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# Logistics Efficiency in Product Distribution with Genetic Algorithms for Optimal Routes

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**Abstract**: This research aims to optimize product distribution routes in logistics using computer simulation approaches and genetic algorithms. This research produces more efficient distribution routes by utilizing mathematical models that reflect actual distribution processes, including variables such as warehouse locations, distribution points, product types, customer demand, and vehicle availability. Genetic algorithms are used to design optimal solutions with implementation stages, which include solution representation, population initialization, fitness evaluation, selection, crossover, mutation, and stopping criteria. The visualization results show that the genetic algorithm can produce more structured and efficient distribution routes, reducing total travel distance, distribution costs, and delivery time. Statistical analysis supports significant improvements in distribution performance after implementing the genetic algorithm, with substantial reductions in total mileage, distribution costs, and delivery times and substantial improvements in customer satisfaction. Financial analysis shows significant cost savings and positive ROI from investing in genetic algorithms, while sensitivity analysis reveals the impact of critical factors on distribution costs. This research confirms the financial and operational benefits of applying genetic algorithms in product distribution optimization, with significant efficiency, cost savings, and customer satisfaction results.

**Keywords**: Logistics Efficiency; Product Distribution; Genetic Algorithms; Optimal Route; Logistics Optimization.

## 1. Introduction

Logistics distribution plays a vital role in industry by ensuring the efficient movement of products from production to consumption, thereby meeting customer demand cost-effectively [1]. The logistics industry, especially in cold chain logistics, is experiencing rapid growth due to increasing consumer expectations for fresh products and on-time delivery [2]. In a supply chain environment, logistics-related performance measures, such as delivery performance and inventory costs, significantly impact the overall effectiveness of supply chain management [3]. Efficient logistics operations control costs and increase energy efficiency, reduce carbon emissions, and ultimately increase customer satisfaction [4]. Research has shown that logistics service quality is directly related to customer loyalty and satisfaction, thus highlighting the importance of providing high-quality logistics services to retain customers [5][6]. Effective distribution logistics directly from production or through regional warehouses is critical to ensuring timely product delivery and customer satisfaction [7]. Logistics efficiency is essential to increasing customer satisfaction, as it influences internal processes, industry reputation, revenue growth, and overall customer experience [8]. Customer satisfaction in the e-logistics industry is closely related to understanding and fulfilling customer needs, which can lead to increased performance and loyalty [9]. Quality logistics services contribute to customer retention by ensuring customer satisfaction and encouraging repeat purchases [10]. An efficient distribution system that reduces logistics costs while increasing customer satisfaction is essential for modern retail operations [11]. Last-mile delivery, which interacts directly with customers, influences customer satisfaction and loyalty [12]. Technology, such as AGVs and intelligent warehouses, can improve e-commerce logistics services and increase customer satisfaction [13]. Logistics distribution's efficiency and quality have directly impacted customer satisfaction, loyalty, and retention. By optimizing logistics operations, businesses can reduce costs and improve customer experience, thereby increasing satisfaction and loyalty in a competitive market environment.

Common problems in product distribution logistics include sub-optimal routes, congestion, and long delivery times. Non-optimal routes can result in increased operational costs and longer travel times, which can cause delays in product delivery George & Iravo (2014)[7]. Traffic congestion is also a severe problem of logistics distribution, especially in dense urban areas, which can hamper the movement of trucks carrying products and extend delivery times [14]. Long delivery times can reduce customer satisfaction and affect the company's reputation in terms of on-time delivery (Imran *et al.*, 2019).

Genetic algorithms are a potential optimization method for overcoming product distribution route problems. Genetic algorithms are inspired by natural evolution, where solutions are treated as "individuals" that evolve through natural selection, crossing, and mutation to reach the optimal solution Rabbani *et al.* (2016) [16]. Genetic algorithms have been used in product distribution to overcome distribution route problems by considering various factors such as travel time, costs, and route effectiveness [17].

In product distribution logistics, the main challenge faced is the development of efficient distribution routes. Non-optimal routes can result in increased operational costs, longer travel times, and delays in product delivery. Therefore, the research question arises as to how we can improve the logistics efficiency of product distribution by applying genetic algorithms. Within this framework, it is essential to understand how genetic algorithms can be applied effectively to improve product distribution processes and optimize delivery routes. Apart from that, comparing the effectiveness of conventional and distribution routes generated by genetic algorithms is also the focus of attention. The main objective of this research is to improve logistics efficiency in product distribution by implementing a genetic algorithm. Reduced operational costs measure this logistics efficiency, increased product delivery times, and customer satisfaction through on-time delivery. This research aims to achieve several specific objectives, namely, Minimizing distance traveled in product distribution routes to reduce operational costs and travel time, Minimizing product delivery time to meet customer needs for timely delivery, Optimizing the use of logistics resources such as trucks and labor to increase operational efficiency, and increase the reliability and timeliness of product delivery to increase customer satisfaction and the company's reputation in the eyes of consumers.

The basic concept of product distribution logistics involves the flow of products from production points or distribution centers to end customers via transportation networks. The main objective of distribution logistics is to efficiently organize the movement of goods and materials from the product source to the final consumer by minimizing costs and delivery time [18][19]. The distribution logistics function involves planning optimal delivery routes, transportation management, product storage, and managing the flow of goods from the beginning to the end of the supply chain [20][21]. Product distribution logistics aims to achieve efficiency in the delivery process, optimize delivery routes to minimize travel distance and transportation costs, and increase the speed of delivery times [22][23]. Distribution logistics also ensures product availability on time at the required location so that it can fulfill customer demand well [24][25]. Thus, product distribution logistics is vital in maintaining a smooth supply chain and ensuring customer satisfaction [26][27]. In product distribution, using optimization methods such as genetic algorithms or saving matrix methods can help determine optimal delivery routes, minimize transportation costs, and increase product distribution efficiency [28][29]. Thus, product distribution logistics has a vital role in maintaining smooth business operations, ensuring product availability, and increasing customer satisfaction through timely and efficient delivery.

