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Multi-Objective Physician Scheduling using Non-Dominated Sorting Native Binary Particle Swarm Optimization with Deallocation Method

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ABSTRACT

Scheduling Optimization is a critical operation in Hospital Management. A good medical personnel schedule can overcome a lot of troubles for operational staff, management and the medical personnel. This problem can be solved using single objectives optimization and multi objectives optimization. In previous research, the scheduling optimization problem was solved single-objectively using Native Binary Particle Swarming Optimization (NBPSO). In this research, the researcher attempted to solve the problem multi-objectively using Non-Dominated Sorting Native Binary Particle Swarming Optimization (NSNBPSO). In this research, a constraint handling method was proposed called deallocation method which produced schedules that met the requirement of all constraints. In the performance comparison, researcher compared the performance of the proposed NSNBPSO and the previous NBPSO. The metrics used for the comparison were Coverage Rate, Hypervolume and Processing Time.NSNBPSO successfully produced 10 Solutions which provided more options to the stakeholder. However, NSNBPSO produced infeasible solutions and violated constraints in this research. Therefore, deallocation method was proposed and implemented to help NSNBPSO producing feasible solutions. The performance result showed that NSNBPSO with deallocation method had 35% more average hypervolume value than NBPSO, 50% of solutions from NSNBPSO dominated solution from NBPSO in coverage rate evaluation. However, it needed 85% more processing timeandcan still be considered acceptable.

Keywords: Binary Particle Swarm Optimization, Deallocation, Non-Dominated Sorting, Physician Scheduling

1. INTRODUCTION

Hospital is an institution managed to tend and cure those who need of attention in medical, surgical or dental which are done not for personal interest [1]. To serve its function, hospital relies on the ability of medical personnel in its operational process. Medical Personnel becomes one of main resource that must be managed with caution. According to Santos & Eriksson, physician scheduling is how to manage and distribute physician time in performing job at hospital [2]. One way to manage medical personnel is to schedule them efficiently allowing the hospital to use time management efficiently. Time management is very important in order to realize a good healthcare service, achieve high satisfaction and enable other healthcare dimension such as efficiency [3]. However, to schedule them efficiently is very complex and hard to generalize and takes a very long time. Inefficiency in scheduling can impacts the wellbeing of physician and their patients[4].

There are two ways to solve this problem namely using single objectives optimization and multi objectives optimization approaches. Single objectives approach will find the best single solution and combine multiple objective functions into one single objective function [5].Multiple objectives optimization will find non-dominated/pareto-optimal solutions from its process[6].When we say a pareto-optimal is when the solution cannot increase its benefits from one aspect without sacrificing another aspect[7]. Each solution cannot be considered better than the other by considering its objectives[8].

This research will continue the last research conducted by Hidayatiand Wibowo[9] which solved the multi objectives optimization problem using by assigning weight coefficient to each objective and combine it into one single objective using Native BPSO and Novel BPSO[10]. According to Fang et al.[10], the assigning weight coefficient in single objective optimization approach is highly subjective and will depend on preference. Solving this problem using multi objectives has its own benefits:(a) It improves decision making[11]; (b) and can make decision making process in decision maker as it should be[5].

This paper presents a variant of BPSO approach using Native BPSO to solve the physician constrained scheduling problem through multi objective optimization. To allow BPSO to solve multi objective problem, some process from NSGA-II which are non-dominated sorting, crowding distance and binary tournament selection[12] were added while the moving particle method will use Native BPSO. Then deallocation method is proposed to handle each specific constraint in this research. Deallocation method deallocated schedule when it violated constraints during the moving particle process, crossover process and at the end of iteration to handle each specific constraint. Detailed deallocation method will be explained in Section 4. Therefore, the research output and recommendations are expected to give benefits to the hospital in increasing the quality of services to patients by improving the scheduling system made by previous researchers [9] and producing a scheduling system that satisfies multiple objectives and constraints in this research.

