All roads lead to the places of your interest: An on-demand, ride-sharing visitor transport service

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Abstract: Successful visitor transport within large tourist sites should balance visitor experience and operating costs. Inspired by the model of sharing economy, we design a "user-centered" intelligent visitor transport system to improve the efficiency and quality of experience of transport service in large tourist sites. The system's core approach is a three-stage heuristic model based on Pareto optimality. Results of the proposed service indicate a drastic reduction of visitor delay time and an improvement in energy efficiency. The proposed scheduling schemes for organizers are more diversified and adaptable than the existing service.

Keywords: Intelligent system, Visitor transport, Sharing economy, On-demand ride service

INTRODUCTION

The exponential growth of tourism activities in recent years, particularly the use of private cars for tourism purposes, has caused severe traffic congestion and pollution (Pettebone et al., 2011). The daily commute of residents could be disrupted by increased traffic congestion, crowding in public transit, and noise and air pollution as a result of visitor movement (Mace et al., 2013; White, 2007). These effects may, in turn, negatively affect tourism development (Goebel et al., 2020; Zhou et al., 2019). Nonetheless, public visitor transport has shown significant positive environmental, economic, and social implications for the development of the travel and tourism industry (Downward et al., 2004; Khadaroo et al., 2007; Lumsdon, 2006). For example, facilitating the movement of more visitors using less space and fuel diminishes traffic congestion and pollution in tourist destinations (Daniels et al., 2018). The easy access to tourist destinations generates more visits, employment opportunities, and business activities (Tomej et al., 2020), which translate to improvements in the local community's standard of living, and ultimately winning support for tourism development from satisfied residents (Kanwal et al., 2020).

In 1972, Denali National Park started utilizing shuttle buses as an alternative to private cars (Singer et al., 1986). The introduction of the shuttle bus within large tourist sites continues to exhibit positive results within its first few years of use, such as strengthening carrying capacity, increasing visual screening, reducing traffic congestion, crowding, and environmental pollution (Mace et al., 2013). However, current shuttle bus systems and other forms of visitor transport have problems. Visitor transport is one of the key factors influencing visitor experience and trip satisfaction (Yang et al., 2019a). (1) Although visitors highly value the idea of freedom (Holly et al., 2010; Taff et al., 2013), most travel routes or circuits of visitor transport within tourist sites are planned and designated (e.g., the Grand Canyon National Park has only four fixed routes of shuttle buses). (2) Another major drawback with the utilization of visitor transport is its accessibility. Visitors need to transfer multiple times to places of interests (POIs) or even find that the available transport does not cover all POIs (Wilson et al., 2018). (3) Long waiting time and detours (White, 2007) may also lead to low visitor and resident satisfaction (Prideaux, 2000). (4) Moreover, additional and inefficient utilization of transport resources may lead to excessive costs to service providers (White, 2007) and exacerbate air pollution and environmental degradation in local communities (Downward et al., 2004). (5) In response to these problems, various measures have been taken to reduce the negative impacts of visitor transport, such as traffic restriction and public transportation promotion, unfortunately with little success (Downward et al., 2004).

Surprisingly, little research discusses innovating visitor transport with the consideration of maximizing social, economic, and environmental benefits (Downward et al., 2004; Khadaroo et al., 2007; Lumsdon, 2006) while minimizing costs (Brida et al., 2014). Most studies focus on mere technical improvements (Buhl et al., 2019). Therefore, reducing redundant operation costs by efficiently matching the supply of vehicles with the demand for rides deserves distinctive attention.

Advances in new technologies (Neuhofer et al., 2014) and the success of the innovative model of sharing economy, an economic model that enables individuals to share access to under-utilized goods or services for monetary or nonmonetary benefits (Leung et al., 2019), such as Uber and Lyft, pave the way for visitor transport development. Although studies warn about the negative effects of sharing economy, e.g., overuse of services or goods caused by the reduction in the cost of accommodation makes the destination overloaded (Tussyadiah et al., 2016), it has shown positive impacts on the triple bottom line—the coordinated development of three interacting “pillars” of sustainability, encompassing economic, social and environmental subsystems (Yang et al., 2019b). First, the sharing economy makes efficient use of underused resources; it stimulates micro-entrepreneurship, reduces the unemployment rate, and contributes to economic growth (Hossain, 2020). Second, the sharing economy facilitates social bonding between service providers and consumers and promotes a close relationship between travelers and the local community (Tussyadiah et al., 2016). Third, the sharing economy provides consumers with great access to underused resources, which has a positive impact on environmental sustainability. In general, the on-demand ride-sharing visitor transport system is designed on the basis of the concept of sharing economy (Zach et al., 2020), which helps promote the sustainable development of tourist destinations.

The purpose of this study is to develop an on-demand ride-sharing visitor transport system that addresses the problems of assigning buses to matched visitors and scheduling the shuttle bus operation route. In particular, the proposed system adopts an automated process that allows shuttle bus managers to match bus drivers with visitors on very short notice. The system plays the core role in improving efficiency (i.e., trade-off between delay time and cost) throughout request receipt, request allocation, route scheduling, and solution selection. The system also tackles the issue of sustainability in large tourist sites, thereby promoting the development of autonomous driving and e-mobility in the travel and tourism industry. Such a system marks a step toward the design of an intelligent and sustainable visitor transport system (Cohen et al., 2019).

The operational problem associated with on-demand ride-sharing is a vehicle routing problem (VRP), which involves requests of pickup and drop-off over a certain timeframe (Hyland et al., 2020). Optimization of the visitor transport system involves two sub-problems, namely, visitor request allocation and vehicle route planning, which can be modeled as the variation of VRP with simultaneous pickup and delivery (VRPSPD) (Min, 1989). Although VRPSPD has been widely applied in various fields (e.g., logistics, medical services, transportation, etc.) and a multitude of approaches have been proposed over the past few decades (Iassinovskaia et al., 2017), the existing approaches of relevant research on Uber and Lyft are not applicable in the tourist scenario. In reality, the requested pickup time of visitors at the same stop varies, and the requested pickup stop and drop-off stops from different visitors may refer to the same stops. Hence, a vehicle must visit each stop more than once. The time spent in waiting or detouring is universally disliked by visitors (del Mar Pamies et al., 2016), and a vehicle needs to pick up and drop off visitors as timely as possible. All the above considerations are opposite in most VRPSPD-related studies (Montane et al., 2006).

