MULTI-CRITERIA DECISION-MAKING MODEL ON CLOSE-OPEN MIXED VEHICLE ROUTING PROBLEM FOR MIDDLE-MILE DELIVERY OPTIMISATION

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ABSTRACT: Middle-Mile Delivery (MMD) is perceived to carry less importance in supply chain management and has the least potential for improvement, prompting many companies to skip this step in logistics. Although MMD is studied as part of the Vehicle Routing Problem (VRP), it receives less attention than last-mile delivery. Nevertheless, MMD is typically more predictable, presenting greater opportunities for enhancements. An optimised middle-mile distribution network can reduce transportation costs and delivery times. The main challenges of MMD include route distance, the locations of distribution centres, and delivery duration. Routing is an essential element of logistics, significantly contributing to economic growth. Inefficient routing may result in elevated expenses, especially for courier and logistics companies. Nodes, also known as distribution centres, are critical components in the distribution system. The initiation or termination of these nodes is frequently restricted by corporate constraints, rendering such modifications challenging. Consequently, optimisation initiatives must prioritise the selection of nodes according to their relevance to the company's comprehensive delivery process. This study presents a hybrid approach for the Close-Open Mixed Vehicle Routing Problem (COMVRP), which addresses both open and closed routes while integrating Multi-Criteria Decision Making (MCDM). The objective is to reduce the overall delivery distance. We propose a refined Genetic Algorithm (GA) that integrates with the Analytical Hierarchical Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). In managerial decision-making, the AHP-TOPSIS method is used to improve an initial COMVRP generated by the nearest neighbour algorithm. The AHP technique focuses on criteria weights, whereas TOPSIS emphasises delivery centres' performance as the priority node. This solution set achieves ideal GA performance, displaying minimal route distances with external vehicle deployment. The calculation results also showed that the proposed model reduced the total route distance by 4.86%, which exceeded the standard COMVRP model with 28.03% less than the current postal delivery system.

KEYWORDS: *Middle-Mile Delivery; Close-Open Mixed Vehicle Routing Problem; Multi-Criteria Decision Making, Analytical Hierarchy Process; Technique for Order Preference by Similarity to Ideal Solution; Postal Delivery.*

1.0 INTRODUCTION

In supply chain management, middle-mile delivery (MMD) is frequently regarded as a less contributing step than first-mile and last-mile deliveries. It has the least room for optimisation, resulting in many companies skipping the middle-mile logistics distribution step. The combination of the first- and middle-miles within the role of data source and sustainability impact on digital transformation has been less thoroughly examined, implying that the middle-mile involves optimisation concerns [1]. Moreover, MMD is an internal shipping step in the supply chain management that supports final shipping effectiveness. More transporters and shipping routes are needed to fulfil this task, making MMD inefficient, time-consuming and challenging.

Concerns regarding MMD have been extensively studied in Vehicle Routing Problem (VRP) but are less intense than last-mile delivery. Middle-mile flows are typically more steady and predictable, providing more improvement opportunities. It aligns with previous evidence whereby an optimal middle-mile distribution network reduces transportation costs, delivery time, and carbon emissions [2]. The main challenges of MMD are route mileage, delivery centre locations, and delivery time. Many logistics companies have implemented VRP and all variants to optimise delivery through several algorithms. Past research proposed a model of logistics distribution optimisation method simulated by the genetic testing algorithm [3]. Furthermore, the involvement of human decision is also needed to overcome VRP with realistic solutions. During the intermediate phase of the logistics process, products are distributed to e-commerce order fulfilment centres where essential activities, such as order sortation, picking, and packing, are conducted. The issue faced by MMD route optimisation is usually indicated by the selection of nodes in the distribution network, with priorities on route and time efficiency.

Pos Indonesia is a state-owned enterprise that plays a crucial role in providing postal services across the provinces of Indonesia [4], including both universal and specialised government services. The rapid growth of e-commerce and advancements in information technology have significantly impacted the postal industry, creating competition from courier and express delivery companies as well as online transportation providers. To remain competitive in this evolving market, Pos Indonesia must optimise its logistics and delivery networks by improving route selection and fleet efficiency and reducing transportation costs. Recent evidence showed that optimising distribution systems by reducing storage facilities and utilising decision support frameworks can significantly enhance last-mile delivery efficiency and reduce costs [5]. By incorporating data analytics, network optimisation, and real-time decision-making, Pos Indonesia can better meet the increasing demand for fast and reliable delivery, driven by the rise of e-commerce [6] and customer expectations for services like Same-Day Delivery [7].

The Vehicle Routing Problem (VRP) was introduced by Dantzig [8] and focuses on optimising multiple delivery routes at minimal cost while adhering to constraints like vehicle capacity and visiting each customer once. An alternative to such issue is the Open Vehicle Routing Problem (OVRP) whereby vehicles do not return to the depot after completing deliveries, making it useful for situations where internal fleets are insufficient and necessitate the use of external vehicles [9]. Recent research on OVRP has expanded through the adaptations of Green OVRP [10] and multi-objective variants [11]. Advances in algorithms, including Tabu Search and Ant Colony Optimisation [12], have been applied to solve complex OVRP challenges and explore its applications in other areas, such as crowd shipping, ride-sharing, and bus routing [13-14]. The complexity of VRP and its variants, including the Close-Open Mixed Vehicle Routing Problem (COMVRP), has led to the use of metaheuristic algorithms like Genetic Algorithms, which are proven effective in optimising routes for electric vehicles and reducing total travel distance [12-13]. These approaches offer practical solutions to logistics companies for efficient, cost-effective fleet management.

This study explored the complexities of postal delivery optimisation as constrained by business rules using a Close-Open Mixed Vehicle Routing Problem (COMVRP) model integrated with Multi-Criteria Decision Making (MCDM) techniques, specifically AHP and TOPSIS. The solution was based on delivery history data from the Postal Processing Centre (PPC) in Bandung 40400 and a Monte Carlo Simulation (MCS) was used to predict optimal delivery routes. By analysing delivery patterns and prioritising nodes through AHP and TOPSIS, this study ranked delivery routes and simulated future patterns, thus enhancing delivery efficiency. The integration of external vehicles into the COMVRP model, along with precise optimisation techniques, supports future delivery patterns and allows for improved delivery performance based on historical data, addressing the real-world challenges of postal operations.

