KESATRIA: Jurnal Penerapan Sistem Informasi (Komputer & Manajemen)
Terakreditasi Nomor 204/E/KPT/2022 | Vol. 4, No. 4, Oktober (2023), pp. 1148-1157

Comparative Analysis of Binary Particle Swarm Optimization on Dynamic Value Methods for Cognitive and Social Aspects and Its Implementation in Hyper-Heuristic

Safan Capri[1], Oscar Edward Guijaya[2], Antonius Filian Beato Istianto[3], Antoni Wibowo[4]
[1,2,3,4] Computer Science Department, Binus Graduate Program - Master of Computer Science - Bina Nusantara University, Jakarta, Indonesia.
E-mail: [1]safan.capri@binus.ac.id, [2]oscar.guijaya@binus.ac.id, [3]antonius.istianto@binus.ac.id, [4]anwibowo@binus.edu

Abstract

Particle Swarm Optimization (PSO) is a population-based optimization which include the use of cognitive and social terms. The cognitive term is represented with the variable of c_1 while social term is represented with the variable of c_2. Both values can be assigned between 0 and 1. The contribution of this research is to compare which role is superior in the Binary Particle Swarm Optimization (BPSO) metaheuristic with Dynamic Increase Cognitive Decrease Social (DICDS) and Dynamic Decrease Cognitive Increase Social (DDCIS) methods, as well as its implementation in the Modified Multi-Objective Agent-Based Hyper-Heuristic (MOABHH). The experiments were carried out 30 times on data set 2 from [1]. The result is that the DDCIS method is 0.4% better in objective value than the DICDS method. This is also proven with the average of number of solutions in the DDCIS method which is more 2.3 solutions than the DICDS method based on the evaluation results carried out by Modified MOABHH. In addition, Modified MOABHH which is run simultaneously with the DICDS and DDCIS methods provides better objective value results of 0.6% compared to the average of both results for each of these methods which are run separately.

Keywords: *Binary Particle Swarm Optimization, Dynamic Decrease Cognitive Increase Social, Dynamic Increase Cognitive Decrease Social, Metaheuristic, Modified Multi-Objective Agent-Based Hyper-Heuristic*

1. Introduction

PSO is a population-based optimization method that is popularly used and has been introduced since 1995. According to [2], the PSO metaheuristic is widely used in various aspects because it has the advantages of simple implementation and fast convergence speed. According to [3], PSO is rooted in two main components, namely in general its relationship to artificial life (A-life), and specifically to groups of birds, schools of fish, and swarming theory. The PSO metaheuristic uses a method where each bird does not know exactly where the food source is, but they will follow which bird is closest to the food source.

The following is a PSO flow diagram according to [4].

KESATRIA: Jurnal Penerapan Sistem Informasi (Komputer & Manajemen)
Terakreditasi Nomor 204/E/KPT/2022 | Vol. 4, No. 4, Oktober (2023), pp. 1148-1157

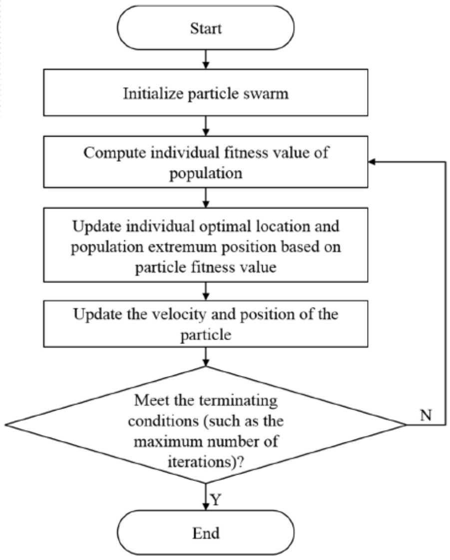

Figure 1. PSO Flow Diagram [4]

According to [5], the PSO algorithm to find the shortest path is as follows:

a) The swarm group is initialized with a number of particles N, where each particle has a random position and velocity constants.
b) The particle path is optimized after comparing with the pbest and gbest paths.
c) If the particle path is shorter than the local best (pbest) path, then the particle path is updated as the new local best path. Next, a comparison is made with the global best (gbest) route.
d) Particle positions and velocities are updated according to equations 1 and 2.
e) These steps are followed until the required minimum path is obtained.

