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A Simulated Annealing for Heterogenous Fleet Vehicle Routing Problem with Multiple Trips and Pickup-Delivery

Firda Nur Rizkiani[1], Rosmala Sari[2], Arif Imran[3]
[1,2,3]Department of Industrial Engineering, Institut Teknologi Nasional Bandung, Bandung, Indonesia
[1]Department of Digital Supply Chain, Telkom University, Bandung, Indonesia

Email: firdaarizkiani@telkomuniversity.ac.id[1], sarirosmala13@gmail.com[2], imran@itenas.ac.id[3]

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ABSTRAK

Salah satu masalah paling krusial dalam Supply Chain Management (SCM) adalah perancangan jaringan distribusi yang secara signifikan memengaruhi biaya total. Salah satu masalah umum dalam distribusi adalah bagaimana merancang rute kendaraan yang optimal. Masalah ini dikenal sebagai Vehicle Routing Problem (VRP). Sebuah variasi VRP yang dikenal sebagai Heterogeneous Fleet Vehicle Routing Problem with Multiple Trips and Pickup and Delivery (HFVRPMTPD) memiliki karakteristik berikut: jenis kendaraan yang berbeda, perjalanan ganda, dan pengambilan serta pengantaran secara simultan. Penelitian ini membantu dalam menyelesaikan masalah yang dihadapi oleh Perusahaan Distribusi Liquefied Petroleum Gas (LPG) yang mengantarkan dan mengumpulkan tabung gas secara simultan dengan menggunakan jenis kendaraan yang berbeda-beda dan dapat melakukan perjalanan ganda sepanjang waktu operasi. Saat ini, perencanaan rute hanya didasarkan pada pengalaman pengemudi, yang mengakibatkan peningkatan jarak total, dan akhirnya mengarah pada waktu pengiriman yang tidak efisien. Peneliti mengusulkan pendekatan Simulated Annealing (SA) dengan menggunakan Savings Matrix dan Nearest Neighbor untuk mendapatkan solusi awal, dengan tujuan meminimalkan jarak total. Hasil penelitian menunjukkan bahwa rute yang diusulkan memberikan solusi yang lebih baik dalam hal jarak total dibandingkan dengan solusi saat ini dari perusahaan. Analisis sensitivitas terhadap parameter SA juga dilakukan untuk menilai kinerja algoritma yang diusulkan.

***Kata kunci**:* Jaringan Distribusi, *Vehicle Routing Problem, Heterogeneous Fleet Vehicle Routing Problem with Multiple Trips and Pickup and Delivery, Savings Matrix, Nearest Neighbor, Simulated Annealing*

ABSTRACT

One of the most critical issues in Supply Chain Management (SCM) is the design of distribution networks that substantially affects the total cost. Designing optimal vehicle route plan is the most common issue in distribution. This problem is known as Vehicle Routing Problem (VRP). A VRP variant known as Heterogeneous Fleet Vehicle Routing Problem with Multiple Trips and Pickup and Delivery (HFVRPMTPD) involves the following characteristics: heterogenous vehicles, multiple trips, and simultaneous pickup and delivery. This research helps to solve the problems encountered by a Liquefied Petroleum Gas (LPG) Distribution Company which operates by delivering and collecting simultaneously the gas cylinders using heterogenous vehicle in multiple trips throughout the operation time. Currently, the route planning is solely based on the driver's experience, resulting in increased total distance, and consequently leading to inefficient delivery times. We propose a Simulated Annealing (SA) with the initial solution obtained using Saving Matrix and Nearest Neighbor, aiming at minimizing the total distance. The results indicate that the proposed route

provides a better solution in terms of total distance compared to the current solution of the company. Sensitivity analyses of the SA parameter are also conducted to assess the proposed algorithm's performance.
***Keywords**: Distribution Networks, Heterogeneous Fleet Vehicle Routing Problem with Multiple Trips and Pickup and Delivery, Savings Matrix, Nearest Neighbor, Simulated Annealing*