2.0 METHODOLOGY

Although the MCDM technique could identify the optimal choices for the COMVRP model, the AHP and TOPSIS methods were also evaluated in consideration of the specific issues. Both AHP and TOPSIS were employed to address the numerical complexities encountered in this simulation. It involved the following processes, as illustrated in Figure 1.

Step 1: Integrate specialised insights from the operation manager.

Step 2: Utilise AHP to conduct processing, which derives criteria from DC according to the weighting established by the AHP method.

Step 3: Implement the TOPSIS method to process the weight criterion results and produce a set of DC rankings priority based on the given information.

Step 4: Convert data into the format specified by MCS to rank DC. When contrasted with the route determination process in the PPC zoning system, the simulation outcomes will reveal the

DC ranking, which will then be utilised to establish DC priority.

Step 5: Findings from MCS in the DC ranking priority will serve as a preliminary solution for GA, aiming to enhance the optimisation performance of COMVRP to achieve the most effective PPC delivery.

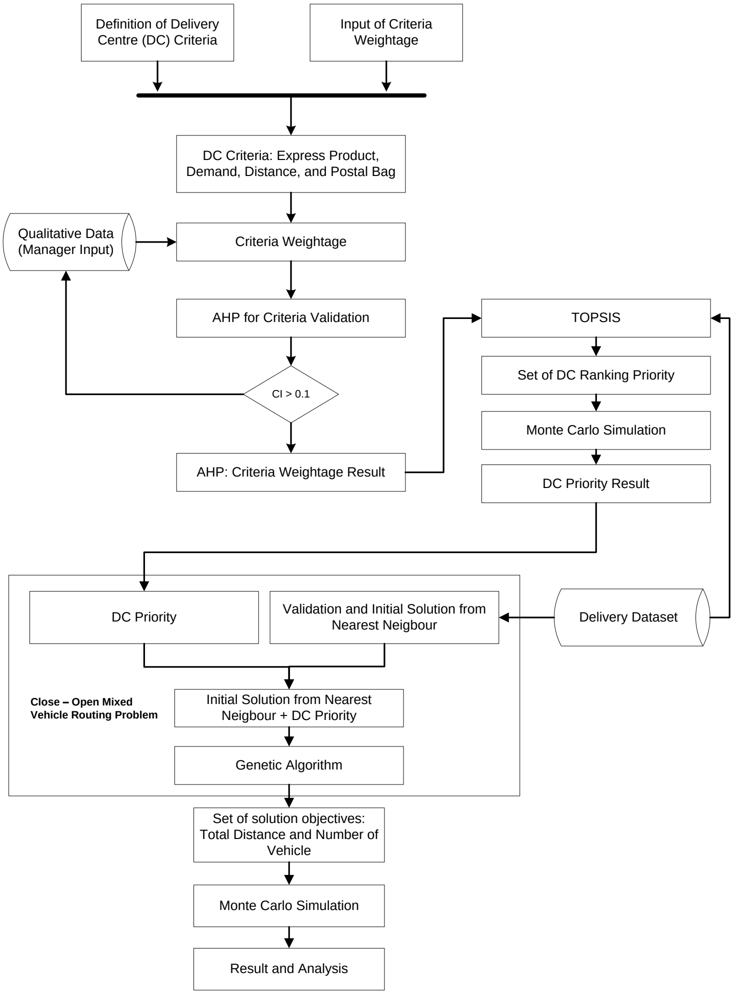

Figure 1: A Proposed Method

2.1 The Proposed Model

COMVRP builds upon the conventional VRP by incorporating elements from both the Open and Closed VRP models. Although similar to the traditional VRP, Open VRP distinguishes itself by allowing routes to conclude after all customers have been served, without the requirement for vehicles to return to the initial depot [17]. In this context, COMVRP involves a mix where some vehicles return to the initial depot, whereas in the traditional VRP, all vehicles must return to the depot. The mixed vehicle approach will be implemented according to this proposed model. Specifically, COMVRP incorporates the following constraints:

i. Routes used by internal fleet vehicles must commence and conclude at the original point of PPC.
ii. External fleet vehicle routes must commence at the initial PPC and conclude at the final DC.
iii. Each DC is visited by only one vehicle.
iv. Each route is assigned to only one vehicle.
v. The cumulative demand from all DCs on a specific route should not exceed the vehicle's capacity.

The mathematical model for COMVRP [17], including the constraints and defined objective functions, is shown in Formula (1) to (9). Formula 8 demonstrates an improvement aimed at enhancing the algorithm's performance, particularly in determining a more efficient distance by first identifying the critical nodes that must be traversed. Such identification is based on historical data and conducted using the AHP and TOPSIS methods.

Objective Function:

$$\text{Min } Z = \sum_{k \in K} Fk \sum_{i \in N} x_{0i}^{k} + \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} c_{ij} x_{ij} - \sum_{k \in K2} \sum_{i \in N} c_{i0} x_{i0}^{k} \tag{1}$$

Constraints:

$$\sum_{k \in K} \sum_{i \in V\, i \neq j} x_{ij}^{k} = 1,\ \forall\, j \in N \tag{2}$$

$$\sum_{i \in V\, i \neq j} x_{ij}^{k} - \sum_{i \in V\, i \neq j} x_{ji}^{k} = 0,\ \forall\, j \in V,\ \forall\, k \in K \tag{3}$$

$$\sum_{j \in R} q_j \left(\sum_{i \in V} x_{0i}^{k} \right) \leq \text{Maxcapacity},\ \forall\, k \in K2 \tag{4}$$

$$\sum_{i \in N} x_{0i}^{k} \leq 1, \forall\, k \in K \tag{5}$$

$$\sum_{k \in K1} \sum_{i \in N} x_{0i}^{k} = Nu \tag{6}$$

$$x_{ij}^{k} \in \{0,1\}\ \forall\, i, j \in V, \forall\, k \in K, i \neq j \tag{7}$$

