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A constraint programming approach for multi-objective tourist trip design problem with mandatory visits: A case study for İzmir Turkey

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A B S T R A C T

The Orienteering Problem (OP) is an optimization problem that finds the locations and routes that will return the highest profit/benefit, starting from the initial location of the traveler/vehicle, visiting these locations, and ending with the starting location of the tour within a given time or distance limit. There is no obligation to visit all locations in the problem structure. OP has many real-life applications, such as staff routing and disaster relief routing. In this study, OP with Time Windows (OPTW), an extension of OP, is discussed with hotel selection and mandatory visits. Although the main objective of OPTW is profit maximization, it is also essential to minimize the total travel time to complete the tour efficiently. For this reason, we consider the OPTW as a multi-objective problem. In the problem considered here, it is assumed that the profit/benefit, travel time between locations, service period, and time interval that each location can be visited are determined to be known. Within the scope of the study, first, a Mixed Integer Programming (MIP) model is prepared for the problem. Since the proposed mathematical model does not provide solutions in a reasonable time for large networks, the problem is solved by a Constraint Programming (CP) approach. Attractive tourist points of interest for Izmir, one of Turkey's major tourist cities, are determined, and the proposed method is applied to the real-life problem. The problem is modeled as Multi-Objective OPTW with MIP and CP and solved. Also, sensitivity analysis is performed by considering two different scenarios.

1. Introduction

The Orienteering Problem (OP) involves selecting a group of points from the given n nodes and creating the shortest route between the selected points while maximizing the total benefit (Gunawan et al., 2016). It can be regarded as a variant of the widely known Travelling Salesman Problem (TSP). When determining a route in which all points are included in the TSP, the objective is generally to minimize the total distance traveled or the total cost. Still, in OP, there is a certain period, and in this time period, as many points as possible that have higher profits are tried to be included in the route to maximize the total benefit. Therefore, OP is known as a TSP where the destinations are selected (Vansteenwegen et al., 2011). Like TSP, OP has different structures as Team OP, Time-Dependent OP, and OP with Time Windows (OPTW) (Karabulut & Tasgetiren, 2020; Cédric Verbeeck et al., 2017).

OP has many application areas and is frequently studied for planning tourist groups' routes in the literature. The tourist route planning structure is one of the most suitable structures for OP. When planning the route of a tourist group, the trip

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duration is limited, and efforts are made to ensure that tourists visit as many points as possible that have higher profits in this limited time. After determining the places to visit, the decision to be made is the order of the points to be visited, that is, the tour route (Gavalas et al., 2014). It may vary according to the application areas, but generally, there is a time interval for the points to be visited, like museums have opening and closing times. Such situations are added to the problem as a time window; the earliest and latest times are determined to visit each designated point. These points are prevented from being visited outside these time intervals (Gavalas et al., 2014; Vansteenwegen et al., 2011). These types of problems are called OPTW in the literature.

When planning a tourist route with OP, it is assumed that the tour starts and ends at a specific hotel point. However, determining the hotel where tourists will stay in real-life is also a problem. While deciding the hotel point, selecting a place close to the points will ensure that more points are visited in the specified time period and the travel time is reduced (Divsalar et al., 2013). Although this issue is often addressed in multi-day plans, it can also significantly improve a single-day plan. Another critical issue in OP is Mandatory Visits. When the problem to be solved is determined, it may be mandatory to visit some points. For example, there may be must-see places in the area when choosing the route of a tourist travel plan, or some long-term customers may need to be visited when determining a customer visit route (Lin & Yu, 2017). The main objective of OP is to maximize the total benefit. However, the decision-maker may aim to minimize cost and benefit maximization in real-life problems. One of the main costs for OP, the fuel consumption of the vehicle used, depends on travel distance or travel time. In other words, when planning a tour, it is aimed to have a plan that minimizes the total cost while maximizing the total benefit. Of course, having multiple objectives requires multi-objective optimization (Wisittipanich & Boonya, 2020).

The OP is a combinatorial optimization problem, and it has an NP-Hard structure (Golden et al., 1987). For this reason, many approaches are developed as solution methods. In addition to mathematical programming, heuristic and meta-heuristic methods reduce the solution time (Gunawan et al., 2016) as OPTW. To bring the problem closer to real-life, the selection of hotels and mandatory visit issues are included, and both benefit maximization and cost minimization are determined as objective functions. Cost is handled as total travel time in this study. To solve the problem, first, a mixed integer programming (MIP) mathematical model is proposed. Then, to reach a solution in a shorter time, the problem is solved by Constraint Programming (CP), which is one of the exact solution methods to get a solution in a shorter time.

The remainder of this study is structured as follows; a detailed literature review of OP studies based is presented in Section 2. In Section 3, the problem is defined, then the solution methodology is explained. In Section 4, a real case study for İzmir is performed. In Section 5, the results are presented, and sensitivity analysis is conducted considering two scenarios. Finally, in Section 6, the study is summarized, and a horizon for future studies is given.

2. Literature review

OP and its extensions find comprehensive coverage in the literature as mathematical optimization problems. These problems are handled as both combinatorial optimization problems and real-life applications. Wide application areas, numerous variants of OP, and the development of many methods to solve the problems have led to the writing of literature research articles on the subject (Gavalas et al., 2014; Gunawan et al., 2016; Vansteenwegen et al., 2011).

