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A COMPREHENSIVE REVIEW ON SWARM INTELLIGENCE & PARTICLE SWARM OPTIMIZATION

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ABSTRACT

There are various optimization algorithms have been developed inspired by Swarm Intelligence. SI algorithms applied to all areas almost including engineering discipline. The SI based algorithms have advantages over traditional optimization algorithm that is nature inspired. It is a global heuristic method for optimization firstly introduced by James Kennedy and Eberhart in 1995. PSO has attracted many researchers due to its easiness which led to many modifications and improvements of the basic PSO. This paper introduced well about Swarm intelligence and a particle swarm optimization algorithm which is worldwide used in most all arena of current scenario of research and this optimization algorithm solves various kinds of optimization problems by a broad description of the algorithm and various variants that have been developed so far using PSO.

KEYWORDS: Metaheuristic, Optimization, PSO, Swarm Intelligence

Swarm Intelligence has involvement in many researches in various fields. Bonabeau et al. (1999) defined SI as "The emanating collective intelligence of groups of similar agents". Swarm intelligence is the discipline which resembles the natural phenomena where individuals work collaboratively to accomplish certain task. A normal swarm intelligence system is consisting of many individuals; individuals may be identical or belongs to different group. One of the major characteristic of swarm intelligence is fault tolerance because of self-organized nature Keller, E. F. (2009). The SI system is composed of many individuals in a natural phenomenon and none of the individual has charge to control over all the system. If an individual fails then charge transfer to another individual. It is based on decentralized control and self-organization. Self-organization, in this kind of phenomena is due to the local interactions of the individuals with each other and with their environment. Examples of such natural phenomena are herds of land animals, colonies of ants, flocks of bird termites; fish schooling etc. They also stated that self-organization relies on four fundamental properties of multiple interactions, fluctuations, positive feedback, and negative feedback. Multiple interactions occur when the swarm particles share information among themselves within the search space. Fluctuations are useful for randomness of the swarm agents. Positive and negative feedbacks are useful for gaining and stabilization respectively. The second property of SI states the division of work which is defined as the concurrent performance of tasks by agents. This division mechanism allows the swarm to solve complex problems that require individuals to work as team.

General Swarm Principles

The self-organizing processes in SI emerge a wide variety of collective behaviors that are intended to solve a given optimization problem. (Eberhart, R., & Kennedy, J.1995) and Garnier, S. et al. (2007) describe various important principles in Swarm intelligence.

Coordination

The each and every swarm should be capable of giving information to other in the groups about the surroundings. They should communicate to each other. This function extends to particular spatio-temporal distributions of individuals, to reach a defined goal.

Cooperation

Cooperation is very general an important task to achieve a goal. It happens when group achieve together a task that could not be done by a individual. The individuals must combine their efforts in order to successfully solve a problem that goes beyond their individual abilities.

Principle of Diverse Response

Resources should not be concentrated in a narrow region. The distribution should be designed so that each agent will be maximally protected facing environmental fluctuations.

Principle of Stability

The population should not change its mode of behavior every time the environment changes.

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Principle of Adaptability

The swarm is sensitive to the changes in the environment that result in different swarm behavior.

Major Swarm intelligence Algorithms

Table 1: Important SI Algorithms

Algoritms	Author	Year
Ant Colony Optimization	Dorigo,M,et al.	1991
Particle swarm optimization	Eberhart& Kennedy (1995)	1995
Bee colony optimization	Dervis Karaboga (2005)	2005
Intelligent water drops	Shah-Hosseini	2007
Firefly algorithms	Xin-She Yang (2008)	2008
Cuckoo search	Xin-she Yang and Suash Deb	2009
Bat algorithm	Xin-She Yang	2010

The market of Swarm intelligence is increasing day by day and it is asked to reach 92.37 million by 2024 from 5.83 million in 2017 a report provided by CAGR2.

