

# Application of TOPSIS-LP and New Routing Models for the Multi-Criteria Tourist Route Problem: The Case Study of Nong Khai, Thailand

## Wasana Phuangpornpitak

Department of Logistics Management, Faculty of Business Administration and Information Technology, Rajamangala University of Technology, Isan Khonkaen Campus, Thailand  
wasana.ch@rmuti.ac.th

## Wanita Boonchom

Department of Management, Faculty of Business Administration and Information Technology, Rajamangala University of Technology, Isan Khonkaen Campus, Thailand  
vanita.bo@rmuti.ac.th

## Kittanathat Suphan

Department of Tourism and Hospitality Management, Faculty of Business Administration and Information Technology, Rajamangala University of Technology, Isan Khonkaen Campus, Thailand  
kittanathat.su@rmuti.ac.th

## Watchara Chiengkul

Department of Tourism and Hospitality Management, Faculty of Business Administration and Information Technology, Rajamangala University of Technology, Isan Khonkaen Campus, Thailand  
watchara.ch@rmuti.ac.th

## Thanawat Tantipanichkul

Department of Tourism and Hospitality Management, Faculty of Business Administration and Information Technology, Rajamangala University of Technology, Isan Khonkaen Campus, Thailand  
pacharaphat.bo@rmuti.ac.th (corresponding author)

Received: 17 April 2024 | Revised: 5 May 2024 | Accepted: 13 May 2024

Licensed under a CC-BY 4.0 license | Copyright (c) by the authors | DOI: <https://doi.org/10.48084/etasr.7523>

## ABSTRACT

This study investigates the application of a new mathematical routing model, integrated with the TOPSIS Linear Programming (TOPSIS-LP) approach, to optimize tourist routes in Nong Khai, Thailand, within a Multi-Criteria Decision-Making (MCDM) framework. The research demonstrates the efficacy of TOPSIS-LP by consistently ranking the same alternative as the optimal route, achieving the highest rankings across various Multi-Attribute Decision Making (MADM) methods, including MOORA, WASPAS, and ARAS. These methods displayed significant consistency in outcome evaluation, with Spearman Correlation Coefficients (SCC) of 0.952 for MOORA WASPAS, and ARAS, indicating the influence of diverse weighting and aggregation strategies in route optimization. Moreover, the study confirmed a perfect alignment (SCC of 1.00) between TOPSIS-LP and the traditional TOPSIS method, affirming that the enhancements to the LP components maintained the integrity of the original model. The findings provide invaluable insights for tourism planners aiming to improve tourist satisfaction and operational efficiency and contribute to the academic discourse by highlighting the practical utility of sophisticated mathematical models in real-world scenarios. This research not only advances the methodological practices in tourist route optimization, but also sets a benchmark for future research aimed at enhancing the effectiveness, robustness, and adaptability of MADM methods in the tourism sector.

*Keywords-tourist routing problem; routing model; TOPSIS; TOPSIS-LP; multi-criteria tourist routing problem*

## I. INTRODUCTION

Optimizing tourist routes in culturally and naturally rich destinations presents a multifaceted challenge that requires careful management to balance the needs of the tourists, environment, and local communities. This process involves addressing the diverse preferences of tourists, logistical travel constraints, and the imperative to support sustainability efforts. Notably, strategic route optimization contributes to environmental conservation by reducing congestion and encouraging visits to less frequented conservation areas, thus minimizing tourism's environmental footprint [1-4]. Economically, the former plays a pivotal role in diversifying income sources within communities and stimulating local economies through enhanced tourist spending and job creation. In addition, optimized routes promote cultural preservation and foster community engagement, significantly improving residents' quality of life [5-7]. Furthermore, for tourists, such optimization ensures a richer, more personalized travel experience, heightening satisfaction, while offering unique educational insights into the destination's heritage and natural landscapes. Overall, the effective optimization of tourist routes underscores the importance of integrated tourism management strategies that harmonize environmental conservation, economic growth, social well-being, and enrich the travel experience [8-11]. The optimization of tourist routes is a complex issue, necessitating a balance between minimizing travel distances and costs and maximizing tourist satisfaction and engagement with attractions. Traditional methods like the Traveling Salesman Problem (TSP) and Shortest Path (SP) often inadequately address the multi-faceted criteria required for optimizing tourist experiences due to their singular focus on minimizing the distance or transportation cost [12-14].

The TSP, central to combinatorial optimization, aims to identify the shortest route visiting each city (from a group of cities) once before returning to the start [14-18]. Similarly, the SP algorithm, especially Dijkstra's algorithm, is crucial in determining efficient travel paths, optimizing time or distance between nodes [19]. Both TSP and SP have been integral to solving routing challenges, with their adaptability to different problem demands and goals. Typically, mathematical routing models strive to minimize travel distance or enhance transportation cost-efficiency. However, tourist routing demands the consideration of more criteria. Achieving optimal solutions can be complex, and crafting detailed models may not be always feasible. Therefore, exploring alternative methods is vital for effective problem resolution, making solutions more practical and accessible. Overcoming the challenges of multi-criteria routing involves integrating additional methods with the existing models. A comprehensive solution may necessitate a varied approach, employing multiple methodologies to address the complexities of routing problems effectively.

The optimization of decisions among alternatives by considering multiple criteria, which are frequently in conflict, is the central focus of the substantial field of operations research and management science known as Multi-Criteria Decision Making (MCDM), including Multi-Objective

Decision Making (MODM), and Multi-Attribute Decision Making (MADM) [20]. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a notable MADM technique. The determinant of TOPSIS is the alternative that is most distant from the Negative Ideal Solution (NIS) and has the shortest Euclidean distance from the Positive Ideal Solution (PIS). Since its inception, the TOPSIS has been applied across a broad range of fields. Authors in [21] employed a combined approach of TOPSIS and the Analytic Hierarchy Process (AHP) to evaluate and select sustainable suppliers within the electronics supply chain. Authors in [22] utilized TOPSIS to assess the sustainability of various energy sources, considering factors, such as efficiency, cost, and environmental impact. Furthermore, in [23], TOPSIS has been applied to improve software efficiency and optimize its management. TOPSIS method has been implemented across numerous disciplines. These applications include, but are not limited to, healthcare [23], real estate [24], urban and regional planning [26], agro-tourism clusters [26], information technology [27], parameter optimization [29], and project selection [30]. A recent development in the field introduced a mathematical representation of the TOPSIS with linear programming (TOPSIS-LP) [23, 32] This model adheres to the core principles of TOPSIS while providing several advantages: it simplifies the process into a single step of creating a normalized matrix, after which the compiled data are integrated into the proposed mathematical model. This approach effectively reduces the errors associated with the traditional multi-step calculations of the initial TOPSIS method. Furthermore, this model is compatible with a variety of optimization software, rendering it exceptionally suitable for complex issues that involve multiple criteria and alternatives.

Nong Khai, Thailand, is a Mekong River-facing settlement with significant historical significance. It is a teeming fusion of Lao and Thai cultures, supporting itself through commerce, tourism, and agriculture [33, 34]. The tourist routing problem in Nong Khai, Thailand, is a complex problem that needs careful attention to be paid to various criteria. Nevertheless, establishing connections between the possible destinations in a manner that optimizes tourist contentment while safeguarding the environment and indigenous customs is a multifaceted task. An intriguing problem is the arrangement of efficient travel routes in such a way that tourists can choose the most appropriate route independently. This problem is a multi-criteria/objective routing problem that demands the allocation of available resources for maximum benefit, whilst other relevant decision criteria require concurrent consideration. Thus, this issue belongs to the category of MCDM problems, specifically known as the Multi-Criteria Tourist Routing Problem (MCTRP). The MCTRP calls for the choice of an efficient approach to resolve this case.

