2301-9069 (e)
1829-8370 (p)

Kapal: Jurnal Ilmu Pengetahuan dan Teknologi Kelautan
(Kapal: Journal of Marine Science and Technology)

journal homepage : http://ejournal.undip.ac.id/index.php/kapal

Selection of the Best Ship Route For Container Shipping Optimization Models Using Heuristic Algorithms

Jon Mangatas Budiarto Sirait[1)*)], Gunawan[1)], Allesandro Setyo Anggito Utomo[1)]

[1)] Department of Mechanical Engineering, Faculty of Engineering, University of Indonesia
Jl. Margonda Raya, Kampus UI Pondok Cina, Depok, Indonesia 16424
[*)] Corresponding Author: Jon.mangatas@ui.ac.id

Article Info

Keywords:
Ant Colony Optimization; algorithm;
Asymmetric Travelling; Salesman Problem;
Genetic Algorithm;
Ship Route Optimization;

Article history:
Received: 02/02/2023
Last revised: 19/05/2023
Accepted: 20/05/2023
Available online: 20/05/2023
Published: 12/06/2023

DOI:
https://doi.org/10.14710/kapal.v20i2.51642

Abstract

The role of ships is essential for world trade to transport goods between countries and regions. Therefore, issues such as the selection of ship routes are crucial in efforts to minimize operational costs. However, most of the ship's operational costs are from fuel consumption, and fuel prices vary significantly at each port. This study implements an optimization method using a heuristic algorithm for selecting ship routes to minimize operational costs. Data on sea mile distances between ports, ship speed, engine power, and fuel prices for each port are processed into an Asymmetric Travelling Salesman Problem (ATSP) model. Application of 2 heuristic algorithms, namely: Genetic Algorithm and Ant Colony, to solve the ATSP model with the minimum fuel cost objective function. Variations in route selection's initial/final destinations are also performed as additional test parameters of each algorithm. The results show that the Ant Colony algorithm provides eight routes with lower fuel costs. In comparison, the genetic algorithm provides two routes with lower fuel costs. This proves the Ant Colony algorithm is more effective in selecting ship routes with minimum fuel costs.

1. Introduction

Distributing goods between regions has increased due to fluctuating prices and rising fuel costs. With container scarcity, shipping companies, ship owners, and other stakeholders must prioritize efficiency. The logistics industry plays a vital role in social life and the supply of social needs through transportation. Economic development and improving people's lives are closely linked to the logistics industry [1]. The network design comprises the selection of harbors and transshipment stations and their connection by a network of main routes for large cargo ships and local routes for smaller feeder ships, which collect and distribute the cargo [2]. Sea transportation is a widely used shipping process that supports the economy from source to destination by efficiently and effectively moving goods or services and related information to meet customer needs. Ports worldwide handle more than 70% of global trade by value and approximately 80% by volume. As a result, sea transportation costs are significant [3].

Network optimization in shipping container ships. Container routing issues in liner shipping differ from those in bum or special cargo shipping. The logistical distribution problems in container shipping relate to many shipments, multiple pick-up and delivery points, multiple routing options, strict service schedules, and complicated container exchange processes according to different route services. Based on the existing problems, it is essential to determine the optimal route for container cargo and fuel operations to realize an optimal shipping system with minimum shipping costs according to the ship and port capacity on each route [4].

As a maritime or archipelagic country with more than 13,466 islands and about two-thirds of its territory is the sea, Indonesia faces several problems related to the maritime logistics system and price disparity between the eastern and western regions of Indonesia [5]. The leading cause of this problem is the imbalance in the flow of goods between the two regions because most of the container shipping from the East to the West has almost no goods to transport, which makes shipping costs higher. Therefore, the Indonesian government initiated the Sea Highway program, a sea transportation service concept involving 24 port strategies to reduce national logistics costs and lowering price disparities between regions for an evenly distributed economy in Indonesia. This program began operating in 2016 with six service route networks connecting the main ports with sub-feeder ports on the minor islands. As a PT project, Pelni is a state-owned company. After evaluating its implementation, the Indonesian government agreed by deciding to improve route services by increasing service routes to 13 ports. This program continuously improves yearly, focusing on enhancing shipping route services and container flows.

A dynamic programming algorithm and a greedy algorithm have been applied by [6], to solve the Knapsack problem in freight transportation. The basic concept and the steps of using both algorithms were described in the paper, including comparing the results. But not considering shipping routes.

According to the research by [7], route optimization of township logistics distribution considers customer satisfaction based on an adaptive genetic algorithm compared to the traditional algorithm by validating the effectiveness of the proposed algorithm to compare the results between the two algorithms. This study solves the cost-minimizing routing problem:

- The total cost of the distribution process
- The penalty fee for the delivery of vehicles exceeding the specified time interval
- The charge of allocating vehicles
- The penalty fee for vehicle loads

This problem includes the distribution of goods for customer satisfaction in the shortest time.

In this study, the heuristic algorithm optimization model provides the best container ship shipping routes regarding fuel operating costs to determine the optimal value of container cargo and obtain efficiency for shipping companies by developing the Travelling Salesman Problem (TSP) model to solve the problem of container ship routes with optimum fuel costs. It aims to meet customer needs and achieve the shortest distance under constraints such as minimum cost and fastest time.

Based on the background described in the previous section, the problem discussed in this study is how to determine routes for container ship services from the West to the East in Indonesia for shipping companies so that low fuel costs can be obtained. The purpose of the problems discussed is to determine shipping routes for container ships by minimizing ship fuel costs from the west end to the east end by stopping at each port which is the parameter of this research. The benefit of this research is to get an overview of the network design of container ship route services in Indonesian territory for shipping companies by considering low fuel costs so that shipping companies can apply the results as alternative solutions to reduce ship operations and improve the quality of shipping network services.

2. Methods

2.1. Vehicle Route Problems

Several methodologies can be used to determine shipping routes: stages to be done systematically to obtain the best results. In the needs analysis stage, the problem to be solved is defined. From various kinds of research and journals read, problems in ship routes are chosen to be a problem that will be sought for a solution. The processed variables are nautical mile distance, ship speed, and engine power. The issue of vehicle routing has been extensively researched by researchers worldwide. This study focuses on the problem of determining the route for container ships at several destination ports to be visited. Along the shipping route, choosing the route of sailing ships stopping at each port is a parameter in the study to minimize ship operations, in this case, the fuel cost for container ships. The type of ship and distribution channels strongly influences the optimization of distribution channels. Optimizing the LNG distribution route using the Greedy Algorithm approach considers ship capacity, speed, the distance between delivery points, transportation costs, and customer demand [8].