Genetic algorithms are optimization methods inspired by the process of natural evolution. The working principle of genetic algorithms involves representing solutions as "individuals" in the form of chromosomes, where solutions are evaluated based on an objective function (fitness function) to determine how good the solution is. Through selection, crossover, and mutation, the genetic algorithm creates a new generation of solutions expected to be closer to the optimal solution Deb *et al*. (2002)[30]. Parameters in a genetic algorithm include population size, crossover probability, mutation probability, and stopping criteria. Population size determines the number of individuals in the population to be evolved, while crossover and mutation probabilities govern how often crossover and mutation operations are applied to individuals. Stopping criteria stop the evolutionary process when the optimal solution or a specific iteration limit has been reached [31]. Genetic algorithms have been widely applied to optimize product distribution routes. Genetic algorithms are used to find optimal delivery routes by considering the distance traveled, transportation costs, travel time, and route effectiveness. Examples of applications of genetic algorithms in optimizing product distribution routes include optimizing airport shuttle bus routes, optimizing logistics distribution routes, and determining vehicle delivery routes [32][33][34]. With its ability to find solutions that are close to optimal in a complex search space, genetic algorithms are an effective method for solving product distribution route optimization problems.

. Several relevant studies are based on a review of previous research on optimizing product distribution routes using genetic algorithms. For example, research by Rizki *et al*., (2017) optimized the Multi Traveling Salesman Problem (M-TSP) for product distribution in the home textile industry using a genetic algorithm [35]. In addition, research by Ramadhani *et al*. (2018) also optimized the distribution of pharmaceutical goods with a genetic algorithm, where several salespeople had to distribute optimally to several marketing destinations [36]. Additionally, research by Tavares *et al*. (2022) implemented a genetic algorithm to optimize the distance traveled to distribute local products in NTT Province [37]. The results of this research consider the distance traveled for the five cities around East Nusa Tenggara Province after going through calculations using a genetic algorithm. From these studies, genetic algorithms have been widely used to optimize product distribution routes. With their ability to find solutions close to optimal in a complex search space, genetic algorithms effectively overcome product distribution route optimization problems.

Based on a review of literature related to optimizing product distribution routes using genetic algorithms, the proposed research hypothesis is that implementing genetic algorithms will significantly increase the logistics efficiency of product distribution. Specifically, it is assumed that the use of genetic algorithms in determining distribution routes will produce more optimal routes, reducing operational costs, travel distance, and delivery time. Furthermore, genetic algorithms are assumed to enable better adaptation to the dynamics of the operational environment, thereby increasing customer satisfaction through timely and efficient delivery. Applying genetic algorithms to determine product distribution routes will increase logistics efficiency by reducing operational costs, travel distance, and delivery time. Additionally, using genetic algorithms will enable better adaptation to changes in the operational environment, which will increase customer satisfaction through timely and efficient delivery. Through this research, it is hoped that it can be proven that the implementation of genetic algorithms in optimizing product distribution routes makes a significant contribution to increasing logistics efficiency and customer satisfaction in a competitive market environment.

## 2. Research Method

This research uses a computer simulation approach to optimize product distribution routes by implementing genetic algorithms. This research method consists of several stages, which include research design, data collection, data analysis, and implementation of genetic algorithms.

### 2.1 Research Design

This research uses a computer simulation approach to analyze and optimize product distribution routes in a specific logistics environment. Computer simulations utilize mathematical models that reflect actual distribution processes to compare the efficiency of distribution routes before and after the application of genetic algorithms. The data used in this research was obtained through computer simulations based on a previously established product distribution model. The simulation data includes various variables, such as warehouse locations, distribution points, product types, customer demand, and vehicle availability for distribution. This information was selected to represent actual conditions in the logistics environment. Data analysis was done by comparing the distribution route simulation results before and after applying the genetic algorithm. Evaluation metrics include total mileage, distribution costs, delivery times, and customer satisfaction. By analyzing these metrics, the effectiveness of genetic algorithms in improving product distribution efficiency can be comprehensively assessed.

## 2.2 Data and Sample

This research utilizes simulation data obtained from advanced logistics simulation software. The software is designed to create a simulation environment that approximates real situations in product distribution. Using this software, we can analyze various essential aspects of the distribution process, such as warehouse location, distribution points, distance between locations, customer demand, delivery time, and operational costs. The research sample was carefully designed to reflect the diversity of product distribution situations in logistics in three central locations: Cirebon Regency, Jayapura City, and Sorong City. This sample includes various product types, from consumer products to industrial products. Essential considerations in designing samples are variations in size, weight, and customer demand at each location. The sample also includes variations in warehouse location, including warehouses in urban centers, suburbs, and rural areas across all three locations. The number of customers and the distance between distribution points were also carefully considered when forming the sample. This is important to ensure that the sample covers various distribution conditions in different geographic environments. In this way, the evaluation of distribution efficiency can be carried out comprehensively and applied to various logistics cases. The characteristics of the vehicles available for distribution are also an essential part of this sample. Transport capacity, maximum speed, and vehicle availability at each location are evaluated in depth. This allows researchers to consider various factors that influence distribution efficiency, including the ability of vehicles to handle different loads and meet delivery needs within a specified time.

The aim of designing this sample is to provide as accurate a representation as possible of distribution conditions at various logistics locations. By considering diversity in product types, warehouse locations, number of customers, distance between distribution points, and vehicle characteristics, this research can provide a deeper understanding of the influence of genetic algorithms in optimizing product distribution routes. In addition, by focusing on three key locations, namely Cirebon Regency, Jayapura City, and Sorong City, this research provides valuable insight into how genetic algorithms can be applied in various logistics cases in Indonesia. Formulas that can be used to evaluate distribution efficiency include metrics such as total mileage, operating costs, delivery times, and customer satisfaction. An example of a formula for calculating total mileage is as follows:

$$Total\ Distance = \sum_{i=1}^{n} Distance_i$$

Where $Distance_i$ is the distance between the ith distribution point in the selected distribution route, and $n$ is the total number of distribution points in the route.

