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Optimization of vehicle routing problem using guided local search and simulated annealing

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ABSTRACT

Transportation concerns in the supply chain are important because they have the potential to greatly raise logistical requirements. The proposed solution to the issue is the vehicle routing problem. The Heterogeneous Fleet Vehicle Routing Problem (HFVRP) model will be implemented in this study using the metaheuristic methodology together with the Guided Local Search (GLS) and Simulated Annealing (SA) approaches for case studies. Python 3.10 software was used to analyze the SA and GLS, and the Google OR-Tools module was used. Implementing the SA and GLS algorithm based on data from the case study in a logistics company involved in the distribution of chicken feed and gas is the goal of this project. By doing so, it will be possible to determine whether the current situation is ideal or if it could be improved to reduce the number of vehicles used, find the best route, lower shipping costs, and increase efficiency. The findings of this study show that when compared to the GLS algorithm, research employing SA produces better outcomes in terms of cost and route management. According to actual data, SA increases income by an average amount between 3% and 10%.

Keywords: HFVRP; simulated annealing; guided local search; OR-Tools, Python

1. INTRODUCTION

Distribution is considered as producers can reach their target market with their products and services. To ensure the continued existence of the business, distribution, therefore, refers to the transfer of commodities produced by the company from producers to customers. The distribution of commodities is referred to as logistics. Logistics plans and manages the movement of products from the producer or producer to the consumer. Logistics is a set of tasks that involves organizing, carrying out, and keeping track of processes for goods or services, energy, or other resources as they move from their point of origin to their point of use. As an example, controlling the flow of items, finished goods, and information related to a line of business is an example of logistics, which has a different connotation.

Transport is one of the most crucial factors in the logistics system that must be considered in attention. One-third of logistics expenses go toward transportation, which has a significant impact on system performance [1]. Transportation activities refer to the movement of goods along the supply chain from one place to another. The role of transportation in the movement of commodities includes moving finished things, as well as raw materials, components, work-in-progress, and raw resources. Transportation issues come up when deciding how to distribute them. Every industry needs the most economical transportation method, so the best solution-finding problem-solving strategies are required.

Increase the use of existing cars for transportation to make the system more effective. Finding the best route with the shortest distance is crucial for lowering transportation expenses, reducing the use of cars, and enhancing customer service. When resolving the Vehicle Routing Problem (VRP) a set of routes that are each completed by a single vehicle and begin and end at their respective depots are chosen, ensuring that all customer requirements, operational restrictions, and overall transportation costs are met [2].

VRP has several varieties, which are: VRP with Time Windows (VRPTW), Pickup and Delivery Problem (PDP), Heterogeneous Fleet VRP (HFVRP), Multi-depot VRP (MDVRP), Periodic VRP (PVRP), and many more. In this paper, the type of VRP that will be used is Heterogeneous Fleet Vehicle Routing Problem (HFVRP) as followed by the real data. HFVRP has referred to vehicles that have different capacities, for example using different vehicle types based on the vehicle fleet in each vehicle type category [3].

Not all organizations, large or small, have vehicles with the same (homogeneous) capacity [4]. Also, numerous businesses have changing vehicle capabilities, making today's conventional VRP issues troublesome to bargain with. So, with the nearness of a modern VRP variety called the Heterogeneous Fleet Vehicle Routing Problem (HFVRP) which can illuminate the issue of vehicle routing with changing sorts and capacities (heterogeneous) and has been demonstrated to be able to be executed in genuine conditions.

The company uses a variety of fleets that are classified as HFVRP considering the issues encountered, particularly in this case study that was examined. The choice of route is still manual. Considering this, the goal of this project is to find a solution to the vehicle routing problem by making concepts and steps while minimizing costs, mileage, and the number of cars employed, as well as obtaining the best route selection outcomes using SA and GLS algorithms.

2. LITERATURE REVIEW

The idea of HFVRP has been extensively used by earlier researchers using a variety of techniques. Since the 1980s, studies have been conducted utilizing the HFVRP model [5], [6]. GAMS software has been used in research on HFVRP for the distribution of liquefied petroleum gas (LPG) [7]. It has also been studied using HFVRP to compare the Clark and Wright algorithm method and the solution from LINGO for distribution (LPG) cylinder [8]. Additionally, fuel distribution utilizing a fleet of 8 clients has been studied by the HFVRP [4].

The Evolutionary Algorithm (EA) algorithm has been used to optimize the HFVRP with Time Window [9]. Using Last Mile Delivery, HFVRP optimization with Time Window has been done in metropolitan areas [10]. By merging the outcomes with integer linear programming, Capitated HFVRP with Time Window for route difficulties for pharmaceutical product delivery has also been conducted [11]. HFVRP with Soft Time Window has been used to handle branch and bound route difficulties in fast-moving consumer goods (FMCG) industries utilizing LINGO software [12]. For food and beverage firms, research using the sweep algorithm method and the HFVRP approach has been conducted with the solution method employing Mixed Integer Linear Programming and the LINGO software tool [13].

