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Novel search space updating heuristics-based genetic algorithm for optimizing medium-scale airline crew pairing problems

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Abstract

This study examines the crew pairing problem, which is one of the most comprehensive problems encountered in airline planning, to generate a set of crew pairings that has minimal cost, covers all flight legs and fulfils legal criteria. In addition, this study examines current research related to crew pairing optimization. The contribution of this study is developing heuristics based on an improved dynamic-based genetic algorithm, a deadhead-minimizing pairing search and a partial solution approach (less-costly alternative pairing search). This study proposes genetic algorithm variants and a memetic algorithm approach. In addition, computational results based on real-world data from a local airline company in Turkey are presented. The results demonstrate that the proposed approach can successfully handle medium sets of crew pairings and generate higher-quality solutions than previous methods.

Keywords: Airline crew scheduling, Crew pairing, Set-covering, Genetic algorithm, Heuristics.

1. Introduction

Airline companies have used operations research techniques to solve planning and scheduling problems since 1950 [1]. These techniques greatly impact planning and managing the operations of airlines. Advances in computer technology and optimization models have allowed more complex issues to be addressed and overcome; thus, airline-related problems can be solved in a shorter period of time. These models have saved millions of dollars, and many airline companies have established operations research departments [2].

Planning and operational problems are the most common issues encountered by airline companies. Each problem has its own characteristics and objectives. Airline crew scheduling is among the major planning problems referred to frequently in the literature. Crew expenses are the second largest expense for airlines after the cost of fuel. Because fuel costs cannot be reduced, effective and economical crew scheduling is highly valued by airline companies. Because staff costs are the largest expense that can be controlled by airline companies, scheduling cabin crew members in the most efficient manner is of utmost importance for airline planning [3]. Given its economic aspect and huge impact on operations, airline crew scheduling, which is comprehensive in nature, is an NP-hard optimization problem that must be solved under numerous constraints. The economic significance and complexity of this problem has attracted the attention of the operations research community in recent years. To facilitate a solution to this problem, various exact and meta-heuristics-based methods have been developed [4-12].

Because of its cumbersome nature, airline crew scheduling has been divided into two consecutive stages: crew pairing and crew rostering. The main

objective of the crew pairing process is to find the pairings with minimum cost that cover all flights within legal rules. Crew rostering (or crew assignments) is conducted for all legal pairings generated in the previous stage [13]. This study analyses the crew pairing problem. The inputs of the crew pairing problem are the flight legs included in the airline's timetable. Considering the scope of the crew pairing process in real life, it is not possible to generate all crew pairings (which is acceptable for large airlines). Additionally, generating a large quantity of crew pairings would make the optimization phase more difficult. Most of the studies in the literature have solved the problem by generating as few crew pairings as possible [14, 9].

In this study, a dynamic-based genetic algorithm is proposed for medium-scale scheduling problems. The objective is to find a set of minimum-cost crew pairings that meets the demand for each flight leg in the airline's timetable within all legal limits. The major differences between our study and previous genetic algorithm studies are as follows:
1) A genetic algorithm has been developed to solve medium-scale crew pairing problems. 2) Previous studies considered a particular element of the generated crew pairings and excluded the rest from the solution set, whereas in our study, all legal pairings are generated and their subsets are considered. 3) The length of the chromosome representing a solution changes dynamically in each iteration. Thus, the chromosome length varies during the optimization run. 4) Our study also has multi-objective characteristics because we represent penalty values for more than one KPI (key performance indicator) in the objective function. The high cost of crew pairing and the number of deadheads have been minimized. For these problems, new heuristic algorithms have been developed.

The rest of this paper is organized as follows. Section 2 provides an overview of the background and describes the airline crew pairing problem. Section 3 explains the proposed evolutionary algorithms. Section 4 presents a case study from Turkey and compares the performances of different evolutionary algorithms applied to this case study, and it also describes the experimental results and analyses. Finally, Section 5 presents the conclusions.

2. Background

2.1. Crew pairing

Studies on airline crew pairing have used the set-covering and set-partitioning models. Information on studies that have solved airline crew scheduling problems by exact, approximate or meta-heuristic methods is given in Tables 1 and 2.

In most airline crew scheduling research, matheuristic studies are performed that utilize both heuristic and exact approaches. We can define matheuristics as optimization algorithms generated by the interoperation of meta-heuristics and mathematical programming methods. Column generation and integer programming (heuristic branch-and-bound) are the most commonly used methods.

2.2. Memetic algorithm

A memetic algorithm (MA) is a heuristic algorithm that uses local search (LS) techniques and is a genetic algorithm and hybrid-structured evolutionary algorithm (EA). MAs are enhanced population-based EAs that were first developed by Moscato [38] to solve discrete optimization problems. The main components of MAs are crossover, mutation and hill climbing [39]. LS algorithms attempt to improve the current solution. Within MAs, hill climbing, tabu search and simulated annealing are used as LS algorithms. MAs are used to solve NP-hard problems by combining genetic algorithms (GAs) and LS techniques [40].

Our ultimate objective is to develop a GA that can handle medium data sets in an effective manner and generate outcomes that are of high quality.

2.3. Related works

Because current approaches are not sufficient for solving large-scale problems, most studies apply integrated heuristics with these approaches. Several studies have been performed on the application of GAs based on meta-heuristics to the airline crew scheduling problem in the literature. In these studies, the set-partitioning (SP) problem or set-covering (SC) problem is generally considered to solve the crew pairing optimization problem. Both problems have been shown to be NP-complete [41].

In Zeren and Ozkol's study [9] of 700 flights, Ozdemir and Mohan's study [42] of 300 flights,

Table 1. Overview of previous studies that used meta-heuristics and matheuristics for the airline crew scheduling problem.

Author (Year)	Fleet Assignment	Aircraft Routing	Crew Pairing	Crew Rostering	Problem Type	Application	Flight Data	Data Access	Airline/ Country	SC /SP	Solution Methods
Lavoie et al. [15]	-	-	x	-	2 Weekly	Real	up to 329	Private	Air France	SC	Column generation, generalized linear programming and shortest path
Levine [16]	-	-	x	-	-	Real	-	Private	-	SP	Hybrid genetic algorithms
Chu et al. [17]	-	-	x	-	Daily	Real	-	Private	American Airlines	-	Zero-one integer program
Desaulniers et al. [18]	-	-	x	-	Weekly	Real	between 154 and approximately 1200	Private	Air France	SP	Nonlinear IP and Dantzig-Wolfe decomposition
Merle et al. [19]	-	-	x	-	-	*Real*	986	Private	-	SP	Linear programing, column generation
Yan and Chang [20]	-	-	-	x	Weekly	Real	-	Private	Taiwan airline	SP	Shortest path problem and column generation
Mercier et al. [21]	-	x	x	-	Daily	Real	up to 700	Private	-	-	Benders decomposition and column generation
Zeghal and Minoux [22]	-	-	-	x	Monthly	Real	-	Private	TunisAir	-	Integer linear program
Medard and Sawhney [23]	-	-	x	x	-	Real	-	Private	-	SC/SP	Column generation
Mercier and Soumis [24]	-	x	x	-	Daily	Real	up to 500	Private	-	-	Benders decomposition, column generation
AhmadBeygi et al. [25]	-	-	x	-	Weekly	Real	329	Private	U.S Airlines	SP	Column generation and integer programming
Papadakos [26]	x	x	x	-	Daily and Weekly	Real	372 and over 2100	Private	European and North American airlines	SP	Enhanced Benders decomposition and accelerated column generation
Deng and Lin [8]	-	-	x	-	Daily	*Real (Ozdemir & Mohan, 2001)*	-	Private	-	-	Ant colony optimization and swarm intelligence
Ionescua and Kliewer [27]	-	-	x	-	Daily	Real	396-427	Private	European Airline	SP	Column generation
Saddoune et al. [28]	-	-	x	x	Daily, Weekly and Monthly	Real	between 1011 and 7527	Private	North American Airline	SP	Column generation and bi-dynamic constraint aggregation
Duck et al. [29]	-	x	x	-	-	Random generated	-	Private	-	SP	Column generation and Dynamic programming
Aydemir-Karadag et al. [11]	-	-	x	-	Daily	Random generated	100 and 200	Private	-	SC	Column generation, genetic algorithm
Azadeh et al. [10]	-	-	x	-	Daily	Random generated	25, 50, 100 and 150	Private	-	-	Particle swarm optimization, genetic algorithm and ant colony optimization
Cacchiani and Salazar-González [30]	x	x	x	-	Daily	Real	100-150	Private	-	-	LP-relaxation by column generation

SC: Set covering, **SP:** Set partitioning.

Table 2. Continue.

