International Journal of Innovative Research and Scientific Studies, 8(5) 2025, pages: 2226-2236

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Optimizing the allocation of advanced life support ambulance parking in densely populated urban areas of Bangkok: A spatial and multi-criteria decision-making approach

Rapee Udomsub[1], Nanthi Suthikarnnarunai[1*]

[1]*School of Engineering, University of the Thai Chamber of Commerce, 26/1 Vibhavadee-Rangsit Rd., Dindaeng, Bangkok 10400, Thailand.*

Corresponding author: Nanthi Suthikarnnarunai (*Email: nanthi_sut@utcc.ac.th*)

Abstract

This research aims to develop guidelines for allocating Advanced Life Support (ALS) emergency ambulance parking spots in Bangkok, particularly in areas with high population density, to enhance the efficiency of emergency response within 8 minutes. The concept of spatial analysis is applied alongside the mathematical model Set Covering Problem (SCP) with the Greedy Algorithm and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which is a multi-criteria decision-making method to identify appropriate Emergency Medical Services (EMS) parking spots, utilizing the Value of a Statistical Life (VSL) as a variable to support policy decision-making. The results of the study indicate that integrating road network data and population density significantly enhances the efficiency of parking lot planning. When the number of parking lots increases from 13 to 48, the model can expand the service area within 8 minutes to 73.39% (Greedy) and 63.30% (TOPSIS) at an average speed of 30 km/h, increasing to 95.45% and 93.95%, respectively, at an average speed of 60 km/h. TOPSIS employs the population density criterion per area, which results in accurate parking lot allocation in densely populated regions. Although the Greedy Algorithm only utilizes the statistical life value criterion for its calculations, the area coverage rate is superior to that of the TOPSIS method when compared spatially using GIS. SCP is appropriate for enhancing the area coverage rate. In situations where budget constraints hinder investment at every point, TOPSIS is an effective solution for urgent parking lot allocation.

Keywords: Ambulance parking spots, Emergency medical services, Multi-criteria decision-making, Spatial analysis, Value of a Statistical Life (VSL).

DOI: 10.53894/ijirss.v8i5.9443
Funding: This study received no specific financial support.
History: Received: 7 July 2025 / **Revised:** 10 August 2025 / **Accepted:** 13 August 2025 / **Published:** 22 August 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

Emergency Medical Services (EMS) are a vital mechanism for reducing loss of life and disability resulting from accidents and emergencies in urban areas. They help mitigate treatment difficulties and economic impacts [1]. This is especially relevant in the context of Bangkok, a capital city with a population of over 10 million people, including a continuous influx of residents and workers. Consequently, the demand for health services has steadily increased, emphasizing the importance of efficient EMS systems to address the growing needs of the urban population [2].

The current demographic characteristics of Bangkok also reflect the trend of high population density and an increasing proportion of elderly people in the long term [3]. The elderly are a group at high risk of emergency illnesses because they often have multimorbidity. The tendency of the elderly to live alone is also increasing [4]. These factors are linked to the survival rate of patients [5]. A major challenge for EMS services in Bangkok is severe traffic congestion [6]. This congestion is an obstacle that prevents emergency ambulances from providing services in a timely manner [7]. Urban areas with high population density also experience more emergencies during the day than at night. Planning and identifying emergency ambulance parking spots that can respond to emergencies effectively and promptly is essential [8]. This is crucial given the circadian pattern of service demand [9]. According to the hospital's initial assessment, 13 ALS emergency ambulance parking spaces might not be sufficient to accommodate the current emergency scenario. Enhancing EMS efficiency requires the integration of geospatial data with facility location models and the application of the value of statistical life (VSL) economic concepts derived from Willingness to Pay (WTP) to systematically prioritize space and investments [10, 11].

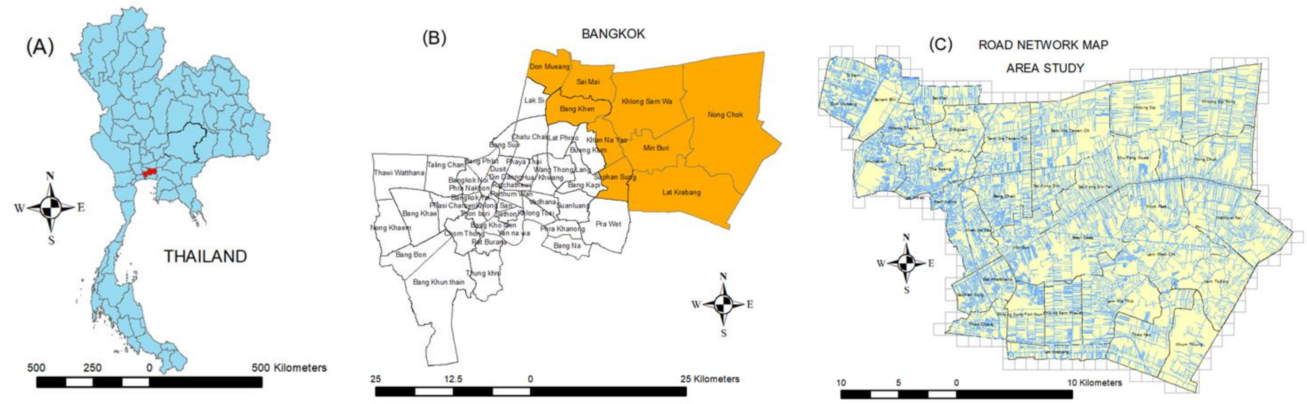

Figure 1.
Geographic location of study area: a) Thailand, b) Bangkok, c) Aera 9 districts and road network.

The goal of this study is to create a model that can properly assign emergency ambulance parking spots. To improve the EMS system's efficiency so that, in accordance with the accepted standards, patients can be reached within 8 minutes. In order to properly arrange the selection sequence under resource restrictions, the Set Covering Problem model with a Greedy Algorithm is utilized [12]. Multi-criteria decision-making techniques such as TOPSIS were also applied [13]. To cover areas in high-density regions, Nazarabadian et al. [14] proposed strategic models for emergency service allocation Nazarabadian et al. [14]. Gago-Carro et al. [15] emphasized the importance of timely services in remote areas where populations remain underserved [15]. These models often involve multiple objectives and incorporate the Value of Statistical Life (VSL) data for policy decision-making [16]. VSL is calculated from data obtained through willingness-to-pay (WTP) questionnaires using the double-bounded dichotomous choice CVM technique, which is an accepted method in health economics research and safety policy analysis [17]. This technique is also appropriate for the economic conditions and population structure of Thailand [18].

