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OPTIMASI SISTEM DISTRIBUSI PADA SALAH SATU DISTRIBUTOR MAKANAN DI KABUPATEN GOWA

DISTRIBUTION SYSTEM OPTIMIZATION AT A FOOD DISTRIBUTOR IN GOWA REGENCY

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Abstrak — Distribusi adalah proses penyaluran barang, jasa, atau informasi dari produsen ke konsumen dengan tujuan untuk mencapai efisiensi dan pemerataan. PT XYZ merupakan perusahaan manufaktur yang memproduksi kecap, saus, cuka, dan sirup, serta mendistribusikan produknya melalui kanal tradisional dengan mempekerjakan salesman. Saat ini, penentuan rute kunjungan salesman masih berdasarkan pengalaman, sehingga belum optimal dari segi jarak, waktu, dan biaya. Penelitian ini bertujuan untuk memperoleh rute yang lebih efisien dengan membandingkan dua algoritma metaheuristik. Pengumpulan data dilakukan melalui wawancara dengan pemilik perusahaan dan salesman, yang kemudian dianalisis menggunakan perangkat lunak MATLAB. Hasil penelitian menunjukkan bahwa kedua algoritma mampu menghasilkan rute yang lebih efisien dibandingkan dengan rute awal. Algoritma Tabu Search terbukti lebih unggul karena waktu komputasinya secara signifikan lebih singkat (0,005 detik) dibandingkan dengan algoritma genetika (113 detik), namun tetap mampu menghasilkan solusi yang mendekati optimal. Rute awal yang ditempuh mencakup jarak 63,74 km, waktu 177 menit, dan biaya sebesar Rp54.181. Sementara itu, hasil optimasi menunjukkan penghematan jarak (62,68 km), waktu (174 menit), dan biaya (Rp53.278), dengan peningkatan efisiensi sekitar 2%. Dengan demikian, algoritma Tabu Search direkomendasikan sebagai metode yang efektif untuk menentukan rute kunjungan salesman guna mendukung efektivitas distribusi produk di PT XYZ.

Kata kunci: algoritma genetika, optimasi, algoritma *tabu search, optimasi, travelling salesman problem*

Abstract — Distribution is the process of disseminating goods, services, or information from a source to a destination with the aim of achieving efficiency and equity. PT XYZ is a manufacturing company that produces soy sauce, sauce, vinegar, and syrup, distributing its products through traditional channels employing a sales force. Currently, the determination of visit routes is based on the experience of the salesmen, resulting in suboptimal performance in terms of distance, time, and cost. This study aims to identify more efficient routes by comparing two metaheuristic algorithms. Data were collected through interviews with the company owner and salesmen and subsequently analyzed using MATLAB. The results indicate that both algorithms generated routes more efficient than the initial one. The Tabu Search algorithm proved to be superior due to its significantly shorter computation time (0.005 seconds) compared to the genetic algorithm (113 seconds), while still yielding a near-optimal solution. The existing route covered 63.74 km, took 177 minutes, and cost IDR 54,181. In contrast, the optimized route resulted in savings in distance (62.68 km), time (174 minutes), and cost (IDR 53,278), achieving an efficiency improvement of approximately 2%. Therefore, the Tabu Search algorithm is recommended as an effective method for determining salesmen's visit routes to enhance the effectiveness of product distribution at PT XYZ.

Keywords: genetic algorithm, optimization, tabu search algorithm, travelling salesman problem

I. INTRODUCTION

In the contemporary industrial era, the logistics industry is experiencing rapid growth [1]. Effective logistics services are essential for enhancing customer satisfaction, expanding market share in e-commerce, and strengthening a product's competitive edge [2]. Achieving these outcomes depends on robust logistics management, particularly within the distribution process. Distribution channels, which comprise a complex system of intermediaries transferring goods from manufacturers to end-users, play a critical role in business operations. Consequently, the selection of an optimal distribution channel is vital for a company to maintain its competitiveness in the marketplace [3].

An important aspect of supply chain logistics is the planning of transportation and distribution, as this process allocates resources to optimize the delivery of finished products [4]. The selected route significantly influences the speed, cost, and overall efficiency of vehicle transportation [5]. Therefore, developing scientifically optimized distribution routes based on actual operational needs and characteristics is crucial. Effective route planning can increase delivery speed and reduce distribution costs, thereby generating greater economic benefits. This challenge is particularly relevant to **PT XYZ**, a company in the manufacturing and distribution sector, which frequently experiences delivery delays that lead to a decline in its service level.

