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OPTIMIZATION OF TOURIST ROUTES IN BATAM CITY USING INTEGER LINEAR PROGRAMMING WITH DESTINATION CATEGORY CONSTRAINTS

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Abstract. *Tourist route planning plays an important role in improving travel efficiency and visitor experience in urban tourism areas. Batam City has numerous tourist destinations with diverse characteristics, making route planning under realistic constraints a challenging task. Classical Traveling Salesman Problem (TSP) models assume that all destinations must be visited, which is often impractical in real tourism scenarios. Therefore, this study proposes an optimization model for tourist routes in Batam City using Integer Linear Programming (ILP) with destination category constraints. The proposed model enables the selection of a subset of destinations from a larger candidate set while determining the optimal visiting sequence. The objective function minimizes the total travel distance represented by fixed driving distances obtained from digital map services. Several constraints are incorporated into the model, including route continuity, subtour elimination, and category restrictions that limit the number of destinations selected from specific categories such as beaches, shopping malls, and cultural sites. The model is implemented in Python using the PuLP optimization library and evaluated across four scenarios with varying category constraint settings. In the main scenario, the model produces an optimal route visiting 11 destinations with a total travel distance of 123.6 km. Scenario analysis further shows that category selection significantly influences total travel distance, with differences of up to 53.8% observed across scenarios despite a constant number of selected destinations. These findings indicate that ILP provides a flexible and effective framework for constrained tourist route optimization in urban tourism contexts, and that category-aware constraints offer meaningful insight into the trade-off between destination diversity and route efficiency.*

Keywords: Category Constraints, Integer Linear Programming, Routing Optimization

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1. Introduction

Tourist route planning is an important issue in urban tourism management because it influences travel efficiency, visitor experience, and the utilization of local tourism resources. Batam City, located in the Riau Islands Province of Indonesia, is widely recognized as one of the country's prominent tourism and commercial destinations, supported by its strategic geographic position and diverse attractions such as coastal tourism, shopping areas, and recreational facilities [1]. The continuous development of tourism infrastructure and visitor activities in Batam significantly increases the city's potential as a major tourism destination [2], which highlights the need for systematic methods to support efficient travel planning within the city. However, the spatial distribution and heterogeneity of tourist destinations create challenges in determining efficient visitation routes, particularly when tourists face limitations in travel distance, time, or visiting capacity. Consequently, mathematical optimization approaches are required to support tourist route planning in Batam. Previous work on tourist route planning in Batam has also been explored using heuristic approaches such as Ant Colony Optimization [3]; however, such methods do not guarantee globally optimal solutions and do not incorporate structured destination category constraints.

In operations research, the Traveling Salesman Problem (TSP) is a classical combinatorial optimization model that determines the minimum-cost tour visiting each location exactly once. Although extensively studied, the assumption that all destinations must be visited is often unrealistic in tourism contexts, where travelers typically select only a subset of available locations. This limitation motivates the development of routing optimization models capable of integrating destination selection and visitation sequencing within a unified mathematical framework.

Integer Linear Programming (ILP) provides a rigorous approach for modeling discrete routing decisions through binary variables and linear constraints. ILP formulations enable explicit representation of routing continuity, subtour elimination, and additional structural or policy-based restrictions while guaranteeing globally optimal solutions within solvable computational limits [4]. Compared with heuristic or metaheuristic approaches commonly applied in tourism itinerary optimization, ILP offers stronger mathematical interpretability and reproducibility.

Several studies have addressed the problem of tourist route planning under various constraints. Gavalas et al. [5] provide a comprehensive survey of algorithmic approaches for the Tourist Trip Design Problem (TTDP), establishing that selective routing models -in which only a subset of destinations is visited- more accurately reflect practical tourism behavior than classical TSP formulations that require visiting all nodes. Ruiz-Meza and Montoya-Torres [6] further confirm through a systematic review of 102 research papers that exact optimization methods such as ILP remain underexplored in the TTDP literature relative to heuristic and metaheuristic approaches, highlighting an opportunity for rigorous mathematical formulations in this domain. Bolzoni et al. [7] further demonstrate that incorporating category constraints into itinerary planning produces routes that better align with tourist preferences, as travelers naturally think in terms of destination categories rather

than individual locations; however, their approach relies on heuristic algorithms based on clustering and does not guarantee globally optimal solutions. Suliman et al. [8] demonstrate the applicability of ILP to self-drive tourist route optimization in an urban context, confirming the suitability of exact optimization methods for problems of this type, but their formulation follows the classical TSP structure in which all candidate destinations must be visited, without incorporating any form of subset selection or category-based restrictions.

To the best of our knowledge, no prior work has combined exact ILP-based optimization with simultaneous subset selection and category-based exact constraints within a single unified model for tourist route planning. Motivated by this gap, this study proposes an ILP-based tourist route optimization model for Batam City that integrates destination category constraints while selecting only a fixed number of destinations from a larger candidate set. The objective is to minimize total travel distance using fixed driving distances between destinations, enabling consistent optimization while preserving practical interpretability. This formulation positions the problem as a selective routing optimization model rather than a classical TSP and provides a mathematically explicit framework for constrained tourist route planning in an urban tourism environment.