The literature review reveals that the combination of a mathematical routing model with the TOPSIS-LP method offers an effective solution to the challenges of tourist route optimization in Nong Khai, Thailand. This study introduces a novel mathematical model that incorporates principles from the

SP model, adapted to accommodate the intricacies of tourist preferences and the distinct characteristics of destinations. This model is further integrated with the TOPSIS-LP approach. Nong Khai, with its diverse array of attractions ranging from historical sites to natural wonders, serves as an ideal setting for implementing and evaluating this innovative model. The method begins by generating all possible routes using the new mathematical framework. Following this, a decision matrix is created, classifying each route as an alternative and including various relevant decision-making criteria. The process culminates with the application of the TOPSIS-LP model to determine the relative closeness coefficient, thus identifying the most suitable route for tourists. This approach provides a systematic and effective means of enhancing tourist travel plans in Nong Khai. Ultimately, this integration of the new mathematical model with the TOPSIS technique introduces a groundbreaking approach to tackle tourist routing issues, enriching both academic research and the practice of tourism management. The findings of this study not only resolve specific routing challenges in Nong Khai, but also pave the way for further studies on the use of advanced optimization techniques to improve tourism experiences in various destinations.

II. THE PROPOSED METHOD

This section presents a groundbreaking strategy for solving the MCTRP by integrating a novel routing model with the TOPSIS-LP model. This approach's effectiveness is showcased via a case study conducted in Nong Khai, Thailand. Figure 1 illustrates the framework proposed in this study, providing a visual representation of the methodology applied.

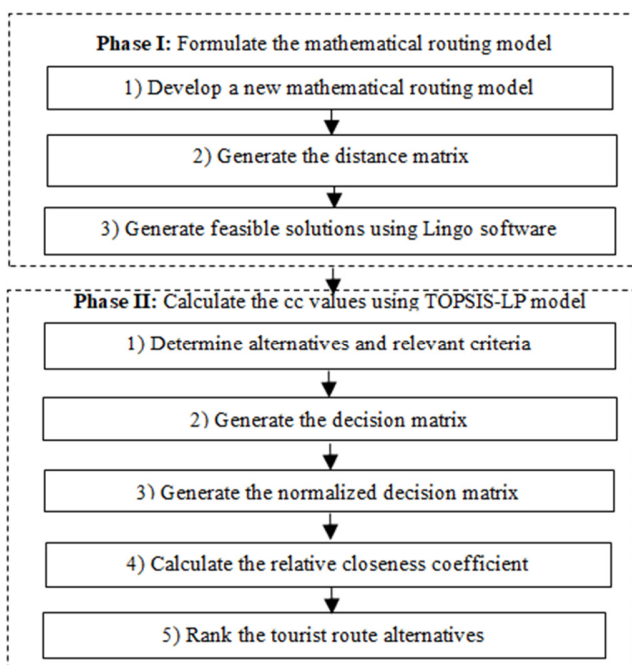


Fig. 1. The framework outlined in this study.

A. Phase I: Formulation of the Mathematical Routing Model

The mathematical model represents an extension of the SP model with adjusted objective function and constraints.

1) Developing the New Mathematical Routing Model

The mathematical framework focuses on an optimization problem that involves routing with constraints, but with just one objective function. The components of the model, including the sets, parameters, decision variables, objective function, and constraints, have been modified to accommodate the changes in the context.

• Indices

The indices  $i, j$  represent a collection of nodes that encompasses the depot, tourist, and hotel nodes, denoted as  $i, j = \{1, 2, \dots, N\}$ . Furthermore,  $ij$  constitutes a set of directed edges connecting these nodes.

• Parameters

$N$ : Total number of nodes.

$Q$ : The number of the selected hotels.

$T$ : Maximum allowable driving time.

$St$ : Service time at each tourist node.

$H$ : index for each hotel node.

$d_{ij}$ : Parameters for the distance between node  $i$  to node  $j$ .

$r_j$ : Rating of each location.

• Decision Variables:

$X_{ij}$ : Binary variable that equals to 1 if the path from node  $i$  to node  $j$  is taken and 0 otherwise.

$Y_j$ : Binary variable that equals to 1 if the node  $j$  is visited, and 0 otherwise.

$U_j$ : Continuous variable used for eliminating sub-tours and ensuring valid routes.

• Objective Function:

$$\text{Maximize } Z = \sum_{j=2, j \in H}^N r_j Y_j \tag{1}$$

• Constraints:

$$\sum_{j=1}^N X_{ij} = Y_j, \forall i \tag{2}$$

$$\sum_{j \in H}^N Y_j = Q, \forall i \tag{3}$$

$$X_{i1} = 0, \forall i \tag{4}$$

$$\sum_{j=2, j \in H}^N X_{1j} = 1 \tag{5}$$

$$\sum_{i=1}^N X_{ij} \leq 1, \forall j: j > 1, j \notin H \tag{6}$$

$$\sum_{i=2, i \in H}^N X_{il} = \sum_{j=2, j \in H}^N X_{lj}, \forall l \quad (7)$$

$$\sum_{i=1}^N \sum_{j=2, j \in H}^N dt_{ij} \cdot X_{ij} + \sum_{j=2, j \in H}^N st \cdot Y_j \leq T \quad (8)$$

$$X_{ii} = 0, \forall i \quad (9)$$

$$X_{ij} = 0, i \in H, j = 1, 2, 3, \dots, N \quad (10)$$

$$U_i - U_j + N \cdot X_{ij} \leq N - 1, \forall i, \forall j, i > 1, j > 1, i \neq j \quad (11)$$

$$\sum_{i=1}^N X_{ij} = 1, \quad (12)$$

$$X_{ij} \in \{0, 1\}, \forall i, \forall j \quad (13)$$

$$Y_j \in \{0, 1\}, \forall j \quad (14)$$

Equation (1) seeks to maximize the total rating of tourist attractions visited, taking into account only individual tourist nodes (excluding the depot and hotels).

Equation (2) guarantees that the total of the incoming pathways  $X_{ij}$  for each node  $j$  must be equal to the visitation status  $Y_j$ .

Equation (3) ensures that the total number of the visited hotels is equivalent to  $Q$ .

Equation (4) ascertains that there are no connections leading to the depot.

Equation (5) certifies that the sum of all edges from the depot (node 1) to every other node  $j$  is exactly 1.

Equation (6) ensures that every tourist node is visited just once.

Equation (7) assures flow continuity by stipulating that the number of paths entering any intermediate node matches the number of paths exiting it.

Equation (8) certifies that the total time spent on driving and visiting attractions does not exceed the allotted time limit  $T$ .

Equation (9) guarantees that no connections exist between identical nodes.

Equation (10) stipulates that there are no links between the hotel and any other nodes.

Equation (11) ensures that all nodes are incorporated into a single tour by prohibiting the creation of sub-tours.

Equation (12) ascertains that only one route can be taken from any node to the selected hotel.

Equations (13) and (14) ensure that the variables  $X_{ij}$  and  $Y_j$  are binary.

