Optimization of Vehicle Routing Problem in the Context of E-commerce Logistics Distribution

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***Abstract*—2E-MDCVRP is a multi-depot, capacity, two-echelon vehicle routing issue. Satellites make it possible to collect and sort orders. In this paper, a 2E-MDCVRP model will be designed to be applied to e-commerce. In the completion stage, the researcher developed a 2E-MDCVRP solution with two stages of completion. The first stage is finding the best route for the satellite to travel to the customer. In the first stage of work, satellites are plotted as centroids in clusters using the k-Means algorithm to obtain k-set clusters. To determine route scheduling using the RNN algorithm in determining travel routes in the second echelon. The second stage uses the trial-and-error method to determine the first echelon's routing schedule. This research aims to minimize the operational application, fuel consumption, vehicle maintenance, vehicle oil change, and handling costs. Moreover, at the end of the paper, the researcher simulate the model that has been built and test the model's effectiveness by comparing it with the classic MDCVRP model, which is similar to the Same-Day Delivery model. The test results show that the 2E-MDCVRP model can make better total distance and cost improvements than the classic MDCVRP model carried out by Same-day Delivery.**

***Index Terms*—Last Mile, Logistics Distribution, E-Commerce, 2E-MDCVRP, Optimization.**

I. Introduction

E-Commerce nowadays takes on a significant role in logistics where the flow of transactions can be expansive. So in need of analysis to minimize operational application, fuel consumption, vehicle maintenance, vehicle oil change, and handling costs. Online to offline (O2O) commerce is the newest model of e-commerce transactions where digital marketing applications attract online consumers to offline stores. In Indonesia, this business model has started to bloom since 2015, when the Matahari Mall company was first carried out. This business concept has succeeded in elevating the economy of retail stores.

The potential for an O2O commerce strategy that can lift MSMEs is because many offline stores have difficulty selling products due to restrictions on consumer mobility during the pandemic. Late last year, e-commerce companies in Indonesia such as Shopee, Gojek, Grab, Tokopedia, and other e-commerce companies offered the latest logistics delivery called Same-day delivery. Same-day delivery is a combination of picking up packages from stores and then delivering them to customers. The logistics distribution VRP model is defined as MDCVRP.

In today's logistics competition, innovation is needed to explore the potential of e-commerce service users even more. One of the innovations in shipping O2O commerce is to combine several orders from consumers to reduce shipping costs. A satellite is needed as a temporary terminal to combine shipments at several depots. This satellite helps collect several orders from several depots and then distribute them to customers.

The weakness of the e-commerce logistics system in Indonesia is that there is no alternative for combining shipments of goods from several stores or depots. They are resulting inexpensive shipping costs when ordering from several different stores. In this paper, the author will create and e-commerce logistics model which will make shipping more effective and economical for customers. All the triggering factors previously mentioned result in an intelligent logistics model. Innovative logistics modeling is needed to provide solutions for speed and accuracy in doing work. Thus, applying a MDCVRP mathematical model that can combine shipments by involving one collection point called a satellite will be. This model will optimize routing to reduce operational application, fuel consumption, vehicle maintenance, vehicle oil change, and handling fees by optimizing the entire logistics distribution supply chain system.

This paper will develop the 2E-MDCVRP model to optimize the logistics distribution. The model is a two-echelon freight distribution system. The network consists of several depots, several first-level intermediate points, which will be referred to as satellites for simplicity in naming, and

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several customers, each with associated requests. In the two-echelon transportation, there are two levels, the first level connects the depot with the satellite, and the second level connects the satellite with the customer. For each class, the associated vehicle fleet is the vehicles that will operate only to bring the item to the considered echelon. This research aims to minimize operational application, fuel consumption, vehicle maintenance, vehicle oil change, and handling costs. Operational application, fuel consumption, vehicle maintenance, and vehicle oil change costs are affected by mileage. At the same time, the number of items ordered influences handling fees.

Scheduling VRP in the first echelon between the depot and the satellite using the trial-and-error method. This method can be used because the experiment is carried out with a small number of depots and satellites in this paper. Then in the second echelon, grouping is carried out and then looking for the shortest route using the Repetitive Nearest Neighbor (RNN) algorithm. At the end of the article, a comparison of the 2E-MDCVRP model with MDCVRP will be presented.

