

# Utilizing Heuristic Algorithms Based on Destination Ratings for Enhancing Travel Planning

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**Abstract:** As urban travelers seek personalized and efficient travel planning solutions, the utilization of heuristic algorithms has gained significant attention. This study focuses on the optimization of travel itineraries by integrating destination ratings and flexibility into the algorithm. The objective is to enhance personalized travel experience by considering traveler preferences and efficient scheduling of destinations. The method involves utilizing a Genetic Algorithm (GA) framework and collecting destination ratings creating flexible scenarios, where the locations of the destinations can be changed. The outcomes demonstrate the effectiveness of the algorithm in generating optimized travel itineraries. The substitution of a destination, for example a cafe in the flexible scenario resulted in a significant reduction in total travel time by about 14.3%. This indicates the algorithm’s capability to optimize travel schedules by incorporating flexibility and considering destination ratings. The study’s implications include enhanced personalization, improved travel efficiency, and a more satisfying travel experience.

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## 1. INTRODUCTION

In recent years, the investigation for personalized and efficient travel experiences has become increasingly prominent among travelers. The plenty of destination choices, coupled with the desire for unique itineraries, has led to a growing interest in leveraging advanced algorithms to assist in travel planning processes (Xiang et al., 2015). Heuristic algorithms have gained considerable attention due to their ability to provide optimized recommendations based on specific criteria (Gad, 2022).

Travelers are often faced with the challenge of selecting destinations that align with their preferences and interests. As the number of potential destinations grows, there is a need for efficient and effective methods to evaluate and prioritize these choices. In recent years, the concept of rating of destinations has gained significant attention as a valuable tool in trip planning (Terttunen, 2017). (Miguéns et al., 2008) investigates the consumer-generated content (CGC) on TripAdvisor, specifically focusing on the city of Lisbon. It explores how users collaborate and contribute to shaping the destination’s image on this online social networking site. The study highlights the relevance of user-generated content for travel planning by analyzing a sample of Lisbon hotels. In the same vein, (Bigne et al., 2023) investigate the relationship between star ratings, sentiments expressed in online reviews,

and their impact on the customer experience. Using deep learning, natural language processing, machine learning, and artificial neural networks, the study analyzes the online reviews from TripAdvisor about tourism attractions in Venice. The findings indicate that sentiment valence aligns with star ratings, and there is a cancel-out effect observed in mixed-neutral reviews between positive and negative sentiments related to the service experience dimensions.

A recent study analyses the impact of specific attributes in online travel reviews on cognitive, affective, and conative images of a destination, drawing on the elaboration likelihood model and the cognitive-affective-conative model of destination image. Using an experimental survey design with four scenarios, the study explores the effects of high versus low star ratings on the perception of Santa Claus Village, Finland. The findings indicate that high-rating reviews primarily influence cognitive image, while low-rating reviews have a significant impact on affective image. Additionally, the study reveals that reviews contribute to the formation of destination image (Guo & Pesonen, 2022).

Several previous studies used heuristic algorithms to enhance travel planning. (Miller & Roorda, 2003) developed an activity scheduling microsimulation model that utilized heuristic methods to organize activities and trip diary information, considering the timing and duration of household members’ activities. (Charypar & Nagel, 2005)

focused on planning the daily activity chain, using a mathematical formulation based on geometric distance between activities in an optimization algorithm. Another study introduced an approach combining activity-based modeling and a genetic algorithm (GA) framework to generate schedules for travelers using electric vehicles (EVs) in an urban environment, demonstrating its effectiveness in satisfying traveler needs and improving travel efficiency (Rizopoulos & Esztergár-Kiss, 2020). (Esztergár-Kiss et al., 2018) proposed a novel method considering flexible demand points and transportation modes to plan and schedule activity chains, achieving a reduction in total travel time. Additionally, (Sabbani et al., 2019) utilized an ant colony optimization algorithm to plan daily activity chains with flexible mobility solutions, showing improved travel performance by incorporating adaptability in the transportation system.

While numerous studies have focused on trip related optimization, considering factors, such as travel modes, timing, and spatial constraints, the specific influence of destination ratings on itinerary generation remains unexplored. Therefore, this paper aims to address this research gap by proposing a novel approach that integrates destination ratings into the trip planning process. By incorporating destination ratings, our study contributes to enhancing the personalization and relevance of travel itineraries.

