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A Robust Optimizing Reverse Logistics Model for Beef Products Using Multi Depot Vehicle Routing Problem

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***Abstract* -** Beef is a perishable product and requires special handling. Demand for beef also fluctuates quite high and is heavily influenced by various religious events and traditions in Indonesia. Under these conditions, for various reasons, beef products are returned from customers to distributors. An increase in the number of products returned from customers leads to high costs and the risk of product damage. The research created an optimization model for product distribution and product recall from customers with minimal costs and risks. The research applied a clustering method using the Density-Based Spatial Clustering (DBSCAN) algorithm to determine the density of customers' locations and the number of orders. Optimization of distance and distribution and withdrawal costs applied Multi Depot Vehicle Routing Problem (MDVRP) and Mixed Integer Linear Programming (MILP) mathematical modeling. The results indicate three customer clusters with one noise, with the most potential customers in cluster 1. From this condition, product delivery optimization is based on the distance and number of shipments from the two central warehouses. Optimization uses of MDVRP and MILP to model and make company-owned trucks more profitable at high rental truck replacement costs. The research produces a robust model for changes in the truck number and capacity based on sensitivity analysis.

Keywords: reverse logistics model, beef products, Multi Depot Vehicle Routing Problem (MDVRP)

I. INTRODUCTION

Reverse logistics is an activity to manage product returns from customers for various reasons by providing added value (Liao, 2018). In reverse logistics activities, adding value to products is carried out to avoid further damage and cause waste that can damage the environment. Reverse logistics activities have much to do with product delivery and retrieval (Zhou, Cai, Xiao, Chen, & Zeng, 2018). Hence, the company must be able to balance the needs of the transportation fleet to deliver consumer goods and, at the same time, attract product returns from customers (Abbas & Farooquie, 2019). However, this condition impacts higher shipping costs, difficult product delivery and recall routes, and the number of fleets that are difficult to adjust to the needs of product recalls and deliveries.

Moreover, beef is an agro-industrial product that is easily damaged. Hence, shipping and handling require special handling and higher costs (Lu, Zhang, Zhu, Luo, & Hopkins, 2019) for these agro-industrial products to have a longer shelf life (Huang & Chen, 2021). Handling these shipments uses refrigerated trucks and refrigerated storage rooms, known as a cold chain. One of the examples is PT. CAM. It is a food distributor company for beef and chicken located in Cilengsi. The company's customers are spread across regions such as West Java, Banten, Jakarta, Surabaya, Bali, and several areas in Sumatra (Paduloh, Djatna, Muslich, & Sukardi, 2019). With this condition, the company faces many obstacles in distributing products to customers. Constraints include the distance of the customer's location, the uncertain time of demand, and the unstable number of requests. These conditions encourage the researchers to optimize the problems faced by the company. One of the solutions is using clustering.

Many studies on clustering have been done. Moreover, there are also many types of clustering. For example, previous research discusses various types of clustering and their applications, including K-Means, C Means, DBSCAN, and other clustering methods (Taha, 2020). Then, another previous research also uses K-Means clustering to create customer clusters based on customer type, the price offered, average product quality, and average performance. After the cluster is obtained, customer repairs are carried out so that, in the end, they can follow the company's demand and provide low prices and focus on customer improvement (Paduloh, Djatna, Sukardi, & Muslich, 2020). Previous research also develops clustering using Whale Optimization Algorithm (WOA) to find the best method and most suitable for the problems. WOA is a new swarm-based class metaheuristic algorithm inspired by the humpback of whale method in hunting fish called bubble-net feeding. Bubble net feeding is whales circling their prey toward the water's surface, resembling a logarithmic spiral (Nasiri & Khiyabani, 2018).

Density-Based Spatial Clustering with Noise (DBSCAN) is a clustering method with an approach that builds a cluster or group based on the density level that is close to a certain point. There are two parameters in DBSCAN, namely epsilon ("eps") and minimum point ("MinPts"). Epsilon determines the radius or distance between the center point of "x" and its surroundings. Meanwhile, MinPts is intended as the minimum number of cluster members within the epsilon radius ("eps") (Sheridan et al., 2020). DBSCAN in previous studies has been used for the detection of anomaly flight during the approach phase (Sheridan et al., 2020), exploration for data conventions to obtain highly inclined angles (Zaki & Meira, 2018), and fast clustering algorithm by trimming distance calculations for high dimensional data which is not required in DBSCAN (Chen et al., 2018).

