

Dynamic Programming-Based Travel Route Planning Model

Xinrui Guo

*Department of Transportation Engineering, Dalian Maritime University, Dalian, China
3375029859@qq.com*

Abstract: Under China's 144-hour transit visa-free policy, an increasing number of foreign tourists aim to explore multiple cities in-depth within a limited timeframe. In this context, this paper proposes an intelligent route planning model based on dynamic programming. The model integrates the entropy weight method and TOPSIS to evaluate six categories of 12 indicators—including climate, transportation, and cultural factors—to select the top 50 high-scoring cities. By incorporating high-speed rail transit time constraints, a dynamic programming algorithm is designed to optimize tourist itineraries. Experimental results demonstrate that the dynamic programming model covers 11 cities (e.g., Guangzhou→Shenzhen→Changsha→Wuhan→Nanjing→Shanghai) within 144 hours (including 12 hours per city for sightseeing and 4 hours of buffer time), with a total duration of 123 hours, significantly outperforming the greedy algorithm (9 cities, 134 hours). Through state compression and pruning strategies, the model reduces computational complexity from factorial ($O(n!)$) to exponential ($O(n^2 \cdot 2^n)$), balancing efficiency and optimality. The study validates the model's potential to enhance tourist satisfaction and tourism economic benefits, while suggesting future extensions to multi-modal transportation planning and dynamic preference adaptation.

Keywords: DP, TOPSIS, State compression pruning, Tourism economic benefits

1. Introduction

With China's ongoing advancement of its "Visa Facilitation+" strategy, the number of inbound foreign tourists in 2024 reached 64.88 million, marking an 82.9% increase compared to pre-pandemic levels, reflecting a robust rebound in international travel demand. Notably, visa-free entries accounted for 31% of the total, surging by 112.3% year-on-year, underscoring the pivotal role of policy liberalization in boosting cross-border mobility. This unprecedented growth is primarily attributed to the comprehensive upgrade of the 144-hour transit visa-free policy, which introduced several critical improvements: the maximum stay duration was extended from 72 hours to 240 hours, eligible entry ports increased from 39 to 60, and the policy coverage expanded from 19 to 24 provinces. For the first time, cross-provincial travel is now permitted under this scheme, removing a major constraint for foreign travelers who previously had to limit their journeys within a single province.

These policy breakthroughs not only institutionalize the possibility for tourists to engage in "in-depth exploration"—visiting lesser-known regions, experiencing diverse local cultures, and partaking in longer itineraries—but have also catalyzed significant economic impact. In 2024, tourism-related consumption exceeded 100 billion yuan, driving synergistic growth in adjacent sectors such as hospitality, catering, transportation, and cruise tourism. The positive spillover effects reinforce the

strategic value of tourism facilitation as a lever for regional economic revitalization and international soft power projection.

However, despite the surge in tourist arrivals and evolving expectations for enriched travel experiences, existing research and planning tools largely remain confined to single-objective optimization frameworks. For instance, certain studies concentrate exclusively on minimizing transportation costs, often at the expense of cultural immersion or scenic diversity. Conversely, some approaches emphasize maximizing the number of attractions visited, yet fail to account for real-time changes in tourist preferences, such as spontaneous interest in local events, weather-dependent activities, or crowd avoidance.

Traditional multi-criteria decision-making (MCDM) methods, such as TOPSIS, are also limited in this regard. While these methods enable trade-offs across multiple static indicators, they generally lack the capacity to incorporate time-sensitive, dynamic variables, resulting in rigid, non-personalized recommendations that do not adapt to a tourist's evolving context or preferences.

To overcome these limitations, this study proposes a novel integrated urban tourism planning framework that seeks to optimize personalized itineraries through the comprehensive synthesis of 12 key indicators, systematically grouped under six major categories: environmental conditions, cultural heritage value, transportation accessibility, economic cost-efficiency, social engagement potential, and real-time contextual factors. This multi-dimensional framework ensures that both quantitative and qualitative aspects of the tourist experience are taken into account.