Author (Year)	Fleet Assignment	Aircraft Routing	Crew Pairing	Crew Rostering	Problem Type	Application	Flight Data	Data Access	Airline/ Country	SC /SP	Solution Methods
Muter et al. [31]	-	-	x	-	Daily and Weekly	Real	96, 135, 490	Private	Turkey	SC	Row and column generation and multi-label shortest path
Saddoune et al. [32]	-	-	x	-	Daily, Weekly and Monthly	Real	between 1011 and 7527	Private	North American Airline	-	Column generation
Salazar-González [33]	x	x	x	x	-	Real	between 100 and 150	Private	Binter Canarias S.A	-	Integer programming and mixed integer linear programming
Zeren and Ozkol [13]			x		Monthly	Real	between 15656 and 17318	Private	Turkish Airlines	SC	Integer programming, Column generation and heuristics
Chen and Chou [34]	-	-	-	x	-	Real	-	Private	-	-	Genetic algorithms
Kasirzadeh et al. [35]	-	-	x	x	-	Real	-	Private	US carrier	SC	Column generation
Quesnel et al. [36]	-	-	x	-	Monthly	Real	Between 271 and 479, and also from 1463 to 1987.	Private	North American Airline	SP	Column generation
Yildiz et al. [37]	-	-	x	-	Weekly	Real	378 and 470	Private	-	SC	Column generation

Table 3. Overview of previous studies that used genetic algorithms for the airline crew scheduling problem.

Author (Year)	Crew Pairing	Crew Rostering	Problem Type	Application	Flight Data	Data Access	Airline/ Country	Formulation
Beasley and Chu [44]	x	-	-	Random generated	-	Private	-	SC
Levine [16]	x	-	-	Real	-	Private	-	SP
Ozdemir and Mohan [42]	x	-	Daily	Real	-	Private	-	-
Kerati et al. [45]	-	x	-	-	-	Private	-	-
Kornilakis and Stamatopoulos [14]	x	-	Monthly	Real	2100	Private	Olympic Airways	SC
Chang [43]	x	x	Weekly	Real	about 700	Private	Taiwan	-
Souai and Teghem [7]	x	x	Daily	Real	up to 631	Private	-	SP
Zeren and Ozkol [9]	x	-	Monthly	Real	714	Private	Turkish Airlines	SC
Azadeh et al. [10]	x	-	Daily	Random generated	25, 50, 100 and 150	Private	-	-

Kornilakis and Stamatopoulos's study [14] of 2100 flights, Chang's study [43] of 700 flights and Sou and Teghem's study [7] of 631 flights, the results were generated without using all pairs. However, in this study, all pairs are produced, and by updating the solution space dynamically, the GA yields better solutions in big column numbers.

Using the dynamic approach proposed in this paper, we were able to generate solutions that are of better quality using much larger data sets than those used in studies that include GAs. An overview of previous work on relevant GA studies is provided in Table 3.

2.4. Fundamental definitions and rules

Crew pairing problems attempt to determine the crew pairing with minimum costs that would meet the needs of each flight leg on the schedule. The airline timetable is used as an input at this stage. Then, duties and pairings are generated according to the rules laid down by the airline companies, the Directorate General of Civil Aviation (DGCA) and the Federal Aviation Administration (FAA). Fig. 1 shows the duties and crew pairings generated in line with the flight legs used in the airline's timetable. The following definitions are used to address the crew pairing problem [3]:

Flight (flight leg or leg): Period between aircraft (AC) take off and AC landing.

Duty: Period comprising one or more flight legs, including the briefing time, which is the preparation period for the duty, and the debriefing time, which is the preparation period of the AC for the next flight crew.

Crew pairing: Period comprising one or more duties. Crew pairings also include the rest periods between duties.

The limits that must be respected to ensure that a duty or crew pairing is legal consist of a rest period, connection time, flight time and duty time. *Connection times* for a duty period must be within a certain range (minimum and maximum). The *total flight time* refers to the time spent in a duty period, the *block time* refers to the flight time during a duty, and the number of flight legs must not exceed the given ranges. A certain period is also allocated for *briefing* before each duty period and *debriefing* at the end of each duty period. The rules applied for crew pairing vary according to airlines and countries. The rules for the crew pairing problem can be found in [46].

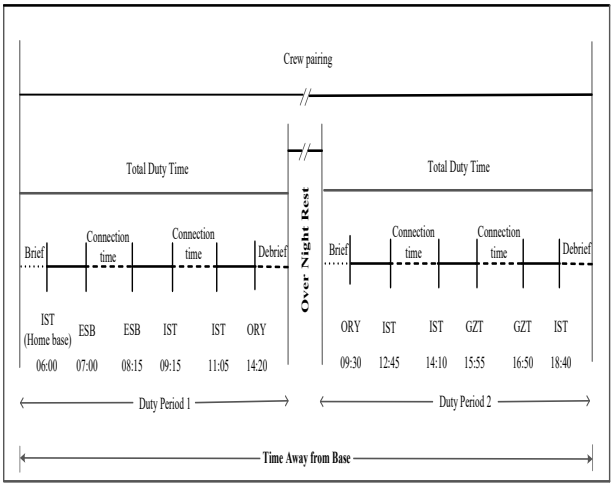


Fig. 1. Example of a crew pairing with an IST airport as the crew base.

Connection time: A connection during duty is called a sit connection time, which is the time between two consecutive flight legs in a duty. Generally, airlines consider minimum and maximum sit connection times, which are usually between 30 min and 3 h (sometimes 4 h).

Rest: A connection between two duty periods is called a rest, layover or overnight connection.

Brief: The elapsed time before the first leg of the duty.

Debrief: The elapsed time after the last leg of the duty.

Deadhead: If a crew member flies as a passenger rather than as a cockpit or cabin attendant, this flight is regarded as a deadhead flight for that crew member. Deadhead flights should be minimized because they reduce the passenger transport capacity and the crew utilization efficiency [13].

3. Proposed Methodologies

In this study, we propose a fast, strong and dynamic-based GA approach for airline crew pairing. The algorithm's main logic provides a sub-optimal solution for medium-scale problems by solving them in small subsets. The proposed method uses a small subset of the problem that continuously repeats itself in line with the information obtained from the GA solution. The pairings that worsen the solution in the subset and the pairings that improve the solution in the main set are continuously replaced to develop updated heuristics.

The proposed methodology consists of five stages. (1) All legal crew pairings are generated (pairsAll). (2) A subset is formed by randomly (knowledge-based random) choosing pairings from the generated crew pairings, including all flights (select the initial from pairsAll). (3) The steps of the GA are applied to optimize the problem. (4) After the GA produces a certain iteration, the population's best chromosome and pairings of this chromosome are kept in memory for the next round. Then, the loop returns to stage 3, and the pairings that will improve the solution (low-cost) in the main set are searched instead of the pairings that will worsen the solution (high-cost) in the subset. In addition, the other developed heuristics algorithm and alternative pairings that will produce the fewest deadheads for each flight are searched. (5) The best crew-paring solution set is obtained by continuously executing procedure stages 3 and 4 until the loop ends. The schematic diagram of the proposed methodology for the crew pairing problem is shown in Fig. 2.

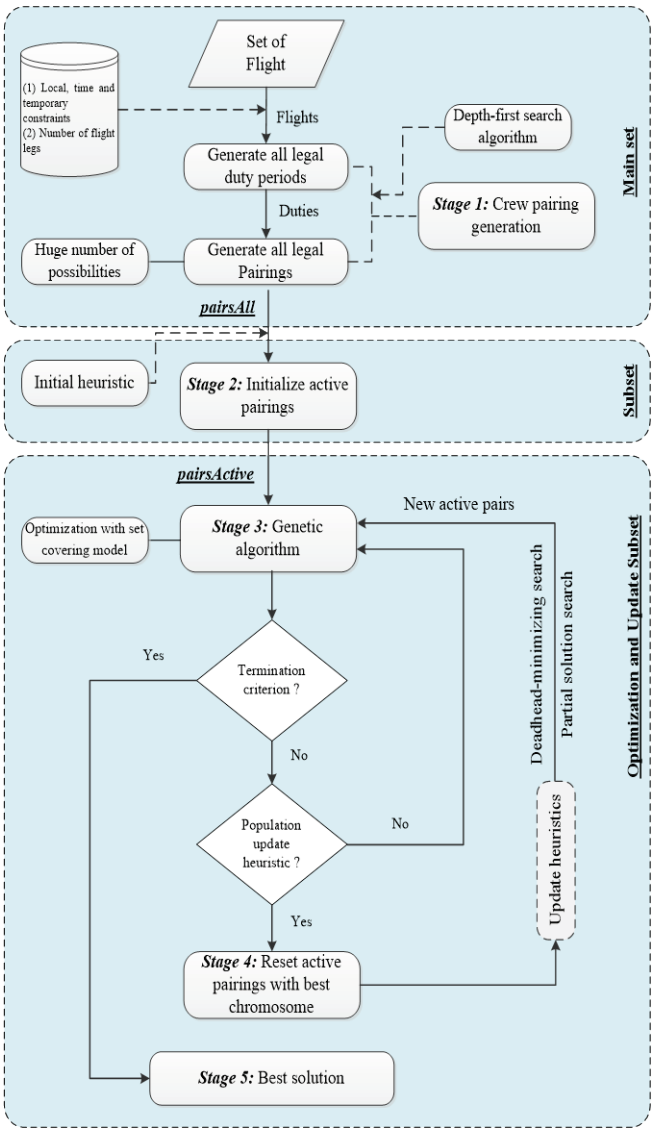


Fig. 2. Stages of the proposed dynamic-based GA methodology.