1. INTRODUCTION

Supply Chain Management (SCM) is a strategic approach that involves various the planning, coordination, and control of various activities in the production, procurement, and distribution as well as the management of goods and services. Its primary goal is to optimize the overall efficiency, cost-effectiveness, and responsiveness of the entire lifecycle of product or services, from the acquisition of raw materials to delivering the final product to customers. One of the challenges within SCM encountered by companies is the occurrence of delays in the distribution process. As businesses become more globalized and complex, SCM plays a crucial role in optimizing operations, especially reducing the overall distribution costs. Distribution involves the process of delivering products from manufacturers to consumers. Furthermore, approximately half of the total selling price of products or services can be attributed to distribution expenses. As a result, it is crucial for every company to effectively and efficiently these activities, including the optimization of distribution routes, scheduling of vehicles, and determining the appropriate number of vehicles to employ. This challenge is commonly referred to as Vehicle Routing Problem (VRP). Numerous studies have been conducted and implemented in many real cases related to the VRP, such as a Liquid Petroleum Gas (LPG) distribution company.

PT. X is one of the 3 kg LPG gas agents in Bandung city responsible for distributing gas to stores. Gas distribution activities are conducted daily, with varying demand quantities at each store. The distribution routes currently used are solely based on driver's experience, leading to a decrease in driver productivity. The distribution issue faced by PT. X falls under the category of Heterogeneous Fleet Vehicle Routing Problem with Multiple Trips and Pickup and Delivery (HFVRPMTPD), as the vehicle capacities for picking up and delivering gas cylinders to different stores vary, allowing each vehicle to make multiple trips. Therefore, this research aims to determine distribution routes using the savings matrix, nearest neighbor, and simulated annealing methods to obtain routes with the minimum distance.

This paper is organized as follows. In Section 2, an overview of the related literature is presented. Section 3 describes the problem description and explains how our methodology is employed in this study. The details of the proposed SA algorithm are described in Section 4. Next, Section 5 presents the experimental setup, results, and analysis. It includes the comparison between SA output and current condition to show the efficiency of the proposed algorithm. Finally, notable findings and insight derived from the research are summarized in Section 6.

2. LITERATURE REVIEW

2.1 Vehicle Routing Problem (VRP)

The Vehicle Routing Problem (VRP) is a problem related to finding the optimal routes to be used by a set of vehicles to serve customers [1]. This problem is commonly encountered in the field of logistics for delivering products to various locations. According to [2], the Vehicle Routing Problem (VRP) consists of several types, including the following:

1) Capacitated Vehicle Routing Problem (CVRP)
   CVRP is a type of VRP where customer demands are known in advance, and the vehicles used for

delivering products or services have limited capacities.

2) Vehicle Routing Problem with Time Windows (VRPTW)
VRPTW is a type of VRP where customers can only receive products or services within specific time windows.
3) Vehicle Routing Problem Multiple Trips (VRPMT)
VRPMT is a type of VRP where vehicles have multiple routes to fulfill customer demands. Vehicles start from the depot to serve multiple customers on the first trip, then return to the depot to replenish products and start a second trip, and so on until all customer demands are satisfied.
4) Multiple Depot Vehicle Routing Problem (MDVRP)
MDVRP The Multiple Depot Vehicle Routing Problem (MDVRP) is a type of VRP where multiple depots are used to deliver products or services to customers. Each depot has vehicles with limited capacities for conducting deliveries.
5) Vehicle Routing Problem with Pickup and Delivery (VRPPD)
VRPPD is a type of VRP where vehicles not only perform deliveries from the depot to customers but also carry out pickups from other customers and deliver them to other customers.
6) Vehicle Routing Problem with Heterogeneous Fleet of Vehicles (VRPHFV)
VRPHFV is a type of VRP where there are several different types of vehicles with varying capacities and operational costs.
7) Stochastic Vehicle Routing Problem (SVRP)
SVRP is a type of VRP where there is uncertainty in customer demand, or the time required to serve customers. Customer demand or the time needed to serve customers is considered a stochastic variable that can change randomly.
8) Periodic Vehicle Routing Problem (PVRP)
PVRP is a type of VRP where deliveries are made within predetermined time periods, such as daily or weekly deliveries.

2.2 Saving Matrix

Saving matrix is a heuristic method aimed at minimizing the total distance, time, or cost while considering the constraints in distribution network [3]. This approach was introduced by [4]. [5] discovers that this approach is accomplished through resource efficiency, indicating that the greater value of savings, the higher the level of savings achieved. The advantage of this method offers the flexibility for adjustments regarding the constraints such as vehicle capacity, delivery time, the number of vehicles, etc [6]. In addition, there are four stages of this method involves: (1) determining the distance matrix, (2) establishing the saving matrix, (3) allocating customers to vehicles, and (4) sequencing customers within routes. An example of this approach is given in [7]. The illustration of the saving matrix is presented in Figure 1.