In this work, we present an efficient tourist attraction route planning model that leverages advanced algorithmic strategies to intelligently recommend optimal travel routes. These recommendations are dynamically adapted based on tourists' individual time constraints and real-time contextual information, such as weather forecasts, traffic congestion levels, local event schedules, and public transportation status. Unlike traditional systems that disproportionately prioritize popularity-based attraction rankings, our model holistically integrates practicality and experiential quality, ensuring that recommendations are not only efficient but also meaningful and personalized.

By factoring in these dynamic and contextual elements, our model aims to maximize overall tourist satisfaction within limited time windows. We hypothesize that, when compared to conventional itinerary planning tools, the proposed framework will significantly enhance tourist experience, improve route efficiency, and better align with individual travelers' evolving preferences, ultimately contributing to more sustainable and engaging urban tourism.

2. Problem modeling

2.1. Problem hypothesis

This study addresses the travel route optimization problem within the context of urban tourism planning. Given the high capacity and operational efficiency of China's public transportation system—particularly its high-speed rail network—the number of individual tourists exerts negligible influence on overall system performance. Therefore, we narrow our focus to individual-level itinerary planning, allowing for more precise modeling and personalized optimization.

Specifically, we consider a scenario in which a foreign tourist enters China via the Guangzhou port of entry and intends to visit as many cities as possible within a 144-hour (6-day) timeframe. To ensure meaningful engagement in each destination, we assume that the tourist will allocate a minimum of 12 hours for sightseeing in each city. Additionally, a 4-hour buffer period is reserved to accommodate unforeseen contingencies such as travel delays or adverse weather, thus enhancing the robustness and feasibility of the proposed itineraries.

Based on this setting, we formulate a dynamic programming model that seeks to efficiently construct travel routes. The model assumes that direct high-speed rail connections constitute the

primary mode of intercity transportation, leveraging the extensive coverage and reduced transit times characteristic of China's HSR system. Real-world datasets—including high-speed rail timetables and the spatial distribution of tourist attractions—are incorporated to evaluate intercity accessibility and temporal feasibility.

The objective of the model is to maximize the number of cities visited within the global constraint of 144 hours. In essence, the model aims to identify an optimal travel route that enables the tourist to explore the largest possible set of cities while ensuring a minimum duration of stay in each location for in-depth cultural and recreational experiences. This optimization approach reflects a multi-dimensional trade-off between travel efficiency, experience quality, and itinerary resilience.

2.2. Comprehensive score model

Given that international tourists visiting China cannot explore all attractions in each city due to their limited stay duration, this study adopts the "City Optimal Attraction Selection Principle", which assumes that only the highest-rated attraction is visited in each of the top 50 cities based on comprehensive evaluations.

The model processes standardized data from 352 cities, incorporating factors such as attraction ratings, climate, transportation accessibility, environmental sustainability, and population density. By integrating the TOPSIS method and entropy weight method [1], a comprehensive score is calculated for each city, from which the top 50 cities are selected.

In this context, $\hat{X}_{ij}$ represents the standardized data, X_{ij} represents the original data. Median: Serves as a measure of central tendency instead of the mean, avoiding distortion of the data distribution by extreme values. *IQR*: Defined as the difference between the third quartile (Q3) and the first quartile (Q1), reflecting the dispersion of the middle 50% of the data.

$$\hat{X}_{ij} = \frac{X_{ij} - \text{Median}}{IQR} \quad (1)$$

where Median is the median of the feature, and IQR represents the interquartile range.

For data approximately following a normal distribution (e.g., temperature), the StandardScaler is applied for normalization. μ_j and σ_j represent the mean and variance of each category of data, respectively. The formula is defined as:

$$\hat{X}_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j} \quad (2)$$

For positive indicators, the range standardization method (min-max normalization) is applied, X_j represents each column, with the formula defined as:

$$\hat{X}_{ij} = \frac{X_{ij} - \min X_j}{\max X_j - \min X_j} \quad (3)$$

After unifying the dimensional quantities, the entropy weighting method is used to calculate the weights, which can be divided into three steps:

- (1) The entropy value of the j -th-term index is calculated, e_j : the information entropy of the j th index reflects the degree of dispersion of data distribution, p_{ij} : the city of i is in the proportion of j indicators and n : the number of cities