The constraint from AHP-TOPSIS:

$$\sum_{j \in R} q_j \left(\sum_{i \in V} x_{0i}^{k} \right) \leq \text{Maxcapacity}, \forall\, k \in K2, R = \text{DC priority from AHP-TOPSIS} \tag{8}$$

Decision variables:

$$x_{ij}^{k} = \begin{cases} 1 \\ 0 \end{cases} \tag{9}$$

The value is 1 if vehicle *k* serves *j* after serving *i* and 0 if otherwise.

c_{ij} = travel cost from DC *i* to DC *j*
c_{i0} = travel cost from DC *i* to PPC
F_k = fixed cost for vehicle k
K = vehicle set K = {K1 ∪ K2}
K1 = internal fleet set (vehicle owned by the company)
K2 = external fleet set (external vehicle)
MaxCap = vehicle maximum capacity
Nu = maximum number of internal fleet
q_j = demand from DC *j*
V = set of nodes
x_{ij}^{k} = vehicle *k* serves for DC *j* after visiting DC *i*
x_{i0}^{k} = vehicle *k* returns to PPC after visiting DC *i*
x_{0i}^{k} = vehicle *k* serves for DC exactly after vehicle starts from PPC
R = DCs priority

Formula (1) represents the objective function, which aims to minimise the total operating costs of the vehicles. These costs include both fixed costs, such as maintenance and transportation for the internal fleet, and variable costs related to using external vehicles. Constraint (2) ensures that each distribution centre (DC) is visited exactly once by a single vehicle. Constraint (3) requires each vehicle to leave DC immediately after completing its service. Constraint (4) guarantees that the total demand served by a vehicle on any route does not exceed its capacity. Constraint (5) ensures that only one vehicle departs from the depot for each route. Constraint (6) restricts the number of internal fleet vehicles to not exceed the available quantity (Nu). Lastly, Constraint (7) defines a binary variable, i, for each vehicle k, where i is 1 if vehicle k visits point j after serving node i, and 0 if otherwise. Additionally, Constraint (8) is added to integrate route priorities for DCs based on the AHP-TOPSIS-MCS simulation. Formula (9) specifies the decision variables.

2.2 Case at Hand

Pos Indonesia utilised a hub-and-spoke model for its distribution network, with the PPC Bandung 40400 serving as the hub and nearby post offices or DCs acting as the spokes, as illustrated in Figure 2. The shipping value chain at Pos Indonesia operates as follows: Post offices receive mail and packages from customers. At scheduled times, a vehicle collects and transports these items from the DC to the PPC. The PPC then conducts a sorting process before sending the items to the destination PPC. Various transportation modes, including trucks, trains, ships, and airplanes, are used for distribution. Upon arrival at the destination PPC, another sorting process takes place before the items are delivered to each DC and ultimately to the intended recipients. The PPC is tasked with the responsibilities of planning, organising, executing, and overseeing the policies related to the collection, processing, transportation, delivery, and reporting within its operational domain, aiming to ensure both efficiency and effectiveness.

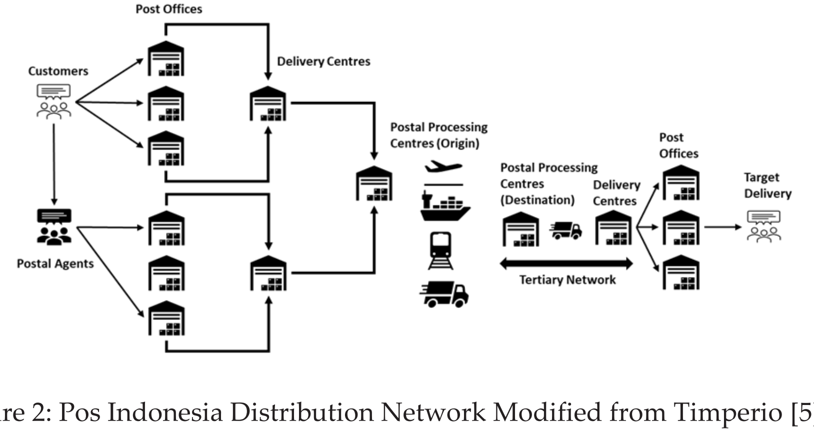

Figure 2: Pos Indonesia Distribution Network Modified from Timperio [5]

This research gathered historical delivery data from the PPC's operational deliveries over three months. It included information on products/services, destination distribution centres (DCs), DC demand, shipment weight, vehicles used, routes taken, and shipment dates. In total, 19,850 records were collected. Table 1 presents the average monthly demand based on this data.

Table 1: The demands of all DCs

Delivery Centres	September	November	December	October	Total
Dc Asiaafrika 4040e	7150	36157	37398	32379	113084
Dc Cikeruh 4040j	4251	14700	14814	15289	49054
Dc Cikutra 4040f	4471	19578	24479	18849	67377
Dc Cimahi 4040i	3904	15788	15272	15614	50578
Dc Cipedes 4040c	4847	21378	19425	19352	65002
Dc Dayeuhkolot 4040g	3520	12101	12439	14241	42301
Dc Lembang 4040l	2141	6152	6434	5930	20657
Dc Majalaya 4040m	2401	8654	9131	9494	29680
Dc Padalarang 4040k	2033	10378	10194	8630	31235
Dc Sekejati 4040a	6889	26392	24579	24903	82763
Dc Situsaeur 4040d	4016	16262	16864	16168	53310
Dc Soreang 4040h	4155	12967	13834	14549	45505
Dc Ujungberung 4040b	4656	20543	18210	18348	61757
Total Demand (Kg.)	54434	221050	223073	213746	712303

Vehicle: PPC Bandung 40400 deployed six vehicles for postal deliveries. Detailed information about these vehicles is provided in Table 2. Additionally, the statistics indicate that the average speed of these vehicles was 30 km/h.

