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A Multi-Criteria Decision Approach for Optimized Route Planning in Retail Distribution

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Abstract. Route planning is vital for logistics efficiency. Not only responsible to manage the whole delivering process, but also arrange the shipping with optimum route, increase customer satisfaction and logistics cost control. Even though route planning and delivery are repetitive processes, many problems are still found in this area such as: mistaken in route assignment, over truck capacity, and mistakes in truck allocation that lead to failed delivery. This study presents a multi-criteria decision approach to optimize retail delivery routing. Sales order data for a distribution firm was tested using weighted scoring of capacity, distance, and route azimuth parameters to create straight-line paths between drop points. Comparative analysis showed 33% vehicle reduction and around 40% savings in time over manual planning, demonstrating cost and service improvements.

Keywords: Route Planning, Route Optimization, Multi-Criteria Decision Analysis, Retail Distribution, Transportation Management System, Smart Logistics

1. Introduction

Transportation planning in the logistics process is one of the key elements in modern business, it takes an important role in the decision-making process in an organization, not only in the Supply Chain part, but also in the production until the sales process (Daroń, 2022). Transportation planning is not only a process to determine the best delivery route, but also the process to increase customer satisfaction and control the logistics cost. Recent development in technology such as robotics and automation, artificial intelligence, business intelligence and big data, cloud computing etc. are expected to implement in the manufacturing and logistics process to be transform become smart manufacturing and logistics. Smart logistics expected to increase flexibility in adaption to market and customer needs changing. Smart logistics must rely on technology to increase their process to be more efficient (Barreto et al., 2017).

Logistics cost in Indonesia reach 23.5% from gross domestic product. The number is quite high compared to 13% logistics cost in Malaysia (Wibowo, 2022). Logistics cost cover all the cost in logistics process like delivering, warehousing, and handling cost. World Bank survey in 2016 said that delivering cost takes 48% from total logistics cost (Bennis, 2022). In Indonesia, the high cost caused by geographical, infrastructure and fuel cost.

Route assignment in delivering process was repetitive process in logistics, due to traditional way many problems are still found in this process such as mistaken route assignment, truck over capacity, or wrong truck type selection. These mistake lead to undelivered sales order to customer. In short-term, this inefficient on delivery process impact to logistics cost increase, organization needs to spend more money to do redelivery process. If this bad delivery experience happened in long-term period, it will decrease the customer satisfaction and tend to lose customer.

Since introduced in 1959, vehicle routing problem (VRP) was improved to several types, such as: capacity constraint, cross-docking, cumulative capacitated VRP and electric VRP, etc. Capacity constraint is a VRP technique that consider maximizing the capacity, while cross-docking is an improvement VRP technique that add depots as cross-docking. Cumulative capacitated VRP have an objective to minimize waiting time between the drop points.

In current process, transportation planning team done the route planning in manual way. Along the process, they did not consider the route path and to maximize truck capacity. The objective of route planning is to deliver all the orders to customer. Based on the current condition, there is an opportunity to improve the route planning process by maximize the capacity, reduce trave time then reduce transportation cost.

This study aims to improve the current route planning by produce optimum route planning. The optimum route objective is maximizing truck capacity and reduce travel time by generate straight-line route based on the angle of customer location using azimuth based on customer order data. The route planning process will be considering certain criteria using Multi-Criteria Decision Analysis.

2. Literature Review

2.1. Logistics

Contributions Logistics is a strategic process in organization that cover material replenishment and procure, inventory movement and storage to generate maximum profit with minimum cost (Christopher, 2016). Logistics process development since Industry 1.0 around 18th centuries, to Industry 4.0 which integrate digital and technology in the process describe in following figure:

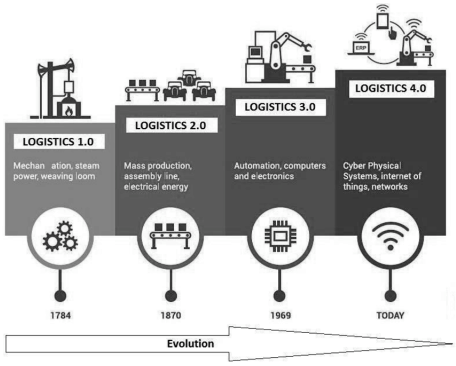


Fig. 1: Logistics evolution (Dembińska, 2018)

2.2. Vehicle Routing Problem

In traditional way, the objective of Vehicle Routing Problem (VRP) is solving logistics transport problem by calculate and determine vehicle route to delivery order to customer with minimum distance and cost (Ahmed et al., 2022). Since published at 1959, VRP was improve to several types (Agárdi et al., 2022), such as:

- Capacity Constraint is the traditional VRP model in which vehicles with limited carrying capacity need to pick up or deliver items at various locations. The limitation of this model is focus only in vehicle capacity, and need another algorithm to solve route sequencing.
- Cross-Docking is another variant of VRP where a set of homogeneous vehicles are used to transport orders from the suppliers to the corresponding customers via a cross-dock (Wen et al., 2009). The advantages of this model are makes supply chain process more efficient by removing the warehousing process and makes the distribution process well-ordered. This model is not suitable to apply in retail distribution due to the delivering process rely on the vehicle fleet.
- Cumulative Capacitated VRP is a relatively new variant of the classical capacitated vehicle routing problem in which the objective is to minimize the sum of arrival times at customers (min-sum) instead of the total route distance (Bruni et al., 2019).
- This study objective is to improve the current model of VRP not only to fulfil the capacity of vehicle, but also reduce travel time by generating straight-line route based on customer location.

