A Niche Particle Swarm Optimization- Perks and Perspectives

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***Abstract*— Optimization is a method for searching the best candidate solution to lessen or expand the value of the objective problem. Broadly speaking algorithms can be orgabized into four main classes, i.e. biology-based algorithms, physics-based algorithms, sociology-based algorithms, and human intelligence-based algorithms. Swarm-intelligence (SI) based algorithms appeared as a commanding family of optimization techniques. The paper aims to commence a brief review of meta-heuristic algorithms especially Particle swarm optimization (PSO) and its sister variants in short. The understudy paper covers all important aspects of swarm intelligence PSO with deep insight learning for practitioners and scholars.**

Keywords*— *Artificial intelligence; evolution-based optimization; hybrid optimization; microgrid; swarm-based optimization

I. INTRODUCTION

Optimization is a systematic procedure for finding the solution of the highest candidate that can be measured to minimize or maximize the value of an objective through selecting the sum of specified variables [1]. The first literature related to optimization is named "Theory of Minima and Maxima" was first printed in 1917 by H. Hancock in which the search space is mainly classified into two basic steps; exploration and exploitation (E&E). Exploration is an algorithm's proficiency to expand the issues in the search region while exploitation is the capability to recognize optimal solutions near a favorable one. Meta-heuristic is one of the higher-level procedures, which is immune to problems conceptualization and solver constraints in principle [2]. This procedure has attributes of high pliant and efficiency, which offers particular merits in solving functions of complex objectives that amalgamate with non-convex and non-smooth problems. For example in the hybrid photovoltaic–battery stacks for electric vehicle (EV) charge scheduling the problem persisted. Compared with traditional optimization methods, meta-heuristics have surpassed capabilities not only it conserve in local optima but due to its stochastic nature, it also extensively look into the whole search region. To solve the optimization issues, several optimization schemes have been appearing to tackle nonlinear problems. These techniques is categorize according to the variety of search space and intent features. Mixed-integer programming, linear, non-linear programming, dynamic programming, queuing theory, game technique are under the umbrella of the conventional algorithm category. The fitness function is a common parameter used to determine an automated iterative search like GA or PSO. Any system, which is a design based on a multi-objective optimization problem with several parameters that can usually be formulate as below:

$$f_x = \{f_1(x), f_2\,(x), \dots\dots\dots\dots\dots . f_m(x)\} \qquad (1)$$

$\forall\ to\ g(x) \leq 0$ and $h(x) = 0$ where,

x = Vector design, problem space
$f(x)$ = Objective functions of the vector
$f_m(x)$ = m^{th}objective function
$g(x)$ = Set of inequality
$h(x)$ = Set of equality constraints.

Numerous multi-objective modifications of PSO have been proposed in the literature in the last decade to find the best optimal solution and others considering the Paretian optimum solution [3].

This paper contribute a unique review of canonical PSO and its variants reading in fast insight style.

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II. META-HEURISTIC PORTFOLIO OPTIMIZATION ALGORITHMS

Heuristics is a hit and miss implementation technique for generating reasonable solutions to a complex issue in a relatively realistic period [2]. Alan Turing was presumably the pioneer who used heuristic algorithms during the II World War when he cracked German Enigma ciphers where Dr. Turing, who developed a cryptanalytic machine, the Bombe, in 1940, helped to crack their code. The bombe used the algorithm of heuristic, as Turing said, to look for the possible correct configuration encrypted in an Enigma message around 10^{22} different combinations. However, the operators resolve certain problems of stability but they do not address the problems regarding variable operating point, time delay, and nonlinear loads. Optimization methods are often used to resolve these issues by adjusting the parameters of the controller [2, 4].

Meta-heuristic algorithm is used to optimize the controller parameters because of simple to implement, based on an easy concept, and do not need gradient details [5]. Meta-heuristics is commonly accepted as successful techniques for multiple failures in tough optimization, which are difficult to solve under certain restrictions and with precise fixed methods. In other words, the meta-heuristics are not limited to a specific problem but they provide a solution (normally optimization) for various problems. They provide complimentary reasoning and search methods to solve complex problems. Meta heuristic algorithm can be group into four main categories.

