

Ruiz-Meza, José; Montoya-Torres, Jairo R.

Article

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A systematic literature review for the tourist trip design problem: Extensions, solution techniques and future research lines

José Ruiz-Meza^{a,b,*}, Jairo R. Montoya-Torres^a

^a Facultad de Ingeniería, Universidad de La Sabana, km 7 autopista norte de Bogotá, D.C, Chía, Colombia

^b Programa de Ingeniería Industrial, Corporación Universitaria del Caribe, Sincelajo, Colombia

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ABSTRACT

The tourism sector represents an opportunity for economic growth in countries with tourism potential. However, new trends in global tourism require efficiency in tourism supply chain management. One of the main changes is the trend of personalized tourism, which includes the management of itineraries by the tourist. The tourist trip design problem is the problem associated with personalized trip design. This problem has been modeled in the field of Operations Research in different ways, being the Orienteering Problem the most widely applied in the specialized literature. The objective of this paper is to carry out a systematic review of the contributions made to the tourist trip design problem. A review taxonomy is proposed to analyze the main variants, objectives, and solution techniques. Also, future research lines are analyzed and proposed to enrich the literature and provide new solutions to real problems.

1. Introduction

Tourism is one of the industries that has shown great growth over the years as a source of income and development of new technologies [1]. This industry generates a large direct and indirect impact on the world economy and promotes local development through the creation of jobs and the sustainable use of the resources available in the regions [2,3]. However, tourism development is limited by the infrastructure and transport network in the tourist area. Therefore, transportation plays a crucial role in terms of accessibility to points of interest (POI) and in some cases defines the attractiveness of these sites [3,4]. Also, there are restrictions on supply and access to information for supply chain actors; generally, tourist packages and static routes are designed, which show the lack of tools that allow planning the travel itinerary with real-time information [5]. All these aspects limit the ability to respond positively to the shift from mass tourism to an independent travel market under the new orientation of personalized tour itineraries [6–8].

The problem associated with the construction of personalized tourist itineraries is named the Tourist Trip Design Problem (TTDP), which was introduced in the literature by Vansteenwegen and Van Oudheusden [9]. The TTDP consists of planning a tourist travel itinerary to visit various POIs without exceeding restrictions associated with time, transportation, budget, tourists' preferences, among others [6,8–12].

The TTDP plays a critical role in improving the travel experiences of tourists, the success and quality of tourist attractions, increasing economic benefits, and improving the competitiveness of the tourism supply chain [8,12–15]. With the application of techniques to solve the TTDP, personalized tourist routes are calculated, which become the basis for the construction of applications and intelligent mobile guides (MTG) [10,16,17]. Likewise, the information of all the actors in the chain is organized and structured to improve access to tourist routes and facilitate decision-making, even under conditions of uncertainty [9,18].

The main objective of this paper is to conduct a systematic review and analysis of the literature on the main contributions that have been made to the TTDP. In the literature, previous publications have already reviewed some aspects of the tourist route design problem, such as the application of metaheuristics, by Vansteenwegen et al. [19]. Moreover, Souffriau and Vansteenwegen [20] discussed the functionalities and considerations presented by travel planning systems. Some reviews focused on the application of variants of the Orienteering Problem (OP) to model the TTDP. For instance, Gavalas et al. [21] review the different OP variants used to model the TTDP and the applied solution techniques. Shcherbina and Shembeleva [22] conducted a literature review that includes models applied to generate tourist routes such as the OP, the Cruise Itinerary Problem, and the One-Period Routing Bus Problem. Gunawan et al. [16] perform a literature review on the different variants

* Corresponding author at: Facultad de Ingeniería, Universidad de La Sabana, km 7 autopista norte de Bogotá, D.C, Chía, Colombia.

E-mail addresses: jose.ruizm@cecar.edu.co (J. Ruiz-Meza), jairo.montoya@unisabana.edu.co (J.R. Montoya-Torres).

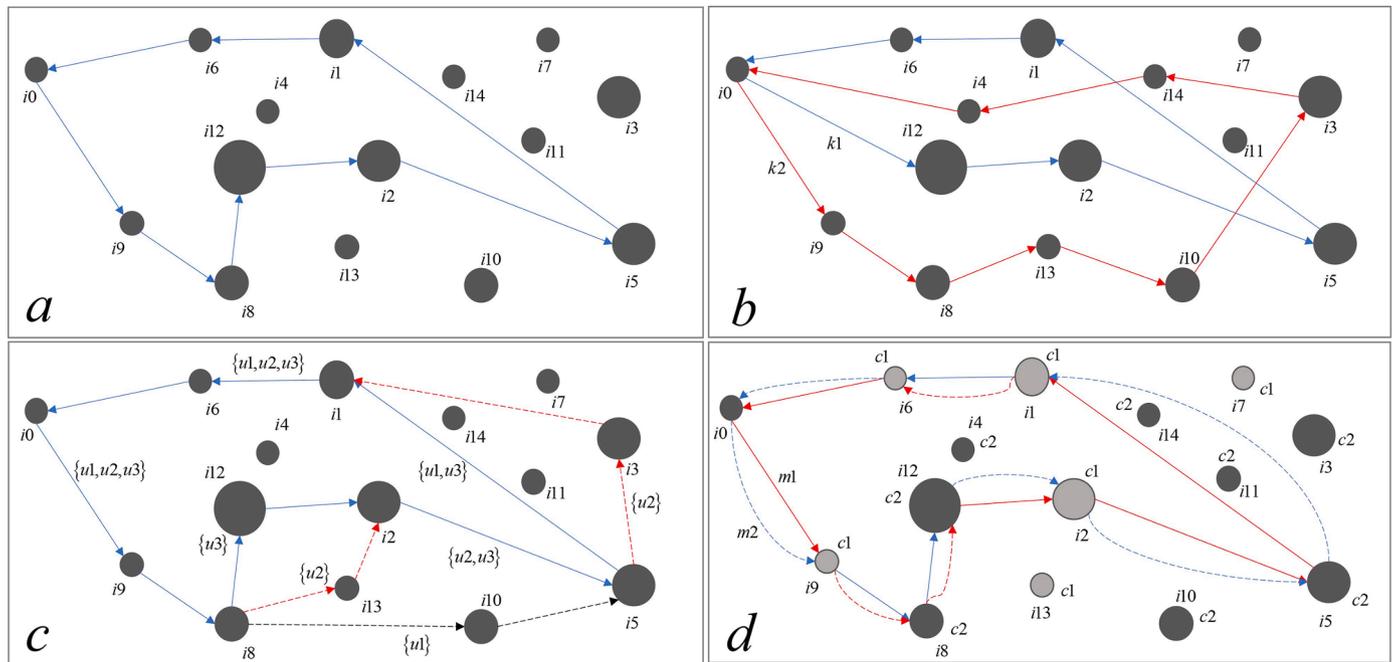


Fig. 1. Illustrative representation of the TTDP and some variants (a. basic TTDP, b. with multiple routes, c. with heterogeneous preferences, and d. multiple transport modes).

and solution techniques of the OP and the implementation to solve, among others, the TTDP problem, the mobile-crowdsourcing problem, and the theme park navigation problem. Lim et al. [23] reviewed the developed tools found on the web, the type of information, and data in tourism itinerary planning. The authors work on a smaller scale on the application of Operations Research (OR) to itinerary planning. Similarly, Herzog et al. [24] conduct a focused review of tourism recommender systems and do not directly address the representation of the problem. Finally, Vansteenwegen and Gunawan [25] carried out a state-of-the-art review of the different benchmark instances used in the OP with time windows (OPTW) and the Team Orienteering Problem with Time Windows (TOPTW), which includes applied data for TTDPs. The authors detail different papers in which exact, and metaheuristic techniques have been applied to solve the OPTW and TOPTW, even in tourism problems.

The current paper builds upon those previous reviews by studying the works published on the TTDP from its first appearance in 2007 until February 2021. This paper also considers some works dating back to 2000, which present interesting contributions to the development of problems associated with the construction of routes for tourism. The documents found in the period 2010–2021 represent 86.75% of this review, a percentage that demonstrates a significant quantity of documents after the publication period of the review conducted by Souffriau and Vansteenwegen [20]. Compared to this paper, our review presents a different taxonomy that extends the time of study and covers the last ten years of contribution. Similarly, the number of documents in the period 2014–2021 represent 64.7%, which updates the revision made by Galvalas et al. [21] and 58.82% in the period 2015–2021 with reference to the work of Gunawan et al. [16]. In our paper, we extend these reviews by focusing on recent contributions to the literature on the use of new variants (e.g., green, fuzzy, variable duration, packages) and algorithms (e.g., hybrid approaches, firefly algorithm) not included in previous reviews. On the other hand, a survey of the main steps of the metaheuristics used to solve the TTDP, the solution times, and the comparison with other techniques in the literature and the best-known solutions are summarized. In this sense, our taxonomic framework divides the works according to the objectives, i.e., single-objective, and multi-objective problems. Additionally, we review the variants

developed according to the aims and the solution techniques implemented (exact, heuristic, and metaheuristic).

In addition, a different taxonomic framework is presented to detail the modeling approaches that have been used for travel planning in the context of tourism based on the Operations Research techniques. Our paper extends the review conducted by Shcherbina and Shembeleva [22] since we additionally discuss the applied variants and solution techniques, from which an analysis is carried out to outline future research directions. The remainder of this paper is structured as follows. Section 2 presents the generalities about the TTDP. Section 3 describes the review methodology. Findings of the review process according to the taxonomic analysis are shown in Section 4. Section 5 discusses the findings and outlines some opportunities for future research. Finally, conclusions are given in Section 6.

2. The tourist trip design problem

Planning a tourist trip is a complex process [11,12,26–28] due to the different planning conditions and the numerous options of tourist products associated with sun and beach, cultural, religious, nature, and other activities [29]. McKercher [30] groups tourism products into five major families: business, pleasure, human endeavor, personal quest, and nature.

The aim of the TTDP is to plan tourist routes so that the tourist can visit different points of interests (POIs) without exceeding a budget [6, 8–12]. A POI is a node or destination within a tourist route that offers something useful, interesting, or necessary for a tourist’s travel experience [1,31–33]. Planning is done based on POI opening and closing times, available transportation, budget, distances and travel times between POIs, values assigned to POIs, individual tourist preferences, among other constraints [8,19,34–36].

For an illustrative example of the TTDP, let us consider a tourist u who wishes to visit a set of POIs $i = \{0,1,2,\dots,I\}$. Each POI is represented by circles on a plane (see Fig. 2). $i=0$ is start and end node of the route. Each POI has a benefit for the tourist. In our example, the profit represents the size of the circle. That is, the larger the circle, the greater the profit generated by the POI. Tourists do not need to visit all POIs due to time restrictions, tourist’s monetary budget, among others. Tourists

Table 1
Number of documents obtained per equation and database.

	Scopus	ScienceDirect	Springer	Sage	Emerald	Web of Science	Total
First query	54	51	36	1	1	14	157
Second query	2	35	20	0	1	2	60
Third query	2	16	11	0	0	1	30

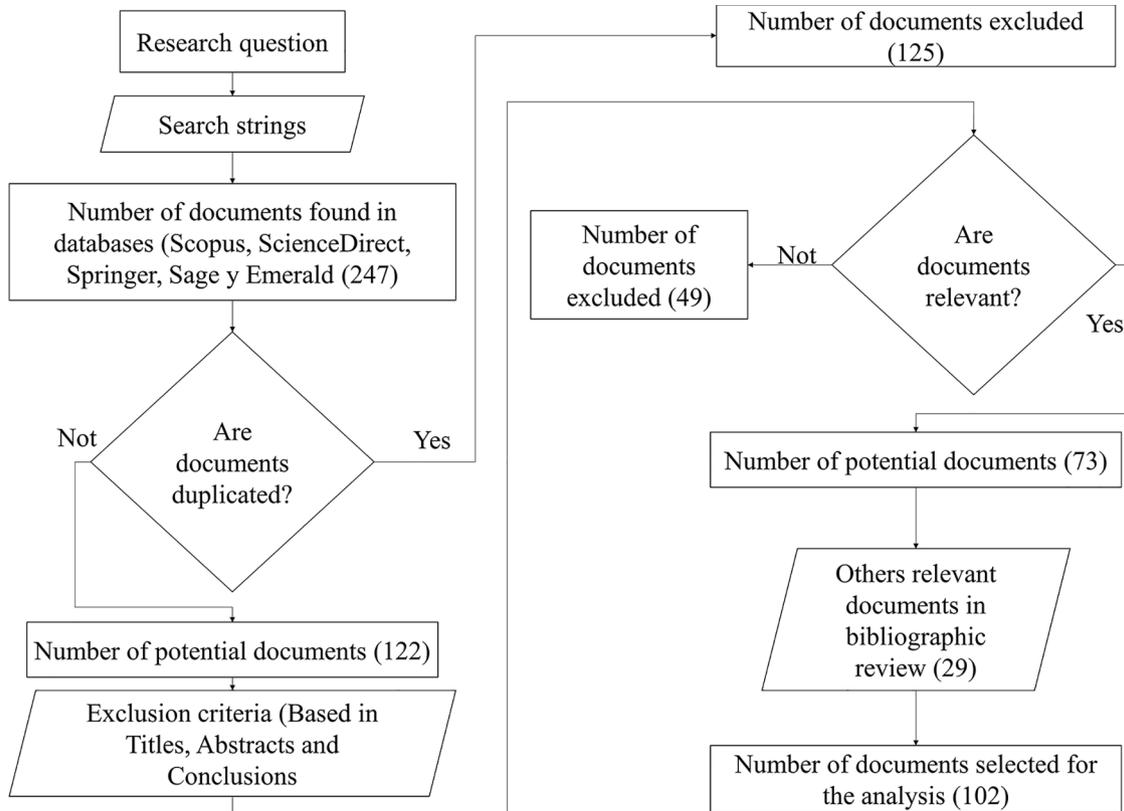


Fig. 2. Flow chart of review process.

should try to visit the POIs that generate the most benefit. Several $k = \{0, 1, 2, \dots, K\}$ routes can be generated, which can represent several days for the itinerary. To explain different examples of the TTDP, we consider an instance with 14 nodes, two possible routes or scheduling days, three tourists, two categories of POIs, and two modes of transportation. An example of a tourist route that considers the route $\{i_0, i_9, i_8, i12, i2, i5, i1, i6, i0\}$ is shown in Fig. 1a. However, there may be some variations in the itinerary. A variant is to plan for two or more days (multiple routes). Thus, the itinerary is planned so as not to repeat visits to POIs on $k1$ (first day) and $k2$ (second day) (see Fig. 1b). On the first day, route $k1 = \{i_0, i12, i2, i5, i1, i6, i0\}$ is performed, and on the second day, route $k2 = \{i_0, i9, i8, i13, i10, i3, i14, i14, i0\}$ is performed.

The construction of the itinerary can also be done for a tourist group $u = \{1, 2, 3, \dots, U\}$. Additionally, each tourist may have specific preferences over some POIs different from other tourists (heterogeneous preferences). In this case, a route is constructed to allow tourists to visit some POIs different from other tourists (see Fig. 1c). Tourists $u1, u2,$ and $u3$ travels together on route $\{i_0, i9, i8, i15, i1, i6, i0\}$. However, in arc $\{i8, i15\}$ tourist $u1$ travels $\{i8, i10, i15\}$, tourist $u2$ travels $\{i8, i13, i12, i15\}$, and finally, tourist $u3$ travels $\{i8, i12, i2, i15\}$.

