# MULTIPLE CHOICE STRATEGY FOR PSO ALGORITHM – PERFORMANCE ANALYSIS ON SHIFTED TEST FUNCTIONS

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## KEYWORDS

PSO, Optimization, Evolutionary Algorithms, Swarm intelligence, Shifted test functions

## ABSTRACT

A new promising strategy for the PSO (Particle swarm optimization) algorithm is proposed and described in this paper. This new strategy presents alternative way of assigning new velocity to each individual in particle swarm (population). This new multiple choice particle swarm optimization (MC-PSO) algorithm is tested on two different shifted test functions to show the performance on problems that are not constant in time. The promising results of this alternative strategy are compared with the not modified PSO version.

## INTRODUCTION

Optimization started to play a crucial part for almost every engineering and informatics tasks during recent years. Optimization problems often represent very complex tasks and non-heuristic methods are very limited in finding of the proper solutions. As the complexity of optimization problems increases, the non-heuristic methods may not be able to solve them even in very distant future, whereas the new heuristic methods can solve such tasks. Among these so called "soft-computing" methods belong evolutionary algorithms, which are inspired by evolution theory and natural behavior, and have helped to achieve very impressive results in solving various problems.

## PSO ALGORITHM

Particle swarm optimization algorithm is the evolutionary optimization algorithm based on the natural behavior of bird and fish swarms and was firstly introduced by R. Eberhart and J. Kennedy in 1995 (Kennedy, Eberhart 1995, Eberhart, Kennedy 2001). As an alternative to genetic algorithms (Goldbeg, David, 1989) and differential evolution (Storn, Price, 1997), Given its unique principle and good performance, PSO is often used to solve different difficult optimization problems and in general, this algorithm is widely modified (Arani et al., 2012, Keshavarz, Zamani, 2013, Pluhacek et al., 2013).

Term "swarm intelligence" (Eberhart, Kennedy, 2001) can be explained as an capability of particle swarms to exhibit surprising intelligent behavior assuming that some form of communication (even very primitive) can occur among the swarm particles (individuals).
In each generation, a new location of a particle is calculated based on its previous location and velocity, where by velocity is understood "velocity vector" i.e. velocity for each dimension of the problem.
Known disadvantages of basic PSO algorithm are the rapid acceleration of particles which causes them to abandon the defined area of interest and poor local search capability. For these reasons, several modifications of PSO were introduced to handle these problems. (Shi, Eberhart 1998)
Within this research, PSO strategy with linear decreasing inertia weight (Shi, Eberhart 1998) was used. Default values of all PSO parameters were chosen according to the recommendations given in (Kennedy, Eberhart 1995, Eberhart, Kennedy 2001). Inertia weight is designed to influence the velocity of each particle differently over the time (Nickabadi et al., 2011). In the beginning of the optimization process, the influence of inertia weight factor $w$ is minimal. As the optimization continues, the value of $w$ is decreasing, thus the velocity of each particle is decreasing, since $w$ is the number < 1 and it multiplies previous velocity of particle in the process of new velocity value calculation. Inertia weight modification PSO strategy has two control parameters $w_{start}$ and $w_{end}$. New $w$ for each generation is then given by Eq. 1, where $i$ stands for current generation number and $n$ for total number of generations.

$$w = w_{start} - \frac{\left(\left(w_{start} - w_{end}\right) \cdot i\right)}{n} \tag{1}$$

$$\begin{aligned} v(t+1) &= w \cdot v(t) + c_1 \cdot Rand \cdot (pBest - x(t)) \\ &+ c_2 \cdot Rand \cdot (gBest - x(t)) \end{aligned} \tag{2}$$

Where:

$v(t+1)$ – New velocity of particle.
$v(t)$ – Current velocity of particle.
$c_1$, $c_2$ – Priority factors.

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*pBest* – Best solution found by particle.
*gBest* – Best solution found in population.
$x(t)$ – Current position of particle.
*Rand* – Random number, interval <0,1>

New position of particle is then given by Eq. 3, where $x(t+1)$ represents the new position:

$$x(t+1) = x(t) + v(t+1) \tag{3}$$

## MULTIPLE CHOICE PARTICLE SWARM OPTIMIZATION ALGORITHM (MC-PSO)

A new strategy, which is proposed in this research, alters the original way (Eq. 2) of calculating the particle velocity for the next generation. At first, three numbers $b_1$, $b_2$ and $b_3$ are defined at the start of algorithm. These numbers represent limit values for different rules, so they should follow the pattern: $b_1 < b_2 < b_3$. In this study following values were used:

$b_1 = 0.2$, $b_2 = 0.4$, $b_3 = 0.7$.