Thus, this study formulated multiple objectives on the basis of Pareto optimality, which is a measure of efficiency in the multi-objective context (Chinchuluun et al., 2007) where several conflicting objectives must be accounted for within an optimization process. The study developed a three-stage heuristic approach (HA), that is, strategies for problem solving that use a practical method not guaranteed to be optimal or perfect, but sufficient for the immediate goals (Ahmed, 2016). Each solution provides one scheme including the number of shuttle buses, routes of the shuttle buses (i.e., departure time, stops passed, and the order of stops), and the number of passengers to be served. The implementation of the solution is as follows: the request data, including pickup stop, drop-off stop, number of passengers, and expected pickup time, sent to the shuttle bus system by the user from the mobile phone is pre-acquired, then the system allocates the requests to shuttle buses and schedules their corresponding routes according to the proposed HA. Further, the system generates a variety of delay time–cost trade-off solutions, that is, schemes. Finally, managers choose an operation scheme according to real-time demand and personal preference.

The proposed study contributes to the existing literature in three ways. Theoretically, our design emphasizes "user-centeredness," focusing on visitors and service providers (Buhl et al., 2019). Their involvement in our design thinking process (Buhl et al., 2019) can be seen as a form of "social technology," which is a prescriptive process where multidisciplinary teams take a user-oriented approach to come up with relevant solutions to complex or "wicked" problems (Warren et al., 2018). Practically, the proposed approach not only considers multiple practical constraints in the tourist scenario, but also achieves a drastic improvement in visitor experience in terms of reducing delay time and energy efficiency in terms of reducing operating costs. Hence, the proposed system can enhance tourism sustainability more comprehensively than existing methods. Most importantly, owing to its simplicity and practicality, the proposed transport system can be widely applied in large tourist sites, such as national parks, theme parks, or mega-event sites, where a public visitor transport system is required. In addition, our approach provides diversified and adaptable transport scheduling schemes for managers. Technically, from the perspective of operations research, we abstract the proposed problem as an optimization problem, which is full of complexity (e.g., the variant of VRP, two conflicting objectives, and various constraints in the tourism scenario). The innovative approach shows better performance than the existing approach in three aspects. (1) This study optimizes the solutions of transport schemes by integrating the population evolution and individual iteration algorithm to improve search performance. (2) This study codes the solutions by using a direct coding method based on multipart chromosome to improve the efficiency of our approach. (3) This study also develops a replacement strategy to achieve a beneficial balance between the diversity and quality of solutions.

METHODOLOGY

This study addresses the visitor transport system optimization problem within a large tourist site by considering two potentially conflicting objectives. The first objective function of this study is to minimize the delay time (i.e., time spent waiting for a vehicle and vehicle detours) of visitors. Generally, visitors want to spend less time waiting and traveling in a vehicle (Ryan et al., 2018) and more time enjoying POIs in tourist sites. Thus, a visitor transport is expected to arrive at the requested drop-off stop as soon as possible. The second objective function of this study is to minimize the overall transport cost. Generally, the cost is composed of the fixed cost and variable cost. The variable cost depends on the total travel distance and the unit cost.

In addition, the entire transport system must fulfill a series of constraints. (a) The route of each vehicle starts at the origin depot and ends at the final depot. (b) Only one vehicle implements each request. (c) Vehicles are empty when they depart from the origin depots and arrive at the final ones, and the capacity of the vehicle in the whole trip cannot exceed its maximum capacity.

To solve the essential variation of VRPSPD, an non-deterministic polynomial combination optimization problem (Liu et al., 2013), multiple objectives are formulated on the basis of Pareto optimality, and a three-stage HA integrated with population evolution and individual iteration algorithm is developed. HAs are divided into individual iteration and population evolution algorithms according to the objects on which the optimization process depends. Individual iteration has strong local search ability but falls easily into local optimization, whereas population evolution algorithms have a strong global search ability and can avoid the risk of falling into local optimization.

Initialization Stage. This stage involves the construction of the solution coding and the initial solution set. Unlike indirect coding that requires many iterative processes to decode it into a route results, and a population evolution algorithm in most VRP-related studies (Ai et al., 2009), this study designs a direct coding method based on the multipart chromosome to improve efficiency. Each part represents the route of a vehicle. After solution coding, a two-step method is proposed to construct the initial solution. In the first step, all requests are allocated randomly to some vehicles (some vehicles may not receive requests). In the second step, we initially use a random method to sort the request list of each vehicle and then optimize the route of each vehicle by using a variable neighborhood search (VNS) structure called

Move-Best to improve the quality of the initial solution. For every vertex visited in each vehicle route, we check the feasibility that a vertex can be removed from its current position to a better position in the same route to shorten the length of the route. We implement the feasible move solely with the highest decrease in total route length (Divsalar et al., 2014).

Evolution Stage. This stage consists of global search and local search (Liao et al., 2018). We use genetic algorithm (Osman et al., 2005) in global search for exploring a new local space of solutions to add to the solutions' diversity, and the VNS (Mladenović et al., 1997) in local searches for improving the solutions' quality (Parouha et al., 2016). Global search is used in the evolution of request allocation, whereas local search is adopted in the evolution of route planning, thus achieving solutions with a beneficial tradeoff between two conflicting objectives.