The main purpose of Vehicle Routing Problem (VRP) is to distribute products at the lowest possible cost to consumers with a certain number of vehicles (Abdurrahman, Ridwan, & Santosa, 2018). In the VRP concept, the vehicle departs from the depot to deliver the product to all consumers and returns to the central warehouse. There have been many optimizations using VRP (Fatma, 2018), such as optimizing product recalls returned from customers for electrical and electronic equipment cases. According to Gu et al. (2020), VRP is the most important factor when companies want to make shipping costs efficient. Another previous research also optimizes delivery with different customer conditions and types (Abdurrahman et al., 2018).

The MDVRP is a variation of VRP. In MDVRP, several central warehouses act as product distributors and fulfill all customers' requests (Fitriana, Moengin, & Kusumaningrum, 2019). In MDVRP, the number of trucks used and the central warehouse location are predetermined. Then, each vehicle starts its journey and ends in the same central warehouse where the vehicle first departs, and each truck only visits the customers once.

Many MDVRP applications have been carried out with various improvements and additional methods. For example, previous research uses MDVRP to consider a homogeneous vehicle fleet (Barma, Dutta, & Mukherjee, 2019). It also uses a 2-opt algorithm to minimize the total MDVRP routing distance (Fitriana et al., 2019). Another previous research compares genetic algorithm and ant colony optimization (Samsuddin, Othman, & Yusuf, 2020). The previous research also optimizes excess vehicles, depots, and route lengths with penalties and the Iterated Local Search (ILS) algorithm (Ospina-Toro, Toro-Ocampo, & Gallego-Rendón, 2018). Meanwhile, another previous research uses the travel budget time formula for vehicle distribution and the probability density function for gray delivery time. It also uses the fuzzy gradient function to see customer satisfaction. It results in building a multi-depot by taking into account customer satisfaction and minimal costs (Yuan, Zhang, Liu, & Wu, 2020).

The MILP approach is used to complete many cases (Ghahremani-Nahr, Kian, & Sabet, 2019; Liao, 2018). Previous researchers widely use MILP to solve the problem of uncertainty (Brahimi & Aouam, 2016). In this case, the uncertainty lies in the number of returned products, such as who and where the customers will return the product. So, this method is considered to reduce uncertainty. MILP is often used in mathematical modeling for system analysis and optimization. MILP can provide a flexible and robust approach to solving large and complex problems frequently encountered in industrial symbiosis and process integration. In MILP, a linear programming model uses integers to optimize the desired goal to determine the objective function before creating the model. Decision variables in MILP using integers and Booleans are an advantage for MILP, but some MILPs use fractions. Then, the available limitations can be decisive decision variable values so that the optimal value of the objective function can be found (Taha, 2020). According to Zhou, Gong, Wu, and Xu (2017), MILP can be applied to optimize the distributed channel allocation and rate control network. Then, it is found that the MILP is the best solution for case stochastic in reverse supply chain network to solve uncertainty in the Caller Detail Record (CDR) case study (Trochu, Chaabane, & Ouhimmou, 2018). It can also be used to design a supply chain network with network density (Çalık, 2020). Previous research makes reverse logistics network design for product recovery and uncertainty remanufacturing (Liao, 2018).

Based on these conditions, the research aims to optimize distribution costs from the central warehouse to customers and product withdrawals from customers to the central warehouse. In the research, the shipping route will be optimized with the lowest possible cost. The proposed solution to the problem uses a Multi Depot Vehicle Routing Problem (MDVRP) and groups customers' locations and the number of orders using DBSCAN clustering. Then, the state of the art of the research is the optimization of recalling and shipping food product costs using MDVRP. It is combined with clustering using DBSCAN to optimize each customer's delivery point and distance. The research is expected to result in customer clusters, minimum costs, optimal routes, truck types, and workforce.

II. METHODS

The research begins by clustering all customers based on the distance and the average number of commonly disordered products. Then, clustering is needed to find out the customers' characters based on the area or city where the customers gather. The research uses DBSCAN clustering, considering that DBSCAN can group data based on density. According to the case of shipments from PT. CAM's customers, the customers are divided into 21 cities, with the types of customers who are routine, non-routine, and order at any time. Hence, it is very appropriate to apply for DBSCAN. In addition, the number of orders also varies with a considerable distance. So, the density principle in DBSCAN is worth trying to maximize all these conditions.

