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Time-dependent, activity-based itinerary personal tour planning in multimodal transportation networks

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ABSTRACT
This article investigates personal, activity-based tour planning (TP) for tourists in public transportation networks. The objective is to propose an effective framework based on tour parameters, including starting days and times, duration, priority rates of cities, a list of activities and their duration, and a list of transportation means. The subsequent TP should consider the duration of trips to maximize the scores for visiting and acting in a given time frame. In this framework, two nested modules are of primary interest: first, in the main module, the order of the visited cities is determined using a genetic-based strategy; second, in the subordinate module, the shortest path in a multimodal network is obtained based on an adapted Dijkstra algorithm. Since TP is either personal or activity based, constraints of activity duration and periods of enduring activities are considered in the main framework. To evaluate the capabilities of the proposed framework, data are used from real transportation networks in 15 major cities in Iran. Then, several tour planners are employed in order to substantiate the performance of the proposed evolutionary framework. The resulting average relative error of the performed trials is 4.38%, and the simulation therefore vividly demonstrates that the proposed framework is suited for attaining optimum tour plans.

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KEYWORDS
Itinerary planning; multimodal transportation networks; time-dependent; genetic algorithm

1. Introduction
At present, tour planning (TP) can be regarded as a vital task for the effective handling of transportation networks. Due to growing planning complexities, the demand for efficient tour planners has been on the rise. Cumulative energy overheads have forced societies to use public transportation more frequently. In addition, as an alternative solution, intelligent navigation systems can assist people in utilizing transportation facilities more resourcefully. Hence, multimodal TP used in finding optimal paths can be a crucial requirement to utilizing different transportation means, both in terms of public transportation facilities and private vehicles (Gräbener, Berro, and Duthen 2010; Liu 2011; Liu and Meng 2009).

Many tourists actively gather additional information about the cities they plan on visiting. They may possibly even plan their entire trip based around contextual information about their preferred cities, their desired activities, and the restrictions that come with such choices. When doing so, however, many tourists encounter technical hurdles that make it difficult for them to make an easy, correct decision about the cities they want to visit, or about choosing or eliminating specific activities during their trip. The respective sequences they go through looking for activities or target locations can be determined based on data mining strategies (Garcia et al. 2013; Wang and Cheng 2001).

Choosing the right location, and also arranging and organizing the trip in general, is a vital problem for many tourists. As a result, the ultimate choice may simply be a result of a preferred target location based on their personal interests. The subsequent activities are then decided on based around that location preference. In this respect, it can be beneficial to develop a TP system that considers the individual interests of each tourist, helping them obtain preferable travel paths based on their aforementioned conditions.

For example, a tourist may have a preference to visit a city only for a limited and very specific period of time. Clearly such time constraints on the length of the trip then do not make it feasible to visit all favoured places. The tourist is therefore required to pick out the most favourable point of interests based on his/her preferences. Such an itinerary plan can be seen as a form of an orienteering problem (OP), where a set of control points are given, together with related scores as well as
a road network plan. The OP assists in generating a route along certain points, maximizing the total score while remaining subject to certain constraints. The objective of planning, therefore, is to discover the sequence of the most favoured cities that can be visited during a restricted time span (Abbaspour and Samadzadegan 2011; Archetti, Hertz, and Speranza 2007; Bouly, Dang, and Moukrim 2010; Boussier, Feillet, and Gendreau 2007; Ke, Archetti, and Feng 2008; Qin, Lim, and Xu 2009; Souffriau et al. 2008; Vansteenwegen and Van Oudheusden 2007; Wang, Golden, and Wasil 2008).

In this article, a TP framework is designed based on tour parameters such as start day and time, duration, priority rate of cities, a list of activities and their temporal extent, and a list of transportation means in order to compute an optimum schedule for maximizing the overall score for visited cities.

2. Literature review

Previous studies in this field can be categorized first as studies concerned with finding the shortest path, and second as those concerned with tour scheduling.

