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Research Article

A Biobjective Approach to Assigning Recreational Activities to Medical Tourists

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Abstract:

Medical tourism is a growing market due to cost savings for patients and access to treatments unavailable in their home country. Countries offering high-quality medical services at affordable prices have great opportunities for growing their revenue and shares in this market. To increase the welfare of tourists and revenues associated with healthcare tourism, this study proposes a mathematical model for planning the integration of recreational activities to the medical schedules of healthcare tourists. The model achieves this by providing access for medical tourists into appropriate recreational activities based on their medical conditions, availability schedules, and budgets. The proposed integer programming model maximizes a weighted sum of total tourist satisfaction points and profits generated from assigning tourists to recreational activities. It incorporates medical restrictions, ensuring that medical tourists are directed to activities suitable for their medical conditions. The Pareto-efficient frontier for patient satisfaction and company profit is determined utilizing the integer programming model. The proposed model aims for a higher quality experience for medical tourists, optimizing their access to recreational activities while promoting economic growth in the health tourism sector. Computational tests demonstrate that the proposed model efficiently solves instance sizes that may arise in practical contexts and enables iterative solutions for obtaining Pareto-efficient frontiers.

1. Introduction

Medical tourism is a growing sector, as individuals from around the world seek lower-cost in high-quality medical services or access to treatments not available in their home countries. Cost savings is a major driver of health tourism. Medical procedures in Türkiye are significantly less expensive than in many European countries and United States of America, despite competitive quality. This provides an affordable option, particularly for individuals who do not have insurance coverage for the necessary procedure. Another advantage of healthcare tourism is the access to treatments and procedures that may be unavailable or heavily regulated in certain countries. Additionally, medical tourism offers the opportunity to combine medical treatment with a relaxing holiday. Many popular medical tourism destinations provide historical or natural sites, beautiful beaches, and other attractions, enabling medical tourists (interchangeably, patients or shortly tourists) to recover in a pleasant and soothing environment.

To further enhance the economic impact of medical tourism, a viable strategy is to guide health tourists to vacations or other recreational activities. This can be achieved through the creation of packages that include sea side, nature, cultural and historical tours or by offering programs with partners in tourism and entertainment sectors. Such initiatives would enrich the experience of health tourists and contribute to the growth of tourism sector by increasing their participation in other tourism activities. When directing health tourists to recreational activities, it is essential to consider capacities that the company can allocate for activities, associated costs, and the medical conditions of the tourists, as well as their preferences on various kinds of touristic activities. Balancing costs and revenue is crucial, and budget and health restrictions of tourists should be taken into account.

Medical tourism offers cost savings, access to treatments, and the opportunity to combine medical treatment with a vacation. A mathematical model that considers capacity constraints, costs, demand, and health restrictions can assist in directing health tourists to suitable recreational activities, generating revenue while providing a high-quality experience. To account for medical tourist satisfaction, the model should incorporate the preference of tourists regarding numerous touristic activity types.

This study aims to develop a model that jointly optimizes the profitability of health tourism along with medical tourist satisfaction by enabling healthcare tourists to engage in suitable touristic activities aligned with their preferences and medical schedule. By incorporating medical constraints associated with different activities available to medical tourists, as well as considering the cost, pricing, and operational constraints of recreational tourism businesses, this research seeks to guide the formulation of effective strategies for planning the operations of touristic service providers and directing a larger volume of patients towards diverse tourism activities.

Remaining of the paper is organized as follows. In Section 2, literature review on the applications of optimization in the tourism area and related operations research problems are presented. In Section 3, the problem is defined in its details delving into the practical aspects. Section 4 is dedicated to presenting the formal mathematical definitions and the integer programming models, culminating with an analysis of computational results derived from the integer programming model runs for a profit maximizing model and the biobjective model. Additionally, the construction and interpretation of the Pareto efficient frontier based on the biobjective integer programming model is discussed in Section 4. Finally, the paper is drawn to a conclusion in Section 5.

2. Literature Review

In recent years, there has been an increasing interest in utilizing operations research and optimization techniques to address the challenges in both healthcare area and tourism planning. This literature review initially focuses on the application of operations research and optimization in tourism planning, highlighting various studies that have addressed this problem.

Zhu et al. (2012) [1] present a study on the tour planning problem. They propose a framework for designing tour trips with desirable sites while considering budget and time constraints. To tackle the computational infeasibility of solving the mixed-integer linear programming problem, they develop a heuristic method based on local search ideas, which provides efficient and good approximation solutions.

Vansteenwegen et al. (2011) [2] introduce an expert system, which integrates a selection of attractions with the route plan. The study considers the interests and trip constraints of users, matching them to a database of locations to predict personal interests.

Brilhante et al. (2015) [3] propose, an unsupervised framework for planning personalized sightseeing tours in cities. They extract spatio-temporal information about tourists' itineraries from geo-referenced photo albums, matching them to Points of Interest. The personalized sightseeing tour recommendation is formulated as an instance of the Generalized Maximum Coverage problem, and the resulting trajectories are scheduled on the tourist agenda using a Traveling Salesman Problem approach.

Leong and Ladany (2001) [4] present a model for optimal cruise itinerary design, focusing on selecting destinations to visit, visit duration, and visit sequence. They employ a near-optimal heuristic approach to demonstrate the application of their model in selecting cruise itineraries, showcasing decision support capabilities for cruise operators.

