
Clustering-Allocation Model Under Risk, and Emissions Factors: Evidence from an Indonesian Region

Pipit Sari Puspitorini

Department of Industrial Engineering, Faculty of Engineering, Universitas Islam Majapahit, Indonesia

Email : puspitorini_ie@unim.ac.id

ABSTRACT

This study contributes to risk-based location-allocation problems by constraining time and emergency medical services (EMS) carbon emissions. During the COVID-19 pandemic, this study develops a location set covering the problem of implementing ambulance allocation to optimize opening new facilities and the cluster with the highest emission value in heritage cities. This study also presents an integer linear program considering risk, time, and carbon emissions at three facilities with demand locations. The model was also validated using two cluster methods, K-means clustering and Agglomerative Hierarchical Clustering, with Python software and Google Collaboratory machine learning (GCC). The findings revealed the opening of three facilities and clusters with potential points, with the highest emission values at M_3 (0.575% (kg). M_2 potential point, with a value of 5832 represents the highest risk. Furthermore, the validation results indicate that the distance significantly total energy consumption (BTU) and carbon emissions (kg). This study ignores the vehicle category. It can be used as a reference by decision-makers by considering these parameters and making a clear contract with a third party in ambulance procurement for humanitarian logistics. The model will help provide insight into another region's relevant emergency medical center. Furthermore, research can anticipate strategies to deal with pandemic outbreaks.

Keywords: location-allocation model, cluster, carbon emissions, risk, and set covering problem

INTRODUCTION

Logistics is the key to a modern economy. Logistics also outline and control material and information streams in organizations and the civil and individual sectors. A vital issue for future humanity is the distribution of humanitarian aid [1]. The emergence of Humanitarian Logistics to alleviate human [2]. According to [3], the challenge faced by humanitarian logistics is uncertain rescue strategy in disaster occurrence. Likewise, [4] explained that humanitarian aid distribution with timely (medicine, food, water, and more) to affected areas is the biggest challenge worldwide and the time window is 72 hours after a disaster, otherwise, an opportunity for survival is a crisis [5], [6], [7]. Logistics deals with human rights operations and humanitarian logistics, focusing on the response at search, rescue, and life sustainability [8], implementing and controlling inefficiencies, goods, and material storage from the original point to the destination point called the disaster area, to suffer disaster's victims [9]. Moreover, it also refers to helping vulnerable people who are affected by natural disasters. Humanitarian logistics comprises procurement, movement, local transportation, tracking and tracing, customs clearance, warehousing, and last-mile delivery [10][10]. Humanitarian logistics strive to reduce the number of natural and artificial disasters. The calamities that struck Indonesia, particularly the pandemic issue that has plagued the country over the past two years as a result of the coronavirus-19 spread from a location discovered in Wuhan City, a province in China, where there was a significant risk of population loss, are examples of this.

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According to [11], disaster logistics is a component of logistics and supply chain management. In humanitarian logistics, there are four players: governments, aid agencies, the military, donors, private sector companies, and nongovernmental organizations (NGOs). The most important responsibility is to minimize costs. Research on humanitarian logistics applied to the government, especially in emergency medical services (EMS), has been conducted by several researchers, one such study is the research developed by [12] in Bangkok. This in EMS aims to determine the location of the ambulance using a spatial-temporal approach based on two factors, demand and risk. In addition, the need for ambulances in Indonesia has increased by 20% from the average demand for three thousand units per year during the pandemic [13]. For this reason, we save patients' lives by ambulance, especially in areas affected by the COVID-19 pandemic.

Conversely, In this study, we extended the location model [12], which is the first to include the location model. Using the queuing theory's basic, the ambulance location model was created, which states that the ambulance should be placed at position q . (probability). If ambulance k fulfills demand j , then the demand fulfilled at location j is $p_j (1 - q_k)$. Remarkably, state-of-the-art allocation of ambulances considers risk, time, and carbon emissions. However, there are significant risks, short lead times, consideration of the location, types, and number of commodities, and unforeseen demands.

Therefore, the objective of this study is to maximize the maximum possible set covering the problem of ambulance allocation based on time, risk, and emissions. The most pertinent is:

1. How can we open an optimal new facility based on time and the most significant risk?
2. Which cluster with potential points has the highest emission value?

The remainder of this study is structured as follows: section 1 reviews the background and plenty of the gaps in previous studies, as well as the proper literature. Section 2 discusses the development of the framework for this study. Then, section 3 discusses the location-allocation model extended for the maximal covering problem and by integer programming in the issue in detail. Finally, section 4 concludes further research in section.

FRAME REFERENCES

According to [14], The Set Covering Problem involves calculating the minimum cost of a group of potential facilities so that demand may be met by only one. The optimal solution to this NP-complete problem is extremely challenging to find. Applications of set coverage problems include finding the least number of facilities from all sites with a maximum distance or standard time, political districting, truck routing, locating swabs and fire stations, and airline and airline staff scheduling. In contrast, the Maximal Set Covering Problem (MSCP) evaluates the number of facilities covered (served) over the most significant service distance or in the shortest possible time. Humanitarian logistics is one of the answers to the set covering problem. Some research on humanitarian logistics is interesting to develop to achieve a better life. Table 1 explains twelve researchers on the location-allocation problem coverage problem, factors, and models in disaster management. Based on a review of research from 2008 to 2021, the researchers developed a model [12] and [15] based on two factors, namely travel time and carbon emissions as key decisions in designing the gap with one added travel time of eight minutes as a constraint.

