

# Clustering-based NSGA-II on Multi-Objective Location-Routing Problem

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## ABSTRACT

Determining facility locations and planning routes for efficient goods/materials distribution in the supply chain, known as the location-routing problem (LRP), poses a significant challenge in logistics. This research focuses on developing a method to achieve desirable outcomes in LRP with soft time windows by integrating clustering techniques with the NSGA-II algorithm. A case study is conducted to optimize commodities distribution in D.I Yogyakarta, Indonesia using the proposed method. The study demonstrates how clustering can enhance the results of the multi-objective location-routing problem with time windows (MLRPTW) through analysis. The solution set reveals that the clustering-based NSGA-II outperforms the classical approach in terms of both objective functions (cost minimization and service level maximization). By grouping retailers based on similarities in location and opening time windows, the method improved population initialization, resulting in lower distribution center (DC) costs and higher retailer satisfaction. Retailers within the same cluster tend to share the same DC, which is closer in proximity, and also tend to have similarities in terms of working hours (time windows). Moreover, incorporating clustering within NSGA-II decreases the computational time which is preferable by the decision maker. We also explored and compared k-medoids as a clustering method alternative, the result shows there is no significant improvement compared to k-means.

## Keywords:

Location-routing problem; multi-objective; Non-dominated Sorting Genetic Algorithm (NSGA)-II; clustering; last-mile delivery

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## 1. Introduction

Last-mile delivery refers to the final distribution or delivery process from companies to customers or retailers (Guerrero & Díaz-Ramírez, 2017). For retail companies, last-mile delivery is an ongoing challenge that is inseparable from the functioning of their businesses. Last-mile delivery is a stage in the supply chain that is generally inefficient and contributes to 28% of logistics costs (which is the highest compared to other stages). Researchers stated that last-mile delivery is the most challenging part of logistics but also the most crucial aspect for businesses to maximize customer satisfaction and profit (Ismail & Jokonya, 2023). The efficiency of last-mile delivery is also contingent upon one of the tactical decisions within the supply chain, service network design. The ability to optimize service network design is essential for companies to tackle the challenges in last-mile delivery.

To create a service network design, determining the location of facilities and distribution routes are the most critical issues (Windras Mara et al., 2021), which is often referred to as the location-routing problem (LRP). Research in the field of LRP continues to increase year by year (Windras Mara et al., 2021). However, due to the complexity of this problem, many researchers are still exploring LRP further. Nagy & Salhi (2007) defined LRP as the planning of determining locations by involving aspects of distribution route planning. Meanwhile, Drexel & Schneider (2015) defined LRP more generally as a mathematical optimization problem that must produce at least two interdependent

decisions: 1) which locations to use, 2) which distribution routes to build, which customer clusters to create, and how to sequence deliveries to customers. In simple terms, LRP consists of 2 sub-problems, namely facility location problem (FLP) and vehicle routing problem (VRP). In terms of decision-making phases in supply chain management, these two sub-problems are in different phases. FLP belongs to the strategic decision level, which is long-term in nature, while VRP belongs to the tactical or operational decision level, which is short or medium-term in nature and often changes.

The advancement of research in the Location-Routing Problem (LRP) can be observed through the development of models, scenarios, solution methods, physical characteristics, and objective functions involved in these studies. The methods commonly employed can be classified into two categories: exact methods and approximation methods (including classical heuristics, meta-heuristics, and simulations). Furthermore, scenario development encompasses the utilization of different types of data (deterministic, fuzzy, or stochastic), planning periods (static, periodic, or dynamic), objectives (single or multiple), time windows structure (not considered, soft-time windows, hard time windows), and many more factors. As for the objective functions commonly used in LRP models, they can be classified as follows: monetary, environmental, equity, and performance ([Windras Mara et al., 2021](#)).

When an LRP model incorporates time windows, the problem is better known as LRP with time windows (LRPTW). Time windows can be represented as a hard constraint where the distribution process can only be done during the time window period, or as a soft constraint where the distribution process can be done outside the time window with penalties ([Windras Mara et al., 2021](#)). The concept of time windows was introduced by [Kolen et al \(1987\)](#) when researching VRP using the branch-and-bound method to minimize the total travel distance of the route created. [Semet & Taillard \(1993\)](#) conducted real-life VRP research using the tabu search method and considered time windows in delivery. More specifically in LRP, [Zarandi et al. \(2013\)](#) studied capacitated LRP by considering transportation time and demand as fuzzy variables using fuzzy chance constraint programming (CCP). [Gharavani & Mostafa \(2015\)](#) applied LRPTW with semi-soft time windows where late delivery would result in penalty costs.

Regarding objective function, multi-objective (MO) is widely used in LRP where the optimization goals are not only focused on one objective, called MLRPTW (multi-objective location-routing problem). In most cases, supply chain optimizations have a focus on cost minimization or profit maximization before incorporating other objective functions such as: maximizing customer/retailer satisfaction level, balancing driver's workload, minimizing carbon emissions, etc. However, in a competitive business situation, it is important to not only consider economic-centric objective function but also gain more competitive advantage for the supply chain. Thus, this method proposes a multi-objective location routing problem while simultaneously minimizing cost and maximizing service level. When optimization objectives are more than one, this makes the problem classified as NP-hard which is a complex problem ([Liu et al., 2011](#)). Generally, NP-hard problems are solved using metaheuristic methods. For example, the particle swarm optimization (PSO) which has been modified is used to solve MO problems, thus called MOPSO. The development of MOPSO has been done by many researchers such as [Parsopoulos & Vrahatis \(2002\)](#) who developed a weighted aggregation approach, [Hu & Eberhart \(2002\)](#) with dynamic neighborhood PSO, and [Coello et al. \(2005\)](#) using a secondary repository. Also, [Parayoga & Asih \(2021\)](#) tried to compare the performance of MOPSO and NSGA-II in solving basic distribution cases (MLRPTW) and found that in general, the performance of NSGA-II is still better. This research successfully addressed this problem within a shorter computational time compared to [Dharmika \(2019\)](#), who solved the case using exact goal programming. Despite NSGA-II seems as the most appropriate method for MLRPTW with metaheuristics, the service levels obtained from this model are still low and far from optimal.