Chia et al. (2016) [5] propose an offline approach for generating an optimal vacation routing plan, considering operating hours and duration of stay constraints. They utilize a traveling salesman problem algorithm to find the shortest path, but extend it by calculating arrival times and minimum stay durations at each stop for generating efficient plans that satisfy operating hours and duration of stay constraints.

Delalic et al. (2019) [6] introduce algorithms based on heuristic methods, such as simulated annealing and genetic algorithms, for optimal city selection and concert tour planning. They emphasize the importance of including social media analytics, to maximize the profit and better analyze concert tour planning.

Jean-Marc (2005) [7] focuses on applying meta-heuristics, to problems devised on real-world sightseeing tour planning. The research aims to provide decision support for users in planning their trips and explores multiple objective combinatorial optimization problems.

Vargas and Sendales (2016) [8] optimize the schedule of a tourist trip plan in a city with complex street directions and numerous places of interest. They extend the Traveling Salesman Problem by minimizing the total distance traveled by tourists while ensuring they visit each place only once and return to the starting point.

Perera et al. (2018) [9] propose a platform for sustainable tourism management that includes prediction, optimization, and optimal path generation modules. Their optimization algorithms, including genetic algorithms and iterated local search, aim to determine the number of tourists that can be accommodated in each location while ensuring environmental sustainability. The optimal path generating problem is related to the Traveling Salesman Problem.

Silva et al. (2018) [10] address the problem of elaborating travel itineraries considering visitor profiles, travel distances, costs, and attraction values. They formulate the problem as a traveling salesman problem with profits and priority prizes. The authors present an optimization model based on mixed-integer programming and a tailored tabu search algorithm. They apply statistical techniques, such as multivariate correspondence analysis, to analyze real data.

Overall, these studies demonstrate the diverse approaches and effectiveness of operations research and optimization techniques in tourism planning. From heuristic methods and meta-heuristics to mathematical programming and hybrid approaches, these techniques provide decision support, optimize itinerary design, personalize trips, and consider various constraints and objectives to enhance the tourism experience for travelers.

Applications of operations research in tourism planning have been framed into various classical optimization problem categories -mostly combinatorial- and mathematical program formulations. Scheduling problems involve the allocation of resources to tasks or activities to meet specific objectives. In the healthcare sector, scheduling problems arise in various contexts including surgical scheduling and appointment scheduling. Several studies have addressed scheduling problems in healthcare and proposed models and methods to solve them. Rahimi and Gandomi (2021) [11] provide an overview of operating room and surgical scheduling models and methods. Another study by Ala et al. (2023) [12] focuses on simulation approaches to appointment scheduling systems in healthcare. Reviews on appointment scheduling [13] and numerous other applications of scheduling in the context of healthcare [14] are available for the interested reader. Additionally, there are many studies for staff scheduling and rostering reviewed in [15,16] for general settings and in [17] for the context for hospitality management.

The proposed integer model addresses the unique problem defined in this study, which is in the intersection of healthcare and tourism, and aims to provide medical tourists with access to appropriate recreational activities based on their medical conditions, availability for different activity types, activity preferences and budgets. Our model aims to jointly maximize the total satisfaction points and profits earned from these tourists by an optimal assignment of medical tourists to different recreational activities.

3. Problem Definition

In recent years, medical tourism has gained popularity as hospitals and medical companies invest substantial resources in marketing and executing healthcare services internationally. Private hospitals often establish offices abroad to promote healthcare services provided in Türkiye and engage with potential patients, ensuring high-quality patient care through contracts and initial assessments. Although patient schedule typically includes travel dates and appointments for examinations, tests, and treatments, recreational activities are seldom incorporated, if at all.

The healthcare service fees in Türkiye are relatively low compared to many European countries and the United States, making it an attractive option for residents who may not have insurance coverage or seek lower-priced alternatives. Moreover, Türkiye offers accessible healthcare services at affordable costs, including travel expenses. In both cases, medical tourists are usually on a budget and allocate a portion of their funds for international travel. This budget often includes expenses that would have been spent on leisure, recreation, and vacation had they not been visiting for healthcare purposes. Considering that most medical procedures do not severely limit patients, and when there are such limits, safe recreational alternatives are available, there is potential economic and welfare value in combining healthcare tourism with vacation and recreation themes. In addition to benefiting patients; hospitals, healthcare companies, and tourism companies can generate revenue by offering recreational activities to medical tourists. However, any recreational activities or vacations must be planned carefully, respecting the appointments and constraints imposed by the planned tests and treatments.

Tests, treatments and other medical procedures pose constraints, in ruling out certain tour types for certain days preceding or following the procedure. However, among the many other activity types available for the days not occupied by the procedures, the patient prefers some to the others. Therefore, it is crucial for the mathematical model to incorporate patient preference as well as the medical restrictions on optimizing assignment of touristic activities.

In our proposed framework, we assume that a tourism company specializing in recreational activities receives an anonymized list of medical tourists scheduled to arrive in Türkiye and depart on specific days within the planning horizon. The patient schedule, including the days dedicated to tests or treatments, is provided along with any constraints related to the patient condition and medical procedures (see Table 1 for a list) that limit their participation in certain types of touristic activities. For instance, a cardiac evaluation may involve a reassessment on the third day following the tests, which blocks all activity types on that day, or an endodontic procedure may rule out gourmet tours for the four days that follow, but not trekking or sightseeing. Furthermore, it is assumed that a preference questionnaire is included within the medical tourism procedures, enabling the medical company to determine the preference scores the medical tourist attributes to various activities and the budget allocation specific to recreational activities outside healthcare services.