First, a previous study [12] determined optimal ambulance locations based on risk factors that minimize response time It refreshes to severity, population density, the number of older adults, and the public events held in that Bangkok area. Researchers compare the maximum covering location problem (MCLP) demand and risk values model. The results show that the MCLP risk model allocates nine ambulances based on five risk factors and on the contrary allocates eight ambulances that do not cover the entire area that can serve victims quickly. Nevertheless, The results obtained are fifty-six locations considered based on time and risk in a Geographic Information System (GIS). Furthermore, the second study aims to maximize the number of potential victims in allocated shelters at an out-of-danger distance using a GIS tool and a capacitated maximum covering location model of Tunceli province. The result covered five shelters in 1 km distance of population and all Conversely, by 4700 m distance limit and ignoring the capacities can cover all people.

Second, two researchers have investigated the issue of carbon emissions. As stated in [16], this uses CO₂ emissions to support urban economic growth. He is reviewing a dynamic system of three scenarios of CO₂ emissions in a million tons, namely, 11,492, 0.529, and 7,250 in Jakarta for 2029. Policymakers can use practical implications as role models for sustainable urban development, with input from environmental aspects to guide the best life for the future. Results reveal decreasing CO₂ emissions from fossil energy by up to 15%. In contrast, CO₂ emissions contribute to two-thirds of emerging markets and developing economies and will increase by almost 5% to near peak in 2021, as reported by [17]; [18]. In addition, we investigate a location-allocation model for Emergency evacuation centers to minimize disaster risk flood victims. The goals are to enhance planning and distribution, human deductions and property losses, and improve emergency operations. A flood vulnerability model for disaster-prone communities using the output of mapping flood maps in the study area. The model shows inaccessible emergency evacuation centers with a 60-minute limit of 6.27%.

Table 1. Brief reconstruction literature on the disaster management location-allocation model
Abbreviation:

Model/Disaster variables		Authors												
		[19]	[12]	[20]	[21]	[12]	[16]	[9]	[18]	[22]	[15]	[17]	[3]	This paper
Problems	Loc-Alc	√	√	√	√	-	-	-	-	-	-	-	-	-
Factors	Risk	√	-	-	-	√	-	-	-	-	-	-	-	√
	Cost	-	-	-	√	-	-	-	-	-	-	-	-	-
	Time	-	-	√	-	-	-	-	√	√	√	-	√	√
	Carbon Emissions	-	-	-	-	-	√	-	-	-	-	√	-	√
Models	CMCL	-	-	-	-	-	√	-	-	√	√	-	-	-
	VRP	√	-	-	-	-	-	-	-	-	-	-	-	-
	DRM	-	-	√	-	-	-	-	-	-	-	-	√	-
	LSCP	-	-	-	-	√	-	-	-	-	-	-	-	√
	SCAN	-	-	-	-	-	-	√	-	-	-	√	-	-
	MLMs	-	-	-	-	-	-	-	√	-	-	-	-	-
Coverage problem	DLG	-	-	-	-	-	√	-	√	√	-	-	-	-
	EMS	-	-	-	√	√	-	-	-	-	-	-	-	√
	ER	-	-	-	-	-	-	-	-	√	-	-	-	-
	EHL	-	-	-	-	-	-	√	-	-	-	√	-	-
	EEC	-	-	-	-	-	-	-	√	-	-	-	-	-
Method/Tools	IP/MINLP	-	-	√	-	√	√	√	-	√	-	√	√	√
	Bio-objective	-	-	-	√	-	-	-	-	-	-	-	-	-
	Meta-heuristics	√	-	-	-	-	-	-	-	-	-	-	-	-
	GIS	-	-	-	-	√	-	-	√	-	√	-	-	-
	Phyton	-	-	-	-	-	-	-	-	-	-	-	-	√

Loc-Alc = Location-allocation; CMCL=Capacitated maximal covering location; DRM=Distributionally robust model (DRM); LSCP= Location set covering problem; SCAN= Set covering and analytic network

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process; MLMs= Machine learning models; DLG= Deluge; EMS= Emergency medical services; ER= Emergency rescue; EHL= Emergency humanitarian logistics; EEC= Emergency evacuation centers; VRP= Vehicle routing Problems; IP/MINLP= Integer programming; GIS= Geographic information system;

METHOD

Reasons for choosing the method used (1) K-means clustering and Agglomerative Hierarchical Clustering, K-means aims to minimize the distance within one cluster and between clusters based on data similarity with speed and is easy to implement but difficult in determining the optimal number of clusters. On the other hand, for larger dataset processes and limitations. (2). Maximal Covering Location Problem (MCLP) is an efficient and optimal mathematical model solution in determining the location of facilities that aims to maximize the total demand that can be served on time by considering various parameters such as distance, cost, capacity, and service time. Datasets processing uses Python software and Google Collaboratory Machine Learning (GCC). In the model developed by [12], the author created a maximal set covering problem (MSCP) model. by adding one constraint, namely that the ambulance travel time to the location does not exceed eight minutes, implying that the eight minutes allocated are the author's assumptions. Although the primary goal of this model is to maximize the coverage distance, the previous paper above maximizes risk coverage to open new facilities. The risk coverage allocation model is completed in five stages, which are as follows: (a) risk accessibility. Creation of a model It is solved using a Geographic Information System (GIS) approach with five risk factors and a risk value output in this model. The outcome is the input for the next step (b). developing a location-allocation model with one added constraint, namely, travel time, (c) numerical examples of numbers, (d) discussion, (e) validation, and conclusion. Figures 1 depict the maximal set covering problem (MSCP) model of facility demand location with extended time constraints and the method of developing the model by time constraints.