2. Theory

2.1. *Integer Linear Programming (ILP)*

Integer Linear Programming (ILP) is an optimization framework to solve decision-making problems in which the objective function and all constraints are linear [4], while some or all decision variables are restricted to integer values [9,10]. In ILP, particularly routing and selection problems, binary variables are commonly used to represent decision such as whether a destination is visited or whether a connection between two destinations is included in a route.

In general, an ILP model with minimizing objective can be expressed in the following standard form [11]:

$$\begin{aligned} &\text{Minimize} && z = \sum_{j=1}^{n} c_j x_j, \\ &\text{Subject to:} \\ &&& \sum_{j=1}^{n} a_{ij} x_j \leq b_i, \\ &&& x_j \geq 0, \end{aligned}$$

for $i = 1, 2, \cdots, m$ and $j = 1, 2, \cdots, n$, where:

z : minimize objective function,
c_j : coefficient of the objective function,
x_j : decision variables,
a_{ij} : coefficient of the decision variable,
b_i : right hand side value.

In optimization problems based on routing and selection, the decision variables are typically restricted to binary values to represent discrete choices, such as whether a connection between two destinations is selected. Therefore, the integer restriction in the ILP formulation is specialized as [9,10]:

$$x_{ij} \in \{0, 1\}, \qquad \forall i, j,$$

where $x_{ij} = 1$ if that route from i to j is selected or included in the solution, and $x_{ij} = 0$ otherwise.

ILP has been widely applied in routing, scheduling, and network optimization due to its flexibility to incorporate structural constraints into a unified linear framework. In particular, integer programming formulations have long been used to model routing problems such as the Traveling Salesman Problem, demonstrating the suitability of ILP to represent travel-distance minimization and route-connectivity constraints [8]. Therefore, ILP provides an appropriate mathematical foundation for the constrained tourist route optimization model developed in this study.

2.2. *Graph Representation and Driving Distance*

The tourist destinations and their connections can be represented as a directed graph $G = (V, E)$, where V denotes the set of destinations and $E \subseteq V \times V$ represents the set of feasible travel paths between destinations. Each edge $(i, j) \in E$ is associated with a weight d_{ij}, which denotes the travel distance from destination i to destination j.

In this study, the distance parameter d_{ij} is defined using driving distance obtained from digital map services. Compared to Euclidean distance, driving distance provides a more realistic representation of actual travel conditions since it considers the road network structure and accessibility between locations.

The distances are arranged in a matrix $D = [d_{ij}]$, where $d_{ij} \geq 0$ and $d_{ii} = 0$. In general, the matrix may be asymmetric (i.e., $d_{ij} \neq d_{ji}$) due to differences in travel routes or road directions. Based on this representation, the total travel distance of a route is formulated as

$$\sum_{i \in V} \sum_{\substack{j \in V, \\ j \neq i}} d_{ij} x_{ij},$$

which serves as the objective function to be minimized in the proposed optimization model.

2.3. *Decision Variables and Subset Selection*

In routing optimization problems, decision variables are used to represent whether a connection between two destinations is included in the route. In this study, binary decision variables are defined as:

$$x_{ij} = \begin{cases} 1, & \text{if the route from destination } i \text{ to destination } j \text{ is selected,} \\ 0, & \text{otherwise,} \end{cases}$$

for all $i, j \in V, i \neq j$.

To represent whether a destination is included in the route, additional binary variables are introduced as:

$$y_i = \begin{cases} 1, & \text{if destination } i \text{ is selected,} \\ 0, & \text{otherwise.} \end{cases}$$

The use of both edge variables x_{ij} and node variables y_i enables the model to simultaneously determine the structure of the route and the subset of destinations to be visited.

Unlike the classical Traveling Salesman Problem (TSP), which requires all nodes to be visited exactly once, the model in this study allows only a subset of destinations to be selected from the available set. This formulation reflects realistic tourism scenarios, where travelers are constrained by time, distance, or preferences, and therefore cannot visit all available locations.

The relationship between x_{ij} and y_i ensures that a destination is considered visited if and only if it is connected by selected routes. This structure forms the basis of a selective routing model, in which destination selection and route construction are integrated within a single optimization framework.

2.4. *Subtour Elimination Constraints*

In routing optimization models, it is necessary to ensure that the selected edges form a single connected route rather than multiple disconnected cycles, commonly referred to as subtours. Subtours represent infeasible solutions because they imply separate routes that are not connected within a single tour.

To eliminate subtours, the Miller–Tucker–Zemlin (MTZ) [12,13] formulation is employed. This approach introduces auxiliary variables u_i for each destination $i \in V$, representing the visiting order of the destinations in the route.

The MTZ constraints can be expressed as

$$u_i - u_j + nx_{ij} \leq n - 1, \qquad \forall i, j \in V, i \neq j,$$

where n denotes the number of destinations. These constraints prevent the formation of smaller cycles by enforcing a consistent ordering among visited nodes.

