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Particle Swarm Optimization Algorithm and Its Application: A Systematic Review

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ABSTRACT

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique inspired by the social behavior of bird flocking or fish schooling.[7],[14] Introduced by Kennedy and Eberhart in 1995, it has rapidly evolved into a robust optimization algorithm capable of solving complex non-linear and multi-modal problems. This seminar explores the foundational principles of PSO, including its biological inspiration, operational framework, mathematical modeling, and historical development. The literature survey showcases key improvements and use cases across domains. The formulation section elaborates the velocity and position update rules, parameter roles, and optimization dynamics. A comparison with other evolutionary algorithms like Genetic Algorithms and Ant Colony Optimization is also made to understand PSO's advantages and limitations. The report concludes with a look at potential enhancements and emerging trends in PSO research.

Keywords: - Swarm, Optimization, Flocking, Stochastic, Adaptations, Pseudocode, Neural, Convergence Taxonomy, Gaussian, Histograms

1. INTRODUCTION

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique inspired by the social behavior of bird flocking and fish schooling.[7],[14] Introduced by Kennedy and Eberhart in 1995, it has developed into an effective method for solving complex non-linear and multi-modal problems. This seminar presents the fundamental principles of PSO, including its biological inspiration, working mechanism, mathematical modelling, and development. It also reviews major advancements and application areas. In PSO, each solution is treated as a particle moving in the search space with a certain velocity. Each particle updates its position based on its own best experience and the best position of the swarm, along with some randomness. Through continuous iterations, the swarm gradually approaches the optimal solution. [7],[13] PSO has gained wide popularity due to its simplicity and fewer parameters.[14] However, PSO faces limitations such as slow convergence in high-dimensional problems, poor performance on complex datasets, and the tendency to get trapped in local optima.[9],[13] These issues arise due to velocity fluctuations and restricted search space exploration. To overcome these challenges, several variants and hybrid approaches have been developed by integrating evolutionary techniques such as Genetic Algorithms, Differential Evolution, and other operators like crossover and mutation. These improvements enhance performance and reduce the chances of premature convergence, though challenges still remain in high-dimensional cases. This work aims to provide a systematic overview of PSO, its variants, and applications across domains such as healthcare, environment, industry, and smart cities.[1],[4],[10] It also highlights key performance aspects like accuracy, efficiency, convergence rate, and computational cost, while discussing recent developments, opportunities, and challenges in PSO research.

2. LITERATURE REVIEW

Throughout the centuries, nature has served as a major source of inspiration. Swarm Intelligence (SI), an important branch of Artificial Intelligence, is based on the collective behavior of social organisms. Among SI techniques, Particle Swarm Optimization (PSO) is one of the most widely used algorithms. Since its introduction by Kennedy and Eberhart in the mid-1990s, PSO has undergone continuous modifications, leading to new applications, improved variants, and theoretical studies focusing on parameters and algorithm behavior.[7],[13]

This work surveys PSO applications across domains such as healthcare, environmental, industrial, commercial, and smart city systems.[1], [4], [5], [10] It also evaluates technical characteristics like accuracy, efficiency, and performance through different case studies, highlighting both advantages and limitations. PSO originated from studies in social psychology and computer simulations of dynamic systems. It models solutions as particles moving through a search space, where each particle updates its position based on its own best experience and that of the swarm. Through iterative updates, the swarm converges toward the optimal solution. PSO has gained popularity due to its simplicity, adaptability, and strong performance, along with its ability to hybridize with algorithms such as Genetic Algorithms (GA) and Differential Evolution (DE). Various improvements have been introduced, including different neighborhood topologies, parameter simplification, and hybrid models to enhance convergence and handle complex problems. Research has also focused on challenges such as stagnation, dynamic environments, and high-dimensional optimization. Several review studies have contributed to the development of PSO. Early works provided foundational insights, trends, and research challenges, while later studies explored applications in neural networks, image processing, energy systems, wireless sensor networks, and industrial optimization. Other research highlighted parameter tuning, mutation operators, clustering techniques, and hybrid approaches to improve performance. Although these studies demonstrate the versatility and effectiveness of PSO, limitations remain, including insufficient evaluation metrics, a lack of statistical validation, and reduced performance in complex or high-dimensional problems. Overall, PSO continues to evolve with ongoing research focusing on improving efficiency, adaptability, and application scope across diverse fields. This chapter reviewed the development, improvements, and applications of PSO. It also discussed key contributions from previous studies along with their limitations. The analysis indicates that PSO remains a powerful optimization technique, but further research is required to enhance its robustness, scalability, and applicability in complex real-world problems.