The distribution process at many companies, including PT XYZ, continues to rely on the experience of the sales force. The operational demands require salesmen to efficiently service numerous locations, such as traditional markets, grocery stores, and food stalls. The challenges these salesmen face in optimizing their daily routes are a classic example of the Traveling Salesman Problem (TSP). The TSP is an optimization problem that seeks the shortest possible route to visit a set of locations, traditionally assuming that travel times are deterministic and constant. However, in many real-world logistics applications, travel times are dynamic, varying with the time of day due to factors like traffic congestion [6]. The relationship between minimizing travel time and minimizing distance is not always linear, making the choice between these objectives complex [7]. The TSP is closely related to the Vehicle Routing Problem (VRP), a complex combinatorial optimization problem focused on finding the most efficient routes for a fleet of vehicles to serve a designated set of customers and return to the starting depot [8], [9]. The primary objective of the VRP is to minimize overall costs, time, and distance, subject to various constraints [10]. To address these complex problems, researchers and practitioners have developed sophisticated solution methods, including metaheuristic approaches like Tabu Search and Genetic Algorithms. Tabu Search is a metaheuristic algorithm that explores the solution space for a near-optimal solution while using a memory structure to avoid cycling and escape local optima. Similarly, the Genetic Algorithm is an adaptive heuristic inspired by the principles of natural selection and genetics. This study will employ these two algorithms to determine an optimized routing strategy for the salesmen at PT XYZ, with the ultimate goal of improving operational efficiency and enhancing customer satisfaction. The scope of this research assumes deterministic travel times and does not consider more complex constraints such as time windows or vehicle capacity.

II. LITERATURE REVIEW

A. Route Optimization

The increasing complexity of global logistics and transportation networks necessitates the adoption of intelligent and efficient route optimization strategies. Businesses in sectors such as e-commerce, supply chain logistics, and urban delivery services grapple with numerous challenges, including rising fuel costs, traffic congestion, delivery delays, and environmental concerns. Traditional route planning methods, which rely on historical data and manual scheduling, have proven inadequate for the dynamic nature of modern transportation. The inability of these conventional systems to adapt to real-time disruptions leads to inefficiencies that negatively impact operational costs, delivery schedules, and customer satisfaction. Therefore, route optimization is essential for improving operational margins [11].

Traditional methods for optimizing delivery routes have typically prioritized minimizing distance-based costs. Modern approaches, however, also incorporate minimizing travel time as a key objective. Nevertheless, the relationship between time and distance is not always linear, and the trade-off between them can be complex [7]. To enhance the efficiency of distribution, algorithmic approaches are significantly more effective than adhering to static, predetermined routes [12]. The challenge of routing is formally addressed by the Vehicle Routing Problem (VRP).

Considerable progress has been made in modeling and solving the VRP and its variants, particularly those with capacity constraints. Researchers and practitioners have introduced more accurate and efficient solution algorithms and refined models, enabling the effective handling of large-scale routing challenges [13]. Optimal delivery routing is fundamentally a VRP, a cornerstone problem in combinatorial optimization that involves identifying the most efficient set of routes for a fleet of vehicles to serve a given group of customers [14].

B. Traveling Salesmen Problem (TSP)

The Traveling Salesman Problem (TSP) is extensively used in educational settings, as it provides an effective model for introducing the fundamental concepts of optimization and quantitative analysis [15]. Its intriguing nature has captured the attention of researchers across various disciplines, leading to continuous advancements in solution techniques. Despite decades of study, the TSP remains a significant challenge, with dedicated competitions organized to further explore its complexities [16]. The inherent difficulty of solving TSP instances is well-documented [17].

The TSP is one of the most widely studied combinatorial optimization problems. Its objective is to find the shortest possible tour for a salesman to visit a set of cities exactly once and return to the starting point, minimizing the total distance or cost. This problem is classified as NP-Hard, as its computational complexity increases exponentially with the number of cities. The TSP remains highly relevant today due to its direct applications in logistics, transportation, circuit design, and navigation systems. In recent years, metaheuristic approaches such as the Genetic Algorithm, Ant Colony Optimization, and Particle Swarm Optimization have gained prominence for their ability to efficiently find near-optimal solutions for large-scale TSP instances.

