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Using a heuristic approach to design personalized urban tourism itineraries with hotel selection

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ABSTRACT

Urban tourism is a worldwide form of tourism and is one of the most important social and economic impetus for urban development. The urban tourism market has been increasingly dominated by the demand for personalized experiences. Accordingly, this study aims to design personalized itineraries with hotel selection for multi-day urban tourists. A two-level heuristic approach is proposed, which embeds genetic algorithm, variable neighborhood search, and differential evolution algorithm into the structure of memetic algorithm. A case study in Xiamen, a coastal city in Southeast China, is carried out to evaluate the performance of our approach. Results of paired sample t-tests show that our proposed approach is remarkably superior to existing methods. In addition, compared with previous methods, our approach can design more reasonable and personalized itineraries for tourists.

1. Introduction

Since the 1980s, the demand for urban tourist destinations has been growing rapidly and cities have become tourist destinations to be explored rather than merely "gateways" for international and domestic tourists (Ashworth & Page, 2011; Ben-Dalia, Collins-Kreiner, & Churchman, 2013; Gotham, 2007). In recent years, the significant opportunities and tremendous challenges brought about by tourism to urban development have been increasingly recognized (Pearce, 2001). On the one hand, urban tourism has gradually become one of the most important and worldwide forms of tourism (Ashworth & Page, 2011). It has also become one of the most important social and economic impetus for urban development (Edwards, Griffin, & Hayllar, 2008; Law, 1992; Russo & van der Borg, 2002; Selby, 2004; van der Borg, Costa, & Gotti, 1996). On the other hand, the postmodern tourism era has witnessed substantial changes in tourist behaviors as the demand for personalized experiences progressively dominates the tourism market (Hyde & Lawson, 2003; Kotiloglu, Lappas, Pelechrinis, & Repoussis, 2017; Novelli, Schmitz, & Spencer, 2006; Rodríguez, Molina, Pérez, & Caballero, 2012; Uriely, 2005; Yeh & Cheng, 2015). Therefore, personalized tour itinerary design has evolved as one of the relevant emerging fields in urban tourism research, which facilitates tourists' understanding of the social condition and culture of the city they visited within a limited time (Lee, Chang, & Wang, 2009; Liu, Xu, Liao, & Chen, 2014; Sun & Lee, 2017; Wong & McKercher, 2012).

Personalized tour itinerary design is defined as a tourist trip design problem (TTDP), which involves planning tour routes for tourists according to their preferences and requirements and maximizing their entertainment while considering numerous constraints (Vansteenwegen & Van Oudheusden, 2007). TTDP is a complicated and arduous task, which involves selecting points of interest (POIs, e.g., tourist attractions, hotels, etc.) and scheduling trips (Rodríguez et al., 2012; Souffriau, Vansteenwegen, Vanden Berghe, & Van Oudheusden, 2013; Zhu, Hu, Wang, Xu, & Cao, 2012). Given the major role of TTDP-related research aimed to enhance experiences of tourists (Wong & McKercher, 2012) and competitive advantages of tourism destinations (Kang & Gretzel, 2012; Vittersø, Vorkinn, Vistad, & Vaagland, 2000), this research domain has gained substantial interest over the past several decades (Hsu, Lin, & Ho, 2012; Lee et al., 2009; Liao & Zheng, 2018; Liu et al., 2014; Rodríguez et al., 2012; Tsai & Chung, 2012; Zheng & Liao, 2019; Zheng, Liao, & Qin, 2017). Existing studies have effectively enhanced the capability of personalized services. However, previous research placed relatively less emphasis on hotel selection, which is an important component of tourism activities. The significant effect of hotel location on tourist mobility patterns in the urban context has been extensively recognized (Lew & McKercher, 2006; McKercher, Shoval, Ng, & Birenboim, 2012; McKercher & Lau, 2008; Shoval, McKercher, Ng, & Birenboim, 2011). In turn, tourism activities affect tourists' hotel selection. In reality, itineraries for multi-day tours are infeasible or suboptimal when hotel selection is not considered. However, TTDP

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with hotel selection (TTDP-HS) is more complex than general TTDP owing to the interrelationship between hotel selection and day trip design. Recognizing the limitations of existing studies on TTDP-HS in the urban context, we investigate the variants of orienteering problem (OP) that have already been successfully utilized to handle other complex versions of TTDP (Gavalas, Konstantopoulos, Mastakas, & Pantziou, 2014; Gunawan, Lau, & Vansteenwegen, 2016).

Divsalar, Vansteenwegen, and Cattrysse (2013) initially presented the OP with hotel selection (OPHS), which is essentially an extension of OP. They analyzed the characteristics of OPHS and then proposed a skewed variable neighborhood search (VNS) method for this problem. A year later, they established a memetic algorithm (MA) to improve the performance of the algorithm (Divsalar, Vansteenwegen, Sörensen, et al., 2014). They further extended OPHS to OPHS with time window (OPHS-TW) (Divsalar, Vansteenwegen, Chitsaz, et al., 2014). Apart from the aforementioned studies, several others have tried to design effective approaches to solve OPHS (Sohrabi, Ziarati, & Keshtkaran, 2017; Toledo & Riff, 2015). To the best of our knowledge, these studies are the most comprehensive explorations on OPHS, but they demonstrate numerous shortcomings despite their pioneering explorations. First, they only highlight spatial structures (including vertex selection and sequencing) but ignore the duration of time spent at each vertex. TTDP involves spatial and temporal structures (time allocation for vertices). The former is a discrete variable, whereas the latter is a continuous variable. To date, scarce attention has focused on optimization problems involving discrete and continuous variables, except the studies of Zheng and colleagues (Liao & Zheng, 2018; Zheng et al., 2017; Zheng & Liao, 2019). However, they focused on day trip design but overlooked hotel selection. Second, tourists' personalized and diversified requirements for hotel selection require consideration. For instance, some tourists may independently decide on all or a few of the hotels in their itineraries, whereas other tourists may be flexible with regard to hotel selection. The solutions of TTDP-HS must accommodate the personalized requirements of different tourists.

This study effectively fills these gaps by concentrating on designing personalized travel itineraries for tourists in the urban context by considering hotel selection and spatial–temporal structure of day trips. This problem is complicated owing to the multiple constraints of tourists, attractions, and hotels. Inspired by the MA proposed by Divsalar, Vansteenwegen, Sörensen, et al. (2014), we solve the TTDP-HS by introducing a heuristic approach (HA). HA contains a global search level that utilizes a genetic algorithm (GA), concentrating on optimizing the sequence of intermediate hotels, and a local search level embedded with a VNS and a differential evolution algorithm (DEA), with an aim to optimize day trips between hotels (involving vertex selection, sequencing, and time allocation). The differences between our approach and existing methods lie in the following aspects: (1) Our approach applies a three-dimensional matrix embedded by double-layer and variable-length chromosomes for coding solutions. (2) It optimizes the solutions of the TTDP-HS with discrete and continuous variables by embedding GA, VNS, and DEA into the structure of MA. (3) It employs an improved mutation strategy in GA to enhance the quality of the solutions. (4) It adjusts the structure of VNS to obtain a favorable tradeoff between the quality of solutions and computational complexity.

We carry out a case study in Xiamen, China to assess the performance of the proposed approach. The results of the paired sample t-tests confirm that the proposed HA performs better than existing methods. Moreover, our approach can design more reasonable and personalized itineraries for tourists in the urban context compared with previous methods.

The rest of the paper is organized as follows. Section 2 extensively reviews the latest literature concerning TTDP and related issues. Section 3 develops a mathematical model to deal with TTDP-HS. Section 4 describes the proposed HA in detail. Section 5 presents the case study conducted in Xiamen to evaluate the performance of our proposed approach. Finally, Section 6 provides the conclusions and suggestions for future research directions.

2. Literature review

As the relevant contributions brought about by tourism to urban economy and continuous social development have been increasingly recognized (Edwards et al., 2008; Law, 1992; Pearce, 2001; Russo & van der Borg, 2002; Selby, 2004; van der Borg et al., 1996), the academia has demonstrated growing interest on tourist activities in cities (Edwards & Griffin, 2013; Lew & McKercher, 2002, 2006; McKercher et al., 2012; McKercher & Lau, 2008; Shoval et al., 2011; Shoval & Isaacson, 2007). Existing studies offer insights into tourist behavior and preferences, which in turn can improve the level of tourism destination management, including travel itinerary design, tourism product exploitation, and service facility planning (Zheng et al., 2017). In particular, personalized tour itinerary design has become one of the most important emerging fields in urban tourism research, which facilitates tourists' understanding of the social condition and culture of the city they visited within a limited time (Lee et al., 2009; Liu et al., 2014; Sun & Lee, 2017; Wong & McKercher, 2012). Considering that the demand for personalized experiences has increasingly dominated the tourism market (Hyde & Lawson, 2003; Kotiloglu et al., 2017; Novelli et al., 2006; Rodríguez et al., 2012; Uriely, 2005; Yeh & Cheng, 2015), TTDP research has attracted substantial attention over the past several decades. TTDP can be roughly divided into day and multi-day tour itinerary designs.

