Simulated Annealing Algorithm for Vehicle Routing Problem with Simultaneous Pick Up and Delivery: A Case Study of Liquid Petroleum Gas Distribution

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Abstract

Liquid Petroleum Gas (LPG) distribution has become very important because LPG is a commodity used by the community every day. Late deliveries and high distribution costs due to non-optimal routes will have an impact on customer satisfaction. One company that conducts LPG 3 kg distribution for the East Jakarta region is PT Kurnia Cipinang Jaya. The company has a problem determining distribution routes that are not optimal that affect the high total distance travelled by their trucks and an increase in distribution cost. This problem can be solved using the VRPSPD model, where the vehicle delivers and picks up LPG 3 kg simultaneously at the destination. One of the methods used to get the optimal route is the Simulated Annealing (SA) algorithm. This research indicated that the SA algorithm could produce a feasible solution with fast computation time on all instances. At the same time, the exact method requires a long computational time, and in some cases, it does not produce a feasible solution. The optimization method results show that it can save the total Distance travelled 380 km with a fuel cost savings of Rp 451.250,00 for one week, compared to the nearest neighbour scenario used by the company.

Keywords
Distribution, VRPSPD, Simulated annealing.

1. Introduction
Logistics is a part of supply chain management that handles the flow of goods, information, and funds in an effectively and efficiently way, from the origin point to the destination through a process of procurement, storage,

transportation, distribution, and delivery services (*Kementerian Perdagangan Republik Indonesia*, 2015). One of the activities in the logistics process is distribution, which is the activity of moving goods from producers to customers in the right type, quantity, time, and quality. A good distribution process will increase the efficiency of resource use and customer satisfaction.

The distribution strategy of a product depends on the product characteristics. In distributing LPG 3 kg, PT Pertamina uses an agent as one of the logistics service providers distributing products to consumers. The Agents have a vital role in the distribution pattern of LPG 3 kg from PT Pertamina to the customers. It is because customers cannot buy LPG 3 kg directly to SPBE (Stasiun Pengisian dan Pengangkutan Bulk Elpiji).

PT Kurnia Cipinang Jaya is one of the LPG 3 kg agents that serves LPG 3 kg distribution to several areas in East Jakarta. LPG 3 kg is commonly distributed using a truck with 560 gas cylinders capacity. The truck departs from a depot (agent) to deliver fully contained LPG 3 kg and pick up empty LPG 3 containers simultaneously at the same time. However, in the current practice, the determination of distribution routing is only based on the proximity suggested by the truck driver. The route chosen may not be the best routing decision and lead to an increase in total Distance travelled and distribution costs. Moreover, that ineffective routing can affect product delivery delays and reduce satisfaction from customers. Therefore, this research proposes an approach that the company can use to make a more efficient distribution plan of LPG 3 kg.

This problem can be seen as a variant of the Capacitated Vehicle Routing Problem (CVRP). CVRP is an optimization model to determine the most efficient route the vehicle is being used to serve all the customer demand with the limitation of the vehicle capacity. However, the problem considered in this study is more related to the Vehicle Routing Problem Simultaneous Pickup and Delivery (VRPSPD). The VRPSPD model is used when one vehicle will simultaneously send and collect goods to customers. The VRPSPD model is considered a non-polynomial hard problem. It is difficult to be solved to optimality with an increase of problem size. Thus. This study decides to use an approach method to produce near-optimal values and relatively fast time.

There are several kinds of research published related to the VRPSPD. Montane and Galvao (2006) discussed VRPSPD and solved it using tabu search for a problem that consisted of 87 set problems (40 to 50 clients). Tabu search algorithm in his research uses three types of movements and a 2-opt procedure. Ai-min et al. (2009) proposed particle swarm optimization (PSO) to solve VRPSPD with three benchmark data. The solution was decoded, which later needed to be transformed into a priority customer and a priority matrix for vehicles used. Redi et al. (2012) proposed the simulated annealing algorithm for solving VRPSPD. In this study, the vehicle must deliver and pick up damaged equipment that needs to be repaired at the support facility. The research aim is to minimize the total cost of using a Landing Craft Tank (LCT). In another study, the simulated annealing algorithm is shown to effectively solves VRPSPD problems by setting a high initial temperature, slowly temperature decrease, and a large number of iterations (Wang et al., 2013). It is also supported by research from Juniarto et al. (2011) that using simulated annealing was proven to achieve the optimum global value with 500 total iterations. This study proposes using a simulated annealing algorithm to provide a solution for the LPG 3 kg distribution route modelled as the VRPSPD. Therefore, this research will determine the distribution route of 3 kg LPG at PT Kurnia Cipinang Jaya using the VRPSPD model and the simulated annealing algorithm. The results were then compared with the result currently used by the company. It can be seen that this research can obtain optimal solutions and produce low distribution costs.

