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Optimization of Ship's Route Scheduling Using Genetic Algorithm

Vivi Nur Wijayaningrum*, Wayan Firdaus Mahmudy
Faculty of Computer Science, Brawijaya University
Jalan Veteran 8, Malang, Indonesia, Ph./Fax:+62341-577911
*Corresponding author, e-mail:vivinurw@gmail.com

Abstract

Route scheduling is a quite complicated process because it involves some determinant factors. Several methods have been used to help resolve the NP-hard problems. This research uses genetic algorithm to assist in optimizing ship scheduling, that where there are several ports to be visited by some ships. The goal is to divide the ship to go to a specific port so that each port is only visited by one ship to minimize the total distance of all ships. The computational experiment produces optimal parameters such as the number of popsize is 30, the number of generations is 100, crossover rate value is 0.3 and mutation rate value is 0.7. The final result is an optimal ship route by minimizing the distance of each ship.

Keywords*: genetic algorithm, ship, route*

1. Introduction

In the area of communication and transportation, the problems concerning the route and scheduling is an area of extensive research. The stable economic growth in trade resulting in an increased need for transport of goods. There are four types of modes of transport are often used for delivery of goods, namely trucks, trains, planes, and ships.

Indonesia with more than 18,000 islands, is the largest archipelago in the world [1]. With so many islands in Indonesia, the manufacturers often choose to use the ship in order to send goods production between islands.Most ships are used to deliver the goods assign ships to the weekly frequency for long-distance shipping services. As a result, the goods to be sent must be stored in warehouses or in port beforehand, causing increased costs for storage. To reduce these costs, plan of ship service of goods shippers is expected to be optimized in terms of schedules and allocation of ships on some routes [2]. Fuel cost has the highest calculation proportion among the various operational costs of sea shipping. High fuel consumption gives adverse impact on the environment because it produces CO_2 and NO_x emissions that cause air pollution and climate alteration [3] [4].Therefore, ship's route scheduling is important to be taken to minimize the travel distance so that the fuel consumption can be as little as possible.

In the previous research, genetic algorithm is used to determine the allocation of berths for container ships in the harbor. The purpose of this allocation planning is to minimize the amount of time service for each ship [5]. A similar study conducted to optimize the scheduling of the train route using genetic algorithms with artificial neural networks with the aim of minimizing the delay time [6]. Each gene on chromosome describes a train that is assigned to a route which is represented by the value of its genes [7].Genetic algorithm is also used to optimize route of stacker in automatic warehouse because stacker can not increase its speed so it takes much time in the process of transportation goods [8]. In this study, genetic algorithm is used to optimize the ship's routescheduling because genetic algorithm have a powerto produce good solutionsfor somereal complex problems [9] [10]. This paper presents a model to solve the problem of scheduling a port visit to minimize the distance so that the fuel consumption is reduced. The proposed solution is trying to save fuel consumption of each ship along the way to visit all the ports.

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2. Genetic Algorithm

Genetic algorithms mimic the process of biological evolution to solve a problem, which solution was formed consisting of several possible solutions [6]. Genetic Algorithm (GA), developed by Holland in 1975, is an optimization and search method based on the principle of the evolution theory. In the GA, the solution generated randomly. The GA saves the population of possible solutions for several generations. The population consists of a string of chromosomes. A chromosome consists of a number of genes. In a population, the number of genes in a chromosome is usually the same as the other chromosomes. Each gene has a numerical value of binary or integer. The GA process begins by selecting a parent chromosome based on its fitness value that describes the quality of the chromosome. Then the descent solution produced by crossover and mutation [11].

In contrast to other optimization methods, genetic algorithm can be called efficient in solving problems with the extensive search area. There is no guarantee that the result obtained from genetic algorithm is an optimal solution, but this algorithm can provide an acceptable solution with reasonable processing time[6].

3. Research Method

The definition of a scheduling problem can be exemplified that there are a number of ships that have different capacities. Each ship sends goods from one port to the other with a certain distance.

In this case, there are 21 ports to be visited by three ships which is shown in Table 1.