In the case studied, the company has two central warehouses for two distribution of shipping directions. So, in the research, MDVRP is applied to beef products. MDVRP optimization is carried out using MILP with Lingo 17.0 software. MILP is expected to provide optimal solutions based on the formulation, research objectives, and limitations according to the company's conditions. Based on data and conditions in the field, the research uses delivery and withdrawal data to and from customers for one year.

Distribution problems in the multi-depot vehicle routing problem model with daily truck driver contracts are the focus that is sought in the research. The optimal solution of the occasional driver-to-multi-depot vehicle routing problem model is obtained using integer linear programming. The initial stage is to formulate problems that exist in the company. The formulation of the distribution problem uses the MDVRP model with the rental driver by making objective functions. The objective function of the MDVRP model with rental drivers is to minimize distribution costs at two company-owned warehouse locations, using two types of vehicle ownership: company-owned and leased vehicles. The next step is to determine the constraints to solve the MDVRP model. This obstacle is making assumptions and defining the distribution problem formulation using MDVRP. The MDVRP model's refinement with a rental driver is carried out using the MILP method. The research framework can be seen in Figure 1.

III. RESULTS AND DISCUSSIONS

The requirements must be met for formulation and optimization, including trucks used for delivery using refrigerants following the storage requirements for food products in frozen and cold conditions. The formulations use the focus on daily and weekly customers who are regular or routine. Further requirements for customer applications are that the customers must also apply the cold chain and store food products according to government regulations and Hazard Analysis and Critical Control Points (HACCP). In product returns, the customer's warehouse location is appropriate and accessible by refrigerated vehicles. Information on returning food products is given at least one day before the recall request date, and the request is made in writing.

The set and parameters are as follows. It has I as defining for all depots, j as defining for all consumers, k as define for all vehicles, N as a number of indexes, d_j as demand in j, Q_k as a capacity truck of k, w_k as drivers' salary, and C_{ij} as movement costs from location i to location j. Moreover, the decision variable has x_{ijk} as the value of a variable. It has 1 if vehicle k is used and 0 if it is not used. Meanwhile, in S_k, the value of the variable is 1 if using company k vehicles for distribution and 0 if it is not used. The formulation aims to minimize distribution costs, company-owned trucks, and rental vehicles. Overall, the objective function that aims to minimize costs in distributing food products can be written as seen in Equation (1).

$$\min z = \left(\sum_{i,j \in I \cup J} C_{ij} X_{ijk} + W_k S_k\right) + \sum_{i,j \in I \cup J} f_{ij} x_{ijk} \quad (1)$$