WTP will be higher according to the experience of the assessor. If the assessor or their family members have experienced an emergency illness, they are more likely to pay to reduce the risk or chance of a similar incident [19]. This reflects a human behavioral tendency to avoid reliving traumatic or violent experiences they have encountered [20]. And when the WTP value is used to assess the VSL, the value obtained helps in making investment decisions so that the EMS system can respond to emergencies in a timely manner that is worthwhile. When compared to the costs incurred from the loss of life, this is due to the increased treatment costs associated with severe symptoms, because the emergency ambulance is slow to reach the patient at the scene.

2. Materials and Methods

2.1. Study Area

The study area covers 9 districts in the northwest of Bangkok, encompassing an area of 712.10 square kilometers. The area was selected using 12 years of historical statistical data (2010-2022) from EMS data provided by the National Institute of Emergency Medicine (NIEM), along with population data, area size, and ALS parking locations in hospitals. All data were analyzed spatially using a geographic information system (GIS) to identify regions that still cannot receive timely emergency medical services. According to the criteria of the National Institute of Emergency Medicine, emergency ambulances must be able to reach emergency patients at the scene within 8 minutes from the time of notification. The study area is spatially diverse, comprising business districts, densely populated residential areas, and suburban zones. During rush hours, the average travel speed in high-activity zones is approximately 30 kilometers per hour, which directly impacts the efficiency of emergency medical services [6]. In areas with high activity, there are often many emergency reports [9]. Road accidents, in particular, are a major cause of sudden death in urban areas [21].

2.2. Data used in the Research

This study uses data from four primary sources:

2.2.1. Demographic and area data: area size, population density, frequency of emergency ambulance calls, and road routes

2.2.2. Ambulance parking coordinates: government hospitals, private hospitals, schools, and Public Health Centers (PHCs)

2.2.3. Response Time data: average emergency patient access at the scene

These three groups of data are secondary data from two government agencies: the National Institute of Emergency Medicine and Bangkok City Hall.

2.2.4. The VSL data is calculated from information obtained through the Willingness to Pay (WTP) questionnaire, which employs the double-bounded dichotomous choice contingent valuation method (CVM) technique. Better resource allocation and response times will be made possible by this information, which will be essential for assessing the efficacy of urban emergency medical services. Understanding the connections between hospital locations, ambulance call volume, and population density can help us enhance overall emergency response planning.

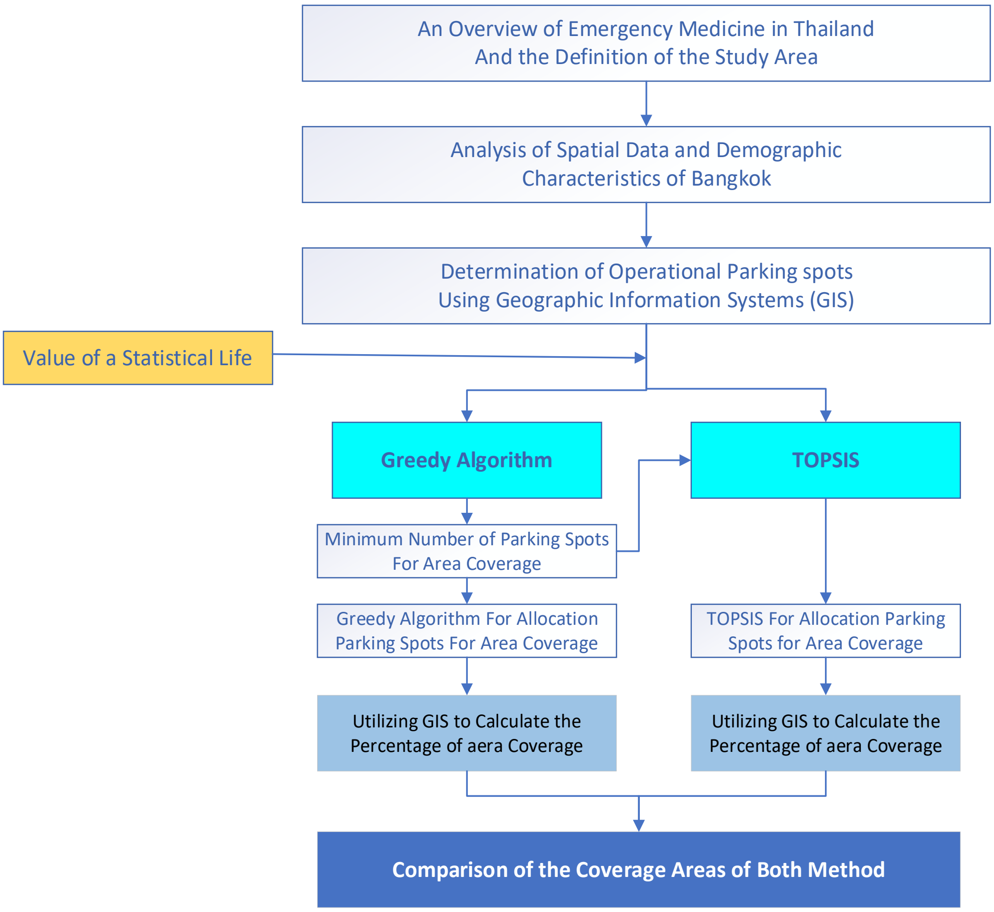

Figure 2.
Flowchart of the research methodology

2.3. Value of a Statistical Life: VSL

This research uses the VSL value as an important variable, helping to identify the urgency of each ALS emergency ambulance point that was initially determined in each area. It can also assist in considering the appropriate budget allocation for each area. The obtained VSL value does not depend solely on household income levels. Other influential factors include perceptions based on experiences of the emergency itself or with family members. The age of household members is also related; families with young children or elderly individuals tend to affect the WTP used to calculate the VSL. Additionally, the ratio of emergency ambulances to the population in the area is a significant factor influencing response time in each area [22] especially in densely populated areas.