## 2. METHODOLOGY

### 2.1 Optimization framework

The Traveling Salesman Problem (TSP) is a well-known combinatorial optimization problem (Hoffman et al., 2013). In this study, we adapt the TSP framework to incorporate destination ratings as a factor influencing the schedule of destinations. The objective is to determine a schedule that minimizes travel time while considering the ratings of each destination. Given a set of destinations  $\{a_1, a_2, a_3, \dots, a_n\}$ , where each destination  $a_j$  is associated with a known destination rating  $R(a_j)$  and travel time between destination pairs  $T(a_i, a_j)$ , the objective is to optimize the schedule. To tackle this problem, we utilize a Genetic Algorithm (GA) inspired by the processes of natural evolution. The GA algorithm utilizes key concepts, such as generation, mutation, selection, and crossover to iteratively improve the schedule (Mirjalili, 2019). The mathematical representation of Equation (1) is used to determine the scheduling of destinations that minimize travel time while considering destination ratings. Equation (2) represents a constraint that ensures each destination is visited once by assigning a value of 1 when the traveler moves from destination  $i$  to  $j$ , and 0 otherwise. Equation (3) accounts for the symmetric distance between destinations.

$$\min U = \sum_{i=1}^{n-1} (T(a_i, a_j) + (R(a_j))) \quad (1)$$

where:

$U$  is the utility function that aims to minimize overall travel time while considering the destination ratings,

$T(a_i, a_j)$  represents the travel time from destination  $a_i$  to  $a_j$ ,

$R(a_j)$  denotes the rating or attractiveness of destination  $a_j$

$$\sum_j = 1, j \neq i, a_{ij} = 1, \text{ for } i = 1, 2, \dots, n \quad (2)$$

$$a_{ij} = a_{ji}, \text{ for } i, j = 1, 2, \dots, n \quad (3)$$

### 2.2 Flexibility in destination choice

Spatial flexibility in destination selection refers to the ability of individuals to choose from a range of locations for their destinations based on personal preferences and limitations. Traditionally, planning methods apply fixed locations for destinations, assuming that people regularly commute to the same places. However, spatial flexibility recognizes that individuals may choose alternative destinations that fulfill the same purpose while offering higher levels of satisfaction or meeting their specific preferences. Therefore, in this study we take into account the preferences of travelers and consider two distinct priorities:

1. Fixed destination: This concept implies that certain destinations or destinations are associated with specific predetermined locations. For example, going to work or attending a specific event may require individuals to visit a particular place.
2. Flexible destination: In this case the individuals have the flexibility to choose alternative locations that serve the same purpose. In other words, individuals can select from different places that offer similar services or amenities. This flexibility enables individuals to consider factors, such as rating of destination and personal preferences when deciding on their destination.

This study identifies the importance of allowing individuals to choose destinations that best suit their needs and preferences by incorporating spatial flexibility of destination. This approach accounts for the influence of the destination ratings factor, enabling travelers to make informed decisions that optimize their overall travel experience.

### 2.3 Study area

For this study, the research was conducted in the city of Budapest. The capital of Hungary is a rich touristic destination along the beautiful banks of the Danube River (Mahdi & Esztergár-Kiss, 2022). The city is divided into two main parts, Buda and Pest, connected by several iconic bridges. Buda, situated on the western side of the river, is known for its historic sites, while on the eastern side lies Pest, a bustling hub of destination with wide boulevards, vibrant neighborhoods, and culinary delights (Mahdi & Esztergár-Kiss, 2021).

To retrieve destination ratings, a Python code was designed to collect data from Google in July 2022 (Mahajan et al., 2021). Using web scraping techniques, the code automatically extracted rating information for various

destinations in Budapest. The collected rating data served as a crucial input for the GA utilized in the study. Alongside another variable, such as travel time between destinations, the ratings were incorporated into the algorithm to optimize the scheduling of destinations and generate personalized travel itineraries.

To assess the performance of the proposed algorithm, we provide an example of the suggested destinations in Table 1.

**Table 1. An illustrative example of the suggested destinations**

| Name of Destination           | Abbr. | Latitude  | Longitude | Type     | Rating |
|-------------------------------|-------|-----------|-----------|----------|--------|
| Hungarian Parliament Building | P     | 47.508222 | 19.045488 | Fixed    | 4.8    |
| House of Terror               | T     | 47.507700 | 19.065058 | Fixed    | 4.1    |
| Hungarian National Museum     | M     | 47.492417 | 19.062639 | Fixed    | 4.5    |
| Cafe                          | C1    | 47.496328 | 19.051134 | Flexible | 4.0    |
| Hotel                         | H     | 47.501356 | 19.056529 | Fixed    | -      |

### 3. RESULTS

The results the two scenarios are evaluated in terms of the order of visited destinations, the mode of transportation, and the total travel time.