Day tour is considered a convenient and cost-effective exploration of a tourist destination for many tourists (Holloway, 1981; Ryan & Gu, 2007). Consequently, designing personalized day tour itineraries has attracted much attention (Vansteenwegen & Van Oudheusden, 2007). Various approaches have enhanced the archetypal problem to establish a better reflection of reality. Souffriau, Vansteenwegen, Berghe, and Oudheusden (2011) abstracted the cycle trip planning as the arc orienteering problem, and they proposed a metaheuristic method to design itineraries for recreational cyclists. Tsai and Chung (2012) designed personalized itineraries for tourists in theme parks by considering real-time information and tourist behaviors. Liu et al. (2014) aimed to design real-time personalized itineraries for self-driving tourists. Zheng et al. (2017) considered the factors of aesthetic fatigue and variable sightseeing values, and they introduced a four-step heuristic algorithm combing a GA and DEA. Liao and Zheng (2018) further explored TTDP in a time-dependent stochastic environment to obtain other realistic itineraries. Considering that tourism is typically a group activity and the heterogeneous preferences of group members, Zheng and Liao (2019) presented a HA on the basis of Pareto optimality to design day tour itineraries for heterogeneous tourist groups.

A multi-day tour itinerary planning model has also been recently explored. Apart from the issues involved in day tours, many other issues are involved in designing a multi-day tour itinerary problem, such as vertex allocation to particular days and hotel selection. Lee et al. (2009) presented an ontological recommendation multi-agent to provide tourists with personalized travel itineraries to enjoy Tainan City. To offer personalized travel itineraries for tourists, Rodríguez et al. (2012) established a tourist support system by using a mathematical model and interactive multi-criteria techniques. Souffriau et al. (2013) modeled itinerary planning problems with multiple days as multi-constraint team orienteering problem (TOP) with numerous time windows. They subsequently designed a fast and effective algorithm to handle this problem. Kotiloglu et al. (2017) proposed a framework to generate personalized multi-day tour itineraries while considering different day availabilities. Cenamor, de la Rosa, Núñez, and Borrajo (2017) and Sun and Lee (2017) provided tourists with personalized multi-day tour itineraries on the basis of user-generated content gathered from a social network.

These studies effectively enhance the capability of personalized services, but they scarcely focus on hotel selection, which is an important component of tourism activities. Hotel location has been extensively recognized to significantly affect urban tourism (Bégin, 2000;

Godinho, Phillips, & Moutinho, 2018; Li, Fang, Huang, & Goh, 2015; Urtasun & Gutierrez, 2006; Wall, Dudycha, & Hutchinson, 1985) as well as hotel performance (Ben Aissa & Goaied, 2016; Lado-Sestayo, Otero-González, Vivel-Búa, & Martorell-Cunill, 2016; Shoval, 2006; Yadegaridehkordi, Nilashi, Nasir, & Ibrahim, 2018) and tourist satisfaction (Liu, Teichert, Rossi, Li, & Hu, 2017; Yang, Mao, & Tang, 2018). Moreover, location serves as an important attribute in a tourist's hotel selection (Aksoy & Ozbuk, 2017; Rianthong, Dumrongsiri, & Kohda, 2016). In recent years, a growing number of studies have confirmed the impact of hotel location on tourist movements in urban destinations. Lew and McKercher (2006) and McKercher and Lau (2008) believed that hotel location may induce the formation of tourist movement patterns as territorial models. Shoval et al. (2011) emphasized that tourists likely spend more time in areas adjacent to a hotel. McKercher et al. (2012) stated that hotel location has significant impact on places and time allocation of first-time and repeat tourists. Tourists' planned activities in turn affect their hotel choices. In reality, itineraries that do not consider hotel selection for multi-day urban tours may be infeasible. However, the interrelationship between hotel selection and day trip design renders TTDP-HS more complex than general TTDP. Recognizing the limitations of previous studies on TTDP-HS in the urban context, we investigate the variants of OP that have already been successfully utilized to deal with other complex versions of TTDP (Gavalas et al., 2014; Gunawan et al., 2016).

OPHS is an extension of the OP (Divsalar et al., 2013). Its goal is to determine a tour of maximal score comprising connected trips with limited time budget and each trip should start and end in one of the available hotels (Divsalar et al., 2013). Divsalar and colleagues substantially explored OPHS: They employed a skewed VNS approach to handle OPHS while considering the balance between the quality of solutions and algorithm efficiency (Divsalar et al., 2013). A year later, they further explored this problem while considering time window (OPHS-TW). Subsequently, they designed a hybrid genetic algorithm with a variable neighborhood descent (VND) phase to attain an efficient solution to the problem (Divsalar, Vansteenwegen, Chitsaz, et al., 2015). To improve the performance of the algorithms, Divsalar, Vansteenwegen, Sörensen, et al. (2014) developed a memetic algorithm (MA) that contains two levels: a global search level and a local level. The former is aimed at optimizing the sequence of intermediate hotels on the basis of GA, and the latter focuses on the selection and sequencing of vertices between hotels using VND. Apart from the aforementioned studies, several others attempt to design effective approaches to solve OPHS. These approaches include a hyperheuristic approach based on a hill-climbing procedure (Toledo & Riff, 2015) and an approach based on greedy randomized adaptive search procedure (Sohrabi et al., 2017).

These studies have substantially contributed to the research on OPHS, which inspired us to explore TTDP-HS in the urban context. However, we cannot directly apply the methods proposed in the previous studies to address our problem for two reasons. (1) The studies on OPHS regard the duration of time spent at vertices with a definite value. Time allocation for vertices should also be optimized according to tourists' characteristics because each tourist may wish to spend a different amount of time at a vertex (Liao & Zheng, 2018; Zheng et al., 2017; Zheng & Liao, 2019). Simultaneous optimization of spatial and temporal structures will undoubtedly increase the difficulty as the former is a discrete variable, whereas the latter is a continuous one. (2) Tourists' personalized and diversified requirements for hotel selection warrant much consideration. Consequently, we take into account the following improvements. First, we consider hotel selection and spatial–temporal structure of day trips by embedding GA, VNS, and DEA into the structure of MA to design reasonable and personalized itineraries for tourists. Second, recognizing the complexity of TTDP-HS, we employ a series of measures to achieve a balance between the quality of solutions and computational complexity, such as improving mutation strategy in GA and adjusting the structure of VNS.

Table 1
Mathematical notations and descriptions.

Notations	Descriptions
$\boldsymbol{V}$	Set of vertices in the urban destination
$\boldsymbol{V_A}$	Set of attractions in the urban destination
$\boldsymbol{V_H}$	Set of hotels in the urban destination
D	Number of days in the tour, i.e., the number of trips
$T^k_{\max}$	Time budget in the kth trip, $k = 1, \ldots, D$
τ^k	Time that the tourist starts the kth trip
n^k_i	Number of discrete visits to the vertex v_i in the kth trip
M^k	Number of total stages in the kth trip, that is, the sum of n^k_i
Λ^k_j	Vertex visited at the jth stage in the kth trip, $j = 1, 2, \ldots, M^k$
$[to^k_i, tc^k_i]$	Time window of a_i in the kth trip
$t(\Lambda^k_j, \Lambda^k_{j+1})$	Travel time needed between Λ^k_j and Λ^k_{j+1}
ta^k_j	Arrival time at vertex Λ^k_j
ts^k_j	Actual start time visiting the vertex Λ^k_j
te^k_j	Departure time from vertex Λ^k_j
p_i	Tourist's preference value for v_i, $p_i \in [0, 1]$
t_i	Average duration of visits at v_i by previous tourists
d^k_j	Time duration spent at the vertex Λ^k_j
x^k_{ij}	If the tourist visits v_i at the jth stage in the kth trip, set $x^k_{ij} = 1$; otherwise, 0

3. Mathematical model construction

The tourist trip design problem with hotel selection (TTDP-HS) is an extension of the TTDP that provides a set of tourist attractions associated with a score and several available hotels. The goal is to maximize a tourist's utility by determining a fixed number of connected day trips. Each day trip should determine the combination of attractions, sequencing, and time allocation within the time budget ($T^k_{\max}$). Moreover, it should start and end in one of the hotels. We analyze similar problems in previous studies, bearing in mind that TTDP-HS has additional difficulties owing to the investigation of the time allocation spent in attractions and hotel selection. To avoid confusion, this study follows the terminology defined by Divsalar et al. (2013): "trip" is used for day trip itineraries, whereas the "tour" refers to the multi-day tour itineraries, including an ordered set of trips.

This section presents the mathematical model that characterizes TTDP-HS. Table 1 displays the mathematical notations and descriptions used in this study. Most urban destinations contain numerous interconnected tourist attractions and hotels. In addition, most tourists start their urban tour from a particular location and end their tour at another. Other urban tours have the same starting and ending location. The starting and ending locations of the tour have a significant impact on the design of urban tourism itineraries. Tourists' initial starting and final arrival locations, which can be transport stations (e.g., airport and railway station) or hotels, require consideration. For demonstration purposes, let $\boldsymbol{V}$ be the set of vertices, which includes four types of vertices, namely, attractions ($\boldsymbol{V_A} = \{a_1, a_2, \ldots, a_N\}$), hotels ($\boldsymbol{V_H}\{h_1, h_2 \ldots, h_M\}$), initial starting locations ($\boldsymbol{V_I}$), and final arrival locations ($\boldsymbol{V_F}$). In addition, let the kth trip be the itineraries planned for the kth day, with v^k_j denoting the jth vertex in the kth trip. Sections 3.1 and 3.2 present the objectives and constraints of the model, respectively.