On the other hand, POIs can be grouped into a set of categories $c = \{1, 2, 3, \dots, C\}$ (e.g., sun and beach, museums) (Clustered-POIs). Therefore, the category of POIs to be visited can be established. It is even possible to force the inclusion of POIs to the route regardless of the category (mandatory visits). Similarly, there may be a set of transport

modes $m = \{1, 2, 3, \dots, M\}$ available to travels between arcs. These considerations for the itinerary are shown in Fig. 1d. The route (red lines) prioritizes cluster $c1$. However, it is obliged to include the POIs $i8, i12,$ and $i2$, regardless of whether they belong to cluster $c2$. In addition, the route selects the following modes of transport in sequence to perform each arc: $\{m1, m2, m2, m1, m1, m1, m2, m1\}$.

The TTDP has been proven to be NP-hard [12,37,38]. This complexity means that heuristic or metaheuristic algorithms are mostly used to provide good solutions in reasonable computational times [39]. Also, the solution techniques applied to the TTDP are used as a starting point for the design and development of various intelligent tools such as electronic tourist guides and advanced digital applications that facilitate tourist decision-making [40,41]. There are different online tools and applications for tourism planning such as eCOMPASS, TourRec, e-Tourism, City Trip Planner, EnoSigTur, Scenic Athens, TripBuilder, CT-Planner, TripAdvisor, DieToRec, Heracles, TripSay, among others. A more detailed review of these types of tools can be found in [23,24, 42–44].

3. Review methodology

This paper followed the principles of a systematic literature review (SLR), which means that a protocol is defined to reduce possible sources of bias arising from authors making idiosyncratic decisions at different stages of the review [45]. The quality of the review depends on the rigor

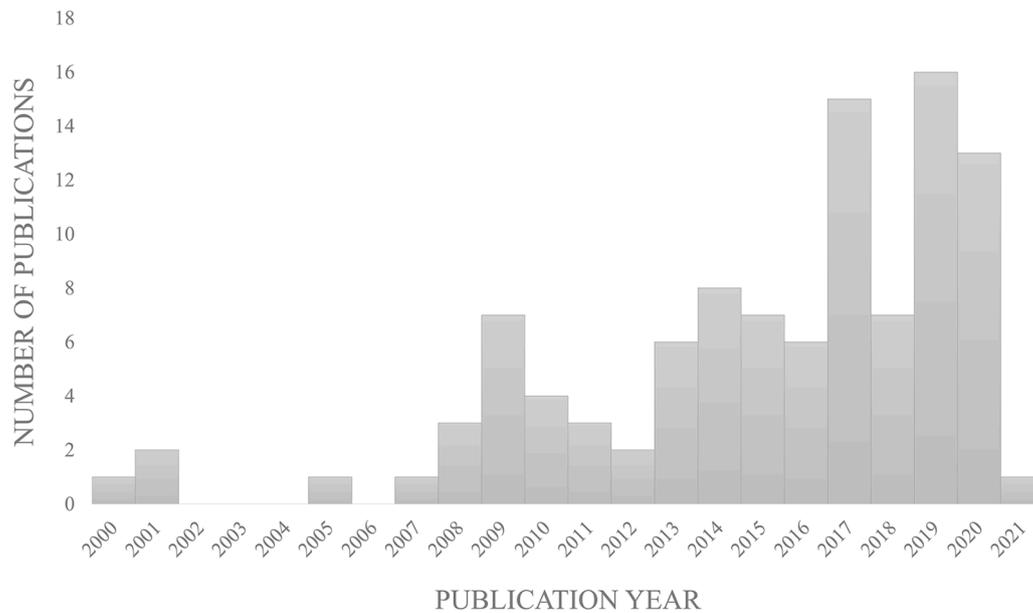


Fig. 3. The number of published documents by year.

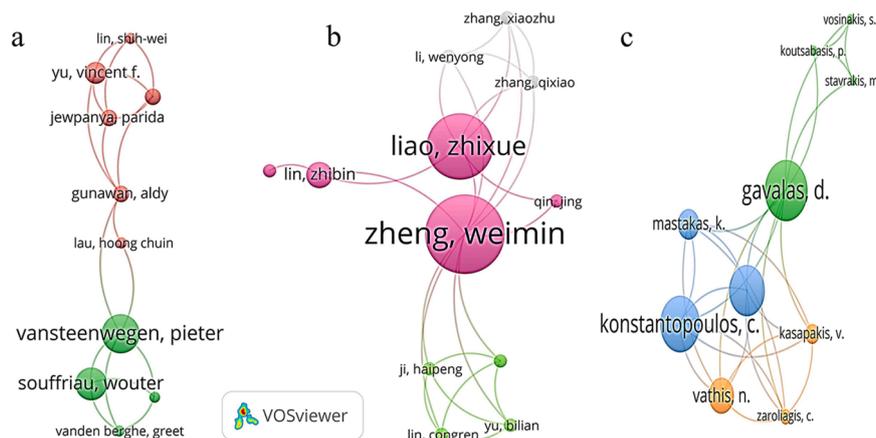


Fig. 4. Co-authorship networks for authors Vansteenwegen-Souffriau, Zheng-Liao, and Konstantopoulos-Gavalas.

of the process to find many documents associated with the research questions [46]. The TTDP can be approached from operations research under different modeling approaches. This leads to the research questions: *How is the tourism trip design problem modeled? What are the main variants applied in the TTDP?* Likewise, the TTDP aims to satisfy the requirements of tourists, so it is pertinent to analyze the models' objectives and solution strategies.

The TTDP aims to maximize the total score obtained in the route, which is associated with each POI [47]. However, problem conditions may suggest applying more than one objective at a given time. Both single-objective and multi-objective models are observed in the literature on TTDP applications. Generally, the objectives of this type of problem are: maximize the total score associated with the visit to each POI [35,36,39,40,48,49], maximize the scores according to the POI category [50], maximize the score considering multimodal transport where the weights of the arcs used and the waiting time are minimized [51], minimize the time spent on the route [52], among others. Considering that there are different objectives that the TTDP can pursue, the following research questions guide this purpose: *What objectives does the TTDP address? What are the solution techniques applied in the TTDP?* In addition, under realistic conditions, there is a lot of uncertain information, which leads us to examine: *How have TTDPs been addressed under*

uncertainty? Finally, with this analysis, we consider identifying trends on the TTDP. Therefore, we reviewed the suggestions of the work on future lines and the reviews made in previous works to identify some established bases and taxonomy used. Thus, we formulate our final research question: *What are the future research lines to expand the TTDP literature?* Based on this, we constructed three search equations that define the interest of the review:

- Query 1: "tourist trip design problem".
- Query 2: ("tourist trip design problem" AND (survey OR review)).
- Query 3: ((Multiobjective AND "tourist trip design problem") OR ("tourist trip design problem" AND uncertainty)).

The queries were applied in the main indexed databases such as Scopus, Science Direct, Springer, Web of Science, Sage, and Emerald to obtain a greater number of publications. In addition, for this review, we considered (i) all publications up to February 15–2021, (ii) only research articles, book chapters, conference papers, and review articles, and (iii) only publications in English. The first query covers the problem in a general way to include modeling approaches, variants, solution techniques and to obtain an overview of future research lines. Next, the second query limits the search to reviews conducted to analyze applied

taxonomies. Finally, the third query refines the interest to identify paper dealing with multiple objective functions and uncertainty, while single-objective models are contained in the first query. Table 1 shows the number of documents per query and database.

Overall, a total of 247 documents were found, of which 125 were excluded due to duplication, resulting in a total of 122 documents. Afterwards, titles, abstracts, and conclusions of all these documents were screened to determine whether they fit within the scope of this review. A total of 49 documents was excluded. Then, in an additional step, the references cited in the selected documents were reviewed and 29 other relevant documents were added. In this regard, the review is based on a total of 102 short-listed documents, containing 18 book chapters, 51 journal articles, 5 review articles, and 28 conference papers/proceedings. The flow chart of the review process is detailed in Fig. 2.

Based on the research questions, a taxonomy scheme for the literature on TTDPs is defined. The taxonomy is divided into categories and subcategories. The first category corresponds to the review of the contributions in terms of objectives developed. The structure is built upon problems that consider single objective and multiple objectives. The subcategories in both categories are (i) applied variants, highlighting uncertainty variants and tourist groups (ii) and solution techniques (exact, heuristic, and metaheuristic).

4. Findings

4.1. Publications over time and network of principal authors

A first outcome of this review is the description of the number of publications per year (see Fig. 3). In general terms, an exponential grow of the number of papers per year is observed, with considerable number of contributions appeared in the years 2017, 2019, and 2020. Over these years, there is an average of 15 publications/year. In addition, based on the review of the main databases outlined before, the main authors who have contributed to the specialized literature on the TTDP were identified. A network of authors is constructed with the help of the VOSviewer software [53]. There are several clusters of authors who contribute to the literature, but it does not show a working relationship between all of them. The most relevant clusters are shown in Fig. 4.

4.2. Modeling approaches for the design of tourist routes and itineraries

The itinerary design consists of the scheduling of visits to different POIs on a closed or open route (i.e., starting and ending at the same node, or starting and ending at different nodes, respectively) [22]. Different types of modeling approaches can be applied for route planning. One of the first used modeling approaches was the use of the well-known Traveling Salesman Problem (TSP). Although the TSP can be seen as effective starting point for solving tourism routing problems, there are several aspects that it does not consider such as activity selection, accommodation, multiple objectives, and tourist preferences [54]. These aspects are included by Godart [55] obtaining the Trip Planning Problem (TPP), which aims at designing a one-day tour that maximizes the total of all sites visited.

Another problem associated with the construction of tourist routes is the Cruise Itinerary Problem, introduced by Leong and Ladany [56]. This problem defines the construction of the best route for a cruise ship departing from a base port, making a tour with several stopovers (set of places and routes) and returning to the home port at the end of the tour. The speed of the cruise in each arc should allow tourists to appreciate the scenery, marine life, among other aspects of certain areas. Deitch and Ladany [57], work on the One-Period Bus Touring Problem (BTP), which consists of scheduling a set of routes to visit tourist sites in a way that maximizes the tourist's entertainment and considering cost, distance, and time. Unlike the Cruise Itinerary Problem, the BTP is focused on the scenic routes and not on the stopovers the travelers make on a cruise ship. In the same line of bus travel, the City Bus Tour Problem (CBT) is

used to represent a city bus service that provides travel along tourist routes while minimizing operation times and costs [58].

Brilhante et al. [59] work on the Trip Cover Problem that considers route building for tourists who visit an area generally for the first time and do not know the times and duration of the trip in each POI. The problem is modeled using the Generalized Maximum Coverage (GMC) problem. Yu et al. [52] propose the Optimal Tourist Problem (OTP), which is modeled using two approaches. The first one is the Reward-Maximizing Tourist (RMT) where the total information collected from POIs is maximized, while the second approach is the Budget-Minimizing Tourist (BMT) which aims at minimizing the time spent on the tour to increase the final obtained reward. Likewise, in [21] emphasizes some variants of the VRP that can model the TTDP, such as the Distance Constrained Vehicle Routing Problem (DVRP) and the Minimum Path Cover Problem (MPCP). DVRP allows to compute a set of routes of minimum cardinality covering all nodes without exceeding a travel distance constraint. This model can be applied to determine the number of days to complete an itinerary without exceeding the daily time available. Unlike the DVRP, the MPCP can start at the depot and end at two different nodes [21,60].

For the TTDP, the most basic modeling approach is the OP [9,22]. The OP can be considered as a selective routing problem to determine the order and set of nodes to visit to maximize the benefit without exceeding given budget and time. The OP is a combination of the knapsack problem (KP) and the TSP [16,41,61] associated with the sport of "orienteering"; in this sport, a group of people using a map and a compass must move around an area starting from a control point to find and visit other points scattered in the area in a given time [62]. The winner is the person or team that achieves the highest score within the defined time when returning to the initial checkpoint (each place visited represents a score) [47,63]. An extension of the OP is the Team Orienteering Problem (TOP) [39], which differs from the OP by considering the construction of several routes simultaneously. The OP and TOP variants have been used in the literature to represent tourism problems and other logistical and defense problems [64]. Based on [65], the formulation of TOP as the main TTDP modeling approach is as follows. Let us consider a directed graph $G = (V, A)$ where $V = \{1, 2, 3, \dots, i\}$ corresponds to the set of vertices and $A = \{(i, j)\}$ is the set of arcs. $V = 0$ is the starting node. Each node i has an associated s_i score. Unlike the TSP, not all nodes must be visited, and the construction of various routes $k \in K$ is considered. The start and end node of the route are fixed. There is a travel time matrix t_{ij} . The route must not exceed the maximum available time budget T_{max} . Binary variable x_{ijk} takes value of 1 if a trip is performed on the arc (i, j) belonging to the route k . Each vertex i can be included in only one route. Binary variable y_{ik} takes value 1 if a vertex i is included in route k , 0 otherwise. Finally, the variable u_{ik} denotes the position of the vertex i in the path k , when included. The integer problem formulation is as follows.

$$\max \sum_{i=1}^{N-1} \sum_k^K s_i y_{ik} \tag{1}$$

$$\sum_{j=1}^N \sum_k^K x_{ojk} = \sum_i \sum_k^K x_{iNk} = K \tag{2}$$

$$\sum_k^K y_{ik} \leq 1; \forall i = 1, \dots, N - 1 \tag{3}$$

$$\sum_i^{N-1} x_{ihk} = \sum_{j=1}^N x_{hjk} = y_{hk}, \forall h = 1, \dots, N - 1, \forall k \in K \tag{4}$$

$$\sum_i^{N-1} \sum_{j=1}^N t_{ij} x_{ijk} \leq T_{max}; \forall k \in K \tag{5}$$

Table 2
Summary of percentages by type of objective and solution techniques.

Type	Percentage	Solution techniques	Percentage	Modeling approach	Percentage
Single objective	67.64%	Exacts	15.54%	OP - TOP	79.66%
		Heuristics	26.53%	Others	20,34%
		Metaheuristics	57.93%		
Multi objective	24.5%	Exacts	12%	OP - TOP	48%
		Heuristics	20%	Others	52%
		Metaheuristics	68%		
Reviews	7.86%				

$$2 \leq u_{ik} \leq N; \forall i = 1, \dots, N, \forall k \in K \tag{6}$$

$$u_{ik} - u_{jk} + 1 \leq (N - 1)(1 - x_{ijk}); \forall ij = 1, \dots, N, \forall k \in K \tag{7}$$

$$x_{ijk}, y_{ik} \in \{0, 1\}; \forall ij \in N, \forall k \in K \tag{8}$$

Equation (1) maximizes the collected score. Constraints (2) ensure that the path starts at vertex 0 and ends at N . Constraints (3) ensure that a vertex belongs to only one path. Constraints (4) ensure flow. Constraints (5) ensure that the time budget is not exceeded. Constraints (6) and (7) avoid sub-tours. Finally, constraints (8) define the nature of the variables.

Another form of tourism is carried out using bicycles as a mode of transportation. Verbeeck et al. [66] apply an extension of the OP to solve the Cycle Trip Planning Problem (CTPP). In this problem, the benefit is not in the POIs but in the arcs. Therefore, the Arc OP (AOP) variant is used to model it. The Prize-Collecting Rural Postman problem (PRPP) is another approach that can be applied to model TTDP problems that present arc rewards by maximizing the difference between profit and travel cost [21,67]. In addition, for mountain biking if a path length constraint is established, another modeling approach that can be implemented is the Outdoor Activity Tour Suggestion Problem (OATSP) [68].