## 2) Generation of the Distance Matrix

This study aims to gather data regarding the geographical coordinates of depots, tourist sites, and hotels in Nong Khai

Province, Thailand. Subsequently, the actual distances between these points will be computed utilizing Google maps. Ultimately, the factual distance matrix of the case study will be acquired.

## 3) Generate Feasible Solutions using the Proposed Mathematical Routing Model

This study will model a scenario where a tourist stays at a hotel for one night and two days, using the proposed mathematical model to generate all potential travel routes. The process for developing these routes includes the following steps:

- **Step 1:** The tourist travels from the starting point, typically a train station, to the primary tourist attractions, which are selected based on their ratings. The tourist then stays at a pre-determined hotel identified through the proposed mathematical routing model.
- **Step 2:** The next day, the tourist departs from this hotel to visit the remaining attractions, ensuring no repetition of the sites visited the previous day. After completing this itinerary, the tourist returns to the train station, using the route determined by the second application of the proposed mathematical routing model.
- **Step 3:** The tourist then checks into a different hotel, and the process described in steps 1 and 2 is repeated until all hotels have been evaluated.

This iterative process produces a series of alternative tourist routes, equal to the number of hotels considered. These routes are then analyzed using the TOPSIS-LP model and ranked according to the established decision-making criteria.

## B. Phase II: Calculate the Relative Closeness Coefficient using the TOPSIS-LP Model

This section employs the TOPSIS-LP model to calculate the relative Closeness Coefficient (CC), aiming to prioritize the alternative routes developed in the preceding phase. This evaluation is conducted under various pertinent decision criteria. The procedure for determining the relative proximity coefficient using the TOPSIS model includes the following steps:

### 1) Determine Alternatives and Relevant Decision Making Criteria

In the decision-making process, it is crucial to comprehensively assess all viable alternatives. This study incorporates results from all potential travel routes identified in the first phase. The selection of criteria should be relevant, measurable, and comprehensive, directly connected to the goal of pinpointing the most appropriate travel route that meets them. The pertinent decision criteria identified for this research are: hotel rating (C1), total travel distance (C2), and room rates (C3).

### 2) Generate the Decision Matrix

All potential alternatives along with the associated decision criteria will be utilized to construct the decision matrix, as outlined in (15):

$$X = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} & \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \dots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \end{matrix} \quad (15)$$

In this model,  $A_i$  (where  $i = 1, 2, \dots, m$ ) denotes the alternatives,  $C_j$  (where  $j = 1, 2, \dots, n$ ) represents the criteria associated with the performance of these alternatives, and  $x_{ij}$  indicates the inputs (or outputs) of the alternative  $i$  concerning criterion  $j$ .

3) Generate the Normalized Decision Matrix

The normalized decision matrix, referred to as the  $Y$  matrix, guarantees that each criterion contributes equally to the decision-making process, as delineated in (16):

$$Y = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} & \begin{bmatrix} y_{11} & y_{12} & \dots & y_{1n} \\ y_{21} & y_{22} & \dots & y_{2n} \\ \vdots & \vdots & \dots & \vdots \\ y_{m1} & y_{m2} & \dots & y_{mn} \end{bmatrix} \end{matrix} \quad (16)$$

The normalized performance of the alternative  $i$  with respect to criterion  $j$  is denoted by  $y_{ij}$ . Equations (17) and (18) are employed to compute the normalized performance of alternative  $i$  for beneficial and cost criteria, respectively.

$$y_{ij} = x_{ij} / \sqrt{\sum_{i=1}^m x_{ij}^2} \quad (17)$$

$$y_{ij} = 1 - \left( x_{ij} / \sqrt{\sum_{i=1}^m x_{ij}^2} \right) \quad (18)$$

4) Calculate the Relative Closeness Coefficient

The TOPSIS-LP model is formulated by incorporating each alternative  $i$  with a set of criteria  $j$  within the normalized decision matrix, represented as  $y_{ij}$ . The weights assigned to the relevant criteria are denoted by  $w_j$  and are determined by decision makers or the tourists themselves. The variables  $\lambda_i^-$  and  $\lambda_i^+$  signify the optimal weights for calculating the distances between the ideal solution in the negative case and the ideal solution in the positive case, considering alternative  $i$ . For each criterion  $j$ ,  $y_j^-$  and  $y_j^+$  represent the negative and positive ideal values, respectively, where  $y_j^- = \min\{y_{ij}\}$  and  $y_j^+ = \max\{y_{ij}\}$ , for  $j = 1, 2, 3, \dots, n$ . The relative closeness coefficient value ( $CC_i$ ) for a set of alternatives  $i$  (where  $1 \leq i \leq n$ ) is defined by the equation group (19) [31].

$$CC_i = \max \lambda_i^- \left( \sum_{j=1}^n \sqrt{w_j^2 \left( (y_{ij}^-)^2 - (y_j^-)^2 \right)} \right) \quad (19.1)$$

$$\lambda_i^- \left( \sum_{j=1}^n \sqrt{w_j^2 \left( (y_{ij}^-)^2 - (y_j^-)^2 \right)} \right) + \quad (19.2)$$

$$\lambda_i^+ \left( \sum_{j=1}^n \sqrt{w_j^2 \left( (y_{ij}^+)^2 - (y_j^+)^2 \right)} \right) = 1, \forall i$$

$$\lambda_i^- \left( \sum_{j=1}^n \sqrt{w_j^2 \left( (y_{ij}^-)^2 - (y_j^-)^2 \right)} \right) \leq$$

$$\lambda_i^+ \left( \sum_{j=1}^n \sqrt{w_j^2 \left( (y_{ij}^+)^2 - (y_j^+)^2 \right)} \right) + \quad (19.3)$$

$$\lambda_i^+ \left( \sum_{j=1}^J \sqrt{w_j^2 \left( (y_{ij}^+)^2 - (y_j^+)^2 \right)} \right)$$

$$\lambda_i^- = \lambda_i^+ \quad (19.4)$$

$$\lambda_i^-, \lambda_i^+ \geq 0 \quad (19.5)$$

$$i = 1, 2, \dots, m, \quad j = 1, 2, \dots, n$$

5) Ranking the Tourist Route Alternatives

The  $CC_i$  quantifies the proximity of each alternative or travel route to the ideal solution. An alternative with a higher  $CC_i$  value is considered superior and will be ranked more favorably.

III. RESULTS

This section presents the research findings and discusses the results, which include two main phases of calculations: the practical solutions derived from the proposed mathematical routing model and the results obtained from calculating the  $CC_i$  implementing the TOPSIS-LP model. These results were achieved following the research procedures outlined above. The detailed outcomes of the research follow.

A. Results of Practical Solutions obtained by the Proposed Mathematical Routing Model

This work begins by gathering relevant data, specifically the geographical coordinates of depots, points of interest, and lodging facilities in Nong Khai, Thailand, to facilitate the creation of the decision matrix. Figure 2 illustrates the locations of these places within the province. Google Maps were deployed to obtain the actual distance matrix. The resulting relevant data and distance matrix for the case study are displayed in Tables I and II, respectively.

After obtaining the distance matrix, the Lingo software systematically tested the proposed algorithm, based on (1)-(14). Here, the scenario is defined with specific parameters:  $N$  represents the total number of nodes,  $Q$  is the number of the selected hotels, set to 1,  $T$  is the maximum allowable driving time, established at 480 minutes, and  $St$ , is the service time at each tourist node, which is 60 minutes. The outcomes of the viable solutions derived from the suggested algorithm and the three relevant decision criteria were utilized to construct the decision matrix seen in Table III.