Genetic algorithm is commonly used to address optimization and search problems that rely on bioinspired operators, such as crossover and mutation operators (Ahmed, 2016). Crossover is the operator where randomly selected pairs of chromosomes are mated to create new chromosomes, whereas mutation diversifies randomly to alter some position values (genes) of a chromosome (Ahmed, 2016). According to direct coding, traditional crossover and mutation operators cannot ensure the quality and efficiency of optimization at the same time. To solve this problem, we develop an improved crossover operator as follows. (a) A solution in the population is selected as the target parent, which evolves into an offspring by the crossover operator. Another solution selected from the population serves as a crossover parent used to evolve the target parent. (b) Suppose that λ denotes the number of routes in the target parent and β denotes the crossover rate. $[\lambda\times\beta]$ shows that routes selected randomly from the target parent have remained with the offspring ($\lceil x \rceil$ represents the minimum integer greater than x), whereas the other routes are deleted. (3) Requests that already exist in the offspring are removed from the crossover parent, and the remaining vertices in the crossover parent are inserted into the offspring in turn. After the implementation of the crossover operator, the Move-Best structure proposed in the initialization stage**Error! Reference source not found.** is used to further optimize the offspring obtained by the crossover operator.

In global search, a set of offspring generated together with their parents forms a new population P'. Local search aims to find a better solution in P' through individual iteration. Generally, a higher quality solution can generate better offspring by individual iteration. Thus, iterating only for better solutions in P' is reasonable. However, this method may reduce the diversity of samples, which, in turn, may increase the risk of falling into local optimization. Hence, to balance quality and diversity, we utilize the roulette wheel selection rule in the repeated siftings of P' to construct the solution set to be optimized in the local search. The roulette wheel selection rule is based on the selection probability, which is determined by the fitness function (i.e., objective functions). The better the fitness function is, the more likely the solution will be selected. However, our study involves multiple conflicting objectives. Thus, we use the crowded comparison operator proposed by Deb et al. (2002) to design a fitness function. For a detailed illustration of the fitness function, we refer to Martín-Moreno et al. (2018).

VNS has been applied successfully in VRP-related studies (Grangier et al., 2016) on account of its simplicity, robustness, and generality (Hansen et al., 2010). VNS executes the procedure of neighborhood transformation systematically for improved solutions according to several structures, including Insert, Move-Best, Two-Opt, Swap-Best, Extract-Insert, and Extract2-Insert to obtain improved solutions (Divsalar et al., 2014). In light of our study problem, we adopt two neighborhood structures (i.e., Swap-Best and Move-Best) in our approach. Swap-Best exchanges two requests between two routes to reduce operating cost and delay time. Move-Best changes the vehicle visit order of vertices in one route, as mentioned in the initialization stage.

Fig. 1 about here

Fig. 1 illustrates the VNS process with pseudocode. The input of this process is the solution to be optimized (S) and the neighborhood structures (i.e., Swap-Best and Move-Best), then the output of this process is optimal solution S^* (Lines 1–2 in Fig. 1). Initially, parameter k is equal to one (Line 3 in Fig. 1). Lines 4–16 in Fig. 1 show the entire process of VNS. First, we conduct Swap-Best to generate a new solution S'. If S' dominates S, then S is replaced by S' and we return to Swap-Best until a solution that dominates S cannot be found. Otherwise, Move-Best is implemented. The VNS process will not stop until two neighborhood structures are finished, wherein optimal solution S^* is the final output.

Updating Stage. We balance two conflicting objectives by exploring a set of solutions based on Pareto optimality. The Pareto-optimal ϵ refers to a solution from which a feasible deviation to a multi-objective optimization problem brings improvement to one of the objectives and degradation to some other objective (Parkes et al., 2016). All the ϵ are stored in the Pareto-optimal set Θ. Each iteration generates a set of solutions, and only ϵ has a chance to remain for the next iteration. To keep the size of Θ unchanged, the optimal solution search strategy proposed by Zheng et al. (2019) is employed. Details of the optimal solution search strategy are adopted from Zheng et al. (2019).

In each iteration, each solution in P’ generates its offspring. Each solution is replaced by the offspring if the offspring is superior to the parent (solution). In this manner, the quality of the population is improved continuously in each iteration while keeping its size unchanged. Additionally, to avoid the reduction of the diversity of P’ caused by VNS, which increases the risk of falling into local optimization, while maintaining the local search capability of the solution optimization, we introduce a replacement strategy in the updating stage. Each solution in P’ not replaced by its offspring after a predetermined number of iterations ξ is deleted. A new solution generated through the initial solution construction (as mentioned in initialization stage) is placed into P’.

CASE EVALUATION

We secured the collaboration of a large horticulture exposition garden in China (hereafter Horti-Expo Garden in short), and involved the recipients of our innovation, that is, managers and operations experts of the tourism service provider and visitors in our design thinking process from problem framing to experimentation and iteration (Buhl et al., 2019). Together with the managers and technical experts of the service provider, we analyzed the likely party size of each visitor group from a large amount of historical data, which helps us determine the number of visitors for each ride request. In addition to the historical data, with our input, the service provider further conducted a survey among visitors to capture data about pickup and drop-off stops. The information will help us simulate a request by determining the most likely next stop that an individual or a group of visitors would request when they are at a specific point within a tourist site.

The Horti-Expo Garden enjoys a high reputation and attracts a large number of visitors. It received over 1.2 million visitors in 2019. The shuttle bus service provided by the Horti-Expo Garden is the main visitor transport inside the site. The Horti-Expo Garden covers a total area of 10.82 km^2, including nine islands and various POIs. Fig. 2 shows a map of the Horti-Expo Garden, including the road network, shuttle bus stops, and existing bus routes.

Fig. 2 about here

3.1 Identifying the Episode of Tourist Experience for Improvement

At present, 24 identical shuttle buses operate in the Horti-Expo Garden. Eighteen of them are used on weekdays, whereas all 24 buses are used on weekends, holidays, and during event times. Each bus has the capacity of carrying 14 passengers. Three types of services are offered: standard, chartered, and point-to-point. For standard bus service (Fig. 2), 15 shuttle buses are distributed evenly as three groups for three fixed routes. Buses run every 25 minutes (i.e., time from departure to return), and each group (i.e., five shuttle buses) runs a total of 21 round trips per day in winter. Visitors who purchase a standard ticket of 30 RMB are free to get on and off buses as frequently as they like. More convenient services are provided with the other nine shuttle buses. One is the chartered service, which charges 200 RMB per hour. Visitors who avail of the chartered service can travel to any POI at any time. The other is a point-to-point service, where buses run from the West Gate (numbered 1 in Fig. 2) to the Moonlight Ring (numbered 10 in Fig. 2) without stop.