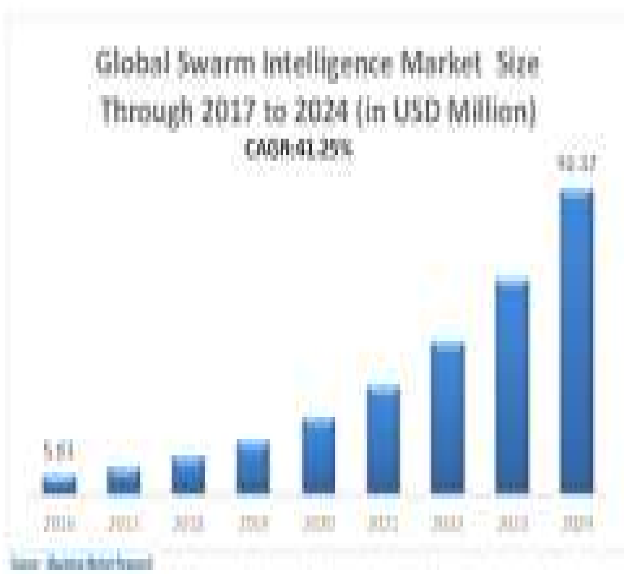

Figure 1: Swarm intelligence Market
(https://www.maximizemarketresearch.com/market-report/global-swarm-intelligence-market/7222/**)**

PARTICLE SWARM OPTIMIZATION ALGORITHM

Evolutionary computation (EC) algorithms are well being used due their global search ability to solve the problem. According to Kennedy, J., & Eberhart, R. (1995) and Shi, Y., & Eberhart, R. (1998), Particle swarm optimization (PSO) is a comparatively recent EC technique, which is less expensive computationally than other existing EC algorithms as GA.PSO was first proposed by (Eberhart, R., & Kennedy, J. 1995) they simulated the swarming behavior or social behavior of individuals like flock of birds, ant, bee, insect and fish schooling for their simulation and came to the conclusion that this behavior can be used for the problems of optimization and results can be more optimized. The individual elements are called as an agents or particles in the whole search space. A swarm can be a group of same type of agents. They execute the primary task and communicate locally among the group in their search space. There is no centralized control of the agents. Every agent can be treated as equal priority.

The position of a particle i, in the search space is normally represented by a vector $\vec{x}_i$. Each particle of the swarm is also associated with particle velocity $\vec{v}_i$ which is needed to update in each iteration of the algorithm.The movement of the particles in the search space is governed by two vectors- personal based solution ($\vec{p}_{bst}$) and global best solution ($\vec{g}_{bst}$). $\vec{p}_{bst}$ and $\vec{g}_{bst}$ are calculated by using an objective function f(x). The position vector $\vec{x}_i$ is updated based on above two vectors $\vec{p}_{bst}$ and $\vec{g}_{bst}$ so the basic entities that we need to maintain for PSO algorithm are listed below

- Position vector of the particle $\vec{x}_i$
- Velocity vector of the particle $\vec{v}_i$
- Particle personal based solution vector $\vec{p}_{bst}$
- Global based solution vector $\vec{g}_{bst}$
- An objective functionf(x).

The updating of position of the particles happens based on the following two basic equations

$\vec{v}_i = \chi \; [\vec{v}_i + C_1 \overrightarrow{\epsilon_1} (\vec{g}_{bst} - \vec{x}_i) + C_2 \overrightarrow{\epsilon_2} (\vec{p}_{bst} - \vec{x}_i)]$……………...……..…………………(1)

$\vec{x}_i = \vec{x}_i + \vec{v}_i$ ……………………………..(2)

Where χ is called the constriction factor and $\chi < 1$. This is basically acted like friction slowing the particles so that linear exploration is auctioned.