One classic heuristic for solving routing problems is the savings matrix method, often used to calculate the potential distance saved by combining different delivery points [18]. This approach, also known as the Clarke and Wright savings algorithm, constructs routes by iteratively merging trips to reduce total transportation costs and travel distance. It can also be applied to optimize vehicle allocation from facilities with different capacities [19]. The algorithm generally proceeds as follows:

1) **Determine the Distance Matrix.** The process begins by calculating the round-trip distance between the central depot (distribution center) and each delivery point. This can be accomplished using digital tools like Google Maps or through manual odometer readings.
2) **Compute the Savings Matrix.** A savings matrix is created to quantify the benefit of merging two separate delivery routes. The savings, S(x,y)S(x, y)S(x,y) gained by combining the routes to points x and y from the depot (0) is calculated using the formula:

$$S(x,y) = \mathrm{Dist}(\mathrm{Center},x) + \mathrm{Dist}(\mathrm{Center},y) - \mathrm{Dist}(x,y) \quad (1)$$

This equation measures the distance saved by traveling between points x and y directly instead of returning to the depot between deliveries.

3) **Assign Delivery Points to Routes.** Initially, each delivery point is assigned its own route. The algorithm then iteratively combines routes based on the savings matrix, starting with the pair of points offering the highest savings. A merge is only considered feasible if the combined load of the two points does not exceed the vehicle's capacity. This process continues until no more feasible merges can be made.
4) **Sequence the Points Within Each Route.** After the routes are formed, the sequence of visits within each route must be optimized to further minimize travel distance. A simple heuristic like the Nearest Neighbor method can be used to create an initial sequence, which can then be refined to ensure all constraints are met.

C. Tabu Search and Genetic Algorithm

Among various metaheuristic methods, Tabu Search (TS) is frequently utilized to address complex scheduling and routing problems [20]. As a metaheuristic, TS is adept at navigating solution spaces to find near-optimal outcomes, and its performance can be assessed under distinct multi-objective strategies [21]. TS systematically explores solutions while employing a memory structure, known as a "tabu list," to prevent cycling and escape local optima, thereby guiding the search toward a global optimum.

The Genetic Algorithm (GA) is another powerful metaheuristic effective in solving optimization problems, including scheduling strategies aimed at minimizing costs [22] . The GA is an adaptive search method inspired by the principles of natural selection and biological genetics. In this study, both Tabu Search and the Genetic Algorithm were selected to optimize the daily routes for salesmen at the subject company. Effective vehicle route optimization is critical, as improvements in route and time efficiency directly translate to reduced operational costs and enhanced service quality.

III. METHOD

This research was conducted at **PT XYZ**, located in Gowa Regency. The methodology was structured into four primary stages: (1) Introduction, (2) Data Collection, (3) Data Processing, and (4) Analysis and Conclusion Drawing Stage. The research workflow is illustrated in the flow diagram in Figure 1.

The first stage is the introduction. This initial stage involved both field and literature studies. The field study consisted of direct visits to PT XYZ to observe the existing distribution process and identify a representative route for analysis. The literature study focused on examining established methods for solving the Traveling Salesman Problem (TSP), with a particular emphasis on the Tabu Search and Genetic Algorithm, which were slated for implementation using MATLAB. The second step is Data Collection. This stage involved gathering both primary and secondary data. Primary data were obtained through direct interviews with the owner and a salesman at PT XYZ to gather information on the company profile, distribution procedures, and operational challenges. Secondary data were compiled from relevant literature, scientific publications, and other credible sources to support the analysis. The third is Data Processing Stage, in this stage, the collected data were processed using the Tabu Search and Genetic Algorithm implemented in MATLAB. The objective was to generate an optimal distribution route by minimizing three key metrics: distance, time, and cost. The last is Analysis and Conclusion Drawing Stage. The final stage involved a comparative analysis between the existing route and the optimized routes generated by the two algorithms. The analysis focused on quantifying the improvements in travel distance, delivery time, and operational costs. The algorithm that produced the superior result was identified and formed the basis for recommendations to improve the routing strategy for the PT XYZ sales team. Finally, conclusions from the study and suggestions for future research were formulated. Figure 1 illustrates the research flow diagram.

