Applications and Variants of Particle Swarm Optimization: A Review

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ABSTRACT:
Particle Swarm Optimization (PSO) has become popular choice for solving complex and perplexing problems which otherwise are difficult to interpret by traditional methods. PSO algorithm is a heuristic approach with two main advantages: it has fast convergence, and it uses only a few control parameters. But the performance of PSO depends on its parameters and may be dominated by premature convergence and stagnation problem. To overcome these problems, the moderation in PSO algorithm can be accomplished by varying the different constraints of the algorithm. This paper discusses various state of the art variants of the PSO and applications of PSO in the field of signal processing, electronics, robotics, image processing, etc. The variants of PSO algorithm not only ensures fast searching in the multidimensional search space but also the solution is nearly accurate to global optimal solution.

Keywords:
Swarms, PSO, Convergence, optimal design, FIR filters, IIR filters.

1. INTRODUCTION
A concept to optimize the non-linear functions using PSO was firstly introduced in 1995. It was developed by James Kennedy and Russell Eberhart. It requires only primordial mathematical operators, and is computationally inexpensive in terms of both memory specification and speed [24]. The testing found the implementation productive in several kinds of problems. It is an extremely straightforward algorithm that seems to be effective for optimizing a wide range of functions. Much further research need to be performed on the simple concept of bird flocking, fish schooling, and swarming theory [59].

PSO is an optimization technique in which particles are initialized randomly and based on the movement and intelligence their position and velocity are updated for each random particle. To solve the problem social interaction between particles is conceptualized. The concept of PSO lies in accelerating each particle towards its personal best and global best locations, with a random weighted acceleration at each step [1]. Each particle in the swarm seeks to modify its position. The modification of particle’s position $v_{i}^{t+1}$ can be mathematically modeled according to the Eq.(1):

$$v_{i}^{t+1} = W * v_{i} + \alpha * C_{1} * [gbest^{t} - x_{i}^{t}] + \beta * C_{2} * [gbest^{t} - x_{i}^{t}]$$

where $W$ is the inertia weight parameter that controls the tradeoff between gbest and pbest of the swarm. Its value is set less than one. $C_{1}, C_{2}$ are the learning parameters that indicates the relative attraction towards gbest and pbest and $\alpha, \beta$ are random numbers ranging between $[0, 1]$. Also, the new position, $x_{i}^{t+1}$ of the $i^{th}$ particle is updated by Eq.(2):

$$x_{i}^{t+1} = x_{i}^{t} + v_{i}^{t+1}$$

$v_{i}$ can be bounded with some range [$v_{min}, v_{max}$]. On calculation of the new position, the particle flies to that location and ultimately at the final iteration, the global best solution becomes the optimal solution searched by PSO.
1.1 Flowchart of PSO

In the initial step as shown in Fig. 1, the algorithm defines the solution space, fitness function, and the population size. The next step is to initialize the current position $x_{id}$, the velocity of the particle $v_{id}$, the global best position $g_{best}$ and the personal best position $p_{best}$.

![Flowchart of the PSO](image)

Now, for each particle updates velocity and position according to Equation (1) and (2) respectively and then evaluates the fitness function. If fitness($x$) is better than fitness $p_{best}$, then $p_{best}=x$ and if fitness($x$) is better than $g_{best}$, $g_{best}=x$ and the algorithm moves to the next particle. The flowchart keeps on moving to the next particle until the number of iterations equal to the maximum iteration or fitness ($g_{best}$) is good enough. If the
number of iteration is not equal to the maximum number of iteration, loop continuous and if fitness (gbest) is good enough for the global optimum solution, the solution is gbest and the optimum solution is achieved.

1.2 Limitations of Conventional PSO
The conventional PSO exhibits the problems of premature convergence, stagnation and revisiting of the same solution over and again. The most typical problem is when the particles are closer to gbest they tend to quickly converge on it and become stagnant (no longer update) while the other more distant particles pursue their searching [3]. But the stagnancy of particles can be eliminated by slightly varying the random parameters of each particle in every iteration. The other disadvantage of PSO algorithm is that it has a low convergence rate in the iterative process.

