Abstract
Flight and Maintenance Planning (FMP) addresses the question of which available aircraft should fly and for how long, and which grounded aircraft should perform maintenance operations, in a group of aircraft that comprise a unit. The objective is to achieve maximum availability of the unit over the planning horizon. The availability of a unit is expressed in terms of the total number of aircraft that are available to fly and of the total residual flight time (remaining flight time until next maintenance) of all available aircraft. Computational experience with optimization models that have been developed for the FMP problem shows that their computational effort increases rapidly with problem size. As a result, the applicability of these models on large problems is quite limited. To this end, we study two heuristic solution procedures for the FMP problem in this work and we present results which illustrate their computational performance and evaluate the quality of the solutions that they produce. A very important outcome of the analysis of these results is that, besides maximizing the fleet availability level, it is also very crucial to ensure that this level remains relatively constant throughout the entire planning horizon. A novel multiobjective formulation that addresses this issue is proposed, along with some important properties which point to several interesting directions for future research.

Key Words: Fleet Availability, Flight and Maintenance Planning, Multiobjective Mixed Integer Linear Program, Heuristic Solution Procedures.

1. Introduction
Flight and Maintenance Planning (FMP) addresses the question of which available aircraft should fly and for how long, and which grounded aircraft should perform maintenance operations, in a group of aircraft that comprise a unit. The objective is to achieve maximum fleet availability over the planning horizon. Fleet availability is expressed in terms of the total number of aircraft that are available to fly (aircraft availability) and in terms of the total residual flight time of all available aircraft (residual flight time availability). The residual flight time of an aircraft is defined as the total remaining time that this aircraft can fly before it has to be grounded for maintenance check. FMP is a very
important decision making problem arising in the operation of numerous types of fleets, involving military or fire-fighting aircraft, rescue choppers, etc.

The research literature dealing with airline operations is quite rich. Most of the published research in this area, however, has been directed towards problems in the commercial airline industry, which have different objectives and requirements than those in the Air Force. Several authors have presented reviews of models and methods for problems related to airline operations. Arguello et al. (1997) study models and methods for dynamic management of airline operations in case of irregular situations. Gopalan and Talluri (1998) survey models and solution techniques for various airline problems that include fleet assignment and maintenance routing decisions. Barnhart et al. (2003) present an overview of several important areas of operations research applications in the air transport industry, as well as a brief summary of the state of the art.

In the context of military aircraft operations, Radosavljevic and Babic (2000) consider the problem of determining the optimal assignment of fighter plane formations to enemy formations and solve it via fuzzy logic and integer linear programming. Kurokawa and Takeshita (2004) propose a neural network method for air transportation planning in the Japan Air-Self Defense Force. This method partitions the master problem into three subproblems which are successively solved by three neuron blocks. Yeung et al. (2007) develop a model-based methodology for mission assignment and maintenance scheduling of systems with multiple states. The authors utilize heuristics and simulation to solve the model and illustrate its application on a hypothetical scenario of a fleet of aircraft.

FMP is an important decision making problem encountered in several diversified areas (see for example Jardine and Hassounah, 1990). The published research dealing with the FMP problem as described in this work, however, is rather limited. Sgaslik (1994) introduces a decision support system for maintenance planning and mission assignment of a helicopter fleet, which partitions the master problem into two subproblems. The first subproblem is used to assign helicopters to inspections and to exercises, while the second one is used to assign helicopters to missions. The author develops two elastic mixed integer programs to formulate these two subproblems and solves them using standard optimization software. Pippin (1998) develops a mixed integer linear program and a quadratic program to model the flight hour allocation problem. Both models try to find a flight hour allocation that ensures a steady-state sequence of aircraft into phase maintenance. The U.S. Department of the Army has released a Field Manual (US DoA, 2000), which describes an “aircraft flowchart”, for scheduling periodic inspections and deciding which aircraft should fly in certain missions. The first heuristic approach that we study in this work is based on this tool.

2. FMP Optimization Models

One of the most crucial decisions that need to be made towards the development of optimization models for the FMP problem regards the choice of the objective function. Maximizing the readiness to respond to external threats is the most appropriate measure of effectiveness for this application. This readiness is usually defined as the total number of aircraft that are available to fly; however, this number alone gives no information about the way that the total residual flight time of the wing is distributed across the squadrons and the individual aircraft. Therefore, a first important question that arises is whether the
aircraft or the residual flight time availability of the unit should be the overall model objective.