2.3. Multi-Criteria Decision Analysis

Multi-Criteria Decision Analysis is a method to support decision-making process to solve complex problem with consider multiple option. Multi-Criteria Decision Analysis is very useful when used to consider multiple option simultaneously (Jahan et al., 2016). Multi-Criteria Decision Analysis is a good framework to compare multiple criteria for simple calculation with few criteria (Schey et al., 2017).

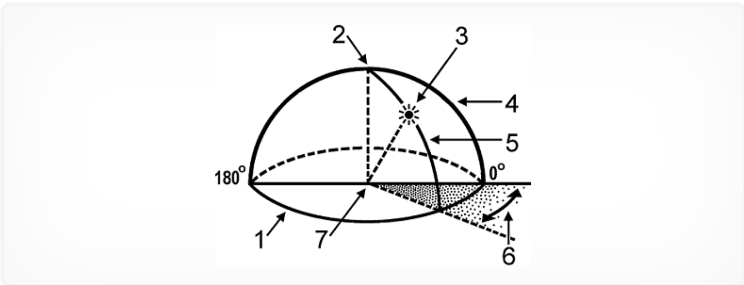
This research used multiple dimensions such as capacity in kilogram and distance in meter. To compare the dimensions in one unit, the data needs to normalize. This research used Linear-Max technique to calculate normalization then use the result for determine delivery priority for certain order. Refer to previous research from (Vafaei et al., 2016) Linear-Max is the best normalization technique compared to Linear Max-Min, Linear Sum, Vector, and Logarithmic normalization.

Table 1: Normalization technique

Normalization technique	Condition of use	Formula
Linear: Max (N1) [14]	Benefit criteria	$n_{ij} = \frac{r_{ij}}{r_{max}}$
	Cost criteria	$n_{ij} = 1 - \frac{r_{ij}}{r_{max}}$
Linear: Max-Min (N2) [14]	Benefit criteria	$n_{ij} = \frac{r_{ij} - r_{min}}{r_{max} - r_{min}}$
	Cost criteria	$n_{ij} = \frac{r_{max} - r_{ij}}{r_{max} - r_{min}}$
Linear: sum (N3) [14]	Benefit criteria	$n_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$
	Cost criteria	$n_{ij} = \frac{1/r_{ij}}{\sum_{i=1}^{m} 1/r_{ij}}$
Vector normalization (N4) [2]	Benefit criteria	$n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$
	Cost criteria	$n_{ij} = 1 - \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$
Logarithmic normalization (N5) [2]	Benefit criteria	$n_{ij} = \frac{\ln(r_{ij})}{\ln(\prod_{i=1}^{m} r_{ij})}$
	Cost criteria	$n_{ij} = \frac{1 - \frac{\ln(r_{ij})}{\ln(\prod_{i=1}^{m} r_{ij})}}{m-1}$

2.4. Astronomical Azimuth Determination

Azimuth is the direction given by the angle between the meridian and the line measured in a clockwise direction (Dimal et al., 2009). Azimuth is the horizontal direction expressed as the angular distance between the direction of a fixed point and direction of the object.



1 horizon **2** zenith **3** star
4 meridian **5** vertical circle **6** azimuth
7 observer

Fig. 2: Illustration of Azimuth

The astronomic azimuth related to astronomic meridian, longitude, and longitude. All these information is obtained when using the geoid as the model to represent the shape of earth. Azimuth (θ) direction and distance (d) between two latitude and longitude points determined using Haversine formula (Masatu et al., 2022) in following equation:

$$a = \sin^2\left(\frac{\Delta\emptyset}{2}\right) + \cos\emptyset_1 * \cos\emptyset_2 * \sin^2\left(\frac{\Delta\lambda}{2}\right)$$

$$d = 2R\,\arctan2\left(\sqrt{a}, \sqrt{1-a}\right)$$

$$\theta = \arctan2(\sin\Delta\lambda * \cos\emptyset_2, \cos\emptyset_1 * \sin\emptyset_2 - \sin\emptyset_1 * \cos\emptyset_2 * \cos\Delta\lambda)$$

a = an intermediate step;

$\emptyset_1$ = latitude of origin point;

$\emptyset_2$ = latitude of next point (destination);

λ_1 = longitude of origin point;
λ_2 = longitude of next point (destination);
$\Delta\emptyset = \emptyset_2 - \emptyset_1$;
$\Delta\lambda = \lambda_2 - \lambda_1$;
d = distance;
R = radius of the earth, expressed in meters (R = 6371 KM)

3. Methods

In traditional way, the objective of vehicle routing problem is to design a trip start from depot, visit the customers, then return to depot. Along the years, vehicle routing problem was improved not only to deliver the goods with minimum cost, but also considering truck capacity, cross-docking, cumulative capacitated vehicle routing problem, and electric VRP.

