Tourist Trip Planning Functionalities: State–of–the–Art and Future

Wouter Souffriau and Pieter Vansteenwegen

Katholieke Universiteit Leuven
Centre for Industrial Management
Celestijnenlaan 300A, 3001 Leuven, Belgium

Abstract. When tourists visit a city or region, they cannot visit every point of interest available, as they are constrained in time and budget. Tourist recommender applications help tourists by presenting a personal selection. Providing adequate tour scheduling support for these kinds of applications is a daunting task for the application developer. The objective of this paper is to demonstrate how existing models from the field of Operations Research (OR) fit this scheduling problem, and enable a wide range of tourist trip planning functionalities. Using the Orienteering Problem (OP) and its extensions to model the tourist trip planning problem, allows to deal with a vast number of practical planning problems.

1 Introduction

Many tourists visit a region or a city for one or more days. It is not possible to visit every tourist attraction or cultural heritage site during such a limited period, so the tourist has to make a selection of what he believes to be the most valuable Points of Interest (POI). This personal selection is based on information found on web sites, in articles in magazines or in guidebooks from specialised book stores or libraries. Once the selection is made, the tourist decides on a route, keeping in mind the opening hours of the POIs and the available time.

Tourists face several difficulties when following that procedure. Information provided in guidebooks can be out–of–date, e.g. opening hours may change. Also, guidebooks cannot provide temporal information: temporary exhibitions in museums change all the time, some POIs are (partly) closed due to renovation and theatres change their programme regularly [Dunlop et al., 2004]. Tourists have to combine the information from different sources and decide which information is the most reliable. Moreover, selecting the most valuable POIs, i.e. those of the greatest interest to the tourist, is not easy. Usually tourists will be happy if they devise a somewhat attractive and feasible schedule, but they have no idea whether better schedules are possible.

Some guidebooks acknowledge these problems and propose generic visitor tours through a city or region. Of course these tours are constructed in order to satisfy the interests of the majority rather than the specific interests of individuals [Cheverst et al., 2000]. Generic visitor tours do not take user context into account, e.g. the start and end location, the available time, the current time, the weather, etc. Kramer et al. [2006] have analysed the diversity of gathered tourist interest profiles and conclude that they are surprisingly diverse. This conclusion supports the idea of creating personalised tours instead of proposing generic visitor tours. Furthermore, tourists today want to use their free time in an optimal way and they expect to be well informed on what a city or specific POI can offer [Oppermann and Specht, 1999, Keyson, 2004].

Web–based decision support applications are excellent aids for tourists who want real support for tourist planning problems. Based on an interest profile, up-to-date POI information and trip information, a (near-) optimal and feasible selection of POIs and a route between them can be suggested [Vansteenwegen and Oudheusden, 2007]. Also, most tourists today move within a limited crowded area of very attractive POIs. Kramer et al. [2006] state that a system enabling personal selection and routing of POIs will help to spread tourists more evenly across the destination region, which helps to prevent crowds.

Since the Second World War, the science of Operational Research (OR) has been applied to a vast range of problems in different sectors. OR is concerned with applying mathematics, statistics, optimisation technology, etc. to provide decision makers with (near-) optimal solutions to complex problems in military contexts, manufacturing, transportation, logistics, finance, etc. However, the field of tourism, in particular personalised trip planning, has been largely ignored.

Godart [2001] uses the Travelling Salesperson Problem (TSP) as a starting point to plan trips. His TSP with Activities and Lodging Selection (ALS) automatically selects POIs and lodging. The Multiple Objectives extension (MOTSP–ALS) minimises transport and accommodation costs at the same time. Finally, Preference Based MOTSP–ALS also maximises the attractiveness of the lodging and the activities. This complicated model turned out to be difficult to solve. This research resulted in a web based tour planner, YourTour[1].

