Time apart while together: A smart trip design for group travelers

Zhixue Liao

School of Business Administration, Southwestern University of Finance and Economics, 555, Liutai Avenue, 611130, Chengdu, China. Email: liaozhixue@swufe.edu.cn

Weimin Zheng

School of Management, Xiamen University, 422 South Siming Road, 361005 Xiamen, China. Email: zhengweimin@xmu.edu.cn

Zhibin Lin

Durham University Business School, Mill Hill Lane, Durham, DH1 3LB, United Kingdom. Email: zhibin.lin@durham.ac.uk

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Abstract:
Family or friends traveling in a group often have different preferences and some of which may conflict with each other. Existing smart tourism recommender systems have not adequately addressed this important issue. This study attempts to tackle the problem by incorporating a "joining and forking" strategy into the system design, which allows members to have certain "time apart" to enjoy their treat separately and "time together" to co-create shared experience and memory. A comparison test was conducted based on a total of 50 groups of tourists in an island destination of Kulangsu in China. The results indicate that our new design outperforms five state-of-the-art baseline methods and realize a good balance between individual experience and co-experiences with group members.

Keywords: Smart tourism; Tourist group; Trip design; Recommender system; Multi-objective optimization.

1 Introduction

Tourists often travel in groups to spend time with family, friends, or significant others to co-create shared experiences and memories (Su, Cheng, & Huang, 2021), and to strengthen family or social ties (Hsu & Huang, 2008; Pearce, 2005). Shared experience in group tourism can be a source of happiness, but it can also be a cause of tension (Melvin, Winklhofer, & McCabe, 2020). On the one hand, members enjoy their quality time together, which is conducive to enhancing friendship or family bonds (McCabe, 2009; Mikkelsen & Stilling Blichfeldt, 2015). On the other hand, tension could arise when conflicts of preferences are difficult to compromise. For example, in a "grand travel" group that includes seniors and children (Gram et al., 2019), the children may insist on visiting a roller coaster, while the elderly dislike it. Thus, accommodating the differences is essential for everyone to have an enjoyable and memorable holiday together.

Technology advances in recent years have driven the development of smart destinations and tourism service applications to enhance tourist experiences (Jeong & Shin, 2020; Pan et al., 2011). Tourism organizations have increasingly utilized smart tour design or recommender systems to help tourists make optimal trip decisions (Zheng, Huang, & Lin, 2021a). Artificial intelligent agents, such as Google Trips, are regarded as one of the popular smart tourism applications (Shi, Gong, & Gursoy, 2021). A recent study reported that an artificial intelligence agent can help travelers save approximately 90% of their time searching for information (Shi et al., 2021). The complex task of trip planning can now be automated through smart recommender systems (Ji et al., 2021; Kotiloglu et al., 2017; Zheng, Liao, & Lin, 2020b). Nevertheless, Most recommender systems mainly target individuals or groups without considering the diversity of preferences within a travel group (Mohammad Arif, Du, & Lee, 2015).

Conflicting preferences among group members can reduce the effectiveness of a group recommender system significantly (Delic, Masthoff, & Werthner, 2020). According to the information and decision-making perspective of group diversity (Phillips et al., 2004), although the diversity of information in a group increases the pool of knowledge and helps to generate better decisions, the diversity of preferences may induce conflict and damage the well-being and social bond among group members (Triana et al., 2021). To solve this problem, prior researchers often rely on methods of aggregation to develop a group preference model (Garcia, Sebastia, & Onaindia, 2011). The critical problem of these methods is that niche individual preferences are often ignored (Kinoshita & Yokokishizawa, 2008). Zheng and Liao (2019) attempt to address the issue based on the assumption that the differences in tourist preferences can be reconciled. However, some preferences and requirements of group members are often irreconcilable in reality, e.g., a member's favorite points of interest may happen to be another member's unwanted points. For such a group, the existing systems are unable to generate any tour recommendation that will match everyone's preferences and it has been a persistent challenge for group recommender system researchers (Delic et al., 2020).

This study thus aims to take the challenge by developing an innovative approach to group trip design that incorporates an improved "joining and forking" strategy (Nagata et al., 2006) considering multiple constraints related to tourist attractions and group members. The objectives are to maximize the benefits of traveling in a group and minimize the potential conflicts derived from the diversity of preferences among group members. To do so, we allow part of the recommended routes to be different for each group member and take into account the differences between the starting/ending time and the locations of each member while optimizing the route's spatial-temporal structures. Technically, we adopt a two-phase heuristic approach to solving the tourist trip design problem (Zheng & Liao, 2019). In the preprocessing phase, we code the situations and construct the initial solution. In the hybrid evolution phase, we use an adaptive learning mechanism to improve the system's performance. Our design outperforms five state-of-the-art baseline methods, based on data collected from 50 groups of tourists in an island destination of Kulangsu in China.

2 Literature review

2.1 *Smart service applications and smart tourism destination*

A smart tourist destination is defined as a destination that provides services to the tourists in real-time through the application of artificial intelligence, the internet of things, and other smart technologies (Gretzel et al., 2015; Xiang, Tussyadiah, & Buhalis, 2015). The tourism industries have greatly benefited from the advances in smart technologies (Pappas et al., 2021), which help to stage, create and co-create touristic experiences (Xiang, Stienmetz, & Fesenmaier, 2021). Indeed, the development of a smart tourism destination is expected to considerably improve tourists' experiences, enjoyment and satisfaction by offering tailored services to match their needs and preferences (Bogicevic et al., 2017; Pappas et al., 2021; Williams, Rodriguez, & Makkonen, 2020).

Smart service applications, such as a recommender system provide an interface between tourists and the technological infrastructure that integrate with the destination's physical infrastructure to create or co-create tourist experiences (Huang et al., 2017). A recommender system is essentially a decision support system (Weng et al., 2021). It helps visitors plan tourism activities and trips more efficiently. The system thus saves tourists the time of information search, while enabling them to explore and enjoy the destination in greater depth, leading to better destination image and ultimately destination competitiveness. However, the intensity of competition for destinations to attract visitors is rising among destinations, and improving the design of smart systems is imperative (Hamid et al., 2021).

2.2 *Smart service design*

Tourism as an industry is experience-centric and service-intensive (Avlonitis & Hsuan, 2017; Zomerdijk & Voss, 2010), and service design is a key research priority for the industry (Storey & Larbig, 2018). The interaction between the tourists the technological systems co-creates the experiences that can be dynamically and optimally tailored to the tourist needs and preferences, based on the real-time context (Larivière et al., 2017). Moreover, understanding tourists and their context and service interfaces are the keys to developing a superior service system (Yu & Sangiorgi, 2018). The front end of service design is often “fuzzy” (Clatworthy, 2011), which requires interdisciplinary knowledge and collaboration in the design of a smart service system, yet service designers and technology developers often work in a silo. In this study, we embrace the key process of a service design framework, including design, analysis, development, and testing before launch (Yu & Sangiorgi, 2018). We shift from the conventional product-oriented approach by proactively considering the diversity of preferences among a tourist group and the social well-being of each individual member (Chen et al., 2021).