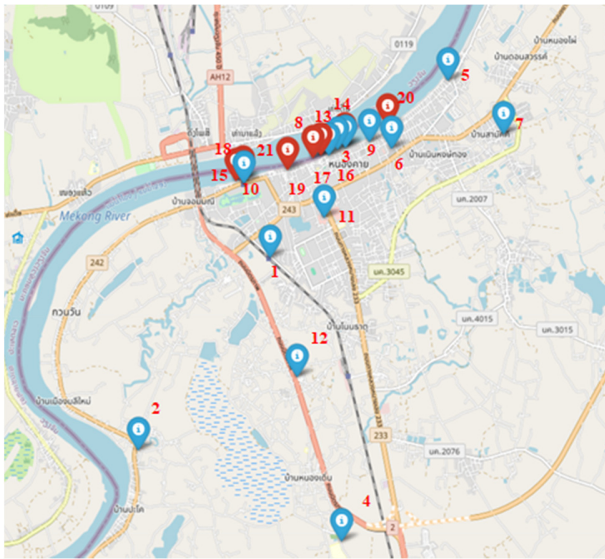


Fig. 2. The locations of various places within Nong Khai, Thailand. © Google.

TABLE I. LOCATION DETAILS WITHIN NONG KHAI

Name (ID)	Type	Latitude	Longitude
Railway Station (1)	Depot	17.86473	102.731
Ban Pako Community (2)	Tourist	17.82773	102.7025
Tha Sadet Market (3)	Tourist	17.88584	102.7474
Aquarium Museum (4)	Tourist	17.81032	102.7466
Phrathat La Nong Khai (5)	Tourist	17.89877	102.7696
Wat Pho Chai (6)	Tourist	17.88563	102.7574
Sala Kaeo Ku (7)	Tourist	17.88837	102.7816
Walking Street (8)	Tourist	17.88426	102.7437
Wat Lamduan (9)	Tourist	17.88691	102.7525
At Talat Rotfai (10)	Tourist	17.87887	102.7255
Asawann Complex (11)	Tourist	17.87238	102.7427
Ban Mai Market (12)	Tourist	17.84185	102.7369
Daeng Namnueng (13)	Tourist	17.88549	102.7457
Rimkhong River View (14)	Hotel	17.88623	102.7472
Chorfah Gallery Hotel (15)	Hotel	17.87941	102.7237
Mut Mee Guest House (16)	Hotel	17.88429	102.7421
Baansabai Rimkhong (17)	Hotel	17.88389	102.7404
Sabai Porch Hostel (18)	Hotel	17.87962	102.7247
Amanta Hotel (19)	Hotel	17.88152	102.7349
Mehong Hotel (20)	Hotel	17.88991	102.7565
Sam Orr Riverside Hotel (21)	Hotel	17.87999	102.7252

TABLE II. DISTANCE MATRIX

ID	1	2	3	4	5	6	7	8
1	0	5.6	3.8	8.8	6.7	4.5	7.4	3.5
2	5.6	0	13.2	5.7	13.7	11.2	14.1	12.7
3	3.8	13.2	0	13.4	3.2	1.6	4.7	2.1
4	8.8	5.7	13.4	0	14.4	11.9	13.4	11.1
5	6.7	13.7	3.2	14.4	0	2.4	2.6	3.7
6	4.5	11.2	1.6	11.9	2.4	0	3.1	2.4
7	7.4	14.1	4.7	13.4	2.6	3.1	0	5.2
8	3.5	12.7	2.1	11.1	3.7	2.4	5.2	0
9	4.3	13.8	0.8	11.9	2.2	1	4	1.4
10	2.9	10.6	3.9	10.8	5.9	4	7.2	2.2
11	2.1	9.8	3	9.5	5.1	4	5.5	1.8
12	4.2	9.6	7.3	6.4	9.3	7.5	9.7	6.5
13	3.7	13	1.7	11.3	3.7	1.8	4.9	0.2
14	3.8	13.2	0.1	11.4	3.8	1.9	5	0.8
15	3.1	10.4	4.1	10.5	6.1	4.2	7.3	2.3

16	3.8	12.6	2.1	11.1	4.1	2.2	5.2	0.2
17	3.7	12.2	2.3	11.4	4.3	2.4	5.4	0.6
18	3	10.5	4	10.9	6	4.1	7.2	2.2
19	2.9	11.7	2.9	10.8	4.9	3	6	1.2
20	4.9	14.2	1.3	12.4	1.7	0.5	3.4	1.8
21	2.9	10.6	3.9	10.8	5.9	4	7.2	2.2

ID	9	10	11	12	13	14	15	16
1	4.3	2.9	2.1	4.2	3.7	3.8	3.1	3.8
2	13.8	10.6	9.8	9.6	13	13.2	10.4	12.6
3	0.8	3.9	3	7.3	1.7	0.1	4.1	2.1
4	11.9	10.8	9.5	6.4	11.3	11.4	10.5	11.1
5	2.2	5.9	5.1	9.3	3.7	3.8	6.1	4.1
6	1	4	4	7.5	1.8	1.9	4.2	2.2
7	4	7.2	5.5	9.7	4.9	5	7.3	5.2
8	1.4	2.2	1.8	6.5	0.2	0.8	2.3	0.2
9	0	3.6	2.6	7	1.4	1.5	3.8	1.8
10	3.6	0	2.9	5.9	2.4	2.6	0.2	2
11	2.6	2.9	0	4.4	2	2.2	2.9	1.9
12	7	5.9	4.4	0	6.7	6.2	5.5	5.7
13	1.4	2.4	2	6.7	0	0.5	2.6	0.4
14	1.5	2.6	2.2	6.2	0.5	0	2.7	0.6
15	3.8	0.2	2.9	5.5	2.6	2.7	0	2.2
16	1.8	2	1.9	5.7	0.4	0.6	2.2	0
17	2	1.6	1.9	5.6	0.8	1	1.9	0.5
18	3.6	0.1	2.7	5.4	2.4	2.6	0.1	2.1
19	2.6	1.1	1.9	5	1.4	1.6	1.3	1
20	0.5	3.7	3.2	7	1.5	1.3	3.8	1.8
21	3.6	3.7	2.7	5.3	2.4	2.6	0.2	2

ID	17	18	19	20	21	Rating (w)	Room rate (rc)
1	3.7	3	2.9	4.9	2.9	None	None
2	12.2	10.5	11.7	14.2	10.6	23.7	None
3	2.3	4	2.9	1.3	3.9	251	None
4	11.4	10.9	10.8	12.4	10.8	1.5	None
5	4.3	6	4.9	1.7	5.9	174	None
6	2.4	4.1	3	0.5	4	517	None
7	5.4	7.2	6	3.4	7.2	29.2	None
8	0.6	2.2	1.2	1.8	2.2	14.7	None
9	2	3.6	2.6	0.5	3.6	147	None
10	1.6	0.1	1.1	3.7	3.7	4.4	None
11	1.9	2.7	1.9	3.2	2.7	3.2	None
12	5.6	5.4	5	7	5.3	86.6	None
13	0.8	2.4	1.4	1.5	2.4	107	None
14	1	2.6	1.6	1.3	2.6	7.5	2800
15	1.9	0.1	1.3	3.8	0.2	2.8	1800
16	0.5	2.1	1	1.8	2	1.5	400
17	0	1.8	0.8	2.1	1.7	5.7	890
18	1.8	0	1.2	3.7	0.1	0.259	900
19	0.8	1.2	0	2.6	1.1	14.1	2300
20	2.1	3.7	2.6	0	3.7	0.1	850
21	1.7	0.1	1.1	3.7	0	3	600