2. APPLICATIONS OF PSO
Due to its simplicity and fast convergence PSO has been used in various applications. Various important and latest applications in different areas are reviewed as follows:

- **Antennas**: PSO is used in the antenna design area which includes various applications like the optimal control and design of phased arrays [16], design of broadband antenna [21], design and modeling of Yagi-Uda antenna arrays [7], reconstruction of far-field radiation pattern [55], design of conformal antenna array [9].

- **Biomedical**: Biomedical applications include the biological and pharmaceutical aspects. These include optimization of biomechanics of human movement, provides cancer classification along with survival prediction [41], DNA pattern prediction and detection, design of drug, planning of radiotherapy, secondary structure specification of RNA, electroencephalogram analysis and synthesis. [47].

- **VLSI Design**: VLSI design applications include conceptual designing, RF circuit synthesis [38], design of antennas [33], filter design [51], wideband CMOS amplifier design, logic circuit design, motor design, design of power systems [4].

- **Electronics and Electromagnetics**: There is a wide range of applications in the areas of electronics and electromagnetic which have used PSO. These include on-chip inductors, fuel cells and temperature control based on FPGA [23], AC transmission system control, microwave filters, electromagnetic shape design [2], generic electromagnetic design and optimization applications [18], optimal design of high speed CMOS [43], conductor and semiconductor optimization [17], frequency selective surface design [13], configuration of parallel processor and FPGA’s arrays, digital circuit design.

- **Neural Networks**: Neural networks are combined with PSO in large number of applications. These include neural network control for nonlinear processes [45], reversal of neural networks, design of radial basis function networks [50], neural gas and product unit networks, wavelet neural networks [22], cellular neural networks.

- **Robotics**: The application of PSO in robotics include control of robotic arms and operator, motion and path planning along with control parameters, robot running, obstacle evasion, robotic swarm, voice control of robots, unmanned vehicle navigation [11].

- **Signal Processing**: The signal processing is a vast field having large number of applications employing optimization techniques. These include flatness of signal and pattern recognition, design of optimal FIR & IIR filters, nonlinear adaptive filtering, blind detection, speech coding, 2D IIR filter designing, design of QMF bank [1].

3. VARIANTS OF PSO
In order to improve the performance of the PSO, various search techniques are employed. Also, the problems of the premature convergence, sudden velocity change etc. are avoided which leads to introduction of various variants of PSO as discussed:
• **2-D Otsu PSO (TOPSO):** In order to improve the PSO performance, the optimal threshold selecting search is combined with PSO and better results are recorded with this algorithm. The effective threshold selection method of image segmentation based on PSO is embedded into two-dimensional Otsu algorithm. Traditional image segmentation methods are time-consuming computation and become an obstacle in real-time application systems but in this approach PSO deals with threshold selection of image segmentation [54].

• **Active Target PSO (APSO):** To maintain the diversity of PSO and to prevent tapping in the local optimum, a new term named as ‘active target’ is also employed [61].

• **Adaptive PSO (APSO):** In simulating process of PSO, some particles lost their ability of searching in local and global optimum and thus their velocity approximates to zero as the position does not have a favorable change. To overcome this problem, APSO method is used in which such particles are replaced by new fresh ones such that their relationship with the other particles are kept as before [57].

• **Attractive Repulsive Particle Swarm Optimization (ARPSO):** The major drawback of PSO is premature convergence. This method uses the two phases named attractive and repulsive to overcome this problem. The velocity updating equation is used; addition and subtraction operations are introduced respectively in the two phases. The attractive phase, attract the particles towards each other while the particles got repelled from each other in repulsive phase [39].

• **Best Rotation PSO (BRPSO):** This algorithm is designed for optimizing multimodal functions and to accomplish this many sub-swarms are initialized from the swarm. For multimodal functions, the normal PSO converges too fast thus increases the problem of stagnation but BRPSO, avoids the stagnation as the population moves from one local minima to another during execution of best round. Also, the periodic rotation is performed among the particles to obtain better results [6].

• **Binary PSO (BPSO):** The BPSO differs from PSO in defining the search space. In PSO movement in space means value of position of particle changes in one or more existing dimension. However, any change in probability of the position coordinate from zero to one is considered as moving in space [25].

• **Comprehensive Learning PSO (CLPSO):** In this approach, novel learning strategy is employed in which particle’s velocity is updated by analyzing the historical best information of all other particles. Using this strategy, the diversity of the swarm is preserved [30].