2.3 *Traveling with family and friends*

Tourist groups, particularly families, are an important target market for the tourism industry (Melvin et al., 2020). The social aspect of tourism experiences is an essential part of an enjoyable and memorable holiday, which is a holistic experience that combines individual and social elements (Chen et al., 2021; Helkkula, Kelleher, & Pihlström, 2012). The social value of tourist experience is co-created when tourists interact with others, such as friends, family, and other travel companions (Rihova et al., 2018). Melvin et al. (2020) further revealed various practices of family holidays, such as information sharing and interactions, which contribute to family bonding, memories, entertainment, and learning. A holiday can be seen as a time for a family to reconnect with each other, given that working parents are busy outside holiday times and do not have much time to spend with their children (Mikkelsen & Stilling Blichfeldt, 2015).

In addition to traveling as a family for holidays, group travel and tourism may be driven by visiting friends and relatives, thus involving multiple families traveling together, not just a single family (Hajibaba & Dolnicar, 2018). Group tourism may also be organized by people attending leisure or business events, who could be old friends or new acquaintances (Fairley, 2003; Larsen & Bærenholdt, 2019). From the perspective of social psychology, traveling together facilitates social interactions, which fulfill people’s need for social connection with others and belongingness, contributing to positive physical and psychological well-being, for example relieving stress and generating positive emotions (Lin et al., 2019).

The benefits of traveling together often fail to materialize because of individual differences in needs and preferences, and neglecting the differences could even result in tensions, disappointment, frustration, or anxiety (Gram et al., 2019). Therefore, a good trip design must consider the group diversity, collaborative information search and decision-making processes to enhance individual and group experiences.

2.4 *Group diversity*

Group diversity refers to the individual differences within a group (Jansen & Searle, 2021). The literature focuses on three main types of group diversity. The first two types are classified as surface-level diversity, i.e. individual difference that is readily observable, including demography diversity, such as age and gender, as well as job-related diversity, e.g., experience, education, or information diversity (Delic et al., 2020). The third type is the deep-level diversity that is not easily observable, such as personality, values, beliefs and attitudes (Triana et al., 2021). The value dimension of the deep-level diversity further includes personal preferences, in addition to work and life-related values (Triana et al., 2021).

Group diversity is considered a double-edged sword, because it can have both positive and negative effects on the emergent states (e.g. cohesion, commitment, and satisfaction, group identification), the group process (communication, collaboration and information sharing), and ultimately individual well-being and the group performance (Triana et al., 2021). Two major theoretical approaches are frequently drawn upon to explain the effects of group diversity, i.e. the social categorization perspective and the information processing and decision-making perspective. The social categorization perspective posits that the differences in a group could have negative effects, because people are more likely to be attracted to those similar to themselves and the shared characteristics help foster the positive emergent states and facilitate the group process (Horwitz & Horwitz, 2007; Tsui & O'reilly III, 1989). In contrast, the information processing and decision-making perspective argues that group diversity, particularly the job-related one is helpful for the group to achieve positive outcomes, because diversity creates a larger pool of information, generating more thought-out decisions (Triana et al., 2021). Although there are potential conflicts arising from the diversity, if managed well, the benefits generated from the diversity may outweigh the challenges (Phillips et al., 2004).

2.5 *Group information search and decision-making*

Planning a trip for a group is a complex information search and decision process (Jeng & Fesenmaier, 2002; Pappas, 2021; Pröll & Retschitzegger, 2000), which involves information search (Fardous et al., 2019) and several sub-decisions, such as the choice of points of interest, activities, travel companions, time to be spent, and route (Jeng & Fesenmaier, 2002). As the destination is not their normal place of residence, the information needed for the members of a tour group to plan the trip can be daunting. The findings by Fardous et al. (2019) indicate that the planning process involves several stages, from initial co-planning to information seeking and sharing, choice prioritization, and finally reaching a collaborative decision. This process involves give-and-take negotiations to avoid or resolve conflicts in perceptions and preferences. In other words, the diversity in the group complicates the trip planning task.

Surface-level diversity can be effectively handled, since the diversity in demography has very limited effects, while information diversity has small but positive effects (Triana et al., 2021). However, empirical research has consistently suggested that the diversity of preferences, a deep-level diversity, has a significant negative effect on the decision process, individuals' satisfaction with the group choice and happiness with being of the group (Delic et al., 2020). Group members, therefore, have to be collaborative during information search and decision making, which involves interaction among members and relies on a certain degree of mutual understanding (Mohammad Arif et al., 2015). Coordination becomes highly difficult with the increase in the size of the group, although a large group brings substantial resources and energy, which could enhance tourism enjoyment (Su et al., 2021). The difficulty in trip planning may increase due to certain members in the group who are more influential in pursuing their own goals than others; for example, children have a strong influence in determining tourism activities in a family holiday (Blichfeldt et al., 2011).

Tourists in a group can divide their information search tasks into several subtasks, allocate workload to certain members, and discuss search results together for effective planning (Mohammad Arif et al., 2015). Many activities in the stage of information search are often performed by the younger members of the family because they are more technology-savvy in today's digital era. Not all aspects of the information receive the same level of attention, and some are regarded as more important than others (Jeng & Fesenmaier, 2002). How tourists search for information and make decisions is influenced by numerous factors, including knowledge and expertise, learning, and information search costs (Gursoy & McCleary, 2004). To reduce users' burden of information search and facilitate decision making (Guo et al., 2019), various group-oriented smart recommender systems have been developed and adopted in industries, such as movies, videos, music, restaurants, and tourism (Kargar & Lin, 2021).

2.6 *Group recommender systems*

A recommender system is designed to automatically provide personalized information that closely matches the user's needs and preferences(Zheng et al., 2021b). The purpose is to reduce information search effort, improve decision quality, and consequently better consumption experience (Kargar & Lin, 2021). A group tour recommender system attempts to offer the best itinerary that maximizes the group well-being without sacrificing individual well-being (Anagnostopoulos et al., 2017). To do so, design researchers adopt two major approaches to generate group recommendations, both rely on the aggregation of preference (Masthoff, 2015). One approach is the aggregation of individual recommendations, which combines the recommendations generated for each group member. The other one is to aggregate the group members' profiles to create a virtual user and then generate recommendations for the virtual user. Different strategies have been used to aggregate group preferences, including Average (use group's average rating), Without Misery (remove items that are below a certain threshold), Least Misery (use the minimum ratings), Most Pleasure (use the maximum ratings), and Dictatorship (use a single group member's ratings). The Average strategy and its variants are widely used. Ardissono et al. (2001) used a weighted Average strategy with the consideration of the size and relevance of subgroups. Nguyen and Ricci (2018) applied a different weighted Average strategy on the basis of the group members' discussion. Herzog, Laß, and Wörndl (2018) synthesized multiple aggregation methods in designing their tour recommender system suitable for individual and group users.

