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A crow search algorithm for aircraft maintenance check problem and continuous airworthiness maintenance program

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ABSTRACT

This research discusses the maintenance problem of a small commercial aircraft with propeller engine, typed ATR-72. Based on the maintenance records, the aircraft has average 294 routine activities that have to be monitored and done based on determined threshold interval. This research focuses on developing a metaheuristic model to optimize the aircraft's utility, called Crow Search Algorithm (CSA) to solve the Aircraft Maintenance Problem (AMP). The algorithm is developed and tested whether a younger metaheuristic method, CSA, is able to give better performance compared to the older methods, Particle Swarm Optimization (PSO) and other hybridized method PSO with Greedy Randomized Adaptive Search Optimization (PSO-GRASP). Several experiments are performed by using parameters: 1000 maximum iteration and 600 maximum computation time by using four dataset combinations. The results show that CSA can give better performance than PSO but worse than PSO-GRASP.

INTRODUCTION

The airline industry, which has a limited source of income, mainly depends on the revenues obtained by giving services to their passengers using their aircraft [1]. The resilience of the aircraft cannot match the high desire of airlines to use their aircraft in most cases. Each aircraft must be maintained periodically so that it has a longer lifetime and it is ready to be used whenever it is needed. When the maintenance is being carried out, the airline can not use their aircraft to do their operational activities. The airlines need better schedules to retain their incomes, which show when they operate the plane and when they send their aircraft to the maintenance facility. This kind of research is categorized as an Aircraft/Aeronautical Maintenance Problem (AMP) [1], [2].

Several types of research have been conducted similar to AMP, but with the additional route, constraints called Aircraft Maintenance Routing Problem (AMRP). Al-Thani, Ahmed, & Haouari [3] developed an exact mixed-integer programming model that includes a polynomial number of variables and constraints about the status of the Operational Aircraft Maintenance Routing Problem (OAMRP). Cui, Dong, & Lin [4] developed a heuristic method, variable neighborhood search (VNS) to improve their integer linear programming (ILP) that can generate a suboptimal solution quickly in a reasonable time to solve this kind of problem. Başdere, & Bilge [5] developed two types of AMRP models, ILP and heuristic method based on compressed annealing by modifying the connection network representation. Safaei, & Jardine [6] formulated a formulation of the aircraft maintenance routing problem in which maintenance requirements are built as generalized capacity constraints, ensuring sufficient maintenance opportunities are available within the planned routes to satisfy the maintenance demands of individual aircraft. Ezzinbi, et al [7] developed a combination of the Particle Swarm Optimization (PSO) algorithm and the Genetic Algorithm (GA) to minimize the total maintenance costs of AMRP. PSO is a metaheuristic method developed based on the behavior of a flock of birds or fish, where the organism's social behavior consists of individual actions and influences from other individuals in a group [8]. The results of these combination models showed the effectiveness of the solution in reducing computational time. Deng, Santos, & Curran [9] developed a practical dynamic programming based methodology to minimize the wasted interval between checks. The model takes aircraft type, status, maintenance capacity, and other operational constraints into consideration. Eltoukhy, et al [10] developed two models: mixed-integer linear programming (MILP) with a modified connection network and a solution algorithm model like compressed annealing (CA) to tackle medium and large-scaled problems of OAMRP. The results showed better solution qualities in much shorter computational times.

AMRP generally has a maintenance scheduling problem. The first maintenance activity that must be generated consists of developing a schedule for carrying out inspection activities called A-Check, C-Check, and D-Check. The other activities are certain routine maintenance activities that must be carried out in the hangar, namely as the Continuous Airworthiness Maintenance Program (CAMP). The difference between inspection activities and CAMP is the process carried out by inspection activities, not directly handling the requested components, but the parts must be visually inspected first [11]. The inspection process must be carried out on a scheduled basis, but the maintenance or replacement activity of a component depends on the results of inspection checks on the related part. CAMP activities are minor maintenance activities that are carried out based on directions from aircraft manufacturers, and the activities must be carried out on a scheduled basis [12]. Both of these activities must be well scheduled. Even though CAMP consists of minor maintenance activities, the maintenance activities must be carried out in the hangar. Thus, the aircraft cannot discharge for operational activities. The fewer aircraft maintenance intervals occur, the more productivity of the aircraft will be. Research on this issue has previously been carried out by Adianto, & Siswanto [13] for AMP problems using the Particle Swarm Optimization (PSO) metaheuristic method that has been hybridized with Greedy Randomized Adaptive Search Procedures (GRASP). The research shows that the developed PSO-GRASP can complete AMP well.

