# A Routing with Simultaneous Pickup and Delivery Considering Carbon Emissions and Time Windows

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**Abstract.** The necessity for transportation is growing since human lifestyles change rapidly. Furthermore, since e-commerce has become widely used, more goods have been transported through delivery and courier companies. Nevertheless, transportation is responsible for around one-fifth, or 23%, of carbon emissions worldwide. This research will develop the Vehicle Routing Problem with Simultaneous Pickup and Delivery (VRPSPD) model considering carbon emissions and time windows through an actual case study in one of Indonesia's courier and delivery companies. The metaheuristics methods of Large Neighborhood Search (LNS) and Simulated Annealing (SA) are used to solve this VRPSPD model. Both algorithms are executed with Python. The proposed SA algorithm's daily total cost is Rp 1.953.198,84, while LNS is Rp 1.813.115,99. It has been shown that LNS provides a superior solution than SA due of its lower total cost, which leads to lower emissions, distance, and travel time.

**Keywords:** Vehicle routing, Simultaneous pickup and delivery, Carbon emissions, Simulated Annealing, Large Neighborhood Search.

## 1    INTRODUCTION

The necessity for transportation is growing since human lifestyles change rapidly. People and goods both depend on transportation for their mobility. Nevertheless, transportation is responsible for around one-fifth, or 23%, of carbon emissions worldwide [1]. In the meantime, carbon emissions are currently a huge issue because of their potential to contribute to environmental damage and global warming. In addition to using environmentally friendly fuels for transportation, one strategy to cut down on carbon emissions is to optimize routing for reducing travel times and distances.

Courier and delivery companies should also contribute to the decrease of carbon emissions by implementing proper routing practices. Furthermore, since e-commerce has become widely used, more goods have been transported through delivery and courier companies. That is why effective management is essential for the operations of courier and delivery companies. In addition to optimizing the route, the mechanism used in the pickup and delivery process should be taken into consideration. This process will impact the delivery time and resource allocation, such as vehicles and drivers.

The routing problem of simultaneous pickup and delivery (VRPSPD) has been extensively studied and implemented in real-world systems. VRPSPD is extensively

utilized in logistics systems that require a two-way flow of goods, such reverse logistics and delivery and courier services. This research will develop the VRPSPD model through an actual case study in one of Indonesia's courier and delivery companies.

This delivery and courier company is a State-Owned Enterprise (BUMN) with multiple branch offices across Indonesia, including one in Yogyakarta. The company provides pickup and delivery services to 99 locations in Yogyakarta. Unfortunately, the company's separate pickup and delivery procedures lead to excessive delivery times and travel distances. This contributes to low customer satisfaction because deliveries are frequently delayed and the delivery cost is fairly high [2].

This study presents a Vehicle Routing Problem with Simultaneous Pickup and Delivery (VRPSPD) while considering carbon emissions and time windows. Carbon emissions in this study are transformed into emissions costs in the objective function in order to address sustainability concerns. In the meanwhile, the operating hours of the depot and its nodes are defined by time windows. This time window has the consequence of forcing the vehicle to wait until it opens if it comes earlier than the customer's time window. Meanwhile, the pickup and delivery process cannot be completed if the vehicle comes after the customer's time windows [3].

The metaheuristics methods of Simulated Annealing (SA) and Large Neighborhood Search (LNS) are used to solve this VRPSPD model. The method was selected since VRPSPD is a large-scale NP-hard combinatorial problem. Both SA and LNS can construct an outstanding solution for the large-scale VRPSPD problem [4]. Numerous VRPSPD problems have been effectively resolved by SA, as seen in the researches [5], [6], and [7]. SA is frequently employed in various types of VRPs including VRPSPD because of its ease of use along with its ability to prevent local minima by applying metropolis criterion [8]. In the meantime, LNS includes greater neighborhoods making it useful for exploring solution space [9]. LNS is also capable of solving numerous VRPSPD problems, such as in [10], [11], [12], and [13].