The process of executing an aggregation method is time-consuming, and a scaling problem can be also experienced because the aggregation model's performance decreases as the group size increases. The recommendations generated through the model are rarely able to satisfy each individual's needs because the individual's preferences are compromised during aggregation. Table 1 summarises the major works' contributions, factors considered, optimization targets, and the handling of irreconcilable conflicts of preferences. From the table, we can see that most works do not attempt to handle the irreconcilable conflicts of preferences among group members, except Nagata et al. (2006). For example, Zheng and Liao (2019) explore the methods that can reach an appropriate balance between fairness for each member and the total utility of the group. Kargar and Lin (2021) attempt to make a compromise by eliciting must-visit and preferred points of interest. However, these methods have an underlying assumption that the differences in tourist preferences can be reconciled. In reality, some preferences and requirements of group members are irreconcilable. As a result, the designed route is unable to meet the needs of all tourists. Prior studies show that personality diversity can be handled successfully in the design of a group recommender system, while conflicting preferences among group members are highly challenging for the design work (Delic et al., 2020)

Table 1 A comparison of major works dealing with group tour recommendations

Previous studies and the present study	Contributions	Factors considered	Optimization target	Handling irreconcilable conflicts?
Ardissono et al. (2001, 2003)	Uses aggregation methods to elicit a group's profile and then designs routes using the group preference model.	POI selection and sequencing, time spent in POIs, Mutil-day tour	Satisfaction score	×
Garcia et al. (2011)	Adopts the aggregation mechanisms to combine the group's preferences.	POI selection and sequencing	Fairness among group members	×
Kinoshita and Yokokishizawa (2008)	Recommends combinations of tourist attractions for a group considering the preferences of group members	POI selection and sequencing, characteristics of tourist attractions	Preferences of group members are achieved	×
Zheng and Liao (2019)	A heuristic approach using Pareto optimality to meet group member preferences.	POI selection and sequencing, time spent in POIs	Total utility of the group and the fairness of individual members	×
Nagata et al. (2006)	Proposes the joining and forking strategy to handle the heterogeneous tourist preference	POI selection and sequencing	Satisfaction score	√
Kargar and Lin (2021)	Generates itineraries that cover all must-visit POIs and as many as preferred POIs for each tourist	POI selection and sequencing, time spent in POIs, multi-day tour, spending budget	Fairness among group members, traveled distance, the time or money.	×
Ruiz-Meza, Brito, and Montoya-Torres (2021); Ruiz-Meza and Montoya-Torres (2021)	Proposes a multi-objective model for the design of tourist itineraries considering CO2 emissions.	Travel costs and budgets，selection of transport modes ， POI selection and sequencing.	Individual profit，equity in group profit, CO2 emissions.	×
This study	Incorporates a "joining and forking" strategy for the personalization of tourism experiences while fostering group co-experience	POI selection and sequencing, time spent in POIs, Differences trip start and end time and locations.	To achieve a favorable total utility of group and the percentage of shared experience.	√

Note: POI = point of interest

In this study, we argue that this limitation can be resolved by using the so-called "joining and forking strategy" proposed by Nagata et al. (2006); that is, for the common points of interest, members join together as a group (joining); and for individual's uncompromising points of interest, the group can split up during the trip (forking). Only one study, i.e., Nagata et al. (2006) has attempted to address the issue. However, several important elements have not been addressed in Nagata et al. (2006), for example, the conflict between one member's "must-visit" point and another member's "must-avoid" point in a group and time allocation in each point. In addition, they handled the potentially conflicting objectives using a combination weight method, which is mostly subjective and can be controversial.

The current study addresses these problems by adopting a multi-objective optimization approach based on Pareto optimality that incorporates the joining and forking strategy; this mechanism is also suitable from a social value perspective because as previously stated, individual "time apart" and the "time together" for the group as a whole mutually enhance each other's value (Mikkelsen & Stilling Blichfeldt, 2015). In addition, our model further considers each member's starting/ending time and locations of the route to optimize the route's temporal-spatial structure.

3 Methodology

3.1 *Mathematical models*

The objectives of our model are to achieve a favorable balance between total utility and shared experience with consideration of the differences between the starting/ending time and the locations of each member while optimizing the route's spatial-temporal structures.

The entire trip of the *k*th tourist can be organized into M^k stages according to her/his discrete visits to vertices. Let u_j^k be the utility obtained by the *k*th tourist at the *j*th stage, which is based on the individual preference for the vertex and the actual time taken at the vertex. The total utility acquired by the whole group is described as Eq. (3.1), where *K* is the group size.

$$f_1 \quad Max \quad U = \sum_{k=1}^{K} \sum_{j=1}^{M^k} u_j^k \tag{3.1}$$

Apart from the total utility, the proportion of shared experience should also be considered. We let ϕ_{ij} be the similarity between tourist *i*'s and *j*'s route ($\phi_{ij} \in [0,1]$), which depends on the number of vertices that two tourists visit together. Therefore, the second objective function is to maximize the shared experience among the group, as shown in Eq. (3.2):

$$f_2 \quad Max \quad S = \frac{2 \cdot \sum_{i=1}^{K} \sum_{j=i+1}^{K} \phi_{ij}}{K \cdot (K-1)}. \tag{3.2}$$

In designing a personalized tour route, we consider both the technical and personalized constraints. For the technical aspect, the first stage is when a tourist enters an attraction and the last stage is when the tourist leaves the attraction, and in between, visiting one point of interest (POI) is counted as one stage, starting from the 2nd to the $M^k - 1$ th stage. For the personalized constraints, we take into account both "must-visit" and "must-avoid" vertices as well as time budget. We include the kth tourist's "must-visit" vertices, and exclude the "must-avoid" vertices, and the *k*th tourist's total time of the trip (including traffic time, duration time, and waiting time in the vertices) should be less than her/his time budget.

3.2 *Solution approach*

The tourist trip design problem is a typical non-deterministic polynomial hard problem, which can be solved by using a heuristic approach (Zheng et al., 2020b). We design a two-phase heuristic approach based on adaptive learning. In the preprocessing phase, we code the situations through a chromosome that is multi-layer and variable-length asymmetric and construct the initial solution set using a random-eclectic method. In the hybrid evolution phase, we adopt an adaptive learning mechanism to improve the system's performance.

3.2.1 Preprocessing phase

This phase involves two tasks: solution coding and initial solution set generation.

(1) Solution coding

We consider three factors when designing the structure: (1) we incorporate the joining and forking strategy in the route design, that is, the tour routes may be different for each group member; (2) the solution involves continuous and discrete variables; and (3) the solution dimensions cannot be determined in advance because the vertices visited by the tourist can potentially change.