This research will develop further models using another metaheuristic method, namely Crow Search Algorithm (CSA). Crow Search Algorithm (CSA) is a population-based technique that works according to the habits of crows in finding food and storing food that has been obtained into their hidden nests [14]. CSA is one of the metaheuristic methods that is relatively new and has just been developed to solve engineering problems [14], DNA fragment assembly [15], and economic dispatch problems [16]. The authors are interested in developing CSA to solve AMRP and compare the results of previous researches [13] using PSO-GRASP.

RESEARCH METHODS

Problem Definition

There are two primary data used in this optimization process, CAMP and inspection check data, which consist of the latest maintenance/checking activity data as well as the number of working hours needed to carry out these activities. Inspection checks that will be considered do not only type A and B as conducted by Sriram, & Haghani [17] but all types of inspection, such as type A, type B, type C, biennial, and so on. The inspection type for the aircraft follows the policy of each airline as the aircraft owner. However, in determining the inspection interval time, the airline must consider Federal Aviation Regulations (FARs) for the operating environment and the intended use of the aircraft. Every maintenance interval must be set so that each inspection activity must provide the best value for the aircraft performances [18]. CAMP may undergo a revision, amendment, or change its activities following a decision issued by the aircraft manufacturer. The bill is carried out if the effectiveness of the previous CAMP arrangement is lower than the required standard. The airline equips with the Continuing Analysis and Surveillance System (CASS) to know the level of effectiveness. The objective of CASS is continuously conducting observations, investigations, data collection, analysis, and decision improvement actions to ensure that all parts of the maintenance program implemented can be run effectively [19].

Mathematical Formulation

Mathematical Model Index

There are several indexes used in this mathematical model. Explanations related to the index can be seen in the explanation below.

i : inspection activities (based on the Inspection Check Document) that must be carried out on the aircraft. $\bar{I} = \{1, 2, \dots, I\}$

r : maintenance activities (based on CAMP Document) that must be carried out on the aircraft. $\bar{R} = \{1, 2, \dots, R\}$

t : a collection of aircraft maintenance periods in a plan horizon of aircraft use. $\bar{T} = \{1, 2, \dots, T + 1\}$

Mathematical Model Variable

There are several variables used in the mathematical model. Explanation related to each variable is divided into several sections, including explanations related to decision variables, independent variables, and dependent variables. Below will be explained further related to the decision variable.

$x_{i,t}$: binary variable to define whether inspection activity i is done at the t period

$y_{r,t}$: binary variable to define whether maintenance activity r is done at the t period

The independent variables used in this mathematical model will be explained below.

n_i^{ins} : the nearest time (next do) inspection activity i being done

n_r^{main} : the nearest time (next do) maintenance activity r being done

t_i^{ins} : time threshold for inspection activity i

t_r^{main} : time thershold for maintenance activity r

γ_i^{ins} : time interval for inspection activity i being maintained

γ_r^{main} : time interval for maintenance activity r being maintained

d_i^{ins} : time duration for inspection activity i being maintained

u : minimum utility/operational time of aircraft when not maintained

h : planning horizon

The dependent variables used in this mathematical model will be explained below.