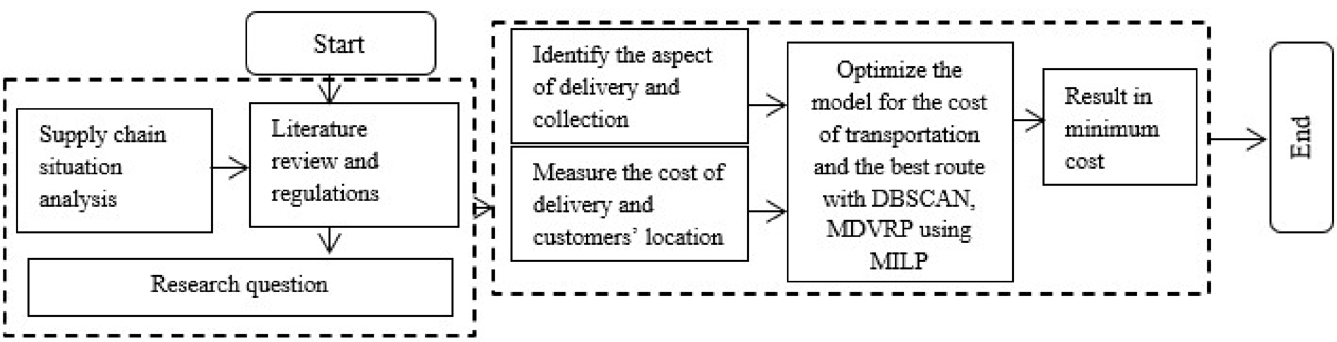

Figure 1 Research Framework

As a whole, the equation focuses on the process of sending and recalling products through distribution centers. Equation (2) shows that the order is made via a product recall and delivery letter. It is carried out simultaneously. In Equation (3), it is found that the distribution center carries out vehicle management for product delivery and product recall. Then, Equation (4) shows that the vehicle departs from the distribution center and returns to the distribution center. Equation (5) shows that each vehicle has a certain route and must return to (Distribution Centre) DC after making the delivery until it finishes. Then, Equations (6) and (7) are limitations that each customer can only be visited once by the same used truck. For each delivery, it is intended to prevent vehicles not conforming to the delivery route. Then, in Equation (8), the number of products sent and withdrawn must not exceed the capacity of the vehicle. Therefore, the recall is made according to the capacity of the truck used. Equation (9) shows the elimination of sub-routes so that vehicles do not return to customers visited. Then, route continuity and transfer of vehicles from one customer to another customer are according to the route, as shown in Equation (10). Vehicles only visit customers according to delivery and withdrawal orders on Equation (11). There are no vehicles from the same customer in Equation (12), and the distribution center warehouse has been determined in Equation (13). The binary function for decision-making is shown in Equation (14). The binary function is used in making a decision whether the company will use company-owned or rented trucks.The equations can be seen as follows.

$$\textstyle\sum_{j\in J} X_{ijk} = s_k, \quad i \in I, \quad k \in K, \tag{2}$$

$$\textstyle\sum_{j\in J} X_{ijk} = 0, \quad i \in I, \quad k \in K, \tag{3}$$

$$\textstyle\sum_{j\in J} X_{ijk} = s_k, \quad i \in I, \quad k \in K, \tag{4}$$

$$\textstyle\sum_{j\in J} X_{ijk} = 0, \quad i \in I, \quad k \in K, \tag{5}$$

$$\textstyle\sum_{k\in K} \sum_{i\in I\cup J} x_{ijk} = 1, \quad j \in J, \tag{6}$$

$$\textstyle\sum_{k\in K} \sum_{i\in I\cup J} x_{ijk} = 1, \quad i \in J, \tag{7}$$

$$\textstyle\sum_{j\in J} d_j \sum_{i\in I\cup J} x_{ijk} \leq Q_k, \quad k \in K, \tag{8}$$

$$u_{ik} - u_{jk} + N x_{ijk} \leq N - 1, \quad i,j \in J, \quad k \in K, \tag{9}$$

$$\textstyle\sum_{\substack{i\in I\cup J \\ l\neq i}} x_{ilk} - \sum_{\substack{j\in I\cup J \\ l\cup J}} x_{ljk} = 0, \quad l \in J, \quad k \in K, \tag{10}$$

$$x_{ijk} \leq s_k, \quad i,j \in I \cup J, \quad k \in K, \tag{11}$$

$$x_{ijk} = 0, \quad i = j, \quad i,j \in J, \quad k \in K, \tag{12}$$

$$x_{iik} = 0, \quad i \in I, \quad k \in K,$$

$$X_{ijk} \in \{0,1\}, \forall i, j, \tag{13}$$

$$w_k \in \{0,1\}, \forall i, j. \tag{14}$$

The research begins by describing the actual conditions in the field and analyzing the problems faced by the company to arrange delivery and pick-up optimally. Then, Figure 2 is used to understand the conditions in the field. Based on the flow diagram in Figure 2, the delivery and collection of returned products are carried out. Suppose that the recall process is carried out simultaneously with the delivery of beef products. The withdrawal process is carried out based on a withdrawal request obtained from the customer's Person in Charge (PIC). The delivery route is determined based on the truck's distance and maximum load volume. The company currently has 12 trucks to distribute and handle customers' requests of varying volumes and types of trucks. Currently, the company also has 250 active customers. Some are regular customers with a fixed order quantity and little change. Meanwhile, other customers do not have routine orders but have longer and last orders with incidental requests.

Field data used for customer clustering are arranged in one table so that the data can represent existing conditions. The analysis begins by verifying 250 customers and 308 delivery locations. The second step is to analyze the average shipments from December 2018 to April 2019. PT CAM's largest customers in terms of the number of orders are in Jakarta, Bogor, Tangerang, and Bekasi, with a total of 60%. The details are Jakarta with 32%, Bogor with 11%, Tangerang with 10%, and Bekasi with 8%. Then, customers with the highest number of shipments are in Tangerang, which is equal to 25%. It is followed by Bekasi with 24%, and Jakarta and Bogor with 14% each. Jakarta, Bogor, Tangerang, and Bekasi areas account for 76%. The company also uses 12 trucks to

