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Optimisation of Flight and Maintenance Planning for Defence Aviation with Modified Artificial Bee Colony Algorithm

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ABSTRACT

The planning of flight operations and maintenance is a crucial activity for both commercial and military aircraft. Military aircraft have to be always mission-ready. The task of ensuring this can become quite challenging when several operational requirements and maintenance constraints are to be fulfilled simultaneously. This paper, therefore, addresses the optimisation of flight and maintenance planning (FMP) when several diverse factors such as aircraft flying hours (AFH), flight cycles (FC), calendar life, annual flying requirement (AFR), etc. are to be factored in. Such a problem has not been considered previously. Because the problem can become unwieldy to solve by other methods, two schemes, that is, the genetic algorithm (GA) and modified artificial bee colony (ABC) algorithm for constrained optimisation have been utilised. The objective is to maximise the utilisation rate (UR) of aircraft, while also satisfying other operational and maintenance constraints. The algorithm is tested on a fleet of eight aircraft. In addition to a one-year planning period, a planning horizon of ten years has also been simulated. The results show that both the GA and modified ABC algorithm can be effectively used to solve the FMP problem.

Keywords: Optimisation; Flight; Maintenance planning; Defence aviation; Genetic algorithm; Artificial bee colony algorithm

NOMENCLATURE

ABC	Artificial bee colony
AFH	Annual flying hours
AFH_i	It is the number of flying hours of an aircraft over one year
AFR	Annual flying requirement
CFT	Cumulative flight time. It is the sum of actual flying hours flown by aircraft
FC	Flight cycle. Comprises of one take-off and landing
FC_i	the number of flight cycles of aircraft *i* on day *t*
FH_i	Flying hours
FH_i	The number of hours aircraft *i* has flown on day *t* of the month
FMP	Flight and maintenance planning
GA	Genetic algorithm
IP	Integer programming
max_yr	Maximum Hours an aircraft can fly per year
N_active_t	the minimum number of active aircraft on any day *t*
OPR	Operational aircraft. Number of aircraft actually flown
S_i	Decision parameter of the algorithm that indicates whether aircraft *i* is active or in storage
sust	Sustainability. It is the number of flying hours before an aircraft is due for maintenance or inspection
sust_min	Minimum sustainability
$sust_t$	Sustainability at a given time *t*
SVC	Serviceability. The number of aircraft which are fly-worthy at any given time
TAD	Total available days. It is the number of days an aircraft is available for Flying
TFA	Total Fleet Availability. The sum of the residual flight hours of all aircraft before they fall due for maintenance
Ts	Starting day of the 30-day period over which *UR* is calculated
UR	Utilisation Rate. The average number of hours an aircraft flies every month
UR_i	Utilisation Rate of i^{th} aircraft

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1. INTRODUCTION

Military aviation requires that a minimum number of serviceable aircraft are always available to meet various requirements and a certain number of hours are flown by each aircraft every month and over the year. Simultaneously, various kinds of maintenance tasks or inspections have to be performed on aircraft to keep them in a serviceable state. A need, therefore, arises to balance flying and maintenance to ensure that both flying and maintenance requirements are met. This activity is called flight and maintenance planning (FMP). During the FMP, it is decided as to which available aircraft can fly, for how long, and on which aircraft, maintenance can be performed. Currently, there are various methods by which FMP is carried out, the most common of them being, manually. The U.S. Department of the Army[1] uses a technique called sliding scale scheduling or aircraft flowchart graphical tool. However, such manual methods can prove very time consuming when a large number of aircraft and constraints are involved. In the following sub-sections, several alternatives are discussed to a manual approach proposed in the commercial and defence sectors.

1.1 Related Works

1.1.1 Commercial Aviation

FMP had its origins in the commercial aviation sector. Flight scheduling and routing have been subjects of interest in the operations research field for many decades. However, before the 1970s the amount of optimisation work in the flight scheduling domain was limited due to the lack of computational resources. The first formulation of a practicable linear integer program (IP) to solve for optimal flight scheduling, routing, and fleet size was carried out in 1971 by Levin[2]. Since then, various works regarding flight scheduling and routing, crew scheduling, equipment selection, usage, and passenger-mix were carried out. Models and methods were developed by Feo & Bard[3] to deal with maintenance planning in complex routing networks. Hane[4], *et al*. carried out fleet assignment for a daily, domestic flight schedule including maintenance constraints. These models were generalised and improved upon by Clarke[5], *et al*. and Sriram and Haghani[6] to capture additional aspects of maintenance scheduling, including a heterogeneous fleet of aircraft. Papakostas[7], *et al*. also proposed long-term and short-term operational aircraft maintenance planning methodologies.