On the other hand, the Vacation Planning Problem (VPP) defined by Gavalas et al. [69] is an extension of the TTDP that includes a suggestion of destinations, hotel zones, and distribution of days of stay in the tour. The VPP calculates the number of days the tourist should spend in each region considering the hotel zones and POIs along the route. Therefore, the VPP is considered a variation of the OP with hotel selection (OPHS) introduced in [70].

To the best of our knowledge, these are the most relevant modeling approaches for tourism planning problems. The conceptual and/or mathematical formulations of the remaining modeling approaches to tourism itinerary planning are developed in Appendix A.

Other relevant findings from the total number of documents reviewed are summarized in Table 2.

4.3. Single objective function

Majority of the reviewed papers (67.64%) considers a single optimization objective, consisting in the maximization of the benefits associated with POIs. 79.66% of the single-objective papers are modeled as OPs and TOPs. The set of variants studied in the literature optimizing a single objective are detailed below. This section first presents the variants studied so far in the literature (Section 4.3.1), followed by the analysis of solution techniques (Section 4.3.2) including exact approaches, heuristics, and metaheuristics.

4.3.1. Variants

Modeling real situations leads to include several extensions in the formulation (e.g., time windows, time dependencies, transportation modes, among others) [9,11,1216]. The TTDP has undergone several extensions over time to obtain the most realistic possible planning. In this regard, there are variants applied such as single-route planning [50, 71], which is applied in 36.23% of the documents in this section. Other

variants include: the planning of several simultaneous routes that sometimes simulate planning by days (63.76%) [9,72,73]; time windows denoting the opening and closing times of each POI (69.56%) [56, 72]; or even multiple time windows that consider different opening and closing times at the POIs (e.g., different museum tour times) (4.34%) [11].

The selection of the transportation mode to travel between POIs is another significant extension to the TTDP. This extension is called multimodal transport and is used in 15.94% of the short-listed documents. Similarly, another variant that allows considering the mode of transport used in each arc is time-dependent (TD) (15.94%). TD allows the inclusion of transport times based on delays and other situations that affect travel time, such as walking from a POI to the bus station (15.94%) [74]. In the case of group itineraries, the heterogeneous preferences of tourists are important in defining the level of individual satisfaction (2.89%). These preferences appears when each tourist within a group is interested in visiting a specific POI or type of POIs as opposed to other tourists in the group. Therefore, the benefits and scores of each POI may vary based on these individual preferences [8]. Another extension is the hotel selection (7.24%), which determines the starting and ending point of the route (being a hotel in this case) [28,75]. On the other hand, there are the multi-constraints that ensure time limits in each POI, budgets to be spent in each POI, among other aspects, that delimit the construction of the route (7.24%) [76,77]. There are also variations in the profit calculation of each POI (2.89%) and grouping of POIs into clusters, categories, or super POIs (13.04%). In these cases, grouping can generally be made by the type of activities or geographic position. The clustering of POIs serves to organize points of interest with similar characteristics or that belong to the same category (i.e., different restaurants in an area). The grouping facilitates the programming of routes in case a tourist or group of tourists intend to focus on a specific type of POIs or the selection among different categories.

When the attraction of the route is not in the POIs (nodes), instead the paths (arcs) are the attractions of the route, the score is considered in arcs, or arcs and POIs when it is a combination of both (AOP and Mixed OP-AOP) (10.14%) [66,68]. The model can also be extended by adding multiple periods for planning (1.44%) [11]. Another extension that has been little studied corresponds to the previous tourists' experiences in the itinerary programming (1.44%). This extension consists of analyzing the information of previous tourists and including it in prediction algorithms for the calculation of the profit [78]. Similarly, the popularity of a POI can be denoted according to the number of previous visits [79].

Brilhante et al. [59] apply user-interest (2.89%). This variant is associated with the tourist's interest in each POI, where the profit calculation of each POI is determined by considering a popularity vector that relates the relevance of each destination and a tourist preference vector that indicates the tourist's interest in each POI category. On the other hand, there is the inclusion of breaks along the route (1.44%), which can be used for tourists to eat or take short rests while on his/her itinerary [80]. Trachanatzi et al. [81] apply the capacitated TOP (CTOP) (1.44%), suggesting that transportation is limited due to the capacity constraint of each vehicle. This variant can be of great use in representing tour group problems, due to compliance with capacity constraints on the vehicle fleet used, whether homogeneous or heterogeneous. Based on the requirements of tourism industries, Zhao

Table 3
Variants and solution techniques applied in single-objective tourist itinerary problems.

Author (s)	Route type		solution techniques			Variants	Author (s)	Route type		solution techniques			Variants
	ORt	MRt	Exact	Heuristic	Metaheuristic			ORt	MRt	Exact	Heuristic	Metaheuristic	
[57]	X			X			[73]		X			Hybrid: Strict Iterated Local Search and Time-relaxed Iterated Local Search	TW-TD
[56]	X			X		TW	[58]	X		X			AOP / Mixed (OP-AOP)
[71]	X		X				[87]		X			Greedy Randomized Adaptive Search Procedure	TW-U
[17]	X				Guided Local Search		[88]		X			Iterated Local Search	TW-AOP / Mixed (OP-AOP)
[89]		X			Guided Local Search	TW-MC	[90]	X			X		
[72]	X				Genetic Algorithm	TW-MM	[11]		X			Hybrid: Collaborative Filtering and Iterated Tabu Search	MTW-MT-MC
[40]		X			Iterated Local Search	TW-TD	[91]	X			X		TW-CP
[36]	X				Iterated Local Search	TW	[92]	X		X			AOP / Mixed (OP-AOP)
[65]		X			Iterated Local Search		[86]		X			Hybrid: Tabu Search, k-means	HP-TW-MC
[93]		X			Guided Local Search	TW	[94]	X			X		CP
[19]		X			Iterated Local Search	TW	[95]	X			X		TW-MM-PV
[34]		X			Iterated Local Search	TW-TD-MM	[29]		X	X		Two-level Particle Swarm Optimization with Multiple-learning Terms	TW-MM
[96]		X			Iterated Local Search	TW-TD-MM	[78]	X			X		Ex-U
[28]		X	X	X		TW-HS	[97]	X				Hybrid: Genetic Algorithm and Differential Evolution Algorithm	TW-PV
[98]		X			Tabu Search	TW	[99]		X		X		TW
[41]		X			Greedy Randomized Adaptive Search Procedure	MTW	[100]		X			Evolutionary Algorithm Based on Partition Crossover	TW
[35]	X				Label Correcting Algorithm	TD	[12]	X				Hybrid: Random Simulation incorporating Genetic Algorithm and Differential Evolution Algorithm	TW-TD-U
[77]		X			Tabu Search	TW-MC	[84]	X		X			MM-G
[59]	X			X		TW-UI	[101]		X			Hybrid: Embedded Greedy Randomized Adaptive Search Procedure - Variable Neighborhood Search	TW-CP
[102]		X			Iterated Local Search	TW-TD-MM	[101]	X		X	X	Hybrid: Greedy Randomized Adaptive Search Procedure, Variable Neighborhood Search and DFS-Based Tree Search with Pruning	TW-G
[38]		X			Randomized Cluster Ratio and the Cluster Search Cluster Routes	TW	[103]		X			Greedy Randomized Adaptive Search Procedure	TW-CP-U
[68]	X			X		AOP / Mixed (OP-AOP)	[39]		X			Greedy Randomized Adaptive Search Procedure	TW-CP-U
[48]		X			SlackRoutes	TW-TD-MM	[80]		X			Iterated Local Search	TW-CP-B
[104]	X			X		TW	[99]		X			Randomized Cluster Ratio and the Cluster Search Cluster Routes	TW-HS-CP
[105]		X		X			[106]	X			X		HS-G
[66]	X		X		Iterated Local Search	AOP / Mixed (OP-AOP)	[107]		X		X		TW-U
[10]		X		X	SlackRoutes	TW-TD-MM	[81]		X				C

(continued on next page)

Table 3 (continued)

Author (s)	Route type		solution techniques			Variants	Author (s)	Route type		solution techniques			Variants
	ORT	MRT	Exact	Heuristic	Metaheuristic			ORT	MRT	Exact	Heuristic	Metaheuristic	
[108]		X			The Time Dependent CSCRoutes and The Time Dependent Slack CSCRoutes		[75]		X			Hybrid: Differential Evolution Algorithm with Distance Related	
[76]		X			Simulated Annealing	TW-MC	[109]		X		X	Hybrid: Genetic Algorithm, Variable Neighborhood Search, and Differential Evolution Algorithm	TW-HS
[85]		X	X			HP-AOP / Mixed (OP-AOP)	[110]		X			Hybrid: Evolutionary algorithm and local search techniques	TW-CP
[52]	X		X			MM	[111]	X				Genetic Algorithm	HS-G
[112]		X			Fireworks Algorithm	TW	[113]		X			Hybrid: k-means method with Genetic Algorithm	TW-TD-CP-UI
[114]		X			Greedy Randomized Adaptive Search Procedure		[82]		X	X			DC
[115]		X			Iterated Local Search	TW-AOP / Mixed (OP-AOP)	[116]		X			Greedy Randomized Adaptive Search Procedure	TW
[117]		X			Hybrid: ILS with Average Slack	TW	[118]	X				Genetic Algorithm	TW-MM-UI-CP
[119]		X			Iterated Local Search, Simulated Annealing	TW-Mixed TOP							

and Alfandari [82] added a new extension called diversity constraints (1.44%), which implies that during the construction of an itinerary, *m* routes can share at most *s* common POIs. Finally, "green" models have also been developed, such as the use of electric vehicles (EVs) for transportation (4.34%) [83] and the calculation of CO₂ emissions in transportation (1.44%) [84].

Uncertainty. When considering uncertainty, extensions such as the prediction of tourist movements within a tourist route based on GPS positioning (1.44%) [78], the inclusion of stochastic time-dependent parameters (travel and waiting times) (4.34%), and finally, fuzzy travel time, scores, and constraints (3.34%) have been considered.

Tourist group. This field is scarce in the TTDP literature. Few works include the construction of group itineraries. Generally, this variant is associated with heterogeneous preferences of tourists in the same group. Initially, Malucelli et al. [85] develop a new problem called Multi-Commodity Orienteering Problem with Network Design to model the cycle-tourist problem. Different classes of users are considered in the same group, and the benefit obtained on the route is maximized based on their individual preferences. Finally, Sylejmani et al. [86] consider mutual relationships in the tourist group and heterogeneous preferences.

A complete overview of this taxonomy is given in Table 3. This taxonomy considers the 20 variants described above for single-objective models, using the following notation: one route [ORT], multiple route/days [MRT], heterogeneous preferences [HP], time window [TW], multiple time window [MTW], time-dependent [TD], multimodal transport [MM], arc selection /mixed AOP [AOP/Mixed OP-AOP], experiences [Ex], profit variations in the POI [PV], hotel selection [HS], clustered POIs/category POI [CP], user-interest [UI], multi-period [MP], green [G], multi-constraints [MC], uncertainty [U], break [B], capacitated [C], and diversity constraints [DC].

4.3.2. Solution techniques applied for the single objective problem

Exact methods. The application of exact solution techniques corresponds to 15.54% of the total number of reviewed documents optimizing a

single objective. This situation arises due to the computational complexity of the problem when solving medium- and large-sized instances. Exact solution techniques are generally applied to verify model optimality with small instances and as a point of comparison with approximate methods. In the BTP inclusion by Deitch and Ladany [71] the model is solved using LINDO software obtaining optimal results for 57 nodes on a route of attraction sites between Beer-Sheva and Jerusalem. Verbeeck et al. [66] apply a Branch and Cut approach to solving the Cycle Trip Planning Problem associated with tourism, to build customized hiking routes (ecological or nature tourism) [17]. The results are compared with the Iterated Local Search (ILS) metaheuristic. In the same field of CTPP associated with tourism problems, Malucelli et al. [85] code the mathematical model and solve it by ILOG CPLEX v12.5.0.0.0 for a total of 83 nodes. Yu et al. [52] use mixed-integer linear programming (MIP) to solve the OTP, BMT, and RMT by obtaining exact integer solutions in a real case with 20 nodes.

Bagloee et al. [58] solve the CBT for 100 nodes using the CPLEX solver coded in General Algebraic Modeling System (GAMS) optimization software. Mrazovic et al. [92] initially solve the tourist trip design considering POI and arc scoring using the IBM ILOG CPLEX Optimizer v12.6.3 solver for a set of instances from 10 to 100 nodes at high computational times (up to 15 h). Yu et al. [29] use the CPLEX solver to obtain exact results for instances of 25–100 nodes and compare the performance of their proposed algorithm, a two-level particle swarm optimization with multiple social learning terms (2L-GLNPSO). Susanty et al. [84] applied dynamic programming for the trip design that minimizes distance and CO₂ emissions in a real case of 41 nodes. Wang et al. [101] studied the TTDP with electric vehicles (ETDP) and applied a Branch and Bound algorithm to obtain exact solutions on real instances of up to 58 nodes and compare them with a heuristic technique. Divsalar et al. [120] employ CPLEX IDE Version 12.6 to solve the Multi-Level Multi-Period Orienteering Problem with Multiple Time Windows (ML-MP-OP-MTW). This problem considers TTDP with mandatory POIs to visit, different time windows, and service levels. Finally, Zhao and Alfandari [82] applied Branch and Price and Branch-and-Cut-and-Price algorithm to solve the TOP-DC with instances from 21 to 66 nodes.

Heuristics. Heuristic algorithms allow to solve the hard problems in

Table 4
Variants and solution techniques applied in multi-objective tourist itinerary problems.

Author (s)	Route type		Solution techniques			Variants	Author (s)	Route type		Solution techniques			Variants
	ORt	MRt	Exact	Heuristic	Metaheuristic			ORt	MRt	Exact	Heuristic	Metaheuristic	
[54]		X			Multi-objective Simulated Annealing		[132]		X	X	Adjusted Iterated Local Search	TW	
[125]	X			X		TW-MM-CP	[133]		X		Multi-objective Evolutionary Algorithm Relying on Pareto Dominance and a Pareto Front	TW	
[50]	X				Pareto Ant Colony Optimization and Variable Neighborhood Search based Pareto extension		[8]		X		Hybrid: Ant Colony Optimization and Differential Evolution Algorithm	HP-TW	
[51]	X				Adaptive Genetic Algorithms	TW-TD-MM	[134]		X		X	TW-CP-Pk-B	
[6]		X			Tabu Search	TW	[135]		X		Genetic Algorithm with neighborhood niching strategy	TW-CP-B-HS	
[126]	X				Tabu Search	TD-U	[136]		X		Genetic Algorithm and Analytic Hierarchy Process	TW-HS	
[127]		X			Simulated Annealing	TW	[137]	X		X		TW-VD	
[128]		X			Particle Swarm Optimization		[138]		X		Preference-Guided Firefly Algorithm		
[129]		X		X		TW-CP-UI	[141]		X		Global Local and Near-Neighbor Particle Swarm Optimization	TW	
[79]	X			X		CP-UI	[142]		X		Hybrid: Nondominated Sorting Heuristic Approach, Particle Swarm Optimization, and Differential Evolution Algorithm	TW-TD-MM-Pk	
[130]	X			X		CP-UI	[143]		X		Hybrid: Firefly Algorithm with a method called "Related Coordinates"		
[131]		X			Hybrid: Multi-objective Evolutionary Algorithm and Constraint Programming	TW	[139]		X	X	swarm intelligence graph-based pathfinding algorithm (SIGPA)	MP	

short computational times. They can be classified as constructive, improvement, and relational techniques [121]. In our review, we identified that 26.53% of the single-objective problems were solved using heuristics. Deitch and Ladany [57] applied an improvement heuristic to solve the BTP. Leong and Ladany [56] solved the Cruise Itinerary Problem using a near-optimal heuristic approach. Zhu et al. [28] solved a TOP to design a tourist trip with the most desirable sites, subject to various budget and time constraints using a local search heuristic. Brillhante et al. [59] applied a greedy algorithm as the basis of a tool for tourism trip planning based on the GMC problem. Maervoet et al. [68] applied an improvement heuristic based on spatial filtering within a feasibility window constructed with the geographic coordinates of the POIs. The filtering allows identifying each feasible POI and later, calculating the shortest route.