Table 1. Port Visited

Number	Port Name
1	Ambon
2	Balikpapan
3	Bengkulu
4	Cilacap
5	Cirebon
6	Gresik
7	Jakarta
8	Jambi
9	Kalianget
10	Kupang
11	Makassar
12	Manado
13	Medan
14	Palembang
15	Panjang
16	Pekanbaru
17	Pontianak
18	Sabang
19	Samarinda
20	Semarang
21	Sorong

3.1. Chromosomes Representation

The first step in building GA is to define the exact representation of chromosomes (encoding). A good chromosomes representation is very important because it will affect the effectivity of GA in exploring the search space [12].

On this issue, the chromosome is represented using a permutation that describes the sequence of ports that should be visited by every ship. Chromosomes that may be established are:

[21 12 18 8 3 6 7 2 1 10 11 17 9 20 5 15 13 16 14 19 4]

Based on the chromosome representation, the possibility of routes could be set up for each ship so that each port is only visited by only one ship in the delivery process, shown in Table 2.

Table 2. Route of Each Ship

Ship	Route
1	0 → 21 → 12 → 18 → 8 → 3 → 6 → 7 → 0
2	0 → 2 → 1 → 10 → 11 → 17 → 9 → 20 → 0
3	0 → 5 → 15 → 13 → 16 → 14 → 19 → 4 → 0

Port in Surabaya is assumed as the initial location of all ships, which is represented by the number 0. Each ship has sequences list of ports to be visited. The digit is written after digit 0 is the port number that should be visited by every ship. After visiting all ports based on the sequences list, all of the ships will end at the port in Surabaya.

In the example, the ship 1 will make trip from the port in Surabaya and then to Sorong, Manado, Sabang, Jambi, Bengkulu, Gresik, Jakarta, and then back again to Surabaya.

3.2. Fitness Function

In the previous study, the function of fitness value is calculated using the total distance traveled and time of service on any port as a reference in calculating the fitness value[13]. While in this study, a modified fitness function used is a calculation based on the total distance traveled by all the ships, so the fitness function used is formulated in Equation 1.

$$F = \frac{10000}{D = \sum_{r \in R} \sum_{n \in V_r \subseteq V} d_{r,(n-1)n}} \quad (1)$$

where r isa route included in R, R is a collection of routes, n isa port is included in Vr, Vr is a collection of nodes included in the route r, m is a ports are included in V, V is a collection of the visited ports, and $d_{r,(n-1)n}$ is the distance between ports (1, 2, ..., n) of route r.

A list of the distance between ports in Indonesia are shown in Table 3. These distance data are taken from www.sea-distances.org which measured in nautical miles.

Table 3. Distance between Ports in Indonesia (nautical miles)

Port Name	Ambon	Balikpapan	Bengkulu	Cilacap	...	Semarang	Sorong	Surabaya
Ambon	0	885	1651	1232	...	1114	346	980
Balikpapan	885	0	1103	883	...	583	1025	481
Bengkulu	1651	1103	0	532	...	568	1896	726
Cilacap	1232	883	532	0	...	631	1500	689
...	...	...	...	...	...	...	...	...
Semarang	1114	583	568	631	...	0	1359	194
Sorong	346	1025	1896	1500	...	1359	0	1253
Surabaya	980	481	726	689	...	194	1253	0

Based on data from Table 3, fitness value can be calculated using Equation 1 as follows:

$$F = \frac{10000}{6912 + 4462 + 5006} = 0.6105$$

3.3. Crossover

Crossover is a genetic operator used to generate new chromosomes by selecting two parents to do crossover. Crossover means exchange a part of chromosome 1 with another part of chromosome 2. Chromosome produced could be better than both parents. The 3 types of crossover are single point (1-point), 2-point and 4-point [11].

In this research, 1-point crossover method is used because this method is simple [6]. In this method, the two chromosomes will be chosen at random, then one cut point also selected randomly as the exchange limit of genes on both chromosomes to produce one chromosome offspring for every one crossover process. Figure 1 illustrates the 1-point crossover.

Parent 1	0	1	2	3	5	4	6	7
Parent 2	0	3	4	6	2	1	5	7
Offspring	0	1	2	3	4	6	5	7

Figure 1. 1-pointCrossover

3.4. Mutation

Mutation operator are used to maintain the diversity of the population so as to expand the search area and help the search algorithm out from local optimum solutions [14]. Mutation method used in this research is swapping mutation which is done by selecting two genes on a chromosome randomly, then exchange those two genes [15]. Figure 2 illustrates the process of swapping mutation.