TABLE III. THE DECISION MATRIX FOR THE CASE STUDY

Alternatives	Criteria		
	C1	C2	C3
R1: 1-12-13-6-7-5-9-3-14-11-8-10-4-2-1	7.5	49.8	2800
R2: 1-12-3-9-13-7-5-6-15-11-2-4-10-8-1	2.8	62.7	1800
R3: 1-6-5-7-9-3-12-13-16-8-10-2-4-11-1	1.5	58.9	400
R4: 1-3-9-5-7-6-12-13-17-10-8-2-11-4-1	5.7	72.05	890
R5: 1-5-3-6-13-9-12-7-18-2-4-11-8-10-1	0.26	71.2	900
R6: 1-13-6-9-3-12-7-5-19-8-11-10-4-2-1	14.1	59.8	2300
R7: 1-12-13-3-9-5-7-6-20-4-11-10-2-8-1	0.1	73.35	850
R8: 1-5-13-6-3-9-7-12-21-2-11-4-10-8-1	3.0	80	600

B. Calculation Results of Relative Closeness Coefficient using the TOPSIS-LP Model

The defined criteria can be organized into two distinct categories: beneficial criteria and cost criteria. The only beneficial criterion is the hotel rating (C1). The cost criteria consist of the total travel distance (C2) and room rates (C3). After forming the decision matrix, the next step involves generating the normalized decision matrix using (16) - (18). The weights for each criterion are determined by a research team with over 10 years of experience in the tourism industry, designed to provide travel itinerary recommendations for tourists. However, the specific weights applied to these criteria may vary according to individual traveler preferences. This process culminates in a comprehensive normalized decision matrix, as shown in Table IV.

TABLE IV. NORMALIZED DECISION MATRIX FOR THE CASE STUDY

Alternatives	Criteria		
	C1	C2	C3
R1	0.4282	0.7357	0.3612
R2	0.1599	0.6672	0.5894
R3	0.0856	0.6874	0.9087
R4	0.3255	0.6176	0.7970
R5	0.0148	0.6221	0.7947
R6	0.8051	0.6826	0.4753
R7	0.0057	0.6107	0.8061
R8	0.1713	0.5754	0.8631
y <sup>+</sup>	0.8051	0.7357	0.9087
y <sup>-</sup>	0.0057	0.5754	0.3612
w	0.5	0.25	0.25

Upon obtaining the relevant parameters displayed in Table IV, the associated parameter values are input into the TOPSIS-LP model, as indicated by (19), and are subsequently computed using Lingo software. Details of the Lingo code are portrayed in Figure 3. The resulting values, which are the relative closeness coefficients, are presented in the last column of Table V.

TABLE V. THE RELATIVE CLOSENESS COEFFICIENTS AND RANKING FOR EACH ALTERNATIVE

Alternatives	CC	Rank
R1: 1-12-13-6-7-5-9-3-14-11-8-10-4-2-1	0.4800	2
R2: 1-12-3-9-13-7-5-6-15-11-2-4-10-8-1	0.2286	6
R3: 1-6-5-7-9-3-12-13-16-8-10-2-4-11-1	0.2876	5
R4: 1-3-9-5-7-6-12-13-17-10-8-2-11-4-1	0.4434	3
R5: 1-5-3-6-13-9-12-7-18-2-4-11-8-10-1	0.2155	8
R6: 1-13-6-9-3-12-7-5-19-8-11-10-4-2-1	0.7863	1
R7: 1-12-13-3-9-5-7-6-20-4-11-10-2-8-1	0.2174	7
R8: 1-5-13-6-3-9-7-12-21-2-11-4-10-8-1	0.3199	4

As indicated in Table V, alternative R6 possesses the highest CC value, suggesting that this route is the optimal choice based on the decision criteria and the assigned weights of each criterion. The network of travel routes for R6 is depicted in Figure 4. The itinerary begins at Railway Station (1) where tourists will sequentially visit Daeng Namueng (13), Wat Pho Chai (6), Wat Lamduan (9), Tha Sadet Market (3), Ban Mai Market (12), Sala Kaeo Ku (7), and Phrathat La Nong Khai (5) on the first day. After completing these visits, travelers will spend the night at Amanta Hotel (19). On the

following day, upon departure from the hotel, their route includes stops at Walking Street (8), Asawann Complex (11), At Talat Rotfai (10), Aquarium Museum (4), and Ban Pako Community (2), before returning to Railway Station (1) to conclude their tour.

```

MODEL:
SETS: ALTERNATIVE/1..8/:CC,SP,SN,RHO,DEL ;
CRITERION/1..3/:Yn,Yp,W; IJ( ALTERNATIVE,
CRITERION) : Y ; ENDSSETS
DATA:Y= 0.4282, 0.7357, 0.3612
0.1599, 0.6672, 0.5894
0.0856, 0.6874, 0.9087
0.3255, 0.6176, 0.7970
0.0148, 0.6221, 0.7947
0.8051, 0.6826, 0.4753
0.0057, 0.6107, 0.8061
0.1713, 0.5754, 0.8631;
Yp= 0.8051, 0.7357, 0.9087;
Yn= 0.0057, 0.5754, 0.3612; W = 0.5, 0.25, 0.25;

ENDDATA
MAX = @SUM(ALTERNATIVE ( I) : CC(I));
@FOR(ALTERNATIVE(I) : CC( I) =
RHO(I) * (@SQRT(@SUM(CRITERION(J) :W(J)^2*( Y(I, J)-
Yn(J))^2))) );
@FOR(ALTERNATIVE(I) :
RHO(I) * (@SQRT(@SUM(CRITERION(J) :W(J)^2*( Y(I, J)-
Yn(J))^2))) +
DEL(I) * (@SQRT(@SUM(CRITERION(J) :W(J)^2*( Yp(J)-Y(I,
J))^2))) = 1 );
@FOR(ALTERNATIVE(I) : RHO(I)-DEL(I)=0 );
@FOR(ALTERNATIVE(I) :
RHO(I) * (@SQRT(@SUM(CRITERION(J) :W(J)^2*( Y(I, J)-
Yn(J))^2))) <=
RHO(I) * (@SQRT(@SUM(CRITERION(J) :W(J)^2*( Y(I, J)-
Yn(J))^2))) +
DEL(I) * (@SQRT(@SUM(CRITERION(J) :W(J)^2*( Yp(J)-Y(I,
J))^2))) );
@FOR(CRITERION(J) : W(J)>=0); @FOR(ALTERNATIVE(I) :
RHO(I)>=0);
@FOR(ALTERNATIVE(I) : DEL(I)>=0);
END
    
```

Fig. 3. The Lingo code for the case study.