This study aims to optimize the route planning by maximizing truck capacity and reduce travel time along the delivery process. The result of this study is straight-line delivery route based on angle of customer location using azimuth, in the other hand consider multiple variables using Multi-Criteria Decision Analysis method.

$$\min \textstyle\sum_{l \in L} x_{ol} \max \textstyle\sum_{o \in O} x_{ol} = 1$$

This route planning process consider two decision variables, first is maximize the fulfilment of truck capacity, the process will stop when it reaches the maximum capacity of the vehicle. In this study, it only used one type of truck with 2.500 KG capacity. The second one is maximum drop points. This decision variable is set to generate the result more equally within same delivery area. As we know in retail distribution, it possible to have a lot of small order and bulk order at the same time. Rather than to delivery all small order in one truck with failed delivery possibility, this decision variable set with maximum drop points is fifteen (15). When the process iteration comes to thirteen (13), it will filtering open order with the remaining of truck capacity. So, the truck capacity still can be maximized in the last two iteration process.

$$x_{ol} = \begin{Bmatrix} \begin{cases} 1 & IF\ maximum\ truck\ capacity\ reached \\ 0 & Otherwise \end{cases} \end{Bmatrix}$$

$$x_{ol} = \begin{Bmatrix} \begin{cases} 1 & IF\ maximum\ drop\ points\ reached \\ 0 & Otherwise \end{cases} \end{Bmatrix}$$

Muti-Criteria Decision Analysis plays important role on this research to determined which next drop point to be selected. Decision takes after considering multiple variables such as route, distance, and gross weight. Those variables divided into three types which are selection criteria, benefit criteria, and cost criteria. Benefit criteria formulated to correspond the high value to maximum value (maximize – benefit), otherwise cost criteria formulated to correspond the high value to minimum value (minimize – cost). Criteria with type selection used as selection rule within the process, these criteria did not used any formula.

Benefit Criteria

$$n_{ij} = \frac{r_{ij}}{r_{max}}$$

Cost Criteria

$$n_{ij} = 1 - \frac{r_{ij}}{r_{max}}$$

There are three criteria used as variable in this research:

- Route
  This variable used for sorting and selecting the order based on customer route / location.

- Distance
  This variable categorized as cost criteria. The distance obtained from calculate using Haversine formula based on two coordinate (longitude and latitude) locations.
- Truck Capacity
  This variable categorized as benefit criteria. One of this method objectives is to maximize truck capacity fulfilment. Only one type of truck used in this study, which pick-up truck (2500 kg) as used in this research distribution company.

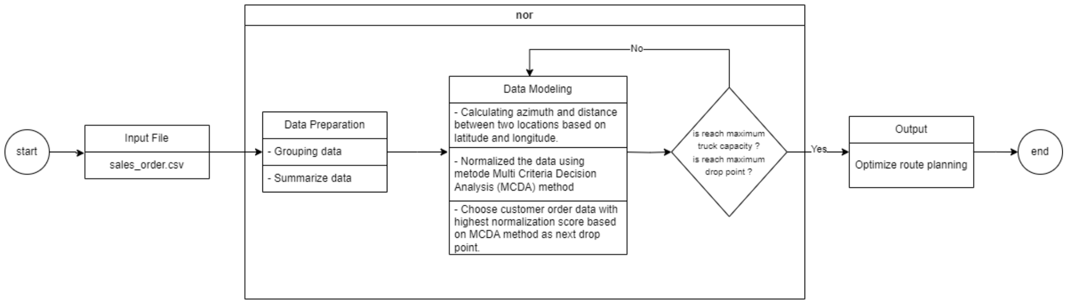


Fig. 3: Optimize route planning flow process.

This method consists of four stages. Starts from data preparation which aggregating the gross weight for each customer. Continue to calculate the angle and distance from start node (depot) to next node (drop point location). Normalize the data using Muti-Criteria Decision Analysis, next node of the route determines by the highest performance score from the dataset. This process repeated and stopped when it meets to decision variable which truck fulfilled or maximum drop point reached. This procedure will be iterated for all order data to produce optimize route planning as an output.

3.1. Data Preparation

First stage of this method is data preparation. Data preparation is a crucial step to identifying and handling missing or incomplete data point on the dataset. This study used sales order data from a retail distribution company located in Batam, Indonesia. First the data read from Comma-separated values (CSV) format, then aggregated by customer attributes. Fig. 4 shows summarization of gross weight (in kilograms) for each customer id.