Table 1. *Medical procedures frequently applied in the context of healthcare tourism and considered in this study.*

Medical Procedures
General health check-up
Cardiac evaluation
Gastroenterological examination
Endoscopic examination
Ophthalmic examination
Refractive surgery
Dermatological evaluation
Dermatological intervention
Cosmetic surgery
Hair restoration surgery
Reconstructive plastic surgery
Dental examination
Endodontic therapy
Dental cavity filling
Physiotherapy

The healthcare tourism company organizes and conducts various types of vacations, touristic, and recreational activities (see Table 2 for a list). Each activity has a specific duration, and the company can schedule each tour type starting on any day throughout the planning horizon until the last day feasible for the completion of the activity. Each activity also has a capacity, indicating the maximum number of participants for activities starting on a specific day. Scheduling a tour on a particular day incurs fixed costs, representing expenses that do not vary with the number of tourists, such as tour guide fees and transportation vehicle rentals. Variable costs, on the other hand, depend on the number of tourists and include expenses like individual transportation and accommodations.

Table 2. *Types of activities offered by the (recreational) tourism company aside from the medical procedures.*

Types of Vacation or Recreational/Touristic Acitivities
Seaside vacation
Blue voyage
Thermal vacation
Trekking
Natural and historical sightseeing
City tour
Gourmet tour
Pastoral retreat

In the following section, we develop an integer programming model to maximize the profits of a recreational tourism company. The model assigns one or more types of activities to healthcare tourists while respecting their medical constraints, recreational budget, and tour capacities.

4 Methods

4.1 The Integer Programming Model

The healthcare provider is considered to fix plans for a group of m medical tourists for the next T days. The tourism company follows along with this planning horizon, and offers n different activity types, activity type j at price p_j, with variable cost c_j, fixed cost f_j, duration d_j, and the activity type has capacity K_j, $j \in \{1, \dots, n\}$.

The healthcare provider anonymously provides the restriction schedule for each medical tourist, which determines which activity types can be attended on which days. Then, it is a matter of simple calculation with the duration of the activity type to compute the parameter U_{ijt} with binary value, indicating whether patient i can start activity j on day t.

Each medical tourist i has an arrival date A_i, denoting arrival at the beginning of the day, and departure date D_i, denoting departure at the end of the day, thus, $A_i, D_i \in \{1, \dots, T\}$. Tourist i has budget B_i, and also i has a preference on each activity type j, v_{ij}, which carries information on preference regarding both the kind of activity and its duration.

x_{ijt} is a binary variable indicating with value 1 if tourist i attends an activity of type j starting on day t. Variables x_{ijt} are defined unless their value will be fixed at 0, that is, on the index set

$$I = \{(i, j, t) \in S: U_{ijt} = 1, A_i \le t, t + d_j - 1 \le D_i\},$$

where $S = \{1, \dots m\} \times \{1, \dots, n\} \times \{1, \dots, T\}$. Five other index set definitions are practical for the mathematical programming formulation:

$$I_i = \{(j, t): (i, j, t) \in I\},$$

$$I_{jt} = \{i: (i, j, t) \in I\},$$

$$T_i = \{t: (i, j, t) \in I\},$$

$$T_{ij} = \{t: (i, j, t) \in I\},$$

$$S_{it} = \{(j, \tau): (i, j, \tau) \in I, max\left(t - d_j + 1, 1\right) \le \tau \le min(t - d_j + 1, T)\}.$$

First four of these are for indexing in one or two dimensions where x_{ijt} is defined, and the last one denotes the days such that an activity of type j that medical tourist i starts on these days continue on day t.

The binary variable y_{jt} denotes whether the tourism company initiates an activity of type j on day t. For y_{jt}, we define index sets for mathematical programming formulation notation as follows:

$$J = \{(j, t): j = 1, \dots n,\ t = 1, \dots, T - d_j + 1\}.$$

$$J_j = \{1, \dots, T - d_j + 1\}.$$

We formulate the integer program as follows:

$$max \sum_{(i,j,t)\in I}\left(\lambda p_j - \lambda c_j + \sigma(1-\lambda)v_{ij}\right) x_{ijt} - \lambda \sum_{(j,t)\in J} f_j y_{jt} \quad (1)$$

$$s.t. \ \sum_{(j,\tau)\in S_{it}} x_{ij\tau} \le 1 \qquad i = 1, \dots, m \quad t \in T_i \quad (2)$$

$$\sum_{t\in T_{ij}} x_{ijt} \le 1 \qquad i = 1, \dots, m \quad j = 1, \dots, n \quad (3)$$

$$\sum_{i\in I_{jt}} x_{ijt} \le K_j\, y_{jt} \qquad j = 1, \dots, n \quad t \in J_j \quad (4)$$

$$\sum_{(j,t)\in I_i} p_j\, x_{ijt} \le B_i \qquad i = 1, \dots, m \quad (5)$$

$$x_{ijt} \in \{0,1\} \qquad (i, j, t) \in I \quad (6)$$

$$y_{jt} \in \{0,1\} \qquad j = 1, \dots, n \quad t \in J_j. \quad (7)$$

The objective function, (1), is the convex combination of the total preference points $\sum_{(i,j,t)\in I} v_{ij}\, x_{ijt}$ and profit $\sum_{(i,j,t)\in I}(p_j - c_j)\, x_{ijt} + \sum_{(j,t)\in J} f_j y_{jt}$ given a fixed coefficient λ representing relative weights of profit and tourist satisfaction. There is an additional factor, σ, assuring that profit and total preference have similar scales. The computation for this coefficient is discussed in Subsection 4.3.

