Optimizing the Heterogeneous Fleet Vehicle Routing Problem with Time Window on Urban Last Mile Delivery

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Abstract. The growth of the e-commerce business in Indonesia during the COVID-19 pandemic has increased the demand for last mile delivery (LMD) services. LMD activities with a large frequency of trips can increase logistics operational costs if operational handling is not carried out optimally. Optimization of LMD distribution routes is applied as an operational handling and also as a solution to the vehicle routing problem (VRP). VRP is an important problem to consider in transportation modeling where an optimum route plan is desired to obtain the minimum cost. The purpose of this paper is to optimize the last mile delivery route using the Heterogeneous Fleet Vehicle Routing Problem with Time Window (HFVRP-TW) model in urban areas. The route optimization process is carried out by developing and applying the HFVRP-TW model using data from one of the express delivery companies in Jakarta, Indonesia, and then simulating and forming several operational scenarios. The results of the analysis show that the application of route optimization with variations in vehicle types reduced operating costs by an average of 58.46% - 65.98% compared to the existing conditions. Scenario evaluation is carried out to obtain the scenario with the lowest operational cost. The evaluation results show that the best scenario is a scenario that has the closest characteristics to existing conditions, where there is no change in the type of vehicle used and optimization is only applied to operational routes. However, several other scenarios using a variety of different vehicle types still resulted in a reduction in operating costs of more than 50%.

Keywords: Last Mile Delivery, Logistic Distribution System, Vehicle Routing Problem, Route Optimization, Heterogeneous Fleet, Time Window.

1. Introduction

The COVID-19 pandemic has disrupted economic growth in many business sectors in many countries, except in the e-commerce business sector [1]. The total volume of e-commerce transactions in Indonesia increased by US $ 2.4 billion in April 2020 and increased by 26% from the monthly average for the second quarter of 2019 [2]. The fast growing e-commerce industry has contributed to the expansion of the express delivery market or last mile delivery [3]. Last Mile Delivery (LMD) is a series of activities and processes from the last transit point to the delivery destination point, namely at the B2C/end user level [4].

The increasing demand from Last Mile Delivery Service (LMDS) users has resulted in more expeditions [5]. Last Mile Delivery Service (LMDS) activities with a frequent expeditions and no operational optimization can increase logistics operational costs [6]. Logistics costs are costs that cover all costs for the movement of goods in the supply chain process or what is called by vehicle operational cost (VOC). VOC is the sum of the total fixed costs of vehicles per year and variable costs of vehicles per year [7].

LMD optimization is done by implementing distribution route optimization, which is a solution to Vehicle Routing Problem (VRP) [8]. VRP has become one of the important issues to consider in transportation modeling since it was first coined by Dantzig and Ramser in 1959 [9]. VRP is defined as a problem where an optimum route
plan is desired to obtain the minimum cost and travel time [10]. VRP involves the process of optimizing the customers delivery sequence and delivery routes of LMD vehicles [11]. Various variations of VRP have been developed, such as VRP with time windows, VRP with backhaul, and VRP with pickup and delivery. Heterogeneous Fleet Vehicle Routing Problem with Time Window or abbreviated as HFVRP-TW is a modification of VRP with time windows.

The aim of this paper is to optimize the last mile delivery route using the HFVRP-TW model in urban areas. This paper is arranged in the following order: Section 2 explains the methodology that covers the entire research process along with the data sources, mathematical model development, and software tools explanation. Section 3 presents the scenario optimization and scenario evaluation results. Section 4 provides the conclusion and suggestion for further research.

2. Methodology

The HFVRP-TW model was developed and applied to optimize last mile delivery in urban areas. The data used came from an express delivery company, specifically the same day delivery service in Jakarta, Indonesia, which was not stated for privacy purposes. The optimization process was carried out by simulating and forming several operational scenarios. The data required includes depot location, customer’s address, latitude and longitude coordinates, type of vehicle, number of vehicles, vehicle capacity, service time, earliest start time and latest end time (time window). Time window is the two sides of time where each customer must be serviced on or after the earliest time and before the latest time.