A combat wing is one of the main elements in the hierarchy structure of a typical Air Force and is typically subdivided into squadrons. Wing officials are responsible for monitoring the wing’s availability, while squadron officials are responsible for monitoring the availability of each individual squadron. Thus, besides maximizing the fleet availability of the wing, it is also very important to maximize the fleet availability of each squadron. Although a certain degree of synergy seems to exist between wing and squadron availability, optimizing one of the two may, in some cases, have a negative effect on the optimization of the other. For example, it may be necessary for the availability of a squadron to assume a value smaller than its optimal, in order for the availability of the wing to be maximized. As a result, a related issue that needs to be addressed is whether maximization of the wing or of the squadron availability should have higher priority.

Another relative important issue is whether the minimum or the total fleet availability over a given planning horizon should be the overall objective. In the first case, the model will focus on finding the maximum fleet availability level that can be ensured in each time period of the planning horizon. In the second case, the model will focus on finding the maximum fleet availability that can be attained cumulatively over all time periods of the planning horizon. One of the ways to address this issue is to maximize the total fleet availability over all periods, while also imposing a constraint which ensures that it will not drop below a critical level in any period of the planning horizon.

Objective related issues like the ones discussed above can be addressed with the development of multiobjective optimization models for the FMP problem, such as the one proposed by Kozanidis and Skipis (2006). That model is a mixed integer linear program (MILP) with 4 objectives: maximization of the minimum aircraft and residual flight time availability of the wing and of each squadron, respectively. In order to avoid dealing with multiobjective models and the difficulties that such problems introduce, another alternative is to adopt a single one out of these objectives and replace the remaining ones with associated constraints. In this case, however, the obtained solution may not be satisfactory with respect to the objectives that were omitted. This is because the model will only focus on providing given bounds for them, without any special concern for optimizing them.

The above discussion implies that a number of different factors should be taken into consideration when choosing the overall objective function of the model. The user should make this decision based on the specific characteristics and requirements of each application. Furthermore, a systematic study that considers different objective functions may be necessary in order to reach the most preferable solution.

3. Heuristic Solution Procedures

Computational experience with optimization models that have been developed for the FMP problem shows that their computational effort increases rapidly with problem size. As a result, their applicability on large problems is quite limited. This raises the need to develop alternative intelligent approaches that will enable us to address large FMP instances. To this end, we compare the computational performance and solution quality of two heuristic solution procedures for the FMP problem in this work. The development of these
procedures is presented in detail by Kozanidis et al. (2008). In the next sections, we use the terminology and notation introduced in that work and in the work by Kozanidis and Skipis (2006), which, for space consideration, are not literally repeated here.

3.1 Aircraft Flowchart Heuristic (AFH)

AFH is based on the “aircraft flowchart” (US DoA, 2000), which is a 2-dimensional graphical tool currently being used for the production of military aircraft flight and maintenance plans not only in the Hellenic Air Force (HAF) but in many other Air Force organizations worldwide, too. The aircraft flowchart provides a visual representation of the fleet availability of a unit. It tries to establish a wide range of equally spaced aircraft grounded for maintenance service. This prevents bottlenecks in the maintenance station and ensures a smooth utilization of the maintenance station. More importantly, it ensures a fairly constant level of aircraft availability.

A very important characteristic of AFH is that the solution that it returns for a given problem instance is always the same, independently of what the exact objective functions of the model are. This is because AFH does not directly try to maximize the fleet availability, but expects that this will be achieved through the minimization of the total deviation indices (see Kozanidis et al., 2008). As a result, even when a solution with higher fleet availability exists, AFH will prefer another one with lower, if this leads to a lower deviation index.

Current requirements for reporting a unit’s availability do not always give a clear picture of its actual level of readiness, since the aggregate report figures do not contain individual aircraft residual flight time data. As a result, officials often report certain aircraft as available, although their actual residual flight time is practically too small to enable them to participate in missions. For example, Pippin (1998) refers to a real case in which a unit reporting a high level of readiness for deployment was not able to deploy when called to do so, due to the lack of proper individual flight hour management which was previously unnoticed. Based on this discussion, another advantage of AFH is the fact that by establishing a better separation in phase inspections and a smooth utilization of the maintenance station, it prevents such undesirable situations.