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln p_{ij}, \text{ and } p_{ij} = \frac{\hat{X}_{ij}}{\sum_{i=1}^n \hat{X}_{ij}} \quad (4)$$

- (2) Calculate the coefficient of variation, d_j : The difference coefficient of the j th index. The smaller the entropy, the smaller the d_j , the larger the difference coefficient, and the higher the importance of the index.

$$d_j = l - e_j \quad (5)$$

- (3) Determine the weight, w_j : the weight of the j th indicator, m : number of indicators

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad (6)$$

The TOPSIS method is then used for sorting, and the steps are as follows:

- (1) Construct a weighted normalization matrix, v_{ij} : the weighted normalized value of the i -th city on the j -th index.

$$V = (v_{ij})_{n \times m}, \quad v_{ij} = w_j \times \hat{X}_{ij} \quad (7)$$

- (2) Determine the positive / negative ideal solutions, V^+ : the set of maximum values of all positive indicators (such as scenic spot ratings) in the ideal solution. On the contrary, V^- .

$$V^+ = \{\max v_{ij} | j \in J^+\}, \quad V^- = \{\min v_{ij} | j \in J^-\} \quad (8)$$

(J^+ is a set of positive indicators, J^- is a set of a negative indicators)

- (3) The Euclidean distance to the positive / negative ideal solution is calculated for each scheme, D_i^+ : the distance of the i city from the positive ideal solution, D_i^- : the distance of the i city from the negative ideal solution.

$$D_i^+ = \sqrt{\sum_{j=1}^m (v_{ij} - V_j^+)^2}, \quad D_i^- = \sqrt{\sum_{j=1}^m (v_{ij} - V_j^-)^2} \quad (9)$$

- (4) The relative proximity was calculated, C_i : the comprehensive score of the i -th city, the closer the value is to 1, the closer it is to the ideal solution.

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, \dots 0 \leq C_i \leq 1 \quad (10)$$

- (5) Arrangement plan

3. Dynamic programming model

Route planning, as a classic NP-hard problem, faces the core challenge of exponentially expanding solution spaces with increasing problem scales, making it intractable to identify optimal solutions within polynomial time [2-4]. The introduction of a dynamic programming model addresses this complexity through structured decomposition, breaking the original problem into interconnected subproblems. By leveraging state transition equations to store intermediate results, the model effectively avoids redundant computations. Central to dynamic programming is Bellman's principle of optimality, which states: "An optimal policy has the property that, regardless of the initial state and initial decision, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision." Its mathematical proof typically employs contradiction: assuming suboptimal solutions to subproblems, one could construct a superior solution that contradicts the original problem's optimality, thereby necessitating the optimality of subproblem solutions [5].

Dynamic programming decomposes a problem into multiple interrelated stages, where decisions at each stage influence the state of subsequent stages. By defining state variables and state transition equations, it models the recursive relationships between stages. For instance, in route planning, the

selection of a current node directly impacts the set of reachable paths thereafter. The method enhances efficiency by storing solutions to subproblems in matrices, enabling direct retrieval for future computations and eliminating redundant calculations [6,7].

The version needs to satisfy constraints and maximize the number of access points, i. e.:

$$dp[i][S \cup \{i\}][r - c_{ji}] = \max_{j \in \text{Preceding, Text}} (dp[j][S][r] + l) \quad (11)$$

$dp[i][S][r]$ represents the maximum number of cities that can be visited when the current node is city i , the set of cities that have been visited is S , and the remaining resources (such as time) are r .

Preceding text represents the cities visited and satisfying the constraints.

$S \cup \{i\}$ represents that the current city i is added to the set S of visited cities, indicating path extension. $r - c_{ji}$ represents the remaining resources minus the resource consumption from j to i (such as traffic time).