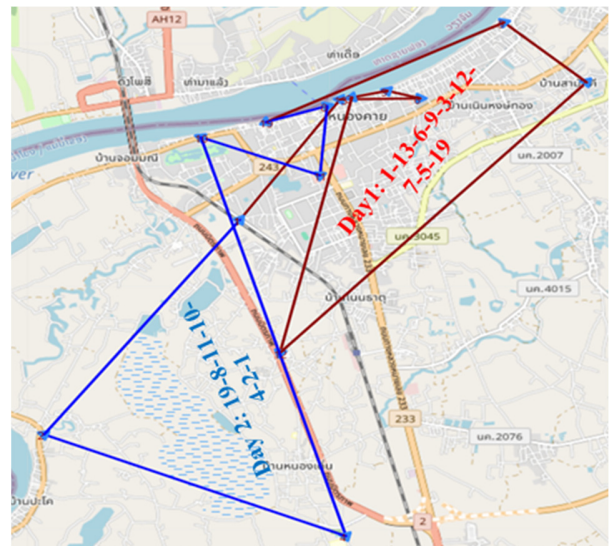


Fig. 4. The network of travel routes for R6.

C. Sensitivity Analysis and Discussion

Sensitivity analysis is widely utilized to ensure the reliability and stability of solutions. This paper details a two-phase sensitivity analysis process. Initially, nine scenarios are constructed to model varying weights of criteria. Subsequently, the second phase applies various MADM techniques to conduct

a comparative analysis. Initially, the weight adjustment method was applied according to the scenarios outlined below:

- Case 1: Weights determined by decision-makers.
- Case 2: Equally distribute weights.
- Case 3: Distribution of 50% to beneficial criteria and 50% to cost criteria.
- Case 4: Allocation of 60% to beneficial criteria and 40% to cost criteria.
- Case 5: Allocation of 70% to beneficial criteria and 30% to cost criteria.
- Case 6: All weights (100%) assigned to beneficial criteria and none (0%) to cost criteria.
- Case 7: All weights (100%) assigned to cost criteria and none (0%) to beneficial criteria.
- Case 8: Distribution of 30% to beneficial criteria and 70% to cost criteria.
- Case 9: Distribution of 40% to beneficial criteria and 60% to cost criteria.

Table VI presents the ranks of alternatives throughout the alternative cases.

TABLE VI. RANKS OF THE ALTERNATIVES THROUGHOUT

Alternatives	Rankings for each case								
	1	2	3	4	5	6	7	8	9
R1	2	5	2	2	2	2	8	7	3
R2	6	8	6	6	5	5	6	8	8
R3	5	4	5	5	6	6	1	4	5
R4	3	2	3	3	3	3	5	2	2
R5	8	7	8	8	8	7	4	6	7
R6	1	1	1	1	1	1	7	1	1
R7	7	6	7	7	7	8	3	5	6
R8	4	3	4	4	4	4	2	3	4

As evidenced by Table VI, the sensitivity analysis across the cases highlights significant performance variability. Scenario R6 consistently outperforms the others, achieving top ranks in most cases, demonstrating robustness and effectiveness under a diverse set of conditions. Other scenarios, like R1, R4, and R5, also exhibit strong performances but are more variable across different cases. Scenario R3 uniquely excels in Case 7, indicating specific adaptability to the conditions of that case. Conversely, certain scenarios, such as R7, display lower performance in some cases, suggesting potential weaknesses or areas for improvement. The analysis underscores the importance of Scenario R6's strategy, which might be leveraged for its high adaptability and efficacy. Overall, the results are crucial for informed decision-making, helping to pinpoint the most reliable strategies under varying conditions and highlighting the need for adjustments in less robust scenarios. In the second phase, various MADM techniques were employed to perform a comparative analysis. Figure 5 and Table VII show the comparison of the proposed TOPSIS-LP model with TOPSIS [20], MOORA [35], WASPAS [36], and ARAS [37].

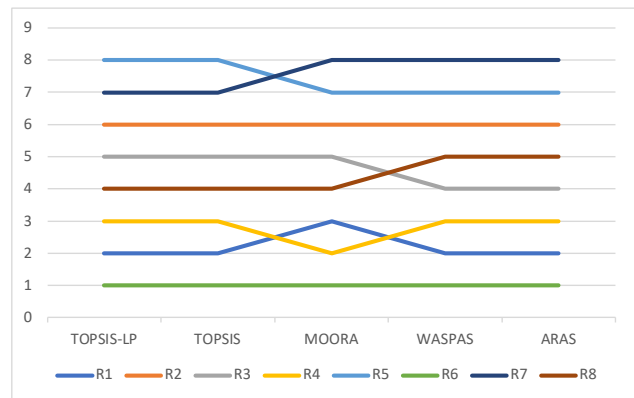


Fig. 5. A comparison analysis of the results obtained from the proposed TOPSIS-LP model with other methods.

TABLE VII. COMPARISON OF THE RANKING PERFORMANCE OF EACH MADM METHOD FOR THE CONSIDERED CASE STUDY

Alternatives	Rankings for each MADM method				
	TOPSIS-LP	TOPSIS	MOORA	WASPAS	ARAS
R1	2	2	3	2	2
R2	6	6	6	6	6
R3	5	5	5	4	4
R4	3	3	2	3	3
R5	8	8	7	7	7
R6	1	1	1	1	1
R7	7	7	8	8	8
R8	4	4	4	5	5

Based on the MADM analysis, alternative R6 is determined to be the most resilient option. It continuously obtains the highest rating across different approaches. This indicates a clear agreement on the superiority of R6, regardless of the MADM approach used. Furthermore, the recently suggested TOPSIS-LP approach has a flawless connection with the original TOPSIS method, as evidenced by a Spearman correlation coefficient of 1.00. This implies that both methods yield identical ranking results. The strong correlation seen between TOPSIS-LP and the original TOPSIS indicates that the modifications or linear programming elements added to TOPSIS-LP do not affect the decision-making outcome, at least based on the given data. This implies that the improvements in TOPSIS-LP preserve the decision structure and priorities of the original TOPSIS, or that the alternative rankings are unambiguous and resistant to changes in methodology. The correlations between MOORA (0.952), WASPAS (0.952), and ARAS (0.952) and TOPSIS-LP are high but significantly lower. This indicates that there is a substantial agreement between these approaches and TOPSIS-LP, but there are minor variations in how each method assesses and prioritizes the alternatives. The variations in the outcomes may arise from the distinct characteristics of each method's approach to the assessment of alternatives, including the weighing mechanism, the consolidation of criteria, or the optimization procedure. In general, the consistently high ranking of R6 increases confidence in its selection as the best alternative, and the strong correlations between approaches support the dependability of the MADM processes utilized in the evaluation.



#### IV. CONCLUSIONS

The objective of this study was to evaluate and optimize tourist routes using a novel mathematical model integrated with the TOPSIS-LP model. The findings of this work demonstrate the efficacy of the TOPSIS-LP method, particularly when applied to complex multi-criteria decision-making problems within tourism management. The robustness of Alternative R6, consistently achieving the highest rankings across various MADM methods, underscores its effectiveness as the optimal tourist route in the studied region. This research confirms the strong alignment between the newly implemented TOPSIS-LP and the traditional TOPSIS method, achieving a Spearman correlation coefficient of 1.00. This indicates that despite the enhancements made to the linear programming aspects of TOPSIS, the fundamental decision-making framework remains unaffected. Such findings validate the modifications added to TOPSIS-LP, ensuring that they maintain the integrity and priorities of the original model without compromising decision quality.

