(REVIEW ARTICLE)

The particle swarm optimization (PSO) algorithm application – A review

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Abstract

Particle Swarm Optimization (PSO) is one of the concepts of swarm intelligence inspired by studies in neurosciences, cognitive psychology, social ethology and behavioural sciences, introduced in the domain of computing and artificial intelligence as an innovative collective and distributed intelligent paradigm for solving problems, mostly in the domain of optimization, without centralized control or the provision of a global model. The PSO method has roots in genetic algorithms and evolution strategies and shares many similarities with evolutionary computing such as random generation of populations at system initialization or updating generations at optima search. This paper presents an extensive literature review on the concept of PSO, its application to different systems including electric power systems, modifications of the basic PSO to improve its premature convergence, and its combination with other intelligent algorithms to improve search capacity and reduce the time spent to come out of local optimums.

Keywords: Swarm; Algorithm; Optimization; Particle; Application

1. Introduction

The method of particle optimization (PSO) is one of the concept of swarm intelligence [1] inspired by studies in neurosciences, cognitive psychology, social ethology and behavioural sciences, introduced in the domain of computing and artificial intelligence [2] as an innovative, collective and distributed intelligent paradigm for solving problems, mostly in the domain of optimization, without centralized control or the provision of a global model [3, 4].

In the utilization of PSO for multivariable optimization problems, the swarm takes a specified size corresponding to the variables of the objective function(s). The particles are individually located with initial random locations with zero velocity in the multidimensional design space. Particles of the swarm represent possible solutions in the search pace, possessing position and velocity [5].

In this particle arrangement and behaviours, each particle keeps track of its positions in the search space and its behaviour will depend on the best position it has discovered and on the best overall position that any member of the swarm has achieved so far. With this behavioural arrangement, gross effect of the design space is optimized. The PSO method works by considering the parametric optimization as an unconstrained D-dimensional minimization problem as follows [6].

Min $f(x)$ = $[x^1, \ldots x^j \ldots x^D]$-   -   -   -   -   -   -   -   1

Where $x^1, \ldots x^j \ldots x^D$ are particles to be optimized in the form of a D-dimensional vector$(f(x))$.

As already outlined, each particle has position and velocity at any time t, so that, x_i^j and v_i^j are the position and velocity respectively of the ith particle on the jth dimensional space. As the swarms meanders in the search space, individual positions and velocities are updated as follows: [7, 5 and 8].

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$$v_i^j = \quad w.v_i^j + C_i \text{ r and } 1_i^j.\left(Pbest_i^j - x_i^j\right) + C_2 \text{ r and } 2_i^j,(gbest^j - x_i^j), \quad - \quad - \qquad 2$$

$$x_i^j = x_i^j + V_i^j.\Delta t. \ - \qquad - \qquad - \qquad - \qquad - \qquad 3$$

Where: $x_i = \left(x_i^1 \dots \dots x_i^j \dots \dots x_i^D\right)$- $\qquad$ - $\qquad$ - $\qquad$ - $\qquad$ - $\qquad$ - $\qquad$ 4

$$V_i = \left(v_i^1 \dots \dots v_i^j \dots \dots v_i^D\right) \qquad - \qquad - \qquad - \qquad - \qquad - \qquad 5$$

Equations 4 and 5 represents the position and velocity of the ith particle in the D-dimensional search space.

$$Pbest_i = \left(Pbest_i^1 \dots Pbest_i^j \dots Pbest_i^D\right) - \qquad - \qquad - \qquad - \qquad - \qquad - \qquad 6$$

$$gbest_i = \left(gbest_i^1 \dots gbest_i^j \dots gbest_i^D\right) - \qquad - \qquad - \qquad - \qquad - \qquad - \qquad 7$$

Equations 6 and 7 represents the best position of the ith particle and the overall best position of the swarm so far. Δt is the time interval or step between iterations; C_1 and C_2, the acceleration constants representing cognitive and social learning rates; $rand\ 1_i^j$ and $rand\ 2_i^j$ are randomly generated numbers. The inertia weights necessary to balance the global and local search abilities is represented with w.

2. PSO algorithm combined with other intelligent algorithms

While iteratively searching for optimal particles, premature convergence is one of the limitations of the PSO algorithm. To reach to an optimum value, particle swarm optimization depends on interaction between particles. If this interaction is restrained algorithm's searching capacity will be limited, thereby requiring long time to come out of local optimums [9]. Many developments including combination of PSO with other intelligent algorithm have been developed to solve this problem. An improved algorithm for Particle Swarm Optimization (PSO) named Elite Particle Swarm Optimization with Mutation (EPSOM) was proposed by [10]. The EPSOM algorithm improves the individual quality of the swarm and accelerates the convergence. Meanwhile, mutation operation which is employed in this new algorithm is to guarantee the diversity of the swarm and to decrease the risk of plunging into local optimum.