Table 2: Distribution routes of PPC Bandung 40400 (source: P3M PPC Bandung 40400)

Number of Route	Route Flow	Vehicle Capacity (ton)
Route-1	PPC to DC Situ Saeur, then to DC Asia Afrika, and finally returns to PPC.	1.5
Route-2	PPC to DC Dayeuhkolot, then to DC Katapang, followed by DC Soreang, and finally returns to PPC.	1.5
Route-3	PPC to DC Cikutra, then to DC Lembang, and return to PPC.	1.5
Route-4	PPC to DC Cipedes, then to DC Padalarang, then to DC Cimahi, then to DC Cimahi, and finally return to PPC.	1.5
Route-5	PPC to DC Ujung Berung, followed by a shift to DC Cikeruh and returns to PPC.	1.5
Route-6	PPC to DC Cikeruh, then to DC Majalaya, and subsequently returns to PPC.	1.5

Distance: The distances between any two different DCs and PPC were collected from PPC Bandung 40400. It can also be determined by predefined routes, as shown in Table 3.

Table 3: The distance between PPC and DCs

DC Nodes	DC SE	DC SS	DC AA	DC KTP	DC DYK	DC CD	DC CA	DC CKH	DC LEM	DC MJA	DC PDL	DC CMH	DC UJB	DC PDL
DC SE	0	6.9	5.9	11.2	5.6	12.2	5.26	12.6	18.3	7.3	13.7	14.3	8.3	0
DC SS	6.9	0	4.8	6.2	9.24	6.1	5.22	19	10.2	11.7	7.7	9	11.5	6.9
DC AA	5.9	4.8	0	10.8	8.98	7.5	2.5	9.4	13.7	11.5	10. 4	8.3	6.7	5.9
DC KTP	11.2	6.2	10.8	0	8.9	12.1	11.2	23.1	16.2	12.4	8.4	11.5	19.3	11.2
DC DYK	5.6	9.2	8.9	8.9	0	15.4	8.46	17.7	18.5	2.1	15.9	16.4	13.9	5.6
DC CD	12.2	6.1	7.5	12.1	15.4	0	8.54	22.2	10	17.5	13.1	8.8	13.7	12.2
DC CA	5.3	5.2	2.5	11.2	8.5	8.5	0	12.6	13.4	10.9	13.7	11.1	4.2	5.3
DC CKH	12.6	19	9.4	23.1	17.7	22.2	12.5	0	26.5	14.4	25.7	20.3	8.5	12.6
DC LEM	18.3	10.2	13.7	16.2	18.5	10	13.4	26.5	0	21.2	18.2	15	14.5	18.3
DC MJA	8.8	11.7	11.5	12.4	2.1	17.5	10.9	14.4	21.2	0	17.8	16.4	13.6	8.8
DC PDL	13.7	7.7	10.4	8.4	15.9	13.1	13.6	25.7	18.2	17.8	0	8.9	19.9	13.7
DC CMH	14.4	9	8.3	11.5	16.4	8.8	11.1	20.4	15	16.4	8.9	0	17.4	14.4
DC UJB	8.3	11.5	6.7	19.3	13.9	13.7	4.16	8.5	19.5	13.6	19.9	17.4	0	8.3

Delivery Route in the tertiary network served as an extension of the PPC and was responsible for transporting postal items from the PPC to the DCs. To manage this network, the PPC deployed six vehicles that operated daily, making two trips per day. These vehicles were primarily of the GrandMax type, each with an average capacity of 1.5 tonnes.

3.0 RESULTS AND DISCUSSION

3.1 COMVRP Results

The dataset of shipment delivery history from PPC Bandung 40400 over a three-month period was used to generate a series of solutions. Each delivery was optimised using the COMVRP model, resulting in a total of 100 solutions, as illustrated in Figure 3. This result aligns with a previous study whereby the implementation of COMVRP involving external/rented EVs significantly impacted company efficiency as there was no need for charging time like owned EVs before returning to the depot as well as a reduction in route mileage [15].

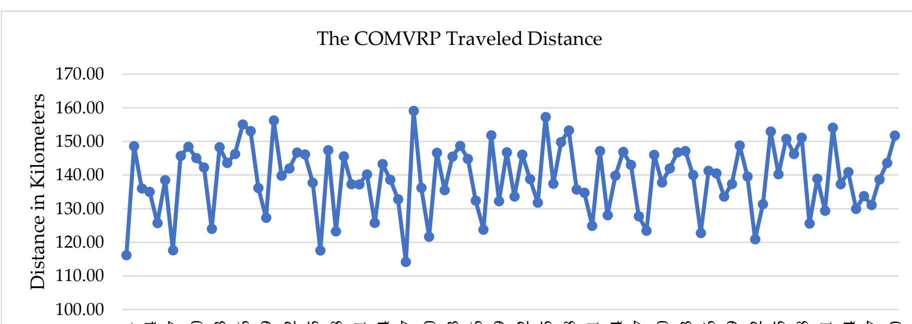

Figure 3: COMVRP Computational Result for Distance Travelled

Each proposed solution specified the details of daily deliveries, including the number of routes, travel distance, travel time, demand, and the utilisation of internal or external vehicles. Compared to the existing route, the proposed solutions consisted of six routes spanning a total distance of 184.8 kilometres. The COMVRP model corroborated these results by demonstrating optimised delivery routes using a single external vehicle, as depicted in Figure 4. According to the historical data, the total distance travelled per delivery was less than that of the current route, thus reducing the average travel distance to 139.8 kilometres with four routes.

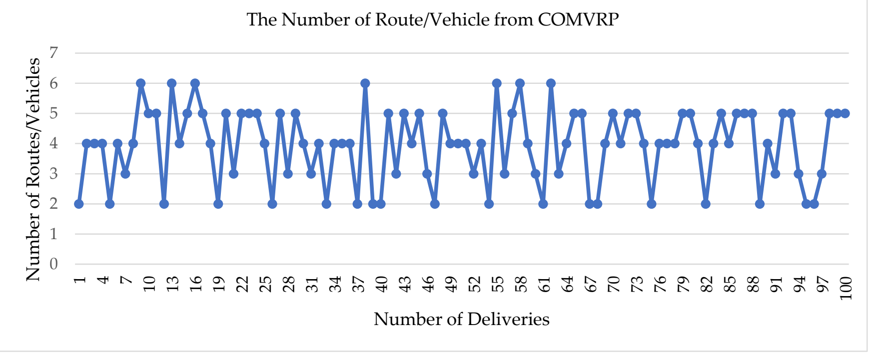

Figure 4: The COMVRP Computational Results for the Number of Routes/Vehicles

The COMVRP results indicate that the current delivery model's route distribution pattern can be improved as the average number of routes and vehicles used is suboptimal.

