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Research Article

Vehicle Routing Problem in A Medical Facility Waste Collection Company: A Comparative Analysis of Guided Local Search, Simulated Annealing, and Tabu Search Algorithm

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Abstract: Vehicle Routing Problem (VRP) is closely related to real-life situations, particularly in logistics. Therefore, this research aimed to 1) solve VRP problem faced by a waste management company by comparing three algorithms, namely guided local search, tabu search, and simulated annealing. 2) summarize the development of VRP by comparing several variants, and 3) assess the environmental impact through sensitivity analysis. The combined VRP variants are described as the Heterogeneous Fleet Distance Constrained Capacitated VRP with Time Windows because they reflect the current situation of the waste management company. In this context, a model was developed using Python programming language, specifically with a library called Ortools by Google, which is specialized for combinatorial optimization problem. The tests showed that the best algorithm for solving VRP was the path most constrained arc, used as the initial solution generator and guided local search as the optimization algorithm. This combination produced the best result for distance optimization, though it did not address workload balance and average working time. Another conclusion is that the total distance would increase by having more constraints and dimensions.

Keywords: Guided local search; Heterogenous fleet distance constrained capacitated Vehicle Routing Problem (VRP) with time windows; Simulated annealing; Tabu Search; Traveling salesman

1. Introduction

The current research investigates the capabilities of three metaheuristics algorithms incorporated within Ortools. Typically, Ortools is a tool developed by Google for optimization problem, to solve VRP of combined variants/constraints (Ruiz-Meza et al., 2020). The algorithm examined was Guided Local Search, Tabu Search, and Simulated Annealing. Specifically, the research draws on a real-life situation from a medical facility waste collection company, which inspired the combination of VRP variants used in this context. The four VRP variants considered are heterogeneous fleets with a fixed number of vehicles, distance constrained, capacitated, and time windowed, collectively referred to as Heterogenous Fleet Distance Constrained Capacitated VRP with Time Windows (HFDCCVRPTW). Given that this VRP model closely imitates a real-life situation, the accuracy of the research has significant implications for the waste management company, as the inputs and VRP components are structured to reflect their actual conditions. Over the years, new variants have

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been introduced, allowing real-life VRP to be solved with increasing accuracy (Zheng et al., 2020; Gromicho et al., 2015). Additionally, various models have been incorporated into VRP computation to enhance route planning efficiency, such as adding a threshold waste level to VRP decision-making (Akhtar et al., 2016; He et al, 2014) and considering carriage dimensions with time window constraints (Sitompul and Horas, 2021).

Various methods, such as incorporating node geometry, as demonstrated for enhanced spatial reuse in wireless networks (Adriansyah et al., 2015) may offer additional improvements in route planning efficiency. But the most widely used method is metaheuristic algorithm, which has been used for decades to solve VRP problem (Yakıcı, 2017). Numerous efforts have also been made to combine various algorithms to reduce computation time and improve results regarding their objective function. Significant research has been conducted on hybrid algorithm to solve the problem (Silvestrin and Ritt, 2016; Tarantilis et al., 2008). Aside from hybrid algorithm, many bio-inspired algorithm have been introduced to solve VRP (Pereira and Tavares, 2009). One of the recent bio-inspired algorithms is the Hybrid Spotted Hyena Optimizer Algorithm used to optimize fuel consumption in a Distance Constrained VRP (Utama et al., 2023). Similarly, metaheuristic approaches have also proven effective in other optimization domains, such as using a mean grey wolf optimization algorithm for optimal task scheduling in cloud environments (Natesan and Chokkalingam, 2019). Furthermore, with new carbon emission laws in European countries, research incorporating electric vehicles and charging stations has been carried out (Noiz et al. 2022).

Various algorithms have been developed to solve VRP and other optimization problem (Praveen, 2019). While a single algorithm can work effectively as a hybrid, some flaws can sometimes be solved by incorporating another algorithm (Musil, 2018; Han et al., 2009). An example of this algorithm is Hybrid Metaheuristics, which combines Genetic Algorithm and Simulated Annealing to solve a Permutation Flowshop Scheduling Problem (Utama et al., 2019). In recent years, the increase in computational power has made Machine Learning a valuable tool for solving VRP, such as in determining the appropriate metaheuristic algorithm for a specific VRP, known as Algorithm Selection Problem (ASP) (Karimi-Mamaghan, 2022).