$o_{i,t}^{ins}$: the nearest converted time (next do) of inspection activity i being done at t period

$o_{r,t}^{main}$: the nearest converted time (next do) of maintenance activity r being done at t period

τ_i^{ins} : converted time threshold for inspection activity i

τ_r^{main} : converted time thershold for maintenance activity r

ϕ_i^{ins} : converted time interval for inspection activity i being maintained

ϕ_r^{main} : converted time interval for maintenance activity r being maintained

δ_i^{ins} : converted time duration for inspection activy i being maintained

c_t : the time of maintenance being done at t period

m_t : total time duration of all maintenances being done at t period

$\iota_{i,t}^{ins}$: the real interval for inspection activity i needed being done at t period

$\iota_{r,t}^{main}$: the real interval for maintenance activity r needed being done at t period

$\acute{\iota}_{i,t}^{ins}$: the real interval for inspection activity i not needed being done at t period

$\acute{\iota}_{r,t}^{main}$: the real interval for maintenance activity r not needed being done at t period

Mathematical Equation

Dataset I and R can be obtained through inspection and maintenance activity data that will be entered in the optimization model, while the T dataset requires certain calculations. Every routine inspection and maintenance activity have two-time units: calendar days and flight hours. Both datasets must be scheduled to follow sets of T which can be calculated in advance using equation (1).

$$\mathrm{T} = \left[\frac{h}{\min\left(\min\limits_{\mathrm{i}\in\bar{\mathrm{I}}}\left(\gamma_i^{ins}\right), \min\limits_{\mathrm{r}\in\bar{\mathrm{R}}}\left(\gamma_r^{main}\right)\right)}\right] + 1 \qquad (1)$$

The developed model can only process one unit of time, for example the daily unit. If there are components data that still has flight hours unit of time, they must be converted first to daily units. The conversion process can be carried out by dividing the time value in units of flight hours by the time value of flight hours targeted by the airline for specified aircraft in one day.

Equations (2), (4), (6), and (8) are used to convert next do, intervals, thresholds, and inspection duration data, consecutively. Equations (3), (5), and (7) are used to convert next do, intervals, and thresholds of CAMP activities, consecutively.

$$o_{i,t}^{ins} \begin{cases} n_i^{ins} & \text{, calendar days} \\ n_i^{ins} \;/\; u \text{ ,} & \text{flight hours} \end{cases} \qquad (2)$$

$$o_{r,t}^{main} \begin{cases} n_r^{main} & \text{, calendar days} \\ n_r^{main} \;/\; u \text{ ,} & \text{flight hours} \end{cases} \qquad (3)$$

$$\tau_i^{ins} \begin{cases} t_i^{ins} & \text{, calendar days} \\ t_i^{ins} \;/\; u \text{ ,} & \text{flight hours} \end{cases} \qquad (4)$$

$$\tau_r^{main} \begin{cases} t_r^{main} & \text{, calendar days} \\ t_r^{main} \;/\; u \text{ ,} & \text{flight hours} \end{cases} \qquad (5)$$

$$\phi_i^{ins} \begin{cases} \gamma_i^{ins} & \text{, calendar days} \\ \gamma_i^{ins} \;/\; u \text{ ,} & \text{flight hours} \end{cases} \qquad (6)$$

$$\phi_r^{main} \begin{cases} \gamma_r^{main} & \text{, calendar days} \\ \gamma_r^{main} \;/\; u \text{ ,} & \text{flight hours} \end{cases} \qquad (7)$$

$$\delta_i^{ins} \begin{cases} d_i^{ins} & \text{, calendar days} \\ d_i^{ins} \;/\; u \text{ ,} & \text{flight hours} \end{cases} \qquad (8)$$

Based on the index and the converted values, an aircraft maintenance schedule is arranged with the targetted schedule being developed to provide the maximum aircraft utilization value. The preparation of the aircraft maintenance schedule is calculated based on the model below.

