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Comparison of Crossover and Mutation Operators to Solve Teachers Placement Problem by Using Genetic Algorithm

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Abstract. The placement of elementary school teachers is an NP-complex problem. Teacher placement can be optimized by considering several factors that influence their performance, including the distance of teacher's residence to school, age, and gender of the teacher. This paper discusses the solution model of the problem based on genetic algorithms by finding a chromosome formation that represents the possibility of teachers placement solution, composing a population, and finding the recommended combination of two selected mutations operators and two selected crossover operators to achieve optimal results. The selected mutation operators were Reverse Sequence Mutation (RSM) and Partial Shuffle Mutation (PSM), while the selected crossover-operators were Single Point Crossover (SPX) and Ordered Crossover (OX). The combined performance of these operators is measured based on the fitness value and running time of the program. Based on experiments, it can be concluded that the combination of OX-PSM with mutation probability 1:20 gives the lowest minimum fitness value compared to other combinations of crossover and mutation operators. The running time of the combination of OX-PSM is stable in any mutation probability, ranging from 39,5 – 41 minutes.

1. Introduction

One effort to improve the quality of education is through the optimal placement of teachers to support the performance of teachers in schools. The issue of structuring and equitable distribution of teachers has been discussed in several studies as written by Sujati [1], Widyaningrum [2], Wahyuni [3], and Prawiasad [4]. There are several factors that affect teacher performance, including the distance between a teacher's residence to school, age, and gender. From the data of the teacher placement in Magelang Regency, it was found that some teachers live very far from schools so that it affects the physical condition of the teacher because they travel long distances to schools. Increasing age and gender factors are also very likely to have impacts on teacher performance if the domicile is too far from the school. Therefore the success of teacher placement can be determined by the total minimum distance between the teacher to the school so that the teacher's performance could be maintained.

This problem is not easy to solve because of the large number of possible combinations of schools and teachers. In computer science, this problem includes NP-complete problems that are difficult to solve and require a very long time to achieve optimal results when done conventionally. A potential way to solve this kind of problem is by using genetic algorithms. The performance of the genetic algorithm is determined, among others, by the representation of the encoding solution, the crossover, and the mutation operator. There are many crossover and mutation operators known in genetic algorithms.

This paper discusses a model solution using genetic algorithms to solve teacher placement problems, by finding a combination of mutation and crossover operators to get good results. Previously, Abdoun et.al. [5] have concluded that two mutation operators that perform well are Reverse Sequence Mutation (RSM) and Partial Shuffle Mutation (PSM). Picek et.al. [6] have examined the performance comparisons of several crossover operators and concluded that the operator with the best performance is Single Point Crossover (SPX). However, Picek et.al. [6] have never compared SPX with the Ordered Crossover (OX) operator. In the previous study [7] the authors had tried to implement SPX crossover operators and combined them with exchange mutation operators, but the results were not optimal because the program execution time was still quite long and the resulting fitness value was not satisfactory. To improve the optimization of the teacher placement model using genetic algorithms, this study examines the performance of the RSM and PSM mutation operators and combines them with SPX and OX crossover operators. To evaluate the result, the performance of these combined operators is measured based on the fitness value and running time of the program.

2. Genetic Algorithm

Genetic algorithms are heuristic optimizations inspired by natural and genetic selection. This algorithm was developed by Holland [8] and Goldberg [9]. In genetic algorithms, the population of a potential solution is called a chromosome, which is expressed as a series of alphabets or numbers (usually binary numbers). Each chromosome represents a solution to a problem. Each chromosome also has a fitness value that shows how good a chromosome is as a solution to a particular problem.

The process of finding solutions with genetic algorithms begins with the random selection of a group of chromosomes. The initial chromosome is carried out a process to evaluate how good the chromosome is if chosen to be the solution to the problem being discussed. If the results of the evaluation are not satisfactory, then the process is repeatedly carried out to produce new chromosomes by using genetic operators, namely crossover and mutation. At each new set of chromosomes that are formed, an evaluation is done by recalculating the fitness value.

In general, the steps for genetic algorithms are as follows [8][9][10]:
1. Randomly generate n chromosomes as the initial population
2. For each chromosome in the population, calculate fitness value f(x)
3. Generate a new population by repeating the following steps until the new population is complete:
   a. Choose two chromosomes c1 and c2 as parents based on their fitness values. The higher the fitness values, the higher possibility of the chromosome being selected as parents.
   b. Using a particular crossover rate, apply crossover on c1 and c2 to produce child chromosome c.
   c. Using a particular mutation rate, apply mutation on chromosome c to produce a new offspring.
   d. Place the new offspring in the population
4. Replace the previous population with the new population
5. If stopping criteria have not been met, return to Step 2.