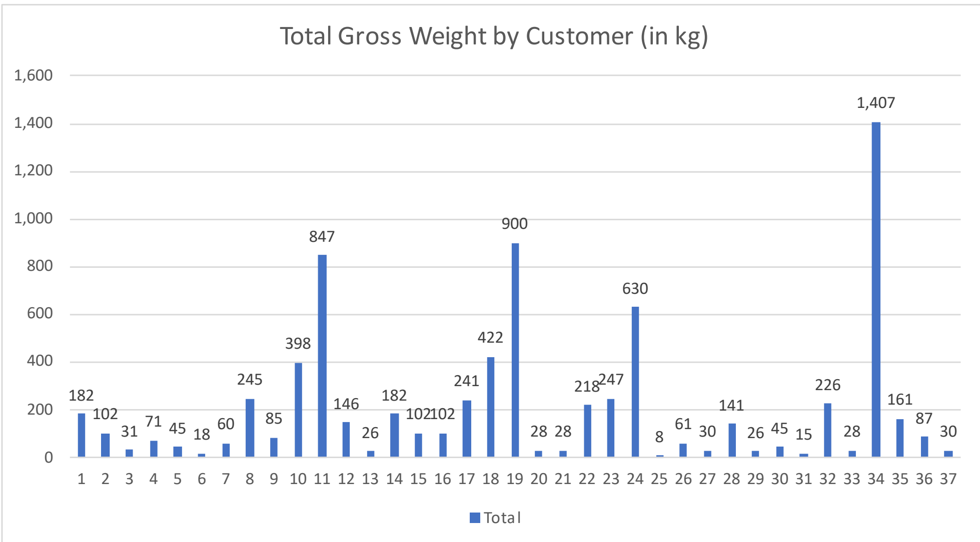


Fig. 4: Summarize daily customer demand

```
FUNCTION SummarizeData ()
BEGIN
    data = READ FILE 'sales_order.csv'
    data = GROUP BY "outlet", "latitude", "longitude"
           SUMMARIZE "gross_weight", "volume"

    ADD COLUMN TO DATAFRAME "proposed_shipment"
    ADD COLUMN TO DATAFRAME "proposed_shipment_sequence"
    ADD COLUMN TO DATAFRAME "distance"
    ADD COLUMN TO DATAFRAME "forward_azimuth"

    RETURN data
END
```

Fig. 5: Summarize order data algorithm

3.2. Azimuth and Distance

In this study, sales order data will be clustering based on customer location. Azimuth plays important role in this process to provide distance and angle between two customer location. This process used to determine sequence of route planning. Fig. 6 shows the distribution location of Depot on blue dot and customer location on red dot. Drop point spreads over the entire of Batam island. Azimuth helps to clustering customer location when generating the route planning and provide an angle between customer locations to make this route planning process more optimized.

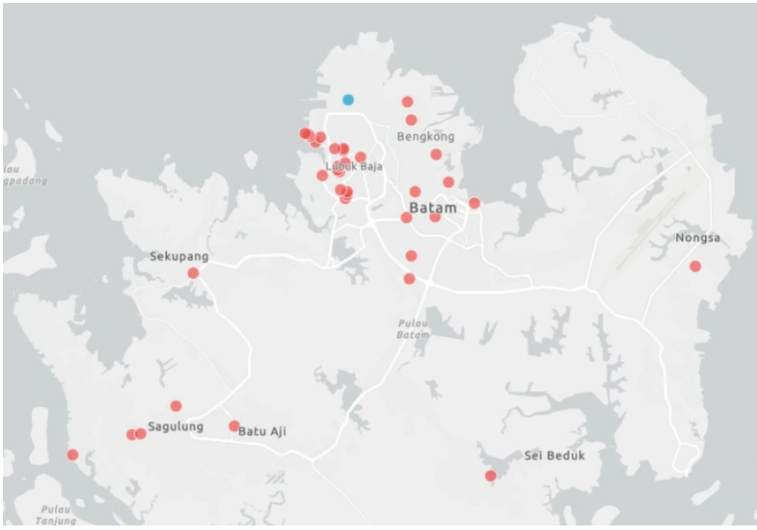


Fig. 6: Distribution of depot and customer location

Azimuth calculation performed using Haversine and Bearing formula describe in the following algorithm Fig. 7 and Fig. 8. Haversine formula used to computing distance between two points on the surface of the sphere using the longitude and latitude of the two points multiplied with radius of the earth.

```
FUNCTION Haversine (latitude1, longitude1, latitude2, longitude2)
BEGIN
    /* calculate distance between latitude and longitude */
    dLat = (latitude2 - latitude1) * MATH.pi / 180
    dLon = (longitude2 - longitude2) * MATH.pi / 180

    #convert to radians
    lat1 = (latitude1) * MATH.pi / 180
    lat2 = (latitude2) * MATH.pi / 180

    a = ( POW(MATH.sin(dLat / 2), 2)
        + POW(MATH.sin(dLon / 2), 2)
        * MATH.cos(latitude1) * MATH.cos(latitude2))

    rad = 6371
    c = 2 * MATH.asin(MATH.sqrt(a))
    distance = rad * c

    RETURN distance
END
```

Fig. 7: Haversine formula

While bearing is an angle measured clockwise from the north direction. In this study, bearing used to clustering customer location while route planning process. To limit the route process, when generating the route planning bearing is set to 90°, it clustered the customer location into four cluster. This number can be change as needed when it leverages in larger distribution process.

```
FUNCTION Bearing (latitude1, longitude1, latitude2, longitude2)
BEGIN
    two_pi = MATH.pi * 2
    theta = MATH.atan2(longitude2, longitude1,
                       latitude2 - latitude1)

    IF (theta < 0) THEN theta = two_pi

    bearing = MATH.degrees(theta)

    IF (bearing < 0) THEN bearing + 360
    ELSE IF (bearing > 360) THEN bearing - 360
    ELSE bearing
    END IF

    RETURN bearing
END
```

Fig. 8: Bearing formula

The route generated in 90° angle from depot to first drop point as starting location. While selecting the sequence, sales order data will be select for customer located in the 90° range. For example, in Fig. 9 shows first drop point located in 140° from depot, then the next sequence node of route will select the sales order data for customer located in range from 90° to 180°. It shows that the second drop point located in 130° and the last drop point located in 115° before back to depot as starting point.