$$\max \mathrm{Z} = \frac{\sum_{t\,\in\,\bar{\mathrm{T}}}\left(c_{t+1} - c_t\right)}{c_{T+1} + m_T} \qquad (9)$$

$$\sum_{i\in\bar{I}} x_{i,t} \geq 1, t \;\forall\; \bar{T} \qquad (10)$$

$$\sum_{r\in\bar{R}} y_{r,t} \geq 0, t \;\forall\; \bar{T} \qquad (11)$$

$$o_{i,t+1}^{ins} - o_{i,t}^{ins} \geq 0, i \;\forall\; \bar{I}\,, t \;\forall\; \bar{T} \qquad (12)$$

$$o_{r,t+1}^{main} - o_{r,t}^{main} \geq 0, r \;\forall\; \bar{R}\,, t \;\forall\; \bar{T} \qquad (13)$$

$$m_t - \sum_{i\in\bar{I}}\left(x_{i,t}\, \delta_i^{ins}\right) = 0, t \;\forall\; \bar{T} \qquad (14)$$

$$\iota_{i,t}^{ins} - x_{i,t}\left(c_{t+1} + \phi_i^{ins} + m_t\right) = 0, i \;\forall\; \bar{I}\,, t \;\forall\; \bar{T} \qquad (15)$$

$$\acute{\iota}_{i,t}^{ins} - \left(1 - x_{i,t}\right)\left(o_{i,t}^{ins} + m_t\right) = 0, i \;\forall\; \bar{I}\,, t \;\forall\; \bar{T} \qquad (16)$$

$$o_{i,t+1}^{ins} - \left(\iota_{i,t}^{ins} + \acute{\iota}_{i,t}^{ins}\right) = 0, i \;\forall\; \bar{I}, t \;\forall \bar{T} \qquad (17)$$

$$\iota_{r,t}^{main} - y_{r,t}\left(c_{t+1} + \phi_r^{main} + m_t\right) = 0, r \;\forall\; \bar{R}, t \;\forall\; \bar{T} \qquad (18)$$

$$\acute{\iota}_{r,t}^{main} - \left(1 - y_{r,t}\right)\left(o_{r,t}^{main} + m_t\right) = 0, r \;\forall\; \bar{R}, t \;\forall\; \bar{T} \qquad (19)$$

$$o_{r,t+1}^{main} - \left(\iota_{i,t}^{ins} + \acute{\iota}_{i,t}^{ins}\right) = 0, r \;\forall\; \bar{R}, t \;\forall\; \bar{T} \qquad (20)$$

$$x_{i,t}\, o_{i,t}^{ins} - c_{t+1} \geq 0, i \;\forall\; \bar{I}, t \;\forall\; \bar{T} \qquad (21)$$

$$y_{r,t}\, o_{r,t}^{main} - c_{t+1} \geq 0, r \;\forall\; \bar{R}, t \;\forall\; \bar{T} \qquad (22)$$

$$o_{i,t+1}^{ins} - \tau_i^{ins} \geq 0, i \;\forall\; \bar{I}, t \;\forall\; \bar{T} \qquad (23)$$

$$o_{r,t+1}^{main} - \tau_r^{main} \geq 0, r \;\forall\; \bar{R}, t \;\forall\; \bar{T} \qquad (24)$$

$$c_1 = 0 \qquad (25)$$

$$x_{i,t}, y_{r,t} \in \{0,1\} \qquad (26)$$

Equation (9) is an objective function of the model to minimize the total maintenance time. Equation (10) ensures that the maintenance decision generates at least consists of one inspection activity that must be carried out in each period. Equation (11) provides that the conclusion that there is no minimum limit for CAMP activities in each period. Equations (12) and (13) ensure that the next do value generated in period t + 1 always has a value higher than the value in period t in the inspection and CAMP activities, respectively. Equation (14) ensures the calculation of the total duration of maintenance activities equal to the length of each inspection activity in period t.

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Equations (17) and (20) calculate the value of next do in the period t + 1 of both inspection and CAMP activities in sequence. Calculations in equations (17) and (20) can only be done if equations (15) and (18) have finished being calculated, related to differences in values. Equations (16) are valid whenever activities need to be done in period t. Otherwise, equations (19) will be used. Equations (21) and (22) assure that the next do data in period t always have a higher value or the value of the current day variable in period t + 1 for both inspection and CAMP activities in sequence. Equations (23) and (24) ensure that the next do data in the t + 1 period always have a value greater or equal to the threshold value of the inspection and CAMP activities in sequence. Equation (25) ensures the value of the current days in period 1 has a value of 0. Equation (26) guarantees that the decision variables in both activity, inspection, and CAMP have binary values (0 or 1).