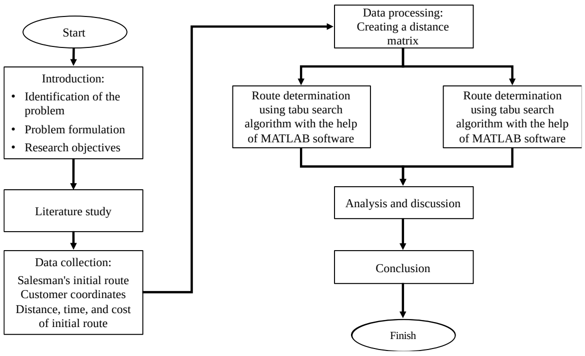

Figure- 1. Research Flow Chart

IV. RESULT AND DISCUSSION

A. Result

1) Data Collection

The data for this research were gathered through a literature review, observations, and interviews with a salesman at PT XYZ. The salesman's schedule covers six days a week, from Monday to Saturday. Among these, Wednesday was identified as having the highest number of visit points, with a total of 26 locations to be visited in a single day. After this specific route was identified, a distance matrix was created using Google Maps to measure the travel distance between each point, with data accuracy verified through direct observation. Table 1 displays the coordinate data for all 26 locations, which serves as a numerical reference for the route analysis. Meanwhile, Figure 2 provides a visual map of the salesman's route to illustrate the spatial layout of the visit points.

Table- 1. Coordinates of salesman visit points

Visit Code	*Longitude*	*Latitude*
1	-5.222418492	119.4637646
2	-5.205902657	119.449108
3	-5.210720567	119.4542852
4	-5.21182099	119.4558154
5	-5.181018565	119.441413
6	-5.175111552	119.4439406
7	-5.175388078	119.4295336
8	-5.175281227	119.4295121
9	-5.177464083	119.4137784
10	-5.169406017	119.417395
11	-5.165608119	119.4190327
12	-5.127316163	119.4317284
13	-5.139056638	119.456635
14	-5.140199224	119.4580023
15	-5.165876031	119.4580764
16	-5.185344581	119.4689976

17	-5.195379945	119.46918
18	-5.218803739	119.4768084
19	-5.232556192	119.5089211
20	-5.219432376	119.4771463
21	-5.220148392	119.478461
22	-5.221475861	119.4878602
23	-5.222779366	119.4891899
24	-5.234732297	119.5227799
25	-5.232290623	119.5112097
26	-5.262757809	119.5341752
27	-5.26660384	119.5385613

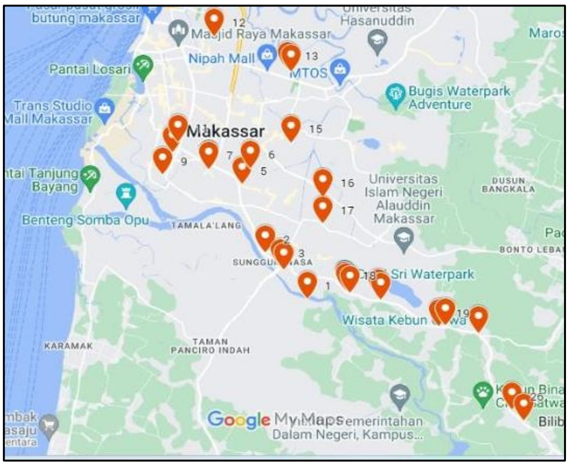

Figure- 2. Salesman visit point maps
(Source: Google Maps)

2) Tabu Search Algorithm

In working on the TSP with a Tabu Search algorithm, programming software assistance is needed, such as MATLAB to facilitate algorithm computation. In MATLAB, a function is first designed on the editor tab with the algorithm code. After that, on the editor tab, the program is run. A warning will appear in the command window to enter the distance matrix input. Then the existing distance matrix is input using the code D. Then, by using the designed Tabu Search algorithm function, the next step is to determine the maximum iteration to be used. The maximum iteration used in this study is 100. After that, the results of the function appear, which can be seen in Figure 3 below.

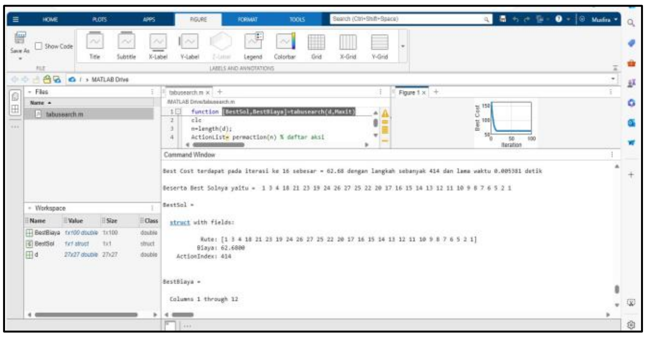

Figure- 3. Results of running using the tabu search algorithm function D

In Figure 3, it can be seen that the best solution was obtained in the 16th iteration of 100 iterations with the route 1-3-4-18-21-23-19-24-26-27-25-22-20-17-16-15-14-13-12-11-10-9-8-7-6-5-2-1 and a total distance of 62.68 km. The best solution was obtained with a total computing time of 0.005381 seconds. The graph of the results using the Tabu Search algorithm can be seen in Figure 4.