3.1. Objective of the model

As described earlier, TTDP-HS aims to maximize tourists' utility during the entire tour. Given some tourists' possible repeated visits in popular attractions during their tour (Tsai & Chung, 2012), the kth trip can be divided into M^k stages as presented in Eq. (3.1). Here, n^k_i denotes the number of discrete visits to v_i during the kth trip, and N represents the number of attractions in the destination.

$$M^k = \sum_{i=1}^{N} n_i^k \tag{3.1}$$

The utility gained by a tourist at each stage depends mainly on the vertex visited at this stage (Λ_j^k). Specifically, it has a close link with the tourist's preference value (p_i) for the corresponding vertex, the amount of time spent at the vertex (Erdoğan & Laporte, 2013), and the marginal utility associated with the vertex. Tourists' preferences affect their choice of tourist attractions (Pearce, 1988) as well as their utilities obtained from different tourist attractions (Castellani, Pattitoni, & Vici, 2015; Taplin & Min, 1997). Many earlier investigations demonstrate that marginal utility is typically a decreasing function of duration time spent at the same vertex owing to aesthetic fatigue (Afsar & Labadie, 2013; Liao & Zheng, 2018; Zheng et al., 2017). In accordance with these considerations, the utility acquired at the jth stage in the kth trip can be derived on the basis of Eq. (3.2). In the equation, $MS_i^k(t)$ represents the tourist's marginal subjective sensation obtained from v_i at moment t in the kth trip. The latter is a non-negative decreasing function of time (for a detailed description of $MS_i^k(t)$, see Zheng et al. (2017)). x_{ij}^k is a 0–1 discrete variable: $x_{ij}^k = 1$ if the tourist visits v_i at the jth stage in the kth trip; otherwise, 0. ts_j^k denotes the actual start time of the visiting vertex Λ_j^k, whereas te_j^k expresses the departure time fromΛ_j^k. In most cases, ts_j^k is constantly unequal to the arrival time at Λ_j^k (ta_j^k), given that the time windows of the vertices may compel early tourists to wait. Thus, we calculate ts_j^k on the basis of Eq. (3.3), where $[to_i^k, tc_i^k]$ is the time window of v_i on the kth day.

$$u_j^k = \int_{ts_j^k}^{te_j^k} \left\{ \sum_{i=1}^{N} [MS_i^k(t) \cdot p_i^k \cdot x_{ij}^k] \right\} \mathrm{d}t \tag{3.2}$$

$$ts_j^k = \max[ta_j^k, to_i^k] \tag{3.3}$$

We assume that the utility is only associated with each tourist attraction rather than the hotels or routes between vertices. Therefore, we can calculate the utility acquired during the kth trip on the basis of Eq. (3.4). Eq. (3.5) denotes that the total utility obtained during the entire tour is equal to the sum of all the trips, where D means the number of days in the tour, that is, the number of trips.

$$u^k = \sum_{j=1}^{M^k} u_j^k \tag{3.4}$$

$$U = \sum_{k=1}^{D} u^k \tag{3.5}$$

3.2. Constraints of the model

Designing personalized tour itineraries for a tourist requires satisfying the following types of constraints: (1) permanent technical constraints, which guarantee the validity and practical significance of the designed itineraries, as illustrated in Eqs. (3.6)–(3.12), and (2) personalized constraints, representing the specific requirements and preferences of the tourist, as depicted in Eqs. (3.13)–(3.16) (Rodríguez et al., 2012). Specifically, Eq. (3.6) restricts a tourist to start the tour from the initial starting location and end the tour at the final arrival location. Eqs. (3.7)–(3.8) ensure that each trip starts from one of the available hotels from the second day to the Dth day and ends the tour in one of hotels from the first day to the D-1st day. By contrast, Eq. (3.9) restricts visiting only one tourist attraction at each stage from the second to the $M^k - 1$st stage during each day trip.

$$\sum_{v_i \in V_I} x_{i1}^1 = \sum_{v_j \in V_F} x_{jM^D}^D = 1 \tag{3.6}$$

$$\sum_{v_i \in V_H} x_{i1}^k = 1, \quad k = 2, \cdots, D \tag{3.7}$$

$$\sum_{v_j \in V_H} x_{jM^k}^k = 1, \quad k = 1, \cdots, D-1 \tag{3.8}$$

$$\sum_{v_i \in V_A} x_{ij}^k = 1, \quad j = 2,3, \cdots, M^k - 1 \tag{3.9}$$

Eqs. (3.10)–(3.12) guarantee the connectivity of time and path, where y_{ij}^k is a 0–1 discrete variable. If a visit to v_i is followed by a visit to v_j in the kth trip, then y_{ij}^k is set to 1; otherwise, 0. Tourists usually have a set of compulsory vertices (e.g., "must-visit" attractions and mandatory hotels) or "must-avoid" vertices in mind before starting their tours. If the itinerary does not include their favorite vertices or includes unwanted vertices, then it will affect their tourism experience (Liao & Zheng, 2018; Tsai & Chung, 2012; Zheng et al., 2017). Eqs. (3.13)–(3.14) ensure the inclusion of compulsory vertices in the corresponding itineraries, whereas Eq. (3.15) ensures the exclusion of "must-avoid" vertices. S_C^k denotes the set of compulsory vertices for the kth day trip, and $\tilde{S}_C$ expresses the set of compulsory vertices that the visit date is unspecified. $\boldsymbol{S_A}$ denotes the set of vertices that should be avoided.

$$te_j^k + t(\Lambda_j^k, \Lambda_{j+1}^k) = ta_{j+1}^k, (\forall\, j = 1,2,\cdots,M^k - 1) \tag{3.10}$$

$$\sum_{v_i \in V_I \cup V_H \cup V_A} y_{ij}^k = \sum_{v_l \in V_A \cup V_H \cup V_F} y_{jl}^k, \ \forall\ v_j \in V_A;\ v_i \neq v_j,\ v_j \neq v_l \tag{3.11}$$

$$\Lambda_{M^k}^k = \Lambda_1^{k+1}, \ k = 1,2, \cdots, D-1 \tag{3.12}$$

$$\sum_{k=1}^{D} \sum_{j=1}^{M^k} x_{ij}^k \geq 1, \quad if \quad v_i \in \tilde{S}_C \tag{3.13}$$

$$\sum_{j=1}^{M^k} x_{ij}^k \geq 1, \quad if \quad v_i \in S_C^k \tag{3.14}$$

$$\sum_{k=1}^{D} \sum_{j=1}^{M^k} x_{ij}^k = 0, \quad if \quad v_i \in S_A \tag{3.15}$$

Usually, tourists have an overall time budget for their tour, including the total number of days to stay at the tourist destination and the length of time planned for each day. If the time constraint is disregarded in the itinerary suggestion, then tourists will feel very rushed or may not have enough time to visit their favorite attractions, which will affect their experience (Tsai & Chung, 2012). Eq. (3.16) restricts the total visitation time in each trip to no more than the time budget $T_{\max}^k$, where $ta_{M^k}^k$is the arrival time at $\Lambda_{M^k}^k$, that is, the time arrival at the hotel or the final arrival location, and τ^k is the time that the tourist starts her/his kth trip.

$$ta_{M^k}^k \leq \tau^k + T_{\max}^k \tag{3.16}$$

4. Solution approach

TTDP-HS is essentially a variant of orienteering problem (OP), which has been proven to be an NP-hard combination optimization problem (Golden, Levy, & Vohra, 1987). Our problem necessitates optimizing the spatial–temporal structures of day trips and considering hotel selection, in which an interrelationship exists between them. Therefore, TTDP-HS can be regarded as a typical bilevel optimization problem (BOP), which is considerably more challenging than the general TTDP. As a population-based metaheuristic comprising an evolutionary framework and a set of local search algorithms (Moscato, 1989; Neri & Cotta, 2012), memetic algorithm (MA) is widely considered suitable for BOP. In particular, Divsalar, Vansteenwegen, Sörensen, et al. (2014) proposed the MA for OPHS, in which a genetic algorithm (GA) focused on optimizing the sequence of intermediate hotels, whereas a variable neighborhood descent (VND) was developed to

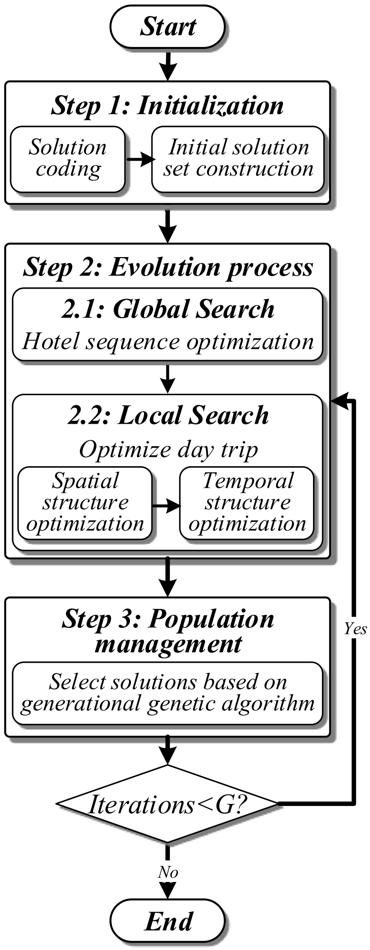

Fig. 1. Methodological framework.

design the day trips (involving the selection and sequencing of vertices) between hotels. This approach inspires our study but may be inapplicable in directly solving TTDP-HS as it fails to optimize the duration time spent at vertices. Therefore, we propose a three-step heuristic approach (HA), which involves initialization, evolution process, and population management. Fig. 1 presents the framework of the approach.