Based on the numerous components available for solving VRP in Ortools, it is essential to determine the optimal combination of the features, such as the first solution strategy, which identifies the initial solution (Saint-Guillain et al., 2017). This algorithm is used to optimize the initial solution based on the objective function, and to enhance the command used to stop the optimization criteria (Karagül et al., 2018). ConsEquationuently, the research focuses on a comparative evaluation of the three algorithms, aiming to identify the best first solution strategy and stopping criteria for solving VRP.

The current waste collection system used by the company rEquationuires updating to meet their specific needs. The data used are often prone to errors due to significant human participation, hence, the system needs to be extensively revised. By accurately representing the problem and using precise input data, the VRP result is expected to assist the company in optimizing resources to the maximum extent. This research adjusted to the waste management company's current situation, ensuring all considerations in using Ortools are in line with the company’s needs. All data used in this context are obtained from the company, while some are based on research and the author's assumption. Additionally, the software developed to simulate VRP will be iteratively improved, with each iteration adding new variants to show the effect of additional constraints on VRP.

VRP examined in this research is static and deterministic, implying that the simulation excludes the probability of traffic jams and accidents. The objective function is to optimize a single dimension, namely distance. Additionally, the investigation describes the impact of adding constraints to VRP. It is important to be aware that the three objectives of this research form a triad. First, the research breathes new life into established methods by assessing their adaptability and robustness in a contemporary setting. Second, it relies on the toolkit offered by optimization software to identify the best combinations for addressing complex real-world problem. Lastly, it addresses the practical challenges of waste management collection. The combination of these objectives provides a comprehensive exploration of historical resonance, technological confluence, and real-world impact within the context of VRP optimization.

2. Methods

2.1. VRP

There are several key steps for solving a combinatorial optimization challenge of VRP (Clarke and Wright, 1964; Dantzig and Ramser, 1959). The first step included defining the scope or variants of VRP and the second consisted of collecting variant-specific data, as each variant had distinct inputs. Furthermore, the third step comprised establishing clear objectives and constraints. In this context, a mathematical model was necessary to determine the aspects VRP should optimize and the specific constraints that was applicable. The fourth step incorporated selecting a method to generate an initial solution while adhering to constraints, and an algorithm to optimize the solution based on the objective function. Finally, the main challenge was to translate these steps into a functional model capable of solving VRP, processing inputs, creating an initial solution considering constraints, and optimizing the constraints using an optimization algorithm in line with the objective function (Manguino and Ronconi, 2021; Demir et al., 2019).

In this context, i and j denoted nodes within the matrix and N represented the node matrix used in the problem. Additionally, K indicated the number of available vehicles, and k was the vehicle number, while Zero denoted the depot. The objective of this research was to minimize the total traveling distance, as defined in Equation. (1). Equation (1) shows that the objective of the VRP is to minimize the total distance that vehicle k travels from point i to j. Equation. (2) and (3) ensure the continuity of the VRP, where when a vehicle enters a node, it will surely exit it. Equation. (4) shows that the amount of vehicle that exits the depot must not exceed the available vehicle at the depot. Equation. (5) shows that the sum of vehicle that exits the depot must Equationual the sum of the vehicle that enters the depot. Equation. (6) shows that the capacity of the vehicle k when it travels from the depot should be Equationual to zero. Equation. (7) shows that at the end of the trip, vehicle k's capacity should not exceed its maximum capacity. Equation. (8) shows that the distance traveled by vehicle k when it travels from the depot should be Equationual to zero. Equation. (9) shows that the total distance at the end of the trip should not exceed the maximum distance the vehicle is capable of traveling. Equation. (10) shows that the vehicle arrival time at point i should be between the time window, where a_i is the minimum time allowed and b_i is the maximum time allowed. Equation (11) shows that the time vehicle k arrived at point j must be Equationual to the arrival time of the vehicle at point i, added with the service time it spent there and the total time it took from point i to point j.