To improve the performance, some researchers have explored the incorporation of clustering algorithms to enhance the efficiency and effectiveness of the delivery process. Some researchers tried to add clustering algorithms to get more optimal results in a shorter time in solving MLRPTW. [Hosoda & Irohara \(2019\)](#) applied k-means clustering with parameter modification in solving LRPTW. The model applied clustering so that decision-makers can know which customers are served using insource and outsource, then mixed integer programming is applied to form routes on insource clusters. [Wang et al. \(2018\)](#) applied k-means clustering algorithm as a first step before solving MLRPTW problems with metaheuristic methods. The clustering process is done simultaneously with the routing process to evaluate the results of their combination.

[Wang et al. \(2018\)](#) demonstrated the importance of accurate clustering in optimizing distribution networks, minimizing logistics costs, preventing supply disruptions, and enhancing customer satisfaction. The application of accurate clustering enables the grouping of customers/retailers based on similarity in characteristics such as demand type, time windows, and, of course, geographical proximity. This grouping is expected to improve the service level.

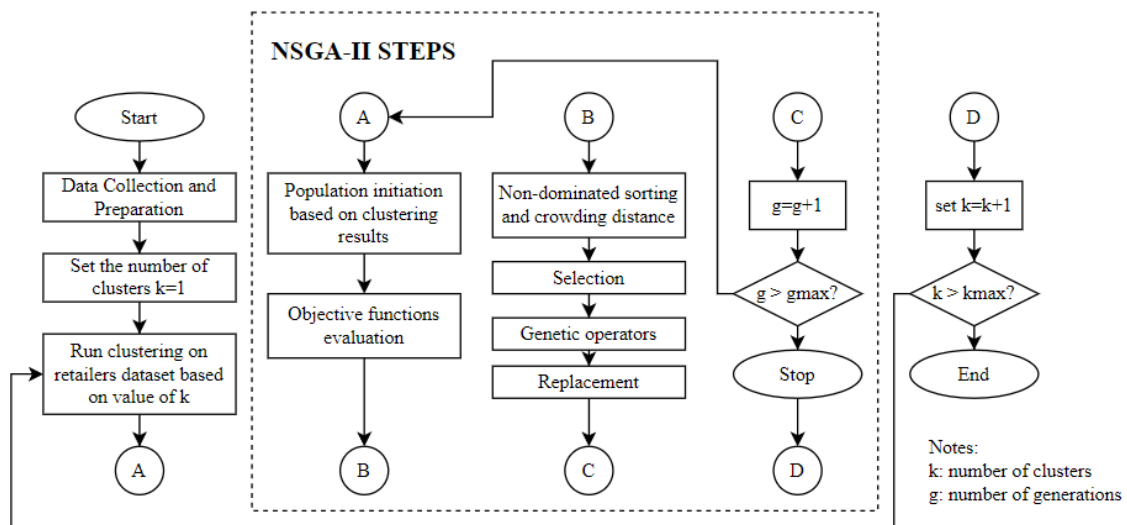
When clustering is combined with a metaheuristic model, it provides a wide range of feasible solutions as an initiation. However, research on the implementation of clustering remains intriguing because if the resulting clusters do not align with the required criteria (e.g., an excessive number of clusters), it can disrupt the optimality of the generated solutions [Wang et al. \(2018\)](#).

Incorporating clustering in MLRPTW is an interesting topic to be further observed. [Wang et al.'s \(2018\)](#) and [Hosoda & Irohara's \(2019\)](#) research needs to be developed further, the use of clustering methods other than k-means allows for more optimal results in terms of achieving objective functions or model completion time. The k-medoid method can be considered because several studies show that the results given are better than k-means. [Shah & Singh \(2012\)](#) compared the performance of k-means and k-medoids and found that the performance of k-medoids is generally better because it is more robust against the presence of outliers which often arise in various datasets.

This research discusses the application of clustering-based NSGA-II (with k-means and k-medoids) in MLRPTW. The clustering method will be carried out as an initialization step and will simultaneously determine the distribution route using NSGA-II. We aim to find the best MLRPTW method by comparing the classical NSGA-II and the two clustering-based NSGA-II, considering their relative effectiveness (objective functions) and efficiency (computational time). Two objective functions are considered in this paper: monthly logistics cost and retailer service level. Moreover, this research also provides some improvements related to the parameters and techniques to have a more applicable version of the clustering-based NSGA-II.

## 2. Methodology

The model starts with retailer clustering based on location and time windows. Then, one closest DC will be assigned to the cluster and NSGA-II will be applied to iteratively generate the route and optimize both objective functions. The method is depicted in Figure 1 which is adapted from [Wang et al. \(2018\)](#).



**Figure 1.** Illustration of the proposed clustering-based NSGA-II for MLRPTW, adapted from ([Wang et al., 2018](#))

There are two tiers of iterations within the model, the NSGA-II iteration, and the clustering method iteration. The parameters applied to NSGA-II are independent of those associated with the clustering parameters. Concerning the steps within NSGA-II, non-dominated sorting is carried out by selecting the first front (i.e., the front not dominated by other fronts from any of the objective functions). The chosen selection method is binary tournament selection and crowding distance, while the employed genetic operators consist of cycle crossover and swap mutation ([Celine, 2020](#)).

### 2.1 Problem Statement

This paper addresses a distribution network comprising a distribution center and retailers (single-echelon network). This problem is generally encountered in the distribution network of grocery minimarkets, where the company has several retailers scattered across various cities. The company always seeks to minimize costs and

maximize service levels for each of its retailers who have time windows. Therefore, this problem can be classified as a multi-objective location-routing problem with time windows (MLRPTW).

### 2.2 Model Setting

We define a supply distribution network consisting of  $D$  potential DC ( $d \in D$ ), and  $I$  retailer ( $i \in I$ ). The goods distribution flows from the DC to the retailer connected by  $K$  corresponding vehicle ( $k \in K$ ). Without losing the nature of business, the distribution system is following these assumptions:

1. The material flow and distribution network before the DC are not considered.
2. The retailer's demand is deterministic and homogeneous.
3. The capacity of each DC is considered unlimited.
4. No limitation on the number of available vehicles
5. Vehicle speed is constant (50 km/h)

### 2.3 Mathematical Programming Model

#### 2.3.1 Mathematical Model

The proposed MLRPTW is formulated as a mixed-integer programming model with two objective functions which are minimizing logistics cost and maximizing retailer service level. The model is designed to simultaneously generate three main aspects: determine the best location for distribution centers (DC), assign each retailer to the most appropriate depot, and create an efficient routing system that can serve all retailers respecting the objective function.