CSA Model

Crow Search Algorithm (CSA) is a population-based technique metaheuristic which works according to the habits of crows in finding and storing food that has been obtained into their hidden nests [14]. The hidden storage is carried out by crows so that other crows do not steal their food. The crow has good intelligence in a case it is going for food will pay attention to the movements of other birds and act following the conditions of these movements. When the crow is careless, the other crow steals food from the hidden nest left for hunting. Another intelligence ability possessed by crows is that they can recognize the faces of other crows.

Based on the ability of these crows, this CSA algorithm can be formed with the following conditions.

1. Crows live in a group.
2. The crow can remember the position of its secret storage.
3. Crows can follow other crows to steal other crows' prey.
4. The crow can protect its catch prey from the theft of other crows based on specific probabilities.

The CSA implementation, which aims to optimize the problems, has several procedures. Several main aspects can make the CSA method generate optimal solutions based on the behavior of crows, including the process of creating new positions for each individual and the memory of crows in storing prey information [14]. Calculations related to the process of generating the latest individual solutions can be seen in equations (31) and (32)

$$\mathrm{x}^{\mathrm{i},(\mathrm{iter}+1)}=\begin{cases}\mathrm{x}^{\mathrm{i,iter}}+\mathrm{r_i}\times\mathrm{FL}^{\mathrm{i,iter}}\times(\mathrm{m}^{\mathrm{j,iter}}-\mathrm{x}^{\mathrm{i,iter}}) & \mathrm{r_j}\geq\mathrm{AP}^{\mathrm{j,iter}}\\ \text{random position,} & \text{otherwise}\end{cases}\tag{31}$$

$$\mathrm{m}^{\mathrm{i},(\mathrm{iter}+1)}=\begin{cases}\mathrm{x}^{\mathrm{i},(\mathrm{iter}+1)} & \mathrm{f}\left(\mathrm{x}^{\mathrm{i},(\mathrm{iter}+1)}\right)\text{ better than }\mathrm{f}(\mathrm{m}^{\mathrm{i,iter}})\\ \mathrm{m}^{\mathrm{i},(\mathrm{iter}+1)} & \text{otherwise}\end{cases}\tag{32}$$

The two equations consist of two indices, including the following:

a. Individual set $\bar{I}$ $\{1,2,...,I\}$
b. Iteration set $\bar{K}$ $\{1,2,...,K\}$

Both of these equations have several interrelated variables:

$v_{p,a}$: individual p movement speed at iteration a

$x_{p,a}$: solution to individual p at iteration a.

$m_{p,a}$: the best solution of each individual to individual p at iteration a.

$\mathrm{r_p}$: random numbers in decimal form from 0 to 1 relating to individual p.

In equation (27), there are a number of parameters that can be adjusted manually as follows:

FL : the maximum speed at which each individual moves towards the generated solution.

AP : the ratio of alertness of each individual to other individuals.

All crows generate new target positions in the search space with the note that one crow will try to follow randomly chosen another crow to find out where the other crow is storing its food based on other crows' memory. In generating the latest solutions such as in equation (31), each individual considers the best position stored in their memories. The calculation of the memory of each individual can be seen in equation (32).

In the mathematical notation can be seen if the value of the destination function generated at the latest position is better then the memory will be updated according to the latest position. If not, the crow will then restore the memory of the previous position.

GRASP

GRASP is a method of finding optimal solutions developed by Feo, & Resende [20]. This method is adaptive so that it can be used in various optimization cases. The adaptability of this method is the generated solution will continue to be updated in each iteration following the represenative solution solved by the GRASP method. The GRASP method consists of two iteratively stages: the construction and the local search stage until the best solution is found.