Then, through state compression and pruning strategy [8], the algorithm iterates to find two paths that preferentially retain the path with more access points under the same nodes and resources. There are three key strategies:

(1) Recursive formula for the most short-circuit problem:

For reverse derivation, gradually calculate the shortest path from each node to the end point:

$$f_k(s_k) = \min_{u_k} (d(s_k, u_k) + f_{\{k+1\}}(s_{\{k+1\}})) \quad (12)$$

Where $f_k(s_k)$ represents the shortest distance from the k -stage state s_k to the end point. u_k represents the choice of the next path, $d(s_k, u_k)$ represents the cost of choice such as time and money, meaning of $f_k(s_k)$ and $f_{\{k+1\}}(s_{\{k+1\}})$ is basically the same, the purpose is to avoid double counting.

(2) Dominant relationships under resource constraints

If the path Q_{si} is better than Q_{si}^* in both resource consumption and access points, it is dominated and Q_{si}^* can be pruned.

(3) Hamilton Dynamic programming of the paths

The state compression is binary, $f[i][j]$ is the length of the shortest path with node j as the end point under state i (the set of access codes in binary numbers), and the recursive formula is:

$$f[i][j] = \min_{k \in S} (f[i \oplus (1 \ll j)][k] + w(k, j)) \quad (13)$$

$i \oplus (1 \ll j)$ removes node j from state i (that is, flips the j th bit of the binary number) to get the previous state. Where j is the binary state, $w(k, i)$ is the weight from k to i .

The core idea of dynamic planning in solving the most short-circuit problem is reverse order recursion and state compression, which greatly improve the efficiency through problem decomposition, reuse sub-problem solution, combined with pruning strategies (such as dominant relationship). For Hamilton path problems, state compression takes the complexity from the factorial level $O(n!)$ Down to $O(n^2 \cdot 2^n)$, making it practically feasible at $n < 20$.

4. Experiments and results

4.1. Experiment setup

The dataset consists of detailed tourism information from 352 major cities in China. For each city, a dedicated CSV file contains data on 100 tourist attractions, with attributes such as name, address, official website, detailed descriptions, operating hours, ratings, suggested visit durations, seasonal recommendations, ticket pricing, and travel tips. Additionally, we compiled city-level contextual data

including population density, environmental quality index, transportation accessibility index, climate conditions, and cultural heritage index.

High-speed rail (HSR) data was also incorporated into the experimental setup. We collected information on all direct HSR connections between cities, including travel durations. These realistic transportation constraints were critical for ensuring that the generated travel routes are not only optimal in theory but also executable in practice. For the experimental parameters, we assumed that the tourist begins their journey from one of several major cities (e.g., Guangzhou, Beijing, etc.), and allocates 12 hours for sightseeing in each destination. A buffer time of 4 hours is included to accommodate possible delays and transitions between cities. The goal of the experiment is to find the route that visits the maximum number of cities within the 144-hour limit, using real inter-city HSR routes.

Two algorithms were implemented and compared: greedy algorithm [9,10] (GA) and dynamic programming (DP) [11-12]. We first used the TOPSIS method to select the top 50 cities based on comprehensive tourism indicators. For each selected starting city, we evaluated the number of cities visited, total time consumed, and a composite satisfaction score derived from attraction quality and travel experience. This experimental setup provides a rigorous basis for comparing algorithmic performance and validating the practicality of our model in real-world tourism scenarios.

4.2. Experimental analysis

To evaluate the effectiveness of our travel route planning system, we utilized the TOPSIS method to calculate comprehensive scores for multiple cities based on key travel metrics. As shown in Table 1, Beijing, Shanghai, and Shenzhen rank among the top cities in terms of attractiveness and accessibility. We selected the top 50 cities as candidate destinations and obtained the average direct high-speed rail travel time between them. This data served as input for the dynamic programming algorithm to determine optimal travel routes under fixed time constraints.