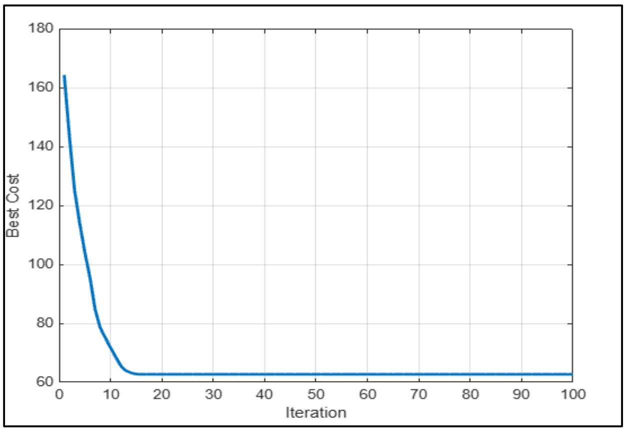

Figure- 4. Graph of results from running using the tabu search algorithm function

Figure 4 shows that the total distance decreases from iteration 1 to 16 and then remains constant from iteration 16 to 100. This convergence occurs because the Tabu Search algorithm utilizes a tabu list, which prevents the search from revisiting recent solutions. This mechanism helps guide the algorithm out of local optima and toward a more globally optimal solution.

3) Genetic Algorithm

To solve the TSP using a Genetic Algorithm (GA), MATLAB was employed to facilitate the computation. A custom function for the GA was implemented in MATLAB and executed using the collected distance matrix as input. Key parameters for the GA include the population size (number of chromosomes) and the maximum number of generations. Determining an appropriate population size is crucial for the GA's performance. Too few chromosomes can limit the exploration of the search space, while too many can significantly increase computation time. According to Goldberg (1989), a larger population size fosters greater diversity, which helps prevent premature convergence where genetic operators fail to produce superior offspring. However, an excessively large population can increase computational demands without yielding proportional improvements. To identify the optimal parameters for this problem, experiments were conducted with population sizes of 50, 75, 100, 125, and 150 chromosomes. The initial results are shown in Figure 5.

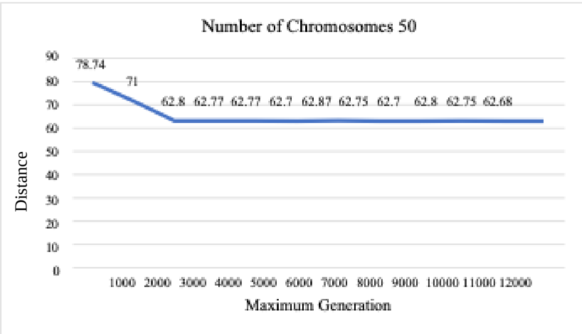

Figure- 5. Performance graph with a population size of 50 chromosomes

As shown in Figure 5, when using a population size of **50 chromosomes**, the total distance decreased

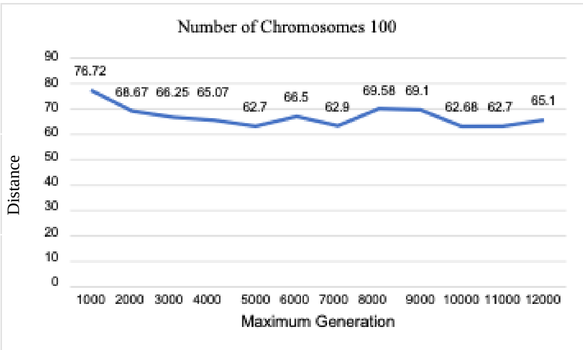

Figure- 6. Performance graph with a population size of 100 chromosomes.

between 1,000 and 3,000 generations. However, beyond 3,000 generations, there was no significant improvement. The best result for this trial was obtained at 12,000 generations. This performance plateau suggests that a small population size hindered a thorough exploration of the search space. Consequently, the experiment was repeated with a population size of **100 chromosomes** to encourage greater solution diversity. The results of this trial are shown in Figure 6.

Figure 6 shows that with a population of **100** chromosomes, the total distance fluctuated before converging. The lowest total distance in this trial was obtained at 10,000 generations. The experiment was then continued with a population size of 125 chromosomes, and the results are presented in Figure 7.