Additionally, the auxiliary variables are bounded as:

$$1 \leq u_i \leq n, \qquad \forall i \in V.$$

The incorporation of MTZ constraints ensures that the resulting solution forms a single valid route, thereby maintaining route feasibility within the optimization model. The MTZ formulation, while compact and widely used in routing optimization models, is known to produce relatively weak LP relaxations [14]. Nonetheless, it remains a practical and commonly adopted choice for moderate-sized problem instances due to its simplicity of implementation.

Several alternative approaches have been proposed for subtour elimination, including the Dantzig–Fulkerson–Johnson (DFJ) formulation and flow-based formulations such as the single-commodity flow approach. DFJ formulations generally provide stronger linear programming relaxations but may require a large number of

subtour constraints and separation procedures [15], while flow-based formulations introduce additional flow variables and constraints [16]. In this study, the MTZ formulation is retained because of its relatively compact structure and straightforward implementation within the proposed ILP model. This choice is appropriate for the moderate-sized problem considered in this study, which consists of 20 candidate destinations. Although alternative formulations may provide stronger relaxations, the simplicity of MTZ is considered sufficient for obtaining optimal solutions for the problem size investigated here.

2.5. *Destination Category Constraints*

In practical tourism planning, different categories of destinations may have different levels of importance depending on traveler preferences. Therefore, the model allows flexible constraints for each category rather than enforcing a uniform selection rule.

Let K denote the set of destination categories, and let $C_k \subseteq V$ represent the subset of destinations belonging to category $k \in K$. For each category, lower and upper bounds are imposed to control the number of selected destinations.

The category constraints are formulated as:

$$L_k^{min} \leq \sum_{i \in C_k} y_i \leq L_k^{max}, \qquad \forall k \in K,$$

where y_i is a binary variable indicating whether destination i is selected, and L_k^{min}, L_k^{max} denote the minimum and maximum number of destinations allowed for category k, respectively.

This formulation provides flexibility in modeling different travel preferences, such as requiring at least one destination from certain categories while allowing optional or multiple selections from others. As a result, the model becomes more adaptable and better reflects realistic tourism planning scenarios.

3. Result and Discussion

3.1. *Model Formulation*

The tourist optimization problem in this study is formulated as a binary Integer Linear Programming (ILP) model on a directed graph $G = (V, E)$. The model aims to determine a subset of destinations and the corresponding route that minimize total travel distance while satisfying routing and category constraints.

Sets and Indices

$$\begin{aligned} V &: \text{ set of tourist destinations,} \\ i, j \in V &: \text{ indices of destinations,} \\ K &: \text{ set of destination categories,} \\ C_k \subseteq V &: \text{ set of destinations belonging to category } k \in K. \end{aligned}$$

Parameters

d_{ij} : driving distance from destination i to destination j,

$L_k^{\min}$: minimum number of destinations to be selected from category k,

$L_k^{\max}$: maximum number of destinations to be selected from category k.

Decision Variables

$$x_{ij} = \begin{cases} 1, & \text{if the route from } i \text{ to } j \text{ is selected,} \\ 0, & \text{otherwise.} \end{cases}$$

$$y_i = \begin{cases} 1, & \text{if destination } i \text{ is selected} \\ 0, & \text{otherwise.} \end{cases}$$

$u_i \in \mathbb{Z}$ = auxiliary variable representing visit order.

Objective Function

Minimize total travel distance:

$$\min \sum_{i \in V} \sum_{\substack{j \in V, \\ j \neq i}} d_{ij}\, x_{ij},$$

Constraints

(1) Flow Conservation

$$\sum_{\substack{j \in V, \\ j \neq i}} x_{ij} = y_i, \quad \forall i \in V,$$

$$\sum_{\substack{i \in V, \\ i \neq j}} x_{ij} = y_j, \quad \forall j \in V.$$

(2) Subtour Elimination (MTZ)

$$u_i - u_j + n\, x_{ij} \leq n - 1, \quad \forall i, j \in V,\ i \neq j,$$

$$1 \leq u_i \leq n, \quad \forall i \in V.$$

(3) Category Constraints

$$L_k^{\min} \leq \sum_{i \in C_k} y_i \leq L_k^{\max}, \quad \forall k \in K.$$

(4) Binary and Integer Constraints

$$x_{ij} \in \{0, 1\}, \quad y_i \in \{0, 1\},$$

$$u_i \in \mathbb{Z}.$$

3.2. *Data Description*

The dataset used in this study consists of a set of tourist destinations in Batam City. The candidate destinations were identified through online searches of tourist attractions in Batam City, focusing on destinations that are among the well-known tourist attractions in the city. The destinations were selected to represent the main categories considered in the model, namely beaches, shopping malls, cultural attractions, and other tourist attractions. In addition, destinations were included when their locations and driving distance information could be reliably identified from online map services. The resulting set of 20 destinations was constructed to provide a representative and sufficiently diverse candidate set for the proposed ILP model, rather than to constitute an exhaustive ranking of the most popular tourist destinations in Batam. Some of the destinations is classified into a predefined category to support the implementation of category-based constraints in the optimization model.