Two variants of AFH called AFH1 and AFH2 are described in Kozanidis et al. (2008). These variants function in a similar way and exhibit very minor differences. Their application requires a number of minor decisions in each period of the planning horizon. For this reason, they compute a “priority index” for each squadron at the beginning of each period, and make all relevant decisions thereafter based on this index. The first such decision regards the allocation of the maintenance station’s time capacity to the grounded aircraft. The priority index of squadron $m$ in period $t$ is defined as the flight load of squadron $m$ in period $t$, divided by its total residual flight time at the beginning of period $t$. The maintenance station gives priority to the aircraft that belong to the squadron with the highest priority index first, and so on.

Besides determining the order in which the aircraft will receive maintenance service, the priority indices are also used to determine the order in which the squadrons will occupy dock space that is emptied at the maintenance station. Thus, the aircraft that belong to the squadron with the highest priority index value are considered first, and so on. In the work of Kozanidis et al. (2008), the decision of whether a specific aircraft will be grounded in
period $t+1$ or not is made based on whether its current residual flight time is smaller or equal to its current proportionate flight load. The proportionate flight load of each available aircraft is computed by dividing the flight load of the corresponding squadron by the total number of available aircraft in that squadron.

In general, the aircraft and the residual flight time availability increase as the number of aircraft exiting the maintenance station in each period increases, too. Therefore, it is very important that the maintenance station always remains busy, in order to ensure that there is a constant stream of aircraft finishing maintenance. In view of this, the performance of the heuristic seems to improve when it grounds every aircraft that can finish its maintenance service in a single period. This observation has also been confirmed through computational experiments and has led us to revise the rule for grounding aircraft. Thus, the new rule that has been adopted is that, whenever a dock space is available, the aircraft with the lowest residual flight time from the squadron with the highest priority index is grounded if a) its proportionate flight load over the current period is greater or equal to its residual flight time at the beginning of the same period, or if b) this aircraft will finish its maintenance service in one period. Checking whether an aircraft will finish its maintenance service in one period or not is trivial, since the time capacity of the maintenance station is known. The above rule for determining whether an aircraft should be grounded or not has been adopted for both AFH1 and AFH2. The remaining steps of the two heuristics are exactly the same as described in Kozanidis et al. (2008).

The FMP problem exhibits a myopic behavior which stems from the fact that it must be solved repeatedly in successive planning horizons. In order to see why this is true, consider the case in which an aircraft must be normally grounded for maintenance at the beginning of the first period of the next planning horizon, i.e. period $T+1$. When this aircraft is grounded in that period, the unit’s fleet availability could decrease (and in any case won’t increase), even if it completes its maintenance service in a single period. This is due to the fact that this aircraft can not exit the maintenance station before the second period of the next planning horizon. As a result, the solver will have no motivation to ground this aircraft for maintenance in that period. This could have a negative impact on the objective function values of the model over the next planning horizon, since it increases the likelihood that the maintenance station will remain idle and the stream of aircraft finishing maintenance will be interrupted. In view of this and in order for the results of the heuristic to be directly comparable with the results obtained by MILP, the two variants of AFH have been slightly modified. Thus, only aircraft that will exit the maintenance station by period $T+1$ are grounded for service by AFH1 and AFH2. Although this is a decision which is inefficient in the long term, as explained above, the novel formulation that we propose in Section 4 addresses this issue quite successfully.

### 3.2 Horizon Splitting Heuristic (HSH)

This heuristic makes use of the simple idea of splitting the original planning horizon into several consecutive ones, and solving an FMP subproblem for each of them. The smaller horizons do not necessarily need to have equal lengths. The quality of the solution obtained this way is expected to be inferior to the one obtained when the problem is solved up front for the entire planning horizon. On the other hand, the total computational time needed in order to reach a solution is expected, in general, to decrease, especially as the length of each smaller horizon decreases. This is mainly because the computational effort needed to
reach an optimal solution with MILP is expected, in general, to increase with problem size, as verified by the computational results of the next section.