3.2 Monte Carlo Simulation Results for COMVRP Solution

The MCS encompasses a range of statistical sampling methods that can be employed to approximate solutions for quantitative issues [18]. In the context of COMVRP, this simulation produces a collection of solutions to estimate the number of internal and external vehicles utilised and the total distance covered across all routes. Given that the variable values were derived from the historical delivery data, they were modelled using a normal distribution. Table 4 summarises the frequency of specific routes appearing within the solution set.

Table 4: The COMVRP Average Number of Vehicle/Route

Number of Routes	Frequency	Distribution Density	Cumulative Distribution Function	Tag Number	MCS	Number of Routes
2	19	0.19	0.19	0 - 19	25	3
3	13	0.13	0.32	20 - 32	54	4
4	30	0.30	0.62	33 - 61	99	6
5	31	0.31	0.93	62 - 92	60	4
6	7	0.07	1.00	93 - 100	45	4
Total	100	Average				4

Table 4 presents the frequency of different numbers of routes occurring over 100 delivery simulations. Specifically, there were 19 instances with two routes, 13 instances with three routes, 30 instances with four routes, 31 instances with five routes, and seven instances with six routes. This simulation was based on an estimate of four routes or vehicles. To estimate delivery mileage, grouping and averaging were performed according to the simulated frequencies (Table 5).

Table 5: The COMVRP Average Number of Mileage

Distance		Average	Frequency	Distribution Density	Cumulative Distribution Function	Tag Number	Simulate	Distance
112	118	115	4.00	0.04	0.04	0 - 4	97	157
119	125	122	8.00	0.08	0.12	5 - 12	74	150
126	132	129	11.00	0.11	0.23	13 - 23	66	143
133	139	136	25.00	0.25	0.48	24 - 48	43	136
140	146	143	20.00	0.20	0.68	49 -68	37	136
147	153	150	24.00	0.24	0.92	69 - 92	4	115
154	160	157	8.00	0.08	1.00	93 - 100	67	143
Total	100	Average						140

The cumulative distribution function determines the probability of the distance travelled for each shipment according to the chosen routes. This function employs a normal distribution model to estimate the total distance for each delivery, as depicted in Figure 5.

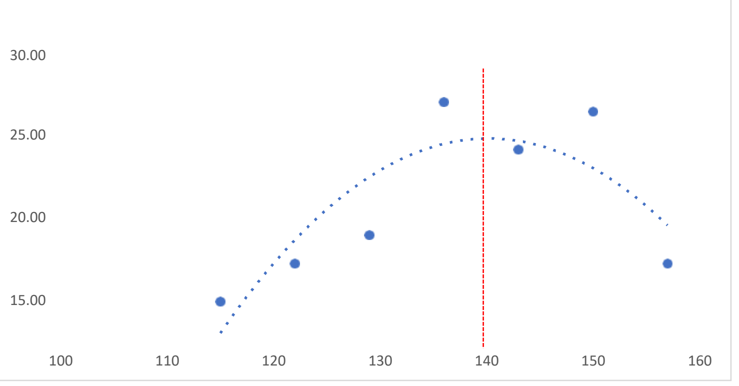

Figure 5: The COMVRP travelled distance average

In the analysed set of 100 solutions, the average mileage for each delivery route was 140 kilometres. Computational results from COMVRP, which pertained to the delivery routes developed by PPC Bandung 40400 Pos Indonesia (as detailed in Table 2), were optimised using a zone-based approach [19]. This optimisation method included the integration of external vehicles to decrease operational costs [6].

In this study, MCS was utilised to assess the practical applicability of the solutions derived from the COMVRP optimisation process. MCS is widely employed in modelling and simulation within this domain [20]. The results indicate that it is feasible to reduce the number of vehicles from the six currently used vehicles across 184.8 kilometres of delivery routes to four internal vehicles and one external vehicle with 140 kilometres, thus increasing efficiency by 23.91%. Additionally, the COMVRP with MCS results demonstrate a reduction in the total distance travelled and that external vehicles can dynamically adjust priority routes based on demands from DCs. The distribution manager's role is crucial for ensuring the model's practicality and realism. The proposed model integrating the distribution manager's role into an MCDM technique, specifically using AHP-TOPSIS, can further improve the model's optimisation.

3.3 AHP – TOPSIS – MCS Results

The MCDM technique was employed to optimise routing through the evaluation of various alternatives. Both AHP and TOPSIS methods were utilised to address numerical challenges within this simulation. The following steps outline the procedure:

Step 1: The distribution manager determines the weighted criteria by integrating insights from experts.

Step 2: The AHP method processes these criteria to determine the weight assigned to each DC.

Step 3: The TOPSIS technique processes the weighted criteria to establish a priority ranking for the DCs.

Step 4: The DC priority rankings are formatted for input into the MCS. The simulation results will then reflect these rankings, which will be used to prioritise the DCs compared to the current routing.

Figure 1 illustrates this process in detail. After analysing the dataset and assessing the performance of DCs for prioritisation, four key criteria were identified:

i. Postal Bag: This refers to the number of postal bags needed for delivery, each containing collected items.
ii. Demand: This represents the total weight (in kilograms) of items delivered to a DC.
iii. Distance: This denotes the distance in kilometres between the PPC and the DC, as well as between different DCs.
iv. Express Product: This includes items requiring expedited handling, such as Q9, Same-Day Delivery, and Special Express services.

The AHP technique was used to assign weights to these criteria, which would then determine the priority of each DC.