## 2     METHODOLOGY

### 2.1     Problem Formulation

The VRPSPDTW problem is presented in this section using a Mixed Integer Programming (MIP) model. The MIP is developed from [14], [6], and [15]. Sets

$N$     = set of customers, $\{1, 2, 3, …, n\}$
$N_0$   = set of customers and the depot, $N_0 = N \cup \{0\}$
$V$     = set of vehicles, $\{1, 2, …, k\}$
$r$     = set route from each vehicle, $\{1, 2, …, R\}$

Parameters

| | |
|---|---|
| $Q_k$ | = capacity of vehicle $k \in V$ |
| $c_{ij}$ | = distance between nodes $i \in N_0$ dan $j \in N_0$ |
| $d_j$ | = delivery load customer $j \in N$ |
| $p_j$ | = pickup load customer $j \in N$ |
| $s_i$ | = service time *customer i* |
| $C_s$ | = service cost |
| $C_f$ | = fuel cost |
| $C_e$ | = emission cost |
| $FC$ | = fuel consumption |
| $\varepsilon$ | = fuel emission factor |
| $o_i$ | = earliest time for visiting node $i$ |
| $c_i$ | = latest time for visiting node $i$ |
| $t_{ij}$ | = time travel between nodes $i$ to $j$ |

Decision variables

$x_{ijk}$ = $\begin{cases} 1, \text{ if arc (i,j) is visited by vehicle k} \\ \quad 0, \text{ otherwise} \end{cases}$

$B_k$ = $\begin{cases} 1, \text{ if vehicle k is used} \\ \quad 0, \text{ otherwise} \end{cases}$

| | |
|---|---|
| $y_{ijk}$ | = total pickup load |
| $z_{ijk}$ | = total delivery load |
| $ar_{ik}$ | = arrival time vehicle $k$ in node $i$ |
| $dep_{ik}$ | = departure time vehicle $k$ in node $i$ |

The MIP models are expressed as follows:

$$\min Z = \sum_{v=1}^{V} \sum_{i=0}^{n} \sum_{j=0}^{n} \left[ C_s \times B_k + C_f \times c_{ij} + C_e \times FC \times \varepsilon \right] x_{ijk} \tag{1}$$

Subject to

$$\sum_{j\in N_0} x_{0jk} = 1, \forall k \in V \tag{2}$$

$$\sum_{j\in N} x_{1jk} = \sum_{i\in N} x_{i1k}, \forall k \in V \tag{3}$$

$$\sum_{i\in N_0} x_{i0k} = 1, \forall k \in V \tag{4}$$

$$z_{0ik} = \sum_{i\in N_0} \sum_{j\in N} d_j x_{ijk} \forall k \in V \tag{5}$$

$$y_{0ik} = 0, \forall i \in N, \forall k \in V \tag{6}$$

$$\sum_{i\in N_0} \sum_{k\in V} z_{ijk} - \sum_{i\in N_0} \sum_{k\in V} z_{jik} = d_j, \forall j \in N \tag{7}$$

$$\sum_{i\in N_0} \sum_{k\in V} y_{jik} + \sum_{i\in N_0} \sum_{k\in V} y_{ijk} = p_j, \forall j \in N \tag{8}$$

$$\sum_{i\in N} \sum_{k\in V} z_{iok} = \sum_{i\in N} d_i \tag{9}$$

$$\sum_{i\in N} \sum_{k\in V} y_{iok} = \sum_{i\in N} p_i \tag{10}$$

$$y_{ijk} + z_{ijk} \leq Q_k x_{ijk}, \forall i \in N_0, \forall j \in N_0, \forall k \in V \tag{11}$$

$$o_i < ar_{ik} < c_i, \forall i \in N_0, k \in V \tag{12}$$

$$ar_{jk} = \sum_{i\in N, i\neq j} x_{ijk}(dep_{ik} + t_{ij}), \forall j \in N_0, k \in V \tag{13}$$

$$ar_{ik} \geq a_i \sum_{i\epsilon N.i\neq i} x_{iik}, \forall j \epsilon N_0, k \epsilon V \tag{14}$$

$$ar_{jk} + s_i \sum_{i\epsilon N, i\neq j} x_{ijk} = dep_{jk}, \forall k \in V \tag{15}$$

$$dep_{jk} \leq c_j, \forall k \in V \tag{16}$$

$$x_{ijk} \epsilon \{0,1\}, \forall i \epsilon N_0, \forall j \epsilon N_0, \forall k \epsilon V \tag{17}$$

$$B_k \epsilon \{0,1\}, \forall i \epsilon N_0, \forall j \epsilon N_0, \forall k \epsilon V \tag{18}$$

$$y_{ijk} \geq 0, \forall i \epsilon N_0, \forall j \epsilon N_0, \forall k \epsilon V \tag{19}$$