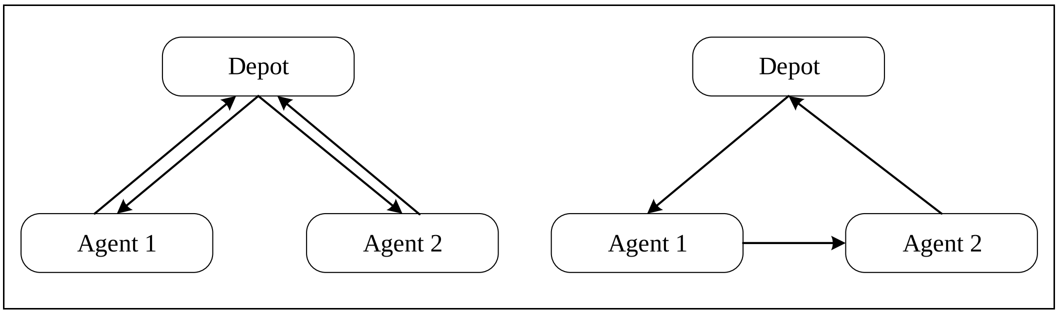


Figure 1. Illustration of Saving Matrix

2.3 Nearest Neighbor

Nearest Neighbor, a greedy heuristic method, is used to find the shortest distance in a route. Fundamentally, this approach operates by prioritizing nearby stores when establishing the order of visited stores [3]. In other words, it starts by initiating the route from the depot, then selecting the closest customer from it, followed by choosing the subsequent nearest customer from the current point. Once all customers have been visited, then stop. Steps of this method can be seen in [8].

2.4 Simulated Annealing

Simulated Annealing (SA) algorithm operates based on the principle of a physical annealing process. Annealing is a technique of producing better-aligned metal with low energy-state crystallization by gradually cooling it down [9]. It is then applied to solve complex optimization problems, such as Travelling Salesman Problem (TSP) [10].

The optimization procedure of SA aims to search for a (near) global optimum, imitating the slow cooling process in the physical annealing process. This approach begins by generating an initial solution. Subsequently, at each iteration, a new solution is selected from the predefined neighborhoods of the current one. This objective function value of the new solution is compared with the current best solution, determining whether an improvement has been achieved. If the new solution's objective function value is better (smaller in minimization problem), the new solution replaces the current one. The search proceeds by processing with a new iteration referred to the new solution. A new solution that is worse with a larger objective function value may also be accepted as the new current solution. This algorithm does not restrict the search only to solutions that decrease the objective function value, but it allows for moves that might increase it as well. Therefore, this feature prevents the SA procedure from becoming trapped in the local optimum.

In the last decades, several studies have applied SA for solving the various types of VRP because it is one of the promising alternatives to deal with these problems and has proven to provide good results. Simulated Annealing was implemented with constant temperature and temperature that decreases in the Hybrid Vehicle Routing Problem (HVRP), where vehicles use two types, namely fuel and electricity. The aim of this research is to minimize the total travel cost among customers. The results obtained indicate that the use of SA with constant temperature is closer to the optimum solution compared to SA with decreasing temperature [11]. The capacitated vehicle routing problem (CVRP) can be solved using simulated annealing, which employs three operators: exchange, insertion, and reversion. The results indicate that the simulated annealing algorithm can determine the optimal routes for 23 instances [12].

3. PROBLEM DESRIPTION

The Heterogenous Fleet Vehicle Routing Problem with Multiple Trips and Pickup and Delivery (HFVRPMTDP) is an extension of the classical VRP that integrates components derived from VRPHFV, VRPMT, and VRPDP. The HFVRPMTDP model involves where heterogenous vehicles carry out both deliveries and pickups to customers in multiple trips during their operational time. Achieving optimality becomes challenging as the problem size increases. Consequently, this problem falls into the category of NP-hard problems, resulting in the utilization of metaheuristic approach to generate nearly optimal solutions within a relatively fast time.

