Modeling recreational systems using optimization techniques and information technologies

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Abstract Due to intrinsic complexity and sophistication of decision problems in tourism and recreation, respective decision making processes can not be implemented without making use of modern computer technologies and operations research approaches. In this paper, we review research works on modeling recreational systems.

Keywords Recreational system · tourism · modeling

1 Introduction

The importance of information, efficient information management, and decision support in recreation and tourism is steadily increasing due to the evolution of new technologies and high-capacity storage media.

Tourism and recreation planning and management problems lie at the cross-roads of multiple disciplines, and for this reason may be described by a set of interacting models. The decision making processes associated with a utilization of recreational resources and tourism and recreation planning and management fall into the category of complex situations requiring very thorough consideration and analysis. Due to intrinsic complexity and sophistication of decision problems in tourism and recreation, respective decision making processes can not be implemented without making use of modern technological means, especially computer technology. Optimization and simulation modeling techniques have been widely used in the field of tourism and recreation planning and management.

Some of the models published in literature deal with a multitude of problems in the field of cruises (dealing with scheduling, pricing and routing), national parks (congestion, scheduling, pricing), hotel industry (pricing, price segmentation, discrimination,

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and infiltration, size), touring (time-windows, multiple period tours, round trips), staging of sports events (pricing, scheduling), reservation systems (price changes with time, Bayesian approaches (Ladany (1977) [58]).

Modeling of recreational systems is a fascinating area of research. But we are unable to grasp the immensity. For other models of recreational systems, readers are referred to the book (Ladany (ed.) (1975) [71]) which contains many different models in many recreational areas, from visits in Zoos to analysis of orchestral performance.

The objective of this paper is to survey research works on modeling recreational systems. First, Section 2 presents a model of optimal investment policy for the tourism. Next, Section 3 discusses the wide range of tour routing problems: the orienteering problem which is the simplest model of the Tourist Trip Design Problems; itinerary design and optimization problems; information and communication technologies for tourist trips planning; discrete model of optimal development of a system of tourist routes. Section 4 discusses reservation models: overbooking and revenue management; online and offline reservation models; the multi-knapsack problem as an example of a reservation problem; the multi-knapsack problem with overbooking; temporal knapsack problem. Section 5 explains how integer goal programming can be used to model planning urban recreational facilities.

2 Optimal investment policy for the tourism

Paper by Gearing et al. (1973) [37] supposes that the country, or geographical area, under consideration is subdivided into N particular touristic locations, or "touristic areas" (t.a.) and that, at any t.a. i, there exist K_i specific proposed projects which may be undertaken. These projects represent competing investment proposals, and they cover a wide range of possible investments. It is assumed that each t.a. has included as the first two proposed projects the following:

(1) A planning project, i.e., a proposal for a detailed development plan of the touristic area, and
(2) A project which is designed to bring the infrastructure and food and lodging facilities of a given t.a. up to minimally sufficient level, which was designated "minimal touristic quality" (m.t.q.).

At each t.a., the proposed projects, if undertaken, exhibit certain dependencies in the form of precedence relations derived from factors such as physical necessity, logical preference, and functional interdependence. These precedence relationships are independent between t.a.'s but, at each, the following standard convention was adopted:

(i) If a t.a. does not have a formal plan of development, the planning project precedes all others, and
(ii) If a t.a. does not have infrastructure and food and lodging up to m.t.q. standards, the necessary improvements are considered as a single project to precede all others except the planning project.

Associated with every proposed project j at touristic area i is an estimated cost of completion c_{ij} . The total cost of project development considering all N t.a.'s is equal to the amount of touristic investment, then the total cost cannot exceed the amount, b, budgeted for capital expenditures in the tourism sector.

Authors proposed to assess a measure d_{ij} of benefit associated with project j at t.a. i. Introducing binary decision variables x_{ij}:

$$x_{ij} = \begin{cases} 1, & \text{if project } j \text{ is to be developed at touristic area } i; \\ 0, & \text{otherwise.} \end{cases}$$

we can formulate the model

$$\sum_{i=1}^{N} \sum_{j \in K_i} d_{ij} x_{ij} \to \max$$

subject to

$$\sum_{i=1}^{N} \sum_{j \in K_i} c_{ij} x_{ij} \leq b,$$

(budget constraint)

$$x_{ip} - x_{iq} \geq 0, \quad i = 1, \ldots, N; \quad \text{some } p, q,$$

(precedence constraints)

$$x_{ij} = 0, 1, \quad i = 1, \ldots, N; \; j \in K_i.$$

The approach taken here involved the identification and selection of 17 criteria which constituted the essential ingredients of "touristic attractiveness". The criteria were grouped into five categories:

- **A. Natural factors**: 1) natural beauty; 2) climate;
- **B. Social factors**: 1) artistic and architectural features; 2) festivals; 3) distinctive local features; 4) fairs and exhibits; 5) attitudes towards tourists;
- **C. Historical factors:** 1) ancient ruins; 2) religious significance; 3) historical prominence;
- **D. Recreational and shopping facilities:** 1) sports facilities; 2) educational facilities; 3) facilities conducive to health, rest and tranquility; 4) night-time recreation; 5) shopping facilities;
- **E. Infrastructure and food and shelter:** 1) infrastructure above "minimal touristic quality"; 2) food and lodging facilities above "minimal touristic quality".

Shcherbina (1985) [91] develops models of perspective planning of recreational systems, with the Crimea taken as an example. Penz (1975) [76] proposed a linear programming model which represents visitor movement via transition matrices can help identify park capacity for visitors seeking various recreational experiences. It was supposed that park capacity for visitors is a function also of visitor movement behavior among the locations. The constraints of the model express capacities for both man-made facilities and ecological criteria as a function of visitor requirements.

