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DYNAMIC PARAMETERIZATIONS OF PARTICLE SWARM OPTIMIZATION AND GENETIC ALGORITHM FOR FACILITY LAYOUT PROBLEM

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ABSTRACT

Surrounded by an assortment of intelligent and efficient search entities, the hybridization of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are proven to be a comprehensive tool for solving different kinds of optimization problems due to their contradictive working approaches. In addition, the two algorithms have achieved a remarkable improvement from the adaption of dynamic parameterizations. In this work, dynamic parameterized mutation and crossover are individually and in combination hybridized with a PSO implementation. The performances of different dynamic parameterizations of the hybrid algorithms in solving facility layout problem are compared with single PSO. The comparison revealed that the proposed technique is more effective.

Keywords: particle swarm optimization, genetic algorithm, hybridization, dynamic parameterizations, facility layout problem.

INTRODUCTION

The research on meta-heuristics has broadly discussed how hybridization works better than a single implementation [1-3]. Similarly, the advantages given by PSO hybridization approach is gaining a rising attention until recently [4-6]. This especially makes sense in the way of hybridizing PSO with GA, due to the specialty of GA operators that can control the algorithm search intensity and diversity[7-9]. The single PSO is commonly known with a good intensity search but less diversity to widely explore the potential solutions, thus the GA operators is possible to be adapted for improving the PSO search ability. Additionally, many researchers have discovered that the PSO has achieved better performance with dynamic parameterizations[10-12].

To the best of our literature study, the implementation of PSO-GA hybridization with dynamic parameterizations is very limited. Furthermore, there exist very few studies that utilized PSO-GA hybrids for facility layout problem (FLP) mainly with the dynamic parameterizations.

The FLP is a well-studied combinatorial optimization problem that emerged in a variety of problems such as layout design of hospitals, schools, airports, networking and backboard wiring. The most common objective in FLP is minimizing the facility resources costs that are determined based on the flow between the facilities and the distance between each facilities locations. Due to the dynamic and impulsive environment in today's industry operations, dynamic FLP appears to be very important. The dynamic FLP extends the static FLP by involving the changes in resources flow over multiple periods as well as the costs of rearranging the layout.

The contribution of this paper is two-fold. First, it provides a new framework of PSO-GA hybridization with dynamic parameterization settings. Second, it presents the comparative performance of the proposed algorithms in solving the facility layout optimization problem.

This paper is organized as follows. Section 2 describes the research background of facility layout problem and dynamic parameterization of PSO. Section 3 presents the proposed algorithm followed by the experimental results in Section 4. Section 5 presents the results and the conclusion remark is given at the last section.

BACKGROUND

Facility layout problem (FLP)

The formulated model of the FLP used in this paper was adopted from [13]. The definitions are as follows:

- All facilities have equal location.
- The distances between all facilities are priori determined.
- The number of periods is known.
- The main objective of FLP is to minimize the sum of resources flow and the cost of layout rearrangement during the planning stage. Each location is assigned to one facility and each facility is assigned to one location at each period. The cost of layout rearrangement to the resources flow is shifted between locations in consecutive periods.

The used of well-known meta-heuristics approaches for FLP has been well reviewed by [14]. The literature indicated very limited number of approaches that used Particle Swarm Optimization (PSO) [27]. Based on the literature, the existing PSO approaches for FLP are listed in Table-1.

Table-1. PSO on FLP.

Reference	Year	Hybridization	Dynamic parameterization
[15]	2010	Single PSO	X
[16]	2011	PSO-local search	/
[17]	2010	Single PSO	X
[18]	2012	PSO	X
[19]	2013	PSO-SA annealing	/

Based on the reviewed literature in Table-1, PSO hybrids with other methods have become an attractive approach. Besides, there exists a need to support dynamic parameterization on FLP due to the need of layout rearrangement. Therefore, an extensive study on the two approaches seems to be quite important on the FLP.

Dynamic parameterizations of PSO

The success story written about PSO in solving a particular problem is often subjected to the proper parameter setting, either constant or dynamic along the search iteration. Dynamic parameterizations allow changeable value of parameters, which is derived from random, time-vary or adaptive formulation[20-21]. This paper focuses on the last approach of dynamic parameterizations.

There exists a number of adaptive parameterizations used in PSO. As listed in Table-2, the identified adaptive approaches are dependent several adaptive factors including personal fitness and best fitness. Personal fitness is the personal best position of a particular particle, while best fitness is the current best fitness found by the whole particles in the current iteration. Additionally, the global best position of the whole swarm along all the number of iterations is defined as global fitness.

Table-2. Performance factors of different dynamic parameterizations in PSO.