Vansteenwegen and Oudheusden [2007] advocate the use of the OP and its extensions to solve Tourist Trip Design Problems (TTDP). The OP integrates automated selection of locations with finding the shortest path, and is therefore highly appropriate to model TTDPs. The objective of this paper is to demonstrate how a wide range of real–life tourist trip planning functionalities can be enabled by using the OP. First, Section 2 presents an overview of systems that compose tours of POI visits. Next, Section 3 discusses the wide range of planning–related functionalities that are offered by these systems and compares them based on the functionality they offer. Section 4 explains how the OP and its extensions can be used to model trip planning functionalities. Finally, Section 5 concludes this paper.

[1] http://www.yourtour.com

2 State–of–the–Art

Instead of recommending pre–packaged tours, or sorting POIs by estimated interest value as recommender systems do, scheduling approaches typically try to determine the combination of POIs that maximise the joint interest.

Soo and Liang [2001] present a software agent that recommends a trip plan through dialogue with the user. Custom trips to the city of Taipei, China, are proposed by first letting the tourist select his hotel(s) and next automatically filling the available time with POI visits in an nearest–neighbour fashion.

Ardissono et al. [2002, 2003] describe their INteractive TouRist Information GUidE (INTRIGUE) for the city of Torino, Italy. It is a fuzzy logic based recommender system that is able to provide an explanation why a recommendation has been made. Moreover, INTRIGUE has a tour scheduling functionality that enables composing group tours taking into account opening hours and locations of the POIs and time restrictions of the tourist group members. Unfortunately, very little technical details on the scheduling algorithm are provided.

Suna and Lee [2004] present a multi–agent system that advises personalised tourist routes using a vector based recommendation technique to calculate personal interest values in geographical objects. A shortest path algorithm minimises the normal cost of arcs in the road network divided by their personal interest values in order to calculate personalised point–to–point routes. A tourist trip is calculated by modelling the POI selection problem as a prize collection TSP, which is to be solved with the method of Dell' Amico et al. [1998]. Despite the promising ideas, Suna and Lee [2004] do not evaluate the system thoroughly.

Maruyama et al. [2004a,b] present P-Tour, a personal navigation device that calculates tourist routes. They use a variant of the TSP with profits that aims at finding a circuit that minimises travel costs minus collected profit [Feillet et al., 2005]. The P-tour routing algorithm selects and routes a number of POIs that are defined by a location, a visiting duration, an importance score and an optional constraint on arrival time. Maruyama et al. [2004a] maximises the weighted sum of (1) the importance of selected POIs, (2) the importance of selected POIs that satisfy a time restriction, minus (3) the total travel distance, while Maruyama et al. [2004b] only use (2) minus (3). The route search engine achieves a gap of less than 2% from the optimal solution in 15 seconds, for one small instance of 30 POIs. Users have to enter personal importance scores themselves for each POI.

Shiraishi et al. [2005a,b] extend P-Tour in two ways. First, they search for undesirable situations during the execution of the planned route (wrong route, behind or or ahead of schedule) and warn the user in an appropriate manner. Second, the route search engine is extended to take multiple conflicting evaluation functions into account: they contrast the weighted sum function of Maruyama et al. [2004b] together with the total travel expense. Kinoshita et al. [2006] extend P-Tour for multiple days. The total set of POIs is partitioned across different areas. Every day a selection of POIs of a predetermined area is to be visited, including accommodation to spend the night. A three day instance is solved in 19.6s with a gap of 0.7% from optimality, taking into account the pre–

partitioning of the POIs, which possibly discards significantly better solutions. Nagata et al. [2006] extend the P-Tour system in order to plan group tours. Every member of the tourist group is allowed to state a preference value, a duration and a latest arrival time for each POI. Also, every member has a starting and an end point, a time restriction on the total tour and a speed. The objective is to find a schedule that forks and joins the group along the way to visit POIs.