The pbest and gbest values are updated with equations (1) and (2) which are known as the velocity and distance equations respectively.

$$v(t+1) = wv(t) + c_1 r_1 [\hat{x}(t) - x(t)] + c_2 r_2 [g(t) - x(t)] \qquad (1)$$

$$x(t+1) = x(t) + v(t+1) \qquad (2)$$

where:
v = velocity of particle at time t; x = position of particle at time t;
c_1 = acceleration constant for cognitive component; c_2=acceleration constant for social component
r_1, r_2 = stochastic random constant
$\hat{x}$ = local best for particle; g = global best for particle; w = inertia weight at iteration t

In its implementation, according to [6], the PSO algorithm was developed for continuous-valued search spaces and most of its modified versions work in continuous space, so it cannot be used to optimize discrete-valued search spaces. According to [7], the binary version limits the values of the components xi and yi to elements taken from the set {0, 1} with no restrictions on the value of the velocity, vi, of a particle. When using velocity to update position, velocity is limited to the range [0, 1] and treated as a probability. This is done with the sigmoid function in equation (3) and for the velocity update in equation (4).

$$\mathrm{sig}(x) = \frac{1}{1+\exp(-x)} \qquad (3)$$

$$v_{i,j}(t+1) = v_{i,j}(t) + c_1 r_{1,j}(t)[y_{i,j} - x_{i,j}(t)] + c_2 r_{2,j}(t)[\hat{y}_j - x_{i,j}(t)] \qquad (4)$$

The updated velocity equation is no different from PSO, namely:

$$x_{i,j}\ (t+1) = \begin{cases} 0 & \text{if } r_{3,j}\ (t) \geq \text{sig}(v_{i,j}\ (t+1)) \\ 1 & \text{if } r_{3,j}\ (t) < \text{sig}(v_{i,j}\ (t+1)) \end{cases} \quad (5)$$

where $r_{3,j}$ (t) $\sim$ U (0,1) is the uniform random variate.

In the dynamic value method for Cognitive and Social, the author uses Hyper-Heuristics to prove the research results on basic BPSO. According to [8], Hyper-Heuristics are high-level heuristics to reduce the difficulty in selecting the most appropriate low-level heuristics (LLH) for a particular problem. This search methodology uncovered several algorithms capable of solving a wide variety of problems, with little or no direct control from humans. It is described as a "heuristics for selecting heuristics" or an automated methodology for selecting or generating heuristics for solving difficult computational problems.

MOABHH is a Hyper-Heuristic which is designed as a multi-agent system that uses voting concepts to overcome the Algorithm Selection Problem in Multi-Objective Optimization. With the election outcome *EO*, the Hyper-Heuristic agent in MOABHH can dynamically determine more or less participation percentage $pp \in PP$ in producing new solutions for certain $llh \in LLH$.

2. Research Methodology

In this research, the author compares the factors for using cognitive learning and social learning in PSO using the DICDS and DDCIS methods. The author runs basic BPSO with these two methods, and then uses Modified MOABHH which combines the two methods and evaluates the implementation results.

The use of the DICDS and DDCIS methods is based on the inspiration from the results of other research [9], which is the use of the Dynamic method in GA for mutation and crossover ratios. The author implemented the Dynamic method into DICDS and DDCIS for cognitive learning and social learning at PSO. The DICDS method starts with a value of zero for the cognitive aspect ($c_1 = 0$) and a value of one for the social aspect ($c_2 = 1$), and as the number of generations added, the cognitive value increases while the social value decreases. On the other hand, the DDCIS method starts with a value of one for the cognitive aspect ($c_1 = 1$) and a value of zero for the social aspect ($c_2 = 0$), and as the number of generations added, the cognitive value decreases while the social value increases.

Furthermore, in implementing Modified MOABHH, the author uses MOABHH which was discovered by [8]. In a separate research experiment, the author modified the model to Modified MOABHH. In this research, the author implemented the BPSO metaheuristic using the DICDS and DDCIS methods to compare the results. The data set used is data set 2 from [1].

Table 1. Research Data Set [1]

#	Contents of Research Data Set 2				
1-10	[0,0,0,0,0,1],	[0,0,0,0,0,1],	[1,0,0,0,0,0],	[0,1,1,0,0,0],	[0,1,0,0,1,0],
	[0,0,0,1,1,0],	[0,0,0,0,0,0],	[1,0,0,0,1,0],	[0,0,1,1,0,1],	[0,1,0,1,1,0]
11-20	[0,1,1,0,0,1],	[1,1,0,0,0,0],	[0,1,0,1,0,1],	[0,0,0,0,0,0],	[0,0,0,1,1,0],
	[0,0,0,0,1,1],	[1,1,0,0,0,0],	[1,1,0,1,0,0],	[0,0,0,0,1,1],	[0,1,0,1,0,1]
21-30	[1,1,1,0,0,0],	[0,0,0,1,1,0],	[0,1,0,0,1,1],	[1,0,0,0,0,1],	[1,0,0,1,0,0],
	[0,1,1,0,0,1],	[1,0,0,1,0,1],	[0,0,1,1,1,0],	[0,1,0,1,0,1],	[0,0,0,0,0,1]
31-40	[0,0,0,0,0,1],	[0,1,1,1,1,1],	[0,0,0,0,1,1],	[1,0,0,1,0,1],	[0,0,0,0,0,1],
	[1,1,0,0,0,1],	[0,1,1,1,1,1],	[1,1,0,0,0,0],	[0,0,0,0,0,1],	[0,0,1,1,0,1]