In the last of these studies, Gunawan et al. (2016) examine many articles published in recent years, revealing the variants of the problem that have emerged in the last five years as well as the existing literature reviews. In the study, solution approaches, application areas, and benchmark instances are given for all variants of OP, and suggestions for future studies are presented. First, a chronological summary is given for the classic OP, and in this summary, Team OP (TOP), OPTW, and Time-Dependent OP (TDOP) are included. After giving basic information about the subjects, benchmark instances in the literature are presented for each variant, and the solution methods are explained. In the discussion section, the need for exact solution methods is emphasized. Since Multi-Objective OP, Multi-Period OP, and OP with Hotel Selection are given in previous literature review articles, in this study, the same review structure is applied for the other extensions of the problems that emerged recently for Classical OP. After giving information about these extensions, the application areas of the problem are emphasized. In the article, special titles are opened for Mobile Crowdsourcing Problem and Tourist Trip Design Problem, and other application areas are gathered under a separate title.

After Gunawan et al.'s (2016) literature review, studies on OP and its variants continue. These studies generally focus on finding new and faster solution approaches. Even if the problem structures to be solved are tried to be changed, the Time Window structure is generally integrated into the problems. For example, Karabulut & Tasgetiren (2020) discuss Team OP with Time Windows. After providing an introduction and general information about the problem with the literature review, the authors present a constructive heuristic with the proposed Evolution strategy. The main feature of the proposed strategy is that it produces new solutions with the Ruin and Recreate method. According to the numerical experiments, it has been emphasized that the hybrid method is effective for benchmark instances and provides seven new "best-known" solutions. In another study where TOP is handled with Time Windows, partial scores are added to the problem structure (Yu et al., 2019). The authors propose a Selective Discrete Particle Swarm Optimization algorithm to solve the problem. Different motion schemes are used for the movement from the first solution point determined by this method, and the best one is selected. In the article, the mathematical model is also given, the proposed algorithm is applied to TOP, TOPTW, and Partial Scored TOPTW, respectively. After the experimental studies, it is stated that the results obtained for TOP and TOPTW are comparable, and a high-quality solution is produced for the Partial Scored TOPTW with the instances generated.

Similarly, Yu et al. (2019) discuss the TOPTW problem, this time with time-dependent scores. Here, the Mathematical Model is given, and a Hybrid Artificial Bee Colony algorithm is proposed to solve the problem. The hybridization of the algorithm is achieved with an acceptance rule based on Simulation Annealing. The algorithm is tested with small, medium, and large instances, and it is stated that it produces high-quality and comparable solutions with other meta-heuristics.

Another OP variant, TDOP, is frequently used with Time Windows. Verbeeck et al. (2017) present a MIP model for the problem and use the Ant Colony System meta-heuristic to reach effective solutions in less solution times. The authors evaluate their algorithms with realistic data based on the Belgian road network. They can achieve excellent results in short computation times. In their other studies, the same authors discuss the travel time between two locations with a stochastic structure depending on the departure time from the first point. The authors start the study by mentioning OP and its applications, emphasizing the importance of traffic. They use the Ant Colony System meta-heuristic as a solution method and a prediction algorithm. They evaluate this solution method, which is defined as the Stochastic Ant Colony System Algorithm, with similar data. The results of OPTW are evaluated in a stochastic environment and compared with optimal solutions. The authors state that the stochastic Ant Colony System results are much better than the optimal solutions, but the algorithm requires a longer computation time (C. Verbeeck et al., 2016).

As emphasized before, OP has many application areas. However, the Tourist Trip Design Problem (TTDP) is the best known and most studied. Therefore, a literature review article discusses this application of OP (Gavalas et al., 2014). In this article, the authors provide general information about TTDP and the solution methods. The authors state that the main structure of the problem is based on OP and TOP but it also includes different structures. They provide a comparative analysis between alternative solution approaches for each problem, detail open research issues, and make recommendations for future studies. In TTDP, the time intervals at which visiting points accept visitors are of great importance. This situation can be handled easily with OPTW. For example, Gavalas et al. (2015) tried to solve TDTOP with Time Windows for TTDP. The authors use a cluster-based heuristic for the solution and real POI datasets compiled from the metropolitan area of Athens (Greece) to test the accuracy of the heuristic. As a result of the evaluations, it is stated that good quality solutions are obtained for large-scale data.

One important decision when planning a tourist route is to determine the hotel where the tourists will stay. Making the hotel selection and route planning can increase the number of points visited and decrease travel time. Hotel Selection is frequently studied in the literature by integrating different problems in the last decades. In these studies, the problem is considered as Orienteering Problem with Hotel Selection (OPHS), and it is generally studied for multi-day planning. The OPHW, which is studied by Divsalar et al. (2013) for the first time in the literature, is defined as follows: "Given with a set of hotels, N vertices are presented, and each vertex is assigned a score while hotels have no score. The time needed to travel from one vertex to another is known for all pairs. The time available for each trip is limited by a certain time budget that can be different for each trip. The goal is to determine a tour that maximizes the total score collected. The tour consists of connected trips and visits each vertex at most once. Every trip should start and end in one of the available hotels." The authors present a MIP model for the newly generated problem. Then, they use the Skewed Variable Neighborhood Search algorithm to solve the handled problem and question the algorithm's efficiency with the instances generated. In another study conducted for the same problem, Sohrabi et al. (2020) used the Greedy Randomized Adaptive Search Procedure. The authors reveal the differences between the methods and methods used for OPHS in the literature and explain the algorithm procedure in detail. Next, they test the proposed method with benchmark instances.

