The Comparison of Genetic Algorithm and Ant Colony Optimization in Completing Travelling Salesman Problem

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Abstract. Traveling Salesman Problem abbreviated as TSP, is a NP-hard problem that is often applied in various applications. TSP is a polynomial problem, so the solution is exponential. One way to improve the resolution of NP-hard problems is to use probabilistic algorithms such as genetic algorithms, ant colony optimization algorithms, and others. In this study genetic algorithm (GA) was applied with ordered crossover method and reciprocal mutation method. And also use the ant colony algorithm (ACO). This research will compare the performance of the two algorithms. The data used are 10, 20, ..., 100 cities, so the result shows that the ant colony algorithm is able to find a shorter distance than the genetic algorithm, but the genetic algorithm shows a better speed of completion than the ant colony algorithm.

Keywords : Travelling Salesman Problem, Genetic Algorithm, Ant Colonies Optimization

1 Introduction

Traveling Salesman Problem (TSP) is a well-known optimization problem and is often used to test the performance of various algorithms. TSP itself is pretty much applied in the real world. The main problem of TSP is that a salesman must visit a number of cities, with the distance between cities already known beforehand. Each city can only be visited once and must return to the city of origin. Travel costs that are considered by the salesman can be in the form of distance, time, fuel, comfort, and so on. [1]

Various methods are applied to handle TSP problems. The method is divided into two, namely the conventional method and the heuristic method. The conventional method is a method with ordinary mathematical calculations, while the heuristic method a technique designed for solving a problem more quickly when conventional methods are too slow, or for finding an approximate solution when classic methods fail to find any exact solution. This is achieved by trading optimality, completeness, accuracy, or precision for speed. In a way, it can be considered a shortcut. Genetic Algorithm (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Soccer Games Optimization (SGO), are some examples of heuristic method algorithms for optimization [2][3].

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Genetic algorithms are algorithms that are widely used to overcome complex optimization problems. This algorithm adopts the concept of the evolution of living things and natural selection in the science of biology, where individuals who are unable to adapt will be removed naturally. Simply put, genetic algorithms are used to build the best solution from many pre-existing solutions [4].

The ant colony optimization algorithm is an algorithm that adopts ant behavior. Naturally, ants are able to find the best route from the nest to the food source or vice versa. The ants in the colony, are able to find the route of travel based on footprints as a special sign on the path that has been passed before. The more members of the colony cross the lane, the clearer it will be for colony members to recognize the previous path. As an optimization algorithm, ant colony algorithms are algorithms specifically designed to solve path search problems.

Because both algorithms are heuristic algorithms to solve NP-hard, the researcher considers it necessary to do a comparison. The comparison is to find out which of these two algorithms is better in finding the shortest distance in the case of TSP and efficient in terms of time.[5][6][7]

2 Theoretical Background

2.1 Travelling Salesman Problem

The problem of Traveling Salesman problem (TSP) is one of the most studied examples in combinatorial optimization. This problem is easy to express but very difficult to solve. TSP can be stated as a problem in finding a minimum distance of a trip to a number of n cities, where the cities are only visited once and end with re-visiting the city of departure. More theoretically, TSP is a representation of the complete Graph and weighs G = (V, E) with the V set of vertices that represent the set of points, and E is the set of edges. Each edge (r, s) ∈ E is the value (distance) drs which is the distance from city r to city s, with (r, s) ∈ V.

Characteristics of TSP:

a. There are n points (cities)

b. From point i to point j is connected by edge E (i, j) with weight D (i, j)

c. Travelling starts from and ends at the same point

d. Except for the departure point, the other points must be visited once

e. From n! (n factorial) combination of travel solutions, the optimum solution is the shortest distance travelled

2.2 Genetic Algorithm

Genetic algorithms are search algorithms developed from the concepts of genetics and the theory of natural evolution. Genetic theory and the theory of evolution were put forward by Charles Darwin, a biologist. In the concept of genetics, it is stated that every organism is a system consisting of organs, and each organ consists of a collection of cells. Each cell is subdivided into a number of chromosomes, with each chromosome consisting of genes that are

DNA blocks. DNA blocks produce certain characteristics/characteristics of living things. The characteristics/characteristics of each living thing differ from one another. Each gene consists of a set of alleles which each carry a variety of certain characteristics. While the theory of natural evolution is the process of selecting members from various populations. Selection occurs naturally or because of natural factors that affect the survival rate of an organism. This survival is due to the high adaptability of the organism to environmental changes [8][9][10][11].

