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Evolutionary algorithms for solving the airline crew pairing problem

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ABSTRACT

Solving the airline crew pairing problem (CPP) requires a search to generate a set of minimum-cost crew pairings covering all flight legs, subject to a set of constraints. We propose a solution comprising two consecutive stages: crew pairing generation, followed by an optimisation stage. First, all legal crew pairings are generated with the given flights, and then the best subset of those pairings with minimal cost are chosen via an optimisation, process based on an evolutionary algorithm. This paper investigates the performance of two previously proposed genetic algorithm (GA) variants, and a memetic algorithm (MA) hybridising GA with hill climbing, for solving the CPP. The empirical results across a set of benchmark real-world instances illustrate that the proposed MA is the best performing approach overall.

1. Introduction

Operations research (OR) methods provide a comprehensive set of tools to address airline problems. The airline industry has utilised OR techniques extensively since the 1950s (Barnhart & Talluri, 1997), and OR models have had an enormous influence on operations and planning within the airline industry. Advances in optimisation models and computer technology have enabled airlines to deal with problems that are more complex. The fundamental airline problems can be classified as planning or operational problems: the first stage is the planning, and the second is the operations. Each category of problems has its own unique characteristics and objectives. The planning process generally comprises four main steps (Barnhart et al., 2003; Bazargan, 2004; Klabjan, 2005): flight scheduling, fleet assignment, aircraft routing, and crew scheduling. The operational processes are revenue management, gate assignments, and irregular operations. The output of one stage is the input of the next stage. In this study, we look at crew scheduling in the planning process.

Crew scheduling is one of the most important planning problems for all airlines as the total crew cost, including salaries, benefits, and expenses, is the second largest cost component, after fuel costs (Bazargan, 2004). Unlike the fuel costs, a large percentage of flight-crew expenses can be controlled (Anbil et al., 1992; Barnhart & Cohn, 2004; Demirel & Deveci, 2017; Deng & Lin, 2011; Desaulniers et al., 1997; Klabjan, Johnson, Nemhauser, Gelman, & Ramaswamy, 2001; Kohl & Karisch, 2004; Pavlopoulou, Gionis, Stamatopoulos, & Halatsis, 1996). Crew costs (annual crew expenses, salaries, and benefits) for a selection of major US airlines are presented in Table 1. Airline crew scheduling problems are NP hard, which means they cannot be exactly solved in a reasonable computation time (Aydemir-Karadag, Dengiz, & Bolat, 2013; Deveci & Demirel, 2015).

Airline crew scheduling (ACS) is generally divided into crew pairing problems (CPP), and crew rostering (or crew assignment) problems. Crew rostering has less impact on total crew costs compared to the crew pairing process (Zeren & Ozkol, 2016). In this paper, we focus on the first stage of the crew scheduling problem. The aim of this CPP study is to generate a set of minimal-cost crew pairings, covering all flight legs.

We present a two-stage model for the airline CPP: crew pairing generation and optimisation. The model has been formulated as a set covering problem (SCP). In this study, we have applied three evolutionary algorithms (EA), two genetic algorithm (GA) variants, and a memetic algorithm (MA), for solving the CPP. In addition, the elasticity of these two methods is compared. All of the approaches developed for observing the effectiveness of the study and comparing the results, are tested on twelve different datasets obtained from a Turkish domestic airline. The performance evaluation results show that the MA is a useful and effective heuristic algorithm for solving the airline CPP.

The rest of the paper is organised as follows: Section 2 provides an overview of the background, Section 3 describes the airline CPP, the proposed EAs are explained in Section 4, and Section 5 presents a case study from Turkey, a comparison of the performance of different EAs applied to this case study, and the experimental results and analysis in Section 6. Finally, Section 7 presents the conclusion of this study.

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Table 1
Crew costs for major US airlines (Bazargan, 2010).

Carrier	Number of flight crew	Flight crew expenses ($)	Crew expense/ operating expense (%)
Alaska	1455	180,845,000	5.57%
AirTran	1632	157,383,851	6.00%
American	11,166	1,152,808,000	4.48%
Continental	4867	623,767,000	4.05%
Delta	12,299	802,811,000	3.84%
Southwest	5915	965,329,000	9.13%
United	6478	757,020,000	3.44%
US Airways	5275	482,044,882	3.39%

2. Background

2.1. Crew pairing

Crew pairing and crew rostering are considered as separate, but related problems. The first process is crew pairing generation, which constitutes the main topic of this study. The second sub-process is crew rostering. In this stage, crew assignments to all crew pairings generated in the prior crew pairing generation stage, are done (Zeren & Ozkol, 2016). Both problems can be solved by similar procedures (Valdes & Andres, 2010). Traditionally, the airline CPP can be formulated as a set partitioning problem (SPP), or SCP, and then optimisation methods (mathematical models) are used to solve it (Yan & Tu, 2002). From a literature study, the majority of crew-scheduling problems are seen as either an SCP or SPP. For example, Chu, Gelman, and Johnson (1997) solved a set partitioning zero-one integer programme for CPP. This paper presents a graph-based branching heuristic, applied to a restricted SPP representing a collection of best pairings. Mingozzi, Boschetti, Ricciardelli, and Bianco (1999) formulated a SPP with side constraints, where each column of the side constraints matrix corresponds to a feasible duty, which is a subset of tasks performed by a crew. Borndorfer, Schelten, Schlechte, and Weider (2006) proposed a method using the column generation approach for solving airline crew-scheduling problems that is based on a set partitioning model. Medard and Sawhney (2007) solved a set covering model as the first step, and the second with a set partitioning model of crew-scheduling problems. Reisi-Nafchi and Moslehi (2013) investigated the cockpit CPP. The SPP has been used for modelling the problem. Their focus is on solving the column generation sub-problem.