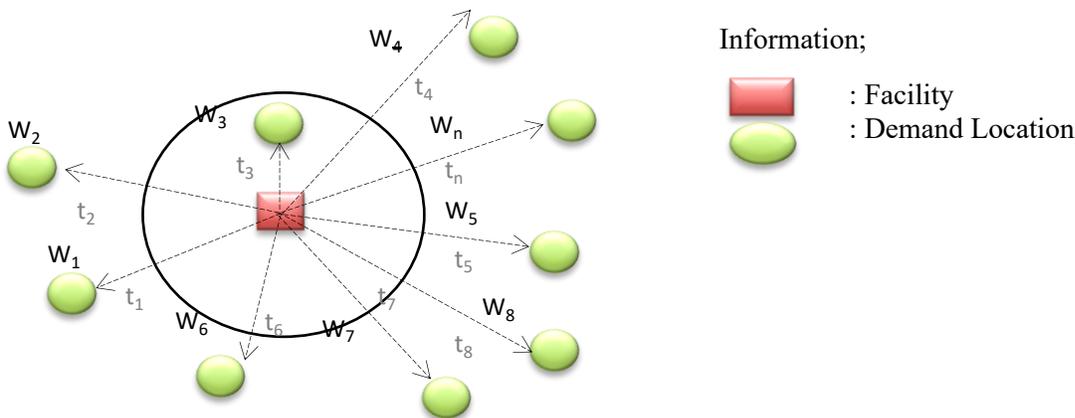


Figure 1. Illustration of the maximal set covering problem model.

Mathematics Model

Before developing the model, we will show some formal notations namely index, parameter, and variable. Index describes the definition of set sites from the starting point and the goal to be achieved. While the fixed value used to define the model characteristics is called a parameter. Variables are elements used to achieve certain goals and which can be changed. Decision variables are used to determine the decision whether a location will be opened (1) or not

(0). By understanding the index, parameters, and variables, decisions can be used to optimize facilities that can be more effective by decision-makers

Index/Sets:

i : Site, where $i \in S$

j : Potential site, where $j \in Z$

h : Risk site,

S : Set of sites

Z : Set of potential sites

Parameters:

R_i : Risk value of specific site

P : Total potential site

L_{ih} : Risk factor h of specific site i

E_{ih} : Risk effects h on specific site i

T : Travel time

Decision variables:

$$\beta_j = \begin{cases} 1, & \text{if site } i \text{ forced } j \\ 0, & \text{otherwise} \end{cases}$$

$$x_j = \begin{cases} 1, & \text{if the location is selected } j \\ 0, & \text{otherwise} \end{cases}$$

$$y_j = \begin{cases} 1, & \text{if site } i \text{ is coverage of at least one} \\ 0, & \text{otherwise} \end{cases}$$

Objective Function : [23]

$$R_i = \prod_{h=1}^5 (L_{ih} \times I_{ih}) \tag{1}$$

$$\text{Maximize} = \sum_i R_i * y_i \tag{2}$$

Constraints:

$$1) \sum_{j \in w_i} x_j \geq y_i, \quad i \in V \tag{3}$$

$$2) \sum_{j \in w_i} x_j \leq P \tag{4}$$

$$3) \beta_j \leq x_j, \quad j \in Z \tag{5}$$

$$4) x_j \in \{0,1\}, \quad j \in Z \tag{6}$$

$$5) y_i \in \{0,1\}, \quad j \in S \tag{7}$$

Development model :

Objective Function:

$$\text{Maximize} = \sum_i R_i * y_i \tag{8}$$

The value of R_i is obtained as follows:

$$R_i = \prod_{h=1}^5 (L_{ih} \times I_{ih}) \tag{9}$$

Constraints:

$$1) \sum X_i = 5, \quad i \in S \tag{10}$$

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$$2) \quad \sum_{j \in w_i} x_j \geq a_{ij} y_i, \quad i \in S \quad (11)$$

$$3) \quad \sum_{j \in w_i} x_j \leq P \quad (12)$$

$$4) \quad \beta_j \leq x_j, \quad j \in Z \quad (13)$$

$$5) \quad x_j \in \{0,1\}, \quad j \in Z \quad (14)$$

$$6) \quad y_i \in \{0,1\}, \quad j \in Z \quad (15)$$

Decision variables:

$$\beta_j : \begin{cases} 1, & \text{if site } i \text{ forced } j \\ 0, & \text{otherwise} \end{cases}$$

$$a_{ij} : \begin{cases} 1, & \text{if } t_{ij} \leq T, T = 8 \text{ minutes} \\ 0, & \text{otherwise} \end{cases}$$

$$x_j : \begin{cases} 1, & \text{if the base location is selected } j \\ 0, & \text{otherwise} \end{cases}$$

$$y_j : \begin{cases} 1, & \text{if area point } i \text{ is coverage of at least one} \\ 0, & \text{otherwise} \end{cases}$$

Equations 8-15, can be explained as follows, namely (a) Maximizing the value of risk coverage is the goal function, which is depicted in the eighth equation. The objective function is designed to maximize risk coverage in dealing with pandemic disasters, Redaksi, (2021) that PPKM is level 1 so that people can help crowds in their activities, as well as recently there was a natural disaster, namely flooding. According to Chaicharoenwut et al., (2018a), there are five types of risks and their definitions. These risks are the frequency of accidents (emergency medical services); Severity of accidents (the level of accidents that require agile medical treatment); Population density (demand for emergency services), Number of elderly (the number of elderly who require rapid medical treatment); and Public events (public events that cause crowds). (b) At least three facilities satisfy the first restriction; (c) The second restriction states that a maximum travel time of eight minutes applies to the area served by at least one ambulance base (travel time used by the facility does not exceed eight minutes), (d) The third restriction is the maximum number of P that can develop or the total number of potential sites below P, (e) The fourth restriction ensures that the j place has been closed, dan (f) The fifth and sixth constraints create a binary decision variable that determines whether or not P opens, x_j and y_j (allocated or not).