- Notations, Sets, and Parameters

**Table 1.** Parameters and Decision Variables

Symbol	Definition
$D$	Set of potential DC ( $d \in D$ )
$R$	Set of retailers ( $r \in R$ )
$K$	Set of vehicle type ( $k \in K$ )
$U_{ik}$	Auxiliary variable for subtour elimination (vehicle $k$ on retailer $i$ )
$g^d$	Fixed cost of DC $d$
$f_k$	Fixed cost of vehicle $k$
$VC_k$	Variable cost of vehicle $k$
$E_r$	Demand of retailer $r$
$Q_k$	Capacity of vehicle $k$
$dis_{ij}$	Distance from node $i$ to node $j$
$t_{ij}$	Time needed from node $i$ to node $j$
$Start_{dk}$	Departure time of vehicle $k$ from DC $d$
$End_{dk}$	Return time of vehicle $k$ to DC $d$
$[A_r, B_r]$	Time windows of retailer $r$
$T_r$	Arrival time to retailer $r$
$S_r$	Service time at retailer $r$
$[Open_d, Close_d]$	Time windows of DC $d$
$N$	Number of retailers
$WT$	Working duration
$L(T_r)$	Service level of retailer $r$ (given the goods are delivered at time $T_r$ )
$EET_r$	Endurable earliness time (the earliest service time that retailer $r$ can endure when a service starts earlier than $A_r$ )

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$ELT_r$	Endurable lateness time (the latest service time that retailer $r$ can endure when a service starts later than $B_r$ )
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• Decision Variables:

$X_{ijk} \in \{0,1\} = 1$  if vehicle  $k$  travels from node  $i$  to  $j$  directly and 0 otherwise

$Y_d \in \{0,1\} = 1$  if DC  $d$  is opened and 0 otherwise

$V_k \in \{0,1\} = 1$  if vehicle  $k$  is used and 0 otherwise

$Z_{rd} \in \{0,1\} = 1$  if retailer  $r$  is served by DC  $d$

$$L(T_r) = \left\{ \begin{array}{ll} 0 & \text{if the goods are delivered before } EET_r \\ \frac{T_r - EET_r}{A_r - EET_r} & \text{if the goods are delivered between } EET_r \text{ and } A_r \\ 1 & \text{if the goods are delivered between } A_r \text{ and } B_r \\ \frac{ELT_r - T_r}{ELT_r - B_r} & \text{if the goods are delivered between } B_r \text{ and } ELT_r \\ 0 & \text{if the goods are delivered after } ELT_r \end{array} \right\} \quad (1)$$

• Objective Function

$$\text{Min} \left( f_1 = \sum_{d \in D} g_d Y_d + \sum_{k \in K} f_k V_k + \sum_{i,j \in D \cup R} \sum_{k \in K} X_{ijk} \text{dis}_{ij} V C_k \right) \quad (2)$$

$$\text{Max} \left( f_2 = \frac{1}{I} \left( \sum_{r \in R} L(T_r) \right) \right) \quad (3)$$

Subject to:

$$\sum_{k \in K} \sum_{i \in D \cup I} X_{ijk} = 1, \quad \forall j \in R \quad (4)$$

$$\sum_{i \in D} \sum_{j \in R} X_{ijk} \leq 1, \quad \forall k \in K \quad (5)$$

$$\sum_{d \in D} Y_d \geq 1 \quad (6)$$

$$\sum_{i \in D \cup R} X_{ijk} = \sum_{j \in D \cup R} X_{ijk}, \quad \forall k \in K, i \in D \cup R \quad (7)$$

$$\sum_{j \in R} \sum_{i \in D \cup R} D_j X_{ijk} \leq Q_k V_k, \quad \forall k \in K \quad (8)$$

$$U_{ik} + U_{jk} + N X_{ijk} \leq N - 1, \quad \forall i, j \in R, k \in K \quad (9)$$

$$\sum_{i \in D \cup R} X_{di} + X_{ir} \leq 1 + Z_{rd}, \quad \forall d \in D, j \in R, k \in K \quad (10)$$

$$Y_d \geq X_{ijk}, \quad \forall d, i \in D, j \in R, k \in K \quad (11)$$

$$T_r + S_r \leq B_r + (WT - B_r) \times (1 - L(T_r)), \quad \forall r \in R \quad (12)$$

$$Start_{dk} \geq Open_{d'}, \quad \forall k \in K, d \in D \quad (13)$$

$$End_{dk} \leq Close_{d'}, \quad \forall k \in K, d \in D \quad (14)$$

$$-M(1 - X_{ijk}) - (T_j - T_i - S_i - t_{ij}) \leq 0, \quad \forall i, j \in R, k \in K \quad (15)$$

$$M(1 - X_{ijk}) - (T_j - T_i - S_i - t_{ij}) \geq 0, \quad \forall i, j \in R, k \in K$$

$$-M(1 - X_{djk}) - (T_j - Start_{dk} - t_{dj}) \leq 0, \quad \forall j \in R, d \in D, k \in K$$

$$M(1 - X_{djk}) - (T_j - Start_{dk} - t_{dj}) \geq 0, \quad \forall j \in R, d \in D, k \in K$$

$$-M(1 - X_{idk}) - (End_{dk} - T_i - t_{id}) \leq 0, \quad \forall i \in R, d \in D, k \in K$$

$$M(1 - X_{idk}) - (End_{dk} - T_i - t_{id}) \geq 0, \quad \forall i \in R, d \in D, k \in K$$