1.1.2 Defence Aviation

Aircraft maintenance scheduling under various constraints, for the Swiss Air Force, has been discussed by Steiner[8]. Mixed IP has been a common approach to solve this problem as done by Cho[9]. Pippin and Bradley[10] established a mixed IP flight hour allocation model for army helicopters. An optimisation model in which the FMP problem is formulated as a mixed-integer linear program with the twin objectives of maximising the number of available aircraft and maximising the number of available flight hours was developed by Kozanidis and Skipis[11]. Work was done by Safaei[12], *et al.* on a mixed-integer optimisation model for workforce-constrained maintenance scheduling for a fleet of military aircraft that could be solved by generic optimisation software. Kozanidis[13], *et al.* addressed the problem of generating a joint flight and maintenance plan for a unit of mission aircraft. A linear programming optimisation model for FMP for the Royal Netherlands Air Force's CH-47D Chinook transport helicopter fleet was developed by Verhoe[14], *et al*. A mixed-integer linear programming approach was adopted by Shah[15], *et al.* to carry out aircraft maintenance planning for the Sukhoi-30MKM fleet of the Royal Malaysia Air Force. Similarly, more recently, Peschiera[16] *et al.* used Mixed Integer Programing for long term planning of French Airforce aircraft's flight and maintenance operations.

1.2 Contribution of this Paper

Heuristics approaches used to solve the FMP problem have often performed poorly in the past as seen by Gavranis and Kozanidis[17]. Kozanidis[13], *et al*. and Kozanidis[18], *et al*. have stated that the linearised approach is suboptimal. Also, in[13] and[18] the optimisation problem is split into smaller problems and each parameter optimised independently. Whereas in this paper, a joint optimal approach has been adopted and optimisation over the entire fleet, and not individual aircraft is carried out. Cho[9], Pippin and Bradley[10] and Raju[19], *et al.* have used aircraft serviceability (SVC), which is the number of flight-ready aircraft at any given point, as a performance measure which is akin to the fully mission capable rate. To the best of the authors' knowledge, no FMP solution has yet been proposed which fulfills the multiple requirements of minimum serviceable aircraft, monthly and yearly flying hours, etc., while taking into consideration different types of maintenance inspections (calendar based, flight-time and flight-cycle based). Such a scheme is therefore attempted in this paper. Genetic Algorithm (GA) and the modified Artificial Bee Colony (ABC) Algorithms have been used. A new objective function is formulated to maximise the Utilisation Rate (UR). Flight and maintenance plans have been implemented for a period of one year and also for a large period of ten years. The details of population size and optimisation variables are explained in Section 2.4. GA and ABC were chosen because simulating flight patterns for such a long period of time would make exhaustive search algorithms prohibitively expensive in terms of computational time. GA and ABC are probabilistic methods that do not search the entire solution space and are contemporary algorithms for solving complex problems.

2. METHODS

2.1 System Model

The problem involves meeting the following conditions *simultaneously*:

- At least a certain number of aircraft should be in a serviceable state.
- No aircraft should fly more than a specified number of hours per year (*max_yr*).
- Annual Flying Requirement (*AFR)* for the unit is met.
- Each aircraft flies a minimum number of hours per month.
- Sustainability and serviceability are always above a minimum threshold.

The following assumptions have been made:-

- All aircraft are homogenous in terms of age, type & make, and service history.
- The type and periodicity of maintenance inspections, are independent of the age of the aircraft, and will not change in the planning period.
- Unscheduled corrective maintenances carried out to rectify unforeseen defects, if any, are not considered.

To re-capitulate, *FH* denotes flying hours, that is, the number of hours flown by each aircraft. *FC*, the flight cycle is one take-off and landing. *UR*, is the average number of hours aircraft fly every month. Let us denote UR_i as the *UR* of the i^{th} aircraft, FH_i as the number of hours aircraft *i* has flown on day *t* of the month and FC_i as the number of landing-take off cycles of aircraft *i* on day *t*. Then, we can derive the formula for the calculation of UR_i as follows:

$$UR_{i,Ts} = \frac{\sum_{t=Ts}^{Ts+30} (FH_{i,t} * FC_{i,t})}{30} * S_i,\ \forall i \in [1,8] \tag{1}$$

where

$$S_i = 1,\ \forall\ i \in Active\ Aircraft \tag{2}$$

$$S_i = 0, \forall\ i \in Inactive\ Aircraft(or\ in\ storage) \tag{3}$$

T_s is the starting day of the 30- day period over which *UR* is calculated and S_i is a decision parameter of the algorithm that indicates whether aircraft *i* is active or in storage.

2.2 Problem Formulation

Based on the discussion in the previous section, the problem can be formulated as:

$$maximize \sum_t \sum_i UR \tag{4}$$

subject to the constraints of:

$$N\_active_t = 5, \forall t \in [1, T] \tag{5}$$

$$AFH_i \leq 880, \forall i \in [1, 8] \tag{6}$$

$$\sum_i AFH_i \geq AFR \tag{7}$$

$$UR\_active_{i,t} \geq UR\_min, \forall i \in [1, 8], t \in [1, T] \tag{8}$$

$$\sum_i SVC_{i,t} \geq SVC\_min, \forall i \in [1, 8], t \in [1, T] \tag{9}$$

$$sust_t \geq sust\_min, \forall t \in [1, T] \tag{10}$$

$$FH_j - FH_{j-1} \leq 147, \forall j \in maintenance\ dates \tag{11}$$

$$FC_j - FC_{j-1} \leq 37, \forall j \in maintenance\ dates \tag{12}$$

The optimisation objective, shown by Eqn (4) is the *UR* summed over the aircraft and the planning horizon. Equation (4) is therefore the objective function that is to be maximised. N_active_t is the minimum number of active aircraft available for flying on any day *t*. AFH_i or Annual Flying Hours are the daily *FH* of an aircraft summed over one year. *AFR* is the total flying hour requirement from the fleet comprising all the aircraft, over a year. Equation (5) states that the number of active aircraft at any given time N_active_t should be 5. Equation (6) sets the constraint that the annual flying hours do not exceed 880 h. Equation (7) sets the condition that the annual flying hours is at least equal to or greater than the annual flying requirement. Equation (8) sets the constraint requiring the *UR* of every active aircraft to be greater than the minimum value. Equation (9) sets the constraint for the total number of serviceable aircraft at any time to be greater than a minimum. The minimum figure has been chosen as 5. Equation (10) sets the requirement for sustainability (the remaining flight time of aircraft before they need to be serviced or inspected) to be greater than a minimum at any given time. Equations (11) and (12) require that flight hours and flight cycles of any aircraft do not exceed a particular value between two consecutive scheduled calendar maintenance dates. These have been set, for academic interest as 147 and 37 respectively. Scheduled total fleet availability (*TFA*) increases by the number of residual flight hours (147 hours) whenever a maintenance inspection is completed on an aircraft. Cumulative flight time (*CFT*) is the sum of actual flying hours achieved by the aircraft during flying. *SVC* is the number of fly worthy aircraft on any day, while the number of aircraft that are actually flown are operational aircraft (*OPR*). Availability is the total duration of flight readiness of the aircraft or fleet over the entire planning horizon.

2.3 FMP Using Modified ABC Algorithm

In recent times several constrained optimisation problems have presented themselves in which it is in-feasible to search the entire solution space. For such problems, evolutionary algorithms present a viable method of optimisation. ABC algorithm proposed by Karaboga[20], is a typical meta-heuristic optimisation approach which provides a search process based on the intelligent behaviours of honey bees. ABC algorithm by default, is an unconstrained optimisation algorithm. To handle constraints in this problem, the ABC algorithm has been modified to handle constraints using Deb's rules as done by Sharma and Anpalagan[21]. The aircraft maintenance cycle and other parameters are fed as inputs to the ABC algorithm. Deb's rules consist of a probabilistic selection scheme for feasible solutions based on their fitness values and in-feasible solutions based on their violation values.

2.4 Initial Population

The colony consists of the daily flight hours and flight cycles of each aircraft. After each iteration in the population, the fleet parameters serviceability and utilisation rate are calculated from the colony values and are used to evaluate the constraint violation and objective function. Figure 1 shows a sample initial population for eight aircraft for a planning period of one year, 360 days. The *FH* and *FC* are allocated for each day of the year for each aircraft. The *FH* can take any value satisfied by the constraint that *FH* for each aircraft per day should be at least 2 and not exceed 6. The value of *FC* is '0' if the aircraft does not fly, and '1' if it flies. The initial population of random solutions *FH* and *FC* are randomly generated for each of the 360 days for each of the eight aircraft. The random solutions for two aircraft and part of the eighth aircraft are shown in Fig. 1. Therefore, for a fleet of eight aircraft, the dimension of each element in the colony works out to be a large number, ie., 360 x 8 x 2 = 5760. Correlating with the honey bees' behaviour, every element of the initial population is a randomly generated food source. This corresponds to the random solution to the problem. In each iteration, for each solution in the population, the fitness value is the nectar amount, which is calculated using the optimisation function and constraint violations. In each iteration, the best (food) source is selected based on Deb's rule. The Pseudo code of the algorithm is shown in Fig. 2.

3. SIMULATION AND RESULTS

MATLAB ™ has been used to implement the model. HP Pavilion 15- p028TX Notebook, with Intel Core i3 Processor (4th Generation), Clock Speed: 1.9 GHz, 8 GB DDR3 RAM was used. The simulations were carried out for a period of one year because the FMP is usually done for one year. The actual values of the parameters have not been mentioned for preserving confidentiality. The maximum hours each aircraft needed to fly in the year (*max_yr*) were allotted different values, Max Flying Hour (*FH*)/day was chosen as 6h, Minimum *FH*/ day as 2h, and the *AFR* was also set to different values. The exact values chosen are mentioned in the appropriate places. For the initial simulation, *max_yr* was chosen as 880h and the *AFR* as 2500h. A mention of how the control parameters of the ABC algorithm were chosen would be relevant here. It is