Genetic algorithm flow follows the steps below:
a. Form the initial population by initializing the genes in the chromosome
b. As long as the termination condition has not been fulfilled then run:
   i. If the crossover requirement is met, then: {Choose the parent chromosome; Run crossover};
   ii. ii. If the mutation requirements are met, then: {Select the parent chromosome; Run mutation;}
c. Return the fittest chromosome as a result of the algorithm.

The genetic algorithm as part of the evolution algorithm is a probability algorithm that maintains a population of P with the K chromosomes in it. Each chromosome in a population consists of genes. The genes in the chromosomes are cities that are initialized in such a way as in Figure 1, below.

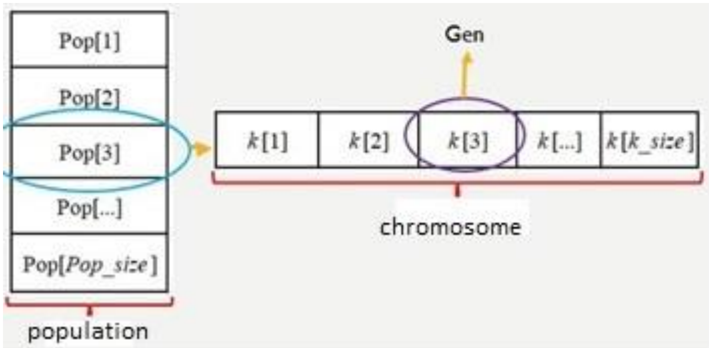

Fig 1. Population

In the concept of evolution, a good individual will have good endurance. Likewise in genetic algorithms, chromosomes that have the highest fitness value are good chromosomes and will continue to survive in each iteration, while those with low fitness values will be eliminated when there are new individuals with better fitness value than them. The fitness value in this TSP is the number of cities visited. To be able to carry out the crossing or crossover process, the chromosome selection method is used to be used as a parent by applying the roulette wheel technique. In this method, the selection of parents is based on their fitness value. The better the individual's fitness value, the greater the chance to be chosen [12]. Assumed all individuals are placed on a roulette wheel as in Figure 2, the likelihood of each individual depends on the cumulative probability of the chromosome and its fitness value. The calculation of the chromosomal cumulative probability by adding between the chromosomal probability at the time and the previous chromosome probability, while calculating the chromosome probability is to divide the chromosomal fitness value by the total fitness value of the population.

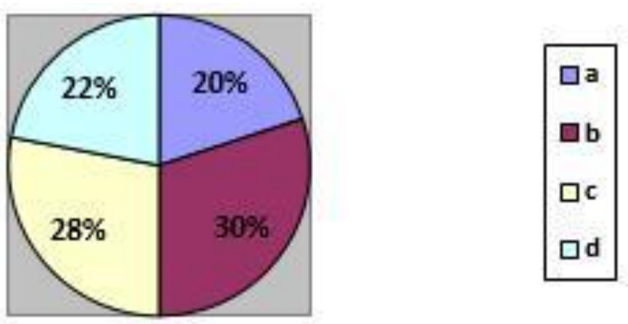

Fig 2. Roulette Wheel

There are many techniques that can be applied in chromosome crosses, one of which is Order Crossover (OX). OX builds offspring by choosing tour sub-sequences from one parent, then taking from the other parent cities that are not in the sub-sequence. Choose a sub-sequence tour by determining the bottom pot and the pot for sub-sequences [13]. The cities taken are placed sequentially in filling empty positions on the chromosome, as shown in Figure 3.

P1	2	1	5	4	7	8	9	3	6	10
P2	1	5	4	6	10	2	8	7	3	9
O1	5	4	9	4	10	2	8	7	6	10
O2	4	6	10	2	7	8	9	3	1	5

Fig 3. Ordered Crossover

In the concept of evolution, as time goes by individuals have the chance to experience mutations even though the chances are very small. For example, a mutation occurs after 1000 times of crossover or 1: 1000 against crossover. There are many techniques that can be applied in the genetic algorithm mutation method, one of them is the Reciprocal-exchange technique or by exchanging positions on two genes in the chromosome [13]. Examples of mutations with the Reciprocal-exchange technique are shown in figure 4.