Each medical tourist is busy with at most one activity on day *t*, considering activities of all type that can start on day t, or that can extend onto day *t* due to their durations. This is defined in the formulation by equation (2). Equation (3) constrains that each tourist is assigned to an activity of type *j* at most once. Equation (4) is the capacity constraint for activity *j* staring on day *t*, and equation (5) is the budget constraint for tourist *i*. (6)-(7) indicate that the problem is a pure integer programming problem.

4.2 Computational Results

There are 15 medical procedures that can be assigned to a patient with probabilities in Table 3, assigned uniformly in the planning horizon, possibly some coinciding on the same day. Each medical tourist is assigned a window of 15 days within the planning horizon, and medical procedures sampled according to probabilities in Table 3 are distributed uniformly in these 15 days. After the medical procedures are randomly assigned, additional days before the first and after the last procedures are added according to discrete uniform distribution (1,…,7), which set the arrival and departure dates. The head or tail side of the stay is extended if the window is at the end or beginning of planning horizon, respectively.

Table 3. *Probabilities a patient receives a certain medical procedure.*

Medical Procedure	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Probability	0.08	0.1	0.15	0.05	0.2	0.2	0.15	0.05
Medical Procedure	**9**	**10**	**11**	**12**	**13**	**14**	**15**	
Probability	0.1	0.18	0.1	0.03	0.05	0.13	0.2	

The parameters for touristic activities offered by the company is in Table 4. Note that each activity type in Table 2 can be offered in alternative packages regarding number of days, for instance, one day seaside tours are available, as well as those up to seven days.

Table 4. *Parameters for touristic activities offered by the tourism company. Each tour type is offered in various tour packages in different activity durations. Natural or historical sightseeing is shortly written as "sightseeing".*

Activity	**Duration d_j (days)**	**Price p_j (TL/person)**	**Variable Cost c_j (TL/person)**	**Fixed Cost f_j (TL)**	**Capacity K_j (#people)**
Seaside 1	1	800	400	600	4
Seaside 2	2	1493	696	689	4
Seaside 3	3	2150	963	747	4
Seaside 4	4	2786	1213	792	4
Seaside 5	5	3405	1450	828	4
Seaside 6	6	4013	1677	859	4
Seaside 7	7	4610	1897	885	4
Blue Voyage 2	2	2898	0	7464	10
Blue Voyage 3	3	4259	0	10752	10
Blue Voyage 4	4	5598	0	13929	10
Blue Voyage 5	5	6920	0	17027	10
Blue Voyage 6	6	8229	0	20063	10
Blue Voyage 7	7	9527	0	23049	10
Thermal 1	1	500	300	400	4
Thermal 2	2	933	522	459	4
Thermal 3	3	1344	722	498	4
Thermal 4	4	1741	909	528	4
Trekking 1	1	300	80	300	15
Trekking 2	2	580	155	345	15
Trekking 3	3	852	227	374	15
Trekking 4	4	1120	299	396	15
Trekking 5	5	1384	369	414	15
Sightseeing 2	2	746	348	566	20
Sightseeing 3	3	1075	482	693	20
Sightseeing 4	4	1393	606	800	20
Sightseeing 5	5	1703	725	894	20
Sightseeing 6	6	2006	839	980	20
City Tour 1	1	500	250	200	30
City Tour 2	2	871	435	303	30
City Tour 3	3	1204	602	387	30
City Tour 4	4	1516	758	459	30
Gourmet Tour 1	1	700	400	300	15
Gourmet Tour 2	2	1352	746	487	15
Gourmet Tour 3	3	1988	1075	647	15
Pastoral Ret. 3	3	1527	456	498	15
Pastoral Ret. 4	4	1949	566	528	15
Pastoral Ret. 5	5	2357	669	552	15
Pastoral Ret. 6	6	2752	767	572	15
Pastoral Ret. 7	7	3137	861	590	15

Tourist budget is distributed uniformly between 2000 and 22000 TLs. Mean and standard deviations of satisfaction scores for a sample of m=*300* medical tourists is presented in Table 5.

Table 5. *Mean (top) and standard deviations (bottom) for tourist preference scores for various tour types and durations, from a sample of m=300 medical tourists. The score is per each day of the tour,* v_{ij}/d_j *is displayed, to point out the "boredom" effect, i.e., reducing marginal utility with each additional day in a specific tour type.*

	Tour Duration (days)						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Seaside Vacation	7.85	7.71	7.63	7.59	7.58	6.27	5.53
	2.17	2.44	2.64	2.77	2.86	2.88	3.48
Blue Voyage	-	8.27	8.21	8.17	8.15	7.41	7.11
	-	2.03	2.19	2.31	2.39	2.89	3.94
Thermal Vacation	6.33	5.88	5.64	5.51	-	-	-
	2.74	3.23	3.51	3.66	-	-	-
Trekking	5.57	5.3	5.15	5.06	5	-	-
	2.86	3.12	3.3	3.41	3.48	-	-
Sightseeing	-	7.15	7.05	7	6.99	6.18	-
	-	2.78	2.99	3.15	3.26	3.31	-
City Tour	7.17	6.94	6.81	6.74	-	-	-
	2.59	2.92	3.13	3.27	-	-	-
Gourmet Tour	5.65	5.22	4.98	-	-	-	-
	2.89	3.27	3.5	-	-	-	-
Pastoral Retreat	-	-	5.51	5.4	5.33	4.12	3.43
	-	-	3.13	3.28	3.37	2.88	2.91