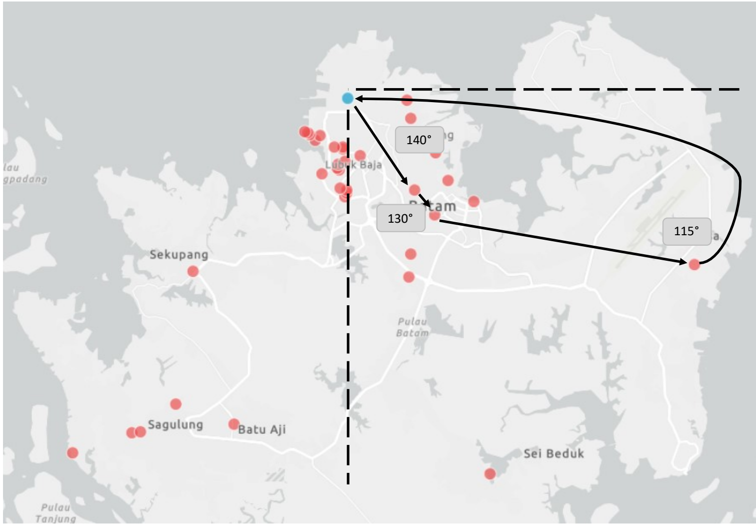


Fig. 9: Drop point selection simulation

In drop point selection stage, first drop point determine based on MCDA result considering weight and distance as parameters. For the next sequence, Azimuth calculated to provide distance and angle for every sales order data based on customer location. This result used as reference from second iteration of drop point selection to filtered sales order data located in 90° range from first drop point. Fig. 10 describe how the algorithm perform to calculate start and end range in this process.

```
FUNCTION StartEndAzimuth (azimuth)
BEGIN
    IF (row["forward_azimuth"] > 0)
        AND (row["forward_azimuth"] <= 90)
        THEN start_azimuth = 0

    ELSE IF (row["forward_azimuth"] > 90)
             AND (row["forward_azimuth"] <= 180)
             THEN start_azimuth = 90

    ELSE IF (row["forward_azimuth"] > 180)
             AND (row["forward_azimuth"] <= 270)
             THEN start_azimuth = 180

    ELSE IF (row["forward_azimuth"] > 270)
             AND (row["forward_azimuth"] <= 360)
             THEN start_azimuth = 270

    ELSE start_azimuth = 0

    END IF

    end_azimuth = start_azimuth + 90

    RETURN start_azimuth, end_azimuth
END
```

Fig. 10: Start end Azimuth

3.3. Multi-Criteria Decision Analysis

Multi-Criteria Decision Analysis (MCDA) helps to evaluate and prioritize sales order data based on various criteria to decide. MCDA plays the important role in this stage to determine which order will be select then add to node sequence as next drop point. One of process in Multi-Criteria Decision Analysis is calculate normalization. Normalization used for getting same measurement from various variables, in this case the variables are measure in kilograms, kilometers and degrees. Normalization result, it continues to calculate performance score for each data, then rank the dataset. First rank considered as best node to select as the sequence drop point. Fig. 11 shows how the normalization, performance result and rank perform in MCDA process.

```
FUNCTION Normalization (normalization_data)
BEGIN
    ["norm_gross_weight"] = ["gross_weight"] / max(["gross_weight"])
    ["norm_distance"]     = 1 - (row["distance"] / max(["distance"]))
    ["performance_score"] = ["norm_gross_weight"] + ["norm_distance"]
    ["rank"]              = SORT BY ["performance_score"] DESCENDING
END
```

Fig. 11: Normalization technique

This stage is a sub-process while generating the route planning. MCDA plays important rules to normalize the dataset for selecting first rank of normalization as best sales order data to pick for next drop point sequence. This process will iterate until met decision variable condition, which truck capacity fulfilled, or maximum drop point reached. For an examples of MCDA process, these three following tables show iteration steps when sales order data normalized.

Table 2: Normalization process step 1

Customer Code	Gross Weight (kg)	Forward Azimuth	Distance (meters)	Gross Weight Normalization	Distance Normalization	Perfromance Score	Rank
34	1,407	187	2,887	1.00	0.84	1.84	1
24	630	186	2,037	0.45	0.89	1.33	2
11	847	222	9,265	0.60	0.48	1.08	3
17	241	189	2,675	0.17	0.85	1.02	4
28	141	217	1,841	0.10	0.90	1.00	5
32	226	199	3,163	0.16	0.82	0.98	6
8	245	181	3,779	0.17	0.79	0.96	7
7	60	196	2,008	0.04	0.89	0.93	8
35	161	185	3,584	0.11	0.80	0.91	9
3	31	186	1,973	0.02	0.89	0.91	10
27	30	229	2,133	0.02	0.88	0.90	11
37	30	232	2,173	0.02	0.88	0.90	12
13	26	226	2,128	0.02	0.88	0.90	13
29	26	218	2,132	0.02	0.88	0.90	14
5	45	183	2,535	0.03	0.86	0.89	15