Table 1 Matrix Distance of Sea Miles Between Ports

	Dumai	Jakarta	Batam	Surabaya	Makassar	Manado	Bitung	Ambon	Timika	Merauke
Dumai	0	687	189	867	1153	1412	564	1636	2161	2413
Jakarta	687	0	598	386	806	1539	1517	2068	1812	2017
Batam	189	598	0	1016	1235	1871	1874	2399	1997	2948
Surabaya	867	386	1016	0	437	1253	1231	1782	1451	2720
Makassar	1153	806	1235	437	0	812	790	1341	1124	2279
Manado	1412	1539	1871	1253	812	0	63	566	805	1504
Bitung	564	1517	1874	1231	790	63	0	551	1088	1489
Ambon	1636	2068	2399	1782	1341	587	566	0	537	1042
Timika	2161	1812	1997	1451	1124	805	1188	537	0	357
Merauke	2413	2017	2948	2720	2279	1504	1489	1042	357	0

Another method uses integer linear programming to develop the model by applying a greedy algorithm for ship allocation and determining the optimal shipping frequency on each route with scheduling calculations [9]. The goal is to obtain the optimal solution at a minimum cost from the alternative solutions. The approach used in the Genetic Algorithm and Ant Colony chooses the route with the lowest fuel costs, hoping the optimization process will produce a globally optimum solution. Operational costs in the case of shipping only consider fuel costs and do not include shipping cost components.

2.2. Indonesian Port Data

This research needs data regarding the distance between ports in ships' operational routes [10]. In addition, the price of fuel for ships at each port [11], the speed of container ships [12], and the power of the ship's main engine and auxiliary engines [13]. The data is from related journals and online sites that provide reliable information. Container ship speed data, container ship engine power. Before, scenario calculation is needed to analyze the model's ability to adapt to several conditions that often occur in container shipping. Primary data for the numerical example calculation are presented in Tables 1–5.

Table 2. LSFO and HSFO Fuel Prices at Each Port

Harga	USD/Ton
Jakarta	1084
Surabaya	1095
Dumai	1257
Batam	1257
Makassar	1272
Manado	1272
Bitung	1272
Ambon	1284
Timika	1284
Merauke	1284

In designing the model, the data that has been collected is processed into a mathematical model of the Asymmetric Travelling Salesman Problem (ATSP) so that it can be solved with a predetermined optimization algorithm. The development of the Travelling Salesman Problem model is aimed at the initial/final destination of the port being visited in one route operation. Therefore, the shipping route aims to minimize fuel costs. Based on research by[14] application of the travelling salesman genetic algorithm problem with time window: a case study of the laundry shuttle route, an optimization of the travel route is obtained with a combination of paths that will be traversed once and return to the starting point.

Table 3. Average Ship Speed by Type Boat Dimension

Tipe Kapal	V (knots)
Auto Carrier	18.7
Bulk	14.5
Container Ship	21.6
Cruise Ship	20.9
General Cargo	15.2
Miscellaneous	13.0
OG Tug	14.5
RORO	16.8
Reefer	19.5
Tanker	14.8

Design a mathematical model of the existing problems, and design an optimization program using the Python programming language using two heuristic algorithms, namely the genetic algorithm and Ant Colony Optimization. The objective function of both programs is to find shipping routes with the lowest fuel costs. Two outputs from each algorithm program will be obtained: The selection of ship routes and operational costs for ship fuel.

Table 4. Average Ship Engine Power (Air Resources Board, 2005)

Tipe Kapal	Rata-Rata Daya Mesin Utama (kW)	Rata-Rata Daya Mesin Bantu (kW)
Auto Carrier	10.700	2.850
Bulk Carrier	8.000	1.776
Container Ship	30.900	6.800
Cruise Ship	39.600	11.000
General Cargo	9.300	1.776
RORO	11.000	2.850
Reefer	9.600	3.900
Tanker	9.400	1.985

Source: Air Resources Board, 2005

3. Model Building

3.1. Asymetric Travelling Salesman Problem

There are several stages in designing the Asymmetric Travelling Salesman Problem (ATSP) mathematical model. Data/parameters regarding engine capacity, the distance between ports, ship speed, and fuel prices for each port are processed into a matrix. Operational time is obtained by dividing the distance between ports by the ship's speed. The matrix will be the input for the optimization program using the two heuristic algorithms. Therefore, the problems faced by the two optimization algorithms are the same so that the results or performance of the two algorithms can be compared. This mathematical model can be solved with various kinds of algorithms, both exact algorithms and approximation algorithms. The travelling Salesman Problem can be used to select the route with the lowest cost. This can be done by creating a Travelling Salesman Problem matrix worth the cost between cities [15].

$$[D_{ij}]_{nxn} = \begin{bmatrix} D_{11} & D_{12} & \cdots & D_{1n} \\ D_{21} & D_{22} & \cdots & D_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ D_{n1} & D_{n2} & \cdots & D_{nn} \end{bmatrix} \quad (1)$$

The difference is how each algorithm approaches searching for route selection with each algorithm's approach and how to process input data from various data that has been collected. The data regarding the distance between the ten ports obtained is made into a matrix $[S_{ij}]_{nxn}$.

$$[S_{ij}]_{nxn} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix} \quad (2)$$

N is the number of ports in one ship operating route. In this study, ten ports were used. J_{ij} represents the distance from port i to port j in nautical miles, and $\forall_{i,j}$ = 1,2,....,n. Calculation of shipping time from between ports as a matrix $[T_{ij}]$nxn. The cruise time matrix is obtained by dividing the distance between ports by the speed of the container ship, which is 21.6 knots. T_{ij} represents the time the ship needs to sail from port i to port j.

$$[T_{ij}]_{nxn} = [S_{ij}]_{nxn} / V = \begin{bmatrix} S_{11}/V & S_{12}/V & \cdots & S_{1n}/V \\ S_{21}/V & S_{22}/V & \cdots & S_{2n}/V \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1}/V & S_{n2}/V & \cdots & S_{nn}/V \end{bmatrix} = \begin{bmatrix} T_{11} & T_{12} & \cdots & T_{1n} \\ T_{21} & T_{22} & \cdots & T_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ T_{n1} & T_{n2} & \cdots & T_{nn} \end{bmatrix} \quad (3)$$

