commonly encountered in hyperbolic spiral-like movements across various applications.

To solving the problem for effective gateways SCE-PSO based clustering approach has been proposed [6] and also considering load of the gateways for novel fitness function. The results outperformed in terms of execution time, lifetime of the network, power consumption, number of sensor nodes die and number of gateways die.

This novel meta-heuristic algorithm [7] draws inspiration from the inhibition caused by the body heat radiation of penguins and their enchanting, spiral-like movements dictated by the distance. The EPC (Emperor Penguin Colony) behavior commences with a population comprising a group of penguins. The objective function value is calculated based on the heat intensity and the distance traveled.While PSO is classified as an evolutionary algorithm, its foundational model initially sought to study and simulate the choreographed flight of bird flocks. Evolutionary methods within this framework involve biological processes like mutation, selection, and reproduction. These simulations have been adapted to emulate the collective behaviors observed in groups of animals, often drawing inspiration from natural phenomena. This alignment with natural processes is a common characteristic shared with other algorithms, such as the Firework Algorithm and Harmony Search.The main advantage of PSO belongs to the evolutionary algorithm which uses the swarm intelligence based on Population where each particle represents a candidate solution. Here [8] the optimization benefits are need to be adjusted within and also it can easily implement. Even if PSO compared with local search methods it does not require prior skill about the gradient of the optimized function. Because of distinctive distribution strategy of the swarm were developed where shuffled complex evolution is incorporated. On the other hand, shuffling mechanism conserves and helps to inhibit premature convergence. In this paper all four PSO variants were raised in different proposed version using SCE PSO techniques.

A new method has been enhanced in the PSO [9] algorithm to extend the network's lifetime. Additionally, the proposed protocol improves the distribution of sensors, outperforming other comparable protocols and implementing a well-optimized clustering system that further extends the network's lifespan. The comparison between the proposed protocol and other alternatives clearly demonstrates its effectiveness in significantly prolonging the network's lifetime.

An enhanced version of the Particle Swarm Optimization (PSO) algorithm was introduced [10] in pioneering research. Over time, its demonstrated efficiency and effectiveness have established it as a valuable meta-heuristic approach across various research domains tackling complex optimization problems. To address scenarios where populations become trapped in local optima, nine CPSO (Chaotic Particle Swarm Optimization) methods were employed to improve the performance of the PSO approach. Additionally, the Sinai chaotic map was utilized to identify potential SNP barcodes. The results further confirm that the CPSO method proves to be more effective and adaptable, particularly when dealing with large datasets. The usage of PSO in different Quality of service (QOS) parameters [11] to show the optimized resource allocation. Choosing the appropriate approach in advanced existing services to expand the number of applications and coordinate into complex composited services through service configuration. For efficient service composition as a developing approach a new hybrid method proposed to improve load balancing problem in the future. Each set eventually, good optimal solution. It does not focus on mechanism of agent-based method which can consider as challenge where dissemination part is important.

Particle swarm optimization has gained wide range of acceptance in easy implementation. To improve the efficiency, effectiveness and capability to handle with the addition of other stochastic, meta-heuristic approaches to model diverse the real-world applications. This proves ANFIS system importance. Many nonlinear problems have been solved that the proposed method [12] fits with better results than the conventional ones. Here the optimistic ANFIS uses antecedent and consequent parameters which reduces the overall error rate. Hence, proposed PSO based is well suited in building a systematic and structured predictive model.

The basic concepts of PSO in current situation based on the criteria of originality of its most important strain at the time of prevalence, potentiality and development for new research path. The gateway has multiple outgoing sequence flows receives such as data gathering, transmission and aggregation etc. In this paper, the novel fitness function is reasoned by providing the no. of relay nodes, distance and coverage factor of the network. To enhance routing effectiveness, a novel fitness function is employed, considering the utilization of relay nodes to alleviate the heavy workload on the cluster heads. This approach contributes to the extension of the network's lifespan [13].