3.3.1 Performing AHP

The initial stage of implementing the AHP method entailed specifying the criteria derived from the delivery dataset. These criteria are comprehensively outlined in Table 6.

Table 6: The Criteria of DC Performance

No	Criteria	Description
1	Postal Bag	Amount of postal bag.
2	Demand	Amount of weight for every DC.
3	Distance	Distance from PPC to DCs and between the DCs.
4	Express Product	Amount of weight of the express product.

These equations were employed to construct the normalised pairwise matrix. The process began with the distribution manager entering the significance levels of the criteria. Next, the criteria were compared in pairs and Formula (10) was used to produce the normalised pairwise comparison matrix as shown in Table 7. This matrix was subsequently processed to determine the consistency index using Formula (11) to (17).

Table 7: Significance of Pairwise Comparison Matrix Values

Value	Definition	Significance
1	Equal importance	Two elements contribute equally to the objective.
3	Moderate importance	Experience and judgment slightly favour one element over another.
5	Strong importance	Experience and judgment strongly favour one element over another.
7	Very strong importance	One element is favoured very strongly over another and its dominance is demonstrated in practice.
9	Extreme importance	The evidence favouring one element over another is of the highest possible order of affirmation.
2,4,6,8	It can be used to express intermediate values.	

The following formulas were used to normalise the pairwise matrix:

$$\mathrm{N_{ij}} = \frac{\mathrm{C_{ij}}}{\sum_{\mathrm{i}}^{\mathrm{n}} \mathrm{C_{ij}}} \tag{10}$$

Rows and columns are represented by i and j, respectively. The normalised form of the pairwise comparison is denoted as Nij. Both i and j can take any value from 1 to 4, corresponding to the four criteria. Afterwards, weights for the selected criteria were calculated using the following formula to ensure accuracy:

$$\mathrm{W_i} = \frac{\sum_{\mathrm{i}}^{\mathrm{n}} \mathrm{N_i}}{\mathrm{n}} \tag{11}$$

Here, i represents a column index, where $i = 1, 2, 3, 4, \ldots, n$, and n is the total number of selected criteria. N_i represents the value from the normalised matrix, while W_i denotes the weight assigned to each criterion. Alternative weights are calculated similarly, denoted by A_i. After calculating the scores, the option with the highest score is selected.

$$\text{score} = \sum \mathrm{W_i} * \mathrm{A_i} \tag{12}$$

After calculating the weighted sum, the ratio of the weighted sum to the criterion weight is determined using Formula (13):

$$\mathrm{WS_i} = \mathrm{C_i} \times \mathrm{W_i} \tag{13}$$

WS_i represents the weighted sum for the i-th criterion. In this context, C_i denotes the element of the pairwise comparison matrix and W_i denotes the weight assigned to the i-th criterion.

$$\mathrm{R_i} = \frac{\mathrm{W\,S_i}}{\mathrm{W_i}} \tag{14}$$

CI represents the Consistency Index, CR is the Consistency Ratio, and RI refers to the Random Consistency Index. The term λ_{max} denotes the maximum value of the eigenvalue. These concepts are essential principles of AHP. The Random Index (RI) is calculated using the following formula:

$$\lambda_{max}= \frac{\sum_i^n R_i}{n} \tag{15}$$

$$CI= \frac{\lambda_{max}-n}{n-1} \tag{16}$$

$$CR= \frac{CI}{RI} \tag{17}$$

As shown in Table 6, this study identified four criteria, leading to a random index of 0.9. The eigenvalues were calculated using the AHP method, as detailed in Table 8. The first operation manager considered the number of postal bags to be less significant than demand with the evaluation being based on pairwise comparisons of distance and express products. Distance was prioritised over demand and express products were regarded as more important than both demand and distance. In contrast, the second operation manager ranked demand, distance, and express products higher than the number of postal bags, similarly prioritising distance over demand, express products over demand, and express products over distance.

Table 8: Significance of Pairwise Comparison Matrix Values

No	Criteria	Eigen Value
1	Postal Bag	0.0727
2	Demand	0.1623
3	Distance	0.2679
4	Express Product	0.4971

Once the weight values for each criterion were determined, the TOPSIS method used these weights to rank the DCs according to the provided dataset.

3.3.2 Performing TOPSIS

TOPSIS was used to determine the optimal ranking of DCs. First, the actual values must be entered and normalised using Formula (18):

$$\overline{X_{ij}}= \frac{X_{ij}}{\sqrt{\sum_{j=1}^m X_{ij}^2}} \tag{18}$$

The normalised element is represented as X_{ij}. Here, j indicates the column index, which can be 1, 2, or 3 in this case. $\overline{X_{ij}}$ refers to the original, non-normalised value in the matrix. The weighted normalised matrix is then calculated using Formula (19):

$$V_{ij} = \overline{X_{ij}} \times W_j \tag{19}$$

Here, W_j represents the weight assigned to the criterion. This weight was determined in the earlier section on AHP computation. V_{ij} refers to the normalised value of the matrix element. Next, the ideal best and worst values for each criterion are identified. For a beneficial criterion, such as express product, the ideal best value is the highest value in the column; for a non-beneficial criterion, it is the lowest value in the column. The ideal worst value refers to the inverse of the ideal best value based on the concept of opposites. Finally, Euclidean distances between the ideal best and worst values are calculated, as detailed in Formula (20) and (21):

$$S_i^{+} = \sqrt{\sum (V_{ij} - V_j^{+})^{\wedge} 2} \tag{20}$$

$$S_i^{-} = \sqrt{\sum (V_{ij} - V_j^{-})^{\wedge} 2} \tag{21}$$

In this context, S_+^- and S_i^- represent the Euclidean distances from the ideal best and worst values, respectively. The performance score is computed based on these distances and the alternative with the highest performance score is selected. The performance score is calculated using Formula (22):

$$p^{ij} = \frac{S_+^-}{S_i^+ + S_i^-} \tag{22}$$

In line with the AHP-TOPSIS method, Figure 6 depicts the priority ranking of DCs based on the evaluated criteria. It demonstrates the impact of each delivery repeated 100 times on the priority ranking of DCs according to the weighted criteria. The graph shows the ranking outcomes obtained from the TOPSIS analysis, revealing the priority of each DC and highlighting those with the highest and lowest rankings for each delivery. This result aligns with another study [21] whereby the hybridization of AHP and TOPSIS can yield superior choices for route determination and enable decision-makers to assess simulation outcomes according to their preferences and priorities, leading to more informed and robust decisions even with uncertain variables.