2.1. Shortest path

In this section, past efforts on finding shortest paths in road networks (public transportation network (PTN)) and multimodal transportation networks (MTN) are reviewed in three subsections.

2.1.1. Shortest path in road networks

Leading studies were conducted during the 1950s and 1960s by Dijkstra (Dijkstra 1959), Bellman, and Ford (Bellman 1958; Ford and Fulkerson 1962), and Hart, Nilsson, and Raphael (Hart, Nilsson, and Raphael 1968). In former works, several strategies were utilized to reduce the search space. To accelerate the basic shortest path algorithms, researchers focused on developing speeding-up techniques (Bauer et al. 2010; Bauer, Delling, and Wagner 2011; Wagner and Willhalm 2003, 2007).

2.1.2. Shortest path in PTN

There are principally two methodologies to deal with the inherent temporal nature of transportation networks: time-independent and time-dependent approaches (Müller-Hannemann et al. 2007). The Earliest Arrival Problem can be tackled by an adapted Dijkstra’s technique in both time-independent and time-dependent approaches (Bauer, Delling, and Wagner 2011; Pyrga et al. 2008).

2.1.3. Multimodal routing

The Label-constrained Shortest Path Problem (LCSPP) can be tackled via multimodal planning. Barrett et al. conducted a comprehensive theoretical study about the complexity of LCSPP based on various types of languages (Barrett, Jacob, and Marathe 2000).

2.2. Tour scheduling

The Tour Planning Problem (TPP) has been investigated by two major groups of researches:

1. The first group tackled TPP through a mathematical approach, because the problem is NP-hard and the objective of the algorithms was not an application-oriented approach. (Ke, Archetti, and Feng 2008; Liang, Kulturel-Konak, and Smith 2002; Michel, Gilbert, and Frederic 1998; Tang and Miller-Hooks 2005).

2. The other group focused on realizing TPP by planning an optimum itinerary. Most of the studies conducted by this group have been designed around an optimal route rather than around planning a tour in transportation networks. (Abbaspour and Samadzadegan 2009; Aifadopoulou, Ziliaskopoulos, and Chrousoiou 2007; Androutsopoulos and Zografos 2009; Lee, Kang, and Park 2007; Niknafs, Shiri, and Javidi 2003). The remaining research by this group concerns planning and scheduling tours in transportation networks.

Maruyama et al. have proposed an effective personal navigation system to handle TPP (Maruyama et al. 2004). In their system, first the tourist provides P-tour with points of interest using their ranked rates, as well as constraints of entrance; then, P-tour delivers a near-optimal plan. In that research, a genetic algorithm (GA) is employed to tackle the planning task. This system was later enhanced to allow planning of a multi-objective tour and to provide navigation to the users (Shiraiishi et al. 2005). This system does not model user activities and MTN.

Hagen et al. (2005) proposed an effective system for trip planning and tourist guidance, called Dynamic Tour Guide. The objective of their system was to plan a personal tour and to provide a navigational system and certain descriptions based on the location. They applied Tour Building Blocks (TBBs) to represent the points of interest. In addition, the ontology was developed via a tree of concept classes for each TBB. The matching degree between the profile of a user and TBB could be calculated, and then, based on an assignment of interest-matching points, the algorithm focuses on tackling the problem by maximizing the sum of the interest-matching points within an agreed-upon time.
frame (Hagen et al. 2005). This research also does not model user activities and MTN.

Zografos and Androutsopoulos (2008) proposed a set of criteria to lexicographically optimize the itinerary plan. Parameters such as total travel time, number of transfers, and total walking and waiting time were to be optimized to depart at the start and arrive at the end within some indicated time window. Based on their formulation, the itinerary planning problem was formulated as a SPP in a time schedule multimodal network with time windows and time-dependent travel times. An efficient, dynamic-programming-based strategy was utilized to tackle the problem (Zografos and Androutsopoulos 2008). This study does not model the rate of interest, or user activities.

