# Dynamic population size and mutation round strategy assisted modified particle swarm optimization with mutation and reposition

Chiabwoot Ratanavilisagul*

*Dept. of Technology Computer Faculty of Technical Education,*
*Rajamangala University of Technology (RMUTK)*
*Bangkok, Thailand*

**Abstract**

Particle swarm optimization (PSO) is a population-based stochastic search algorithm. This algorithm is utilized to solve the optimization problem. It suffers the problems of trapping in local optimum and premature convergence. Nowadays, both problems can be solved by mutation and reposition techniques apply with PSO (MRPSO). However, this technique use over evaluation calls for solution searching. This research paper proposed a technique to minimized evaluation call. This proposed is called DPM-MRPSO. The concept of adaption evaluation call depends on results from improvement solution of mutation technique and PSO technique. The proposed technique is tested on twenty-four benchmark functions and obtains satisfied search results.

*Keywords:* Swarm Intelligence; Particle Swarm Optimization; optimization; dynamic population; Mutation Operator.

## 1. Introduction

Kennedy and Eberhart [1] introduced Particle Swarm Optimization (PSO) in 1995. It is motivated by the behavior of flying bird and their communication mechanism. This algorithm attempts to search for better solution in the solution space by the best position found in the whole swarm (GBEST) attracts other particles to converge toward it. The advantages of PSO [2] are its simplicity, rapid convergence, and few parameters to be adjusted. However, disadvantages of PSO [2] are premature convergence to a local optimum and high chances of trapping in the local optimum.

To overcome disadvantages of PSO, many researchers [3-6] increased searching diversity in the population of PSO by adding the mutation technique and the reposition technique in the process of PSO. The experiment results of these researches showed both techniques can increase searching performance of standard PSO and obtain better solutions than standard PSO. R. Chiabwoot and K. Boontee [4] proposed mutation technique and reposition technique apply to PSO. This algorithm is called MRPSO. From the experiment results show that MRPSO succeeds in finding the best solution from many optimization problems. However, the weak point of MRPSO is using over evaluation call. Recently, S. Wichaya and K. Boontee [7] proposed dynamic population technique apply to MRPSO. This technique is called Dm-MRPSO. It can reduce evaluation call and maintain finding the best results. However, it must adapt many parameters which are complicated to apply to general problems. Moreover, it must still adjust inappropriate population size and mutation round to solve problems.

This paper proposed a novel dynamic population size and mutation round technique apply to MRPSO in order to reduce evaluation call of MRPSO and maintain its searching results. I investigated adjusting population size and mutation round to suitably deal with any given problem. The population size and mutation round are automatically adjusted according to solve problems by considering the number of improving solutions of PSO technique or mutation technique.

## 2. Related Work

### *2.1. A modified particle swarm optimization with mutation and reposition*

MRPSO improve performance of PSO by using mutation technique and reposition technique. The mutation technique of MRPSO enhances the diversity in the population. However, PSO with mutation of MRPSO has a chance to trap in local optimum. Therefore, reposition technique of MRPSO is added into PSO. The reposition technique is applied when the trappings occur. In order that particles jump out local optimum then they search for new areas. Hence, search results of MRPSO are better than search results of PSO. However, MRPSO uses over evaluation call to search for the best solution. Therefore, MRPSO is the static population size techniques which population size and mutation round are stable forever running. It cannot adjust population size and mutation round to solve problem appropriately.

### *2.2. Dynamically movement control in modified particle swarm optimization with mutation and reposition*

S. Wichaya and K. Boontee [7] proposal the stop and go particle swarm optimization (SGPSO) apply with MRPSO to reduce using evaluation call of MRPSO. This technique is called Dm-MRPSO. The main concept, in each generation, Euclidean distance of each particle from GBEST is less than or equal to threshold value (R-radius). That particle is updated position and mutation. On the other hand, Euclidean distance of each particle from GBEST is more than R-radius. That particle is not updated position and mutation. The experiment results of them showed that Dm-MRPSO succeeds the best solution with reduced evaluation call when it is compared with MRPSO. However, this technique has to set many addition parameters from MRPSO such as $S_{de}$, $S_{in}$ $S_{st}$ and k. Moreover, these parameters are not criterion for value determination. So, determination of these parameters is complicated to apply general problems. If determination of these parameters is wrong, the search results of Dm-MRPSO may be poorer than the search results of MRPSO.