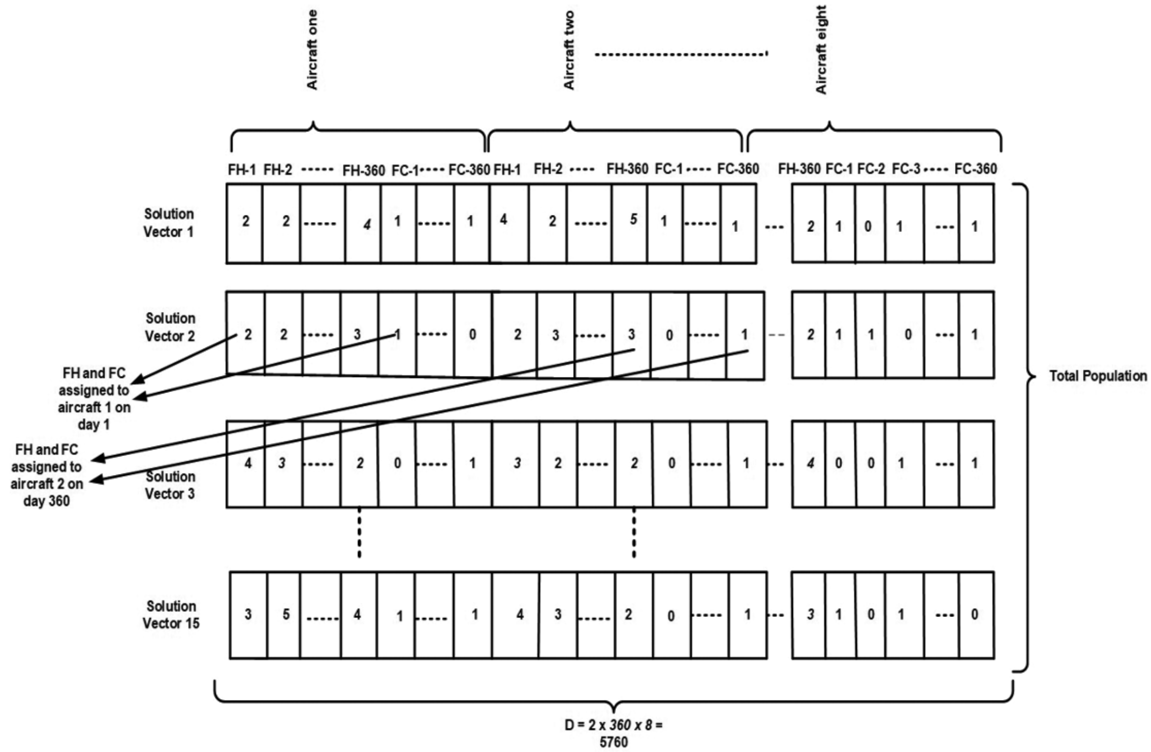

Figure 1. The population matrix for eight aircraft.

Pseudo Code
1. Inputs for ABC algorithm
Parameters for ABC algorithm
Np = colony size (employed bees + onlooker bees)
Food Number = Np/2, Food Number decides the number of solutions tested per iteration - accordingly Np is chosen
max.cycles = After how many iterations, the algorithm should stop, i.e., stopping criteria is decided by 'max.cycles'
D = No. of variables in the optimization problem
SPP = scout production period
FMP Problem Related Parameters
$N\_active_t = 5$
$AFH_i \leq 880$
$FH_j - FH_{j-1} \leq 147$
$FC_j - FC_{j-1} \leq 37$
2. Generate **random initial population** (**food sources**) $x_{i,j}$ with inputs as number of *FH* and *FC*, as shown in figure 1, for each aircraft using the expression
$x_{i,j} = \min(x_{i,j}) + (\max(x_{i,j}) - \min(x_{i,j})) * \text{rand}(0,1)$
3. Evaluate this initial population using equation (4) to (12)
4. set cycle = 1
5. repeat
6. Generate **new food source positions** (solutions) in the neighbourhood of $x_{i,j}$ using the expression
$x_{i,j} = x_{i,j} + \emptyset(i,j)(x_{i,j} - x_{k,j})$
where 'k' is a solution in the neighbourhood of i, $\emptyset$ (i,j) is a random number generated in the range [-1,1]
7. Evaluate these solutions
8. Apply greedy selection between x_i and v_i
9. Probabilities of each of these solutions x_i is calculated based on their **fitness values** (**nectar**) as follows
$P_i = fit_i / \sum_{i=1}^{Sn} fit_i$
where Sn is the number of food sources.
The fitness fit_i is calculated as
Fitness(x_i) = $1/(1+f_i)$, **if $f_i \geq 0$** (or) Fitness(x_i) = $1 + \text{abs}(f_i)$, **if $f_i < 0$**,
where f_i is the objective function value for the solution x_i
Normalize the values of probabilities obtained into [0,1]
10. Produce new solutions v_i for the onlooker bees using x_i, assign probabilities to them, and based on that evaluate the solutions
11. Based on greedy selection select between x_i and v_i
12. Determine the abandoned food sources. If there are any abandoned sources, replace them with new food sources produced by scout bees. The new food sources are produced by scout bees using the following expression
$x_{i,j} = \min(x_{i,j}) + (\max(x_{i,j}) - \min(x_{i,j})) * \text{rand}(0,1)$
13. memorize the best food source found so far
14. set cycle = cycle+1
15. run till cycle = max.cycles

Figure 2. Pseudo code for ABC algorithm.