RESULT AND DISCUSSION

With 132,434 inhabitants and a 20.21 km² area, Mojokerto City is a district in East Java. This region lies 50 km southwest of the provincial seat of East Java. In this case, we add a minimum time service of eight minutes for an ambulance to the model. There are 14 prospective sites across the City of Mojokerto, specifically the cities of M₁, M₂, M₃, M₄, M₅, M₆, M₇, M₈, M₉, M₁₀, M₁₁, M₁₂, M₁₃, and M₁₄. The risk assessment's two main components are the likelihood of risk and the effect of risk (impact) on the facility's opening. Based on data from 14 cities, The R-value is derived from equation 2, the comparison between factors and risk effects for a prospective candidate site. In contrast, the M₅ area with the highest risk value has the highest risk value. The risk assessment's two primary components are the chance of risk (likelihood) and the influence of risk (impact) on the facility's opening. In contrast, the M₅ area with the highest risk value has the highest risk value. The assumption is that ambulances are dispatched to high-risk regions, such as regions where the risk value exceeds 1000 ($R_i \geq 1000$). The travel time is converted to a distance matrix. The distance traveled (t) to the facility was less than eight minutes. The uniform straight motion (GLB) at a constant speed

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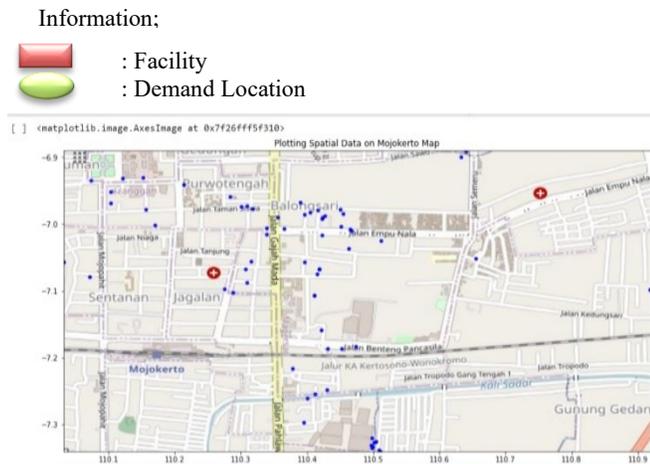
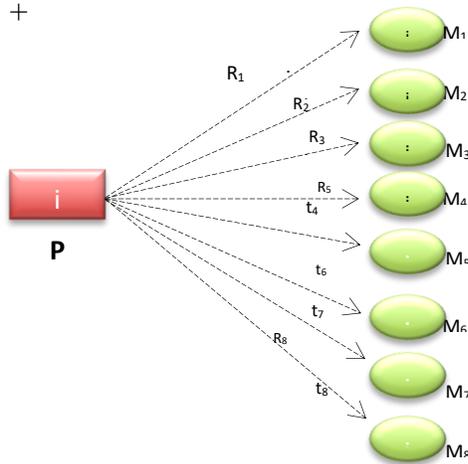
of 70 km/s is called velocity (v). It is also known as motion without acceleration. The distance divided by the speed yields the travel time (t). Thus, the formula was, $t = \frac{s}{v} = \frac{km}{km/s}$. Furthermore, the value of risk is illustrated in Table 2.

Table 2. Risk values for the five variables

Location	R-value	Location	R-value	Location	R-value
M ₁	648	M ₆	972	M ₁₁	486
M ₂	5832	M ₇	2916	M ₁₂	1458
M ₃	1296	M ₈	3888	M ₁₃	3888
M ₄	1944	M ₉	4374	M ₁₄	2916
M ₅	8748	M ₁₀	972		

Ten areas have a high danger level: M₂, M₃, M₄, M₅, M₇, M₈, M₉, M₁₂, and M₁₄. The M₅ area has the highest risk level, with a risk value of 8748 and an average of 3431. the following sites are in that order: 5832, 1296, 1944, 8748, 2916, 3888, 4374, 1458, 3888, and 2916. Ten applicants for possible ambulance allocation regions must be granted a time limit of eight minutes. They estimated eight minutes because the Mojokerto City area is relatively close and the traffic is not too heavy. An ambulance will be assigned or placed using the sixth equation. Yi opens if the potential area meets the high-risk area among the 10 potential candidate areas. In the third and fourth constraints in equations 12 and 13, the allocation is limited to less than 8 min (T≤8 minutes). There are ten areas with a risk value above 1000 among the 14 probable locations; M₂, M₃, M₄, M₅, M₇, M₈, M₉, M₁₂, M₁₃ dan M₁₄. Figures 2 (a) and (b) depict the distribution of facilities based on risk and the distribution of facilities based on the geographical data mapping of Mojokerto.

+



(a) Risk-based facility allocation

(b) Mapping of spatial data for Mojokerto City Figure 2a

and b. risk and Spatial mapping-based facility allocation Mojokerto city

Table 3 depict the location of the covered ambulance with P=3, Only three options identified in possible locations, namely M₂, M₆, and M₁₄, were found based on the importance of risk and distance. The allocated ambulance travels at 70 km/h. They cover demand location, risk value (R-value), distance (d), and time (t).

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Table 3. Fourteen locations in possible candidate areas with their risk values.