2. THEORY AND METHODS

2.1 Native BPSO

Native BPSO (NBSPO) is the binary version of PSO, which is easy to implement and has less parameter to adjust [13], used to solve discrete binary optimization problem [14].The search space in NBPSO is a hypercube where particle move to nearer or farther from corners of hypercube by flipping various numbers of bits [15]. It will use another particle feedback to reach the objective [16], hence the global search play significant role in discovering solutions for the algorithm [17]. The velocity vector of $V_{s,t}$ is a probability that a bit will be in one state or another and must be constrained in the interval the interval [0.0, 1.0] using Sigmoid Logistic Transformation from the original velocity equation and $X_{s,t}(t+1)$ value will be either 1 or 0. The velocity value will be compared to a random number r_3 in the same range [0.0, 1.0]. If the velocity value is higher than the random value, then $X_{s,t}\ (t+1)$ will take the value of 1, otherwise it will be zero. Refer to (1) and (2) below for the general PSO velocity formula and the Sigmoid function, respectively.

$$V_{s,(t+1)} = w_t . V_{s,t} + c_1 . r_1 . (P_{best,t} - X_{s,t}) + c_2 . r_2 . (G_{best} - X_{s,t}) \quad (1)$$

$V_{s,t}$: velocity of particle-*s* at iteration-*t*
$X_{s,t}$: position of particle-*s* at iteration-*t*
w_t : inertia weight at iteration-*t*
$V_{s,t-1}$: velocity of particle-*s* at iteration-*t-1*
c_1, c_2 : constant learning factors
r_1, r_2, r_3: random values generated between 0 and 1
P_{best} : position of local best for particle-*s*
$P_{s,t-1}$: position of particle-*s* at iteration-*t-1*
G_{best} : position of global best for the swarm

$$S(V_{s,t}) = \frac{1}{(1 + e^{-V_{s,t}})} \quad (2)$$

from Sigmoid function value, the particle's next position $X_{s,t}\ (t+1)$ will be updated using the following condition:

$$X_{s,t} = \begin{cases} 1\ if\ r_3 < S(V_{s,t}) \\ 0\ if\ r_3 > S(V_{s,t}) \end{cases} \quad (3)$$

This transformation is expected to move the particle slowly towards the two local and global best values.

2.2Non-Dominated Sorting

In non-dominated sorting, every solution fitness value will be compared with another solutions in population in order to identify which solutions that are dominated with the other solution and otherwise. After the comparison, non-dominated solutions will be grouped into one group called non-dominated front or pareto front. After the first pareto front was formed, comparison will be performed again ignoring the solutions in pareto front until all the solutions in population enter the front. The last front will contain solutions are dominated by other solutions in the population[18].

3. RESEARCH METHODOLOGY

The data for the research is taken from RSUD Soediran Mangun Sumarso, one of the state hospitals located in Wonogiri, Central Java, Indonesia. The existing scheduling data is used to capture expected goal, constraints and challenges. Then using the collected data, a mathematical model was designed to formulate the constraints and objective functions.

The proposed multi-objectives optimization method, NSNBPSO, are implemented using the constraints and objectives functions using moving particle method from NBPSO [14]. In this research, the produced solutions are required to fulfil all the constraints presented in this research. Therefore, researcher proposed a constraint handling method designed to handle specific constraints in this research. This method is called deallocation method.

To measure the performance of this algorithm, performance comparison was performed by comparing one solution from previous research with each solution from NSNBPSO. The performance comparison was using Hypervolume, Coverage Rate and Processing Time as the performance indicators.

The algorithm was implemented in python language as an application that produced spreadsheet files that contained solutions from the algorithm. The application also contains hypervolume, coverage rate and processing time metrics evaluation as performance evaluations that will be performed at the end of the algorithms process. The hypervolume performance evaluation is based on hypervolume algorithm variant 3 by Fonseca et al. [19] reimplemented and optimized by Simon Wessing.

4. MATHEMATICAL MODEL

This research will use mathematical model designed to meet the requirement of the selected hospital for the research. The model made is to reflect the regulations and constraints of the hospital and will be used to achieve the end goal of the scheduling, which is to distribute physician assignments as fair as possible through balancing shifts assignments and number of working days in a month.

4.1. Assumptions

This research will use the following assumptions in the scheduling model:

1. Emergency room is a 24/7 service that operates every day, 7-days a week, 24-hours a day[20].
2. The research will use an example of a mother and child hospital, where the research will have three types of physicians, i.e. general doctors, Pediatricians and Obstetricians/Gynecologists.
3. All clinics operates 7-days a week from Monday to Sunday.
4. Month used in this research is January 2020 and will ignore public holiday therefore workdays will be between Monday until Sunday. 1 January will be started in Monday and it goes on until 31 Wednesday

The research uses the following parameters in the model:

1. Num_gd = number of general doctors.
2. Num_pd = number of Pediatricians.
3. Num_od = number of Obstetricians/Gynecologists.
4. i = index of physicians, as listed and described in Table-I below.