Approach name	Dynamic factor	Researcher
Speed	Personal fitness, best fitness	[12]
Rank	Global fitness, Personal fitness	[22]
Ratio	Personal fitness	[23]
ISA	Particle position	[24]

THE PROPOSED ALGORITHM

In this study, the proposed PSO hybrid consists of three algorithms. The first includes mutation operator, the second uses crossover and the third considering both mutation and crossover inclusion as illustrated in Figure-1. The dotted line represents three different implementations that are optional either with dynamic crossover, dynamic mutation or both dynamic crossover and mutation. The particles are chosen probabilistically in proportion to their fitness before the hybridization process. Inspired by [25], the periodic crossover was replaced with the adaptive crossover probability. Figure-2 presents the algorithm.

The r and r1 threshold values are each one set to a random number between the interval [0, 1]. The values were then compared to each particle's probability Cp of crossover to decide, whether this particle's randomly chosen position d should be modified using pbest crossover. As defined by [25], the adjustment to dimension d can be done by using an average of two particles' relevant pbest values. In the algorithmic listing at Figure-2, the crossover probability Cp and the mutation probability Mp of all particles are calculated at line 2 and line 3 respectively. The mutation operation used a Gaussian operation that returns a random number within the range of the particle dimension. The α is restricted within 0.1 times of the particle dimension.

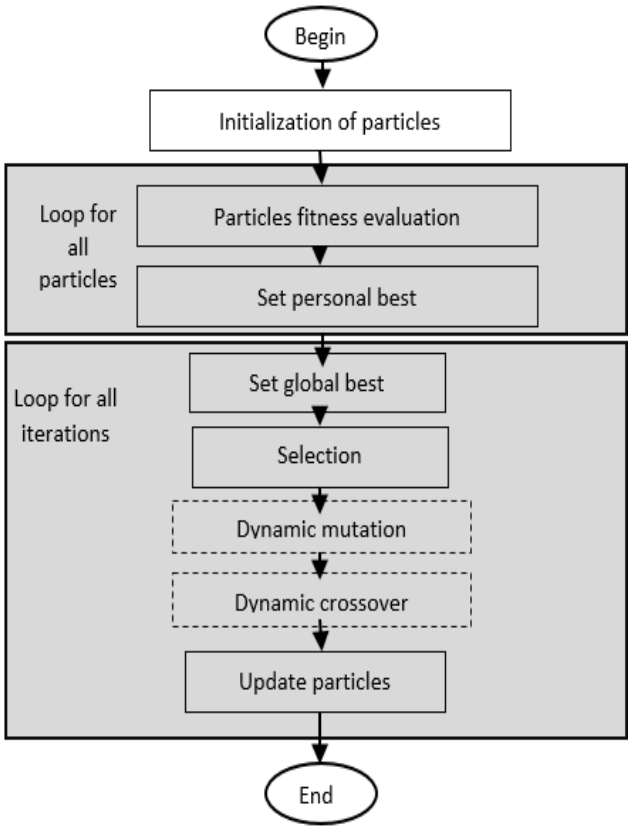

Figure-1. Dynamic parameterizations in PSO-GA.

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ForEach particle in the population do
Calculate dynamic crossover probability, Cp
Calculate dynamic mutation probability, Mp
Set r to a uniform random number [0,1]
Set r1 to a uniform random number [0,1]
Set d to a uniform random integer [0, dimension]
Set d1 to a uniform random integer [0, dimension]
Choose pbest1, pbest2 uniformly randomly among all n particles
ForEach particle in the population do
 If r < Cp then
    x_id = x_id + pbest1_d + pbest2_d / 2
If r1 < Mp then
    x_id1 = x_id1 + Gaussian(α);
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Figure-2. Dynamic crossover and mutation.

The following Figure-3 presents the PSO hybrid with crossover.

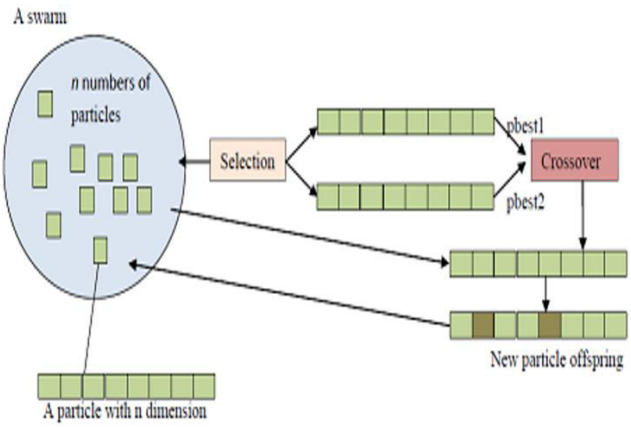

Figure-3. PSO hybrid with crossover.