Parent	0	1	3	4	6	2	5	7
Offspring	0	4	3	1	6	2	5	7

Figure 2. Swapping Mutation

3.5. Selection

Selection is an important part of the genetic algorithm because it can affect the convergence rate. The selection method used is elitism selection. The basic principle of the elitism selection is choosing a chromosome that has the best fitness value. Chromosomes with the best fitness value chosen will have a chance to survive in the next generation [16].

4. Results and Discussion

Tests carried out on the parameters that are used in genetic algorithm, which consists of testing *popsize*, testing the number of generations, testing the crossover rate (*cr*) value, and testing the mutation rate (*mr*) value.

Testing *popsize* is used to determine the number of chromosomes in order to produce the best optimal solution in this problem. The number of *popsize* to be tested are 10, 20, 30, 40, and 50. The number of generations is 150, were obtained from previous research [17]. While the *cr* and *mr* value used are 0.4 and 0.05, which is the result of tests conducted by Iliopoulou [18]. *Popsize* trials performed 5 times with the test results shown in Figure 3.

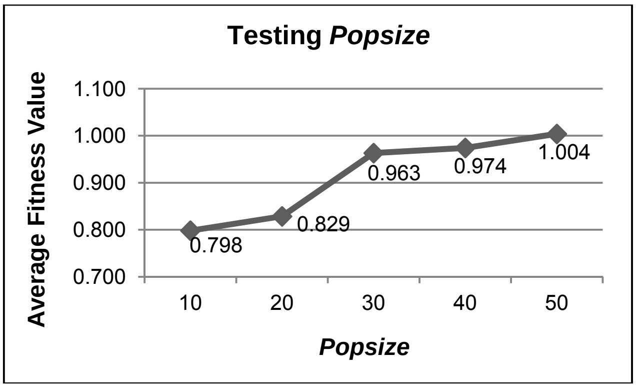

Figure 3. The Result of Testing *Popsize*

The graph of testing results in Figure 3 show that more and more *popsize*, the average fitness value generated will likely increase. In general, by increasing *popsize*, fitness values obtained will be better because of genetic algorithm has a broader search area. However, at a certain point, the fitness value does not increase significantly.The average fitness value of *popsize* 10 to 30 increased, while the average value of fitness with a number above 30 tend to be stable. This shows that 30 is the most optimal *popsize*.

The second testing is the testing of generation number, which is used to determine the best number of generations to produce the optimum solution in this problem. The number of *popsize* which is used is 30, is used to test the number of this generation because the number can be considered an average yield the most optimal fitness value. While the value of *cr* and *mr*, using the limit values used in the previous trials. The trial results generation amount shown in Figure 4.

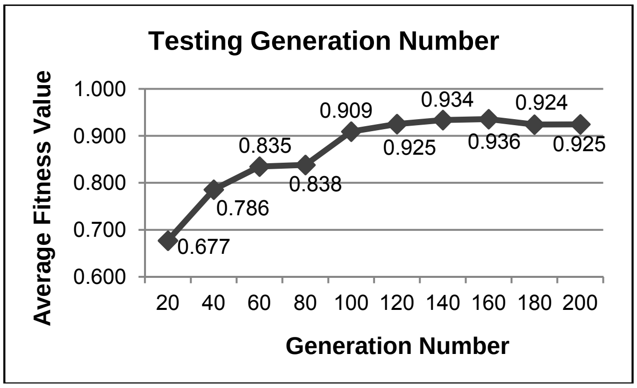

Figure 4. The Result of Testing Generation Number

The graph of testing in Figure 4 shows that the more the generation number, the average fitness value generated will likely increase. The average fitness value in generation 20 to 100 increased, while the average fitness value with the generation number in over 100 tends to be stable. This indicates that the 100 is the most optimal generation number. Pattern of increase fitness value which is comparable to the increase of generation number was also found in the research entitled "Genetic and Particle Swarm Hybrid QoS Anycast Routing Algorithm" [19].

The last testing is the testing of*cr* and *mr* value, which is used to determine the best*cr* and *mr*value to produce the optimum solution in this problem. The *popsize*which is used is 30 and the generation number used is 100 because it was considered the number could produce the most optimal average fitness value. The*cr* and *mr*value which is used in this test chosen by considering *cr* and *mr*value at each test scenario for a total amount equal to 1 because the tests performed must be fair, which means the offspring number produced in each test scenario should have the same total amount. The trial results generation number shown in Figure 5.