Table 1 Relative Weights and Rank Order of Seventeen Criteria of "Touristic Attractiveness"

N	Criterion	Weight	Rank
1.	Natural beauty	0.132	1
2.	Climate	0.099	4
3.	Artistic and architectural features	0.051	9
4.	Folk festivals	0.029	14
5.	Distinctive local features	0.026	15
6.	Fairs and exhibits	0.011	17
7.	Attitudes towards tourists	0.054	7
8.	Ancient ruins	0.057	6
9.	Religious significance	0.053	8
10.	Historical prominence	0.065	5
11.	Sports facilities	0.046	10
12.	Educational facilities	0.015	16
13.	Resting and tranquility	0.032	13
14.	Night-time recreation	0.045	11
15.	Shopping facilities	0.036	12
16.	Infrastructure above m.t.q.	0.131	2
17.	Food and lodging above m.t.q.	0.125	3

3 Tour routing

3.1 Orienteering Problem

The tour planning process is a process consisting of selecting and combining possible attractions, lodges, services-facilities, and transportation modes in a manner that optimizes the tourists preferences and satisfies the tourists resources of time and money. For tourists visiting a city or region it is often impossible to visit everything they are interested in. Thus, they have to select what they believe to be the most valuable attractions. Making a feasible plan in order to visit these attractions in the available time span is often a difficult task. These planning problems are called Tourist Trip Design Problems (TTDP) (Vansteenwegen and Van Oudheusden (2007)) [103]. The Orienteering Problem is the simplest model of the TTDP.

The name "Orienteering Problem" (OP) originates from the sport game of orienteering (Chao et al. (1996)) [20]. While the OP was originally modeled for the sport of orienteering, it has practical applications in production scheduling and vehicle routing as discussed by Golden et al. (1987) [44]. Readers are referred to the recent survey paper by Vansteenwegen, Souffriau, and Van Oudheusden (2011) [102] for a systematic review of the OP literature.

The Orienteering Problem (OP) can be described as follows: given n vertices, each vertex i has a score s_i. 0 and the scores of the starting vertex denoted by 1 and the ending vertex denoted by n are set to 0; i.e., $s_1 = s_n = 0$. The arc between vertices i and j has a cost c_{ij} associated with it. Since n vertices are usually considered in the Euclidean plane and the distance and travel time between vertices are determined by the geographical measure, they are assumed to be known quantities and distance is used as the representative of cost. Each vertex can be visited at most once. Therefore, the objective of the OP is to maximize the score of a route that consists of a subset of vertices starting from vertex 1 and finishing at vertex n without violating the cost (distance) constraint $\max T$. The OP can be seen as a combination between the Knapsack Problem (KP) and the Traveling Salesman Problem (TSP). The OP shows similarities to the binary knapsack problem [94]. Each location of the OP can be seen as an item, its score as the profit, and the available time budget as the capacity of the knapsack. The main difference is that the total weight in the knapsack problem is independent of the order of the selected items. In the OP, the total traveling time depends explicitly on the order of the selected locations, which increases the complexity of the problem significantly.

The OP can be formulated as an integer programming problem (see Vansteenwegen et al. (2011) [102]). The following decision variables are used: $x_{ij} = 1$ if a visit to vertex i is followed by a visit to vertex j 0 otherwise; u_i = the position of vertex i in the path.

$$\sum_{i=2}^{n-1} \sum_{j=2}^{n} s_i x_{ij} \to \max \tag{1}$$

(objective function (1) is to maximise the total collected score)
subject to

$$\sum_{j=2}^{n} x_{1j} - \sum_{i=1}^{n-1} x_{in} = 1, \tag{2}$$

(the path starts in vertex 1 and ends in vertex n)

$$\sum_{i=1}^{n-1} x_{ik} = \sum_{j=2}^{n} x_{kj} \leq 1, \quad k = 2, \dots, n-1, \tag{3}$$

(constraints (3) ensure the connectivity of the path and guarantee that every vertex is visited at most once.)

$$\sum_{i=1}^{n-1} \sum_{j=2}^{n} t_{ij} x_{ij} \leq T_{\max}, \tag{4}$$

(constraint (4) ensures the limited time budget)

$$2 \leq u_i \leq n, \quad i = 2, \dots, n, \tag{5}$$

$$u_i - u_j + 1 \leq (N-2)(1 - x_{ij}), \quad i, j = 2, \dots, n, \tag{6}$$

(constraints (5) and (6) are necessary to prevent subtours)

$$x_{ij} \in \{0, 1\}, \quad i, j = 1, \dots, n. \tag{7}$$

A recent application of OP is the Mobile Tourist Guide (Souffriau et al., 2008) [94]. This application requires high quality solutions in only a few seconds of calculation time. Souffriau and Vansteenwegen (2010) [96] show that using the OP and its extensions to model the tourist trip planning problem, allows to deal with a vast number of practical planning problems.

3.2 Itinerary design and optimization problem

By itinerary (tour) planning problem is meant the problem that involves generating a schedule or itinerary to visit some points of interest (POIs) which are achieved through a transportation network and satisfies some objective function(s), given a set of constraints. The tour may be either closed in which the first and last point are the same or open where the first and last point are different. It is common to use the term of tour for closed one in tourism. This problem may have several applications in different fields. For instance, a citizen may wish exit her home to visit some stores and return there; hence she may need to plan a tour to minimize the spent time or maximize the number of visiting stores. Tour planning problem may be considered as a variation of well-known Traveling Salesman Problem (TSP). Tour planning is a NP-hard problem and to solve this problem, several methods and techniques have been proposed up to now (Gutin and Punnen (2002)) [48].