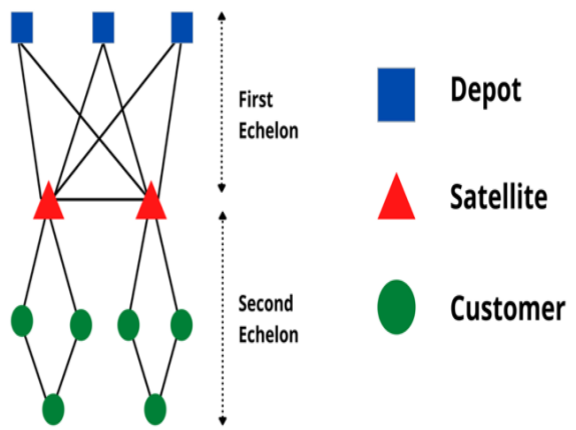

Fig. 1. Network 2E-MDCVRP

II. Research Methods

A. O2O Commerce Business

The O2O Commerce business model is new in e-commerce [1]–[3]. Research on the distribution of e-commerce has also been carried out by [4]. In 1959, Dantzig and Ramser first introduced the VRP problem, initially known as the trucking dispatching problem, which involves routing gasoline shipments to several gas stations by finding the shortest route. Then several types of VRP were developed along with the method and the shortest route.

In this study, we will use the RNN method, which is an improvement from the Nearest Neighbor method, by finding a solution with the repeated Nearest Neighbor method. After exploring the solution space, the optimal solution will be chosen. This method shows better results than his elder brother, Nearest Neighbor. Several studies related to using the RNN, including [5], solving the traveling salesman problem using the parallel RNN algorithm on the optoelectronic architecture OTIS-Hypercube and OTIS-Mesh [6]. Meanwhile, the fast RNN algorithm for large point clouds applications [7]. In line with this, [8] finds the shortest distance by extending the Nearest Neighbor heuristic to the k-RNN algorithm. The RNN to seek relevant feedback is also carried out[8].

The resolution of 2E-MDCVRP is carried out in two phases. In the first phase, we complete the satellite and customer distribution routing, where the model in the first phase is the MDCVRP model. In determining the destination of vehicles from each satellite, it is necessary to cluster with the satellite as the centroid. The cluster method used is the k-Means clustering method. Many VRP studies use customer clustering by Ant colony optimization [9]–[11], Efficient heuristic algorithms [12], [13], two- optimization of autonomous delivery vehicle [14], hybrid genetic algorithm [14]–[17], Annealing Search Optimization Algorithm [7], tabu search [18], fuzzy [19], Artificial Bee Colony (AB) [20], Binary Particle Swarm Optimization [21], Hybrid Cuckoo Search [22]. In statistical computing [23], there are many benefits of optimization, including being able to provide optimization globally [24]–[27], presenting a larger set of solution spaces [28]–[30], providing several optimal solutions [31]–[34] , calculating fast computations [35]–[39], and providing high accuracy in finding solutions [40]–[44].

The clustering method is used to homogeneity the customer's location within the group by satellite [45]. After the second stage is the MDCVRP problem. Due to the number of experiments with a small number of depots and satellites, the authors use the trial-and-error method in finding solutions between depots and satellites.

Based on the literature search, we have not found a suitable model for delivering parcels on O2O in cities that allow merging shipments from different depots. Here we present a new model involving satellite as a temporary stopover, where the function of the satellite is to collect orders made by customers online from several depots. Moreover, later, it will be sent simultaneously. The summary methodology of this research is as follows:

- First, the distribution flow is designed in 2 stages to provide options for combining shipments with satellites as temporary transit points.
- Second, in this model, the objective function minimizes operational application, fuel consumption, vehicle maintenance, vehicle oil change, and handling costs.
- Third, the completion of the solution in 2E-MDCVRP is completed in 2 phases. The first phase is solving problems between the satellite and the customer using the heuristic RNN method. In the second phase, the trial-and-error method determines the optimal travel from depot to satellite and back to depot again.
- Fourth, we create some groups between the satellite and the customer using k-Means with the satellite as the centroid and then solve it using the RNN algorithm and make comparisons between 2E-MDCVRP and MDCVRP.