a well-known fact that the choice of parameters plays an important role in the effectiveness of the ABC algorithm. If the best or optimum parameters are not chosen correctly, premature convergence may result, diversity in the search space may not happen, and intensification of search around best solution regions may not take place. Therefore, different values of control parameters were chosen before each run and their effects on the performance of the ABC algorithm were investigated. Based on such manual analysis, in the simulations, the value of modification rate (*MR*) equal to 0.8, colony size (*NP*) equal to 30, Food Number equal to 15 (colony size / 2), and the maximum generations equal to 15000 was used. The scout production period (*SPP*) is equal to 0.5 x *NP* X *D*, where *D* is the dimension of the problem. Experiments were repeated 30 times each starting from a random population with 15 food sources. For each parameter setting, the simulations were carried out 30 times and the average of those are presented here as results obtained by the proposed schemes. Simulations were carried out for both GA and modified ABC algorithm.

3.1 Cumulative Flight Time, Total Fleet Availability and Utilisation Rate

The efficacy of the algorithm in determining the parameters of interest, namely the *CFT*, *TFA*, and *UR*, for the number of aircraft and the planning horizon are explained in this section.

3.1.1 Cumulative Flight Time, Total Fleet Availability

Figure 3 shows the *TFA* and *CFT* of the fleet of eight aircraft on the Y-axis against the number of days in the planning period on the X-axis. The number of days in the planning period is 360. As mentioned earlier, *TFA* is simply the sum of the residual flight time (147 hours) of each aircraft when it comes out of maintenance and commences flying. Also, the *CFT* is the sum total of the hours flown by each aircraft. The cumulative flight times are shown for both the algorithms, ABC and GA. In Fig. 3, the *CFT* ultimately obtained at the end of 360 days for the ABC algorithm and GA are seen to be equal. On a few other days, the *CFT* for ABC algorithm is a little lower as compared to that of GA, which means aircraft offer themselves for more maintenance opportunities should a need arise, while still achieving the maximum *CFT*.

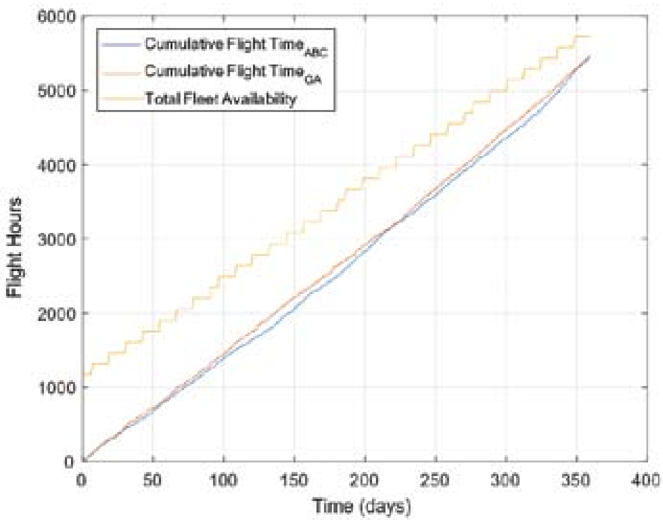

Figure 3. Cumulative flight time and total fleet availability.

3.1.2 Utilisation Rate

Figure 4 depicts the UR, that is, average hours flown by aircraft for each month in the planning horizon of 360 days. Figure 4 shows that the mean utilisation rate achieved by the ABC algorithm is greater than that achieved by GA. Further, Figs. 3 and 4 show that ABC and GA perform similarly in terms of cumulative flight time and utilisation rate per month.

3.1.3 Time for optimisation, Average Serviceability, Average Operational Aircraft

Table 1 shows the time taken for optimisation, *TFA*, *CFT*, average *SVC*, average *OPR,* and fleet *UR* over a period of 360 days for eight aircraft calculated by ABC algorithm and GA. It can be seen that the ABC algorithm took 3590s to calculate all these parameters. It can also be seen from Table 1, that GA takes more than 6.9 times the amount of time taken by ABC to achieve the final solution. The ABC outperforms GA in terms of maximum fleet UR and average OPR.

Table 1. Comparison of ABC and GA performance

Algorithm	*t*	*TFA* (*T*)	*CFT* (*T*)	Avg *SVC*	Avg *OPR*	Fleet *UR*
ABC	3590s	5880	5463	7.9111	3.7222	57.69
GA	24892s	5880	5470	7.9111	3.6444	56.01

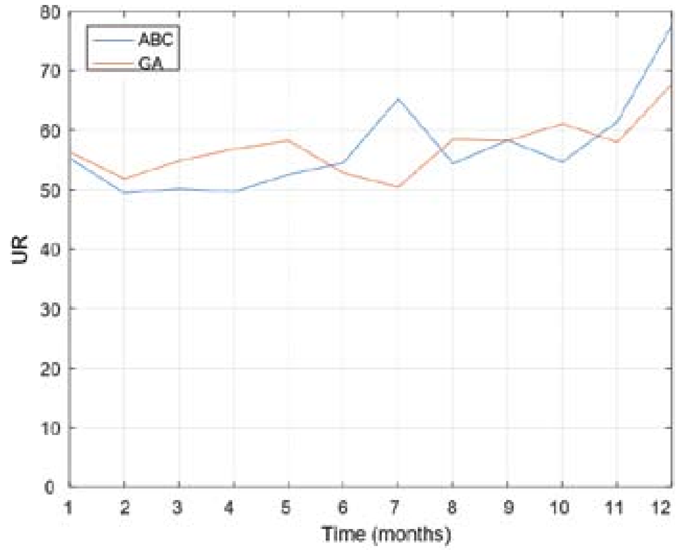

Figure 4. Mean utilisation rate for each month.