There are various methods for solving HFVRP, including heuristic and metaheuristic strategies. When compared to conventional heuristic procedures, the quality of the solutions produced by metaheuristic methods is frequently substantially higher [14]. By emphasizing thorough investigation of the solution space, metaheuristics are a type of heuristic that improves on traditional heuristics. Typically, metaheuristics combine solution recombination with intricate environmental search rules. Numerous different metaheuristics have been suggested for vehicle route difficulties [15].

Simulated annealing is one of the metaheuristic methods. The focus of SA is to find the global minimum of a given objective function while avoiding local minima. Its low complexity allows it to be used in a variety of optimization situations, not just VRP. This approach is called a metallurgical annealing process, where a solid material is heated to a temperature at which it becomes liquid, then cooled slowly and uniformly until the solid state is restored and the metal particles rearrange into their molecular structures with minimal energy [15].

Research using the HFVRP concept has also been completed using the SA algorithm. Studies modifying SA for HFVRP with numerous cross-docks have been conducted [16]. In contrast to standard HFVRP, the VRPCD retrieval process involves the vehicle acquiring goods from multiple vendors, which are then brought to the cross-dock for collection before being sent to various locations. The product is transferred to the customer's location after the consolidation

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procedure. Furthermore, a study was performed using SA on vehicles with heterogeneous routes, which yielded a very good solution with up to 20.18% performance improvement of the solution, just at a computational time [17].

A study of two-dimensional loading-constrained HFVRP (2L-HFVRP), a new variant of VRP using the SA method with heuristic local search, was also performed and the results obtained were valid [18]. The VRP study was conducted at SA using Python programming. Program code is designed according to mathematical formulas that are converted into functions during programming [19]. A study was conducted on the design of a newspaper company's vehicle route using HFVRP to reduce delivery costs. The technique used in this study is SA and using Python concerning the CVRP module in Google OR Tools. The results have shown optimal results in terms of total travel distance and total travel cost, as well as distance reduction [20].

Guided local search (GLS) is a memory-based technique and hence comparable to tabu search. However, it works by adding a penalty term to the cost function based on how close the search GLS is to one of the metaheuristic methods [21]. Most heuristic search techniques are based on local search (LS). It looks through the pool of potential answers. LS can swiftly identify sound solutions. GLS has been used to solve a nontrivial number of issues and has proven to be effective and efficient. With only a few parameters to adjust, it is simple to construct and use. The GLS tenets can be summed up as follows. GLS is a meta-heuristic technique that is applied on top of LS algorithms. One must first create a set of features for the potential solutions before applying GLS. Certain features are chosen and penalized when LS becomes caught in local optima. The goal function is enhanced by the collected penalties as LS explores the solution space [22].

A study of VRP with Time Windows has been done using Guided Local Search to avoid local minima. Regarding problem classes with lengthy routes, GLS performs 7% better than these methods. GLS did not perform as well in classes with shorter routes and was outperformed by up to 2.3% outcome of performance. The implementation of a route memory would significantly improve the performance of GLS in these instances [21].

GLS also has been done for VRP with backhauls and TW. GLS was compared to GRASP, while GLS needed more computational work than GRASP but with a better result. Also, stated that the GLS algorithm is resulting in a better solution than GA and performs better than the GRASP algorithm when minimizing the total distance of the route [23]. Another researcher performed the GLS algorithm for VRP. To better direct the search to viable answers, execute several experiments to ascertain how local search might be paired with perturbation, pruning, and problem-specific knowledge. The final heuristic computes excellent answers for a variety of benchmark scenarios in a matter of seconds or minutes. As a result, it offers a viable technique for solving routing issues that have computational time constraints. On the other hand, if more calculation time is available, it might also serve as a starting point for more modifications to produce even better solutions [24].

A Hybrid GLS has been solved by the VRP with Intermediated Replenishment Facilities (VRPIRF) with the purpose to find the optimal route for fleet vehicles. There were three steps of the solution to complete the research. A construction heuristic with cost-saving benefits is used to arrive at the initial solution in the first step of the solution approach. The first solution is enhanced in the second step by using tabu search within the variable neighborhood search approach. In the third stage, a guided local search is used to eliminate low-quality components of the completed product. Whereas the consumer removals and reinsertions diversify the search process, GLS seeks to remove subpar aspects from the solution. The algorithm was successfully tested for robustness, and consequently, 54 new VRPIRF instances covering various problem characteristics were created and presented [25].

3. RESEARCH METHOD

3.1 Research flow

Based on the framework of the flowchart in **Figure 1**, this study was carried out. Problem identification is the preliminary study that establishes the context of this investigation. The definition of the problem, its objectives and benefits, as well as the amount of the study carried out are all determined in the identification of the problem. Furthermore, conducting a literature study by looking for references from earlier research linked to this topic. The topics taken in this literature study relate to supply chain management, VRP, HFVRP, and metaheuristic methods which will later be useful as a reference for completing this research. After that, seek strategies for selecting the proper optimization strategy to acquire optimal outcomes with references that have been written in the literature study.

