

# Particle Swarm Optimization: Intelligent Parameter Tuning

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**Abstract**—Particle Swarm Optimization (PSO) is an optimization algorithm that models the flocking behaviour of certain species of animals in order to solve stochastic real-value problems. These algorithms use control parameters to make slight adjustments to how the swarm behaves. In this report the author will be discussing the results of using a brute force approach to find these control parameters.

## I. INTRODUCTION

A Particle Swarm Optimiser (PSO) is, as described by Lazincia [1], an optimization algorithm that attempts to emulate the flocking/schooling behaviour of birds or fish when searching for food. This optimization can occur in a number of dimensions, each spanning across  $\mathbb{R}$  [2]. Each particle in the swarm has two primary components of influence: cognitive and social. A third component, called the inertia weight, is used to regulate the maximum velocity that a particle can move at in a certain direction [3]. In this report, the author will explore the feasibility of finding the optimum value for each of these components by using a brute force search in a subset.

## II. BACKGROUND

As discussed in section I, the two components that influence a particle's behaviour is cognitive and social. The cognitive component refers to the influence that a particle experiences due to the best position it has found so far [4]. A more animalistic analogy of this would be that if you feed a bird it will be more inclined to visit your house in the future to get more food. The social component refers to how a particle is influenced by the best position found by other particles in the neighbourhood [4]. The analogy here would be that if you feed one bird the other birds in the flock might be more inclined to also visit your house to get food. There is a trade-off between these two components. The cognitive component favours exploration of the search space, while the social component favours exploitation of the global best position.

The last parameter is the inertia weight developed by Shi and Eberhart (1998). The role of this parameter is to balance global search and local search. [4] and thus controls the velocity a particle can move at. The inertia weight was originally proposed in order to avoid the velocity clamping mechanism that was used before.

In order to test the feasibility of the brute force approach four objective functions were used.

- Spherical

$$f(\mathbf{x}) = \sum_{i=1}^d x_i^2 \quad (1)$$

- Ackley

$$f(\mathbf{x}) = -20e^{-0.2\sqrt{\frac{1}{d}\sum_{i=1}^d x_i^2}} - e^{\frac{1}{d}\sum_{i=1}^d \cos(2\pi x_i)} + 20 + e \quad (2)$$

- Michalewicz

$$f(\mathbf{x}) = -\sum_{i=1}^d [\sin(x_i) \sin^{2*10}(\frac{ix_i^2}{\pi})] \quad (3)$$

- Katsuura

$$f(\mathbf{x}) = \frac{10}{d^2 \prod_{i=1}^d} (1 + i \sum_{j=1}^{32} \frac{|2^j x_i - \text{round}(2^j x_i)|}{2^j})^{\frac{10}{d^{1.2}}} - \frac{10}{d^2} \quad (4)$$

The topology that was used is the star topology, as prescribed by the project specifications. This model states that all the particles in the swarm are connected to all other particles in the swarm. This means that there is only one neighbourhood and all particles belong to it. This approach means that the global best position (gbest) will be used as the current optimum.

The brute force approach used in this report refers to the systematic exhaustive evaluation of a parameter that falls in a finite set of numbers. Since the range that these three parameters usually fall in is known and small, it might prove to be a feasible option to find these parameters via this approach.

## III. IMPLEMENTATION

A swarm of 20 particles was used to solve all the objective functions in a 20-dimensional space. The restrictions on  $w$ ,  $c_1$  and  $c_2$  was specified as follows:

- $w \in [-1.1, 1.1]$
- $c_1 + c_2 \in (0.0, 5.0]$
- $c_1 = c_2$

Each of these values had a step size of 0.1.