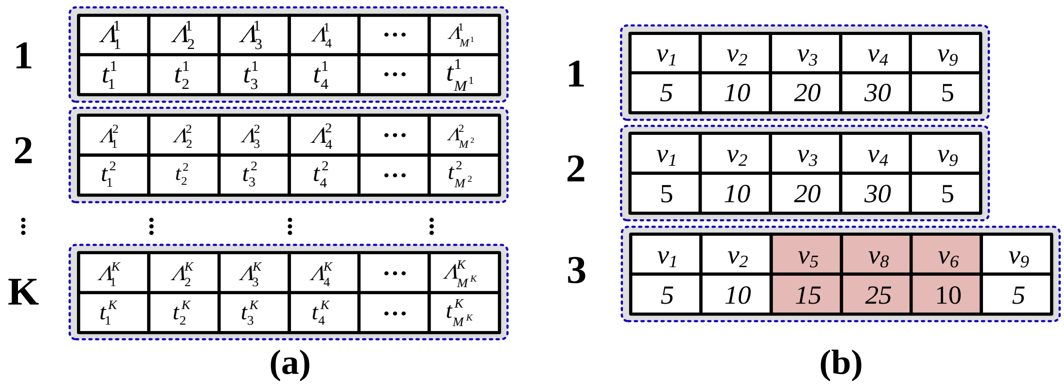

Fig. 1 Example of solution coding

Fig. 1(a) shows an example of solution coding, where each dotted box represents a member's route. Fig. 1(b) is a concrete example. We suppose that the group has three members: the first two members choose exactly the same route (successively visit v_1, v_2, v_3, v_4, and v_9, and the values of time spent are 5, 10, 20, 30, and 5 min, respectively), while the third member was briefly separated from the other two members during the trip and visited v_5, v_8, and v_6.

(2) Initial solution set

Previous studies show that an optimal solution often falls on the boundary of solution space, while the initial solutions generated using the main methods such as random, greedy, and eclectic methods fall inside the solution space (Tessema & Yen, 2009). As shown in Fig. 2(a). it is extremely difficult for the internal solution to evolve to the boundary optimal solution. Therefore, we introduce a new method named random-eclectic method (shown in Fig. 2(b)): First, we create a random number between zero and one; if it is larger than a predefined threshold, we generate an initial solution using the eclectic method; otherwise, an initial solution is generated using constraint relaxation method. According to this rule, a total of Q initial solutions are generated and stored in the initial solution set, where Q denotes the population size.

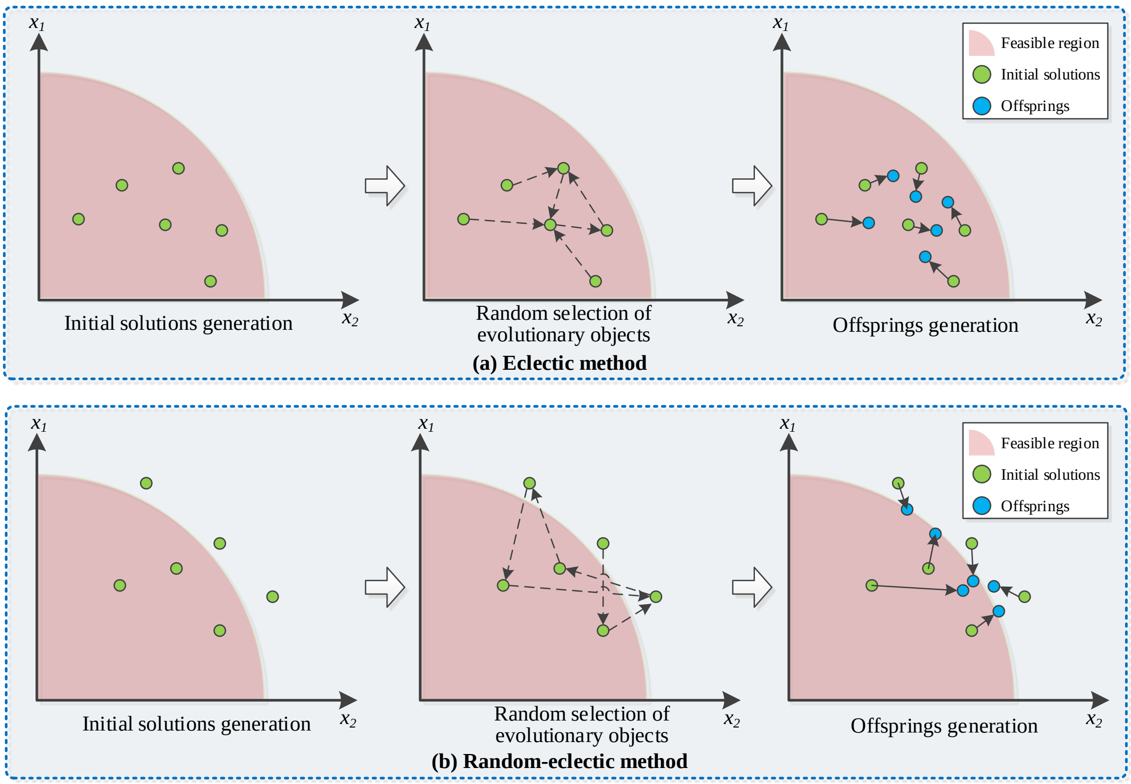

Fig. 2 Comparison between the eclectic and the random-eclectic methods

3.2.2 Hybrid evolution phase

We adopt a hybrid evolution strategy based on adaptive learning, which consists of an evolutionary stage division and an evolutionary strategy selection.

(1) Evolutionary stage division

We divide the evolution process into three stages of an early episode, peak episode, and late episode according to the evolution features to achieve the trade-off the efficiency and performance: a) The early episode stage aims to optimize the solution set as efficiently as possible; b) the purpose of the peak episode is to avoid evolution falling into the optimal; and c) the late episode stage focuses on reducing the turbulence in the search process and promotes the convergence of the algorithm. Each stage is further divided into the learning process and the reinforcement process: the former aims to test each alternative evolutionary strategy separately to find the optimal evolutionary strategy at this stage; while the latter optimizes the solution set by using the evolutionary strategy selected in the learning process. Fig. 3 shows the division of the evolutionary stages.

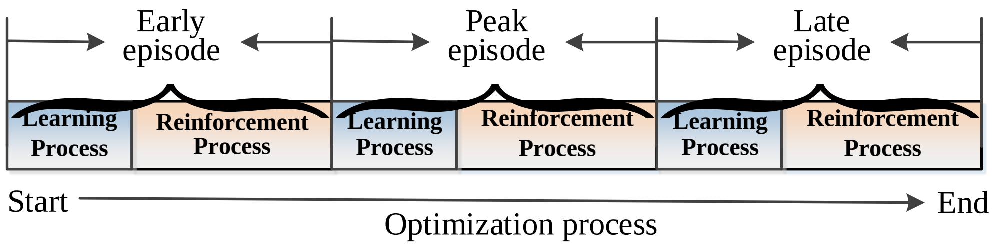

Fig. 3 Evolutionary stage division

(2) Evolutionary strategy selection

Choosing a suitable evolution strategy for each stage is the core task of hybrid evolution. The tourist trip design problem concerned in this study involves continuous and discrete variables, which can be optimized by combining specific algorithms. We list the algorithms that are widely used to optimize continuous variables (e.g., DE/rand/1 and DE/best/1) and discrete variables (e.g., GA, ACO, PSO, and VNS) according to the existing research (Das, Mandal, & Mukherjee, 2013). Suppose that $\boldsymbol{\Xi}=\{\xi_1,\xi_2,\cdots,\xi_M\}$ is the set of discrete variable optimization algorithms, while $\boldsymbol{\Psi}=\{\psi_1,\psi_2,\cdots,\psi_N\}$ is the set of continuous variable optimization algorithms. An algorithm may correspond to a variety of algorithm parameters, which also affect the performance of the algorithm. Suppose that φ_i and γ_j are the numbers of algorithm parameters of ξ_i and ψ_j. Thus, the number of parameters corresponding to the set of discrete (continuous) algorithms can be expressed as $\boldsymbol{\Phi}=\{\varphi_1,\varphi_2,\cdots,\varphi_M\}$ ($\boldsymbol{\Gamma}=\{\gamma_1,\gamma_2,\cdots,\gamma_N\}$). Then, the number of alternative evolutionary strategies (λ) can be calculated on the basis of Eq. (3.3), where M and N are the number of discrete and continuous optimization algorithms, respectively.