Wu et al. [2009] extend the P-Tour system to take the weather forecast into account. For each POI, a timetable is given that contains probabilities for fine, cloudy and rainy weather, every hour. POI preference values are dependent on the current weather while visiting it. The objective is to construct a decision tree that maximises the total expected satisfaction degree. Limited experimental results are presented: an instance of 6 POIs is optimally solved in 6 seconds, compared to 16h with brute force search, and on an instance with 20 POIs, the quality of the greedy construction heuristic is improved 17,9% on average. Overall, P-Tour and its extensions provide interesting ideas, but fail to provide extensive computational experiments.

The Dynamic Tour Guide (DTG) of ten Hagen et al. [2005] calculates personal tours on–the–fly. A tour is a collection of so-called Tour Building Blocks (TBB): sights, restaurants, etc. An ontology consists of a tree of concept classes and describes each TBB. TBBs receive Interest Matching Points by a semantic matching algorithm, representing the interest of the user. After the assignment of Interest Matching Points, an algorithm constructs a tour by maximising the sum of the Interest Matching Points within a given time frame. The algorithm keeps a list of candidate TBBs, sorted by use of gain, i.e. the Interest Matching Point divided by the cost needed to visit the TBB. From the list, the TBBs are removed and inserted in the tour randomly until the available time runs out.

Lee et al. [2007] present a tourist tour planning system for the Jeju province in Korea. They adopt the interest estimation method of Kang et al. [2006] in order to compute vector–based similarities between POIs and users. Next, they add a maximum length constraint to their TSP formulation of the planning problem. Actually, without mentioning it, they use the OP as a model. However, they tackle the problem by solving 2^n distinct TSPs of n POIs, instead of 1 OP, which is a computationally very expensive approach. Their high performance cluster manages to offer a solution within 5 seconds when $n < 22$.

Castillo et al. [2008] present a multi–agent based system for planning tourist visits. A user agent first captures the user's interest. Next, a Case Based Reasoning agent predicts interesting activities. Finally, the planning agent takes these interesting activities as input and outputs a plan. The planning takes the following items into account: opening hours, preferences of the user, prices of meals and transports, locations and multi–modal means of transport. Two types of goals can be specified: totally and partially instantiated goals, e.g. visit a specific museum, respectively a type of museum. The planning problem is translated to predicate logic. Predicate logic AI planning modules use tree search to come up with a feasible plan and route to perform the activities. There is no integration of selection and routing, and no evaluation of the proposed system is presented.

Lee et al. [2009] present a recommendation system that allows planning personalised travel routes to Tainan City, China. Their ontology based multi–agent system consists of a context decision agent and a travel route recommendation agent. The context decision agent first finds concepts of the ontology that match the tourist's requirements. Next, the travel route recommendation agent uses fuzzy logic to select and sort a top three of historic sites and a top five of local gourmet food stores. A TSP that deals with these eight locations, is solved. Experimental results present two small examples as evaluation, but no performance benchmarks. The system makes a distinction between selection and routing.

Niaraki and Kim [2009] developed a method for personalising route planning network impedances. They evaluate multiple criteria that are defined in an ontology describing road segments. The user states his preferences for attributes such as traffic volume, safety, POI presence, etc. based on which the weights in the road graph are calculated. Common shortest path algorithms such as Dijkstra [Gallo and Pallattino, 1986] and A* [Pearl, 1984] can be used to calculate personal point–to–point routes.

Yu and Chang [2009] developed a framework for the personalised recommendation of hotels, restaurants and POIs. They have combined these three functionalities in a tour recommendation process that recommends a personalised tour based on the user's current time and location and his interests. A prototype was built for the city of Taipei, Taiwan.

We developed the City Trip Planner[2], which is a web–based tourist decision support system that proposes city trips tailored to the user's context and personal interests [Vansteenwegen et al., 2010]. The system plans city visits of multiple days, with for each POI multiple time windows which can differ from day–to–day. Moreover, lunch breaks can also be scheduled and the local tourist office can suggest a few POIs to be included in a trip. The City Trip Planner integrates the selection of POIs and the routing between them. It uses the OP to model trip planning problems and fast heuristic algorithms [Vansteenwegen et al., 2009] to solve them. To the best of the author's knowledge, such an integrated system is unique. An extensive evaluation, with user statistics, is available in Vansteenwegen et al. [2010].