In this paper, the mathematical modeling is expressed mathematically and includes several variables, restrictions, and decision variables. Additionally, programming for mathematical models will be done to make the optimization process easier to perform after the actual data is available. The actual data retrieval will then be completed, and implemented into the Google Maps application, and the SA and GLS algorithm-based solution will be run in Python within the Spyder software.

Verification and validation methods are used to determine whether the model is in line with the targeted study. Validation seeks to formally recognize or approve something, typically after investigation, whereas verification seeks to demonstrate the existence or reality of something or to ensure that it is true [26]. After the process of verification and validation, analyze the findings to choose the best route while also reducing the cost of routing. The overall finding, whether the metaheuristic method utilized can identify the best path and suggestions for further study are included in the study's conclusions and recommendations.

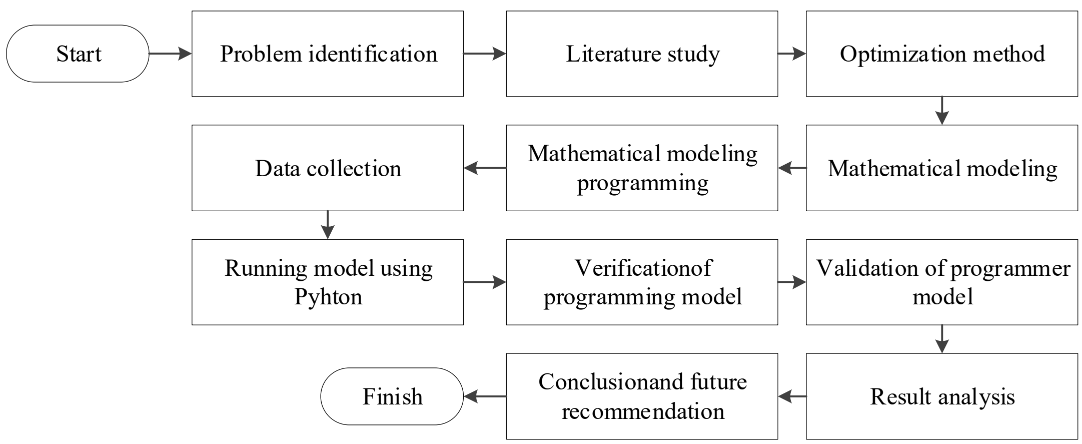

Figure 1. Flowchart of the research

3.2 Collection of data

The data obtained in this study were run on data based on a case study of a logistics company dealing with chicken feed and gas distribution, and the data are in route format. Data were collected in the form of depot coordinates, destination location coordinates, logistics cost data, and travel time data using time estimation from Google Maps.

3.3. Mathematical Modelling of HFVRP

Mathematical models are used as presentations in mathematical form to understand the conditions in this case study and to make it easier to create a programming language in Python. The goal of this study is to minimize operational costs or travel money with the maximum income earned. Revenue is obtained from collecting road fees and billing fees which are fixed prices from the chicken feed company. Based on actual data, data that can be minimized is the cost of travel money with the result being maximum and optimal income.

This mathematical model is made based on the objective of minimizing operational costs or road fees for drivers. The following is a modification of the mathematical model from the research [17] which has been adapted to the conditions of this research as follows:

$$MIN\ TC = \sum_{keK} \sum_{ieJ_0} \sum_{j,j} c_{ij} x_{ijk} \tag{1}$$

$$\sum_{ieJ_0} \sum_{keK} x_{ijk=1}\ i \in J_o \tag{2}$$

$$\sum_{ieJ_0} \sum_{jeJ_0} \sum_{keK} x_{ijk=1} \leq U_k \quad k \in K \tag{3}$$

$$\sum_{jeJ_0} x_{0jk} = 1 \quad k \in K \tag{4}$$

$$\sum_{jeJ_0} x_{0ik} = 1\ k \in K \tag{5}$$

$$x_{ijk} \in \{0,1\}(i,j \in J, k \in K) \tag{6}$$

Initial c_{ij} is the travel distance from customer i to consumer j, C_{ij} is the number of customer requests that will be sent $j \in J$, U^k is the capacity of the vehicle, and K is the initial of the vehicle. n is the number of customers. The variables x, y, and z are binary integers.

The objective function of the mathematical model that minimizes operational costs is equation (1). Except for the depot, barrier (2) states that each k vehicle may only visit the place once. Limiter (3) states that the number of available vehicles does not exceed K when k vehicles depart from the depot to complete the distribution process. Constraints (4) and (5) ensure that k vehicles each start at a depot or warehouse point, and each route ends back at a depot or warehouse point. The variables x, y, and z are choice variables with only a value of 0 or 1, according to constraint (6).