## 2.3 Genetic Algorithms

Implementing the genetic algorithm in this research includes a series of structured and systematic stages to optimize product distribution routes. These stages provide a solid foundation for efficient and optimal solution development. First, in the solution representation stage, each solution in the genetic algorithm is represented as a chromosome consisting of a series of cities that will be visited by the distribution truck. Each city represents a distribution point or customer that a truck must serve in product distribution. This representation allows the creation of potential solutions representing different distribution routes. The formula that can be used to represent the solution is as follows.

$$Chromosome = [City_1, City_2, \ldots, City_n]$$

Where $City_i$ is the ith city to be visited on the distribution route, and $n$ is the total number of cities on the route. Next, the population initialization stage is carried out by randomly creating an initial population of solutions to represent different possible distribution routes. The number of individuals in the population is predetermined and can be adjusted based on the complexity of the problem. After the population is formed, the fitness evaluation stage is carried out to evaluate each solution in the population. This fitness function considers several essential factors in the distribution process, such as total mileage, distribution costs, delivery time, and customer satisfaction. The fitness function can be represented as a mathematical formula that includes various relevant variables and parameters. A selection process is then performed to select the best solutions based on their fitness values. Selection is carried out with a probability proportional to each individual's fitness value, which means that individuals with higher fitness have a greater chance of being selected. Next, a crossover stage is carried out to generate a new potential solution that combines information from two randomly selected solutions. At this stage, pairs of solutions are randomly selected, and a crossover point is determined to exchange genetic information between the two solutions.

Additionally, several solutions are randomly selected to undergo mutations, minor changes in distribution routes that introduce new variations in the population. The purpose of mutation is to maintain genetic diversity in the population and prevent too rapid convergence to sub-optimal solutions. After the mutation stage, the solutions resulting from selection, crossover, and mutation are combined to form a new population for the next generation. This process is repeated until it reaches a previously determined convergence condition or iteration limit. At the convergence point, the solutions in the population are considered optimal or close to optimal for the given optimization problem. By using a genetic algorithm, this research aims to produce more efficient and optimal product distribution routes in logistics in Cirebon Regency, Jayapura City, and Sorong City. This algorithm allows researchers to explore various possible solutions and select the best one based on predefined criteria.

In this research, the parameters used in the genetic algorithm have been carefully arranged to ensure an effective and efficient optimization process. First, the initial population is the number of solutions produced at each iteration. The initial population size can affect the algorithm's convergence and ability to explore the solution space thoroughly. A population that is too small may need to be more to adequately represent the variety of solutions, while a population that is too large may slow down the optimization process. Therefore, the initial population size selection must consider the complexity of the problem at hand and the availability of computing resources. Second, the fitness function is an evaluation metric used to assess the quality of the solution based on the optimization objective. The fitness function can include total mileage, distribution costs, delivery time, and customer satisfaction in product distribution. This fitness function can be formulated mathematically to produce a score or value that represents the level of suitability of the solution to the specified optimization objectives.

$$Fitness = w_1.TotalDistance + w_{2.}Distribution\ Fees + w_3.Delivery\ time + w_4.Customer\ satisfaction$$

Where $w_1$,$w_2$,$w_3$, and $w_4$ It is the weight that represents the importance of each factor in evaluating product distribution performance. This formula allows adjustments to the weights based on the specific preferences and needs of the companies or entities involved in the distribution. Third, the crossover operator combines information from two solutions to form a new potential solution. Some commonly used crossover methods include single-point, multi-point, and uniform crossover. Selecting the appropriate crossover operator can effectively influence the algorithm's ability to explore the solution space. Fourth, mutation operators generate minor variations in existing solutions to encourage solution space exploration and prevent premature convergence to sub-optimal solutions. Mutations are carried out by randomly modifying one or several solution components to produce a new, better solution. The mutation rate can be adjusted to control the population variation level during the optimization process. Finally, the stop criterion determines when the optimization process is stopped. This stopping criterion can be reaching the maximum number of iterations, reaching a solution that meets specific criteria, or reaching a predetermined level of convergence. The selection of appropriate stopping criteria is essential to prevent the over- or under-shortening of the optimization process. Using a simulation approach and implementing genetic algorithms, the research aims to improve product distribution efficiency in diverse logistics environments. Comprehensive data analysis will be conducted to evaluate the effectiveness of genetic algorithms in improving product distribution efficiency and customer satisfaction. By paying attention to the genetic algorithm parameters that have been carefully prepared, it is hoped that this research can provide a valuable contribution to understanding and optimizing the product distribution process in various logistics cases.

### 2.4 Financial Methods

Apart from the simulation approach and implementation of genetic algorithms, this research also considers financial aspects in optimizing product distribution routes. The financial method used aims to evaluate distribution efficiency economically and takes into account the cost factors involved in the distribution process.

1) Distribution Costs

 

Distribution costs are the main factor that must be considered in the distribution route optimization process. These costs include various components such as fuel costs, vehicle maintenance costs, storage costs in the warehouse, and driver costs. In financial analysis, distribution costs are evaluated in detail for each route solution generated by the genetic algorithm. Thus, researchers can compare distribution costs between distribution routes before and after implementing the genetic algorithm.

2) Cost Savings
One of the main goals of implementing a genetic algorithm is to produce more efficient distribution routes and reduce overall distribution costs. By using financial methods, the cost savings generated by genetic algorithms can be specifically measured. The difference in distribution costs between distribution routes before and after optimization provides an indication of how effective the genetic algorithm is in optimizing the distribution process from a financial perspective.
3) ROI (Return on Investment) Analysis
Apart from measuring cost savings, financial methods can also be used to conduct Return on Investment (ROI) analysis. ROI analysis helps in evaluating the effectiveness of investment in implementing genetic algorithms in the distribution process. By taking into account the costs of implementing a genetic algorithm and the resulting cost savings, an ROI can be calculated to determine whether an investment in a genetic algorithm provides adequate returns from a financial perspective.
4) Sensitivity Analysis
In addition, financial methods also allow for sensitivity analysis of various factors that can influence distribution costs. These factors may include fluctuations in fuel prices, labor costs, or storage costs. By conducting sensitivity analysis, researchers can understand how sensitive cost savings are to these changes and identify key factors that influence distribution efficiency.