While planning tourist routes, the total benefit is maximized by visiting as many points as possible that have higher profits. Some of the points included in the trip plan are more important than others. Therefore, it is desirable to include these points in the solution by giving higher scores. However, these points are not guaranteed to be included in the optimum solution. In such situations, if there are must-see points in the trip plan, these points can be added to the model as Mandatory Points or Mandatory Visits. OP with Mandatory Visits is studied for TOP by Lin & Yu (2017) for the first time in the literature. They define the problem as a new extension where some points are mandatory, must be visited, and some points are optional. Then, they develop a MIP model and Multi-start simulated annealing algorithm to solve the problem. They apply these solution methods on small and large-sized instances derived from existing TOPTW instances. They state that the proposed Multi-start simulated annealing algorithm provides better solutions in less computation time than the MIP model. They also compare the proposed algorithm with Simulated Annealing and Artificial Bee Colony algorithms and state that the Multi-start simulated annealing algorithm produces a better quality solution. Lu et al. (2018) address the same problem with exclusionary constraints in another study. They also present a MILP model to solve the problem and propose a Memetic Algorithm. The Memetic Algorithm consists of a a dedicated tabu search procedure, a backbone-based crossover, and a randomized mutation procedure. The authors use benchmark instances to evaluate the algorithm and use the hybrid Variable Neighborhood Search algorithm, previously used for the same problem in the literature to compare with other methods. They reveal that the suggested algorithms perform better than other methods by statistical analysis.

Classic OP has only one objective, and this objective is maximizing total benefit. In a problem such as planning tourist routes, it aims to show tourists as many important places as possible. However, the problem should be taken into account by the tourist and the organizer of the tour. From this aspect, the organizer will want to minimize the cost while maximizing the total benefit. To handle these two objectives simultaneously, the model should be designed as multi-objective, and Multi-Objective Optimization methods should be used for the solution. There are studies dealing with cost minimization along with benefit maximization. In one of them, Bederina & Hifi (2017) handle TOP as a multi-objective and propose a multi-objective evolutionary algorithm based on the Non-dominated Sorting Genetic Algorithm and local search operators for the solution. Bederina & Hifi (2017) propose a mathematical model for the problem that treats the total benefit as negative and the objective as minimization. Then, the authors explain the proposed algorithm procedure in detail. For comparison, they use benchmark instances and state that the results offer a wide range of Pareto-optimal solutions for decision-makers. They also identify that the proposed algorithm is compatible with the best bounds in the literature. Hapsari et al. (2019) consider TOPTW for multi-objective planning of tourist routes in the following years. They determine the second objective as minimum time to minimize cost while maximizing benefit. The procedure for the proposed Adjustment Iterated Local Search algorithm is given after the MILP model. Then, the algorithm's efficiency is measured by comparing it with Multi-start Simulated Annealing, Simulated Annealing, Artificial Bee Colony, and Iterated Local Search algorithms using the generated benchmark instances. The results show that the proposed algorithm reaches solutions for large problems faster. On the other hand, Wisittipanich & Boonya (2020) focus directly on TTDP, aiming to maximize tourist satisfaction and simultaneously minimize the total travel cost. In the study, the problem is formulated as a MIP model, and the Global Local and Near-Neighbor Particle Swarm Optimization method is performed together with the swap strategy for the solution. The proposed method and strategy process is explained with visual support, and the method has been tested for ten problems based on a real case in the city of Chiang Mai. As a result, it is stated that the proposed method gives good results for all cases.

As seen in the previous studies, various solution methods are developed for many OP variants. Since the exact solution methods are insufficient for large-scale data sets, researchers aim to find near-optimal solutions with heuristic and meta-heuristic algorithms. However, exact solution methods for large-scale OPs are still lacking in the literature. Although the first method that comes to mind for exact solution methods is Mathematical Programming, CP can also provide effective solutions, especially for combinatorial optimization problems.

CP is an exact solution method especially used for scheduling problems in the literature, but it can be applied to almost all combinatorial optimization problems. Similar to Mathematical Programming, the problem should be modeled formally and solved with a software solver. Although the modeling form is like Mathematical Programming, CP allows constraints and variables to be handled more flexibly. The problem can be expressed more clearly with its global constraints. CP has a limited number of applications for OP so far. In the literature, CP for OP was first used by Gedik et al. (2017). They use CP for TOPTW. After introducing the problem, the authors mention the solution methods applied earlier in the literature. They emphasized that there is only one exact solution method for TOPTW, and this method is the branch and price algorithm used by Tae & Kim (2015). And the authors suggest a new exact solution method. After the model is presented and verified with a sample, some search algorithms are tried to increase the method's effectiveness.

Furthermore, the proposed model is evaluated with benchmark instances, emphasizing that it is comparable with state-of-art algorithms. In another study, Hu et al. (2018) developed a multi-objective evolutionary algorithm based on Gedik et al.'s (2017) CP model. The developed method is applied for multi-objective TOPTW. When the method is tested with benchmark instances, it provides many new non-dominated solutions.

In this study, the OPTW problem is differentiated by introducing various new constraints, and MIP and CP models are developed for the defined novel problem. The effectiveness of the proposed models is tested with real-life data based on a TTDP to be made in the Izmir region of Turkey.

3. Methodology

In this section, the handled problem is introduced, and the proposed mathematical models for the problem are presented with definitions. Firstly, the MIP model is presented, and then, the CP model is represented.

3.1 Mixed Integer Programming Model

The handled problem aims to determine the route that will provide maximum benefit with minimum travel time. The problem is defined on an undirected graph expressed as $G = (N, A)$, where N represents the set of nodes on the graph, and A is the set of arcs between nodes. The places that can be visited and the locations of the hotels are expressed as a node for each, and the connections between nodes are defined in the set of $A = \{(i, j): \forall i, j \in N, i \neq j\}$. In the current route to be created, it is assumed that the routes to be followed for the vehicle to be used are clear. It is assumed that the travel time ($TT_{i,j}$) of the vehicle between points cannot be negative and $TT_{i,j} = TT_{j,i}$. Each visiting point has the profit P_i and the time spent Vt_i at the point. There are also the earliest (S_i) and the latest visit (F_i) times for each point. In addition, it is assumed that the vehicle leaving the hotel returned to the same hotel after stopping at the visiting points. It is accepted that some points in the problem have to be visited and these points are defined in a different set (Z). Unlike the classic OP, here, hotel selection is also made. In this way, besides finding the most suitable tour, the most suitable hotel is selected among the options. The points that can be selected for the hotel are defined in the Hotel set. It should be noted here that the hotel selection concept differs from the OPHS literature. The MIP model prepared within the scope of the study is given below. A multi-day program is made in the OPHS literature, and hotel selection is made separately for each day's plan. In our problem, a one-day plan is considered, and hotel selection is made only once.