3. METHODOLOGY ADOPTED

3.1 Self-Organization Features

The SI system is characterized by a significant feature known as self-organization. In this process, the components of a system that start in a disordered state interact locally, leading to the formation of a coordinated or global order. This process is marked by spontaneity, meaning that no agent inside or outside the system controls the interactions. Bonab [2] described the self-organization in swarms through three main aspects:

1. Robust dynamical non-linearity, which includes both positive and negative feedback mechanisms. Positive feedback is used to develop beneficial structures, while negative feedback ensures that these structures remain stable and prevents instability in the collective behavior.
2. A balance between exploration and exploitation, which is essential for generating useful solutions. This balance is effectively managed by the SI approach.
3. Multiple interactions, where individual agents in the swarm use information from neighboring agents, allowing information to spread throughout the network.

3.2 Standard PSO Algorithmic Structure

In the PSO algorithm, a group of particles continuously updates their positions across iterations, enhancing the efficiency of the search process. To find the optimal solution, each particle adjusts its movement based on its previous best position (personal best) and the best position found by the entire swarm (global best) [15].

For a minimization problem, the following equations can be used:

where i represents the index of the particle, t is the current iteration number, f is the objective function to be minimized, x is the position vector (or a potential solution), and N is the total number of particles in the swarm.

At each iteration t + 1, the velocity v and position x of each particle i are updated using the following equations:

$$\mathbf{p}^{t}_{best_i} = \mathbf{x}^{*}_{i} \mid f(\mathbf{x}^{*}_{i}) = \min_{k=1,2,\ldots,t} (\{f(\mathbf{x}^{k}_{i})\}), \tag{1}$$

where $i \in \{1, 2, \ldots, N\}$, and

$$\mathbf{g}^{t}_{best} = \mathbf{x}^{t}_{*} \mid f(\mathbf{x}^{t}_{*}) = \min_{\substack{i = 1,2,\ldots,N \\ k = 1,2,\ldots,t}} (\{f(\mathbf{x}^{k}_{i})\}). \tag{2}$$

Let f be an objective function that needs to be minimized.

This function takes a vector of N real numbers, each representing a potential solution, and outputs a single real number that indicates the value of the function. The gradient of this function may be difficult to calculate or entirely unknown. Therefore, the algorithm focuses on finding the global minimum, which is known as the best solution.

$$\mathbf{v}^{t+1}_{i} = \omega \mathbf{v}^{t}_{i} + c_1 \mathbf{r}_1 \left(\mathbf{p}^{t}_{best_i} - \mathbf{x}^{t}_{i}\right) + c_2 \mathbf{r}_2 (\mathbf{g}^{t}_{best} - \mathbf{x}^{t}_{i}), \tag{3}$$

$$\mathbf{x}^{t+1}_{i} = \mathbf{x}^{t}_{i} + \mathbf{v}^{t+1}_{i}, \tag{4}$$

where i denotes the particle's index, t is the current iteration's number, f is the objective function to be optimized (minimized), x is the position vector (or a potential solution), and N is the total number of particles in the swarm. The following equations update, at each current iteration t + 1, the velocity v and position x of each particle I as:

3.3 Practical Swarm Optimization Mechanism

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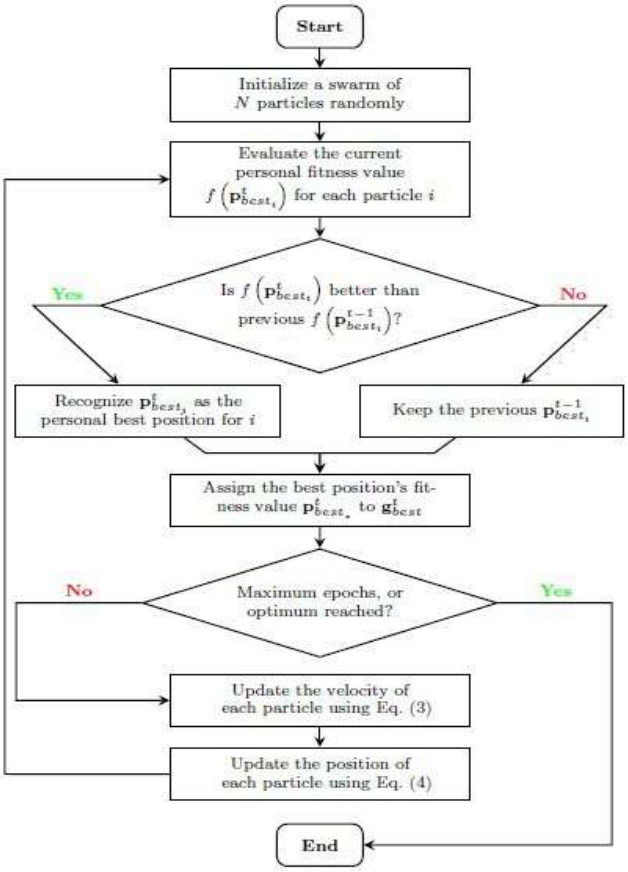