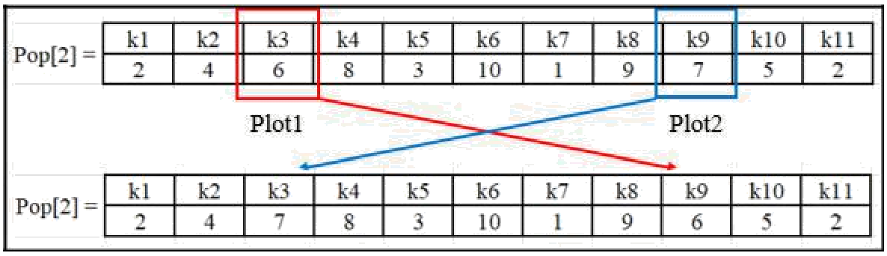

Fig 4. Reciprocal Mutation

2.3 Ant Colonies Optimization

Ant Colonies Optimization (ACO) is adopted from the behavior of ants in finding pathways, as a multi agent simulation that uses natural ant metaphors to solve physical space problems. Ants can build a path from the nest to the food source and then return to the nest via the fastest path. The constructed pathway is called pheromone trails. The ants on the way always leave pheromones in the path they pass. Each pathway has a different quantity of pheromones. The difference in pheromone levels shows how often the path is passed. The more levels of pheromone left in a pathway, the more often the pathway is used, and can be ascertained as the fastest path. Pheromones are chemicals that originate from the endocrine glands and are used by living things to recognize the same sex, other individuals, groups, and to help the reproduction process. Unlike hormones, pheromones spread outside the body and can only affect and be recognized by other similar individuals (one species). The pheromone relic process is known as stigmery, which is a process of modifying the environment that not only aims to remember the way back to the nest, but also allows the ants to communicate with their colonies. Ant System (AS) is the first ACO algorithm, proposed by Marco Dorigo in his PhD thesis in 1992. Furthermore, the US was further developed into several new ACO algorithms. The development of the US includes elite-US, rank-based US, and US MAX-MIN, Ant Colony System (ACS), and Ant-Q. The main difference between the US and its derivatives is how to do pheromone updates, and also some additional details in the pheromone path argument. In this study, the ACO algorithm used is ACS [6] [14].

The stages of the ACS algorithm for solving TSP problems can be explained in the following:

Step 1:

Assume the number of ants as much as N. Determine the same initial pheromone number τ_{ij}^1 for all inter-city segments. Notation (1) at τ indicates iteration to. For simplicity, you can use the initial value $\tau_{ij}^1 = 1$ for all sections of ij. Determine the visibility between cities as 1 / distance from each city to another city. Calculate the iteration set, t = 1.

Step 2:

a) Calculate the probability (p_{ij}) to choose the next city using equation (1)
b) Certain segments will be chosen by ants based on random numbers in the range (0.1). For that we need to also determine the range of cumulative probabilities associated with the choice of segments. So if there is a possibility that the segment will be selected, there will

be a selection of probability ranges. This particular segment chosen by ant k is determined by using the lottery loop process (roulette-wheel selection). The segment that has a large multiplication value ρ and η has a big chance to be selected.

$$Next\ City = \begin{cases} argmax_{l \in J_r^k}\{[\tau_{ru}]^{\alpha}[\eta_{ru}]^{\beta}\},\ 0 < q < 1 \\ \frac{[\tau_{rs}]^{\alpha}.[\eta_{rs}]^{\beta}}{\sum_{u \in J_r^k}[\tau_{ru}]^{\alpha}.[\eta_{ru}]^{\beta}},\ q\ lainnya \end{cases} \quad \ldots\ldots (1)$$

Step 3:

a) Generate random numbers r in the range (0.1), for each ant for each segment to be selected. Determine the discrete value that represents the segment for ant k by using random numbers from step 2 and the cumulative probability area in the lottery circle. Each ant will undergo a certain route.
b) Evaluate the value of the objective function by calculating the total distance of each route by ants k, fk, k = 1, 2, ..., N. Determine the best trajectory between N segments or paths that have been chosen by different ants:

$$F_{best} = \min_{k=1,N} \{f_k\} \quad \ldots\ldots (2)$$

Step 4:
Test the convergence of the process. In this case, convergence can be interpreted if all ants take the same best path. If it is not convergent, the ant colony will return to the nest and start searching for food again. Set iteration, t = t + 1, and update pheromone for each segment by following formula:

$$(\tau ij)^{(t)} = (\tau ij)^{(old)} + \sum_{k=0}^{n} \Delta\tau(k) \quad \ldots\ldots (3)$$

Where (τ_{ij}) (old) declares the number of pheromones from the previous iteration left behind after evaporation. Δτ (k) the amount of pheromone added by the best ant to the segment and added to the ant that follows the same segment (if there are more than one ant taking the same path). The evaporation rate of the pheromone decay factor ρ is assumed to be between 0.5 to 0.8. With the value $(\tau_{ij})^{(t)}$ we proceed to step 2. Step 2, 3, and 4 are repeated until the convergent process is when all ants choose the same best path. Or we can stop after the maximum number of iterations is reached [6] [15].

3 Research Method

The data used in this study amounted to 10 data, with each data being tested 10 times to obtain average results. Variations that used in the data are 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100 city points. In each test, the algorithm parameter values are always constant.