Although the standard bus service is designed to be used by the majority of visitors, only a few of them choose to use the service due to fixed routes with few choices, poor accessibility, and loss of freedom. These limitations are identified as the episode of tourism experience for improvement in the present project (Moscardo, 2017).

3.2 Understanding Visitor Ride Requests

Given that the performance in balancing visitor experience and operating costs is greatly affected by the number of requests, we generate a set of visitor ridership-based requests randomly according to the information obtained from staff and visitors, including the popularity of POIs and the number of fellow passengers in one travel party.

Table 1 shows the information about visitor requests. For example, when the visitor ridership is 100 in one day, 19 requests are generated randomly, where Υ_1 refers to a ride starting at t=55 from ν_{16} to ν_{17} for 2 visitors.

The proposed approach is validated against several existing approaches widely used in VRP. These approaches, which are considered baselines, are the genetic-based algorithm (NSGA-II), particle swarm optimization (M-PSO), and ant colony optimization (M-ACO). We adopt a classic assessment instrument, the inverted generational distance (IGD) proposed by Zitzler et al. (2003), to evaluate the performance of the multi-objective optimization problem related approaches. The better a method performs, the smaller the corresponding IGD values. Then we conduct the Wilcoxon's signed-rank test to further confirm any statistical difference between the IGD of our proposed HA and those of the baseline approaches. The results in Fig. 3 show that the HA exhibits significant improvement over NSGA-II, M-PSO, and M-ACO with the same level of significance ($z = -2.803$, $p = 0.002$).

Fig. 3 about here

The above results show that our approach is more advantageous than several existing approaches. Take the request set as shown in the first line of

Table 1 (visitor ridership = 100, N = 19) as an example. Fig. 4 highlights transport cost in blue and red, respectively, according to our approach and the current approach of the Horti-Expo Garden. In terms of our proposed system, five buses run 32.8 km in total with a delay time of 82 min. By comparison, in the current system of the Horti-Expo Garden, 15 buses (buses are sometimes idle or driven in turns) run 106.6 km in total with a delay time of 410 min. The current system requires thrice the number of buses, thrice the mileage, and fivefold delay time compared with our proposed shuttle bus system.

Fig. 4 about here

The main difference between our proposed system and the current system lies in the different operations in terms of bus departure time and bus route planning. Instead of fixed departure time and fixed routes in the Horti-Expo Garden, we schedule each bus route and departure time flexibly according to the request information. For example, Fig. 5 shows the route for one bus, which starts its trip from the depot and then visits stop numbers in the following order, 11-10-17-4-2-9-5-19-13, successively. Fig. 5 (left) reflects the change in the number of passengers on the bus.

Fig. 5 about here

RESULTS AND DISCUSSION

4.1 A Diversified Scheme of Visitor Transport Operation

Our approach provides diversified and adaptable schemes for the managers of large tourist attractions. Most previous VRP-related studies consider only one solution that can achieve the best objective value. By contrast, we create a set of Pareto solutions on the basis of our approach for managers with diverse managerial traits due to conflicting objectives. Take the request set with 1,000 visitor ridership in

Table 1 as an example. Thirty Pareto solutions for this request set are generated, and the relationship between two objectives are shown in Fig. 6. The Y-axis denotes the total delay time, and the X-axis denotes the overall bus operating cost. Therefore, managers can select one of the solutions to achieve a better tradeoff between two objectives on the basis of the X–Y axis information according to their preferences. For instance, if a manager is seeking to reduce costs, then he may implement the scheme with the first solution, which entails one bus in operation with 31,903 min delay time and a cost of 446 RMB.

Fig. 6 about here

4.2 An Adaptable Scheme of Visitor Transport Operation

A successful visitor transport system should adjust its vehicle routes, the number of vehicles used, and the departure frequency according to different visitor requests at different times (e.g., more requests generated during peak times). Current visitor transport systems within tourist sites generally adjust their operating schemes according to daily visitor ridership. However, we consider more scenarios in this study, that is, different visitor ridership at different times of day. Take three situations, 100, 500, and 1,000 visitor ridership (as shown in

Table 1) in a day, as examples. For each situation, we produce a set of Pareto solutions for managers. To compare the operating performance in different situations, we select the middle solution of each Pareto solution set as a representative. These solutions (marked with arrows in Fig. 7) consider two objectives equally important. For situations with 100, 500, and 1,000 visitor ridership, we assign 4, 7, and 11 vehicles into use, and finally obtain mileage of 33.4 km, 70.9 km, and 109.9 km, respectively.

Fig. 7 about here

IMPLICATIONS AND CONCLUSIONS

Current visitor transport systems in large tourist sites have various problems, such as long waiting time, detours, and inaccessibility. These limitations not only weaken visitor satisfaction but also incur operating costs from inefficient use of resources. Thus, system design is essential for improving the visitor experience and transport sustainability (Vogt et al., 2020).

Drawing inspiration from the sharing economy model (Cachon, 2020), we take the shuttle bus as a representative to design an on-demand, ride-sharing visitor transport system. We adopt the Pareto optimality to balance multiple objectives and develop a three-stage HA that combines population evolution and individual iteration algorithm, and considers the complexity and significance of visitor transport (Zhang et al., 2019). The case study confirmed that our proposed approach greatly improves the transportation of visitors in three key aspects: (a) improving visitor experience by reducing time spent in waiting and vehicle detours; (b) removing unnecessary operating costs by matching the supply of vehicles efficiently with the demand for rides; (c) providing diversified and adaptable transport operation schemes; and consequently, promoting the sustainable development of large tourist sites.