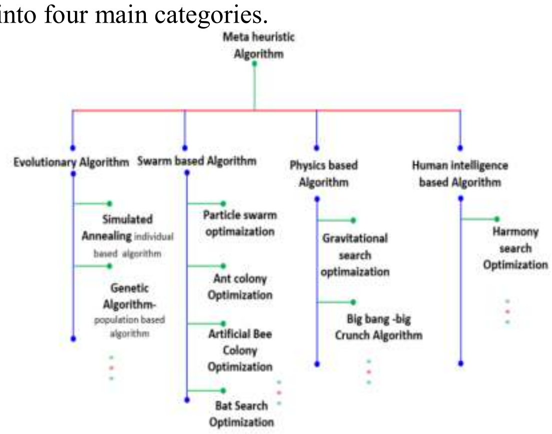

Fig.1. Hierarchy of Meta-heuristic algorithm

Metaheuristics are easily appropriate to the various conundrum, as they often presume problems like black boxes. In other words, mostly the system's inputs and outputs are essential for a meta-heuristic. Mostly meta-heuristics have the mechanisms of derivation-free that stochastically optimize the problems. The optimization cycle begins with random solutions and it is not necessary to determine the search spaces derivative to identify the optimum. This made meta-heuristics extremely applicable to real issues with expensive or uncertain derivative details [6]. In general, meta-heuristics can be categorized into two major catagories: population-based and singular-based solution. In the former category, a single candidate solution begins with the search process. This sole candidate solution is strengthened during the iterations process. However, Metaheuristics of population-based use a variety of solutions (population) to perform the optimization. In this case, the process begins with randomized multiple solutions, and above the course of variations, this population will have to increase.

Swarm Intelligence is the significant branch of meta-heuristics population-based optimization inspired by the collective conduct of flock of birds in localized and self-organized manner. The use of SI techniques, inspiration comes primarily from flocks, herds, natural colonies, and creature schools in nature [7]. The SI techniques include Cuckoo Search Algorithm (CSA), Dolphin Echolocation (DE), Artificial Bee Colony Algorithm (ABCA), Grey Wolf Optimizer (GWO), Firefly Algorithm (FA), Firefly Optimization Algorithm (FOA), Bat Algorithm (BA), Harmony Search and Whale Optimization Algorithm (WOA). Among all SI based optimization, PSO get a distinct place. Figure 2 depicts the SI behavior of PSO.

Fig.2. A flock of birds SI- PSO

III. PARTICLE SWARM OPTIMIZATION

The multifarious PSO is a SI algorithm initiated by Russell Eberhart and James Kennedy in 1995, which is a metaheuristic computation stochastic search algorithm iteratively modified and goes until the termination criterion met [8]. The pioneer termed particles not points in the algorithm because it relates to velocity and acceleration terms. It consider as evolutionary Computation (EC) practices that simulates the collective attempts of the swarm, like schooling of fish, animal herding, bacteria molding, ant colonies, or a flock of birds [9] where they search for food in groups in a confined area. Because of its benefits such as global convergence, robustness, and easy implementation capability, this algorithm has been identified as a popular sizing technique. It is an iterative flow procedure, which explores the region to find the optimal method for fitness function [10]. The niching algorithm retains an individual swarm (population), in which each particle/agent/bird constitutes a candidate solution. Particles adopt a modest response that emulates the performance of adjacent particles and achievements. The PSO algorithm gives a logical method and superior-performance operation. It does not involve any optimization problem to be differentiable as entailed by other conventional optimization procedures [11]. It can be rigorously be applied to irregular, noisy, time-variant type optimization scenarios. Firstly, fewer particles are involved to tune the metaparameters that support high-speed optimization procedure and resilient convergence. Secondly, the so-far best parameters can be utilized as initial values. Furthermore, the procedure can individually be framed for each control objective, so an accurate solution is expected [12]. The application of non dominated sorting in the canonical PSO to rank it and to rectify non-dominated solutions received so far.