Pseudocode
Step 1: In E_1, the vehicles depart from each depot and travel around the satellite, ending at each depot.
Step 2: In E_2, the vehicles depart from each satellite and travel around the customers, ending at each satellite
Step 3: Each vehicle has at most one route.
Step 4: Each customer only through one vehicle
Step 5: Each customer only goes through one satellite
Step 6: Each vehicle does not carry more than capacity
Step 7: The type of vehicle is defined as homogeneous
Step 8: Minimize operational application, fuel consumption, vehicle maintenance, vehicle oil change, and handling costs

The notations and decision variables are given in the appendix section. In addition, the objective function (4.1) minimizes the total operational application, fuel consumption, vehicle maintenance, and vehicle oil change costs of trips in E_1 and E_2 and handling fees.

$$\begin{aligned} min & \sum_{k\in V_d}\sum_{i\in E_1}\sum_{j\in E_1} CV_{ij}w^1_{ij}x_{ijk} + \sum_{k\in V_s}\sum_{i\in E_2}\sum_{j\in E_2} CV_{ij}w^2_{ij}y_{ijk} + \sum_{k\in V_s} H_k \sum_{j\in V_c} D_k \\ & + \sum_{k\in V_d}\sum_{i\in E_1}\sum_{j\in E_1} \alpha_{ij}w^1_{ij}x_{ijk} + \sum_{k\in V_s}\sum_{i\in E_2}\sum_{j\in E_2} \alpha_{ij}w^2_{ij}y_{ijk} \\ & + \sum_{k\in V_d}\sum_{i\in E_1}\sum_{j\in E_1} \beta_{ij}w^1_{ij}x_{ijk} + \sum_{k\in V_s}\sum_{i\in E_2}\sum_{j\in E_2} \beta_{ij}w^2_{ij}y_{ijk} \\ & + \sum_{k\in V_d}\sum_{i\in E_1}\sum_{j\in E_1} \gamma_{ij}w^1_{ij}x_{ijk} + \sum_{k\in V_s}\sum_{i\in E_2}\sum_{j\in E_2} \beta_{ij}w^2_{ij}y_{ijk} \end{aligned} \quad (4.1)$$

With

$$D_k = \sum_{j\in V_c} d_j z_{kj}, \forall k\in V_s \quad (4.2)$$

Constraint (4.3) guarantees that the number of routes in E_1 cannot exceed the number of vehicles in E_1.

$$\sum_{i\in V_d}\sum_{i\in V_s} x_{di} \le m^1 \quad (4.3)$$

Constraint (4.4) guarantees that the number of vehicles leaving the depot will be the same as the number of vehicles returning to the depot.

$$\sum_{i\in V} x_{jk} = \sum_{i,j\in E_1, i\neq k} x_{ki}\ \forall k\in E_1 \quad (4.4)$$

Constraint (4.5) guarantees that the number of routes in each level should not exceed the number of vehicles in the k^{th} echelon.

$$\sum_{k\in V_s}\sum_{j\in V_c} y_{kj} \le m^2 \quad (4.5)$$

Constraint (4.6) represents the set of satellite capacity limits.

$$\sum_{J\in V_c} y_{kj} \le m_{sk} \forall k\in V_s \quad (4.6)$$

Constraint (4.7) guarantees that each route in cap E sub $1(E_1)$ begins and ends at one satellite.

$$\sum_{j\in V_c} y_{kj} = \sum_{j\in V_c} y_{jk}\quad \forall k\in V_s \quad (4.7)$$

Constraint (4.8) shows the number of deliveries on E_1 must match the number of requests from the satellite.

$$\sum_{i\in E_1, i\neq j} Q^1_{ij} - \sum_{i\in E_1, i\neq j} Q^1_{ji} = \begin{cases} D_j & j \textit{ not a depot} \\ \sum_{i\in V_c} - d_i & \textit{otheriwise} \end{cases} \quad \forall j\in E_1 \quad (4.8)$$

Constraint (4.9) shows the number of deliveries on E_2 must match the number of requests from the customer.

$$\sum_{i\in V_s\cup k, i\neq j} Q^2_{ij} - \sum_{i\in V_s\cup k, i\neq j} Q^2_{ji} = \begin{cases} z_{kj}d_j & j \textit{ not a satellite} \\ -D_i & \textit{othewise} \end{cases} \quad \forall j\in E_2,\ \ \forall k\in V_s \quad (4.9)$$