$$z_{ijk} \geq 0, \forall i \epsilon N_0, \forall j \epsilon N_0, \forall k \epsilon V \tag{20}$$

$$ar_{jk}, dep_{jk} \geq 0 \tag{21}$$

The objective function is composed of service cost, fuel cost, and emission cost, as represented by Equation (1). The service cost is defined as daily driver salary. The salary is based on the Regency and City Minimum Wage (UMK) of the Special Region of Yogyakarta Province (DIY) of Rp 2,125,898 divided by 20 working days per month resulting in Rp 106,294.9 [16]. The value fuel cost is obtained by dividing the price of gasoline per liter (Rp 10,000) by the vehicle's fuel consumption per liter [17]. The vehicle takes 13.5 km of fuel per liter, which adds up to a fuel cost of Rp 741 per kilometer [18]. According to the study [19], the emission cost in Indonesia is Rp 407.6/kg. Meanwhile, the fuel emission factor is 3.08 kg/l [20].

Every vehicle departs from the depot, as guaranteedby constraint (2). Constraint (3) guarantees that vehiclesarriving at one location must proceed to the next.According to constraint (4), All vehicles that havefinished their journey must return to the depot.Constraint (5) represents the total delivery load at thebeginning of the route, while constraint (6) expresses thetotal pickup load at the same time. The updated deliveryload and pickup load constraints are (7) and (8),respectively. The fulfillment of the delivery and pickupdemands is guaranteed by constraints (9) and (10). Acapacity constraint based on constraint (11) states thatthe entire load for pickup and delivery should not exceedthe vehicle's capacity. Equations (12)-(16) are timewindows constraints. Constraint (12) guarantees that thevehicle departure time falls inside the nodes' openingand closing times. The vehicle arrival time is calculatedusing constraint (13). Constraint (14) ensures that thearrival time does not fall below the point's opening time.The vehicle departure time is determined by constraint(15). Equation (16) ensures that the departure timecannot exceed the nodes' closing time. Decisionvariables are defined by constraints (17) through (21).

## 2.2    Simulated Annealing in VRP

Kirkpatrick, Gelatt, and Vecchi introduced Simulated Annealing (SA) in the early 1980s [21]. The idea behind simulated annealing is to heat the material to a very high point when the structure begins to "melt," and then to cool it using a highly specific temperaturedropping plan [8]. The metropolis criterion, which allows for the acceptance of a new solution that is worse than the prior one, makes SA unique.

SA has been successfully applied to severalproblems such as Knapsack problem, TravelingSalesman Problem (TSP), Scheduling, dan VehicleRouting Problem (VRP). In VRP, SA can offer an idealsolution for determining the vehicle routes. Researchsuch Yu et al. [22], which attempts to identify vehicleroutes with hybrid power sources,

employ SA to solveVRP difficulties. Baños et al. [23] apply SA to calculatevehicle routes by taking time windows into account.Considering package lockers, Yu et al. [24] created theSA algorithm for VRP. In the meanwhile, Birim [25]utilized the cross-docking aspects of the SA method forVRP.

### 2.3    Large Neighborhood Search in VRP

Shaw proposes a technique called LargeNeighborhood Search (LNS). Using a combination ofdestruction and repair, LNS enhances the initial solution[26]. LNS is a common algorithm for solvingoptimization problems, including VRP.When solving optimization problems, LNS firstdestroys some of the solution elements, then repairs thedestroyed elements as many times as the maximumnumber of iterations allowed. For the CapacitatedVehicle Routing Problem (CVRP), Akpinar [27]employed LNS. VRP study has been carried out byDumez et al. [10] using a variety of distribution options(lockers and shops). LNS is used in research Grangier etal. [28] to find cross-docking VRP solutions.Concurrently, François et al. [29] applied LNS tocompute routes by taking into consideration multi trips.

## 3    RESULTS AND DISCUSSIONS

The company has a depot in Plemburan, Yogyakarta, which services 99 nodes for delivery and pickup. The nodes are consisted of branch offices (KCP) and agents (agen). The purpose of this study is to design a route that serves 99 nodes and returns to the depot while enabling simultaneous pickup and delivery. However, it also makes capacity and time windows constraints possible.

There are twelve vehicles of the same type, each with a 1000 kg capacity. Operating hours for the depot are 8 a.m. to 10 p.m., while the other 99 nodes are open from 8 a.m. to 4 p.m. Additional information required for routing consists of the pickup and delivery loads, travel time matrix, and distance matrix data.