The initialization step comprises solution coding and initial solution set (***ISS***) construction. The solutions are coded using a three-dimensional matrix embedded by double-layer and variable-length chromosomes, whereas the ***ISS*** is constructed on the basis of the roulette-wheel selection rule. The evolution process adopts a genetic operator to optimize the sequence of hotels in the global search level. By contrast, we combine variable neighborhood search (VNS) and differential evolution algorithm (DEA) to optimize the spatial–temporal structures of day trips in the local search level. The population management step chooses the solutions for the next iteration on the basis of generational GA. Sections 4.1, 4.2, and 4.3 thoroughly illustrate each step.

4.1. Step 1: initialization

Most tourists decide beforehand the total number of days to visit and the location of arrival and departure in a city for a multi-day tour. That is, the starting and ending locations are fixed, which are denoted as v_I and v_F, respectively. TTDP-HS involves designing day trips and optimizing the hotel selection during the tour. Coding the solution requires creating a three-dimensional matrix, and each block denotes a day trip (as shown in Fig. 2 (a)). As for a day trip, tourists cannot foresee the number of vertices to visit. Apart from the spatial structure of day trips, the duration time spent at each selected vertex requires optimization. Accordingly, we code the day trip using a double-layer and variable-length chromosome introduced by Zheng et al. (2017) and Liao and Zheng (2018). The upper layer denotes the selection of vertices and their sequencing, and the lower layer represents the duration of time spent at corresponding vertices (see Fig. 2 (b)). We use a specific example to clarify the process of solution coding (see Fig. 2 (c)). The solution in Fig. 2 (b) indicates that the tourist stays at h_2, h_1, and h_4 during his/her four-day tour, in which the third day trip successively visits a_3, a_5, a_4, and a_2. The tourist stays at these attractions for 100, 150, 120, and 110 min, respectively.

Multi-day tour itinerary design in the urban context includes several hotels and tourist attractions. Such a composition forms several hotel and attraction combinations. First, we randomly construct a set of solutions following the above illustration. Considering the constraints enumerated in Section 3.2, we then select feasible solutions. To achieve a balance in the relationship between diversity and quality of solutions, we choose the feasible solutions to generate the ***ISS*** following the selection rule of the roulette wheel.

4.2. Step 2: evolution process

The structure of MA raised in this study has two optimization levels, namely, the global search level targeted at optimizing the sequence of intermediate hotels and the local search level aimed at optimizing the day trips between hotels (involving vertex selection, sequencing, and

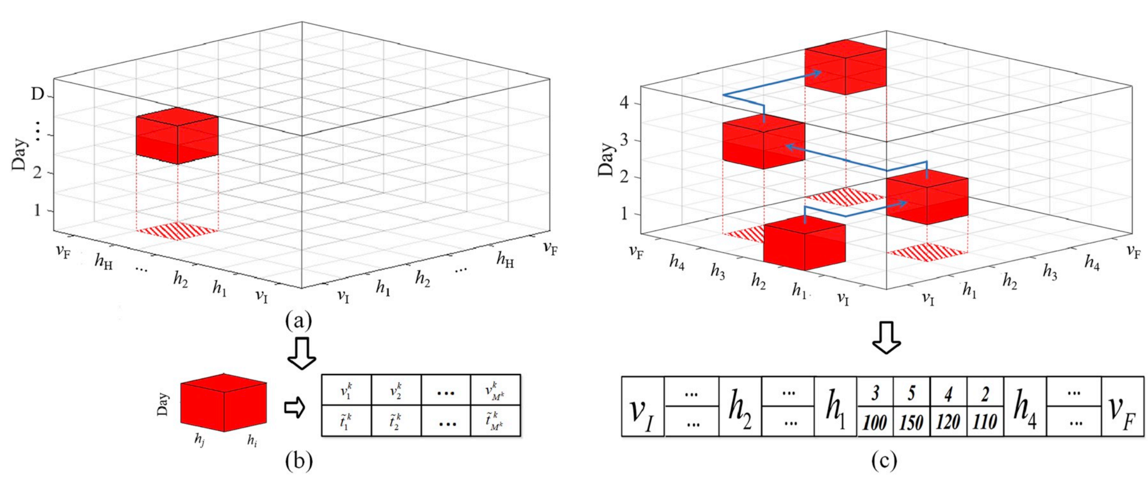

Fig. 2. Example of solution coding.

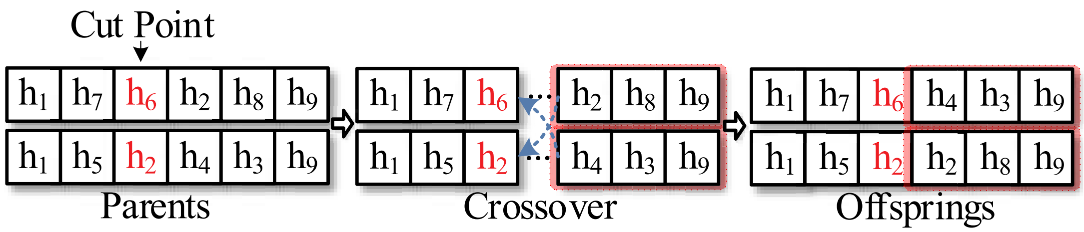

Fig. 3. Single-point crossover.

time allocation). Sections 4.2.1 and 4.2.2 describe the global and local searches, respectively.

4.2.1. Global search

Global search aims to optimize the sequence of intermediate hotels, which is a discrete decision variable. We evolve this variable using GA, which is commonly applied to address discrete optimization problems by relying on bio-inspired operators (e.g., crossover and mutation) (Midgley & Cooper, 1995; Osman, Abo-Sinna, & Mousa, 2005). Crossover is an operator substituting some of the genes from one parent with the corresponding genes of the other, and mutation encompasses another matter that changes one or more genes in a chromosome from their initial values (Potts, Giddens, & Yadav, 1994). The global search adopts a single-point crossover and a two-point mutation to evolve the sequence of intermediate hotels. For clarity, Fig. 3 presents an example to explain the crossover. This process includes three steps. (1) Two solutions are randomly selected from the ***ISS***, and their hotel sequences serve as the parents (i.e., h_1-h_7-h_6-h_2-h_8-h_9 and h_1-h_5-h_2-h_4-h_3-h_9). (2) A point is randomly selected as the cut point (shown as red font in Fig. 3). (3) The new solutions (i.e., offspring) are determined as concatenations of parts from the two parents (i.e., h_1-h_7-h_6-h_4-h_3-h_9 and h_1-h_5-h_2-h_2-h_8-h_9).

Similarly, Fig. 4 illustrates the two-point mutation. (1) A solution in the ***ISS*** is randomly selected, and its hotel sequence serves as the parent (suppose one of the offspring in Fig. 3 is selected, that is, h_1-h_7-h_6-h_4-h_3-h_9). (2) We first randomly choose a mutation point (i.e., h_7 in Fig. 4). (3) In turn, we evaluate the feasibility and results of the exchange between the other points and the mutation point. An example is evaluating five potential exchanges ($h_7 \leftrightarrow h_1$, $h_7 \leftrightarrow h_6$, $h_7 \leftrightarrow h_4$, $h_7 \leftrightarrow h_3$, and $h_7 \leftrightarrow h_9$). (4) The feasible exchanges with minimum tour time ($\sum ta^{k}_{M^k}$) are conducted (i.e., $h_7 \leftrightarrow h_3$).

4.2.2. Local search

The local search focuses on the spatial–temporal structures of day trips between hotels (involving vertex selection, sequencing, and time allocation). Mladenović and Hansen (1997) proposed VNS as a metaheuristic, which systematically executes the procedure of neighborhood change into the search for better solutions (Blum & Roli, 2003). Owing to its superior performance (e.g., simplicity, robustness, and generality) (Hansen, Mladenović, & Moreno Pérez, 2010), VNS has successful applications in OP-related studies (Divsalar et al., 2013; Divsalar, Vansteenwegen, Sörensen, et al., 2014; Labadie, Mansini, Melechovský, & Calvo, 2012; Schilde, Doerner, Hartl, & Kiechle, 2009; Tricoire, Romauch, Doerner, & Hartl, 2010). Considering that a day trip involves discrete and continuous variables, we evolve the spatial structure using VNS and optimize the time spent at selected vertices on the basis of DEA, which is particularly suitable for handling continuous optimization problems (Liao & Zheng, 2018; Plagianakos, Tasoulis, & Vrahatis, 2008; Zheng et al., 2017).