The study has theoretical and practical implications. First, our design is "user-centered;" it focuses on visitors and service providers (Buhl et al., 2019) and their involvement in our design thinking process (Buhl et al., 2019). Hence, our proposed system provides thorough and diverse user support for solving the proposed complex problem (Warren et al., 2018). The system provides timely and speedy movement between POIs, with little waiting and detouring time, thereby enhancing access and mobility of visitors, which are important facets of tourism experience (Tussyadiah, 2020). For operations managers of large tourist sites, our proposed system simplifies their tasks by generating diversified and adaptable routes automatically and by reducing operating costs significantly, thereby strengthening the attractiveness and competitiveness of a tourist site. This contribution is highly significant because, like all public transport systems, passenger experience and operational efficiency are two conflicting objectives where operators need to make a trade-off (Ho et al., 2018). The innovation in this study provides an essential means to resolve this critical problem (Buhl et al., 2019; Downward et al., 2004; Hjalager, 2015; Klewitz et al., 2014). On top of the benefits for visitors and service providers are the positive effects on the environment and the local community because of reduced energy used, traffic, and pollution. Hence, our design has the perceived usefulness of a sustainability-oriented innovation as defined by Garay et al. (2019), that is, it is economically, socially, and environmentally useful.

Second, our design can be widely applied. Use and interaction are essential features of our design (Gretzel, 2011). Just like the systems behind Uber and Lyft, our proposed system allows visitors to send their requests to the visitor transport system through mobile devices. The visitor transport routes are then created according to visitor requests, with consideration of vehicle resources, road network conditions, and geographic distributions of various POIs. Given its usefulness and ease of use, our design can be applied to various tourist sites, such as natural attractions (e.g., Yosemite National Park), theme parks, and resorts (e.g., Universal Parks and Resorts) as well as multiple venues of a mega-event (e.g., Olympic Games, Expo, or large festivals), wherein shuttle buses and other visitor transport are widely used or needed.

Finally, our proposed mathematical model and algorithm are useful for advancing the design of a sustainable mobility system that delivers: (a) superior performance through the combination of population evolution and individual iteration algorithm, (b) high efficiency produced by a multipart chromosome-based direct coding method, and (c) beneficial balance between service quality and energy efficiency.

LIMITATIONS AND FUTURE RESEARCH

With the development of new digital technologies such as IoT, big data, artificial intelligence, mobile Internet (particularly 5G) as well as fully autonomous electric vehicles (Cohen et al., 2019), existing transportation systems will be continuously upgraded and become “smart transportation systems” (Yan et al., 2020). In the future, visitor mobility systems will be “smarter” and more sustainable. However, we are only at the initial stage of a truly smart mobility system, and more research is needed. Future technologies will allow transport planning and vehicle dispatching in real-time, which requires dynamic and deterministic modeling that provides real-time re-optimization (Ho et al., 2018).

Specific to our proposed on-demand shuttle transport system, several future works could further advance the field. First, future attempts in visitor transport scheduling may incorporate stochastic and fuzzy optimization, because uncertain situations are inevitable in reality. For example, visitors may not arrive at the pickup stop at the scheduled time, and vehicles cannot ensure a certain travel time due to possible vehicle damage or road congestion. Second, all the input data in this study are known before request allocation and vehicle route planning, which is unrealistic during vehicle operations. Hence, the input data must be revealed or updated, over time, in future exploration due to the continual arrival of visitor requests. Such iteration brings an unbounded planning horizon but significant improvement in the utilization of vehicle capacity. Finally, detailed circumstances should be considered, such as the vehicle preferences (e.g., smoke-free vehicles instead of smoking vehicles, and open vehicles instead of closed vehicles), road network structure, types of POIs, and geological landform.

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Table 1 Request information

Visitor ridership	Set of requests	Requests
100	$\{Y_1, Y_{2, \ldots,} Y_{19}\}$	$Y_1=\{\nu_{16}, \nu_{17}, 2, 55\}, \ldots, Y_{19}=\{\nu_{13}, \nu_2, 3, 33\}$
200	$\{Y_1, Y_{2, \ldots,} Y_{44}\}$	$Y_1=\{\nu_5, \nu_{11}, 3, 13\}, \ldots, Y_{44}=\{\nu_4, \nu_{19}, 7, 30\}$
300	$\{Y_1, Y_{2, \ldots,} Y_{57}\}$	$Y_1=\{\nu_9, \nu_{10}, 4, 10\}, \ldots, Y_{57}=\{\nu_4, \nu_5, 2, 18\}$
400	$\{Y_1, Y_{2, \ldots,} Y_{76}\}$	$Y_1=\{\nu_3, \nu_6, 7, 8\}, \ldots, Y_{76}=\{\nu_7, \nu_1, 7, 20\}$
500	$\{Y_1, Y_{2, \ldots,} Y_{100}\}$	$Y_1=\{\nu_{16}, \nu_{17}, 2, 55\}, \ldots, Y_{100}=\{\nu_{13}, \nu_2, 3, 33\}$
600	$\{Y_1, Y_{2, \ldots,} Y_{127}\}$	$Y_1=\{\nu_{15}, \nu_1, 6, 59\}, \ldots, Y_{127}=\{\nu_{14}, \nu_{10}, 6, 36\}$
700	$\{Y_1, Y_{2, \ldots,} Y_{142}\}$	$Y_1=\{\nu_2, \nu_{17}, 6, 59\}, \ldots, Y_{142}=\{\nu_5, \nu_{17}, 5, 22\}$
800	$\{Y_1, Y_{2, \ldots,} Y_{157}\}$	$Y_1=\{\nu_6, \nu_{12}, 4, 54\}, \ldots, Y_{157}=\{\nu_{12}, \nu_{16}, 5, 22\}$
900	$\{Y_1, Y_{2, \ldots,} Y_{172}\}$	$Y_1=\{\nu_{19}, \nu_4, 5, 23\}, \ldots, Y_{172}=\{\nu_{17}, \nu_6, 7, 30\}$
1,000	$\{Y_1, Y_{2, \ldots,} Y_{205}\}$	$Y_1=\{\nu_{13}, \nu_{12}, 4, 49\}, \ldots, Y_{205}=\{\nu_1, \nu_{12}, 5, 33\}$