The velocity,  $\mathbf{v}_i$ , of a particle,  $par_i$ , will be used to update the position,  $\mathbf{x}_i$ , of  $par_i$ , as follows:

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \quad (5)$$

where,

$$\mathbf{v}_i(t+1) = w\mathbf{v}_i(t) + c_1\mathbf{r}_1 \otimes (\mathbf{p}_i(t) - \mathbf{x}_i(t)) + c_2\mathbf{r}_2 \otimes (\mathbf{g}_i(t) - \mathbf{x}_i(t)) \quad (6)$$

where,

$\mathbf{p}_i$  refers to the personal best position of  $par_i$ ,  
and,

$\mathbf{g}_i$  refers to the global best position of the entire swarm.

$\otimes$  refers to componentwise multiplication of vectors.

$w$  used in equation 6 is the inertia weight as discussed in section I.

$c_1$  and  $c_2$  used in equation 6 represents the cognitive and social components respectively as discussed in section I.

Since PSO is a stochastic algorithm a single run can have abnormally good or bad results. Each set of possible combinations between  $w$ ,  $c_1$  and  $c_2$  has been tested 30 times and the average result of all 30 runs has been taken as the optimal result for the specific configuration. The best configuration's result, along with the corresponding values for  $w$ ,  $c_1$  and  $c_2$  is stored each time a new optimum is found.

A simple pseudo code version of the entire algorithm is shown in algorithm 1 and 2:

```

initializeSwarm()
while not (stopping condition) do
  foreach particle in swarm do
    var objectiveFunctionResult =
      particle.getObjectiveFunctionResult() if
        objectiveFunctionResult < particle.personalBest
      then
        /* Save current position as personal best */
      end
    if objectiveFunctionResult <
      particle.neighbourhoodBest then
        /* Save current position as neighbourhood
           best */
      end
    end
  end
  foreach particle in swarm do
    particle.updateVelocity() particle.updatePosition()
  end
end
return particle[0].neighbourhoodBest

```

**Algorithm 1:** Main PSO Algorithm

#### IV. RESEARCH RESULTS

The algorithm managed to obtain values for all the parameters to all the objective functions. The results were as follows:

- Spherical

```

var bestSolution = infinity for w <- -1.1 to 1.1 do
  for c1 <- 0.1 to 2.5 do
    c2 = c1
    for currentRun <- 1 to 30 do
      /* call "solvePSO" function which is
         algorithm 1 */
      var bestResult +=
        objectiveFunction(solvePSO())
    end
    if bestResult/30 < bestSolution["result"] then
      bestSolution["result"] = bestResult
      bestSolution["w"] = w
      bestSolution["c1"] = c1
      bestSolution["c2"] = c2
    end
  end
end

```

**Algorithm 2:** PSO Parameter Finding

- Optimum  $\approx 3.4 \times 10^{-193}$
- $w = 0.6$
- $c1 = 1.1$
- $c2 = 1.1$
- $x_0 \approx 1.6 \times 10^{-98}$
- $x_1 \approx -6.2 \times 10^{-98}$
- $x_2 \approx 1.8 \times 10^{-98}$
- $x_3 \approx 1.4 \times 10^{-98}$
- $x_4 \approx -8.6 \times 10^{-98}$
- $x_5 \approx 2.1 \times 10^{-98}$
- $x_6 \approx 3.0 \times 10^{-98}$
- $x_7 \approx 1.0 \times 10^{-97}$
- $x_8 \approx -1.9 \times 10^{-98}$
- $x_9 \approx 7.4 \times 10^{-99}$
- $x_{10} \approx -1.9 \times 10^{-99}$
- $x_{11} \approx 1.6 \times 10^{-97}$
- $x_{12} \approx 9.9 \times 10^{-98}$
- $x_{13} \approx 1.6 \times 10^{-97}$
- $x_{14} \approx -2.7 \times 10^{-98}$
- $x_{15} \approx -2.1 \times 10^{-97}$
- $x_{16} \approx 1.2 \times 10^{-97}$
- $x_{17} \approx -7.1 \times 10^{-98}$
- $x_{18} \approx 1.0 \times 10^{-97}$
- $x_{19} \approx -4.2 \times 10^{-97}$