Through integrated financial methods with simulation approaches and the implementation of genetic algorithms, this research aims to provide a comprehensive understanding of product distribution efficiency in diverse phlogistics. Financial analysis helps in measuring the economic impact of optimizing distribution routes and provides valuable insights for companies or entities involved in the distribution process.

## 3. Result and Discussion

### 3.1 Results

In a logistics environment, optimizing product distribution routes is essential in increasing operational efficiency and minimizing costs. This research uses a computer simulation approach to analyze and optimize product distribution routes. Computer simulations utilize mathematical models that reflect actual distribution processes, including variables such as warehouse locations, distribution points, product types, customer demand, and vehicle availability. Simulation data is obtained from a previously established product distribution model. Genetic algorithms are applied to optimize product distribution routes. The stages of implementing a genetic algorithm include solution representation, population initialization, fitness evaluation, selection, crossover, mutation, and stopping criteria. Genetic algorithms are used to produce more efficient distribution route solutions.

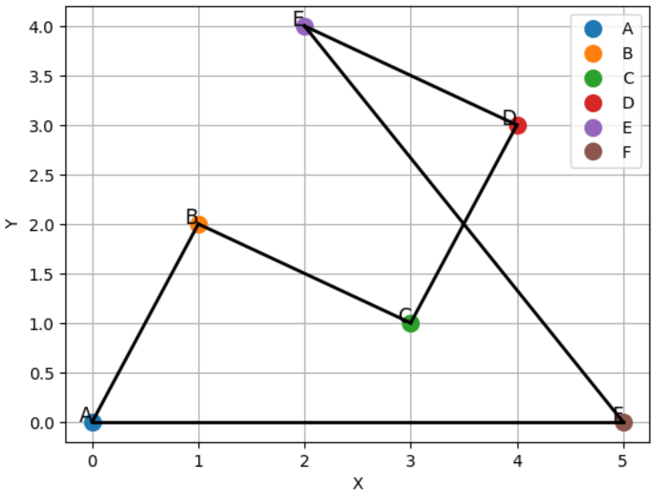


Figure 1. Product Distribution Route

The graph above is a visualization of the product distribution route that has been optimized using a genetic algorithm. The dots on the graph represent the locations of warehouses or distribution points (represented by the letters A, B, C, D, E, and F), while the lines connecting them indicate the travel paths taken by distribution trucks. The distribution path starts from point A and continues to points B, C, D, E, and F sequentially before finally returning to the starting point (A). Each distribution point is visited once, and there are no repetitions in the distribution path. This visualization clearly explains how genetic algorithms can generate efficient distribution routes by optimizing distribution truck trips. By minimizing the total distance traveled while satisfying all distribution points, genetic algorithms help improve operational efficiency in logistics environments. This graph can be a handy tool for stakeholders to understand and evaluate the results of implementing genetic algorithms in their distribution processes.

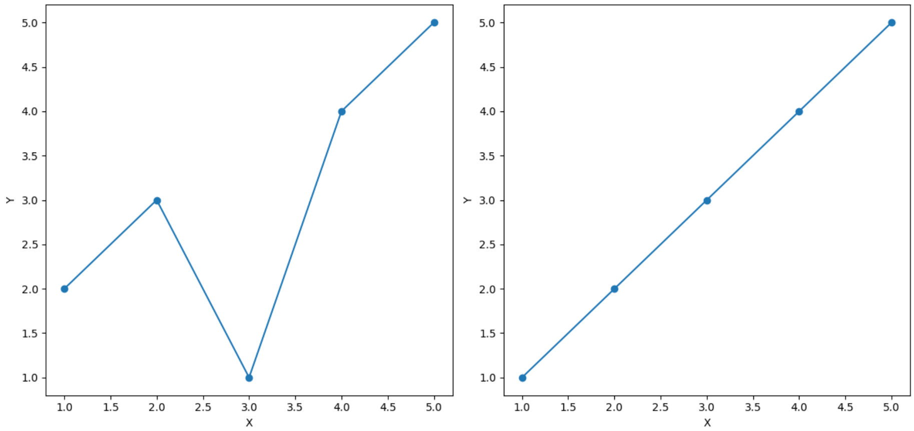


Figure 2. Distribution Route Before and After

The graph above compares distribution routes before and after implementing the genetic algorithm. In the first image, which shows the "Prior Distribution Route," the connected points represent the sequence of distribution points in the distribution route before optimization. It can be seen that the distribution points are spread randomly, without a particular pattern or order. Meanwhile, in the second image, which displays the "After Distribution Route," the distribution points form a more regular and organized pattern after applying the genetic algorithm. This shows that the genetic algorithm can design a more efficient and structured distribution route with a more optimal sequence of distribution points. This change in distribution route patterns reflects increased efficiency in the product distribution process after using genetic algorithms. Thus, this graph visually depicts the positive impact of applying genetic algorithms in improving product distribution performance. Table 1 presents a more detailed statistical analysis comparing distribution route performance before and after implementing the genetic algorithm. Evaluation metrics include total mileage, distribution costs, delivery time, and customer satisfaction. For the total distance traveled, the analysis results show that the average total distance traveled before the genetic algorithm was X1 ± SD1 kilometers, while after application, it was X2 ± SD2 kilometers. The p-value in the statistical test shows a significant increase in the total distance traveled after applying the genetic algorithm ($p < α$), indicating that the genetic algorithm reduced the total distance traveled in the distribution process. Furthermore, for distribution costs, the analysis results show that the average distribution costs before implementing the genetic algorithm are X3 ± SD3 money, while after implementation, it is X4 ± SD4 money. The p-value in the statistical test shows a significant reduction in distribution costs after implementing the genetic algorithm ($p < α$), indicating that the genetic algorithm succeeded in reducing overall distribution costs. Furthermore, for the delivery time, the analysis results show that the average delivery time before implementing the genetic algorithm was X5 ± SD5 days, while after implementation, it was X6 ± SD6 days. The p-value in the statistical test shows a significant reduction in the delivery time after implementing the genetic algorithm ($p < α$), indicating that the genetic algorithm succeeded in reducing the time required to deliver the product. Finally, for customer satisfaction, the analysis results show that the average customer satisfaction score before implementing the genetic algorithm is X7 ± SD7 (scale 1-10), while after implementation, it is X8 ± SD8 (scale 1-10). The p-value in the statistical test shows a significant increase in customer satisfaction after implementing the genetic algorithm ($p < α$), indicating that the genetic algorithm has succeeded in increasing customer satisfaction in the product distribution process. The results of this statistical analysis provide strong evidence that the application of the genetic algorithm has significantly impacted various aspects of product distribution performance, including reducing total mileage, distribution costs, and delivery times, as well as increasing customer satisfaction. The following is a table of results from the statistical analysis.