The number of activities is fixed as n=*39*. We initially compare the solution times of the integer programming model to a preliminary model (8)-(15) devised in [18], where arrival and departure dates are not defined, i.e., the medical tourists are assumed available throughout the short planning horizon considered in the study, except for medical restrictions. The model also does not incorporate tourist preference and has higher number of variables and constraints, not defining index sets used in (1)-(7):

$$max \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{t=1}^{T-d_j+1} (p_j - c_j)\, x_{ijt} - \sum_{j=1}^{n} \sum_{t=1}^{T-d_j+1} f_j\, y_{jt} \quad (8)$$

$$s.t. \ \sum_{j=1}^{n} \sum_{\tau=max(1,t-d_j+1)}^{min(t,T-d_j+1)} x_{ij\tau} \le 1 \quad i = 1, \dots, m \ \ t = 1, \dots, T \quad (9)$$

$$\sum_{t=1}^{T-d_j+1} x_{ijt} \le 1 \quad i = 1, \dots, m \ \ j = 1, \dots, n \quad (10)$$

$$\sum_{i=1}^{m} x_{ijt} \le K_j\, y_{jt} \quad j = 1, \dots, n \ \ t = 1, \dots, T - d_j + 1 \quad (11)$$

$$\sum_{j=1}^{n} \sum_{t=1}^{T-d_j+1} p_j\, x_{ijt} \le B_i \quad i = 1, \dots, m \quad (12)$$

$$x_{ijt} \le U_{ijt} \quad i = 1, \dots, m \ \ j = 1, \dots, n \ \ t = 1, \dots, T - d_j + 1 \quad (13)$$

$$x_{ijt} \in \{0,1\} \quad i = 1, \dots, m \ \ j = 1, \dots, n \ \ t = 1, \dots, T - d_j + 1 \quad (14)$$

$$y_{jt} \in \{0,1\} \quad j = 1, \dots, n \quad t = 1, \dots, T - d_j + 1. \quad (15)$$

8 data instances are generated for each of cases $m \times T = \{5,10,20\} \times \{30,40\}$. For each sample, (1)-(7) is solved setting $v_{ij} = 0$ for $i = 1, \dots, m, j = 1, \dots, n$, and $\lambda = 1$ (the integer programming model devised, "IP" solution). But also, arrival and departure dates are loosened for each medical tourist, $A_i = 1$ and $D_i = T$ for $i = 1, \dots, m$ (this is called the "IP-A1DT" model. This is done for comparability with (8)-(15) (the "Preliminary" model). All models are solved for each case and sample instance using Gurobi Optimizer [19] as a single batch in randomized order running concurrently on an AMD Ryzen Threadripper 3960X 24-Core Processor, 32GB of RAM, with default solver settings except a time limit of 3600 seconds. The optimality threshold for relative gaps in objective values with the linear programming (LP) relaxation (IP gap, shortly) is set at 0.5%, in order to observe more terminations at optimality and compare solution times, particularly of IP-A1DT and Preliminary models.

Table 6 displays the average number of variables and constraints for each case. Arrival and departure dates additionally reduce the number of constraints besides variables for the IP model, since, for instance T_i is empty in (2) outside arrival-departure interval of a medical tourist. Besides reducing the number of variable and constraints, arrival and departure dates rule out many activity assignments significantly shortening solution time and reducing IP gaps at termination, when compared to corresponding IP-A1DT and Preliminary samples. Principally, the difference of the Preliminary model with IP-A1DT, is the constraint (13) and the larger number of variables associated with keeping in the model redundant variables corresponding to U_{ijt}=*0* in the model (Table 6). Additionally, on days that the tourist is busy with a medical respective variable and constraints are not included in the model. Thus, the set indexing pays off for IP-A1DT as well, compared to the Preliminary model. Although this pattern is not supported for small instances, and is not visible for larger instances due to time limit (Figure 1), IP gaps for larger instances point out the efficiency gain by IP-A1DT (Figure 2).

Table 6. *Number of variables and constraints for IP, IP-A1DT and Preliminary models with different problem sizes, as averages over samples of size 8.*

		Number of Variables		
m	**T**	**IP**	**IP-A1DT**	**Preliminary**
5	**30**	2075	4834	6408
	40	2329	7080	8748
10	**30**	3171	8480	11748
	40	3446	12538	16038
20	**30**	5324	16433	22428
	40	5559	24085	30618
50	**30**	11416	38369	54468
	40	11292	58166	74358
		Number of Constraints		
m	**T**	**IP**	**IP-A1DT**	**Preliminary**
5	**30**	1319	1404	6758
	40	1705	1843	9148
10	**30**	1573	1734	12448
	40	1962	2226	16838
20	**30**	2077	2412	23828
	40	2465	2996	32218
50	**30**	3589	4410	57968
	40	3958	5305	78358

A computational evidence on the complexity of the problem is apparent, as an increase in planning horizon from 30 to 40 increases computation times for small instances more than two folds, and doubling number of tourists has an effect of several folds.