Table 1: Index of Physician

i	Doctor Code	Description
1	Gd01	General doctor #01
2	Gd02	General doctor #02
3	Gd03	General doctor #03
4	Gd04	General doctor #04
5	Gd05	General doctor #05
6	Gd06	General doctor #06
7	Gd07	General doctor #07
8	Gd08	General doctor #08
9	Gd09	General doctor #09
10	Gd10	General doctor #10
11	Gd11	General doctor #11
12	Gd12	General doctor #12
13	Gd13	General doctor #13
14	Pd01	Pediatrician #01
15	Pd02	Pediatrician #02
16	Pd03	Pediatrician #03
17	Pd04	Pediatrician #04
18	Od01	Obstetrician/Gynecologist #01
19	Od02	Obstetrician/Gynecologist #02

5. j = index of physician assignment, as listed and described in Table-II below.

Table 2: Index of Physician Assignments

j	Assignment Description	Applicable for
1	Morning shift in Emergency Room	General doctor
2	Day shift in Emergency Room	General doctor
3	Evening shift in Emergency Room	General doctor
4	Regular assignment, which covers out-patient clinic, in-patient visit and other regular work	General doctor
5	Regular assignment, which covers out-patient clinic, in-patient visit, surgery appointment, if any, and other regular work	Pediatrician
6	On-call assignment	Pediatrician
7	Regular assignment, which covers out-patient clinic, in-patient visit, surgery appointment, if any, and other regular work	Obstetrician/ Gynecologist
8	On-call assignment	Obstetrician/ Gynecologist

6. k = calendar date {1,2,3,4,5, ... ,Num_days}.
7. Num_days = number of days in a month.
8. HLD = Sundays and public holidays of the month.

4.2. Decision Variable

The assignment of physicians is depicted below in (4).

$$X_{i,j,k} = \begin{cases} 1 \\ 0 \end{cases} \quad (4)$$

Where:

X : position of particle
i : index of physician
j : index of physician assignment
k : index of date of the month

4.3. Hard Constraints

1. Applicable assignments for physicians:
   a. Physicians' assignments for General doctors are with index j = {1,2,3,4}. Therefore, within a monthly schedule, sum of general doctor assignments for j = {5,6,7,8} must be equal to zero. Refer to equation (2) below.

$$\sum_{i=1}^{Num\_gd} \sum_{j=5}^{8} \sum_{k=1}^{Num\_days} X_{i,j,k} = 0 \quad (5)$$

   b. Physicians assignments for Pediatricians are with index j = {5,6}. Therefore, within a monthly schedule, sum of Pediatricians assignments for j = {1,2,3,4,7,8} must be equal to zero. Refer to equation (3) below.

$$\sum_{i=Num\_gd+1}^{Num\_gd+Num\_pd} \sum_{j\in\{1,2,3,4,7,8\}} \sum_{k=1}^{Num\_days} X_{i,j,k} = 0 \quad (6)$$

   c. Physicians assignments for Obstetricians/Gynecologists are with index j = {7,8}. Therefore, within a monthly schedule, sum of Obstetricians/Gynecologists assignments for j = {1,2,3,4,5,6} must be equal to zero. Refer to equation (4) below.

$$\sum_{i=Num\_gd+Num\_pd+1}^{I} \sum_{j=1}^{6} \sum_{k=1}^{Num\_days} X_{i,j,k} = 0 \quad (7)$$

2. There can only be a maximum of one assignment per physician in one day. Refer to equation (5) below.

$$\sum_{j=1}^{8} X_{i,j,k} \leq 1 \quad (8)$$

3. General doctors must be assigned a day off on the next day (date k+1) after an assignment of night shift in Emergency Room (assignment j=3). Refer to equation (6) below.

$$X_{i,3,k} + X_{i,1,k+1} + X_{i,2,k+1} + X_{i,3,k+1} + X_{i,4,k+1} \leq 1 \quad (9)$$

4. Every physician cannot be assigned for a total number of working days in a month that exceeds Num_days. Therefore, the number of working days in a month should be between 1 to Num_days. Refer to equation (7) below.