3.1. Crew pairing generation

The aim of this stage is to obtain a set of all legal crew pairings. The crew pairing generation method consists of two stages: (1) duty generation and (2) pairing generation. In the first stage, all legal duties are generated using the set of flights (see Section 2.4). A depth-first search algorithm is employed for duty generation. In the second stage, crew pairings are generated from flight duties with a similar algorithm (depth-first search algorithm) after duty generation. This algorithm searches in the space of all possible subsets of all flight legs [14].

Algorithm 1 Pseudocode of the pair generation

```
1   Procedure GeneratePairings (pairList)
2       currentPair = create an empty pair;
3       for each duty do
4           if duty starts from homebase
5               Insert duty to currentPair;
6               SearchForPairings (currentPair, pairList)
7               Remove duty from currentPair;
8   Procedure SearchForPairings (currentPair, pairList)
9       for each duty (that starts from the arrival station of
currentPair arrives) do
10          Insert duty to currentPair;
11          if currentPair is valid (whether ends at the
same homebase city)
12              Insert currentPair to pairList;
13          if currentPair can have more duties
14              SearchForPairings (currentPair, pairList);
15          Remove duty from currentPair;
```

The *GeneratePairings* method is a recursive procedure that allows us to search for duty connections that form all possible crew pairings. In the first phase, all duties are reviewed in the main procedure. For duties starting from the homebase, the procedure is executed to

search for possible duties that can be added to the pairing. The steps of this process are shown between lines 2 and 7. In the second phase, however, duties finishing at the homebase sub-procedure are executed to search for possible duties that can be added to the pairing. Any suitable duties are searched for in lines 9 and 10 and added to the *currentPair*. In lines 11 and 12, the generated pairing is added to the *pairList* if applicable. In lines 13 and 14, if the length of the current pairing allows us to add more duties, then *recursive procedure* reruns in the search space. The *pairList* is the list of all valid pairings created by the recursive code.

For an airline crew pairing problem that consists of f flights, d duties and p pairings of duties, the cost function of the CPP (crew pairing problem) can be defined as follows:

The total duty duration is used as the duty cost in the code and can be formulated as given in Eq. (1):

$$Duty\ cost = Min\left(C_j^{duty}\right) = \sum_{i=1}^{f} a_{ij}\left(C_i^{flight} + \sum_{l=1}^{f} a_{lj}u_{il}C_{il}^{connectionTime}\right)$$

$$\forall j = 1,2\ldots,d$$

The first and second part of the duty cost equation can be defined as follows:

(1) Required pay for each flight in each duty and
(2) Connection time between flights.

The first and second part of the pairing cost equation can be defined as in Eq. (2):

(1) Required pay for each duty in each pairing (duty cost) and
(2) Connection time expenses between duties (hotel cost).

$$Pairing\ cost = Min\left(C_k^{pair}\right) = \sum_{j=1}^{d} b_{jk}\left(C_j^{duty} + \sum_{q=1}^{d} b_{qk}h_{jq}C_{jq}^{restPeriod}\right)$$

$$\forall k = 1,2,\ldots,p$$

The elapsed time includes a briefing period before the first leg of the duty and a debriefing period after the last leg of the duty.

i=1,2,…,f (f Є F: set of all flight legs)
j=1,2,…,d (d Є D: set of all legal duties)
k=1,2,…,p (p Є P: set of all legal pairings)

Table 4. Mathematical notation of crew pairings.

Notation	Define
C_j^{duty}	The basic payment for a duty j.
C_i^{flight}	The cost of each flight i.
$C_{il}^{connection\ Time}$	The connection time cost between two consecutive flights i and l.
$C_{jq}^{restPeriod}$	The rest time cost between two consecutive duties j and q.
a_{ij}	If flight i is covered by duty j, $a_{ij} = 1$; otherwise, $a_{ij} = 0$.
a_{lj}	If flight l is covered by duty j, $a_{lj} = 1$; otherwise, $a_{lj} = 0$.
u_{il}	If flight i follow flight l, $u_{il} = 1$; otherwise, $u_{il} = 0$.
b_{jk}	If duty "j" is covered by pairing k, $b_{jk} = 1$; otherwise, $b_{jk} = 0$.
b_{qk}	If duty "q" is covered by pairing k, $b_{qk} = 1$; otherwise, $b_{qk} = 0$.
h_{jq}	If duty j follows duty q, $h_{jq} = 1$; otherwise, $h_{jq} = 0$.

Algorithm 2 Pseudocode of the initial subset

```
1   Procedure InitializeActivePairs (Flights, pairsAll,
    pairsActive, maxStep)
2       initialize step = 0
3       While (step < maxStep)
4           initialize temporaryFlights = Flights
5           initialize coveredFlightList = {}
6           While (temporaryFlights.length > 0)
7               select a random flight F_i out of
temporaryFlights.
8               if (F_i has not been included by
coveredFlightList yet)
9               find the "crew pairing list" PL that includes
pairings that cover F_i with minimum deadheading (by
checking coveredFlightList) out of pairsAll.
10              select a random pairing P out of PL
and Insert P to pairsActive.
11              add all flights of P to
coveredFlightList.
12          remove F_i from temporaryFlights.
13      step++
```

3.2. Initial pairing (subset) selection with heuristic solution

Unlike other studies, this study generates a knowledge-based random subset \to cover all flights among all generated pairings, and then this subset continues to renew itself. A heuristics approach is developed below for generating the initial subset.

3.3. Set covering master model for optimization

Selecting the set with the best crew pairing is modelled as an SC or SP problem in the literature. The SC model is used in this study because there is a clear analogy between the SC model and the crew pairing problem. In this model, each row represents a flight in the airline time table, and each column represents a generated crew pairing. In addition, F represents the flight set, and P represents the legal pairings created by these flights. The SC problem for the crew pairing problem can be defined as follows [6, 13]:

The SC model perfectly fits and provides all the representation needs of the crew pairing problem.

Set covering:

$$Min(z) = \sum_{j=1}^{p} c_j * x_j \qquad (3)$$

Which is subject to

$$\sum_{j=1}^{p} a_{ij} * x_j \geq 1 \qquad \forall i \in F \qquad (4)$$

$$x_j \in \{0,1\} \qquad \forall j \in P$$

$$x_j = \begin{cases} 1 & if\ pairing\ j\ is\ selected; \\ 0 & otherwise \end{cases}$$

$$a_{ij} = \begin{cases} 1 & if\ flight\ leg\ i\ is\ covered\ by\ pairing\ j; \\ 0 & otherwise \end{cases}$$

Eq. (3) shows the objective function in which the total cost is calculated. Eq. (4) indicates the constraint that guarantees that all flights (rows) are covered at least once. If this equation equals 1 (*=1*), then it becomes an SP model.

3.3.1. Genetic algorithm optimization

Genetic algorithm have been introduced by Holland [47] to understand the adaptive search processes of natural systems. GAs are inspired by the evolutionary phases of biological organisms in nature. GAs can be applied to combinatorial optimization and machine learning and represent a popular class of EAs [48]. The primary logic of genetic algorithm attempt to improve a population of candidate solutions by iteratively applying a set of genetic operators (crossover and mutation) and creating new individuals then replacing the old individuals with the ones. The proposed GA for solving the crew pairing problem is described in this section.

Representation is the most important part of a GA. Binary coding is used for the crew pairing problem, and two types of models are recommended for the solution to the crew pairing problem by incorporating a GA. These models are column-based presentation [44] and row-based presentation [49]. Column-based presentation is considered in this study.

3.3.1.1. Initialise the population

The initial population is the first stage of the GA. Each chromosome in this population represents a possible solution to a problem. A heuristics approach is suggested to cover each flight while the initial population is generated.