3.4 Data analyzing

In this research, the data was examined using google maps for route selection and Python 3.10 for Simulated Annealing and Guided Local Search Algorithm. Finding road fees, costs, vehicles used, and ideal routes based on distance matrices as well as information on road fees, expenses, and vehicles in the case study data are the goals of the Python coding results. Each distance from the warehouse to the coordinates of the breeders is divided by 5 as an assumption of 1 liter every 5 km in the distance matrix.

Depending on the driver, each vehicle has different parameters for burning diesel fuel. The bigger the charge, the more diesel fuel is burned. In addition, the terrain of the vehicle's road influences diesel or fuel, the smoother the road conditions traveled by the vehicle, the more effective the fuel burning of the vehicle's diesel. Each day begins with the creation of a matrix of data, after which vehicle classes, stopping spots, deliveries, routes, and locations are entered into distinct files to facilitate writing coding. The programming code presented below was created using OR-Tools' recommendations. Google Developers [27] and there is also a merger for coding between Vehicle Routing with Pickups and Deliveries [28] and Capacity Constraints [29] using an algorithm SA and GLS [30].

3. RESULT AND DISCUSSION

3.1 General picture of distribution system

In this case study, the vehicle fleets have various capacities in the maximum range of 8000 kg and 10000 kg. There are 19 vehicles in total with a 3908 cc-power available for distribution. 16 vehicles with the Mitsubishi Colt Diesel brand and 3 with the Mitsubishi HDL brand. The delivery from the depot to the client in this case study, which is the chicken coop, is the distribution system.

Vehicles make one trip from the depot or warehouse to the customer before returning. The one trip in question is the one where the total load hits the maximum capacity, and each trip must meet the maximum capacity to reduce expenses while maintaining driver and vehicle safety standards to not be overloaded. The head of the warehouse decided on the number of trips for each vehicle as well as its final destination. One example of a trip description is shown in Figure 2.

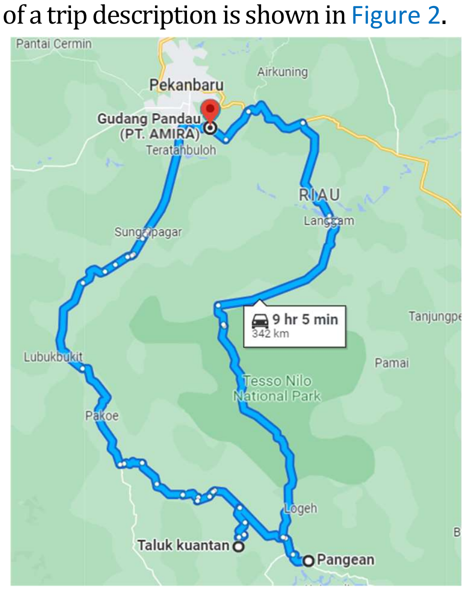

Figure 2. Example of trip

Based on the route findings produced by the GLS and SA procedures, the aggregate distance and adjusted cost traveled by each fleet are calculated. The stated shipping route in transit is the initial stage in resolving the HFVRP problem, and it ultimately yields the best route solution with the shortest distance and lowest cost. Delivery routes are obtained by collecting raw data containing the name of the breeder, address, coordinates and amount of cargo, travel allowance, and costs. While fees are the amount that will ultimately be invoiced to the chicken feed using a billing system, travel money is the driver's gross income.

In this case study, the distribution firm's approach is that the distribution party issues travel money in advance and is invoiced to the chicken feed company at the end of the week. The income of the distribution company whose data was used for the case study is then determined by deducting the costs of invoicing and travel expenses. The cost information has been made a fixed cost, and if diesel fuel prices rise, new costs may also rise. The chicken feed company has already established the costs' respective rates following an agreement with the distribution party. The fee that will be charged to the chicken feed company is calculated by multiplying this rate by the quantity of load that the farmer has ordered. Travel fees are decided by the distribution party based on the location and in this study the ultimate goal of identifying a better route and decreasing expenses or increasing profits.

Due to the company's belief that short distances produce more results than long distances, the percentage between costs and road fees fluctuates, ranging from 40 to 60% of the profits obtained by the distribution party. If the driver completes the near and distant excursions, and the results acquired by the driver and the distribution party are equivalent, costs will later be compensated for one another. The distribution party's income is calculated by subtracting the driver's road fee from the billing costs.
221 farmers are customers for the delivery of chicken feed and gas, and each day the needs of the consumers are different. Customer information in the form of coordinates is entered into Google Maps to determine the distance nearest to them. This information is then transferred to Excel and saved as a.csv file so that Python 3.10 can be used to process it.

3.2 Data processing technique

Python was used to collect the results of this 15-day research project. The simulation is done on a computer with an Intel Core i7-7700k Processor 4.2GHz. The modified mathematical model was converted into coding so that Python can read and run the mathematical modeling. After multiple tests, it was determined that a runtime of 300 seconds or 5 minutes produced superior results for SA and GLS. So that the outcomes are better than before, it was chosen to conduct a test for 15 days with a runtime of 300 seconds.