3.2 Convergence with Number of Generations

The results of convergence with the number of generations are shown in Fig. 5. In this figure, the objective value, namely the UR is plotted against the number of generations keeping the population size constant as 50, the number of aircraft as 8, and the time period as 360 days. Figure 5 shows that the ABC algorithm converges far faster than GA and reaches close to a value of approximately 57.5 in a fraction of the generations (1.1 e4) taken by GA (1.6 e6), thus reducing the amount of time we require to obtain a solution using ABC algorithm. It is to be noted here that the values on the y-axis of Fig. 5 are negative since the objective function is actually being minimised.

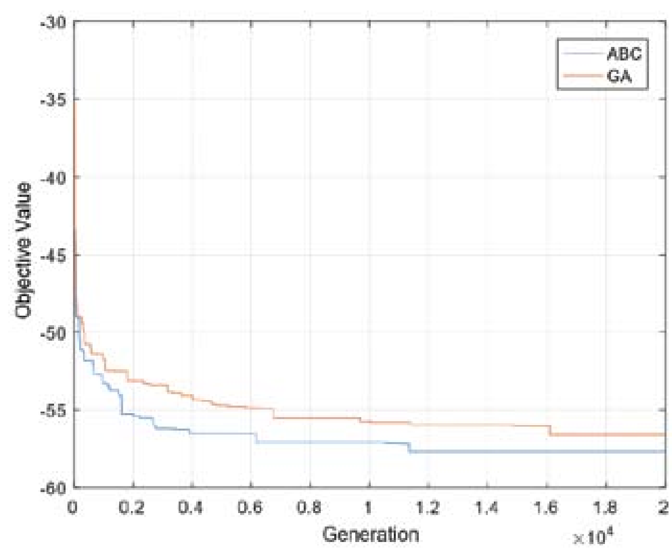

Figure 5. Convergence of objective value with generations.

3.3 Convergence with Population Size

In Fig. 6, the objective value is plotted against population size, keep the number of generations constant at 15000, the planning period as 360 days, and the number of aircraft as 8. Figure 6 shows that the ABC algorithm, compared with the GA, converges faster with population size as well. This implies

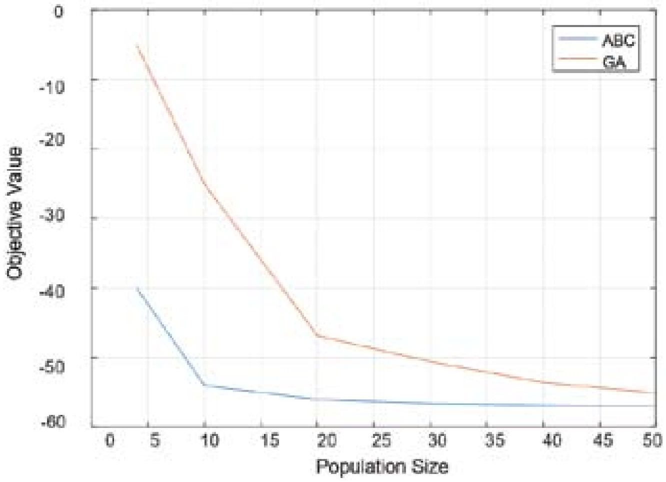

Figure 6. Convergence with population size.

we need fewer computational and memory resources to run the ABC algorithm.

3.4 Flight and Maintenance Planning

Figure 7 shows the number of operational aircraft out of the total of 8, which have actually flown for each day of the planning horizon of 360 days while using the ABC algorithm. Similarly, Fig. 8 for GA depicts the number of operational aircraft obtained for each day of the year, while using GA. These plots can assist the operators and maintainers in planning which aircraft to fly and which not to.

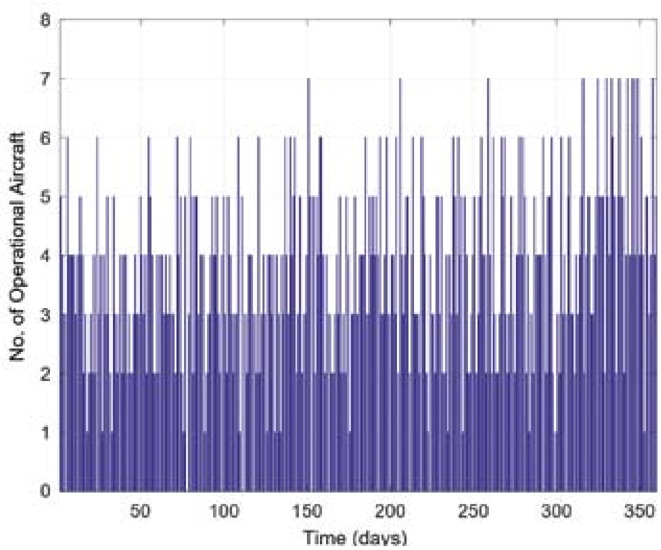

Figure 7. Operational Aircraft vs Day of the Year computed by ABC.