$$X_{ijk} = \{0, 1\}, \quad \forall i, j \in D \cup R, k \in K \quad (16)$$

$$Y_d = \{0, 1\}, \quad \forall d \in D \quad (17)$$

$$V_k = \{0, 1\}, \quad \forall k \in K \quad (18)$$

$$Z_{rd} = \{0, 1\}, \quad \forall r \in R, d \in D \quad (19)$$

$$U_{ik} \geq 0, \quad \forall i \in R, k \in K \quad (20)$$

$$T_r \geq 0, \quad \forall r \in R \quad (21)$$

$$Start_{dk} \geq 0, \quad \forall d \in D, k \in K \quad (22)$$

$$End_{dk} \geq 0, \quad \forall d \in D, k \in K \quad (23)$$

Function (1) is used to determine the perceived service level of the retailer based on the delivery time to the retailer. This function is written in fuzzy form and produces a service level value between 0 and 1, according to the accuracy of the delivery. Equation (2) is the objective function for minimizing the total logistics cost, while Equation (3) is the objective function for maximizing the service level. Equation (4) ensures that each retailer is only served once. Equation (5) ensures that each route is only passed once by each vehicle. Equation (6) sets the condition that at least one distribution center (DC) is opened. Equation (7) is the flow conservation constraint to ensure that vehicle  $k$  that has visited a point will exit from that point. Equation (8) is the capacity constraint for each vehicle. Equation (9) is the subtour elimination constraint to ensure that each vehicle will not visit the same point twice, except for DC, and each route must start and end at DC. Equation (10) specifies that the retailer will be served by the same vehicle departing from the serving depot. Equation (11) ensures that the vehicle only departs from the selected DC. Equation (12) accommodates the service level that will be obtained for each retailer. Equations (13) and (14) respectively ensure that the vehicle departs after the DC opening time and returns before the DC closing time. Equation (15) is used to update the arrival time at each retailer and DC. Equations (16-19) ensure that the associated variables are binary. Meanwhile, equations (20-23) are non-negativity constraints for the corresponding variables.

The mathematical model has been verified using simple cases through LINGO software. The verification process was conducted via tracing, demonstrating that this mathematical model is capable of yielding outcomes consistent with actual observations.

#### 2.4 Retailer Clustering Analysis

Before applying the clustering-based NSGA-II, determining an optimal number of clusters is crucial as it affects the effectiveness of an algorithm. When each cluster member is desired to have a high degree of similarity, a larger number of clusters is required. Conversely, if each cluster member does not need to be highly similar, a smaller number of clusters is sufficient (Kothari & Pitts, 1999). The number of clusters that are too small results in poorly separated data, while an excessively large number of clusters increases computational time and leads to overfitting of the data. Therefore, this research starts with identifying the optimal number of clusters as the iteration limit in the clustering-based NSGA-II algorithm.

The clustering method is applied to group retailer data according to their similarity in characteristics. The characteristics used in this study are latitude, longitude, and retailer time windows. The latitude and longitude features are chosen since location could determine distance which leads to minimizing route distance (cost minimization) as well as minimizing delivery time (service level maximization). Meanwhile, the time windows feature is chosen to ensure that retailers with similar time windows are served simultaneously (leads to service level maximization). The use of the clustering method is expected to prioritize delivery routes to retailers with similar characteristics, after obtaining an initial set of retailers randomly. The clustering results determine the selected distribution centers (DCs) for each retailer. The DCs selected for each cluster are the closest to the cluster center, thus there is a possibility that the same DC may be assigned to different retailers. The chromosome initialization process in the population is carried out using the k-means clustering method. To determine the maximum number of significant clusters, this study uses the elbow method and silhouette value. Both methods are commonly used in determining the number of clusters in k-means clustering because they can provide reliable and accurate results (Nanjundan et al., 2019). We employed both methods to avoid potential biases that may occur when relying solely on one method.

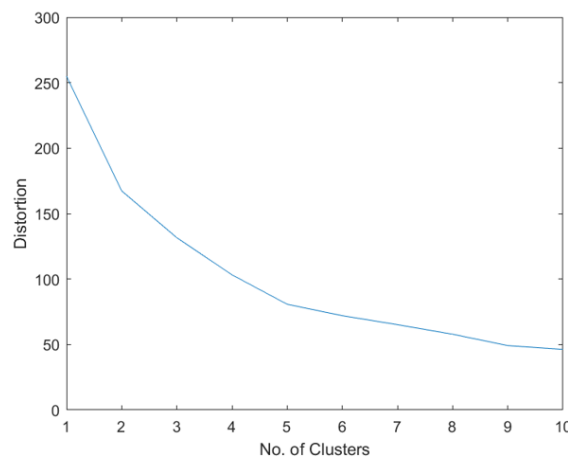
### 3. Methodology

#### 3.1 Clustering Analysis

##### 3.1.1 Clustering Analysis with Elbow Method

With the elbow method, the optimal number of clusters can be determined from the graph of the number of clusters (k) against the distortion. Generally, a larger number of clusters will provide a better explanation of the variation, where the error from each point's location to the cluster center will be lower. However, having too many clusters will increase the time and cost of the clustering process. Moreover, having too many clusters may result in overfitting, which makes the insights gained from the clustering process insignificant.

The elbow method is used to select the number of clusters where the change in distortion is still significant. When the change in distortion from cluster k to cluster k+1 is no longer significant, this method suggests choosing cluster k.

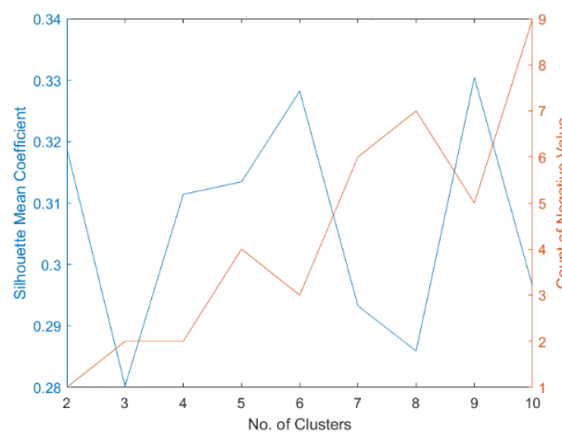


**Figure 2.** Maximum number of cluster analysis with Elbow Method

From Figure 2, the change in distortion begins to flatten out when the number of clusters reaches 6. Adding another cluster to make it 7 only slightly decreases the distortion value, indicating that using a maximum of 6 clusters is sufficient for the NSGA-II model iteration based on clustering. However, it should be noted that the elbow method is subject to some level of subjectivity in determining the point where the change in distortion is no longer significant. Therefore, it would be better to check with other methods in making decisions about the number of clusters to be used.

##### 3.1.2 Clustering Analysis with Silhouette Value

The evaluation process for selecting the optimal number of clusters using the silhouette value method is based on maximizing the average silhouette value for all points in each k (number of clusters) and minimizing the number of points that have negative silhouette values in each k.



**Figure 3.** Maximum number of cluster analysis with Silhouette Value

From Figure 3, it can be observed that there is no significant trend for the silhouette mean coefficient. However, the number of negative silhouette scores continues to increase as the number of clusters increases. The highest value of the silhouette mean coefficient is achieved when the number of clusters is 6 and 9. However, a decrease occurs for clusters 7 and 8, accompanied by an increase in the number of negative silhouette scores. Therefore, this study will focus on iterating up to 6 clusters, which is also consistent with the analysis results obtained using the elbow method for determining the optimal number of clusters.