### 3.1    Computational Results with Simulated Annealing

First, the initial temperature (T0), final temperature (Tf), and α need to be defined for the Simulated Annealing (SA) process. The tuning parameter results are shown next in Table 1.

**Table 1.** SA Parameter Tuning

| T0 | Tf | α |
|---|---|---|
| 100 | 0,001 | 0,99 |

$T_0 = 100$ was chosen based on research by Syaiful et al. [30]. The objective of choosing a $T_f$ of 0,001, which is not too low, is to maintain a balance between the exploration and exploitation processes. [30]. To_minimize the possibility of being stuck in the local optima, set α to 0,99, which will increase the rate of temperature depreciation [31].

The VRPSPDTW problem's SA algorithm was created using Python. After running this algorithm program ten times, the solution with the lowest objective function result is chosen. Table 2 displays SA's the routing findings.

**Table 2.** Routing from SA Algorithm

| Vehicle | Route |
|---|---|
| 1 | KCP Pathuk – Agen Soragan – KCP Karangmalang – KCP Prambanan – Agen Cebongan – KCP Moyudan – Agen Paingan – KCP Cangkringan – KCP wirobrajan |
| 2 | KCP Sedayu – KCP Mlati – KCP Danurejan – Agen Medari – KCP Banguntapan – Agen Ngasem – Agen Agro – Agen Nusa Indah – Agen Kadisoka – KCP Tegalrejo |
| 3 | KCP Pingit – Agen Mlangi – Agen Tahunan – Agen Karang Waru – Agen Kuncen – Agen Wirogunan – KCP Airport – Agen Yudha – KCP Ngemplak – Agen Kopma UGM |
| 4 | Agen Umbulmartani – KCP Piyungan – Agen Pos druwo Paris – Agen Gracia Abadi – Agen Dongkelan – Agen Eben – KCP Ngaglik – KCP Berbah – Agen Ukrim – KCP Gondomanan |
| 5 | Agen Bulaksumur – KCP Godean – Agen Minggir – KCP Seyegan – Agen Fetih – Agen Pringwulung – Agen Tajem – KCP Banyuraden – Agen Besi Jangkang – Agen Mancasan |
| 6 | KCP Muja Muju – KCP Kasihan – KCP Minggir – Agen Tamanan – Agen Katamso – Agen Sonosewu – Agen Makmur – Agen Kronggahan – Agen Mantap – Agen Terban |
| 7 | KCP Kalurang – Agen Concat – Agen Jogoragan – KCP Bantul – Agen Jambusari – Agen Menukan – KCP Krapyak -Agen Wonorejo – KCP Minomartani – Agen Sorowajan |
| 8 | KCP Babarsari – Agen Primanatan – KCP Gondolayu – KCP Kemusuk – Agen Tegal Gendu – Agen Maguwo STTA – KCU Yogyakarta – Agen Suryowijayan – KCP Kalasan – Agen Tamantirto |
| 9 | KCP Turi – KCP Mantrijeron – KCP Gamping – Agen Mawar Baciro – Agen Lempuyangan Doktor Soetomo – KCP Condongcatur – KCP Cewon – Agen Besi Sedan – KCP Tempel – KCP Kotagede |
| 10 | KCP Pakem – Agen Sinduadi – Agen Jlagran – Agen Wonocatur – Agen Rajawali – KCP Mergangsan – Agen Melfindo Seturan – KCP Sleman – Agen Gito Gati – Agen Tegaltirto |

Ten of the twelve cars that are available are being utilized for the vehicle routing generated by the SA algorithm. Each vehicle visits nine to ten nodes. Operationally, the vehicles begin and end at the depot, however the depot is not listed on the vehicle route in the previously mentioned Table 2. the solution has an objective function value of Rp 1.953.198,84 with a total distance of 1067.41 km from all vehicles for an entire day. The routing results have been verified to be within the capacity and time window constraints, with the vehicle's departure time not exceeding the closing hours and its arrival time not exceeding the opening hours. The capacity of the vehicles will not surpass the vehicle's maximum capacity of 1000 kilograms. Fig. 1 illustrates the solution convergence graph found in Table 2.
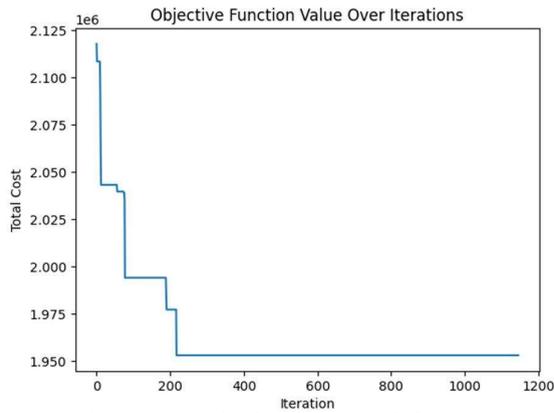
**Fig 1.** Near-Optimal Solution Graph from SA