The VSL valuation was conducted through the assessment of people's willingness to pay (WTP), which reflects the value that individuals are willing to pay for themselves or their family to reduce the risk of a medical emergency [23]. The questionnaire was designed based on the principles of the Contingent Valuation Method (CVM), which is an accepted method for valuing things that are difficult to measure in monetary terms, such as the value of the environment and the value of health [10, 11].

The sample group in this study consisted of people aged 18 years and over in the Bangkok area. According to the table of Krejci and Morgan, the sample size was at least 384 people at the 95% confidence level [24] and it was increased to 400 people for convenience in evaluation and data analysis. The sampling technique used was Quota Sampling to cover the population in different areas in a balanced manner. The analysis was conducted with a Logit Model using Maximum Likelihood Estimation (MLE) to estimate WTP for access to emergency medical services within 8 minutes and was used to calculate the value of life statistics (VSL) of the target population. The willingness-to-pay functions are in the form of a linear equation.

$$WTP = \sum_{i=1}^{n} X_i \beta_i + e_i \qquad (1)$$

WTP is the willingness to pay. X_i is the independent variable that is expected to affect the willingness to pay. Has the coefficient of the variable obtained from the estimation been the error vector. β_i is the vector of errors. e_i is the number of independent variables.

If we combine the answers obtained from the 4 models and write them as a Likelihood Function as follows

$$\begin{aligned}L_j(\beta' x_j \mid t) = {} & \Pr(\beta' x_{1^j} + \varepsilon_{1^j} > Bid^1, \beta' x_{2^j} + \varepsilon_{2^j} \geq Bid^2)^{YY} \times \\ & \Pr(\beta' x_{1^j} + \varepsilon_{1^j} \geq Bid^1, \beta' x_{2^j} + \varepsilon_{2^j} < Bid^2)^{YN} \times \\ & \Pr(\beta' x_{1^j} + \varepsilon_{1^j} Bid^1, \beta' x_{2^j} + \varepsilon_{2^j} \geq Bid^2)^{NY} \times \\ & \Pr(\beta' x_{1^j} + \varepsilon_1 < Bid^1, \beta' x_{2^j} + \varepsilon_{2^j} < Bid^2)^{NN}\end{aligned}$$

The statistical valuation of life is calculated by dividing the willingness-to-pay value by the risk that can be changed to decrease or increase, as in the equation.

$$VSL = \frac{\Delta WTP}{\Delta R} \qquad (2)$$

VSL is Value of a Statistical Life. *Δ* WTP is willingness to pay to avoid potential risks. *Δ*R is a change in risk that decreases or increases.

Table 1.
Estimation of the Mean Willingness to Pay.

Statistical	Estimates
Log-likelihood:	-469.759
Mean Willingness to Pay (WTP):	530.63
95% Confidence Interval for Mean WTP	(463.82-597.44)

Value of a Statistical Life (VSL) = $\frac{\Delta WTP}{\Delta R} = \frac{530.63}{8.09 \times 10^{-5}}$ = 6,557,873 Thai Baht (THB)

*Δ*R was estimated based on increased mortality rates associated with cardiovascular and respiratory diseases.

2.4. Spatial Analysis Using Geographic Information Systems (GIS)

Population density maps were created using a geographic information system (GIS) program to show areas according to population density, which is important information for determining the location of ambulance parking spots in line with the road network [25] considering factors affecting the ability of emergency ambulances to reach patients in a timely manner [9].

The study area has a complex infrastructure and diverse behavioral characteristics of service users [26]. Therefore, it is necessary to systematically plan the area. Starting from finding the distance to reach the patient within 8 minutes along the actual road by analyzing the Service Area from the original 13 parking spots. The GIS analysis found that there were many service gaps in the area. Initially, additional ALS emergency ambulance parking spots were determined to be appropriate for the area and the needs of the people in each district [27]. Considering the locations that can be used together with agencies under the supervision of Bangkok City Hall for convenience in policy coordination in the case of requesting access to some areas together, the parking spots are determined at 26 Public Health Centers (PHCs) and 23 schools, with a total of 49 new parking spots. When combined with the original 13 parking spots, there will be a total of 62 ALS emergency ambulance parking spots, covering both densely populated areas and suburban areas.

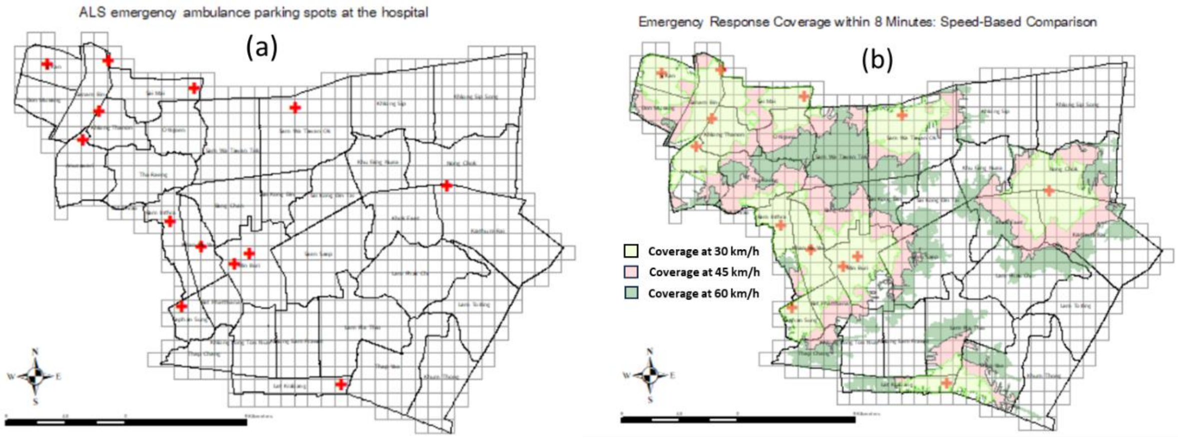

Figure 3.
a) ALS ambulance parking in hospital (2021), b) Coverage areas 13 Location.