The variable neighborhood search

```
Input: S; Swap-Best, Move-Best;
Output: S*;
Set k=1;
while {k≤2}
    if {k=1} then
        Swap-Best (S) to generate S′;
    else
        Move-Best (S) to generate S′;
    end if
    if {S′ ≻ S} then
        Set S=S′;
    else
        Set k=k+1;
    end if;
    S*=S;
end while;
Return S*.
```

Figure 1. VNS Process

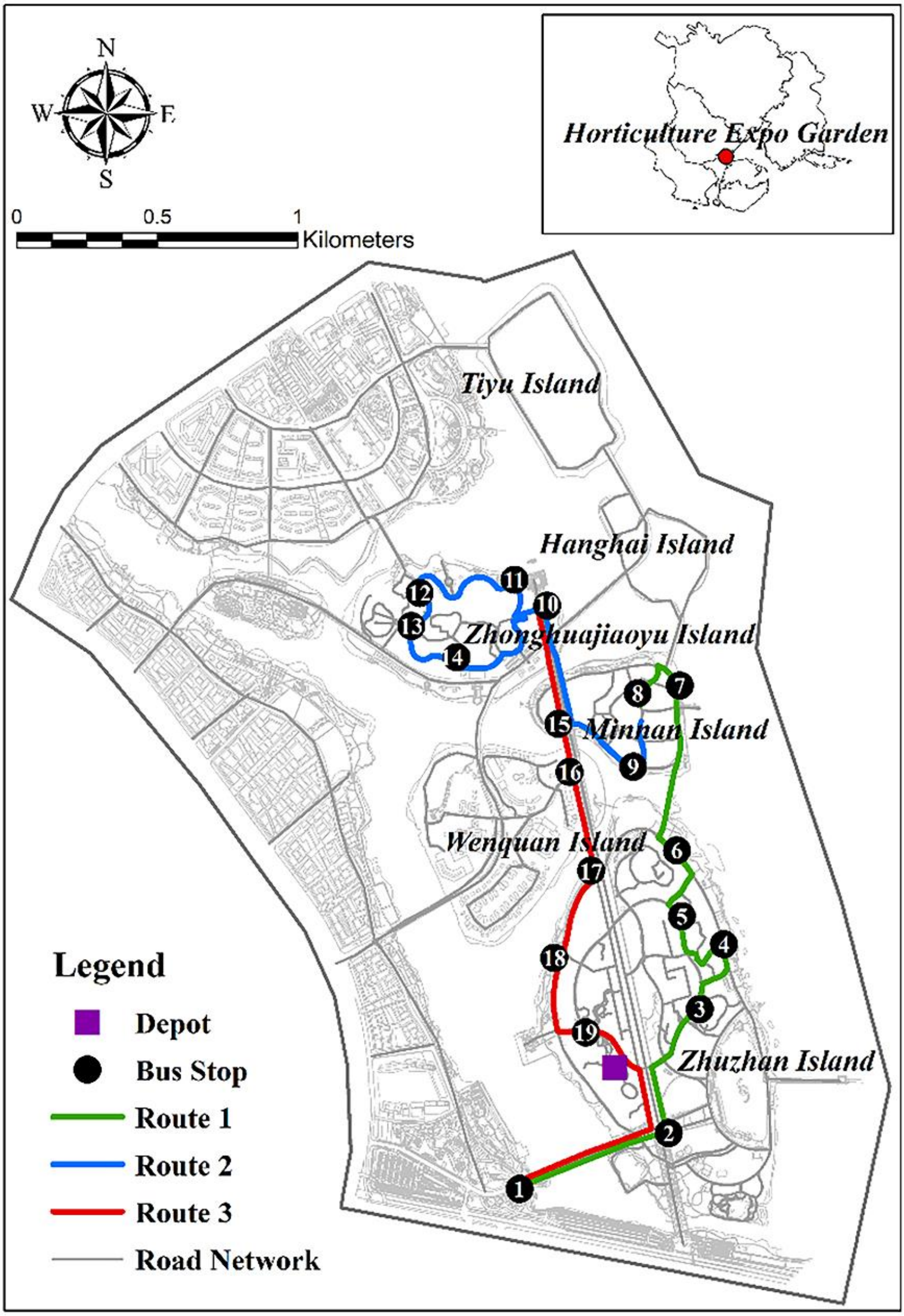

Figure 2. Map of Horti-Eexpo Garden

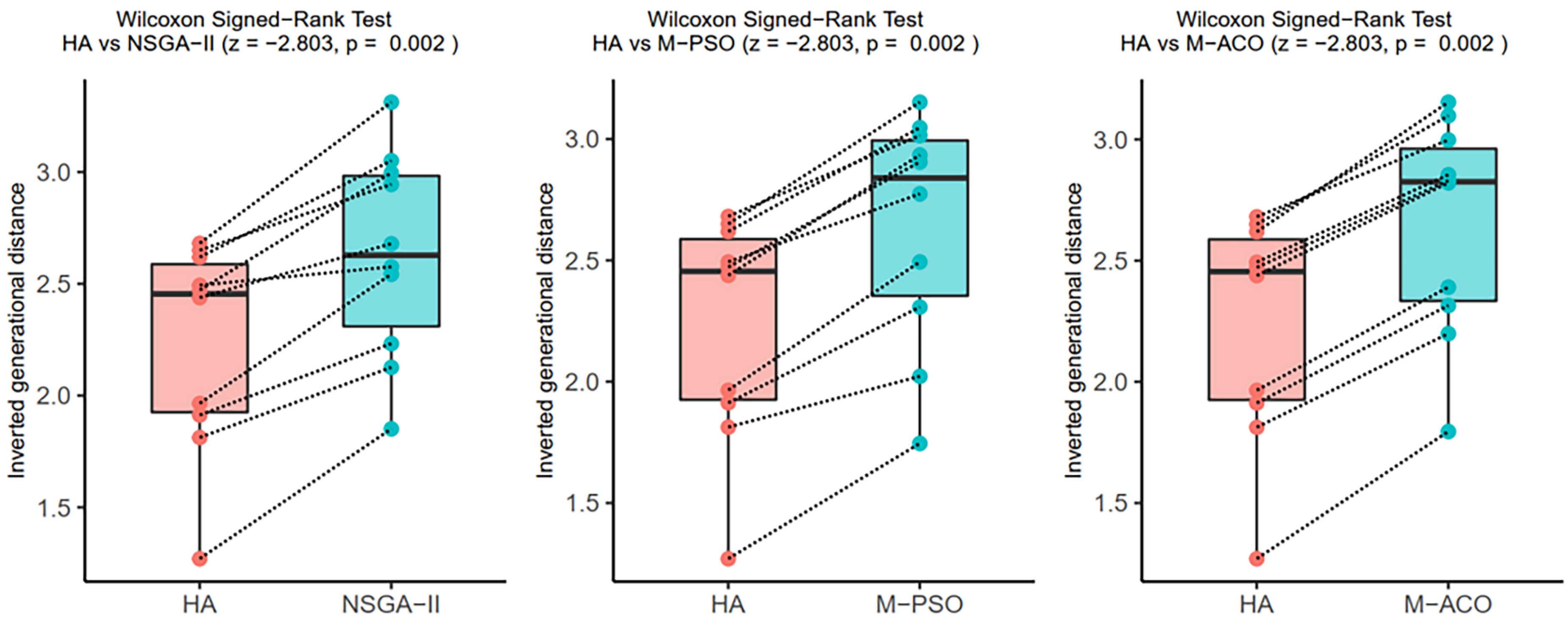

Figure 3. WSR Test Results