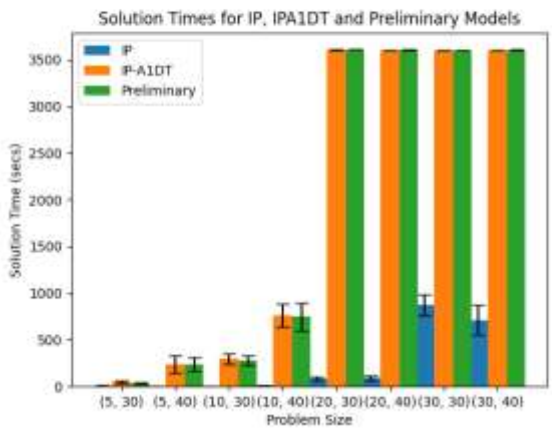

Figure 1. *Solution times for IP, IP-A1DT and Preliminary models for* $m \times T = \{5,10,20\} \times \{30,40\}$*. Whiskers on bars represent standard errors for samples of size 8.*

Efficient solution of IP, is critical for iterations required for determining the Pareto-efficient frontier in the biobjective setting of (1)-(7). The results for the biobjective approach are discussed in the next section.

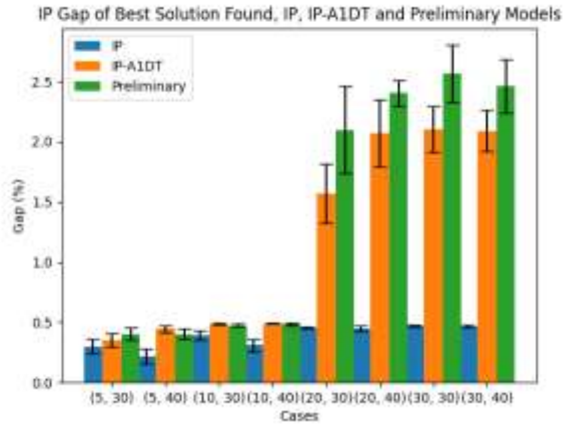

Figure 2. *IP gaps for IP, IP-A1DT and Preliminary models for* $m \times T = \{5,10,20\} \times \{30,40\}$*. Bars represent averages and whiskers on bars represent standard errors for samples of size 8. Due to reaching time limit for large instances, efficiency of IP-A1DT and Preliminary models can be compared by lower gaps for IP-A1DT.*

4.3 The Pareto-efficient Frontier

Before delving into the application of the Weighted Objective method and the derivation of the Pareto-efficient frontier, it is essential to provide a concise overview of biobjective optimization. When dealing with multiobjective problems, various approaches, such as Lexicographic Ordering and Goal Programming, can be considered. In Lexicographic Ordering, one of the objectives takes precedence, and the optimization process strives to achieve the best possible outcome in the primary objective before addressing the secondary objectives. In our context, prioritizing profits over tourist satisfaction may seem logical at first glance. However, our analysis of the Pareto-efficient frontier reveals that such a prioritization could lead to missed opportunities for exceptionally high levels of customer satisfaction. Goal Programming, on the other hand, formulates the problem by setting specific target values for both objectives and aims to minimize deviations from these targets while optimizing the overall solution. In our study, determining specific target values for customer satisfaction, which is subject to individual patient preferences, proves to be a challenging task. Additionally, the unpredictable schedule availability of customers further complicates this approach. Moreover, due to the combinatorial complexity of our problem, estimating profit scales in advance is not feasible, making Goal Programming less suitable. The Epsilon-Constraint Method would similarly require numerous explorative steps to set limits on the secondary objective. In contrast, the results obtained from a Pareto analysis provide a more straightforward and readily available perspective. Therefore, in this study, we opt for the Weighted Objective approach to address the biobjective programming challenge effectively. This method, when coupled with efficient integer programming solutions, allows us to derive the Pareto-efficient frontier for various problem instance sizes. The Pareto-efficient frontier represents a spectrum of trade-offs between the two objectives, enabling decision-makers to select a solution that aligns with their strategic preferences. The relative weight parameter λ represents the importance assigned by the decision maker, typically the tourism company, to the strategic approach of balancing medical tourist satisfaction and profit. The specific strategic choices available in terms of these two criteria can only be determined by iteratively solving the model with a range of λ values and obtaining the Pareto-efficient frontier. The Pareto-efficient frontiers are obtained for each test instance with synthetic data of various sizes (cases: $m \times T = \{50,100,150\} \times \{40\}$), by solving (1)-(7) for known only after iteratively solving the model for λ values ranging from 0 to 1.

For each data instance, the coefficient σ is computed to bring the two objective components to similar scales. The model is run twice for the respective data instance, separately optimizing for profit ($\lambda = 1$) and medical tourist satisfaction ($\lambda = 0$), with a time limit of 600 seconds and an IP gap of 10%. σ is calculated as the ratio of the linear relaxation upper bounds of profit maximization and satisfaction maximization, which are at most 10% away from the approximated maximum values attainable for profit and satisfaction. For each data instance, initially the coefficient σ that brings the two objective components to similar scales is computed. The model is run for the respective data instance twice, for profit (λ=1) and medical tourist satisfaction (λ=1) objectives separately, with a time limit of 600 seconds and an IP gap of 10%. σ is then the ratio of linear relaxation upper bounds of profit maximization and satisfaction maximization, which are at most 10% off from the approximated maximum values attainable for profit and satisfaction. The runs for the range of λ for constructing the Pareto-efficient frontier are taken as a batch for each problem size on the hardware and software setting mentioned above, with a time limit of 7200 seconds and an IP gap of 0.5%.