3.5 Ten Year Simulation

After carrying out FMP for a period of one year, the planning period was extended for a longer duration and considered a period of ten years. The advantage was taken of the fact that minor variations are permitted in the maintenance cycle parameters, that is, maximum hours each aircraft can fly in a year, annual flying requirement, maximum and minimum hours to be flown per day, to find out more optimised maintenance

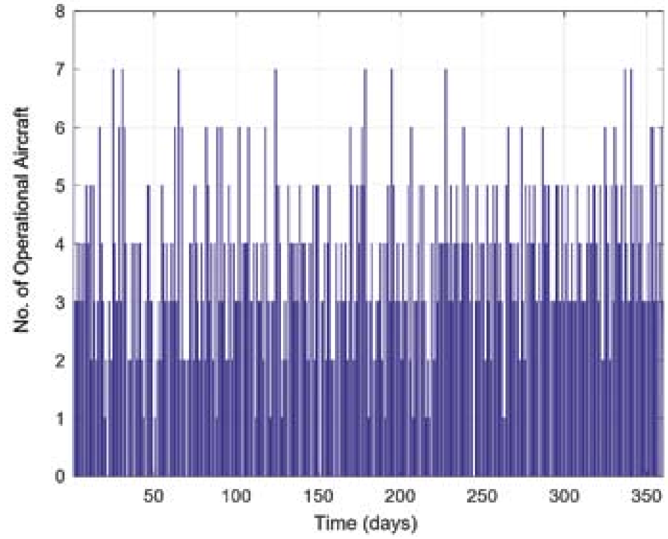

Figure 8. Operational Aircraft vs Day of the Year computed by GA.

cycle conditions for the ten-year simulation. Simulations were carried out for three different values of the number of maximum hours an aircraft can fly in a year (*max_yr*), namely 600h, 880h & 1000h. For each of these three values, Table 2 shows the *CFT* (*Total*), average *SVC*, average *OPR*, mean *UR,* and the *TAD* of each of the eight aircraft in each year of the planning horizon of ten years. The values obtained are very encouraging since they meet those desired by the user.

Table 2. Fleet performance vs *max_ yr* for max *FH*/Day =6, min *FH*/Day =2, *AFR*=2500

Parameter	*CFT* (*T*)	Avg *SVC*	Avg *OPR*	Mean *UR*	*TAD*
600	4641	7.9111	3.2806	48.3438	144 152 140 154 152 155 142 156
880	5021	7.9111	3.4278	52.3021	144 146 149 155 153 154 155 154
1000	5168	7.9111	3.5111	53.8333	140 149 148 154 157 152 162 153

For example*, SVC* of 7.9111 (out of 8 aircraft) for all the three *max_yr* values of 600h, 880h, and 1000h, indicates that almost the entire fleet of 8 aircraft is serviceable, that is fly-worthy and the number of serviceable aircraft is well above 5 as specified by equation (5). Similarly, the values of mean *UR*, that is 48.3438h, 52.3021h, 53.8333h indicate that the aircraft can be exploited in an optimum manner allowing time for flying and maintenance. For example, when *max_yr* is 600h, the maximum, equal hours aircraft can fly every month is 600/12 which is 50h. A figure of 48.343h has been obtained which can be considered satisfactory. The average *OPR* values generated of 3.2806, 3.4278, and 3.5111 ensure that the aircraft can be flown in a conservative manner and yet achieve the annual flying hours required. The *TAD* for each of the eight aircraft which ranges from 140 to 162, in each year of the 10-year period, would ensure that sufficient time is available for planned and unforeseen maintenance even when the requisite annual flying hours and *UR* are attained. In

Table 3, the parameter *AFR* takes four different values, 2000h, 3000h, 4000h, and 5000h, and the corresponding *CFT*, average *SVC*, average *OPR*, mean *UR,* and *TAD* are shown. The values obtained are again similar to that in Table 2 and very desirable as already explained above. In Table 4, the parameter daily flight limits (maximum and minimum hours each aircraft is to fly per day) are varied (as 6h and 2h, 8h and 2h and 8h and 0h) and the corresponding *CFT*, average *SVC*, average *OPR*, mean *UR* and *TAD* are shown. Taking the optimum data from these three tables, the parameters used for the 10- year simulation were: *max_yr*=1000, *AFT* =3000, Max Min *FH*/Day = 6,2. The population size= 30 and maximum iterations = 15000. The outcomes are shown in Tables 5, 6, and Fig. 9. Table 5 shows that an avg *SVC* of 7.8133 (out of 8 aircraft) can be obtained which is very good, well above the requirement of minimum 5 serviceable aircraft. The mean *UR* of 47.9625h per month also is well within a figure of 75h per month. The average *TAD* for each aircraft in each year of the 10-year period ranges from 140 to 165. This means that an aircraft is available approximately half a year for flying and other half-year for maintenance also. Figure 9 shows the *CFT* and *TFA* for the entire simulation period of 10 years. Again, the findings are similar to that of Fig. 3 described in section 3.1.1 above.

