Solving patient admission scheduling problem using constraint aggregation

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1 Introduction

Hospital admission is a necessary step in the treatment of most diseases. However, the demand for health services is increasing rapidly, resulting in a shortage of medical resources. Therefore, Hospital admission management is a fundamental challenge for many hospital departments. It is important to improve performance by using bed resources as efficiently and effectively as possible. The patient admission scheduling (PAS) problem consists of assigning patients to beds over a given planning horizon to maximize treatment efficiency, patient satisfaction, and hospital utilization while meeting all necessary medical constraints and considering patient preferences as much as possible.

Due to the high-quality performance of exact algorithms in the literature, this paper focuses on how better formulations – in this case, through reducing the model by aggregating constraints – can help further improve the efficiency in solving the IP model of the PAS problem. This is as opposed to working on the algorithmic side. To assess how effective these formulation improvements are, we use an exact method provided by the state-of-the-art MIP optimization solver.

2 Solution Method

To solve the PAS problem, we employ a two-stage optimization approach that depends on solving the IP model and incorporates an aggregation procedure to reduce the model size to improve the performance of the algorithm. Our approach starts with solving a patient-room assignment (PRA) problem to generate a partial solution. In particular, it is challenging to directly solve the PRA problem in the whole solution space due to the large scale. Thus, it solves a simplified PRA (SPRA) problem with a limited solution space to generate a high-quality solution before solving the PRA model. Then, to explore optimal global solutions, it solves the PRA problem using the solution obtained in SPRA as the start solution. We proposed a new gender policy constraint and three aggregated constraints to reduce the size of the PRA and SPRA models. Secondly, our approach solves a patient-bed assignment (PBA) problem to allocate patients to beds of a specific room according to the PRA solution, which is subsequently validated by an application made available online [1] by Demeester et al. (2010).

3 Computational results

We discuss the results of our proposed solution method on instances provided by Demeester et al. (2008). In order to compare our best results with those obtained in previous works,

1. https://people.cs.kuleuven.be/~wim.vancroonenburg/pas/

we perform experiments by running the program for a time limit of 24 hours as the previous research. Due to the differences in machine performance and Gurobi version between us and previous literature studies, we implement the MIP model of Bastos et al. (2019), which generates the most best known solutions, with a warm start to solve the PRA problem and set the default settings of Gurobi consistent with the literature. Table 1 contrasts the best-known solutions with our best results. Under the header "Literature Results", we present the best-known solutions associated with solution times for each of the 13 benchmark instances. We show the results generated by the two-stage approach with the literature's MIP model in the first stage under the header "MIP of Bastos et al. (2019)" and report our results generated by the two-stage approach using $AGC_0\&TC$ model under the header "IP of $AGC_0\&TC$".

We note that our approach generated new best-found solutions for 6 out of the 13 tested benchmark instances (note that solutions obtained for instances 1,3,5,6 and 7 were the same as best known solutions reported in the literature ; nevertheless, they were proven to be optimal by our PRA model within an hour). Furthermore, the optimality of the solution was also proven, for instance 2. Although we have not proven the optimality of instances 4 and 8, the gaps of them to the optimal are very low ($< 1\%$). The above results show that a reduced model by aggregated constraints can improve the solution quality significantly.

TAB. 1 Comparison between best know solutions and IP result (new best found solutions in **bold**, proven optimal solutions in star*).

Instance	Literature results			MIP of Bastos et al. (2019)					IP of $AGC_0\&TC$				
	Reference	BKS	Time	Obj	Time to best	Time to end	LB	GAP (%)	Obj	Time to best	Time to end	LB	GAP (%)
1	Bastos et al. (2019)	651.2	41437	651.2*	4229	19670	651.2	0.00	651.2*	303	1805	651.2	0.00
2	Bastos et al. (2019)	1128.0	86400	**1125.6**	30082	86400	1116.2	0.84	**1125.6***	2947	25358	1125.6	0.00
3	Bastos et al. (2019)	761.6	86400	761.6	10584	86400	758.6	0.40	761.6*	1315	13561	761.6	0.00
4	Bastos et al. (2019)	1151.6	86400	1151.6	23864	86400	1142.8	0.77	**1151.0**	21138	86400	1150.0	0.09
5	Bastos et al. (2019)	624.0	86400	624.0*	1073	5196	624.0	0.00	624.0*	286	521	624.0	0.00
6	Bastos et al. (2019)	792.6	8251	792.6*	6979	11111	792.6	0.00	792.6*	1185	1097	792.6	0.00
7	Bastos et al. (2019)	1176.4	19683	1176.4*	451	3105	1176.4	0.00	1176.4*	139	696	1176.4	0.00
8	Bastos et al. (2019)	4063.0	86400	**4058.6**	47334	86400	4030.2	0.70	**4058.6**	3184	86400	4038.0	0.51
9	Guido et al. (2018)	20832.8	1900	21109.4	71202	86400	19872.8	6.22	**20677.4**	85995	86400	19862.4	4.10
10	Guido et al. (2018)	7806.4	1923	7882.8	85023	86400	7696.6	2.42	**7799.8**	85991	86400	7680.4	1.55
11	Guido et al. (2018)	**11536.2**	1826	12014.8	48384	86400	10937.6	100	11630.2	48000	86400	10727.1	8.42
12	Guido et al. (2018)	**22707.2**	1905	24776.0	11068	86400	21845.0	13.42	23234.2	48000	86400	21686.0	7.14
13	Guido et al. (2018)	9109.8	964	9148.8	64035	86400	8863.2	3.02	**9102.2**	67091	86400	8869.3	2.63

* BKS - Best Known Solution in literaturem as reported by the corresponding reference.

Références

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