$$\text{minimize} \quad \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=0}^{K} d_{ij}\,x_{ijk} \tag{1}$$

Subject to:

$$\sum_{j\in\delta^{+}(i)}\sum_{k=0}^{K} x_{ijk} = 1 \tag{2}$$

$$\sum_{i\in\delta^{-}(j)}\sum_{k=0}^{K} x_{ijk} = 1 \tag{3}$$

$$\sum_{j\in\delta^{+}(0)} x_{0j} \leq |K| \tag{4}$$

$$\sum_{i\in\delta^{-}(0)} x_{i0} = \sum_{j\in\delta^{+}(0)} x_{0j} \tag{5}$$

$$\sum_{j=0}^{n}\sum_{k=0}^{K} q_{0jk} = 0 \tag{6}$$

$$\sum_{i=1}^{n}\sum_{j=0}^{n}\sum_{k=0}^{K} c_i x_{ijk} \leq C \tag{7}$$

$$\sum_{j=0}^{n}\sum_{k=0}^{K} d'_{0jk} = 0 \tag{8}$$

$$\sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=0}^{K} d'_{ij} x_{ijk} \leq D \tag{9}$$

$$a_i \leq t_{ik} \leq b_i \quad (10) \qquad x_{ijk}(t_{ik} + T_{ij} + s_i - t_{jk}) \leq 0 \quad (11)$$

A repeating notation was x_{ijk}, which denoted the number of times vehicle k traveled from nodes i to j. However, in this research, vehicles could travel only once from one node to another. Since the objective function used in VRP was distance, the simulation did not consist of probability. Cost-related data was not provided by the company, and calculating the shortest travel time between two points was impractical due to unpredictable factors such as traffic that affected travel time.

2.2. Algorithm

The three algorithms discussed were metaheuristic, each designed to avoid being trapped in local optima (Almufti et al., 2003). It should be acknowledged that some could determine the global optima quicker compared to others. Occasionally, the algorithm produced similar results, depending on their compatibility with the initial solution (Ionita and Luchian, 2005). Success depended on selecting a good initial neighborhood for optimization and effectively moving and escaping the local optima (Dhaenens and Jourdan, 2016).

Guided local search is the further development of local search algorithm (Dhaenens and Jourdan, 2016; Tarantilis et al., 2008). Typically, there are several elements in guided local search that are interesting to investigate. In this context, guided local search enhanced the results of local search by penalizing moves with the highest cost, thereby increasing their utility (Porumbel and Hao, 2020). Furthermore, the algorithm modified the objective function by adding certain features, combining the usual objective function with these penalties to guide the search more effectively. Simulated annealing is an algorithm that can theoretically find the global optimum when its initial temperature is sufficiently high (Dhaenens and Jourdan, 2016; Yu et al., 2016; Nikolaev and Jacobson, 2010). It should be acknowledged that the algorithm used probability to find a more optimized solution (Bei et al., 2023). In addition, simulated annealing focused on finding the energy of the initial solution and comparing it to a new solution (Pemasinghe and Abeygunawardhana, 2021). When the new solution had lower energy, it would be selected as the new current solution.

According to (Silvestrin and Ritt, 2016; He et al., 2014; Rothlauf, 2011), tabu search algorithm used a feature called tabu list. The most significant features of a solution were added to the tabu list, and any features on the list could not be used in the optimization process (Subash et al., 2022). Furthermore, tabu factor determined the number of features from tabu list that could be reused. In a situation where tabu factor was 1, then none of the features could be used. Moreover, when the value was 0.5, only half of the features could be used. This implied that tabu factor played a big part in escaping the local optima.

2.3. Sensitivity Analysis

Sensitivity Analysis is a method used to determine the way changes in input values (Kardos et al., 2023) affect the output value of a black box computer simulation model (Kleijnen, 2008). Shifting the simulation input value by a factor of x, resulted in 2^x combinations to be simulated. However, with more than two factors, the number of simulations changed to 2^{x-1}. Robust simulation optimization was also needed to account for the uncertainty of inputs from an environmental perspective (Kleijnen, 2008).