Column generation method is a widely used technique to solve the crew-scheduling problems. Lavoie, Minoux, and Odier (1988) proposed a new approach to crew pairing as an SCP, where the column generation approach was used to solve the problem. Cordeau, Stojković, Soumis, and Desrosiers (2001) presented a solution methodology that combines benders-decomposition and column-generation. Yan and Chang (2002) developed two different networks for the crew pairings, using real data from C-Airlines. The model was formulated as an SPP, and a column generation approach was developed to solve the problem. Díaz-Ramírez, Huertas, and Trigos (2014) presented a column generation approach for solving the aircraft maintenance-routing problem, and the crew-scheduling problem.

Heuristic and meta-heuristic methods have also been widely studied (Cacchiani & Salazar-González, 2013; Maenhout & Vanhoucke, 2010).

Stochastic gradient descent can be used instead of LP approaches, and constitute a fundamental step of mathematical methods. However, even LP problems are not sufficient to yield the integer solutions that we need; this type of development could even be the topic of a separate, low-level research project.

2.2. Related work

In this section, genetic and memetic algorithm approaches in airline crew pairing areas are examined. Genetic algorithms generally perform better than other meta-heuristics in binary problems. In addition, GAs are preferred because they have subjects of sufficient comparative approaches and studies. As current approaches are not sufficient to solve large-scale problems, these approaches are used together with integrated heuristics in most of the studies. Several studies on the application of GAs, based on meta-heuristics, to the airline crew scheduling problem are found in the literature. In these studies, the SP or SC problem are generally considered to solve the crew pairing optimisation problem. Both of them are proven to be NP-complete (Garey & Johnson, 1979).

An MA is a heuristic algorithm that uses local search (LS) techniques, and is a GA-based and hybrid-structured EA. MAs are enhanced population-based EAs that were first developed by Moscato (1989), with the aim of solving discrete optimisation problems. EAs are a class of search and stochastic P-metaheuristics that have been successfully applied to both real world and complex problems. Their success lies in solving difficult optimisation problems by various domains (continuous- or combinatorial-optimisation, machine learning, etc.) (Talbi, 2009).

There are several GAs based on meta-heuristics studies in the literature regarding the airline crew scheduling problem. Beasley and Chu (1996) presented a GA-based heuristic for non-unicost SC problems. They also proposed several amendments to basic GAs, including a new fitness-based crossover operator (fusion), a variable mutation rate, and a heuristic feasibility operator customised specifically for the SC problem. Levine (1996) proposed a hybrid GA that comprises a steady-state GA and a local search heuristic. Ozdemir and Mohan (2001) used a GA applied to a flight graph presentation that represents several problem-specific constraints. Kerati, El Moudani, de Coligny, and Mora-Camino (2002) solved the airline crew-scheduling problem by improving two criteria in their earlier studies. They proposed a heuristic GA approach to the airline crew-scheduling problem. In their study, this optimisation problem is split into two parts, and solved separately. Their aim was to demonstrate the solutions obtained by using the GA and cost functions. Kornilakis and Stamatopoulos (2002) proposed a two-phased procedure for CPPs. The first step included a depth-search algorithm for the pairing generation, and this problem was solved by using a GA with an SC formulation. Chang (2002) addressed the performance of the crew-scheduling process itself, together with the flexibility of an irregular operator, by developing an aircrew-scheduling model. To solve this problem, a GA was utilised, and it produced successful outcomes. Souai and Teghem (2009) proposed a methodology based on a hybrid GA. In their study, three heuristics were developed to tackle the restriction rules within the GA's process. Zeren and Ozkol (2012) investigated a new solution of the CPP using GAs. They also created new genetic operators in their study. Azadeh, Farahani, Eivazy, Nazari-Shirkouhi, and Asadipour (2013) presented a particle swarm optimisation (PSO) algorithm, synchronised with a local search heuristic, to solve the crew-scheduling problem. Moreover, two other hybrid algorithms based on GAs and ant colony optimisation (ACO) algorithms, have been designed to solve this problem.

3. Airline crew pairing problem

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 majority of Turkish carriers generate monthly plans so as to have more one- or two-day pairings. Longer pairings are undesirable because of their operational difficulties. This condition is sometimes changed according to legal rules. The most important characteristics of efficient crew utilisation are the pairings, which cover all flight legs and minimise total costs. The crew pairings are constrained by rules defined by FAA safety regulations, company collective-agreement rules, and crew unions. Under these constraints, the airline companies obviously want to determine the lowest cost, and most optimal possible pairings,