Then, the PSO hybrid with mutation and the PSO hybrid with both crossover and mutation are presented in the following Figure-4 and Figure-5 respectively.

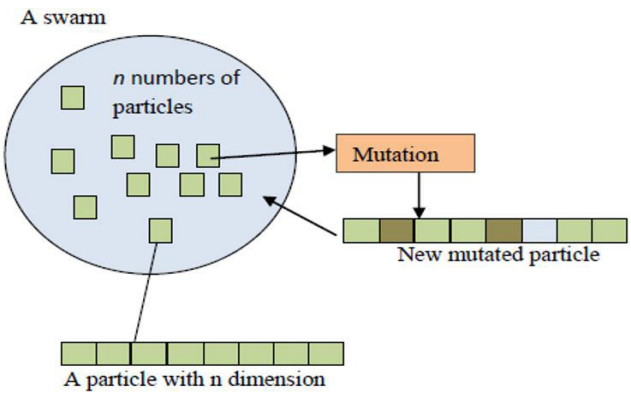

Figure-4. PSO hybrid with mutation.

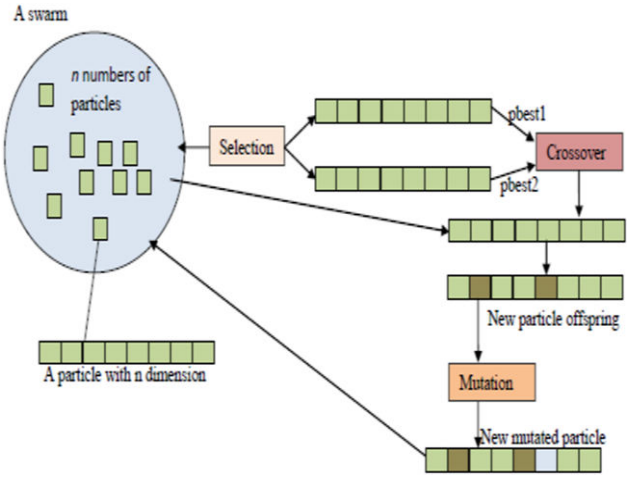

Figure-5. PSO hybrid with crossover and mutation.

Dynamic parameterization approach

Based on the empirical experiments in [21] that compare different dynamic parameterization approaches in the PSO-GA hybrids, the ISA adaptive approach introduced by [24] is found to be the most effective. The approach finds ratio between the particle's distance to its pbest and the distance of its pbest to gbest as presented in the following Equation. (1).

$$ISA_{id} = |x_{id} - pbest_{it}|/|pbest_{it} - gbest_t| + \varepsilon \quad (1)$$

where x_{idt} is the position of the ith particle in the dth dimension at iteration t. The personal best position of the ith particle in the tth iteration is denoted as $pbest_{it}$ while $gbest_t$ is the current global best position of the whole swarm,εis a positive constant close to zero. The following Equation. (2) determines the values of crossover and mutation probabilities.

$$P_{it} = 1 - \alpha\,(1/1 + e^{-ISA_{id}}) \quad (2)$$

Particle encoding

The encoding scheme is simple, each particle represents a valid permutation where each dimension of the particle represents a location and each value represent the corresponding facility. For example, for n=4, the particle {3 4 2 1} indicates that the third facility is assigned to the first location, fourth facility to second location, second facility to third location and first facility to fourth location. The solution encoding involves the 0-1 binary integer decision variables X_{ij} enabling a randomly generated solution. Figure-6 illustrates the definition of particles.

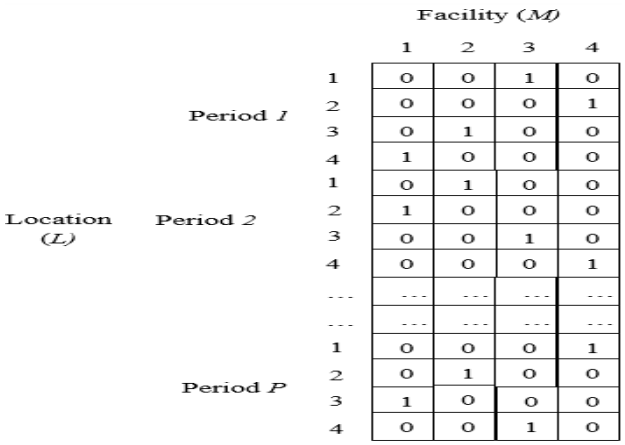

Figure-6. Particles encoding.