C_1, C_2 : control the relative attraction to the global best and personal best found solutions

$\in_1, \in_2$: Vector of random variables drawn with uniform probability from [0, 1].

```
FOR EACH particles i
Randomly initialize v_i, x_i = p_i
     Evaluate f(p⃗_bst)
     g⃗_bst= avg max{f(p⃗_bst)}
REPEAT
     FOR EACH PARTICLE  i
     Update particle position
x⃗_i according to equation 1 and
2
     Evaluate f(x⃗_i)
          Update    personal
     best
     IF f(x⃗_i) > f(p⃗_bst) then
          p⃗_bst= x⃗_i
          //update    global
     best
     IF f(x⃗_i) > f(g⃗_bst) then
          g⃗_bst  =  avg  max
     {f(p⃗_bst}
Until  termination  criteria
reached
```

PSO PARAMETERS

Swarm Size

The Swarm size is the number of particles present in the swarm. As large number of particles can work a large level of a search space; therefore it required less iteration so as to achieve the optimal solution of a given problem. In contrast a tremendous swarm size rushes the complexity that being computational and time complexity.

Iteration Number

Number of iterations is a basic problem in swarm size. A poor number of iterations can end the program whereas large number of iterations can generates a redundant computational data and time complexity which is not create optimal results.

Velocity Component

The velocity updation factor as in equation (1) has three terms. The first term is the leading velocity vectors i.e. the present direction & the magnitude of the particle's velocity. It is centered on the memory of an agent in agreement with its proficiency. The natural component of PSO is that a particle wants to reappear to its original position, to get local best position. The later component is the social component. This is the knowledge to an individual particle by societal communication among particles, which constantly encourages the particle to travel in the direction of the global best position, knowledgeable by its locality.

Acceleration Coefficients

The variables C_1 and C_2 are known as acceleration coefficients, that try to generate an equilibrium between the cognitive component of a particle and social component of the velocity.

- If $C_1 = C_2 = 0$ in equation 1 then equation 1 will be $\vec{v}_i = \vec{v}_i$ which says that all the particles retain to oscillate with their initial velocity but there is no search condition.
- If $C_1 = C_2$, then all particles will travel towards average g_{bst} and p_{bst} values.

ELEMENTS USED IN PSO

These are the basic element that we used in PSO algorithm and it is very important to understand these terms.

- **Particle** We can define the particle as $P_i \in [a, b]$ where $i = 1,2,3,4,5, \dots \dots \dots \dots D$ and $a, b \in R$ where R is real numbers and D is dimension.
- **Velocity Update** Velocity vector is used to determine the direction and speed of a particle. Velocity of a particle can be is updated by the equation (1).
- **Fitness Function** Fitness Function is the function used to find the optimal solution. Normally it is an objective function defined by researcher according to the research problem.
- **Global Best** It is the position of a particle achieved among all the particles visited in the search space.
- **Local Best** It is the best position of a particle among its all positions in a search space.
- **Position Update** All the particles try to move toward the best position g_{bst} to get optimal value. Each particle in a search space updates their positions to find the global optimal value and this value Position is updated by equation (2).

FLOW CHART OF PSO ALGORITHM

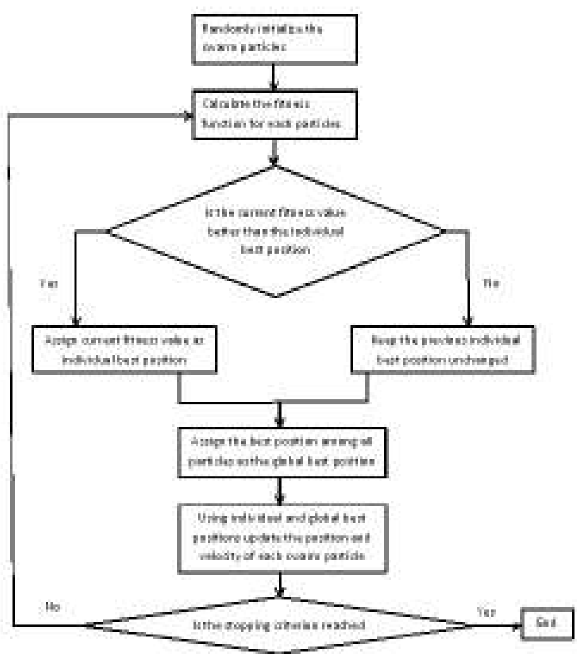

Figure 2: Flow Chart of PSO Algorithm

Table 2: Important websites of PSO

Name of the websites	URL
Particle swarm optimization	http://www.scholarpedia.org/article/Particle swarm optimization
Particle swarm optimization	http://www.swarmintelligence.org/
Particle swarm central	http://www.particleswarm.info/
PSO visualization	http://www.projectcomputing.com/resources/psovis/
PSO toolbox	http://psotoolbox.sourceforge.net/
Particle swarm optimization toolbox	http://atoms.scilab.org/toolboxes/PSO

APPLICATIONS OF PSO

There is huge number of paper available for application of PSO. We study some papers.