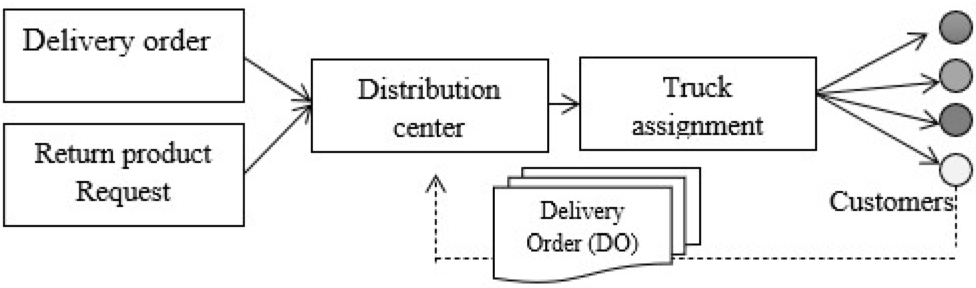

Figure 2 Flow Chart Deliveries and Recall Product from and to Customers

make deliveries to meet the demand, as shown in Table 1. It has 1 truck with a capacity of 11 tons, 4 truck with a capacity of 6 tons with total 24 tons, 6 trucks with a capacity of 2,5 tons with total 15 tons, and 1 truck with a capacity of 1 ton. So, the total capacity is 51 tons.

The number of product shipments per region can be seen in Table 2. Overall, the company has nine major delivery areas: Bali, Bandung, Bekasi, Bogor, Jakarta, Kalimantan, Sumatra, Surabaya, and Tangerang. The areas with the most oversized shipments of beef products are Tangerang, Bekasi, and Bandung, which reach 6 to 8,3 tons per day.

Based on the number of product shipments per area with daily and monthly averages, Table 3 shows data on delivery intensity data based on how often customers request products and distributors send them. Its purpose is to see the needs of trucks based on the intensity of delivery of these products.

Management of data clustering with DBSCAN is carried out based on Figure 2. The process begins with data collection and selection. The data, in this case, are the delivery of food products to customers. Next, data transformation is carried out to convert the raw data into data fields needed in the clustering

Table 1 Total Trucks Used by Company

Type of Truck	Number of Truck			Volume (kg)	Total (kg)
	Owned	Rental	Total		
Fuso	1	0	1	11.000	11.000
Double Ankle	2	2	4	6.000	24.000
Ankle	4	2	6	2.500	15.000
L300	1	0	1	1.000	1.000
Total	**8**	**4**	12	**20.500**	**51.000**

Table 2 Average Delivery per Customer per Month

No	Area	Average Delivery (Ton)	
		Daily	Monthly
1	Bali	738,2	17.716,6
2	Bandung	6.912,3	165.896,4
3	Bekasi	5.992,8	143.826,1
4	Bogor	3.907,5	79.018,4
5	Jakarta	2.585,3	62.047,8
6	Kalimantan	0,5	11,7
7	Sumatra	783,9	18.812,6
8	Surabaya	1.225,6	29.414,9
9	Tangerang	8.382,6	201.182,0
Total		**30.528,7**	**717.926,7**

Table 3 Delivery Intensity Based on Delivery Area

No	Customer	Daily	Weekly	Monthly	Yearly	Spot Order	Total
1	Bali	2	3	1	1	2	9
2	Bandung	5	11	2	5	6	29
3	Bekasi	3	6	8	2	13	32
4	Bogor	8	25	15	11	32	91
5	Jakarta	10	30	13	14	16	83
6	Kalimantan	0	0	1	0	0	1
7	Sumatra	0	8	0	1	0	9
8	Surabaya	3	8	3	1	2	17
9	Tangerang	7	6	6	6	12	37
Grand Total							**308**

process based on the DBSCAN algorithm. At this stage, each cluster's average value becomes the basis for the distribution of route delivery based on the 12 existing trucks. The last stage is to get customer clusters based on distance and the number of orders. The clustering results using DBSCAN clustering in RStudio obtain four clusters, as shown in Figure 3.