Afterwards during the calculation of new velocity of each particle a random number $r$ is generated from the interval <0, 1>. Finally the new velocity is calculated based on following four rules:

If $r \leq b_1$ a new velocity of particle is given by Eq. 4:

$$v(t+1) = 0 \tag{4}$$

If $b_1 < r \leq b_2$ a new velocity of particle is given by Eq. 5:

$$v(t+1) = w \cdot v(t) + c \cdot Rand \cdot (x_r(t) - x(t)) \tag{5}$$

Where $x_r(t)$ is the position of randomly chosen particle.

If $b_2 < r \leq b_3$ a new velocity of particle is given by Eq. 6:

$$v(t+1) = w \cdot v(t) + c \cdot Rand \cdot (pBest - x(t)) \tag{6}$$

If $b_3 < r$ a new velocity of particle is given by Eq. 7:

$$v(t+1) = w \cdot v(t) + c \cdot Rand \cdot (gBest - x(t)) \tag{7}$$

The priority factors $c_1$ and $c_2$ from original equation (Eq. 2) are replaced within this novel approach with a new parameter $c$. In this novel strategy parameter $c$ defines not the priority (which is naturally given by $b_1$, $b_2$ and $b_3$ setting) but the overstep value. In other words how far past the target (*pBest*, *gBest* or random particle) can the active particle go. Within this initial research, parameter $c$ was set to 2.

## TEST FUNCTIONS

In order to investigate on the performance of a new multiple choice strategy for PSO algorithm on functions closer to real problems than static test functions, two shifted test functions were chosen. The position of shifted function global optimum moves with each start of the algorithm but keeps the basic function characteristic thus simulates the time-variant real problems.
Following shifted test functions were used in this study:

Shifted 1st De Jong`s function is given by Eq. 8.

$$f(x) = \sum_{i=1}^{\dim} (x_i - shift_i)^2 \tag{8}$$

Function minimum:
Position for $E_n$: $(x_1, x_2 \ldots x_n) =$ ***shift***
Value for $E_n$: $y = 0$

Shifted Rastrigin`s function is given by Eq. 9.

$$f(x) = 10\dim + \sum_{i=1}^{\dim} (x_i - shift_i)^2 - 10\cos(2\pi x_i - shift_i) \tag{9}$$

Function minimum:
Position for $E_n$: $(x_1, x_2 \ldots x_n) =$ ***shift***
Value for $E_n$: $y = 0$

$Shift_i$ is a random number from interval <-5.11, 5.11>. Where <-5.11, 5.11> are the low and high bounds for the population individuals. ***Shift*** vector is randomly generated on each start of the optimization process.

## ESPERIMENT SETUP

The control parameters of PSO algorithm were set up in the following way:

Population size: 100
Generations: 500
$w_{start}$: 0.9
$w_{end}$: 0.4
Dimension: 40, 100, 1000

Within all performance testing two PSO versions were used. The first one was the classic not modified PSO with linear decreasing inertia weight, noted PSO Weight. The second one was the new multiple choice strategy PSO version (noted MC-PSO).

From the statistical reasons, optimization for each setting was repeated 100 times. Tables 1 and 2 contain statistical evaluation of the results obtained for Shifted 1st De Jong`s function and Shifted Rastrigin`s function. Furthermore the history of the best found solution was tracked for each run along with the mean history of global best value (see Figures 1-6). The best obtained results are highlighted by the bold number.

Table 1: Results – Shifted 1st De Jong´s function

| Dimension: | 40 | | 100 | | 1000 | |
|---|---|---|---|---|---|---|
| PSO Version: | PSO Weight | MC-PSO | PSO Weight | MC-PSO | PSO Weight | MC-PSO |
| Mean CF Value: | 76.7202 | **13.069** | 443.34 | **180.526** | 8394.55 | **7098.29** |
| Std. Dev.: | 20.3527 | 6.37184 | 51.2814 | 40.5187 | 249.932 | 271.386 |
| CF Value Median: | 76.2736 | 12.6879 | 444.301 | 181.723 | 8412.06 | 7086.47 |
| Max. CF Value: | 130.102 | 29.1458 | 579.137 | 293.427 | 8929.99 | 7786 |
| Min. CF Value: | 36.802 | **3.08677** | 330.788 | **99.3495** | 7772.37 | **6502.95** |

