Probability Learning Based Feasible and Infeasible Tabu Search for Airport Gate Assignment

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1 Introduction

Airport gate assignment is an important decision problem that airport professionals must face every day. The problem involves in assigning each aircraft to an available gate to meet operational requirements while maximizing the convenience for passengers and airport operation efficiency. In this work, we study the passenger-oriented gate assignment problem (GAP) that aims to minimize the total walking distance.

In this model, G is the set of airport gates, F is the set of aircraft, a_i is the arrival time of aircraft i, d_i is the departure time of aircraft i, c_{ij} is the number of passengers transferring from aircraft i to aircraft j, w_{lm} is the walking distance between gates l and m, x_{il} is a binary decision variable taking the value of 1 if aircraft i is assigned to gate l, and it is 0 otherwise. On the basis of these parameters and decision variables, GAP can be formulated as the following mixed integer nonlinear program :

$$\min \quad Z(S) = \sum_{i\in F}\sum_{j\in F}\sum_{l\in G}\sum_{m\in G} c_{ij}w_{lm}x_{il}x_{jm} + \sum_{i\in F}\sum_{l\in G}(c_{i0}w_{l0} + c_{0i}w_{0l})x_{il} \tag{1}$$

$$\text{s.t.} \quad \sum_{l\in G} x_{il} = 1, \ \forall i \in F \tag{2}$$

$$x_{il}x_{jl}(d_j - a_i)(d_i - a_j) \geq 0, \ \forall i, j \in F, \ \forall l \in G \tag{3}$$

$$x_{i,l} \in \{0, 1\}, \ \forall i \in F, \ \forall l \in G \tag{4}$$

This model is the basis of many GAP variants and has been extended in the literature to other GAP formulations. As such, an algorithm designed for this model can be adapted to solve other related problems. We investigate the GAP by proposing an effective heuristic algorithm.

2 Probability learning based feasible and infeasible tabu search

We propose a probability learning based feasible and infeasible tabu search (PLFITS) algorithm to solve the GAP [3], which integrates a feasible and infeasible tabu search procedure within the probability learning based framework [4]. During the PLFITS search process, problem-specific knowledge is learned via its probability learning procedure. The learned information, recorded in a probability matrix, is applied to guide the algorithm toward promising search regions. As such, PLFITS iteratively explores the given search space by alternating between probability learning and local search to attain a better balance of search diversification and intensification. Its general scheme is composed of four main components : a gate selection strategy (to select a gate for each aircraft according to the probability matrix), a strategic oscillation procedure (to allow the search to oscillate between the feasible and infeasible search spaces to find high-quality local optimal solutions), a probability updating rule (to update the probability that each aircraft should be assigned to each gate according to feedback information), and a probability smoothing technique (to forget some aged decisions that are considered obsolete). The algorithm repeats the these four components until a stopping condition is reached.

3 Computational results

We report computational results of the proposed algorithm on a set of 20 real-world benchmark instances collected by Cheng et al. [1] arising from Incheon International Airport (ICN). These instances can be classified into three groups by setting the percentage of transfer passengers π respectively to 0.1, 0.3, and 0.5. Comparisons are made with two reference algorithms, including a simulated annealing tabu search (SATS) [1], and a tabu search with path relinking (TSPR) [2]. We run ten times our PLFITS algorithm to solve each instance with the same time limit (200 seconds on Intel Xeon E5-2670 2.5GHz). Table 1 shows the comparative results, including the best and average objective values, the average computing times, and the gaps between the best objective values attained by PLFITS and the best-known results, indicating the PLFITS algorithm dominates the reference algorithms (better results are highlighted in bold). In particular, PLFITS reports improved best-known solutions (new upper bounds) for all the 20 ICN instances with improvements ranging from 2.6% up to 11.85%.

TAB. 1 – Comparative results on the ICN instances.

			SATS		TSPR		PLFITS			
Date	Instance size	π	f_{best}	t_{avg}	f_{best}	t_{avg}	f_{best}	f_{avg}	t_{avg}	Gap
Friday	294x74	0.1	27091415	170	26945560	185	**25926530**	26081164.50	114.82	-3.78
Saturday	290x74	0.1	27001350	174	26800315	185	**25966585**	26087735.00	95.25	-3.11
Sunday	304x74	0.1	30016505	193	29764555	201	**28910295**	29053005.00	104.92	-2.87
Monday	297x74	0.1	27554290	185	27668210	207	**26699195**	26852055.50	122.00	-3.10
Tuesday	290x74	0.1	26055045	180	25780535	196	**24906875**	24983420.50	122.11	-3.39
Wednesday	279x74	0.1	25092430	151	24875240	173	**24227945**	24315138.00	127.04	-2.60
Thursday*	289x74	0.1	27515505	168	27155365	190				
Friday	294x74	0.3	29325270	184	29274210	196	**27158465**	27269086.00	143.94	-7.23
Saturday	290x74	0.3	29378545	194	29272310	224	**26977360**	27130970.50	117.11	-6.67
Sunday	304x74	0.3	31690910	199	31642165	226	**29673555**	29788407.00	136.52	-6.22
Monday	297x74	0.3	29798700	219	30025230	228	**27739185**	27887095.50	155.72	-6.91
Tuesday	290x74	0.3	28050095	189	27898320	211	**25712685**	25807973.00	131.25	-6.80
Wednesday	279x74	0.3	27816840	156	27588215	174	**25456930**	25637756.50	145.80	-7.73
Thursday	289x74	0.3	29472105	186	29402315	205	**27056815**	27218636.50	145.57	-7.98
Friday	294x74	0.5	31679360	199	31304880	213	**27879920**	28099215.00	121.33	-10.94
Saturday	290x74	0.5	31436665	195	31337070	213	**27971855**	28036805.00	155.17	-10.74
Sunday	304x74	0.5	35011240	217	35050585	261	**30861150**	30981396.00	166.91	-11.85
Monday	297x74	0.5	31989310	213	31900725	234	**28559395**	28692073.50	165.01	-10.47
Tuesday	290x74	0.5	30112340	198	30069210	223	**26664255**	26782922.00	120.78	-10.70
Wednesday	279x74	0.5	29751435	175	29667010	201	**26457175**	26615683.50	134.41	-10.82
Thursday	289x74	0.5	31896375	194	31755335	228	**28087180**	28266150.00	155.12	-11.47

* The data of this instance is no more available in the literature (the authors of [1] failed to provide the initial data).

Finally, the probability learning and the mixed feasible-infeasible search strategies are general and can be used to tackle other airport gate assignment problems with different objectives and constraints or other problems with complex constraints. For further research, more efforts are needed to investigate exact and approximation methods with quality guarantees.

Références

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