Abbaspour and Samadzadegan (2011) developed an interconnected framework based on GA techniques to model TPP and multimodal SPP. In their approach, TP is the main module and finding the shortest path is the secondary module (Abbaspour and Samadzadegan 2011). This project only considers urban settings with short timescales and has a high degree of computational complexity.

Garcia at el. (2013) presented a personal tour guidance named PETs. In their study, the task of the Tour Trip Design Problem (TTDP) was investigated. TTDP considers time windows to provide more appropriate services and suggestions (Garcia et al. 2013). This system does not, however, model user activities.

Some of the disadvantages of previous studies are revealed as inefficiency in larger search spaces, use of unrealistic samples, high computational complexity, and not modelling MTN (except for the last three studies). Furthermore, this study is not comparable to existing studies, because those earlier studies only consider urban contexts with short time-scales, whereas this study includes plans of travel between two or more cities, which is a more difficult task. There is no restriction in time, and intercity activities should be modelled. This study can also provide an effective method for storing the time data in transportation networks.

- Public transportation systems and personal preferences are considered. According to the nature of these networks, there exist some temporal restrictions to a trip, since with public transportation facilities the departure time can be determined based on timetables and schedules.
- The duration of user activities in every city and their time periods are considered.
- The duration of a tour is limited, and the time span of the planned trip should be less than this constraint.
- A tour can be either closed or open. In closed tours, the tourist will ultimately return to the starting city, whereas in open tours, the end destination is not same as the starting city.
- The tourist can rate the cities based on their significance to set some criteria for visiting all cities or only some of them.

The problem is modelled based on a directed and weighted graph $G(V, E, W)$, where $V$ is the set of cities and $E$ is the set of edges between cities. For every edge, a weight of $W(C_i, C_j)$ is assigned that represents the time interval of connecting edges between $i$th city ($C_i$) and $j$th city ($C_j$). The weights of edges are time dependent; hence, their values will change during travel.

The model of the modified problem can be reformulated as:

$$
\text{max}(\sum (P_iY_i))
$$

Subject to:

$$
\sum_i X_{ij} f(\tau) + \sum_i \text{Dur}_{act_i} \leq DT, \quad (2)
$$

$$
\sum_{i \in S} X_{ik} = \sum_{j \in S} X_{kj} \leq 1, \quad (3)
$$

$$
\sum_{j \in S} X_{ij} \leq |S| - 1 \forall S \subset V, |S| \geq 3, \quad (4)
$$

$$
Y_i, X_{ij} \in \{0, 1\}. \quad (5)
$$

In this mathematical formulation, Equation (1) shows the objective function in which $P$ is the priority rate of each city. The variable $Y$ is assigned to each city. $Y$ is a binary variable that is either 0 or 1; when $Y$ is equal to 1, the city is active in the tour plan, otherwise it is inactive. The constraint of Equation (2) shows that the itinerary trip plan should be restricted to the determined duration of the tour (DT). In this

3. Definition and formulation of the problem

In this study, the selective travel salesperson problem (Laporte and Martello 1990) is developed and extended based on the objective of a tourist trip plan. As a result, some distinct themes are considered in this problem, such as:
restriction, $X_{ij}$ is a binary variable that indicates the connection of $i$th and $j$th cities. If these two cities are connected, $X_{ij}$ is equal to 1, otherwise it is equal to 0. The function $f(\tau)$ shows the travel time required between two cities. The parameter $Dur\_act$ represents the duration of activities in each city, as given by the assessment method that will be expressed in Section 4.3.

The constraint in Equation (3) validates that each city is visited only once in the tour plan. The constraint in Equation (4) prevents internal loops in the tour. The set of cities used in the solution is $S$, and $|S|$ is the cardinality of this set.