T ≤ 8 min														
Potential area	M ₁	M ₂	M ₃	M ₄	M ₅	M ₆	M ₇	M ₈	M ₉	M ₁₀	M ₁₁	M ₁₂	M ₁₃	M ₁₄
Ri	648	5832	1296	1944	8748	972	2916	3888	4374	972	486	1458	3888	2916
X	11	9	13	8	10	7	9	3	10	11	9	3	4	9
T	5	3	10	9	5	5	10	11	10	11	7	10	13	7
V	70	70	70	70	70	70	70	70	70	70	70	70	70	70
Yi	0	1	1	1	1	0	1	1	1	0	0	1	1	1
Ri*Yi	0	5832	1296	1944	8748	0	2916	3888	4374	0	0	1458	3888	2916

The comparison of the three sites, specifically (P₁) with the point of the M₂ location, will cover M₇, M₈, M₁₂, and M₁₄; R-value is 5832; d=9 km, and t=3 minutes. (P₂), where R-value is 8748, d is 10 km, and t is 5 minutes, the M₆ facility point will cover M₄, M₅, and M₉. (P₃) encompassing R-value=2016, d=9 km, and t=7 minutes with M₂ covered by M₁₄ facility points and M₃ covered by M₃. nonetheless, according to Table 4, the objective function derived from the three regions is 17496, with the corresponding risk values in each area being 5832, 8748, and 2916. In contrast, the ratio index is 0.132%.

Table 4. Comparison and Risk values of potential ambulance placements

Potential Point	R-Value	Distances (km)	Times (minutes)	Velocity (km/hour)	Covering	Potential Point	M ₂	M ₆	M ₁₄
P ₁ M ₂	5832	9	3	70	Ri	Ri	5832	874	2916
P ₂ M ₆	8748	10	5	70	Yi	Yi	1	1	1
P ₃ M ₁₄	2016	9	7	70	Ri*Yi	Ri*Yi	5832		
						Obj.Function	17,496		
						Populace	132.434		
						Index Ratio	0.13		

In the development of the location-allocation model, there are three potential locations for placing ambulances; M₂, M₆, and M₁₄ covering areas 4, 3, and 2, respectively. This discussion converts mileage to carbon dioxide exhaust gas. It causes high economic activity and air pollution, including carbon dioxide increase in economic development, and human welfare is significantly proportional. Rusiawan et al., (2015) demonstrated how the dynamics modeling system anticipated lowering carbon dioxide emissions without hurting economic growth, particularly Gross Domestic Product (GDP), through a case study in Jakarta. In contrast to research, Timothy, (2021) use of resources and carbon emissions affect the growth of climate change. Global carbon dioxide emissions will increase by roughly 5.8% in 2020 and persist and rebound by nearly 5% in 2021.

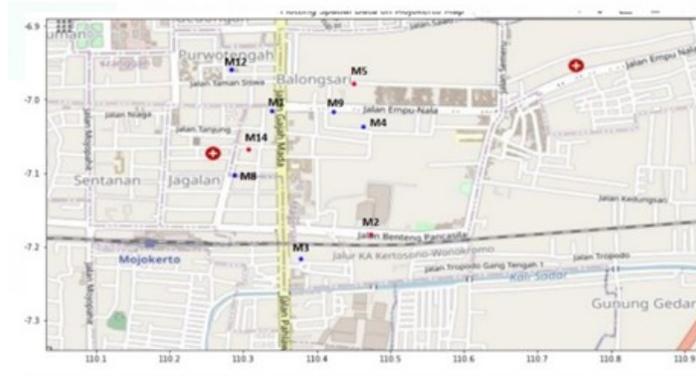


Figure 3. Ambulance location placement with P=3 covered in Mojokerto City

The study results compare four measurement devices; energy BTU, carbon dioxide emissions (kg), distance (km), and consumption, as shown in Figure 4. The emissions and energy parameters have values of 2.5 and 3025 BTU, respectively. The x-axis represents the measured value, and the y-axis represents the location, total energy consumption, and measured value. At potential points, M₂, M₁₄, and M₆, with a distance of 9 km and 10 km, will consume a total consumption of 0.17 L and emit a total carbon dioxide of 2.35 kg. There are four colours used consumption (liters), distance (km), CO₂ emission (kg), and emission/BTU (green, red, orange, and blue).

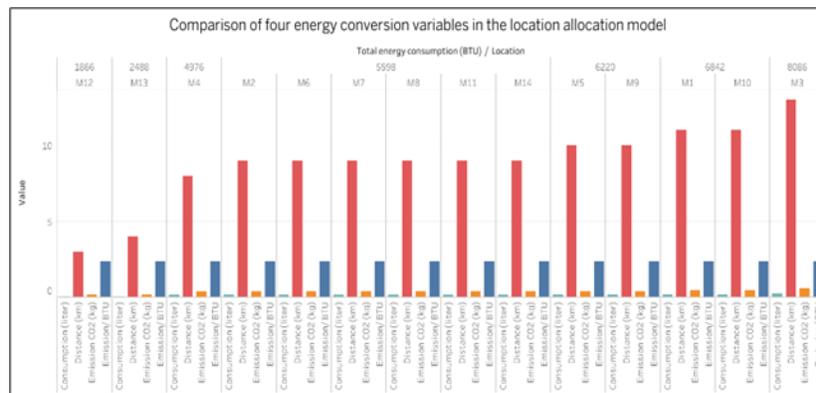


Figure 4. Comparison of four energy consumption variables in the location-allocation model.

Figure 5 compares actual and forecasted conditions for dioxide emissions. The highest and lowest natural consumption energy (liters) and Co₂ emissions (kg) in M₃ and M₁₂ were 0.24484:0.0565 and 0.57537: 0.13278. Meanwhile, the data statistics with the three-month moving average method show that the M₁₁, M₁₂, M₁₃, and M₁₄ locations experienced a significant decrease.