Table 3: Normalization process step 2

Customer Code	Gross Weight (kg)	Forward Azimuth	Distance (meters)	Gross Weight Normalization	Distance Normalization	Perfromance Score	Rank
24	630	186	2,037	0.70	0.89	1.59	1
11	847	222	9,265	0.94	0.48	1.42	2
17	241	189	2,675	0.27	0.85	1.12	3
32	226	199	3,163	0.25	0.82	1.07	4
8	245	181	3,779	0.27	0.79	1.06	5
28	141	217	1,841	0.16	0.90	1.05	6
19	900	218	17,866	1.00	0.00	1.00	7
35	161	185	3,584	0.18	0.80	0.98	8
7	60	196	2,008	0.07	0.89	0.95	9
3	31	186	1,973	0.03	0.89	0.92	10
27	30	229	2,133	0.03	0.88	0.91	11
37	30	232	2,173	0.03	0.88	0.91	12
13	26	226	2,128	0.03	0.88	0.91	13
29	26	218	2,132	0.03	0.88	0.91	14
2	102	180	3,663	0.11	0.79	0.91	15

Table 4: Normalization process step 3

Code	Weight (kg)	Azimuth	(meters)	Normalization	Normalization	Score	
17	241	189	2,675	0.99	0.83	1.82	1
8	245	181	3,779	1.00	0.76	1.76	2
32	226	199	3,163	0.92	0.80	1.72	3
28	141	217	1,841	0.58	0.88	1.46	4
35	161	185	3,584	0.66	0.77	1.43	5
2	102	180	3,663	0.42	0.77	1.19	6
7	60	196	2,008	0.25	0.87	1.12	7
36	87	182	3,928	0.36	0.75	1.11	8
5	45	183	2,535	0.18	0.84	1.02	9
3	31	186	1,973	0.13	0.88	1.00	10
27	30	229	2,133	0.12	0.87	0.99	11
37	30	232	2,173	0.12	0.86	0.99	12
13	26	226	2,128	0.11	0.87	0.97	13
29	26	218	2,132	0.10	0.87	0.97	14
33	28	189	2,828	0.12	0.82	0.94	15

After a route planning generated, the process will have re-started to generate another route planning until all sales order data have been processed. If there is any case when sales order data cannot be plan, that sales order will be hold then include to next route planning process.

3.4. Route Planning Creation Process

Route planning process is an iterative process which have several sub-processes inside, which calculate distance and angle for each sales order data, setting start and end Azimuth range, normalize the sales order data using MCDA method, and select sales order data for next drop point. This process will loop through all sales order data in the dataset. It stops when truck capacity is fulfilled or maximum drop point in current route planning iteration reached. In this study, it only used one type of truck with capacity 2.500 kilograms and set maximum drop point as agreed with the team by fifteen (15) drop points. Route planning iteration process show in this following algorithm:

```
FUNCTION RoutePlanning (sales_order_data)
BEGIN
FOR row in sales_order_data
    tmp_capacity = bucket_capacity + row["gross_weight"]

    IF ((tmp_capacity <= MAXIMUM_TRUCK_CAPACITY)
        AND (bucket_capacity <= MAXIMUM_TRUCK_CAPACITY)
        AND (proposed_shipment_sequence <= 15))
        THEN ["proposed_shipment"] = "Proposed Shipment " + bucket_id
             ["proposed_shipment_sequence"] = proposed_shipment_sequence
             origin_latitude = ["latitude"]
             origin_longitude = ["longitude"]
             bucket_capacity = bucket_capacity + ["gross_weight"]

            proposed_shipment_data = FILTER proposed_shipment_data
                                     WHERE ["proposed_shipment"] is BLANK
            length_of_dataframe = length(proposed_shipment_data)
            proposed_shipment_sequence = proposed_shipment_sequence + 1
            tmp_capacity =0
    BREAK
    ELSE IF tmp_capacity > MAXIMUM_TRUCK_CAPACITY
            origin_latitude = 1.168005277747106
            origin_longitude = 104.01004496683078
            bucket_id = bucket_id +1
            bucket_capacity = 0
            proposed_shipment_data = FILTER proposed_shipment_data
                                     WHERE ["proposed_shipment"] is BLANK
            length_of_dataframe = length(proposed_shipment_data)
            proposed_shipment_sequence = proposed_shipment_sequence + 1
            tmp_capacity =0
    BREAK
    ELSE CONTINUE
```

Fig. 12: Route planning creation process

4. Result and Discussion

This section presents the implementation of the generated route planning using the Multi-Criteria Decision Analysis method. This experimentation used a daily demand from a retail distribution company located in Batam, Indonesia. The result compared with existing route planning created by Transportation Planning team of the company in manual way. Maximum drop point sets as fifteen (15) to limit the process and avoid failed delivery, also one truck capacity is set for 2.500 kilograms. The variables have been provided and agreed with the team.

4.1. Existing Route Planning Result

Existing route planning result which created in manual way shows in Table 5. Transportation planning team determined the route planning in manual way. The route planning fall apart frequently due to human mistakes, such as wrong route, over truck capacity, wrong truck selection, etc. For this daily demand, there are six trucks planning generated for 7.620 kilograms demand, 343.8 kilometers, with 17 hours 25 minutes travelled time. Capacity for each truck must be less than 3.000 kilograms (small truck).

This data used as reference for comparing with route planning generated with Multi-Criteria Decision Analysis method.