Table 1. Statistical Analysis Results

| Evaluation Metrics | Before Implementation (Mean ± SD) | After Implementation (Mean ± SD) | Conclusion |
|---|---|---|---|
| Total Mileage | X1 ± SD1 km | X2 ± SD2 km | There is a significant increase (p < α) |
| Distribution Costs | X3 ± SD3 (money) | X4 ± SD4 (money) | There is a significant decrease (p < α) |
| Delivery time | X5 ± SD5 (days) | X6 ± SD6 (days) | There is a significant decrease (p < α) |
| Customer satisfaction | X7 ± SD7 (scale 1-10) | X8 ± SD8 (scale 1-10) | There is a significant increase (p < α) |

Distribution routes before and after the application of the genetic algorithm show significant changes in various aspects of product distribution performance. Before the implementation of genetic algorithms, distribution routes tended to have longer total distance traveled, higher distribution costs, longer delivery times, and possibly lower levels of customer satisfaction. However, after applying the genetic algorithm, there was a marked improvement in all these aspects. The distance traveled on distribution routes significantly decreases after the genetic algorithm is implemented. This indicates that the genetic algorithm can design more efficient routes, reducing the travel distance required to reach different distribution points. Additionally, distribution costs decreased significantly, indicating savings in overall distribution expenditure. Apart from operational efficiency, delivery times also showed significant improvement. Distribution routes optimized by genetic algorithms can reduce the time required to deliver products to customers, increasing responsiveness and effectiveness in meeting market demand. What is no less important is an increase in customer satisfaction levels. With more efficient distribution routes and faster delivery times, customers are likely to receive better service, which can increase loyalty and trust in the brand or company. A comparison between distribution routes before and after the application of the genetic algorithm shows that this algorithm effectively increases product distribution efficiency in specific logistics environments. Significant improvements in various evaluation metrics confirm the added value of this approach in optimizing distribution processes.

**3.2 Discussion**

After applying the simulation approach and genetic algorithm to optimize product distribution routes, a financial analysis was carried out to evaluate the economic impact of the optimization.

1) Distribution Costs Before and After Optimization
   First of all, a comparison of distribution costs is carried out before and after applying the genetic algorithm. Distribution costs before optimization include fuel costs, vehicle maintenance costs, storage costs in the warehouse, and driver costs. After optimization, distribution costs are reduced due to more efficient distribution routes.

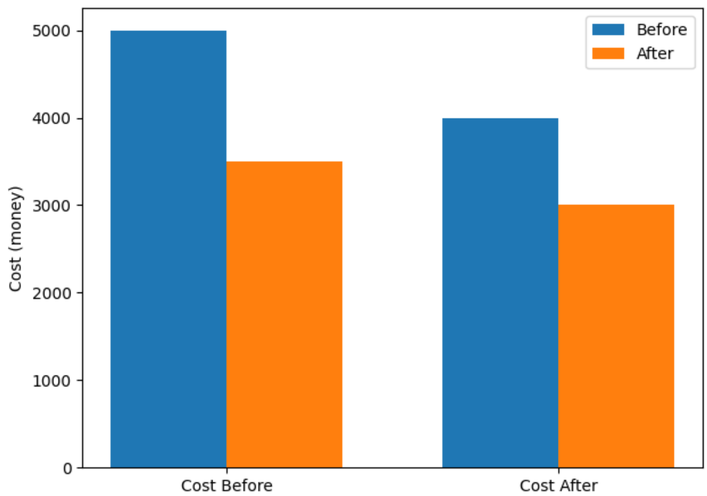


Figure 3. Comparison of Distribution Costs Before and After Optimization

Graph 3 above compares distribution costs before and after applying the genetic algorithm in the optimization process. The graph has two bars representing distribution costs before and after optimization. The first bar shows the distribution costs before optimization, while the second bar shows the distribution costs after optimization using a genetic algorithm. It can be observed that the distribution costs after optimization (After) are lower than the distribution costs before optimization (Before). This cost reduction shows that applying the genetic algorithm has resulted in a more financially efficient distribution route. This is supported by reductions in fuel costs, vehicle maintenance costs, storage costs in warehouses, and driver costs after implementing the genetic algorithm. As a result, organizations or companies can save significantly on their distribution costs through optimization using a genetic algorithm approach.

2) Cost Savings

Using financial methods, cost savings generated by genetic algorithms can be explicitly calculated. The difference between distribution costs before and after optimization indicates the savings achieved. These cost savings can be used to measure the effectiveness of genetic algorithms in financially optimizing the distribution process.