Algorithm 3 Initial population algorithm

```
1   Procedure InitialPopulation (pairsActive, Flights,
    Population)
2       for (each chromosome in population)
3           for (each flight Fi in Flights list)
4               if (Fi is covered by pairsActive list)
5                   if (number of covers in chromosome
of Fi < 1)
6                       find the "crew pairing list" PL
that includes Fi out of pairsActive.
7                       if (PL ≥ 1)
8                           select a random pairing P
out of PL.
9                           insert P to chromosome.
10          add chromosome to Population.
```

We generate the initial population using the *InitialPopulation* method with the *pairsActive* and *Flights* lists. The *pairsActive* list is a pairing subset that is chosen among all pairings and covers each flight at least *n* time(s). The *Flights* list is a set in which all flights exist. The *populationSize* points to the chromosome number in the population. In line 2, the *"for" loop* activates each *chromosome* in the *population.* In lines 3 and 4, whether any pairing in *pairsActive* covers each F_i flight is verified. If this F_i

flight is covered, then whether this flight has been covered before in the genes of the *chromosome* in line 5 is verified. If this F_i flight has not been previously covered in the genes of the chromosome, then the pairings that cover this flight in line 6, i.e., *crew pairing list (PL),* are identified. In lines 7, 8 and 9, if there is a pairing P that covers this flight and the number of pairings is more than one, then a P is randomly chosen among the *PL* and added to the chromosome; in other words, the related chromosome's gene is *true*. The loop starts for the first chromosome of the population. After all flights are activated, the loop is added into the chromosome list in line 10 and continues until the break condition is met.

3.3.1.2. Fitness function

The fitness value of a chromosome equals the objective function of the problem. The fitness value indicates the degree to which a chromosome fits the structure of the objective function (max or min). The main objective is to minimize the total cost of the objective function. The fitness function is used to calculate the cost of each chromosome in the population. The best set solution (chromosome) must cover all flights in the airline's timetable. Calculating the fitness function is not standard, and although similarities may be observed, each work is unique. The fitness function adopted in this study is defined in Eq. (5) using the following terms:

c_j = cost of pairing j;
s_i = cost of flight i;
h_j = hotel transportation cost of pairing j;
n_j = number of night stays of pairing j;
i = 1,2 ... ... f ($f \in F$: set of all flight legs);
j = 1,2 ... ... p ($p \in P$: set of all pairings).

$$Fitness\ function\ (Min) = \sum_{j=1}^{p}\left(c_j x_j + \sum_{i=1}^{f} s_i y_i\, a_{ij}\right) + \sum_{j=1}^{p} n_j h_j x_j \quad (5)$$

Parameters of the model;

$c_j > 0,\quad s_i > 0 \ and \quad h_j > 0$;

$x(j) \in \{0,1\} \qquad \forall j \in P$

$$x(j) = \begin{cases} 1 & \text{if pairing } j \text{ is selected;} \\ 0 & \text{otherwise} \end{cases}$$

$$y(i) = \begin{cases} 1 & \text{if flight } i \text{ is a deadhead;} \\ 0 & \text{otherwise} \end{cases}$$

$$a(i,j) = \begin{cases} 1 & \text{if flight leg } i \text{ is covered by pairing } j; \\ 0 & \text{otherwise} \end{cases}$$

Eq. (5) shows that the first statement of the equation provides the total cost of the crew pairings in the solution set of the chromosomes (see details in Section 3.1). The second statement provides the total deadhead cost that would occur in the event of multiple coverages of a flight in the solution set. Deadheads represent the crew staff, excluding the actual commissioned crew, who travel to another base as passengers on the aircraft. If a flight is covered more than once, then the flight would bring an extra cost to the airline. The penalty value here is calculated by setting it equal to the cost of a deadhead flight. The third statement is the hotel transportation costs.

3.3.1.3. Genetic operators

Because the crossover and mutation operator is the stage of transferring genetic information to the new generation, the selection phase of the chromosomes that cross will be important. In this study, a binary tournament selection method was used because it performed better than other selection operators. After selecting the ancestor (mother and father) chromosomes to produce new children, the crossover operator is applied. Single point crossovers, two point crossovers, and uniform crossings have been attempted using crossover operators, and the single point crossover is the best performing operator of the algorithm. The bit-flip mutation operator was applied to ensure that the algorithm does not catch local (local) maxima and local minimum spots.

3.3.1.4. Local search heuristics

3.3.1.4.1. Repair heuristic

The child chromosomes obtained after the crossover and mutation processes are not guaranteed to be feasible. Beasley and Chu [44] attempted to repair non-feasible chromosomes that could be formed by the method they proposed. A chromosome should be covered by each leg in flight set. Eq. (6) determines the crew pairing that should be added to the solution set to cover unscheduled flights.

$$\frac{Cost\ of\ crew\ pairing}{Number\ of\ non\ covered\ flights\ included\ in\ CP} \quad (6)$$

As a first step, to make non-feasible chromosomes feasible, flights not covered in the solution set and the possible crew pairings that can be included in the solution set to allow these flights to be covered in the solution set are identified. The above equation is used to determine which crew pairings to include in the solution set so that non-covered flights are covered. The steps of the algorithm used in the study are as follows (Algorithm 4):

Algorithm 4 Pseudocode of the repair

```
1   Procedure Repair (Flights, pairsActive)
2       initialize notCoveredFlightList = {}
3       for each flight F_i in Flights do
4           if (F_i can not be covered by chromosome)
5               Insert F_i to notCoveredFlightList;
6       if (notCoveredFlightList is empty such that all
flights covered in the solution)
7           exit;
8       for each flight F_j in notCoveredFlightList do
9           find the best (according to Eq. 6) pairing P_i
out of pairsActive that covers F_j
10          add P_i to chromosome.
11          update notCoveredFlightList (remove all
flights of P_i from notCoveredFlightList).
```

The pseudocode for the repair of unsuitable chromosomes is shown in Algorithm 4. For the *Repair* function in line 1, the *Flights* and *pairsActive* lists are used as input. *Flights* is the list of all flights, and *pairsActive (subset)* is a pairing subset selected from the pairings in *pairsAll* that covers all flights. In line 2, *notCoveredFlightList* is generated for the flights that are not covered in the solution set (chromosome). Between lines 3 and 5, whether all flights in the flight list are covered in the solution set is determined, and the flights that are not covered are added to the *notCoveredFlightList* set. In lines 6 and 7, if all flights are covered, the solution ends. In line 8, optimum pairing is searched for each flight that is not covered in the *notCoveredFlightList* set. In lines 9 and 10, the best pairing is found according to equality 4, and the found pairing is added to the solution set (*pairsActive*). In line 11, if each flight other than F_j in this pairing covers one of the flights in the *notCoveredFlightList* set, then this flight is removed from the *notCoveredFlightList* set.

3.3.1.4.2. Modified best-improvement local search method

A local optimization step is incorporated to render the solution algorithm more effective. This algorithm is a local optimization process that ensures that the fitness of a chromosome is not impaired once it is made feasible, even when it is omitted from the solution set of redundant crew pairings [44]. This process is implemented immediately after the initial population and mutation processes. Many strategies can be applied for the LS and include (1) first improvement and (2) best improvement. Here, best improvement of the LS is applied. To obtain the best improvement using this strategy, all possible moves are tested for a solution so that the best neighbouring solution can be selected [48]. The pseudocode for the best improvement is given in Algorithm 5.

Algorithm 5 Local optimization heuristic

```
1   Procedure LocalSearch (Population, Flights,
    pairsActive)
2       for (each chromosome in population)
3           for (each pair P_i in pairsActive)
4               if (P_i is covered by chromosome)
5                   setGene (P_i, false)
6                   if (all flights in Flights not covered
by chromosome)
7                       setGene (P_i, true)
```

Even if crew pairings are removed from the solution set, the pseudocode of the local optimization heuristics where the chromosome compliance is not violated is as presented in Algorithm 5. In line 2, the algorithm runs for each chromosome in the population. In line 3, the loop runs for each pairing P_i for *pairsActive.* In lines 4 and 5, if P_i is in the solution set, then it is removed from the P_i solution set. In lines 6 and 7, if all flights in the *Flights* set are not covered, then P_i is returned to the solution set.

3.3.1.5. Population replacement strategies

The last step of the GA is population replacement. In this step, the surviving parent and child chromosomes are selected. Because the number of populations is fixed, a chromosome selection strategy ensures that this number remains fixed. The two main approaches used in the population replacement stage are the generational and steady-state approaches [48]. This study adopts the steady-state approach. An elitist approach is also tested;

however, the steady-state approach is preferred because it delivered better results. In this approach, one or two offspring are generated in each iteration. Then, this child chromosome replaces (1) the worst individual in the population or (2) its parents.

3.4. Update heuristics

3.4.1. Deadhead-minimizing pairing search heuristic

This stage can be considered an alternative pairing search stage. The purpose of the developed heuristics approach is to decrease the number of deadheads because they decrease passenger capacity and crew utility efficiency. Therefore, the airlines always require that the number of deadheads be kept at an optimum level [13]. The best chromosome among those in the population is identified first, and the remaining chromosomes in the population are then removed from the solution set. In addition, the best chromosome is an alternative solution. Finally, alternative pairings that will decrease the number of deadheads are searched by checking how many times each flight was covered among the best chromosome, i.e., pairings in the alternative solution. This search procedure is conducted between all pairings that are generated, starting from the ones that cover deadheads the most, and alternative identified pairings are added to the subset. An example alternative pairing search that will decrease the number of deadheads is shown in Fig. 3.

