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Implementation of Hybrid Genetic Algorithm for Solving the Teacher Placement Problem

Ni Komang Ayu Wirayanti[1,a] | Haris Sriwindono[2,b*]

[1]Informatics Department, Sanata Dharma University, Yogyakarta,, Indonesia
[2]Informatics Department, Sanata Dharma University, Yogyakarta, Indonesia
[a]komangayuwirayanti@gmail.com, [b]haris@usd.ac.id

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Abstract:

The teacher placement problem is a combinatorial problem that would take a very long time to solve in a deterministic way. In this study, the problem will be solved using a hybrid genetic algorithm, which combines genetic algorithms with local search methods. The genetic algorithm operators used include roulette wheel selection, two point crossover, and scramble mutation. While the local search used is reverse, insert, and swap local search. The results showed that from the three experiments using hybrid genetic algorithms, it was found that hybrid genetic algorithms were more effective than ordinary genetic algorithms. The use of hybrid genetic algorithm with swap local search technique produces the best total minimum distance (10099.09 km) at a mutation probability ratio of 1:250, number of chromosomes 10, and number of iterations 500. The hybrid genetic algorithm can improve the placement of teachers and is expected to contribute to improving the quality of education in Magelang district where the primary data is obtained.

Keywords: Hybrid Genetic Algorithm, Teacher Placement, Local Search

Introduction:

Optimizing teacher placement by considering the total distance between teachers' homes and schools is an important issue in education management. Long distances not only negatively impact the efficiency of travel time and costs, but can also affect teachers' welfare and performance. Therefore, an effective optimization approach is needed to minimize this total distance, so that teacher placement can be done more efficiently.

Genetic algorithms have long been used as one of the popular optimization methods, mainly due to their ability to find near-optimal solutions in a variety of complex problems. It works by mimicking the process of natural evolution, using selection, crossover, and mutation mechanisms to generate new solutions from a population of existing solutions [1]. However, conventional genetic algorithms often face challenges in terms of convergence and quality of the final solution, especially when trapped in locally suboptimal solutions.

To overcome these limitations, this study proposes the use of hybrid genetic algorithm, which combines genetic algorithm with local search technique to improve the optimization performance [2]. The local search technique used in this research includes three main operations: insert, reverse, and swap. Insert works by moving one element to another position in the solution, reverse reverses the order of elements in the solution segment, and swap swaps the positions of two elements in the solution. By integrating these "local search" operations, the algorithm is expected to explore the solution space more effectively, avoid local solution traps, and speed up the process of finding the optimal solution.

Previous studies have demonstrated the effectiveness of hybrid approaches combining genetic algorithms and local search in solving various optimization problems. These hybrid techniques have been shown to outperform standalone genetic algorithms or other optimization methods in terms of solution quality and convergence speed.

This study aims to evaluate the effectiveness of the hybrid genetic algorithm in optimizing the total distance between teachers' homes and schools, especially the State Elementary School in Magelang District, Central Java. It is expected that by applying the local search technique in the genetic algorithm, the quality of the solution can be significantly improved compared to the conventional genetic algorithm. Thus, this research not only contributes to the development of more efficient optimization methods, but also provides practical solutions for better teacher placement planning.

This paper will discuss the application of hybrid genetic algorithms to placement using the two-point crossver method as a cross-breeding operator (Crossover), Scramble Mutation as Mutation operators, Roulette wheel as the parent selection operator, and reverse, insert and swap technique as local search algorithm.

Literature Review:

This section specifically discusses pure genetic algorithms and hybrid genetic algorithms.

Genetic Algorithm

Genetic algorithms have emerged as a powerful heuristic optimization technique, drawing inspiration from the principles of natural selection and genetics. This optimization method involves a population of potential solutions, referred to as chromosomes or a population, which evolve successively from one generation to the next through the application of genetic operators such as selection, crossover, and mutation.