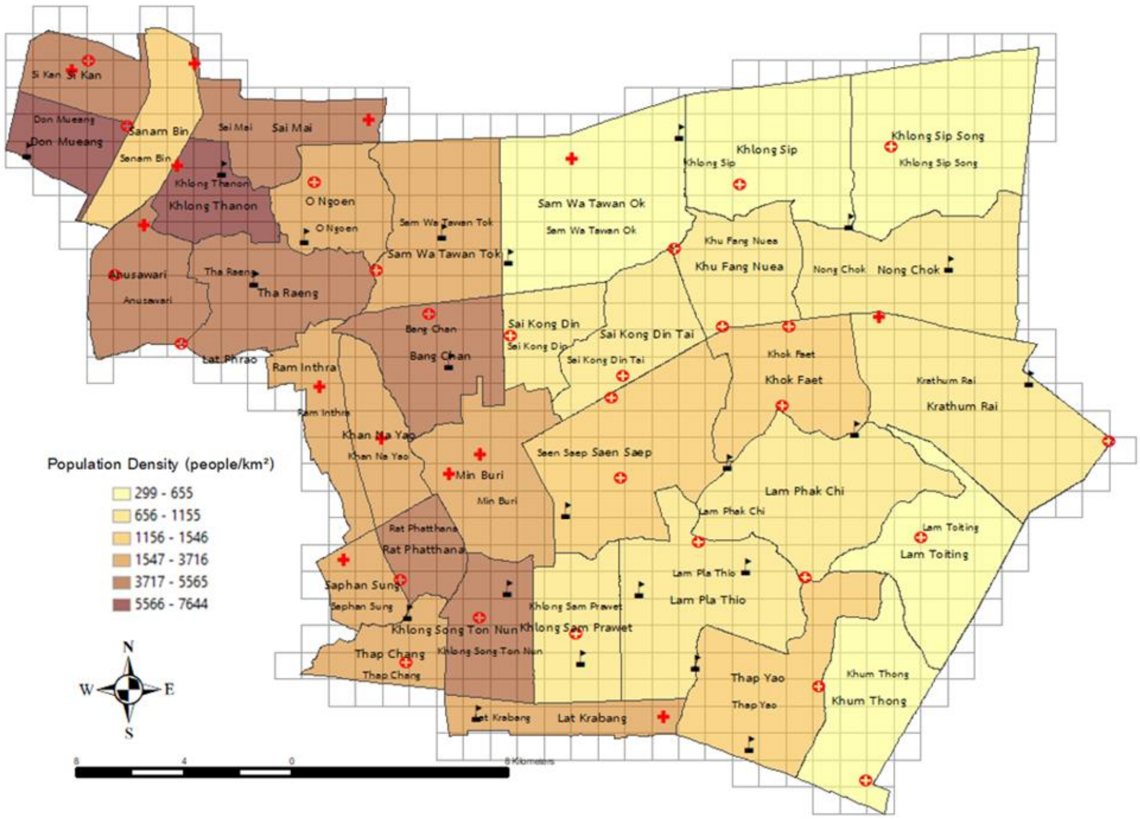

Figure 4.
Preliminary Allocation Plan for ALS Emergency Ambulance Parking Spots.

Figure 4 shows the population density in each subdistrict. We divide the population density data into 6 levels, ranging from 299-655 people per square kilometer to 5,566-7,644 people per square kilometer. Darker colors indicate higher population density, which is an area with high demand for EMS services. This is important information for allocating ambulance parking spots appropriately according to population density.

2.5. Set Covering Problem (SCP)

The Set Covering Problem (SCP) model is used under the condition of limited resources [28, 29]. This model is applied to identify emergency ambulance parking spots that can reach patients within 8 minutes in Bangkok [30] using the greedy algorithm heuristic, more ambulance parking spots were allocated based on the idea of covering the service area as much as possible under resource constraints [16]. The heuristic concept is effective in solving the SCP problem with constraints [31] which can be applied to EMS systems that help cover the service area as much as possible first in each round of processing. Then, gradually add parking spots in the next round until the overall service is complete under the condition of limited resources [12, 29].

SCP (Greedy Heuristic) helps to determine the least number of emergency ambulance parking spots while still being able to cover the area. The VSL value is applied instead of the cost of opening the service. It will select the spots with the highest value of life first, differing from the previous model that selects the spots with the lowest cost first. Set of possible service points (Potential Facility Sites), Set j =1…n. Set of demand areas (Customer Sites), Set i =1…m. Parameters c_j is the cost of setting up a service point at the location j. a_{ij}=1 If the service point is located at j . Can provide service at the location i , 0 If service cannot be provided. Variables x_j=1 if a service point is set, 0 if no service point is set.

Objective Function: $$Minimize \sum_{j=1}^{n} c_j x_j \tag{3}$$

Constraints: $$Subject\ to \sum_{j=1}^{n} a_{ij} x_j \geq 1 \quad i = 1, 2, ..m \tag{4}$$

$$x_j = 0\ or\ 1 \quad j = 1, 2, \ldots, n \tag{5}$$

The goal of Equation 3 is to identify the minimum number of stations needed to reduce costs while still ensuring coverage for all incident points within a specified time frame constraint. Equation 4 requires that every incident point (j) be served by at least one station within a given time frame. This means that for each incident point, there must be at least one station that can be reached within the critical time coverage. Equation 5 requires the value of the variable x_j to be the number 0 or 1.

Using Value of Statistical Life (VSL) instead of cost c_j

Substitute $WTP_i = \sum_{i=1}^{n} X_i \beta_i + e_i$ Enter into the equation $VSL = \frac{\Delta WTP}{\Delta R}$

New equation of will become

$$VSL = \frac{\Delta \left(\sum_{j=1}^{n} \beta_j x_{ij} + e_i \right)}{\Delta R} \tag{6}$$

Whereas $c_j = VSL$. Substituting Equation 6 into Equation 3 will yield the new Set Covering Problem Model.

$$\text{Minimize} \sum_{j=1}^{n} VSL.x_j \tag{7}$$

Set Covering problem calculation using a greedy heuristic to reduce the number of emergency ambulance parking spots initially determined. The selected location is the one that can cover the most, based on the life value, by selecting the point with the highest VSL value first.

Greedy Heuristic for Solving the Set Covering Problem

Let $VSL_j = c_j$

Step 1: If c_j = Max, for any j = 1, 2, …, n, assign x_j = 1 and remove all coverage constrains (rows) where x_j appears with a coefficient of +1.

Step 2: If c_j < Max, for any j = 1, 2, …, n, and x_j does not appear +1 in any remaining constraint, assign x_j = 0.