Fig. 1: PSO Flowchart

4. APPLICATION

This part aims to deliver a technical review of the specified PSO applications found in the existing literature, in alignment with the SR approach implemented in this study. Figure 2 illustrates A detailed taxonomy of PSO applications across several areas, including healthcare, environmental, industrial, commercial, smart city, and general factors.[1], [4], [5], [10] To develop successful solutions for PSO applications, it's important to identify potential difficulties. Enabling more efficient and feasible PSO implementation in real-world applications. Studies on key concerns are evaluated to support PSO applications in specific contexts. In order to support PSO applications in a specific context related to these challenges, studies concentrating on a few key aspects are discussed. For example, in environmental applications, the primary contexts are flood control, pollution forecasting, economic emission dispatch, parameter identification of Photo Voltaics (PV), segmentation and classification of plants, flood control and routing, water quality monitoring, and many other issues, are addressed in aspects of environmental PSO applications. This work proposes a taxonomy of PSO uses in research investigations, focusing on particular subjects. To address problems and challenges in different sorts of PSO applications, I focused on certain categories.

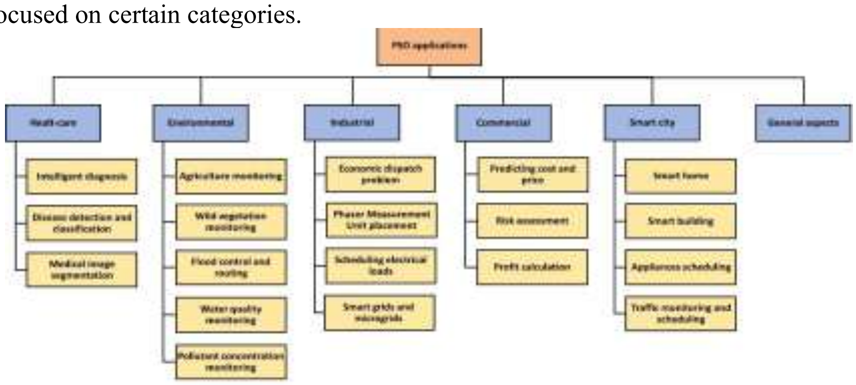

Fig. 2: Taxonomy of PSO Application

5. RESEARCH GAPS/CHALLENGES & FUTURESCOPE

Despite the wide application of Particle Swarm Optimization (PSO) across various domains, several challenges remain, providing directions for future research. PSO often suffers from premature convergence, where particles get trapped in local optima due to random initialization, limiting its ability to find the global optimum. Issues such as stagnation, particle stability, and parameter randomness require further investigation. Although historical memory improves search efficiency, adaptive memory size and parameter tuning remain critical challenges. The performance of PSO is highly dependent on proper selection of control parameters and swarm topology; however, systematic guidelines for their selection are still lacking. Future research should focus on simulation-based parameter tuning, heuristic optimization, and adaptive topology selection. Additionally, high-dimensional problems pose significant difficulties due to large search spaces, necessitating advanced techniques such as feature selection and hybrid methods to improve classification accuracy. PSO has been successfully applied in areas such as neural networks, image processing, bioinformatics, and recommendation systems. However, many applications still face limitations, including computational complexity, lack of integration between techniques, and insufficient real-world adaptability. Emerging approaches like hybrid PSO models, Gaussian PSO, and integration with other algorithms have shown improved performance but require further exploration. Overall, future research should aim to develop robust, adaptive, and scalable PSO variants capable of addressing complex, high-dimensional, and dynamic optimization problems while improving convergence speed, accuracy, and computational efficiency.

6. CONCLUSION

PSO is a powerful tool for solving complex optimization problems in ML and DL. It offers an edge in global search capabilities, model tuning, and robust performance under noisy conditions.[1],[10] While computationally intensive, its performance gains and flexibility make it a key component in modern AI workflows, particularly in AutoML and Neural Architecture Search.