4. Proposed methodology

The goal is to plan a tour during a reasonable amount of time in such a way that the travellers receive the highest benefit from their visits and activities in the chosen cities. The planning procedure has four main phases, as can be seen in Figure 1. The first phase is the initialization of user data, including starting day and time of the tour, priority rates for cities, activities, time to be spent in each city, and the total duration of the tour. The second phase, which can be regarded as the main step, is the trip scheduling based on a GA optimization strategy. In the third phase, the shortest paths are determined based on the start times in MTN. In this step, the main purpose is allowing the algorithm to determine the source and destination cities along with the departure times of the respective selected vehicles, in order to finally yield the most appropriate path for the trip based on time and nominated destinations. The last phase is performed within the database that stores and records the timetables for public transportation facilities.

4.1. Modelling PTN

The heart of PTN can be a timetable. A timetable is a tuple $(C, S, M, \Pi)$, where $C$ shows the elements of the connection, $S$ is the set of stations, $M$ is the set of means of transportation, and $\Pi$ shows the periodicity of the timetable. Elements of the connection in $C$ can be defined as a tuple $c = (M, C_1, C_2, \tau_1, \tau_2)$. It can be interpreted as a vehicle $M \in M$ traveling from city $C_1 \in S$ to city $C_2 \in S$, departing at $C_1$ at time $\tau_1 < \Pi$ and arriving at $\tau_2 < \Pi$. Arbitrary travel times between two cities, expressed as times $\tau_1$ and $\tau_2$, can be obtained using a $\Delta$ function (Pajor 2009):

$$|\Delta| = \begin{cases} \tau_2 - \tau_1 & \text{if } \tau_2 > \tau_1 \\ \Pi - \tau_2 + \tau_1 & \text{otherwise} \end{cases}.$$  \hspace{1cm} (6)

Figure 1. Proposed framework.
4.2. Multimodal route planning

In this study, the shortest path between two cities at departure time $\tau$ is obtained based on an adapted Dijkstra’s algorithm. To facilitate this, Dijkstra’s technique needs to be temporalized. The main objective is to obtain the shortest path at departure time $\tau$. In the time query process, the time-dependent (temporal) form of the algorithm is the same as its time-independent form. However, the edges of the network show first-in–first-out properties. This means that only two modifications have to be made: first, adding the trip departure time $\tau$ to the input data and calculating the weights of the edges at the current time. Suppose that $e = (v_1, v_2)$ is the edge whose weight should be determined. The time of edge $e'$ obtained by function $f_e$ is equal to the departure time $\tau$ along with the time distant through $v_1$, as shown by $Dist_s(v_1)$. In Dijkstra’s algorithm, the weights of edges are therefore obtained by $f_e(\tau + Dist_s(v_1))$. Based on the utilized time query approach, the shortest path should be determined at departure time $\tau$ (Pajor 2009; Pyrga et al. 2004, 2008).

4.3. The model of personal activity-based intercity trips

During a trip, tourists perform various activities at various times and in various locations. The amounts and restrictions of such activities therefore play a key role in TP. The plan of activities can regulate arrival at certain places at specific times, as well as the amounts of activities performed at each respective place. In TP, the places, time instants, and activities are planned in order to minimize idle time and assist the tourist in making the best decisions based on his/her restrictions. Here, the periodic time of the PTN timetable is set at 1 week. The total tour time in each city is obtained by adding the time of travel and the time needed for the performed activities. The duration of the activities can be determined based on Algorithm 1. The inputs for this algorithm are the preferred cities, the arrival times at each city, as well as the start and the end times for activities. Its output is $Dur_{act}$, which represents the duration of activities. The elements of the tour can be seen in Figure 2.

Algorithm 1. Calculating the duration of an activity.