The first stage was developing a mathematical model for the model HFVRP-TW. Mathematical model HFVRP-TW is described in detail in sub section 2.1. The second stage was planning scenario development that includes variations of the type of LMD vehicle used. In this paper, two types of vehicles were used, namely motorbikes (V1) and pickup boxes (V2). Motorbikes and pickup boxes are the types of vehicles that most frequently used for LMD activities [12]. This type of motorcycle uses a box installation on the back or right and left side to increase shipping capacity even though the capacity of V1 is more limited than V2. As for the V2 type, the box capacity depends on the size of the vehicle.

The third stage was calculating the amount of vehicle operating costs per kilometer for V1 and V2 vehicle types. Vehicle operating costs are divided into two parts, namely variable costs and fixed costs. Variable cost component consists of fuel costs, filter oil maintenance costs, tire replacement costs, routine tune up services and spare costs. Meanwhile, fixed cost consists of vehicle depreciation costs, vehicle tax costs, and driver salaries [7]. The calculation of vehicle operating costs was based on the market price for August 2020. For the variable costs, specifically for fuel costs, it depends on the VKT value taken for each type of vehicle. Therefore, to calculate the variable cost, the VKT value obtained through the simulation results is needed.

The fourth stage was employing the model application with the VRP Spreadsheet Solver from [13] for simulations on existing conditions and optimization scenarios. VRP Spreadsheet Solver is an open source software for vehicle routing problems that is operated on the Microsoft Excel Add In using the Visual Basic for Applications (VBA) programming language and the use of the public Geographical Information System (GIS). The algorithm used in the VRP Solver was metaheuristic Large Neighborhood Search (LNS). The VRP solver had slightly different objective functions from the HFVRP-TW model in sub-section 2.1. In this paper, the VRP Solver functioned to determine the vehicle kilometers traveled (VKT in kilometers) for each type of vehicle and resulted in total operating costs for two conditions, namely the existing conditions and the optimization scenario.

The fifth stage was presenting a comparative analysis between the operational costs of the existing conditions and the optimization scenario, and then evaluating the scenario based on the objective function to get the best scenario with the most optimum route.

2.1 Mathematical Model of HFVRP-TW

The Heterogeneous Fleet Vehicle Routing Problem with time window (HFVRP-TW) is a mathematical model to minimize operational costs with the following mathematical formulation. Let $N = \{0, 1, 2, ..., n, n + 1\}$ is the set of customers and the depot (0 and n + 1 correspond to the depot) and $\forall i \in N$, $k$ is a vehicle of one type of vehicle $m$, where $k = \{0, 1, m\}$ and $k \in K_m$. $K_m$ is the set of vehicles for each type of vehicle. Type of vehicle $m =$
{0, 1, 2, ..., M} and m ∈ M where M is the association of different vehicle types. i is the origin of the expedition and j is the purpose of the expedition. Following are the objective functions and constraints of the HFVRP-TW model.

\[ \text{Min } Z = \sum_{m=1}^{M} \sum_{k=1}^{K_m} \sum_{i=0}^{n} \sum_{j=1}^{n+1} (\alpha_m \cdot c_{ijkm} \cdot X_{ijkm}) \] (1)

Subject to:

\[ \sum_{j=1}^{n} X_{oijkm} \leq 1 \quad ; \quad \forall k \in K_m \quad ; \quad \forall m \in M \] (2)

\[ \sum_{i=0}^{n} X_{i(n+1)km} \leq 1 \quad ; \quad \forall k \in K_m \quad ; \quad \forall m \in M \] (3)

\[ \sum_{i=0}^{n} \sum_{j=1}^{n+1} X_{ikmg} - \sum_{j=1}^{n+1} X_{jkmg} = 0 \quad ; \quad \forall g \in N \] (4)

\[ \sum_{m=1}^{M} \sum_{k=1}^{K_m} \sum_{i=0}^{n} X_{ijkm} = 1 \quad ; \quad \forall j \in N \quad ; \quad N \neq 0 \] (5)