In the fixed scenario (Figure 1), where the Cafe (C1) was set as a fixed destination with a rating of 4 stars, the algorithm suggested a specific order of visiting destinations: Hungarian Parliament Building (H-P), Parliament Building to House of Terror (P-T), House of Terror to Hungarian National Museum (T-M), Museum to Cafe (M-C1), and finally, Cafe back to the hotel (C1-H). The mode of transportation used in this scenario included Bus, Tram, and Metro. The total travel time for this fixed scenario was 70 minutes.

Specifically, the Cafe destination (C1) is set as a flexible choice, where the rating of this destination is 4.0. This allows us to evaluate how well the algorithm adapts to various Café type of choices and optimizes the overall itinerary according to traveler preferences and ratings. The effectiveness of the algorithm in generating optimized travel plans considering the rating factor can be examined together with the flexibility of the Cafe destination.

In the flexible scenario (Figure 2), the Cafe (C1) was designated as a flexible destination, allowing the algorithm to consider alternative Cafe choice. In this scenario, the algorithm substituted the originally suggested Cafe (C1) with an alternative location (C2), which had a rating of 4.8 stars and was within a three-minute walk from the M destination. The resulting order of visited destinations was Hungarian Parliament Building (H-P), Parliament Building to House of Terror (P-T), House of Terror to Hungarian National Museum (T-M), Museum to the alternative Cafe (M-C2), and finally, the alternative Cafe back to the hotel (C2-H). The mode of transportation utilized in this scenario included Bus, Tram, and Walking. The total travel time for this flexible scenario was reduced to 60 minutes.

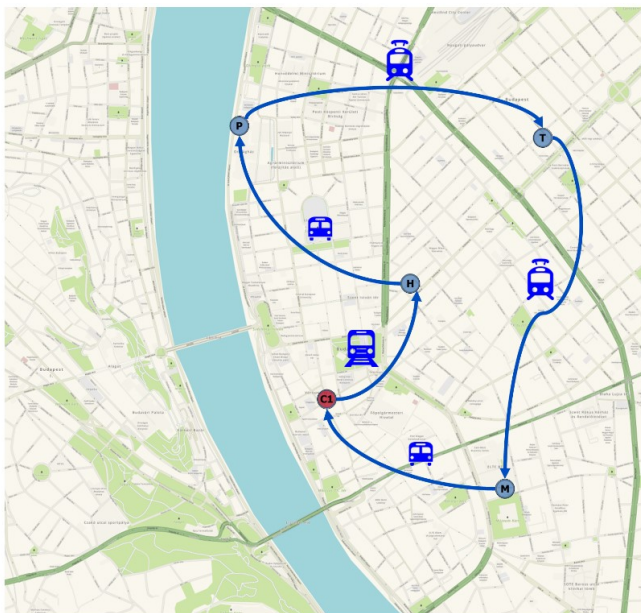


Fig. 1. Optimization results for travel itinerary: fixed scenario

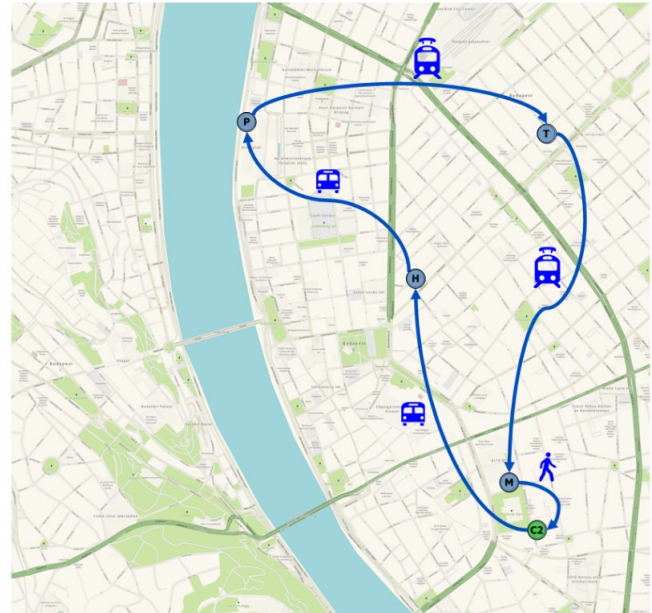


Fig. 2 Optimization results for travel itinerary: flexible scenario

The outcomes presented in Table 2 indicate that adopting flexibility in the activity chain by substituting the Cafe destination significantly reduced the total travel time and considering the preference of traveler. This demonstrates the

optimization capabilities of the algorithm and highlights the potential for improved travel efficiency through flexibility scenarios.