Input: ($ArriveT$, $Active$, $AET$, $AST$)

Output: Duration of Activity ($Dur_{act}$)

$AST = Activity \text{ Start Time}$

$AET = Activity \text{ End Time}$

$ArriveT = Arrival \text{ Time to } i^{th} \text{ City}$

$Active = Activity \text{ Duration}$

\begin{align*}
1) \quad S_E &= AET - AST; \\
2) \quad Dur_{act0} &= AST + Active; \\
3) \quad \text{ if } (ArriveT \leq AST) \\
4) \quad \text{ Wait1} &= AST - ArriveT; \\
5) \quad \text{ elseif } (ArriveT \geq AET); \\
6) \quad \text{ Wait1} &= 24 - ArriveT + AET; \\
7) \quad \text{ else} \\
8) \quad \text{ Wait1} &= 0; \\
9) \quad Dur_{act0} &= Active + ArriveT; \\
10) \quad \text{ end} \\
11) \quad ArriveT &= AST; \\
12) \quad \text{ if } (AET < AST); \\
13) \quad S_E &= S_E + 24; \\
14) \quad AST &= 0; \\
15) \quad AET &= S_E; \\
16) \quad ArriveT &= ArriveT - AST; \\
17) \quad \text{ end} \\
18) \quad \text{ if } Dur_{act0} > AET; \\
19) \quad Active1 &= \text{ mod}(Active, S_E); \\
20) \quad Iter &= (Active - Active1) / S_E; \\
21) \quad \text{ if } Active1 = 0 \\
22) \quad Iter &= Iter - 1;
\end{align*}

Figure 2. Elements of the tour.
Active1 = S_E;
end //end if Active1 = = 0
Dur_act = Wait1+Iter×24+Active1;
else
Dur_act = Wait1+Active;
end

4.4. GA-based tour scheduling

The best scheduling and ranking of cities is the main objective of TP, assisting the tourist in obtaining the maximum score from the visited cities during a predetermined time. In this study, a GA-based strategy is utilized to tackle the TP task. For the proposed model, the inputs are start day and time of the tour \( (TSD, t) \), duration of the tour \( (DT) \), chromosomes generated based on the cities, duration of activities and time period of performing activities in each city (plan), and the array of input city chromosomes, which are favoured cities for tourists with their respective priority rates (costs).

In the presented GA-based strategy, each solution should be represented as a chromosome. In order to implement this method, the required steps can be summarized as follows:

- **Step 1:** The coding strategy is the initial step towards organizing the routes. Based on the coding method, the initial random population is generated which holds a series of chromosomes. TP can be treated as a combinatorial optimization problem. The values of the solutions depend on the combination of \( n \) cities in each chromosome. Here, the routes are coded in combined mode, and each city is assigned a fixed number from 1 to \( n \) throughout the procedure. Note that the length of each chromosome is constant and the size of the initial random population of routes is equal to \( n \).

- **Step 2:** The second step is to assess each chromosome based on fitness values. Hence, the value of each tour can be computed based on Figure 3. In this study, since the first and last cities should be the same, the value of these cities is not considered in the fitness function. In Figure 3, MMSH is a function that selects the transportation networks with the shortest path. The function \( DActive \) can obtain the duration of activities based on Algorithm 1. \( TDay \) computes the day and time of the tour by the start time of the tour according to Algorithm 2. Furthermore, \( Y \) indicates the selected cities in the tour plan.

- **Step 3:** Natural selection. The selection rate \( X_{rate} \) identifies those chromosomes that can survive until the next generation (see Equation (7)).

\[
Num_{keep} = X_{rate} \times Num_{population} \quad (7)
\]

- **Step 4:** Selection. This operation can select some old solutions to breed a new generation of chromosomes. In this operation, two new offsprings should be generated based on two nominated chromosomes in the mating pool. The procedure is performed until \( (Num_{population} - Num_{keep}) \) offsprings have evolved. There are some selection strategies, such as tournament, roulette wheel, and linear rank selection. In this research, roulette wheel selection is employed (Engelbrecht 2007; Haupt and Haupt 2004).

- **Step 5:** The crossover operation. Because the problem is combinatorial, order crossover with constant start and end genes is utilized here.

- **Step 6:** Mutation operation. Regarding the combinatorial nature of the TP task, swap mutation is carefully chosen with constant first and last genes, which is an altered class of traditional mutation operators.

- **Step 7:** In the seventh step, the values of generated chromosomes are calculated based on the fitness function. Then, the number of \( (Num_{population} - Num_{keep}) \) chromosomes should be extracted using the elitism strategy.