Parameters:

N	Set of all points $i \in 1..(n+m)$
I	Set of points that can be visited $i \in 1..n$
Z	The set of mandatory visits $Z \subset N$
$Hotel$	A set of hotel points to choose from $h \in 1..m$
$TT_{i,j}$	Travel time from point *i* to point *j*
P_i	Profit of point *i*
S_i	The earliest time that point *i* can be visited
F_i	The latest time that point *i* can be visited
Vt_i	Visit time of the visit at point *i*
M	A large enough constant

Decision Variables:

Y_{ij}	$\begin{cases} 1, \text{if the point uses connection between } i \text{ and } j \\ 0, \text{otherwise} \end{cases}$
C_i	$\begin{cases} 1, \text{if point } i \text{ is visited} \\ 0, \text{otherwise} \end{cases}$
L_i	Leaving time from point *i*
A_i	Arrival time to point *i*

$$max \sum_{i=1}^{n} P_i C_i \tag{1}$$

$$min \sum_{i}^{n+m} \sum_{j=1}^{n+m} Y_{ij} TT_{i,j} \tag{2}$$

subject to

$$\sum_{i=1}^{n+m} Y_{ij} - \sum_{i=1}^{n+m} Y_{jk} = 0 \ ; \ \forall j \in N \tag{3}$$

$$\sum_{i=1}^{n+m} Y_{ij} - \sum_{i=1}^{n+m} Y_{jk} = 0 \ ; \ \forall j \in N \tag{4}$$

$$C_j \geq \sum_{i=1}^{n} Y_{ij} \ ; \ \forall j \in I \tag{5}$$

$$TT_{ij} \leq A_j - L_i + M(1 - Y_{ij}) \ ; \ \forall i,j \in N \tag{6}$$

$$TT_{ij} \geq A_j - L_i + M(Y_{ij} - 1) \ ; \ \forall i,j \in N \tag{7}$$

$$L_i = A_i + Vt_i \ ; \ \forall i \in I \tag{8}$$

$$A_i \geq S_i \ ; \ \forall i \in I \tag{9}$$

$$L_i \leq F_i \ ; \ \forall i \in I \tag{10}$$

$$L_i = 0; \ \forall i \in Hotel \tag{11}$$

$$A_i \leq 0; \ \forall i \in Hotel \tag{12}$$

$$\sum_{h}^{m} \sum_{j=1}^{n} Y_{hj} = 1 \tag{13}$$

$$\sum_{i=1}^{n} Y_{ij} \geq 1 \ ; \ \forall j \in Z \tag{14}$$

$$A_i, L_i \geq 0 \ ; \ \forall i \in N \tag{15}$$

$$Y_{ij}, C_i \in \{0,1\} \ ; \ \forall i,j \in N \tag{16}$$

The objective function (1) maximizes the total profit of the points visited. The other objective function (2) minimizes the total travel time. Constraint (3) is the balance constraint for each point. Constraint (4) allows each point to be visited at most once. Constraint (5) allows the points visited to be identified. Constraints (6) and (7) add the departure time to the travel time to determine the arrival time to the relevant point. Constraint (8) adds the visiting time at any point to the arrival time, allowing it to determine when it leaves the relevant point. Constraints (9) and (10) are time window constraints. With Constraint (11), the vehicle leaves the hotel at the start. Constraint (12) ensures the vehicle returns to the hotel before the end of the time window. Constraint (13) allows only one hotel to be selected. Constraint (14) provides a mandatory visit to the lunch point. Constraints (15) and (16) are decision variable constraints.

3.2 Constraint Programming Model

As stated before, CP is one of the exact solution method alternatives for combinatorial optimization problems with its global constraints in modeling, variables that can be defined as intervals, and flexibility. Although OP is a well-known combinatorial optimization problem on which much work is presented, CP is used for this problem only by Gedik et al. (2017). The authors discuss TOPTW in their studies and propose a CP model for this problem. Here, a model is established similar to the study of Gedik et al. (2017), but OPTW is enhanced with real-life constraints such as mandatory visits and hotel selection.

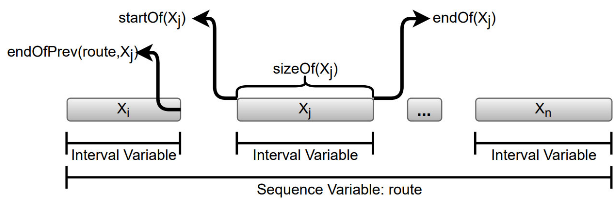

Fig. 1. Visual representation of Interval and Sequence variables

The set definitions and parameters used are the same as the MIP model. For decision variables, interval type and sequence type variables are used. The interval-type variables contain the start time, end time, and size values in one variable. Interval type variables can be optional or mandatory; this information is specified with a constraint in the MIP, while it is specified in the variable definition in the CP (IBM, 2014). Sequence-type variables store information in the order in which variables defined by the interval type are processed. The types of variables used, and the information defined on them are shown visually in Figure 1. The two variables defined based on this information are as follows;

Decision Variables:

X_i Optional interval variable defining the visit to point *i* with a duration of visit Vt_i.

$route$ Sequence variable indicating the order in which points are visited.