Based on Fig 1. the costs are decreasing significantly as the iteration continues The SA exploration phase starts at the beginning of the iteration, when the solution change leads to a significant decrease in the total cost. Subsequently, when the temperature dropped, the exploitation process began, altering only a small portion of the solution because the search was concentrated on its neighborhood area. This leads to a lower or even constant decrease in the total cost, which results in the convergence of solutions in the 200s iteration.

## 3.2    Computational Results with Large Neighborhood Search

The Large Neighborhood Search (LNS) algorithm's parameters are specified in Table 3.

**Table 3.** Parameter Tuning LNS

| T | DoD min | DoD max |
|---|---------|---------|
| 1000 | 0,1 | 0,4 |

The significance of selecting the maximum number of iterations (T) of 1000 is that solution convergence must be achieved [32]. The Degree of destruction (DoD) is used to determine the number of solution elements that must be destroyed, which will impact the balance between exploration and exploitation [33].

Similar to the SA algorithm, LNS is executed ten times with Python. Afterwards, the near-optimal solution is chosen based on the smallest total cost. The outcomes of 99 nodes' routing through LNS are shown in Table 4.

**Table 4.** Routing from LNS Algorithm

| Vehicle | Route |
|---|---|
| 1 | Agen Soragan – Agen Surowijayan – Agen Wonocatur – Agen Mawar Baciro – Agen Ukrim – Agen Jambusari – KCP Ngaglik – KCP Kaliurang – KCP Mlati |
| 2 | Agen Cebongan – Agen Tegal Gendu – Agen Dongkelan – KCP Mergangsan – KCP Babarsari – Agen Fetih – Agen Kadisoka – Agen Jlagran – KCP Ngemplak – Agen Makmur |
| 3 | KCP Gondolayu – Agen Concat – KCP Turi – Agen Sinduadi -Agen Agro – KCP Gamping – KCP Muja Muju – Agen Sorowajan – KCP Mantrijeron – Agen Ngasem |
| 4 | Agen Mancasan – Agen Rajawali – KCP Minomartani – KCP Pakem – KCP Cangkringan – Agen Besi Jangkang – KCP Gondomanan – KCP Sewon – Agen Tahunan – Agen Kronggahan |
| 5 | Agen Gito Gati – KCP Seyegan – Agen Lempuyangan Doktor Soetomo – Agen Eben – KCP Prambanan – Agen Tamantirto – Agen Sonosewu – KCP Sedayu – Agen Primanatan – Agen Yudha |
| 6 | KCP Kalasan – KCP Kasihan – Agen Terban – Agen Wirogunan – KCP Wirobrajan – KCP Condongcatur – Agen Tajem – KCP Banguntapan – KCP Godean – KCP Kemusuk |
| 7 | KCP Karangmalang – Agen Bulaksumur – Agen Gracia Abadi – KCP Krapyak – Agen Katamso – Agen Pos Druwo Paris – KCP Moyudan – Agen Minggir – KCP Minggir – KCP Tempel |
| 8 | Agen Karang Waru – Agen Besi Sedan – Agen Melfindo Seturan – KCP Piyungan – KCP Pathuk – Agen Maguwo STTA – Agen Mantap – Agen Kopma UGM – Agen Paingan – Agen Umbulmartani |
| 9 | Agen Wonorejo – Agen Mlangi – KCU Yogyakarta – Agen Menukan – Agen Tamanan – KCP Kotagede – KCP Bantul – KCP Berbah – Agen Tegaltirto – Agen Nusa Indah |
| 10 | Agen Kuncen – Agen Pringwulung – KCP Tegalrejo – KCP Banyuraden – KCP Airport – Agen Jogoragan – KCP Pingit – KCP Danurejan – KCP Sleman – Agen Medari |