Abido, M. A. (2002) and Liang, R. H et al. (2011) applied PSO algorithm for Optimal power flow, Salomon, C. P et al. (2010) & Acharjee, P., & Goswami, S. K. (2009) uses for load flow, and Gaing, Z. L. (2004) uses for the designing of PID controller in Automatic voltage Regulator (AVR) system and Yapici, H., & Çetinkaya, N. (2017) for improvement in power loss in electrical power system. Nimtawat , A & Nanakorn, P. (2011) given a PSO algorithm for beam-slab designs for civil area for rectangular floor. Suresh A et al. (2015) applied PSO to predict how long a patient stay in the hospital and stated that PSO is to be better that other prediction. PSO also has been used for Job scheduling by a company Li, J. Q., et al. (2010), Wen, Pet al. (2016) uses PSO for Elevator door system. Wu et al. (2016) proposed many applications of PSO in the sector of Railway for their control mechanism, scheduling, and route layout planning. In scheduling used PSO method to find the optimal schedules. Rashidi al, et al. (2008) indicated the application of PSO to solve various optimization problems in the field of power systems for electrical. Jain N.K et al. (2016) uses PSO to multi-objective economic load dispatch problem.

VARIANTS OF PSO

The PSO method is mathematically tested so many researchers are trying to improve the PSO with its parameters. Therefore, PSO has many variants with many parameters such as Inertia weight, initialization and lots of other techniques available. The details of some PSO variants are given below.

J.Kennedy & Eberhart (1997) developed the first discrete version of PSO and M.Clerc (2004) got good results on different variants of the PSO especially for TSP. AI-Kazemi et al. (2000) also used same method as M.Clerc (2004) and named as multi-phase discrete PSO. Bergh F, et al. (2001) proposed a cooperative edition of PSO model where each and every component of the solution vector is individually optimized by a low dimensional PSO. However, individual tuning gets individual problem parameters that not always successful, particularly when parameters are trying to sum up. So, Van den Bergh and Engelbrecht also developed a hybrid PSO that reduces the size of swarm efficiently, and required less computation time as well as convergence maintenance.

M. Løvbjerg et al. (2001) uses velocity vector and position vector rule and combined with the ideas to generate sub populations, concluded that PSO have the potential to accomplish fast convergence and find better solution.

Van den Bergh, F & Engelbrecht A. P.(2002) introduced a new variants called guaranteed convergence PSO (GCPSO) in which particles execute search randomly around Global X_{bst} in space defined by a scaling factor. The algorithm performs better than original PSO model in a uni-modal while gives same results in multimodal .The scaling factor requires prior knowledge and to be optimally set.

Andrew Lim, et al. (2003) combined hill climbing method with PSO with to solve the Bandwidth minimization problem in network. Because the adaptive search heuristics algorithms are problem specific.

There are various modifications have done in the original algorithm, M.Benedetti et al. (2008) enhance memory in radio communication. There are many variants like: comprehensive learning particle swarm optimizer (CLPSO) by Liang, J. J et al. (2006), self-learning particle swarm optimizer (SLPSO) by Li, Changhe (2011) and Orthogonal learning particle swarm optimization (OLPSO) by Zhan, Z. et al. (2010) which do not need any parameter for tuning. These algorithms have a structure that is totally different from the PSO but based on PSO.

Jabeen H, et al. (2009) proposed an opposition based PSO method, claimed that by the social development, a person is bad then his adversary is good. They generate two population one is good and other is bad after calculate the fitness. One of them is selected to run PSO.