#	Contents of Research Data Set 2				
41-50	[0,1,0,1,0,0],	[0,0,0,1,0,0],	[1,0,1,1,0,1],	[1,0,0,0,1,0],	[0,0,0,0,0,0],
	[1,0,1,0,0,0],	[1,0,1,0,0,0],	[1,1,1,1,0,0],	[1,0,1,0,0,0],	[1,0,1,0,1,0]

51-60	[1,0,1,1,1,0],	[0,0,0,0,0,0],	[1,0,1,0,1,1],	[0,0,0,1,0,1],	[1,1,0,0,0,0],
	[0,0,0,0,0,0],	[0,0,1,1,1,1],	[0,1,0,0,0,1],	[0,0,1,0,1,1],	[1,1,0,1,0,1]
61-70	[1,1,0,0,0,1],	[0,0,0,0,0,1],	[0,0,1,0,1,1],	[1,0,1,0,1,1],	[0,1,1,0,0,1],
	[0,1,0,0,1,0],	[1,1,0,0,0,0],	[1,0,0,0,1,0],	[0,1,0,0,0,0],	[1,1,1,0,0,0]
71-80	[0,0,0,0,1,0],	[0,0,1,0,0,0],	[0,0,0,0,0,0],	[1,1,0,0,1,1],	[1,0,0,0,0,1],
	[1,0,0,0,0,1],	[1,0,1,1,1,0],	[0,0,1,1,0,1],	[0,1,0,0,1,0],	[0,0,0,0,1,1]
81-90	[1,1,0,0,0,0],	[0,1,0,0,1,0],	[1,0,1,1,1,1],	[1,0,0,0,0,0],	[0,0,1,0,1,0],
	[1,1,1,0,0,1],	[0,1,1,1,1,0],	[0,0,0,1,0,0],	[0,0,0,0,0,1],	[1,0,1,1,1,1]
91-	[1,1,0,1,0,0],	[1,0,0,1,0,0],	[0,0,1,0,1,1],	[1,1,0,0,1,1],	[0,0,0,0,0,0],
100	[0,0,0,1,1,1],	[0,0,0,0,0,0],	[0,0,1,0,0,0],	[0,1,0,1,1,1],	[1,0,0,1,1,0]
101-	[1,1,0,0,0,0],	[0,1,1,1,0,1],	[0,0,0,0,0,1],	[0,1,1,0,0,0],	[1,0,1,1,0,1],
110	[0,0,1,1,1,0],	[0,0,0,1,0,1],	[1,0,0,1,0,0],	[1,0,0,1,1,0],	[0,0,0,1,0,0]
111-	[0,0,0,0,1,1],	[1,0,0,0,1,0],	[0,1,1,0,0,0],	[1,1,1,1,0,0],	[1,1,0,0,0,0],
120	[0,0,0,0,1,1],	[1,0,0,1,0,1],	[1,1,0,0,1,1],	[0,1,0,1,1,0],	[0,0,0,0,0,0]
121-	[1,0,0,0,1,0],	[0,0,0,1,1,1],	[0,0,1,0,1,0],	[0,0,1,0,1,0],	[1,0,0,1,1,0],
130	[0,0,0,1,0,0],	[0,0,0,1,1,1],	[1,1,1,1,1,0],	[1,0,0,1,1,0],	[0,0,1,0,0,1]
131-	[1,0,0,1,0,0],	[1,1,1,0,0,1],	[0,1,1,1,1,1],	[0,0,1,1,0,0],	[1,1,0,1,1,1],
140	[0,0,1,0,1,1],	[0,1,1,0,1,1],	[0,1,0,1,0,0],	[1,1,1,1,0,1],	[0,0,1,0,0,0]
141-	[0,1,0,0,1,1],	[0,0,1,0,0,0],	[1,1,0,0,0,0],	[1,1,0,1,1,1],	[1,1,1,1,1,0],
