Advantages of PSO are that it is easy to implement as there are only a few parameters to adjust, and has been successful in many areas such as optimising a neural network1 and piecewise modelling2. However, for complex problems such as the 25 benchmark problems in the CEC2005 (The 2005 IEEE Congress on Evolutionary Computation) it performed poorly.

Where these networks do well is not falling into problems caused by local optima which is a main concern for other optimisation techniques such as gradient decent4. PSOs do not acknowledge the gradients of the search space thus are able to avoid such issues. PSOs are not the only optimisation algorithm, with other heuristic approaches including genetic algorithms5, harmony search6 and simulated annealing7. The drawback with all of these options, including PSO, is that when applying these algorithms there is no guarantee they will produce the optimal solution, only a good one. However where not possible to deterministically find the optimal solution they are a good option.

Issues of PSO, outlined by Dou et. al8, suggest problems lie with velocity decay and becoming trapped at local minima. They posit the velocity of particles in a swarm decay too fast causing step length when revising parties too decrease so far that the search efficiency reduces dramatically, or even halts. Furthermore, much like traditional optimisers, such as gradient decent, PSO can also become trapped at local minima if the minima is strongly deceptive. The probability of a particle finding a better option is smaller, thus the search becomes sluggish. Providing clear points for improvement. Due to such problems a number of solutions have been outlined 9 10 11 , such as constriction type PSO (CPSO)12. CPSO introduces a constriction element that causes particles to converge on a local optima faster by prevents particles ‘aimlessly wandering’ within the search space.

To overcome this local minima issue the concept of particles using worst locations was put forward by Yang et. al.13, which simply used these in place of the pbest and gbest metics. Since then it has been further developed to use information from both the best and worst locations to inform particle movement14 15, culminating in PSO AWL16. In PSO AWL By utilising both metrics, particles are able to maximise velocity increases when in bad areas but it decreases when the particle moves away, preventing stagnation at local minima16.

Topology of particles has also been suggested as an area for improvement within particle swarms alongside improvements to trajectories. Watts17 showed that two main factors impact flow of information through particles in a network : degree of connectivity amongst the net, the amount of clustering (when nodes are close to one another) and the shortest distance from one node to another. It was shown that by altering a networks topology it could be made more or less accurate, with the results being highly dependent on the problem in question.

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