The process of reproduction of new individuals is facilitated by these genetic operators, with the aim of exploring the search space and identifying the fittest solutions [3]. Genetic algorithms have been widely adopted across various domains, including bioinformatics, due to their ability to handle complex problems without the need for additional information about the problem itself. [4]

The development of genetic algorithms can be attributed to the pioneering work of John Holland and David Goldberg, who introduced this concept in the 1960s and 1970s. The fundamental premise of genetic algorithms is the "survival of the fittest" principle, where the most suitable individuals within a population are selected for reproduction, passing on their desirable traits to the next generation.

The performance of genetic algorithms is largely dependent on the capabilities of the genetic operators employed. Selection operators are responsible for identifying the chromosomes that will be used to generate new individuals, while crossover operators combine genetic information between chromosomes to explore the search space. Additionally, the mutation operator plays a crucial role in maintaining population diversity and preventing premature convergence or local optima. [4][5][6]

The future of genetic algorithms may involve the development of "open-ended" evolutionary algorithms, which aim to increase complexity and find diverse solutions, rather than converging to a single "best" solution from the initial population.

The steps in Genetic Algorithm are as follows:

1. Initialize a population of candidate solutions (chromosomes)
2. Evaluate the fitness of each individual in the population
3. While the termination condition is not met:
   a. Select parents from the population based on their fitness
   b. Apply crossover to the selected parents to create offspring
   c. Apply mutation to the offspring
   d. Evaluate the fitness of the new offspring
   e. Replace the least fit individuals in the population with the new offspring

4. Return the best individual in the final population as the solution

Hybrid Genetic Algorithm

The foundation of hybrid genetic algorithms lies in their ability to combine the strengths of ordinary genetic algorithms with other optimization techniques, resulting in a more robust and efficient problem-solving approach. Genetic algorithms, inspired by the principles of natural selection, are a powerful optimization method that can navigate complex search spaces and find near-optimal solutions [3][4][6]. By incorporating additional strategies, such as local search or other heuristics, hybrid genetic algorithms can leverage the global exploration capabilities of genetic algorithms while also exploiting local information to refine the solutions. [4] The hybridization process allows for the creation of more diverse and adaptive algorithms that can tackle a wider range of optimization problems, making them a valuable tool in various fields, from engineering to bioinformatics.

The step of the Hybrid Genetic Algorithm with Local Search:

1. Initialize a population of candidate solutions (chromosomes)
2. Evaluate the fitness of each chromosome in the population

a. While termination criterion is not met:
   a. Select parent chromosomes based on their fitness
   b. Apply genetic operators (crossover and mutation) to create offspring chromosomes
   c. For each offspring chromosome:
   Apply the certain local search method to improve the chromosome's fitness
   d. Evaluate the fitness of the new offspring chromosomes after local search
   e. Replace the least fit chromosomes in the population with the new offspring

3. Return the best solution found

Method:

a. Research Data.

Data about teachers and primary schools was acquired from the Magelang District Education Office. The teacher data set has 636 elements, including the teacher's name, id_teacher, and the coordinates of their residence. In the meanwhile, the school's name, location, and id_school are included in the data. Every school is thought to have six study groups. The Haversine formula is used to determine the distance between the teacher's home and the school based on the preceding facts. [7][8]

b. Chromosome Representation

The chromosome expresses a solution, which is how to arrange instructors in classrooms to minimize the overall distance. The chromosome in this instance is expressed as an array with a length of 636 characters, the contents of which constitute the teacher's identity, so that it may be exposed to the genetic algorithm operator. In contrast, each school in the array represents a set of six courses. [8] This may be explained as Fig. 1 illustrates.