VNS systematically changes the neighborhood in two interactive phases: a variable neighborhood descent (VND) to search for a local optimum and a perturbation phase to leave the corresponding local optimum. This study designs two perturbation strategies, namely, randomly exchanging day trips (see Fig. 5(a)) and randomly deleting vertices from day trips (see Fig. 5 (b)). The structures successively contained in VND are Insert, Move-Best, Two-Opt, Swap-Best, Extract-Insert, and Extract2-Insert (Divsalar, Vansteenwegen, Sörensen, et al., 2014). In accordance with the problem raised in this study, we adjust the structure of VNS to achieve a beneficial tradeoff between the solutions' quality and algorithm's efficiency. The descent in this study includes four neighborhood structures (Inset, Move-best, Two-Opt, and Swap-best). (For a detailed illustration of the four neighborhood structures, see Divsalar, Vansteenwegen, Sörensen, et al. (2014)).

Fig. 6 illustrates the process of VNS with the pseudo-code. Given the solution to be optimized (S), two perturbation strategies (P_1 and P_2) and four neighborhood structures (N_1, N_2, N_3, and N_4), the output of this process is the optimal solution (S^*) (lines 1–2 in Fig. 6). Initially, S^* equals S, and the parameter i equals 1 (lines 3–4 in Fig. 6). The entire process of VNS is shown in the lines 5–23 of the figure. First, we conduct perturbation strategy P_i to generate a perturbation solution $S(i)$

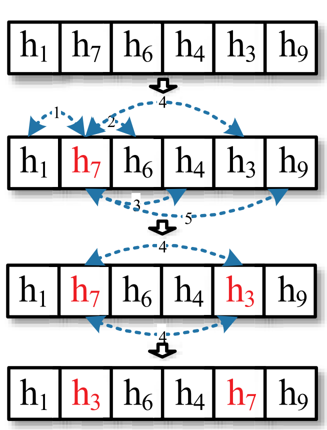

Fig. 4. Two-point mutation.

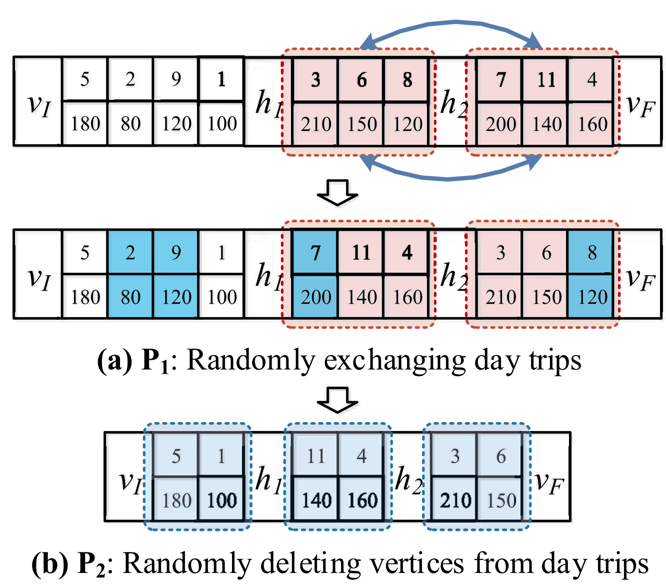

Fig. 5. Examples of two perturbation strategies.

The variable neighborhood search

```
1.  Input: S; P_1, P_2; N_1, N_2, N_3, N_4;
2.  Output: S*;
3.  Set S*=S;
4.  Set i=1;
5.  while {i≤2}
6.      P_i(S*) to generate S(i)
7.      Let j=1;
8.      while {j≤4}
9.          N_j(S(i)) to generate S_j(i);
10.         if {f(S_j(i))>f(S(i))} then
11.             Set S(i) = S_j(i);
12.             Set j=1;
13.         else
14.             Set j=j+1;
15.         end if;
16.     end while;
17.     if {f(S(i))>f(S*)} then
18.         Set S*=S(i);
19.         Set i=1;
20.     else
21.         Set i=i+1;
22.     end if;
23. end while;
24. Return S*.
```

Fig. 6. Process of VNS.

(line 6 in Fig. 6). Then, we repeat the four neighborhood structures until the local optimal solution (*Si*) is obtained (lines 7–16 in Fig. 6). If *S(i)* is superior to the incumbent optimal solution (S^*), then replace ***S(i)*** with S^* and return to the first perturbation strategy; otherwise, the next perturbation strategy (lines 17–22 in Fig. 6) is conducted. The process stops when all perturbation strategies are finished.

Upon completing the optimization of the day trips' spatial structure, another task of local search is carried out to evolve the time spent at the corresponding vertices, which represent a continuous decision variable. This task introduces a DEA to optimize the evolution results of the VNS. The process relies on operations, such as mutation, crossover, and selection. For a detailed introduction of the DEA, see Zheng et al. (2017).

4.3. Step 3: population management

New solutions are generated in each iteration. The set of new solutions generated at the gth iteration is denoted as ***NP(g)*** and those generated in the previous iteration as $\boldsymbol{P(g-1)}$. The population management step presents a generational genetic algorithm using a simple and flexible procedure to achieve a balance in the relationship between solutions' diversity and quality (Sörensen & Sevaux, 2006). First, a candidate solution set (***CSS***) is constructed by combing ***NP(g)*** with $\boldsymbol{P(g-1)}$. Second, the solutions in ***CSS*** are sorted in terms of their quality. Third, $Q \times \delta$ solutions with the best quality are chosen for the next iteration. Here, Q and δ are the parameters of the algorithm denoting the population size and selected proportion, respectively. To fill the remaining solutions in ***P(g)***, the same operations are performed, but only the solutions with a hotel sequence different from the earlier selected solutions are chosen. If the number of solutions with different hotels sequences remains less than Q, then random selection is carried out in the remaining solutions in ***CSS*** until the number of solutions in ***P(g)*** equals Q.

5. Performance evaluation and discussion

5.1. Case study area

This study aims to design personalized multi-day urban tour

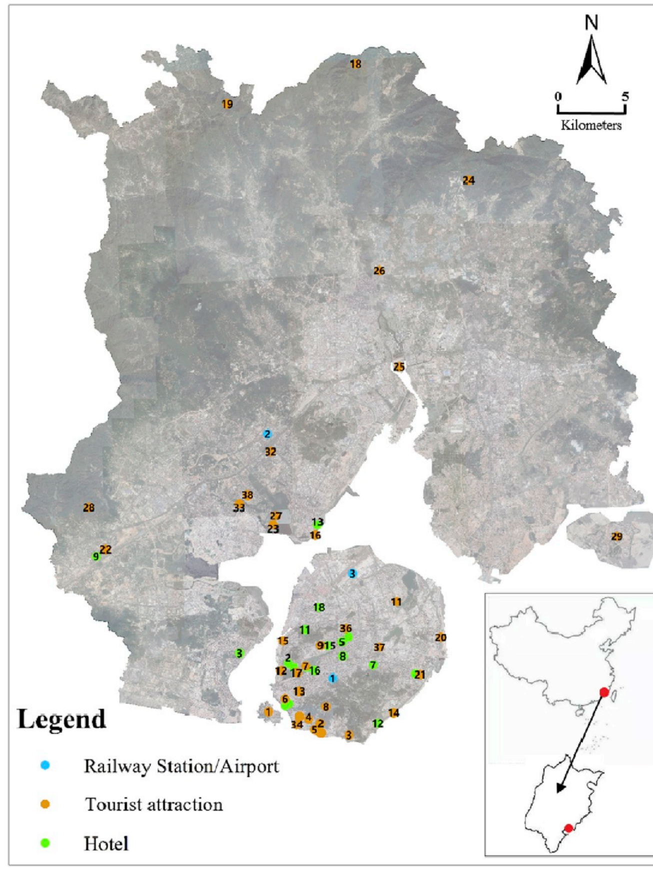

Fig. 7. Xiamen City map.

itineraries with hotel selection for tourists. Accordingly, the process of deciding on the location of the case study must consider tourism popularity, tourist attractions, and hotel distribution of the urban destination. Xiamen, a coastal city in Southeast China, is our choice owing to its reputation and status as a well-developed, mature urban destination in China (Chen & Xiao, 2013; Xiao, 1997). Over 89 million tourists visited Xiamen in 2018, increasing by 13.7% in 2017. Among them, 39.7 million tourists who visit Xiamen opt to take a multi-day tour. Xiamen has numerous attractions and hotels, thus rendering the self-initiated design of suitable travel itineraries complicated for tourists. Therefore, TTDP-HS is significant in enhancing tourists' experience and promoting the tourism competitiveness of Xiamen. Fig. 7 shows a map of Xiamen City and the distribution of 18 five-star hotels (represented as green nodes) and 38 main tourist attractions (represented as yellow nodes) in the destination. Moreover, two railway stations and an airport are operating in Xiamen, namely, the Xiamen Railway Station (v_{RS}), Xiamen North Railway Station (v_{NRS}), and Xiamen Airport (v_{XMN}). Fig. 7 presents the distribution of the three vertices as blue nodes.