A novel particle swarm optimization algorithm [11]: Multi-Swarm and Multi-Best particle swarm optimization algorithm. In order to make full use of the searching information, the novel algorithm updates the population's position and velocity by following multi-pbest and multi-gbest instead of single pbest and single gbest. Accordingly, the population is not trapped by local optimum position easily.

To solve the premature convergence problem of the PSO, [20] proposed a novel particle swarm optimization based on swarm particles equilibrium distribution. A new particle which can measure the swarm equilibrium of distribution degree was proposed to effectively avoid particle clustering within a sub-area of the search space.

In modified particle swarm optimization (PSO) algorithm [12]. Their method integrates the particle swarm optimization with the simulated annealing algorithm. It can solve the problem of local minimum of the particle swarm optimization, and narrow the field of search continually, so it has higher efficiency of search. The algorithm was applied to the function optimization problem and simulation shows that the algorithm is effective.

Another hybrid particle swarm optimization (OPSO) algorithm, which combines the advantages of Neider-Mead simplex method (SM) and particle swarm optimization (PSO) algorithm to solve systems of nonlinear equations was proposed by [13]. Numerical computation results show that the approach has great robust, high convergence rate and precision, it can give satisfactory solutions of nonlinear equations.

A hybrid approach incorporating an enhanced Nelder-Mead simplex search scheme into a particle swarm optimization (PSO) with the use of a center particle in a swarm for effectively solving multi-dimensional optimization problems was proposed by [14]. To show the effectiveness of the proposed approach, 18 benchmark functions were adopted for optimization via the proposed approach in comparison to existing methods.

A new variation of the particle swarm optimization algorithm basing on group decision (GDPSO) was also proposed by [15]. The algorithm takes each particle as an individual decision-maker and uses the basic particle information such as the position of individual history and fitness value to decide a new position. In this way, using the position replaces the

global best position. So the space of searching is expanded and the population diversity is increased. The GDPSO algorithm can improve the convergence speed and the capacity of global searching as well as the avoidance of premature convergence.

The simultaneous perturbation particle swarm optimization which is a combination of the particle swarm optimization and the simultaneous perturbation optimization method was proposed by [16]. The method has global search capability of the particle swarm optimization and local search one of gradient method by the simultaneous perturbation. Comparison between these methods and the ordinary particle swarm optimization were shown through five test functions and learning problem of neural networks.

A new algorithm for the multimodal function optimization based on the particle swarm optimization (PSO) was developed by [17]. This method, called the multi-grouped particle swarm optimization (MGPSO), keeps basic concepts of the PSO, and, thus, shows a more straightforward convergence compared to conventional hybrid type approaches. The usefulness of the proposed algorithm was verified by the application to various case studies, including a practical electromagnetic optimization problem.

Due to the slowness and the locality of convergence for Simple Particle Swarm Optimization (PSO) in solving the complex system optimization, [30], proposed a Two Stage Composite Particle Swarm Optimization (TS-CPSO) as an improved PSO with the strategy of gradual range contraction. The designing ideas and the implementation of TS-CPSO were given, and the convergence analysed by simulation. All the results indicate that the new type of algorithm was able to converge to the global optimal solution and could efficiently avoid the premature phenomenon.

Particle swarm optimization based on chaotic neighbourhood search (PSOCNS) was proposed by [38]. The algorithm avoids premature convergence by searching each small area which is defined by all particles by chaotic search and then jumped out of local optimization. The experiment results demonstrate that the PSOCNS proposed is better than the basic particle swarm optimization algorithm in the aspects of convergence and stability.

Similarly, to prevent that particles of the PSO from easily falling into local optima point in optimization of high-dimensional and complex functions, [18] proposed a novel two sub-swarms exchange particle swarm optimization based on multi-phases (TSEM-PSO). The particle swarm was divided into two identical sub-swarms, with the first adopting the standard PSO model, and the second adopting the proposed model, When the two sub-swarms evolve steady states independent, the exchange number of particle is different in different searching phase and its amount is gradually decreasing which can increase the information exchange between the particles, improve the diversity of population and meliorate the convergence of algorithm. Experiment results show that the TSEM-PSO is superior to standard PSO and TSE-PSO algorithm.

3. PSO applied to electric power systems

The PSO method has roots in genetic algorithms and evolution strategies, therefore it shares many similarities with evolutionary computing such as random generation of populations at system initialization or updating generations at optima search but also differs from it in not using evolution operators such as crossover and mutation or, in that each particle owns memory. Because of these similarities PSO has, many of the preferable properties of GA and used successfully in many fields [6]. Expanded PSO method for reactive power and voltage control considering voltage security assessment was proposed by [19]. Hybrid PSO, evolutionary PSO, and constriction factor to find optimal mapping between unit load demand and pressure set point in a fossil fuel power unit was used by [21]. A GA hybrid with PSO to find the optimal design of a plate-fin heat exchanger was applied by [22]. Based on literature PSO has been found to be robust, flexible, and stable. It is insensitive to local optima or saddle and suitable to solve complex optimization problems with many parameters. PSO is fast in solving nonlinear, non-differentiable multi-modal problems and just like GA it does not require gradient computation [1].