On the other hand, Herzog and Wörndl [104] applied a constructive algorithm to design a tool to plan multi-region composite trips for independent tourists based on the Oregon Trail Knapsack Problem. Rahman et al. [105] designed an insertion heuristic that allows creating tour packages for 1, 2, or 3 days starting from one point and ending each day at a hotel. Gavalas et al. [10] and Gavalas et al. [99] initially developed two new cluster-based heuristic algorithms. The first is Cluster Search Cluster Ratio (RCRatio) and the second is Cluster Search Cluster Routes (CSCRoutes), both applied to the TTPD modeled as a TOPTW. These algorithms are published years later after the publication of the

development of the extensions made by the authors of these two algorithms. These extensions named the Time-Dependent CSCRoutes (TD_CSCR) and the Time-Dependent Slack CSCRoutes (TD_S/CSCR) allow to include the management of time-dependent travel times between different locations/POIs. The new algorithms are applied to solve the Time-Dependent TOPTW (TDTOPTW).

For the development of the Xenia tourism planning tool, Korakakis et al. [90] apply the HDBSCAN-SLINK version that uses SLINK instead of Prim's algorithm to obtain better solutions. Laß et al. [91] presented the web application TourRec that enables context-aware tour recommendations in arbitrary locations around the world. The authors include two relevant aspects when constructing an itinerary: time of day (e.g., morning, midday, afternoon, night) and previous visits to the POIs according to its category (e.g., arts and museum, food, shopping). The algorithm combines the benefit of each POI according to the category, time of day, and user preference, and then calculates the distance based on Dijkstra's algorithm. The algorithm proposed by Wörndl et al. [94] considers the planning of short trips within a city where the user performs the trips by walking. The problem is modeled as an OP and is solved with variations of Dijkstra's algorithm. The authors not only employ Dijkstra to find the shortest route, but it also allows finding solutions for the TTDP.

Wu et al. [95] proposed a tourism planning model to maximize the utility denoted as the tourist experience, considering preferences for

attractions, mode of transportation, attraction attributes, time, and cost budget. The improvement algorithm designed by the authors consists of 7 steps. (1): initialization of parameters, (2): a review of the node and insertion in the list of candidates, (3): the selection of the transport mode that generates the highest utility and review of compliance with time constraints, (4): inclusion of the selected node complying with the constraints, (5): calculation and review of compliance with total time and overall travel cost constraints, (6): the selection of the route with the highest utility, and finally, (7): the end of the algorithm and printing of the solution. Zheng et al. [78] developed a heuristic prediction algorithm (HPA) to predict the next location of the tourist within an attraction, which allows to improve management capacity, minimize crowds, optimize resources, among other very positive aspects of tourism planning. Wang et al. [101] developed a constructive heuristic to solve the ETTDP problem for medium- and large-sized instances. Later, Karbowska-Chilinska and Chociej [106] applied a greedy heuristic approach to solve the multistage TTDP with electric vehicles, taking as a basis the OP with hotel selection, in which instead of hotels, one has electric charging stations. Gavalas et al. [99] developed a heuristic that requires two phases to solve the VPP. The first phase is offline and generates a clustering of POIs through a hierarchical broad categorization depending on the region. The second phase is online and consists of user interaction with the tool to manage the optimal routes to be performed each day in the region or destination selected by the tourist, considering the POI's clusters.

On the other hand, Karunakaran et al. [107] addressed the field of hyper-heuristics, which are high-level search methodologies for solving computationally difficult problems by exploring search spaces of low-level heuristics [122]. The authors applied island models using a multitasking approach to construct clusters through the k -means method and exploit their relationship with genetic programming-based hyper-heuristic (GPHH) performance to obtain efficient routes. Similarly, Toledo et al. [123] develop a hyper-heuristic based on a Large Neighborhood Search to solve an OP with hotel selection. The algorithm employs several low-level heuristics such as Insert, Replacement, Two-opt, Move, Swap, Extract-insert, Extract2-insert, Extract5-insert, Hotel-improvement, Hotel2-improvement, and Hotels-crossover, to improve the solutions.

Jackson and Mei [109] applied the same GPHH approach to solve the stochastic TOPTW; however, the authors added a clustering approach based on the DBSCAN algorithm in which POIs belonging to a group are assigned a score called neighborhood score (NS). These POIs have greater benefits to be added to the route.

Meta-heuristics. To solve the single-objective TTDP, 57.93% of the reviewed papers applied metaheuristic techniques, which are algorithms developed based on the guidance and modification of heuristic techniques [6,124]. Souffriau et al. [17] applied Guided Local Search (GLS) based on an initial greedy solution and improved with insert and replace moves. The algorithm is compared with Data Transformation Graph (DTG), and both metaheuristics are applied to a set of real instances of up to 50 nodes associated with factories, monasteries, restaurants, museums, architectural, and historical sites in the city of Ghent, Belgium. The results show better benefits with GLS. Vansteenwegen [89] also applied GLS and compared it with the use of Variable Neighborhood Search (VNS), determining the higher efficiency of VNS for instances of 319 attractions. The author also applied Iterated Local Search (ILS) obtaining very efficient results for the Multiple Constrained TOPTW (MCTOPTW) problem for instances of up to 288 attractions. Vansteenwegen et al. (2009) performed a comparison of two local search heuristics and GLS applied to the TOP.

Later, other authors implemented ILS as a solution algorithm. Garcia et al. [40] solve the multi-path TOP problem with time windows (MPTOPTW) as the basis of personalized electronic guidance (PET) for tourist decision-making. This model considers public transportation and

adapts to real-time conditions. Souffriau et al. [36] solved the TTDP as an OPTW considering POI opening times and available tourist time for instances of up to 50 nodes. Vansteenwegen et al. [65] solved a TOPTW obtaining solutions with a gap of 1.8%. Garcia et al. [34] develop the TOPTW time-dependent and transport consideration (TDTOPTW) and solved with Dijkstra's algorithm and ILS. Verbeeck et al. [66] introduced the Cycle Trip Planning problem taking the arc-oriented problem as a basis and solved it with an exact method for small instances and then applied ILS for large-sized instances. Vansteenwegen et al. [19] reviewed the metaheuristics applied to solve the tourism planning problem identifying the use of GLS, VNS, ILS and introducing a new metaheuristic called Skewed Variable Neighborhood Search (SVNS). Gavalas et al. [10] implemented three more algorithms to solve this problem which are extensions of the ILS. The algorithms are called the Time-Dependent ILS (TD_ILS), the Average Travel Times CSCRoutes (AvgCSCR), and Average ILS (AvgILS). Gavalas et al. [119] introduce the Mixed TOP with Time Windows (MTOPTW) and employ simulated annealing and ILS to solve it, obtaining better solutions with ILS. Subsequently, Gavalas et al. [115] proposed a new tool for tourist trip planning called Scenic Athens, for which the dimensions of the POIs and the tours that can be done are considered, in addition to the attractions that are in the arcs. Therefore, the problem is modeled as a MTOPTW and is solved through ILS. Finally, Almira and Maulidevi [80] developed an ILS in which a random perturbation is included that initially removes different POIs from the route and subsequently included through a greedy heuristic.

Abbaspour and Samadzadegan [72] applied a Genetic Algorithm (GA) to solve the TTDP considering only the time and multimodal transport criteria. Karbowska-Chilinska and Chociej [111] applied a GA to solve the EVTTDP. Later, for the development of the recommending system called SMARTCAL (Smart Tourism in Calabria) as a platform for tourism itinerary management, De Maio et al. [118] developed a GA to solve the OPTW that considers waiting times in each POI category and multimodal transport. On the other hand, Sylejmani and Dika [98] and Sylejmani et al. [77] developed a Tabu Search (TS) algorithm. The first, to solve the TOPTW in which tourists are not allowed to arrive at POIs before their opening time, and the second, to solve the TTDP problem modeled as a MCTOPTW.

Vansteenwegen et al. [47] modeled the TTDP as a TOPTW and solve it with a Greedy Randomized Adaptive Search Procedure (GRASP), to design a web-based tourism decision tool (City Trip Planner). Expósito et al. [114] also applied GRASP to solve the TTDP problem with multiple routes, considering that a tourist may take several days in an area with several POIs. Brito et al. [87] developed a fuzzy GRASP. These authors consider a fuzzy objective function. Expósito et al. [103] used Fuzzy GRASP for a new variant of TTDP where POIs are grouped into several categories with fuzzy scores and travel time constraints. This new extension is called Tourist Trip Design Problem with Clustered POIs (TTDPclu). Expósito et al. [39] added the imposition of minimum/maximum bounds on the number of points of interest belonging to each of the clusters visited on the same route and solved it with the same fuzzy algorithm. Moreno-Pérez et al. [116] applied a GRASP to solve a TOPTW in the development of a prototype recommender system (RS) for route construction in maritime tourism or blue tourism, taking the city of Tenerife, Spain, as the study area.

Other algorithms have been used such as Label Correcting Algorithm (LCA) applied by Li and Fu [35] for the time-dependent TTDP considering the dynamics that can occur in route selection due to travel delays. Gavalas et al. [48] and Gavalas et al. [10] presented the architecture of the eCOMPASS application, which allows the organization of personalized tourist routes taking as a basis a TDTOPTW. These authors considered urban transportation and proposed an algorithm called SlackRoutes to obtain solutions. The structure of this algorithm presents an offline and an online phase that allows first to perform a clustering of the POIs and to obtain a list of these clusters based on geographic location criteria. Subsequently, the selected POIs are inserted into the

route. Routes in dense clusters facilitate transport and solution times. The selection of POIs uses a quality criterion inspired by the h-index. Therefore, at least a total of h POIs with a benefit equal to or greater than h must be included in the cluster. The route construction logic considers dense clusters with high POI benefit values. Lin and Yu [76] developed an extension of Simulated Annealing (SA) with resumption strategy (SA-RS) to solve the multi-constraint, multi-time-window team-oriented problem (MCTOPMTW).

To solve a new TTDP that redefines benefits in POIs and calculates dwell times based on the "the metric of compactness" as a basis for the design of a tourism recommender system called JSP webpage, Ding et al. [112] employ Fireworks Algorithm (FWA) and compared it with ILS and GRASP showing a higher efficiency. The metric of compactness is treated as a parameter with values $[0,1]$ that helps calculate the length of stay in a POI. The metric of compactness is calculated based on the POIs that can be visited per day and the ratio between visit and transport times. Yu et al. [29] developed a multimodal TOP with time windows (MM-TOPTW) motivated by the development of a tourist travel design application when multiple modes of transportation are available for tourists to choose from during their trip and solved it using Two-level Particle Swarm Optimization with Multiple-learning Terms (2L-GLNPSO). Ghobber et al. [100] first applied Evolutionary Algorithm Based on Partition Crossover (EAPX) to solve the TTDP modeled as a TOPTW, obtaining better solutions compared to ILS and Granular Variable Neighborhood Search Based on Linear Programming (GVNS).

Within the set of hybrid techniques, Konstantopoulos and Orfanos [117] developed an ILS algorithm hybridized with Average Slack to solve the TOPTW applied to the TTDP. Ayala et al. [73] work on the tourist travel design problem with travel instructions (TTDP-TI), taking as a basis a TDOPTW and apply two ILS-based solution approaches named Strict ILS (SILS) and Time-relaxed ILS (TRILS). The authors proposed the construction of a route that, in addition to considering time dependency, includes the travel instructions in each arc with real data (i.e., the time the user takes to board the bus, to change buses, time to reach the nearest stations). Generally, ILS employs a parameter to control the iterations in which no improvements to the current route are found. This is a stopping criterion of the algorithm. However, SILS logic allows for new iterations by removing and penalizing POIs that do not fit the time windows and resetting the iteration control parameter. In this sense, this solution repair process is returned to ILS to continue iterations until a feasible path is obtained. On the other hand, the TRILS logic gradually increases travel times to allow for route constriction. Finally, the authors developed a hybridization between these two approaches called Precise Hybrid ILS (PHILS). PHILS allows analyzing each POI where there is a violation of time windows and performs the gradual increase of the travel time to verify if the POI can be entered. The solutions and positions obtained are saved so as not to start from the base solution. The POI is removed from the route if another solution is found from the same position. Kotiloglu et al. [11] proposed an algorithm that articulates Collaborative Filtering (CF) and Iterated Tabu Search (ITS) to solve the TTDP problem based on "Filter-First, Route-Second". The TTDP is modeled by introducing the OPTW with multiple periods.

Zheng et al. [97] built a tourism recommender system that considers aesthetic fatigue and variable tourism value. The authors proposed a four-step hybrid heuristic algorithm including a GA and Differential Evolution Algorithm (DEA). Liao and Zheng [12] developed a hybrid algorithm based on Random Simulation (RS-H²A) incorporating GA and DEA to design a customized route of a one-day tour in a stochastic time-dependent environment. Wang et al. [101] presented a tool called eTOUR for tourist trip planning that considers "super POIs" (clustering of POIs that are very close geographically). The base solution algorithm is a hybrid Embedded GRASP-VNS and DFS-Based Tree Search with Pruning. Trachanatzi et al. [81] developed an algorithm that combines DEA with Distance Related (DRDEA) considering the travel times in each arc calculated as Euclidean distances to solve the CTOP. Tenemaza et al. [113] combined the k -means method with GA. The first method is

applied for the construction of POI clusters according to the geographical area and user interests. The GA is used to obtain the routes to solve the TTDP modeled as a TDOPTW. Zheng et al. [75] propose a TTDP with hotel selection (TTDP-HS) to build personalized itineraries with hotel selection for multi-day trips of urban tourists. A two-level memetic algorithm incorporating GA, VNS, and DEA was developed. Jriji et al. [110] also applied a memetic algorithm combining an evolutionary algorithm and local search techniques to solve the TTDP with clustered POIs.

In addition, Appendix B contains a complete analysis of the meta-heuristic solution techniques for the single-objective TTDP. It details the main aspects of the development of these techniques, the main parameters, the solution times, the types of instances used, and the solutions compared with the best-known solutions in the literature (BKS).

4.4. Multi-objective function

The literature review shows that 24.5% of the papers consider more than one objective in their formulation, and of these, 48% are modeled as OPs or TOPs. Godart [54] minimizes transportation costs, activity costs, lodging costs, and maximizes activities and tourist accommodations. Castillo et al. [125] presented a model that considers the set of activities, the duration, and defined a clustering scheme for geographically close locations (i.e., the geographic proximity of some POIs) that substantially reduces the distance or travel time to go from one place to another; so, POIs are grouped as a super-POI. These authors considered three objectives: minimization of the amount of free time of tourists, minimization of travel time between POI's, and maximization of profit. Schilde et al. [50] developed a multi-objective function that maximizes the score on the different POI categories and the benefits associated with each one. Abbaspour and Samadzadegan [51] maximized the score obtained on the route and minimized the waiting time and weights of each arc within the route in multimodal transport. On another hand, Rodríguez et al. [6] minimized distance, costs of activities, gap between planned and executed time, and maximized profit.