Constraints (4.10) and (4.11) show the capacity limits for the first and second echelon.

$$Q^1_{ij} \le C^1 x_{ijk}, \forall i,j\in E_1, i\neq j, \forall k\in V_d \quad (4.10)$$

$$Q^2_{ijk} \le C^2 y_{ijk}, \forall i,j\in E_2, i\neq j, \forall k\in V_s \quad (4.11)$$

Constraints (4.12) and (4.13) force no residual flow on the route, making a backflow of each route to every depot in the first echelon and to every satellite in the second echelon.

$$\sum_{i\in V_s} Q^1_{iv_d} = 0 \quad (4.12)$$

$$\sum_{j\in V_c} Q^2_{jv_s} = 0 \quad (4.13)$$

Constraints (4.14) and (4.15) state that customer j is assigned to satellite k only if it receives from the same satellite.

$$y_{ijk} \le z_{kj}\ \forall i\in E_2, \forall j\in V_c,\ \forall k\in V_s \quad (4.14)$$

$$y_{jik} \le z_{kj}\ \forall_i \in E_2, \forall j\in V_c, \forall k\in V_s \quad (4.15)$$

Constraints (4.16) and (4.17) guarantee that only one route in the second echelon passes through each customer.

$$\sum_{i\in E_2} y_{ijk} = z_{kj} \forall k\in V_s, \forall j\in V_c \quad (4.16)$$

$$\sum_{i\in E_2} y_{jik} = z_{kj} \forall k\in V_s, \forall j\in V_c \quad (4.17)$$

Constraint (4.18) guarantees that each customer must be allocated to only one satellite.

$$\sum_{i\in V_s} z_{ij} = 1\ ,\ \forall j\in V_c \quad (4.18)$$

Constraint (4.19) allows route in the second to be started from satellite k only if the first level route has already provided service.

$$y_{kj} \le \sum_{l\in E_1} x_{kl}\ \forall k\in V_s, \forall j\in V_c \quad (4.19)$$

Constraints (4.20), (4.21), (4.22), (4.23) are the limits of the decision variables.

$$y_{ijk} \in \{0,1\},\ \forall i,j\in E_2,\ k\in V_s \quad (4.20)$$

$$z_{kj} \in \{0,1\}, \forall k\in E_2, \forall j\in V_c \quad (4.21)$$

$$x_{ijk} \in \{0,1\},\ \forall i,j\in E_1,\ k\in V_d \quad (4.22)$$

$$Q^1_{ij} \ge 0, \forall i,j, \in E_1, Q^2_{ijk} \ge 0,\ \forall i,j\in E_2, \forall k\in V_s \quad (4.20)$$

B. Experimental Study

In this study, a small experiment was carried out involving five depots, two satellites, and eight teen customers, where these points were located around the city of Medan, Indonesia. In Figure 3, the gray icon represents the depots, the red icon means the satellite, and the green icon represents the customer. The first stage: Determining the optimal route scheduling between satellites and customers. Clustering will help to make the search for solutions more efficient and optimal scheduling between satellites and customers. A delivery cluster will be created between satellites and customers with k-Means. The satellite is the center of the cluster. In Figure 3, each cluster has one satellite. Each satellite will send packets to around customers who have been clustered. The red dot is the first cluster, and the green dot is the second cluster. Each customer will be served by one satellite so that each customer will be served delivery from only one satellite. In Figure 4, the flow route for vehicle 1 and vehicle 2. The solution is obtained using the RNN algorithm to find the optimal routes.