## 3. Proposed Work

If population size or mutation round determination is under, searching cannot encounter the best solution. On the other hand, population size or mutation round determination is over, searching has to use many evaluation call. Hence, population size or mutation round should be automatically adjusted to solve problems appropriately. Normally, if MRPSO does not encounter trapping in local optimum, GBEST is improved until it can meet the best solution. But, if MRPSO encounter trapping in local optimum, GBEST is stagnant. In next time, MRPSO will execute reposition to solve trapping in local optimum. One factor of trapping in local optimum is population size or mutation round that is not enough to search for the global optimum. Hence,

Chiabwoot Ratanavilisagul, Dynamic Population Size and Mutation Round Strategy Assisted Modified Particle Swarm Optimization with Mutation and Reposition, Procedia Computer Science, Volume 86, 2016, Pages 449-452, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2016.05.078.

reposition of MRPSO can indicate that should enhance population size or mutation round. The simple technique to indicate that should increase population size or mutation round that is considered from results from improvement GBEST that come from PSO technique or mutation technique. Thereby, this paper proposed a novel dynamic population size or mutation round technique to decrease evaluation call in searching of MRPSO. Moreover, this technique can decrease complication of adjusting population size or mutation round. The proposed technique is called dynamic population size and mutation round strategy assisted modified particle swarm optimization with mutation and reposition (DPM-MRPSO). The concept of proposed technique is explained as follows: the begin stage, both population size and mutation round are defined to have small amount in order to use small evaluation call. If population size and mutation round is not enough to search for global optimum, MRPSO is trap in local optimum then MRPSO executes reposition. After executed reposition, if ratio from improving solution of PSO is more than or equal ratio from improving solution of mutation, population size are increased because PSO technique can solve this problem better than mutation technique, so it should enhance population size. On the other hand, if ratio from improving solution of mutation is more than ratio from improving solution of PSO, mutation round is increased because mutation technique can solve this problem better than PSO technique, so it should enhance mutation round. The proposed technique is called dynamic population size and mutation round strategy assisted modified particle swarm optimization with mutation and reposition (DPM-MRPSO). Pseudo code of DPM-MRPSO is shown below:

```
Initial particles of each particle
While (termination condition ≠ true) do
  Evaluate the fitness of each particle
  If GBEST is improved by PSO, NP = NP + 1
  If fitness of each particle is better than PBEST, update PBEST
  If fitness of each particle is better than GBEST, update GBEST
    Update each particle position
    Apply mutation technique of MRPSO
    If GBEST is improved by temporary solution, NM = NM + 1
      If times of GBEST consecutive unchanged ≥ TR
        Apply Reposition technique of MRPSO
        Calculation RNP according to Eq. 1
        Calculation RNM according to Eq. 2
        If RNM > RNP
          RM = RM + 1
        Else
          POP = POP + NPOP
        End if
        If POP > MAXPOP
          POP = MAXPOP
        End if
        If RM > MAXRM
          RM = MAXRM
        End if
        PNP = NP
        PNM = NM
        reset NP and NM
    End if
End while
```

Where POP is the population size, RM is the mutation round, TR is the threshold of reposition, NP is number of improving GBEST by PSO technique, NM is number of improving GBEST by mutation technique, PNP is the previous number of improving GBEST by PSO technique, PNM is the previous number of improving GBEST by mutation technique, MAXPOP is the maximum value of POP, MAXRM is the maximum value of RM, NPOP is the population size which are increased in each reposition.