This paper is organized as follow. In section 2, an overview of the related literature on the vehicle routing problem and its variants is presented. Section 3 describes the model formulation of VRPSPD and the simulated annealing algorithms. Experimental results and comparisons with the other approach are presented in Section 4. Finally, conclusions and future research are described in Section 5.

2. Literature Review

This section explains the literature review, which contains the theoretical basis to support this research, including the concept of VRP, CVRP, VRPSPD, and the optimization method, including the exact and simulated annealing methods.

2.1 Vehicle Routing Problem (VRP)

Dantzig and Ramster first introduced the vehicle routing problem in 1959. VRP plays a vital role in distribution management and has become one of the most studied combinatorial optimization problems. VRP aims to design a set of *m* vehicle routes with low cost, where each vehicle starts and ends at the depot, and each customer is only served once by the vehicle. Moreover, the total demand brought does not exceed the vehicle capacity. Transportation cost contributes 1/3 to 2/3 of the entire distribution costs (Toth and Vigo, 2002). The purpose of VRP itself is mainly to minimize the distance travel, time, and transportation costs. However, in its application, several VRP variations are adjusted to the existing limitations, such as Capacity Vehicle Routing Problem (CVRP), Vehicle Routing Problem with Time Windows (VRPTW), and Vehicle Routing Problem with Simultaneous Pick Up and Delivery (VRPSPD).

2.2 Capacitated Vehicle Routing Problem (CVRP)

CVRP is a variant of VRP that consider vehicle capacity limit using a homogeneous type of vehicle. It starts from one depot with deterministic demand for each customer (Toth and Vigo, 2002). CVRP aims to minimize total costs by considering the number of routes and travel times to serve all customers. The formulation of CVRP. is defined on a complete undirected graph *G= (N, A),* where V is the set of a vertex consisting of customer and depot, and *A* is the set of the arc connecting each vertex. Each customer *i* (i = 1, …, |*N*|) is associated with non negative demand (d_i) and the demand at the depot is d_0 = 0. Set K represent vehicle with the capacity of each vehicle equals to C. To make sure the feasibility of route, it is assumed that $d_i < C$ for each customer. Each customer must be travelled the route once, and it is assumed that *K* must be greater than K_{min}. K_{min} is the minimum number of vehicles required to serve all customers.

2.3 Vehicle Routing Problem with Pick Up and Delivery

Vehicle Routing Problem with Pick Up and Delivery (VRPPD) is a variant of CVRP. VRPPD assumed that the customer *i* is associated with demand type d_i and p_i that represent a homogenous commodities demand to deliver or pick up the goods to customer *i*. Sometimes only one quantity demand $q_i = d_i - p_i$ is used for each customer *i*, which indicates a difference between delivery and pickup of the demand (there is a negative value). Where each customer *i*, O_i is denoted as the starting point of the delivery demand and D_i is denoted as the point of destination. VRPPD strives to find *K* vehicle trips that have the minimum costs, such as each route starts from the depot, each customer is visited once on a trip, and the vehicle load during the trip must be non-negative and not allowed to exceed the vehicle capacity *C*. The starting point and destination of the demand are usually the same (for example, the two-point associated with the depot as in CVRP), so there is no need for stating an exact origin and designation. Further models consider this problem as a VRP with Simultaneous Pickup and Delivery (VRPSPD). Both VRPPD and VRPSPD are NP-Hard due to the generalization of CVRP that appears when $O_i = D_i = 0$ and $p_i = 0$ for every $i \in N$.

2.4 Exact Method

The exact method aims to obtain the optimal or the best solution among all possible combinations of solutions. Several known exact methods are classical algorithms such as dynamic programming, branch & X family algorithm (branch and bound, branch and cut, branch and price). It also includes algorithms developed in the operations research community, such as constraint programming and the A* family as a search algorithm. Some software is commonly used to reduce the complexity of applying exact methods, such as AMPL, CPLEX, LINDO, MPL, OMP, XPRESS. The software makes it possible to apply the exact method to solve problems easily. It is due to the software being simpler compared to coding each of the algorithms manually. Although the exact method is practical for solving a small scale problem, this method is not recommended to solve complex with large size instances problems. It is because the software will take a longer computational time with the growth of problem size. Therefore, to solve complex problems, it is necessary to have methods with a faster computational time but still be able to solve them with a high-quality solution. Thus methods consisting of heuristic and metaheuristic methods are preferable for this type of problem.