3. Results and Discussion

The flowchart process began with initializing the environment and entering the data, followed by initializing Ortools. SubsEquationuently, the dimensions such as capacity and time were entered, with distance as the basic dimension since the objective function for VRP was to minimize distance. For Ortools to start the optimization, an initial solution had to be found, but when the initial solution was unavailable, the model terminated.

The model continued to run the search until the termination criteria, based on time, were reached. The analysis compared the three algorithms to each other using the initial solution as a benchmark, making it essential to show the initial solution. The computation results were graphed as shown in Figure 1 b, c, d, and e, which clearly illustrated the vehicle and its utilization, along with the standard deviation. Typically, the graph style was inspired by Zheng et al., (2016), showing the vehicle locations and time stamps. By examining the graph, the difference in vehicle movement flow could be observed. This graphical representation provided more information compared to a typical VRP chart.

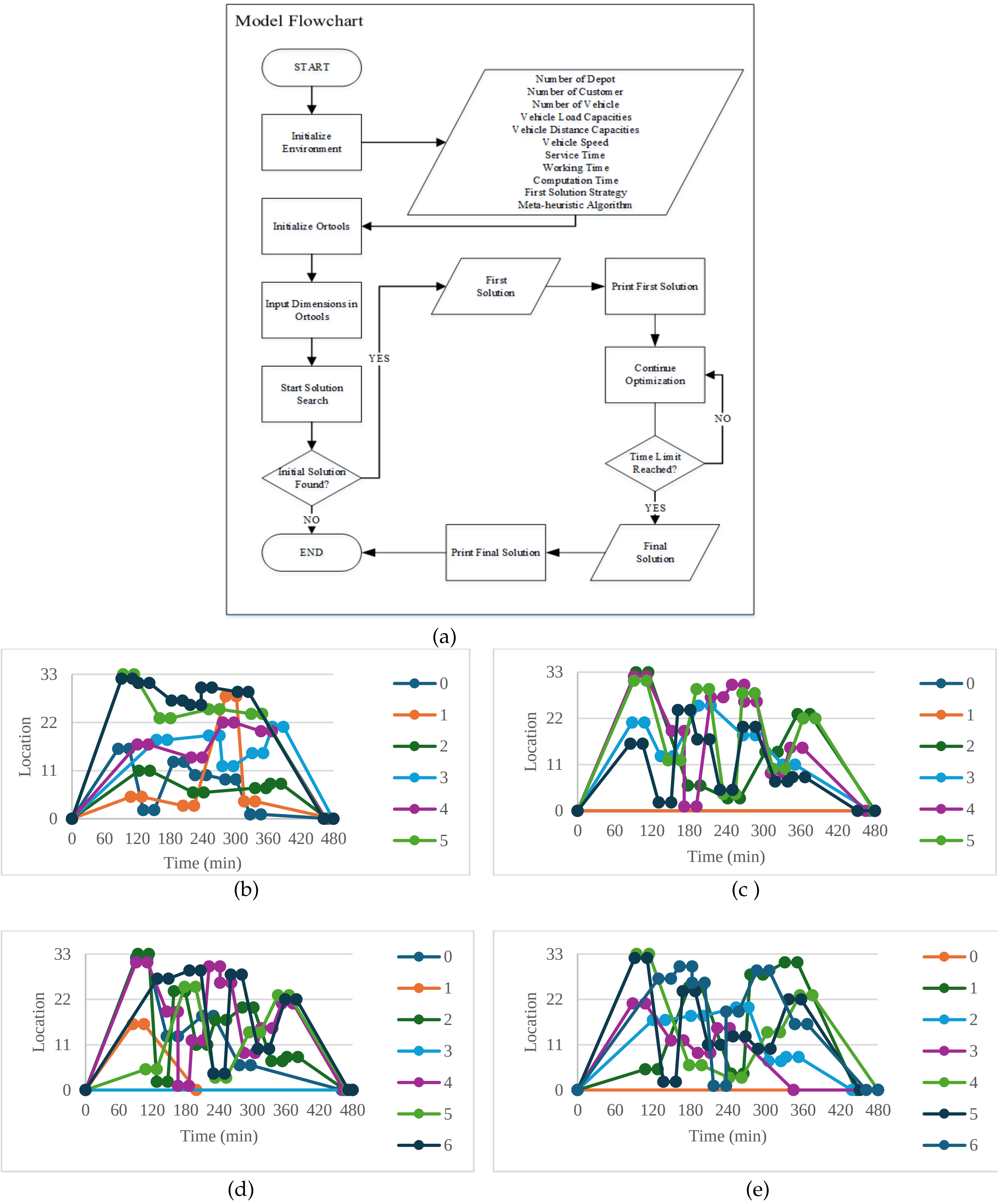
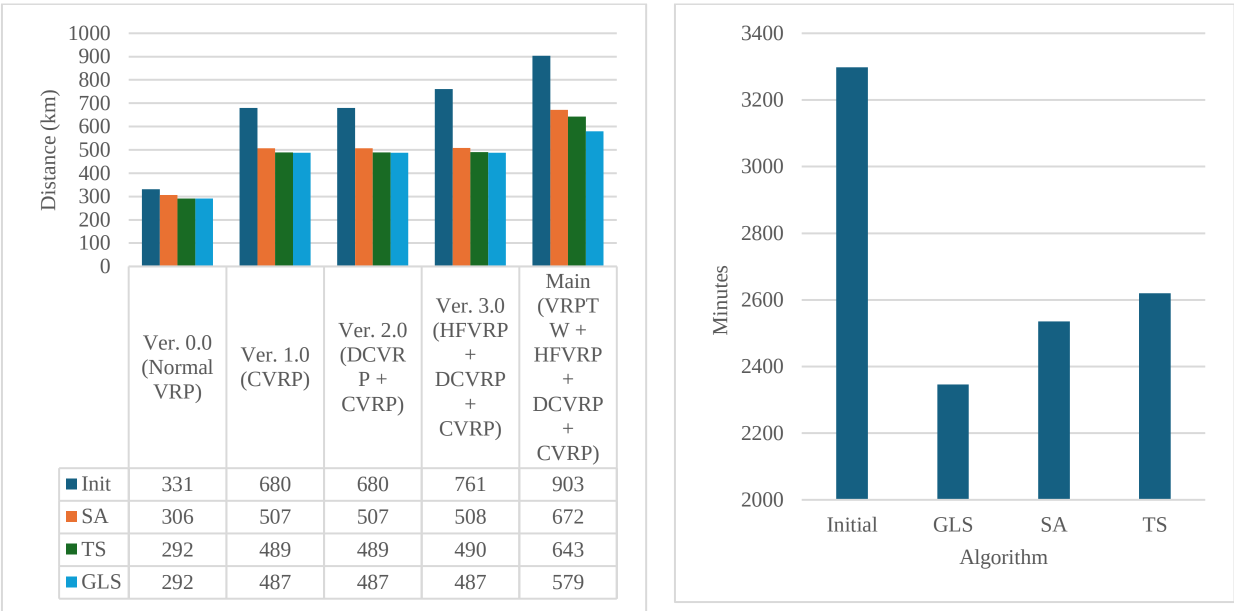


Figure 1 (a) Model Flowchart, (b) Initial Solution, (c) Guided Local Search Optimization Result, (d) Tabu Search Optimization Result, (e) Simulated Annealing Optimization Result

The impact of added dimensions could be seen in Figure 2a, where each constraint caused a significant increase in the rEquationuired distance. As constraint multiplied, the vehicle's mobility was constrained, limiting the nodes it could access. With the limited number of nodes that the vehicles could access, the distance naturally increased. ConsEquationuently, it was observed that there was a stagnant amount between the first and second versions. This scenario was due to the distance constraint, originally designed for a week of operation, being scaled down to a day.