The time window information of all determined points is defined on X_i variable. The objective function and constraints created with the specified parameters and decision variables are given below;

Objective Functions:

$$max \sum_{i=1}^{n+m+1} P_i * presenceOf(X_i) \tag{17}$$

subject to

$$first(route, X_1), \forall\, i \in Hotel \tag{18}$$
$$last(route, X_{n+m+1-i}), \forall\, i \in Hotel \tag{19}$$
$$startOf(X_i) \;= 0, \forall\, i \in Hotel \tag{20}$$
$$endOf(X_{n+m+1-i}) \le F_{n+m+1-i}, \forall\, i \in Hotel \tag{21}$$
$$presenceOf(X_i) = presenceOf(X_{n+m+1-i}) \quad \forall\, i \in Hotel \tag{22}$$
$$\sum_{i \in Hotel} presenceOf(X_i) = 1 \tag{23}$$
$$\sum_{i \in Hotel} presenceOf(X_{n+m+1-i}) = 1 \tag{24}$$
$$presenceOf(X_i) \;\; \forall\, i \in Z \tag{25}$$
$$noOverlap(route, Ttime) \tag{26}$$

The objective function (17) maximizes the total profit collected. Since the specified interval variable is optional, it can be checked whether the variable exists with the global constraint presenceOf. presenceOf returns 1 if the optional interval variable exists, 0 if not. Constraint (18) ensures that if X_i exists in the specified sequence variable, it is in the first place. Similarly, Constraint (19) ensures that if $X_{n+m+1-i}$ is in the specified sequence variable, it is in the last place. While Constraint (20) ensures that the departure time from one of the hotels is at 0, Constraint (21) ensures that the return to the hotel point is before the determined time. Constraint (22) guarantees that the tour ends in the hotel where it started. Constraints (23) and (24) ensure that not more than one hotel point is included in the solution. Constraint (25) ensures that all points in the set of points that must be visited are included in the solution. These points are where lunch is planned for our problem. This constraint, which separates the problem from the classical OP, would increase the suitability of the problem to real-life for a trip to be planned throughout the day. Finally, with the global constraint noOverlap (26), it is provided that the interval type variables are not processed simultaneously; that is, points are not visited at the same time. In addition, the minimum time to pass between points is the travel time specified by Ttime. Only TransitionDistance functions can be used within the noOverlap constraint. For this reason, Ttime is defined as TransitionDistance function, which specifies the travel time. Since the same interval variable cannot be defined more than once in CP, "$n + m + 1 - i$" points are also defined as hotel points to complete the route at the same point.

As stated earlier, although the objective of a classical OP is to maximize the total profit, it is also important to minimize the cost for a tour planner. Since the multi-objective handling of the problem is a problem in itself, there are few studies in the literature. However, CP has a function called staticLex that handles multi-objective problems. Using this function, it is easy to handle different objectives at the same time. So, we can replace the objective function with Eq. (27) stated below.

$$\max \text{staticLex}\left(\sum_{\text{i}=1}^{\text{n+m+1}} \text{P}_\text{i} * \text{presenceOf}(\text{X}_\text{i}), -\sum_{i=1}^{n+\text{m}+1}\left(startOf(X_i) - endOfPrev(route, X_i, 0{,}0)\right)\right) \tag{27}$$

staticLex allows the objectives within the function to be dealt with simultaneously. These objectives can be two or more. However, when writing objectives into the function, they should be ordered in order of importance, from more important to less important. For our problem, since the objectives are profit maximization and travel time minimization, the travel times are considered negative in the objective stated as maximization. While calculating travel times, CP's global constraints are used again. As mentioned before, if the variable X is present, startOf indicates X's starting time, and it returns 0 if variable X is not present. endOfPrev represents the end of the interval variable that is previous to the interval in the sequence variable. For this reason, the interval variable must be given with the sequence variable to which it belongs. Other inputs of the function show the values that the interval variable takes when it is first order in the solution and does not exist in the solution (IBM, 2014). Both are indicated as 0 here.

4. A case study for Izmir, Turkey

As stated in the literature review section, OP is a frequently used problem structure in designing tourist routes. It enables touring the touristic spots in a specified area in a way that will provide the highest profit. However, it is necessary to collect data about the region to calculate the total benefit, determine the route between points, and determine when these points can be visited. In this study, a trip plan to be made in Izmir, which is the third largest city in Turkey, is considered. In this case, it is aimed to provide the highest profit in a limited time.

Izmir has many historical and touristic places. In this study, only the important places in the central region are included among the mentioned places. While determining the places to visit, the locals and travelers' suggestions are considered. In addition, the A Day in Izmir Tourism Guide prepared by the metropolitan municipality is also used (IMM, 2021). After determining the points to be visited, the profits of these points are determined according to the information received from the local people. The designated people are asked to score the points to be visited and the profits are calculated by taking the geometric mean of the scores given for each point.

Table 1
Points and information determined for tourist travel design

	Point of Interests (i)	Start(S_i)	Finish(F_i)	Profit (P_i)	Duration(Vt_i)
1	Hotel points	07:00	20:00	-	-
2	Kordon	07:00	20:00	81.99	60
3	Konak (Clock Tower)	07:00	20:00	71.46	45
4	Historical Elevator (Dairo Moreno Street)	07:00	20:00	75.52	45
5	Kemeraltı Bazaar	09:00	18:00	70.85	90
6	Agora Open Air Museum (Smyrna)	09:00	18:00	65.98	60
7	Historic Naval Ship Museum	09:00	17:00	66.39	60
8	Hisar Mosque	07:00	20:00	61.67	45
9	Kızlarağası Inn	09:00	20:00	62.91	60
10	KültürPark (Fair)	10:00	20:00	72.3	75
11	Balçova Cable-car	10:00	20:00	89.18	90
12	Kadifekale	11:00	16:00	17.28	60
13	Alsancak Sevgi Yolu	09:00	20:00	52.71	60
14	Kıbrıs Şehitleri Street	12:00	13:30	69.46	45
15	Izmir Archaeological Museum	09:00	18:00	58.24	60
16	Izmir Toy Museum	09:00	17:00	60.1	45
17	St. Polycarp Museum	15:00	17:00	69.32	45
18	Atatürk Museum	10:00	16:00	79.88	60
19	Ahmet Piriştina Izmir City Archive and the Museum	08:30	17:30	64.37	45
20	Izmir Mask Museum	09:00	17:00	62.09	45