4. PSO applied to miscellaneous problems

The PSO method has been applied in the optimal scheduling of hydro system. Here, [24] proposed an enhanced particle swarm optimization algorithm (EPSO) to solve optimal daily hydro generation scheduling problem. The feasibility and effectiveness of the proposed EPSO method was demonstrated for optimal daily generation scheduling of a hydro system and the test results were compared with those of other methods in terms of solution quality and convergence property. The simulation results showed that the proposed method was able to obtain good solution. The calculation of critical depth, an essential parameter in hydraulic engineering, in horseshoe cross section open channels, based on PSO

algorithm was presented by [25]. The consistency of the model was checked through certain examples, numerical examples demonstrated the capacity, accuracy and simplicity of the present PSO model. The results showed that the application of their algorithm may be used for solving other similar hydraulic engineering problems and equations like normal depth. A method for seismic wave impedance inversion in order to improve the fine structure inversion ability of igneous rocks for the exploration of underlying strata, based on particle swarm optimization (PSO) was developed by [26]. The results showed that the inversion based on PSO method has a better result for this igneous area. An application of particle swarm optimization for optimizing the process parameters in turning of PEEK CF30 composites presented by [27]. The PSO program gives the minimum values of the considered criteria and the corresponding optimal cutting conditions. A random dimension velocity updated PSO proposed by [40]. Simulations were used to test the proposed PSO based several benchmark functions and then the proposed PSO was applied to the dynamic economic dispatch problems of power system. All the simulations prove the efficiency of the proposed method.

5. Modified PSO applications

A novel multi-objective endocrine particle swarm optimization algorithm (MOEPSO) based on the regulation of endocrine system was proposed by [29]. The results indicate that the designed method is efficient for some multi-objective optimization problems. A multi-objective optimized support vector machine (SVM) algorithm which is proved effective for binary-class fingerprint classification was developed by [39]. The results showed that the algorithm can reduce the work from manual operation for testing suitable parameters of SVM. A new correlated modified particle swarm optimization (COM-PSO) was developed by [31]. The results of simulations and convergence performance were compared with the original PSO. The improvement of results, the convergence speed, and the ability to simulate the correlated phenomena by the proposed COM-PSO were discussed by the experimental results. A new particle swarm optimization (PSO) that incorporates a hybrid mutation strategy was proposed by [32]. They used the Monte Carlo method to investigate the behaviour of the particle in PSO. The results revealed the essence of the particle's trajectory during executions and the reasons why PSO has relative poor global searching ability especially in the last stage of evolution. A new particle swarm optimization algorithm (NPSO) for dealing with the portfolio model from stocks market in which the optimal and sub-optimal positions of each particle were considered in the iteration process, and the crossover operation is used to avoid premature, this was presented by [33]. The result showed that NPSO outperforms PSO in algorithm tests, which prevents premature and has better convergence ability. An adapted Particle Swarm Optimization (PSO) algorithm for the inverse kinematic solution of the robot that is designed for reduction in fracture treatment with external fixator and it is applied to this robot which has six degrees of freedom was proposed by [34]. The proposed method has been tested on a robot with 3 linear and 3 rotation axes and much better results have been obtained in comparison with classical PSO. A hybrid improved particle swarm optimization (IPSO) algorithm for the optimization of hydroelectric power scheduling in multi-reservoir systems, this was proposed by [35]. The scheduling results of the IPSO algorithm were found to outperform PSO and to be comparable with the results of the dynamic programming successive approximation algorithm. The immune algorithm-based particle swarm optimization (IA-PSO) by involving the immune information processing mechanism into the original particle swarm optimal algorithm proposed and developed by [36]. The result demonstrates that IA-PSO can achieve both a superior load distribution scheme and a higher convergence precision as compared to PSO, and will hopefully be applied to solving more extensive optimization problems.

6. Conclusion

Particle swarm optimization is an innovative, collective and distributed intelligent paradigm for solving problems, mostly in the domain of optimization, without centralized control or the provision of a global model. Several of these applications and an apt insight into the algorithm operation have been presented. Issues related to premature convergence around the local minima have been addressed in the light of the reviewed literature. Furthermore, improvement on the traditional PSO have been reviewed using appropriate literature to give leverage to the algorithm's searching capacity.

Compliance with ethical standards

Disclosure of conflict of interest

Both authors declare that there is no conflict of interest.

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