Hasuikie et al. [126] applied the Time-Extended Network (TEN) methodology to study time dependencies under uncertainty by constructing copies of the set of nodes for each state in time. Hence, the time-optimal flow problem can be worked as a static network flow in each state by assigning probabilistic scenarios in the parameters to find optimal solutions. The developed multi-objective function maximizes the benefit of tourists in each state. Sylejmani et al. [127] maximized the score obtained on the route and minimized the travel time. Han et al. [128] developed a multi-objective model that maximizes the score and minimizes the distance traveled. Brillhante et al. [129] maximized the score and minimized the costs associated with transportation. Lim et al. [79] and subsequently, Lim et al. [130] developed a multi-objective function that maximizes the popularity and interest of the visited POI's. Hu et al. [131] maximize various types of benefits associated with each control point. Hapsari et al. [132] maximize profit and minimize travel time. Tarantino et al. [133] included five objectives in their model: maximization of score, number of visited POI's and time in POI's, and minimization travel time and POI inclusion. Zheng and Liao [8] developed a bi-objective model to maximize the total utility of the tourist group and maximize the equal importance of individual tourists' preferences. Benjamin et al. [134] developed a greedy algorithm for tour package building that consists of maximizing the number of visited POI's, maximizing the popularity weight of each POI, and minimizing the travel costs.

Huang et al. [135] included three objectives in the Multiple-Itinerary Planning Problem (MIP) which consists of building routes for a set of days. The objectives were the minimization of transit time, the maximization of average benefits generated by visiting POI's, and the maximization of the diversity of POI's visited (i.e., including POI's of different categories in the routes to make the trip more attractive). Yan et al. [136] aim to make the trip reasonable in terms of the fit between

restaurants and hotels, with the lowest cost and travel time. Sebastia and Marzal [137] maximize profit while minimizing visitation and occupancy rates. Trachanatzis et al. [138] used the Multi-Objective Prize-Collecting Vehicle Routing Problem (MO-PCVRP) to simulate the TTDP. Three objectives associated with minimizing the travel distance, minimizing the number of routes, and maximizing the collected prize of the route were evaluated. Zheng et al. [75] developed a bi-objective TTDP with transport mode selection (TTDP-TMC). The objectives are to maximize the utility based on a decreasing function in time and to minimize the route risk which is calculated based on the estimated route compliance at the allocated time. Yan et al. [136] modeled the TTDP as a TSP with three objectives associated with reasonableness, economy, and convenience. The reasonableness is calculated in terms of reasonable times to break in the tour. The economy is calculated based on the costs of travel, food, lodging, and costs per visits to the POI's. The convenience is calculated based on the time the user spends at each POI, traveling between POIs, taking food, and at hotels. Finally, Ntakolia and Iakovidi [139] developed a mixed-integer nonlinear programming (MINLP) model for a tourist itinerary problem with four objectives. These objectives are to minimize the risk factor based on the safety of a route path, minimize the physical fatigue based on the walking tour of users with disabilities or advanced ages, maximize the smoothness of the routes based on minimizing turns and deviations depending on the position of POIs in the area, and minimize the crossings at the arcs.

4.4.1. Variants

As mentioned above, the planning of more realistic tourism itineraries leads to the development of more extensions of the models. In 64% of the short-listed documents with multiple objectives, authors considered time windows and planning for several routes, while 36% of papers perform planning for a single route. 16% of the papers develop models that allow the selection of the mode of transport between nodes, of which 75% apply the time-dependent variant. 28% perform clustering of POI's considering aspects of geographical position or the type of activity offered (e.g., restaurants, beach, museum) [79]. For the use of heterogeneous preferences, only 4%, corresponding to the work developed by Zheng and Liao [8] applies for this extension.

Regarding the user-interest extension (12%), Lim et al. [79] and Lim et al. [130] applied the concept of time-based user interest. For this concept, the level of interest of a tourist for a certain POI depends on the time he/she takes at that POI relative to the average time taken by all other tourists at the same POI. This makes possible to identify the most relevant POIs to be included in the route. Benjamin et al. [134] addressed travel packages (4%), which are itineraries for tourists based on combinations of transportation, accommodation, guided tours, and other services offered by travel agencies [140].

Sebastia and Marzal [137] consider that the visit times in each POI are variable and can be located between time intervals. Therefore, a new extension of the OPTW called Variable Durations (OPTWVD) is added (4%). The objective function of this problem includes penalties for the number of visits and the percentage of occupancy that determines the time interval available for travel and visit of the POI's.

Uncertainty. In regard to uncertainty (8%), Hasuike et al. [126] developed time-dependent parameters such as transport under the TEN approach, generating various probabilistic scenarios to obtain efficient solutions. Also, Zheng et al. [75] considered stochastic transport times, which are addressed using the expectation optimization model.

Tourist group. In the case of multi-objective problems, works considering group itineraries are even scarcer. Only in [8] is this variant included for the construction of group itineraries with heterogeneous preferences. The problem maximizes both the individual benefits of each tourist, as well as the group benefit.

The taxonomy presented in Table 4 considers 14 variants applied in

multi-objective models, using the following notation: One route [ORt], Multiple route/days [MRt], Heterogeneous preferences [HP], Time window [TW], Time-dependent [TD], Multimodal transport [MM], Clustered POIs/Category POI [CP], User-interest [UI], Uncertainty [U], Packages [Pk], Break [B], Hotel selection [HS], Variable durations [VD], and Multi-period [MP].

4.4.2. Solution techniques applied for the multi-objective problems

Exact methods. In the reviewed literature, few papers applied mathematical programming to model multi-objective problems. Hapsari et al. [132] proposed a mixed-integer linear programming (MILP) to model the TOPTW. Solving this model using small instances is used for calibration of parameters and equations. Sebastia and Marzal [137] applied fast CSP solver CHOCO to obtain optimal solutions of the OPTWVD. Finally, Ntakolia and Iakovidi [139] used IBM ILOG CPLEX solver version 12.6.0.0. to solve a tourist route problem modeled as a mixed-integer non-linear programming (MINLP) model.

Heuristics. The application of heuristic techniques accounts for 20% of short-listed papers with multiple objectives. Castillo et al. [125] used the *k*-Nearest Neighbor (*k*-NN) algorithm as a solution basis for the SAMAD tourism planning tool. Brilhante et al. [129] applied a greedy algorithm as the basis of TRIPBUILDER, which is an unsupervised framework for planning personalized sightseeing tours in cities, based on public information such as Wikipedia, Flickr, among other platforms. On another hand, Lim et al. [79] and Lim et al. [130] take user preferences and geo-referenced photo tags to develop a constructive tool called PERSTOUR. The authors considered user journey constraints, such as time limits and the need to start and end the route at specific POIs. Also, user interest levels are based on the duration of the visit using the time-based user interest method. Finally, Benjamin et al. [134] applied a greedy heuristic to improve the building of tour packages based on budget, tourists' length of stay, travel time, places they prefer to visit, package types, and trip departure points.

Meta-heuristics. The application of metaheuristic algorithms implies higher efficiency in computational results [39]. These solution techniques are applied in 68% of the TTDP multiple-objective papers. Godart [54] proposed metaheuristic techniques such as Multi-objective Simulated Annealing (MOSA). Instances with 173 activities, 91 hosting sites, tree origin nodes, and ten days of planning are used. Resolution time is about 20 s. Schilde et al. [50] applied Pareto Ant Colony Optimization (P-ACO) and Variable Neighborhood Search based Pareto extension (P-VNS) to solve the multi-objective OP (MOOP) with random-generated instances and realistic data sets. Abbaspour and Samadzadegan [51] developed two Adaptive Genetic Algorithms to solve the tourist routing problem in an urban environment with multimodal transportation. Rodríguez et al. [6] developed TS that considers Pareto sampling due to the multi-objective programming (MOAMP) type. The authors tested the algorithm with 2154 several tourist attractions and 107 start/end nodes. Hasuike et al. [126] apply a Ten-Expanded Network to address uncertainty. For large-scale problems, the authors use TS to find solutions.

Sylejmani et al. [127] employed SA to build itineraries with multiple days, time windows, rest during the route, maximum tourist budget, and different POI categories. On another hand, the multi-objective model developed by Han et al. [128] considers tourists' preferences based on psychological behaviors, and was solved with Particle Swarm Optimization (PSO) and tested with realistic instances considering 9 nodes of various types of attractions. Hapsari et al. [132] developed a variation of ILS called Adjusted Iterated Local Search (AILS). The results are further tested with mixed-integer linear programming on a small set of nodes. For large instances, it was compared with MSA, SA, ABC, and ILS. Tarantino et al. [133] employed a Multi-objective Evolutionary Algorithm Relying on Pareto Dominance and a Pareto Frontier for multi-objective

TOPTW (MO-TOPTW) model as the basis for an interactive electronic guidebook application capable of recommending personalized multi-day tour itineraries to mobile web users.

Huang et al. [135] proposed a modification of the GA by incorporating a neighborhood niching strategy (NGA) to generate multi-day itineraries. The algorithm performs clustering of similar chromosomes into subgroups. This process partitions the solution search space while maintaining population diversity. Yan et al. [136] developed a GA to solve a multi-objective TSP. Subsequently, the authors applied Analytic Hierarchy Process (AHP) to evaluate routes based on the total cost, the total length of travel, the comfort level, and the effective travel time.

Trachanatzki et al. [138] developed the Preference-Guided Firefly Algorithm (PGFA), which is applied to the building of walking routes for tourists. This algorithm provides efficient decision-making based on the three objectives of minimizing the travel distance, minimizing the number of routes, and maximizing the collected prize of the route. Wisittipanich and Boonya [141] applied a PSO extension called Global Local and Near-Neighbor Particle Swarm Optimization (GLNPSO) to solve the TTDP with data from Chiang Mai City, Thailand. The results compared with the exact solutions obtained with the LINGO software show the efficiency of the algorithm. However, this comparison is only performed with small-size instances due to the problem complexity.

Our review also identified the following hybrid algorithms. The first one was developed by Hu et al. [131] using MOTOPTW to solve the TTDP. The authors consider the benefits of each of the tourist routes and maximize them using a multi-objective function. This model is solved using a hybrid multi-objective evolutionary algorithm called (CPMOEA/D), based on Multi-objective Evolutionary Algorithm (MOEA/D) and Constraint Programming (CP). Zheng and Liao [8] developed a bi-objective model that considers the heterogeneous preferences of tourists in a group and solved it with an approach called Nondominated Sorting Heuristic Approach (NSACDE), which is a hybrid between Ant Colony Optimization (ACO) and DEA. Zheng et al. [75] applied an algorithm including Nondominated Sorting Heuristic Approach, PSO, and DEA (NSHA) to solve the TTPD-MTC in urban environments. Finally, Rigakis et al. [143] developed a hybrid approach combining Firefly Algorithm (FA) with a method called "Related Coordinates" (RC) (FAC). This method allows a transformation to visualize the coordinates of the nodes in a 2-D space. The transformation of the nodes into a 2-D space allows the FA to solve non-probabilistic vehicle routing problems. Therefore, the TTDP is modeled in this work as a MO-PCVRP.

In addition, Appendix B contains a complete analysis of the metaheuristic solution techniques for the multi-objective TTDP. It details the main aspects of the development of these techniques, the main parameters, the solution times, the types of instances used, and the solutions compared with the BKS.

5. Opportunities for future research

Based on the outcomes of the review of short-listed papers, several lines for future research can be identified. As a matter of fact, tourists generally prefer to travel in groups [94]. Therefore, it is necessary to develop models that build group tourism routes. However, this type of group itinerary must also consider the individual benefits for each tourist. Heterogeneous preferences for scheduling group itineraries are a field still little explored (only 2.94% of short-listed documents consider this variant). This variant occurs in group planning when not all tourists agree to visit the same POI's. In this sense, a tourist may visit a POI different from the others or not visit a POI within the same route [12, 75]. The group itinerary should generate equitable benefits for all tourists based on individual time and cost constraints. Therefore, this type of extension can be worked from the equity and benefit distribution dimension [144].

Currently, due to the contingency generated by the SARS-CoV-2 coronavirus (Covid-19), social distancing and maximum capacities are restrictions that are implemented at sites to avoid increases in

transmission rates [145]. Therefore, tourist trip planning should consider the maximum occupancy levels (crowding) in each POI when constructing group itineraries [146]. Likewise, the maximum number of visits to a POI and the waiting times between visits to carry out biosecurity processes such as cleaning and disinfection must be established [99]. These times can be uncertain, which provides a basis for models with uncertain parameters and exploring efficient methods to solve them [12,23,39]. For more realistic scheduling, it is necessary to consider uncertainty in time-dependent parameters such as travel times, waiting times at POIs, and time windows or multiple time windows. Also, we argue that is important to consider grouping POI's according to the type of tourism (e.g., sun and beach, ecotourism, adventure) to facilitate planning according to tourist preferences. However, there may be combinations of clusters according to tourism routes and limited infrastructure resources to create a path with sufficient POIs in a single category.

Another future research line is the analysis of environmental impact of tourist activities, such as the minimization of CO₂ emissions in the transportation process, whether multimodal or not. This extension within the "green" variants is necessary because transportation is one of the processes that generate the most pollution, mainly due to the consumption of fossil fuels translated into greenhouse gas emissions [147–150]. Furthermore, tourism activities generate negative impacts on the environment [151]. This situation constitutes a research opportunity in line with the novel trend of sustainable tourism proposed by the World Tourism Organization (UNWTO) within the Sustainable Development Goals (SDGs) [152–154].

Sustainable tourism can also be approached from the protection of natural areas and the development of nature tourism and ecotourism [155]. Tourism associated with nature reserves and parks is growing rapidly [156]. This type of tourism not only promotes economic development and environmental protection but also has a positive effect on people's health [157]. Therefore, the importance of tourism in the achievement of the SDGs leads countries to manage their policies about sustainable tourism. These policies generate an impact on tourism and a need to redefine different economic and environmental aspects based on emissions policies [158]. A key point within sustainable tourism routes continues to be the use of alternative mobility. Cycling is a mode of transportation that has been gaining popularity in developed countries, is sustainable, and is an efficient alternative for nature tourism [159]. In the cycle routes, the benefit of the tourist is not only in the visit to POIs but also in the arcs [66]. These variants of the OP are called AOP when the profit is in arcs or Mixed (MOP) when the profit is in arcs and POIs [47]. Other areas of work for the AOP are scenic routes which, although not recent, are highly practiced [160]. Therefore, these variants of the OP can be used to model different new problems associated with nature tourism, cycle tourism, and the construction of scenic routes.

In addition, the growing importance that cities are generating as destinations for tourism [161,162] provides several fields that can be approached within the framework of urban tourism. This type of tourism differs from other types of tourism due to its complexity and the activities carried out, which are not associated with leisure, but generally for business, medical purposes, visits to friends and family, and shopping [161]. Urban tourism itinerary planning can consider transportation in urban environments [8,12,75], including several types of vehicles such as electric or autonomous (driverless or automated) [163], or even air mobility. Likewise, profits in arcs and POIs can be included [75].

The use of hybrid optimization algorithms to obtain efficient solutions is another field that requires attention. Only 13.25% of the reviewed papers applied hybrid techniques mainly in single-objective problems. Therefore, the use of hybrid optimization algorithms based on combinations of metaheuristics, matheuristics, and simulation-optimization approaches can be studied [164–166]. With this type of combination, the advantages of each technique are obtained to generate good quality solutions [167]. In this review, only a single work was observed that hybridized a metaheuristic and an exact technique.

In line with the advancement of solution strategies applied to other

problems in the literature based on operations research, it is necessary to analyze the application opportunities for the TTDP. In this sense, there are several trends from the field of operations research that have aroused interest in the scientific community. Among these are the combined methods, particularly with discrete event simulation, the use of data-driven optimization to address issues of uncertainty, and the use of online optimization [168]. This last trend is quite striking in the development of online planning tools. Online optimization can generate real-time contextualized planning for the tourist as a base algorithm for planning platforms.