The weight of the fuel used by the ship can be calculated. It is assumed that the fuel consumption of the main engine is 209 g/kWh, and the fuel consumption of the auxiliary engines is 211 g/kWh. The power of container ships' main engines and auxiliary engines are main engine power = 30,900 kW and auxiliary engine power = 6800 kW.[16] The fuel weight required from each inter-port voyage in a matrix $[F_{ij}]_{nxn}$.

$$K = [(Pe\ x\ Bme) + (Pae\ x\ Bae)]\ x\ 10^{-6} \quad (4)$$

$$[F_{ij}]_{nxn} = [T_{ij}]_{nxn}\ x\ K = \begin{bmatrix} T_{11}\ x\ K & T_{12}\ x\ K & \cdots & T_{1n}\ x\ K \\ T_{21}\ x\ K & T_{22}\ x\ K & \cdots & T_{2n}\ x\ K \\ \vdots & \vdots & \ddots & \vdots \\ T_{n1}\ x\ K & T_{n2}\ x\ K & \cdots & T_{nn}\ x\ K \end{bmatrix} \quad (5)$$

$$= \begin{bmatrix} F_{11} & F_{12} & \cdots & F_{1n} \\ F_{21} & F_{22} & \cdots & F_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ F_{n1} & F_{n2} & \cdots & F_{nn} \end{bmatrix}$$

F_{ij} represents the fuel the ship uses in tons to travel from port i to port j. The fuel price from each port will be incorporated into the matrix to make the Travelling Salesman Problem an asymmetrical form that describes the fuel cost for each voyage.

$$[C_{ij}]_{nxn} = \begin{bmatrix} F_{11}\,x\,f_1 & F_{12}\,x\,f_1 & \cdots & F_{1n}\,x\,f_1 \\ F_{21}\,x\,f_2 & F_{22}\,x\,f_2 & \cdots & F_{2n}\,x\,f_2 \\ \vdots & \vdots & \ddots & \vdots \\ F_{n1}\,x\,f_n & F_{n2}\,x\,f_n & \cdots & F_{nn}\,x\,f_n \end{bmatrix}$$

$$= \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1n} \\ C_{21} & C_{22} & \cdots & C_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ C_{n1} & C_{n2} & \cdots & C_{nn} \end{bmatrix} \quad (6)$$

C_{ij} describes the fuel costs incurred by ships to sail from port i to port j, while f_i describes the fuel price in USD/ton at port i, and $\forall_{i,j}$ = 1,2,....,n. This C_{ij} matrix results from processing the data obtained into an Asymmetric Travelling Salesman Problem, which will later be optimized for route selection.

Table 5. Model Mathematical Asymmetric Travelling Salesman Problem

	Dumai	Jakarta	Batam	Surabaya	Makassar	Manado	Bitung	Ambon	Timika	Merauke
Dumai	0	31,80556	8,75	40,13889	53,37963	65,37037	26,11111	75,74074	100,0463	111,713
Jakarta	31,80556	0	27,68519	17,87037	37,31481	71,25	70,23148	95,74074	83,88889	93,37963
Batam	8,75	27,68519	0	47,03704	57,17593	86,62037	86,75926	111,0648	92,4537	136,4815
Surabaya	40,13889	17,87037	47,03704	0	20,23148	58,00926	56,99074	82,5	67,17593	125,9259
Makassar	53,37963	37,31481	57,17593	20,23148	0	37,59259	36,57407	62,08333	52,03704	105,5093
Manado	65,37037	71,25	86,62037	58,00926	37,59259	0	2,916667	26,2037	37,26852	69,62963
Bitung	26,11111	70,23148	86,75926	56,99074	36,57407	2,916667	0	25,50926	50,37037	68,93519
Ambon	75,74074	95,74074	111,0648	82,5	62,08333	27,17593	26,2037	0	24,86111	48,24074
Timika	100,0463	83,88889	92,4537	67,17593	52,03704	37,26852	55	24,86111	0	16,52778
Merauke	111,713	93,37963	136,4815	125,9259	105,5093	69,62963	68,93519	48,24074	16,52778	0

3.2. Genetic Algorithm Travelling Salesman Problem

At the testing stage, the fitness value in this study is closely related to the objective function, namely minimizing the total cost of fuel spent. The fewer costs incurred, the better the value of fitness.

$$F = 1/f \quad (7)$$

The population size is the same as specified in the program data input. This study used gene permutation techniques to generate the initial population. The selection process uses the tournament method. The selection process to get the best individuals to become these individuals is carried out by crossover and mutation processes. Selection is based on the fitness value of each individual.

At this stage, the crossover process aims to produce a new individual from the marriage of two individuals resulting from the selection process [17]. The mutation process involves exchanging an individual's genes with the gene's inversion value [18]. Mutations are carried out on individuals as a result of the selection process.

3.2 Ant Colony Optimization (ACO) Algorithm Travelling Salesman Problem

At the ant colony algorithm stage, where the ants move from point A (start) to point B (destination), they leave chemical substances and pheromones in every path they take. Help the following ants to determine the path other ants detect the selected pheromone–an algorithm based on adaptive adjusting pheromones on each route. You can see the flow diagram in this study.

Initialize the initial parameters of the ant colony algorithm for N ants to determine the route that produces the minimum total operational costs. Calculates the visibility value based on the input data provided. The fewer costs incurred, the better the visibility value [19].

$$1/d \quad (8)$$

Pheromone update determines the opportunity value from one port to another. In this case, port 1 is designated as the port of departure. Then from the last port, back to port 1. Calculate the probability of visiting another port from port 1 (initial).

$$p_1(1,j) = \frac{\tau(1,j)1\ h(1,j)2}{\sum \tau(1,j)1\ h(1,j)2} \quad (9)$$

In determining the best route with the resulting pheromone matrix from N ants. Probability of path selection and iteration. Calculated to get the route [20].

$$P_{(i,j)} = \frac{\tau_{(i,j)}{}^{\alpha}.n_{(i,j)}{}^{\beta}}{\sum \tau_{(i,j)}{}^{\alpha}.n_{(i,j)}{}^{\beta}} \quad (10)$$

4. Problem solving approach

The optimization model was carried out using Python software and Visual Studio 2019. The genetic algorithm optimization parameters varied: population number, mutation rate, crossover rate, and the number of generations.