For cruise lines, the first important decision is to design the itinerary and price structure in order to maximize total profit in the whole cruising period. An itinerary includes the destination, the ports-of-call and their sequence, the length of stay in each port, the speed of vessel, the departure dates, and the fare structure of the cruises. The aim of itinerary design is to determine when to depart and return, what duration, which destinations, and what fare structure to adopt. Since consumer satisfaction becomes more and more important to any company in recent years, when find the best one from all possible itineraries, cruise lines must consider the attractiveness of every potential scheme to satisfy consumers. Given the start/end base port and total duration of the cruising, Hersh and Ladany (1989) [51] use a two-stage framework to decide the optimal timetable and optimal price for a cruise itinerary under the assumption of "the longer the cruise ship spends at a place, the more attractiveness that stopover location becomes to the tourists". In the first stage, they use multiple nonlinear regression analysis to estimate demand curve for various itineraries. The second stage formulates an integer programming to get required optimal values with the purpose of maximizing the total aggregate attractiveness of the itinerary subject to constrains on the overall duration and budgets of the journey.

Leong and Ladany (2001) [68] consider the cruise itinerary problem, different from other tourist tour problems. The model selects optimally the destinations to visit, visit duration of each stop and visit sequence. A near-optimal heuristic approach is applied to an example based on data of South-East Asia to demonstrate its application as a decision support tool.

Ladany (1999) [63], Deitch and Ladany (2000) [26] consider the one-period bus touring problem (BTP). Objective of BTP is to maximize the total attractiveness of the tour by selecting a subset of sites to be visited and scenic routes to be traveled — both having associated non-negative attractiveness values — given the geographical frame considerations, constraints on touring time, cost and/or total distance. A similar NP-hard problem is the orienteering problem (OP) in which the identical start and end point is specified along with other locations having associated scores. This paper presents a transformation from the BTP to the OP and illustrates the use of an effective heuristic for the OP together with an improvement process, aimed at generating a fast near-optimal BTP solution.

Deitch and Ladany [27] propose a new heuristic for solving BTP based on clustering first, then routing. The results of a real-life touring problem are presented.

The optimal one-period touring problem with identical starting and terminal points is determined in (Deitch and Ladany (2001)) [28]. A one-period linear integer programming model was developed to derive an optimal round-trip BTP solution.

Ladany and Deitch (2005) [64] introduce the BTP with time windows (BTPTW); objective is to maximize the total attractiveness of the tour by selecting a subset of sites to be visited and scenic routes to be traveled while observing time windows associated to each of the network items (tourist sites and scenic road segments). In reality opening hours restrict visit times to sites. Furthermore, tour attractiveness value generated from the site visit can vary depending on the day time or by actual visiting time at the site. This also prevails when traversing scenic road segments.

Godart (2000, 2001, 2003, 2005) [39], [40], [41], [42], [43] uses the Traveling Salesperson Problem (TSP) as a starting point to plan trips. His TSP with Activities and Lodging Selection automatically selects POIs and lodging.

Souffriau et al. (2008) [94] use the OP as the starting point for modeling the TTDP. The OP can be extended by introducing $t_{visit,i}$ for each location i, to take into account the time a tourist needs to visit the location. In order to solve the TTDP, the attractiveness (score) of each location should be determined first. In this approach, the attractiveness is derived from documents containing the full text descriptions corresponding with tourist attractions. Each tourist attraction is uniquely determined by its GPS coordinates and can have multiple documents associated with it. The scores associated to POIs were extracted automatically. Documents related to POIs are indexed using the vector space model and then the similarities between the tourists interests and the documents are calculated. In this way the personalized scores for locations are extracted and used in a guided local search metaheuristic approach to maximize the total score of the visited locations, while keeping the total time (or distance) below the available time budget. A tourist attraction can be visited in function of different fields of interest: e.g., one can visit a church from a religious or from a historical point of view. For each field of interest of an attraction, a different text document is available. Based on the interests of the tourist and the description of the location, the attractiveness of the location is determined (Souffriau et al. (2008)) [94].

A similar tourist trip problem of selecting the most interesting combination of attractions is mentioned by Wang et al. (2008) [107] and Schilde et al. (2009) [83]. Shilde (2009) [83] developed a heuristic solution techniques for the multi-objective OP. The motivation stems from the problem of planning individual tourist routes in a city. Each point of interest (POI) in a city provides different benefits for different categories (e.g., culture, shopping). Each tourist has different preferences for the different categories when selecting and visiting the points of interests (e.g., museums, churches). To determine all the Pareto optimal solutions, two metaheuristic search techniques are developed and applied.

3.3 Information and Communication Technologies and Tourist Trips Planning

Information communication technologies (ICTs) have been transforming tourism globally. ICTs empowers consumers to identify, customise, and purchase tourism products and supports the globalisation of the industry by providing tools for developing, managing and distributing offerings worldwide. Online technologies within the tourism industry have significantly impacted on communications, transactions, and relationships between the various industry operators and with the customer, as well as between regulators and operators (Werthner and Klein (1999)) [109], (Buhalis (2000, 2003, 2008)) [15], [16], [17].