150	[0,1,1,1,1,1],	[0,0,1,0,1,0],	[1,1,0,1,1,1],	[1,0,0,0,0,0],	[0,0,0,0,1,1]
151-	[0,1,1,1,0,1],	[1,1,0,0,0,0],	[0,0,0,1,1,1],	[1,0,0,0,0,0],	[0,0,1,0,0,0],
160	[1,0,0,0,1,0],	[1,0,0,0,0,0],	[0,0,1,1,0,0],	[0,0,0,1,0,0],	[0,1,0,0,1,1]
161-	[0,0,1,0,0,0],	[1,1,1,1,1,0],	[0,0,0,0,1,1],	[0,0,0,0,0,0],	[0,0,0,1,0,1],
170	[0,0,1,0,0,1],	[0,1,0,0,0,0],	[0,0,1,1,0,1],	[0,0,1,1,0,0],	[1,1,1,0,0,0]
171-	[1,1,0,1,0,1],	[0,0,1,0,1,1],	[0,1,0,0,1,1],	[0,1,0,1,0,0],	[0,1,0,1,0,0],
180	[0,1,0,1,0,0],	[1,1,0,0,1,0],	[1,0,0,0,0,1],	[0,0,1,1,1,0],	[1,0,1,0,0,0]
181-	[0,0,1,0,0,0],	[1,1,1,0,0,1],	[0,1,0,1,1,1],	[1,0,1,0,0,1],	[0,0,0,1,0,0],
190	[0,1,0,0,0,1],	[1,1,0,0,1,0],	[0,1,1,1,0,0],	[1,0,0,0,0,0],	[0,0,0,1,0,0]
191-	[0,1,1,0,1,1],	[0,0,0,0,0,1],	[0,1,0,0,0,1],	[1,0,0,0,0,1],	[1,0,0,1,0,0],
200	[0,1,1,1,1,0],	[0,1,1,1,0,0],	[1,1,0,1,0,1],	[0,1,1,0,1,0],	[0,1,0,0,0,1]
201-	[1,0,0,0,0,0],	[1,0,0,0,1,1],	[0,0,1,0,0,0],	[0,0,0,0,0,0],	[1,1,1,1,1,1],
210	[0,0,0,0,1,0],	[0,0,1,0,0,0],	[0,0,0,0,0,0],	[0,1,1,0,1,1],	[1,0,0,1,1,1]
211-	[1,0,0,1,0,0],	[0,1,0,0,0,1],	[1,0,1,0,0,0],	[1,0,1,0,0,1],	[0,1,1,0,1,0],
220	[0,1,1,1,0,1],	[0,0,0,0,0,1],	[0,1,1,0,0,0],	[1,1,1,1,0,0],	[1,1,1,1,0,0]
221-	[1,0,0,1,0,0],	[0,1,1,0,0,0],	[0,1,1,1,1,0],	[0,1,0,1,0,0],	[0,0,0,0,0,0],
230	[1,1,1,0,0,0],	[0,1,0,0,1,0],	[0,1,0,0,0,1],	[1,1,0,0,0,0],	[1,0,0,1,0,0]
231-	[0,0,0,0,0,0],	[1,0,0,0,0,0],	[0,0,1,0,0,1],	[1,0,0,0,1,0],	[0,0,0,0,0,1],
240	[0,0,1,0,0,1],	[0,1,0,0,0,0],	[1,0,1,0,1,0],	[0,0,1,0,1,0],	[0,0,0,1,0,0]
241-	[1,1,0,0,1,0],	[1,1,1,1,0,1],	[0,1,1,1,0,0],	[0,0,1,1,1,0],	[0,1,0,0,1,0],
250	[1,1,1,0,1,1],	[1,1,0,1,1,0],	[0,0,1,1,1,1],	[0,0,1,1,1,0],	[1,0,0,0,1,0]