2.5 Simulated Annealing Algorithm

The simulated annealing algorithm is inspired by a physical analogy in the solids annealing process. It is then applied to solve complex optimization problems, such as Travelling Salesman Problem (TSP) (Kirkpatrick et al., 1983). The annealing process in the manufacture of crystal is the cooling process of a solid object until the structure is frozen at the minimum energy (Bersimas and Tsitsiklis, 1993). The manufacture of crystal does the heating to a

certain point; when the material is hot, the atoms will move freely with a high energy level. And then, the temperature will be slowly dropped until the particles are in the optimum position with minimum energy. A simulated annealing algorithm can be viewed as a local search algorithm that sometimes moves towards a solution with a higher cost or not optimal solution. This movement can be put out from local minimum (Bersimas and Tsitsiklis, 1993). The simulated annealing algorithm starts with determining the initial solution that considers the current solution and the initial temperature. The initial solutions are built around several viable solution neighbourhoods derived from randomly rearranging existing solutions. According to Tospornsampan et al. (2007), three components must be considered when applying the simulated annealing algorithm: the annealing process or the cooling schedule, making rearrangement or neighbourhood, and termination algorithm.

3. Methods

This section explains the research methodology, the problem definition in a mathematical model formulation and the simulated annealing algorithm's pseudocode.

3.1 Methodologies

There are several steps conducted related to the research process of this study. The first step is identifying problems in the company related to the distribution process especially determining the route for the vehicles. The next step is to conduct literature studies related to routing problems and collect the data. The data collected are the weekly demand, the number of vehicles used, the customers address, and the fuel cost companies used. Then, the VRPSPD model based on the company's problem is modelled and solved using AMPL. The next step is to implement a simulated annealing algorithm for solving VRPSPD. Create and calculate small instances and large instances based on demand data from the companies. Performing parameter tuning of large instances to get a better solution and calculated the fuel cost requirements based on the result obtained. Next, calculate the cost currently owned by the company by searching for a route using the nearest neighbour. The last step is to compare the cost owned by the company with the cost of the proposed route solution.

3.2 Mathematical Model

Determination of routing problem at PT Kurnia Cipinang Jaya is considered as a VRPSPD in which the vehicle makes pickup and delivery in visited customer simultaneously. These problems are modelled in a mathematical model that refers to Tasan and Gen (2010). The mathematical model will be used for a dummy data test to determine the model's suitability with the VRPSPD concept. The mathematical model used is as follows:

Notations:

J	Set of customer nodes $\{1...\|N\|\}$
J_0	Set of all nodes including depot $\{0...\|N\|\}$
V	Set of vehicles used $\{1...\|V\|\}$
C	The vehicle capacity
d_{ij}	The Distance between nodes i and j, $(i,j) \in J_0$, $i \neq j$
D_j	The amount of delivery demanded by customer node $j \in J$
P_j	The amount of pickup of customer node $j \in J$
M	A variable to accommodate a large number of $D_j + P_j$ with capacity vehicle C_{ij}, $(i,j) \in J_0$
l'_v	The amount of load by the vehicle $v \in V$ when leaving the depot,
l_j	The amount of load by the vehicle after served customer node $j \in J$
s_j	The variables used to avoid sub tours can be interpreted as the position of node $j \in J$ in the route
X_{ijv}	A binary decision variable that indicates whether vehicle v travels from i to j, $(i,j) \in J_0$ and $v \in V$

$$Minimize = \sum_{i \in J_0} \sum_{j \in J_0} \sum_{v \in V} d_{ij} X_{ijv} \quad (1)$$

$$\sum_{i \in J_0} \sum_{v \in V} X_{ijv} = 1 \qquad j \in J \quad (2)$$

$$\sum_{i \in J_0} X_{ikv} = \sum_{j \in J_0} X_{kjv} \qquad k \in J, v \in V \quad (3)$$

$$l'_v = \sum_{i \in J_0} \sum_{j \in J} D_j X_{ijv} \qquad v \in V \quad (4)$$

$$l_j \geq l'_v - D_j + P_j - M(1 - X_{0jv}) \qquad j \in J, v \in V \quad (5)$$

$l_j \geq l_i - D_j + P_j - M(1 - \sum_{v \in V} X_{ijv})$ $\quad i \in J, j \in J, j \neq i$ (6)