4. Computational Results

In this section, we present results that compare the performance and the quality of the solutions obtained by the heuristic procedures with those of MILP.

4.1 Experimental Design

AFH1 and AFH2 were coded in C/C++ and the code is available upon request. For the solution of MILP and the application of HSH, we apply the weighted sums approach (see Steuer, 1986). Although many alternative approaches exist (see Steuer, 1986 and Ehrarat, 2005), we chose this approach because the solutions that it returns are guaranteed to be nondominated (Steuer, 1986). The user should keep in mind that, in many cases, this approach may only return very few of the existing nondominated solutions, even if the objective weights are diversified.

We consider two distinct sets of objective functions for the model. In the first case, the objectives are the maximization of the total number of available aircraft and of the total residual flight time of all available aircraft, collectively over all periods of the planning horizon. In a way, the wing and each squadron are weighed equally in this case. Therefore, using the notation introduced by Kozanidis and Skipis (2006), the two objectives of the model are the following:

Max $z_1$

Max $z_2$

s.t. $z_1 \leq \sum_{m=1}^{k} \sum_{n=1}^{N} \sum_{t=2}^{T} a_{mnt}$

$z_2 \leq \sum_{m=1}^{k} \sum_{n=1}^{N} \sum_{t=2}^{T} y_{mnt}$

In this case, we introduce strictly positive weights $w_1 = w_2 = 0.5$. For scaling reasons, we multiply the first objective with $Y/2$. This is because increasing $z_1$ by 1 is on the average equivalent to increasing $z_2$ by $Y/2$. A single criterion problem is obtained by substituting these two objectives with the new objective, $\text{Max } Z = (Y/2)w_1 z_1 + w_2 z_2$ and keeping the original functional constraints of the model.

In the second case, the model maximizes the minimum number of available aircraft of the wing and of each squadron, respectively, and the minimum residual flight time of the wing and of each squadron, respectively, over all periods. Using the notation introduced by Kozanidis and Skipis (2006), the 4 objectives of the model in this case are the following:

Max $z_1$
In this case, we introduce strictly positive weights $w_1 = w_2 = w_3 = w_4 = 0.25$. For scaling reasons, we multiply the first objective with $Y/2$, the second objective with $|M|(Y/2)$, and the fourth objective with $|M|$. This is because increasing $z_1$ or $z_2$ or $z_4$ by 1 is on the average equivalent to increasing $z_3$ by $Y/2$, $|M|(Y/2)$ and $|M|$, respectively. A single criterion problem is obtained by substituting the four original objectives with the new objective, Max $Z = (Y/2)w_1z_1 + (Y/2)|M|w_2z_2 + w_3z_3 + |M|w_4z_4$ and keeping the original functional constraints of the model.

For the application of HSH, we apply the weighted sums approach, too. Using the procedure for obtaining a single objective problem described above, we apply the heuristic by splitting the original FMP problem into two subproblems, each having a horizon with half the length of the original one. The resulting mixed integer linear programs of MILP and HSH were solved using version 9.1 of AMPL/CPLEX (see Fourer et al., 2002), with default values where possible. All experiments were performed on a Pentium IV/1.8 GHz dual core processor, with 1 GB system memory.

We used 10 different combinations for the values of $|M|$, $|N_m|$ and $T$ and solved 10 random instances for each of them. The value of $|N_m|$ was always the same across all squadrons. The required flight time for each squadron and period combination was a random number distributed uniformly in the interval $[16|N_m|, 21|N_m|]$. The time capacity of the maintenance station in each period was a random number distributed uniformly in the interval $[21|M||N_m|, 26|M||N_m|]$ and the space capacity was set equal to $0.2|M||N_m|$, rounded down to the nearest integer. The number of available aircraft of each squadron at the beginning of each planning horizon was set equal to $0.8|N_m|$, rounded down to the nearest integer. The residual flight time of each available aircraft was a random number distributed uniformly in the interval $[0,Y]$ and the residual maintenance time of each non-available aircraft was a random number distributed uniformly in the interval $[0,G]$. The values of the other parameters were $L = 0.95$, $U = 1.05$, $Y = 300$, $G = 320$, $X_{\text{max}} = 50$, $Y_{\text{min}} = 0.1$ and $G_{\text{min}} = 0.1$. Several checks were performed after each instance was generated, to ensure that it was feasible.