Because the geometric mean is more advantageous than the arithmetic means in terms of the way it is calculated since it considers the compounds that occur from period to period (Dzombo et al., 2018; Ke, 2013). Then, the time intervals at which these points should be visited are investigated for the time windows. While collecting this data, time intervals of the places, such as museums with certain opening and closing hours, are easily determined. For other venues, the time intervals generally preferred by the locals are used. After the time interval determination, the durations of the visits spent at the points visited are determined based on the same resources. These times include the getting-on and getting-off times of the tourist group. Lastly, the distance between points is determined using Google Maps, and the maximum urban speed limit of 50 km/hour is accepted as the vehicle's speed. Travel times are calculated based on this information. All of the mentioned information is represented in Table 1. The display of the determined points on the map is given in Fig. 2. The table showing the distances between points is given in Appendix-1.

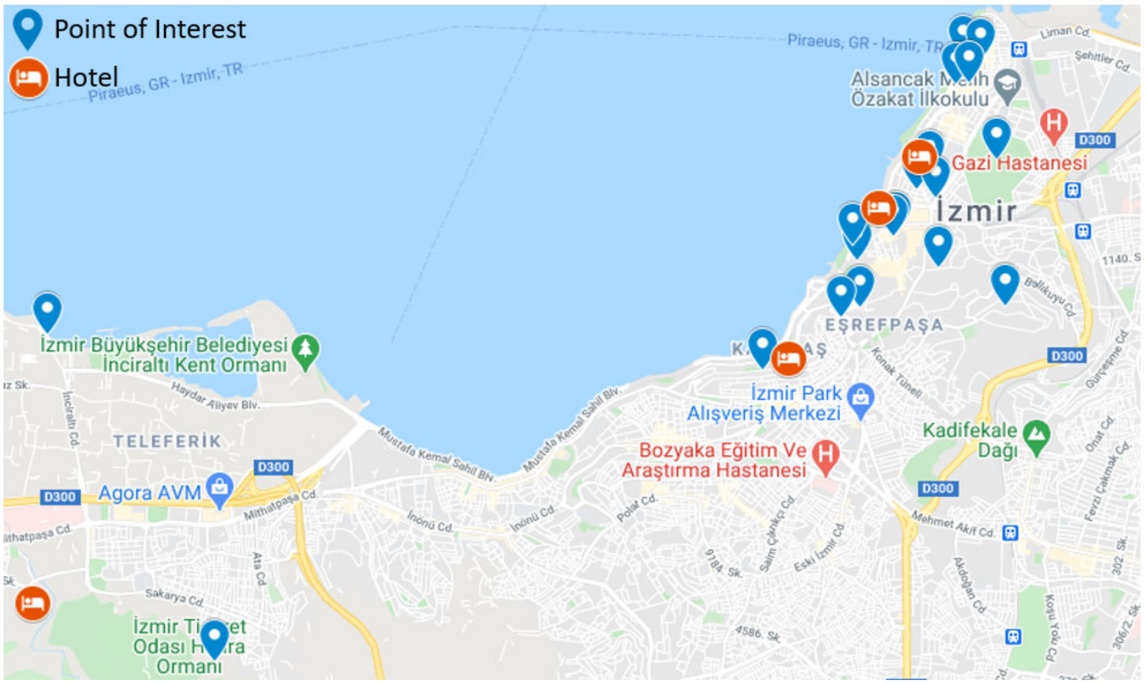

Fig. 2. The display of the determined points on the map

The first row of Table 1 represents hotel points; therefore, their profits are zero. In addition, the time interval for the tourist trip plan is determined as the time window of the hotel points. In this way, the tourist group is enabled to start the tour from the hotel at 07:00 a.m. and return to the same hotel before 08:00 p.m.

Four hotel points are defined in the problem. In addition, mandatory visits have been determined to increase the compatibility of the problem with real-life. This approach aims to include a meal break into an all-day travel plan. Kıbrıs Şehitleri Street, which is among the spots designated for this break and is rich in dining areas, is made compulsory for a meal break. In addition, the time window for this point is set between 12:00 a.m. and 01:30 p.m. for this break to be placed in the middle of the day.

4.1. Computational Results

The models in sections 3.1 and 3.2 run on a computer with Intel Core i5-7200U CPU 2.50 GHz processor and 8.00 GB RAM with a dataset prepared within the case study. First, both models are considered with a single objective. The MIP Model is coded in IBM ILOG CPLEX Optimization Studio 12.10.0 environment and solved using CPLEX solver. The problem takes too long to solve, so the CP model is needed. CP model is coded in the same environment as the MIP model, but CP Optimizer solver is used. CP reaches the optimum solution in four seconds and guarantees the optimum solution in 49.84 seconds in total.