**Table 2. The outcomes of the three scenarios**

|                   |             |     |      |      |         |       |                            |
|-------------------|-------------|-----|------|------|---------|-------|----------------------------|
| Fixed scenario    | Order       | H-P | P-T  | T-M  | M-C1    | C1-H  | Total travel time (70 min) |
|                   | Mode        | Bus | Tram | Tram | Bus     | Metro |                            |
|                   | Travel time | 14  | 17   | 16   | 13      | 10    |                            |
| Flexible scenario | Order       | H-P | P-T  | T-M  | M-C2    | C2-H  | Total travel time (60 min) |
|                   | Mode        | Bus | Tram | Tram | Walking | Bus   |                            |
|                   | Travel time | 14  | 17   | 16   | 3       | 10    |                            |

#### 4. DISCUSSION

The main objective of this study is to generate personalized and efficient travel itineraries by incorporating destination ratings and flexibility into the planning process. Two main scenarios are proposed to evaluate the performance of the algorithm. In the fixed scenario, where the Cafe (C1) was set as a fixed destination with a rating of 4 stars, the algorithm generated a specific order of visited destinations and corresponding modes of transportation. The total travel time for this fixed scenario was 70 minutes. On the other hand, in the flexible scenario, the Cafe was set as a flexible destination, allowing the algorithm to explore alternative Cafe choice, where the suggested Cafe (C1) was substituted with an alternative (C2) with a higher rating of 4.8 stars, and located conveniently near the previous destination (M). The total travel time was reduced to 60 minutes in the flexible scenario. The outcomes from the flexible scenario highlight the significant impact of incorporating destination ratings and flexibility into the travel planning process. The algorithm was able to achieve a substantial reduction in total travel time and improve the travel efficiency for the traveler.

This finding is consistent with the literature review, which emphasized the importance of destination ratings and online reviews in shaping travelers' perceptions and decision-making (Terttunen, 2017; Miguéns et al., 2008; Bigne et al., 2023; Guo & Pesonen, 2022). Moreover, the flexibility scenario demonstrated in the study aligns with previous research on heuristic algorithms in travel planning. The itinerary generated becomes more customized and optimized for the individual traveler's needs by allowing the algorithm to adapt and substitute destinations based on traveler preferences and alternative options (Miller & Roorda, 2003; Charypar & Nagel, 2005; Rizopoulos & Esztergár-Kiss, 2020; Esztergár-Kiss et al., 2018; Sabbani et al., 2019).

While the results presented in this study are promising and indicative of the algorithm's optimization capabilities, it is essential to acknowledge potential limitations. The accuracy and reliability of destination ratings and online reviews can vary, and this may impact the algorithm's performance in real-world scenarios. Additionally, this study focus on only two criteria the travel time and destination ratings. While these two factors are essential in travel planning, they may

not fully capture the complexity of travelers' preferences and interests. Future studies in travel planning algorithms could focus on integrating several factors, such as budget constraints, specific interests, weather conditions, and accessibility options. Additionally, the proposed system can be applied using another algorithm, such as the Ant Colony Optimization algorithm, which can offer new perspectives and advantages in travel planning.

This study can be implicated in several aspects. The integration of destination ratings in the algorithm ensures that travelers receive recommendations based not only on inherent attractiveness but also on subjective evaluations from previous visitors. This leads to more informed and relevant travel itineraries, enhancing the overall travel experience. Additionally, the incorporation of flexibility in the itinerary generation process allows the algorithm to serve individual preferences and adapt to alternative choices, promoting a higher level of personalization and satisfaction for travelers.

The benefits of these findings extend to both travelers and the travel industry. For travelers, the algorithm offers optimized itineraries that match their interests and save time and effort in planning. On the other hand, for the travel industry, the algorithm presents an opportunity to enhance customer satisfaction and loyalty by delivering personalized and efficient travel planning services.

#### 5. CONCLUSION

This study focused on enhancing personalized and efficient travel planning experiences by integrating destination ratings and flexibility into a heuristic algorithm. The proposed algorithm evaluates and ranks potential destinations based on their ratings, ensuring that highly rated locations receive higher priority during the itinerary generation. By incorporating these ratings, the algorithm not only considers the inherent attractiveness of the destinations but also takes into account the subjective evaluations of previous visitors, leading to more informed and relevant recommendations.

The results demonstrated the algorithm's effectiveness in generating optimized travel itineraries based on travel time and destination ratings. Moreover, adopting flexibility by substituting a Cafe location significantly reduced total travel time, showing the algorithm's capability to consider traveler preferences and improve travel efficiency.

## FUNDING

This research was supported by the János Bolyai Research Fellowship of the Hungarian Academy of Sciences (BO/00090/21/6).

## CONFLICT OF INTEREST

The authors declare no conflict of interests.

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