The set of destinations is denoted by V, each destination $i \in V$ is assigned to a category $k \in K$. The categories include various types of tourist attractions such as beach, mall, and culture. Destinations that represent mixed-use recreational facilities, resorts, or unique landmarks (e.g., Barelang Bridge, Ocarina Batam Theme Park) are grouped into a general "Other" category. This grouping is not arbitrary, it is a deliberate modeling strategy to prevent the ILP formulation from becoming over-constrained by too many micro-categories. By maintaining a pool of flexible, general destinations, the model can more effectively explore optimal routes while satisfying the primary categorical constraints. Harris Hotel Batam Center is defined as the depot, representing the fixed starting and ending point of the route.

The depot is fixed in this study to provide a common starting and ending point for all scenarios and to ensure that the effect of destination category constraints can be evaluated consistently. Harris Hotel Batam Center is used as a representative tourist accommodation point in the Batam Center area because of its strategic proximity to Batam Center International Ferry Terminal, a major entry point for international tourists. This makes the hotel a reasonable representative accommodation hub for tourists entering Batam through this gateway. Alternative depot locations are not considered in the current model because varying the depot would introduce an additional decision dimension and could confound the comparison of category-based routing scenarios. The use of a fixed depot is therefore considered an explicit modeling assumption rather than a claim that Harris Hotel Batam Center is the optimal starting point for all tourist segments. The list of destinations along with their corresponding categories is presented in Table 1.

The travel distance between each pair of destinations is obtained using driving distance from Google Maps. These distances are used to construct the distance matrix $D = [d_{ij}]$, which serves as the input parameter in the optimization model.

Table 1. List of Tourist Destinations

No	Tourist Destination	Category
0	Harris Hotel Batam Center	Depot
1	Barelang Bridge	Other
2	Ocarina Batam Theme Park	Other
3	Sekupang Deer Park	Other
4	Golden City	Other
5	Nongsa Beach	Beach
6	Marina Beach	Beach
7	Viovio Beach	Beach
8	Elyora Beach	Beach
9	Nagoya Hill	Mall
10	BCS Mall	Mall
11	Mega Mall Batam Center	Mall
12	Grand Batam Mall	Mall
13	One Batam Mall	Mall
14	Maha Vihara Duta Maitreya	Cultural
15	Batam Grand Mosque	Cultural
16	Vietnam Village	Cultural
17	Raja Ali Haji Museum	Cultural
18	Dino's Gate	Other
19	Nongsa Point Marina and Resort	Other

The matrix D is represented below.