Figure 3 displays Pareto-efficient frontiers for $m \times T = \{50,100,150,250\} \times \{40\}$. The results indicate that the strategic decision is not difficult for the company, as it is possible to achieve significant portions of the maximum attainable profit and satisfaction performance simultaneously. When λ is close to 0.5 for *m=150, 200*, and to 0.6 for *m=50, 100*, nearly 70% of maximum attainable tourist satisfaction and 80% of maximum attainable profit is achieved. Then, with an equal weight given to performance criteria, a high level of total satisfaction score is attained with only a minimal compromise in profit.

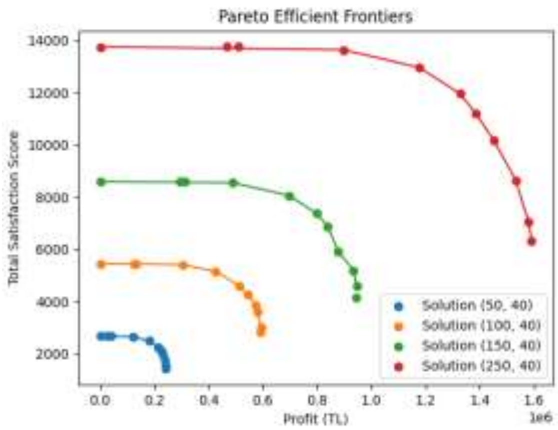

Figure 3. *Pareto-efficient frontiers for problem sizes $m \times T = \{50,100,150,250\} \times \{40\}$. The range for weight parameter λ is [0, 1e-6, 1e-3, .05, .15, .3, .4, .5, .6, .65, .7, .75, .8, .85, .9, .95, 1] for m=150, 200, and [0, 1e-6, 5e-4, .1, .3, .5, .6, .7, .8, .9, 1] for m=50, 100. For display purpose, profit values are replaced by 0 for $\lambda = 0$ cases. Actual profit in each problem size is a very large negative value for pure tourist satisfaction maximization, and the curves extend horizontally to the left.*

The company increases profits within the same planning horizon as the number of tourists registered in the plan increases, as indicated by shift in Pareto-efficient frontiers, which is in proportion to number of tourists. This is possible due to the optimization that tightly schedules the growing number of tourists, taking into account the capacity and alternative days available for each specific tour. The relatively larger instances analyzed here mostly terminate due to the time limit. IP gaps are close to the limit for termination at optimality (0.5%) for the smaller instance (*m=50)*. However, when comparing the problem sizes, a clear pattern emerges where the IP gaps increase with the problem size, as shown in Figure 4. A company that solves problems at this scale and plans for a horizon of several weeks can reasonably increase the solution time limit set at 7200 seconds for computational tests, to gain up to 3% in medium sized instances (*m=100, 150)* and 4% in the larger instance (*m=200)*.

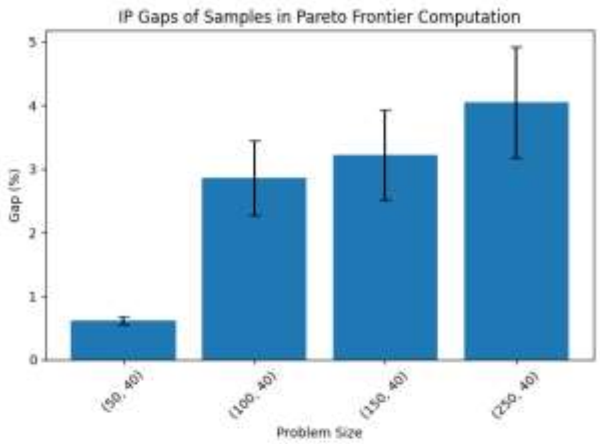

Figure 4. *IP gaps for best solutions found in computations with* $m \times T = \{50,100,150,250\} \times \{40\}$. *Bars represent sample means and whiskers represent standard errors, for the sample size according to the range used for* λ.

5 Conclusion

The proposed model in this study incorporates the health restrictions and preferences of health tourists when recommending various touristic activities. It takes into account the medical procedure undergone by the medical tourist and their corresponding health restrictions, ensuring that suitable activities are recommended based on medical constraints and preferences to enhance their overall experience. The model also considers the capacity and costs associated with different touristic activities while simultaneously maximizing the weighted sum of profit for the tourism company and the overall satisfaction of the tourists within the planning horizon. By deriving the Pareto-efficient frontier for the two criteria, the model provides insights for the company to make trade-offs between profit and customer satisfaction. Immediate research directions arising for this problem concern more efficient solutions of larger problem instances. Enhancing solver times by Branch-and-cut approaches require finding out very effective cuts. Population based search heuristics are candidate approaches for quick solution of larger instances, but for the large solution space defined by triple indexing and complex set of constraints, their performance in terms of time and solution performance to optimality might remain restricted. A viable research direction that can be followed is matheuristics, combining the efficient exploration of the search tree by integer programming solvers with the potential of heuristics to find quick incumbents of high quality. Research directions stemming immediately from this problem primarily revolve around devising more efficient solutions for handling larger instances of the problem. To expedite solver runtimes through the application of Branch-and-Cut approaches, the key lies in identifying exceptionally effective cutting planes. While population-based search heuristics present themselves as promising candidates for solving larger instances, their performance in terms of both time efficiency and solution optimality may be constrained when confronted with the expansive solution space characterized by triple indexing and a complex web of constraints. One fruitful research direction worth pursuing involves the utilization of matheuristics. Matheuristics entail harnessing the dual strengths of integer programming solvers for systematically exploring the search tree and the capability of heuristics to swiftly identify high-quality solutions. This hybrid approach holds the potential to strike a harmonious balance between efficiency and solution quality, making it a compelling avenue for further investigation. Future research additionally could explore different settings of the problem where medical tourists are offered scheduled activities but have the option to accept or decline based on their preferences. This might require scenario generation under probability models and potentially employ bilevel approaches to address the problem effectively.