$l'_v \leq C$ $\quad v \in V$ (7)

$l_j \leq C$ $\quad j \in J$ (8)

$s_j \geq s_i + 1 - n(1 - \sum_{v \in V} X_{ijv})$ $\quad i \in J, j \in J, j \neq i$ (9)

$s_j \geq 0$ $\quad j \in J$ (10)

$X_{ijv} \in \{0,1\}$ $\quad i \in J_0, j \in J_0, v \in V$ (11)

The objective (1) is to minimize the total Distance travelled by vehicle to serve the customers. Constraint (2) ensures that each customer node is served exactly once. Constraint (3) guarantees that for each customer node, the same vehicle arrives at and leaves this node. Constraint (4) initial vehicle loads from the depot is accumulated demand of all customers to be visited. Constraint (5) balances vehicles loads after visiting the first customer node on their route. Constraint (6) balances vehicles loads after visiting the second customer to end customer on their route. Constraint (7) and (8) vehicle load after leaving the depot and after services the customer must be less than same as the vehicle capacity. Constraint (9) ensures sub tour elimination.

3.3 Metaheuristic Algorithm

This study implements a simulated annealing algorithm to solve the VRPSPD. SA is considered a local search algorithm that can move towards a solution with high cost or not optimal solution to hoping that's moving can remove from a local minimum. This algorithm begins with determining the initial temperature, and. If the solution obtained at the current temperature is able to produce a better solution, the solution is being used in the next iteration. However, if the resulting solution is not better, the algorithms would determine with the probability of accepting a worse solution defined as exp(E/T) where E is the difference gap between the new solution and the current solution and T is the current temperature. If the solution is accepted, continue the iteration after several iterations at a fixed temperature. The temperature is lowered according to the alpha value. The process continued until the temperature updated was less than the final temperature set. A more detailed simulated annealing algorithm pseudocode can be seen as follows:

Input: Cooling schedule
$s = s_0$; /*generate of the initial solution*/
$T = T_{max}$; /*starting temperature*/
Repeat
  Repeat /*at a fixed temperature*/
    Generate a random neighbor s';
    $E = f(s') - f(s)$;
    If $E \leq 0$ **Then** $s = s'$ /*accept the neighbour solution*/
    Else accept s' with probability $e^{\frac{E}{T}}$;
  Until equilibrium condition
  $T = g(T)$; /* temperature update*/
Until stopping criteria satisfied/* $T < T_{min}$*/
Output: Best solution found.

4. Results and Discussion

The data collected in this research is demand data related to pickup and delivery for a week at 22 customers locations. The company operates six units of a truck. Then, the dataset was generated based on daily LPG distribution data collected. The dataset is divided into small size instances and large size instances. The small size instance consists of 6 to 10 nodes. Meanwhile, the large size instances are up to 22 nodes. For a small size instance, the customer location is divided into three sub-district. Four instances represent each district. Meanwhile, the large instances are prepared to see if there is a difference between the two mechanisms of delivering LPG for the company. The first mechanism is to let the customer have the equal amount of pickup and delivery. The second mechanism is to see if pickup and delivery amounts that not equal will significantly differ on the generated solution with the first mechanism.

The computational experiment is performed using A Mathematical Programming Language (AMPL) Software and Visual Studio 2017. AMPL is used to verify the result of small instances based on mathematical models, and Visual Studio 2017 uses C# programming language to apply the simulated annealing algorithm. The computer specification used for this research is Processor Intel Core i5-7200U (3.16Hz) with a memory of 4 GB.

4.1 Computational Result for Small Instances

The result of small size instances using the exact and simulated annealing methods are shown in Table 1. It is shown that the simulated annealing algorithm can provide an optimal solution as same as the exact method at almost all the instances. This result indicates that the SA can be used to solve large-size instances. Besides, Increasing the number of total nodes let the computational time required by the exact solution approach also increase. Therefore, the SA algorithm can be an alternative for solving VRPSPD that need a faster computational time without sacrificing too much on the solution quality.