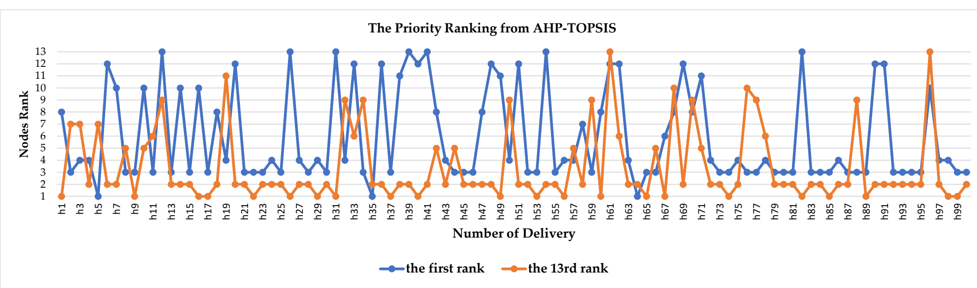

Figure 6: The DC First and Last Ranking Priority from AHP – TOPSIS

3.3.3 Performing Monte Carlo Simulation for TOPSIS Results

The implementation of MCS for setting DC ranking priorities was done according to the following steps. First, the ranking data produced by TOPSIS was converted into a matrix that represents the 13 DCs and their rankings across 100 deliveries (see Table 9) and ranks each DC according to the frequency of DC rankings.

Table 9: The DC Ranking Frequency Matrix

DC Nodes	DC Ranking Frequency													
	1	2	3	4	5	6	7	8	9	10	11	12	13	1
1	3	3	6	4	2	5	6	11	11	5	10	12	22	1
2	0	1	1	2	1	0	2	5	6	5	7	19	51	2
3	43	12	7	6	5	3	4	2	10	6	2	0	0	3
4	18	9	23	10	14	15	4	5	0	0	2	0	0	4
5	0	3	1	2	6	3	9	6	10	12	16	25	7	5
6	1	4	2	9	4	10	9	10	13	16	9	9	4	6
7	1	4	6	5	11	6	14	9	11	9	13	8	3	7
8	7	19	15	17	13	11	7	5	4	0	0	2	0	8
9	0	2	3	5	3	2	3	9	7	18	25	15	8	9
10	5	4	6	5	7	11	15	10	10	14	8	3	2	10
11	3	6	5	7	11	17	14	12	13	4	4	3	1	11
12	12	16	15	14	8	12	9	8	0	4	2	0	0	12
13	7	17	10	14	15	5	4	8	5	7	2	4	2	13

The next step involved determining the frequency distribution and conducting a MCS to centering the data. As indicated in Table 10, the data centering falls within classes 6 and 7, with an average value of 17.333.

Table 10: The MCS Frequency Cumulative Distribution

Object Delivery Centres		Average	Frequency	Distribution Density	Distribution Cumulative Function	Tag Number	Monte Carlo Simulation	ODCSIM
1	22	0.18	4	0.0032733	0.003	0-3	788	22.267
23	44	1.77	39	0.0319149	0.035	4-35	616	13.318
45	66	3.50	77	0.0630115	0.098	36-98	722	13.318
67	88	4.91	108	0.0883797	0.187	99-187	873	22.267
89	110	7.00	154	0.1260229	0.313	188-313	334	9.6818
111	**132**	**9.68**	213	0.1743044	0.487	314-487	662	13.318
133	**154**	**13.32**	293	0.2397709	0.727	488-727	930	22.267
155	176	22.27	334	0.2733224	1.000	728-1000	992	22.267
Total			1222	Average				17.338

Table 10 displays the range of object DCs, which falls between 111 and 132 as well as 133 and 154, with average frequencies ranging from 9.68 to 13.32. The next step involved calculating the average in the MCS by running the specified number of iterations based on the provided formula. The MCS approach allowed the estimation of simulation errors according to the number of iterations performed. The total error was determined using the formula $\frac{3\,\sigma}{\sqrt{N}}$,where σ is the standard deviation of the random variable and N is the number of iterations. The standard deviation, σ, was calculated based on the entire population using the formula $\sigma = \sqrt{\frac{\sum (x-\bar{x})^2}{N}}$, yielding $\sigma = 3.7431$. The desired absolute error value was less than 2%, which was obtained using the formula $\varepsilon = \frac{\bar{x}}{\left(\frac{1}{0{,}02}\right)}$, yielding $\varepsilon = 0.14$ and $\mu = 7$. Therefore, the number of iterations required to obtain results with an error of less than 2% is $N = \left(\frac{3 \times \sigma}{\varepsilon}\right)^2 = 6.434$ as shown in Table 11 and MCS set an average of 10,613.

Table 11: The MCS of 6.434 Iteration

Number of Iteration		0.18	1.77	3.50	4.91	7.00	9.68	13.32
		0-3	4-35	36-98	99-187	188-313	314-487	488-727
1	43	347	117	662	767	354	791	972
2	78	413	39	958	288	342	113	89
3	47	460	150	758	666	729	267	102
…	…	…	…	…	…	…	…	…
6432	66	757	811	576	620	438	519	154
6433	35	54	568	101	132	889	48	142
6434	99	831	831	720	226	892	329	279

Based on the ranking and frequency analysis, the top four prioritised DCs were DC3, DC8, DC12, and DC13. Specifically, these were identified as follows: DCAA (Delivery Center of Asia Afrika), DCCKH (Delivery Center of Cikeruh), DCCMH (Delivery Center of Cimahi), and DCUJB (Delivery Center of Ujungberung).