### 3.2 Real World Application

#### 3.2.1 Data

Accurate data is essential for assessing optimization performance and comparing the results. We used mixed (hypothetical and actual world) data from some previous research. It consists of 9 potential DCs and 86 retailers. The geographical location (latitude and longitude) of retailers obtained from Pradana (2015) and Maruti (2017) based on a retail chain in D.I Yogyakarta, Indonesia whereas the vehicle and data obtained from a survey and calculation from Maruti (2017). Time windows and demand of retailer are hypothetical and randomized by a certain parameter from Pradana (2015).

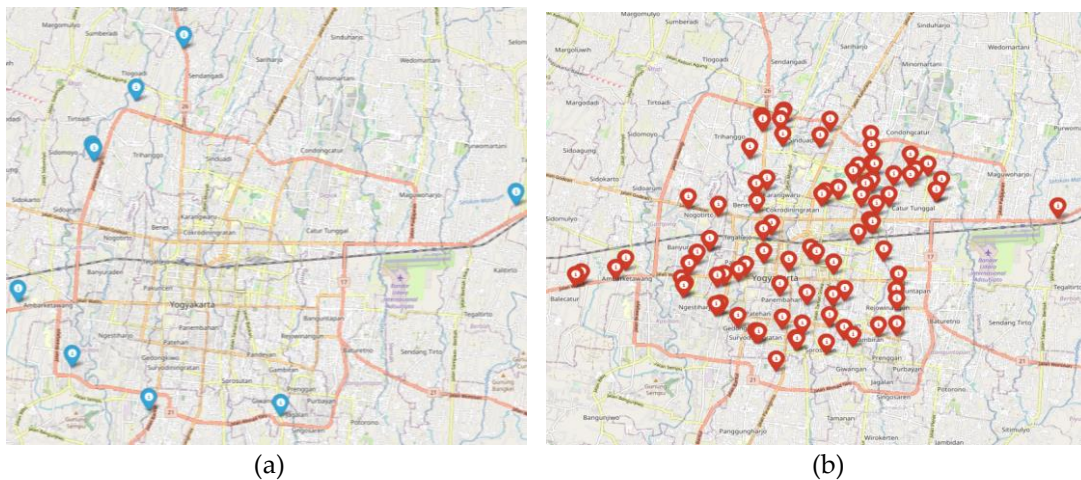


Figure 4. Location of DC and retailers. (a) Candidate of distribution centers locations; (b) Retailers locations.

#### 3.2.2 Result

The NSGA-II clustering-based method was applied to the data to solve the problem of determining the location of distribution centers and routes for distributing essential goods in the Yogyakarta Special Region. The parameters used in this study were based on the research conducted by Wang et al. (2018), with a population size = 100, crossover rate= 0.9, mutation rate=0.1, number of runs= 10, and a stopping criterion of a maximum= 500 generations. Iterations were performed from forming 1 to 6 clusters. The results of the running are shown in Figure 5.

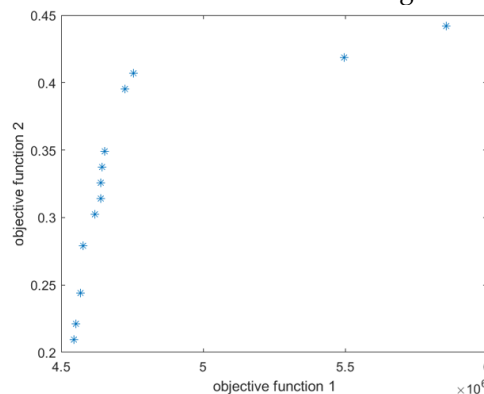


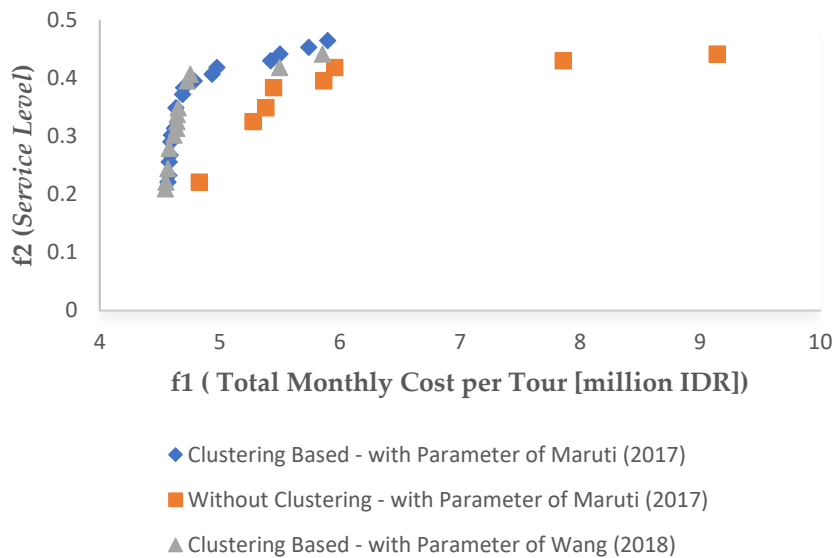
Figure 5. Pareto front of clustering-based NSGA-II on staple commodities distribution case

Based on the model running results, there is a trade-off between objective function 1 (minimizing total cost) and objective function 2 (maximizing service level). This model produces 13 sets of best solutions, where each set of solutions has a different tendency towards the two objective functions. The selection of the best set of solutions is subjective and tailored to the real-world needs and preferences of the decision maker.

Based on the results of the model, we can see that the service level is not satisfying yet, where the maximum service level achieved is only 44%. The possible reasons for the low service level in this case are as follows:

- 1 The NSGA-II clustering-based model's performance in exploring global optimum solutions is not yet optimal.
- 2 The influence of hypothetical time windows data makes it possible that higher service levels will not occur. This can happen if meeting a high service level requires a high cost, making it difficult for solutions that result in high service levels to be Pareto Front.