The use of simulation for problem-solving has also been gaining momentum. For this reason, different works in the field of OR and especially in vehicle routing problems opt for hybrid solution approaches that include simulation. However, within the area of simulation, there is also hybrid simulation that encompasses combinations of discrete event simulation, system dynamics and agent-based simulation [169]. Simulation techniques such as system dynamics are efficient to encompass complex systems such as tourism [170]. Similarly, based on the advancement of optimization algorithms, the use of so-called hyper-heuristics is another promising field for the development of solution techniques for TTDP. Hyper-heuristics allows a high-level search to find or generate low-level heuristics to obtain efficient solutions [123]. This approach has the potential to solve online optimization problems such as tourism planning [171].

Finally, although the field of bio-inspired algorithms is consolidated throughout the literature, different contributions such as Bacterial Foraging Optimization, Cuckoo Search, Forest Optimization, Mayfly Optimization, Sea Lion Optimization, Bat Algorithm, Animal Migration Optimization, among others, have not been applied to TTDP [172,173]. This extensive offer of algorithms increases the possibility of applying new solution techniques to the TTDP. Similarly, there are other Physics-inspired-based metaheuristics such as Quantum Swarm Evolutionary that can be applied to tourism planning problems [174]. In this sense, there is a wide field of research in solution techniques to improve TTDP solutions.

6. Concluding remarks

Tourist itinerary planning is a complex problem known in the literature as the Tourist Trip Design Problem. In this paper, we conducted a systematic review of the TTDP literature in a total of 102 documents to identify the proposed models and solution techniques. This problem is modeled in the field of Operational Research generally as an Orienteering Problem or a Team Orienteering Problem. In some works, it has also been modeled as a Generalized Maximum Coverage Problem, Oregon Trail Knapsack Problem, Vehicle Routing Problem, among others. This paper also presented a taxonomy of problem variants and solution techniques.

Appendix A. Mathematical formulations for TTDP and tourism planning problems

The following is a description of the conceptual and/or mathematical formulations of the different modeling approaches to tourism itinerary planning. Usually, let us a graph $G = (N, E)$ where N is the set of vertices and E is the set of arcs. The route is identified by an undirected link between a node $i \in N$ and a node $j \in N$, and is denoted by a pair $(ij) \in E$. Likewise, to address the problem of arc routing, it is denoted that the arc $(ij) = a \in E$. The main parameters and variables used in each mathematical formulation are detailed in Table 5.

1. TSP

The objective for TSP is to visit as many cities as possible in one tour. The formulation is as follows.

$$\min \sum_i^N \sum_j^N d_{ij}x_{ij} \tag{9}$$

$$\sum_j^N x_{ij} = 1; \forall i \in N \tag{10}$$

The taxonomy initially divides the documents according to the topology of optimization objectives (single and multiple objectives); 67.64% of reviewed papers considered single-objective problems, while 24.5% approached multiple objectives. The most recurrent variants of the single-objective and multi-objective problems were time windows and planning for a set of routes simultaneously. Also, various solution techniques have been used to solve this problem. Heuristic and metaheuristic techniques are mostly used due to the computational complexity. ILS was found to be the most widely applied technique in the reviewed papers, followed by GRASP. Other metaheuristic techniques have also generated efficient solutions, and several authors have ventured into the application of hybrid algorithms.

Considering the NP-hard nature of the TTDP, our review summarizes the main steps for the construction of each metaheuristic, the main parameters used as a function of development and iterations. Similarly, the type of instances used for experimentation (real, corresponding to 62.96% and theoretical, corresponding to 37.03%), the solution times, and the comparison with the results published in the literature are identified. The inclusion of several variants in the problem leads to increase the complexity and propose novel solution techniques. The development of memetic and hybrid algorithms shows great efficiency in terms of solutions, as well as in computational times compared to algorithms such as TS, VNS, GLS, ACO, and ILS. TTDP requires low computational time responses for tourist decision-making. Optimal solutions generally obtained with CPLEX for some instances show that even running mathematical models for up to one hour does not yield the best possible solutions. However, these solutions serve as a basis for comparison for the algorithms.

This review also presented a network of co-authorships, which shows that authors are organized in small networks, without evident link between these networks. Finally, future research lines are proposed related to the new perspectives of world tourism and represent more realistic conditions in the planning problems associated with tourism.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table 5
Indexes, parameters, and variables.

Nomenclature	Description	Nomenclature	Description
$i, j, h \in N$	Set of nodes (POIs)	A_{ij} and P_a	Arc attraction value
$d \in D$	Set of starting nodes	τ_i	Visit time
$u \in U$	Set of users	λ_i	Denote a (sensory) learning rate
$g \in G$	Set of POIs categories	$[C_{min}, C_{max}]$	Path interval of duration
$a \in E$	Set of arcs	w_i	Positive variable. Denote the reward collected.
δ^+	Set of all outgoing arcs	x_{ij} and x_a	Binary variable = 1 if a trip is made on arc a , 0 otherwise
δ^-	Set of incoming arcs	y_{ih}	Binary variable = 1 if a node is visited at time τ_{ih}
d_{ij}	Distance matrix to go from i to j	v_i	Binary variable = 1 if a node is visited, 0 otherwise
t_{ij}	Travel time matrix to go from i to j	γ_{ij}	Positive variable. Denote the number of times a trip has been made on the arc
c_{ij}	Travel cost matrix		
T_{max}	Maximum travel time available	u_i	denotes the position of the vertex on the path
CT	Total budget available	q_d	Binary variable = 1 if d is selected as a start vertex
c_i and c_a	Cost of visit	z_i	Positive variable. Number of times a vertex is visited.
P_i	Node attraction value		

$$\sum_i^N x_{ij} = 1; \forall j \in N \tag{11}$$

$$\sum_{(i,j) \in S} x_{ij} \leq |S| - 1; \forall S \subset N, 2 \leq S \leq N - 2 \tag{12}$$

$$x_{ij} \in \{0, 1\}; \forall ij \in N : i \neq j \tag{13}$$

The objective function (9) minimizes the distance traveled. Constraints (10) and (11) ensure that the traveler visits one city at a time. Constraints (12) avoids sub-tours by considering vertices N. Finally, constraints (13) define the nature of the variables.

2. Cruise itinerary problem

In addition to the defined parameters and variables, for the Cruise Itinerary Problem, a continuous function $P_i(\tau_i)$ is used as the cruise speed varies. Each node has a set m of ordered pairs such that, $\tau_{i0} < \tau_{i1}, \dots, < \tau_{im}$ and $P_{i0} < P_{i1}, \dots, < P_{im}$. Thus, $P_i(\tau_i)$ and $P_i(\tau_{ih})$ are concave functions. For further extension see [56]. This model presents two formulations, linear and non-linear. Both formulations are detailed below.

Linear formulation

$$\max \sum_i^N \sum_h^N P_{ih} y_{ih} \tag{14}$$

$$\sum_h^N y_{ih} - v_i = 0; \forall i \in N \setminus \{0\} \tag{15}$$

$$\sum_j^N x_{ij} - v_i = 0; \forall i \in N \tag{16}$$

$$\sum_j^N x_{ji} - v_i = 0; \forall i \in N \tag{17}$$

$$x_{ij} + x_{ji} \leq 1; \forall ij \in N \tag{18}$$

$$\sum_i^N \sum_h^N y_{ih} \tau_{ih} + \sum_i^N \sum_j^N x_{ij} t_{ij} \leq T_{max} \tag{19}$$

$$\sum_i^N v_i c_i \leq CT \tag{20}$$

$$v_0 = 1, x_{ii} = 0; \forall i \in N \tag{21}$$

$$x_{ij}, y_{ih}, v_i \in \{0, 1\}; \forall ij \in N, \forall h \in N \setminus \{0\} \tag{22}$$

The objective function (14) maximizes the attractiveness of the route. Constraints (15) ensure that a node is visited only if a set visit duration is used. Constraints (16) and (17) denote the flow in and out of a node. Constraints (18) ensure that a node is visited only once. Constraints (19) ensure that the total time is not exceeded. Constraints (20) limits the total cost of the trip. Constraints (21) avoid trips between the same nodes and ensure that the cruise departs from the port. Finally, constraints (22) define the nature of the variables.

Non-linear formulation

To approach $P_i(\tau_i)$ as a continuous function, the sets F and H denoting the continuous and discrete nodes, respectively, are added. The formulation is as follows.

$$\max \sum_i^F v_i P_i(\tau_i) + \sum_i^H \sum_h^N y_{ih} P_{ih} \tag{23}$$

$$\sum_i^F v_i \tau_i + \sum_i^G \sum_h^N y_{ih} \tau_{ih} + \sum_i^N \sum_j^N x_{ij} \tau_{ij} \leq T_{\max} \tag{24}$$

$$\tau_{il} \leq \tau_i \leq \tau_{im}; \forall i \in F \tag{25}$$

$$y_{ih} \in \{0, 1\}; \forall i \in H \tag{26}$$

The objective function (23) maximizes the route attraction as a continuous function. Constraints (24) replace constraints (19). Similarly, constraints (25) and (26) partially replace constraints (22). The rest of the restrictions of the linear model are maintained.

3. BTP

Based on the indexes, parameters, and variables in Table 5, the mathematical formulation of the BTP to maximize profit collected at POIs and arcs is as follows.

$$\max \sum_i^N P_i v_i + \sum_i^E \sum_j^E x_{ij} A_{ij} \tag{27}$$

$$\sum_{i=1}^N y y_{0i} \geq 1 \tag{28}$$

$$\sum_{i=1}^N y y_{i0} \geq 1 \tag{29}$$

$$\sum_i^E \sum_j^E y y_{ij} \geq v_j; \forall j \in N \tag{30}$$

$$\sum_i^N y y_{ij} = \sum_h^N y y_{jh}; \forall j \in N \tag{31}$$

$$x_{ij} \leq y y_{ij}; \forall ij \in E \tag{32}$$

$$x_{ij} + x_{ji} \leq 1; \forall ij \in E \tag{33}$$

$$\sum_{h \notin N'}^N \sum_i^{N'} x_{hi} \geq \sum_i^N \sum_j^{N'} x_{hi} / |N'|; \forall N' \subseteq N, |N'| \geq 2 \tag{34}$$

$$\sum_i^E \sum_j^E t_{ij} y y_{ij} + \sum_i^N \tau_i v_i \leq T_{\max} \tag{35}$$

$$y y_{ij} \in Z, \forall ij \in N \tag{36}$$

$$x_{ij}, v_h \in \{0, 1\}; \forall ij \in E, \forall h \in N / \{0\} \tag{37}$$

The objective function (27) maximizes the attraction of the bus tour. Constraints (28) and (29) ensure that the tour starts and ends at node 0. Constraints (30) ensure that to visit a node, a tour through the arc must be made. Constraints (31) are flow constraints. Constraints (32) ensure that an attraction is given when traversing the arc. Constraints (33) ensure that independent of the walk, the attraction is generated only once. Constraints (34) prevent sub-tour. Constraints (35) ensure that the time available is not exceeded. Finally, constraints (36) and (37) define the nature of the variables. Further explanation can be found in [71].

4. CBT

The CBT is formulated as a variant of arc routing. The origin node o and destination node d are considered. Therefore, $E' \subseteq E$ denotes the set of sites of interest and pickup/dropout points. For further extension see [58]. The mathematical formulation of the CBT is based on the following integer programming.

$$\min \sum_{(ij) \in E} c_{ij} x_{ij} \tag{38}$$

$$\sum_{(i,h) \in \delta^+} x_{hj} - \sum_{(i,h) \in \delta^-} x_{ih} = \begin{cases} -1 \rightarrow \text{if } : h = d \\ +1 \rightarrow \text{if } : h = o \\ 0 \rightarrow \text{if } : h \in N \setminus \{o, d\} \end{cases} ; \forall i \in N \tag{39}$$

$$x_{ij} + x_{ji} \geq 1; \forall ij \in E' \tag{40}$$

$$u_i - u_j + |N|x_{ij} \leq |N| - 1; \forall ij \in N \setminus \{o, d\} : i \neq j \tag{41}$$

$$x_{ij} \in \{0, 1\}; \forall ij \in E \tag{42}$$

$$u_i \in Z^+; \forall ij \in N \setminus \{o, d\} \tag{43}$$

The objective function 38) minimizes the cost associated with the bus trip. Constraints (39) is a flow conservation. Constraints (40) and (42) imply that $0 \leq x_{ij} + x_{ji} \leq 2$ ensuring that the bus travel in the arc cannot exceed 2. Constraints (41) avoid sub-tour. Finally, constraints (42) and (43) define the nature of the variables.

5. GMC for TripCover problem

The set of sites of interest presents an associated to a relevance vector $\vec{V}_i \in [0, 1]^{|G|}$ that measures the importance of the node in the category G. Likewise, each user presents a preference vector $\vec{V}_u \in [0, 1]^{|G|}$ that measures the interest by POI. The User-POI Interest is given by $\Gamma(i, u) : N \times U \rightarrow [0, 1]$, where $\Gamma(i, u) = \alpha \text{sim}(\vec{V}_i, \vec{V}_u) + (1 - \alpha) \text{pop}(i)$. The parameter $\text{pop}(i)$ is a popularity measure for the POI i and $\alpha \in [0, 1]$ defines the level of popularity. Function $\text{sim}(\vec{V}_i, \vec{V}_u)$ is the cosine similarity between user preference and relevance POIs vectors given by $\vec{V}_i \vec{V}_u^T / \|\vec{V}_i\| \|\vec{V}_u\|$. Additionally, one has a maximum time budget Tmax and a vector $\vec{z} = (z_1, \dots, z_M)$ defining the travel time on path $S = \{s_1, \dots, s_M\}$. For further extension see [59]. The rest of the parameters and variables are detailed in Table 5. The mathematical formulation is as follows.

$$\max \sum_i^{|S|} \sum_j^{|N|} \Gamma(i, u) x_{ij} \tag{44}$$

$$\sum_i^{|S|} \sum_j^{|N|} \tau_j x_{ij} + \sum_i^{|S|} z_i v_i \leq \text{Tmax} \tag{45}$$

$$\sum_i^{|S|} x_{ij} \leq 1; \forall j \in \{0, \dots, |N|\} \tag{46}$$

$$\sum_i^{|S|} v_i \geq \sum_i^{|S|} x_{ij}; \forall j \in \{0, \dots, |N|\} \tag{47}$$

$$v_i, x_{ij} \in \{0, 1\} \tag{48}$$

Equation (44) maximizes the score based on User-POI Interest. Constraints (45) prevent the time budget from being exceeded. Constraints (46) ensure that a node is visited only once. Constraints (47) state that if a node is visited, a tour of the arc must be made. Finally, constraints (48) define the nature of the variables.