- **Step 8:** Repeat steps 3–7 with respect to the stopping conditions and quality of the obtained

### Algorithm 2. Calculating the day and time of the tour \( (TDay) \).

**Input:** \( t, TSD \)

**Output:** \( t, TSD \)

1. if \( (t > 24) \)
2. \( tt = \text{mod}(t,24) \)
3. \( day2 = \text{mod}(t-tt,24) \)
4. \( day1 = TSD + day2 \)
5. if \( (day1 > 7) \) && \( (\text{mod}(day1,7) = 0) \)
6. \( day1 = \text{mod}(day1,7) \)
7. else \( (day1 > 7) \) && \( (\text{mod}(day1,7) = 0) \)
8. \( day1 = TSD \)
9. end
10. \( t = tt \)
11. \( SD = day1 \)
12. end
The termination condition is as follows: once the average population fitness is the same as 50 consecutive iterations, terminate it; otherwise, terminate the search after 250 iterations.

5. Experimental results and discussion

The proposed framework is implemented and evaluated based on information collected from 15 major cities in Iran and a set of other cities. The tourism industry of Iran attracts many tourists from other countries, visiting the many historical monuments and enjoying the different culture. Using the proposed TP framework, future tourists could be guided to discover and use most of the available transportation facilities more efficiently.

Although the main purpose of this article is tackling the TP task, trialling are also done to independently substantiate the new methodology for data storing tasks in databases. For that reason, trial results are described in three subsections including data storage, multimodal route planning, and TP tasks.

5.1. Data storage

In Table 1, the results of data storage have been exposed in both ordinary and compressed forms.
As can be seen from Table 1, the average number of movements among starting and ending locations in 1 day is high in all stations; compressed data storage strategies are suited to reducing the number of used entities. When the number of these movements changes in different stations during 1 day, the degree of variations causes the performance of compressed storage to become similar to ordinary storage, and even less efficient. The obtained results in Table 1 reveal that the generally compressed data storage method is efficient enough, especially for bus networks.

<table>
<thead>
<tr>
<th>Transportation mode</th>
<th>Ordinary</th>
<th>Compressed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus</td>
<td>38150</td>
<td>26250</td>
</tr>
<tr>
<td>Airplane</td>
<td>7182</td>
<td>7161</td>
</tr>
<tr>
<td>Train</td>
<td>2778</td>
<td>2938</td>
</tr>
<tr>
<td>Total</td>
<td>48110</td>
<td>36349</td>
</tr>
</tbody>
</table>

5.2. Multimodal route planning

In this study, an adapted Dijkstra's technique is utilized to explore the shortest path in intercity travels. A key issue in multimodal networks is picking out the most preferred transportation networks. The earliest arrival time to the last city for two different departure times in 1 day is calculated and demonstrated in Figure 4. In this query, four networks including airline, train, bus, and taxi networks have been considered. In Figure 5, the query in Figure 4 is demonstrated without the airplane network to reveal the significance of nominated transportation networks. As the periodic time was set to 1 week, the shortest path in two different days with the same departure time is not identical (see Figure 6). Regarding the deterministic nature of Dijkstra's approach, the best solution in every request has been obtained.

Figure 4. Multimodal shortest path in different departure times.

Figure 5. Multimodal shortest path in different departure times without airplane networks.
5.3. Evaluation of tour planning

In order to substantiate the efficiency of the GA-based strategy in scheduling the trip plan, 100 tours with random initial parameters were selected. For each query, the overall results of the proposed framework are obtained during 30 independent tests. In the GA algorithm, the size of the initial population was set to 250, with a selection rate of 50%, and \( \text{Num}_{\text{population}} = 100 \) (in Equation (7)). In each iteration, the 100 best solutions enter into the TP process, while the others are rejected. The results of the trials revealed that the intervals \([0.56, 0.83]\) and \([0.03, 0.17]\) are appropriate for crossover and mutation rates, respectively. In these intervals, there is no significant deviation to find the optimal solutions. Hence, the crossover and mutation probabilities are chosen as 0.65 and 0.09, respectively. The elitism strategy is employed to generate the next population.