Zhao., Y et al. (2009) stated that PSO get faster and good quality solutions due to clustering of the particles in a small region in the search space.

The quality of PSO has been improved so far as well as the robustness. PSO widely used **as** a global optimal algorithm.

CONCLUSION

PSO has implemented by many researchers mathematical in every branch but, for application, only a few researchers have used PSO to develop an application. In a survey it is found that SI reaches 92.37 million by 2024 from 5.83 million in 2017.This review paper intends to describe basic of Swarm intelligence technique and Particle Swarm Optimization algorithm, applications and their various variants developed.

REFERENCES

Abido, M. A. (2002). Optimal power flow using particle swarm optimization. International Journal of Electrical Power & Energy Systems, 24(7), 563-571.

Acharjee, P., & Goswami, S. K. (2009, March). Chaotic Particle Swarm Optimization based reliable algorithm to overcome the limitations of conventional power flow methods. In 2009 IEEE/PES Power Systems Conference and Exposition(pp. 1-7). IEEE.

Al-kazemi, B. S. N. M., & Mohan, C. K. (2000). Multi-phase discrete particle swarm optimization.

Benedetti, M., Azaro, R., & Massa, A. (2008). Memory enhanced PSO-based optimization approach for smart antennas control in complex interference scenarios. IEEE Transactions on Antennas and Propagation, 56(7), 1939-1947.

Bergh, F. V. D., & Engelbrecht, A. P. (2001, July). Effects of swarm size on cooperative particle swarm optimisers. In Proceedings of the 3rd annual conference on genetic and evolutionary computation (pp. 892-899).

Blum, C., & Merkle, D. (2008). Swarm intelligence. Swarm Intelligence in Optimization; Blum, C., Merkle, D., Eds, 43-85.

Bonabeau, E., Marco, D. D. R. D. F., Dorigo, M., & Theraulaz, G. (1999). Swarm intelligence: from natural to artificial systems (No. 1). Oxford university press.

Clerc, M., & Kennedy, J. (2002). The particle swarm-explosion, stability, and convergence in a multidimensional complex space. IEEE transactions on Evolutionary Computation, 6(1), 58-73.

Clerc, M. (2004). Discrete particle swarm optimization, illustrated by the traveling salesman problem. In New optimization techniques in engineering (pp. 219-239). Springer, Berlin, Heidelberg.

Dorigo, M., Maniezzo, V., & Colorni, A. (1991). Positive feedback as a search strategy.

D.Karaboga,"AN IDEA BASED ON HONEY BEE SWARM FOR NUMERICAL OPTIMIZATION," 2005.

Eberhart, R., & Kennedy, J. (1995, November). Particle swarm optimization. In Proceedings of the IEEE international conference on neural networks (Vol. 4, pp. 1942-1948).

Gaing, Z. L. (2004). A particle swarm optimization approach for optimum design of PID controller in AVR system. IEEE transactions on energy conversion, 19(2), 384-391.

Garnier, S., Gautrais, J., & Theraulaz, G. (2007). The biological principles of swarm intelligence. Swarm intelligence, 1(1), 3-31.

Jabeen, H., Jalil, Z., & Baig, A. R. (2009, July). Opposition based initialization in particle swarm optimization (O-PSO). In Proceedings of the 11th Annual Conference Companion on Genetic and Evolutionary Computation Conference: Late Breaking Papers (pp. 2047-2052). ACM.

Jain, N. K., Nangia, U., & Jain, A. (2016). PSO for multiobjective economic load dispatch (MELD) for minimizing generation cost and transmission losses. Journal of The Institution of Engineers (India): Series B, 97(2), 185-191.

Kennedy, J., & Eberhart, R. C. (1997, October). A discrete binary version of the particle swarm algorithm. In 1997 IEEE International conference on systems, man, and cybernetics. Computational cybernetics and simulation (Vol. 5, pp. 4104-4108). IEEE.

Li, J. Q., Pan, Q. K., Xie, S. X., Jia, B. X., & Wang, Y. T. (2010). A hybrid particle swarm optimization and tabu search algorithm for flexible job-shop scheduling problem. International Journal of Computer Theory and Engineering, 2(2), 189.

