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Enhancing Logistics Efficiency: A Case Study of Genetic Algorithm-Based Route Optimization in Distribution Problem

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ABSTRACT

The optimization of route planning is a critical consideration frequently happened in the logistics of product distribution. This study addresses distribution issues, such as long trip distances, which result in high distribution costs. The objective of this research is to increase distribution routes' effectiveness, which will enable it to reach the minimize distance and lower the cost of product distribution. The Travelling Salesman Problem (TSP) can be resolved by using the Genetic Algorithm (GA) technique to optimize the path. Variations in crossover, mutation, and population were made when experimenting with GA. The results of the study indicate that the overall distance travelled decreased from 55.5 km to 30.45 km and that the cost of distributing the product was reduced from Rp 94,350.00 to Rp 51,765.00. There is a about 45% improvement. There is about 45% improvement. This optimisation technique has a favourable effect on the overall financial performance and competitiveness of businesses involved in comparable distribution operations, as well as improving operational efficiency and offering the possibility of cost savings.

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1. INTRODUCTION

Effective organizational management plays a crucial role in minimizing the distances in distribution routing problems. It can create a well-organized company structure [1], optimize the distribution process, and minimize internal bottlenecks that affect operational efficiency. The Traveling Salesman Problem (TSP) is a well-known combinatorial optimization problem that has received significant attention due to its wide range of applications in various fields. TSP involves determining the most efficient route to visit a set of cities exactly once [2], [3]. This problem employs integer programming and combinatorial optimization due to its mathematical complexity and practical applications [4]. TSP has been applied in many areas, such as production scheduling, logistics, and transportation, where finding the optimal sequence of visits is crucial for minimizing costs and improving efficiency [5]. In the context of logistics, TSP is utilized to determine the sequence of drops and the actual cost of shipments, thereby contributing to effective load planning and outbound logistics [3]. Moreover, TSP has been extended to address more complex variations, such as the multiple traveling salesman problem, in which an effective evolutionary algorithm has been proposed to handle bi-objective optimization [6].

TSP has found in many practical applications that address complex optimization challenges. TSP has been used in the transport sector to address issues with public transport and traffic congestion. In professional sports leagues, for example, the use of TSP-based heuristics has been investigated to save airline trip expenses and enhance scheduling [7]. Yang et al. [6] presented the problem's importance in algorithmic research and optimisation techniques by presenting an efficient solution for solving the multiple TSP using NSGA-II. Furthermore, Dornhege et al. [8] illustrated the applicability of TSP in the framework of a multirobot coverage search, highlighting how that coverage planning is NP-hard due to its TSP similarities. This example demonstrates the practical uses of TSP in robots and autonomous systems, where coverage planning relies on finding the shortest, most efficient paths. Additionally, Aswandi et al. [9] proposed TSP in addressing logistics and transportation problems to determine the garbage pickup's shortest path. This study provides a realistic illustration of how the TSP can be used when resource allocation and cost-effective operations based on optimal route. Then, Hidayat et al. [10] developed TSP formulation for trip design and logistics management to analyse fish delivery trips. The importance of the TSP in resolving routing and sequencing issues in supply chain and transportation operations. The TSP has proven to be highly useful in a variety of fields, including algorithmic research, robotics, logistics, supply chain management, and transportation. This is the way to handle problems with operational efficiency planning and resource allocation in a range of real-world situations.

There are some methods and algorithms to identify the optimal solutions for TSP problems, such as Otubamowo et al. [11] compared the effectiveness of GA and simulated annealing (SAA), emphasising the usefulness of both metaheuristic techniques for handling combinatorial optimisation issues. Riazi [12] proposed a GA with a double-chromosome implementation to solve the TSP, emphasizing the ongoing interest and concerns of researchers in this area. Furthermore, Albayrak & Allahverdi [13] focused on developing a new mutation operator to solve the TSP using GA, demonstrating the continuous efforts to enhance the performance and efficiency of existing algorithms for TSP.

In addition, Balaprakash et al. [14] introduced an estimation-based ant colony optimization algorithm for the probabilistic traveling salesman problem, showcasing the utilization of nature-inspired algorithms to address the complexities of TSP. Buriol et al. [15] presented a new memetic algorithm for the asymmetric TSP, highlighting the evolution of algorithmic techniques to address specific variations in the TSP. These studies highlight the methods that have been used for the TSP in any algorithm design and optimization technique.