To have better visibility of the model's performance, we compared the model by the NSGA-II (without clustering and using the same parameters) and clustering-based NSGA-II with [Maruti's \(2017\)](#) parameter. The parameters used in the previous study by [Maruti \(2017\)](#) are the following; a population size = 150, crossover rate= 0.9, mutation rate= 0.1, number of runs= 5, and a stopping criterion of a maximum= 1200 generations. The results of these 3 models are presented in Figure 6 and Table 2.



**Figure 6.** Pareto Front of NSGA-II (Without Clustering) vs. Clustering-based NSGA-II

Based on Figure 6, it can be concluded that the clustering-based NSGA-II produces a better Pareto front than without clustering. Generally, the total cost required is lower, although there is no significant difference in the service level.

**Table 2.** Computational Time and MV Comparison of NSGA-II vs. Clustering-based NSGA-II

Model	Computational Time (s)	MV
NSGA-II	5692	7.04482E-08
Clustering-based NSGA-II with Parameter of <a href="#">Maruti (2017)</a>	38627	8.41413E-08
Clustering-based NSGA-II with Parameter of <a href="#">Wang et al. (2018)</a>	17455	8.56029E-08

The performance of the clustering-based NSGA-II is also better based on the measurement value (MV) for both models, as shown in Table 2. The MV value is obtained from the maximum value of  $f2/f1$  for each solution on the Pareto front, so the higher the MV value, the higher the service level obtained per unit of total logistics cost. Spending

Rp.1 for total logistics cost will result in a service level of  $8.41413E-08$  for clustering-based NSGA-II with [Maruti's \(2017\)](#) parameter and a service level of  $8.56029E-08$  with [Wang et al.'s \(2018\)](#) parameter, while for NSGA-II without clustering, it will only result in a service level of  $7.04482E-08$ . Based on Table 2, it can also be concluded that the performance of the clustering-based NSGA-II model with [Wang et al.'s \(2018\)](#) parameter is better than using [Maruti's \(2017\)](#) parameter.

#### 4. Discussions

Several factors can cause the clustering-based NSGA-II performance to be better than without clustering. These factors include:

1. Homogeneity of retailers in the initial population of chromosome

In the clustering-based NSGA-II model, the sequence of retailers in the chromosome is sorted based on the existing retailer clusters, and then randomized for the sequence of each cluster member. In solving the MLTPTW case with the NSGA-II model, route formation is done according to the sequence in the chromosome. Therefore, the initialization of this clustering-based chromosome makes nearby retailers in terms of location and opening hours tend to be in the same route and DC. The illustration of cluster formation for retailers can be seen in Figure 7, where nearby retailers in terms of location and opening hours are grouped to be on the same route when the model is running. The similarity of routes for nearby retailers in terms of location and opening hours makes it easier for vehicles to deliver goods according to their time windows, thus the service level can be maximized. Meanwhile, in the classical NSGA-II model, route formation is done randomly, and this leads to having some retailers in the same route with significantly different locations and opening hours.

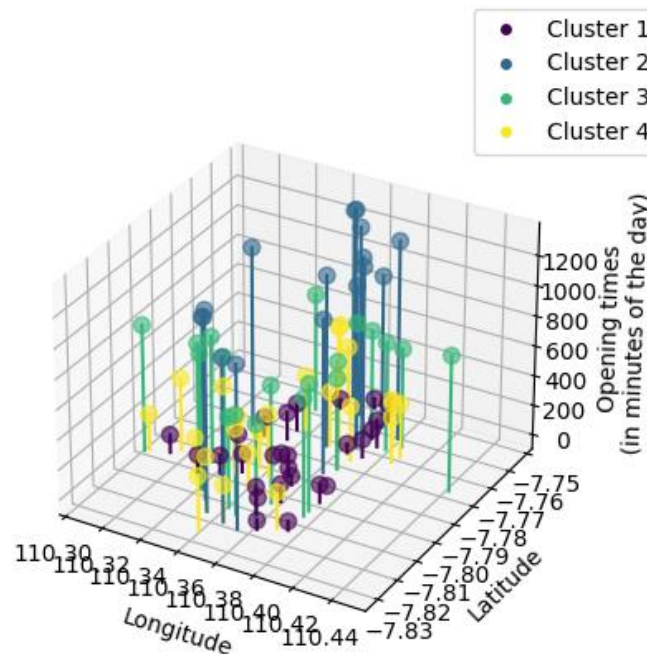
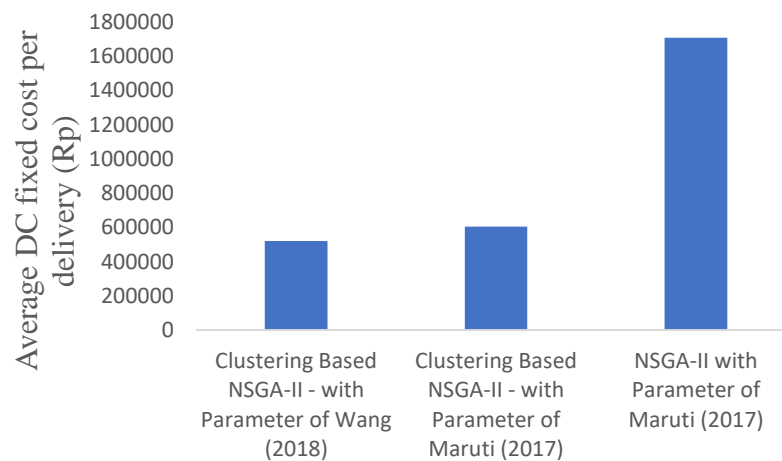


Figure 7. Clustering with 4 clusters sample

The similarity of characteristics among retailers within the same cluster can be observed in the clustering results example for  $k=4$  in Figure 7. For instance, retailers classified into cluster 1 (violet) are distributed among those with opening times ranging from 0-180 minutes in the day (will be open around 12 p.m. to 3 a.m.). On the other hand, retailers belonging to cluster 2 (blue) have opening times ranging from 1020-1320 minutes in the day (will be open around 5 p.m. to 10 p.m.).