Table 4. depicts the routing for 10 vehicles with each vehicle visiting 9 to 10 nodes. It costs Rp 1.813.115,99 for finishing the trip in a single day. The total distance of all vehicles is 899.45 km. Each node is assigned to each vehicle while preserving the time windows and capacity constraints. The convergence graph for the LNS solution represented in Fig 2.
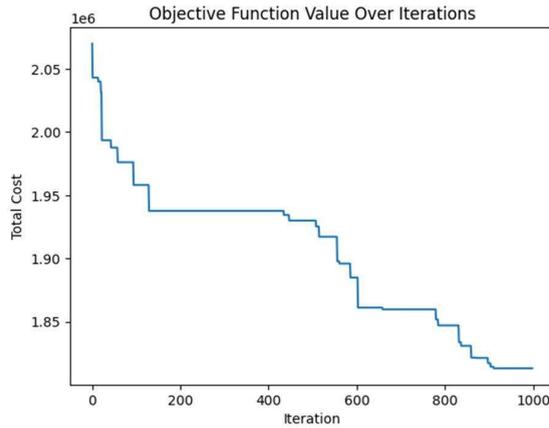
**Fig 2.** Near-Optimal Solution Graph from LNS

LNS experiences more solution modifications than SA due to the destroy and repair procedure, which enables greater exploration of the search space. This increases the number of potential solutions. The reduction in the total cost will be lower and even constant as the number of iterations increases because the exploitation process dominates over exploration and keeps solution improvements localized in the same neighborhood.

### 3.3    Comparative Analysis

A comparison of the SA and LNS algorithms' solution is conducted because the two algorithms give two distinct solutions. The comparison is presented in Table 5.

**Table 5.** Comparative Analysis Between SA and LNS.

| Aspect | SA | LNS |
|---|---|---|
| Total cost | Rp 1,953,198.84 | Rp 1,813,115.99 |
| Emission cost | Rp 99,296.87 | Rp 83,672.28 |
| Total distance | 1067.41 km | 899.45 km |
| Total travel time | 1594 minutes | 1433 minutes |
| Computational time | 27 sec | 24 sec |

Based on Table 5. LNS offers a superior solution with less computational time since LNS explores the search space more thoroughly than SA. LNS enables extensive solution modifications through this exploration process rather than SA limited to exploring its local neighborhood. Consequently, LNS has a broader and more varied solution space coverage than SA. This broader solution space coverage leads to higher number of possible solutions.

LNS also experienced the lower computational time than SA because SA requires more iterations to achieve near-optimal solutions. The high number of SA iterations is due to the little and progressive solutions modification. Furthermore, based on Fig 1.

and Fig 2., SA achieves convergence earlier than LNS because the LNS convergence depends on the selection of destroy and repair operators [10][33].

Since the LNS solution have a lower total cost, the emission cost, total distance, total travel times, and computational time are equally lower than SA. Consequently, it is possible to consider applying the LNS routing solution to the company.

## 4       CONCLUSION

The necessity for transportation is growing since human lifestyles change rapidly. Furthermore, since e- commerce has become widely used, more goods have been transported through delivery and courier companies. That's the reason why transportation is responsible for around one-fifth, or 23%, of carbon emissions globally [1]. Courier and delivery companies should also contribute to the decrease of carbon emissions by implementing routing practices and pickup and delivery mechanism effectively.

This research uses an actual case study of one of Indonesia's courier and delivery companies which provides pickup and delivery services to 99 locations in Yogyakarta. Unfortunately, the company's separate pickup and delivery procedures lead to excessive delivery times and travel distances. We propose a VRPSPD model considering carbon emissions and time windows for this case. This model is solved by Simulated Annealing (SA) and Large Neighborhood Search (LNS).

Out of the 12 cars available, the SA computational result was able to find 10 routes employing 10 different vehicles. The overall distance traveled is 1067,41 km, and the daily operating costs equal to Rp 1.953.198,84. Similar with SA, LNS also find 10 routes. However, the cost is lower than the SA. Total cost for LNS is Rp 1.813.115,99, and the total distance is 899,45 km. SA took 27 seconds to compute, while LNS took 24 seconds. Since the LNS algorithm yields lower total costs, emission costs, total distance traveled, total travel time, and computational time, it can be stated that the solution it generates is better than SA. However, this study is limited to comparing SA and LNS. Comparing to the exact or other metaheuristic methods could potentially be done for further research.

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