3.4 Results and Discussion

Table 11 summarises the priorities for the DCs based on the AHP-TOPSIS-MCS results. The simulation assessed each DC's performance according to specific criteria using the AHP-TOPSIS methods. The MCS then evaluated the importance of each DC based on the provided dataset. Such evaluation revealed which DCs were prioritised and frequently considered in delivery planning by operational managers.

The simulation results showed that several DCs excelled in the four assessed criteria. These DC priorities were incorporated into the initial solution of the GA, as depicted in Figure 6. The GA chromosome combined the nearest neighbour (NN) initial solution with the four DC priorities derived from the AHP-TOPSIS-MCS method.

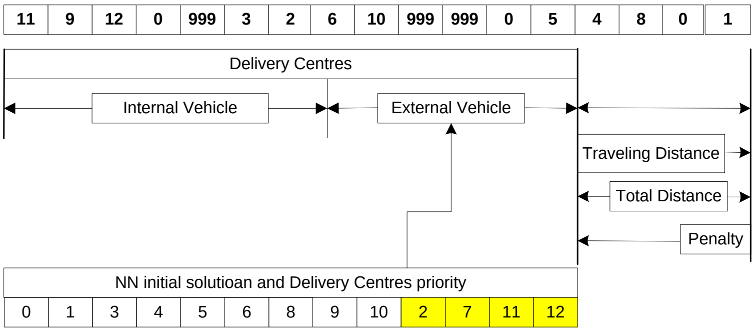

Figure 6: The DCs Priority in GA Initial Solution

The prioritisation of DCs using AHP-TOPSIS-MCS indicated that the four DCs identified by the simulation were prioritised according to the specified criteria. It suggests that these DCs are significant for express product handling and demand capacity. Operational managers can use this information to optimise route planning, scheduling, and vehicle allocation for prioritising postal deliveries. The simulation results from AHP-TOPSIS-MCS were integrated with the nearest neighbour algorithm outcomes to form the initial chromosome for GA in COMVRP. Each delivery scenario will be evaluated using COMVRP, thus generating a new set of solutions as illustrated in Figure 7.

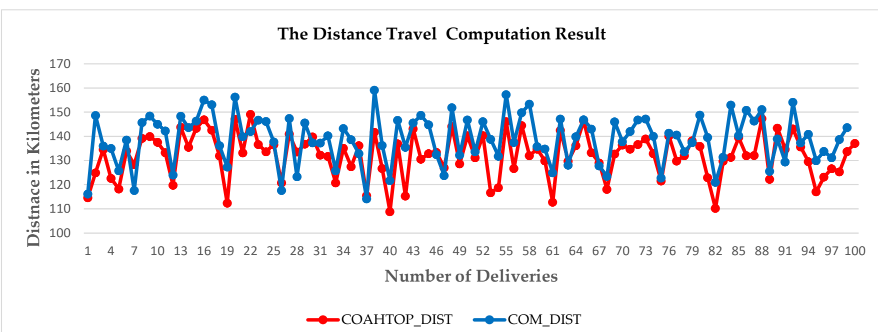

Figure 7: Comparing the Travel Distance

Simulation results from the 100 datasets indicated that the MCDM-COMVRP model converged faster on average across 100 iterations compared to the COMVRP model with an average route mileage of 133 kilometres. This improved performance was also reflected in the computational time, as depicted in Figure 8. There was higher efficiency by 4.86% compared to COMVRP and 28.03% compared to the existing delivery.

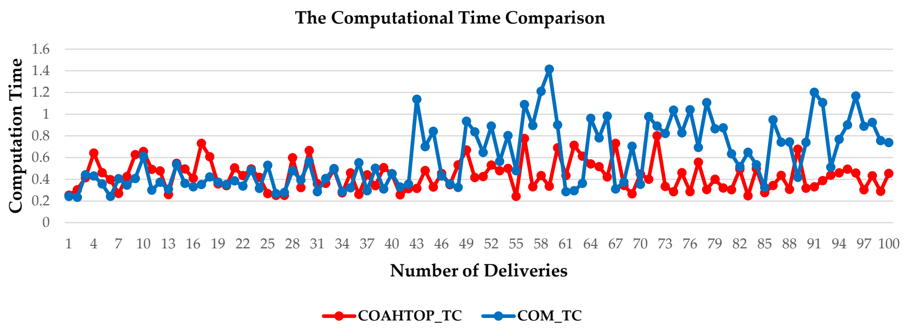

Figure 8: Comparing the Travel Distance

The results from MCS indicated an average of four routes or vehicles. When comparing routes between COMVRP and the MCDM-COMVRP approaches, the proposed algorithm demonstrated that each external vehicle route prioritised passing through the designated DCs.

4.0 CONCLUSION

The proposed algorithm reduced mileage in dataset-based delivery scenarios while also improving computational efficiency. Despite considering four criteria outlined in the constraints and sometimes referring to priority rankings of DCs, the algorithm must still account for DCs that need to be visited. This might lead to longer travel distances and increased mileage in certain cases. Many metaheuristic algorithms rely on their inherent capability to find optimal solutions, with GA often being used in such processes. Computational results showed that determining the number of prioritised DCs could reduce the mileage from 140 kilometres based on the COMVRP results to 133 kilometres based on the proposed method, increasing efficiency by 4.86% and achieving the shortest computing time by 28.03% compared to the existing delivery. The simulation results indicate that optimisation can be achieved by utilising the existing distribution network. It also involves an external fleet through the application of the COMVRP model while engaging internal stakeholders who possess experience and historical delivery data analysis using the AHP-TOPSIS technique.

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AUTHORS' CONTRIBUTIONS

S. Nirwan and N. Heriyana: Writing-Original Draft Preparation, Data Curation, Validation; M. H. L. Abdullah: Validation, Writing-Reviewing and Editing; S. S. Rahim: Writing-Reviewing; S. Nirwan and Mubassiran: Software Development.

CONFLICTS OF INTEREST

The manuscript has not been published elsewhere and is not under consideration by other journals. All authors have approved the manuscript, agreed with its submission, and declared no conflict of interest.

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