In this research, we proposed a distribution network for an LPG Distribution Company. The company serves cylinders of LPG distribution to several areas in Bandung. Currently, the distribution routing is

only based on the proximity suggested by the driver. Consequently, it leads to an increase in the overall distance covered and requires longer delivery times. This is due to the ineffective route.
The distribution starts from a depot to deliver fully contained LPG and collects empty one to customers simultaneously. Additionally, each vehicle can deliver more than 1 trip within a single day, utilizing several heterogenous vehicles with distinct capacities. The study also considers the practical considerations such as the number of vehicles, the vehicle's capacity, and working hours limitation. The company ensures that the daily demands of all agents (customers) are fulfilled while aiming to minimize the total distance travelled. The agent's daily demand and the distance matrix are presented in Table 1 and Table 2, respectively.

In addition, various steps have been undertaken in this research. The first step involves identifying problems within the company, especially determining the distribution route. Then, a review of the relevant literature is conducted, followed by collecting the data. Next, the proposed SA is developed for solving HFVRPMTPD. Additionally, a set of experiments were carried out to evaluate how changes in parameters affect the performance of the objective function. Lastly, a comparison is made between the overall distance associated with the current condition and the obtained results.

Table 1. Daily Demand (Unit)

Agent	**Daily Demand (Unit)**						**Total**
	Mon	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	
A1	0	50	0	50	0	50	**150**
A2	50	90	100	100	50	0	**390**
A3	0	120	0	120	0	120	**360**
…	…	…	…	…	…	...	**…**
A41	120	0	120	0	0	120	**360**
A42	0	50	0	50	0	50	**150**
Total	**3360**	**2800**	**3360**	**2800**	**2800**	**3160**	**18280**

Table 2. Distance Matrix (km)

Agent	**Distance (km)**						
	A0*	A1	A2	A3	…	A41	A42
A0*		2.40	1.30	0.45	…	3.70	2.80
A1	2.40		1.70	2.20	…	1.60	0.25
A2	1.30	1.70		0.95	…	2.40	1.80
A3	0.45	2.20	0.95		…	3.80	2.90
…	…	…	…	…		…	…
A41	3.70	1.60	2.40	3.80	…		2.90
A42	2.80	0.25	1.80	2.90	…	2.90	

(*) A0 as a depot

4. SIMULATED ANNEALING FOR HFVRPMTDP

The HFVRPMTPD is a special case of VRP, and VRP itself is an NP-hard problem. Therefore, HFVRPMTPD is also an NP-hard problem. We consider using SA due to its effectiveness of its results, where there is a procedure that ensures avoidance of local optima. Additionally, this metaheuristic is frequently employed to solve various types of VRP problems. Therefore, the SA algorithm that is inspired by annealing process is used to solve HFVRPMTPD problem, aiming to determine the optimal solution.

4.1 Solution Representation

A solution representation consists of customer nodes visited daily by each vehicle, referred to as the vehicle's assignment. At both the beginning and the end of assignment, a value of 0 is placed, indicating a depot. Due to multiple trips for each vehicle within a single day, each solution may consist of more than one assignment which affects the length of solution representations. It will depend on the number of assignments for each vehicle. The number of trips relays on the visited customer nodes and the delivery time adjusted according to working hours. Figure 2 represents a solution from Vehicle 1 on Monday.

0	7	22	13	10	15	39	14	24	0

Figure 2. An Example of Solution Representation

4.2 The Initial Solution

The procedure for generating an initial solution in this study consists of two steps. First, all customers are listed and grouped into clusters using the Saving Matrix approach. Each customer is assigned to a particular cluster based on their savings. Once the customer clustering is completed, the Nearest Neighborhood algorithm is then performed. This method selects the closest customer node according to the currently visited one. This algorithm will continue until all customers have been assigned. This initial solution is as an input solution of the SA algorithm.

4.3 Neighborhood Moves

To improve an objective value, we implement three different neighborhood moves that are as follows: (1) swap, (2) flip, and (3) slide. The currently evaluated solution is denoted as *X* and *N(X)* is the set of its neighborhood solutions. There is only one of the three moves chosen at each iteration, as mentioned above, to generate a new solution *Y*. The swap move will exchange two randomly chosen nodes in *X*. This move often used to solve the VRP, see [13] and [14] for example. Meanwhile, the flip moves reverse the sequence between them. For slide move, it also selects two nodes randomly and then removes the fore nodes and inserts it into another selected node position. The illustration of the results after applying each of the moves can be seen in Figure 3.