Table 2: Results – Shifted Rastrigin´s function

| Dimension: | 40 | | 100 | | 1000 | |
|---|---|---|---|---|---|---|
| PSO Version: | PSO Weight | MC-PSO | PSO Weight | MC-PSO | PSO Weight | MC-PSO |
| Mean CF Value: | 291.148 | **270.97** | 1160.78 | **1077.85** | 17416 | **16795.4** |
| Std. Dev.: | 44.7661 | 44.7673 | 89.1601 | 98.8159 | 316.087 | 359.76 |
| CF Value Median: | 283.37 | 267.804 | 1164.03 | 1083.69 | 17410.8 | 16752 |
| Max. CF Value: | 416.366 | 424.118 | 1353.92 | 1334.8 | 18248.6 | 17773.6 |
| Min. CF Value: | 195.101 | **170.359** | 941.013 | **778.611** | 16487.7 | **16125.3** |

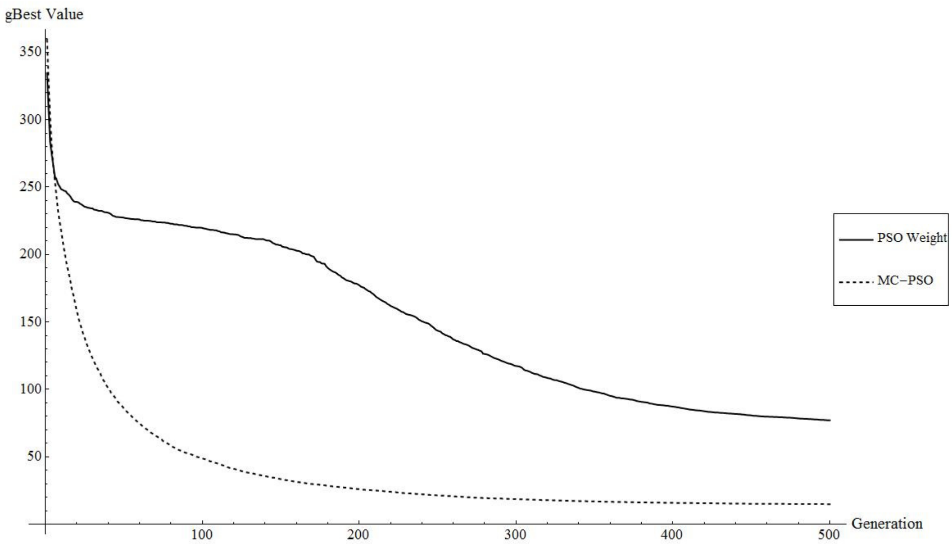


Figure 1: Mean *gBest* history for 100 runs – shifted 1st De Jong`s function – dimension = 40

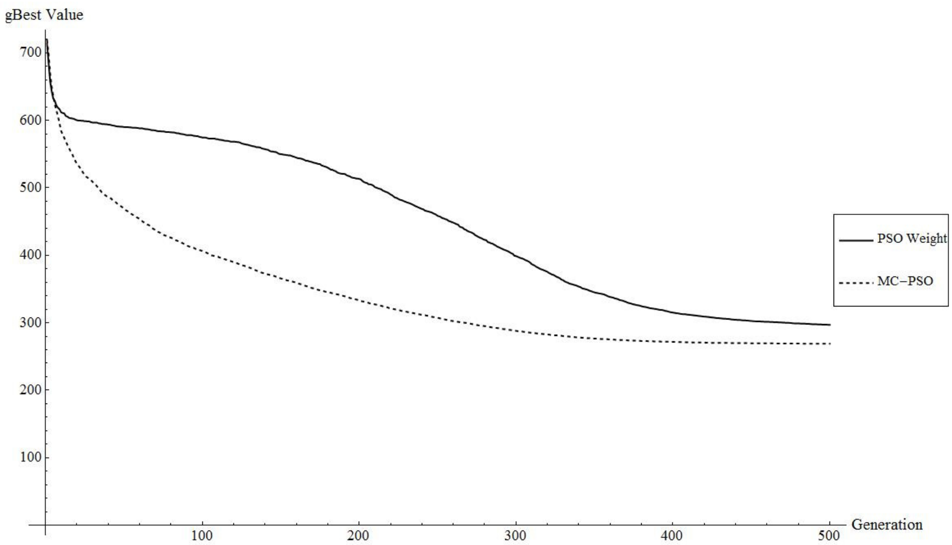


Figure 2: Mean *gBest* history for 100 runs – shifted Rastrigin`s function – dimension = 40