Recommender systems (Ricci (2002)) [78] are commonly defined as applications that e-commerce sites exploit to suggest products and provide consumers with information to facilitate their decision-making processes. Current recommender systems can support tourists in choosing travel products (accommodation, activities, means of transport, etc.), in planning long trips, and in profitably spending time in a specific geographical area such as a region (or a city). In the last case, the system should be able to construct itineraries suited to the tourist's interests. The reason people could be interested in using a recommender system is that they have so many items to choose from — in a limited period of time — that they cannot evaluate all the possible options. A recommender should be able to select and filter all this information to the user. For travel and tourism, the two most successful recommender system technologies are Triplehops TripMatcher (used by www. ski-europe.com, among others) and VacationCoachs expert advice platform, Me-Print (used by travelocity.com). Both of these recommender systems try to mimic the interactivity observed in traditional counselling sessions with travel agents when users search for advice on a possible holiday destination. Di Bitonto et al. (2010) [30], [31] proposed a method for generating tourist itineraries in knowledge-based recommender systems. The method is based on a theoretical model that defines space-time relations among items of intangible cultural heritage (called events) and on transitive closure computation (of the relations), that is able to construct chains of events.

Nowadays, an average tourist plans a vacation using web sites, magazine articles and guidebooks. The inability to modify this holiday plan in real-time motivates the need for a Next Generation Mobile Tourist Guide (MTG). The MTG, a handheld embedded device, is aware of the tourist's preferences, attraction values and trip information. Based on real-time and reliable data, the device can immediately suggest new integrated holiday plans. To develop these holiday plans, additional operations research decision models are required (Vansteenwegen and Oudheusden (2007)) [103]). Instead of recommending prepackaged tours, or sorting POIs by estimated interest value as recommender systems do, scheduling approaches typically try to determine the combination of POIs that maximize the joint interest. An overview of systems providing adequate tour scheduling support for tourist decision support applications that compose tours of POI visits, is presented in (Souffriau and Vansteenwegen (2010)) [96].

The MTGs offer a ubiquitous access, i.e., at anytime, from anywhere with any media, to tourism information such as POIs and available facilities (Schwinger et al. (2005) [84]; Vansteenwegen and Oudheusden (2007) [103]). They may assist tourists during whole of three phases of a travel lifeline, i.e., before, during and after a trip. In pre-trip phase a tourist may use these systems to study and review the POIs to design his/her itinerary. During the trip, these systems provide the tourist with online and offline information and explanation about the visited POIs and re-designing the tour based on changed current parameters. It is also possible for user to add some attributes to points in the database of system. Finally, post-trip phase may include review of visited places and analysis of trip based on saved information in system such as position and time.

Most of the existing MTGs benefit the contextual information to present more suitable and user-friendly information and services to their users. Up to now, many context-aware MTGs have been developed. An almost comprehensive survey of existing systems may be found by Schwinger et al. (2005) [84].

Vansteenwegen et al. (2011) [106] introduce a tourist expert system, called the City Trip Planner, that allows planning routes for five cities in Belgium. It is implemented as a web application that takes into account the interests and trip constraints of the user and matches these to a database of locations in order to predict personal interests. A fast and effective planning algorithm provides an on-the-fly suggestion of a personal trip for a requested number of days, taking into account opening hours of attractions and time for a (lunch) break. The personalized electronic tourist guide is a device that addresses this problem by suggesting, at very short notice, a (near) optimal selection of POIs and a route between them, taking into account the weather, opening hours, crowded places and personal preferences. The application introduced in this paper is based on the tourist trip design problem (Vansteenwegen & Van Oudheusden (2007)) [103].

The Dynamic Tour Guide (ten Hagen et al. (2005)) [49] was the first application to calculate personal tourist trips on-the-fly. In order to construct a tour, the system uses a branch-and-bound algorithm to connect so-called Tour Building Blocks, while maximizing Interest Matching Points that reflect the users personal interest.

Among other Information Technologies, Decision Support Systems (DSS) should be a fundamental tool for tourism management. Baggio and Caporarello (2005) [7] present an overview of DSS usage in tourism management organizations. Shcherbina and Shembeleva (2008) [90] propose to develop and validate a comprehensive computer-based DSS that is based on mathematical modeling of the recreational system and its processes and that will assist planners in evaluating alternative scenarios and planning options. Shcherbina and Shembeleva (2010) [92] discussed Decision Support Systems (DSS) and Spatial Decision Support Systems (SDSS) as an effective technique in examining and visualizing impacts of policies, sustainable tourism development strategies within an integrated and dynamic framework.

3.4 Optimal development of a system of tourist routes

Consider a problem of optimal development of a system of tourist routes. This system involves a set $j = 1, \dots, n$ of tourist objects (TO) which are characterized by their attractiveness π_j (Gearing et al. (1973)) [37], the time τ_j of using TO j and the maximal capacity h_j.

The problem is: to find the optimal allocation of the tourist complexes $i = 1, \dots, m$; to find their capacities and number of tourists getting service; to construct an optimal set of tourist routes, to find intensities x_r of using these routes $r = 1, \dots, k$. As the objective function the revenue of the system may be taken. The sustainability of the tourist routes can be reached using limitations on resources.

We propose to solve this problem using 2 steps.

1st step. Estimation of tourist objects (parameters $\pi_j,\ \tau_j,\ h_j$ are estimated), places of feasible location of tourist complexes are found.

2nd step. Optimal capacities of tourist complexes are found, the optimal set of tourist routes is found, the optimal plan of intensities of using of routes is found. We now consider the two steps in detail. In the 1st step the parameters describing the tourist objects were determined by experts' revue. Places for possible allocation of tourist complexes were chosen An alternative procedure of the estimation of recreational resources consists of the following (Lemeshev and Shcherbina (1986)) [67]. Recreational sites are first evaluated by experts (”promising” or ”not promising”), then these sites were divided into several classes and their attractivenesses were computed using the values of the factors determining the classes. This estimation of recreational resources uses methods of pattern recognition nets. Consider the following discrete optimization model. Consider for simplicity only one season. All tourist objects (TO) are divided into several classes $J_1, \ldots, J_L$ and the number of a TO of class l in the route may be between n_l^- and n_l^+; the minimal M^- and maximal M^+ number of routes are given; the duration T of each route is limited: $T^- \leq T \leq T^+$. The places for tourist complexes location are given by $i = 1, \ldots, m$; J_i^* is a set of TOs which are in neighborhood of TC i; y_i^0 — initial capacity of TC i. The cost c_i of creating one capacity unit in TC i is known; the budget limit K for the development of tourism system is given. Let $\tau_j^{'}$ be a time of using TO j with additional time needed for eating, sleeping etc. Let us introduce binary decision variables $x_{rj},\ z_r$: $x_{rj} = 1$ if TO j is included into route r and $x_{rj} = 0$ otherwise; $z_r = 1$ if route r is included into the system of optimal routes and $z_r = 0$ otherwise.