The results of DBSCAN can be seen in Figure 3 using Software RStudio with Epsilon 7 and a minimum point of 1,8. The Epsilon 7 represents the number of customers within a seven km radius and a minimum shipment of 1.800 kg. Then, the analysis results using RStudio are compared using MATLAB, which can be seen in Figure 4. With the same data, MATLAB obtains three clusters with one noise. As for the details from RStudio, there are four clusters without noise. The details of the area can be seen in Table 4, which is taken from RStudio. The clustering results in Table 4 show that the total number of customers who enter cluster 1 is 301. Next, cluster 2 has 2 customers. Meanwhile, cluster 3 has 0 customers, and cluster 4 has 1 customer.

Next, the research formulates beef distribution problems with the MDVRP model using a driver with a daily work contact. It also overcomes obstacles and completes the MDVRP model with a daily contract driver. Based on existing conditions in the company, it is found that it has 12 trucks, with 8 belonging to

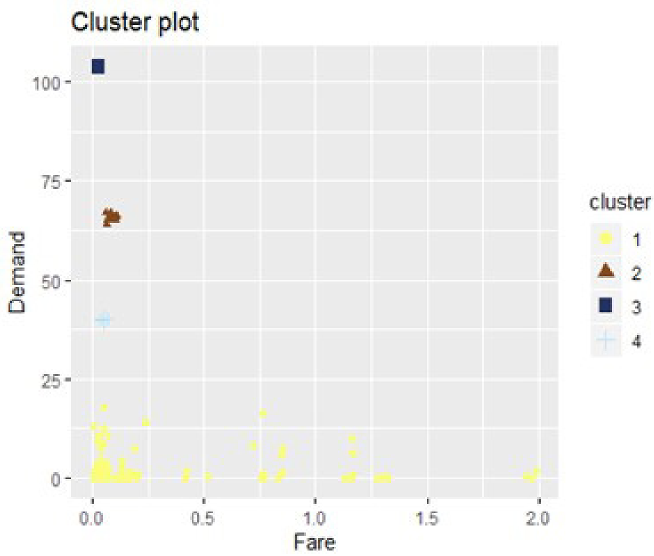

Figure 3 DBSCAN Clustering Result Using RStudio

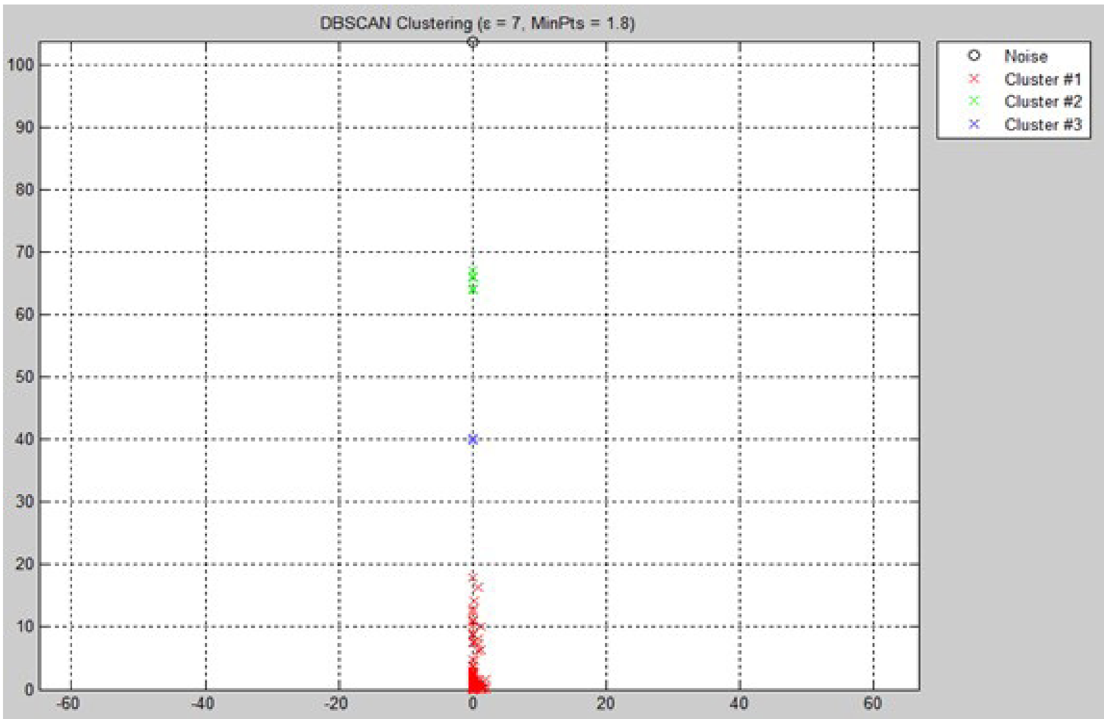

Figure 4 DBSACN Clustering Result Using MATLAB

the company and 4 rental trucks. Specifically, the company has 1 truck with a volume capacity of 11 tons, 4 trucks with a volume capacity of 5 tons, 6 trucks with a volume capacity of 2,5 tons, and 1 truck with a volume capacity of 1 ton.