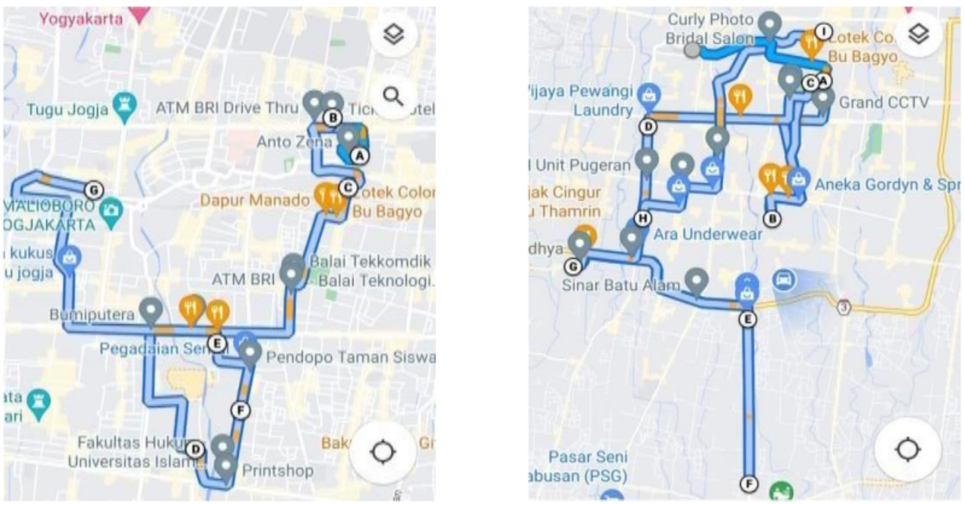
Furthermore, Warren [16] explored the application of solving the TSP on a quantum annealer, indicating the integration of emerging computational paradigms to address combinatorial optimization problems. This study reflects the continuous evolution of algorithmic techniques and the exploration of novel computing platforms for solving complex optimization problems, such as TSP. Additionally, Rego et al. [17] stated the most effective approaches, practical applications, and recent developments in TSP heuristics, highlighting the fluidity of algorithmic research and the ongoing improvement of TSP and solution methods.

The study of the utilization and usefulness of GAs in solving TSP has been a focus of academic research. Gao et al. [18] highlighted the successful application of ant colony optimization methods, including the traveling salesman problem, demonstrating the effectiveness of metaheuristic algorithms in addressing combinatorial optimization problems. Yousefikhoshbakht et al. [19] tested a proposed algorithm based on the Genetic Reactive Bone Route Algorithm with Ant Colony System on standard instances involving 24 to 318 nodes from the literature, showcasing the practical application of genetic algorithm-based approaches to the TSP. Jojo [20] observed the evolution of the algorithm towards the optimal value of the fitness function, indicating the effectiveness of genetic algorithms in converging towards optimal solutions for the TSP. Boyko & Pytel [21] emphasized that genetic algorithms are effective methods for solving both constrained and unconstrained optimization problems, including the TSP, based on natural selection processes. Jain & Prasad [22] proposed the population dynamics in genetic algorithms, which is an important part of the process where an equal number of chromosomes join and exit the population to keep the population size constant.

The existing literature has shown little research attention related specifically to the bread distribution problem. To fill this research gap, this study addresses the challenges associated with distribution inefficiency. The main objective is to minimize the total distance traveled in the distribution networks through the GA. This involves the variation of crucial parameters such as crossover probability, mutation probability, and population size. This study not only contributes to the academic discourse on distribution challenges but also aims to provide actionable insights and practical solutions for industry practitioners and logistics managers. By enhancing the understanding of optimal route planning using GA, this research contributes to the broader field of logistics and supply chain management. This finding offers valuable implications for operational efficiency and cost-effectiveness.

2. METHODS

This study focuses on a case study of a bread distribution company. The company operates a distribution network with nodes along the route. The inefficiencies identified within this network have a significant impact on transportation costs, as shown in Figure 1. It is currently about 55.5 kilometres total, as travelled along a given route. Analysing these inefficiencies is essential to comprehending the difficulties a business has when trying to optimise its distribution procedures. Through an analysis of each node's features and related inefficiencies, this study has objective to find possible routes to increase the distribution system's overall efficiency.