4.1 Genetic Algorithm

The first test is to get the optimal population size. Crossover and mutation 0.3 and generation size 500 were tested in the range of 10 to 100. The test was performed ten times to obtain an average fuel cost from these parameters, as in the figure 1.

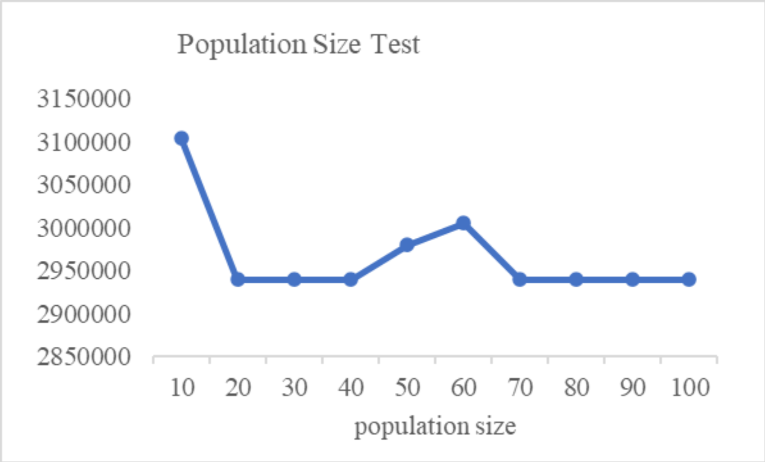


Figure 1. Population Size Testing Graph

The graph proves that the lowest average fuel cost is obtained when the population size is 20-40 and 70-100 with the same fuel value. Whereas the population size was used with the lowest average fuel costs, the population size parameter was chosen to have a value of 30 for determining shipping routes.

The second stage of the trial was carried out to find the optimal generation size. The generation size was carried out ten times with a population size of 30, and the tested generation size was 100; 500; 1000; 1500; and 2000 generations; the combined probability of crossover and mutation is 0.3. The selection method used is the tournament.

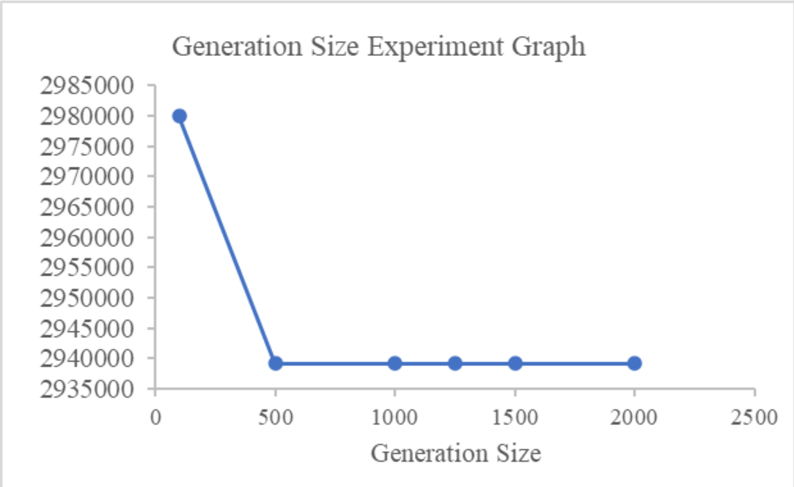


Figure 2. Generation Size trial graph

The figure 2 the generation size; the lowest values range from 500 to 2000, and the highest values are in the generation size of 100, and the trials were carried out ten times. Therefore, the optimal generation size for the travelling salesman problem is 1000 generations because the 500 to 2000 generation sizes already form a straight line. The more generation size does not necessarily make the genetic algorithm more optimal. In addition to the longer processing time, the resulting fuel value is similar to the lower generations. A high generation size will result in the evolution process being carried out more frequently. In every single generation, a recombination process consisting of crossover and mutation will be carried out. So the more generations, the more frequent the recombination process will be. Of course, this will also affect the new individuals produced. The more crossover and mutation processes are carried out, the new individuals produced will be more varied, and it is also possible to vary the value of the fuel produced. That will provide an excellent opportunity to get the minimum fuel value.

The third test was carried out to find the optimal combination of mutation rate probability and crossover rate probability. Determination of this combination is significant to obtain a good solution (close to optimal). A crossover rate that is too large (and a low mutation rate) will deprive the genetic algorithm of opportunities to explore new search areas. The genetic algorithm cannot exploit the optimum local area in the opposite condition (significant crossover rate, low mutation rate). The test was carried out 10 times. The population size is 30, the generation size is 1000, and the combined probability and crossover rates are 0 : 1 to 1 : 0.

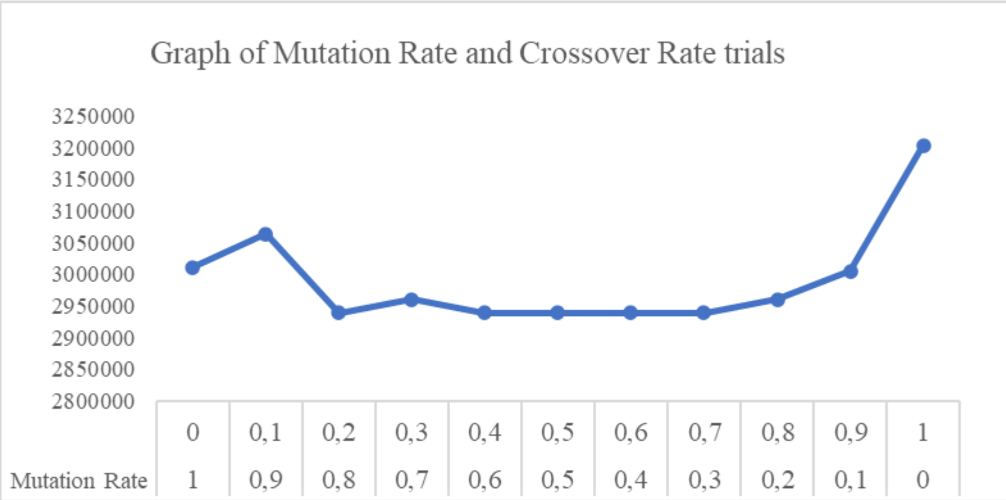


Figure 3. Graph of Mutation Rate and Crossover Rate Size Tests

From the figure 3, the average straight-line fuel cost is obtained when the mutation rate is 0.6 to 0.3 and the crossover rate is 0.4 to 0.7. A high mutation rate with a low crossover rate indicates a search for a solution that is not optimal. Conversely, a high crossover rate and a low mutation rate indicate a solution that could be more optimal. Therefore, to obtain the best route, the parameters for optimizing the genetic algorithm for this problem are selected at the mutation rate and crossover rate values that provide the optimum average fuel cost, namely MR 0.5 and CR 0.5.