$$\lambda = \sum_{i=1}^{M} \varphi_i \times \sum_{j=1}^{N} \gamma_j \tag{3.3}$$

The learning process aims to decide the appropriate strategy from the set of alternative evolutionary strategies (***S****E*) and apply it to the reinforcement process of the corresponding stage. In the learning process, each strategy in ***S****E* is first applied to optimize the initial solution set of this stage; second, the evolution results of each strategy are evaluated; finally, the strategy that achieves the optimal evolution result is selected and used in the reinforcement process.

4 Model performance

4.1 *Case context*

Following Zheng and Liao (2019), we chose the same area, Kulangsu (or Gulangyu), an island destination on the off southeast coast of China (Fig. 4), for testing our proposed approach. The Kulangsu Islet is a well-known scenic spot and a world heritage site in China. It attracts a large number of tourists every year, thanks to its diverse architectural styles, multicultural history and winding coast. There are three piers on Kulangsu Islet, two of which are dedicated for use by tourists (see Fig. 4). There are numerous POIs distributed on the Islet, and the road network is extremely complicated. Most tourists rely on walking to reach each POI. Therefore, there needs to be such a personalized system to help them design the itinerary to maximize their experience.

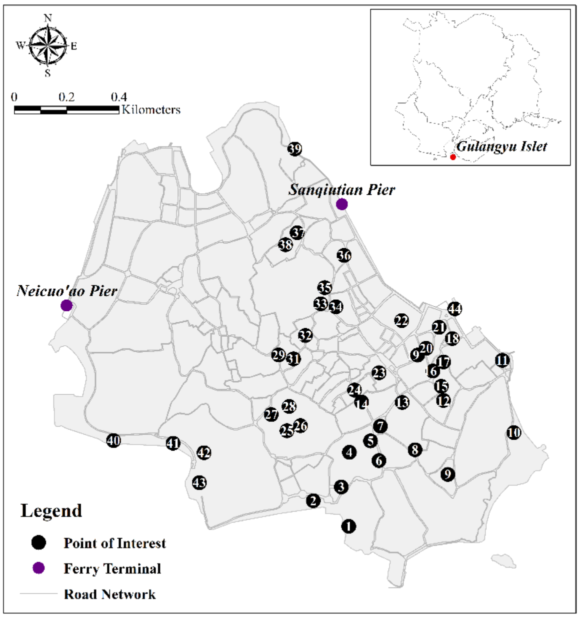

Fig. 4 Map of Kulangsu Islet

4.1.1 Basic information of vertices

The two tourist ferries and 44 popular POIs on the island were used for the empirical studies. Forty-six vertices are shown in Fig. 4, with the time windows listed in Table 2 (Column 4). To establish the average time spent by previous tourists (t_i), we integrated two sources of data, a tourist survey and interviews with the administrators at the Kulangsu Tourism Department. The results are presented in the fifth column of Table 2.

Table 2. Major POIs in Kulangsu

No.	Name	Type	Time window	t_j (min)
v_1	Shuzhuang Garden	POI	[05:00–21:30]	60
v_2	Gangzaihou Seaside Resort	POI	[00:00–24:00]	10
v_3	International Calligraphy and Carving Gallery	POI	[08:15–18:15]	15
…..	…..	….	…..	…..
v_{45}	Sanqiutian Ferry Terminal	En/Exit	[00:00–24:00]	--
v_{46}	Neicuoao Ferry Terminal	En/Exit	[07:20–18:40]	--

4.1.2 Basic information on tourist groups

We collected the basic information of tourist groups in Kulangsu during 8-10 August 2019. We successfully recruited 50 tourist groups at the two tourist ferries (25 each) to participate in our study. The participants were shown the text and photo information about the 44 POIs. The members of the participating groups were asked about their intention to visit each POI (1 indicates the highest interest for a POI; 0, no interest in it) and their “must-visit” and “must-avoid POIs. They were also asked to indicate the starting and ending times and locations. Among the groups, the relationships between the group members include couples without children (n=18), families with children (n=13), and friends (n=19). Moreover, there were 12 groups that had two members, 15 groups that had three members, 7 groups that had four members, and 16 groups that had five and above members (Table 3).

Table 3 Basic information of the sample

Group	Relationship	Number	Preference value list	Budgeted time	S_C	S_A
1	Friends	*3*	P^1:(1.0, .97,…, .61)	[10:00-17:00]	[1, 9, 25]	[5]
			P^2:(1.0, .99,…, .72)	[10:00-17:00]	[1, 17, 18, 25]	[9]
			P^3:(1.0, .93,…, .59)	[10:00-17:00]	[1, 9, 25]	[6]
2	Friends	*2*	p^1: (1.0, .90,…, .76)	[09:00-14:00]	[1, 35]	[22, 26]
			p^2: (1.0, .95,…, .52)	[10:00-14:00]	[1]	None
…	…	…	…	…	…	…
50	Couples	*2*	P^1:(.89, .88,…, .86)	[09:30-17:30]	[1, 22, 25, 28]	None
			P^2:(.94, .92,…, .90)	[09:30-17:30]	[1, 22, 25, 28]	None

4.2 *Alternative evolutionary strategies set determination*

We adopt the algorithms that have been widely applied in the previous studies of tourist trip design problems. Specifically, GA and ACO are selected as the alternative algorithms to optimize the discrete variables, while DE/best/1 and DE/rand/1 are chosen for continuous variable optimization. In addition, each algorithm only sets a high frequency and low frequency according to its evolutionary frequency. Thus, the number of alternative evolutionary strategies (λ) equals to 16 according to Eq. (3.3).