By switching the local search metaheuristic between SIMULATED_ANNEALING and GUIDED_LOCAL_SEARCH, it is possible to ascertain the metaheuristics that were utilized. Run each case study using data that has been saved in.csv format for each date as shown in the image. The raw data files that are input into Python take the form of data files per day, matrices for each day, vehicle data that includes the maximum load capacity and vehicle license plates, breeder data that includes the breeder's name and region (e.g., Taluk Kuantan, Sorek), and the distance in kilometers from the warehouse point to the farmer's address that is found by using Google Maps (longitude and latitude coordinates) to find the shortest and fastest route.

3.3 Result comparison

The data in **Table 1** is one of the actual trip data from day 5 of the 15-day research study. The results of using the SA algorithm are shown in **Table 2**, where the income results are greater than the actual data, which is IDR 12,387,482and the results of road fees have decreased, where previously the travel allowance for drivers was IDR 7,785,000 and after the implementation of SA into the actual data resulted in a reduction in road money of IDR 7,094,101 and then use the GLS algorithm, amount of travel allowance increase to IDR 7,145,634. The actual total income on day 5 is IDR 10,644,100 and this can be seen in **Table 2**.

According to the results obtained using the SA algorithm, there is a change in the destination of the vehicle and the number of trips for each vehicle in comparison to the actual data in **Table 4**. This modification delivers better benefits. With the use of the SA algorithm, the 8135 vehicle receives 1 trip with a different destination in the actual data. To reduce expenses and maximize vehicle utilization efficiency, the SA algorithm and the GLS algorithm collaborate to identify the shortest route with the most cost-effective results.

Table 1. Actual data

Vehicle Plate	Trip	Destination	Load (kg)	Travel allowance	Revenue	Total Revenue
8135	1	Pinggir	2500	Rp620.000	Rp500.000	Rp880.000
		Pinggir	5000		Rp1.000.000	
8455	1	Sorek	3750	Rp435.000	Rp750.000	Rp1.052.900
		Sorek	1500		Rp300.000	
		Sorek	2150		Rp430.000	
		Sp Beringin	100		Rp7.900	
	2	Taluk Kuantan	6500	Rp710.000	Rp1.300.000	Rp590.000
8456	1	Taluk Kuantan	7500	Rp710.000	Rp1.500.000	Rp790.000
8672	1	Ukui	7500	Rp520.000	Rp1.500.000	Rp980.000
8828	1	Keritang	5000	Rp950.000	Rp1.345.000	Rp1.067.500
		Keritang	2500		Rp672.500	
8985	1	Taluk Kuantan	7500	Rp710.000	Rp1.500.000	Rp790.000
9602	1	Lembah Subur	7500	Rp710.000	Rp1.537.500	Rp2.327.500
	2	Taluk Kuantan	7500	Rp710.000	Rp1.500.000	
9638	1	Pasir Putih	8000	Rp185.000	Rp576.000	Rp391.000
	2	Sorek	2500	Rp435.000	Rp500.000	Rp1.065.000
		Sorek	2500		Rp500.000	
		Sorek	2500		Rp500.000	
9659	1	Pasir Putih	6500	Rp135.000	Rp468.000	Rp430.200
		Pasir Putih	1350		Rp97.200	
	2	Ukui	7500	Rp520.000	Rp1.500.000	Rp980.000
9913	1	Sorek	7500	Rp435.000	Rp1.500.000	Rp1.065.000

Table 2. Simulated annealing algorithm implementation

Vehicle Plate	Trip	Destination	Load (kg)	Travel allowance	Revenue	Total Revenue
8135	1	Pasir Putih	6500	Rp116.860	Rp468.000	Rp351.141
	2	Ukui	7500	Rp502.573	Rp1.500.000	Rp997.427
	3	Sorek	2500	Rp130.266	Rp500.000	Rp369.734
		Sorek	2500	Rp129.020	Rp500.000	Rp370.980
		Sorek	2500	Rp108.802	Rp500.000	Rp391.198
8455	1	Pasir Putih	8000	Rp119.719	Rp576.000	Rp456.281
	2	Lembah Subur	7500	Rp 671.647	Rp1.537.500	Rp865.853
8456	1	Pasir Putih	1350	Rp1.705	Rp97.200	Rp95.495
		Taluk Kuantan	6500	Rp674.618	Rp1.300.000	Rp625.382
8672	1	Taluk Kuantan	7500	Rp672.454	Rp1.500.000	Rp827.546
8828	1	Sorek	3750	Rp187.376	Rp750.000	Rp562.624
		Sorek	1500	Rp55.454	Rp300.000	Rp244.546
		Sorek	2150	Rp93.154	Rp430.000	Rp336.846
	2	Ukui	7500	Rp484.343	Rp1.500.000	Rp1.015.657
8985	1	Taluk Kuantan	7500	Rp672.234	Rp1.500.000	Rp827.766
9602		Taluk Kuantan	7500	Rp676.267	Rp1.500.000	Rp823.733
9638	1	Sorek	7500	Rp404.803	Rp1.500.000	Rp1.095.197
9638	2	Sp Beringin	100	Rp3.283	Rp7.900	Rp4.617