Table 5: Existing route planning (manual)

Truck	Delivery Sequence	Total Weight (in kg)	Truck Fulfilment Capacity (%)	Distance Travelled (in km)	Travelled Time (actual)
Truck 1	0-4-11-0	917.5	30.6%	64.9	03:55
Truck 2	0-6-18-19-20-21-11-25-1-8-9-12-22-23-0	2,527.3	84.2%	165.0	06:50
Truck 3	0-7-10-14-15-16-0	845.3	28.2%	23.4	01:20
Truck 4	0-2-5-13-17-26-28-0	615.1	20.5%	54.4	01:20
Truck 5	0-30-31-33-34-35-0	1,655.7	55.2%	13.6	00:50
Truck 6	0-3-24-27-29-32-36-37-0	1,059.0	35.3%	22.5	03:10
Total		**7,620.0**	**40.9%**	**343.8**	**17:25**

4.2. Experiments Result of MCDA Method

To experiment this method, the sales order data, truck capacity, maximum drop point, customer location coordinate has been provided by Transportation Planning team of the company. The process starts by calculating distance and angle of each sales order data using Haversine and Bearing formula. After that, sales order data normalized using MCDA method, then pick the first rank to add to route planning as next drop point sequence.

This experiment generated four route planning with total weight 7.620 kilograms, 345.6 kilometers with 10 hours 26 minutes travelled time -estimated using Google Maps-. Route planning result shows in Table 6 with maps visualization of each route displayed in Fig. 13 captured from Google Maps.

Table 6: Route planning generated using MCDA

Truck	Delivery Sequence	Total Weight (in kilograms)	Truck Fulfilment Capacity (%)	Distance Travelled (km)	Estimated Time Travelled from Google Maps
Truck 1	0-34-24-17-35-7-0	2,499.7	83.3%	15.0	00:36
Truck 2	0-11-32-8-28-19-2-3-25-0	2,498.9	83.3%	132.0	03:37
Truck 3	0-36-5-27-37-33-13-29-31-20-21-6-0	359.9	12.0%	78.6	02:28
Truck 4	0-10-18-23-22-14-1-12-16-15-9-30-4-26-0	2,261.5	75.4%	120.0	03:45
		7.620 KG Total Weight	**63.5% Avg Fulfilment**	**345.6 KM Total Distance**	**02:36 Avg Travel Time**

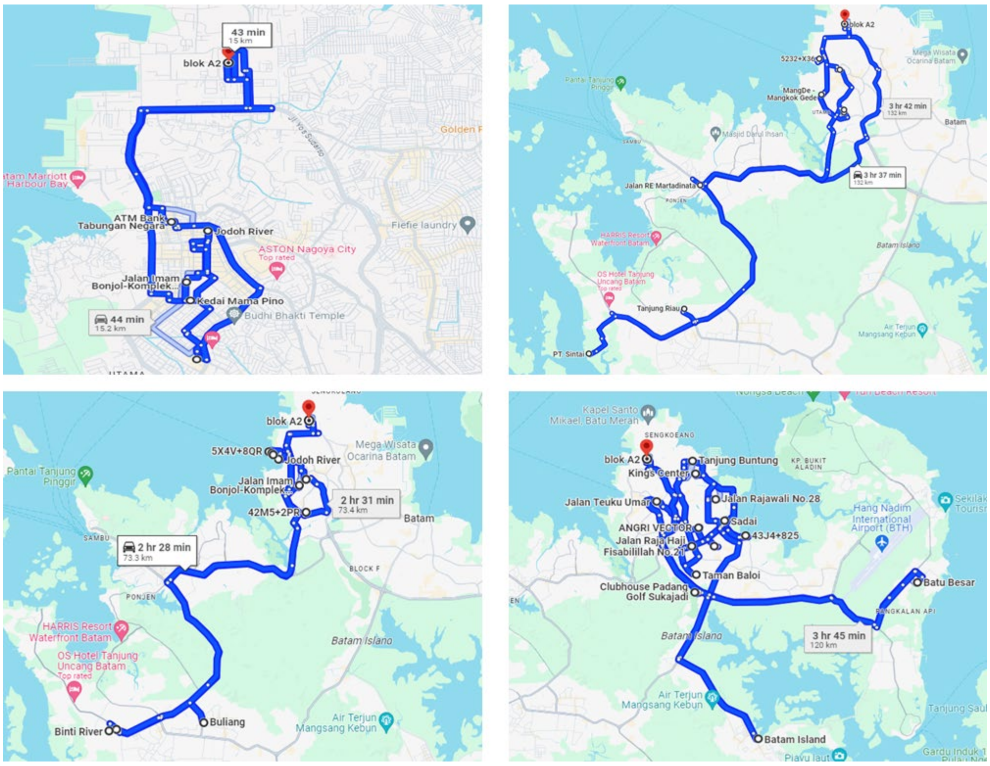


Fig. 13: Maps visualization of optimize route planning using MCDA

The result shows that MCDA method tried to fulfilled truck capacity to maximum truck capacity which is 2.500 kilograms. It reach greater than 63% truck capacity fulfilled from all route planning in average, only one route planning is not maximize the truck capacity which route planning number three (Truck 3). With total drop point for each truck is less than -or equal to- fifteen (15), it generate an estimated 2 hours 36 minutes travelled time. With this number of travelled time, increase the number of success delivery optimistic.

4.3. Comparison of Experiment Result

This section explains the comparison result between existing route planning that created in manual way and route planning generated by MCDA method. In summarize, comparison result shows in Table 7.