2. Number of opened DCs



**Figure 8.** Average DC fixed cost per delivery

The number of opened DCs affects the total logistics costs for each shipment in the case of basic commodity distribution in DI Yogyakarta. In the same case study, [Parayoga \(2021\)](#) mentioned that fixed DC costs contribute to 27% of the total cost per shipment. If we look at the average number of opened DCs for each solution on the Pareto front, it is found that the clustering-based NSGA-II model tends to make decisions that only open one DC. In contrast, the NSGA-II model without clustering tends to open at least two DCs, and Table 3 shows that the average number of opened DCs for each solution is 2.75. This makes the solution from the clustering-based NSGA-II model better at minimizing total costs by minimizing fixed DC costs (by not opening many DCs). The high contribution cost of DCs for each shipment in the NSGA-II model without clustering can also be seen in Figure 8. The non-opening of many DCs is influenced by the number of clusters formed in each iteration. Although the number of opened DCs is not always proportional to the number of clusters, the number of opened DCs will always be less than or equal to the number of clusters in each iteration. If we look at Table 3, it is found that the Pareto front results for the clustering-based NSGA-II model are generally obtained when the number of clusters is 1 or 2, especially when using [Wang et al's \(2018\)](#) parameter.

**Table 3.** Number of DCs opened based on Pareto front result for each model.

Non-dominated solution -th	Number of DCs opened for NSGA-II with <a href="#">Maruti's (2017)</a> Parameter	Number of DCs opened for clustering-based NSGA-II with <a href="#">Maruti's (2017)</a> Parameter	Number of DCs opened for clustering-based NSGA-II with <a href="#">Wang et al.'s (2018)</a> Parameter
1	1	1	1
2	2	1	1
3	3	2	1
4	2	2	1
5	5	2	1
6	3	1	1
7	1	2	1
8	5	1	1
9		1	2
10		1	2
11		1	1
12		1	1

13		1	1
14		1	
15		1	
16		1	
17		1	
Average number of DCs opened	2.75	1.24	1.15

<sup>1</sup> Number of non-dominated solutions produced by each model are varied.

Although it has shown better performance, the computation time required to run the clustering-based NSGA-II model is much longer, about two to three times longer than without clustering. This is because it requires iterations for the six existing clusters. The more maximum number of clusters that want to be observed, the longer the computation time required. Regarding DC selection, the clustering process performed in this model only considers the proximity of the DC location to the centroid (cluster center), without considering DC investment costs. So, there is still a possibility that the model tends to choose DCs that are closer, even though their costs are very high compared to DCs that are relatively cheap but located a little further away.

As a step to improve the algorithm in this model, this research also modified the parameters in the NSGA-II algorithm so that the genetic algorithm process can work faster. The next discussion will focus on modifying the NSGA-II parameters to obtain optimal results in a shorter time with clustering-based NSGA-II.

#### 4.1 NSGA-II Parameter Tuning

In practice, NSGA-II is commonly used for solving cases with time constraints (Wang et al., 2018). By using NSGA-II algorithm parameters from Wang et al. (2018) and Maruti (2017), the clustering-based NSGA-II method tends to require a long time in its model running process. According to Wang et al. (2018), the optimal parameters for solving cases with NSGA-II depend on the scale and problem to be adjusted. Therefore, this study also attempted to modify the genetic algorithm (NSGA-II) parameters so that the running process could be faster while still providing desirable results according to its objective function.

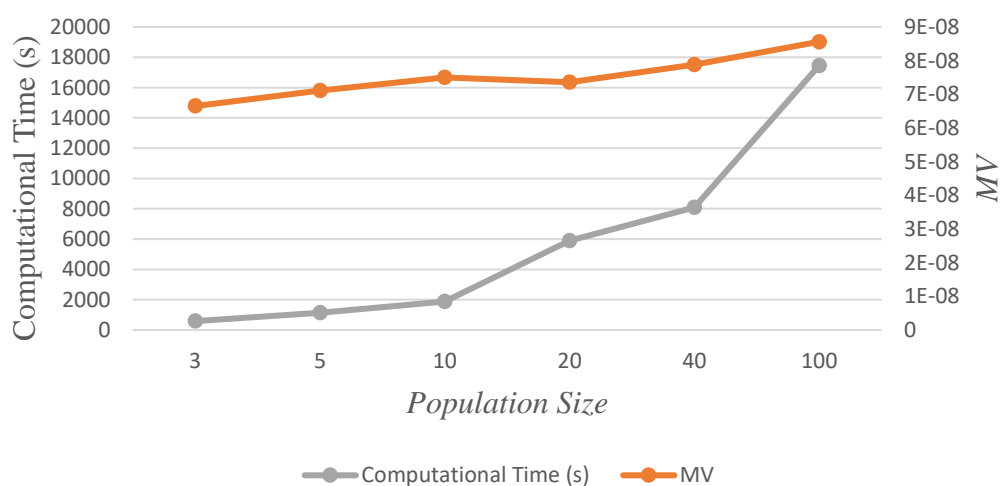


Figure 9. Clustering-based NSGA-II Performance

Sensitivity analysis was conducted by modifying the population size parameter, which has a significant effect on the model's computational time (Pongcharoen et al., 2002). To obtain fast computational time, a scenario was created where the population size was set to 3, 5, 10, 20, and 100, and their performance was compared. The other parameters were set to those of Wang et al. (2018).

Figure 9 shows the performance of each model in terms of MV compared to its computational time. There is generally an increase in MV and computational time as the population size increases. However, when the population size is increased to 20, there is a decrease in MV compared to when the population size is 10. This may occur due to the stochastic factors in the genetic algorithm that may allow a smaller population size to perform better in a certain experiment. Looking at the computational time, there is a significant increase when increasing the population size from 10 to 20.

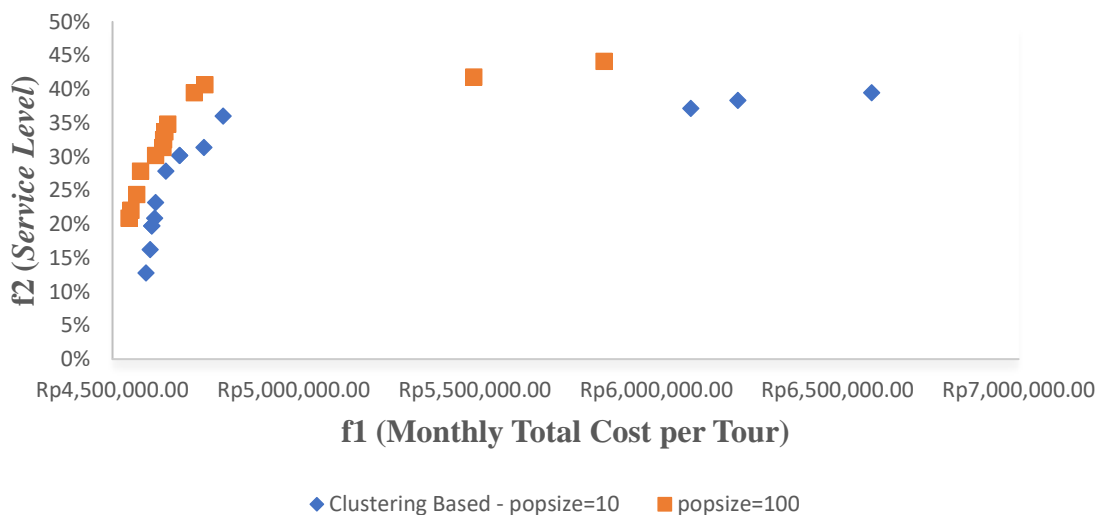


Figure 10. Pareto front of clustering-based NSGA-II with 10 vs. 100 population size