In the above example, the most covered flight among the pairings in the best chromosome is f_3. The pairings that cover this flight are shown as P_{x1}, P_{x2} and P_{x3}, and the flight legs are f_1, f_2, f_3, f_4, f_5, f_6 and f_7. The alternative pairings that cover f_3 together with f_1, f_2, f_4, f_5, f_6 and f_7 among all pairings are P_{y1}, P_{y2}, P_{y3} and P_{y4}. Although flight f_3 in the best chromosome is covered by pairings P_{x1}, P_{x2} and P_{x3}, it can be covered by pairings P_{y2} and P_{y3} together with all flights by the suggested method. Here, the aim is to make more than one flight covered in the solution set minimum. In this manner, the costs in the goal function can be decreased.

An alternative pairing search algorithm pseudocode that will decrease the number of deadheads is shown in Algorithm 6. In line 1, the *bestChromosome*, *Flights*, *pairsAll* and *pairsActive* lists are used as input for the *SearchForDeadheadMin* function. *bestChromosome* includes the genes of the best chromosome (of the solution set) obtained as a result of a certain iteration study of the GA, i.e., the list of pairings; *Flights* is the list of all flights; *pairsAll* is the list of all pairings; and *pairsActive (subset)* is a pairing subset that is chosen among the pairings in *pairsAll* that covers all flights. In line 4, the flights F_i that are most covered in the solution set (*bestChromosome*) are present. In line 5 and 6, if no F_i is found to be covered more than once, then the

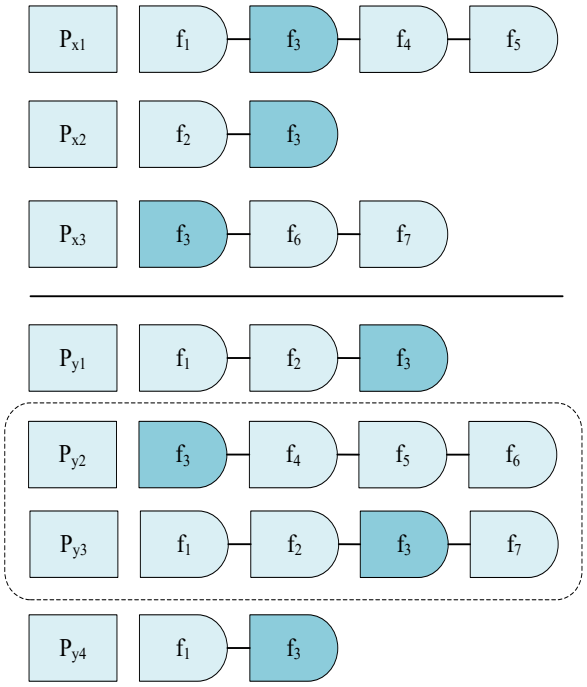


Fig. 3. Alternative pairing search example.

Algorithm 6 Pseudocode of the deadhead-minimizing pairing search

```
1   Procedure SearchForDeadheadMinimizingPairs
    (bestChromosome, Flights, pairsAll, pairsActive)
2       initialize pairsActive = bestChromosome.pairs
3       While (true)
4           find the next flight Fi that is covered by the
solution the most
5           if (Fi can not be found)
6               exit;
7           find the "crew pairing list" PL that includes Fi
out of pairsActive.
8           find the "flight list" FL that includes all the
flights that are covered by PL.
9           search for a “new pairing list” NPL out of
pairsAll that covers all flights in FL with no deadheads.
10          add all pairings from NPL to pairsActive.
```

solution ends. In line 7, pairings that cover flight F_i are found in *pairsActive*, and the *PL* list is generated. In line 8, the flight list, i.e., the set *FL*, which is covered by *PL* and includes all flights, is found. In lines 9 and 10, new pairings that cover all flights in the *FL* list and do not include any deadheads are searched, and the *NPL* list is generated. Then, all pairings in the *NPL* list are added to the *pairsActive* list.

3.4.2. Less-costly alternative pairing search

The less-costly approach can be called the partial solution search. This approach is a procedure for searching for high-quality pairings (low-cost) from the main set (*pairsAll*) to replace low-quality pairings (high-cost) from the best chromosome or subset (*pairsActive*). In other words, the approach can be called the low-cost pairing search procedure. Initially, the pairing with the lowest quality is identified, and a high-quality pairing search is conducted in the main set for flights in the pairing with the lowest quality. This continues until high-quality pairings are found for flights in the pairing with the lowest quality. First, a quality index (QI) is identified, and it is calculated as shown in Eq. (7). According to the values of this index, the pairings are listed from highest quality to lowest. The pairing with the smallest index value corresponds to the pairing with the lowest quality.

$$\text{Quality Index (QI)} = \frac{\textit{Total block time}}{\textit{Total pairing time}} = \frac{\sum_{i=1}^{f} a_{ij}\, M_i^{fly}}{\sum_{j=1}^{d}\sum_{q=1}^{d}(b_{jk}\, M_j^{tft} + b_{jk}b_{qk}h_{jq}M_{jq}^{requiredRest})} \quad (7)$$

$$\forall\, k = 1,2,\ldots,p$$

The pseudocode of the alternative pairing search algorithm that will decrease the number of pairings with low quality is shown in Algorithm 7. According to this algorithm, an example of a less-costly pairing search with four pairings and thirteen flights is depicted in Fig. 4. In line 3, the pairing with the lowest quality, P_i, is found in the best chromosome. Here, the algorithm starts searching from the pairing with the lowest quality. Then, after the pairing with the lowest quality, we aim to find the next pairing with the lowest quality. In lines 4 and 5, if P_i cannot be found, then the solution ends. In line 6, this pairing is used as an initialized value for the

Table 5. Mathematical notation of the quality index.

Notation	Define
M_i^{fly}	The flight time of flight *i*.
M_j^{tft}	The total duty time of duty *j*.
a_{ij}	If flight *i* is covered by duty *j*, $a_{ij} = 1$; otherwise, $a_{ij} = 0$.
b_{jk}	If duty *j* is covered by pairing *k*, $b_{jk} = 1$; otherwise, $b_{jk} = 0$.
b_{qk}	If duty *q* is covered by pairing *k*, $b_{qk} = 1$; otherwise, $b_{qk} = 0$.
h_{jq}	If duty *j* follows duty *q*, $h_{jq} = 1$; otherwise, $h_{jq} = 0$.
$M_{jq}^{requiredRest}$	The required rest time between two consecutive duties *j* and *q*.

i=1,2,....f (f Є F: set of all flight legs)
j=1,2,...,d (d Є D: set of all legal duties)
k=1,2,...,p (p Є P: set of all legal pairings)

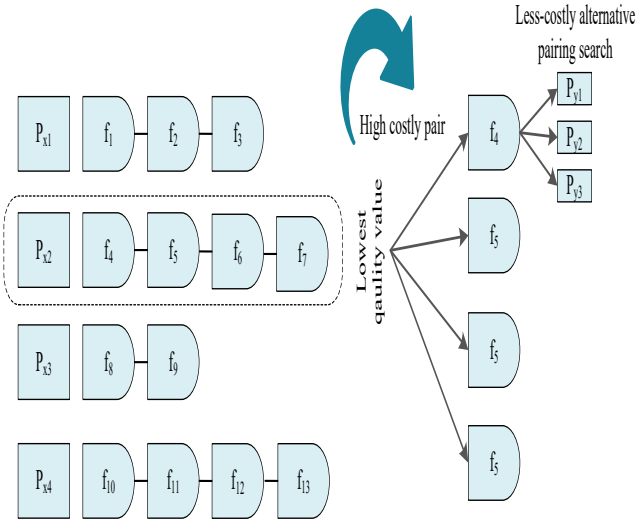


Fig. 4. Alternative less-costly pairing search example.

flights in P_i in the *searchFlights* set. In line 7, the *coveredFlightList* set is generated for the searched flights. In line 8, a low-cost/high-quality pairing is searched for each flight F_i in the *searchFlights* set. While conducting the search, this flight should not be covered by the *coveredFlightList* set at the same time. In line 9, the best pairing P_n (new pairing) that covers

flight F_i in *pairsAll* is found, and this pairing is added to *pairsActive* in line 10. In line 11, all flights of the chosen P_n are added to the *coveredFlightList* list. In line 12, a search is conducted of P_n for each flight F_j. In line 13, a low-cost P_j that covers flight F_j is found. In line 14, all flights that are not covered in the new pairing P_j (and those that are not covered in the *coveredFlightList* set) are added to the *searchFlights* set.