The results of our computational experiments are shown in Tables 1-4. Table 1 presents the solution quality comparison for the 1st set of objectives. More specifically, columns 4-5, 7-
8 and 10-11 of Table 1 show the average and maximum percentage difference between the weighted sums objective value of the solution obtained by the heuristics and that one of the solution obtained by MILP. The columns entitled “IF” show the number of instances for which the heuristics did not return a feasible solution. Columns 13 and 14 show the average and maximum percentage difference between the weighted sums objective value of the solution obtained by MILP and the one that results when the ideal values (see Ehrgott, 2000) of the objectives are used. Of course, a feasible solution for which these values are simultaneously realized may not (and usually will not) exist. Table 2 presents the same results with Table 1 but for the 2nd set of objectives.

| $|M|$ | $|N_m|$ | $T$ | AFH1 % from MILP | AFH2 % from MILP | HSH % from MILP | MILP % from Ideal |
|---|---|---|---|---|---|---|---|
| 3 | 4 | 8 | 7.19 | 10.93 | 2 | 5.20 | 9.37 | 4 | 7.45 | 10.17 | 3 | 4.90 | 5.88 |
| 3 | 4 | 10 | 10.52 | 16.77 | 1 | 7.63 | 11.98 | 3 | 5.71 | 7.19 | 4 | 4.61 | 5.29 |
| 3 | 6 | 6 | 1.87 | 5.83 | 0 | 1.00 | 3.06 | 0 | 3.53 | 5.28 | 3 | 3.16 | 4.23 |
| 3 | 8 | 8 | 2.00 | 3.98 | 0 | 1.67 | 3.25 | 1 | 3.98 | 4.75 | 6 | 4.10 | 6.23 |
| 3 | 8 | 4 | 1.28 | 4.55 | 0 | 0.59 | 1.09 | 0 | 2.62 | 2.93 | 0 | 3.27 | 3.83 |
| 3 | 8 | 6 | 2.45 | 6.27 | 0 | 2.12 | 3.53 | 0 | 5.26 | 6.68 | 0 | 3.78 | 4.68 |
| 3 | 10 | 4 | 0.84 | 2.00 | 1 | 0.26 | 0.92 | 0 | 3.05 | 6.24 | 0 | 2.37 | 2.72 |
| 4 | 4 | 4 | 3.82 | 8.91 | 0 | 0.90 | 1.69 | 1 | 2.03 | 3.90 | 0 | 1.68 | 3.02 |
| 4 | 4 | 6 | 3.91 | 6.96 | 0 | 0.37 | 0.59 | 1 | 3.38 | 5.11 | 1 | 3.03 | 3.85 |
| 4 | 6 | 4 | 2.03 | 6.81 | 1 | 1.87 | 6.81 | 1 | 2.56 | 2.95 | 1 | 2.98 | 3.61 |

Table 1. Comparison of solution quality for the 1st set of objectives

| $|M|$ | $|N_m|$ | $T$ | AFH1 % from MILP | AFH2 % from MILP | HSH % from MILP | MILP % from Ideal |
|---|---|---|---|---|---|---|---|
| 3 | 4 | 8 | 10.56 | 17.02 | 2 | 15.03 | 20.67 | 4 | 9.61 | 27.14 | 2 | 4.90 | 10.90 |
| 3 | 4 | 10 | 20.18 | 31.09 | 1 | 24.45 | 47.09 | 3 | 3.72 | 11.73 | 3 | 1.88 | 3.76 |
| 3 | 6 | 6 | 6.37 | 11.84 | 0 | 11.96 | 17.65 | 0 | 6.76 | 9.66 | 3 | 2.42 | 7.16 |
| 3 | 8 | 4 | 5.56 | 9.42 | 0 | 11.79 | 21.96 | 1 | 3.96 | 9.28 | 4 | 3.41 | 8.36 |
| 3 | 8 | 6 | 4.04 | 7.72 | 0 | 9.51 | 16.17 | 0 | 7.28 | 10.84 | 1 | 3.38 | 5.66 |
| 3 | 8 | 8 | 6.20 | 11.40 | 0 | 13.40 | 17.92 | 0 | 8.34 | 12.83 | 1 | 3.97 | 6.80 |
| 3 | 10 | 4 | 3.40 | 7.21 | 1 | 12.07 | 47.67 | 0 | 7.03 | 12.14 | 1 | 3.79 | 5.85 |
| 4 | 4 | 4 | 7.59 | 18.23 | 0 | 8.49 | 11.71 | 1 | 6.36 | 12.31 | 1 | 0.57 | 2.02 |
| 4 | 4 | 6 | 11.43 | 19.89 | 0 | 8.17 | 18.12 | 1 | 1.45 | 3.36 | 3 | 0.30 | 1.70 |
| 4 | 6 | 4 | 8.66 | 17.14 | 1 | 13.17 | 19.23 | 1 | 9.38 | 14.48 | 1 | 3.33 | 6.74 |