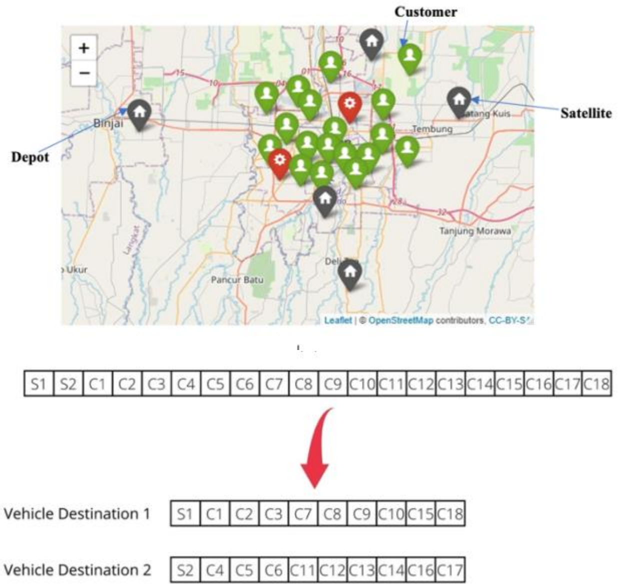

Fig. 3. Map of the depot, satellite, and customer and Chromosome representation for vehicle scheduling using *k*-Means

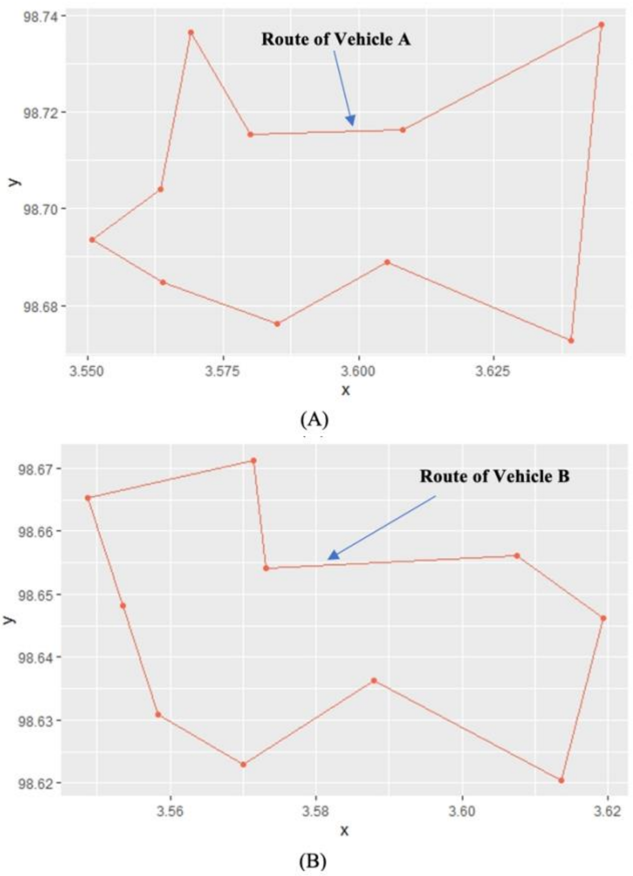

Fig. 4. Route of Vehicle 1 (A), and Rout of Vehicle 2 (B)

The route of the vehicle from each satellite can be seen in Table 1 below.

TABLE I
SATELLITE TO CUSTOMER TRAVEL ROUTES

Vehicle	Route	Distance (Unit)
Satellite 1	S1-C3-C7-C10-C8-C2-C9-C15-C1-C18-S1	0.3121565
Satellite 2	S2-C11-C13-C14-C6-C4-C17-C16-C5-C12-S2	0.2192647
Total		0.5314212

Second stage: Determine the optimal route scheduling between the depot and the satellite.

TABLE II
DEPOT TO SATELLITE TRAVEL ROUTES

Number of Trial	Routing	Total Distance (Unit)
1	D1-S1-S2-D1	0.37051304
2	D1-S2-S1-D1	0.37051304
1	D2-S1-S2-D2	0.32126864
2	D2-S2-S1-D2	0.32126864
1	D3-S1-S2-D3	0.25271623
2	D3-S2-S1-D3	0.25271623
1	D4-S1-S2-D4	0.20470318
2	D4-S2-S1-D4	0.20470318
1	D5-S1-S2-D5	0.32127278
2	D5-S2-S1-D5	0.32127278

Table 2 shows that routing starts at the depot, circles all the satellites, and returns to the depot. From the table above, it can be seen that there is no difference in distance in choosing the first destination in routing due to the small number of satellites. So visiting satellite 1 or satellite 2 first doesn't make a difference in distance.