Vehicle Plate	Trip	Destination	Load (kg)	Travel allowance	Revenue	Total Revenue
9913	1	Pinggir	2500	Rp159.742	Rp500.000	Rp340.258
		Pinggir	5000	Rp406.342	Rp1.000.000	Rp593.658
		Keritang	5000	Rp571.278	Rp1.345.000	Rp773.722
		Keritang	2500	Rp254.678	Rp672.500	Rp417.822

The results of one of the GLS analyses are in **Table 3**. Previously, in **Table 2** it was written that the vehicle with plate number 8135 got a trip, whereas in the GLS results, the vehicle with plate number 8135 got 1 trip and the vehicle generated a lower total income with a difference of IDR 1,290,676. Vehicle with plate number 8456 generates greater income because previously when using the SA algorithm, 8456 only got 1 trip and when using the GLS algorithm got 2 trips. When using the SA algorithm to measure, the load that is loaded is only 7850 kg, so the total income generated has a difference of IDR 1,140,714 which is superior to using SA.

Table 3. Guided local search algorithm implementation

Vehicle Plate	**Trip**	**Destination**	**Load (kg)**	**Travel allowance**	**Revenue**	**Total Revenue**
8135	1	Keritang	5000	Rp575.565	Rp1.345.000	Rp769.435
		Keritang	2500	Rp252.131	Rp672.500	Rp420.369
8455	1	Pasir Putih	8000	Rp118.521	Rp576.000	Rp457.479
	2	Taluk Kuantan	7500	Rp675.729	Rp1.500.000	Rp824.271
8456	1	Pasir Putih	6500	Rp115.691	Rp468.000	Rp352.309
	2	Lembah Subur	7500	Rp674.930	Rp1.537.500	Rp862.570
8672	1	Sorek	3750	Rp185.502	Rp750.000	Rp564.498
		Sorek	1500	Rp54.899	Rp300.000	Rp245.101
		Sorek	2150	Rp92.222	Rp430.000	Rp337.778
	2	Ukui	7500	Rp479.498	Rp1.500.000	Rp1.020.502
8828	1	Sorek	7500	Rp400.754	Rp1.500.000	Rp1.099.246
	2	Sp Beringin	100	Rp3.250	Rp7.900	Rp4.650
		Pinggir	2500	Rp168.143	Rp500.000	Rp331.857
		Pinggir	5000	Rp412.277	Rp1.000.000	Rp587.723
8985	1	Ukui	7500	Rp507.547	Rp1.500.000	Rp992.453
	2	Sorek	2500	Rp138.963	Rp500.000	Rp361.037
		Sorek	2500	Rp137.729	Rp500.000	Rp362.271
		Sorek	2500	Rp117.712	Rp500.000	Rp382.288
9602	1	Taluk Kuantan	7500	Rp675.510	Rp1.500.000	Rp824.490
9638	1	Pasir Putih	1350	Rp1.687	Rp97.200	Rp95.513
		Taluk Kuantan	6500	Rp677.871	Rp1.300.000	Rp622.129
9659	1	Taluk Kuantan	7500	Rp679.503	Rp1.500.000	Rp820.497

The results of using the SA and GLS algorithms show a change of about 3%-10% and the results of using the SA algorithm for day 1 to day 15 that the results using the SA metaheuristic show greater income and can be seen in **Table 4**. On the first day, the initial income was IDR 17,423,000, and after using SA the income increased by IDR 1,569,425 with a revenue of IDR 18,992,425. While using the LGS algorithm, the results obtained are better than the actual data with an increase of IDR 1,542,304 with a result of IDR 18,965,304.

Then followed by day 2, where the initial income was IDR 17,010,500 and the results from SA were superior to the total income, which was IDR 18,239,063, while between TS and SA there was a difference of IDR 44,558. Furthermore, from day 3 until day 15 have differences of IDR 58,240, IDR 45,545, IDR 23,610, IDR 35,445, IDR 24,150, IDR 36,129, IDR 34.139, IDR 15,823, IDR 118,670, IDR 27,491, IDR 26,436, IDR 23,016 and IDR 48,473 sequentially and SA is superior to GLS results. The results obtained using the SA and GLS algorithms are a better solution developed by Python

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programming. Based on research based on the calculation results of the SA algorithm, better route results can be seen by reducing distance, travel time, and travel costs.