Table 6. Genetic Algorithm Best Ship Routes (TSP)

Genetic Algorithm	Distribution Route
Dumai – Dumai	Dumai – Batam – Jakarta – Surabaya – Makassar – Manado – Timika – Merauke – Ambon – Bitung – Dumai
Jakarta – Jakarta	Jakarta – Surabaya – Makassar – Manado – Timika – Merauke – Ambon – Bitung – Dumai – Batam– Jakarta
Batam – Batam	Batam – Jakarta – Surabaya – Makassar – Bitung – Manado – Merauke – Ambon– Timika – Dumai – Batam
Surabaya – Surabaya	Surabaya – Makassar – Bitung – Manado – Timika – Ambon – Merauke – Batam – Dumai – Jakarta – Surabaya
Makassar – Makassar	Makassar – Bitung – Manado – Timika – Ambon – Merauke –Batam – Dumai – Jakarta – Surabaya – Makassar
Manado – Manado	Manado – Bitung – Ambon – Timika – Merauke – Batam – Dumai – Jakarta – Surabaya – Makassar – Manado
Bitung – Bitung	Bitung – Dumai – Batam – Jakarta – Merauke – Surabaya – Timika – Makassar – Ambon – Manado – Bitung
Ambon – Ambon	Ambon – Bitung – Manado – Makassar – Dumai – Surabaya – Jakarta – Batam – Merauke – Timika– Ambon
Timika – Timika	Timika – Ambon – Manado – Bitung – Dumai – Batam – Jakarta – Surabaya – Makassar – Merauke – Timika
Merauke – Merauke	Merauke – Bitung – Jakarta – Dumai – Batam – Surabaya – Makassar – Manado – Ambon – Timika – Merauke

4.2 Ant Colony Optimization Algorithm

This test was carried out on alpha and beta. Testing on alpha and beta values aims to get the best route for travelling salesman problems and minimum fuel costs. Therefore, trials were carried out in the 1 to 9 so that the ports visited were not repeated, and the optimal fuel value was obtained.

The test was carried out with an evaporation range of 0 – 1. The test was carried out repeatedly to get the best route for the travelling salesman problem with an optimal average of fuel costs did not get optimal results. Therefore, the evaporation value obtains optimal results with an evaporation value of 0.1.

5. Results Discussion

From the optimization, there are several outputs from each existing algorithm. The output is in the form of choosing the best route and fuel costs for that route from each algorithm used [20]. The results presented below are based on the following parameters:

- Population size = 30.
- Generation number = 1000.
- Crossover rate = 0.50.
- Mutation rate = 0.50.
- Repetition for experiments = 10.

Optimizing the genetic algorithm to get the best route with several parameter variations of the travelling salesman problem method obtained the best route can be seen in the table 6.