Table 1. Small instances results

Instances	Total Nodes	Total Demand (LPG's Unit)	Exact Method Result (km)	SA Method Result (km)	Objective Value Gap (km)	CPU Time Exact Method (seconds)	CPU Time Exact Method (seconds)	Computation Time Gap (seconds)
Sub district 1								
1	6	890	39	39	0	0.625	0.52	0.105
2	6	830	39	39	0	0.859375	0.97	-0.110625
3	6	760	39	39	0	0.90625	1.51	-0.60375
4	6	980	39	39	0	0.796875	0.7	0.096875
Sub district 2								
5	9	1550	40	40,9	-0.9	47	0.48	46.395
6	10	1620	42,9	42,9	0	1064.83	0.77	1064.06
7	9	1260	38	38	0	555	0.71	554.118
8	9	1450	40	40	0	616	0.78	615.314
Sub district 3								
9	6	920	36	36	0	0.703125	0.78	-0.076875
10	6	910	36	36	0	0.71875	0.64	0.07875
11	6	780	35	35	0	0.875	1.05	-0.175
12	6	930	36	36	0	0.65625	0.74	-0.08375

4.2 Computational Result for Large Instances

Table 2. The results for equal quantity of pickup & delivery large instances

Total *Pickup* (LPG's Unit)	Total *Delivery* (LPG's Unit)	Average Exact Method (km)	CPU Time Exact Method (second)	Average SA Method (km)	CPU Time SA Method (second)
Instances 1					
3360	3360	-	-	273.18	0.888
Instances 2					
3360	3360	135	3600	248.4	1.06
Instances 3					
2800	2800	110	3600	210.4	1.09
Instances 4					
3360	3360		-	263.25	1.30

The calculation of objective values large-size instances with the exact and SA method are shown in Table 2 and Table 3. Table 2 shows the results for instances with equal quantities on the pick up and the delivery demand. Table 3 shows the results for instances with the amounts of the pick up and the delivery demand is not equal. However, Table 2 and Table 3 show that the SA result is not yet configured in terms of parameter setting. The performance of SA depends on the parameter being used relative to the problem. SA has at least four-parameter need to be configured, namely initial temperature, final temperature, alpha value (for cooling schedule), and maximum iteration at each temperature. This study utilizes a one-factor-at-a-time approach to determine the best parameter for settings. The result of the parameter settings are initial temperature equals 1000, final temperature equals 0.001, alpha equals 0.999, and maximum iteration at each temperature equals 100. After parameter settings, the simulated annealing method can produce a high-quality solution comparable to the result from the exact solution approach. Table 4 shows the final results that are obtained based on the simulated annealing method.

Table 3. The results for not equal quantity of pick up & delivery large instances

Total *Pickup* (LPG's Unit)	**Total *Delivery* (LPG's Unit)**	**Average Exact Method (km)**	**CPU Time Exact Method (second)**	**Average SA Method (km)**	**CPU Time SA Method (second)**
Instances 5					
3320	3360	-	-	265.2	1.206
Instances 6					
3360	3410	-	-	146.96	0.948
Instances 7					
2898	2800	115	3600	191.78	1.13
Instances 8					
3360	3350	-	-	283.2	1.014

Table 4. Final solution from optimization method

Instances	**Objective Value (km)**	**Computation Time(second)**	**Total Penalty Initial Vehicle**
1	199	61.83	20
2	132	58.30	0
3	127	60	-
4	178	62.03	10
5	162	67.14	30
6	120	62.96	0
7	138.9	65.64	-
8	181	62.54	20

To compare the result obtained by SA with the solution used in the company, it is assumed that the company used an approach that is closed to the nearest neighbourhood method. The Nearest Neighbour (NN) represents that similar to the company's approach, where the vehicle will visit the closest point to the current vehicle position. Figure 1 illustrates the solution generated by the nearest neighbours. The route illustration is formed based on the optimization result is using instances 2. Meanwhile, the result of the solution generated by SA is illustrated in Figure 2. Further analysis is generated to illustrate the formed route in one week, then the fuel cost calculation based on the total distance travelled per day. The calculation of the total fuel cost in one week is shown in Table 5.