(a) (b)

Figure 1. The current network for distribution system: (a) The initial stop point to the seventh stopping point; (b) Eighth stop to 15th stop

The GA is effective in solving a wide range of optimization problems [23]–[27]. This paper suggests using a GA to optimise routes in the context of transportation logistics in order to solve this issue. Reducing the distance and costs related to the distribution network is the research objective. To improve their performances, this requires varying some essential parameters. Population size, crossover probability, and mutation probabilities were the main variables that were being examined. This study aims to determine the best fitness level for the GA by examining some experimentations of route optimisation. This strategy was selected because it mimics evolution and natural selection. This research is focused on providing important insights into the use and effectiveness of GA by examining their parameters for route optimisation. It emphasis on minimising cost and distance such as distribution networks. The following are the steps in developing the GA method:

1. Initialization:
   First of all, a starting population value (N) is generated randomly. This population is made up of several chromosomes, each of which stands for a tour's successive delivery nodes (called "gens" in GA terminology). Some population sizes (N) were established for each experiment separately.
2. Fitness Evaluation:
   As GA fall under the category of optimization problems, the evaluation of chromosomes or solutions within the population requires the computation of a fitness function, also known as the objective function. The fitness of each individual in the population is evaluated based on a predefined objective function, which, in

the case of the TSP, is typically the total distance or cost of the route. Individuals with shorter routes are considered to have higher fitness levels.

3. Selection:

This phase constitutes the selection process, which determines how GAs choose their parents for next generations. Individuals from the population were chosen for reproduction based on their highest fitness level. The selection process was designed to enhance the probability of transmitting advantageous traits to succeeding generations.

4. Crossover:

This stage holds significant importance within the GA framework, in which two parent chromosomes are paired to generate offspring. This study conducted this process by randomly selecting a pair of chromosomes from the current generation with a specified probability. In this study, the probability of crossover was systematically varied for experimentation, such as 0.95, 0.9, 0.85, 0.8, 0.65, and 0.6. The crossover procedure encompasses diverse types of operators including one-point, two-point, multiple-point, and uniform operators. This study opts for a one-point crossover to produce new offspring. Within the framework of TSP, the crossover operation comprises switching sub-tours between two parent routes in order to generate new potential solutions.

5. Mutation:

The process of mutation is significant because it preserves genetic diversity within a population across generations, guaranteeing a larger area for the GA to search. It is essential to use a suitable mutation probability in order to prevent early convergence. Different mutation probabilities, including 0.01, 0.02, 0.03, 0.04, and 0.05, were included in the experiment. Within TSP, a mutation could include things like moving or switching cities along a particular path. Premature convergence can be avoided because of using this technique, which also makes it easier to use the GA to explore the solution space more thoroughly.

6. Termination:

The final stage in the Genetic Algorithm (GA) involves terminating the search process once a solution that closely approaches or meets the user's expectations is identified. In this study, the decision was made to conclude the GA process after 500 generations. Furthermore, the best-performing chromosome, characterized by the minimum fitness value, was chosen as the solution that approximated the desired optimum for each experiment.

3. RESULTS AND DISCUSSION

This section provides a detailed examination of the outcomes derived from an evaluation of the proposed model. The data utilized for this assessment included a distance matrix among nodes (as shown in Table 1) sourced from a real case study. To carry out an experimental analysis, the proposed model was modelled using Microsoft Excel integrated with a GA add-in, namely, XL-Bit software (refer to Figure 2). All calculations were performed on an AMD Ryzen 3-3200U with a Radeon Vega Mobile Gfx processor at 2.6 GHz with up to 8 GB of RAM.