Trucks 1, 2, 3, 4, 9, 10, and 11 are company-owned trucks, while trucks 5, 6, 7, and 8 are rental trucks. The rental fee per truck unit is Rp20.000.000,00 per year for the double-ankle type and Rp18.000.000,00 annually for the single category. The company rents two double trucks and two single trucks. The total shipping fleet capacities that the company has and leases are 51 tons. The average delivery per day is 30,5 tons. Then, the company has 250 customers with 308 shipping points. In addition, two distribution center warehouses are located in Jonggol and Cilengsi. Table 5 shows that the demand data used in the research is the average data demand for beef products per area per day. The type of routine customers is fewer. It is even far below the capacity of trucks owned and rented by the company today.

Table 6 shows the distance data between customers and distribution centers. The numbers 1 and 2 are company warehouses located at locations 1 (Cilengsi) and 2 (Jonggol) in kilometers (km). Meanwhile, numbers 3 to 10 show customers' orders in kilometers (km). Customers are included in the route order products on a daily and weekly basis.

Based on the conditions in Table 6, the model is tested numerically using the LINGO 17.0 software. The test follows the equations mentioned and the data in Tables 5 and 6. The numerical test results can be seen in Tables 7−9. The test is carried out using three different driver costs. It is intended to see the model finesse and which costs are the most profitable for the company. The salary costs referred to as the salary for contract drivers are Rp25.000,00, Rp15.000,00, and Rp5.000,00.

Table 4 Clustering Result per Customers' Area

Cluster	Bali	Bandung	Bekasi	Bogor	Jakarta	Kalimantan	Sumatra	Surabaya	Tangerang	Total
Noise	0	0	1	0	0	0	0	0	0	1
1	9	27	31	90	83	1	9	17	34	301
2	0	2	0	0	0	0	0	0	2	4
3	0	0	0	1	0	0	0	0	0	0

Table 5 Total Demand Based on Customers' Area per Day

	The Demand for Each Customer											
Index	1	2	3	4	5	6	7	8	9	10	11	12
Demand	738,2	3.456,2	3.456,2	5.992,8	3.907,5	2.585,3	1.225,6	2.794,2	2.794,2	2.794,2	783,9	546

Table 6 The Distance of Each Customer

No Truck	The Distance of Each Customer											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	0,0	1.132,0	3,0	25,0	2,0	6,0	1,0	141,0	16,0	12,0	1,5	6,0
2	1.132,0	0,0	767,0	1,0	1,0	4,0	5,0	6,0	12,0	26,0	298,0	2,0
3	1,0	419,0	0,0	419,0	199,0	41,0	6,0	5,0	4,0	53,0	21,0	0,4
4	2,0	5,0	130,0	0,0	129,0	1,0	2,0	19,0	1,0	3,0	4,5	8,6
5	8,9	1,0	7,0	54,0	0,0	65,0	27,0	3,0	4,0	3,0	0,3	3,4
6	5,6	0,2	2,2	0,9	13,2	0,0	14,1	5,9	0,6	1,0	3,0	0,3
7	5,0	2,0	0,9	4,0	1,0	36,0	0,0	36,0	1,0	1,0	1,0	1,0
8	1,6	5,3	13,2	0,7	1,7	5,0	69,1	0,0	11,3	5,7	3,0	10,0
9	3,0	0,4	2,9	1,7	0,4	2,0	8,0	37,9	0,0	37,4	0,1	0,3
10	1,0	0,6	1,2	1,8	2,0	5,2	4,0	5,0	52,3	0,0	42,3	1,4
11	1,7	1,3	3,6	2,0	3,4	0,8	1,0	5,0	6,0	52,5	0.0	53,0
12	2,3	2,7	5,0	2,0	1,3	1,7	2,6	3,0	10,0	6,8	60,0	0.0

From Table 7, it is found that a daily rental driver with a fee of Rp25.000,00 obtains an optimization value of Rp459.600,00 by using three trucks. These trucks are owned by the company. Truck 1 has a capacity of 12 tons with distribution route from distribution center (1) to customer 4, customer 7, customer 8, customer 12, and distribution center (1). Then, truck 2 and truck 3 have a capacity of 5,5 tons each. This condition shows that the company has an excess of five company-owned trucks and four rental trucks. The optimization results by changing costs from Rp25.000,00 to Rp15.000,00 produce the same route and optimization value of Rp459.600,00, as shown in Table 8.