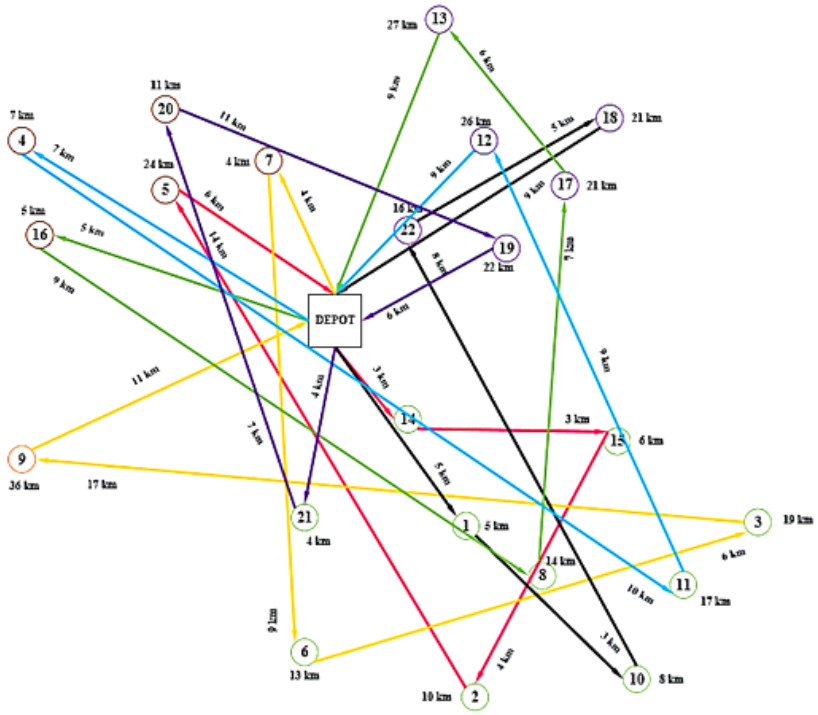

Figure 1. Route companies illustration based on the nearest neighboor scenario

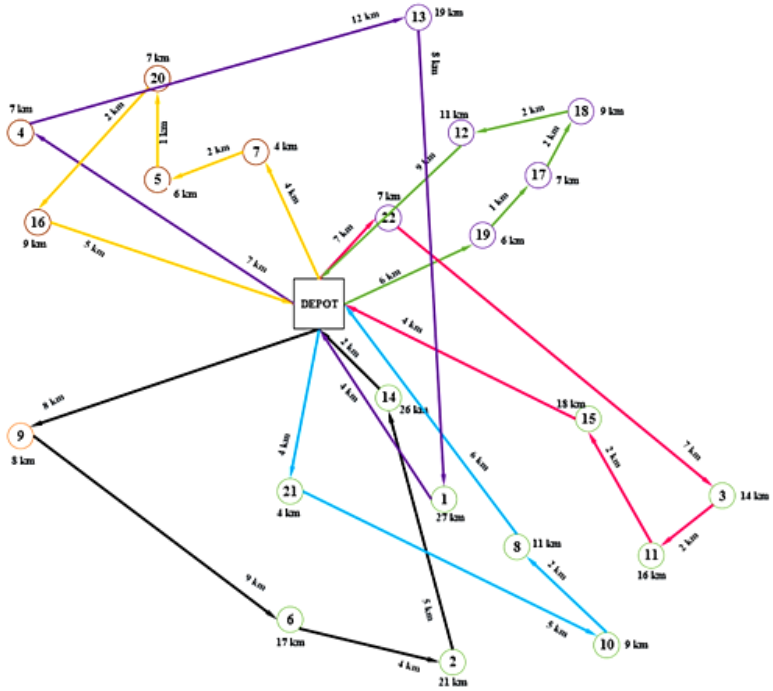

Figure 2. Route illustration based on SA results

Table 5. Calculation of fuel cost

Unit Cost	Calculation Result Based on	Total Distance Traveled (km)	Total Cost
Rp1.187,50	NN scenario in the companies	1241	Rp1.473.687,50
	Optimization Result	861	Rp1.022.437,50

5. Conclusions

This paper describes the use of VRPSPD to model the distribution of LPG 3 kg cases from one agent to several customers. A simulated annealing algorithm is proposed to solve the problem. In VRPSPD, to deliver and pickup LPG 3 kg the route should not exceed the vehicle capacity. The numerical experiments show that the simulated annealing method can get the optimum solution in a reasonable amount of time. Further analysis shows that the distribution route's determination using the simulated annealing method is expected to reduce the total cost compared to the nearest neighbourhood approach.

For future research, additional analysis of the problem characteristics needs to be conducted. A larger size of instances should be considered. In future work, the decision-maker can also escalate the real problem and consider other relevant aspects.

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