- Ackley

- Optimum  $\approx 7.5 \times 10^{-15}$
- $w = 0.3$
- $c1 = 1.6$
- $c2 = 1.6$
- $x_0 \approx 4.7 \times 10^{-16}$
- $x_1 \approx -5.6 \times 10^{-15}$
- $x_2 \approx -3.2 \times 10^{-15}$
- $x_3 \approx -1.5 \times 10^{-15}$
- $x_4 \approx -1.9 \times 10^{-15}$
- $x_5 \approx 1.8 \times 10^{-15}$

- $x_6 \approx 1.5 \times 10^{-15}$
- $x_7 \approx 1.3 \times 10^{-15}$
- $x_8 \approx -3.2 \times 10^{-15}$
- $x_9 \approx -2.2 \times 10^{-15}$
- $x_{10} \approx -2.9 \times 10^{-15}$
- $x_{11} \approx 3.9 \times 10^{-15}$
- $x_{12} \approx 1.4 \times 10^{-15}$
- $x_{13} \approx -6.2 \times 10^{-16}$
- $x_{14} \approx -2.3 \times 10^{-15}$
- $x_{15} \approx -3.5 \times 10^{-15}$
- $x_{16} \approx -1.9 \times 10^{-15}$
- $x_{17} \approx -2.0 \times 10^{-15}$
- $x_{18} \approx -2.0 \times 10^{-15}$
- $x_{19} \approx 8.5 \times 10^{-16}$

• Michalewicz

- *Optimum*  $\approx -19.49$
- $w = 0.6$
- $c1 = 1.0$
- $c2 = 1.0$
- $x_0 \approx 2.20$
- $x_1 \approx 1.57$
- $x_2 \approx 1.28$
- $x_3 \approx 1.11$
- $x_4 \approx 1.72$
- $x_5 \approx 1.57$
- $x_6 \approx 1.88$
- $x_7 \approx 1.36$
- $x_8 \approx 1.66$
- $x_9 \approx 1.57$
- $x_{10} \approx 1.5$
- $x_{11} \approx 1.43$
- $x_{12} \approx 1.63$
- $x_{13} \approx 1.33$
- $x_{14} \approx 1.52$
- $x_{15} \approx -1380.72$
- $x_{16} \approx 1.43$
- $x_{17} \approx 1.57$
- $x_{18} \approx 1.35$
- $x_{19} \approx 1.65$

• Katsuura

- *Optimum*  $\approx 1.08$
- $w = 0.7$
- $c1 = 1.4$
- $c2 = 1.4$
- $x_0 \approx -1.5 \times 10^7$
- $x_1 \approx 4.3 \times 10^8$
- $x_2 \approx -7.6 \times 10^7$
- $x_3 \approx 6.3 \times 10^8$
- $x_4 \approx 3.2 \times 10^8$
- $x_5 \approx -1.0 \times 10^8$
- $x_6 \approx 1.0 \times 10^8$
- $x_7 \approx -1.1 \times 10^5$
- $x_8 \approx 4.9 \times 10^8$

- $x_9 \approx -1.1 \times 10^9$
- $x_{10} \approx 8.7 \times 10^7$
- $x_{11} \approx 4.1 \times 10^8$
- $x_{12} \approx 8.4 \times 10^7$
- $x_{13} \approx -7.9 \times 10^8$
- $x_{14} \approx -1.3 \times 10^8$
- $x_{15} \approx -3.7 \times 10^8$
- $x_{16} \approx -5.1 \times 10^8$
- $x_{17} \approx 5.9 \times 10^8$
- $x_{18} \approx -7.1 \times 10^8$
- $x_{19} \approx -4.5 \times 10^6$

## V. CONCLUSION

As the results in section IV indicate, if a small range for each of the three parameters is known, it is possible to find the optimum value for an objective function. This can even be done in a fairly short amount of time if the objective function is simple, as is the case with equation 1, 2 and 3, but as the complexity (or rather computational time) grows, like with equation 4, this process can become quite lengthy.

Thus, if an equation does not contain a large amount of computational demanding steps, this brute force approach might be a feasible option since it is simple and quick to implement.

## REFERENCES

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