The discrete optimization model for the tourism system development is:

$$\sum_{r=1}^{M^+} \sum_{j=1}^{n} \pi_j \tau_j x_{rj} \to \max$$

subject to constraints:

on the capacity of TO j:

$$\sum_{r=1}^{M^+} x_{rj} \leq h_j,\ j = 1, \ldots, n$$

on the number of objects in route:

$$n_l^- z_r \leq \sum_{j \in J_l} x_{rj} \leq n_l^+,\ r = 1, \ldots, M^+,\ l = 1, \ldots, L$$

on the tourist complex capacities:

$$\sum_{j \in J_i^*} \tau_j^{'} \sum_{r=1}^{M^+} x_{rj} \leq y_i^0 + y_i,\ i = 1, \ldots, m$$

on the route duration:

$$T^- z_r \leq \sum_{j=1}^{n} \tau_j^{'} x_{rj} \leq T^+,\ r = 1, \ldots, M^+$$

on the budget:

$$\sum_{i=1}^{m} c_i y_i \leq K$$

$$x_{rj},\ z_r \in \{0, 1\},\ y_i \geq 0.$$

Solving this mixed integer linear programming problem (MILP) we find the set of optimal routes, intensities of usage these routes and schedule t_{ir} by the formula:

$$t_{ir} = \sum_{j \in J_i^*} \tau_j^{'} x_{rj}$$

4 Reservation models

4.1 Overbooking and Revenue Management

Capacity-constrained service firms such as airlines, hotels, rental car companies, and so on, who sell perishable products or services often face the problem of selling a fixed capacity over a finite booking period to different customer segments. Revenue (or yield) management, a method for managing capacity profitably, is appropriate for such capacity-constrained service firms (Sun (2011)) [98].

Revenue management (RM) has its origins in the airline industry. In fact, revenue management is not limited to the airline industry. RM encompasses all practices of discriminatory pricing used to maximize the profit generated from a fixed amount of resources. The two typical applications of RM are hotel and airline booking polices. The basic idea behind RM is that different consumers of the service offered by a hotel or an airline are willing to pay different amounts for that service. In the aggregate, this variation in willingness to pay gives rise to price elasticity of demand. Given a stochastic process for customers calling in reservations prior to a particular booking date of a hotel or airline, the problem is to devise a policy for booking the set of customers that maximizes the total expected profit of the hotel booking date or airline flight (Badinelli (2000)) [6].

The objective of the RM problem is to maximize the profit generated by a given capacity for service over the long run. This capacity is either the number of rooms in the hotel or the number of seats on an aircraft. Much of the early literature in RM focused on the *overbooking problem* which simplified the objective even more by using occupancy as a performance measure. Overbooking is a practice of booking hotel rooms beyond the capacity of an hotel to allow for the probability of no-shows (See Liberman and Yechialli (1978) [70], Rothstein (1971, 1974, 1985) [80], [81], [82], and Ladany (1976) [56]).

For the sake of space, we do not provide an exhaustive review of the literature that has addressed this problem. Readers are referred to the survey paper by McGill and van Ryzin (1999) [72] and to the book by Talluri and van Ryzin (2004) [99] for a more systematic review of the RM literature.

A number of researchers have developed dynamic programming (DP) models for the airline and hotel/motel overbooking problem. The usual objective in these formulations is to determine a booking limit for each time period before the targeted booking date that maximizes expected revenue, where allowance is made for the dynamics of cancellations and reservations in subsequent time periods and for penalties for oversold rooms. Rothstein (1968) [79] describes the first DP model for overbooking at American Airlines. A similar DP model developed for the hotel/motel industry and extended to two fare classes is described in Ladany (1976, 1977) [56], [57] and Ladany and Arbel (1991) [60]. A control-limit type structural solution to the (one class) hotel overbooking problem is described in Liberman and Yechiali (1977, 1978) [69], [70].

Rothstein (1974) [81] claimed that he found no published model directed specifically to the hotel problem and provided one. His model is an extension of the airline overbooking problem examined previously by Rothstein (1968, 1971) [79], [80]. He used the Markovian sequential decision process to generate booking policies for hotels with one room-type and single-day stays. This problem differs from the airline problem by allowing double occupancy – more than one guest per room.

Ladany (1976) [56] extended Rothstein's airline work to provide a hotel model where there are two room-types: single and double rooms. Stay durations are still limited to single-days only. The author claimed that the model may be extended for many room-types and multiple-day stays.

Bitran and Mondschein (1995) [12] study optimal strategies for renting hotel rooms when a manager faces a stochastic and dynamic arrival of customers from different market segments, considering a fixed capacity and a finite planning horizon. A stochastic, DP model is developed. The model characterizes the optimal policies as functions of the capacity and the time left until the end of the planning horizon.

Bitran and Gilbert (1996) [13] consider the hotel reservation problem and develop a model of reservation booking which explicitly includes the room allocation decisions which are made on the targeted booking date. simple heuristic procedures for accepting reservations are developed.