$$D = \begin{bmatrix}
0 & 20.3 & 4.7 & 19.3 & 6.4 & 21.3 & 24.1 & 57.8 & 75.3 & 7.4 & 6.9 & 0.5 & 7.4 & 1.3 & 3.1 & 1.1 & 55 & 0.2 & 6.7 & 19.8 \\
21.2 & 0 & 26.8 & 25.9 & 27.6 & 39.7 & 20 & 37.5 & 54.9 & 24.5 & 22.8 & 21.8 & 23.3 & 21.1 & 22.8 & 21.1 & 37.8 & 21.4 & 27.9 & 38.1 \\
3.8 & 23.9 & 0 & 18.3 & 3.5 & 25.1 & 21.7 & 61.4 & 78.8 & 7.9 & 8.2 & 4.3 & 8.7 & 3.6 & 4.3 & 4.6 & 61.7 & 3.9 & 3.8 & 25.6 \\
17.3 & 23.1 & 18.4 & 0 & 19.2 & 46.2 & 10.4 & 60.6 & 78.1 & 14.6 & 12.7 & 17.5 & 12.4 & 16.3 & 14.5 & 17.4 & 60.9 & 17.2 & 19.5 & 36.5 \\
5.7 & 26.9 & 3.5 & 19.3 & 0 & 27.1 & 22.6 & 64.3 & 81.8 & 5.2 & 7.3 & 6.3 & 7.8 & 5.6 & 6.3 & 6.7 & 64.6 & 5.9 & 1.1 & 25.5 \\
23.8 & 38.8 & 27.9 & 38 & 29.6 & 0 & 41.4 & 76.3 & 93.8 & 29.7 & 28 & 23.2 & 28.5 & 24.7 & 24.5 & 23 & 76.6 & 23.4 & 33.1 & 5.9 \\
20.4 & 19.4 & 21.8 & 10.3 & 22.6 & 41.4 & 0 & 56.8 & 74.3 & 18 & 16.1 & 21 & 15.9 & 19.7 & 17.9 & 20.8 & 57.1 & 20.6 & 22.9 & 39.9 \\
58 & 36.8 & 63.5 & 62.6 & 64.4 & 76.4 & 56.7 & 0 & 19.7 & 61.2 & 59.6 & 58.5 & 60.1 & 57.9 & 59.6 & 57.9 & 6.7 & 58.1 & 64.7 & 74.9 \\
75.4 & 54.2 & 81 & 80.1 & 81.8 & 93.9 & 74.2 & 19.7 & 0 & 78.7 & 77.1 & 76 & 77.5 & 75.4 & 77 & 75.3 & 24.1 & 75.6 & 82.2 & 92.3 \\
6.9 & 23.6 & 8.3 & 14.9 & 5.1 & 29.3 & 18.2 & 61.1 & 78.6 & 0 & 4.2 & 7.4 & 2.8 & 6.2 & 4 & 7.3 & 61.4 & 7 & 5.4 & 27.8 \\
6.7 & 22.2 & 8.2 & 12.8 & 7.3 & 27.9 & 16.2 & 59.6 & 77.1 & 2.8 & 0 & 7.3 & 0.7 & 6.1 & 4.2 & 7.1 & 59.9 & 6.9 & 7.6 & 26.3 \\
0.6 & 20.4 & 4.7 & 17.1 & 6.5 & 21.9 & 20.5 & 57.9 & 75.3 & 6.8 & 7 & 0 & 7.5 & 1.4 & 3.1 & 1.2 & 58.2 & 0.2 & 6.4 & 20.4 \\
7.8 & 23.7 & 9.5 & 13.4 & 6.5 & 29.4 & 16.7 & 61.2 & 78.7 & 2.1 & 1.7 & 8.4 & 0 & 7.4 & 5.2 & 8.2 & 61.5 & 8 & 6.9 & 27.9 \\
1.1 & 20.6 & 3.4 & 15.8 & 5.2 & 22 & 19.2 & 58.1 & 75.6 & 5.5 & 5.7 & 1.6 & 6.2 & 0 & 1.8 & 1.4 & 58.4 & 1.2 & 5.1 & 20.5 \\
2.7 & 22.6 & 4.2 & 15 & 5.9 & 23.8 & 18.3 & 60 & 77.5 & 3.8 & 4.6 & 3.3 & 5.1 & 2 & 0 & 3.1 & 60.3 & 2.9 & 4.9 & 22.5 \\
0.8 & 20.1 & 4.6 & 17 & 6.3 & 21.1 & 20.3 & 57.6 & 75 & 6.6 & 6.9 & 0.9 & 7.9 & 1.1 & 3 & 0 & 57.8 & 1 & 6.7 & 19.6 \\
55.1 & 37 & 63.8 & 62.9 & 64.6 & 76.7 & 57 & 6.7 & 24.1 & 61.5 & 59.9 & 58.8 & 60.3 & 58.2 & 59.9 & 58.2 & 0 & 58.4 & 65 & 75.2 \\
0.4 & 20.2 & 4.5 & 16.9 & 6.3 & 21.7 & 20.3 & 57.7 & 75.1 & 6.5 & 6.8 & 0.9 & 7.3 & 1.2 & 2.9 & 1 & 58 & 0 & 6.2 & 20.2 \\
6.1 & 27.2 & 3.8 & 19.6 & 1.1 & 27.4 & 22.9 & 64.6 & 82.1 & 5.5 & 7.6 & 6.6 & 8.1 & 5.9 & 4.9 & 6.9 & 64.9 & 6.2 & 0 & 25.8 \\
22.3 & 37.4 & 28.2 & 36.6 & 31.3 & 6 & 39.9 & 74.8 & 92.3 & 25.8 & 26.6 & 21.8 & 27 & 22.7 & 23 & 21.5 & 75.1 & 21.9 & 27 & 0
\end{bmatrix}.$$

3.3. *Computational Results and Analysis*

The proposed ILP model was implemented in Python using the PuLP optimization library and solved using the CBC (Coin-or Branch and Cut) solver. To evaluate the behavior of the model under varying category preferences, four distinct scenarios were constructed. Each scenario imposes a different distribution of category constraints while maintaining a total of 11 selected destinations (excluding the depot), ensuring a fair and consistent basis for comparison. The category constraints applied in each scenario are summarized in Table 2.

Table 2. Category Constraint Settings for Each Scenario

Scenario	**Beach**	**Cultural**	**Mall**	**Others**
S1 (Main)	2	1	2	6
S2 (More Beach)	3	1	2	5
S3 (More Cultural)	2	2	2	5
S4 (More Mall)	2	1	3	5

Main Scenario (S1)

The main scenario (S1) reflects a balanced tourist profile, with category constraints set to exactly 2 beach destinations, 1 cultural destination, 2 mall destinations, and 6 uncategorized (others) destinations. The model returns an optimal solution with a total travel distance of **123.6 km**.

The selected destinations and the resulting optimal route are presented in Table 3 and Table 4, respectively.