Table 2. Comparison of solution quality for the 2nd set of objectives

Tables 3 and 4 compare the computational requirements of MILP and HSH. More specifically, columns 4-5 of Table 3 show the average and maximum computational requirements of MILP for the first set of objectives and columns 6-7 show the average and maximum computational requirements of MILP for the second set of objectives. For some combinations, no solution was returned within a preset time limit of 30 minutes (1800 seconds). For these problems, the objective function values of the solutions that had been found at the end of this time limit were used in the computations of Tables 1 and 2, since these solutions were always feasible. Table 4 shows the same results as Table 3 for HSH. Such results are not reported for AFH1 and AFH2, since their computational requirements are negligible for the problem sizes reported in Tables 3 and 4.
Table 3. Computational requirements (in seconds) for MILP

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Table 4. Computational requirements (in seconds) for HSH

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4.2 Discussion of Results

A first important observation that we can make based on the results of Tables 3 and 4 is that the size of the problem alone is not indicative of the computational effort needed to reach an optimal solution in the case of HSH and MILP. This becomes evident from the fact that even for the same combination, a large variance is exhibited in the computational times required for their execution. Therefore, besides the problem size, the actual values of the problem parameters also have a strong influence on the total computational effort of MILP and HSH.

With respect to the quality of the obtained solutions, MILP always produces the solution with the highest quality, which is additionally guaranteed to be nondominated (see Steuer, 1986). Moreover, the optimal values of the 4 objectives in the solutions produced by MILP appear to be close to their ideal values (see Ehrgott, 2005). This is mainly due to the fact that the objectives of the model are not in direct conflict with each other, but there exists a certain degree of synergy among them. It should be noted though, that the best solution is obtained when all of them are treated as objectives, otherwise the obtained solution may not be satisfactory with respect to the objective that was omitted. This is because if we replace one of the objectives with a corresponding constraint, the model will only focus on providing a given bound for it, without any special concern for optimizing it.

The quality of the solutions produced by AFH1 and AFH2 increases significantly when the 1st set of objectives is used instead of the 2nd one. In fact, the solutions produced by AFH1 and AFH2 are quite satisfactory with the 1st set of objectives and often unacceptable with the 2nd one. Therefore, these two variants of AFH seem more appropriate for the case in
which it is more important to maximize the total availability over all periods than to maximize the minimum availability over all periods.

Tables 3-4 demonstrate that the heuristic procedures can result in considerable computational savings, especially for large problem sizes. These savings, however, come at a price, since the quality of the solutions that they return is inferior to the quality of the solutions obtained by MILP. The quality of the solutions produced by AFH2 when the 1st set of objectives is used seems to be slightly higher than that of the solutions produced by AFH1 and HSH. When the 2nd set of objectives is used, the quality of the solutions produced by AFH1 and HSH seems to be higher than that of the solutions produced by AFH2.