$$1 \leq (\sum_{k=1}^{Num\_days} X_{i,1,k} + X_{i,2,k} + (2 * X_{i,3,k}) + X_{i,4,k}) + Z_i \leq Num\_days \quad (10)$$

4.4. Fitness Functions

1. F_1 = standard deviation for morning-shift assignments in Emergency Room (assignment j=1). Refer to equations (11-13) below.

$$F_1 = \sqrt{\frac{\sum_{i=1}^{Num\_gd} (Y1_i - Mean\_Y1)^2}{Num\_gd}} \quad (11)$$

$$Y1_i = \sum_{k=1}^{Num\_days} X_{i,1,k} \quad (12)$$

$$Mean\_Y1 = \frac{\sum_{i=1}^{Num\_gd} Y_i}{Num\_gd} \quad (13)$$

Where

$Y1_i$: the number of days each general doctor-i is assigned on morning shift in Emergency Room (j = 1) in a month.

Mean_Y1 : average number of working days for all general doctors assigned on assignment-1 in a month.

Num_gd : total number of general doctors.

2. F_2 = standard deviation for day-shift assignments in Emergency Room (assignment j=2). Refer to equations (14-16) below.

$$F_2 = \sqrt{\frac{\sum_{i=1}^{Num\_gd} (Y2_i - Mean\_Y2)^2}{Num\_gd}} \quad (14)$$

$$Y2_i = \sum_{k=1}^{Num\_days} X_{i,2,k} \quad (15)$$

$$Mean\_Y2 = \frac{\sum_{i=1}^{Num\_gd} Y2_i}{Num\_gd} \quad (16)$$

Where

$Y2_i$: the number of days each general doctor-i is assigned on day shift in Emergency Room (j = 2) in a month.

Mean_Y2 : average number of working days for all general doctors assigned on assignment-2 in a month.

Num_gd : total number of general doctors.

3. F_3 = standard deviation for evening-shift assignments in Emergency Room (assignment j=3). Refer to equations (17-19) below.

$$F_3 = \sqrt{\frac{\sum_{i=1}^{Num\_gd} (Y3_i - Mean\_Y3)^2}{Num\_gd}} \quad (17)$$

$$Y3_i = \sum_{k=1}^{Num\_days} (2 \times X_{i,3,k}) \quad (18)$$

$$Mean\_Y3 = \frac{\sum_{i=1}^{Num\_gd} Y3_i}{Num\_gd} \quad (19)$$

Where

$Y3_i$: the number of days each general doctor-i is assigned on evening shift in Emergency Room (j = 3) in a month.

Mean_Y3 : average number of working days for all general doctors assigned on assignment-3 in a month.

Num_gd : total number of general doctors.

4. F_4 = standard deviation for the assignments of combined out-patient clinic, in-patient visit and in-hospital regular work (assignment j=4). Refer to equations (20-22) below.

$$F_4 = \sqrt{\frac{\sum_{i=1}^{Num\_gd} (Y4_i - Mean\_Y4)^2}{Num\_gd}} \quad (20)$$

$$Y4_i = \sum_{k=1}^{Num\_days} X_{i,4,k} \quad (21)$$

$$Mean_Y4 = \frac{\sum_{i=1}^{Num_gd} Y4_i}{Num_gd} \quad (22)$$

Where

$Y4_i$: the number of days each general doctor-i is assigned on combined outpatient clinic, inpatient visit and in-hospital regular work (j = 4) in a month.

Mean_Y4 : average number of working days for all general doctors assigned on assignment-4 in a month.

Num_gd : total number of general doctors.

5. F_5 = standard deviation for Pediatricians assignments of combined out-patient clinic, in-patient visit and in-hospital regular work (assignment j=5). Refer to equations (23-25) below.

$$F_5 = \sqrt{\frac{\sum_{i=Num\_gd+1}^{Num\_gd+Num\_pd}(Y5_i - Mean\_Y5)^2}{Num\_pd}} \quad (23)$$

$$Y5_i = \sum_{k=1}^{Num\_days} X_{i,5,k} \quad (24)$$

$$Mean\_Y5 = \frac{\sum_{i=Num\_gd+1}^{Num_{gd}+Num\_pd} Y5_i}{Num\_pd} \quad (25)$$

Where

$Y5_i$: the number of days each Pediatrician-i is assigned on combined out-patient clinic, in-patient visit and in-hospital regular work (j = 5) in a month.