3. Results And Discussion

The following is research data on the comparison of the DICDS and DDCIS methods and their implementation in Modified MOABHH.

Table 2. Research Results Data

#	Model	Best Objective value	Processing Time	Avg. solution number of Low Level Heuristic	Model Group
1	1st BPSO with DICDS	350,823	0:24:14	6.6	Basic Metaheuristics
1	2nd BPSO with DDCIS	352,312	0:24:14	9.4	Basic Metaheuristics
1	Modified MOABHH	352,784	0:46:16		Modified MOABHH
2	1st BPSO with DICDS	352,219	0:23:34	7.7	Basic Metaheuristics
2	2nd BPSO with DDCIS	352,472	0:23:52	8.3	Basic Metaheuristics

2	Modified MOABHH	353,185	0:47:13		Modified MOABHH
3	1st BPSO with DICDS	358,312	0:27:39	6.6	Basic Metaheuristics
3	2nd BPSO with DDCIS	351,357	0:28:10	9.4	Basic Metaheuristics
3	Modified MOABHH	351,197	0:51:16		Modified MOABHH
4	1st BPSO with DICDS	354,350	0:23:38	7.2	Basic Metaheuristics
4	2nd BPSO with DDCIS	352,735	0:23:20	8.8	Basic Metaheuristics
4	Modified MOABHH	350,809	0:47:12		Modified MOABHH
5	1st BPSO with DICDS	355,764	0:27:41	6.2	Basic Metaheuristics
5	2nd BPSO with DDCIS	350,211	0:27:21	9.8	Basic Metaheuristics
5	Modified MOABHH	351,745	0:55:56		Modified MOABHH
6	1st BPSO with DICDS	354,771	0:23:23	6.2	Basic Metaheuristics
6	2nd BPSO with DDCIS	347,494	0:23:19	9.8	Basic Metaheuristics
6	Modified MOABHH	348,394	0:46:35		Modified MOABHH
7	1st BPSO with DICDS	353,497	0:24:42	6.2	Basic Metaheuristics
7	2nd BPSO with DDCIS	350,819	0:24:47	9.8	Basic Metaheuristics
7	Modified MOABHH	353,848	0:49:57		Modified MOABHH
8	1st BPSO with DICDS	355,320	0:23:23	6.9	Basic Metaheuristics
8	2nd BPSO with DDCIS	356,706	0:23:22	9.1	Basic Metaheuristics
8	Modified MOABHH	354,153	0:46:22		Modified MOABHH
9	1st BPSO with DICDS	349,150	0:20:27	6.6	Basic Metaheuristics
9	2nd BPSO with DDCIS	354,312	0:20:48	9.4	Basic Metaheuristics
9	Modified MOABHH	350,565	0:40:58		Modified MOABHH
10	1st BPSO with DICDS	354,289	0:23:24	6.6	Basic Metaheuristics
10	2nd BPSO with DDCIS	353,063	0:23:25	9.4	Basic Metaheuristics
10	Modified MOABHH	352,150	0:46:40		Modified MOABHH
11	1st BPSO with DICDS	355,046	0:19:15	8.7	Basic Metaheuristics
11	2nd BPSO with DDCIS	351,593	0:20:36	7.3	Basic Metaheuristics
11	Modified MOABHH	347,925	0:40:39		Modified MOABHH
12	1st BPSO with DICDS	356,368	0:20:15	8.0	Basic Metaheuristics
12	2nd BPSO with DDCIS	351,981	0:20:11	8.0	Basic Metaheuristics
12	Modified MOABHH	351,197	0:40:33		Modified MOABHH
13	1st BPSO with DICDS	352,269	0:23:27	6.4	Basic Metaheuristics
13	2nd BPSO with DDCIS	353,872	0:19:18	9.6	Basic Metaheuristics
13	Modified MOABHH	351,018	0:46:53		Modified MOABHH

#	Model	Best Objective value	Processing Time	Avg. solution number of Low Level Heuristic	Model Group
14	1st BPSO with DICDS	355,812	0:23:56	6.9	Basic Metaheuristics
14	2nd BPSO with DDCIS	356,449	0:23:50	9.1	Basic Metaheuristics
14	Modified MOABHH	351,543	0:47:33		Modified MOABHH
15	1st BPSO with DICDS	352,714	0:24:16	6.2	Basic Metaheuristics
15	2nd BPSO with DDCIS	350,896	0:24:15	9.8	Basic Metaheuristics
15	Modified MOABHH	350,896	0:46:59		Modified MOABHH
16	1st BPSO with DICDS	357,016	0:23:53	6.6	Basic Metaheuristics