Algorithm 7 Pseudocode of the less-costly alternative pairing search

```
1   Procedure SearchForLessCostlyAlternativePairings
    (bestChromosome, pairsAll, pairsActive)
2       While (true)
3           find the next pairing Pi that has the lowest
quality value (a metric that is used to give quality points to
pairings, with higher points indicating better quality) out of
bestChromosome.pairs.
4           if (Pi can not be found)
5               exit;
6           initialize searchFlights = flights of Pi
7           initialize coveredFlightList = {}
8           for (each flight Fi that is in searchFlights but
not in coveredFlightList)
9               find the best (according to the quality
metric) pairing Pn out of pairsAll that covers Fi but does not
include any of the flights in coveredFlightList.
10              add Pn to pairsActive.
11              add all flights of Pn to coveredFlightList.
12              for (each flight Fj that is in Pn)
13                  find the pairing Pj that covers Fj in
the last solution (bestChromosome.pairs).
14                  add all uncovered flights (those not
in coveredFlightList) of Pj to searchFlights.
```

3.5. General overview

The final status of the solution approach of the crew pairing optimization problem is indicated in Fig. 5 and Algorithm 8. As shown in the algorithm, flight legs are taken from the airline's timetable as input. In line 3, all possible duties are generated from the flight legs that are taken as input. In line 4, all possible pairings are generated by taking duties that are generated in line 3. In line 5, *pairsActiveList* is a function that generates a pairing subset that is chosen from *pairsAll*. In line 6, we generate the initial population using the *Flights* and *pairsActive* lists. In line 7, the loop runs until the break condition is met. In lines 8, 9, 10 and 11, optimization is performed with the GA until the loop reaches a certain number of iterations. In line 12, the best chromosome of the population is found at the end of the loop. In line 13, alternative pairings that will decrease the number of deadheads are searched by considering the mostly covered flights of pairings in the best chromosome. In line 14, starting from the pairing with the lowest quality in the best chromosome, alternative high-quality pairings are searched.

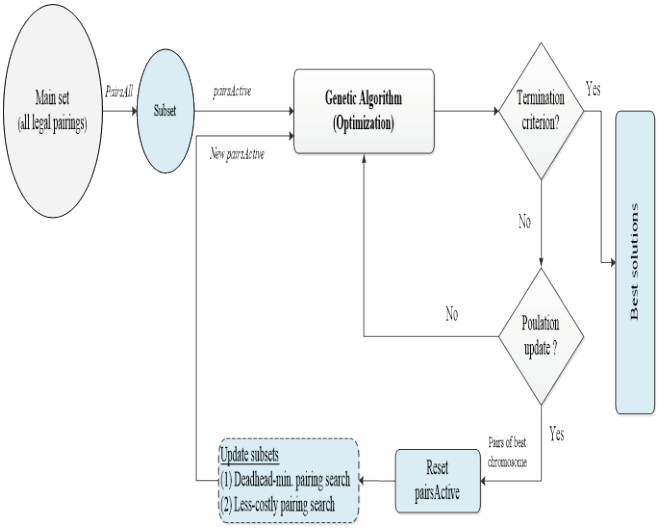


Fig. 5. Overview of the proposed approach.

Algorithm 8 Overview of the proposed algorithm

```
1   Procedure Optimization_Crew_Pairing_Problem
    (Flights, maxIteration)
2       initialize iteration=0
3       dutyList=Generate_Duties (Flights)
4       pairsAllList=Generate_AllPairs (dutyList)
5       pairsActiveList = initializeActivePairs(Flights,
pairsAllList);
6       Initialize population (flights, pairsActive);
7       While (iteration < maxIteration) do
8           Solve_Subset_Genetic_Algorithm
(pairsActiveList, Flights)
9           If (termination criterion is satisfied)
10              Exit;
11          If (Update heuristic run is necessary)
12              Find the bestChromosome
13              Run_Search_Pair_
Deadhead_Minimizing_Approach (bestChromosome, Flights,
pairsAllList, pairsActive)
14
Run_Search_Less_Costly_Alternative_Pair_Approach
(bestChromosome, Flights, pairsAllList, pairsActive)
15          iteration++
16      end While
```

4. Computational Results

The flight data used in this study are associated with the airline timetable of the A310 fleet owned by an airline company in Turkey. This schedule includes 591, 608, 714, 810, 906 and 1002 monthly flight legs for testing. The programme was run on a computer with an Intel® Core ™ 64 2.40-GHz processor on the Java Eclipse platform. Each trial was repeated 30 times. This study assumes that all crew members reside in Istanbul (IST). The test instances and flight legs are presented in Table 6.

The GA is executed for 20,000 iterations, and a subset is updated once every 1000 iterations (excluding pairings of the best chromosome). In this manner, the length of the chromosome dynamically changes once every 1000 iterations. Parent selection is performed using binary tournament selection with a tour size of 4. The population size is set to 30, and the crossover probability is set to 0.8. For each generation of an EA, only two offspring are generated, and they replace the worst individuals of the parent population.

Table 6. Legs and pairings of test instances.

Instances	Flights legs	Duties	Pairings (main set)
1	591	1826	82332
2	608	1907	88624
3	714	2064	208255
4	810	2467	320866
5	906	2771	532115
6	1002	3333	1121408

The duties column in the table above shows the total number of duties generated from monthly flight legs. These duties are generated with a depth-first search algorithm. The pairing column indicates the total number of pairings (the main set) that are generated within the framework of legal restrictions using the duty list. In the same manner as for the duty enumeration, a depth-first search algorithm is used to generate all legal pairings.

In this study, this problem is integrated into three different EAs as an optimization problem: (1) two GA variants and (2) a MA. The overall structure of the proposed EAs (GA1, GA2 and MA) is shown in Table 7.

In GA1, a subset is formed by a deadhead-minimizing pairing search. The initial population of individuals is created randomly. A repair heuristic is then applied on each and every individual within the initial population. Subsequently, in each iteration cycle, two parents (individuals) are selected using the binary tournament selection method. This method chooses the individual with the best fitness among several randomly chosen individuals from the initial population with the tour size. Two new children are then created by applying the crossover to those selected parents, and the children are mutated afterwards. A repair heuristic is applied to potentially non-feasible chromosomes. Then, the worst two individuals in the population are replaced with the best two of the parents and offspring. The subset is updated in each specific iteration until the termination criterion is satisfied. Finally, the best solution is identified.

In the second approach, GA2 is used. Similar to GA1, GA2 starts with a randomly generated initial population and applies repair heuristics to each individual in the population. Deadhead-minimizing and less-costly pairing search algorithms are integrated and used in GA2. Third, after forming the initial population of GA2, a local optimization technique is applied, and this algorithm is called an MA. The other steps in the MA are the same as those of the GA (GA2).

MAs and GAs developed by other authors have also been tested, and the results are provided in Table 8. The KPIs in this table show that among the proposed algorithms, the MA generated better results. However, statistical methods should be used to determine whether significant differences occurred between these algorithms.

The Mann-Whitney-Wilcoxon test is used as a statistical test of the pairwise average performance of two given algorithms for non-parametric tests [50]. The results show that the proposed MA provides less-costly crew pairings.

Table 7. Proposed evolutionary algorithms.

Improving Heuristics	Evolutionary algorithms		
	GA1	GA2	MA
Deadhead-minimizing pairing searching	x	x	x
Less-costly alternative pairing searching	-	x	x
Local optimization techniques	-	-	x

The proposed algorithm was compared with the results of previous studies performed with the same EAs, and the results show that it exhibits significant performance. Kornilakis and Stamatopoulos [14] and

Table 8. KPI-Cost report I for proposed approaches.

KPI	Instance 3			Instance 4			Instance 5			Instance 6		
	GA1	GA2	Memetic	GA1	GA2	Memetic	GA1	GA2	Memetic	GA1	GA2	Memetic
# of subsets	352	800	767	404	614	585	462	736	794	480	1158	881
# of pairings (selected)	264	285	282	309	324	331	344	362	353	349	396	412
# of duties	388	376	373	432	423	422	491	464	454	527	505	512
# of duty days	484	473	470	529	520	519	588	561	551	624	602	609
# of overnights	124	91	91	123	99	91	147	102	101	178	109	100
# of deadheads	39	32	36	36	32	28	45	28	28	40	34	30
Total duty time (h)	3650.08	3616.42	3632.83	3948.58	3938.00	3918.17	4264.17	4192.33	4190.25	4490.75	4458.83	4447.17
Total pairing duration (h)	8423.88	7702.93	7576.35	8710.18	8186.55	8002.97	9640.53	8466.47	8416.35	10537.50	9042.88	8800.52
Total block time (h)	2620.00	2603.25	2608.83	2780.33	2780.67	2770.50	2974.00	2937.92	2935.50	3109.33	3093.25	3085.33
Total overnight duration (h)	2279.75	1573.58	1435.58	2213.17	1670.67	1497.08	2738.92	1640.25	1612.17	3425.08	1897.50	1649.58
Total deadhead time (h)	221.42	198.17	209.33	208.33	209.00	188.67	259.67	187.50	182.67	237.00	210.17	194.33
Total number of pilots for duties	1050	1024	1018	1136	1119	1117	1260	1201	1180	1328	1283	1296
Pairing generation runtime (min)	2.13	1.93	2.24	3.54	3.36	3.44	6.05	5.80	5.56	12.97	12.02	11.79
Total runtime (min)	4.16	4.49	3.91	6.96	5.71	7.08	10.99	18.40	8.55	67.29	98.90	36.41
COST												
Duty day cost	368648	367761	368446	389821	390953	390353	414097	409573	408251	426745	428723	429056
Hotel cost	136785	94415	86135	132790	100240	89825	164335	98415	96730	205505	113850	98975
Hotel transportation cost	1488	1092	1092	1476	1188	1092	1764	1224	1212	2136	1308	1200
Deadhead cost	13285	11890	12560	12500	12540	11320	15580	11250	10960	14220	12610	11660
Total cost	520206	475158	***468233***	536587	504921	***492590***	595776	520462	***517153***	648606	556491	***540891***

Table 9. KPI-Cost report II for performance comparisons of previously proposed memetic algorithm (MA) approaches.