From Table 8, in return, a daily rental driver with a fee of Rp15.000,00 obtains an optimization value of Rp459.600,00 using three trucks. These trucks are owned by the company. Truck 1 has a capacity of 12 tons. Then, truck 2 and truck 3 have a capacity of 5,5 tons each. This condition shows that the company has an excess of five company-owned trucks and four rental trucks.

From Table 9, a daily rental driver with a fee of Rp5.000,00 obtains an optimization value of Rp375.400,00 using four trucks. Two trucks are owned by the company, and two trucks are rental trucks. Truck 1 has a capacity of 12 tons. Truck 3 has a capacity of 5,5 tons. Then, trucks 7 and truck 8 have a capacity of 5.5 tons each.

Table 7 The Results with Fee of Rp25.000,00

Truck Code	Distribution Route	Fare (km)	Total quantity delivery (Rp)	Cost of the company (Rp)
1	1→4→7→8→12→1	1.164	11.296,2	163.600
2	1→3→1	768	4.194,4	148.000
3	1→5→11→1	639	5.474,4	148.000
Total				459.600

Table 8 The Results with Fee of Rp15.000,00

Truck Code	Distribution Route	Fare (km)	Total quantity delivery (Rp)	Cost of the company (Rp)
1	1→4→7→8→12→1	1.164	11.296,2	163.600
2	1→3→1	768	4.194,4	148.000
3	1→5→11→1	639	5.474,4	148.000
Total				459.600

Table 9 The Results with Fee of Rp5.000,00

Truck Code	Distribution Route	Fare (km)	Total quantity delivery (Rp)	Cost of the company (Rp)
1	1→4→7→8→1	1.299	10.750,8	144.400
3	1→5→11→1	221	5.975,6	148.000
7	2→6→2	38	6.041,5	21.000
8	2→9→2	16,6	6.250,4	62.000
Total				375.400

Table 10 Analysis Sensitivities Based on Quantity and Capacity Truck

Eliminate	Capacity	Quantity of Truck	Changes in Total Cost
0	51.000	12	459.600
5(4=3T, 1=1T)	38.000	7	459.600
6(5=3T, 1=1T)	35.000	6	459.600
7(1=5,5T. 5=3T, 1=1T)	29.500	5	632.400
8(2=5,5T. 5=3T, 1=1T)	24.000	4	870.400
9(3=5,5T. 5=3T, 1=1T)	19.500	3	infeasible
1=12T	39.000	11	infeasible
2=5,5T	40.000	10	566.600
3=5,5T	34.500	9	763.800
4=5,5T	29.000	8	infeasible

From the sensitivity analysis results in Table 10, it is known that the model formulation is sensitive to truck capacity, so changes in truck capacity affect shipping costs. This model can accommodate changes in the number of trucks needed to deliver beef products based on the average number of customer orders per city, total truck capacity, minimum order, and distance for each customer. Thus, this model can be used to determine truck capacity and ownership decisions.

IV. CONCLUSIONS

The research achieves optimal distribution costs from the central warehouse to customers and product withdrawals from customers to the main warehouse. Research has also optimized delivery routes at the lowest possible price. It also analyzes product distribution and withdrawal activities to and from customers. It focuses on daily and weekly customers. This is done by maximizing two distribution centers to maximize multi-depot vehicle routes and daily contract drivers. The result is a route optimization and distribution costs. Customers are grouped using DBSCAN cluster analysis to facilitate delivery and withdrawals. It can maximize the total volume of shipments based on density and distance. The result is four clusters. At MDVRP, two distribution centers can accommodate the withdrawal and delivery of customer products, resulting in more optimal distribution costs.

This model also produces a robust formulation against changes in the number of trucks and drivers. However, the research only discusses optimization with two central warehouse locations. Hence, there is still much that can be done for further analysis. For example, future research can consider the place of slaughtering and sources of supply with the needs of the trucks. Then, it can make delivery automation.

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