Original Solution	0	7	22	13	10	15	39	14	24	0
By Swap	0	7	14	13	10	15	39	22	24	0
By Flip	0	7	14	39	15	10	13	22	24	0
By Slide	0	7	13	10	15	39	14	22	24	0

Figure 3. An Example of Neighborhood Solutions

4.4 Simulated Annealing Procedure

The SA is performed after an initial solution is generated. This algorithm begins with establishing the current temperature, denoted as T, as the initial temperature. The SA procedure involves two types of iterations: inner iterations and outer iterations. The inner iteration focuses on finding a new solution based on the current solution utilizing neighborhood moves, detailed explained in Section 4.3. The selection of move is based on the randomly generated value, r_2, ranging from 0 to 1. Moreover, each possible move holds the same probability of being chosen. These moves can move towards a solution with a low cost (better solution) or worse solution. However, if the resulting solution is higher, it would not directly reject. To determine whether the new solution is accepted as the current best solution, a comparison between a random value, r_2, that a range from 0 to 1, with a probability $e^{-\Delta/\beta T}$, where β represents the Boltzmann constant. If $r_2 < e^{-\Delta/\beta T}$, a new solution is accepted as the current best solution. Otherwise, it is rejected.

After an inner iteration cycle is completed, another iteration is generated by reducing T. Lowering the temperature is by multiplying with a constant of alpha, α. The process continued until the termination condition was fulfilled. It depends either on the defined final temperature, T_f, or the defined number of iterations. Otherwise, a new solution is generated by inner iteration cycle. The pseudocode of the proposed SA is shown in Figure 4.

```
SA procedure (T0, Cr, cycle, it, maxit, maxcycle)
Step 1:
        Generating the initial solution, initroute
Step 2:
        Let T = T0 ; cycle = 0; it = 0; bestroute = currentroute = initroute
Step 3:
        cycle = cycle + 1;
    Step 3.1:
        If it <= maxit
        it = it + 1;
        Else go to step 3
        Generating newroute based on currentroute
        Generate r1 ~ U(0,1)
        If r1 ≤ 1/3
                Generate newroute by swap
        Else if (1/3 < r1 < 2/3)
                Generate newroute by slide
        Else
                Generate newroute by flip
    Step 3.2:
        If newroute < currentroute
                currentroute = newroute
        Else
                Calculate diff = newroute – currentroute
                Generate r2 ~ U(0,1)
                If r2 < exp (-diff/T)
                        currentroute = newroute
                Else
                        currentroute = currentroute
Step 4:
        If it = maxit
                T = cr * T;
        Else Go to Step 3
Step 5:
        If cycle = maxcycle
                Terminate the SA Procedure;
        Else Go to Step 3
```

Figure 4. A Pseudocode of the Proposed SA

5. RESULTS AND DISCUSSION

This research is proposed SA algorithm for solving the HFVRPMTDP faced by an LPG Distribution Company. Before we perform the SA algorithm, an initial solution is generated by performing the Saving Matrix and Nearest Neighbor. The proposed SA algorithm was implemented in Matlab. To select the best combination of SA parameters, we utilize 2^k factorial design. To execute 2^k factorial design, we determine each SA parameter's upper and lower bound values using One Factor at A Time (OFAT). Table 3 represents the selected upper and lower bound values of each SA parameter based on the pilot experiment.

Table 3. Upper and Lower Bound Value for SA using OFAT Experiment

Parameter	Lower Bound	Upper Bound
Cr	0.4	0.6
maxit	50	100
maxcycle	5	10

After conducting the OFAT experiment, the 2^k factorial design, with $k = 3$, is performed. In total, there are 8 tested combinations. However, we do not conduct experiments on an initial temperature parameter, defined as T_0. The T_0 is obtained by the average real distance in a 1-day period. Then, the best parameter combination is selected based on the lowest objective value obtained. By using this selection criterion, we obtained C*r* = 0.4, *maxit*= 100, and *maxcycle* = 10. The result is summarized in Table 4. Based on Table 4, the average total distance of 16.79 km for a 1-week period within 0.94 minutes is obtained.