KPI	Instance 3			Instance 4			Instance 5			Instance 6		
	KS	ZO	Memetic	KS	ZO	Memetic	KS	ZO	Memetic	KS	ZO	Memetic
# of subset	4098	4945	767	4759	5747	585	5270	5356	794	5789	7100	881
# of pairing (selected)	214	207	282	224	230	331	252	242	353	278	290	412
# of duties	412	407	373	472	465	422	546	519	454	589	593	512
# of duty days	510	504	470	570	563	519	644	618	551	687	691	609
# of overnights	198	200	91	248	235	91	294	277	101	311	303	100
# of deadheads	96	85	36	143	121	28	168	136	28	194	201	30
Total duty time (h)	3857.83	3818.67	3632.83	4328.08	4206.50	3918.17	4663.00	4582.67	4190.25	4965.00	4994.50	4447.17
Total pairing duration (h)	10268.35	10033.05	7576.35	11446.77	11341.00	8002.97	12933.47	12514.65	8416.35	13363.92	13390.55	8800.52
Total block time (h)	2746.58	2710.92	2608.83	3018.92	2922.33	2770.50	3211.75	3161.67	2935.50	3384.83	3393.58	3085.33
Total overnight duration (h)	4002.92	3834.00	1435.58	4696.92	4686.83	1497.08	5794.83	5507.83	1612.17	5878.92	5883.33	1649.58
Total deadhead time (h)	459.25	405.75	209.33	618.42	464.92	188.67	688.33	613.75	182.67	741.50	786.42	194.33
Total number of pilots for duties	1096	1084	1018	1216	1205	1117	1366	1307	1180	1453	1457	1296
Pairing generation run time (mins)	2.05	2.13	2.24	3.49	3.69	3.44	5.81	5.71	5.56	11.71	11.81	11.79
Total run time (mins)	5.25	7.01	3.91	7.40	9.60	7.08	10.57	12.15	8.55	18.08	21.22	36.41
COST												
Duty day cost	375926	371943	368446	404991	399250	390353	428318	420409	408251	449100	450433	429056
Hotel cost	240175	230040	86135	281815	281210	89825	347690	330470	96730	352735	353000	98975
Hotel transportation cost	2376	2400	1092	2976	282	1092	3528	3324	1212	3732	3636	1200
Deadhead cost	27555	24345	12560	37105	27895	11320	41300	36825	10960	44490	47185	11660
Total cost	646032	628728	***468233***	726887	711175	***492590***	820836	791028	***517153***	850057	854254	***540891***

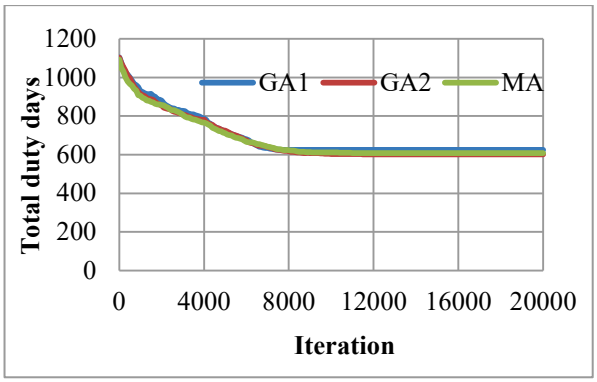
Table 8. Continue.

KPI	Instance 1			Instance 2		
	GA1	GA2	Memetic	GA1	GA2	Memetic
# of subset	441	1313	1148	402	1325	1333
# of pairing (selected)	212	198	206	208	205	217
# of duties	363	345	350	360	351	359
# of duty days	399	381	386	397	387	395
# of overnights	151	147	144	152	146	142
# of deadheads	77	71	63	70	64	80
Total duty time (h)	2972.75	2929.33	2897.08	2994.58	2969.92	3001.00
Total pairing duration (h)	6398.02	6184.13	6204.28	6525.87	6259.87	6236.10
Total block time (h)	2052.17	2020.33	2001.17	2060.00	2045.67	2058.42
Total overnight duration (h)	2512.17	2369.25	2410.92	2614.00	2388.83	2328.17
Total deadhead time (h)	470.42	423.00	383.08	434.58	414.08	430.17
Total number of pilots for duties	814	777	787	810	790	804
Pair generation run time (mins)	1.03	1.05	1.02	1.21	1.19	1.12
Total run time (mins)	2.08	4.44	2.49	2.45	2.64	3.16
COST						
Duty day cost	233151	228893	227602	234712	232262	234476
Hotel cost	150730	142155	144655	156840	143330	139690
Hotel transportation cost	1812	1764	1728	1824	1752	1704
Deadhead cost	28225	25380	22985	26075	24845	25810
Total cost	413918	398192	**396970**	419451	402189	**401680**

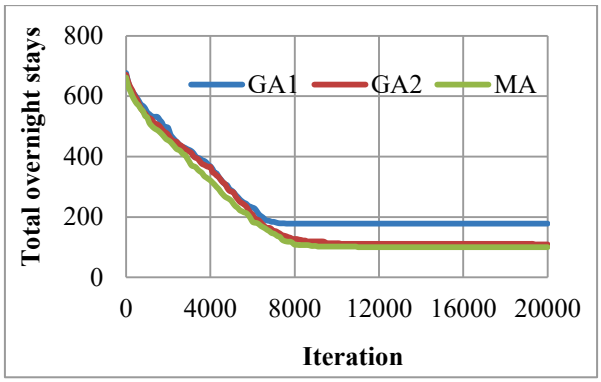
Table 10. Summary report with percent improvement (%).

Comparison of the proposed method	KPI / 100	Instance 3	Instance 4	Instance 5	Instance 6
Kornilakis and Stamatopoulos [14]	Total deadhead time (h)	2.19%	3.27%	3.76%	3.81%
	# of duty days	1.08%	1.09%	1.16%	1.12%
	# of overnights	2.17%	2.72%	2.91%	3.11%
	Total cost	1.37%	1.47%	1.58%	1.57%
Zeren and Ozkol [13]	Total deadhead time (h)	1.93%	2.46%	3.35%	4.04%
	# of duty days	2.19%	1.08%	1.12%	1.13%
	# of overnights	2.36%	2.58%	2.74%	3.03%
	Total cost	1.34%	1.44%	1.52%	1.57%

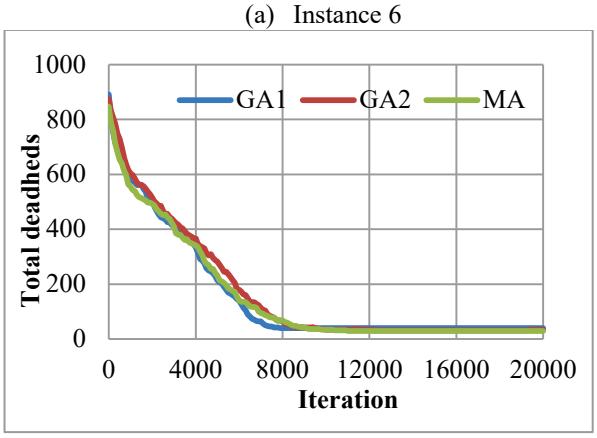
Note: **KS**=Kornilakis and Stamatopoulos [14] and **ZO**=Zeren and Ozkol [13].