For the genetic algorithm, the roulette wheel selection method is used to select the parent to be cross-overred. While the probability of mutation is from 1: 1000, where when a crossover occurs 1000 times, a mutation occurs only. The crossover method is ordered crossover, while the mutation method is reciprocal mutation. Initial population is 10 chromosomes.

Then, for the ant algorithm, the parameters set in this study are $\alpha = 1$, $\beta = 0.5$ and $\rho = 0.9$. Where α is the pheromone weight τ and β is the weight that controls the visibility of the pheromone level τ. While ρ is the level of pheromone evaporation.

4 Result

4.1 Travelling Distance

Results of the distance comparison by the two algorithms is shown in figure 8. Based on the results shown in the figure, both algorithms provide distance results that are directly proportional to the amount of city input. For data of 10 and 20 cities, the results of the genetic algorithm are 2 times the results of ACS. For data on 30 cities, the results of the genetic algorithm are 2.5 times the results of ACS. For data from 40 to 70, the results of the genetic algorithm are about 3 times the results of ACS. For 80 cities data, the results of the genetic algorithm are 3.5 times the results of ACS. As for the data of 90 and 100 cities, the results of genetic algorithms are about 4 times the results of ACS as seen on figure 5.

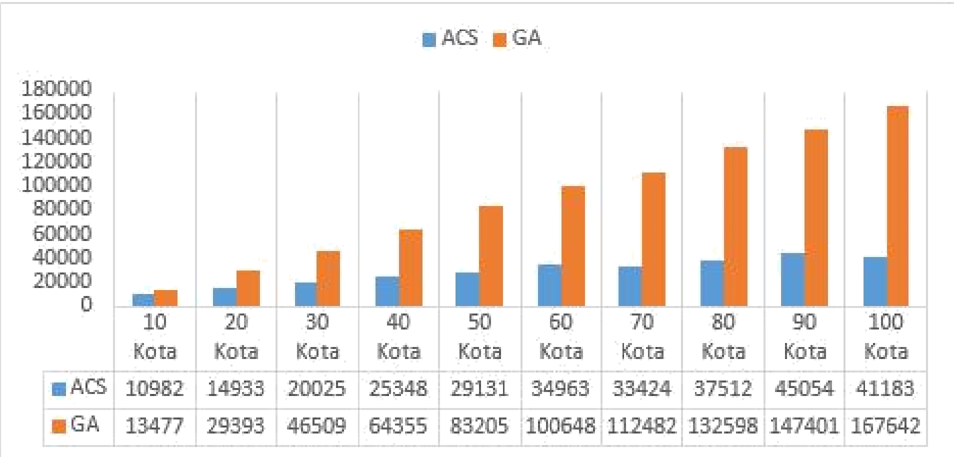

Fig 5. Comparison of the Results of the Distance by The Two Algorithms

4.2 Process Time / Duration

The diagram shown in figure 8 is a comparison of the results of the time / duration of the second process of the algorithm. Based on the results shown in the picture, the length of the second process of the algorithm fluctuates. For data 10 and 20 cities, genetic algorithms are slower than ACS. As for data over 30 cities, genetic algorithms are generally faster than ACS as seen on figure 6.

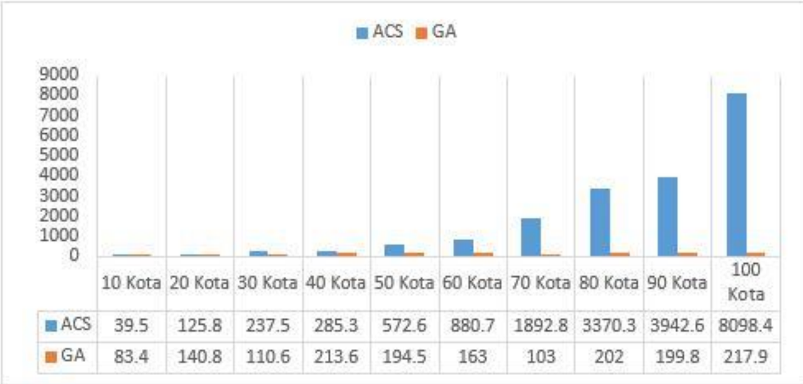

Fig 6. Average time

5 Conclusion

Based on the testing result and analysis that have been carried out in both algorithms, the following conclusions can be drawn:

1) Genetic algorithms and ACO with ACS algorithm successfully used to solve TSP problems.
2) The ACS algorithm is able to find solutions in the form of shorter traveling distances than genetic algorithms.
3) For data over than 20 cities, genetic algorithms generally faster than ACS algorithms in term of data processing.
4) Generally, it cannot be ascertained that the ACS is better than GA and vice versa.

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