Multiple factors related to the tourists, attractions, and hotels require consideration when designing suitable travel itineraries for tourists. Especially, tourists' preferences for particular attractions and hotel locations all have a significant impact on tourists' itinerary choices. Therefore, we gathered several kinds of information concerning the tourist attractions and hotels in Xiamen.

(1) Basic information on tourist attractions and hotels

Xiamen has numerous tourist attractions. However, this study only focuses on 38 attractions, from the recommendation ranking of a major online travel agent (OTA, e.g., Ctrip and Alitrip). Uneven distributions in different districts are observed in these attractions: the attractions in the Xiamen Island (including Siming and Huli Districts) are obviously

Table 2
Basic information of attractions in Xiamen.

No.	Name	District	Time-Window	t_i (min)
a_1	Gulangyu	Siming	[00:00–24:00]	480
a_2	Xiamen University	Siming	[00:00–24:00]	240
a_3	Zeng Cuo An	Siming	[00:00–24:00]	120
a_4	Nanputuo Temple	Siming	[03:00–18:30]	120
a_5	Island Ring Boulevard	Siming	[00:00–24:00]	120
a_6	Zhongshan Street	Siming	[00:00–24:00]	240
…	…	…	…	…
a_{37}	Hui He Stone Cultural Park	Huli	[08:30–17:30]	120
a_{38}	Xiamen Municipal Library	Jimei	[08:00–21:00]	60

denser than those outside the island (including Haicang, Jimei, Tongan, and Xiangan Districts). Fig. 7 depicts the locations of these attractions. The first four columns of Table 2 record the attractions' serial numbers, names, districts in which they are located and the time windows. The average time the former tourists (t_i) spent at each attraction influences the construction of the initial solution during the initialization step. We gathered data on t_i on the basis of the travelogues shared by former tourists in OTA. Then, we recorded the values in the fifth column of Table 2.

A substantial amount of research has confirmed that the hotel location exerts considerable influence on tourist mobility patterns in the urban context (Lew & McKercher, 2006; McKercher et al., 2012; McKercher & Lau, 2008; Shoval et al., 2011), and the hotel selection is integral to TTDP-HS. The Xiamen Statistical Bulletin reports 2262 hotels in Xiamen, including 64 star hotels (18 of which are five-star hotels). Generally, most tourists likely pick hotels of the same grade. Therefore, given our access to hotel information, this study only focuses on the five-star hotels. The locations of the 18 five-star hotels are shown in Fig. 7, and Table 3 present their information. Correspondingly, when choosing respondents, we only focus on those who opt for five-star hotels, which will be introduced in next subsection.

To maintain the representativeness of the samples, we collected tourist information at multiple places and on multiple dates. Specifically, we collected tourist information at Xiamen Station, Xiamen North Station, and Xiamen Airport on April 11, 14, and 17, respectively. The researchers did not choose the respondents subjectively. They were instructed to stand at the exits of the airport (or railway stations) with questionnaires ready and to invite the first passenger they met to participate in the survey. A simple oral interview was conducted to determine the purpose of passengers' visit to Xiamen. Only those passengers who plan to travel in Xiamen would be invited as respondents to participate in the further interviews of this survey. The respondents were shown an introduction with pictures of the 38 attractions and information pertinent to each attraction. Subsequently, the respondents recorded their initial starting locations, final arrival locations, "must-visit" and "must-avoid" attractions, and their preference values for each attraction in the interval from 0 to 1 (1 represents the highest interest for the attraction; 0, no interest). The respondents also recorded their overall tour duration, daily time budget, and requirements for hotels (e.g., hotel grade and mandatory hotels). We only used the samples for those tourists who chose five-star hotels and the multi-day tour option. Finally, according to the sampling date and place of the remaining samples, we randomly selected 100 of them as our test samples. Among the test samples, 48 were male and 52 were female; 43 were collected at Xiamen Airport (v_{XMN}), 28 at Xiamen Railway Station (v_{RS}), and 29 at Xiamen North Railway Station (v_{NRS}); 36 were obtained during the first survey, 31 during the second, and remaining 33 during the final survey. Twelve tourists took the eight-day tour, twenty tourists took the seven-day tour, seven tourists took the six-day tour, twenty-one tourists took the five-day tour, and forty tourists took the four-day tour or less. Table 4 displays the aforementioned information gathered from the 100 tourists.

Table 3
Basic information of five-star hotels in Xiamen.
(2) Tourist information

No.	Name	District
h_1	Hotel Pullman Xiamen Powerlong	Siming
h_2	Pan Pacific Hotel Xiamen	Siming
h_3	Xiamen Gulang Bay Hotel	Haicang
h_4	Millennium Harbourview Hotel Xiamen	Siming
h_5	Central Hotel Jingmin	Siming
h_6	Marco Polo Xiamen	Siming
h_7	Peony International Hotel	Siming
h_8	Hilton Xiamen	Siming
h_9	Xiamen Riyuegu Hotsprings Resort	Haicang
h_{10}	Swiss Grand Xiamen	Siming
h_{11}	Le Meridien Xiamen	Huli
h_{12}	Seaview Resort Xiamen	Siming
h_{13}	Wanda Realm Xiamen North Bay	Jimei
h_{14}	Hotel Nikko Xiamen	Siming
h_{15}	The Westin Xiamen	Siming
h_{16}	Kempinski Hotel Xiamen	Siming
h_{17}	Sheraton Xiamen Hotel	Siming
h_{18}	Xiamen C&D Hotel	Huli

5.2. Algorithm parameters

Several parameters significantly affect the performance of our proposed approach. These parameters include population size (Q), iteration time (G), crossover rate (Pc), mutation rate (Pm), differential rate (F), and selected proportion (δ). Population size (Q) represents the number of candidate solutions, which can affect the ultimate performance and efficiency of the approach. The likelihood of falling into a local optimum rises with the extremely small Q, whereas extremely large Q may cause computational inefficiency. The iteration time (G) determines the number of iterations of the algorithm. A suitable number of iteration times is needed to ensure that the solution in the population has converged to a steady state distribution within an epsilon measure (Pendharkar & Koehler, 2007). The value of G usually depends on the convergent situation. With too few iteration times, we cannot ensure that the solution is fully searched, but too many iteration times result in unnecessary computational costs. The crossover and mutation are two bio-inspired operators for genetic algorithm (GA) to deal with optimization and search problems (Midgley & Cooper, 1995; Osman et al., 2005). The crossover rate (Pc) and the mutation rate (Pm) control the frequency of crossover operator and mutation operator, respectively. The differential rate (F) is a positive control parameter for scaling the difference vector in differential evolution algorithm (DEA) (Qin, Ling Huang, & Suganthan, 2009). A larger F increases the probability of escaping from a local optimum, but if F is too large, it may lead to computational inefficiency (Mallipeddi, Suganthan, Pan, & Tasgetiren, 2011). The selected proportion (δ) is an important parameter used to balance the quality and diversity of population solutions in population management of memetic algorithm (MA). Previous studies on MA indicate that setting Q within the range from 10 to 30 and δ between 0.1 and 0.3 (Sörensen & Sevaux, 2006) is appropriate to achieve a balance between performance and efficiency. Following the preceding analysis and actual situation in Xiamen, we set the parameters of our approach to the values listed in Table 5.

5.3. Performance evaluation

This subsection evaluates our approach by comparing our method with those extensively used in TTDP-related problems, such as standard genetic algorithm (sGA), particle swarm optimization (PSO), and ant colony optimization (ACO) (Gunawan et al., 2016). The MA proposed by Divsalar, Vansteenwegen, Sörensen, et al. (2014) is also used as a baseline. We designed the itineraries for the 100 tourists in accordance with their personal characteristics, constraints, and requirements (see

Table 4
Basic information of the tourists.

Tourist	Gender	Preference Value List	Time Budget	Must-visitAttractions	Mandatory Hotels	Arrival/Departure Location
1	F	[1.0, 1.0, …, .21, .26]	4 days, [12, 12 12, 7]	1	None	v_{RS}, v_{RS}
2	M	[.75, .53, …, .28, .26]	7 days, [4, 10, 10, 10, 10, 10, 4]	None	One day stay in h_9	v_{RS}, v_{XMN}
…	…	…	…	…	…	…
100	F	[.98, .91, …, .43, .89]	5 days [8, 8, 8, 8, 5]	1	None	v_{RS}, v_{NRS}

Table 5
Parameters of the algorithm.

Parameters	*Q*	*G*	*Pc*	*Pm*	*F*	*δ*
Values	30	100	0.3	0.4	0.2	0.1

Table 4); the basic information on the attractions and hotels in Xiamen (see Tables 2 and 3); and the parameters of the algorithm (see Table 5) using our approach and the four baseline methods. To reduce random errors, each method designs the itineraries for each tourist 30 times and averages the utilities of the 30 iterations. Fig. 8 displays the average utility for each tourist acquired by the five methods.