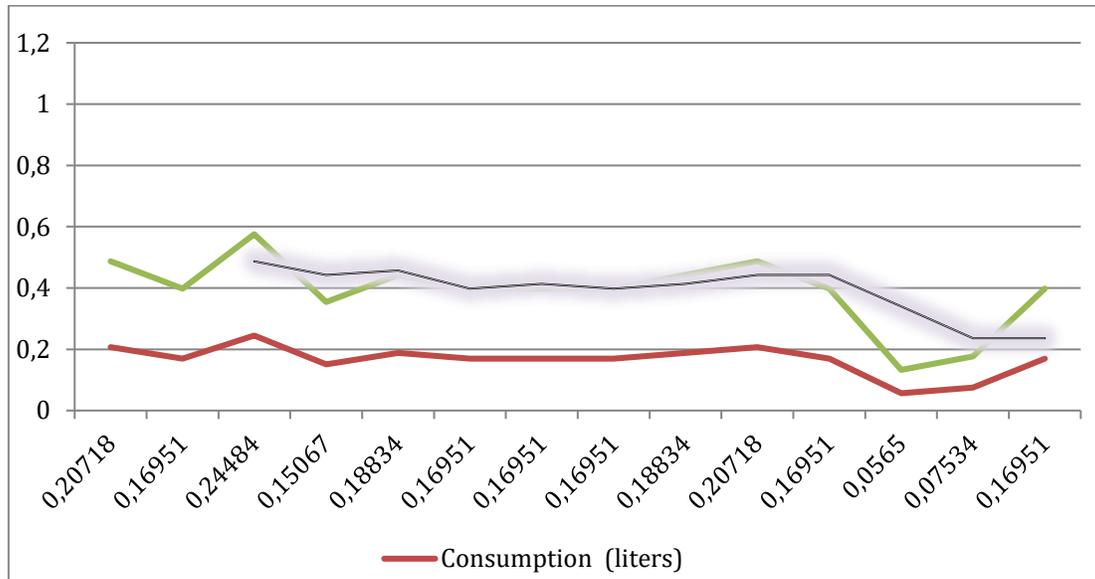


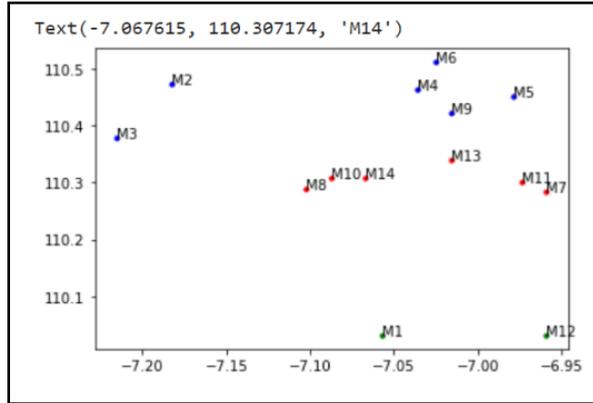
Figure 5. Comparison of actual and forecasted conditions on carbon dioxide emissions

Validation

Hierarchical clustering algorithms (agglomerative method) and partitional clustering algorithms (K-Means) are two main groups of clustering algorithms that offer valuable approaches to clustering validation. Arguments used to validate the results of Agglomerative, including flexibility and ability for more complex data without determining the number of clusters in advance. K-means clustering is favorable in speed, flexibility, efficiency, and ease of implementation on large datasets although it has limitations [25]. The technique used to validate the cluster is the silhouette index. The optimal clustering number is obtained from the minimum and mean distances among clusters. Formula *Silhouette* index [26]

$$\bar{S} = \frac{1}{n} \sum_{i=1}^n \frac{b(i)-a(i)}{\max\{a(i),b(i)\}}$$
 Where $a(i)$ = mean distance node i to others in the cluster. $b(i)$ = minimum distance between node i and another. \bar{S} adalah $-1 \leq \bar{S} \leq 1$. If the value of \bar{S} Is close to 1 then it is a good cluster; if close to 0, otherwise. Using the Python software made available by the Python Software Foundation and powered by the Google Collaboratory engine, often known as Google Colab, the location set covering the problem model is validated. Researchers who want to execute and test Python code can use Google Colab, a free Jupyter notebook hosted on the Google Cloud. K-means clustering and Agglomerative Hierarchical Clustering are the techniques used for model validation (AHC). The number of facilities (potential points) opened on the data set generated from the maximal set covering the problem model and two methods, namely K-means clustering and Agglomerative Hierarchical Clustering (AHC). Figure 6 illustrates two methods.

(a). Value of K-Means Clustering



(b). Value of Agglomerative Hierarchical Clustering

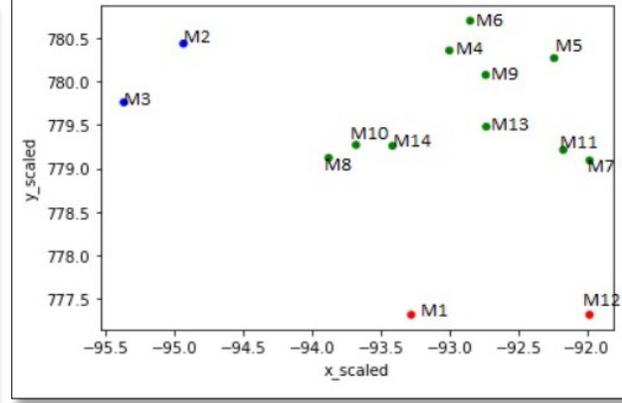


Figure 6. Values of K-Means and Agglomerative Hierarchical Clustering

Based on Figure 6, the K-means clustering model shows three clusters, highlighted in red (K_mC_1), blue (K_mC_2), and green (K_mC_3). Cluster K_mC_1 coverage $M_7, M_8, M_{10}, M_{11}, M_{13}, M_{14}$. Cluster K_mC_2 coverage $M_2, M_3, M_4, M_5, M_6, M_9$ and Cluster K_mC_3 coverage M_1, M_{12} . Second, the bottom-up agglomeration strategy employing the Agglomerative Hierarchical Clustering (AHC) method combines each gene that starts to cluster as one of the genes climbs up the hierarchy. This technique creates three clusters K_mC_1 (red) coverage M_1, M_{12} , Cluster K_mC_2 (blue) coverage, M_2, M_3 , and cluster K_mC_3 coverage $M_4, M_5, M_6, M_7, M_8, M_9, M_{10}, M_{11}, M_{13}$, and M_{14} . Meanwhile, validation using the silhouette index is 0.66 (K-means) and 0.40 (AHC) with an optimal cluster of 3. This value is close to one, so it is called a good cluster. The comparison of the maximal set covering the problem model and clustering methods to determine the demand location is illustrated in Table 5.