\[ \sum_{m=1}^{M} \sum_{k=1}^{K_m} \sum_{j=1}^{n+1} X_{ijkm} = 1 \quad ; \quad \forall i \in N \quad ; \quad N \neq 0 \] (6)

\[ t_s \leq t_{ok} \] (7)

\[ t_{ok} \leq t_e \] (8)

\[ t_{ok} = t_{ok} + \sum_{i=0}^{n} \sum_{j=1}^{n+1} \{ t_{ijkm} + t_{cj} \} \quad ; \quad \forall k \in K_m \quad ; \quad \forall m \in M \] (9)

\[ \sum_{j=1}^{n+1} d_j \cdot X_{ijkm} \leq Q_m \quad ; \quad \forall k \in K_m \quad ; \quad \forall m \in M \] (10)

\[ x_{ijk} \in \{0,1\} \quad ; \quad \forall ij \in N \quad ; \quad \forall k \in K_m \quad ; \quad \forall m \in M \] (11)

The objective of HFVRP-TW is to minimize the operating costs Z. Operational costs are obtained from the multiplication of the vehicle operating cost index (VOC) \( \alpha_m \) and the total length of the expedition \( c_{ijkm} \). The total expedition length is the sum of the expedition lengths for each vehicle k with vehicle type m. Constraints (2) indicate that all vehicles start or leave the depot, while constraints (3) indicate that all vehicles end or enter the depot. Constraints (4) is the balance of vehicle flows where the amount of flow that enters the depot minus the amount of flow that leaves the depot must be equal to 0, and g is the flow of the vehicle. Constraints (5) and (6) indicate that each customer is serviced only once. Constraints (7), (8) and (9) are the time window constraints where \( t_s \) is the earliest time to start LMD vehicle operation, \( t_e \) is the last time to start LMD vehicle operation, \( t_{cj} \) is the unloading time and waiting time for customer j, \( t_{ok} \) is the earliest departure time from the depot, \( t_{ok} \) is the last arrival time to the depot and \( t_{ijkm} \) is the time the vehicle k travels from i location to j location. Constraints (10) is the carrying capacity of one vehicle k, \( d_j \) is the number of customer packages j, and \( Q_m \) is the capacity of the maximum number of packages for the type of vehicle k. Constraint (11) is defined as a binary which only has a value of 0 or 1, if \( X_{ijkm} = 1 \), so the ij track is passed by vehicle k of the vehicle type m, and vice versa.
3. Results and Discussion

The application of the HFVRP-TW model with VRP Solver was divided into two conditions, namely the existing conditions and the optimization scenario. The existing condition used only one type of vehicle, namely V1 with a time window starting at 08.00 - 22.00. Considering that the express delivery service analyzed had the same day delivery service, within that time window, the goods delivered must have arrived at the customer/end user. Analysis of the existing conditions was carried out in one week (7 days) and then two days were selected representing peak and off-peak days. Peak day condition was defined by the largest VKT value and the highest number of packages delivered, while off-peak day condition was defined otherwise [13].

Based on Figure 1, it can be seen that the peak day condition was Friday with the highest number of VKT value and packages compared to other days. It was normal reasoning that Friday is the last day to the weekend, so that the number of same day package delivery demands increased [4]. For the off-peak day condition was on Sunday with the lowest VKT value and the number of packages. It was because Sunday is the last day leading to weekday or Monday, so that the same day package delivery demands decreased [4]. Therefore, the scenario development and further analysis only applied two conditions, namely peak day and off-peak day with scenario planning is presented in Table 1.