6. RMT and BMT

In the formulation of the RMT and BMT based on the Optimal Tourism Problem, a robot (tourist) can make a tour to collect information. The tour starts from a base vertex i and returns to it at the end of the path. The reward depends on the visit time, hence, $Pf_i(\tau_i)$. Where f_i is a function of τ_i . Further explanation can be found in [52]. The total waiting time J_T and reward J_R is given by Eqs. (49) and (50) upon completion of the arcs $E_T \subset E$. The mathematical formulation is as follows.

$$J_T = \sum_i^{E_T} \sum_j^{E_T} d_{ij} + \sum_i^n \tau_i \tag{49}$$

$$J_R = \sum_i^N Pf_i(\tau_i) \tag{50}$$

For the case of RMT, J_R is maximized and $J_T \leq \text{Tmax}$. The formulation is as follows.

$$\max \sum_i^N w_i \tag{51}$$

$$\sum_i^N \sum_{j \neq i}^N x_{ij} d_{ij} + \sum_i^N \tau_i \leq \text{Tmax} \tag{52}$$

$$\sum_{i:i \neq j}^N x_{ij} = \sum_{j:j \neq i}^N x_{ji} = v_i \leq 1; \forall i = 1, \dots, n \tag{53}$$

$$\sum_j^N x_{0j} = \sum_j^N x_{j0} = v_0 = 1 \tag{54}$$

$$u_i - u_j + 1 \leq (n - 1)(1 - x_{ij}); \forall ij = 1, \dots, n : i \neq j \tag{55}$$

$$w_i \leq P_i x_i \tag{56}$$

$$w_i = \tau_i \lambda_i \tag{57}$$

$$x_{ij}, v_i \in \{0, 1\} \tag{58}$$

$$w_i \in \mathbb{Z}^+ \tag{59}$$

Equation (51) maximizes the reward. For which, Eqs. (56) and (57) are introduced to linearize the equation. w_i is a variable containing the payoff at each vertex i . Constraints (52) ensure that $J_T \leq T_{max}$. Constraints (53) ensure that the robot visits the node i only once. Constraints (54) ensure that the robot always visits $i=0$. Constraints (55) avoid sub-tours. Finally, constraints (58) and (59) define the nature of the variables.

For the case of BMT, J_T is minimized and $J_T \geq M_R$. Where M_R is associated with the reward. The formulation is as follows.

$$\min \sum_i^N \sum_{j:j \neq i}^N x_{ij} d_{ij} + \sum_i^N \tau_i \tag{60}$$

Subject to constraints (53) to (60).

7. CTPP

The mathematical modeling of the CTPP is done based on arcs. Therefore, each arc a has a complementary arc \bar{a} . There is a set of vertices $D \subseteq N$ from which the starting node is selected. Further explanation can be found in [66]. The formulation is as follows.

$$\max \sum_a^E P_a x_a \tag{61}$$

$$C_{min} \leq \sum_a^E c_a x_a \leq C_{max} \tag{62}$$

$$\sum_a^{\delta^-(i)} x_a - \sum_a^{\delta^+(i)} x_a = 0; \forall i \in N \tag{63}$$

$$\sum_a^{\delta^+(i)} x_a = z_i; \forall i \in N \tag{64}$$

$$\sum_d^D q_d = 1 \tag{65}$$

$$\sum_a^{\delta^+(S)} x_a + (1 - q_d) \geq \frac{\sum_i^S z_i}{\sum_i^S |\delta^+(i)|}; \forall d \in D, S \subseteq N \setminus \{d\} \tag{66}$$

$$\sum_a^{\delta^+(d)} x_a \leq (|\delta^+(d)| - 1)(1 - q_d) + 1; \forall d \in D \tag{67}$$

$$y_d \leq \sum_a^{\delta^+(d)} x_a; \forall d \in D \tag{68}$$

$$x_a + x_{\bar{a}} \leq 1; \forall a \in E : \exists \bar{a} \in E \tag{69}$$

$$x_a, q_d \in \{0, 1\}; \forall a \in E \tag{70}$$

$$z_i \in \mathbb{Z}^+; \forall i \in N \tag{71}$$

The objective function (61) maximizes profit. Constraints (62) ensure the duration of the route. Constraints (63) and (64) ensure that the number of times an arc is visited the inflow and outflow must be maintained. Constraints (65) ensure the selection of a single exit vertex. Constraints (66) and (67) prevent sub-tour. Constraints [100]) ensure that if a node d is selected as a start node, the vertex i cannot be visited. Otherwise, i can be visited several times. Constraint ((69) avoids trips along the same arc. Finally, constraints (70) and (71) define the nature of the variables.

8. VPP

The VPP is intended to calculate an itinerary that includes hotel accommodation and sites to visit on each day. There is a maximum distance $MaxDist$ willing to be traveled by the tourist within the region, a number of S days available, a maximum number of hotels $MaxH$, a maximum number of destinations $MaxDest$ that the tourist wishes to visit, the start and end location desired by the tourist. The formulation is done through a two-phase algorithm (online and offline). Further explanation can be reviewed in [99].

Appendix B. Analysis of the metaheuristic approach for the TTDP

Table 6 and Table 7

Table 6

Structure, instances used, and comparison with best known solutions (BKS) of the solution technique for single-objective TTDP.

Title	Metaheuristic	Parameters	Structure	Instances Type	CPU time	Average Gap with BKS and others approach
[17]	GLS	Not specified	Solution Initial = greedy, Movements = Insert, Replace, and disturb	Real (Ghent, Belgium)	500 ms (Avg)	Compared with Dynamic Tour Guide (DTG) [175]. GLS is better than DTG (gap of 4.38%)
[65]	GLS	MaxIter = 10	Solution Initial= greedy, Movements = Insert, Replace, swap, move, 2-opt, and disturb	Theoretical	1. Instance: [62]: <1 s (Avg) 2. Instance: [176]: (2.2–2.3)s (Avg) 3. Instance: [177]: 39.68 s (Avg) 4. Instance: [178]: 1 s (Avg)	1. 1.75% 2. 0.81% 3. 6.11% 4. 0.33%
[93]	1. GLS 2. SNVS 3. ILS	1. MaxIter = 10 2. MaxIter = 40 3. MaxIter = 140	GLS and VNS: Initial solution= Insertion GLS movements = Insert, Replace, 2-Opt, Swap, Disturb, and Group SNVNS movements = Group and Remove ILS movements = insert, shake (remove)	Theoretical	1. 5.38 s (Avg) GLS 2. 2.92 s (Avg) SVNS 3. 1.6 s (Avg) ILS	1. 0.56% GLS 2. 0.26% SVNS 3. 1.8% ILS
[40]	ILS	Not specified	Initial solution = Insertion, Movements = insert, shake (remove)	Real (San Sebastian, Spain)	50–100 Nodes = 2.5 s (Avg) Up to 288 Nodes = 0.1 s (Avg)	50–100 Nodes = 5% Up to 288 Nodes = 2.2%
[19]	ILS	MaxIter = 150	Initial solution= Insertion, Movements = insert, shake (remove)	Theoretical	Instances: [179, 180, 181] All: 3.1 s (Avg)	All: 1.8%
[36]	ILS	MaxIter = (10, 20, 40, 100)	Solution Initial = insert, Movements = remove	Theoretical	From [182] • 10 Nodes = 1.75 ms (Avg) • 20 Nodes = 5.5 ms (Avg) • 30 Nodes = 9.75 ms (Avg) • 40 Nodes = 14.75 ms (Avg) • 50 Nodes = 19.75 ms (Avg)	• 10 Nodes = 0% • 20 Nodes = 0.09% • 30 Nodes = 0.24% • 40 Nodes = 1.055% • 50 Nodes = 0.71%
[66]	ILS	MaxNoImprove = 30	Initial solution = insert, Movements = insert, remove	Theoretical	Instances: [183]: 0.6 s (Avg) Instances adapted of [183]: 0.3 s (Avg)	0.4% 0.3%
[10]	1. TD_CSCR 2. TD_S/CSCR 3. AvgCSCR 4. Time-Dependent ILS (TD_ILS) 5. Average ILS (AvgILS).	Not specified	Based on ILS and k-means algorithm. Movements = Insert, replace, shake (remove)	Real (Athens, Greece)	1. m1= 38.69, m2= 85.04 2. m1= 46.97, m2= 109.08 3. m1= 32.05, m2= 66.10 4. m1= 21.90, m2= 85.45 5. m1= 16.32, m2= 60.86	No comparison
[88]	ILS	Not specified	Initial solution = insert, Movements = insert, perturb (remove)	Real (Athens, Greece)	1. 500 Nodes/ 10 Scenic routes = 184 s (Avg) 2. 100 Nodes/ 20 Scenic routes = 237.75 s (Avg) 3. 200 Nodes/ 40 Scenic routes = 455.25 s (Avg)	No comparison
[72]	GA	Population size = 100, Selection rate 50%, Crossover rate = 0.8, and Mutation rate = 0.08		Real (Tehran, Iran)	No comparison	No comparison
[111]	GA	MaxIter = 100, Population size = 50–25, Crossover rate = 0.4, and Mutation rate 0.4		Real (Silesian, Poland)	Comparison based in T _{max} (distance that EV can drive on a single battery charge). Number of brakes D. D= 0:120 km = 2.14 s, 150 km = 4 s, 170 km = 3.28 s, 210 km = 13.25 s, 420 km = 33.44 s. D= 1:120 km = 4.53 s, 150 km = 8.19 s, 170 km = 6.87	Iterations D= 0:120 km = 87, 150 km = 71, 170 km = 59, 210 km = 100, 420 km = 75. D= 0:120 km = 95, 150 km = 68, 170 km = 79, 210 km = 77, 420 km = 73.

(continued on next page)

Table 6 (continued)

Title	Metaheuristic	Parameters	Structure	Instances Type	CPU time	Average Gap with BKS and others approach
[118]	GA	Not specified		Real (Reggio Calabria, Italy)	s, 210 km = 11.98 s, 420 km = 40.5 s. No comparison	No comparison
[98]	TS	Execution times = 10, Taboo list size = 2, 3, 9	Initial solutions: Random, Initial solution with POIs sorted in ascending order, and Initial solution with POIs sorted in descending order, Movements = Large Swap, Small swap, Hill climbing method	Real (Vienna, Austria)	<ul style="list-style-type: none"> • General (40s-60 s) (Avg) • Large Swap: up to 200 s • Small Swap: up to 250 s • Hill climbing: 5s 	No comparison
[77]	TS	Execution times = 30, 46,000 iterations Taboo list size = 5, 19, 15, 20, 25	Movements= Replace, Insert, Swap, Delete, Perturbate, Restart, and Penalize	Theoretical	6 s (Avg)	[180]: 2.96%(Avg) [181]: 6.48%(Avg)
[41]	GRASP	Not specified	Initial solution = Greedy, Local search = Insert	Real (Antwerp, Bruges, Ghent, Leuven, and Mechlin, Belgium)	Not specified	No comparison
[114]	GRASP	Execution times= 100 Restricted candidate list (RCL) size = 3, 5, and 7	Initial solution = Greedy, Local search = Exchange	Theoretical	Instance [62]: 15–28.3s	Standard deviation 24.57 – 37.61
[87]	GRASP	Execution times= 1000 α -cut = 0.2, 0.5, and 0.8 RCL size = 3, 5, and 7	Initial solution = Greedy, Local search = Exchange based on Neighborhood.	Theoretical	Instance: [180]: 555.96 s (Avg)	2.417% (Avg)
[103]	GRASP	Execution times= 1000 α -cut = 0, 0.2, 0.5, 0.8, and 1 τ = 20% RCL size = 3, 4, 5, and 6	Initial solution = Greedy, Local search = Exchange based on Neighborhood.	Real (Island of Tenerife in Spain):	0.02 s – 0.16s	No comparison
[39]	GRASP	Execution times= 100 α -cut Small and Large Instances= 0.2 and 0.4 RCL size Small Instances = 4, 5, 6, 7, 8, 9, and 10 RCL size Small Instances = 5, 6, 7, 8, 9, and 10	Initial solution = Greedy, Local search = Exchange based on Neighborhood.	Theoretical	Instances adapted from [179] Flexible Instance: 0.15 s Tight Instances: 0.07s	Compared with BKS, ACO [179], ILS [19], and VNS [184]. For $k = 1$, the average gap is worse by 1.55%, 1.17%, and 0.97% for BKS, ACO, and VNS, respectively. And better by 1.01% than ILS. For $k = 2$, the average gap is worse by 2.11%, 0.39%, and 1.28% for BKS, ACO, and VNS, respectively. And better by 0.22% than ILS. For $k = 3$, the average gap is worse by 1.34%, 0.3%, and 0.76% for BKS, ACO, and VNS, respectively. And better by 0.34% than ILS. Finally, for $k = 4$, the average gap is worse by 1.71%, 0.95%, 1.02%, and 0.2% for BKS, ACO, VNS, and ILS, respectively. Small Instances: Flexible Instance: 2.5% improved Tight Instances: 3% improved Large Instances: 28% Improved
[116]	GRASP	Not specified	Not specified	Real (Canary Islands)	Not specified	Not specified
[35]	LCA	Priority queue of the node to be processed (Q) = FIFO	Processing the node in priority queue, Judgment, Profit calculation, Optimal route selection	Theoretical	Polynomial = $O(V ^2 E T)$	No comparison
[48]	Slack Routes	MaxIter = Not specified	Initial solution = Insert, Improved = Shake (remove)	Real (Greece)	400 ms (1 tour) to 1.65 s (4 tours)	No comparison
[10]	Slack Routes	MaxIter = Not specified	Initial solution = Insert, Improved = Shake (remove)	Real (Greece and Berlin)	Greece: 350 ms (1 tour), 600 ms (2 tour), 750 ms (3 tour), and 1100 ms (4 tour). Berlin: 400 ms (1 tour), 650 ms (2 tour), 1000 ms (3 tour), and 1650 ms (4 tour).	No comparison
[76]	SA_RS	Maximal Temperature = $(N + M - 1) \times \theta$ s N numbers of locations M numbers of tours	Initial solution = Random, Improved = Neighborhood (swap, insertion, and	Theoretical	Instances adapted from [180] and [181]. 1. Using the Cauchy function	1. For [180] . SA_RS _{BF} : 0.47%, 3.86%, 3.50%, and 4.17%, and for SA_RS _{CF} : (continued on next page)

Table 6 (continued)