Table 5. The validation ratios of the three methods in determining demand location

Scenarios	Methods	Open facilities (P)	Total Clustering	Facilities/ Clustering	Coverages	Demand location
First	Maximal location problem	3	-	P_1	M_2, M_5, M_{14}	3
				P_2	$M_1, M_3, M_4, M_8, M_9, M_{12}$	6
				P_3	$M_6, M_7, M_{10}, M_{11}, M_{13}$	5
Second	K-Means Clustering	-	3	K_mC_1	$M_7, M_8, M_{10}, M_{11}, M_{13}, M_{14}$	6
				K_mC_2	$M_2, M_3, M_4, M_5, M_6, M_9$	6
				K_mC_3	M_1, M_{12}	2
Thirdly	Agglomerative Hierarchical Clustering	-	3	K_mC_1	M_1, M_{12}	2
				K_mC_2	M_2, M_3	2

K_{mC3}	$M_4, M_5, M_6, M_7,$ M_8, M_9, M_{10}, M_{11} M_{13}, M_{14}	10
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The M_3 potential point, with a value of 0.575, has the highest emission need among the three scenarios based on the table above. In contrast, the second and third scenarios occurred in the K_{mC_2} cluster. In the first scenario, P_2 facilities have the farthest distance time, resulting in an energy expenditure of 11 km, 5598 L, and 0.170 BTU. The highest risk of 5832 lies in the M_2 coverage, particularly in the K_{mC_2} cluster in the k-means and Agglomerative Hierarchical Clustering methods.

Based on the fourteen potential locations with K-means clustering and Agglomerative Hierarchical Clustering (AHC), there are 3 clusters were formed (K_{mC_1} ; K_{mC_2} ; K_{mC_3}). Validation of cluster formation using the silhouette index was 0.66 (K-means) and 0.40 (AHC). There is one location that has a high-risk impact (M_5) with an R-value of 8748 from an average of 3431 (0.132%). Meanwhile, the travel time used is less than 8 minutes at a constant speed of 70 km/hour. Vehicles assigned to potential locations (M_2 , M_{14} , and M_6) consume and emit a total of 0.17 L and 2.35 kg of carbon dioxide at a distance of 9-10 km. The results are based on consumption variables (liters), distance (km), CO₂ emissions (kg), and emissions/BTU which show green, red, orange, and blue colors, and the parameters used are emissions and energy which have values of 2.5 and 3025 BTU respectively. In contrast, four locations (M_{11} , M_{12} , M_{13} , and M_{14}) experienced a decrease in dioxide emissions over three months based on the moving average method forecast (Figure 5).

CONCLUSION

This study analyses the situation of maximum set covering by considering risk time and carbon emission. This can occur in another region overseas. Empirical evidence This research concludes that three facilities have opened based on time and the most significant risk on potential point P_2 by 8748. On the other hand, the highest emission value is 0.24484 for cluster K_{mC_2} coverage M_3 . For further research, we will develop a green vehicle routing model to influence carbon emission efficiency, and the government will create policies on intelligent logistics. Indefinitely, regional clustering prioritizes the elderly based on low and moderate risk levels in big cities after pandemic outbreaks. Likewise, this study did not explore a vehicle type. Consequently, hospital administrators should enter into a contract with a third party before deciding on the type of vehicle employed throughout the operation process,

REFERENCES

- [1] X. Taouktsis and C. Zikopoulos, "A decision-making tool for the determination of the distribution center location in a humanitarian logistics network," *Expert Syst. Appl.*, vol. 238, no. PC, p. 122010, 2024, doi: 10.1016/j.eswa.2023.122010.
- [2] I. Alturki and S. Lee, "A systematic survey of multicriteria models in humanitarian logistics," *Int. J. Disaster Risk Reduct.*, vol. 102, no. September 2023, p. 104209, 2024, doi: 10.1016/j.ijdrr.2023.104209.
- [3] Y. Yang, Y. Yin, D. Wang, J. Ignatius, T. C. E. Cheng, and L. Dhamotharan, "Distributionally robust multi-period location-allocation with multiple resources and capacity levels in humanitarian logistics," *Eur. J. Oper. Res.*, vol. 305, no. 3, pp. 1042–1062, 2023, doi: 10.1016/j.ejor.2022.06.047.
- [4] UN OCHA, "Global Humanitarian Overview 2022," 2021. doi: <https://doi.org/10.18356/9789210012423>.
- [5] V. Raja Sreedharan, V. Kek, M. Dhanya, S. Anjali, and P. Arunprasad, "Understanding the role of logistics in humanitarian operations: Key findings and analysis from literatures," *Int. J. Logist. Syst. Manag.*, vol. 36, no. 4, pp. 463–494, 2020, doi: 10.1504/IJLSM.2020.108961.
- [6] B. M. Beamon and B. Balcik, "Performance measurement in humanitarian relief chains," *Int. J. Public Sect. Manag.*, vol. 21, no. 1, pp. 4–25, 2008, doi: 10.1108/09513550810846087.
- [7] H. Dangi, A. K. Bardhan, and A. S. Narag, "Humanitarian relief logistics: An exploratory study for need and