Table 1: Comprehensive ranking of some cities

city	Positive ideal solution distance(D+)	Negative ideal distance(D-)	Comprehensive score index	sorting
Binjing	0.455	0.709	0.608	1
Shanghai	0.422	0.644	0.604	2
Shenzhen	0.581	0.659	0.531	3
Guangzhou	0.592	0.494	0.454	4
Suzhou	0.680	0.488	0.417	5
Wuxi	0.690	0.494	0.417	6
Jinan	0.700	0.497	0.415	7
Chengdu	0.634	0.434	0.406	8
Ya'an	0.830	0.461	0.357	9
Nanjing	0.745	0.380	0.338	10
Hangzhou	0.708	0.358	0.336	11
Xi'an	0.743	0.367	0.330	12

Figure 1 illustrates a sample route generated by the dynamic programming method, starting from Guangzhou. The resulting route — Guangzhou → Shenzhen → Changsha → Wuhan → Nanjing → Shanghai → Hangzhou → Zhengzhou → Beijing → Tianjin — covers 10 cities within a total duration of 123 hours. This itinerary not only satisfies the time constraint but also maximizes coverage of highly ranked cities, demonstrating the model's practical applicability.

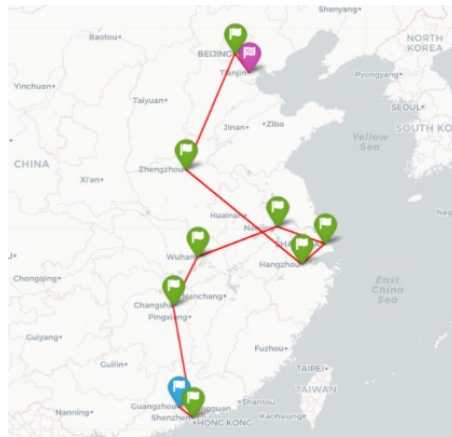


Figure 1: Dynamic planning, starting from the tourist route of Guangzhou

To further assess the robustness and performance of our method, we conducted comparative experiments using different starting cities and benchmarked our approach against a standard greedy algorithm under identical conditions. Figure 2 shows the route generated by the greedy algorithm, which appears less structured, with abrupt jumps between cities and less effective utilization of the high-speed rail network.

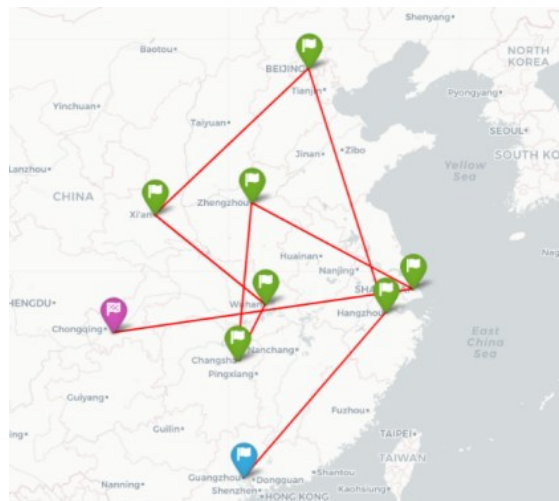


Figure 2: Results of the greedy method

Quantitative comparisons of the two methods are presented in Table 2. The results indicate that the dynamic programming approach consistently visits more cities within the same time constraint and achieves higher average route scores. For example, when starting from Guangzhou, the dynamic programming method covers 11 cities with a total duration of 123 hours and achieves a composite mean score of 5.75, whereas the greedy method only covers 9 cities, consumes 134 hours, and yields a lower score of 5.17. Similar trends are observed across other starting cities, such as Beijing, Changsha, and Zhengzhou.

On average, the dynamic programming approach delivers route scores approximately 8% higher than those of the greedy algorithm. Furthermore, it ensures better time efficiency while offering smoother and more realistic travel paths. These advantages make it particularly suitable for real-world travel planning scenarios, especially for tourists aiming to optimize their travel experience within limited timeframes.