Table 4. Results of the SA and GLS algorithms for total income

Day	Revenue	Result	
		SA	GLS
1	Rp17.423.000	Rp18.992.425	Rp18.965.304
2	Rp17.010.500	Rp18.239.063	Rp18.194.505
3	Rp28.273.750	Rp32.088.054	Rp32.029.814
4	Rp17.241.000	Rp17.853.083	Rp17.807.629
5	Rp10.644.100	Rp12.387.482	Rp12.363.872
6	Rp16.454.650	Rp17.874.407	Rp17.838.962
7	Rp17.395.000	Rp18.309.185	Rp18.285.035
8	Rp19.509.250	Rp20.621.793	Rp20.585.664
9	Rp14.527.250	Rp14.868.823	Rp14.834.684
10	Rp14.249.000	Rp15.098.019	Rp15.082.196
11	Rp22.031.000	Rp22.553.565	Rp22.364.895
12	Rp12.692.000	Rp13.912.541	Rp13.885.050
13	Rp17.338.000	Rp17.983.020	Rp17.956.584
14	Rp12.852.750	Rp13.311.906	Rp13.288.890
15	Rp28.075.500	Rp29.153.899	Rp29.105.416
Total	Rp75.651.250	Rp283.214.164	Rp282.588.500

The results of the SA and GLS algorithms show in **Table 4**that with an increase in income for 15 days there is a reduction in travel money which is calculated based on the distance matrix. An example of a distance matrix using day 5 data is shown in Figure 3. The distance matrix contains the distances obtained by the farmer's coordinates and the distances are measured using Google Maps. The data in the distance matrix is the price of diesel fuel then divided by 5 because the average vehicle spends 1 liter of diesel for 5 km and then multiplied by the coordinate distance of each farmer. The results of these matrix help calculations in Python in determining better costs and routes.

	Gudang	Pinggir	Sorek	Sorek	p Beringi	Taluk K.	Taluk K.	Ukui	Keritang	Taluk K.	embah S	Taluk K.	Pasir P.	Sorek	Sorek	Sorek	Pasir P.	Pasir P.	Ukui	Sorek
Gudang	0	141182	93415,2	97695,8	25166,4	173490	188762	133778	265665	168617	147254	187661	1405,2	101015	106288	97804,4	1405,2	3625,2	129759	93782,4
Pinggir	137279	0	224514	228795	109626	300025	315297	264877	396763	295152	278353	314196	135873	232113	237386	228903	135873	137032	260858	224881
Sorek	150618	282258	0	7110,8	142956	205855	211003	43193,6	175080	205902	56669,6	212105	152024	20997,2	15702,6	7219,4	152024	154244	39174	839,6
Sorek	153644	285283	7110,8	0	145981	208881	214029	46219,2	178105	208928	59695,2	215130	155049	24023	18728,4	10245	155049	157269	42199,8	7478
Sp Beringin	25166,4	109407	85752,6	90033,2	0	198656	213929	126116	258002	193784	139592	212827	26571,8	93352	98625	90141,8	26571,8	28791,6	122096	86119,8
Taluk K.	173532	299895	198503	201528	198698	0	35338	155308	232461	8964,4	175362	34236,4	172126	203974	188790	195241	172126	173285	159787	198870
Taluk K.	188831	315194	203651	206676	213998	35336,6	0	160456	237609	27276,6	180510	1101,4	187426	209122	193938	200389	187426	188584	164935	204018
Ukui	178287	309926	43194	46219,6	170624	155336	160484	0	133066	155383	20053,2	161586	179692	48665,6	33481,2	39932,2	179692	181912	4478,2	43561,2
Keritang	310110	441750	175018	178043	302448	232369	237517	133003	0	232416	151877	238619	311516	180489	165305	171756	311516	313736	136302	175385
Taluk K.	168667	295030	198549	201575	193834	8958,8	27278	155355	232508	0	175408	26176,4	167262	204021	188837	195288	167262	168420	159833	198916
Lembah S.	191763	323402	56670	59695,6	184100	182715	187863	20053,2	151939	182762	0	188964	193168	62141,6	46957,2	53408,2	193168	195388	17954,2	57037,2
Taluk K.	187730	314093	204752	207778	212896	34235	1101,4	161558	238711	26175	181611	0	186324	210224	195039	201490	186324	187483	166036	205119
Pasir P.	1405,2	139776	94820,6	99101	26571,8	172084	187357	135184	267070	167212	148660	186255	0	102420	107693	99209,6	0	2219,8	131164	95187,8
Sorek	136051	267690	20998,4	24024	128388	211346	216494	48683,8	180570	211392	62159,8	217595	137456	0	21193	17736,6	137456	139676	44664,4	21365,6
Sorek	150814	282453	15721,4	18747	143151	196121	201269	33459,8	165346	196168	46935,8	202371	152219	21193	0	12459,6	152219	154439	29440,4	16088,6
Sorek	147338	278978	7240	10265,6	139676	202575	207723	39913,6	171800	202622	53389,6	208825	148744	17717,4	12422,8	0	148744	150964	35894,2	7607,2
Pasir P.	1405,2	139776	94820,6	99101	26571,8	172084	187357	135184	267070	167212	148660	186255	0	102420	107693	99209,6	0	2219,8	131164	95187,8
Pasir P.	3625,2	140935	97040,6	101321	28791,6	173243	188516	137404	269290	168371	150880	187414	2219,8	104640	109913	101430	2219,8	0	133384	97407,8
Ukui	174267	305906	39174,6	42200,2	166604	167140	172288	4478,2	136364	167187	17954,2	173389	175672	44646,2	29461,8	35912,8	175672	177892	0	39541,8
Sorek	150985	282625	839,6	7478	143323	206222	211370	43560,8	175447	206269	57036,8	212472	152391	21364,4	16069,8	7586,6	152391	154611	39541,2	0