16	2nd BPSO with DDCIS	350,850	0:24:04	9.4	Basic Metaheuristics
16	Modified MOABHH	355,180	0:47:29		Modified MOABHH
17	1st BPSO with DICDS	355,590	0:23:19	6.2	Basic Metaheuristics
17	2nd BPSO with DDCIS	350,922	0:23:18	9.8	Basic Metaheuristics
17	Modified MOABHH	349,028	0:45:53		Modified MOABHH
18	1st BPSO with DICDS	349,793	0:24:17	6.6	Basic Metaheuristics
18	2nd BPSO with DDCIS	355,249	0:24:17	9.4	Basic Metaheuristics
18	Modified MOABHH	351,145	0:50:23		Modified MOABHH
19	1st BPSO with DICDS	356,158	0:23:21	6.4	Basic Metaheuristics
19	2nd BPSO with DDCIS	353,269	0:23:19	9.6	Basic Metaheuristics
19	Modified MOABHH	354,025	0:46:08		Modified MOABHH
20	1st BPSO with DICDS	356,069	0:23:08	6.6	Basic Metaheuristics
20	2nd BPSO with DDCIS	353,600	0:23:19	9.4	Basic Metaheuristics
20	Modified MOABHH	350,590	0:46:07		Modified MOABHH
21	1st BPSO with DICDS	354,523	0:23:47	6.2	Basic Metaheuristics
21	2nd BPSO with DDCIS	354,896	0:24:24	9.8	Basic Metaheuristics
21	Modified MOABHH	351,600	0:45:56		Modified MOABHH
22	1st BPSO with DICDS	357,760	0:24:54	6.2	Basic Metaheuristics
22	2nd BPSO with DDCIS	357,150	0:24:29	9.8	Basic Metaheuristics
22	Modified MOABHH	352,040	0:49:01		Modified MOABHH
23	1st BPSO with DICDS	349,994	0:23:17	6.9	Basic Metaheuristics
23	2nd BPSO with DDCIS	355,420	0:23:29	9.1	Basic Metaheuristics
23	Modified MOABHH	351,012	0:47:57		Modified MOABHH
24	1st BPSO with DICDS	361,022	0:22:54	7.7	Basic Metaheuristics
24	2nd BPSO with DDCIS	352,625	0:23:08	8.3	Basic Metaheuristics
24	Modified MOABHH	351,603	0:45:42		Modified MOABHH
25	1st BPSO with DICDS	351,894	0:23:34	6.2	Basic Metaheuristics
25	2nd BPSO with DDCIS	352,749	0:23:31	9.8	Basic Metaheuristics
25	Modified MOABHH	351,028	0:50:45		Modified MOABHH
26	1st BPSO with DICDS	353,219	0:23:22	6.4	Basic Metaheuristics
26	2nd BPSO with DDCIS	353,570	0:23:39	9.6	Basic Metaheuristics
26	Modified MOABHH	344,771	0:46:36		Modified MOABHH
27	1st BPSO with DICDS	354,878	0:22:54	6.2	Basic Metaheuristics
27	2nd BPSO with DDCIS	355,902	0:23:22	9.8	Basic Metaheuristics
27	Modified MOABHH	352,410	0:45:28		Modified MOABHH

#	Model	Best Objective value	Processing Time	Avg. solution number of Low Level Heuristic	Model Group
28	1st BPSO with DICDS	355,063	0:23:19	8.4	Basic Metaheuristics
28	2nd BPSO with DDCIS	356,106	0:23:21	7.6	Basic Metaheuristics
28	Modified MOABHH	354,190	0:46:16		Modified MOABHH
29	1st BPSO with DICDS	355,636	0:23:24	9.8	Basic Metaheuristics
29	2nd BPSO with DDCIS	352,494	0:23:19	6.2	Basic Metaheuristics
29	Modified MOABHH	354,692	0:46:31		Modified MOABHH

30	1st BPSO with DICDS	354,055	0:23:27	6.2	Basic Metaheuristics
30	2nd BPSO with DDCIS	351,782	0:23:21	9.8	Basic Metaheuristics
30	Modified MOABHH	350,239	0:46:15		Modified MOABHH

The following is a summary of the evaluation results on objective value.