Genetic algorithms are commonly used to generate high-quality solutions to optimization and search problems by relying on bio-inspired operators such as mutation, crossover, and selection. Genetic algorithms have often been applied to optimization problems such as scheduling, assignments, route search, and others. The application in the scheduling problem can be found in [11 - 14], while the application in the assignment problem can be seen also in [15] and [16]. The use of genetic algorithms in the field of route search such as Traveling Salesman Problem can be found in [17 - 19].

Dewi et.al. [20] described the use of genetic algorithms to optimize teacher placement. Several variables that were considered in the model namely teacher qualifications, education, age, teaching experience, and work placement status. The fitness value is determined by counting the number of rule violations. The smaller the number of violations, the better the solution was. In [7] the authors proposed different variables to be considered in teacher placement problem, namely the distance of

teacher's residence to school, age, and gender of the teacher. The fitness function is determined based on these variables. However, the result has not been satisfied. In this study, the authors did some experiments by combining RSM and PSM mutation operators with SPX and OX crossover operators to find a better solution.

3. Model Development

Currently, there are no specific factors that are considered for the placement of teachers in the Magelang Regency. The distance between teacher's residence to school can be so far that it causes teacher fatigue, and ultimately reduces teacher performance. It is assumed here that teacher performance will be better when they are assigned to schools closer to where they live. The problem to be solved in this research is how to assign teachers in schools so that the total distance between teachers and schools is minimal. Thus, it is an optimization problem. As the continuation of the previous research in [7], the authors use the same model as described in [7]. In addition to the distance between the teacher's residence to the school, several other factors to consider in this optimization problem are gender and age. Female teachers get priority over men since female teachers take shorter distances than male teachers. Older teachers (those over or equal to 46 years) get closer priority mileage too. This age categorization is taken according to the Indonesian Ministry of Health where adulthood ends at 45, while old age starts at 46 years. In this study, a simplification is made by assuming that each school has 6 teachers. One teacher for each level from grade 1 to grade 6. The distance of a teacher's residence toa school is measured using Google API feature based on the coordinates of the location on Google Maps.

Each chromosome represents a candidate solution. A solution describes the formation of teacher placement in all study groups. A study group is a class consists of several students. Each school is assumed to have 6 study groups. Each teacher will be assigned to one study group. A one-dimensional array is used to express this structure. The array element represents the teacher's identity assigned in a certain study group as seen in Figure 1.   The chromosome length is 6 times the number of schools, where 6 states the number of study groups in one school.

School 1						School 2					
1	2	3	4	5	6	1	2	3	4	5	6
t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}	t_{11}	t_{12}

Figure 1. The representation of chromosome

Initially, 6 chromosomes will be generated randomly or, in other words, 6 random solutions will be generated. Each solution meets the requirement that there is only 1 teacher in each study group. The goodness of each solution (fitness function) is considered based on the total distance of all teachers in the solution to the school. The distance between the teacher and the school is given a certain weight, where the weight is influenced by the age and the gender of the teacher. If the teacher's age is lower than 46 years then the distance weight is 1, but if it is greater than or equal to 46 years then the weight is 0.6 if the teacher is female and 0.8 if the teacher is male as seen on the table 1.

Table 1. Distance's Weight.

Gender	Age < 46	Age ≥ 46
Female	1	0.6
Male	1	0.8

The fitness function which is the total distance (D) will be as follows:

$$D = \sum_{i=1}^{n} w(s_i)$$

The purpose of this optimization is to find a minimum value D, where

$$w = \begin{cases} 1 \,; if\ age < 46 \\ 0.8 \,; if\ age \geq 46\ and\ male \\ 0.6 \,; if\ age \geq 46\ and\ female \end{cases}$$

n = number of study groups = number of teachers
s_i= distance of teacher residence to school

In this study, the roulette wheel selection method is used to select the chromosomes to be mated (cross-overed), where the value of fitness is directly proportional to the probability of chromosomes' electability. The crossover operators being evaluated are Single Point Crossover (SPX) and Ordered Crossover (OX). SPX uses a reference point as a boundary to cross genes on the parent chromosome. This reference point is chosen randomly. After this point is selected, the genes on parent chromosome up this point will be copied to the child chromosome, then the genes on the second parent chromosome will be examined sequentially one by one. If the gene is not in the child chromosome, it will be inserted. In the OX operator, two cut points are randomly selected from the parents' chromosomes. To produce new offspring O1 the genes between the cut points are replaced by the genes in the second parent. The mutation operators being evaluated are Reverse Sequence Mutation (RSM) and Partial Shuffle Mutation (PSM). In RSM, two boundaries of a chromosome are determined. Then the genes between the two boundaries are reversed, while in PSM, some genes from a parent chromosome will be regenerated to produce a new chromosome [5]. The model was implemented using Java language.