When the solutions obtained are examined, it is seen that 14 of 19 points are visited and the total profit obtained is 955.294. The trip starts at the number 1 hotel point at 07:00 a.m. and ends at the same hotel point at 07:58 p.m. Hisar Mosque is the first point visited after the hotel point. Before going to Kıbrıs Şehitleri Street, which is the designated point for lunch, Konak (Clock Tower), Historical Elevator, Izmir Toy Museum, İzmir Mask Museum, Atatürk Museum are visited, respectively. After the break for lunch, the tour passes to Kordon. It continues from this point by Agora Open Air Museum (Smyrna), St. Polycarp Museum, APIKAM, Izmir Archaeological Museum, Kızlarağası Inn, and KültürPark (Fair) visits, respectively. After this point, the tourist group returned to the same hotel.

As mentioned earlier, the cost is also an important factor for tourist trip planners, and the main cost of a trip is the use of vehicles. Therefore, it is important to consider minimizing travel time and maximizing total benefit simultaneously. The staticLex function of CP, which is used for multi-objective models, is helpful for such cases. Using this function, the same model is solved for the multi-objective model this time. The multi-objective model reaches the optimum profit value obtained by the single-objective model in only five seconds. While the total travel time is 43 minutes in the single-objective model, this value is 28 minutes in the multi-objective model. In other words, it has been shown that an alternative solution can reach the optimum total benefit value with less cost with the multi-objective model. However, when solving the multi-objective model, it takes much longer to guarantee the optimum solution than the single-objective model.

4.1. Sensitivity Analysis

In this section, the effects of the changes in the case study on performance are discussed, and the results of the proposed models are examined. In this context, two different scenarios are discussed. In the first of these scenarios, a point that is not included in the solution but is thought to be included is added to the set of mandatory visits. In the other scenario, the duration of the visits is doubled according to the idea of spending longer time at the points visited.

Scenario-1:

Within the scope of Mandatory Visits, the points desired to be included in the solution can be introduced directly to the model, and those points can be guaranteed to be in the solution. An example of this situation is shown at Kıbrıs Şehitleri Street for the lunch break. When the model is solved only by accepting this point as mandatory, it is seen that Kemeraltı Bazaar is excluded from the solution, despite its high profit. It is thought that visiting this point, one of the important tourism points of Izmir, is important for incoming tourists. Within the scope of Mandatory Visits, this point can also be included in the solution by including the compulsory visiting points set. When the model is solved for a single objective in this way, we observe that the optimum total profit decreases to 953.836, and the total travel time is 30 minutes. In addition, when the route formed within the scope of the solution is examined, it is seen that the starting hotel point changes and hotel number 3 is selected. While the number of points visited does not change, the inclusion of the Kemeraltı Bazaar point in the solution causes KültürPark (Fair) point to be out of the solution. Although there is a decrease in the solution time, there is no major difference. When the model is solved for multi-objective, it is shown that the optimum profit value can be reached with less cost as in the previous case. While the total profit value remains the same in the solution, the total travel time decreases to 29 minutes. Even though there are no considerable changes in the solution time of the multi-objective model, the optimum solution is guaranteed in 43.94 seconds this time. When all the results are examined, it can be interpreted that increasing the number of Mandatory Visits for this situation may cause deterioration in the objective value but shorten the solution time.

Scenario-2:

The planning of tourist routes is aimed at introducing more places by showing tourists more points. Therefore, in some cases, visiting periods representing the time spent at the points can be kept short. In this case, although tourists can visit more points, they may not spend enough time at the points they visit. Based on this idea, the durations of the visits are changed within the scope of the second scenario, and all durations are doubled. The problem is run as a single-objective and multi-objective with the updated parameters. In both cases, the solution is reached within a few seconds. In the optimum solution of the single-objective model, the total profit and the number of traveled points are reduced by half compared to the original model. The total profit value is 475.415, and the total number of visited points is 7. In this solution, where hotel number 2 is chosen, the total travel time is 42 minutes. When the model is considered multi-objective, the optimum profit value is reached as in the previous scenarios, and a decrease in the total travel time is observed: 37 minutes. As a result, it is revealed that the increase in the duration of the visits causes a decrease in the number of points visited and thus a decrease in total profit. The multi-objective handling of the model is resulted in an improvement in the total travel time and thus, the cost, as in other scenarios.

5. Conclusion

OP is a type of problem that is frequently used for the Planning of Tourist Routes. However, since the problem is NP-Hard, the solution time of the problem increases exponentially as the number of points increases. There are 23 points in the problem to be solved in this study, including the hotel, so the problem size can be accepted as a medium. Even with a problem of this size, while the MIP model runs for extended periods, the CP model reaches the solution in four seconds and guarantees an optimum in 49.84 seconds. These results show that for OP, CP can be used to solve medium-sized problems quickly and can be a good alternative to heuristics for larger-sized problems.

The multi-objective version of the problem is also applied in the study. It is emphasized that besides maximizing total profit, minimizing cost is important, and one of the main reasons for the cost is using vehicles. Therefore, it is important to consider these two conflicting objectives simultaneously. CP's modeling flexibility is used to solve the multi-objective model. The results show that the optimum total profit value can be achieved with less cost.

In the study, sensitivity analysis is performed to examine the effect of parameter changes on the solution. In this context, two different scenarios are determined, and the CP model is run as single-objective and multi-objective for these scenarios. The analysis results show that the increase in the number of mandatory visits causes a decrease in e total profit, but it provides a small decrease in solution time. In addition, increasing the duration of the visit also causes a decrease in total profit and improves the solution time. Taking the model as multi-objective reveals that there may be alternative solutions for all scenarios where optimum profit value is achieved with less total travel time.

The paper has noteworthy contributions that are intended to be brought into the literature and application area. These contributions can be specified as follows: (1) The Tourist Trip Design Problem is extended with Mandatory Visits; (2) A novel hotel selection procedure is added to the problem to make the problem more realistic; (3) The novel problem is handled as a multi-objective and modeled as MIP; (4) Constraint Programming approach is used to solve the problem; (5) A real application for İzmir, Turkey is presented to show the applicability and reliability of the methodology; (6) Mathematical model is run for different scenarios and the results are obtained; (7) It is aimed that, the proposed method will be used by organizations' aims to improve their tourist trip strategies.