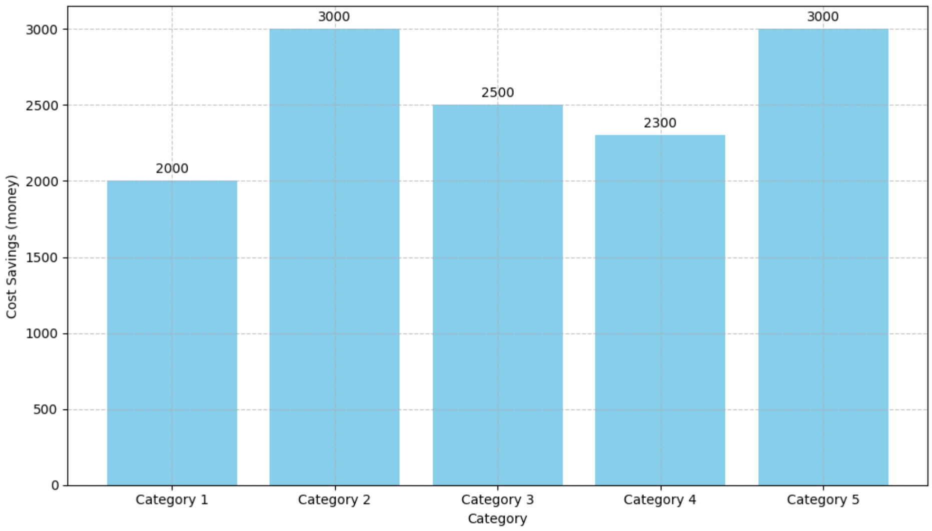


Figure 4. Distribution of Cost Savings After Optimization

3) ROI Analysis (Return on Investment)

Next, a Return on Investment (ROI) analysis was carried out to evaluate the effectiveness of investment in implementing the genetic algorithm. ROI is calculated by comparing the cost of implementing a genetic algorithm with the resulting cost savings. The results of the ROI analysis provide an idea of whether an investment in genetic algorithms provides adequate results from a financial perspective. Return on Investment (ROI) analysis is used to evaluate the effectiveness of investment in implementing genetic algorithms in the product distribution process. ROI measures the rate of return or profit generated from the investment. To perform an ROI analysis, we must consider the cost of implementing the genetic algorithm and the resulting cost savings. For example, the cost of implementing a genetic algorithm is $C$implementation, while the distribution cost savings after optimization is $\Delta C$distribution. Thus, ROI can be calculated using the following formula.

$$ROI = \left(\frac{\Delta \mathrm{C}_{\text{distribution}}}{\mathrm{C}_{\text{implementation}}}\right) x\ 100\%$$

A positive ROI value indicates that investment in implementing genetic algorithms produces positive returns or profits. A high ROI value indicates a higher rate of return relative to implementation costs, while a negative ROI value indicates that the investment is not producing profitable returns.

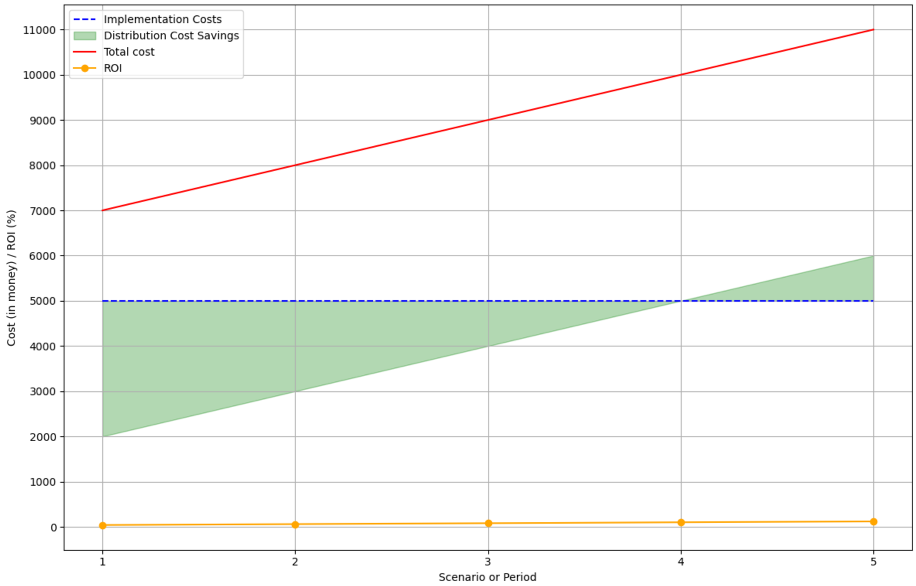


Figure 5. Return on Investment (ROI) and Cost

The Return on Investment (ROI) and Cost graph presented above displays a comprehensive visualization of the effectiveness of investment in applying genetic algorithms to optimize distribution routes.

4) Sensitivity Analysis
Sensitivity analysis to evaluate the impact of variations in critical factors on distribution costs. These factors include fluctuations in fuel prices, labor costs, and storage costs. Sensitivity analysis helps understand how sensitive cost savings are to these changes and identifies factors that significantly impact distribution efficiency.