Figure 7 shows a tour that originates from the initial city No.9 and then passes through 3, 12, 7, 2, 15, 1 before finally returning to city No.9. Furthermore, Figure 8 depicts the tour scheduling plan similar to Figure 7, using the same input parameters for initialization, but with different transportation networks. This allows us to analyse the role of each nominated network in the quality of the solutions.

TP outcomes can also be seen in Figures 9 and 10, which differ from Figures 7 and 8 only in the initial days and times of the tours, while the other parameters are similar. The effects of the start times on the TP outcomes can be seen in related plans. In addition, the priority rates of preferred cities in Figure 7 have been adjusted again and the results of the TP can be seen in Figure 11.

As can be seen, the results of the TP are dependent on the start times. To assess this matter, 100 testing tours with similar parameters and different starting times were planned. The obtained results can be categorized into four classes. From
Figure 12, it can be recognized that 14% of these tours remained unchanged in condition, that in 18% of tours the sequence of visiting cities changed, in 66% the number of selected cities along with the sequence of them was changed, and in 2% of cases no tour was planned.

In order to validate the efficiency and adaptability of the proposed GA-based framework, 100 randomly
generated tours are investigated. Each request is experienced in 30 iterations. In 8% of evaluated tours, the resulting planning was not successful, possibly because of the inconsistency that exists among some of the priority rates of the nominated cities and also the duration of the tour. For the other 92% of the test cases, the average and best solutions are evaluated during 30 recurrences of the algorithm. The relative error of the paths can be attained by (Shi et al. 2007):

$$\text{Err} = \left[ \frac{\text{Ave} - \text{Opt}}{\text{Opt}} \right] \times 100\% $$

where $\text{Ave}$ is the average of the results and $\text{Opt}$ value returns the best of the obtained results during each simulation.

From the obtained error results it can be recognized that:

- In 100 requests, the maximum and average values of $\text{Err}$ are equal to 9.7% and 4.38%, respectively. These statistical values affirm that the qualities of the results are satisfying.

- As may have been perceived before, when the input parameters and duration of a tour are inconsistent, TP tasks cannot be performed.
- For more time-consuming tours, the GA-based procedure requires more iterations, from 53 to 186 in these tests.
- When the starting times change, an alteration in the tour plan can be often realized. TP is therefore a time-dependent task.
- Convergence curves reveal that the proposed technique has a stable behaviour in different situations.

6. Conclusions and remarks

In this paper, a new GA-based tourist planning strategy is developed. The initial parameters of the method are selected carefully based on several tests and trials. To evaluate the capabilities of this framework, information from real transportation networks of 15 major cities in Iran was acquired. Then, 100 tour planners are utilized
to validate the efficiency of the proposed approach. The results of \( Err \) values strongly indicate that the suggested framework is capable of achieving the best tour plans with respect to the given restrictions. The \( Err \) values can likely still be improved by using other evolutionary algorithms in future studies. This relative error may be improved by selecting other algorithms, which can also be explored in future studies.

In TP tasks, different criteria related to the speed of traveling, costs, and transitions can be considered. The results show that the number of transition nodes will increase in the presence of airline networks. To reduce the number of transitions, the weight of airline edges can be increased. In this case, the selected route is not necessarily the route with the earliest arrival time to the destination, but it is the best choice for a tourist. For future research, it is suggested that the TP task should be context-aware, because the earliest arrival at the end destination is not always the best plan, and more parameters may be determined by the user.

It can be concluded from the results that the presented GA-based framework is capable of demonstrating a competent performance for tackling TP problems in larger search spaces. Finally, the present TP problem only considered time, but tourist may also care about the total costs, properties of the PTN, weather conditions, and so on. For future research, other criteria in TP tasks could be an important consideration.

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**References**


Berlin Heidelberg: Springer. doi:10.1007/978-3-540-74484-9_16