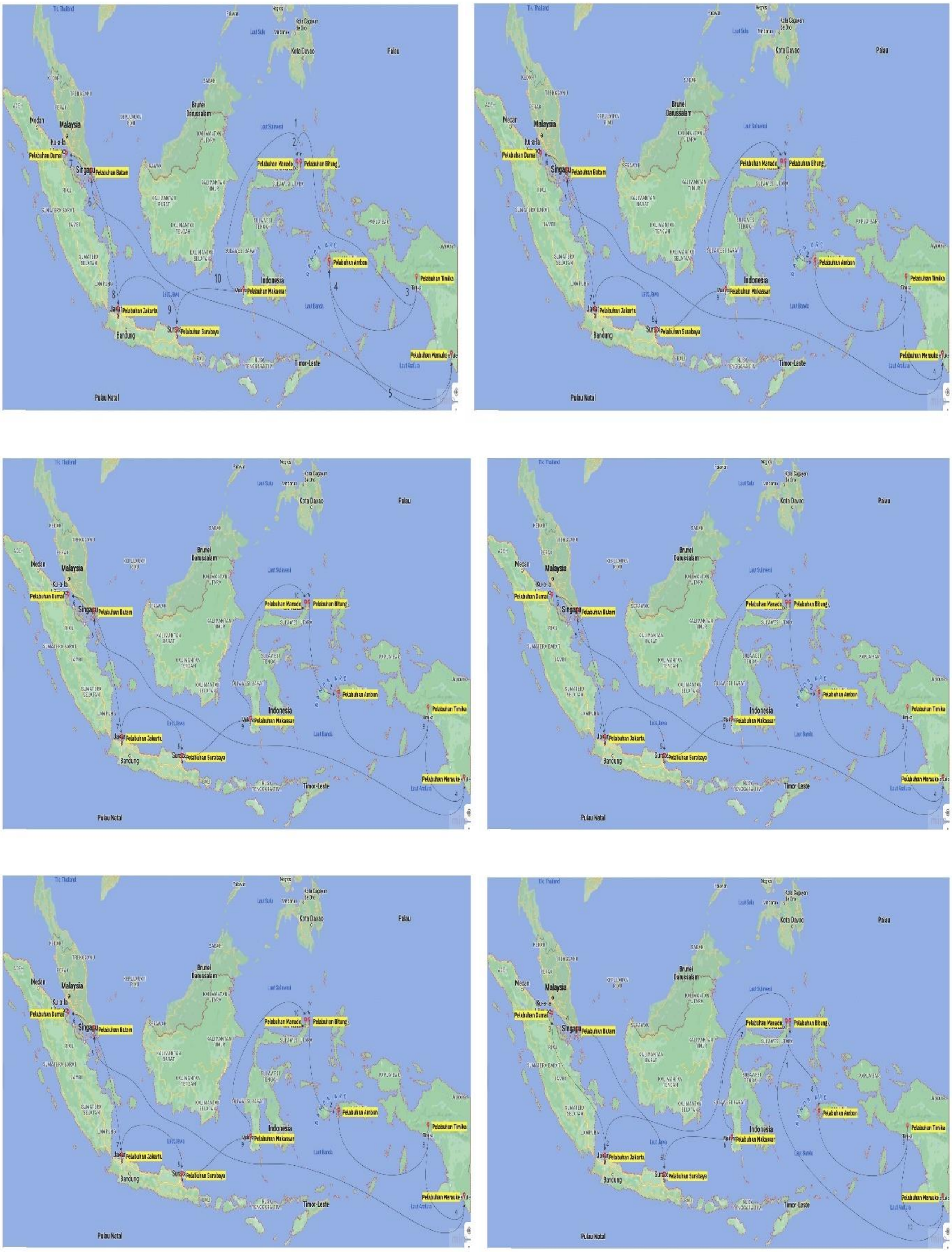


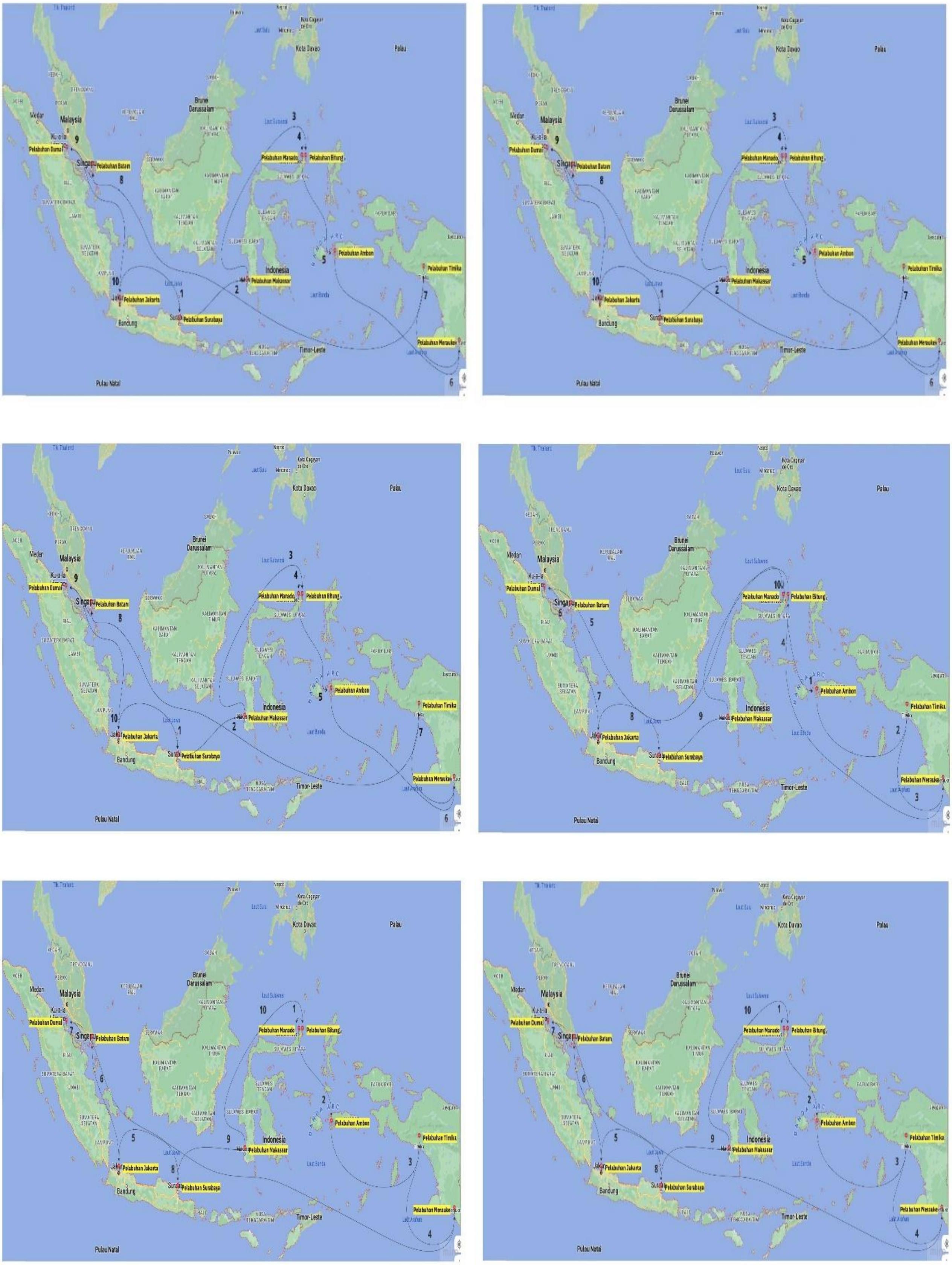
Figure 4. Vessel Route Initial/Final Destination Travelling Salesman Problem Genetic Algorithm

The results of experiments is carried out using a genetic algorithm approach to determine the routes of container ships in Indonesia's western and eastern regions by visiting ports based on the previously described input data. Proving that the selected genetic algorithm from the heuristic method can determine the route of container ships effectively can be seen in table 6, and Figure 4 shows the actualization results of the route obtained by the genetic algorithm.

Table 7. Route Ant Colony Optimization Algorithm

Ant Colony Algorithm	Distribution Route
Dumai - Dumai	Dumai – Batam – Surabaya – Makassar – Manado – Bitung – Ambon – Timika – Merauke – Jakarta – Dumai
Jakarta - Jakarta	Jakarta – Surabaya – Makassar – Bitung – Manado – Ambon – Merauke – Timika – Batam – Dumai – Jakarta
Batam - Batam	Batam – Dumai – Timika – Ambon – Merauke – Manado – Bitung – Makassar – Surabaya – Jakarta – Batam
Surabaya - Surabaya	Surabaya – Jakarta – Timika – Ambon – Merauke – Manado – Bitung – Makassar – Dumai – Batam – Surabaya
Makassar- Makassar	Makassar – Timika – Merauke – Ambon – Manado – Bitung – Dumai – Batam – Jakarta – Surabaya – Makassar
Manado -Manado	Manado – Ambon – Timika – Merauke – Bitung – Dumai –Batam – Jakarta – Surabaya – Makassar – Manado
Bitung - Bitung	Bitung – Manado – Ambon – Timika – Merauke – Jakarta – Batam – Dumai – Surabaya – Makassar – Bitung
Ambon - Ambon	Ambon – Dumai – Surabaya – Batam – Manado – Makassar –Timika – Merauke – Jakarta – Bitung– Ambon
Timika - Timika	Timika – Merauke – Manado – Bitung – Dumai – Batam – Jakarta – Surabaya – Makassar – Ambon – Timika
Merauke - Merauke	Merauke – Timika – Manado – Bitung – Dumai – Batam – Jakarta – Surabaya – Makassar – Ambon – Merauke

In the ant colony algorithm, parameter variations are set to select the best ship route using the travelling salesman problem method. For each test, the problem was executed in 10 trials. ACS parameters were set to the following values (except if differently indicated): m=10, β=2, q0=1, α=1, ρ=0.1, cl=10 [21]. Best route travelling starting/ending destination. Can be seen in the table 7.