TABLE III
CHARACTERISTICS OF BENCHMARK DATA

Instance	n_s	n_d	m^1	m^2	C^1	C^2	CV_{ij}	α_{ij}^k	β_{ij}^k	γ_{ij}^k	H_k
n18-s2-d5	2	5	5	2	45	45	4000	2000	100	100	1000
n18-s2-d4	2	4	4	2	45	45	4000	2000	100	100	1000
n18-s2-d3	2	3	3	2	45	45	4000	2000	100	100	1000
n18--s2-d2	2	2	2	2	45	45	4000	2000	100	100	1000
n18-s2-d1	2	1	1	2	45	45	4000	2000	100	100	1000
n18-1s1-d5	1	5	5	2	45	45	4000	2000	100	100	1000
n18-1s1-d4	1	4	4	2	45	45	4000	2000	100	100	1000

n18-1s1-d3	1	3	3	2	45	45	4000	2000	100	100	1000
n18-1s1-d2	1	2	2	2	45	45	4000	2000	100	100	1000
n18-1s1-d1	1	1	1	2	45	45	4000	2000	100	100	1000

The characteristics of the tests in this paper are as shown in Table 3. There are 10 instances tested with points according to Figure 3. m^1 and m^2 limit the number of vehicles in the first and second echelon. While C^1 and C^2 are the capacity limits of each vehicle in the first and second echelon. CV_{ij} is operational application cost. H_k is handling fees. α_{ij}^k is cost consumption fuel vehicle per kilometre. β_{ij}^k is vehicle maintenance cost per kilometer. γ_{ij}^k is the cost of changing the vehicle oil per kilometre.

C. Data Simulation using R Studio

In processing experimental studies, the author uses Rstudio, R is open-source software widely used to present statistics and graphs. This paper also uses several packages available in Rstudio, namely tspmeta and TSP. Computing experiments were carried out on a Macbook Air with a 1.6 GHz Dual-Core Intel Core i5 processor, 8 GB of 1600 MHz DDR3 memory. In this paper, we compare 2E-MDCVRP with MDCVRP. This paper compares the total distance and total cost of the two types of VRP. The distance generated by processing with the RNN algorithm can be seen in Table 4.

TABLE IV
COMPARISON OF DISTANCES BETWEEN CVRP AND 2E-CVRP

Instance	Tot. Dist. MDCVRP	Tot. Dist. 2E-MDCVRP	*Improvement* (%)
n18-s2-d5	2.96	2.00	32.46%
n18-s2-d4	2.33	1.68	27.74%
n18-s2-d3	1.80	1.48	18.00%
n18-s2-d2	1.23	1.22	0.74%
n18-s2-d1	0.69	0.90	-30.95%
n18-1s1-d5	2.96	1.65	44.33%
n18-1s1-d4	2.33	1.37	40.95%
n18-1s1-d3	1.80	1.21	32.70%
n18-1s1-d2	1.23	1.10	10.50%
n18-1s1-d1	0.69	0.92	-33.93%
Average	1.80	1.35	24.85%

$$Imp = \frac{Tot.Dist.CVRP - Tot.Dist\ 2EMDCVRP}{Tot.Dist\ MDCVRP} x100\%$$

TABLE V
COMPARISON OF THE COSTS OF THE MDCVRP AND 2E-MDCVRP METHODS

Instance	Total Cost MDCVRP	Total Cost 2E-MDCVRP	*Improvement* (%)
n18-s2-d5	2037072	1556400	23,60%
n18-s2-d4	1603506	1300176	18,92%
n18-s2-d3	1238760	1126536	9,06%
n18-s2-d2	846486	911604	-7,69%
n18-s2-d1	474858	655380	-38,02%
n18-1s1-d5	2037072	1315530	35,42%
n18-1s1-d4	1603506	1086834	32,22%
n18-1s1-d3	1238760	940722	24,06%
n18-1s1-d2	846486	829020	2,06%
n18-1s1-d1	474858	669144	-40,91%
Average	1240136,4	1039134,6	5,87%

Based on Table 4, the 2E-MDCVRP model can improve the gap in terms of distance by 24.85% compared to the MDCVRP model. Based on Table 5, the 2E-MDCVRP model can create an average cost gap improvement of 5.87% compared to the MDCVRP model. The test results in Table 4 and Table 5 show that the 2E-MDCVRP model is more effective when the number of depots is more, but if the number of depots is small, the total distance and cost will be worse than the MDCVRP model. This happens because the total distance traveled by the vehicle at each echelon will be further away. This is because vehicles from each echelon, after carrying out their duties, will return to their original place, plus loading and unloading costs on the satellite make this model ineffective when using a small number of depots. However, if the number of depots is increased, it will increase the model's effectiveness. This is because there is a collection of goods on the satellite from each depot for further delivery to the customer, allowing one-time delivery.