Step 3: For each remaining variable, define $\frac{c_j}{d_j}$, where d_j is the number of constraints in which x_j appears with a coefficient of +1. Select the variable k for which $\frac{c_k}{d_k}$ is maximum, set x_k =1, and remove all constraints in which x_k appears with a coefficient of +1. Then, verify the resulting model.

Step 4: If there are no remaining constraints, assign all remaining variables a value of 0 and stop. Otherwise, return to Step 1.

Table 2.
Pseudo code.

Greedy Algorithm: Set Covering Problem

```
x←∅   // Initialize the solution set as empty
while Constraint ≠ ∅ do // Repeat until all constraints are satisfied
  for each j in 1 to n do
    if c_j = Max then
      x_j ← 1
      Remove all constraints in which x_j appears with a coefficient of +1
    else if x_j does not appear in any constraint (coefficient +1) then
      x_j ← 0
  end for
  For each remaining variable x_j, compute S(x_j) = number of constraints in which x_j appears with coefficient +1
  Select the variable x_j with the highest S(x_j)
  x_j ← 1
  Remove all constraints in which x_j appears with a coefficient of +1
end while
For each variable x_j ที่that is still undefined → x_j ← 0
return x
```

After selecting the appropriate emergency ambulance parking spots using the Set Covering Problem (SCP) model, an iterative evaluation was performed using the same initial data through the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, which is a multi-criteria decision-making technique that can efficiently prioritize the suitability of options [32].

2.6. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS uses four criteria for consideration: population density per area, area size, distance from the parking spot to the accident scene, and the value of statistical life (VSL). All four criteria are weighed using the entropy technique [33]. The highest weight is given to VSL, followed by population density per area, area size, and distance, respectively.

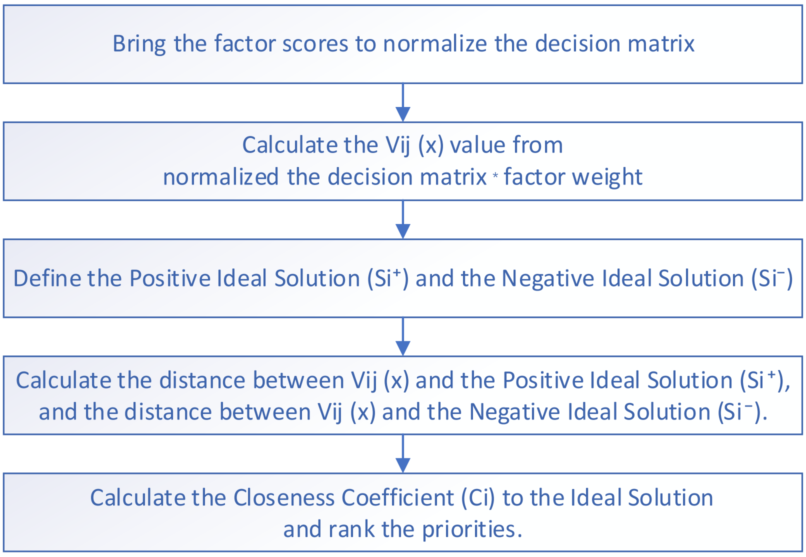

Figure 5.
Working steps of the TOPSIS method.

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method evaluates alternatives based on their geometric distance to the ideal and negative-ideal solutions [34]. The procedure includes normalization, weighting, determination of ideal solutions, separation calculation, and final ranking based on closeness coefficients.

The priority of parking spots obtained from the TOPSIS method was compared with the priority of parking spots from the Greedy Algorithm to analyze the differences in areas with dense populations. The examination was conducted to identify suitable locations, and the results were used to support policy decision-making.

3. Results and Discussion

3.1. Analysis of EMS System Coverage Area

The analysis of EMS service coverage area from the road network using the Network Analyst function in the GIS system found that the original parking spots in 13 hospitals covered 16.13% of the area within a travel time of no more than 8 minutes during rush hour with an average speed of 30 km/h. Meanwhile, the models using the Greedy Algorithm and

TOPSIS to increase parking spots, which increased the total number to 48, were able to significantly increase the coverage rate, which was 73.39% and 63.30%, respectively, under the same conditions. When compared to improved traffic conditions (at speeds of 45 and 60 km/h), the coverage of the models increased sequentially, with the Greedy model providing the highest coverage at 95.45% and the TOPSIS model at 93.95% when calculated from an average speed of 60 km/h. This study shows that the design of a distributed parking network can increase the chance of reaching patients within the standard time more efficiently than the original system.