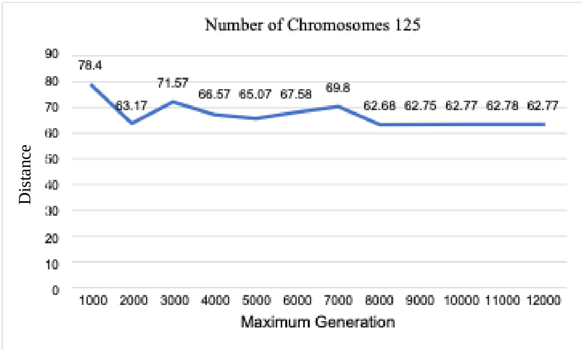

Figure- 7. Performance graph with a population size of 125 chromosomes

As seen in Figure 7, using a population of 125 chromosomes yielded varied results. The lowest total distance was achieved at 8,000 generations, after which the solution did not change significantly up to 12,000 generations. The experiment was then repeated with a population of 150 chromosomes to determine if a more optimal solution could be found. The results from this final trial are shown in Figure 8.

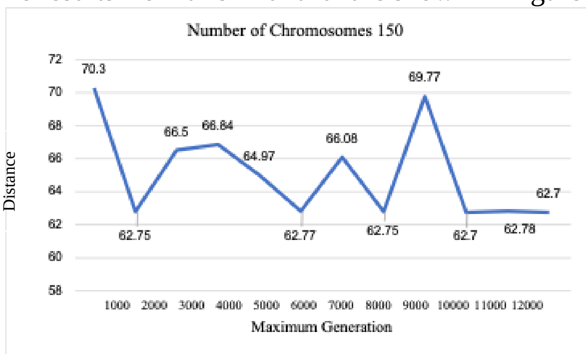

Figure- 8. Performance graph with a population size of 150 chromosomes

Figure 8 indicates that using a population of 150 chromosomes did not yield a more optimal solution than the one found using 125 chromosomes at 8,000 generations. This outcome may occur because an excessively large population can increase computational overhead without a corresponding improvement in solution quality, potentially causing the algorithm to stagnate. For this reason, the experimentation was concluded with the 150-

chromosome trial. The optimal solution identified by the Genetic Algorithm is detailed in Figure 9.

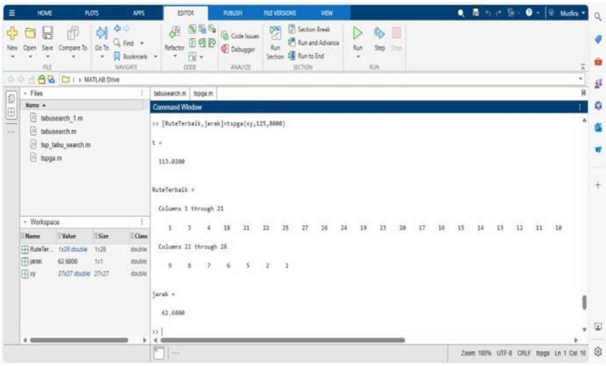

Figure- 9. Graph of results from running using the genetic algorithm function

Figure 9 presents the optimal solution found by the Genetic Algorithm. The best route obtained is 1–3–4–18–21–22–25–27–26–24–19–23–20–17–16–15–14–13–12–11–10–9–8–7–6–5–2–1, with a total travel distance of 62.68 km. This solution was achieved with a computation time of 113.02 seconds, using a configuration of 125 chromosomes and a maximum of 8,000 generations. In this context, the Genetic Algorithm mimics natural selection, where a population of potential solutions (routes) is evaluated using a fitness function. Through iterative processes of selection, crossover, and mutation, the algorithm progressively improves the population toward better solutions. The use of an appropriate number of chromosomes and generations enables a thorough exploration of the solution space, thereby increasing the likelihood of finding a global optimum.

The search for solutions using the Genetic Algorithm was limited to a maximum of 150 chromosomes. A comparison of the performance graphs reveals that the configuration with **125 chromosomes (Figure 7)** demonstrates more stable and efficient performance than the configuration with 150 chromosomes (Figure 8). In Figure 8, the fitness values fluctuate significantly, indicating that the algorithm is still exploring the solution space and has not converged. In contrast, Figure 7 shows that the fitness value decreases rapidly in the early generations and then remains stable, suggesting that a near-optimal solution was found early and consistently maintained. This stability reflects the algorithm's efficiency in exploiting the best solutions.