IV. CONCLUSION

In this study, a Two-Echelon Multi Depot Capacitated Routing Problem model was developed where this model is used in the logistics distribution supply chain model in the context of e-commerce by formulating a problem with objective functions, namely operational application, fuel consumption, vehicle maintenance, vehicle oil change, and handling costs. Combining k-Means Clustering and RNN can optimize the search for solutions from the simulation results. The test results comparing the 2E-MDCVRP model with the classic MDCVRP show that the 2E-MDCVRP model can minimize distance and cost. The 2E-MDCVRP model can make a gap improvement in terms of distance of 24.85% compared to the MDCVRP model. In terms of minimizing costs, the 2E-MDCVRP model can create a gap improvement in terms of average costs of 5.87% compared to the MDCVRP model. The test results show that the 2E-MDCVRP model is more effective when the number of depots is more, but if the number of depots is small, the total distance and cost will be worse than the MDCVRP model. This happens because the total distance traveled by vehicles in each echelon will be further. After carrying out the task, vehicles from each echelon must return to their original place. The cost of loading and unloading the satellite also affects the increase in the cost burden when using a small number of depots. However, suppose the number of depots is increased.

In that case, the effectiveness of this model will be even higher because there is a collection of goods on the satellite from each depot for further delivery to customers, which makes delivery possible at once. The researcher will conduct a comparative study of the solutions resulting from testing the 2E-MDCVRP model using the metaheuristic method, namely the genetic algorithm, compared to the RNN heuristic method.

APPENDIX

Notations And Parameters

V_d = Set of depots $(d_1, d_2, d_3, \dots, d_n)$

V_s = Set of satellites $(s_1, s_2, s_3, \dots, s_n)$

V_c = Set of customer $(c_1, c_2, c_3, \dots, c_n)$

CV_{ij} = Operational application cost kilometer in arc (i, j)

α_{ij}^k = Fuel cost per kilometer in arc (i,j) in the k^{th} echelon

β_{ij}^k = Service vehicle cost per kilometer in arc (i,j) in the k^{th} echelon

γ_{ij}^k = Oil change service cost per kilometer in arc (i,j) in the k^{th} echelon

d_i = Demand from customer i

D_k = Demand change vehicle from satelite k

H_k = Handling costs for loading and unloading operations per unit of transport on satellite k

w_{ij}^1 = Distance travel in arc $(i, j) \in E_1$

w_{ij}^2 = Distance travel in arc $(i, j) \in E_2$

x_{di} = Number of vehicles from depot to node i

x_{jk} = Number of vehicles from node j to k

x_{ki} = Number of vehicles from node k to i

m^1 = Number of vehicles in E_1

m^2 = Number of vehicles in E_2

m_{sk}^2 = Maximum number routes in E_2 starting from satellite k

C^1 = Vehicle capacity in E_1

C^2 = Vehicle capacity in E_2

Q_{ij}^1 = Flow passing through in E_1 from node i to j

Q_{ji}^1 = Flow passing through in E_1 from node j to i

Q_{ij}^2 = Flow passing through in E_2 from node i to j

Q_{ji}^2 = Flow passing through in E_2 from node j to i

Q_{ijk}^2 = Flow passing through in E_2 arc (i, j) and coming from satellite k

Decision Variable

$$x_{ij}^k = \begin{cases} 1 \text{ if vehicle in } E_1 \text{ from depot } k^{th} \\ 0 \text{ Otherwise} \end{cases}$$

$$y_{ij}^k = \begin{cases} 1 \text{ if vehicle in } E_2 \text{ from satellite } k^{th} \\ 0 \text{ Otherwise} \end{cases}$$

$$z_{kj} = \begin{cases} 1 \text{ if customer j is allocated to satellite k;} \\ 0 \text{ Otherwise} \end{cases}$$

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