We conducted paired sample t-tests to further explore whether any statistical difference exists between the utilities obtained by HA and those by the baseline methods. Table 6 details the means and standard deviations of the utilities acquired by the five methods, and Table 7 displays the results of paired sample t-tests. For the first pair (HA–MA), the gap mean was 0.548, and the test results showed that HA acquired remarkably greater utilities ($M = 8.325$, $SD = 4.273$) than those obtained using MA ($M = 7.777$, $SD = 4.136$) (t (100) = 16.133, $p < 0.05$). Similarly, pairs 2 (HA–sGA), 3 (HA–PSO), and 4 (HA–ACO) indicated that our proposed approach performed distinctly better than with sGA, PSO, and ACO.

5.4. Discussion

The results of the paired sample t-tests confirm that our approach can obviously attain better utilities than the existing methods. Moreover, HA can design more reasonable and personalized itineraries for urban tourists than the other methods as the former deals with TTDP while considering hotel selection and time allocation of day trips.

Table 6
Paired sample statistics.

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	HA	8.325	100	4.273	0.427
	MA	7.777	100	4.136	0.414
Pair 2	HA	8.325	100	4.273	0.427
	sGA	7.318	100	3.702	0.370
Pair 3	HA	8.325	100	4.273	0.427
	PSO	7.282	100	3.640	0.364
Pair 4	HA	8.325	100	4.273	0.427
	ACO	7.448	100	4.037	0.404

5.4.1. More reasonable tour itineraries

In general, majority of tourists likely spend most of their time on sightseeing than on road traffic. Our proposed approach completely considers the travel times among the vertices and the location of selected hotels. Therefore, more reasonable tour itineraries can be designed for tourists to reduce unnecessary traffic time consumption.

To examine this issue, we created a comparative test to distinguish our approach with the MA introduced by Divsalar, Vansteenwegen, Sörensen, et al. (2014). A chosen example is Tourist 1 from Table 4, who planned to visit Xiamen for four days with daily budget of 12, 12, 12, and 7 h per day. Fig. 9 illustrates the itineraries designed for this tourist using the selected MA and HA (the left part demonstrates our proposed HA, and the right part presents the MA). Both graphs use different colors to represent the itineraries of different day trips: green for the first day, purple for the second day, blue for the third day, and red for the last day. As shown in the figures, the itineraries designed by HA can effectively reduce detours, rendering the total travel time of the itineraries designed by HA (361 min) obviously less than that of MA (402 min). Fig. 10 presents the time allocation of each day trip designed by HA and MA.

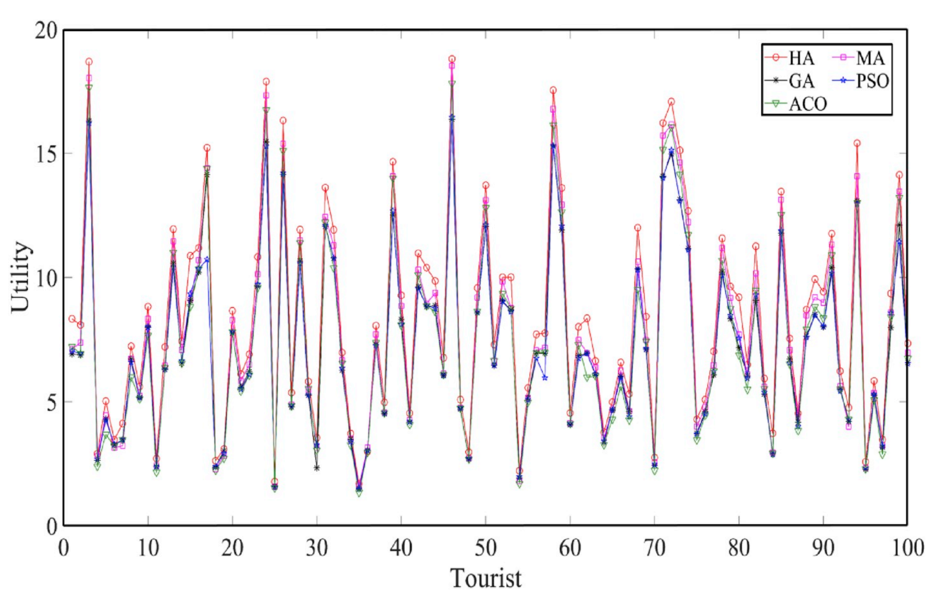

Fig. 8. Average utility for each tourist (HA, MA, sGA, PSO, and ACO).

Table 7
Paired sample *t*-test.

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	HA - MA	.548	.339	.034	.482	.615	16.133	99	.000***
Pair 2	HA - sGA	1.002	.631	.063	.882	1.132	15.967	99	.000***
Pair 3	HA - PSO	1.042	.733	.073	.897	1.188	14.230	99	.000***
Pair4	HA - ACO	.877	.465	.0.47	.784	.969	18.844	99	.000***

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

5.4.2. *More personalized tour itineraries*

Designing personalized travel itineraries necessitates a complete consideration of the requirements and preferences of tourists. In the urban context, tourists' requirements and personal preferences for a hotel also serve as critical factors for the multi-day tour itinerary design. These factors significantly affect the itinerary design. For example, some tourists may request a specific hotel on a particular day, whereas others may prefer not to change the hotels throughout their itineraries. Our proposed approach can effectively consider tourists' personalized requirements. To demonstrate the problem intuitively, tourist 1 in Table 4 was chosen as an example again owing to the flexibility of her hotel selection. For comparison, we set up the following scenarios: (1) The tourist requests to stay at h_9 (Xiamen Riyuegu Hotsprings Resort) at least for one night during her four-day tour. (2) The tourist requests not to change the hotels throughout her tour. Fig. 11 details the itineraries designed for the two scenarios (left part for the first scenario and right part for the second scenario). Fig. 12 presents the itineraries of the two scenarios and the baseline scenario shown in Fig. 9 (left). As shown in Fig. 11, compared with the baseline scenario, the additional hotel selection requirements have a significant effect on the tour itineraries. For the first scenario, when tourists specify their requirement to stay in h_9 on a certain day, the trip on that day should not deviate significantly from h_9 to ensure the full utilization of time budget for that day. For the second scenario, each day trip taken by the tourist contains territorial and linear path characteristics, which are largely consistent with the findings of previous studies (McKercher & Lau, 2008; Shoval et al., 2011). The added requirements for hotel selection significantly increase the time spent on transportation: 380 min and 443 min for the two scenarios, compared with the baseline (361 min). Assuming that the utility is only associated with tourist attractions rather than the hotels,

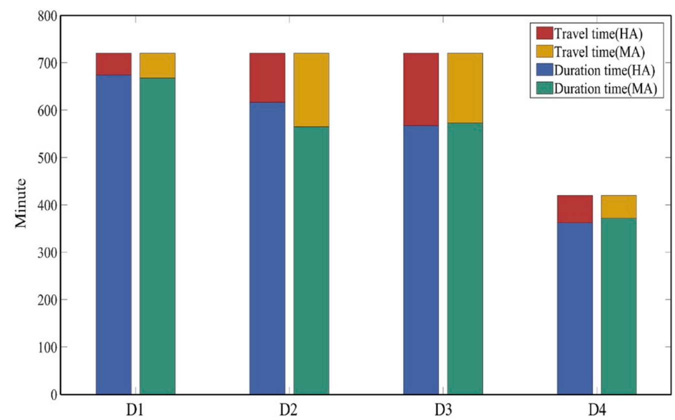

Fig. 10. Time allocation of each day (MA vs. HA).

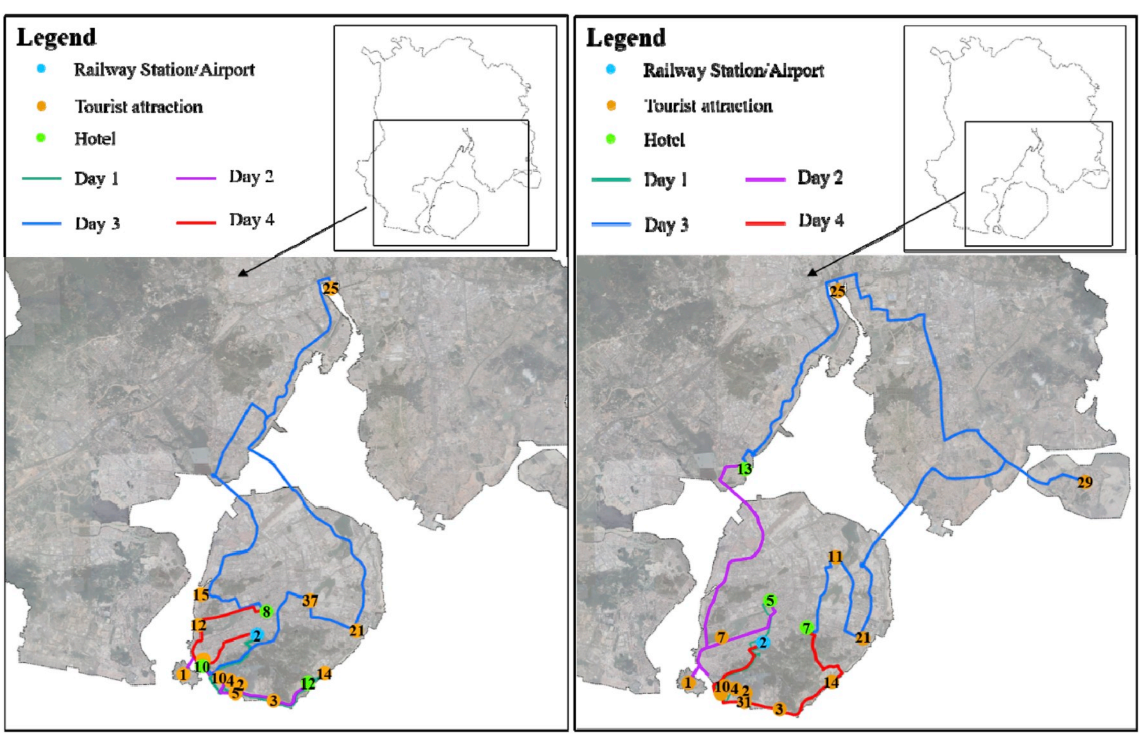

Fig. 9. Itineraries designed by MA and HA.