3 Planning Functionality for Tourist Decision Support

This section first discusses the wide range of planning–related functionalities that are offered by the tour scheduling systems. Next, a comparison between these different systems is provided, based on the functionality they offer.

Personal Interest Estimation quantifies the interest of the tourist in a particular POI, the appropriateness of a hotel or the "beautifulness" of a scenic route. This quantified value can be used to sort POIs and hotels when presenting them to the user. Attributes of the user, which are collected into his user profile, are to be matched with attributes of the location or activity.

[2] http://www.citytripplanner.com

Selection and Routing automatically presents a customised route based on the user's current location, his destination and his available time, which limits the length of the route. This limit implies a selection of POIs, in order to keep the length of the route feasible. When combined with personal interest estimation, the resulting route is tailored to the user's interest.

Mandatory POIs can be considered as "must see". Whenever the tourist is in the neighbourhood of a mandatory POI, it should be presented at the top of his preference list. A POI can be determined mandatory by the provider of the POI information.

Dynamic Recalculation is needed when unexpected events occur. These can make the current selection of POIs or route invalid. Dynamic recalculation detects these infeasibilities and presents a new plan to the user, in "real–time".

Multiple Day Decision Support enables planning for multiple days. The user receives a selection of POI visits for a series of days. Each POI visit only appears once in the total selection.

Opening Hours should be taken into account when visiting the "interior" of POIs. Therefore, the route of selected POIs should take into account the time of the scheduled POI visits, making sure that each visit is planned when the POI is open. The opening hours of each POI are defined by means of a calendar. In the simplest case, a POI is open for a consecutive period during the day, with one opening time and one closing time, for all days. However, POIs can e.g. be closed during lunch, resulting in two opening periods during the same day. Moreover, opening hours tend to differ on different days: a POI can e.g. be closed on Sunday afternoon.

Budget Limitations arise when the tourist has a maximum amount of money to spend. Next to the time budget of the selection and routing functionality, a money budget further constrains the selection of POI visits.

Weather Dependency influences the estimated appreciation of POIs by taking the weather forecast into account. During rainy periods, outdoor visits could be penalised, in favour of indoor visits.

Max–n Type constrains the selection of POIs by allowing to state a maximum number of certain types of POIs, per day or for the whole trip. E.g. maximum two museum visits on the first day.

Mandatory Types enable the tourist to state that a tour or a trip should contain at least one visit of a certain type, e.g. a visit to a church. Mandatory types extend the concept of mandatory POIs.

Scenic Routes allow to visit beautiful routes, next to interesting locations. When moving from one POI to the next, a tourist will not mind a small detour through a car–free street with medieval façades. Although this is not the shortest path between the two POIs, it will be appreciated more than a walk through a regular street.

Hotel Selection automatically selects appropriate hotels when visiting a region for multiple days. The personal interest in the different hotels can be estimated, based on attributes of the hotels such as comfort. The automated selection mechanism will need to take the price of a stay into account, in function of the budget of the total trip.

Public Transportation takes into account metro, train and bus schedules when travelling between POIs. These alternatives to walking need to be considered when distances between POIs are large. They can save considerable amounts of time that could be spend on POI visits.

Group Profiles enable planning for groups of tourists, which differs considerably from single–tourist planning, as a group of tourists may have a broad, possibly conflicting, range of interests. Possible strategies include optimising the joint interests of the group members by selecting locations they are all interested in, or taking turns and alternating interests so that no one feels he has been left out.