However, some control check of PSO are found when encoding the system parameters [13] which are given as;

- Competent global search method, although when trying to solve multimodal composite problems it takes more time to process.
- It has its special parameters of control such as cognitive, social, and weight inertia parameters.

The basic strategy of PSO, in short, are; evaluating the cost value of individual particles; refreshing local and global best cost values and locations; Upgrading the velocity and position of an individual particle.

By using the current position vector, the search method is represented through the following expressions;

Particle position x_i and velocity component v_i represents the step size.

$$X_i^{k+1} = x_i^k + v_i^{k+1} \tag{2}$$

$$v_i^{k+1} = w.v_i^k + c_1 r_1 \left(P_{best,i} - x_i^k\right) + c_2 r_2 (G_{best} - x_i^k) \tag{3}$$

where;

$$X_i = (\, x_1, x_2, x_3, \dots \dots \dots \dots \dots ., x_n) \tag{4}$$

and the velocity vector in the specified dimensional local space.

$$V_i = (v_1, v_{i,} v_3, \dots \dots \dots \dots \dots \dots . v_n) \tag{5}$$

Besides, the optimality of the solution in the PSO algorithm relied on each particle position and velocity update using the above equations [14] inertia constant can be calculated as :

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{iteration_{max}}\right) \times k \tag{6}$$

Inertia weight- w plays a vital role in balancing global as well as the local search. A large value of w facilitates the global while a small value convalesce the local search.

where; i = index of the particle, k = number of iterations
x_i^k *and* v_i^k = Position and velocity of particle i at iteration k respectively;
w = Inertia weight/damping factor constant range zero to unity;
c_1& c_2 = Acceleration/cognitive coefficient, learning factors range 0 to 2;
r_1& r_2 = Random values produced for every velocity upgrade;
G_{best} = The global best position gained depend on the swarm's practices [2];
$P_{best,i}$ = Local optimum position of individual particle i that is gained, relied on its personal best position, correspondingly.

The first term in the above equation $w.v_i^k$ is named the inertia component; it is accountable to retain the particles find in the consistent direction, the decreased value of the inertia weight ω accelerates the swarm's convergence tends toward the optimal position, wheraas the rise value finds the whole target space. The midterm $c_1 r_1 \left(P_{best,i} - x_i^k\right)$ known as the cognitive component, it shows the particle's memory also sometimes recalled as an individual component. The particle (candidate solution) tends to return to the field of search space in which it has high individual fitness while the acceleration coefficient c_1 marks the step size of the particle to move toward its local best position $P_{best,i}$. The last term $c_2 r_2 \left(G_{best} - x_i^k\right)$ known as the social component, it is responsible to move the particle toward the best region found by the swarm so far. The social coefficient c_2 marks the step size of the particle to search the global best position G_{best}.

The position of an individual particle refreshes itself by taking the new velocity and its last position. In such a case, a new search route starts over the updated search region to determine the global optimum solution. This cycle reiterates itself until it encounters the termination statement such as the maximum number of iterations or the requisite cost value. Subsequently, reproducing the swarm through a probabilistic velocity equation and the ability of indulgent, the search process gives elite-performance operation to search the global optimum solution. For these reasons, the PSO has more benefits than other iterative searching algorithms like the Genetic Algorithm (GA), which permits only good genetic information to the descendants. A limited search space is the only weighty drawback of the PSO algorithm. A rapid solution is attained by filtering a limited search area; rather the optimality of the solution is manipulated if the global optimum value is found outside the boundaries. Protracted boundaries, however, permit a finding of global optimum solutions but require much time to find the global optimal point in the search region. Thus, more knowledge about the extremes of parameters will assist to find the search margins. The local and global position in PSO is depicted in Figure 3 as in [15].