Table 3. Summary of the evaluation results on objective value

Row	Basic Metaheuri 1st BPSO with DICDS	2nd BPSO with DDCIS	Basic Metaheu	Modifie d Modified MOABHH	-0.4% %Var of 2nd BPSO with DDCIS to 1st BPSO with DICDS	-0.8% %Var of Modified MOABHH to 1st BPSO with DICDS	-0.5% %Var of Modified MOABHH to 2nd BPSO with DDCIS	-0.6% %Var of Modified MOABHH to Basic Metaheuristics
1	350,823	352,312	351,568	352,784	0.4%	0.6%	0.1%	0.3%
2	352,219	352,472	352,346	353,185	0.1%	0.3%	0.2%	0.2%
3	358,312	351,357	354,835	351,197	-1.9%	-2.0%	0.0%	-1.0%
4	354,350	352,735	353,542	350,809	-0.5%	-1.0%	-0.5%	-0.8%
5	355,764	350,211	352,987	351,745	-1.6%	-1.1%	0.4%	-0.4%
6	354,771	347,494	351,133	348,394	-2.1%	-1.8%	0.3%	-0.8%
7	353,497	350,819	352,158	353,848	-0.8%	0.1%	0.9%	0.5%
8	355,320	356,706	356,013	354,153	0.4%	-0.3%	-0.7%	-0.5%
9	349,150	354,312	351,731	350,565	1.5%	0.4%	-1.1%	-0.3%
10	354,289	353,063	353,676	352,150	-0.3%	-0.6%	-0.3%	-0.4%
11	355,046	351,593	353,320	347,925	-1.0%	-2.0%	-1.0%	-1.5%
12	356,368	351,981	354,175	351,197	-1.2%	-1.5%	-0.2%	-0.8%
13	352,269	353,872	353,070	351,018	0.5%	-0.4%	-0.8%	-0.6%
14	355,812	356,449	356,131	351,543	0.2%	-1.2%	-1.4%	-1.3%
15	352,714	350,896	351,805	350,896	-0.5%	-0.5%	0.0%	-0.3%
16	357,016	350,850	353,933	355,180	-1.7%	-0.5%	1.2%	0.4%
17	355,590	350,922	353,256	349,028	-1.3%	-1.8%	-0.5%	-1.2%
18	349,793	355,249	352,521	351,145	1.6%	0.4%	-1.2%	-0.4%
19	356,158	353,269	354,713	354,025	-0.8%	-0.6%	0.2%	-0.2%
20	356,069	353,600	354,834	350,590	-0.7%	-1.5%	-0.9%	-1.2%
21	354,523	354,896	354,710	351,600	0.1%	-0.8%	-0.9%	-0.9%
22	357,760	357,150	357,455	352,040	-0.2%	-1.6%	-1.4%	-1.5%
23	349,994	355,420	352,707	351,012	1.6%	0.3%	-1.2%	-0.5%
24	361,022	352,625	356,824	351,603	-2.3%	-2.6%	-0.3%	-1.5%
25	351,894	352,749	352,322	351,028	0.2%	-0.2%	-0.5%	-0.4%
26	353,219	353,570	353,395	344,771	0.1%	-2.4%	-2.5%	-2.4%
27	354,878	355,902	355,390	352,410	0.3%	-0.7%	-1.0%	-0.8%
28	355,063	356,106	355,584	354,190	0.3%	-0.2%	-0.5%	-0.4%
29	355,636	352,494	354,065	354,692	-0.9%	-0.3%	0.6%	0.2%
30	354,055	351,782	352,919	350,239	-0.6%	-1.1%	-0.4%	-0.8%
Grand T	**354,446**	**353,095**	**353,771**	**351,499**	-0.4%	-0.8%	-0.5%	-0.6%

Due to the minimization optimization, orange color indicates to the lower performance, while the green color shows the better performance.

Overall, it appears that the DDCIS method is better than DICDS by 0.4% in the objective value evaluation. Another point is that the Modified MOABHH algorithm, which was run simultaneously with the DICDS and DDCIS methods, gave better objective value results of 0.6% compared to the average basic BPSO results with the DICDS method and the DDCIS method which were run separately.

In terms of comparing the performance of Modified MOABHH, which is run simultaneously with the DICDS and DDCIS methods, against the performance of basic BPSO with the DICDS method which is run separately, it appears that Modified MOABHH provides better performance by 0.8%. On the other hand, comparing to the performance of basic BPSO with the DDCIS method, it appears that Modified MOABHH can provide better results by 0.5%. So, it can be concluded that the Modified MOABHH on the BPSO metaheuristic which is run simultaneously with the DICDS and DDCIS methods can provide better results compared to the basic BPSO results with the DICDS method or the basic BPSO results with the DDCIS method which are run separately.

In the application, the author equates the initial population data from Modified MOABHH to LLH1 and LLH2, to be used also by basic BPSO using the DICDS method and basic BPSO using the DDCIS method. Generally, the initial population data of metaheuristic is generated randomly. The author did this for the purposes of assessment with a baseline on the same initial population data.

The following is a summary of the evaluation results on the number of solutions in LLH.

Table 4. Summary of the evaluation results on the number of solutions in the Low Level Heuristic

Average of Avg n_LLH	**Column Labels**		2.3	
Row Labels	**1st BPSO with DICDS**	**2nd BPSO with DDCIS**	Var of 2nd BPSO with DDCIS to 1st BPSO with DICDS	%Var to standard n = 8
1	6.6	9.4	2.8	35%
2	7.7	8.3	0.6	8%
3	6.6	9.4	2.8	35%
4	7.2	8.8	1.6	20%
5	6.2	9.8	3.6	45%
6	6.2	9.8	3.6	45%
7	6.2	9.8	3.6	45%
8	6.9	9.1	2.2	28%
9	6.6	9.4	2.8	35%
10	6.6	9.4	2.8	35%
11	8.7	7.3	-1.4	-18%
12	8.0	8.0	0	0%
13	6.4	9.6	3.2	40%
14	6.9	9.1	2.2	28%
15	6.2	9.8	3.6	45%
16	6.6	9.4	2.8	35%
17	6.2	9.8	3.6	45%
18	6.6	9.4	2.8	35%
19	6.4	9.6	3.2	40%
20	6.6	9.4	2.8	35%
21	6.2	9.8	3.6	45%
22	6.2	9.8	3.6	45%
23	6.9	9.1	2.2	28%
24	7.7	8.3	0.6	8%
25	6.2	9.8	3.6	45%
26	6.4	9.6	3.2	40%
27	6.2	9.8	3.6	45%
28	8.4	7.6	-0.8	-10%
29	9.8	6.2	-3.6	-45%
30	6.2	9.8	3.6	45%
Grand Total	**6.9**	**9.1**	2.3	29%
	Orange color shows the less number of solutions due to the low performance,			
	while the green color shows the larger number of solutions due to the better performance.			