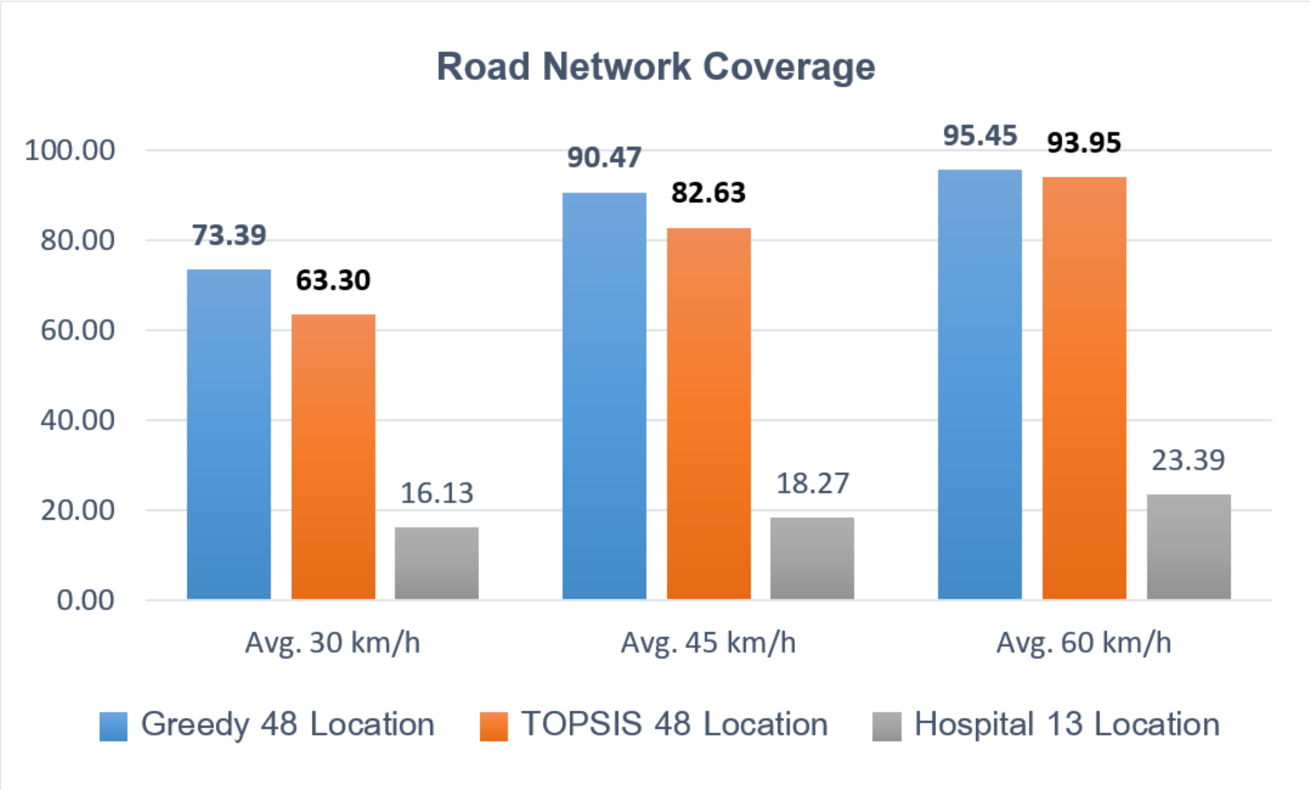

Figure 6.
Emergency Road Network Coverage within 8-Minute Response Time under Different Average Speeds and Allocation Methods.

3.2. Additional Parking Allocation Results Using SCP and TOPSIS Models

Using the Set Covering Problem (SCP) model, along with the Greedy Algorithm and the Multi-Criteria Decision-Making Technique (TOPSIS), helps find additional parking spots effectively, particularly in crowded areas with many emergency risks. Comparing the top 10 rankings of both methods provides insights into their relative performance and suitability for specific scenarios Table 2: Khlong Sam Wa District appears in 4 out of the top 5 rankings in both models, while Bang Khen District also appears in the top rankings, reflecting the consistent spatial importance between the two models despite using different evaluation criteria.

The value of life (VSL), population density, area size, and access distance are all considered by TOPSIS, which has the advantage of increasing the accuracy of parking spot allocation, particularly in locations with high population density. Figure 8 vs Figure 7b.

In comparison, while the Greedy Algorithm makes decisions based on one main factor, it shows the best coverage rate, as seen in Figure 7a, which shows results calculated at an average speed of 60 kilometers per hour. The Greedy model can cover 95.45% of the area, while TOPSIS provides a coverage value of 93.95%, and the original parking system only covers 23.39%.

In addition, TOPSIS is also capable of identifying parking spots that SCP may not choose but are spatially and economically important, such as Sam Wa Tawan Tok PHC and Wat Ko Su-wan-na-ram School, which helps open perspectives for EMS system planning to cover more social dimensions.

The comparison results clearly indicate that SCP is suitable for maximizing coverage, while TOPSIS helps enhance policy criteria. It enables the selection of parking spots in areas that may be overlooked by SCP but are of social importance.

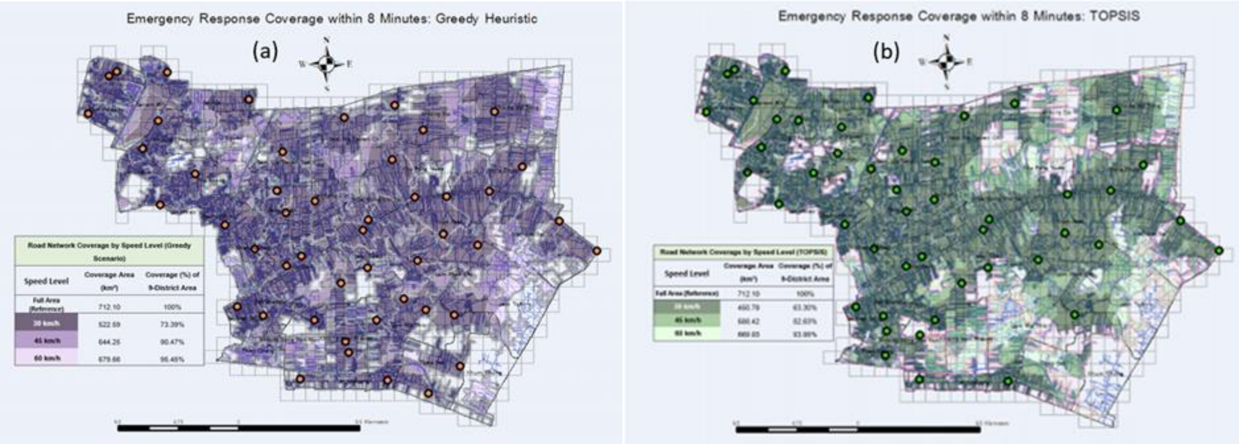

Figure 7.
Emergency response coverage within 8 minutes under different models: a) Greedy Heuristic-based ambulance parking locations, b) TOPSIS-based ambulance parking locations.

Table 3.
Comparison of Top 10 Additional ALS Emergency Ambulance Parking Locations by Greedy and TOPSIS Methods.

Rank	District	Subdistrict	Type	Location Name	Greedy Rank	TOPSIS Rank
1	Khlong Sam Wa	Bang Chan	PHC	Bang Chan PHC	3	1
2	Khlong Sam Wa	Bang Chan	School	Sulao Khlong 1 School	1	2
3	Bang Khen	Tha Raeng	School	Rat-ta-na-ko-sin Som-poch School	4	3
4	Khlong Sam Wa	Sam Wa Tawan Tok	PHC	Sam Wa Tawan Tok PHC	—	4
5	Khlong Sam Wa	Sam Wa Tawan Tok	School	Wat Paen Thong School	2	5
6	Don Mueang	Don Mueang	School	Wat We-lu-wa-na-ram School	8	6
7	Bang Khen	Anusawari	PHC	Wat Trai-rat-ta-na-ram PHC	7	7
8	Sai Mai	Khlong Thanon	School	Wat Ko Su-wan-na-ram School	—	8
9	Don Mueang	Si Kan	PHC	Met-ta Bo-ri-baan PHC	10	9
10	Bang Khen	Anusawari	PHC	Mother and Child PHC	—	10

4. Conclusion

The analysis found that areas with high population density have more medical emergencies, resulting in higher Value of Life (VSL) than other areas, reflecting the potential economic and social losses. Therefore, the establishment of additional ambulance stations in high-density areas can significantly improve the efficiency of the EMS system. Although some areas already have primary hospitals, the addition of secondary stations, such as public health centers (PHCs) or large educational institutions, can help expand the service area, especially during rush hour when the average speed is reduced to 30 km/h, which limits the 8-minute access radius to approximately 4 kilometers. In areas with low population density, there is still a need to establish additional ambulance stations to ensure equal access to EMS services.