Liang, R. H., Tsai, S. R., Chen, Y. T., & Tseng, W. T. (2011). Optimal power flow by a fuzzy based hybrid particle swarm optimization approach. Electric Power Systems Research, 81(7), 1466-1474.

Liang, J. J., Qin, A. K., Suganthan, P. N., & Baskar, S. (2006). Comprehensive learning particle swarm optimizer for global optimization of multimodal functions. IEEE transactions on evolutionary computation, 10(3), 281-295.

Li, C., Yang, S., & Nguyen, T. T. (2011). A self-learning particle swarm optimizer for global optimization problems. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 42(3), 627-646.

Lim, A., Lin, J., & Xiao, F. (2003, August). Particle swarm optimization and hill climbing to solve the bandwidth minimization problem. In MIC2003: The Fifth Metaheuristics International Conference, Kyoto, Japan, August (Vol. 2528, p. 2003).

Løvbjerg, M., Rasmussen, T. K., & Krink, T. (2001, July). Hybrid particle swarm optimiser with breeding and subpopulations. In Proceedings of the 3rd annual conference on genetic and evolutionary computation (pp. 469-476). Morgan Kaufmann Publishers Inc.

Nimtawat, A., & Nanakorn, P. (2011). Simple particle swarm optimization for solving beam-slab layout design problems. Procedia engineering, 14, 1392-1398..

Rashidi, Al., M. R., & El-Hawary, M. E. (2008). A survey of particle swarm optimization applications in electric power systems. IEEE transactions on evolutionary computation, 13(4), 913-918.

Salomon, C. P., Lambert-Torres, G., Martins, H. G., Ferreira, C., & Costa, C. I. (2010, November). Load flow computation via particle swarm optimization. In 2010 9th IEEE/IAS International Conference on Industry Applications-INDUSCON 2010 (pp. 1-6). IEEE.

Shah-Hosseini, H. (2009). The intelligent water drops algorithm: a nature-inspired swarm-based optimization algorithm. International Journal of Bio-Inspired Computation, 1(1-2), 71-79.

Shi, Y., & Eberhart, R. (1998, May). A modified particle swarm optimizer. In 1998 IEEE international conference on evolutionary computation proceedings. IEEE world congress on computational intelligence (Cat. No. 98TH8360) (pp. 69-73). IEEE.

Suresh, A., Harish, K. V., & Radhika, N. (2015). Particle swarm optimization over back propagation neural network for length of stay prediction. Procedia Computer Science, 46, 268-275.

Wen, P., Zhi, M., Zhang, G., & Li, S. (2016). Fault prediction of elevator door system based on PSO-BP neural network. Scientific Research Publishing, Engineering, 8, 761-766.

Yang, X. S. (2010). A new metaheuristic bat-inspired algorithm. In Nature inspired cooperative strategies for optimization (NICSO 2010) (pp. 65-74). Springer, Berlin, Heidelberg.

Wu, Q., Cole, C., & McSweeney, T. (2016). Applications of particle swarm optimization in the railway domain. International Journal of Rail Transportation, 4(3), 167-190.

van den Bergh, F., & Engelbrecht, A. P. (2002, October). A new locally convergent particle swarm optimiser. In IEEE International conference on systems, man and cybernetics (Vol. 3, pp. 6-pp). IEEE.

Yang, X. S., & Deb, S. (2009, December). Cuckoo search via Lévy flights. In 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC) (pp. 210-214). IEEE.

Yapıcı, H., & Çetinkaya, N. (2017). An improved particle swarm optimization algorithm using eagle strategy for power loss minimization. Mathematical Problems in Engineering, 2017.

Zhan, Z. H., Zhang, J., Li, Y., & Shi, Y. H. (2010). Orthogonal learning particle swarm optimization. IEEE transactions on evolutionary computation, 15(6), 832-847.

Zhao, Y., Zu, W., & Zeng, H. (2009). A modified particle swarm optimization via particle visual modeling analysis. Computers & Mathematics with Applications, 57(11-12), 2022-2029.