In today's highly competitive market, market segmentation and control is a powerful way for sellers, particularly for RM sellers, to improve profitability. The objective of segmenting market is to differentiate consumers who are willing and able to pay higher prices from those who are willing to pay lower prices.

Ladany (1996) [61] investigated the optimal market segmentation pricing strategy for rooms of hotels to determine the optimal number of segments to be used and the accompanying number of rooms and price prevailing in each segment, under the assumption of an aggregate non-linear demand function. A single state-variable DP model is formulated to maximize profit, and an efficient reduction in the range of search for the solution of the model is outlined.

Ladany (2001) [59] suggested an efficient single state-variable DP model for the selection of the optimal mix of market segments (the total number of market segments and the specific market segments included) of a hotel. It is evaluated for a given set of potential market segments, when the individual demand curves are known in each segment. It is suggested that the derived static results should be the optimal strategy to be used (instead of unfounded management directives) as input to tactical yield management policies in stochastic environments.

In reality, it is impossible for any company to segment their consumers absolutely. The phenomenon of *infiltration*, the behavior of a higher price consumer diverting to pay a lower price if it is available, is always observed in a realistic market. Ladany and Chou (2001) [62] develop an integer programming model for determining the optimal market segmentation and pricing policy for fixed-capacity service industries to maximize their yield, given a set of defined potential market segments with known demand curves. The model incorporates infiltration of customers from high priced to low priced market segments. Ladany and Chou (2001) [62] discuss the possibility of potential consumers infiltrating from a higher-priced into a lower-priced market segment. In their work, three infiltration situations are discussed: (1) potential consumers of each segment infiltrating to the next lower-priced segment; (2) potential consumers of all segments infiltrating to the lowest priced segment; (3) potential consumers of the highest-priced segment infiltrating to another specific segment. Additionally, the authors argue that it would be more realistic to assume that the infiltration fraction would depend on the difference in price levels between segments.

Cruise lines, like airlines and hotels, belong to traditional RM industries [98]. In a cruise ship, there are many kinds of cabin types and different kinds of class fares, some of which are sold in advance with given purchase restrictions over a finite booking window. All common properties of RM problems (segmented market, fixed capacity, perishable inventory, finite selling horizons, advanced sales and stochastic demand) are observed in the cruise industry.

To determine the optimal market segmentation and price differentiation strategy that a cruise-liner should follow, Ladany and Arbel (1991) [60] consider the optimal number of market segments, as well as the corresponding prices under the assumption of an aggregate linear demand function. In this paper, four situations were investigated: (a) single-price and single-market, (b) optimal segmentation of the unused cabins, (c) optimal segmentation of all cabins, and (d) optimal segmentation allowing for infiltration from higher-priced to adjacent lower-priced segments. However, the assumption of the width (the number of cabins) of each submarket was equal and the linear demand function reduced the universality of the problem.

4.2 Online and offline reservation models

Van Hentenryck (2009) [101] considers online stochastic reservation systems and, in particular, the online stochastic multi-knapsack problems introduced in (Benoist et al. (2001)) [9]. Requests come online and must be dynamically allocated to limited resources in order to maximize profit. Typical applications include, for instance, reservation systems for holiday centers and advertisement placements in web browsers. For instance, a travel agency may aim at optimizing the reservation of holiday centers during a specific week with various groups in presence of stochastic demands and cancellations. The requests are coming online and are characterized by the size of the group and the price the group is willing to pay. The requests cannot specify the holiday center. However, the travel agency, if it accepts a request, must inform the group of its destination and must commit to it. Groups can also cancel the requests at no cost. Finally, the agency may overbook the centers, in which case the additional load is accommodated in hotels at a fixed cost. Observe that these problems differ from the stochastic routing and scheduling considered in (Benoist et al. (2001)) [10] in that online decisions are not about selecting the best request to serve but rather about how best to serve a request.

The *offline* problem is defined in terms of n bins B and each bin $b \in B$ has a capacity C_b. It receives as input a set R of requests. Each request is typically characterized by its capacity and its reward, which may or may not depend on which bin the request is allocated to. The goal is to find an assignment of a subset $T \subseteq R$ of requests to the bins satisfying the problem-specific constraints and maximizing the objective function.

In paper (Lai and Ng (2005)) [66] is proposed a network optimization model in a stochastic programming formulation for hotel revenue management under an uncertain environment.

4.3 The Multi-Knapsack Problem

The multi-knapsack problem (Benoist et al. (2001)) [9] is an example of a reservation problem (Van Hentenryck (2009)) [101]. Here each request r is characterized by a reward w_r and a capacity c_r. The goal is to allocate a subset T of the requests R to the bins B so that the capacities of the bins are not exceeded and the objective function $w(T) = \sum_{r \in T} w_r$ is maximized. A mathematical programming formulation of the problem associates with each request r and bin b a binary variable x_r^b whose value is 1 when the request is allocated to bin b and 0 otherwise. The integer program can be expressed as:

$$\sum_{r\in R,\ b\in B} w_r x_r^b \to \max$$

subject to

$$\sum_{b\in B} x_r^b \leq 1\ (r \in R)$$

$$\sum_{r\in R} c_r x_r^b \leq C_b\ (b \in B)$$

$$x_r^b \in \{0,1\}(r \in R,\ b \in B)$$

4.4 The Multi-Knapsack Problem with Overbooking

In practice, many reservation systems allow for overbooking. The multi-knapsack problem with overbooking (Benoist et al. (2001)) [9] allows the bin capacities to be exceeded but overbooking is penalized in the objective function. To adapt the mathematical-programming formulation above, it suffices to introduce a nonnegative variable y^b representing the excess for each bin b and to introduce a penalty term αy^b in the objective function. The integer programming model now becomes