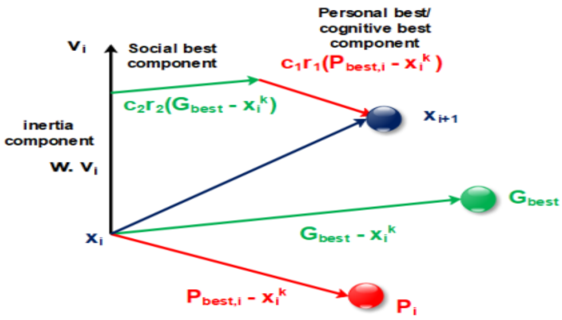

Fig.3. Displacement of particles in a swarm [15].

A. Alternatives of canonical PSO

There are a plethora of different modifications of PSO methods, which usually enhance the applicability by replacing velocity with diagonal matrices [16, 17]. Sometimes no inertia component is taken rather enforce an extreme limit on candidate speed called well-informed PSO. Other famous alternatives using a constriction coefficient are flexible PSO (FPSO), Bare-Bones (BBPSO) [18], modified charged PSO (cPSO), Fully Informed PSO, Linearly decreasing weight PSO (LDWPSO), Guaranteed convergence PSO (GCPSO), Adaptive PSO, Adaptive comprehensive learning A-CLPSO, Binary PSO, Standard Particle Swarm optimization (SPSO), Opposition-Based-Learning-Competitive (OBLC), time-varying acceleration coefficients PSO (TVACPSO), orthogonal learning PSO (OLPSO), self-adaptive learning PSO (SLPSO), parallel PSO (PPSO), Dynamic multi-swarm particle swarm optimizer, Comprehensive learning PSO, enhanced leader PSO (ELPSO) [19]. Similarly, there are also versions for constrained, discrete, and multi-tasking optimization. Some of the emerging PSO briefly written here;

A. Vector Coevolving PSO (VC PSO)

In 2017, Zhang et al. developed this novel vector coevolving particle swarm optimization algorithm (VC PSO) [20]. In VC PSO, the complete dimension of each particle is randomly splitted into numerous segments. Next, randomly optimized each segment by alloting newly designed scalar or learning operators to update the values in each sub-dimension independently. The four scalar operators (increasing, decreasing, hill and lake operator) are designed to enrich the population diversity and avoid premature stagnation. On the other hand, two learning (centralized and decentralized) operators is designed to excel the global and local search performance. The dual randomization mechanism with vector partition and operator assignment made it possible to improve the search quality.

B. Butterfly Particle Swarm Optimization (BFPSO)

Unbiased BFPSO is basically rooted from canonical PSO introduced by Aashish et al. [21]. It recuperates the searching capability with excellent convergence speed; high precision level; snub the problem of premature convergence; takes little time and less iteration for last value conversion. BF PSO exhibits new decision variables such as sensitivity of butterflies (s), likelihood of nectar (p), degree of the node (n) and the non-linear time changing probability coefficient (α).

C. Opposition-Based-Learning-Competitive (OBLC PSO)

In 2016, Zhou et al. proposed [22] the competitive learning which is in cooperated with the opposition-based learning (OBL-CPSO) that assists the algorithm to crack the problems with excellent diversification and intensification abilities along with addressing the delinquent of premature convergence in PSO. In this algo, for each iteration of OBL-CPSO, the competitive learning employs among three best randomly nominated particles from the swarm population and trailed by the evaluation of best, worst and medium fitness value.

D. Local Stochastic Search (LSS PSO)

In 2013, Ding et al. suggested [23] a novel PSO algorithm (LSSPSO) in which the individual particle can search a better local points using local stochastic search scheme to adjust damping factor constant by maintaining a balance between the convergence speed and diversity. It empowers a diversity attractive mechanism to top up the swarm diversity by modifying the divergences among particles.