$$RNP = \frac{NP - PNP}{PNP} \tag{1}$$

$$RNM = \frac{NM - PNM}{PNM} \tag{2}$$

## 4. Experiments and Results

The proposed algorithm is tested on twenty-four well-known benchmark functions [8, 9], listed in Table 1. Parameters are as follows for all experiments: η1 and η2 are both set to be 1.496180 and ω = 0.729844. The number of experiments of each function is 100 runs. The non-PSO parameters are as follows: parameters of Dm-MRPSO are set according to suggested by the original papers [7]. Except population size set to be 100. For DPM-MRPSO, population size set to be 10, RM = 1, MAXPOP = 2000, MAXRM = 20, NPOP = 10. Except from previously mentioned parameters of DPM-MRPSO is defined as same as parameters of Dm-MRPSO. Both Dm-MRPSO and DPM-MRPSO succeeds in finding the best solution all functions in Table 1 for all 100 rounds of testing but, the evaluation call (EC) of these algorithms are different. EC is less, the better the algorithms is. For experimental results, I compare EC between Dm-MRPSO and DPM-MRPSO on the benchmark functions in Table 1.

Table 1. Comparative results of Dm-MRPSO and DPM-MRPSO

| | | | | Dm-MRPSO | DPM-MRPSO | | | |
|---|---|---|---|---|---|---|---|---|
| Problem no. | Problem name | Dimension | Attribute | AVG EC | AVG EC | AVG POP | AVG RM | Improvement (%) |
| 1 | ACKLEY | 50 | multimodal | 1943750 | 1853870 | 172.2 | 6.06 | +4.624051447 |
| 2 | GRIEWANK | 50 | multimodal | 372086 | 143848 | 34.4 | 1.72 | +61.34012029 |
| 3 | RASTRIGIN | 50 | multimodal | 353759 | 89128 | 25.4 | 1.36 | +74.80544665 |
| 4 | ROSENBROCK | 50 | multimodal | 53527700 | 33452600 | 87 | 10.16 | +37.50413337 |
| 5 | SCHWEFEL | 50 | multimodal | 693576 | 214446 | 18.2 | 1.1 | +69.08111007 |
| 6 | COSINE MIXTURE | 50 | multimodal | 248173 | 29930.4 | 16 | 1 | +87.93970335 |
| 7 | EXPONENTIAL | 50 | multimodal | 476707 | 96023.4 | 62 | 2.44 | +79.85693518 |
| 8 | LEVY | 50 | multimodal | 2938590 | 1538510 | 44.6 | 3.06 | +47.64461868 |
| 9 | MICHALEWICZ | 10 | multimodal | 35720400 | 18021800 | 35.6 | 3.14 | +49.54759745 |
| 10 | STEP | 100 | multimodal | 119496 | 17119.8 | 11.4 | 1 | +85.67332798 |
| 11 | SCHAFFER'S F6 | 2 | multimodal | 93057.5 | 74346 | 26.6 | 1.9 | +20.10746044 |
| 12 | HOLDER | 2 | multimodal | 65871.4 | 24379.4 | 25.8 | 1.3 | +62.98940056 |
| 13 | BEALE | 2 | multimodal | 76735.8 | 10272 | 10 | 1 | +86.61380998 |
| 14 | SHUBERT | 2 | multimodal | 11297 | 3000.4 | 10 | 1 | +73.44073648 |
| 15 | GOLDSTEIN-PRICE | 2 | multimodal | 21220.5 | 4389.6 | 10 | 1 | +79.31434226 |
| 16 | SPHERE | 50 | unimodal | 5421920 | 485992 | 10 | 1 | +91.03653318 |
| 17 | PARALLEL | 50 | unimodal | 5292380 | 486321 | 10 | 1 | +90.81092061 |
| 18 | HYPER-ELLIPSOID | 50 | unimodal | 1540870 | 482639 | 10 | 1 | +68.67750037 |
| 19 | ROTATED | 50 | unimodal | 2757640 | 485608 | 10 | 1 | +82.3904498 |
| 20 | HYPER-ELLIPSOID | 50 | unimodal | 4284100 | 484727 | 10 | 1 | +88.68544152 |
| 21 | CIGAR | 50 | unimodal | 9466840 | 1571740 | 58 | 2.22 | +83.39741667 |
| 22 | BROWN | 50 | unimodal | 5056230 | 3457990 | 31 | 1.56 | +31.60932157 |
| 23 | MULTIMOD | 10 | unimodal | 32609600 | 25125100 | 110 | 8.82 | +22.95183014 |
| 24 | ZAKHAROV | 2 | unimodal | 55840 | 6265.2 | 10 | 1 | +88.78008596 |