Table 3. Selected Destinations in Scenario S1

No	**Destination**	**Category**
0	Harris Hotel Batam Center	Depot
11	Mega Mall Batam Center	Mall
17	Raja Ali Haji Museum	Cultural
19	Nongsa Point Marina and Resort	Others
5	Nongsa Beach	Beach
1	Barelang Bridge	Others
6	Marina Beach	Beach
3	Sekupang Deer Park	Others
12	Grand Batam Mall	Mall
4	Golden City	Others
18	Dino's Gate	Others
2	Ocarina Batam Theme Park	Others

Table 4. Optimal Route Sequence in Scenario S1

Step	From	To	Dist
1	Harris Hotel Batam Center	Mega Mall Batam Center	0.5
2	Mega Mall Batam Center	Raja Ali Haji Museum	0.2
3	Raja Ali Haji Museum	Nongsa Point Marina and Resort	20.2
4	Nongsa Point Marina and Resort	Nongsa Beach	6.0
5	Nongsa Beach	Barelang Bridge	38.8
6	Barelang Bridge	Marina Beach	20.0
7	Marina Beach	Sekupang Deer Park	10.3
8	Sekupang Deer Park	Grand Batam Mall	12.4
9	Grand Batam Mall	Golden City	6.5
10	Golden City	Dino's Gate	1.1
11	Dino's Gate	Ocarina Batam Theme Park	3.8
12	Ocarina Batam Theme Park	Harris Hotel Batam Center	3.8
	Total		**123.6**

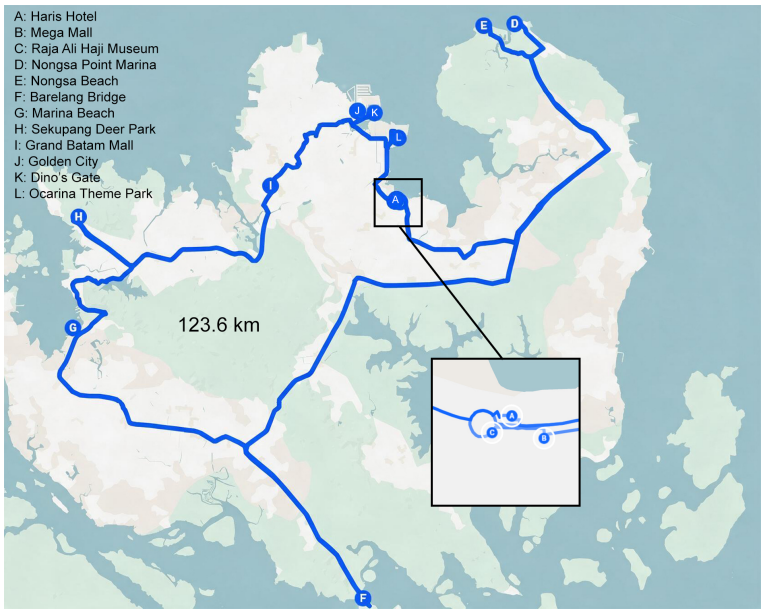


Figure. 1. S1 Routes

The route begins at Harris Hotel Batam Center as the depot and immediately proceeds to nearby destinations in the Batam Center area, namely Mega Mall Batam Center (0.5 km) and Raja Ali Haji Museum (0.2 km). The route then extends eastward toward the Nongsa area, visiting Nongsa Point Marina and Resort and Nongsa Beach before making its longest single leg to Barelang Bridge (38.8 km), which is the most geographically distant destination in the dataset. The route then returns through the western part of the island via Marina Beach and Sekupang

Deer Park, before looping back through several clustered destinations near Batam Center. This structure reveals that the ILP solver effectively organizes the route to exploit geographic proximity, grouping nearby destinations together and minimizing unnecessary backtracking.

Scenario Comparison and Effect of Category Constraints

To further examine how category constraints influence both destination selection and total travel distance, three additional scenarios (S2, S3, S4) were constructed by reallocating one destination slot from the uncategorized group to one of the categorical groups, while keeping the total number of selected destinations fixed at 11.

The computational experiments were conducted using Python with the PuLP optimization library and the CBC solver. The experiments were performed on a computer equipped with an AMD Ryzen 5 5500U processor and 12 GB of RAM. For each scenario, the optimization model was executed 10 times, and the average solution time was recorded. The number of solver iterations and solution status were also recorded for each scenario. The results are summarized in Table 5 and 6.

Table 5. Comparison of Optimal Solutions Across Scenarios (Part 1: Solver Performance)

Scenario	**Time (s)**	**Iterations**	**Optimality**
S1 (Main)	3.4	15136	Optimal
S2 (More Beach)	14.26	95976	Optimal
S3 (More Cultural)	12.43	177895	Optimal
S4 (More Mall)	15.81	203495	Optimal

Table 6. Comparison of Optimal Solutions Across Scenarios (Part 2: Route Results)

Scenario	**Beach**	**Cultural**	**Mall**	**Others**	**Distance (km)**
S1 (Main)	2	1	2	6	123.6
S2 (More Beach)	3	1	2	5	190.1
S3 (More Cultural)	2	2	2	5	106.5
S4 (More Mall)	2	1	3	5	106.8

The results in Table 6 reveal a clear and significant influence of category constraints on total travel distance, even when the total number of selected destinations remains constant across all scenarios.