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References

[1]Zhu, C., Hu, J. Q., Wang, F., Xu, Y., & Cao, R. (2012). On the tour planning problem. *Annals of Operations Research*, 192(1); 67–86. https://doi.org/10.1007/s10479-010-0763-5

[2]Vansteenwegen, P., Souffriau, W., Berghe, G. V., & Oudheusden, D. V. (2011). The City Trip Planner: An expert system for tourists. *Expert Systems with Applications*, 38(6); 6540–6546. https://doi.org/10.1016/j.eswa.2010.11.085

[3]Brilhante, I. R., Macedo, J. A., Nardini, F. M., Perego, R., & Renso, C. (2015). On planning sightseeing tours with TripBuilder. *Information Processing & Management*, 51(2); 1–15. https://doi.org/10.1016/j.ipm.2014.10.003

[4]Leong, T.-Y., & Ladany, S. P. (2001). Optimal cruise itinerary design development. *International Journal of Services Technology and Management*, 2(1–2); 130–141. https://doi.org/10.1504/IJSTM.2001.001595

[5]Chia, W. C., Yeong, L. S., Xian Lee, F. J., & Ch'ng, S. I. (2016). Trip planning route optimization with operating hour and duration of stay constraints. *2016 11th International Conference on Computer Science & Education (ICCSE)*, 395–400. https://doi.org/10.1109/ICCSE.2016.7581613

[6]Delalić, S., Chahin, M., & Alihodžić, A. (2019). Optimal City Selection and Concert Tour Planning Based on Heuristic Optimization Methods and the Use of Social Media Analytics. *2019 XXVII International Conference on Information, Communication and Automation Technologies (ICAT)*, 1–6. https://doi.org/10.1109/ICAT47117.2019.8939040

[7]Jean-Marc, G. (2005). Challenges in real world sightseeing tour optimization using meta-heuristics. *Proceedings of the 6th WSEAS International Conference on Evolutionary Computing*, 233–238.

[8]Vargas, D. F. V., & Sendales, D. A. P. (2016). Optimal scheduling trip plan for tourist. *2016 10th International Conference on Intelligent Systems and Control (ISCO)*, 1–5. https://doi.org/10.1109/ISCO.2016.7727111

[9]Perera, D., Rathnayaka, C., Dilan, S., Siriweera, L., & Rankothge, W. H. (2018). Sustainable Tourism: Application of Optimization Algorithms to Schedule Tour Plans. *2018 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)*, 1–6. https://doi.org/10.1109/R10-HTC.2018.8629826

[10]da Silva, A. A., Morabito, R., & Pureza, V. (2018). Optimization approaches to support the planning and analysis of travel itineraries. *Expert Systems with Applications*, 112; 321–330. https://doi.org/10.1016/j.eswa.2018.06.045

[11]Rahimi, I., & Gandomi, A. H. (2021). A Comprehensive Review and Analysis of Operating Room and Surgery Scheduling. *Archives of Computational Methods in Engineering*, 28(3); 1667–1688. https://doi.org/10.1007/s11831-020-09432-2

[12]Ala, A., Simic, V., Deveci, M., & Pamucar, D. (2023). Simulation-Based Analysis of Appointment Scheduling System in Healthcare Services: A Critical Review. *Archives of Computational Methods in Engineering*, 30(3); 1961–1978. https://doi.org/10.1007/s11831-022-09855-z

[13]Ala, A., & Chen, F. (2022). Appointment Scheduling Problem in Complexity Systems of the Healthcare Services: A Comprehensive Review. *Journal of Healthcare Engineering*, e5819813. https://doi.org/10.1155/2022/5819813

[14]Abdalkareem, Z. A., Amir, A., Al-Betar, M. A., Ekhan, P., & Hammouri, A. I. (2021). Healthcare scheduling in optimization context: A review. *Health and Technology*, 11(3); 445–469. https://doi.org/10.1007/s12553-021-00547-5

[15]Van den Bergh, J., Beliën, J., De Bruecker, P., Demeulemeester, E., & De Boeck, L. (2013). Personnel scheduling: A literature review. *European Journal of Operational Research*, *226*(3); 367–385. https://doi.org/10.1016/j.ejor.2012.11.029

[16]Ernst, A. T., Jiang, H., Krishnamoorthy, M., & Sier, D. (2004). Staff scheduling and rostering: A review of applications, methods and models. *European Journal of Operational Research*, 153(1); 3–27. https://doi.org/10.1016/S0377-2217(03)00095-X

[17]Rocha, M., Oliveira, J. F., & Carravilla, M. A. (2012). *Quantitative Approaches on Staff Scheduling and Rostering in Hospitality Management: An Overview*. . https://doi.org/10.4236/ajor.2012.21016

[18]Yıldırım, E. (2023). *An Integer Programming Model of Recreational Planning in Medical Tourism* [Master's Thesis]. Gebze Technical University.

[19]Gurobi Optimization, LLC. (2023). *Gurobi Optimizer Reference Manual*. https://www.gurobi.com