Table 4 Optimization algorithms and algorithm parameters

Types	Algorithm	Algorithm parameters	
		High frequency	Low frequency
Discrete optimization algorithm	GA	Pc-H=1, Pm-H=0.05	Pc-L=0.5, Pm-L=0.01
	ACO	a-H=0.8, b-H=0.7	a-L=0.4, b-L=0.3
Continuous optimization algorithm	DE/best/1	Fd-H=0.8, Cr-H=1	Fd-L=0.3, Cr-L=0.5
	DE/rand/1	Fd-H=0.8, Cr-H=1	Fd-L=0.3, Cr-L=0.5

Table 5 Alternative evolutionary strategies

No.	Discrete algorithm	Continuous algorithm	Algorithm parameters
1	GA	DE/best/1	High frequency
2	GA	DE/best/1	Low frequency
3	GA	DE/rand/1	High frequency
4	GA	DE/rand/1	Low frequency
…	…	…	…
15	ACO	DE/rand/1	High frequency
16	ACO	DE/rand/1	Low frequency

4.3 *Performance evaluation*

We use five baseline models to test our approach's performance, including the DEA (M-DE), genetic-based algorithm (NSGA-II), ant colony optimization (M-ACO), NSACDE, and particle swarm optimization (M-PSO) (Zheng & Liao, 2019). We used inverted generational distance (IGD) to assess our model's performance against that of the baseline methods in accordance with the general practice using by previous scholars (Li & Zhang, 2009). The smaller the IGD, the better the methods' performance. Following Zheng and Liao (2019), we repeating 30 times the process for each tourist and obtain the average value to reduce random errors.

An analysis of variance (ANOVA) and post-hoc test are conducted to further examine which method had significantly smaller IGD. Table 6 present the results, which indicate that IGD from HA was significantly smaller than that generated from the other five algorithms ($p<0.05$). This indicates the superiority of our method over the competing ones.

Table 6 ANOVA Results and Post-Hoc Multiple Comparison Test

	Sum of Squares	df	Mean Square	F	Sig.	Post-Hoc Test				
						Group	Mean Difference	Sig.	Lower Bound	Upper Bound
Between Groups	15.310	5	3.062	43.442	.000	HA-NSACDE	-.260*	.000	-.395	-.125
						HA-NSGA-II	-.752*	.000	-.887	-.616
						HA-M-ACO	-.401*	.000	-.536	-.265
						HA-M-PSO	-.760*	.000	-.895	-.625
						HA-M-DE	-.751*	.000	-.886	-.616
Within Groups	12.265	174	.070							
Total	27.575	179								

4.4 *Discussion*

The results presented in Section 4.3 show our method achieves the balance between individual experience (time apart) and co-creating experiences (time together), outperforming the existing algorithms. Moreover, our approach can generate more sensible routes through the joining and forking strategy, and more customized routes with consideration of the differences between the starting/ending times and locations of each member.

4.4.1 Route choice diversity

Most recommenders proposed in the previous studies generate a single solution, which cannot be the optimal alternative because tourists in a group often have conflicting objectives. By contrast, our approach provides a diversity of choices. For example, in the first group in Table 3, the time budget was 7 hours (from 10:00 in the morning to 5:00 in the afternoon), there were must-visit and unwanted vertices as indicated by the tourists. Our model generates 60 routes with the total utility of group and shared experience shown in Fig. 5. The tourist group can select one that best matches its requirements. If total utility is the most important for the group, then it may select the first option, which has a total utility of 141.35 and shared experience of 0.14. If the shared experience is the most valuable for the group, then it may choose the last option, with a total utility of 112.86, and shared experience of 0.98. The options are in a spectrum between the two extremes, and the group is free to select an optimal one that has a good balance between the total utility and shared experience.

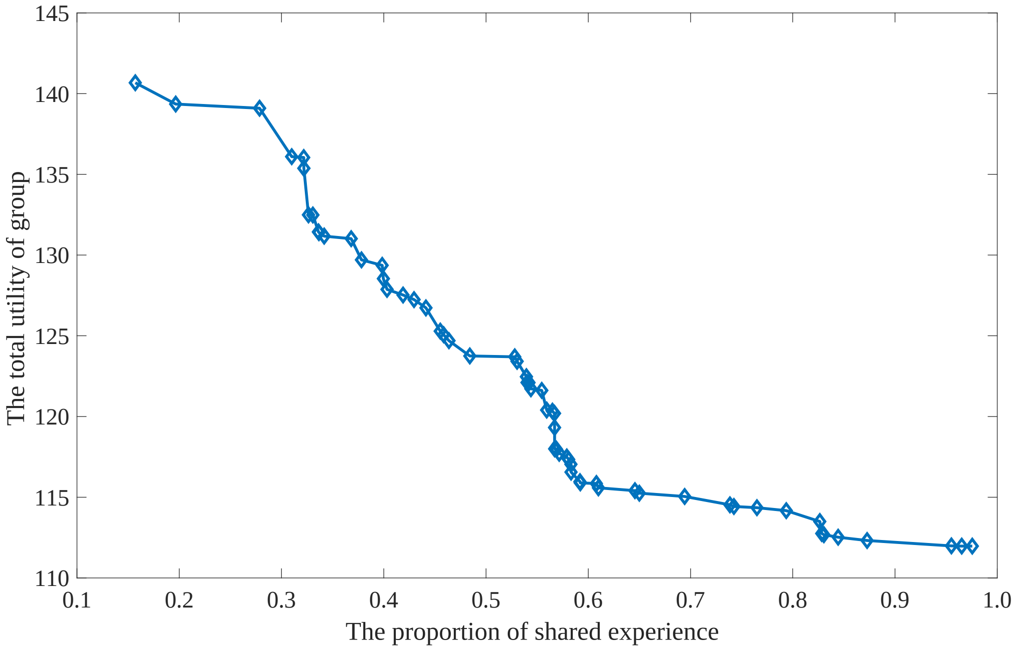

Fig. 5 Relationships between total utility and shared experience (group 1).

4.4.2 Reconciling the irreconcilable

Previous studies have designed itineraries for the heterogeneous tourist groups assuming that the differences in tourist preferences can be reconciled. In reality, some preferences and requirements of group members are irreconcilable. For example, in the first group in Table 3, the second member tends to avoid visit Yu Garden (v_9), which is exactly what the other two members must visit. Neither preference aggregation method (Ardissono et al., 2001) nor NSACDE (Zheng & Liao, 2019) can obtain a feasible solution for this group because no single route simultaneously includes all the members' favorite vertices and excludes their unwanted vertices.

Our study makes up this gap by adopting the joining and forking strategy. Fig. 6 displays the routes designed by HA. First, all the members arrive at Kulangsu at v_{45} and visit v_{36}–v_{22}–v_{21} together. Second, member 2 left the group and visited v_{18}–v_{17}–v_{16}—v_{20}–v_{19}–v_{23}–v_{24}–v_{14} alone because v_{17} and v_{18} were his "must-visit" vertices. Meanwhile, members 1 and 2 continued to visit v_{11}–v_{10}–v_9–v_8 together. Third, embers 2 and 3 met at v_7 and visit v_7–v_5 together, while member 1 visited v_6 alone because v_5 is his "must-avoid" vertex. Finally, all the members converged at v_4 and visited the following trip (v_4–v_3–v_1–v_2–v_{25}–v_{27}–v_{28}–v_{35}), and the trip ends at v_{45}.