Table 3. Fleet performance vs *AFR* for max *FH*/Day = 6 h, min *FH*/Day =2 h, *max_ yr*=1000 h

Parameter	*CFT* (*T*)	Avg *SVC*	Avg *OPR*	Mean *UR*	*TAD*
2000	5152	7.9111	3.556	53.6667	151 152 145 153 151 160 160 162
3000	5036	7.9111	3.4889	52.4583	140 147 147 151 157 154 159 160
4000	5213	7.9111	3.5806	54.3021	151 149 150 153 162 161 156 160
5000	5234	7.911	3.55	54.52	144 151 153 154 151 155 161 165

Table 4. Fleet performance vs max Min *FH*/Day for *max_ yr* =1000, *AFR* =5000

Max	Min	*CFT* (*T*)	Avg *SV C*	Avg *OPR*	Mean *UR*	*TAD*
6	2	5234	7.911	3.55	54.52	144 151 153 154 151 155 161 165
8	2	5306	7.9111	2.9694	55.2708	136 135 145 144 143 142 148 152
8	0	5149	7.9111	3.5	53.6354	145 148 150 154 150 155 160 158

Table 5. Performance metrics of 10 yr simulation

Metric	Value
TFA(T)	47040
CFT(T)	46044
Avg SVC	7.8133
Avg OPR	3.1767
Mean UR	47.9625

Table 6. Total available days of each aircraft

Aircraft No.	TAD
1	1452
2	1470
3	1459
4	1460
5	1474
6	1464
7	1474
8	1469

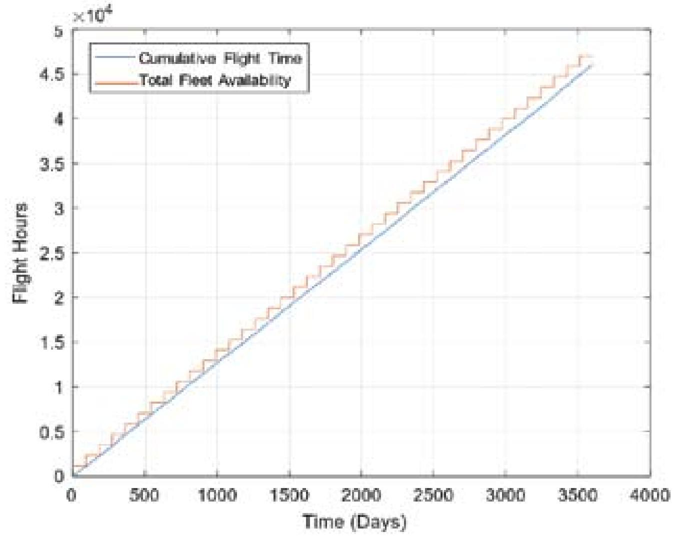

Figure 9. CFT and TFA for full-length simulation.

4. DISCUSSION AND FUTURE WORK

The high average serviceability, along with non-violation of the constraints is an indication that a smooth phase flow is observed in the maintenance cycle, resulting in a highly sustainable fleet where 7 out of 8 aircraft are available for operations nearly all throughout the planning horizon. Thus, this model incorporates more features of the problem than previous models, namely, calendar-based servicing along with flight time and flight cycle-based inspection, and constraints of sustainability, serviceability, flight requirement, and operational aircraft. The implementations with GA and modified ABC algorithms have yielded very useful results. It is also seen that the modified ABC algorithm outperforms the GA by a wide margin in terms of computational time, fleet *UR* and *OPR*, while satisfying all the requirements of the aircraft fleet. The benefits of using this scheme include the following: It applies to more realistic scenarios owing to the added parameters. It can be used to simulate for far longer periods of time than existing works. The model is especially useful when maintenance cycle tables/constraints need to be changed or several maintenance cycles need to be tested to determine the most favourable as the model can quickly run simulations for large periods of time and provide informative fleet metrics. Suggested future work includes adding more parameters such as the distinct maintenance cycles of individual parts of the aircraft (engine, airframe, etc.) and testing the performance on actual flight hour logs instead of simulations.

5. CONCLUSION

The optimisation of flight and maintenance planning carried out with GA and modified ABC algorithm achieves very encouraging results when there are several diverse parameters and requirements to be dealt with. This paper has considered flying hours, calendar-based, and flight cycle-based maintenance inspections. The results have been validated as being optimised due to the findings enumerated in Sections 3.1.1, 3.1.2, 3.1.3, and 3.5. The solutions obtained for the parameters of utilisation rate, annual flying requirement, maximum/minimum flying hours, average serviceable, and operational aircraft are found to be very optimal. It has also been seen that the modified ABC algorithm performs much faster than the GA and simulates long term flight plans in a practicable time frame. This scheme would be very useful to commercial and defence aviation to meet their respective objectives.

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