In future studies, a wider travel plan can be prepared by increasing the number of destinations to be traveled, to question the competence of the method in larger problems, and the results can be compared with meta-heuristics. In addition, CP can be used to solve sub-problems in approaches where the problem is solved by decomposing, thus, the speed of the method can be increased. Since it is easier to create and solve multi-objective models with CP, the number of objectives can be increased by defining different objectives than those specified in the study. In this way, whether there are more qualified alternative solutions can be investigated.

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Appendix 1

Distance(km)	H1	H2	H3	H4	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
H1	0	0	0	0	1,7	2,4	4,2	4,9	2	12,5	2,1	2,3	1,5	12,7	5	1,5	1,9	3,6	4,2	1,5	2	1,1	1,1
H2	0	0	0	0	2,3	0,55	3	3,8	3	11	4,4	4,5	2,2	11,6	5,6	1,3	2,6	2,5	3,1	0,9	1,7	1,4	1,7
H3	0	0	0	0	4,4	1,6	0,7	1,5	3	8,7	2,1	2,2	4,4	4,4	3,1	2,8	4,6	1,2	1,1	2,7	3,7	3	3,8
H4	0	0	0	0	14,1	11,4	9,7	10,6	11,5	3,8	11,2	11,3	14,2	3,4	12,1	11,9	13,7	10,6	11,9	11,8	12,8	12,1	12,8
2	1,7	2,3	4,4	14,1	0	3,4	4,3	5,1	2,6	12,2	2,6	2,9	1,2	12,9	6,9	2,3	1,4	4,2	5,2	2	0,5	1,6	0,55
3	2,4	0,55	1,6	11,4	3,4	0	2,2	1,2	1	11,5	0,85	0,55	3,3	15	3,9	2,5	3,6	2,7	1,9	1,7	2,7	2,1	2,8
4	4,2	3	0,7	9,7	4,3	2,2	0	2,1	4,2	10,2	2,8	3	5	9	5,2	3,5	6	2	1,7	3,4	4,3	3,7	4,4
5	4,9	3,8	1,5	10,6	5,1	1,2	2,1	0	1,5	12	0,65	0,9	2,6	12,3	3,8	1,3	3,1	3,4	3,1	1,6	2,9	2,1	3
6	2	3	3	11,5	2,6	1	4,2	1,5	0	12,2	0,85	2,2	2,6	12,8	3,2	2,3	6,8	2,1	1,9	2,3	2,6	1,3	2,3
7	12,5	11	8,7	3,8	12,2	11,5	10,2	12	12,2	0	10,7	11	12,9	5,5	11,9	11,4	13,2	10	10,7	11,3	12,3	11,6	12,3
8	2,1	4,4	2,1	11,2	2,6	0,85	2,8	0,65	0,85	10,7	0	0,26	2,4	11,9	3,8	2,2	3,4	2,6	2,4	1,2	2,5	1,7	2,6
9	2,3	4,5	2,2	11,3	2,9	0,55	3	0,9	2,2	11	0,26	0	2,6	11,7	3,5	1,1	3,5	3,1	2,8	1,3	2,6	1,9	2
10	1,5	2,2	4,4	14,2	1,2	3,3	5	2,6	2,6	12,9	2,4	2,6	0	13	3,8	2,4	3,7	4,2	3,7	2	1,2	1,1	1,1
11	12,7	11,6	4,4	3,4	12,9	15	9	12,3	12,8	5,5	11,9	11,7	13	0	11,9	12,9	13,1	10,6	10,6	11,3	12,2	11,6	12,3
12	5	5,6	3,1	12,1	6,9	3,9	5,2	3,8	3,2	11,9	3,8	3,5	3,8	11,9	0	5	5,1	3,3	3,1	3,6	4,2	3,4	4,3
13	1,5	1,3	2,8	11,9	2,3	2,5	3,5	1,3	2,3	11,4	2,2	1,1	2,4	12,9	5	0	2,3	3,1	2,9	0,35	1,4	0,4	1,5
14	1,9	2,6	4,6	13,7	1,4	3,6	6	3,1	6,8	13,2	3,4	3,5	3,7	13,1	5,1	2,3	0	4,5	5,1	2,4	1,3	2,1	1,4
15	3,6	2,5	1,2	10,6	4,2	2,7	2	3,4	2,1	10	2,6	3,1	4,2	10,6	3,3	3,1	4,5	0	1,5	2	3	2,3	3
16	4,2	3,1	1,1	11,9	5,2	1,9	1,7	3,1	1,9	10,7	2,4	2,8	3,7	10,6	3,1	2,9	5,1	1,5	0	2,3	3,2	2,6	3,3
17	1,5	0,9	2,7	11,8	2	1,7	3,4	1,6	2,3	11,3	1,2	1,3	2	11,3	3,6	0,35	2,4	2	2,3	0	1,6	0,6	1,7
18	2	1,7	3,7	12,8	0,5	2,7	4,3	2,9	2,6	12,3	2,5	2,6	1,2	12,2	4,2	1,4	1,3	3	3,2	1,6	0	2,9	0,07
19	1,1	1,4	3	12,1	1,6	2,1	3,7	2,1	1,3	11,6	1,7	1,9	1,1	11,6	3,4	0,4	2,1	2,3	2,6	0,6	2,9	0	1,6
20	1,1	1,7	3,8	12,8	0,55	2,8	4,4	3	2,3	12,3	2,6	2	1,1	12,3	4,3	1,5	1,4	3	3,3	1,7	0,07	1,6	0