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- importance of performance measurement system,” *Int. J. Logist. Syst. Manag.*, vol. 13, no. 1, pp. 1–16, 2012, doi: 10.1504/IJLSM.2012.048630.
- [8] M. S. M. Daud *et al.*, “Humanitarian logistics and its challenges: The literature review,” *Int. J. Supply Chain Manag.*, vol. 5, no. 3, pp. 107–110, 2016.
- [9] P. S. Muttaqin, R. A. Finata, and A. A. Masturo, “Facility Location Model for Emergency Humanitarian Logistics Using Set Covering and Analytic Network Process (ANP) Method,” *IPTEK J. Proc. Ser.*, vol. 0, no. 5, p. 49, 2020, doi: 10.12962/j23546026.y2020i5.7931.
- [10] A. S. Thomas, “Humanitarian Logistics : Enabling Disaster Response , Fritz Institute,” p. 17, 2008.
- [11] B. Balcik and B. M. Beamon, “Facility location in humanitarian relief,” *Int. J. Logist. Res. Appl.*, vol. 11, no. 2, pp. 101–121, 2008, doi: 10.1080/13675560701561789.
- [12] P. Chaicharoenwut, J. Koiwanit, P. Changpetch, S. Buatongkue, and C. Yuangyai, “Integrating Spatial-Temporal Risk Factors for an Ambulance Allocation Strategy: A Case Study in Bangkok,” *MATEC Web Conf.*, vol. 192, pp. 1–4, 2018, doi: 10.1051/mateconf/201819201038.
- [13] Masdon, “Kebutuhan Ambulance Meningkatkan Selama Covid-19, DFSK Ubah Super Cab Jadi Ambulance Karoserian,” 2020. [Online]. Available: <https://www.ototrend.com/mob-trend/138-info-mobil/22472-2020-07-03c-17-29>
- [14] M. S. Daskin, *Network and Discrete Location Models, Algorithms, and Applications*. New York: A Wiley-Interscience Publication JOHN WILEY & SONS, INC. Canada, 1995.
- [15] B. Özkan, S. METE, E. ÇELLİK, and E. ÖZCEYLAN, “Gis-Based Maximum Covering Location Model in Times of Disasters: the Case of Tunceli,” *Beykoz Akad. Derg.*, pp. 100–111, 2019, doi: 10.14514/byk.m.26515393.2019.sp/100-111.
- [16] W. Rusiawan, P. Tjiptoherijanto, E. Suganda, and L. Darmajanti, “System Dynamics Modeling for Urban Economic Growth and CO2 Emission: A Case Study of Jakarta, Indonesia,” *Procedia Environ. Sci.*, vol. 28, no. Sustain 2014, pp. 330–340, 2015, doi: 10.1016/j.proenv.2015.07.042.
- [17] G. Timothy, “Global Energy Review 2021,” 2021. [Online]. Available: <https://iea.blob.core.windows.net/assets/d0031107-401d-4a2f-a48b-9eed19457335/GlobalEnergyReview2021.pdf>
- [18] M. Rahman *et al.*, “Location-allocation modeling for emergency evacuation planning with GIS and remote sensing: A case study of Northeast Bangladesh,” *Geosci. Front.*, vol. 12, no. 3, p. 101095, 2021, doi: 10.1016/j.gsf.2020.09.022.
- [19] A. Sadeghi, F. Aros-Vera, H. Mosadegh, and R. YounesSinaki, “Social cost-vehicle routing problem and its application to the delivery of water in post-disaster humanitarian logistics,” *Transp. Res. Part E Logist. Transp. Rev.*, vol. 176, no. August 2022, p. 103189, 2023, doi: 10.1016/j.tre.2023.103189.
- [20] L. Shaw, S. K. Das, and S. K. Roy, “Location-allocation problem for resource distribution under uncertainty in disaster relief operations,” *Socioecon. Plann. Sci.*, vol. 82, no. PA, p. 101232, 2022, doi: 10.1016/j.seps.2022.101232.
- [21] H. Sun, J. Li, T. Wang, and Y. Xue, “A novel scenario-based robust bi-objective optimization model for humanitarian logistics network under risk of disruptions,” *Transp. Res. Part E Logist. Transp. Rev.*, vol. 157, no. December 2021, p. 102578, 2022, doi: 10.1016/j.tre.2021.102578.
- [22] N. M. Hashim, S. S. R. Shariff, and S. M. Deni, “Capacitated maximal covering location allocation problem during flood disaster,” *Adv. Sci. Lett.*, vol. 23, no. 11, pp. 11545–11548, 2017, doi: 10.1166/asl.2017.10325.
- [23] P. Chaicharoenwut, J. Koiwanit, P. Changpetch, S. Buatongkue, and C. Yuangyai, “Integrating Spatial Risk Factors for an Ambulance Allocation Strategy: A Case Study in Bangkok,” in *MATEC Web of Conferences 192; ICEAST 2018*, 2018. doi: <https://doi.org/10.1051/mateconf/201819201038>.
- [24] Redaksi, “Kota Mojokerto PPKM Level 1,” *Merdeka News*, 2021. [Online]. Available: <https://www.merdekanews.id/2021/11/kota-mojokerto-ppkm-level-1-wali-kota.html>
- [25] A. M. Ikotun, A. E. Ezugwu, L. Abualigah, B. Abuhajja, and J. Heming, “K-means clustering algorithms: A

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comprehensive review, variants analysis, and advances in the era of big data,” *Inf. Sci. (Ny)*., vol. 622, pp. 178–210, 2023, doi: 10.1016/j.ins.2022.11.139.

- [26] X. Wang and Y. Xu, “An improved index for clustering validation based on Silhouette index and Calinski-Harabasz index,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 569, no. 5, 2019, doi: 10.1088/1757-899X/569/5/052024.