Table 1. Functionality Overview

	personal interest estimation	distinct selection and routing	integrated selection and routing	mandatory POIs	multiple days	opening hours	budget limitations	group profiles
[Soo and Liang, 2001]	x		x					
[Ardissono et al., 2002, 2003]	x	?	?			x		x
[Suna and Lee, 2004]	x		x					
[Maruyama et al., 2004a,b]			x			x		
[Shiraishi et al., 2005a,b]			x			x	x	
[Kinoshita et al., 2006]			x		x	x		
[Nagata et al., 2006]			x			x		x
[Wu et al., 2009]						x		
[ten Hagen et al., 2005]	x		x					
[Lee et al., 2007]	x		x					
[Castillo et al., 2008]	x	x		x		x	x	
[Lee et al., 2009]	x	x			x			
[Niaraki and Kim, 2009]	x							
[Yu and Chang, 2009]	x		x					
[Vansteenwegen et al., 2010]	x		x	x	x	x		

Table 1 presents a match of the existing tour scheduling approaches with the different functionalities presented above. Only those functionalities that appear in two or more approaches are included. Unknown features have been marked as "?". For the sake of completeness, Castillo et al. [2008] are the only to mention mandatory types and public transportation, Shiraishi et al. [2005a,b] are the only to tackle dynamic recalculation, Wu et al. [2009] weather dependency, Niaraki and Kim [2009] scenic routes and Kinoshita et al. [2006] hotel selection.

All of the presented approaches use some form of personal interest estimation, except for P-Tour and its extensions, which in turn present a wide range of planning functionalities.

A number of approaches offer integrated selection and routing. Soo and Liang [2001], Yu and Chang [2009] use a nearest neighbour approach, which iteratively adds the closest available visit to the tour. Suna and Lee [2004], P-Tour and its extensions, except Wu et al. [2009], use the profitable tour problem as a basis for selection and routing. ten Hagen et al. [2005] use a tree–based search, while Lee et al. [2007] combine a selection problem with a TSP.

Based on these developments, it can be concluded that providing automated POI selection and routing is an upcoming trend in tourist recommender applications. It appears that a large amount of research effort is still required in order to devise efficient tourist decision support techniques, that are able to propose customised tours with acceptable response times. Providing adequate planning support for these kinds of applications is a huge research opportunity in the field of OR.

4 Modelling the Tourist Trip Planning Problem

This section explains how the OP and its extensions can be used to model trip planning functionalities.This approach is applied, for instance, in the City Trip Planner mentioned in Section 2. An OP is a mathematical optimisation problem that consists of a set of locations which are determined by coordinates and a score. The pairwise travel times between the locations are known. The goal is to find a tour that maximises the total score earned by visiting locations. The start and end of the tour do not need to coincide. The total travel time (or distance) cannot exceed a predetermined value, which is called the time budget. Each location can be visited at most once.

All locations with a score represent POIs. The score represents the estimated personal interest of the tourist in the POI, and can be calculated by means of POI recommender techniques. The time budget obviously represents the maximum amount of time the tourist has available. The time needed to visit a location is normally ignored in the OP. However, this visiting time can be added to the travel times between the locations: half of the visiting time is added to each incoming travel time, half to each outgoing travel time. A solution to the OP represents a tourist route. It is obvious that solving the OP entails an integrated solution of the selection and routing problem a tourist faces. We include mandatory POIs as locations with a score that is higher than the sum of the scores of the non–

mandatory POIs. A quality algorithm will always select these mandatory POIs if that is feasible. Dynamic recalculation can be achieved by a fast algorithm, capable of offering a new solution in case of unexpected events that lead to a new TTDP instance.

The "Team OP" (TOP) extends the OP by allowing multiple tours, each limited by a time budget. Again, each location can be visited at most once. The TOP allows to model TTDPs for multiple days. Each tour or vehicle represents one day from a multi–day tourist trip.

The TOP can be extended with multiple constraints, in which each location has Z attributes for each day. Z additional constraints are defined, which limit the selection of vertices. In the envisioned tourist application, we use these additional constraints to enable modelling budget limitations to spend on entrance fees, "max–n types" for each day and for the whole trip and mandatory POI types.