This paper [14] focuses on evaluating collision-free paths that meet specific criteria, such as minimizing path length and ensuring smoothness. Selecting an appropriate curve to define the path is therefore crucial. The primary objective of these algorithms is to find the shortest and smoothest path between two points for effective path planning. In this work, a novel chaotic Particle Swarm Optimization (PSO) algorithm is introduced to optimize the control points of a Bezier curve, with two variants presented: CPSO-I and CPSO-II. The algorithm aims to select the smoothest path that minimizes the overall distance between the start and end points using the optimized control points. Results show that increasing the number of control points enlarges the search space by adding dimensions, which requires a larger number of control points. Additionally, a sufficiently large population size is necessary for the PSO to effectively explore the solution space and ensure optimal results. In Mobile Ad-Hoc Networks (MANETs), the Low

Energy Adaptive Clustering Hierarchy (LEACH) protocol is employed to enhance network longevity by efficiently managing the available energy resources. The selection of Cluster Heads (CHs) in this protocol is accomplished through the utilization of the Artificial Fish Swarm Optimization (AFS) algorithm. The decision-making process for CHs in the MANET involves factors such as mobility, flexibility, remaining energy levels, and the degree of connectivity among nodes. AFS is leveraged to identify the optimal CHs, resulting in increased energy generation and Network Lifetime (NLT). Furthermore, the protocol optimizes the distance between cluster members and their respective CHs by computing the average distance. Their [15] proposed approach effectively reduces packet loss within the network, consequently enhancing overall network efficiency and reducing energy consumption in the recommended routing protocols. Tracking the Maximum Power Point (MPP) under partial shading conditions in photovoltaic (PV) systems can be challenging due to the nonlinear characteristics of the I-V curve. This article introduces an enhanced Artificial Fish Swarm Algorithm (AFSA) for MPP tracking (MPPT) in PV systems [16]. The proposed AFSA incorporates elements from the Particle Swarm Optimization (PSO) algorithm to improve its performance. Known as the CIAFSA approach, it effectively addresses the challenges posed by multiple local extreme value points, as demonstrated by the experimental results. This method offers high accuracy in determining the MPP under real atmospheric conditions and outperforms alternative approaches. Consequently, MPPT's stability and effectiveness are significantly enhanced. This knowledge will be instrumental in meeting the requirements of PV systems under various conditions in future applications.

Many strategies have been proposed for energy-efficient routing in Wireless Sensor Networks (WSNs). However, most of these algorithms primarily focus on energy efficiency [17], emphasizing each node's ability to find the shortest path to the base station, while often neglecting the equally important factor of energy balance, which is crucial for prolonging network lifespan. To address this gap, we have developed effective particle-encoding schemes and formulated multi-objective fitness functions for each of the proposed routing and clustering algorithms. Additionally, these algorithms are designed to be resilient to cluster head failures. In the future, our objective is to design energy-aware routing and clustering algorithms that account for partial and transient gateway failures, as well as to address network sustainability under various conditions. The proposed scheme represents a centralized algorithm that will be implemented by the base station, and we are committed to developing and implementing a distributed algorithm that reduces the burden on the base station, thereby enhancing network efficiency.

An innovative intelligent fault diagnosis method [18] has been developed by combining Empirical Mode Decomposition (EMD), Fuzzy Information Entropy, an enhanced Particle Swarm Optimization (PSO) algorithm, and Least Squares Support Vector Machines (LS-SVM). This approach addresses a critical challenge in the field: the effective early detection of faults in spinning machinery, a limitation of many existing fault diagnosis methods. To assess the effectiveness of the proposed fault diagnostic process, real vibration data from a motor bearing is utilized.The ATSWALM method, which employs an improved PSO algorithm with enhancements including an arctangent-based learning factor and a modified S-shaped function in the W method, in conjunction with LS-SVM for classification, yields an average accuracy rate of 89.50%—the highest precision among the 11 approaches tested for motor bearing fault diagnosis. Advanced detection techniques that integrate evolutionary algorithms and neural networks have proven to be highly effective [19], consistently outperforming traditional machine learning methods in detection accuracy. In this ongoing research, two novel hybrid systems have been developed. The first system is based on gravitational intrusion detection, while the second merges elements of Gravitational Search (GS) and Particle Swarm Optimization (PSO) to create the GSPSO model. Notably, both GSANN and GSPSO-ANN achieved the highest detection rates, with accuracies of 94.90% and 98.13%, respectively, outperforming four other methods. These results were obtained using the NSL-KDD dataset. Another aspect of the study introduced three recent hybrid artificial intelligence optimization models: Adaptive Neuro-Fuzzy Inference System (ANFIS) combined with Cultural (ANFIS-CA), Bees (ANFIS-BA), and Invasive Weed Optimization (ANFIS-IWO) algorithms [19]. These models were applied to flood susceptibility mapping (FSM) in Iran's Haraz watershed. Ten flood-conditioning variables, including both continuous and categorical factors, were analyzed. Flood susceptibility maps were then generated using the ANFIS-CA, ANFIS-BA, and ANFIS-IWO models. The results classified the area into five susceptibility levels: very low, low, moderate, high, and very high [20]. Finally, the performance of the three hybrid optimization models was evaluated using ROC and AUROC curves. As shown in the table, some papers reviewed variations of these methods and tested them under similar conditions.