From the experimental results of average evaluation call (AVG EC) in Table 1 show that DPM-MRPSO outperforms Dm-MRPSO for all test functions because its lower AVG EC than Dm-MRPSO of AVG EC. Moreover, DPM-MRPSO can reduce evaluation cost about 20 to 90% when compare with Dm-MRPSO. Average population size (AVG POP) and average mutation round (AVG RM) show that multimodal functions which are many dimensions such as 50 or 100 are so complicated. These functions need to use big population size and many mutation rounds in order to achieve in finding the best solution. DPM-MRPSO can automatically adjust population size and mutation round to high. On the other hand, for both multimodal functions which are small dimension such as 2 dimensions and unimodal functions are less complicated. These functions need to use small population size and small mutation round in order to achieve in finding the best

Chiabwoot Ratanavilisagul, Dynamic Population Size and Mutation Round Strategy Assisted Modified Particle Swarm Optimization with Mutation and Reposition, Procedia Computer Science, Volume 86, 2016, Pages 449-452, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2016.05.078.

solution. DPM-MRPSO can automatically adjust population size and mutation to low. So, DPM-MRPSO can adjust population size and mutation round to appropriate with solved problems.

## 5. Conclusion

MRPSO which novel technique is developed from PSO succeeds in finding is best solution from many problems. However, this technique uses over evaluation call. Recently, the novel technique which improves MRPSO by reducing costs and can maintain finding best results is called Dm-MRPSO. However, Dm-MRPSO suffers complicated parameters adjusting which is complicated for apply to general problems. Hence, this paper proposes the population size and mutation round are automatically adjusted according to performance of improve solution between PSO process and mutation process. The proposed technique is called DPM-MRPSO. From the experimental results show DPM-MRPSO is better performance of using evaluation call than Dm-MRPSO. Moreover, DPM-MRPSO can adjust population size and mutation round to solve problems appropriately.

## References

[1] Kennedy, J., Eberhart, R. C., 1995. Particle Swarm Optimization. IEEE International Conference on Neural Networks, p. 1942–1948.
[2] Qinghai, B., 2010. Analysis of Particle Swarm Optimization Algorithm. Computer and Information Science, p. 180–184.
[3] Chiabwoot, R., Boontee, K., 2014. A modified particle swarm optimization with dynamic mutation period. Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, p. 1–6.
[4] Chiabwoot, R., Boontee, K., 2014. A modified particle swarm optimization with mutation and reposition. International Journal of Innovative Computing, Information and Control, p. 1–18.
[5] Lin, MO, ZHENG, Hua., 2009. Improved PSO Algorithm with Adaptive Inertia Weight and Mutation. 2009 World Congress on Computer Science and Information Engineering, p. 622–625.
[6] Higashi, N., Iba, H., 2003. Particle swarm optimization with Gaussian mutation. Proc.of the 2003 IEEE Swarm Intelligence Symphosium, p. 72–79.
[7] Wichaya, S., Boontee, K., 2015. Dynamically movement control in modified particle swarm optimization with mutation and reposition. International Congress on Engineering and Information.
[8] Information on http://www.sfu.ca/~ssurjano/index.html
[9] Information on http://www-optima.amp.i.kyoto-u.ac.jp