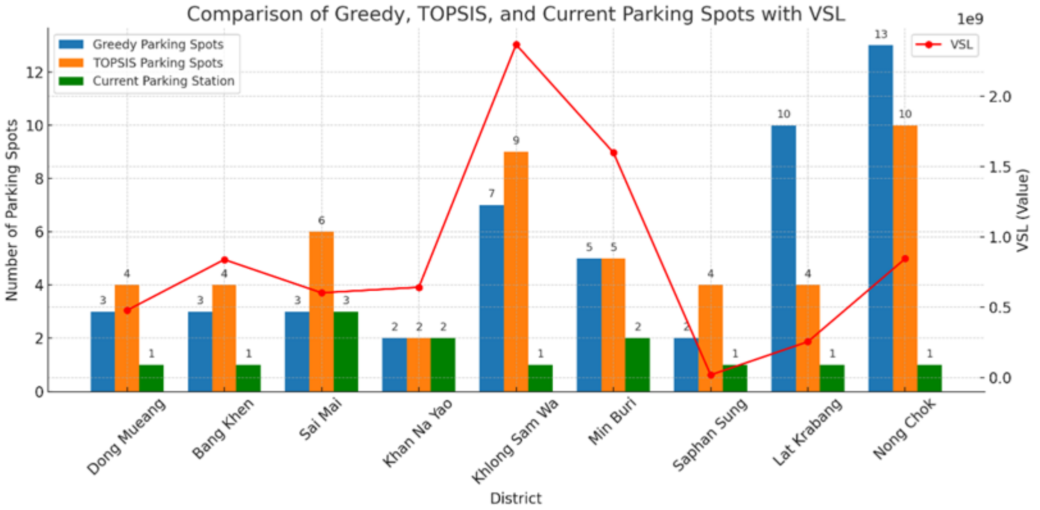

Figure 8.
A comparison of the number of parking spots available using the Greedy and TOPSIS methods in conjunction with VSL.

Also, using VSL criteria along with population data, road networks, and response time combines different types of information, making EMS planning more precise and focused on policies than if we only looked at physical distance. The results indicate that EMS planning based on mathematical models coupled with spatial data and policy factors can produce better performance than traditional planning that relies only on hospital location. In conclusion, integrating diverse data sources and analytical models enhances EMS planning effectiveness, leading to improved response times and resource allocation.

References

[1] A. Akıncılar and E. Akıncılar, "A new idea for ambulance location problem in an environment under uncertainty in both path and average speed: Absolutely robust planning," *Computers & Industrial Engineering*, vol. 137, p. 106053, 2019. https://doi.org/10.1016/j.cie.2019.106053

[2] B. Oke and G. N. Wilson, "Health service impacts and extractive industries: Experiences from health service leaders operating in a resource-dependent region," *The Extractive Industries and Society*, vol. 19, p. 101475, 2024. https://doi.org/10.1016/j.exis.2024.101475

[3] Y. Zhang, R. Wang, and Y. Zhao, "Spatial distribution modeling of emergency facilities under urban density constraint: A GIS-based approach," *International Journal of Disaster Risk Reduction*, vol. 75, p. 102976, 2024.

[4] B. Maloney *et al.*, "Factors impacting loneliness in patients with serious life-limiting illness in the emergency medicine palliative care access (EMPallA) study," *BMC Palliative Care*, vol. 24, no. 1, pp. 1-7, 2025. https://doi.org/10.1186/s12904-025-01699-1

[5] Q. Huang, H. Hu, and J. Chen, "The impact of emergency response time on survival outcomes in out-of-hospital cardiac arrest," *Prehosp Emerg Care* vol. 25, no. 2, pp. 174–181, 2021.

[6] E. Ayaragarnchanakul and F. Creutzig, "Bangkok's locked-in traffic jam: Price congestion or regulate parking?," *Case Studies on Transport Policy*, vol. 10, no. 1, pp. 365-378, 2022. https://doi.org/10.1016/j.cstp.2021.12.016

[7] A. Mukherjee and A. Anwaruzzaman, "Gridlock gloom: A geographical analysis of commuters' perceptions on traffic congestion," *International Journal of Human Capital in Urban Management*, vol. 9, no. 4, pp. 617-636, 2024.

[8] H. Andersson, T. A. Granberg, M. Christiansen, E. S. Aartun, and H. Leknes, "Using optimization to provide decision support for strategic emergency medical service planning–Three case studies," *International Journal of Medical Informatics*, vol. 133, p. 103975, 2020. https://doi.org/10.1016/j.ijmedinf.2019.103975

[9] R. A. Nadar, J. K. Jha, and J. J. Thakkar, "Strategic location of ambulances under temporal variation in demand and travel time using variable neighbourhood search based approach," *Computers & Industrial Engineering*, vol. 162, p. 107780, 2021. https://doi.org/10.1016/j.cie.2021.107780

[10] M. Delgado-Lindeman, J. Arellana, and V. Cantillo, "Willingness to pay functions for emergency ambulance services," *Journal of Choice Modelling*, vol. 30, pp. 28-37, 2019. https://doi.org/10.1016/j.jocm.2018.12.001

[11] H. Seyedin, R. Jamshidi-Orak, and E. Zarei, "Public willingness to pay for improved emergency medical services in urban areas," *Iranian Journal of Public Health*, vol. 49, no. 9, pp. 1721–1728, 2020.