E. Cooperative Coevolving (CC PSO)

The new particle positioning is defined by cauchy and gaussian distributions proposed by Xiaodong Li et al. [24]. CCPSO adopts a new PSO position update scheme to sample new positions in the objective space and a rule to find dynamically the coevolving sub module sizes of the decision variables. On large scale problems, the performance of CC PSO compared well against an evolutionary algorithm such as sep-covariance matrix adaptation evolution strategy CMA-ES [25], some existing PSO algorithms, and a CC differential evolutionary algorithm.

F. Improved global-best-guided (IGPSO)

An improved global best guided PSO with learning operation (IGPSO) is introduced by Ouyang et al. [26]. The particle swarm is separated into current swarm, historical best swarm and global best swarm, and each swarm is nominated as a equivalent searching methodology. For the current swarm, the global neighborhood intensifying scheme is employed to accelerate the global exploration competency. A local learning criterion is exploited to enhance local diversification ability in the historical best swarm. Moreover, probabilistic and opposition based learning operations are dealt with the global best swarm for increasing convergence speed and refining optimization precision. IGPSO outclass other AI algorithms in terms of precision, convergence speed, and non-parametric statistical significance.

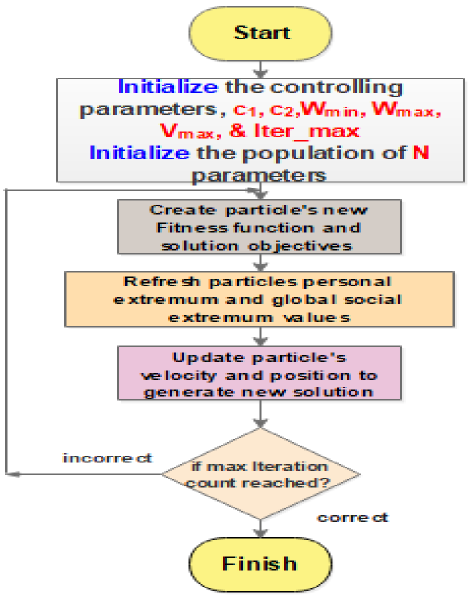

Fig.4. Flow chart of PSO [27]

```
Arbitrarily create the initialize population
repeat
    for i = 1 to population_size do
        if X_i^{k+1} < f ( P_{best,i}) then P_{best,i} = X_i^k
            G_best = min ( P_neighbours );
            for d = 1 to dimensions do
                velocity_update ( ) ;
                position_update ( );
        end
    end
until termination condition is encounter
```

Fig.5. Pseudo-code of PSO

IV. FLOW CHART AND PSEUDO-CODE

In this section, structure of the particle swarm method the pseudo-code are delineated in Figure 4 and 5.

In the flowchart the summary is given. PSO is initiate by group of random particles. In each iteration, the particle refreshes itself by tracing personal P_{bp} and global best P_{bg} value. All particles have a fitness value found by the optimized function.

Table 1 marks the merits and demerits of multifarious PSO algorithm.

TABLE 1. OVERLOOK OF PSO

Merits	Demerits
It is effective in solving issues where accurate mathematical modeling is difficult to find.	Cannot solve dispersal problems.
Optimum computing span.	Premature convergence, caught at a local minimum, particularly with complex issues.
Free from transformation and overlapping.	
Fast convergence depends on the problems.	
Have a greater chance to find global optima and efficiency.	Initial design parameters can be difficult to define.
Robust.	
Able to perform parallel computing.	
Need fewer adjusting parameters.	
Easily deployed.	

V. CONCLUSION

This article extracts the jewels of Particle Swarm and its variants effectively. Since it has proven ameliorate performance and efficient inclusion in managing various dispersed optimization problems. Though, stepping into the mid of twin year a chain of different optimization arises and PSO variants are coming to date. With all of these facts it is undeniable to say that PSO is used as a baseline with all its counterpart state-of –the-art classic meta-heuristic algorithms. The paper depicts the resiliency characteristics and emerging features of PSO in detail.

DISCLOSURE DECLARATION

The scholars affirm that there is no conflict of interest in the research.

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