EXPERIMENTS

Each experiment was repeated for 30 times with 2000 iterations. Therefore, regardless of each algorithm, each of the 30 trials was allowed an equal number of 60000 evaluations (30 particles X 2000 iterations). As to create a fair comparison of all the algorithms, the same seed has been fixed with random number generation so that the initial population is same for all the algorithms. The algorithms were tested on 32 sets of problem obtained from [26]. In the preliminary experiment, the ranges of parameter values were tested. Based on the experimental results, all the best parameter settings for the proposed PSO hybrids are listed in Table-3.

Table-3. Experiment setting.

Parameter	Value
Number of iteration	2000
Number of particles	30
PSO personal and social learning rate (c1,c2)	1.5
Inertia weight	0.6
ISA ε	0.9
ISA α	0.3

Furthermore, the name for each algorithm is AMR for adaptive mutation rate; ACR denotes adaptive crossover rate and ACMR for adaptive crossover and mutation rate.

RESULTS AND DISCUSSIONS

The result of each algorithm are compared with single PSO algorithm as well as with the result obtained by 26 that used Dynamic Programming (DP) approach. Table-4 to Table-7 show the results for the test problems with different facility M and Period P.

The results in Table-4 and Table-5 show that all the PSO hybrids obtained the best solutions for all the 16 solutions with 6 numbers of facility at 5 periods. It is constantly shown in the results that PSO hybrids with dynamic mutation (mainly from AMR) outperform other algorithms for the 16 test problems. Although ACR mostly outperforms single PSO (problem 3, 4, 5, 6, 8), it never performs as well as dynamic mutation-based hybrids either with AMR or with ACMR.

Table-4. Solution results for problems with M = 6, P = 5.

Prob. No.	AMR	ACR	ACMR	Single PSO	DP[26]
1	106401	106411	106401	106411	106419
2	104799	104838	104818	104838	104834
3	104291	104301	104291	104309	104320
4	106382	106380	106382	106491	106509
5	105621	105614	105651	105678	105628
6	103885	103921	103885	103993	103985
7	106396	106405	106396	106405	106447
8	103619	103619	103628	103631	103771

Table-5. Solution results for problems with M = 6, P = 10.

Prob. No.	AMR	ACR	ACMR	Single PSO	DP[26]
9	214299	214310	214301	214311	214313
10	21221	21230	21225	212340	21234
11	207985	207987	207985	207986	207987
12	212702	212711	212702	212730	212741
13	211012	211012	211012	211019	211022
14	209928	209932	209928	2099302	209932
15	214232	214252	214238	214252	214252
16	2125811	2125868	2125811	212585	2125888

Table-6 and Table-7 give the results for the test problems with M=15, P=5 (Problem 17-24) and M=15, P=10 (Problem 25-32) respectively. For the test problems with P=5 (Table-6), both AMR and AMCR obtained the best solution for 6 of the 8 problems. Similar to test problem 1-16 in Table-3 and Table-4, the inclusion of single dynamic crossover effects very small improvement on the performance of the PSO hybrids from the single PSO. However, it can be seen in Table-7 that ACR able to produce better solutions than AMR and ACR in test problem 30 and 32.

Additionally, as given in Table-7, the inclusion of single dynamic mutation outperforms other algorithms only for problem 28, 29, 31 and 32. Both dynamic mutation and crossover in ACMR obtained the best solutions for problem 25, 26, 27 and 32.

Table-6. Solution results for problems with M = 15, P = 5.

Prob. No.	AMR	ACR	ACMR	Single PSO	DP[26]
17	482110	482120	482118	482120	482123
18	485690	485699	485690	485699	485702
19	491287	491303	491300	491303	491310
20	486821	486851	486821	486851	486851
21	491158	491177	491158	491177	491178
22	489841	489841	489841	489841	489847
23	489152	489152	489152	489154	489155
24	493518	493577	493518	493577	493577

Table-7. Solution results for problems with M = 15, P = 10.

Prob. No.	AMR	ACR	ACMR	Single PSO	DP[26]
25	983048	983048	983044	983060	983070
26	983809	983809	983802	983820	983826
27	988572	988572	988569	988631	988635
28	976416	976427	976442	976442	976456
29	982881	982890	982893	982893	982893
30	974421	974420	974431	974431	974436
31	982785	982786	982789	982789	982790
32	988577	988577	988577	988577	988584

CONCLUSIONS

To the best of our knowledge on the state of the art of PSO, dynamic parameterization and hybridization have made significant improvements in solving various kinds of optimization problems. However, very limited approaches on hybridization that used dynamic parameterization. In solving FLP, the PSO hybrids with dynamic parameterization have succeeded in improving the results from the existing best-known heuristic algorithms. Among the three proposed PSO hybrids, most

of the success results emerged from the inclusion of mutation into PSO.

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