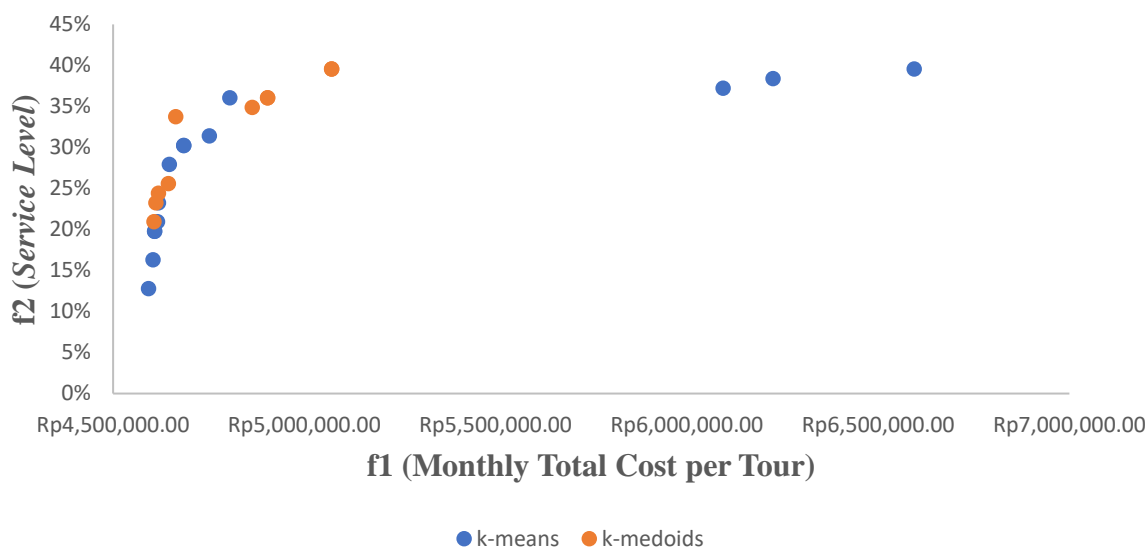
Figure 11. Pareto front of clustering-based NSGA-II with 10 population size vs. NSGA-II with [Maruti's \(2017\) Parameter](#)

A population size of 10 can be an alternative when the running process requires a fast time. With a population size of 10, the time required to run the model can be 10 times faster than using a population size of 100, but the obtained Pareto front results are not significantly different, as shown in Figure 10. It even provides better results compared to the NSGA-II model without clustering from [Celine's \(2020\)](#) study as shown in Figure 11. Therefore, these new parameters can be used when decision-making must be done in a limited time, as well as in the next running process in this study.

While parameter tuning is performed on the clustering-based NSGA-II using k-means, the obtained parameters can also be applied to other clustering methods. As elucidated in Figure 1, NSGA-II parameters are decoupled from clustering parameters, obviating the need for parameter tuning for each clustering method.

#### 4.2 Clustering Method Comparison: K-Means vs. K-Medoids

The use of k-means clustering method is not robust against the presence of outliers. The presence of outliers should be avoided to make the clustering results more reliable. To find an alternative clustering method that is more resistant to outliers, this research also involved the use of k-medoids clustering method. The use of k-medoids is expected to produce more effective and efficient solutions for the same grocery distribution case. Both clustering-based NSGA-II models (k-means and k-medoids based) are run with new parameters, as follows: pop size (Np) = 10, crossover rate (Pc) = 0.9, mutation rate (Pm) = 0.1, no\_runs = 10, and stopping criteria in the form of maximum generation = 500.



**Figure 12.** Pareto front of clustering-based NSGA-II with k-means vs. k-medoids

Both models were run, and the results are obtained as shown in Figure 12. Overall, there is no significant difference in terms of total cost and service level between the two models. The computational time was almost identical, as the required iteration time remained precisely the same for NSGA-II iterations (utilizing the same parameters). Furthermore, the cluster generation time for both methods was efficiently resolved within a very short period using the MATLAB software. However, the total cost range for solutions from the NSGA-II model based on k-medoids is smaller than k-means. In addition, the maximum total cost per shipment for the k-medoids set solution is only Rp5,070,782.05, while in the k-means set solution, it reaches Rp6,594,385.38. Therefore, the use of k-medoids algorithm could be a slightly better alternative for the NSGA-II model based on clustering.

## 5. Conclusion

In this study, we adopted and extended the clustering-based NSGA-II framework for addressing the multi-objective location-routing problem. Our goal was to investigate the effectiveness of incorporating clustering techniques, specifically k-means and k-medoids algorithms, into the classical NSGA-II algorithm for improving solution (minimizing cost and maximizing retailer satisfaction) and reducing computational time. As a result, it enables the identification of homogeneous retailer groups, facilitating better allocation of DC and vehicle for efficient routing and delivery and successfully improving the Pareto front result.

In the practical implication, the clustering-based NSGA-II approach has the potential to revolutionize decision-making processes in last-mile delivery. The model was applied to a study case of commodities distribution in D.I

Yogyakarta, Indonesia. It could provide a lower monthly cost and slightly higher retailer satisfaction in the lower computational time. Hence, through the adoption of this model, practitioners are anticipated to attain solutions that are both more effective and efficient.

Although our study has achieved promising results, we acknowledge some limitations. The proposed framework relies on the assumptions and constraints defined within the multi-objective location-routing problem. Future research could focus on refining and expanding the clustering techniques employed, exploring alternative clustering algorithms, or incorporating additional scenario into the optimization process to further enhance the performance of the framework.

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