	School1						School2					
room	0	1	2	3	4	5	6	7	8	9	10	11
id_T	283	484	223	343	301	307	370	239	323	622	382	352

Figure 1. The representation of chromosome

c. Fitness Function

The fitness function of a chromosome or solution is used to assess its goodness. The total distance traveled by each teacher to go to their separate schools serves as the fitness function in this instance. Since the *Haversine formula* can be used to determine the distances between each teacher and school, it is possible to calculate this fitness function. [9]

d. Selection Method

Using the *roulette wheel* method, chromosomes are chosen for crossover or mutation based on their fitness value, with the likelihood of each chromosome being chosen for either procedure being proportionate. The likelihood of selection increases with fitness score.

e. Crossover

The two-point crossover method uses two reference points as boundaries in crossing between genes. These reference points (P1 and P2) are randomly selected from the length of the chromosomes as seen on Fig 2. After these dots are determined, the genes from the parent chromosome to the first point limit will be copied to the child chromosome. Then, the genes on the parent chromosome will be examined one by one in order. If the gene is not already present in the child's chromosome, it will be added, and vice versa.

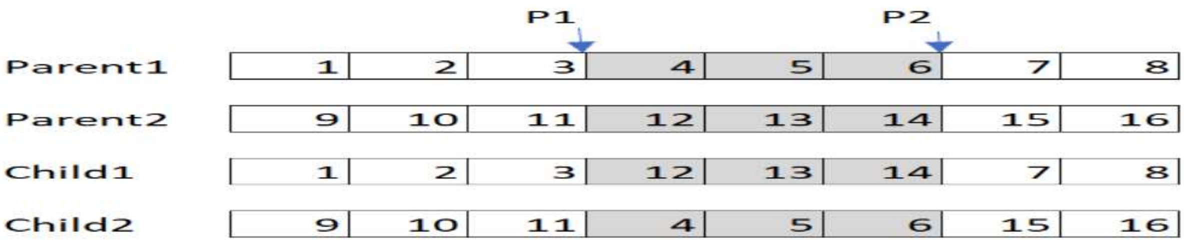

Figure 2. Two Points Crossover Illustration

f. Mutation

Scramble mutation is done by randomly selecting two gene positions in a chromosome. Then the genes were randomly arranged in that positional range as seen on Figure 3. For example, mutations are chromosomes that are selected in the selection process using a roulette wheel.

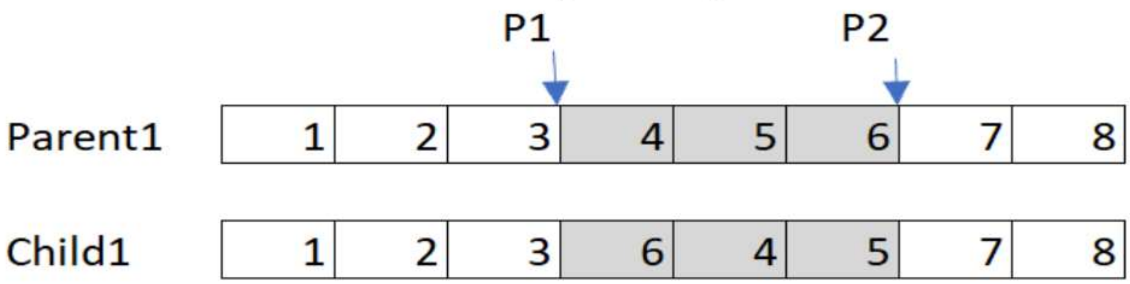

Figure 3. Scramble Mutation Illustration

g. Local search

Local search occurs on chromosomes resulting from the process of crossover or mutation, especially for the most optimal children of the child population and the parent population. After obtaining the child's chromosomes and conducting a fitness evaluation, the next step involves a local search method, such as insertion, reverse or swap. After implementing the local search operator, the child's genetic makeup will undergo changes without reducing the quality of the child's previous chromosomes. The local search operator on this child gene aims to modify the genetic sequence in the chromosome.

h. Population Change.

This step aims to perform the worst chromosome exchange in the iitial population with daughter chromosomes produced through crossover or mutation. If the fitness of child's chromosomes are rated better than the fitness of the chromosomes in the initial population, then the worst chromosome exchange in the population with the child is carried out.

Results:

Experiments were conducted to investigate the impact of various parameters and hybridization techniques on the performance of genetic algorithms. The parameters studied included the initial population size, mutation probability, and the maximum number of iterations.

