



## A REVIEW ON PARTICLE SWARM OPTIMIZATION AND QUANTUM -BEHAVED PARTICLE SWARM OPTIMIZATION

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### ABSTRACT

Bio-inspired algorithms such as particle swarm optimization (PSO) can quickly find the best solution in the problem space. Unlike other optimization algorithms, this one does not require the gradient or any other variable form of the objective function. Maximum and minimum values of functions defined on multidimensional vector spaces are best found using PSO. Due to movement and intellectual ability of swarms, PSO is a probability optimization technique. Using social interaction as a problem-solving tool is common in PSO. It employs a swarm of particles (agents) which move around the search area in search of the best answer. It is a quantum-behaved particle swarm optimization (QPSO) algorithm that outperforms the original PSO in search ability, but has fewer parameters to control. As a result, the QPSO algorithm is prone to becoming trapped in local optima due to the rapid loss of diversity in the data set. Using the quantum particle swarm optimization algorithm, you can be assured of global convergence. Bridge quadratic coding and Gauss chaotic mutation operators form the basis of this algorithm.

**Keywords:** *particle swarm, optimization, multidimensional, quantum-behaved,*

### INTRODUCTION

Real-world engineering technology has made optimization problems more difficult, making them more difficult to solve. Traditional methods have proven to be ineffective in dealing with today's complex issues. Artificial intelligence algorithms, including such particle swarm optimization, are being used to overcome this limitation (PSO). Experts and scholars have made numerous improvements to PSO's performance since 1995. Even though PSO has been called a global optimization algorithm, Van den Bergh has shown that it is not. The quantum particle swarm optimization algorithm was developed by Sun et al. by combining the quantum theory with the PSO algorithm

(QPSO). In the search space, this algorithm ensures that the global best solution is found. A comparison of the proposed algorithm's performance against a variety of benchmark functions shows promise for improvement over the current PSO standard. The global integration of QPSO ensures that global optimization algorithm is determined even if the search iterations are infinite. Because every optimization algorithm has a finite number of iterations, this condition is impossible to meet in real-world situations. A locally optimal or slow convergence can also occur when using QPSO to solve complex problems. Researchers and experts have devised a variety of ways to speed up the QPSO convergence and achieve global

optimality. PSO is a relatively new method, having been created in 1995. However, quantum PSO's improved methods are what make it unique (technique). Improved versions always have many advantages over PSO, such as accuracy, stability, and reliability.

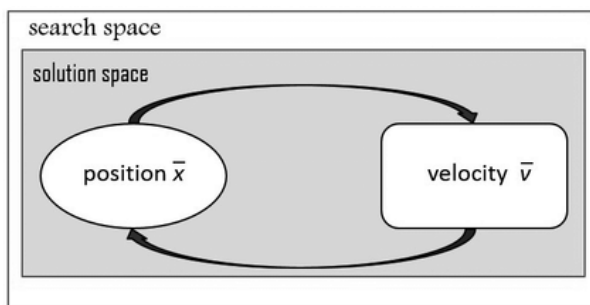


Fig. PSO and QPSO search space

### PERFORMANCE

#### IMPROVEMENTS:

In PSO, the efficiency is not greatly influenced by the amount of peak position and dimensions, which can lead to other issues like local optimization induced by untimely and optimal capacity that is parameter dependent. For this reason, there have been numerous studies on parameter modification, diversity increase, and algorithm variation in order to improve PSO's global optimality and dynamically adjust it. Many other works directly modify PSO in order to achieve convergence speed and better quality in the process of convergence. In other words, PSO variants and hybrids with other approaches. Our improved algorithm made use of two enhancement strategies: "Vector correction strategy" and "Jump out of local optimum strategy." In Congress on Evolutionary Computation 2005, the algorithm was put

to the test with 25 brand-new benchmark instances (CEC2005). Particle swarm optimization (PSO) has been improved significantly, and the development strategies have been found to be effective, according to the experimental results.

#### Quantum-Behaved particle swarm optimization algorithm:

On top of the well-known PSO algorithm, QPSO uses a global optimization method known as QPSO. The velocity-displacement orbit model (Frans, 2006) is no longer a constraint on the algorithm, which instead relies on the Monte Carlo algorithm to determine the particle's location following an update. This algorithm was first proposed in 2004 by Sun and colleagues. Assuming that the particle in space has quantum behaviour, this algorithm wants to introduce quantum computing into particle swarm algorithm. Optimization algorithms can benefit greatly from this method, as it can effectively overcome some of the drawbacks while still retaining its advantages. One of the main goals of this paper is to improve the performance of QPSO while at the same time improving its global optimal ability.

#### PARTICLE SWARM:

Using random positions and velocities as input values, a function is calculated on an inhabitants of particles and the results are displayed. At each time step, the function is recalculated using the new coordinates and the new positions and velocities. Vectors are used to store the coordinates of a new pattern that a particle discovers that is better than the previous ones it has found. Stochastic addition of the distinction between (the best point found thus far)

and the individual's current position causes the path to vibrate around that point. It is also important to note that each particle is defined in relation to other atoms in the population. Adding to its velocity is the probabilistically measured difference between the neighbourhood's best position and the individual's current position. With these modifications to its motion, it will try to find the two positions that are most advantageous to it in the surrounding space.

### Advantages of QPSO:

The traditional particle search strategy in PSO has the drawback of being not able to navigate the a whole search area, which might also lead to the an incomplete search and lose some solutions. The traditional particle search strategy in PSO has the drawback of being not able to navigate the a whole search area, which might also lead to the an incomplete search and lose some solutions. Many researchers have studied multiobjective optimization algorithms based on QPSO because of the faster convergence speed of QPSO than classical PSO. When compared to other algorithms, MOPSO's superiority in terms of speed of convergence was demonstrated in QPSO and adaptive grids were introduced.

### CONCLUSION

The PSO method's fundamentals can be outlined in this paper's findings. The benefits and drawbacks of the technique were mentioned, and also interpretations of its algorithm were provided. Some authors refer to the results as "the most likely optimal global," despite the fact that it's impossible to say with certainty that the result of an optimization method like PSO is indeed the worldwide maximum or minimum. In addition, the PSO algorithm

could be applied to a variety of engineering challenges. A cogeneration system's cost function can be optimised in two ways: first, by optimising the fuel element's spacer grid. The PSO method performed well in both cases, proving its effectiveness. A quantum particle swarm optimization algorithm has been introduced in this paper. If you're looking for an algorithm that uses a probability-searching technique, you'll find this one here.

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