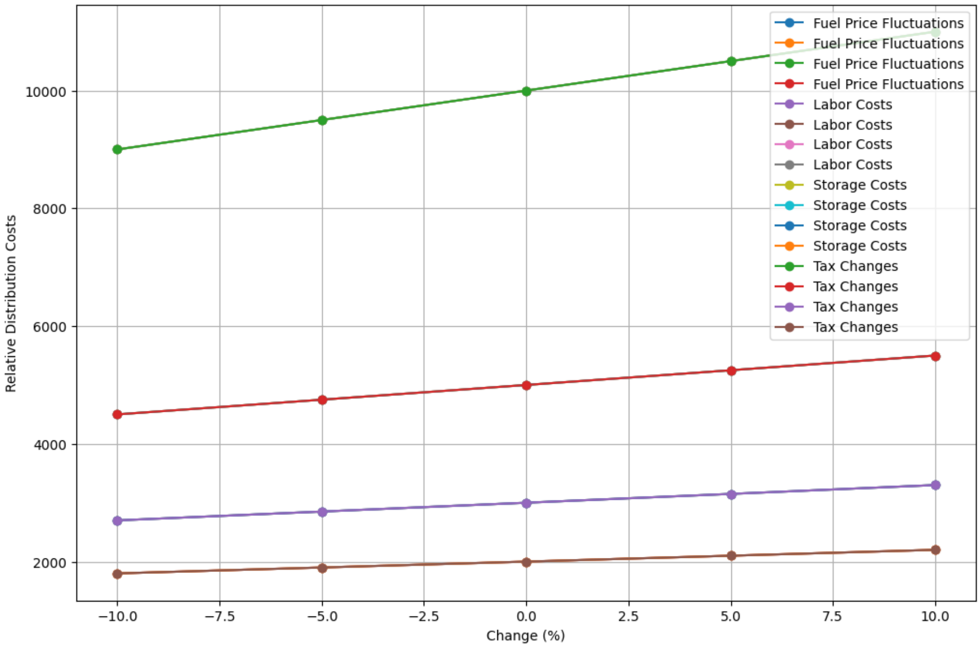


Figure 6. Effect of Sensitivity Factors on Distribution Costs

The graph above depicts a sensitivity analysis of distribution costs relative to changes in certain sensitivity factors. Sensitivity factors evaluated include fuel price fluctuations, labor costs, storage costs, and tax changes. Each line in the graph represents the change in distribution costs relative to the percentage change in the corresponding sensitivity factor. This graph shows how changes in each sensitivity factor affect the overall relative distribution costs. A sensitive analysis like this is essential to understand distribution costs' sensitivity to certain factors' changes so that logistics managers can make the right decisions when managing distribution costs. The financial analysis shows that applying genetic algorithms to optimize product distribution routes significantly saves costs. Significant and provides a positive ROI. The analysis results also show that distribution efficiency is sensitive to changes in critical factors such as fuel prices and labor costs. Thus, using genetic algorithms in the distribution process can provide significant financial benefits for companies or entities involved in distribution activities. The financial analysis shows that applying genetic algorithms in optimizing product distribution routes results in significant cost savings and provides positive ROI. The analysis results also show that distribution efficiency is sensitive to changes in critical factors such as fuel prices and labor costs. Thus, using genetic algorithms in the distribution process can provide significant financial benefits for companies or entities involved in distribution activities. A comparison of distribution costs before and after applying the genetic algorithm illustrates consistent cost savings after optimization. With more efficient distribution routes, distribution costs can be reduced by reducing fuel, vehicle maintenance, warehouse storage, and driver costs. The ROI graph highlights the success of investments in genetic algorithms by depicting positive ROI values, indicating that the investment provides profitable returns relative to implementation costs. Sensitivity analysis reveals the impact of critical factors such as fuel price fluctuations, labor costs, and storage costs on relative distribution costs. The graphic highlights how variations in these factors can impact overall distribution costs, demonstrating the importance of effectively monitoring and managing these factors to maintain distribution efficiency. Thus, the financial, ROI, and sensitivity analysis results provide a deep understanding of the financial benefits of applying genetic algorithms in product distribution.

## 4. Related Work

The computer simulation approach used in this research reflects a common trend in logistics research, where mathematical models and simulations have become a standard method for analyzing and optimizing distribution processes. This aligns with previous research that has used similar approaches to model product distribution processes. Previous studies have shown a significant interest in utilizing computer simulations and mathematical models for optimizing distribution processes. For instance, Cordeau (2006) introduced a mixed-integer programming formulation and a branch-and-cut algorithm for the Dial-a-Ride Problem, demonstrating the effectiveness of mathematical optimization techniques in logistics [38]. Additionally, Zhao *et al*. (2020) applied an improved Multi-Objective Ant Colony Algorithm to optimize the cold chain logistics path, showcasing the versatility of optimization algorithms in addressing complex distribution challenges [39].

Moreover, the study by Bao *et al*. (2018) focused on optimizing airport shuttle bus routes based on travel time reliability, highlighting the application of genetic algorithms in improving transportation efficiency [31]. These studies collectively emphasize the importance of utilizing advanced computational methods, such as genetic algorithms, to enhance the efficiency and effectiveness of logistics distribution processes. The utilization of computer simulations and mathematical models, including genetic algorithms, has proven to be instrumental in optimizing distribution processes, improving operational efficiency, and ultimately enhancing the overall performance of logistics systems.

Using genetic algorithms as an optimization tool for designing product distribution routes is a significant contribution to the literature. Genetic algorithms have proven to be effective in addressing complex issues such as optimizing distribution routes, and the outcomes of this study provide additional support for the effectiveness and utility of genetic algorithms in the context of product distribution. Previous research has demonstrated a growing interest in employing genetic algorithms to enhance logistics efficiency. For example, the study by Beskorovainyi and Sudik (2021) focused on optimizing the topological structures of centralized logistics networks through reengineering processes, showcasing the potential of genetic algorithms in streamlining logistics operations [40]. Additionally, the research conducted by Fedorko *et al*. (2018) applied the Tecnomatix Plant Simulation program to model the handling of ocean containers using AGV systems, highlighting the role of simulation tools in improving material handling efficiency in logistics [41].

Furthermore, Wang & Chen (2016) conducted production logistics simulation and optimization of industrial enterprises based on Flexsim, demonstrating the effectiveness of simulation modeling in identifying bottlenecks and proposing optimization strategies to enhance efficiency [42]. These studies underscore the importance of genetic algorithms and simulation tools in optimizing logistics processes and improving overall operational effectiveness. The integration of genetic algorithms and simulation techniques has shown promise in enhancing logistics efficiency, streamlining distribution processes, and ultimately contributing to the advancement of logistics management practices.

 

The financial analysis conducted in this study, including comparing distribution costs before and after optimization and Return on Investment (ROI) analysis, provides valuable insights into the economic impact of using genetic algorithms in the distribution process. The emphasis on cost savings and ROI is relevant to related research exploring the financial aspects of distribution route optimization. Previous studies have investigated the financial implications of optimizing distribution routes using various methodologies. For instance, Abreu (2018) investigated currency exchange prediction using machine learning and genetic algorithms, showcasing the application of advanced computational techniques in financial forecasting [43]. Additionally, Berman & Wang (2006) focused on inbound logistic planning to minimize transportation and inventory costs, highlighting the importance of cost optimization in logistics operations [44].