Scenario S2, which increases the beach quota from 2 to 3, produces the highest total travel distance of **190.1 km**, an increase of **66.5 km (53.8%)** compared to the main scenario. This substantial increase is attributed to the geographic distribution of beach destinations in Batam. The four available beach destinations (Nongsa Beach, Marina Beach, Viovio Beach, and Elyora Beach) are spread across opposite

ends of the island, and requiring a third beach destination forces the model to select locations that introduce long detours. In particular, the optimal solution for S2 incorporates Viovio Beach and Elyora Beach, both of which are located in the far western part of Batam, resulting in an extended route segment to accommodate them. This finding highlights that beach destinations, despite their tourism appeal, are the most geographically dispersed category and thus the most costly to include in larger numbers.

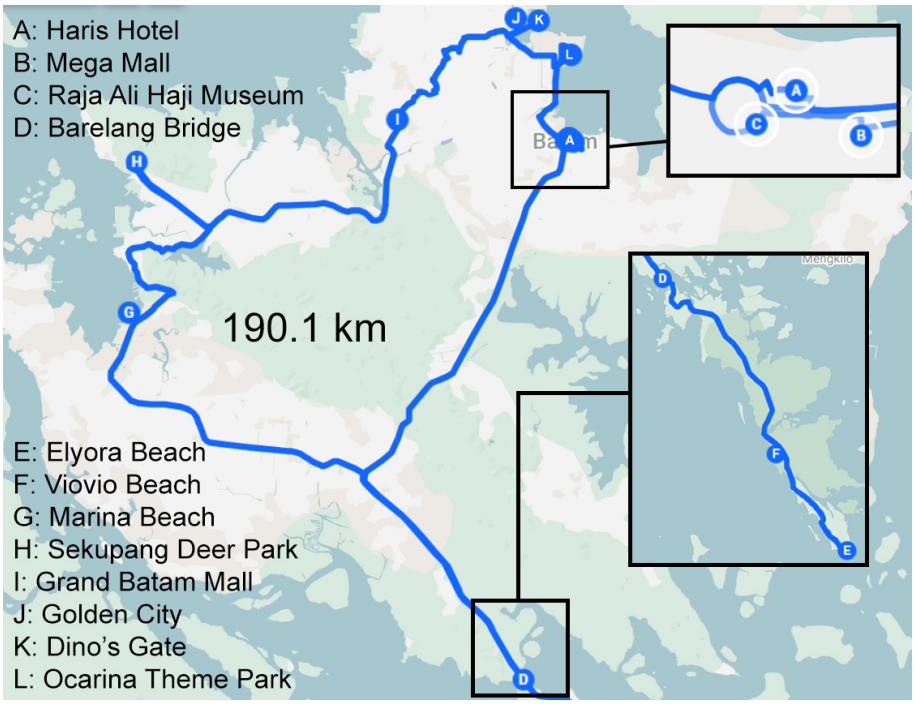


Figure. 2. S2 Routes

In contrast, Scenarios S3 and S4 both yield shorter routes than the main scenario. Scenario S3, which requires 2 cultural destinations instead of 1, achieves the shortest total distance of **106.5 km**, a reduction of **17.1 km (13.8%)** relative to S1. The model selects Batam Grand Mosque and Raja Ali Haji Museum, both of which are geographically close to the depot and to each other, enabling efficient integration into the route without introducing significant detours. This result indicates that cultural destinations in Batam are spatially concentrated near the city center, making them highly compatible with efficient route construction.

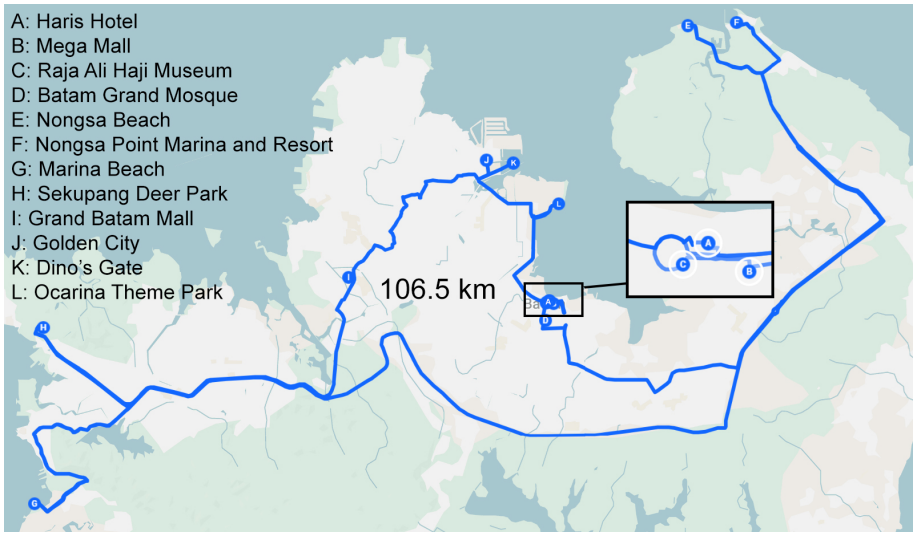


Figure. 3. S3 Routes

Similarly, Scenario S4, which adds one more mall destination (3 total), yields a total distance of **106.8 km**, nearly identical to S3 and also shorter than S1. The selected malls (Nagoya Hill Mall, Mega Mall Batam Center, and Grand Batam Mall) are all situated within the central Batam area and form a compact cluster, allowing the solver to incorporate them with minimal additional travel cost.