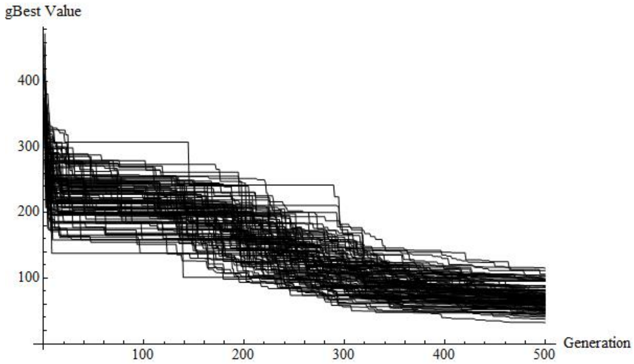


Figure 3: PSO Weight - *gBest* history – shifted 1st De Jong`s function – dimension = 40

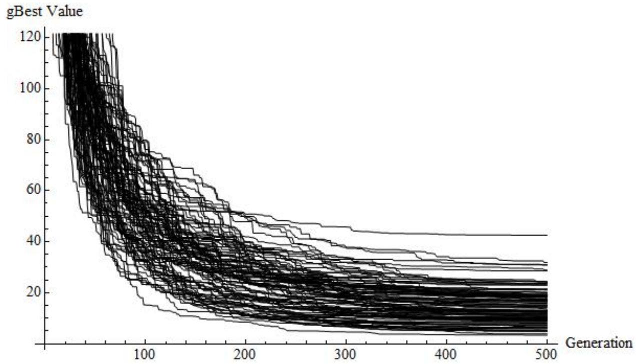


Figure 4: MC-PSO - *gBest* history – shifted 1st De Jong`s function – dimension = 40

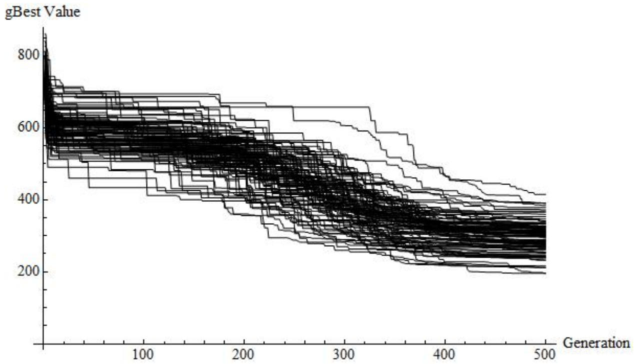


Figure 5: PSO Weight - *gBest* history – shifted Rastrigin`s function – dimension = 40

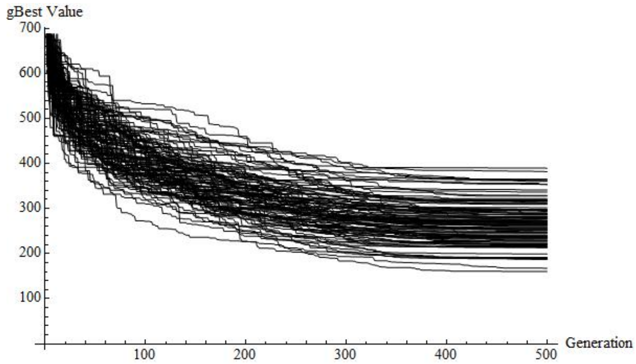


Figure 6: MC-PSO - *gBest* history – shifted Rastrigin`s function – dimension = 40

## BRIEF ANALYSIS OF THE RESULTS

The presented data in Tables 1 and 2 support the claim that presented strategy seems to have positive impact on the performance of PSO algorithm. Furthermore, based on the history of *gBest* presented on Figures 1-6 the multiple choice strategy seems to have very positive impact on the convergence speed of optimization and overall performance of the algorithm.

## CONCLUSION

Novel multiple choice strategy for PSO algorithm was introduced in this paper. The algorithm was tested on two different shifted test functions and results compared with the original version of PSO algorithm with linear decreasing inertia weight. Statistical evaluation was presented in tables and history of the global best value was depicted on figures. This paper brought promising results that motivate the future research focused on this novel strategy.

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