Table 1. Distance matrix

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0,55	0,65	0,75	5,8	4	4,1	3,6	1,6	5,9	1,5	5,7	14	9,8	9,5	7,6
1	0,55	0	0,7	1,2	2	4,5	4,6	4,2	2,1	5,8	2	5,8	14	9,8	9,5	7,7
2	0,65	0,7	0	1,2	5,8	4,1	4,2	3,8	2,1	5,6	1,9	6,2	8,8	9,6	10	7,2
3	0,75	1,2	1,2	0	4,5	3	3,1	3,3	0,9	4,6	0,75	4,9	7,5	8,2	9,1	6,7
4	5,8	2	5,8	4,5	0	4,1	4	7,3	4,3	2,2	4,4	6,1	4,5	4,6	5,2	2,8
5	4	4,5	4,1	3	4,1	0	0,05	3,3	2,5	2	2,1	2,7	5,7	5,9	6,8	4,4
6	4,1	4,6	4,2	3,1	4	0,05	0	3,4	2,5	1,9	2,2	2,7	5,1	5,9	6,7	4,3
7	3,6	4,2	3,8	3,3	7,3	3,3	3,4	0	5,4	6,4	5,2	2,3	9	8,5	7,8	5,9
8	1,6	2,1	2,1	0,9	4,3	2,5	2,5	5,4	0	4,2	0,4	4,6	8,2	7,8	8,7	6,2
9	5,9	5,8	5,6	4,6	2,2	2	1,9	6,4	4,2	0	3,8	4	3,9	4,6	7,1	3,5
10	1,5	2	1,9	0,75	4,4	2,1	2,2	5,2	0,4	3,8	0	4,2	6,8	7,5	8,3	5,9
11	5,7	5,8	6,2	4,9	6,1	2,7	2,7	2,3	4,6	4	4,2	0	6,6	7,4	4,2	1,9
12	9,1	9,1	8,8	7,5	4,5	5,2	5,1	9	8,2	3,9	6,8	6,6	0	0,7	5,4	4,7
13	9,8	9,8	9,6	8,2	4,6	5,9	5,9	8,5	7,8	4,6	7,5	7,4	0,7	0	6,1	5,4
14	9,5	9,5	10	9,1	5,2	6,8	6,7	7,5	8,7	7,1	8,3	4,2	5,4	6,1	0	2,4
15	7,6	7,7	7,2	6,7	2,8	4,4	4,3	5,9	6,2	3,5	5,9	1,9	4,7	5,4	2,4	0

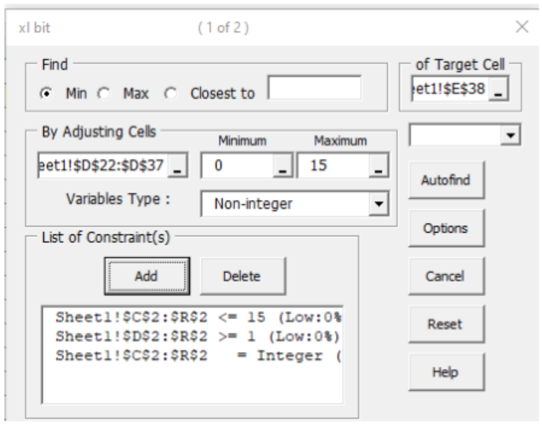


Figure 2. Data processing using XL-Bit software

Table 2 lists the results of the experimental assessment of the TSP model applied to the distribution problem. The table encompasses variations in crossover probability, mutation probability, and population size and systematically examines the impact of different GA parameters on performance. Within this table, "CPUt" represents the computational processing unit time required to solve the problem, measured in seconds, while "Fitness" signifies the fitness value expressed in kilometers.

Table 2. The experimental results

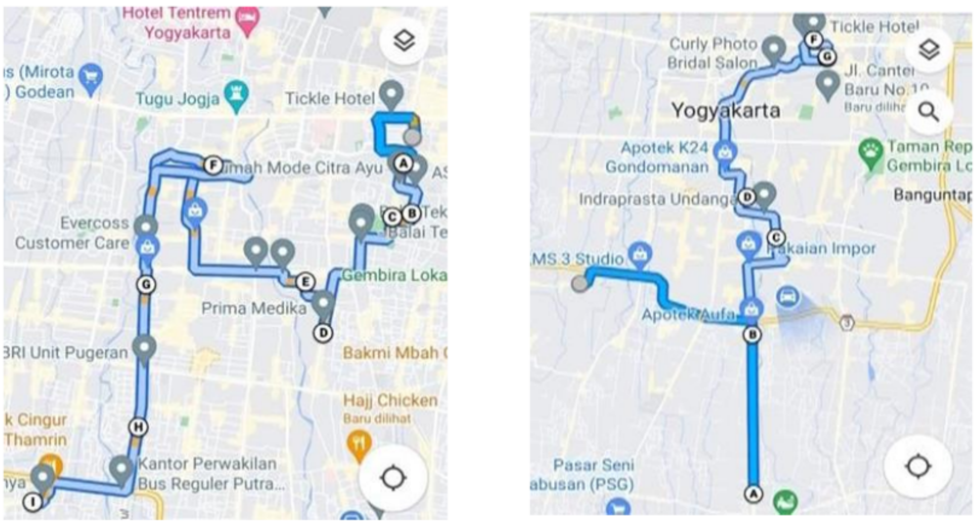
Experiment	Crossover	Mutation	Population size	Generation	Fitness (km)	CPUt (seconds)
1	0,95	0,03	150	500	34,6	73.97
2	0,85	0,01	200	500	34,6	105.44
3	0,8	0,03	250	500	30,45	136.81
4	0,65	0,05	300	500	38,15	191.23
5	0,6	0,02	350	500	37,85	190.1
6	0,9	0,04	100	500	38,15	81.21