Overall, it can be seen that in both DICDS and DDCIS methods which are run in the Modified MOABHH algorithm, the DDCIS method has a greater number of solutions of 2.3 solutions than the DICDS method. This means that based on the results of the evaluation carried out by the heuristic which selected the heuristic, Modified MOABHH has provided a greater number of solutions for the heuristic with better solution results. In this case the DDCIS method is proven to be able to provide better performance than the DICDS method.

In the application, the author provides the same number of solutions, namely 8 solutions for both LLHs. As the evaluation is carried out by Modified MOABHH, the number of solutions for each LLH is adjusted to the performance results of each LLH.

4. Conclusion

The conclusions on the data from this research are the DDCIS method in BPSO is better than the DICDS method by 0.4% in objective value evaluation. This is also proven by the results of the average number of solutions in the DDCIS method with 2.3 more solutions than the DICDS method based on the evaluation results carried out by the Modified MOABHH algorithm. Modified MOABHH, which is run simultaneously with the DICDS and DDCIS methods, can provide a better objective value of 0.6% when compared to the average basic BPSO results with the DICDS method and the DDCIS method which are run separately respectively. The author decided to share resources for further development. Here is a link to download thirty similar coding with different results, namely https://drive.google.com/drive/folders/1jD6KnNmjZF4qEq3UYUjS28BIg6pthrRW?usp=sharing

Acknowledgments

The authors declare that there is no conflict of interest regarding the publication of this paper. This research received no external funding. Conceptualization and formalization: all authors; Implementation: S.C., O.E.G., A.F.B.I.; Experiments: S.C.; Supervision: A.W.; Writing and proofreading the paper: S.C. and A.W. All authors have read and agreed to the published version of the manuscript.

References

[1] K. Augustin, “Multi-Objective Optimization untuk Penjadwalan Kru Penerbangan menggunakan Algoritma Hybrid Genetic Algorithm dan Particle Swarm Optimization”, M.I.T. Thesis, Bina Nusantara University, Jakarta, Indonesia, **(2021)**.

[2] S. Wang, J. Zhu, X. Shen, Q. Wang, R. Shu and J. Cai, “Research on Particle Swarm Optimization Algorithm”, Journal of Physics: Conference Series, vol. 1827, no. 012151, **(2021)**.

[3] J. Kennedy and R. Eberhart, “Particle Swarm Optimization”, Proceedings of ICNN'95 - International Conference on Neural Networks, Perth, Australia, **(1995)** November 27-December 01.

[4] H. Gao, Y. Yang, X. Zhang, C. Li, Q. Yang and Y. Wang, “Dimension Reduction for Hyperspectral Remote Sensor Data Based on Multi-Objective Particle Swarm Optimization Algorithm and Game Theory”, Sensors, vol. 19(6), no. 1327, **(2019)**.

[5] A. Gupta and S. Srivastava, “Comparative Analysis of Ant Colony and Particle Swarm Optimization Algorithms for Distance Optimization”, Procedia Computer Science, vol. 173, **(2020)**, pp. 245-253.

[6] S. Talukder, “Mathematical Modelling and Applications of Particle Swarm Optimization”, M.Sc. Thesis, School of Engineering at Blekinge Institute of Technology, Karlskrona, Sweden, **(2011)**.

[7] F. van den Bergh, “An Analysis of Particle Swarm Optimizers”, Ph.D. Thesis, University of Pretoria, Pretoria, South Africa, **(2001)**.

[8] V. R. de Carvalho, “Using Multi-Agent Systems and Social Choice Theory to Design Hyper-Heuristics for Multi-Objective Optimization Problems”, Ph.D. Thesis,

Escola Politécnica of Universidade de São Paulo, São Paulo, Brazil, **(2022)**.

[9] A. Hassanat, K. Almohammadi, E. Alkafaween, E. Abunawas, A. Hammouri and V. B. S. Prasath, "Choosing Mutation and Crossover Ratios for Genetic Algorithms-A Review with a New Dynamic Approach", Information, vol. 10(12), no. 390, **(2019)**.