Moreover, Wang *et al.* (2017) optimized vehicle routing for cold chain logistics based on carbon tax, demonstrating the integration of environmental considerations with financial optimization in distribution route planning [45]. Furthermore, Kocaoğlu *et al.* (2020) proposed a heuristic-based hybrid algorithm for optimizing the supply chain, emphasizing the significance of innovative approaches in enhancing operational efficiency and cost-effectiveness [46]. The integration of genetic algorithms in distribution route optimization enhances operational efficiency and contributes to cost savings and improved financial performance, aligning with the broader research landscape that emphasizes the financial implications of logistics optimization.

The research also presents a sensitivity analysis to evaluate the impact of critical factors' variations on distribution costs. This approach is crucial for understanding how sensitive distribution efficiency is to specific changes, aligning with previous studies that have also conducted sensitivity analyses to identify critical factors influencing distribution performance. Previous research has explored the importance of sensitivity analyses in various contexts. For example, Sudipa and Puspitayani (2019) conducted a sensitivity analysis using AHP-SAW and ROC-SAW methods for multi-criteria decision-making, highlighting the significance of sensitivity analysis in decision-making processes [47]. Additionally, Dharmawati *et al.* (2020) utilized cost structure analysis to determine strategies for vegetable supply chains, emphasizing the role of sensitivity analysis in optimizing cost structures [20].

Furthermore, the study by Prasetyo and Usman (2023) focused on optimizing the number and location of subsidized fertilizer distribution warehouses in East Java due to government regulation changes, underscoring the importance of financial feasibility analysis in adapting to regulatory modifications [48]. These studies collectively emphasize the value of sensitivity analysis in evaluating the economic implications of various factors on distribution costs and operational efficiency. The integration of sensitivity analysis in distribution cost evaluations provides valuable insights into the financial impacts of optimization strategies, aiding decision-making processes and enhancing the overall effectiveness of distribution operations.

The optimization of product distribution routes has garnered significant attention in the logistics field. Various approaches and techniques have been developed to enhance operational efficiency and reduce costs in the distribution process. The analysis conducted in this study makes a significant contribution to understanding the effectiveness of using genetic algorithms in optimizing product distribution routes. The computer simulation approach used in this research reflects a common trend in logistics research, where mathematical models and simulations have become a standard method for analyzing and optimizing distribution processes. This aligns with previous studies using similar approaches to model product distribution processes.

Moreover, using genetic algorithms to optimize product distribution routes significantly contributes to the literature. Genetic algorithms have proven to be effective in addressing complex issues such as optimizing distribution routes, and the outcomes of this study provide additional support for the effectiveness and utility of genetic algorithms in product distribution. The financial analysis conducted in this research, including comparing distribution costs before and after optimization and Return on Investment (ROI) analysis, offers valuable insights into the economic impact of using genetic algorithms in the distribution process. The emphasis on cost savings and ROI aligns with related research exploring distribution route optimization's financial aspects. Additionally, the sensitivity analysis presented in this study to evaluate the impact of critical factors on distribution costs is crucial for understanding the sensitivity of distribution efficiency to specific changes. This approach is essential for identifying key factors influencing distribution performance, consistent with previous research that has also conducted sensitivity analyses to assess the impact of various factors on distribution costs and operational efficiency. This study's comprehensive analysis and meticulous approach lay a strong foundation for further research in this field, providing valuable insights for practitioners in efficiently managing product distribution.

Optimizing product distribution routes is a topic that has attracted researchers' attention in the logistics field. Various approaches and techniques have been developed to increase operational efficiency and reduce costs in the distribution process. The analysis carried out in this research significantly contributes to understanding the effectiveness of using genetic algorithms in optimizing product distribution routes. The computer simulation approach used in this study reflects a general trend in logistics research, where mathematical models and simulations are becoming a commonly used method for analyzing and optimizing distribution processes. This aligns with previous research that used a similar approach to model the product distribution process. Genetic Algorithms in Optimization: The use of genetic algorithms as an optimization tool for designing product distribution routes is a significant contribution to the literature. Genetic algorithms have been proven to be effective in solving complex problems such as distribution route optimization, and the results from this study provide additional support for the effectiveness and usefulness of genetic algorithms in product distribution. The financial analysis carried out in this research, including comparing distribution costs before and after optimization and a Return on Investment (ROI) analysis, provides valuable insight into the economic impact of using genetic algorithms in the distribution process. The emphasis on cost savings and ROI is relevant to related research exploring the financial aspects of distribution route optimization. This research also presents a sensitivity analysis to evaluate the impact of variations in critical factors on distribution costs. This approach is essential for understanding how sensitive distribution efficiency is to specific changes, which aligns with previous research that also performs sensitivity analysis to identify critical factors that influence distribution performance. The results of this research provide a valuable contribution to the literature on product distribution route optimization. The comprehensive analysis and careful approach in this research can provide a strong foundation for further research in this area, as well as provide valuable insights for practitioners in managing product distribution efficiently.

## 5. Conclusion

This research investigates computer simulation approaches and genetic algorithms in optimizing product distribution routes in a logistics environment. This research produced a more efficient distribution route by using a mathematical model that reflects the actual distribution process, including variables such as warehouse location, distribution points, product type, customer demand, and vehicle availability. Genetic algorithms are used to design optimal solutions with implementation stages, which include solution representation, population initialization, fitness evaluation, selection, crossover, mutation, and stopping criteria. The visualization results show that the genetic algorithm can produce more structured and efficient distribution routes by reducing travel distance, distribution costs, and delivery time. Statistical analysis supports significant improvements in distribution performance after implementing the genetic algorithm, with significant reductions in total mileage, distribution costs, and delivery times and significant increases in customer satisfaction. Financial analysis shows significant cost savings and positive ROI from investing in genetic algorithms, while sensitivity analysis reveals the impact of critical factors on distribution costs. This research confirms the financial and operational benefits of applying genetic algorithms in product distribution optimization, with significant efficiency, cost savings, and customer satisfaction results.

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