Based on the above table, this appears to show the results of experiments with different parameter settings for the GA applied to optimize a distribution network problem. Specifically, six different experiments were conducted with the GA by varying three key parameters

a. Crossover rate: The probability of crossover operation in the GA (values ranging from 0.6 to 0.95)
b. Mutation rate: The probability of mutation operation in the GA (values ranging from 0.01 to 0.05)

c. Population size: The number of solutions evaluated in each generation (values ranging from 100 to 350)

The table shows the impact of these different parameter settings on the performance of the GA in optimizing the fitness function, which in this case is the total length of the distribution network (km). The lowest network length of 30.45 km was achieved in Experiment #3, using a crossover rate of 0.8, a mutation rate of 0.03, and a large population size of 250 over 500 generations. The optimized routes from this experiment are shown in Figure 3. The next best result was Experiment #5, achieving a length of 37.85 km with a slightly lower crossover rate of 0.6, but a higher mutation rate of 0.02. In contrast, the worst result of a 38.15 km network length came from Experiments #4 and #6, which both had relatively lower crossover rates of 0.65 and 0.9 respectively. Experiment #6 used the smallest population (100).



(a) (b)

Figure 3. The network of distribution system after optimization from Experiment #3: (a) The initial stop point to the ninth stop point; (b) The tenth stopping point to the fifteenth stopping point

In addition to affecting the network length optimization, the choice of GA parameters also affects the required computation time, as indicated by the CPU time in seconds. The smallest CPUt of 73.97 seconds was observed in Experiment #1, which used a high crossover rate of 0.95, small mutation rate of 0.03, and a moderate population of 150 over 500 generations. This achieved a reasonably good 34.6 km length using the shortest computation time.

The longest CPUt of 191.23 seconds occurred with Experiment #4's low 0.65 crossover rate, high 0.05 mutation rate, 300 population size, and 500 generations. However, this failed to improve the network length in Experiment #1. Comparing Experiments #1, #3, and #5 shows doubling the population size (150 to 300) over 500 generations scales up CPUt by 2-3x while providing limited fitness improvement. In essence, while factors such as crossover and populations impact network fitness, CPU time appears directly tied to total evaluations (number of generations and population). More evaluations improve the likelihood of finding optimal regions but have diminishing returns and longer runtimes past a point, as demonstrated by these experiments. This computational cost should be traded off based on the need for solution quality and speed.

By applying the GA method in data processing, a comparison of distance and fuel costs can be made between the distribution route distance before and after the optimization process, as shown in Table 3. The table presents data related to the distance, fuel costs, and efficiency improvements from the TSP optimization process. Before the optimization was implemented, the distance was 55.5 km and the associated fuel cost was 94,350 rupiah. However, after applying the optimization, the distance traveled was reduced to 30.4 km while the fuel cost decreased to 51,765 rupiahs. Comparing the before and after metrics shows substantial improvements; there was a 45.2% reduction in distance traveled after optimization. Implementing this TSP optimization process led to significant enhancements, almost halving the required travel distance and the associated fuel costs.

Table 3. Comparison before and after optimization

	Distance (in km)	Fuel costs (in rupiah)	Improvement (in percentage)
Before optimization	55.5 km	94,350	45.2 %
After optimization	30.4 km	51,765	

This experiment demonstrates the tuning process for the GA parameters to achieve improved performance and fitness for the TSP optimization problem. The crossover rate, mutation rate, generation, and population size have a clear impact that could guide the selection of optimal GA configuration settings [28]–[34]. The balance between exploration and exploitation, convergence capacity, and diversity maintenance are all impacted by the experimentation with these factors. Therefore, understanding and optimizing these parameters are crucial for the effective application of GAs in solving complex optimization problems.

4. CONCLUSION

The research objective was to minimize the distance and cost by optimizing the distribution networks. The GA was developed by varying some parameters, such as crossover probability, mutation probability, and population size. The process of experimentation, which involved changing parameters and probabilities, gave important insights into how these parameters affected the fitness level. The results showed that the distance and fuel costs have improvement about 45% which also increase its efficacy in addressing the distribution-routing problem.

This study opens avenues for the further exploration and refinement of GA applications in distribution logistics. Future research could delve into the integration of real-time data and dynamic factors to enhance the adaptability of the algorithm to changing conditions. The findings of this study contribute not only to the optimization of distribution routes but also to the broader field of logistics and operations research.

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