Table 7: Comparison of experiment results

Variable Metrics	Existing Route Planning	MCDA Route Planning	Variance (%)	Remarks
Total Truck	6 route planning	4 route planning	▼-33.3%	reduce number of trucks by two
Average of Truck Fulfilment Capacity (%)	40.9% capacity fulfilled	63.5% capacity fulfilled	▲22.6%	increase 22.6% truck capcaity (fulfilment)
Total Travel Time	17 hours 25 minutes	10 hours 26 minutes	▼-40.0%	reduce 6 hours 59 minutes travelled time

In this experiment, MCDA method generated four route planning, which reduce 33% compared to route planning created in manual way, this number equals to two trucks saving. In terms of average truck fullfilment, this method tried to maximize truck capacity by gain 63,5% in average of truck capacity fulfilment, which increased 22.6% compared to manual way. Finally, MDCA method reduce travelled time 40%, it is arround 6 hours 59 minutes travelled time.

These four following tables show the comparison in different perspective. Table 8 shows the comparison by distance travelled, as the number of trucks reduce by two trucks, the total kilometers are not significantly different. Due to the total travelled distance in both methos is similar, we can see that in Table 9 calculation of fuel consumption is not significantly different also. By assuming one (1) liter of fuel consumption equals to eight (8) kilometers for each truck, and fuel price is IDR 10.000, it increases 0.5% fuel cost.

Table 8: Comparison result by distance travelled in kilometres

Number of Truck	Existing Route Planning	MCDA Route Planning	Variance (%)	Remarks
1	65	15	-76.9%	As the number of trucks reduce by two trucks. Total kilometer for delivery process in both processes did not significantly different.
2	165	132	-20.0%	
3	23	79	235.9%	
4	54	120	120.6%	
5	14		-100.0%	
6	23		-100.0%	
Total	**344**	**346**	0.5%	

Table 9: Comparison result by total fuel cost consumption

Number of Truck	Existing Route Planning	MCDA Route Planning	Variance (%)	Remarks
1	IDR 81,125	IDR 18,750	-76.9%	As the total kilometer not significantly different, it did not have an impact to reduce the fuel cost. With assumption: - vehicle fuel consumption 1 liter for 8 kilometers. - fuel price IDR 10.000.
2	IDR 206,250	IDR 165,000	-20.0%	
3	IDR 29,250	IDR 98,250	235.9%	
4	IDR 68,000	IDR 150,000	120.6%	
5	IDR 17,000		-100.0%	
6	IDR 28,125		-100.0%	
Total	**IDR 429,750**	**IDR 432,000**	0.5%	

While the travelled distance and fuel cost was not decrease. Table 10 shows the comparison by total personnel cost. In assumption that each truck used one (1) driver and one (1) person as helper. By reducing two number of trucks, it can generate cost saving by 33.3% of total personnel cost or equals to IDR 160.000. By overall transporation cost, MCDA method can generate 17.3% cost saving or equals to IDR 157.750 in this experiment comparison between existing route planning process and MCDA method. This cost saving number will look more significant when it multiplies to monthly and annually route planning process.

Table 10: Comparison result by total personnel cost

Number of Truck	Existing Route Planning	MCDA Route Planning	Variance (%)	Remarks
1	IDR 80,000	IDR 80,000	0.0%	Cost saving comes from personnel cost of delivery (driver and helper). By reducing the number of trucks by two, it generates cost saving 33.3% or IDR 160.000 for the day that this method compared. with the assumption: - Driver fee IDR 50.000. - Helper Fee IDR 30.000.
2	IDR 80,000	IDR 80,000	0.0%	
3	IDR 80,000	IDR 80,000	0.0%	
4	IDR 80,000	IDR 80,000	0.0%	
5	IDR 80,000		-100.0%	
6	IDR 80,000		-100.0%	
Total	**IDR 480,000**	**IDR 320,000**	-33.3%	

Table 11: Comparison result by overall transportation cost

Number of Truck	Existing Route Planning	MCDA Route Planning	Variance (%)	Remarks
1	IDR 161,125	IDR 98,750	-38.7%	By total transportation cost, comparing the existing method with MDCA, it shows that MDCA method can reduce the cost by 17.3%, equal to IDR 157.750.
2	IDR 286,250	IDR 245,000	-14.4%	
3	IDR 109,250	IDR 178,250	63.2%	
4	IDR 148,000	IDR 230,000	55.4%	
5	IDR 97,000		-100.0%	
6	IDR 108,125		-100.0%	
Total	**IDR 909,750**	**IDR 752,000**	-17.3%	

These comparation result shows that route planning with MCDA method can increased optimistic of delivery success factor, which can be impacted to increase of distribution performance and generate cost saving.

5. Conclusion

This research experiment to generate a route path using Multi-Criteria Decision Analysis by consider multiple criteria. The objective is to generate optimal route planning by maximize truck capacity and minimize cost and travel time. The result shows that variable sucs as gross weight, distance, route have an impact to route optimization process. By comparing between route planning generated by MCDA method with manual route planning process, it shows that MCDA method not only generate optimize route planning, but also geneate significant savings on daily transportation cost.

The multi-criteria route optimization method offers valuable capabilities for logistics. However, validation using only a single firm limits generalizability. Further implementation across contexts and integration with emerging technologies like AI and machine learning can extend capabilities. Overall, the study provides a baseline framework to enhance retail distribution through digitized decision support.

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