• **Constrained Optimization via PSO (COPSO):** This strategy is used for solving the constrained single-objective problems. In this method, an external file named as tolerant is used which preserves the record of all the investigated particles constraints [5].

• **Cooperative PSO (CPSO):** In this method, cooperative behavior is employed which improves the performance of original PSO. To optimize different components of the solution space cooperatively the swarm is divided into multiple swarms and these are also known as cooperative swarms [8].

• **Cooperatively Coevolving Particle Swarms (CCPSO):** In attempt to address the large-scale optimization problems, a new approach is employed. In this, the effective variable grouping is carried out and the technique is called as random grouping. In addition to large scale problems the complex multimodal optimization problems are efficiently solved by this technique [29].

• **Cooperative Multiple PSO (CMPSO):** This algorithm is enriching with all the conductive and control properties of PSO to increase the efficiency for solving multimodal problems [10].

• **Craziness Particle Swarm Optimization (CR-PSO):** The conventional PSO is modified by introducing an entirely new velocity expression with a new parameter called as ‘craziness velocity’. The CRPSO have better searching capacity even in multidimensional search space and convergence time is also improved [14].

• **Cultural based PSO (CBPSO):** In this method, the effectiveness of cultural algorithm in finding the global optimum using multiple evolution and progresses is employed to overcome the breaking of conventional PSO in global optimal solution [15].
- **Dissipative PSO (DPSO):** Using the self-organization strategy of dissipative structure, DPSO is developed. It improves performance of multimodal functions by introducing a negative entropy so as to construct an open dissipative system however it is far from equilibrium state for driving irreversible evolution process and thus achieve much better fitness [56].

- **Divided range PSO (DRPSO):** The algorithm is mainly designed for clustering of ad-hoc and mobile networks. Based on objective function value, the particles are firstly divided into sub-swarms then the conventional PSO is run in each swarm. Thus, it extends PSO in a distributed computing manner[12].

- **Dynamic adaptive dissipative PSO (ADPSO):** For combining the concept of mutation with PSO, a new technique is presented. In this technique, both the mutation and inertia weight are kept adaptive. The diversity of swarm is improved by having negative entropy and adaptive mutation strategy prevents the local optimum to converge prematurely[42].

- **Dynamic and Adjustable PSO (DAPSO):** This algorithm is presented to provide global optimum solution with probability one. It has the tendency to dynamically adjust the limit position with positive probability distribution along the cycle located by the best position of the swarm[31].

- **Dual Layered PSO (DLPSO):** The algorithm is proposed to design artificial neural networks (ANN). It evolves an optimal ANN controller to provide more efficient results. Dual-layer structure is employed in which one layer is used to optimize the architecture and the second layer connects weight for ANN controller[46].

- **Dynamic neighborhood PSO (DNPSO):** In real world, the multi-objective problems are more in picture, so must be optimized simultaneously. In this dynamic neighbor strategy is employed in which each particle chooses different neighbor in each generation based on the fitness value[19].

- **Estimation of Distribution PSO (EDPSO):** This method hybrids estimation of distribution algorithm and two variants of PSO. It has application in sensor networks with strengthened global optimization ability of PSO and thus can solve the multi-dimensional problems [49].

- **Evolutionary Iteration PSO (EIPSO):** In this technique, a new index named as iteration best is introduced into PSO to improve the solution quality. Then the resulting PSO is embedded with evolutionary programming for further improvements in computational efficiency[27].

- **Evolutionary Programming and PSO (EPPSO):** For improved effectiveness and efficiency, swarm directions are embedded in fast evolutionary programming and thus the convergence rate is improved and the diversity of particles is removed to some extent with mutation[53].

- **Fitness-to-Distance Ratio PSO (FDRPSO):** In this strategy, instead of attracting particles towards gbest the particle moves towards the neighborhood particle of higher fitness. It has new approach added that each particle keeps track of neighborhood particle having better fitness [48].

- **Fuzzy PSO (FPSO):** It is also called as canonical PSO, new approach for optimization. It derives inspiration from group behavior. The individual particle shares the same information content instead of being influenced by the neighbor’s best performer[44].

- **Gaussian PSO (GPSO):** The PSO drawbacks are addressed by Gaussian PSO. It has never a linear distribution and also it searches predominately the area around the global and local best. A new method based on visualization allows the better tuning of the algorithm [40].