The critical factors in implementing the SA algorithm provide a good solution including the utilization of a set of neighborhood moves, the acceptance criterion, and setting of the parameters. By utilizing various neighborhood moves, the SA could explore a wide range of solution spaces so that it may find a promising solution. In the contrary, the SA algorithm enables to escape from the local optimum by utilizing acceptance criterion. Lastly, SA can achieve a good performance by conducting parameter setting for finding an appropriate parameter configuration [15].

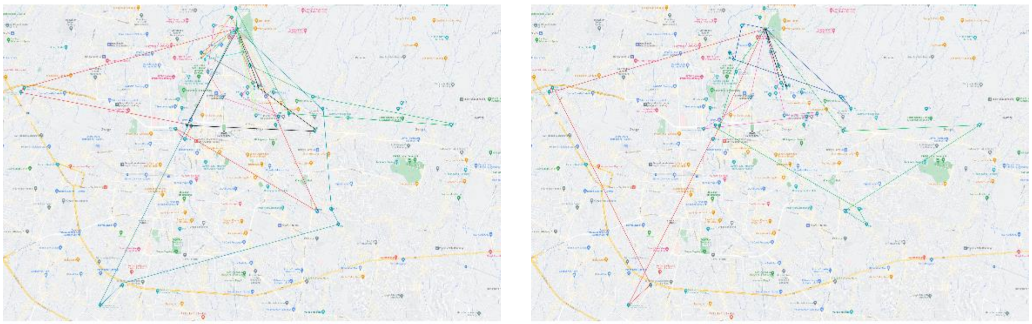
Table 4. The Result of 2^k Factorial Design

Parameters			Results	
Cr	***maxit***	***cyclemax***	**Avg Total Distance (km)**	**CPU Time (mins)**
0.4	50	5	18.19	0.92
		10	16.85	0.92
	100	5	17.78	0.83
		10	16.79	0.94
0.6	50	5	20.27	0.72
		10	17.12	0.84
	100	5	20.93	0.87
		10	16.99	0.96

After the best parameter setting is selected, we perform our proposed SA that will be compared with the real condition. According to the results presented in Table 5, we provide high quality solutions in terms of overall distance and delivery time when compared to the current one. The largest improvement result of the proposed SA is 32.73% on Monday. On average, SA improves the current condition's results by 29.11% in total distance and 10.64% in delivery time. Therefore, we conclude that the proposed SA is effective for solving HFVRPMTPD in this study. The distribution route comparison illustration is shown in Figure 5.

Table 5. A Comparison Result of the Current Condition and the Simulated Annealing

Days	Real Condition		Simulated Annealing		Gap (%)	
	Total Distance (km)	Delivery Time (mins)	Total Distance (km)	Delivery Time (mins)	Total Distance	Delivery Time
Mon	170.31	1398.28	114.56	1260.22	32.73	9.87
Tue	102.35	1081.48	76.19	1020.39	25.56	5.65
Wed	174.91	1415.98	122.93	1285.72	29.72	9.20
Thu	105.52	1087.82	74.18	1016.37	29.70	6.57
Fri	130.85	1138.48	94.64	1001.96	27.67	11.99
Sat	154.37	1312.89	109.20	1042.73	29.26	20.58
Average	**139.72**	**1239.15**	**98.62**	**1104.57**	**29.11**	**10.64**



Current Route Condition The Proposed Route based on SA

Figure 5. A Comparison of Distribution Route Visualization

In addition, we also perform a set of sensitivity analysis on SA's parameter to get a comprehensive perspective the SA parameter influences the objective value. The results are presented in Figs. 6-8. Based on Figure 6, the *Cr* parameter gives an opposite effect on the objective function by changing its value. As the larger of parameter value, a worse solution is obtained as well as the longer time is required. It is due to the higher value of *Cr* parameter that shows a tendency to decline a new solution during the neighborhood search. Consequently, it may tend to get trapped in local optima and require longer time to process.

In contrast, the *maxit* and *maxcycle* parameters seem to slightly influence the objective function by changing its value. When a higher value of these parameters is tested in our proposed SA, the smaller average of the overall distance is obtained while the computation time tends to be longer. It is due to the algorithm that has the probability to explore a wide solution space as the increasing of those parameters value to find for solutions randomly, obtaining an optimal solution.