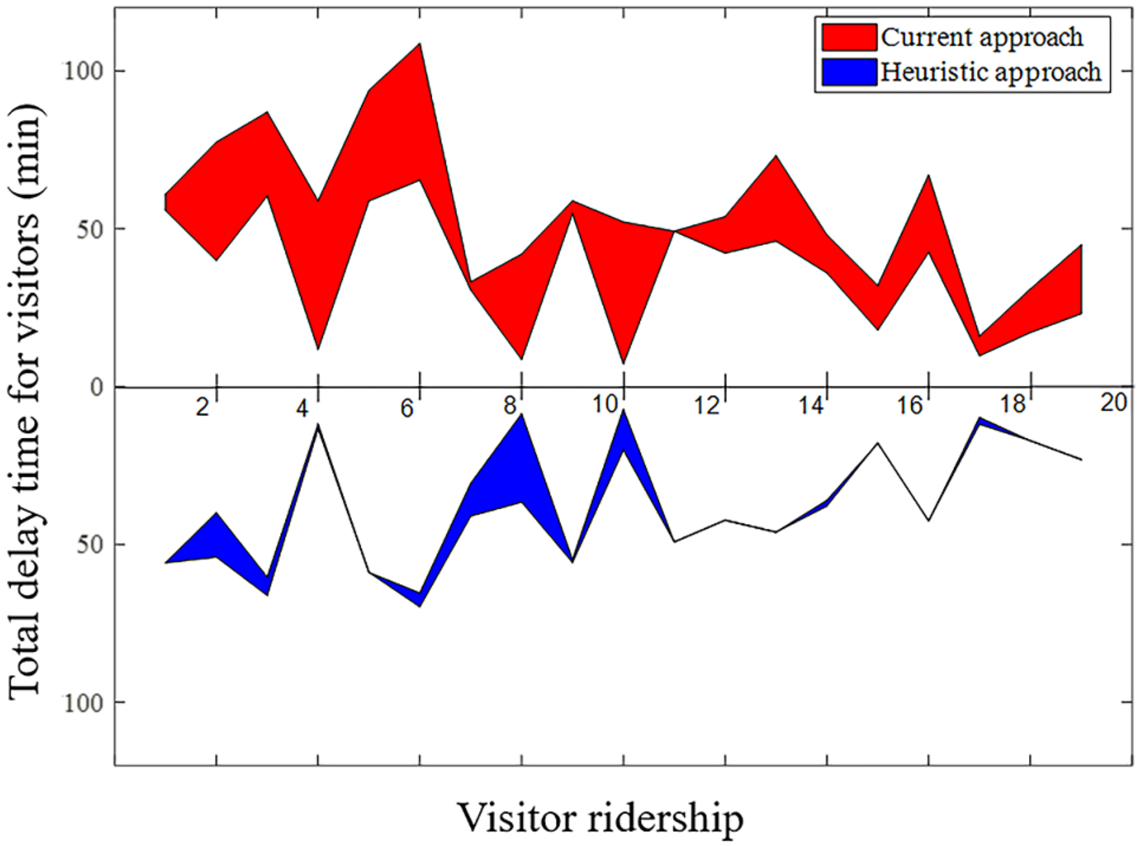

Figure 4. Total Delay Time for Each Request

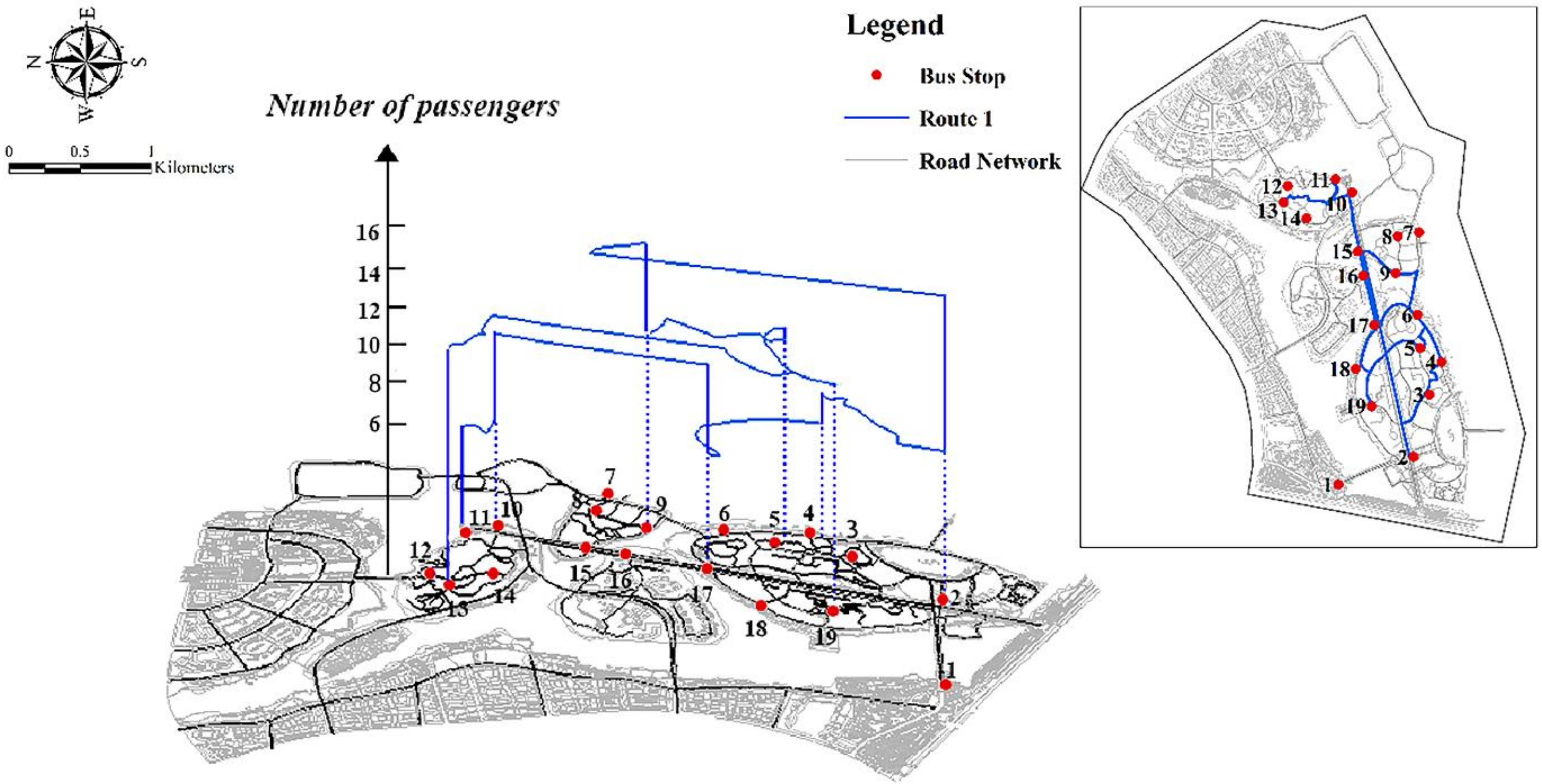

Figure 5. Sample Route for One Bus

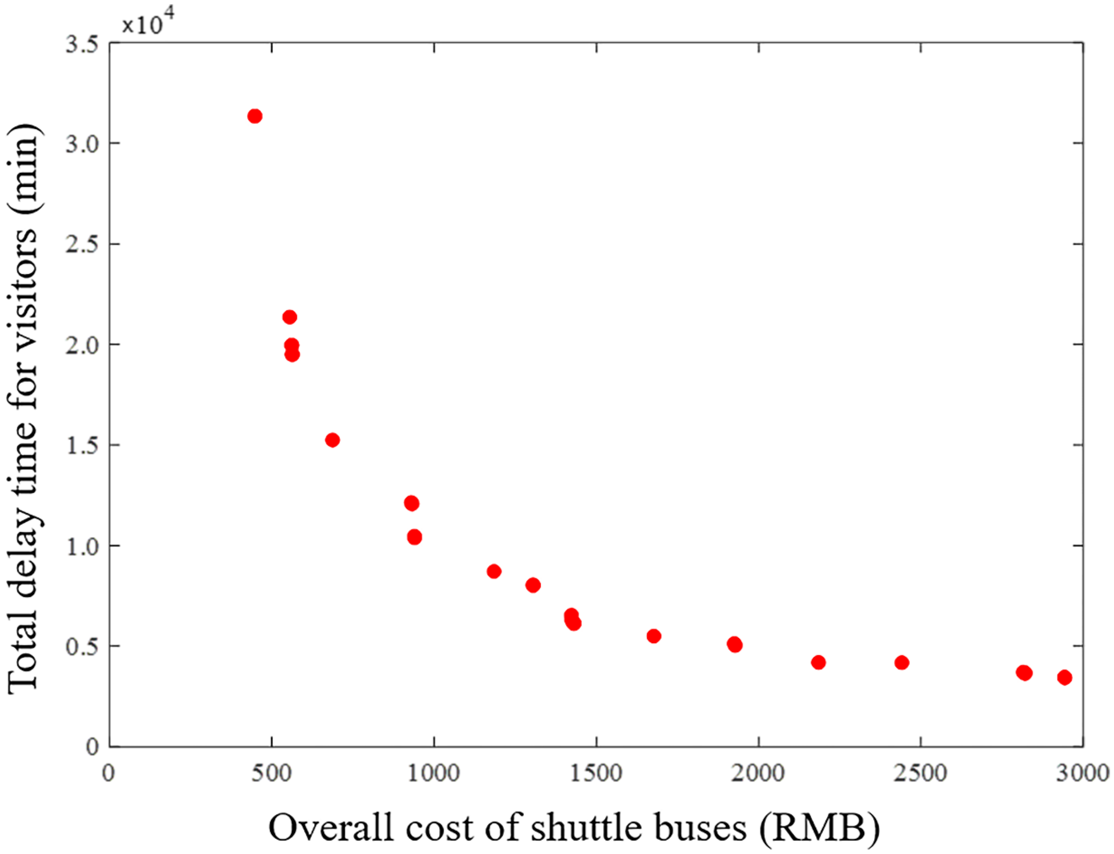

Figure 6. Solutions with Relationships between Two Objectives