The choice of the 125-chromosome configuration is justified because it offers sufficient population diversity without excessively increasing the computational burden. This configuration provides a balanced trade-off between exploration (searching for new solutions) and exploitation (refining existing good solutions), enabling faster convergence without compromising solution quality. Therefore, the use of 125 chromosomes proved to be the most effective in generating an optimal solution with efficient computational time and greater stability, as illustrated in Figure 7.

4) Comparison Of Existing Route, Tabu Search Algorithm, And Genetic Algorithm

Figure 10 displays the **existing route** used by the company, which is 1-3-4-2-5-6-7-8-9-10-11-12-13-14-15-16-17-18-20-21-22-23-19-25-24-26-27-1. The route concludes with the salesman returning to the warehouse after all points have been visited. On this existing route, the total distance traveled is 63.74 km.

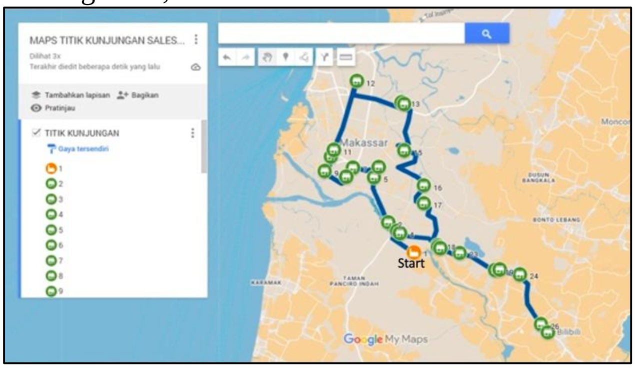

Figure- 10. Existing route

Figure 11 shows the route generated by the Tabu Search algorithm, which is 1-3-4-18-21-23-19-24-26-27-25-22-20-17-16-15-14-13-12-11-10-9-8-7-6-5-2-1. This route has a total distance of 62.68 km. The route from the Genetic Algorithm is shown in Figure 12, which is 1-3-4-18-21-22-25-27-26-24-19-23-20-17-16-15-14-13-12-11-10-9-8-7-6-5-2-1. This route also has a total distance of 62.68 km. Although the visit order differs, the total distance for both algorithm-generated routes is the same.

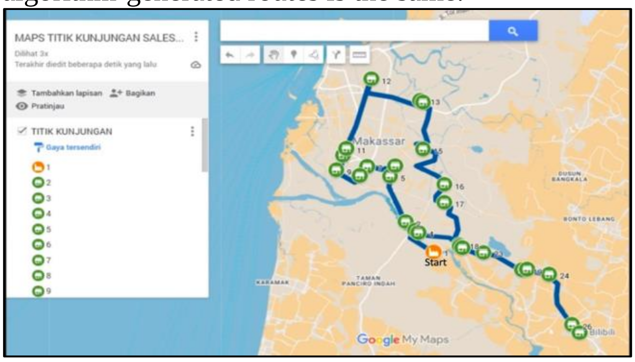

Figure- 11. Proposed route tabu search algorithm

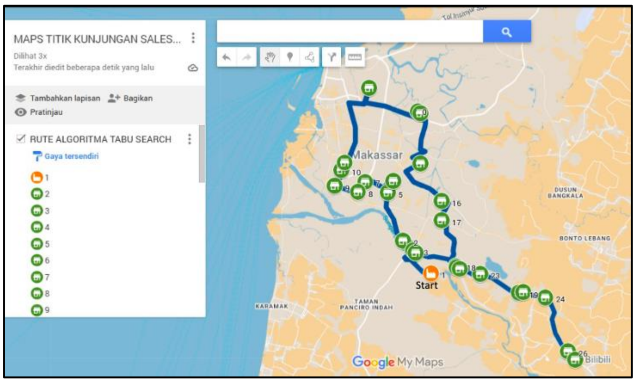

Figure- 12. Proposed route genetic algorithm

To project annual savings, it was assumed that this route is performed once per week, totaling 52 times per year. Based on this assumption, a yearly comparison of total distance, travel time, and costs can be calculated for each route. This comparison is summarized in Table 2.