The analysis deploying MADM methods, including MOORA, WASPAS, and ARAS, demonstrates a notable consistency in the evaluation outcomes, albeit with slight differences. The correlation coefficients achieved with these methods are 0.952 for MOORA, 0.952 for WASPAS, and 0.952 for ARAS. These variations can be attributed to the distinct methodologies each approach uses to weigh and aggregate decision criteria, illustrating the subtle yet impactful differences in how each method manages the complexities of route optimization. The findings of this study offer valuable insights for tourism authorities and planners focused on improving tourist satisfaction and operational efficiency. Also, the study enriches the academic discourse by showcasing the practical utility of sophisticated mathematical models in real-world settings. This not only underscores the relevance of MADM techniques, but also identifies potential avenues for further research aimed at enhancing the effectiveness, robustness, and flexibility of these methods.

In conclusion, the application of the TOPSIS-LP model in this context not only offers a methodological advancement in tourist route optimization, but also serves as a reliable benchmark for future studies aiming to refine multi-criteria decision-making processes in the tourism sector.

#### ACKNOWLEDGMENT

The authors wish to acknowledge the financial support from the Thailand Science Research and Innovation (TSRI) (Contract No. FRB650059/KKN/06-3), which made this research possible. We extend our sincere appreciation to Rajamangala University of Technology Isan Khon Kaen Campus for their substantial support and resources provided.

#### REFERENCES

- [1] H. Han, "Consumer behavior and environmental sustainability in tourism and hospitality: a review of theories, concepts, and latest research," *Journal of Sustainable Tourism*, vol. 29, no. 7, pp. 1021-1042, Mar. 2021, <https://doi.org/10.1080/09669582.2021.1903019>.
- [2] X. Ge and Y. Jin, "Sustainability Oriented Vehicle Route Planning Based on Time-Dependent Arc Travel Durations," *Sustainability*, vol. 15, no. 4, Dec. 2022, Art. no. 3208, <https://doi.org/10.3390/su15043208>.
- [3] A. V. Nobre, C. C. R. Oliveira, D. R. de Lucena Nunes, A. C. Silva Melo, G. E. Guimarães, R. Anholon, and V. W. B. Martins, "Analysis of Decision Parameters for Route Plans and their Importance for Sustainability: An Exploratory Study Using the TOPSIS Technique," *Logistics*, vol. 6, no. 2, May 2022, Art. no. 32, <https://doi.org/10.3390/logistics6020032>.
- [4] F. Lin and H. P. Hsieh, "Multicriteria Route Planning for In-Operation Mass Transit under Urban Data," *Applied Sciences*, vol. 12, no. 6, Mar. 2022, Art. no. 3127, <https://doi.org/10.3390/app12063127>.
- [5] M. Haboub, "The impact of cultural tourism on the local community from a socio-cultural, environmental and economic perspective Nubian village of Gharb Suhail as a viable model.," *International Journal of Eco-Cultural Tourism, Hospitality Planning and Development*, vol. 5, no. 2, pp. 86-116, Dec. 2022, <https://doi.org/10.21608/ijecth.2022.271577>.
- [6] D. S. Noonan and I. Rizzo, "Economics of cultural tourism: issues and perspectives," *Journal of Cultural Economics*, vol. 41, pp. 95-107, Mar. 2017, <https://doi.org/10.1007/s10824-017-9300-6>.
- [7] J. Wang, X. Huang, Z. Gong, and K. Cao, "Dynamic assessment of tourism carrying capacity and its impacts on tourism economic growth in urban tourism destinations in China," *Journal of Destination Marketing & Management*, vol. 15, Mar. 2020, Art. no. 100383, <https://doi.org/10.1016/j.jdmm.2019.100383>.
- [8] J. Qi and Q. Wang, "Tourism Route Selection Model for Tourism Sustainable Development Based on Improved Genetic Algorithm," *International Transactions on Electrical Energy Systems*, vol. 2022, Sep. 2022, Art. no. 4287011, <https://doi.org/10.1155/2022/4287011>.
- [9] D. D'Uva and A. Rolando, "A Method to Select and Optimize Slow Tourism Routes Using a Quality Index Procedure Based on Image Segmentation and DTM Modelling Based on NURBS: The Case Study of Multimodal Access to Inner Places from the Nodes of the Adriatic Coastline's Infrastructure Bundle," *Sustainability*, vol. 15, no. 1, Dec. 2022, Art. no. 373, <https://doi.org/10.3390/su15010373>.
- [10] W. Niu, "A Novel Multiobjective Optimization for Tourism Route Based on Improvement ACO Method and Topology Optimization," *2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 2022, pp. 701-704, <https://doi.org/10.1109/ICICCS53718.2022.9788179>.
- [11] S. Li, T. Luo, L. Wang, L. Xing, and T. Ren, "Tourism route optimization based on improved knowledge ant colony algorithm," *Complex & Intelligent Systems*, vol. 8, no. 5, pp. 3973-3988, Mar. 2022, <https://doi.org/10.1007/s40747-021-00635-z>.
- [12] B. Huang, L. Yao, and K. Raguraman, "Bi-level GA and GIS for Multi-objective TSP Route Planning," *Transportation Planning and Technology*, vol. 29, no. 2, pp. 105-124, Feb. 2007, <https://doi.org/10.1080/03081060600753404>.
- [13] S. Bock and K. Klamroth, "Combining Traveling Salesman and Traveling Repairman Problems: A multi-objective approach based on multiple scenarios," *Computers & Operations Research*, vol. 112, Dec. 2019, Art. no. 104766, doi: <https://doi.org/10.1016/j.cor.2019.104766>.
- [14] P. C. Pop, O. Cosma, C. Sabo, and C. P. Sitar, "A comprehensive survey on the generalized traveling salesman problem," *European Journal of Operational Research*, vol. 314, no. 3, pp. 819-835, May. 2024, <https://doi.org/10.1016/j.ejor.2023.07.022>.
- [15] N. Sathya and A. Muthukumaravel, "A review of the optimization algorithms on traveling salesman problem," *Indian Journal of Science and Technology*, vol. 8, no. 29, pp. 1-4, Nov. 2015, <https://doi.org/10.17485/ijst/2015/v8i1/84652>.
- [16] O. Cheikhrouhou and I. Khoufi, "A comprehensive survey on the Multiple Traveling Salesman Problem: Applications, approaches and taxonomy," *Computer Science Review*, vol. 40, May. 2021, Art. no. 100369, <https://doi.org/10.1016/j.cosrev.2021.100369>.
- [17] M. Abdul-Niby, M. Alameen, A. Salhieh, and A. Radhi, "Improved Genetic and Simulating Annealing Algorithms to Solve the Traveling Salesman Problem Using Constraint Programming," *Engineering, Technology & Applied Science Research*, vol. 6, no. 2, pp. 927-930, Apr. 2016, <https://doi.org/10.48084/etasr.627>.
- [18] H. Jafarzadeh, N. Moradinasab, and M. Elyasi, "An Enhanced Genetic Algorithm for the Generalized Traveling Salesman Problem,"