Table 1. Variant of PSO Algorithms

Variations in PSO	Modification from the Standard PSO	Field / Area	Accuracy & Efficiency
SCE-PSO	A highly effective fitness function has been developed	Clustering approach	Surpassed in network lifetime, execution time, and energy consumption.
Emperor penguin's colony optimization	Developed two modified algorithms, named MEPC1 and MEPC2	Swarm based optimization Algorithm	MEPC1 performed better in 70% of the tested functions, while MEPC2 excelled in 80% of them
Tested distributed versions of PSO	APartW version is comparable with AdaptW&linTimevarW variants	APartW on 11 benchmark function	Inertia weight parameters yield significantly better results compared to the

		s	variant that uses a constriction factor.
An Improved PSO	Minimize the transmission distance and to optimize the energy consumption of the network	Clustering approach	Protocol outperforms other comparative results
CPSO (Chaotic Particle Swarm Optimization)	To identify SNP barcodes for disease analysis	An Improved PSO	The Sinai chaotic map produces the highest x^2 values across different vector spaces.
Hybrid PSO	To improve load balancing problem	– ——	The comparison results show effective
Multi-objective PSO	Enhanced an ANFIS technique with PSO parameter tuning to predict significant numerical associations.		PSO-based ANFIS system is well-suited for developing an efficient and cost-effective predictive model for C6H6
Innovative fitness function	Efficient for improving the lifetime of WSNs	Bio-inspired approach	Number of hops required for each gateway to reach base station
Chaotic PSO	To minimize the total distance between the starting and ending point is selected	Optimizing the control points of Bezier curve	Singer & Sine maps were suitable for both algorithms
Artificial fish swarm	The optimized distance from cluster members to their corresponding CHs	Adhock network (Manet)	Proposed method provides the maximum lifetime as 80 to 140 hrs
PSOEM	Enhances the reliability and	Modified	The CIAFSA method

-FSA	efficiency of MPPT in PV systems under partial shading conditions.	artificial fish swarm algorithms	effectively bypasses the challenge of multiple local extrema
PSO based routing & clustering algorithm	To design and implement a distributed algorithm that reduces communication load on the base station	Clustering approach	
Improved PSO	To optimize the parameters of the least squares support vector machine	Fuzzy information entropy	The ATSWPLM method and LS-SVM achieve an average accuracy rate of 89.50% for motor bearing analysis
PSO-ANN	ANNs are determined to be statistically significant	Intrusion detection	The proposed GS-ANN and GSPSO-ANN achieved maximum detection accuracies of 94.9% and 98.13%, respectively
New Hybrid of ANFIS	To assess the model's performance and predictive capability, RMSE and ROC curve analysis are used	Flood susceptibility modeling	The results showed that ANFIS-IWO produced better output with a lower RMSE (0.359), while ANFIS-BA demonstrated superior prediction capability with a higher AUROC (94.4%).

3. MECHANISM OF PSO

In this method, we will implement the interactive PSO in which the target can be changed. Imagine some x, y plane with some boundaries a square here shows the area for the insects to search the targets.Consider the insects are in different locations while moving randomly one of them has found some food at green location. This green location is so far the based and this insect will inform others about his location. However, this is still not optimal or biggest target.

So how they will reach that target. Imaginary living particle where they can smell hidden source food the one who is closest to the food makes loudest sound then the other particles move around them. Any moving particles come closer to the target then the first one making out the sound others moved to it. This mechanism continues until First one has it.