Mean_Y5 : average number of working days for all Pediatricians assigned on assignment-5 in a month.

Num_pd : total number of Pediatricians.

6. F_6 = standard deviation for Pediatricians on-call assignment (assignment j=6). Refer to equations (26-28) below.

$$F_6 = \sqrt{\frac{\sum_{i=Num\_gd+1}^{Num\_gd+Num\_pd}(Y6_i - Mean_Y 6)^2}{Num\_pd}} \quad (26)$$

$$Y6_i = \sum_{k=1}^{Num\_days} X_{i,6,k} \quad (27)$$

$$Mean\_Y6 = \frac{\sum_{i=Num\_gd+1}^{Num\_gd+Num\_pd} Y6_i}{Num\_pd} \quad (28)$$

Where

$Y6_i$: the number of days each Pediatrician-i is assigned for on-call (j = 6) in a month.

Mean_Y6 : average number of working days for all Pediatricians assigned on assignment-6 in a month.

Num_gd : total number of Pediatrician

7. F_7 = standard deviation for Obstetricians/Gynecologists assignments of combined out-patient clinic, in-patient visit and in-hospital regular work (assignment j=7). Refer to equations (29-31) below.

$$F_7 = \sqrt{\frac{\sum_{i=Num\_gd+Num\_pd+1}^{I}(Y7_i - Mean\_Y7)^2}{Num\_od}} \quad (29)$$

$$Y7_i = \sum_{k=1}^{Num\_days} X_{i,7,k} \quad (30)$$

$$Mean\_Y7 = \frac{\sum_{i=Num\_gd+Num\_pd+1}^{I} Y7_i}{Num\_od} \quad (31)$$

Where

$Y7_i$: the number of days each Obstetrician/Gynecologist doctor-i is assigned on combined out-patient clinic, in-patient visit and in-hospital regular work (j = 7) in a month.

Mean_Y7 : average number of working days for all Obstetricians/Gynecologists assigned on assignment-7 in a month.

Num_od : total number of Obstetricians/Gynecologists.

8. F_8 = standard deviation for Obstetricians/ Gynecologists on-call assignment (assignment j=8). Refer to equations (32-34) below.

$$F_8 = \sqrt{\frac{\sum_{i=Num\_gd+Num\_pd+1}^{I}(Y8_i - Mean\_Y8)^2}{Num\_od}} \quad (32)$$

$$Y8_i = \sum_{k=1}^{Num\_days} X_{i,8,k} \quad (33)$$

$$Mean\_Y8 = \frac{\sum_{i=Num_{gd}+Num_{pd}+1}^{I} Y8_i}{Num\_od} \quad (34)$$

Where

$Y8_i$: the number of days each Obstetrician/Gynecologist doctor-i is assigned for on-call (j = 8) in a month.

Mean_Y8 : average number of working days for all Obstetricians/Gynecologists assigned on assignment-8 in a month.

Num_od : total number of Obstetricians/Gynecologists

9. F_9 = standard deviation for general doctors number of working days in a month. Refer to equations (35-37) below.

$$F_9 = \sqrt{\frac{\sum_{i=1}^{Num\_gd}(Y_i - Mean\_Ygd)^2}{Num\_gd}} \quad (35)$$

$$Y_i = \sum_{j=1}^{8} \sum_{k=1}^{Num\_days} X_{i,j,k} \quad (36)$$

$$Mean\_Ygd = \frac{\sum_{i=1}^{Num\_gd} Y_i}{Num\_gd} \quad (37)$$

Where

Y_i : total number of working days for general doctor-i in a month, with index of 'i' from 1 to Num_gd.

Mean_Ygd: average number of working days for all general doctors in a month.

Num_gd : total number of general doctors.

10. F_{10} = standard deviation for Pediatricians number of working days in a month. Refer to (38-39) below.

$$F_{10} = \sqrt{\frac{\sum_{i=Num\_gd+1}^{Num\_gd+Num\_pd}(Y_i - Mean\_Ypd)^2}{Num\_pd}} \quad (38)$$

$$Mean_{Ypd} = \frac{\sum_{i=Num_{gd}+1}^{Num_{gd}+Num_{pd}} Y_i}{Num_{pd}} \quad (39)$$

Where

Y_i : total number of working days for Pediatrician-i in a month. Refer to equation (44) with index of 'i' from (Num_gd + 1) to (Num_gd + Num_pd).