![Figure 1. VKT and Number of Packages in Existing Conditions](image)

| Day  | Vehicle Kilometer Travelled (km) | Number of Packages |
|------|----------------------------------|--------------------|
| Mon  | 1205                             | 195                |
| Tue  | 1353                             | 230                |
| Wed  | 1290                             | 185                |
| Thu  | 1413                             | 244                |
| Fri  | 1433                             | 291                |
| Sat  | 1263                             | 231                |
| Sun  | 899                              | 138                |

| Scenarios | Vehicle Type |
|-----------|--------------|
| Existing  | V1           |
| SK-1      | V1           |
| SK-2      | V2           |
| SK-3      | V1 & V2      |

Application of the HFVRP-TW model using software produced the following results: Figure 2 presents the total VKT for each type of vehicle and each scenario including the existing conditions, Figure 3 presents the number of vehicles for each type of vehicle and each scenario including the existing conditions and Figure 4 presents the vehicle operating costs for each scenario including the existing conditions.
According to Figure 2, it can be seen that the existing conditions produce VKT values that are much more than the three scenarios for both peak and off-peak days. This is because the existing conditions do not optimize the travel route with the time window limitation, resulting in a large VKT value. This condition is in line with the number of vehicles shown in Figure 3. The existing condition uses more vehicles than the optimization scenario. In addition, peak day conditions produce VKT and more number of vehicles compared to off-peak days, which is normal considering that on peak days, the number of demands serviced was more than off-peak days.

The calculation of the internal cost index or vehicle operating cost is based on market price conditions in 2020. Based on the calculations, it is found that the internal cost index for V1 vehicle type is Rp. 3.397/km and for the V2 vehicle type is Rp.4.687/km. This index is then used to determine vehicle operating costs for each scenario shown in Figure 4.
Figure 4. Vehicle Operational Cost (Rp)

Based on Figure 4, it can be analyzed that the existing conditions produce VOC values that are much more than the three scenarios. This is because the VKT value of the existing conditions is the largest compared to the three scenarios. In the existing conditions, no route optimization is carried out, so when a package needs to be delivered, the operator tends to rush in delivering the package, so that in many cases, one vehicle only delivers one package. The absence of optimization that is carried out operationally can result in the large value of VKT and affect the amount of operational costs for the delivery [8].

Scenario evaluation was carried out to obtain a scenario with minimum operational costs according to the objective function in sub section 2.1. Based on the analysis that was done, SK-1 resulted in a reduction in operating costs of 68.47% (peak day) and 63.50% (off- peak day) compared to the existing conditions. SK-2 resulted in a reduction in operating costs of 63.54% (peak day) and 55.97% (off-peak day) compared to existing conditions, while SK-3 resulted in a reduction of 55.92% (peak day) and 61.00% (off-peak day).

In general, SK-1 is the best scenario with the largest percentage reduction in operating costs for peak day and off-peak day conditions. The use of the V2 type of vehicle, even though it has a much larger carrying capacity than the V1, but in terms of operational costs, the use of the V1 produces more minimum operating costs. This is because the operating cost index for V1 vehicles is much less than V2. SK-1 was a scenario that was closest to the existing condition, using only V1 type of vehicle, but SK-1 implemented route optimization using the HFVRP-TW model, so it produced the most minimum VKT, number of vehicles, and operating costs. However, both SK-1, SK-2 and SK-3 resulted in a reduction in operating costs of more than 50%, so that the use of the variations in vehicle types described in SK-1 to SK-3 becomes less significant if the route optimization is not applied. Therefore, it can be said that the application of route optimization results in a significant reduction in operational costs compared to the existing conditions.

4. Conclusions and Future Study

Optimization of the last mile delivery route with the HFVRP-TW model in urban areas resulted in an average reduction in operating costs of 58.46% - 65.98% compared to the existing conditions. The three scenarios analyzed resulted in a reduction in operational costs by more than 50% for both peak and off-peak day conditions. The best scenario is SK-1 with the scenario characteristics were closest to existing conditions, where there was no change in the type of vehicle used, only carrying out the optimization of operational routes. However, if variations in vehicle types are used on operational routes, such as the SK-2 and SK-3, the result of reduction in operational costs is still above 50%. However, it needs to be examined more deeply considering that the addition of new types of vehicles to logistics operations requires a significant investment cost, so perhaps for the long-term target, SK-2 and SK-3 can be used as alternative options.

The limitations in this paper can be developed for future research. Modifications of the HFVRP-TW model by adding an external cost component can be further investigated to obtain optimal solutions in vehicle routing...
problems that not only consider the operational costs or internal costs, but also the environmental impacts to create sustainable urban logistics transportation.

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