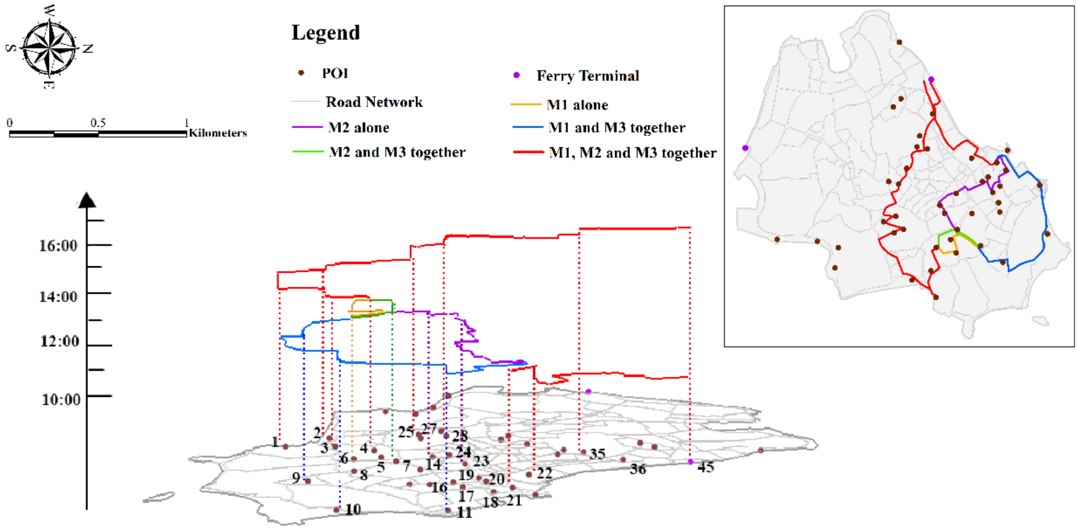

Fig. 6 Routes designed for the first group

4.4.3 Personalization

In our fieldwork, we collected data from a total of 50 groups of tourists, which consist of three types: a) couples without children, b) families with children, and c) friends. From the list of preference values provided by the participants and the list of must-visit and must-avoid attractions, we found some interesting phenomena, that is, there are large differences in the preferences for attractions in the friend groups, and some of them are irreconcilable conflicts (i.e., a certain must-visit POI for one tourist happen to be another's must-avoid). For example, Member 2 of Group 1 indicated that POI 9 must be avoided, but this POI happens to be a must-visit one for two other members in the same group. In contrast, the other two groups (couples without children and families with children) have relatively few differences in preferences for POI and conflicts. It seems that members of the family or couple group are more willing to sacrifice their own personal utility for the greater percentage of shared experience (PSE), this is consistent with the findings by Zheng and Liao (2019). Our approach can design personalized routes for tourists based on the differences in group behavioral characteristics. To illustrate this, we take Group 1 and Group 4 as examples. Group 1 is a friends group that contains 3 members; and Group 4 is a family group containing two parents and a child. Among the 60 routes that we designed for the two groups (as shown in Fig. 7), the value range of PSE of Group 4 is relatively small, mainly concentrated between 0.5-1.0, while the value range of PSE of Group 1 is relatively large, scattered between 0.1-0.97.

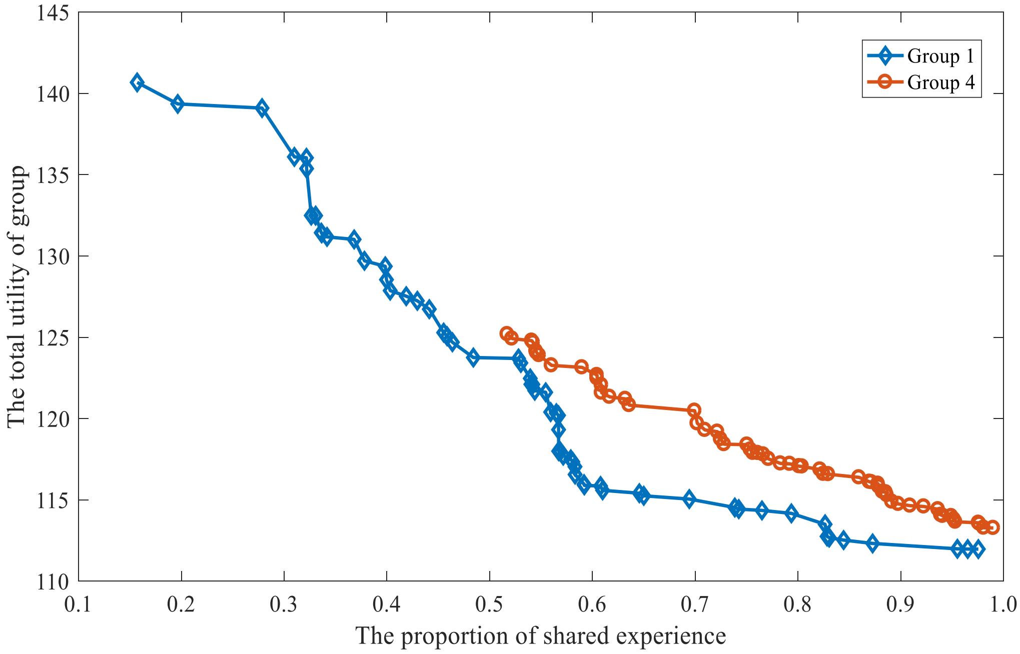

Fig. 7 Routes designed for the first and fourth group

Our approach allows the design of a set of personalized routes according to the differences in the group characteristics, as well as the design of routes for the whole group according to the specific requirements. That is, the individual members and the group as a whole and the time and locations for members to start or end their trip are to be considered, which may be different due to the diversity of requirements. For example, member 1 arrived at the Neicuoao terminal (v_{46}) at 9 a.m., while member 2 arrived at the Sanqiutian terminal (v_{45}) at 10 a.m. due to the limited number of tickets from Xiamen Island to Kulangsu. Our approach fully considers these requirements and characteristics of members and can design a tour route to effectively meet the needs of each member. We illustrate this by using the case of the second group in Table 3. Fig. 8 displays the designed routes: the routes for members 1 and 2 are represented as reds and blue lines, respectively. Specifically, member 1 arrived at the Neicuoao terminal (v_{46}) at 9 a.m. and visited v_{40}–v_{41}–v_{42}–v_{43} alone, while member 2 arrived at the Sanqiutian terminal (v_{45}) at 10 a.m. and visited v_{19}–v_{13}–v_{6} alone. Then, they met at v_2 at 10:46 a.m. and visited v_2–v_1–v_4–v_{25}–v_{26}–v_{28}–v_{35} together. The trip was ended at v_{46} at 14:00.