While it has limitations, ongoing research is focused on enhancing its capabilities through hybridization, parameter tuning, and the development of specialized variants, ensuring its continued relevance in tackling complex optimization problems. The review focused on an in-depth analysis of nine main elements related to PSO strategies towards target search problems, which are PSO variants, application field, PSO inertial weight function, PSO efficiency improvement, PSO termination criteria, target availability, target mobility status, experiment framework, and environment complexity. These nine elements are based on three main considerations of PSO components, target search components, and research field components. For the PSO component, basic PSO is still the most popular among the previous researchers because of its algorithm implementation simplicity. Regarding the PSO inertial weight function and PSO efficiency improvement, the constant weight function and hybridization method remain the popular choice. Target has been found criteria gained the number one selection for the PSO termination criteria. The result in the target search component reveals that most of the previous research set up their research with a single and static target in obstacle-free environments and verified it using a simulation platform. The swarm robotic leads other research fields for obtained the most utilization of PSO in target search problems. Target quantity and target mobility status are important parameters for the target search experiment design.

REFERENCES

[1] Abdel-Basset M, Fakhry AE, El-Henawy I, Qiu T, Sangaiah AK (2017) Feature and intensity based medical image registration using particle swarm optimization. J Med Syst 41(12):197

[2] Abdelkader HE, Gad AG, Abohany AA, Sorour SE (2022) An efficient data mining technique for assessing satisfaction level of online learning for higher education students during the covid-19. IEEE Access

[3] Aberbour J, Graba M, Kheldoun A (2015) Effect of cost function and pso topology selection on the optimum design of pid parameters for the avr system. In: 2015 4th international conference on electrical engineering (ICEE). IEEE, pp 1–5

[4] Abid S, Zafar A, Khalid R, Javaid S, Qasim U, Khan ZA, Javaid N (2017) Managing energy in smart homes using binary particle swarm optimization. In: Conference on complex, intelligent, and software intensive systems. Springer, pp 189–196

[5] Adhikari M, Srirama SN (2019) Multi-objective accelerated particle swarm optimization with a container-based scheduling for internet-of-things in cloud environment. J Netw Comput Appl137:35–61

[6] Al-Thanoon NA, Qasim OS, Algamal ZY (2019) A new hybridfirefly algorithm and particle swarm optimization for tuning parameter estimation in penalized support vector machine with application in chemometrics. Chemom Intell Lab Syst 184:142–152

[7] Alam S, Dobbie G, Koh YS, Riddle P, Rehman SU (2014) Research on particle swarm optimization-based clustering: a systematic review of literature and techniques. Swarm Evol Comput17:1–13

[8] Ali Ghorbani M, Kazempour R, Chau KW, Shamshirband S, Taherei Ghazvinei P (2018) Forecasting pan evaporation with an integrated artificial neural network quantum-behaved particles warm optimization model: A case study in talesh, northern iran. Eng Appl Comput Fluid Mech 12(1):724–737

[9] Ali Yahya A (2018) Centroid particle swarm optimisation for high-dimensional data classification. J Exp Theor Artif Intell 30(6):857–886

[10] Alnaqi AA, Moayedi H, Shahsavar A, Nguyen TK (2019) Prediction of energetic performance of a building integrated photovoltaic thermal system thorough artificial neural network and hybrid particle swarm optimization models. Energy ConversManag 183:137–148

[11] Alswaitti M, Albughdadi M, Isa NAM (2018) Density-based particles warm optimization algorithm for data clustering. Expert Syst Appl 91:170–186

[12] Manikandan R, Saravanan V (2019) A novel approach on particle agent swarm optimization (paso) in semantic mining for web page recommender system of multimedia data: a health careperspective. Multimedia Tools and Applications, pp 1–23

[13] Luo W, Sun J, Bu C, Liang H (2016) Species-based particle swarm optimizer enhanced by memory for dynamic optimization. Appl Soft Comput 47:130–140

[14] Banks A, Vincent J, Anyakoha C (2008) A review of particle swarm optimization. Part ii: hybridisation, combinatorial, multicriteria and constrained optimization, and indicative applications. Nat Comput 7(1):109–124

[15] Barman D, Hasnat A, Sarkar S, Murshidanad MAR (2016) Color image quantization using gaussian particle swarm optimization (ciq-gpso). In: 2016 international conference on inventive computation technologies (ICICT). IEEE, vol 1, pp 1–4

[16]. Beheshti Z, Shamsuddin SM, Hasan S (2015) Memetic binary particle swarm optimization for discrete optimization problems.