The mutation probability refers to the likelihood of mutation compared to crossover. A higher value of n indicates a lower probability of mutation, as the ratio of mutation to crossover becomes 1:n [10]. The experiments focused on the results obtained with a maximum of 500 iterations, as it was observed that no further changes occurred beyond this point. [11]

The study first evaluated the standard genetic algorithm without any hybridization. It then examined the performance of the genetic algorithm when hybridized with local search techniques, including reverse, insertion, and swap operations [12][13]. The results of these experiments are presented in Figures 4 through 7, providing a comprehensive comparison of the different approaches based on the numerical display as seen on Table 1.

The findings suggest that the choice of genetic operators and hybridization techniques can have a significant impact on the algorithm's performance. The exploitation-exploration balance plays a crucial role in the algorithm's ability to navigate the search space effectively.

The importance of carefully selecting the genetic operators and hybridization techniques, as these choices can have a substantial impact on the algorithm's performance. By exploring the various parameter configurations and hybridization approaches, the study offers valuable insights into the trade-offs between exploration and exploitation, which are critical factors in the effective navigation of the search space. Although the specific numerical results are not presented, the paper provides a comprehensive understanding of the experimental framework and the high-level findings, enabling readers to appreciate the significance of the research and its potential implications for further development of genetic algorithm-based techniques.

Table 1. Total Distance from experiment

Mutation Prob	Total Distance			
	AGM	AGH-RLS	AGH-ILS	AGH-SLS
10	10923,063	11026,623	10982,784	10254,152
20	11635,369	10877,1	11188,147	10431,164
50	11589,47	11036,723	11337,48	11030,27
75	11259,278	11231,041	11510,586	10490,4
100	11670,408	11452,269	11610,915	10959,414
250	11754,085	11445,497	11389,541	10099,09
500	11854,068	11339,13	11776,829	11133,733