The solutions produced by HSH, AFH1 and AFH2 are dominated in general. As Tables 1 and 2 depict, they may be infeasible in some cases, even if the original problem is not. For HSH, this is a consequence of the fact that it focuses on optimizing fleet availability for each subhorizon separately, which in turn may lead to a solution at the end of some horizon which is inadequate and incapable of satisfying the flight requirements of the next one. On the other hand, the reason that this may sometimes happen in the case of AFH1 and AFH2 is because they make the relevant decisions sequentially in each period; thus, it is possible to reach a later period in which some of the problem’s constraints can not be satisfied. In such cases, the user has to go back and revise his previous decisions in order to reach a feasible solution. In general, a careful design should address accordingly such difficulties that may arise. Tables 1 and 2 show that the number of instances for which HSH was not able to find a feasible solution was larger than that of AFH1 and AFH2. Similarly, the number of instances for which AFH2 was not able to find a feasible solution was larger than that of AFH1.

An interesting observation that arises from the analysis of the computational results is that since FMP is an on-going problem that is repeatedly solved in successive horizons, the number of periods for which the wing command issues the flight requirements has a strong impact on the long term availability of the unit. As the number of periods over which the command issues the flight requirements increases, the fleet availability of the unit is expected to increase, too, given, of course, that these requirements are kept the same in both cases.

Another interesting observation stemming from the fact that the problem must be solved repeatedly in successive horizons is that such a myopic behavior will always be present, independently of what the exact length of each horizon is. This gives us a strong motive to try to find the maximum fleet availability that can be kept relatively constant over time. This can be achieved by also minimizing the variability of the obtained fleet availability between different time periods, besides maximizing its value. Of course, this has the prerequisite that the flight requirements issued by the wing command will not fluctuate significantly from horizon to horizon. In view of this discussion, the following two objectives can be added in order to accommodate this issue:

\[
\text{Min} \sum_{t=2}^{T+1} (SA_t - \bar{SA})^2
\]
\[
\text{Min} \sum_{t=2}^{T+1} (SY_t - \bar{SY})^2
\]
In the above two expressions, $SA_t$ and $SY_t$ are the total aircraft and the total residual flight time availability, respectively, of period $t$, while $\overline{SA}$ and $\overline{SY}$ are the average aircraft and the average residual flight time availability, respectively, of all periods. As a result of the addition of these two objectives, the model will not only search for the maximum fleet availability level that can be attained, but will also try to ensure that this level does not vary significantly from period to period.

5. Conclusions and Future Research

In this work, we studied two heuristic solution approaches that enable us to solve large FMP instances. We presented experimental results with two sets of objectives, which illustrate the computational performance of these heuristics and evaluate the quality of the solutions that they produce. The analysis of these results provides important insight into the behavior of the heuristics. The first heuristic tries to ensure a smooth utilization of the maintenance station and to prevent bottlenecks, by establishing a smooth sequence of aircraft grounded for service. The solutions produced by this heuristic seem to be quite satisfactory for the 1st set of objectives; however, they are often unacceptable for the 2nd one.

The second heuristic that we studied exhibits a myopic behavior due to the fact that, by construction, it focuses on consecutive subhorizons and not on the entire planning horizon of a given problem. Nevertheless, the solutions that this heuristic produces for practical applications seem to be acceptable. What is even more important is that the computational requirements of both heuristics seem to be considerably smaller than those of the FMP model.

An interesting conclusion that should be pointed out based on the findings of this work is that knowing in advance the flight requirements of the wing command for a greater number of periods can increase the fleet availability of the unit. Another important conclusion is that, besides maximizing the fleet availability level, it also seems very important to try to minimize its variability, in order to ensure that this level remains relatively constant over time.

A very promising direction for future research is the development of an exact branch and bound algorithm, capable of solving for all nondominated solutions of the multiobjective model. This can be made possible by branching on the number of aircraft that enter and exit the maintenance station in each period of the planning horizon. Note that knowing these two for each time period uniquely determines the values of the objective functions. Therefore, in order to conclude whether the associated solution of a subproblem in which these values have been determined is nondominated or not, we only need to check for feasibility and then compare the resulting objective function values with those of previously found solutions.

In summary, the FMP model and the two heuristics provide a set of tools that can be used collectively in order to address this important problem. The final decision on how to utilize these tools in order to get the most effective solution relies upon the user and depends on many parameters, such as the desired compromise between computational time and solution quality. We believe that future research should be directed towards the development and extensive testing of efficient heuristics, such as the ones studied in this work, in order to make the solution of large instances more tractable.
References