Aside from measuring distance, adding time as a new dimension and executing time constraints on node visits, excluding the initial and final depot, showed that the algorithm succeeded in enhancing vehicle efficiency. According to Figure 2b, guided local search algorithm significantly decreased the total travel time of the heterogenous fleet by approximately 30%, while simulated annealing and tabu search achieved a still significant reduction of 20%.



(a) (b)

Figure 2 (a) Versioning Analysis, (b) Time comparison of the Main VRP Version

Table 1 showed that guided local search consistently produced the best results, with tabu search ranking the second, as show in Table 2, factoring in the time required in the results produced. Changing the first solution strategy revealed corresponding changes in the algorithm's final optimization values. By moving and adding the depot, both the initial and the final optimized distances and time significantly decreased. This indicated that the current depot position was too far from the nodes. Adjusting the number of operable vehicles showed that, at the end of the optimization, fewer vehicles were used compared to the initial solution. The importance of an initial solution was crucial in optimization because the reduction in the number of vehicles rendered the initial solution unattainable, even though only five were needed. It should be acknowledged that the same principle applies to nodes. While the initial solution accommodated thirty-five nodes with seven vehicles, only thirty-three could be served with five vehicles.

In the comparison of metaheuristic algorithm, namely Guided Local Search, Tabu Search, and Simulated Annealing, the research proved their adaptability in solving complex VRP with numerous constraints, with Guided Local Search being the best. The choice of software components significantly impacted VRP efficiency, emphasizing the importance of factors such as the first solution strategy and algorithm in enhancing optimization results. This phenomenon described the crucial role of specialized software tools, particularly in optimization, in shaping VRP research. By using real-life input data, the investigation extended optimization beyond distance, considering factors such as fuel consumption and time, leading to substantial savings and efficiency improvements in waste collection. This showed the practical value of addressing real-world constraints and ensuring data accuracy, offering avenues to improve efficiency in logistics operations.

Table 1 Sensitivity Analysis: Total Distance and Vehicle Used

SENSITIVITY ANALYSIS		Total Distance (km)				Vehicle Used			
		Init	SA	TS	GLS	Init	SA	TS	GLS
Original: Local Cheapest Insertion, 1 Depot (Bogor), 33 Nodes, 7 Vehicle		903	672	643	579	7	6	6	5
First Solution Strategy	Path Cheapest Arc	842	692	583	579	7	6	5	5
	Savings	726	700	583	579	6	6	5	5
	Path Most Constrained Arc	711	651	642	579	6	6	6	5
Depot Addition	Multi-depot (2)	855	502	367	365	7	5	4	4
	Multi-Depot (3)	492	401	299	299	5	5	4	4
	Multi-depot (4)	412	348	298	291	5	5	5	4
Moving Depot	West Jakarta	554	417	361	360	5	5	4	4
	Central Jakarta	546	379	334	334	5	5	4	4
	North Jakarta	528	373	321	319	5	5	4	4
Vehicle Amount	-1 (6 Vehicles)	-	-	-	-	-	-	-	-
	+1 (8 Vehicles)	903	669	641	579	7	6	6	5
	+2 (9 Vehicles)	903	672	591	579	7	6	5	5
Nodes Amount	+2 (35 Nodes)	-	-	-	-	-	-	-	-
	+1 (34 Nodes)	901	660	642	581	7	6	6	5
	-1 (32 Nodes)	893	664	579	578	7	6	5	5
	-2 (31 Nodes)	889	668	578	574	7	6	5	5
	-13 (20 Nodes)	662	555	493	493	5	5	4	4
	-23 (10 Nodes)	383	333	327	327	3	3	3	3