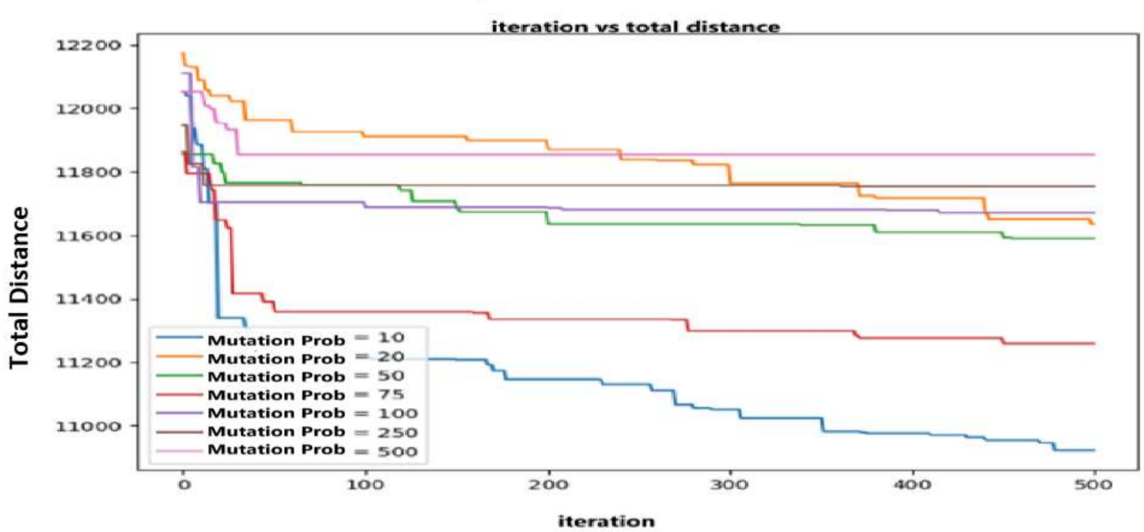

Figure 4. The Result for Ordinary Genetic Algorithm

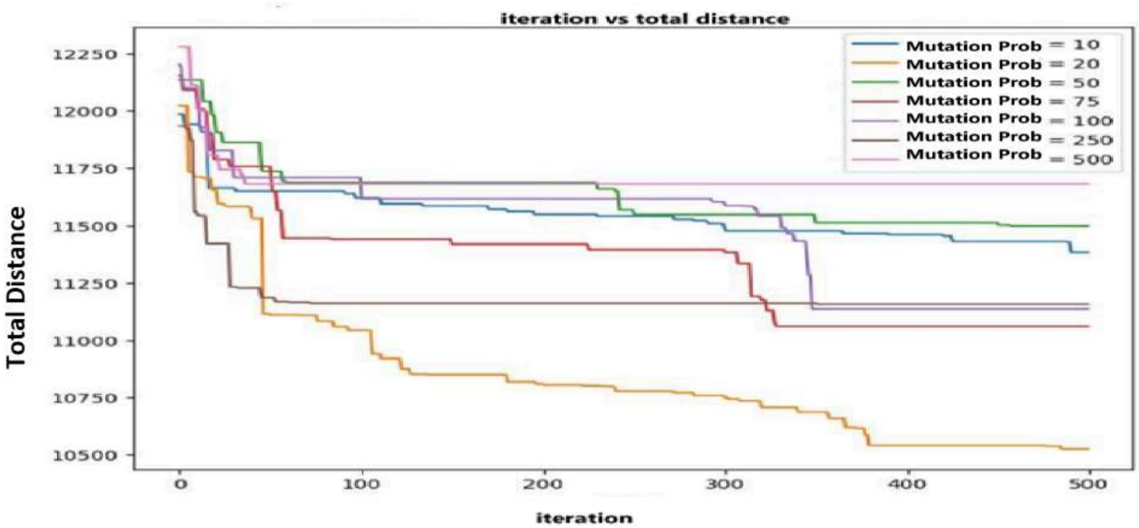

Figure 5. The Result for Hybrid Genetic Algorithm using Reverse

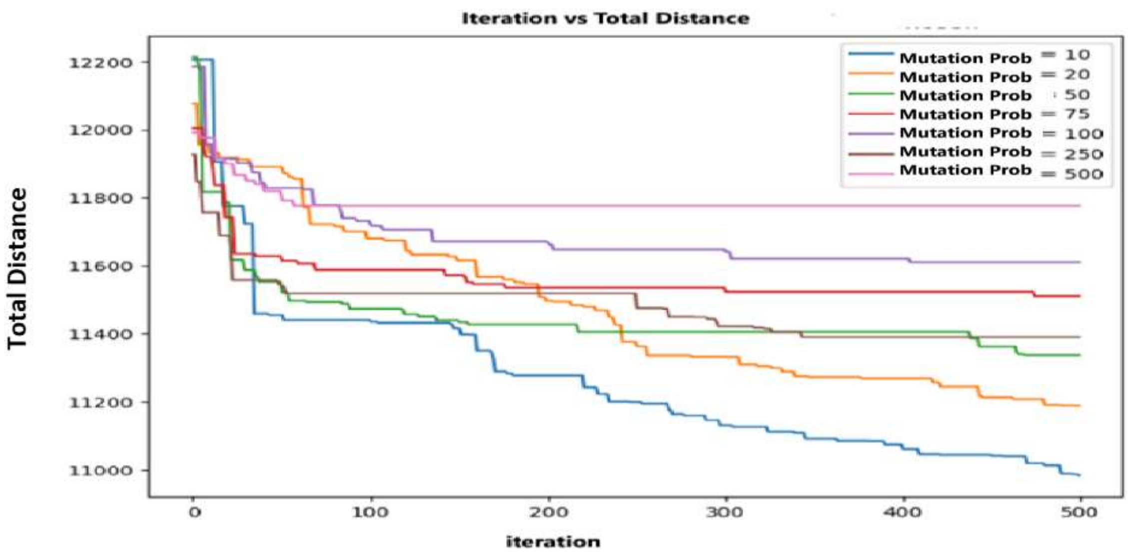

Figure 6. The Result for Hybrid Genetic Algorithm using Insertion

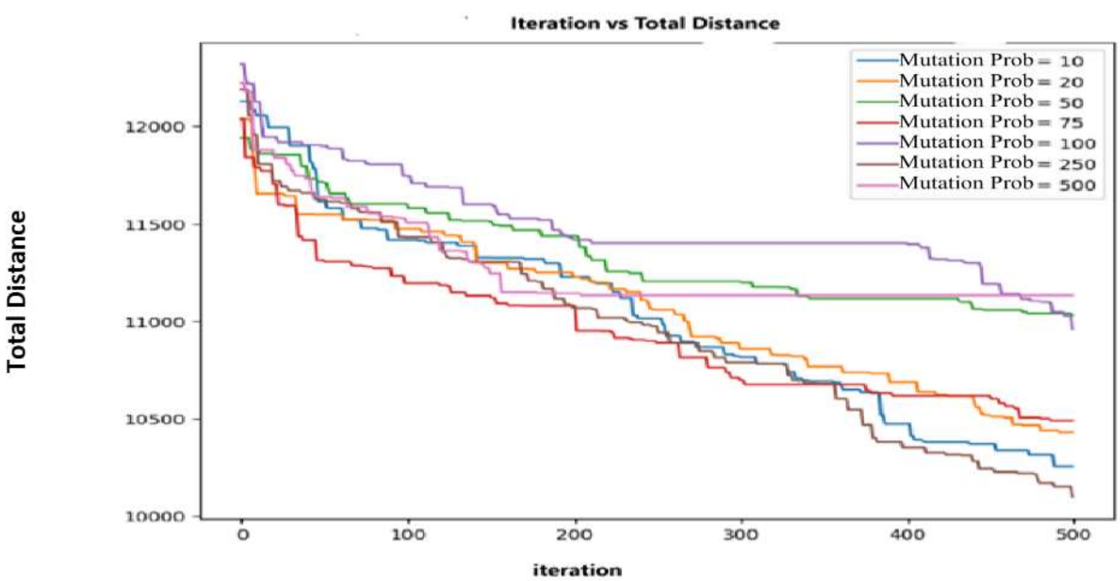

Figure 7. The Result for Hybrid Genetic Algorithm using Swap

Discussion:

The experiments results show that the hybrid genetic algorithm is able to provide the optimal solution for the shortest total distance search compared to the ordinary genetic algorithm. This is due to the presence of local search operators in hybrid genetic algorithms, which makes the algorithm more efficient in finding optimal solutions compared to genetic algorithms without local search operators. In addition, hybrid genetic algorithms require fewer iterations to produce the shortest total distance compared to ordinary genetic algorithms.

Based on the experiments results, the number of populations and iterations affect the optimal solution provided by the hybrid genetics algorithm and the ordinary genetics algorithm. The larger the number of iterations, the better the results obtained. From the 1st to the 4th experiment, the total distance generated became better, so that the most optimal results were obtained from the local search *swap hybrid genetic algorithm* with a mutation probability of 1:250 and the 500th iteration, with the shortest total distance of 10099.09 km. Meanwhile, the ordinary genetic algorithm achieves a mutation probability of 1:10 with the shortest total distance of 10923.063 km.

Conclusion:

Based on the results of the experiment using data from 636 teachers and 109 schools in Magelang Regency, several conclusions can be drawn.

1. The Hybrid Genetic Algorithm demonstrates superior performance compared to the Ordinary Genetic Algorithm
2. The Hybrid Genetic Algorithm generates the minimum total distances across the three approaches examined: Hybrid Genetic Algorithm with Local Search, Reverse Local Search, Insert Local Search, and Swap Local Search techniques.
3. The best results were obtained using the Swap Local Search technique, which produced the lowest total minimum distance of 10099.09 km with a mutation probability ratio of 1:250, 10 chromosomes, and 500 iterations
4. The success of a Genetic Algorithm largely depends on the design and integration of its search operators

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