[12] T. Adamo, G. Ghiani, E. Guerriero, and D. Pareo, "A surprisal-based greedy heuristic for the set covering problem," *Algorithms*, vol. 16, no. 7, p. 321, 2023. https://doi.org/10.3390/a16070321

[13] N. Amani, "Evaluation and selection of hydro power plant location using the analytical hierarchy process-TOPSIS method," *International Journal of Human Capital in Urban Management*, vol. 10, no. 2, 2025.

[14] M. Nazarabadian, M. Razmaramina, and A. Pilehvar, "Analyzing the impact of equitable urban service distribution on citizen mobility: A spatial justice perspective," *International Journal of Human Capital in Urban Management*, vol. 9, no. 4, pp. 653–670, 2024.

[15] I. Gago-Carro, U. Aldasoro, J. Ceberio, and M. Merino, "A stochastic programming model for ambulance (re) location–allocation under equitable coverage and multi-interval response time," *Expert Systems with Applications*, vol. 249, p. 123665, 2024. https://doi.org/10.1016/j.eswa.2024.123665

[16] S. Atta, P. R. S. Mahapatra, and A. Mukhopadhyay, "A multi-objective formulation of maximal covering location problem with customers' preferences: Exploring Pareto optimality-based solutions," *Expert Systems with Applications,* vol. 186, p. 115830, 2021. https://doi.org/10.1016/j.eswa.2021.115830

[17] L. A. Robinson and J. K. Hammitt, "Research synthesis and the value per statistical life," *Risk Analysis,* vol. 35, no. 6, pp. 1086-1100, 2015. https://doi.org/10.1111/risa.12366

[18] A. Rahman, M. T. Khan, and M. A. B. Siddique, "Contingent valuation: A pilot study for eliciting willingness to pay," *Front Public Health,* vol. 9, p. 693062, 2021.

[19] A. Alberini, C. M. Rheinberger, and M. Ščasný, "All cancers are not created equal: How do survival prospects affect the willingness to pay to avoid cancer?," *Journal of Benefit-Cost Analysis,* vol. 14, no. 1, pp. 93-113, 2023. https://doi.org/10.1017/bca.2022.21

[20] J. Geng, N. Yang, W. Zhang, and L. Yang, "Public willingness to pay for green lifestyle in China: A contingent valuation method based on integrated model," *International Journal of Environmental Research and Public Health,* vol. 20, no. 3, p. 2185, 2023. https://doi.org/10.3390/ijerph20032185

[21] N. Phunghassaporn, P. Sukhvibul, S. Techapongsatorn, and A. Tansawet, "Accuracy and external validation of the modified rapid emergency medicine score in road traffic injuries in a Bangkok level I trauma center," *Heliyon,* vol. 8, no. 12, p. e12225, 2022. https://doi.org/10.1016/j.heliyon.2022.e12225

[22] S. Ciarlantini, V. Frontuto, A. Pezzoli, A. Gavros, and C. A. Belis, "Econometric model derived from meta-analysis to estimate VSL and VOLY associated to air pollution at a global level," *Journal of Environmental Management,* vol. 379, p. 124824, 2025. https://doi.org/10.1016/j.jenvman.2025.124824

[23] D. Delgado-Lindeman, M. M. Escribano, and M. Pérez-Mateo, "Estimation of the willingness to pay for improved emergency medical services," *International Journal of Health Planning and Management,* vol. 34, no. 3, pp. 1042–1056, 2019.

[24] R. V. Krejcie and D. W. Morgan, "Determining sample size for research activities," *Educational and Psychological Measurement,* vol. 30, no. 3, pp. 607-610, 1970. https://doi.org/10.1177/001316447003000308

[25] A. Abulibdeh, H. Alshammari, N. Al-Hajri, A. Al-Shamari, and F. Al-Naimi, "Geospatial assessment of healthcare accessibility and equity in Qatar in preparation for the 2022 FIFA world cup," *Journal of Geovisualization and Spatial Analysis,* vol. 9, no. 1, p. 2, 2025. https://doi.org/10.1007/s41651-024-00206-z

[26] S. Golazad, G. Heravi, A. AminShokravi, and A. Mohammadi, "Integrating GIS, agent-based, and discrete event simulation to evaluate patient distribution policies for enhancing urban healthcare access network resilience," *Sustainable Cities and Society,* vol. 111, p. 105559, 2024. https://doi.org/10.1016/j.scs.2024.105559

[27] K. Ueno, C. Teramoto, D. Nishioka, S. Kino, H. Sawatari, and K. Tanabe, "Factors associated with prolonged on-scene time in ambulance transportation among patients with minor diseases or injuries in Japan: A population-based observational study," *BMC Emergency Medicine,* vol. 24, no. 1, p. 10, 2024. https://doi.org/10.1186/s12873-023-00927-2

[28] S.-N. Shetab-Boushehri, P. Rajabi, and R. Mahmoudi, "Modeling location–allocation of emergency medical service stations and ambulance routing problems considering the variability of events and recurrent traffic congestion: A real case study," *Healthcare Analytics,* vol. 2, p. 100048, 2022. https://doi.org/10.1016/j.health.2022.100048

[29] J. Nelas and J. Dias, "Optimal emergency vehicles location: An approach considering the hierarchy and substitutability of resources," *European Journal of Operational Research,* vol. 287, no. 2, pp. 583-599, 2020. https://doi.org/10.1016/j.ejor.2020.03.067

[30] D. Sumrit and K. Thongsiriruengchai, "An optimization model for advanced life support ambulance facility location problem," *Proceedings,* vol. 39, no. 1, p. 10, 2020.

[31] F. Carrabs, R. Cerulli, R. Mansini, L. Moreschini, and D. Serra, "Solving the set covering problem with conflicts on sets: a new parallel GRASP," *Computers & Operations Research,* vol. 166, p. 106620, 2024. https://doi.org/10.1016/j.cor.2024.106620

[32] X. Zhang and H. Wu, "Hesitant fuzzy linguistic Mahalanobis distance-based TOPSIS method for evaluating regional green development levels," *Applied Soft Computing,* vol. 173, p. 112920, 2025.

[33] W. Qu *et al.*, "Entropy-weight-method-based integrated models for short-term intersection traffic flow prediction," *Entropy,* vol. 24, no. 7, p. 849, 2022. https://doi.org/10.3390/e24070849

[34] C. L. Hwang and K. Yoon, *Multiple attribute decision making: Methods and applications*. New York: Springer-Verlag, 1981.