The construction stage is carried out by generating solutions one by one. The made solutions will be rearranged following the calculation of the objective function (the local search stage). At the construction stage, the solution is increased only a small value as a representative of all expected solutions. When the construction phase is completed, a complete solution is generated by considering representative solutions that have been produced at the construction stage.

This study has decision variables in the form of a two-dimensional matrix: $x_{i,t}$ and $y_{r,t}$, each representing inspection tasks and CAMP, at each period ach metaheuristic iteration must produce these variables, as illustrated in Table 1. The metaheuristic iteration can sometimes provide solutions that violate some constraints. To avoid generating invalid solutions, GRASP is implemented in both metaheuristic methods and creates new decision variables filled with the inspection task ID, as illustrated in Table 2.

Table 1. The changes to decision variable form

	Per 1	**Per 2**	**...**	**Per T**
$In-1$	1	0	...	1
$In-2$	0	1	...	1
...	...	...	...	...
$In-I$	0	0	...	0
$Ca-1$	0	0	...	1
$Ca-2$	1	1	...	1
...	...	...	...	...
$Ca-R$	1	0	...	1

Table 2. The changes to decision variable form with GRASP

	Per 1	**Per 2**	**...**	**Per T**
$In-ref$	3	4	⋯	2

Optimation Model

The optimization model developed based on the PSO-GRASP and CSA methods, as in Fig. 1 [13]. Several stages need to be done so that the data can be processed into information and provide optimal calculation results. In the first stage, there is a process of generating data on the assignment of inspection activities using random numbers obtained from both metaheuristic methods.

The entire duration of treatment for each assigned activity is calculated and used to recalculate the end of maintenance activity. The length of the aircraft maintenance duration will affect the utilization of the aircraft. The longer the period, the lower the utilization value. The calculation results will then be validated to ensure the solutions generated do not violate predetermined limits. The optimal solution generated can be found if the value of the objective function or the utility value of the aircraft has a maximum value without any violations of the constraints.

```
Generate referred inspection task.
For ( from p ← 1 to p ← $\bar{P}$ )
    For ( from t ← 1 to t ← $\bar{T}$ )
        Update max period time.
        Update maintenance duration.
        Update next do value of the next period.
        Update utilization of the aircraft.
        Validate generated solution.
    End
    Compute objective function value for each
    solution population.
End
Save maximum objective value of each
generated population
```

Fig. 1. Pseudocode of the optimization model

Every violation committed will provide a penalty value for the objective function of which penalty in each period has a different value. The higher the period being analyzed and experiencing violations, the lower the punishment given. This rule will provide the highest penalty value when the breach occurs in the first period. The calculation of this penalty value can be seen in Equation (33). For example, when the process planning has a maximum period of T equals to 20, and the value is increased in several periods t = {1, 5, 20} and the process experienced a violation is then the penalty value obtained will be worth 2000, 1400 and 100 for each contravention in order. Based on the violation value in each of these periods, it can be concluded that the solution offered has a penalty value of 7400. The results of the penalty calculation are then processed into an objective function value by using equation (34).

$$penalty_t - 100(\bar{T} - t + 1) = 0 \qquad (27)$$

$$of\,value_p - \frac{\sum_{t \in \bar{T}} vld_{p,t}(c_{t+1} - c_t)}{c_{T+1} + m_T} + penalty_t\left(1 - vld_{p,t}\right) = 0 \qquad (28)$$

Experimental Design

There are several parameters used in the study based on the historizal data using the CSA method including inspection activities with 5 activities and 20 activities, combined with 500 and 1000 CAMP activities as in Table 3. Other parameters needed to run the optimization model are the two parameters of the CSA method, namely the parameters of Flight Length (FL) and Awareness Probability (AP).

Table 3. Instance dataset

Group	Inspection task	CAMP task
G1	5	500
G2	5	1000
G3	20	500
G4	20	1000

RESULTS AND DISCUSSION

The CSA model developed is run with the same objective data and functions as previous studies [13] The optimization calculation performed for each model will stop if the iteration has exceeded 1000 repetitions, or the time has reached more than 600 seconds. The test carried out is focused on testing with three planning horizon parameters: 730, 1460, and 2190 days. This condition applied because of internal circumstances.