Mean_Ypd: average number of working days for all Pediatricians in a month.

Num_pd : total number of Pediatricians

11. F_{11} = standard deviation for Obstetricians/ Gynecologists number of working days in a month. Refer to (40-41) below.

$$F_{11} = \sqrt{\frac{\sum_{i=Num\_gd+Num\_pd+1}^{I}(Y_i - Mean\_Yod)^2}{Num\_od}} \quad (40)$$

$$Mean\_Yod = \frac{\sum_{i=Num_{gd}+Num_{pd}+1}^{I} Y_i}{Num\_od} \quad (41)$$

Where

Y_i : total number of working days for Obstetrician/Gynecologist doctor-i in a month. Refer to equation (44) with index-i from (Num_gd + Num_pd + 1) to I.

Mean_Yod: average number of working days for all Obstetricians/Gynecologists in a month.

Num_od : total number of Obstetricians/ Gynecologists.

5. PROPOSED METHOD

5.1. NSNBPSO

Non Dominated Sorting Native Binary Particle Swarm Optimization (NSNBPSO) is a multi-objectives optimization method that uses the non-dominated sorting from NSGA-II to solve discrete problem by producing solutions that are pareto optimal by using modified process from PSO developed by Li[21] to initialize offspring particles but not by using their personal best rather by performing uniform crossover and using moving particle function proposed byKennedy et al.[14]to solve discrete scheduling problem using multi-objective approach. To fulfill constraints introduced in this research and guide the schedule to produce minimized objective function, deallocation method was performed during the crossover process and moving particle process.

NSNBPSO with deallocation method workflow is as follows:

1. Initialize the particles
2. Initialize the offspring particles based on uniform crossover and deallocation method between particles and particle personal best
3. Create Temporary Particles Population
4. Calculate Each Fitness Functions for Each Particles
5. Perform Non-Dominated Sorting, Crowding Distance and Binary Tournament Selection
6. Create Pareto Fronts
7. Replace the initial population with the Non-Dominated Pareto Fronts
8. Get random position of the first pareto fronts to find Global Best
9. Calculate Velocity from Each New Non-Dominated Particles
10. Create new particle position using Native BPSO method or using Novel BPSO method while also performing deallocation method to fulfil constraint.
11. Compare fitness function with particle personal best.If particle has better fitness function average than particle personal best average than store it as particle personal best
12. Check stop criteria if not fulfilled then repeat step 2-11 until stop criteria is met else stop the algorithm

5.2. Deallocation Method

The deallocation method used in this research is to produce schedule that fulfil 6 constraints and minimize 3 fitness function in this research. The following is how the deallocation method is performed in this research:

1. Deallocation method for constraint (5), (6), (7)

When uniform crossover and moving particle in NSNBPSO each of them will have a condition where the algorithm will perform crossover or moving particle on proper assignment index for example in general doctors, crossover and moving particle will be performed on assignment index {1,2,3,4} any other index will be deallocated to zero.

2. Deallocation method for constraint (8)

At the end of both NSNBPSO iteration, each produced schedule will be checked whether it violates constraint (15) or not. If yes, then it will be checked each day if there are more than one assignment index then it will be chosen randomly assignment index for the day and deallocate the rest.

3. Deallocation method for constraint (9)

While performing moving particle process and at the end of iteration in NSNBPSO, it will be performed checking of whether the schedule produced violates constraint (16) or not. If yes, then it will check each day which physician got the assignment index 3 and then next day schedule will be deallocated to zero.

4. Deallocation method for constraint (10)

At the end of iteration in NSNBPSO, it will be checked whether it violates constraint (17) or not. If yes, then it will be checked for one month whether the physician workdays are more than num_days parameter and deallocates the physician workdays randomly until the physician workdays are equal or less than num_days parameter.

5. Deallocation method for Fitness Function (35), (38), (40)

At the end of iteration in NSNBPSO, total schedule count in a month for General Doctor, Pediatricians and Obstetrics/Gynecology. Then it will be chosen the highest total schedule count from each role in a month as maximum schedule then it will be added workdays to the existing schedules until it reaches maximum schedule. The workday addition process is performed by checking available schedule randomly while considering all constraints in this research.