- **Genetic PSO (GPSO):** Genetic PSO has its application in field of image processing specially for polygonal approximation of digital curves. To enhance the performance characteristics, a hybrid strategy is employed embedding a segment-adjusting-and-merging optimizer into the conventional PSO. The hybrid strategy not only improves convergence speed but also provide good-quality results. [60].

- **Heuristic PSO (HPSO):** In this technique, the next particle for updating the velocity and position is chosen so as to increase the probability of solving the problem more efficiently. With heuristics, the particles
are reinitialized with random velocity to overcome premature convergence when particles are moving close to global best position. The implementation of heuristics with PSO provides much better results. [26].

- **Hierarchical PSO (HPSO):** In this method, the gradient information is used for achieving faster convergence without trapping in local minima. It employs random step size and it also avoids the local neighborhood information. This new approach exhibits the features of both PSO and Gradient Descent algorithm [37].

- **Hybrid PSO with Simulated Annealing (SAPSO):** In this approach, PSO is integrated with simulated annealing. It updates inertia weight making it reducing gradually as the generation increases because the search space decreases with iterations. In this approach, the inertia weight is adjusted according to the search space and it is to be noted that both are reducing non-linearly [52].

- **Interactive PSO (IPSO):** It is very difficult to apply common optimization methods for problems which cannot be defined in quantitative way, so interactive optimization is adopted. In interactive PSO information sharing mechanism is different from interactive EC. In this approach, the user compares the new solution with the particle’s best solutions in every iteration and the decision is made by the user itself [36].

- **Restricted Velocity PSO (RVPSO):** The approach is designed which incorporates the impact of feasible region of the swarm on the velocity of particles. This improvement is made in PSO algorithm to make it more applicable to constrained optimization problems (COP). The algorithm is easy to implement because there is only one update equation i.e. position update and also the inertia weight is set to unity. It is combined with DOM to provide very effective and efficient handling of constraints [34].

- **Self-adaptive Velocity PSO (SAVPSO):** In this method, the impact of constraints is utilized for improving the particle’s ability of optimization. The SAVPSO is combined with dynamic-objective constraint-handling method thus appropriately utilizes the knowledge of the feasible region results in improving the search mechanism of PSO from the perspective of constrained optimization problems[35].

- **Self-organization PSO (SOPSO):** The self-organization PSO is based on information feedback. It emphasizes the information interactions between the particles and the randomly generated swarm. It also introduces feedback to simulate the function and through this feedback information, the particles can perceive the swarm state and adopt favorable behavior to modify their positions. Thus, adaptively modifying the exploitation and the exploration of the algorithm, the diversity of the swarm is also preserved [20].

- **Two-Swarm-based PSO (TSPSO):** A new two-swarm based PSO algorithm is introduced, in which the selection procedure is carried out using roulette wheel selection. The two swarms are having different flying trajectory with maximum exploration of solution space and the global exploration ability is also enhanced by setting different parameter. Roulette-wheel-selection based stochastic selection scheme enhances the local exploitation ability and intensively makes particle searching for better feasible solution in the neighborhood. It can easily provide optimum results even for complex problems [28].

- **Variable Neighborhood PSO (VNPSO):** In this method, a hybrid metaheuristic method is introduced which consists of the Variable Neighborhood Search (VNS) and Particle Swarm Optimization. It is designed for solving multi-objective and flexible Job-shop Scheduling Problems. The basic idea lies in driving the particles by a shaking strategy and for the better scheduling solutions neighborhood spaces are explored variably [32].

- **Velocity Limited PSO (VLPSO):** The information about the velocity of particle is very important for searching the best solution, thus the Velocity Limited PSO (VLPSO) is developed. The concept used is smaller the velocity range easier it is to find the best solution as compared to high velocity range. The new approach with defined velocity range can have better convergence efficiency and founds the optimal solution in less iteration [58].
4. CONCLUSION
In this paper, various applications and variants of PSO algorithm are reviewed. It is observed that updating velocity equation along with the inertia weight has the most important impact in the improvement of the PSO performance. A large number of variants have used hybrid approaches in which the adopted approach modifies the swarm population and then the PSO algorithm run over this modified swarm.

REFERENCES