Pelabuhan Dumai
Pelabuhan Batam
Pelabuhan Manado
Pelabuhan Bitung
Pelabuhan Ambon
Pelabuhan Timika
Pelabuhan Makassar
Pelabuhan Jakarta
Pelabuhan Surabaya
Pelabuhan Merauke
Medan
Malaysia
Brunei Darussalam
Kota Davao
Palau
Indonesia
Bandung
Timor-Leste
Pulau Natal

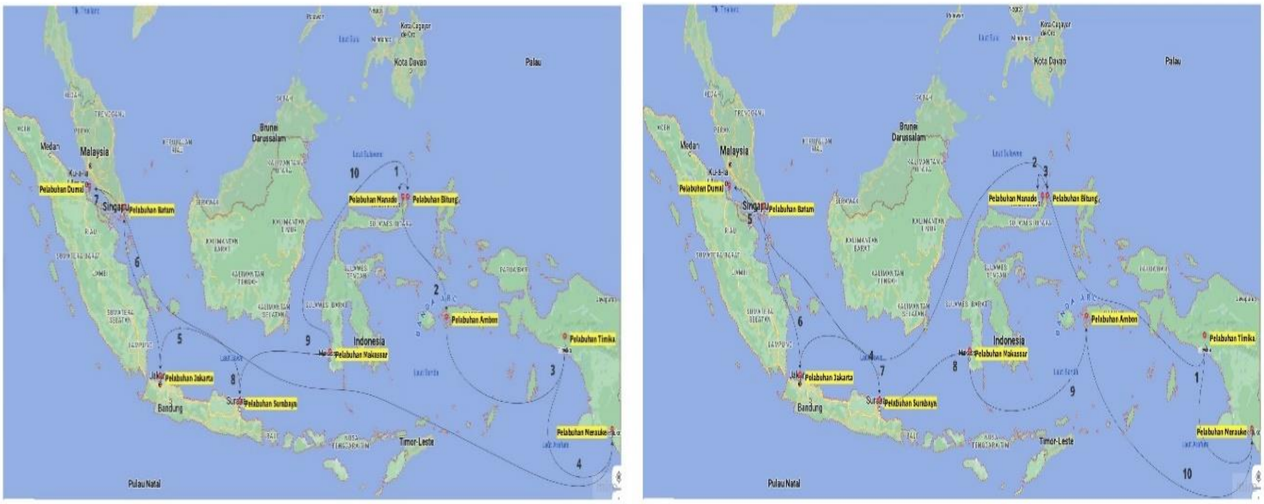


Figure 5. Ship Routes of Initial/Final Destinations Ant Colony Optimization Travelling Salesman Problem Algorithm

The results of the discussion using the ant colony optimization algorithm approach selected from the heuristic method can determine the route of the container ship after performing calculations based on input data so that the route shown in Table 7 is obtained at the port that the container ship will stop at and Figure 5 shows the actual route. This proves that the ant colony algorithm can choose the optimal route.

Each algorithm's fuel cost is in (USD) at each start/end destination, with the average fuel cost of 10 start/end destination points of route selection.

Table 8. Fuel Costs from Route Selection Results for Each Algorithm

Start/Late Destinations	Genetic Algorithm USD/Ton	Ant Colony Algorithm USD/Ton
Dumai – Dumai	2939207	2895643
Jakarta – Jakarta	2939207	2952207
Batam – Batam	3251357	2627023
Surabaya – Surabaya	3557397	2627023
Makassar – Makassar	3063608	2426196
Manado – Manado	3142827	2455835
Bitung – Bitung	2682045	2791956
Ambon – Ambon	3122783	2771540
Timika – Timika	3193248	2717296
Merauke – Merauke	3533190	2629338

Based on the calculations the two-algorithm approach selected from the heuristic method, it can determine the ship's route based on a mathematical model with the input data described earlier. The discussion results obtained the most optimal route with the lowest fuel operating costs using the genetic algorithm approach. Fuel costs 2,682,045 USD/Ton. The ant colony algorithm gets the lowest route with a total fuel cost of 2,426,196 USD/Ton.

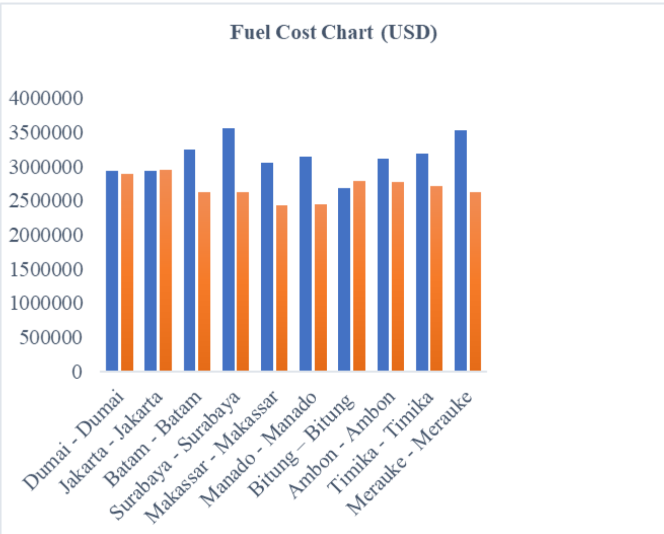


Figure 6. Genetic Algorithm and Ant Colony Route Fuel Cost Graph

Figure 6 compares the total fuel costs at ports visited by container ships using the two-algorithm approach. The genetic algorithm obtains the two lowest routes based on fuel costs, and the ant colony algorithm obtains the eight lowest routes. This proves that the ant colony algorithm is more optimal in determining container ship routes to minimize fuel costs.