- Engineering, Technology and Applied Science Research*, vol. 7, no. 6, pp. 2260-2265, Dec. 2017, <https://doi.org/10.48084/etasr.1570>.
- [19] E. W. Dijkstra, "A note on two problems in connexion with graphs," *Numerische Mathematik*, vol. 1, pp. 269-271., Dec. 1959, <https://doi.org/10.1007/BF01386390>.
- [20] C.-L. Hwang and K. Yoon, "Methods for Multiple Attribute Decision Making," in *Multiple Attribute Decision Making: Methods and Applications A State-of-the-Art Survey*, C.-L. Hwang and K. Yoon, Eds. Berlin, Heidelberg, Germany: Springer, 1981, pp. 58–191.
- [21] R. R. Menon and V. Ravi, "Using AHP-TOPSIS methodologies in the selection of sustainable suppliers in an electronics supply chain," *Cleaner Materials*, vol. 5, Sep. 2022, Art. no. 100130, <https://doi.org/10.1016/j.clema.2022.100130>.
- [22] J. J. Wang, Y. Y. Jing, C. F. Zhang, and J. H. Zhao, "Review on multi-criteria decision analysis aid in sustainable energy decision-making," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 9, pp. 2263-2278, Dec. 2009, <https://doi.org/10.1016/j.rser.2009.06.021>.
- [23] S. Mahmudova, "Application of the TOPSIS method to improve software efficiency and to optimize its management," *Soft Computing*, vol. 24, no. 1, pp. 697-708, Jan. 2020, <https://doi.org/10.1007/s00500-019-04549-4>.
- [24] C. A. S. Araujo, P. Wanke, and M. M. Siqueira, "A performance analysis of Brazilian public health: TOPSIS and neural networks application," *International Journal of Productivity and Performance Management*, vol. 67, no. 9, pp. 1526-1549, Nov. 2018, <https://doi.org/10.1108/IJPPM-11-2017-0319>.
- [25] P. Xie, "Development Ranking in Real Estate Strategy Management in China Based on TOPSIS Method," in *2008 ISECS International Colloquium on Computing, Communication, Control, and Management*, vol. 3, pp. 254-258, Aug. 2008, <https://doi.org/10.1109/CCCM.2008.376>.
- [26] S. Hajduk, "Multi-Criteria Analysis in the Decision-Making Approach for the Linear Ordering of Urban Transport Based on TOPSIS Technique," *Energies*, vol. 15, no. 1, Dec. 2021, Art. no. 274, <https://doi.org/10.3390/en15010274>.
- [27] S. Joshi, M. Sharma, and R. K. Singh, "Performance Evaluation of Agrotourism Clusters using AHP-TOPSIS," *Journal of Operations and Strategic Planning*, vol. 3, no. 1, pp. 7-30, Aug. 2020, <https://doi.org/10.1177/2516600X20928646>.
- [28] B. Oztaysi, "A decision model for information technology selection using AHP integrated TOPSIS-Grey: The case of content management systems," *Knowledge-Based Systems*, vol. 70, pp. 44-54, Nov. 2014, <https://doi.org/10.1016/j.knsys.2014.02.010>.
- [29] V. C. Nguyen, T. Nguyen, and D. Tien, "Cutting Parameter Optimization in Finishing Milling of Ti-6Al-4V Titanium Alloy under MQL Condition using TOPSIS and ANOVA Analysis," *Engineering, Technology & Applied Science Research*, vol. 11, no. 1, pp. 6775-6780, Feb. 2021, <https://doi.org/10.48084/etasr.4015>.
- [30] A. Reyadh and A. Burhan, "Non-Profit Organization Project Selection Process Using the Hygiene Method of Multi-Criteria Decision Making," *Engineering, Technology & Applied Science Research*, vol. 12, no.5, pp. 9097-9101, Oct. 2022, <https://doi.org/10.48084/etasr.5175>.
- [31] P. To-On, N. Wichapa, and W. Khanthirath, "A novel TOPSIS linear programming model based on response surface methodology for determining optimal mixture proportions of lightweight concrete blocks containing sugarcane bagasse ash," *Heliyon*, vol. 9, no. 7, Jul. 2023, Art. no. e17755, <https://doi.org/10.1016/j.heliyon.2023.e17755>.
- [32] A. Sriburum, N. Wichapa, and W. Khanthirath, "A Novel TOPSIS Linear Programming Model Based on the Taguchi Method for Solving the Multi-Response Optimization Problems: A Case Study of a Fish Scale Scraping Machine," *Engineered Science*, vol. 23, May. 2023. Art. no. 882, <http://doi.org/10.30919/es882>.
- [33] S. Piewdang, P. Mekkamol, and S. Untachai, "Measuring Spiritual Tourism Management in Community: A Case Study of Sri Chom Phu Ongtu Temple, Thabo district, Nongkhai Province, Thailand," *Procedia - Social and Behavioral Sciences*, vol. 88, pp. 96-107, Sep. 2013, <https://doi.org/10.1016/j.sbspro.2013.08.485>.
- [34] A. Auesriwong, A. Nilnoppakun, and W. Paraweche, "Integrative Participatory Community-based Ecotourism at Sangkhom District, Nong Khai Province, Thailand," *Procedia Economics and Finance*, vol. 23, pp. 778-782, Jan. 2015, [https://doi.org/10.1016/S2212-5671\(15\)00529-8](https://doi.org/10.1016/S2212-5671(15)00529-8).
- [35] W. K. Brauers and E. K. Zavadskas, "The MOORA method and its application to privatization in a transition economy," *Control and cybernetics*, vol. 35, no. 2, pp. 445-469, Jan. 2006.
- [36] E. K. Zavadskas, Z. Turskis, J. Antucheviciene, and A. Zakarevicius, "Optimization of weighted aggregated sum product assessment," *Elektronika ir Elektrotechnika*, vol. 122, no. 6, pp. 3-6, Jul. 2012, <http://doi.org/10.5755/j01.eee.122.6.1810>.
- [37] E. K. Zavadskas and Z. Turskis, "A new additive ratio assessment (ARAS) method in multicriteria decision - making," *Technological and economic development of economy*, vol. 16, no. 2, pp. 159-172, June 2010, <http://doi.org/10.3846/tede.2010.10>.

## AUTHORS PROFILE



**Wasana Phuangsornpitak** received the B. Eng., M. Eng., and Ph.D. degrees in industrial engineering from Khon Kaen University. She is currently a Lecturer at the Department of Logistics Management, Rajamangala University of Technology Isan, Khon Kaen Campus. Her research interests include vehicle routing problems, transportation problems, mathematical models, decision making models, and optimization.



**Wanita Boonchom** holds a B.Eng. in Industrial Engineering, an M.B.A., and a D.B.A. in Business Administration from Khon Kaen University, Thailand. She is currently an Assistant Professor in the Department of Management at Rajamangala University of Technology Isan, Khon Kaen Campus. Her research focuses on entrepreneurship and behavioral economics.



**Kittanathat Suphan** received the B.A., M.B.A., and Ph.D. degrees in Tourism, MICE, and Hospitality Innovation Management from Khon Kaen University. He is currently a Lecturer at the Department of Tourism and Hospitality Management, and Vice Dean of the Business Administration and Information Technology Faculty, Rajamangala University of Technology, Isan Khon Kaen Campus. His research interests include, tourism management, logistic management in tourism industry, and hospitality management.



**Watchara Chiengkul** received the B. B.A., M.A., and Ph.D. degrees in Business Administration (Hospitality and Events) from Khon Kaen University. He is currently a Lecturer at the Department of Tourism and Hospitality Management, Rajamangala University of Technology, Isan Khon Kaen Campus. His research interests include customer behavior, service marketing, hospitality and event management.



**Thanawat Tantipanichkul** received the B.B.A., M.B.A., and Ph.D. degrees in Tourism, MICE, and Hospitality Innovation Management from Khon Kaen University. He is currently a Lecturer at the Department of Tourism and Hospitality Management, Rajamangala University of Technology, Isan Khon Kaen Campus. His research interests include tourism management, logistic management in tourism industry and community-based tourism management.