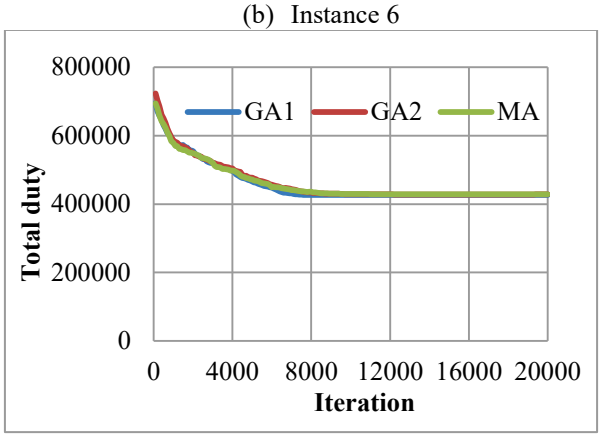
(a) Instance 6



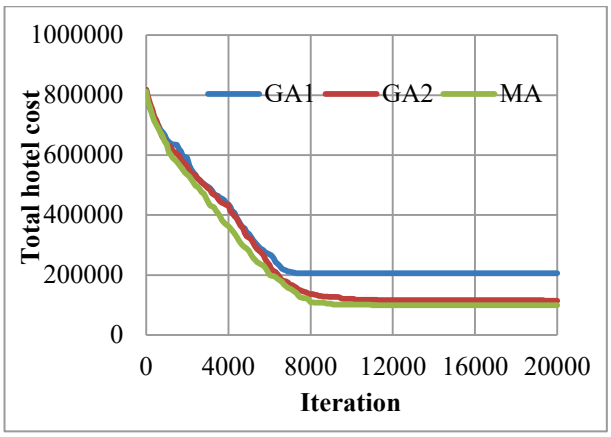
(b) Instance 6



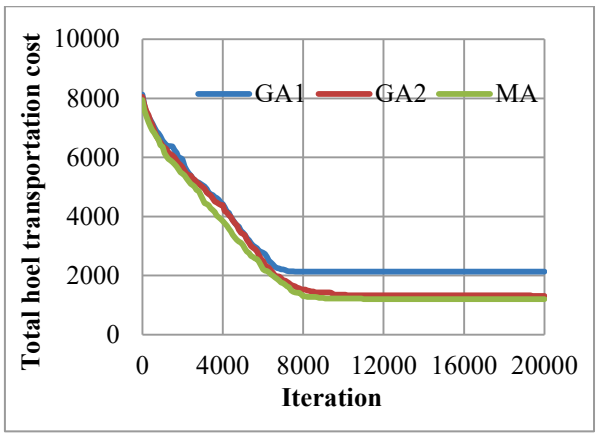
(c) Instance 6



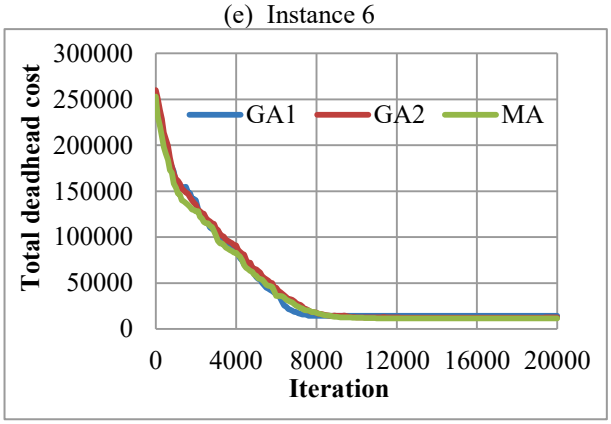
(d) Instance 6



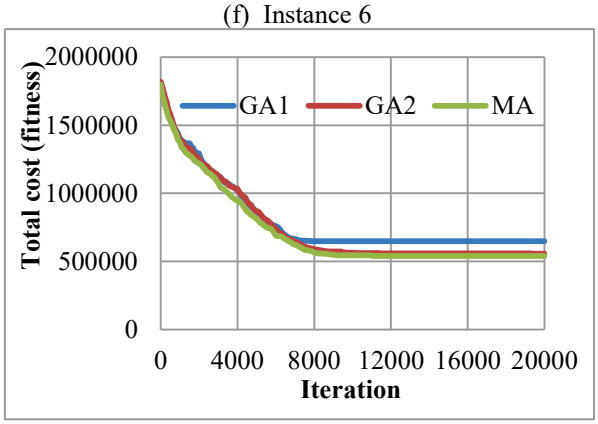
(e) Instance 6



(f) Instance 6



(g) Instance 6



(h) Instance 6

Fig. 6. Summary of the KPI to compare the proposed approaches (instance 6).

Zeren and Ozkol [13] sought to eliminate poor-quality crew rotations to reduce performance problems in their studies, and they successfully eliminated poor-quality crew pairings as long as they stored high-quality crew pairings of a certain amount.

In other words, a pairing subset is generated by choosing a pairing of a certain amount from the main set of all pairings, and it is provided to the GA as input. The difference in our study is that the pairing subset is dynamically and continuously renewed because the GA is optimized. Comparisons of previously proposed MA approaches are summarized in Table 9.

Three important parameters are presented in Tables 8 and 9: total man-days, deadheads, and layovers/ overnights. The solutions are generally evaluated via these three parameters. Evaluating other parameters is meaningful if these three values are close to each other. Because financial costs are not determined, the total cost can provide insights for planning, although the solutions are always evaluated with the three important parameters because of operational difficulties. According to the planning period, the overnight, deadhead and man-day parameters are prioritized based on their level of importance.

Novel dynamic-based GA variations and a MA approach are proposed to obtain a crew pairing solution set with the minimum cost. In Fig. 6, graphics are shown for the following KPIs (e.g., *instance 6*) obtained via the optimization of the proposed approaches: number of deadheads: total number of deadheads; deadhead time: total flight times of deadheads; duty days: total number of duty days; overnight stays: total number of overnight stays; overnight duration: total time of overnight stays; and fitness: total crew pairing cost.

In Table 10, a summary of the critical assessment parameters of the crew pairing is shown, and it indicates that the proposed approach is successful at decreasing the total deadhead time. The deadhead factor is an important KPI, especially in high seasons because the airline's income will decrease when passenger seats are used by the crew. Another important KPI is the number of duty days. In certain months, the airline companies encounter difficulties securing a sufficient number of pilots, particularly in December when certain pilots have reached their annual flight time limits. Therefore, the number of duty days is an important factor. The number of overnights is another factor that must be at the optimum level because it affects the accommodation costs of the airline companies. The total cost value shows a general optimization performance. The results show that the proposed approach generates outstanding total cost values.

Fig. 6 and Table 10 show that the MA-generated solutions present better deadhead, duty day, overnight stay, and total cost values.

5. Conclusions and Future Directions

In this study, a dynamic-based MA approach and GA variations are proposed for the airline crew pairing problem, which has been intensively studied in the literature. Because crew pairing is a main cost-identifying stage of the crew scheduling process, approaches that decrease crew costs, increase crew utility and generate optimum crew pairings are of significant importance. KPIs, such as deadhead time, number of duty days, and number of overnight stays, are submitted along with the financial costs related to crew pairing optimization. These indicators are of significant importance because they facilitate the management of operational challenges in real-world problems.

A unique model and strategies have been developed after reviewing current approaches during the development of the proposed solution. The computational results section shows that the proposed strategy generates highly competitive results when compared with current approaches. The proposed approach is particularly successful at decreasing deadhead time and the number of overnight stays.

The main contributions of this study are as follows:

- A dynamic-based GA has been developed for solving the medium-scale airline crew pairing problem;
- An alternative pairing search (deadhead-minimizing search) approach has been developed that will decrease the deadhead factor;
- A low-cost (high-quality) alternative pairing search (partial solution search) approach has been developed.

Dynamic-based GAs and changes in chromosome length in each iteration were used to resolve the crew pairing problem. The advantage of the proposed approach is that it seeks the solution set with the minimum cost that covers all flights via a GA by generating subsets from millions of main sets. However, using millions of generated crew pairings in the GA as

direct input renders the problem impossible to solve and slows the performance of the algorithm, thereby leading to sub-optimal results. Therefore, one subset is considered instead of all pairings. This subset dynamically changes, i.e., the main set and the subset exchange pairings. The pairings that lead to a sub-optimal solution from the pairing subset are excluded from the solution, and the pairings that lead to an optimal solution from the main set are chosen and added to the subset.

The second contribution is an alternative pairing search approach that will decrease the number of deadheads. In this method, a heuristics approach that searches and finds the pairings that generate the fewest deadheads for each flight is developed, and it sends the pairings that lead to the best solution from the main set to the subset. Concurrently, the approach checks the number of covering flights in the pairings in the subset as explained in Section 3.4.1. If a flight is covered more than once (deadhead) in the pairings, the alternative pairings that decrease the number of deadheads are sought. This search is performed for all pairings starting from the deadhead that is most covered, and it adds the identified alternative pairings to the subset.

The third contribution is that high-quality pairings are searched from the main set and low-quality pairings in the subset are not searched by checking the pairings in the best chromosome. In other words, a low-cost pairing search is performed. As stated in Section 3.4.2, the pairing with the lowest quality is first identified, and then a high-quality pairing search is performed from the main set for the flights in the pairing with the lowest quality for this lowest quality pairing. This procedure continues until it finds the highest-quality pairings for flights in the pairings with the lowest quality. This procedure is conducted according to the quality metric that is assigned to the pairings beforehand.

Detailed comparisons are presented in the tables above, and they clearly show that the proposed approach can generate competitive results when compared with current approaches that use state-of-the-art solvers (the deadhead-minimizing pairing search and less-costly alternative pairing search algorithms).

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