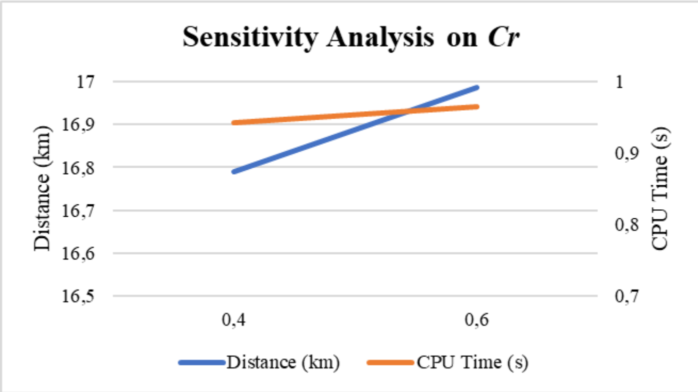


Figure 6. Sensitivity Analysis on *Cr*

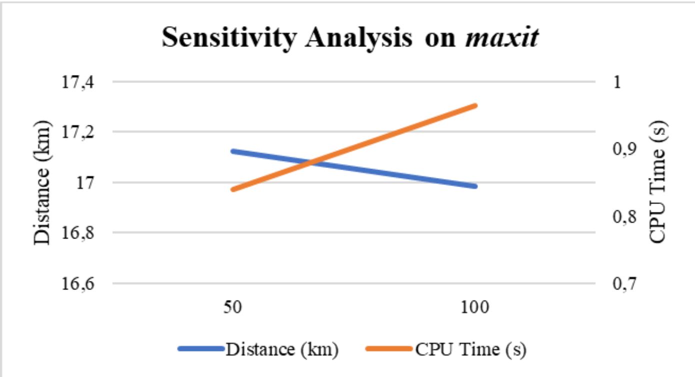


Figure 7. Sensitivity Analysis on *maxit*

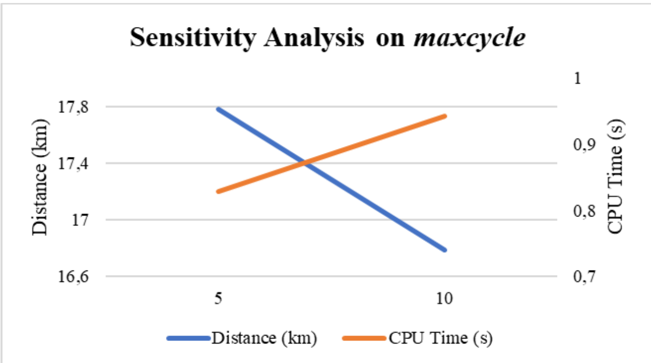


Figure 8. Sensitivity Analysis on *maxcycle*

6. CONCLUSION

In this study, we developed a Simulated Annealing algorithm to solve the Heterogenous Fleet Vehicle Routing Problem with Multi Trips and Pickup-Delivery for real case problems that faced by an LPG Distribution Company. The results indicate that our proposed algorithm performs better than the current condition, as it can achieve a shorter total distance and total delivery time for a 1-week period. Moreover, our method has significantly reduced the overall distance by 31.22%. Similarly, the cumulative shipping time in a week ranged from 9135.12 minutes (about 6 and a half days) to 6597.14 minutes (about 4 and a half days).

Besides, we also carried out a set of experiments on Simulated Annealing operator regarding *Cr*, *maxit*, and *maxcycle*. The *Cr* parameter demonstrates a contrast impact on the objective function as it modifies its value. Increasing the parameter value yields an inferior solution and takes much more computing time. Meanwhile, the *maxit* and *maxcycle* parameters slightly improve the objective function as its value is adjusted. As the parameter value increases, the average total distance declines although it extends computation time. Nevertheless, the increasing computational time is acceptable due to insignificant differences, as it leads to better solutions.

Despite the proposed SA performing well in this research, we are aware that each algorithm has advantages and limitations. Therefore, our proposed SA performance cannot be generalized to all problems before further studies are conducted. However, many other sophisticated metaheuristic algorithms have been developed recently. Further research can address this development of algorithms to enhance the result further. As the size of problems grows larger, the complexity also grows, and the use of metaheuristics becomes more valuable. Additionally, considerations regarding traffic, time windows, stochastic demand, or other relevant aspects can be considered, making the model more closely resemble real distribution systems.

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