$$\sum_{r\in R,\ b\in B} w_r x_r^b - \sum_{b\in B} \alpha y^b \to \max$$

subject to

$$\sum_{b\in B} x_r^b \leq 1\ (r \in R)$$

$$\sum_{r\in R} c_r x_r^b \leq C_b + y^b\ (b \in B)$$

$$x_r^b \in \{0,1\}\ (r \in R,\ b \in B)$$

$$y^b \geq 0\ (b \in B)$$

4.5 Temporal knapsack problem

Here we consider optimal reservation problems (ORP), where requests must be dynamically allocated to limited resources in order to maximize profit. Typical applications include, for instance, reservation systems for holiday centers and advertisement placements in web browsers. For instance, a travel agency may aim at optimizing the reservation of holiday centers during a specific week with various groups in presence of stochastic demands and cancellations. The requests are coming online and are characterized by the size of the group and the price the group is willing to pay. The requests cannot specify the holiday center. However, the travel agency, if it accepts a request, must inform the group of its destination and must commit to it. Groups can also cancel the requests at no cost. Finally, the agency may overbook the centers, in which case the additional load is accommodated in hotels at a fixed cost. Observe that these problems differ from the stochastic routing and scheduling considered in that online decisions are not about selecting the best request to serve but rather about how best to serve a request.

Bartlett et al. (2005) [8] define the temporal knapsack problem (TKP), that is a natural generalisation of the knapsack problem and a natural specialisation of the multi-dimensional knapsack problem. This model named advanced reservation model was earlier proposed in papers (Shcherbina (1983, 1986)) [87], [88].

In the TKP a resource allocator is given bids $j = 1, \ldots, n$ for portions of a time-shared resource — such as CPU time or communication bandwidth or a sharedspace resource — such as computer memory, disk space, or equivalent rooms in a hotel that handles block-booking. Each bid j specifies the amount of resource q_j needed, the time interval $[\alpha_j,\ \beta_j]$ throughout which it is needed, and a price c_j offered for the resource. The resource allocator will, in general, have more demand than capacity $b_t,\ t = 1, \ldots, T$, so it has the problem of selecting a subset of the bids that maximises the total price obtained. Let us introduce decision variables x_j:

$$x_j = \begin{cases} 1, & \text{if bid } j \text{ is selected;} \\ 0, & \text{otherwise.} \end{cases}$$

$$\sum_{j=1}^{n} c_j \cdot x_j \to \max \tag{8}$$

$$\sum_{j \in F_t} q_j \cdot x_j \le b_t,\ t = 1, \ldots, T, \tag{9}$$

$$x_j = 0,\ 1, \quad j = 1, \ldots, n. \tag{10}$$

where

$$F_t = \{j :\ \alpha_j \le i \le \beta_j\}.$$

A *Petrie* matrix is a finite matrix whose elements are either zeros or ones such that the ones in each column occur consecutively. Such matrices have been studied in a molecular biological situation by Fulkerson and Gross (1965) [36] and in archaeology by Kendall (1969, 1971) [53], [54] and Wilkinson (1971) [110]. The problem here treated has arisen from a combinatorial analysis of the theory of the "excluded volume" of a polymer chain (Fixman (1955)) [34], in which Petrie matrices play an important, though hitherto unrecognized, role. The Fulkerson and Gross (1965) [36] paper quotes the interesting fact that Petrie matrices are *unimodular*, that is all square sub-matrices have a determinant which is either -1, 0, or 1. It is possible to construct a correspondence between n by n Petrie matrices and graphs on $n + 1$ vertices with at most n edges, and then to show that precisely those graphs that are spanning trees correspond to nonsingular Petrie matrices.

A binary matrix has the Consecutive Ones Property (C1P) when there is a permutation of its rows that leaves the 1's consecutive in every column. DNA fragment assembly, which leads to interval graphs, which lead into the Consecutive Ones Property (Meidanis et al. (1998)) [73].

In the last three decades, the study of the C1P property for a given 0-1 matrix has found different applications in graph theory (Deogun and Gopalakrishnan (1999)) [29], computer science (Flammini et al. (1993)) [35], (Ghosh (1972)) [47], and genome sequencing (Pevzner (2000)) [77].