The test results can be seen in Table 4. When compared with the results of the PSO method used in study Adianto, & Siswanto [13] with the ones of the CSA method developed, it appears that CSA is better than PSO, especially in small amounts of data. This can be seen from the objective function values of the G1 and G2 datasets for the CSA method, which can give positive value of 76 days, whereas the PSO method results are always negative. Negative values indicate that the solution generated violates certain restrictions. In the G3 and G4 datasets, the results of both PSO and CSA methods show negative values on the objective function value. The PSO-GRASP hybrid method in the research showed better results in the G3 and G4. PSO-GRASP can provide a positive utility value that indicates the solutions do not violate the rules that have been made.

Other results that can be seen from Table 4 are the effects of increasing planning horizon parameter inputs to the optimization results. The optimization results show in all optimization methods that if the planning horizon parameter values continue to increase, the computational time required for each optimization model will be higher. The shortest computational time can be achieved using the PSO-GRASP method. PSO-GRASP can use a short computational time because GRASP can make PSO find the best solution for smaller data because it has gone through the encoding and decode process.

Table 4. Comparison of output results of the heuristic method

ID	Planning Horizon	Group	PSO			PSO-GRASP			CSA		
			(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
Test01	730	G1	453	-277	600.39	782	78.14	110.45	798	76	199.77
Test02		G2	267	-3650	600.64	781	78.11	181.19	798	76	381.94
Test03		G3	1008	-11680	600.25	1100	49	258.64	1009	-14600	618.48
Test04		G4	807	-20440	600.15	923	48.43	390.59	772	-20440	620.55
Test05	1460	G1	639	-821	600.69	1776	77.03	197.65	1482	76	417.56
Test06		G2	480	-2920	600.19	1673	77.35	337.11	1482	76	600.00
Test07		G3	1839	-154760	600.85	2361	46.3	508.42	1829	-267180	620.05
Test08		G4	1804	-143080	600.93	2362	43.4	744.06	1901	-204400	623.57
Test09	2190	G1	856	-26280	601.53	2819	76.84	289.77	2280	76	581.74
Test10		G2	759	-56940	600.53	2669	76.89	496.17	2280	76	600.00
Test11		G3	2636	-575970	600.15	4171	41.99	600.32	2952	-954840	621.27
Test12		G4	2528	-917610	600.93	4419	41.46	600.52	2473	-992070	623.54

Note:
(a) Last Maintainance Finish Time (b) Objective Value (c) CPU Time

CONCLUSION

In this study, the authors investigate the implementation of the metaheuristic method, namely CSA for solving AMP and compare the previous results solved by means developed Adianto, & Siswanto [13]. The results of CSA optimization show that it can provide better performance than the ones of PSO, but cannot beat the performances of PSO-GRASP. In certain datasets, CSA still gives a negative value indicating that the solution still violates the constraints by setting the maximum number of iterations of 1000 iterations or maximum computing time of 600 seconds. CSA and PSO might be able to provide positive objective function values if the optimization process is carried out without considering these two parameters. The computational time used by the CSA method is better than PSO but still inferior to PSO-GRASP. The reason is that GRASP has encoded and decoded processes which can cut computational time in the process of finding an optimal solution. Many interesting topics can be further investigated, including hybridizing CSA with GRASP. This can be seen from the CSA method being able to outperform the PSO method, but when there is a hybrid between PSO and GRASP (becoming PSO-GRASP), the performance of the PSO method is better and exceed of CSA. The hope is that the hybrid CSA with GRASP can improve optimization performance better than CSA or even PSO-GRASP. For subsequent related research, researchers can try to develop another scope of the flight inspection and maintenance scheduling case by reducing the assumptions used in this optimization model. Besides, researchers can focus more on the obtained results of the methods to gain more varied solutions by not sacrificing the value of the objective function obtained

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