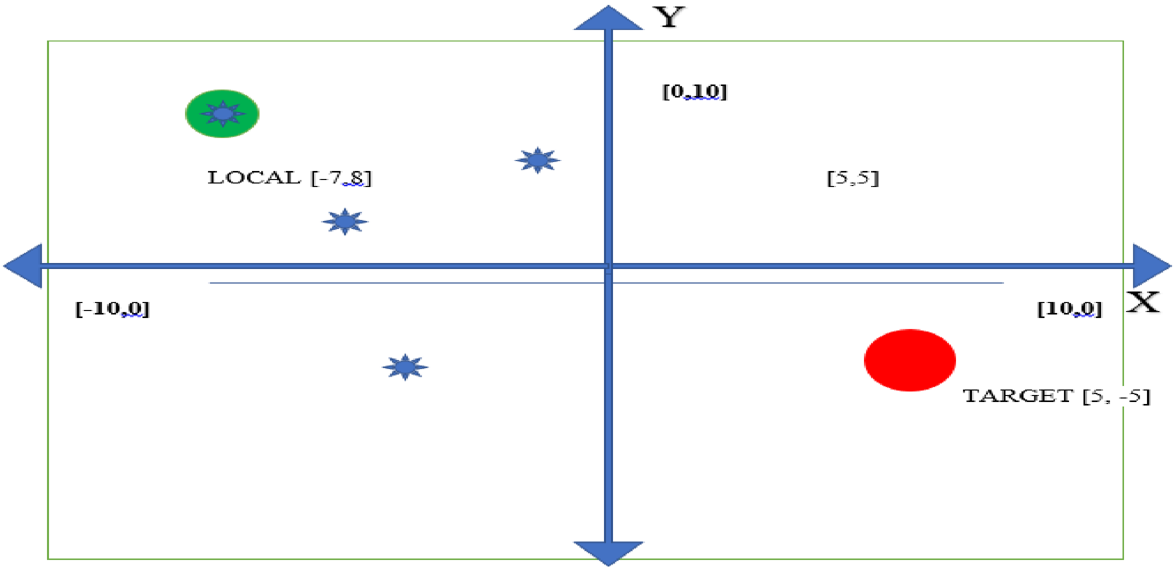

Fig 1: Graphical Representation of PSO

4. EXPERIMENTAL ANALYSIS AND DISCUSSION

The tests were carried out with Python 3.6.7, and the same version of python IDLE was used for coding and scripting on an Intel Core i5 8th Gen, 1.60 GHz CPU, and 8 GB RAM running on the Microsoft Windows 10 platform. The tests are carried out under the assumption of a WSN scenario with a total number of sensor nodes and gateways of 100 * 100 m^2 as given in table 2.

Table 2. Basic Simulation Parameters

Parameter	Values
Area	100×100m^2
Sensor node	100
Initial energy of WSNs	0.5J
Simulation rounds	100
Communication range	87meters