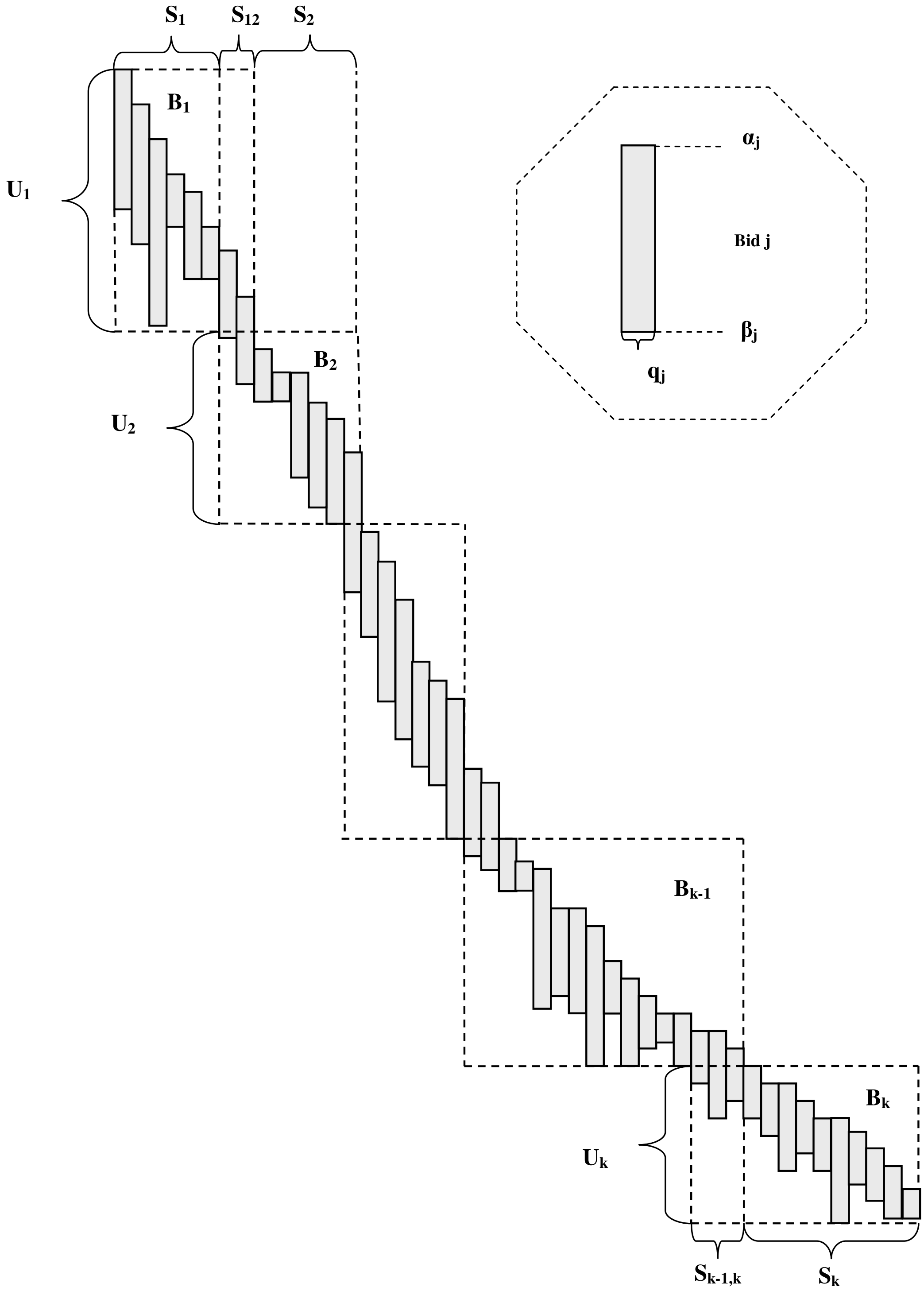

Fig. 1 Petrie's matrix and corresponding blocks.

There are a great number of practical problems in which one is interested in constructing a time line where each particular event or phenomenon corresponds to an interval representing its duration. These include seriation in archeology (Kendall (1969, 1971)) [53], [54], behavioral psychology (Coombs and Smith (1973)) [23], temporal reasoning (Allen (1983)) [4], operations research (Papadimitriou and Yannakakis (1979)) [75], technical diagnosis (Nökel (1991)) [74], circuit design (Ward and Halstead (1990)) [108], and combinatorics (Golumbic and Shamir (1993)) [45]. Indeed, it was the intersection data of time intervals that lead Hajös (1957) [50] to define and ask for a characterization of interval graphs. Other applications arise in non-temporal contexts. For example, in molecular biology, arrangement of DNA segments along a linear chain involves similar problems (Pevzner (2000)) [77].

5 Planning urban recreational facilities with integer goal programming

Some sites $i \in I$ were identified by planners as potential sites for recreational facilities $j \in J_i$ within the city boundaries (Taylor and Keown (1978)) [100]. These sites were selected because of their availability for sale or annexation by the city and their proximity to highly populated areas.

In goal programming model the goals are expressed as soft constraints using two deviational variables for each goal: d^- = underachievement, d^+ = overachievement.

Decision variables of the goal programming model define a particular facility at a site: x_{ij}:

$$x_{ij} = \begin{cases} 1, & \text{if facility } j \text{ is selected at site } i; \\ 0, & \text{otherwise.} \end{cases}$$

Goal constraints for the model are formulated as follows:

A. Area constraints:

$$\sum_{j \in J_i} s_{ij} \cdot x_{ij} + d_i^- = S_i, \quad i \in I_1;$$

(s_{ij} is the area requirement for for the facility j at site i, S_i is the total land available at site i);

B. Cost constraint reflects the total initial construction cost for each facility and the total amount b available for construction purposes only:

$$\sum_{i \in I} \sum_{j \in J_i} c_{ij} \cdot x_{ij} + d_B^- - d_B^+ = b;$$

(c_{ij} is the total initial construction cost for the facility j at site i);

C. Land-cost constraint. As a result of the types of funding available to the city, land and construction budgets must be kept separate with the city providing the major portion of land funding. Technological coefficients (l_{ij}) in this constraint reflect the land cost for each facility and the right-hand side value (b_L) is the total amount for land purchase available to the city:

$$\sum_{i \in I} \sum_{j \in J_i} l_{ij} \cdot x_{ij} + d_L^- - d_L^+ = b_L;$$

(l_{ij} is the land cost for the facility j at site i);
Objective function is usual for goal programming:

$$\sum_{i\in I} P_i^- d_i^- + P_i^+ d_i^+ \to \min$$

(P_i^-, P_i^+ are weights of corresponding goals).

6 Conclusion

Decision makers in tourism planning and management are confronted with a vast field of complex aims, requiring different plans of action. Problems in strategic, and frequently operational planning, are characterized by their complexity, often being intermingled, non-transparent, individualistically dynamic and requiring the achievement of multiple goals. Solving these problems require the use of modern techniques of operations research and up-to-date information technologies.

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