Table 2: Methods comparison

Starting City	Count the number of cities visited(DP)	Count the number of cities visited(GA)	DP time consuming (h)	GA time consuming (h)	route (DP) Composite mean score	route (GA) Composite mean score
Guangzhou	11	9	123	134	5.75	5.17
Beijing	10	9	127.5	137.5	5.77	5.32
Changsha	10	9	126.5	133	5.61	5.29
Zhengzhou	10	9	128.5	131	5.54	5.36
Wuhan	9	9	129	137	5.76	5.37
Xi'an	10	9	129.5	130.5	5.53	5.39
Chengdu	10	9	128	131	5.54	5.34
Chongqing	10	10	126.5	136	5.72	5.29

In summary, the experimental results confirm the superiority of the dynamic programming approach over the greedy algorithm across three key dimensions: route coverage, time efficiency, and path rationality. By integrating comprehensive city scores with high-speed rail connectivity, dynamic programming enables the construction of more optimized and realistic itineraries. Not only does it allow visits to a greater number of cities within the same time constraints, but it also ensures more efficient use of travel time and network infrastructure. The resulting routes are better structured and more aligned with practical travel demands, providing a smoother and more satisfying travel experience for tourists. Overall, this method proves to be highly applicable for real-world tourism planning, offering a significant advantage over traditional heuristic approaches.

5. Conclusion

This study presents an intelligent route planning framework tailored to the increasing demand among foreign tourists for in-depth, multi-city travel under China's 144-hour transit visa-free policy. By integrating the entropy weight method with the TOPSIS approach, the proposed model systematically evaluates 12 indicators across six categories—including climate conditions, transportation infrastructure, and cultural attractiveness—to identify the top 50 cities for potential visitation. Incorporating real-world high-speed rail connectivity constraints, a dynamic programming algorithm is formulated to optimize itinerary planning. Empirical results, using Guangzhou as a case study, demonstrate that the proposed model enables coverage of up to 11 cities within the 144-hour window (allocating 12 hours per city and a 4-hour overall buffer), achieving a total travel duration of 123 hours. This represents a substantial improvement over traditional greedy algorithms, which cover only 9 cities within 134 hours. Furthermore, by employing state compression and pruning techniques, the model effectively reduces computational complexity from factorial $O(n!)$ to exponential $O(N^2 \times 2N)$, ensuring a practical balance between solution optimality and computational efficiency.

References

- [1] Guo Z. *Evaluation of Financial Ability of Port Listed Companies Based on Entropy Weight TOPSIS Model*[J]. *Journal of Coastal Research*, 2020, 103(sp1):182-185.
- [2] S. LaValle, *Planning Algorithms*. Cambridge University Press.
- [3] Chitnis R, Hadfield-Menell D, Gupta A, et al. *Guided search for task and motion plans using learned heuristics*[C]//2016 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2016: 447-454.
- [4] Liu, Y., et al. (2021). *Improved Dynamic Programming for AGV Path Planning*. *IEEE Trans. ITS**, 22(3), 1456-1468.

- [5] Bo S ,Shicai L ,Yongquan Y , et al.*An improved 2-OPT optimisation scheme for Hamilton loop*[J].*International Journal of Computer Applications in Technology*,2020,64(2).
- [6] Mao D ,Lin Y ,Jiayu T . *A Novel Approach to Calculate the Spatial–Temporal Correlation for Traffic Flow Based on the Structure of Urban Road Networks and Traffic Dynamic Theory* [J]. *Sensors*, 2021, 21 (14): 4725-4725.
- [7] Parkinson C ,Boyle I .*Efficient and scalable path-planning algorithms for curvature constrained motion in the Hamilton-Jacobi formulation*[J].*Journal of Computational Physics*,2024,509113050-.
- [8] Toth, P., & Vigo, D. (2014). *Dynamic Programming Pruning*. In **Proc. ICOR** (pp. 112-125). Springer.
- [9] Dongdong L ,Lei W ,Sai G , et al.*Path Planning of AS/RS Based on Cost Matrix and Improved Greedy Algorithm*[J].*Symmetry*,2021,13(8):1483-1483.
- [10] Xiuwu N ,Kaihui Z .*Design of Fast Green Distribution Route Based on Greedy Algorithm*[J].*jaciii*,2023,27(2):143-147.
- [11] Cormen T H, Leiserson C E, Rivest R L, et al. *Introduction to algorithms*[M]. MIT press, 2022.
- [12] Bouman P, Agatz N, Schmidt M. *Dynamic programming approaches for the traveling salesman problem with drone*[J]. *Networks*, 2018, 72(4): 528-542.