Title	Metaheuristic	Parameters	Structure	Instances Type	CPU time	Average Gap with BKS and others approach
		Initial temperature $T_0 = 1$, $B = 1000$, Control coefficient of the cooling schedule $\alpha = 0.90$ $N_{\text{non-improving}} = 10$ $\theta = 0.18$ $\theta = 0.5$	inversion), and Restart strategy		(SA RSCF): 15.32 s 2. Using the Boltzmann function (SA RSBF): 15.22s	0.47%, 2.26%, 2.77%, and 3.53%, for $m = 1, 2, 3$ and 4, respectively 2. For [181]. SA_RS _{BF} : 0.82%, 4.16%, 4.67%, and 4.51% and for SA_RS _{CF} : 2.44%, 5.32%, 4.75%, and 3.98%, for $m = 1, 2, 3$, and 4, respectively No comparison
[112]	FWA	Compactness (0.25, 0.5, and 0.75) Execution times = 20	Initial solution = Random, Improved = • Neighborhood: ○ Explosion Operator (2-opt) ○ Mutation Operator (cross move and 2-opt)• Selection Strategy	Real (Xi'an city, Shaanxi province of China)	10 s and 20 s	
[29]	2L-GLNPSO	Number of particles $I = 30$ Number of iterations $T = 1000$ Number of neighbors $K = 5$ Inertia weight $w = 0.9$ Acceleration constants of the personal best position $C_p = 0.6$ Acceleration constants of the global best position $C_g = 0.6$ Acceleration constants of the neighbor best position $C_n = 1.5$ Number of local search improvement NL = • Instances adapted from [180] = 1000 • Instances adapted from [181] = 1200	Initial solution = Random, Improvement = diversification strategy (Swap, Insertion, Reverse, and Mode change)	Theoretical	Time complexity = $O(m)$ where $m = D1 + D2$. $D1 = N + P - 2$. $D2 = N + P - 1$. N = number of vertices, P = number of paths For [180]: 44.95 s, 71.19 s, 105.505, and 157.96 s (Average for 100 and 200) for $m = 1, 2, 3$, and 4, respectively 1 For [181]: 82.69 s, 185.365 s, 332.29 s, and 542.29s% for $m = 1, 2, 3$, and 4, respectively	For [180]: 1.11%, 2.125%, 1.33%, and 1.025% (Average for 100 and 200) for $m = 1, 2, 3$, and 4, respectively 2. For [181]: 2.36%, 2.7%, 4.085%, and 3.87% (Average for 1–10 and 11–20) for $m = 1, 2, 3$, and 4, respectively
[100]	EAPX	Execution runs = 30 Number of generation NG=50 Number of individuals in half of the population $N = 50$	Initial Solution = Petal algorithm (PA) and diversity (2-opt), Improved = Local search (Swap) Partition Crossover	Theoretical	Not specified	For [180]: 1.39% For [181]: 2.54%
[117]	IIS + Average Slack	Threshold = 0 to 1; steps 0.01.	Initial solution = insertion: • Insertion based on ILS for tours with low total sum of the waiting times. • Insertion based on Average Slack for remaining tours), Improved = Shake (remove)	Theoretical and constructed	Average difference with ILS is a maximum of 1.6s	No comparison
[73]	• SILS • TRILS • PHILS	MaxNoImprove up to 150	• Insertion + Shake + Repair strategy (Remove) • Insertion + Shake + Repair strategy (Exclude) • Insertion + Shake + Repair strategy (Remove and Exclude)	Real (Izmir, Turkey)	15 ms (Avg)	Compared with AvgILS and RepAvgILS (Ander [102]). Without delays, SILS, TRILS, and PHILS are better than RepAvgILS with a gap of 0.07%, 0.05%, and 0.06%, respectively. With delays, SILS, TRILS, and PHILS are better than RepAvgILS with a gap of 0.04%, 0.035%, and 0.05%, respectively. Compared with VNS [184]. The ITS in better up to 0.3%
[11]	Collaborative Filtering (CF) + Iterated Tabu Search (ITS)	Termination condition $\psi_{\text{max}} = 50$ Internal local search restarts $\theta_{\text{max}} = 10$ Termination condition for the local search $\lambda_{\text{max}} = 10,000$ Tabu list size $\delta = 40$ Perturbation mechanism $\gamma = 0.5$	Filter-first, ITS (Greedy heuristic, multi-star local search: intra- and inter-route 2-Opt, 1–0 Relocate, and 1–1 Exchange)	Real (Foursquare data set: NYC, Pittsburgh, San Francisco, and Boston)	5 Nodes = 426.68 s 10 Nodes = 530.66 s 20 Nodes = 2431.8 s 40 Nodes = 3675.53s	
[97]	HA = GA + DEA	MaxIter = 200 Population size $Q = 60$ Crossover rate $P_c = 0.8$ Mutation rate $P_m = 0.05$ Difference rate $F = 0.2$	• Initial solutions = Greedy. • Route coded = double-layer chromosome (upper layer: POI sequence. Lower layer: duration of time at each POI). • GA application = for upper	Real (Jiuzhai Valley National Park, China)	Not specified	Compared with GA, PSO, and ACO [16]. The HA is better with a gap of 5.324, 4.651, and 3.964, respectively.

(continued on next page)

Table 6 (continued)

Title	Metaheuristic	Parameters	Structure	Instances Type	CPU time	Average Gap with BKS and others approach
[12]	RS-H ² A	<ul style="list-style-type: none"> • MaxIter = 200 • Population size $Q = 60$ • Global Search: Crossover rate $P_c = 1$ Mutation rate $P_m = 0.05$ Difference rate $F_d = 0.1$ • Local Search: Crossover rate $P_c = 0.5$ Mutation rate $P_m = 0.01$ Difference rate $F_d = 0.3$ 	layer <ul style="list-style-type: none"> • DEA application = for lower layer • Initial solutions = Greedy and Random • Random simulations • Hybrid evolution Global search: high frequency GA and low frequency DEA. Local search: high frequency DEA and low frequency GA.	Real (Jiuzhai Valley National Park, China)	Not specified	Compared with GA, PSO, ACO, [16], HA [97], and Stochastic Ant Colony System (SACS) [185]. The RS-H ² A is better with a gap of 11.202, 11.966, 10.814, 5.284, respectively.
[101]	1. DFS-Based Tree Search with Pruning 2. Modified Chinese Postman Solution 3. GRASP-VNS	Not specified	Initial solutions = GRASP, Improved = VNS (2-Opt, Remove, Insert)	Real (Beijing and Hangzhou)	1. Polynomial = $O(V^i \log V^i + E^i)$ 2. Polynomial = $O(V^i ^2 \log V^i + V^i E^i + V^i ^3 + E^i ^2)$ 3. $< 5s$	No comparison
[80]	Modified ILS	MaxIter = 100	Initial solutions = greedy, Improved = Swap, Move, Insert, and, Replace, Random perturbation, Greedy heuristic.	Theoretical and Real (Bandung, Indonesia)	Not specified	For adapted [180]: some solution are improved
[81]	DRDE	MaxIter = 50 Population size $NP = 1.2 * N$ Number of generations $L = 500$ Crossover rate $Cr =$ random (0.8 to 0.9) Mutation rate $F =$ random (0.6 to 0.7) Nodes that are not included $Pr =$ random (0.01 to 0.01)*N	Initial solution = heuristic, Improved = Exchange nodes:1 – 1, Exchange nodes:2 – 1, and Remove.	Theoretical	Not specified	Adapted from (C. [186]) and [187] < 0.39%
[113]	k-means method + GA	Population size $NP =$ Not specified Number of generations $L =$ Not specified Crossover rate $Cr =$ Not specified	User's interests, Other users' interest, Cluster (k-means), and Optimized itinerary (GA)	Real (Paris, Rome, and New York)	Not specified	No comparison
[75]	Memetic Algorithm (GS + VNS + DEA)	Iteration time $G = 100$ Population size $Q = 30$ Crossover rate $P_c = 0.3$ Mutation rate $P_m = 0.4$ Difference rate $F = 0.2$ Selected proportion $\delta = 0.1$	<ul style="list-style-type: none"> • Initial solutions = Random • Route coded = double-layer chromosome (upper layer: POI sequence. Lower layer: duration of time at each POI). • Global search (GA) • Local search (1. VNS = Inset, Move-best, 2Opt, and Swap-best). 2 DEA • Solutions' diversity and quality 	Real (Xiamen, China)	Not specified	Compared with GA, PSO, ACO, [16] and MA (A [188]). The approach is better with a gap of 1.007, 1.043, 0.877, and 0.548, respectively.
[110]	MA	Population size $P =$ Not specified Crossover rate $P_c = 0.3$ Mutation rate $P_m = 0.4$ Difference rate $F = 0.2$ Selected proportion $\delta = 0.1$	Initial solutions = Random and 3Opt, Improved = TS (ADD, DRO, and SWAP), Crossover, Mutation, and Updating population	Theoretical	Instances adapted from [179]: $m = 4$ (131.2 s to 1123.4 s)	Compared with VNS [184], ACO [179], and F-GRASP [39]. MA is better with an average of 2.494% and 2.57% than ACO and VNS, respectively. But MA is worse with an average of 0.15% than F-GRASP.

MaxIter = Maximum number of algorithm executions. ms = milliseconds. s = seconds. Avg = average.

Table 7
Structure, instances used, and comparison with best known solutions (BKS) of the solution technique for multi-objective TTDP.

Title	Metaheuristic	Parameters	Structure	Instances Type	CPU time	Average Gap with optimal BKS
[54]	MOSA	Not specified	Not specified	Real (Florida, E.E. U.U)	Not specified	No comparison
[50]	1. P-ACO 2. P-VNS	1. Colony size = 100, MaxIter = 100, pheromone value of $\tau_0 = 10$, evaporation rate of $\rho = 0.01$, weight for the pheromone information $\alpha = 1$, and weight for the heuristic information $\beta = 2$. 2. Iterations $\phi=1000$ and the maximum deterioration $\psi=5\%$.	1. Ant population, Weight vector, Heuristic information, Pheromone information, and Improvement (2-Opt) . 2. Initial solution = greedy algorithm, Weight vector, Improved = two-point exchange move.	Theoretical and Real (Padua, Italy. Vienna, Styria, Carinthia, and Lower Austria, Austria)	Adapted [62] and [189]. Single objective 1_p64: P-ACO up to 8.323 s, P-VNS up to 8.268 s. 1_p66: P-ACO up to 1.408 s, P-VNS up to 11.169s	Single objective = 1_p64 0.14% better. 1_p66 0.26% better.
[51]	Two Adaptive GA	Speed of walking = 4 km/hr • First GA: MaxIter = 400, Selection rate = 50%, Population Size = 250, Natural selection = 100, Crossover rate = 0.7, and Mutation rate = 0.1 • Second GA: MaxIter = 500, Selection rate = 50%, Population Size = 300, Natural selection = 100, Crossover rate = 0.8, and Mutation rate = 0.08	• Initial solutions and Coded (random), Natural selection, Selection, Mating (single-point and two-point crossovers), and Mutation (random). • Initial solutions and Coded (random mode between odd genes), Natural selection, Selection, Mating (single-point and two-point crossovers), and Mutation (random).	Real (Tehran, Iran)	Not specified	9.25% and 11%
[6]	TS + Pareto sampling		• Apply several TS equal to the number of objectives (The first solution obtained for the first objective becomes the initial solution for the next objective). • Apply several TS (global-criterion method)	Real (Andalusia, Spain)	Complexity = M^2N binary variables and $O(M^2N)$ constraints 7.31 s – 25.27s	No comparison
[127]	SA	MaxIter = 210 Proportion of temperature decrease = 0.005 Maximum temperature = 4000 Initial temperature Minimum temperature = 80	Initial solution = Mode 1: insert, Mode 2: orders POIs and insert the POIs in order from most to least satisfied, Mode 3: orders POIs and insert the POIs in order from least to most satisfied, Mode 4: calculates the average distance between POIs and inserts the ones with the shortest distance, and Mode 5: Prioritize POIs with the shortest visit times. Improved = movements (insert, swap, and shake).	Real (Prishtina, Kosova)	39 s (Avg)	No comparison
[128]	PSO	Deviation index of satisfaction degree: depth tour route = 0.018, quick tour route = 0.053 Deviation index of tour route distance: depth tour route = 0.104, quick tour route = 0.172	Optimize the priority factors of the objectives, Analysis of deviations, and Applies PSO.	Real (The Dajue Temple, Beijing)	Not specified	No comparison
[132]	AILS	Perturbation percentage = 40%	Initial solution = heuristic construction, Route sequence reversal process and its evaluation, Perturbation for all the routes	Theoretical	Adapted from [180]: 0.297 s - 1.934s	improvement of 8.744% vs. MSA [190], SA [76], ABC [191], and ILS [19]
[133]	Multi-objective Evolutionary Algorithm Relying on Pareto Dominance and a Pareto Front	Population size = Not specified Maximum generation number of the evolutionary algorithm = Not specified	Initial solutions = random Building a Pareto Frontier, Recombine two randomly selected tours, Generate a child, Mutate, Compare.	Real (Naples, Italy)	Up to 60s	No comparison
[135]	NGA	MaxIter = $D \times 20,000$ (D = number of travel days {1,3,5}), Population Size = 100, Neighborhood groups = 5, Crossover rate = 0.8, and Mutation rate = 0.01	Initial solutions = random Segmentation of the population into groups (Neighborhood Niching Strategy), Mating, Crossover, Mutation, and Repair strategy	Real (Guangzhou, China. Tokyo, Japan. Melbourne, Australia. Vancouver, Canada.	If $D < 3$, them 0.2 s If $D = 5$, them 0.4s	Compared with TS, VNS (Claudia [192]), two-stage algorithm (G. [193]), and Trip Planner (C. [194]) NGA is better.
[136]	GA				Not specified	No comparison <i>(continued on next page)</i>

Table 7 (continued)

Title	Metaheuristic	Parameters	Structure	Instances Type	CPU time	Average Gap with optimal BKS
[138]	PGFA	If POIs = 6, them MaxIter = 20 and Population Size = 6 If 20 > POIs > 6, them MaxIter = 120 and Population Size = 100 If POIs > 20, them MaxIter = 1000 and Population Size = 150 Crossover rate = 0.7 and Mutation rate = 0.03 Population size $W=120$, Number of optimization cycles $L=200$, Number of iterations for the local search $lc=100$, The iteration step for the decision-maker's interaction $L_{DM}=40$, Cluster radius parameter $r_a=0.4$, Initial attractiveness $\beta_0=1$, The light absorption coefficient $\gamma=0.1768$, and Initial randomness scaling factor $\alpha_0=0.5$	Coding, Initial solutions (Not specified), Fitness, Crossover (two-point crossover)	Real (Chengdu, China)	[195] Not specified	No comparison
[141]	GLNPSO	Not specified	Initialize the positions and velocities of the particles, Evaluate the objective function, Update (personal best, global best position, local best positions, and velocities and positions of all particles), Improved = Swap	Real (Chiang Mai, Thailand)	Not specified	0% with real test instances
[131]	CPMOEA/D	MaxIter = 150, Optimization subproblems = 30, Size of the neighborhood = 3, Crossover rate = 0.9, and Mutation rate = 0.3	Decompose the problem into scalars optimization subproblems and applies CP, Determine the neighborhood of each subproblem, Generates initial solutions = random, Apply the crossover and mutation operators, Improve the solution with CP solver, and Review objectives and dominance	Theoretical	[19,179,196] Adapted from [180] All: about 350s	It compares the set coverage, the number of non-dominated objective vectors, the measure of the distribution of the non-dominated set obtained in the objective space, and the inverted generational distance. IGD = 3.485 (Avg)
[8]	NSACDE	MaxIter = 200, Population size = 50, Size of Pareto set = 20, Pheromone heuristic factor = adjusted adaptively, Expectation heuristic factor = adjusted adaptively, Crossover rate = 0.9, Scale factor = 0.8.	Ant population, size of pareto set, pheromone and expectation factor, building the routes, Update the Pareto-optimal set, and the pheromone value, and Update the ants' parameter values (DEA)	Real (Kulangsu, Xiamen, China)	Not specified	It compares the inverted generational distance. IGD = 1.949 (Avg)
[142]	NSHA	MaxIter $G=200$, Population size = 50. Global search: Scale factor = 0.1, High learning intensity with individual optimum = 0.9, Low learning intensity with global optimum = 0.5. Local search: Scale factor = 0.3, High learning intensity with individual optimum = 0.5, Low learning intensity with global optimum = 0.9.	Initial solutions = greedy and coding with a triple-layer, Pareto solution (random simulation), Improved = hybrid evolution structure (PSO + DEA).	Real (Chengdu, China)	608 s (Avg)	It compares the inverted generational distance. IGD = 2.212 (Avg)
[143]	FAC	MaxIter = 500, Population size $W=80$, Number of iterations for the local search = up to 400, Initial attractiveness $\beta_0=1$, The light absorption coefficient $\gamma=1/\sqrt{N}$, Cooling factor = rand [0,95-0,97], and Initial randomness scaling factor $\alpha_0=0.01*N$	Initial solutions = Initial-Swarm heuristic, Feasibility of the updated solutions = Enforce - Feasibility and Augment -Route, Improved = Remove and Exchange.	Theoretical	[195] 25.794 s to 70.254s	Compared to [81]. Better solutions with gap of 1.22%, 0.83%, 1.00%, and 3.19%.

MaxIter = Maximum number of algorithm executions. ms = milliseconds. s = seconds. Avg = average.

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