6. PERFORMANCE RESULT

NSNBPSO with deallocation method successfully produced 10 solutions that did not violate any of this research constraints. Compared with previous research solution which only produce 1 solution, NSNBPSO provides more options for the decision maker to choose the best schedule for the condition. The performance comparison using Hypervolume, Coverage Rate and Processing Time were performed and as follows:

6.1. Hypervolume

Table 3: Hypervolume Performance Result

	Hypervolume Native	Hypervolume from Previous Research Solution	PerbandinganDe ngan Native
Solution-1	306699891,8	154466601,7	Native is bigger
Solution-2	157978811,5	154466601,7	Native is bigger
Solution-3	230061566,2	154466601,7	Native is bigger
Solution-4	63041245,44	154466601,7	Previous Solution is bigger
Solution-5	372810884	154466601,7	Native is bigger
Solution-6	203615160,1	154466601,7	Native is bigger
Solution-7	260759187,2	154466601,7	Native is bigger
Solution-8	225083449,1	154466601,7	Native is bigger
Solution-9	286433154,2	154466601,7	Native is bigger
Solution-10	253867284,7	154466601,7	Native is bigger

9 out of 10 solutions from BPSO has better hypervolume than previous research solutions. This shown that most of the solutions from NSNBPSO has better trade off compared with previous research solution.

6.2. Coverage Rate

Table 4: Coverage Rate Performance Result

NSNBPSO Solution-I			
	NSNBPSO	Previous Solution	Comparison Result
Count of Better Fitness Function	4	6	Previous Solution Has More
NSNBPSO Solution-II			
	NSNBPSO	Previous Solution	Comparison Result
Count of Better Fitness Function	6	4	NSNBPSO Has More
NSNBPSO Solution-III			
	NSNBPSO	Previous Solution	Comparison Result
Count of Better Fitness Function	6	4	NSNBPSO Has More
NSNBPSO Solution-IV			
	NSNBPSO	Previous Solution	Comparison Result
Count of Better Fitness Function	3	6	Previous Solution Has More
NSNBPSO Solution-V			
	NSNBPSO	Previous Solution	Comparison Result
Count of Better Fitness Function	6	4	NSNBPSO Has More
NSNBPSO Solution-VI			
	NSNBPSO	Previous Solution	Comparison Result
Count of Better Fitness Function	6	4	NSNBPSO Has More
NSNBPSO Solution-VII			
	NSNBPSO	Previous Solution	Comparison Result
Count of Better Fitness Function	6	4	NSNBPSO Has More
NSNBPSO Solution-VIII			
	NSNBPSO	Previous Solution	Comparison Result
Count of Better Fitness Function	5	5	The Total Count is Equal
NSNBPSO Solution-IX			
	NSNBPSO	Previous Solution	Comparison Result
Count of Better Fitness Function	5	4	Previous Solution Has More
NSNBPSO Solution-X			
	NSNBPSO	Previous Solution	Comparison Result
Count of Better Fitness Function	5	5	The Total Count is Equal
	Dominated by NSNBPSO	Dominated by Previous Solution	Equal
Count Solutions	5	3	2

In coverage rate indicator shown that 5 solutions out of 10 solution from NSNBPSO helped with deallocation method dominated previous research solution and 2 solutions out of 10 solutions are equal in better fitness function counts compared with the previous research solution. So, the coverage rate of NSNBPSO compared with previous research solution is 0.5.

6.3. Processing Time

Table 4: Processing Time Performance Result

Average Processing Time NSNBPSO (in seconds)	*Processing Time*Previous Solution (in seconds)
45,4890625	6,506

NSNBPSO was shown to have longer processing time compared with previous research algorithm. However, this is caused by more complex and longer process performed in NSNBPSO in order to perform multi objective optimization compared with previous research algorithm only which performed single objective optimization. The longer processing time in NSNBPSO can still be considered acceptable.

7. CONCLUSION

In this paper we successfully modified NBPSO combined with deallocation method to solve a constrained binary multi objective problem through multi objective optimization. NSNBPSO can be used as another approach to improve the quality service of RSUDSoediran Mangun Sumarso. For the next research, we may use another variant of BPSO instead of NSNBPSO.

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