Figure 3. Distance matrix

Based on the distance matrix in Figure 3, the road fee earned by the driver each day decreases based on SA and GLS calculations. The GLS algorithm generates more travel allowances than the SA algorithm from day 1 until day 15. In this study, the ratio taken in the ratio of diesel fuel and distance per kilometer is 1:5. According to the matrix in Figure 3, the results obtained are the best mileage resulting from the SA and GLS algorithms.

Table 5. Results of the SA and GLS algorithms for the total travel allowance

Day	Travel Allowance	Result	
		SA	GLS
1	Rp14.530.000	Rp13.233.364	Rp13.252.261
2	Rp14.355.000	Rp13.861.028	Rp13.894.890

Day	Travel Allowance	Result	
		SA	GLS
3	Rp23.525.000	Rp22.351.196	Rp22.391.763
4	Rp13.490.000	Rp12.877.917	Rp12.910.704
5	Rp7.785.000	Rp7.094.101	Rp7.145.634
6	Rp11.775.000	Rp11.246.943	Rp11.269.246
7	Rp13.425.000	Rp12.510.815	Rp12.527.317
8	Rp14.690.000	Rp13.857.457	Rp13.881.735
9	Rp12.125.000	Rp11.914.427	Rp11.941.783
10	Rp11.680.000	Rp10.830.981	Rp10.842.332
11	Rp15.010.000	Rp14.153.435	Rp14.181.246
12	Rp10.804.459	Rp10.837.560	Rp10.825.809
13	Rp14.184.000	Rp13.412.481	Rp13.432.197
14	Rp9.575.000	Rp8.674.369	Rp8.689.367
15	Rp23.560.000	Rp22.475.201	Rp22.512.577
Total	Rp211.389.000	Rp199.331.275	Rp199.698.862

The total travel allowance that the GLS algorithm generated is IDR 199,698,862 as can be seen in Table 5, while the result that SA generated is IDR 199,331,275. The sA algorithm generated a lower number compared to the GLS algorithm, however, those two metaheuristic algorithms succeeded in reducing the travel allowance compared to the actual data. Referring to the revenue results, the smallest travel allowance will result in a larger income result by using the SA algorithm.

4. CONCLUSION

The purpose of this research has been completed by making concepts and steps and implementing the Simulated Annealing and Guided Local Search algorithms with better final solution comparisons including those based on case study data to minimize the number of vehicles used, minimizing road fees or driver operational costs with routes optimally needed in shipping and minimizing mileage, creating concepts and steps and implementing Simulated Annealing and Guided Local Search algorithms based on case study data.

The first goal is to minimize the travel money required in shipping with the optimal route and minimize the distance traveled. By minimizing the street fee, income increases and is optimal based on the calculation of the SA and GLS algorithms. The answer to this goal is answered by the SA and GLS algorithms. Before using SA and GLS, the determination of the vehicle and the trip was arranged by the head of the warehouse manually. With the SA and GLS algorithms, there is a reduction in fleet usage and with that, there is a reduction and savings in terms of costs.

In addition, several nominal travel fees have been added and reduced because they have been programmed based on the distance from the warehouse (depot) to the breeder. With reduced travel money based on the results of the SA and GLS algorithms, income increases and is optimal according to the SA and GLS algorithms. Based on the results of the SA and GLS algorithms, the resulting percentage is in the range of 40% to 60% greater than the actual data income. The results of determining routes and destinations determined by the SA and GLS algorithms also show better results, which can be seen from the higher income results from the actual situation.

The purpose of these two studies is to show that there are different results as long as the SA and GLS algorithms are run in Python. However, the SA results were superior in 9 days and it can be stated that the SA results were better than the GLS, followed by the GLS and SA results equivalent for 6 days. The equation of results from SA and GLS shows that both SA and GLS algorithms have shown the optimal solution for both. The results of the percentage increase in income generated by SA with an average increase of 3% - 9% from the actual data

To continue this research utilizing various algorithms, such as Particle Swarm Optimization and Genetic Algorithm, as well as single-solution based and population-based for solving employing metaheuristics, some elements might be advised. Future research on the comparison of SA and GLS in other VRP types, as well as in the areas of distribution and delivery, is also possible.

The distribution organizations included in this study can provide noteworthy results when compared to actual circumstances, and from the outcomes produced by the SA and GLS algorithms, there have been route alterations and a reduction in trip costs. The same data can be utilized in future studies, but in greater depth by including additional factors like the driver's age (which affects their endurance), the average speed at which they drive, and the cost of car repair per unit of income.

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