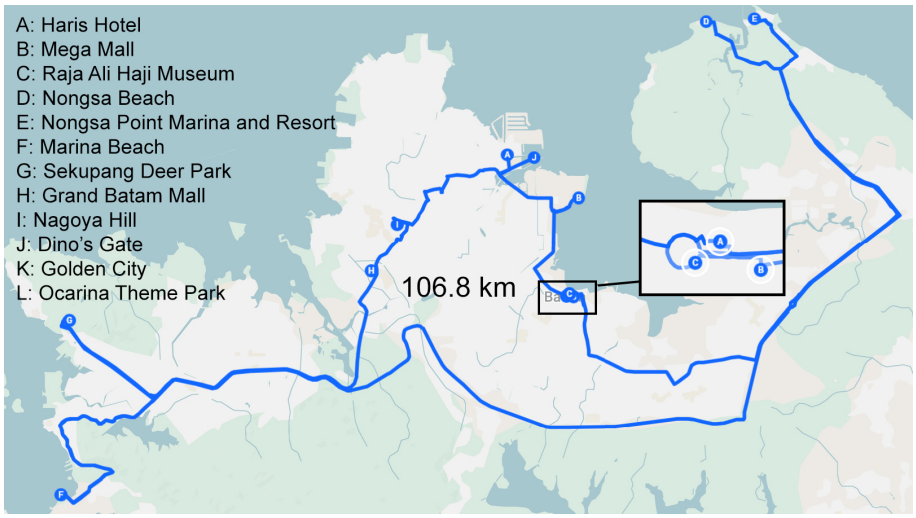


Figure. 4. S4 Routes

Collectively, these results demonstrate that the category of destinations selected has a greater impact on total travel distance than their quantity alone. Destinations

belonging to geographically dispersed categories (such as beaches) significantly increase the route length when more of them are required, whereas destinations in spatially concentrated categories (such as cultural sites and malls) can be added with relatively little impact on total distance. This observation is consistent with findings in the selective TSP literature, where the geographic distribution of selected nodes has been shown to play a significant role in determining tour length [17]. This finding underscores the importance of incorporating category-aware constraints into tourist route optimization models, as it allows the model to reflect realistic travel preferences while providing meaningful insight into the trade-off between destination diversity and route efficiency.

4. Conclusion

This study proposed an Integer Linear Programming (ILP) model for optimizing tourist routes in Batam City under destination category constraints. Unlike the classical Traveling Salesman Problem, which requires visiting all available destinations, the proposed model selects an optimal subset of destinations from a larger candidate set while simultaneously determining the most efficient visiting sequence. The model incorporates flow conservation constraints, subtour elimination via the Miller–Tucker–Zemlin (MTZ) formulation, linking constraints, and category-based restrictions that control the number of selected destinations per category.

The model was applied to a dataset of 20 tourist destinations in Batam City, including beaches, shopping malls, cultural sites, and other attractions, with Harris Hotel Batam Center serving as the fixed depot. Driving distances obtained from Google Maps were used to construct the asymmetric distance matrix, providing a realistic representation of actual travel conditions. The model was implemented in Python using the PuLP optimization library and solved using the CBC solver.

Computational results confirmed that the proposed model consistently produces optimal and feasible solutions under all tested scenarios. In the main scenario (S1), the model selected 11 destinations across all four categories and generated an optimal route with a total travel distance of 123.6 km. The resulting route demonstrates geographically coherent structure, grouping nearby destinations into efficient clusters and minimizing unnecessary backtracking across the island.

Scenario analysis further revealed that destination category has a significant influence on total travel distance, independent of the total number of selected destinations. Increasing the beach quota by one (S2) resulted in the longest route at 190.1 km, an increase of 53.8% relative to the main scenario, reflecting the dispersed geographic distribution of beach destinations across Batam. In contrast, adding one cultural destination (S3) or one mall destination (S4) reduced the total distance to 106.5 km and 106.8 km, respectively, owing to the spatial concentration of these destinations near the city center. These findings demonstrate that the geographic distribution of destination categories is a critical factor in tourist route optimization and that category-aware constraints provide meaningful control over the trade-off between destination diversity and route efficiency.

Overall, the proposed ILP model offers a flexible and mathematically rigorous

framework for constrained tourist route planning in urban tourism environments. The model is readily adaptable to different preference settings by adjusting the category constraint parameters, making it applicable to a wide range of tourism planning scenarios beyond the specific case of Batam City. Future work may consider extending the model to incorporate time windows, multi-day itineraries, or traveler preference weights, as well as exploring scalable solution approaches such as heuristics or metaheuristics to handle larger destination networks.

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