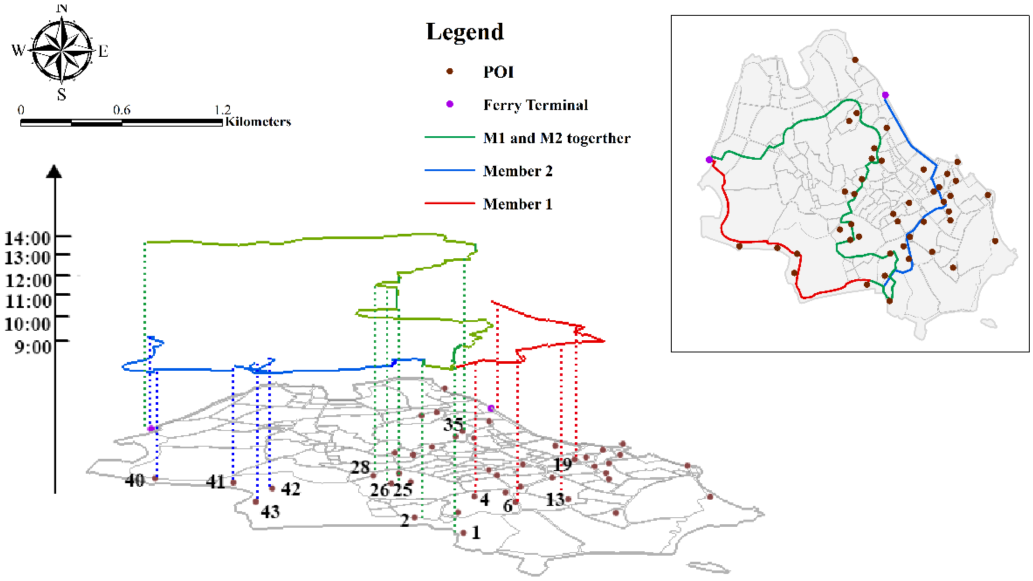

Fig. 8 Routes designed for the second group

5 Conclusions

Spending time together and co-creating a tourism experience are important sources of happiness for members of a tourist group (Melvin et al., 2020); however, inevitable conflicts of preferences exist within the group. A critically challenging task is to design a system that meets everyone's requirements without compromising the time for shared experience and maximizing the total utility value for the group as a whole. In this study, we take the challenge by incorporating the "joining and forking" strategy to handle multiple objectives through Pareto optimality and designing a two-phase heuristic approach based on adaptive learning. Our design allows group travel to have a certain "time apart" to meet individual's unique needs and preferences (personalization) and "time together" to meet all members' social needs, co-create shared experience and memory, and establish social capital (collective engagement) (Mikkelsen & Stilling Blichfeldt, 2015). A comparison test using fieldwork data of 50 tourist groups confirms that our design outperforms the five baseline models in achieving the multiple objectives of individual, relational, social, and collective benefits. Our innovative design is particularly significant for advancing the smart tourism literature because the success of an intelligent system is dependent on tourist trust and adoption (Gretzel, 2011; Park, 2020; I. Tussyadiah, 2020; I. P. Tussyadiah, Zach, & Wang, 2020). Tourism scholars have repeatedly called for integrating the social relationships of tourism in the design of intelligent systems (Gretzel, 2011; I. Tussyadiah, 2020).

This study offers several important implications for research. First, our proposed approach marks the first attempt to design a group tour recommender system without relying solely on the aggregation of preferences. Most existing methods of group recommendations are based on the assumption that the diversity of preferences among group members can be reconciled (Kargar & Lin, 2021; Zheng & Liao, 2019), which does not reflect reality. The aggregation of preferences approaches based on this assumption thus fail to generate recommendations that match the group diversity. Unlike other forms of deep-level diversity that positively contribute to group processes and outcomes, such as information diversity (Jansen & Searle, 2021), the diversity of preferences often has a negative effect on the group process and outcomes (Delic et al., 2020). People love being with families and friends, and the diversity of information, knowledge, abilities, and skills brought by group members contributes to the enjoyment of the tourism experience for everyone, yet conflicts in personal preferences are inevitable (Triana et al., 2021). A good tour recommender design thus should aim to minimize the potential conflicts and maximize the benefits from the group diversity, and the proposed approach in this study marks a significant step forward in this regard.

Second, this study advances the research on smart tourism system design (Xiang et al., 2021). The prominent feature of our approach is the personalization of tourism experiences in our design (Kotiloglu et al., 2017; Zheng et al., 2020a). Our design reflects a clear service blueprint by taking into account the entire spatial-temporal structure of a tourism journey, integrating the multiple distinctive individual preferences rather than relying on a single member within the tourist group (Guo et al., 2019; Masthoff, 2015; Zheng & Liao, 2019). Moreover, in our design, we consider the multidimensional nature of group tourist experience from individual, relational, social, and collective dimensions. Furthermore, our system works equally well when members can accommodate differences. The added benefits of our design are that when the differences are irreconcilable or when members feel they would be better off separated, the system can balance the time for shared experience (time together) and individual exploration (time apart) through "joining and forking", which enhances both individual and collective enjoyment (Melvin et al., 2020; Mikkelsen & Stilling Blichfeldt, 2015).

Finally, from an operational research perspective, our design makes an original contribution to the tourist trip design problem literature (Ruiz-Meza & Montoya-Torres, 2021; Vansteenwegen & Van Oudheusden, 2007; Zheng & Liao, 2019). The design differentiates itself from previous group trip design in three major aspects. First, an adaptive learning mechanism is introduced to improve the approach's performance. Second, a variable-length asymmetric, multilayer chromosome is designed to code the solutions. Third, a random-eclectic method is designed to create the initial solution set to optimize the performance of the approach.

The study offers tourism managers a solid foundation for creating a smarter destination service system through incorporating our design. The system design proposed in this study can be integrated into any current or future smart destination or smart tourism systems, including but not limited to computer/mobile apps or webpages. As far as the users are concerned, they will not actually notice the existence of our system. What they need to do is to enter relevant information in the input interface of their devices that are connected to our system, which will then generate appropriate routes for the group, and show them in the output interface of the user's device. The recommendations will help the user to reduce the burden of information and cognitive efforts in making the right decision. Various tourism organizations, such as attraction sites, tour operators, destination marketing organizations, online travel agencies (e.g., TripAdvisor and Ctrip), or digital maps (e.g., Baidu or Google Map), can integrate our design into their digital information service applications to enhance tourist experience and their business performance and competitive advantages.

The current coronavirus pandemic presents a barrier for people to enjoy travel and tourism (Lu & Lin, 2021). People will not be likely to travel in a large group. Nevertheless, family travel and a small group of close friends traveling together for a holiday will increase post the Covid-19 pandemic. A smart tourism recommender system that integrates our group-oriented approach will come in handy. The pandemic poses unprecedented challenges for the tourism industry. Tourism organizations around the world will speed up the adoption of smart tourism applications, with less competitive firms being driven out of the market. Our research is timely and impactful for destinations and tourism companies to offer personalized services and enhance competitiveness at an extraordinary time, such as the current pandemic.

The model proposed in this study has several limitations and future research could further improve it. First, we did not consider travel costs in our design, and future studies could consider this factor as a constraint for trip design, in addition to time constraints. Second, the empirical test in the current study was based on a questionnaire survey, which cannot objectively and accurately obtain tourists' preference information. Future studies may consider using data mining or machine learning to make up for this deficiency (Zhang, Lin, & Zhang, 2021; Zheng et al., 2022). Researchers can accurately evaluate the tourists' preference for various types of POIs through mining the current tourists' travel notes or comments on some social platforms. Last but not least, our model does not consider tourists' spontaneity in changing the itinerary during the trip, therefore, future research may base on our approach to further develop an adaptive recommender system that adjusts to the changes dynamically.

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