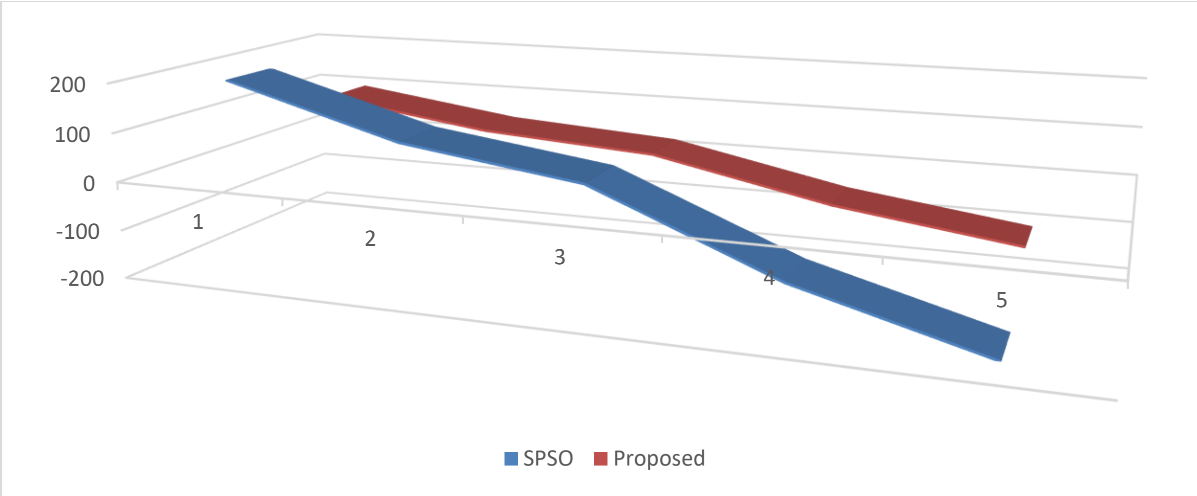

Fig.2. Analysis of Proposed Algorithm with Interactive PSO

In Figure 2. the standard PSO (SPSO) was created to provide a benchmark for the production and evaluation of new PSO variants. An effective general-purpose software kit, recently combined PSO with gradient-based optimization and direct search approaches. Furthermore, there are upgrades and software available.

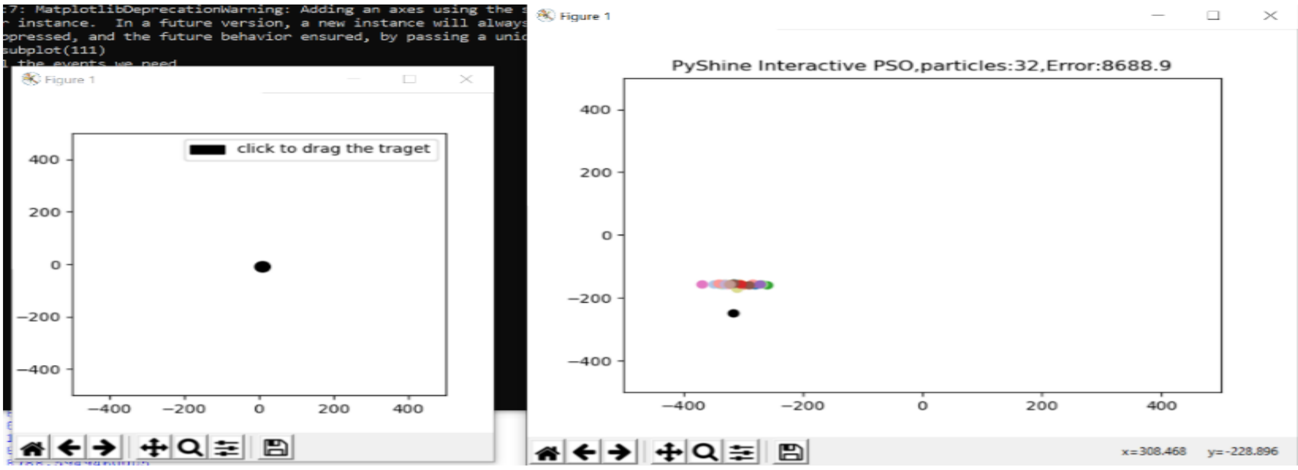

Fig.3. Implementation of Proposed Algorithm with Interactive PSO

Here in figure 3, we can see that now two figures are available and we can use the left figure to set the target position as we move the target. Particles try to minimize the cost which is the distance between them and the target. It observed that without cooperation and due to lack of information the particle failed to find the target and stuck to the boundary.

5. Conclusion and Future Scope

In the first scenario, each population typically operates within a subspace of the initial search space, with each solution vector representing a specific coordinate direction. Consequently, members generate partial solutions that are later combined with those from other populations, resulting in comprehensive solutions in the second scenario. Numerous modifications and variations have been proposed in the vast field of PSO literature, which boasts thousands of contributions. Consequently, one may rightly question how much room remains for future enhancements in the realm of PSO. However, future works could explore deeper improvements in hybridizing PSO with other optimization techniques, refining its performance in dynamic environments, or enhancing its application in specific domains like feature extraction, machine learning, and real-time systems. This analysis serves as a potential catalyst for the ongoing improvement of swarm optimization algorithms, particularly in cases like feature extraction, where further exploration could yield more efficient and scalable methods.

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