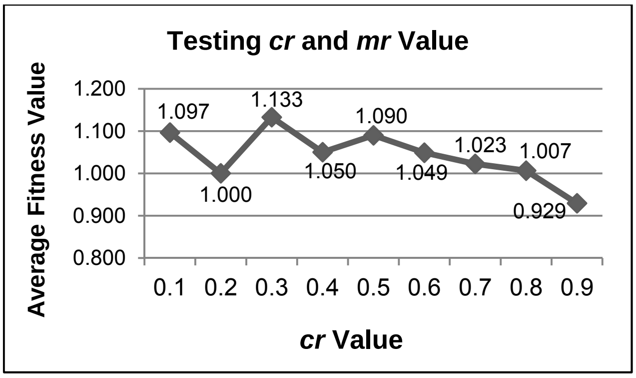

Figure 5. The Result of Testing *cr* and *mr* Value

The testing results of *cr* and *mr* values in Figure 5 shows that the best *cr* and *mr* value to produce the optimal solution is 0.3 for *cr* and 0.7 for *mr*. The high value of *cr* will provide many new chromosome in the population. However, if the *cr* value is too high, a group of genes that causes the best fitness value does not have a chance to stick to one another in a chromosome, which means that these genes are most likely to separate and cause the fitness value becomes smaller. In contrast, if the *cr* value is too low, it does not produce new offspring with a sufficient amount [20].

Table 4 shows the results given by the system by using the optimal parameter values which have been obtained from the test results consisting of the number of *popsize* is 30, the generation number is 100, *cr* value is 0.3 and *mr* values is 0.7, with the fitness value is 1,099.

Table 4. The Result Using the Optimal Parameter Values

Ship	Route
1	0 → 20 → 16 → 13 → 18 → 8 → 14 → 17 → 0
2	0 → 10 → 1 → 21 → 12 → 11 → 19 → 2 → 0
3	0 → 5 → 7 → 15 → 4 → 3 → 6 → 9 → 0

The results in Table 4 explains that the sequence of ports that should be visited by the ship 1 are Surabaya, Semarang, Pekanbaru, Medan, Sabang, Jambi, Palembang, Pontianak, and back again to Surabaya. The sequence of ports to be visited by the ship 2 are Surabaya, Kupang, Ambon, Sorong, Manado, Makassar, Samarinda, Balikpapan, and back again to Surabaya. The sequence of ports to be visited by ship 3 are Surabaya, Cirebon, Jakarta, Pajang, Cilacap, Bengkulu, Gresik, Kalianget, and back again to Surabaya.

Table 5 shows a comparison between the fitness value of random scheduling and scheduling which is done by using a genetic algorithm. The results showed the ship scheduling using genetic algorithm generates an average fitness values higher than random scheduling.

Table 5. Comparison Fitness Value

Trial Number	Fitness Value of Random Scheduling	Fitness Value of Scheduling using Genetic Algorithm
1	0.6105	1.0990
2	0.5850	1.0452
3	0.4162	1.0307
4	0.4580	1.0654
5	0.6239	1.1119
Average	0.5387	1.0704

Genetic algorithm is also compared with greedy algorithm. Greedy algorithm starts by selecting a port which has the shortest distance to the initial location. A route created by selecting the next port by considering the distance of the nearest port. Genetic algorithm also gives higher average fitness value than greedy algorithm that is equal to 1.0171. This proves that the ship’s route scheduling optimization using genetic algorithm is able to provide better results with higher fitness value by minimizing the distance.

5. Conclusion

Based on the testing results, it was concluded that genetic algorithms can be used to determine the ship's route scheduling using distance data between ports as a factor to calculate the fitness value. The best algorithm parameters used to generate the optimal solution are 30 for *popsize*, 100 for the generation number, 0.3 for *cr* value, and 0.7 for *mr* value.

In the next study, the application of algorithms for ship's route scheduling can be done by adding fuel to the calculation of fitness value, considering the fuel used for each ship could have been different. In addition, the use of the required time limit on each ship to visit each port can also be taken into account. With the growing complexity of the problems, the solutions produced may also be more complex, so it needs hybridization of genetic algorithm with other algorithms to produce a better solution. Exploiting neighborhood solutions using variable neighborhood search (VNS) will be considered in the next study [21].

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