6. Conclusion

This research is the route optimization problem by considering ship speed, initial distance, and destination by minimizing fuel costs using genetic and ant colony optimization algorithms. First, we understand the research background of the logistics route optimization problem, discuss the current research results and related research problems, and provide improvements to existing problems. Then, we create a mathematical model for the research problem by constructing an objective function. After the research, the problem-solving method is proposed, and the improvement of the method is described in detail. Finally, simulation comparisons were carried out to verify the effectiveness and superiority of the proposed method. To increase the depth and breadth of research of the following aspects must be further strengthened: (1) Considering freight demand as a parameter and considering other aspects of operational costs in determining the best route (2) An in-depth study of the nature of complex logistics distribution networks must be carried out, (3) Further research, economic analysis data will increase the relevance of the analysis results to actual conditions because the results of economic analysis are significant to price disparities.

References

[1] T. Notteboom, T. Pallis, and J. P. Rodrigue, "Disruptions and resilience in global container shipping and ports: the COVID-19 pandemic versus the 2008–2009 financial crisis," Maritime Economics and Logistics, vol. 23, no. 2, pp. 179–210, Jun. 2021, doi: 10.1057/s41278-020-00180-5.

[2] T. Gudehus and H. Kotzab, "Maritime Logistics," in Comprehensive Logistics, Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 823–842. doi: 10.1007/978-3-642-24367-7_23.

[3] M. Ghorbani, M. Acciaro, S. Transchel, and P. Cariou, "Strategic alliances in container shipping: A review of the literature and future research agenda," Maritime Economics and Logistics, vol. 24, no. 2, pp. 439–465, Jun. 2022, doi: 10.1057/s41278-021-00205-7.

[4] H. Wang, W. Mao, and L. Eriksson, "A Three-Dimensional Dijkstra′s algorithm for multi-objective ship voyage optimization," Ocean Engineering, vol. 186, Aug. 2019, doi: 10.1016/j.oceaneng.2019.106131.

[5] Rumaji and A. Adiliya, "Port Maritime Connectivity in South-East Indonesia: A New Strategic Positioning for Transhipment Port of Tenau Kupang," Asian Journal of Shipping and Logistics, vol. 35, no. 4, pp. 172–180, Dec. 2019, doi: 10.1016/j.ajsl.2019.12.004.

[6] G. Ilham Sampurno and E. Sugiharti, "Comparison of Dynamic Programming Algorithm and Greedy Algorithm on Integer Knapsack Problem in Freight Transportation," Scientific Journal of Informatics, vol. 5, no. 1, pp. 2407–7658, 2018, [Online]. Available: http://journal.unnes.ac.id/nju/index.php/sji

[7] H. Cui, J. Qiu, J. Cao, M. Guo, X. Chen, and S. Gorbachev, "Route optimization in township logistics distribution considering customer satisfaction based on adaptive genetic algorithm," Math Comput Simul, vol. 204, pp. 28–42, Feb. 2023, doi: 10.1016/j.matcom.2022.05.020.

[8] M. A. Budiyanto, I. K. Singgih, A. Riadi, and G. L. Putra, "Study on the LNG distribution to Mobile Power Plants using a Small-Scale LNG Carrier for the case of the Sulawesi region of Indonesia," Energy Reports, vol. 8, pp. 374–380, Apr. 2022, doi: 10.1016/j.egyr.2021.11.211.

[9] C. Natalia, M. Holine, and A. Silalahi, "A simultaneous container assignment and ship scheduling optimisation model in container shipping," Asian Journal of Shipping and Logistics, vol. 37, no. 3, pp. 213–219, Sep. 2021, doi: 10.1016/j.ajsl.2021.05.002.

[10] http://ports.com/sea-route/, "Sea Route and Distance," May 20, 2022. http://ports.com/sea-route/ (accessed May 20, 2022).

[11] https://shipandbunker.com/prices/apac, "Asia/Pacific Bunker Prices," May 20, 2022. https://shipandbunker.com/ (accessed May 20, 2022).

[12] ICF International, "Current Methodologies in Preparing Mobile Source Port-Related Emission Inventories Final Report," 2009.

[13] C. Appendix, "Oceangoing Ship Survey Summary Of Results 2005 OCEANGOING SHIP SURVEY SUMMARY OF RESULTS Stationary Source Division Emissions Assessment Branch," 2005.

[14] D. A. Suprayogi and W. F. Mahmudy, "Penerapan Algoritma Genetika Travelling Salesman Problem with Time Window: Studi Kasus Rute Antar Jemput Laundry 121."

[15] K. P. Ghadle and Y. M. Muley, "Travelling salesman problem with MATLAB programming," 2015. [Online]. Available: www.ijaamm.com

[16] H. Poehls, "Lectures on ship design and ship theory," 1979.

[17] A. Hussain, Y. S. Muhammad, M. Nauman Sajid, I. Hussain, A. Mohamd Shoukry, and S. Gani, "Genetic Algorithm for Travelling Salesman Problem with Modified Cycle Crossover Operator," Comput Intell Neurosci, vol. 2017, 2017, doi: 10.1155/2017/7430125.
[18] Z. Hussain Ahmed, "An experimental study of a hybrid genetic algorithm for the maximum travelling salesman problem," 2013. [Online]. Available: http://www.iaumath.com/content/7/1/10
[19] Y. S. Tyas and W. Prijodiprodjo, "Aplikasi Pencarian Rute Terbaik dengan Metode Ant Colony Optimazation (ACO)," IJCCS, vol. 7, no. 1, pp. 55–64, 2013.
[20] M. Dorigo and L. Maria Gambardella, "Dorigo and Gambardella-Ant Colony System Ant Colony System: A Cooperative Learning Approach to the Travelling Salesman Problem," 1997. [Online]. Available: http://iridia.ulb.ac.be/dorigo/dorigo.htmlhttp://www.idsia.ch/~luca
[21] K. Ghoseiri and S. F. Ghannadpour, "Multi-objective vehicle routing problem with time windows using goal programming and genetic algorithm," Applied Soft Computing Journal, vol. 10, no. 4, pp. 1096–1107, 2010, doi: 10.1016/j.asoc.2010.04.001.