In case of budget limitations, an extra location attribute is used to represent the entrance fee for a POI, and an extra contraint defines the money budget available to spend. Max–n types are modelled in a similar way: an extra location attribute is set to 1 if the location is of a particular type, 0 otherwise, and an extra contraint defines the maximum number of visits of that type. Note that the model also enables max–n type and budget constraints to be defined per day, e.g. visit maximum one church on the first day, or spend at most €100 on the second day. In this case, an extra constraint is added for that particular day.

Mandatory POI types, e.g. visit at least n churches, are a bit more complicated to model. Every visit to a POI of this type is copied. The copied visit receives a score that is higher than the sum of all regular visits, cfr. a mandatory POI. For each couple, an extra constraint is added, indicating that the original visit and the copied visit are mutually exclusive. For all copied visits of the considered type, one extra attribute is added and set to 1 for a copied visit, 0 for an original visit, and one extra constraint is added, which limits the total selection to the preferred number of visits of that type. When during the search this preferred number is not yet reached, the copied visits will be preferred over their original counterparts. When the number is reached, all other copied visits of the type under consideration will not influence the search any further. However, the original POI visits will still be considered with their normal scores.

The most studied extension of the TOP is the TOP with Time Windows (TOPTW). In this extension, each location is assigned a TW, with an opening time and a closing time. A visit to a location can only start during this time window. On arrival before opening, waiting is allowed, until opening, in order to collect the score. A feasible solution does not violate any TW constraint. The TOPTW enables modelling opening hours of POIs in the TTDP. However, only one TW can be defined per location, implying that a POI can have only one opening and closing time per day. Moreover, in the case of multiple days, a POI has an identical opening and closing time for any day.

We overcome this drawback by extending the TOPTW to the Multiple Constraint TOP with Multiple Time Windows. Each location is extended allowing

W TWs for each day, instead of one. Also, the TWs can be different on different days. This enables modelling opening hours of POIs by allowing multiple opening hours per day, and different opening hours each day.

The multiple constraints extension described above, can be used to model multiple TWs: locations with multiple TWs are split up into different visits to the same location, with one TW, and adding an extra constraint allowing only one visit to the actual location. Moreover, weather dependency can also be modelled by splitting up a POI: the POI with a TW marking a sunny period has a higher score than the same POI with a TW for a rainy period, and only one of both can be visited.

The City Trip Planner system, described above and evaluated in Vansteenwegen et al. [2010], proves that the OP and its extensions are very appropriate to model personalised trip planning. If the tourist trip planning problem is modelled as an (extension of the) OP, a large battery of algorithms are readily available for re-usage. The interested reader is referred to Vansteenwegen et al. [2011] for a recent survey on solution techniques.

5 Conclusions

Providing adequate tour scheduling support for tourist decision support applications is a daunting task for the application developer. An overview of systems that compose tours of POI visits, is presented. The wide range of planning–related functionalities that are offered by these systems, is discussed and the systems are compared based on these functionalities. Next, this paper demonstrates that existing OR models enable a wide range of current and future tourist trip planning functionalities.

We use the basic OP model, as it integrates selection and routing of tourist attractions. Mandatory POIs can be easily incorporated and dynamic recalculation is achieved by using fast solution techniques, which present solutions in nearly real–time. The model is iteratively extended with multiple tours, multiple constraints, time windows and multiple time windows. This paper explains how these extensions can be used to enable the planning of multiple days, budget limitations, max–n types, mandatory POI types, taking opening hours of POIs into account and how to tackle weather dependency.

The City Trip Planner described above shows that algorithms are available to deal with these models for real–life tourist planning problems. In addition to the City Trip Planner, we have also incorporated the model into another web–based tourist decision support system, namely an on–line cycle route planner for the province of East–Flanders offers personalised cycle routes based on user preferences. This web–based system is extended with an SMS service that provides cyclists “in the field” with routes on demand [Souffriau et al., 2010].

Future work includes incorporating support for scenic routes, hotel selection, public transportation and group profiles.

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