Table 2 Sensitivity Analysis: Total Travel Time and Average Total Time

SENSITIVITY ANALYSIS		Total Travel Time (min)				Average Total Time (min)			
		Init	SA	TS	GLS	Init	SA	TS	GLS
Original: Local Cheapest Insertion, 1 Depot (Bogor), 33 Nodes, 7 Vehicle		3298	2620	2535	2346	471.14	436.67	422.50	469.20
First Solution Strategy	Path Cheapest Arc	3116	2675	2356	2345	445.14	445.83	471.20	469.00
	Savings	2774	2701	2356	2345	462.33	450.17	471.20	469.00
	Path Most Constrained Arc	2730	2555	2529	2346	455.00	425.83	421.50	469.20
Depot Addition	Multi-depot (2)	3214	2181	1781	1775	459.14	436.20	445.25	443.75
	Multi-Depot (3)	2170	1901	1600	1600	434.00	380.20	400.00	400.00
	Multi-depot (4)	1953	1764	1616	1577	390.60	352.80	323.20	394.25
Moving Depot	West Jakarta	2350	1949	1763	1760	470.00	389.80	440.75	440.00
	Central Jakarta	2329	1837	1684	1684	465.80	367.40	421.00	421.00
	North Jakarta	2270	1817	1645	1659	454.00	363.40	411.25	414.75
Vehicle Amount	-1 (6 Vehicles)	-	-	-	-	-	-	-	-
	+1 (8 Vehicles)	3298	2611	2527	2346	471.14	435.17	421.17	469.20
	+2 (9 Vehicles)	3298	2620	2381	2346	471.14	436.67	476.20	469.20
Nodes Amount	+2 (35 Nodes)	-	-	-	-	-	-	-	-
	+1 (34 Nodes)	3312	2601	2549	2370	473.14	433.50	424.83	474.00
	-1 (32 Nodes)	3248	2576	2325	2322	464.00	429.33	465.00	464.40
	-2 (31 Nodes)	3217	2568	2303	2291	459.57	428.00	460.60	458.20
	-13 (20 Nodes)	2353	2038	1856	1856	470.6	407.6	464	464
	-23 (10 Nodes)	1321	1173	1155	1155	440.3	391	385	385

4. Conclusions

In conclusion, the latest version of the model effectively represented a combination of various VRP variants relevant to the waste collection process of the waste management company. The combined variants were known as Heterogenous Fleet Distance Constrained Capacitated VRP with Time Windows (HFDCCVRPTW). Specifically, guided local search was the best algorithm for optimizing the problem with Ortools. When evaluated with 33% nodes, and with local cheapest insertion as an initial solution, this algorithm achieved a reduction of 35% in the initial distance. For optimal usage of Ortools in solving problem, the best first solution strategy to use was the path most constrained arc with guided local search as its optimization algorithm in a one-hour computation time. This outcome was achieved by considering factors such as node amount, vehicle utilization, and computation time. ConsEquationuently, the optimization algorithm could address the objective constraint, namely the total distance, the element linear to the distance, and the total travel time. However, the algorithm was unable to accommodate the standard deviation of the total time, the average total time, and the number of vehicle used. Several recommendations were made to enhance optimization, which included: (1) Improving research accuracy, which comprised integrating data on traffic conditions and historical fuel usage by the diverse vehicle fleet. In this context, traffic significantly affected the efficiency of transportation. Therefore, by gathering data on traffic patterns, road restrictions, and blockages, there was an improvement in the simulation model's accuracy in measuring distance and time. Additionally, modifying the model to calculate costs, rather than focusing on distance, could be more practical for business decisions, considering factors such as fuel consumption and prices. (2) Research currently lacked specific details, such as waste transfer rates, which could impact results. Using a generic 20-minute service time for all vehicle stops, regardless of the amount of waste collected, might not have accurately reflected reality. Therefore, collecting more detailed data on waste transfer time was crucial for investigating VRP constraint. (3) Gathering up-to-date data about company's waste collection process and software condition was essential for identifying and addressing any deviations before implementing VRP simulation model. This data should cover workload balance, driver overtime, visited nodes, vehicle distances, and a comprehensive cost analysis of the problem's impact on the waste management company. (4) Consideration should be given to adding a new variant called VRPIFR (VRP with intermediate replenishable facilities), where vehicles could refuel to work longer. Since it was unclear whether vehicles were refueled daily or as needed, this variant could provide more realistic modeling for the research.

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