Table- 2. Comparison of existing route, tabu search algorithm, and genetic algorithm

Method	Existing	*Tabu Search Algorithm*	Algoritma Genetika
Route	1-3-4-2-5-6-7-8-9-10-11-12-13-14-15-16-17- 18-20-21-22-23-19-25-24-26-27-1	1-3-4-18-21-23-19-24-26-27-25-22-20-17-16-15-14-13-12-11-10-9-8-7-6-5-2-1	1-3-4-18-21-22-25-27- 26-24-19-23-20-17-16- 15-14-13-12-11-10-9-8-7-6-5-2-1
Travel Distance (km)	3,314.58	3,259.36	3,259.36
Travel Tine (Minute)	9,204	9,048	9,048
Travel Cost (Rp)	2,817,412	2,770,456	2,770,456

Based on Table 2, it is evident that by using the Tabu Search algorithm and the Genetic Algorithm, the total distance traveled, travel time, and travel cost are improved compared to the company's existing route. The Tabu Search algorithm and the Genetic Algorithm produce different routes but have the same total distance, travel time, and travel cost. Both the Tabu Search algorithm and the Genetic Algorithm can produce more efficient routes compared to the existing route used by the company. For one year, the initial route resulted in a total distance traveled of 3,314.58 km, a travel time of 9,204 minutes, and a travel cost of IDR 2,817,412. With the Tabu Search algorithm, the results obtained were a distance traveled of 3,259.36 km, a total travel time of 9,048 minutes, and a travel cost of IDR 2,770,456. Similarly, the Genetic Algorithm yielded a distance traveled of 3,259.36 km, a total travel time of 9,048 minutes, and a travel cost of IDR 2,770,456.

B. Discussion

A comparison between the Tabu Search and Genetic Algorithm was conducted to understand their respective advantages and disadvantages. This analysis helps determine the most appropriate algorithm for solving the salesman visit route problem at PT XYZ. The application of both algorithms shows that they can produce more efficient routes than the existing one used by the company. Over a one-year period, the initial route has a total distance of 3,314.58 km, a travel time of 9,204 minutes, and a travel cost of IDR 2,817,412. In contrast, the Tabu Search algorithm yielded a distance of 3,259.36 km, a travel time of 9,048 minutes, and a travel cost of IDR 2,770,456. The Genetic Algorithm produced identical results for distance, time, and cost, confirming that both methods are more efficient than the existing route.

In terms of parameter setting, both algorithms require precise configuration to obtain optimal results. Tabu Search relies on parameters such as tabu tenure and neighborhood size. Similarly, Genetic Algorithms require careful tuning of parameters like population size, crossover probability, and mutation probability to perform effectively.

The results show that the routes proposed by both the Tabu Search and Genetic Algorithms yield identical savings. Both algorithms provide an efficiency improvement of **2%** over the existing route when projected over a year. Specifically, the annual distance traveled is reduced by 55.22 km, travel time is reduced by 156 minutes, and travel costs are reduced by IDR 46,956.

The Tabu Search algorithm demonstrates its superiority in computational speed, finding an optimal solution in just 0.005381 seconds by employing its tabu list mechanism to escape local optima. In contrast, the Genetic Algorithm explores the search space more comprehensively through its mechanisms of selection, crossover, and mutation. This allows it to find a high-quality solution, but with a significantly longer computation time of 113.02 seconds. The GA's result was achieved using the optimal parameter combination identified during the experimentation phase.

For this specific application, Tabu Search can be considered the more practical solution due to its ability to avoid re-exploring previously visited solutions. This allows the algorithm to progress efficiently through the search space. Furthermore, Tabu Search is deterministic, providing more stable and consistent results compared to the stochastic nature of Genetic Algorithms. It also tends to converge more quickly as it focuses on an intensive search around the best solutions found.

V. CONCLUSION

The optimized salesman routes at PT XYZ were generated using the Tabu Search and Genetic Algorithm with assistance from MATLAB. The route generated by the Tabu Search algorithm is 1-3-4-18-21-23-19-24-26-27-25-22-20-17-16-15-14-13-12-11-10-9-8-7-6-5-2-1. The route from the Genetic Algorithm, using 125 chromosomes, is 1-3-4-18-21-22-25-27-26-24-19-23-20-17-16-15-14-13-12-11-10-9-8-7-6-5-2-1.

Both algorithms produced different sequences of visit points but resulted in the same total travel distance, time, and cost. The optimized distance of 62.68 km represents a slight improvement over the original route of 63.74 km, indicating that both algorithms were equally effective in optimizing the route's length.

The optimization led to an estimated 2% annual saving in distance, time, and cost. Specifically, the total annual distance was reduced by 55.22 km, travel time by 156 minutes, and travel costs by IDR 46,956. While both algorithms provided the same level of optimization, the Tabu Search algorithm was significantly faster, with a computation time of only 0.005381 seconds compared to 113.02 seconds for the Genetic Algorithm.

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