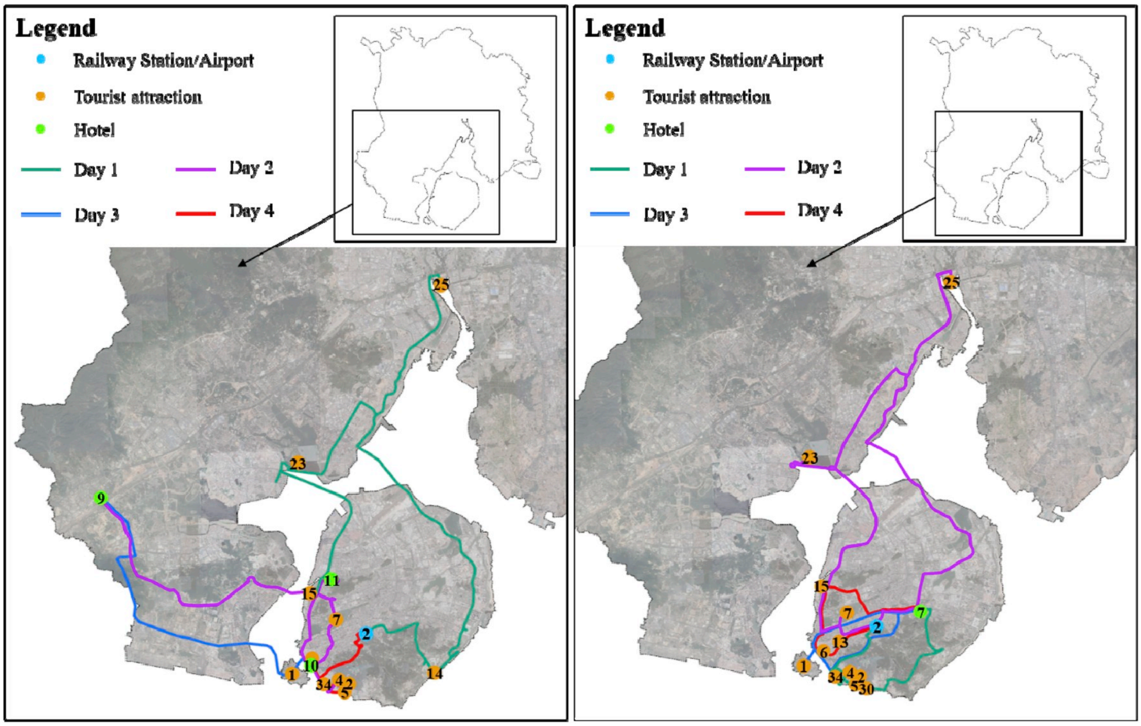

Fig. 11. Itineraries designed for different hotel selection requirements.

the additional requirements for hotel selection lead to lower utilities achieved by the tourist: 7.826 and 7.466 for the two scenarios, compared with the baseline (8.278).

6. Conclusions and future research directions

Urban tourism has evolved into a critical worldwide tourism phenomenon (Ashworth & Page, 2011). It is also one of the most important social and economic impetus for urban development (Edwards et al., 2008; Law, 1992; Russo & van der Borg, 2002; Selby, 2004; van der Borg et al., 1996). In addition, the demand for personalized experiences dominates the current tourism market (Hyde & Lawson, 2003; Kotiloglu et al., 2017; Novelli et al., 2006; Rodríguez et al., 2012; Uriely, 2005; Yeh & Cheng, 2015). On this note, personalized tour itinerary design greatly contributes in improving tourists' experiences and enhancing the advantages of urban tourism competitiveness (Lee et al., 2009; Liu et al., 2014; Sun & Lee, 2017; Wong & McKercher, 2012).

An extensive literature review of previous studies on TTDP reveals that most studies overlook hotel selection when designing personalized itineraries. However, the impact of hotel location on tourist mobility patterns in the urban context has been extensively recognized (Lew & McKercher, 2006; McKercher et al., 2012; McKercher & Lau, 2008; Shoval et al., 2011). Therefore, our proposed approach considers hotel selection and spatial–temporal structure of day trips and offers more reasonable and personalized itineraries for tourists than other methods. The profound complexity of this problem is due to the interrelationship between hotel selection and day trip design. To overcome the difficulties involved, we introduce a HA to solve TTDP-HS. The HA contains two levels, namely, the global search level focusing on optimizing the sequence of intermediate hotels and the local search aiming at optimizing the day trips between hotels.

To evaluate the performance of our approach, we conducted a case study in Xiamen, China. The results of the paired sample t-tests validated the distinct superiority of our proposed approach over other existing methods. Further discussions on the factors involved explained why our approach can design more reasonable and personalized itineraries for tourists than other existing methods. Our study significantly contributes to expanding the current research on TTDP. Furthermore, it possesses extensive applicability and practical significance in tourism management. First, our study puts forward an effective approach to

V_{RS}	4	2	3	14	h_{12}	5	10	1	h_{10}	37	21	25	15	h_8	12	6	V_{RS}
	156	272	124	122		105	84	427		143	58	298	68		119	243	

(1) Baseline situation

V_{RS}	14	25	23	15	h_{11}	2	6	7	h_9	1	h_{10}	34	5	4	V_{RS}
	128	313	53	60		278	274	57		596		138	121	119	

(2) First situation

V_{RS}	34	4	2	5	30	h_7	13	7	23	25	h_7	1	h_7	15	6	V_{RS}
	114	118	248	121	66		122	55	60	331		610		77	278	

(3) Second situation

Fig. 12. Itineraries designed for the three scenarios.

design personalized tour itineraries for tourists in the urban context. This approach codes solutions through a three-dimensional matrix embedded with double-layer and variable-length chromosomes. It optimizes the solutions involving discrete and continuous variables by embedding GA, VNS, and DEA into the structure of MA. It employs an improved mutation strategy in GA to improve the solutions' quality. Finally, it adjusts the structure of VNS to reach a balance in the relationship between the solutions' quality and efficiency. Second, our approach may draw widespread interest in the tourism sector, given that the demands for personalized experiences control the current tourism market (Novelli et al., 2006). Tourists can utilize our approach as a supporting mechanism when planning their travel itineraries. This ideal scenario foreshadows enhanced travel experiences. Tourism enterprises (e.g., travel agencies) can also exploit this approach by offering tourists with customized urban tourism products. Moreover, our approach can potentially facilitate the promotion of the service level of urban destinations, gaining advantage in an increasingly competitive marketplace.

Several potential directions are worthy of further exploration. First, enhancing the feasibility of the designed itineraries challenges future research to consider other characteristics of a hotel, given that hotel location is not the only factor affecting tourists' hotel choice. Hotel price and accessibility to attractions, airports, universities, and public transportation also require consideration. In addition, the number of hotels can significantly affect the efficiency of the approach (Divsalar et al., 2013; Divsalar, Vansteenwegen, Sörensen, et al., 2014), so designing more efficient approaches for TTDP-HS is worthwhile. Second, cities generally have multimodal transportation networks (Abbaspour & Samadzadegan, 2011). Therefore, incorporating the selection of transportation modes into TTDP in the urban context may be an interesting research opportunity of high practical value. Third, many previous studies realize the differences in tourist behavior between domestic and foreign tourists (Crotts & Pizam, 2003; Li, 2014; Xu, Morgan, & Song, 2009; Xu & Zhang, 2016), so designing personalized tourism itineraries for urban inbound tourists based on their personal characteristics is a potential direction. Finally, diverse types of tourist attractions in cities may exist. Some can be abstracted as vertices, whereas others can be regarded as arcs (e.g., greenway, coastline, river, and street). Future attempts should explore the combination of the OP and arc routing problem with profits when designing itineraries for urban tourists.

Author contribution

Dr. Weimin Zheng is the person in charge of the project, who is responsible for the overall design of the project and the writing of the paper.

Mr. Haipeng Ji is responsible for the design of the heuristic approach.

Mr. Congren Lin is involved in the design of the heuristic approach.

Ms. Wenhui Wang is involved in case study section.

Ms. Bilian Yu is involved in case study section.

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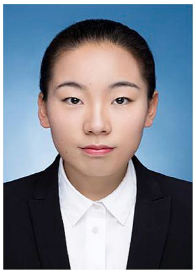

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