4. Result and Discussion

To measure the performance of RSM and PSM combined with selected crossover techniques SPX and OX, several experiments were conducted with various parameters as follows: number of population = 6 chromosomes, number of generation = 5000, number of study groups which is equal to the number of teachers = 636, whereas the probability of a mutation to the crossover varies from 1:20, 1: 40, 1:60, 1:80, 1:100, 1:200, 1:300, 1:400. The experiments were carried out on 636 teacher data in Magelang Regency with distribution as described in table 2.

**Table 2.** Distribution of Teacher.

Gender	Age < 46	Age ≥ 46	Total number
Female	51	394	445
Male	20	171	191

The performance of the combined operators was measured based on the minimum fitness value and the running time of the program. Table 3 describes the minimum fitness value and running time of each experiment, while figure 2 and figure 3 describes the graphical view of the table. There are four combinations of mutation operators and crossover techniques, namely OX-PSM, OX-RSM, SPX-PSM, and SPX-RSM. The notation of OX-PSM means Ordered Crossover techniques combined with Partial Shuffle Mutation operator. Other notations have corresponding meanings.

Table 3. Minimum Fitness Values & Running Time of the Experiment.

Mutation Probability	Minimum fitness value				Running time			
	OX-PSM	OX-RSM	SPX-PSM	SPX-RSM	OX-PSM	OX-RSM	SPX-PSM	SPX-RSM
20	11162,31	11675,85	11856,38	11842,49	41,017	52,233	54,17	34,90
40	11431,48	12076,68	12029,99	12131,82	40,233	52,017	34,80	35,97
60	11415,08	12014,34	12159,14	12082,07	39,217	49,267	53,18	31,68
80	11663,90	11835,79	12208,96	12290,99	40,167	49,083	44,25	33,82
100	11558,53	12310,93	12196,76	12321,79	38,950	51,700	42,10	36,08
200	12232,04	12172,18	12396,71	12301,75	39,500	48,450	34,30	35,10
300	12093,54	12330,10	12322,98	12377,53	39,517	49,083	63,05	35,10
400	12401,35	12538,51	12494,64	12378,91	40,733	52,650	79,08	29,03
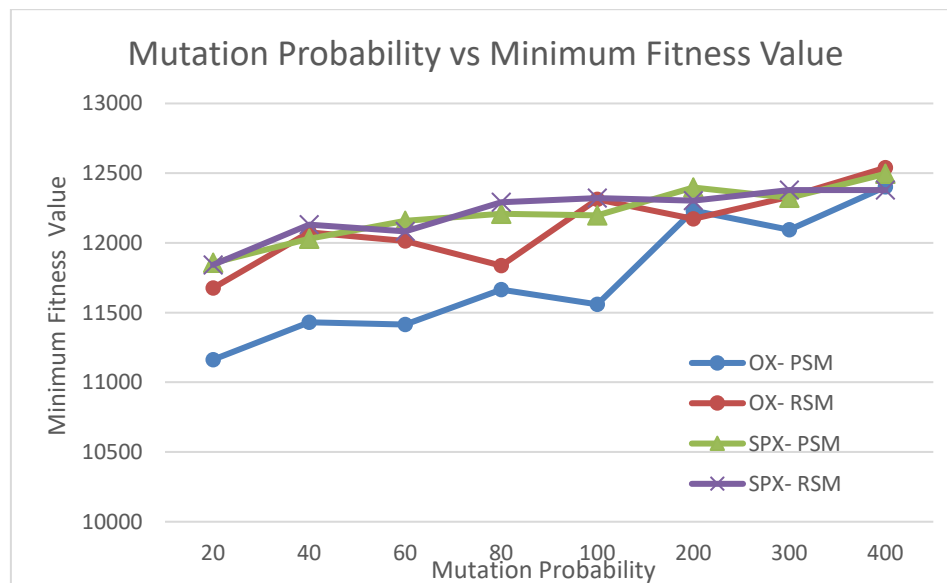
Figure 2. Mutation Probability vs Minimum Fitness Values of the Experiment.
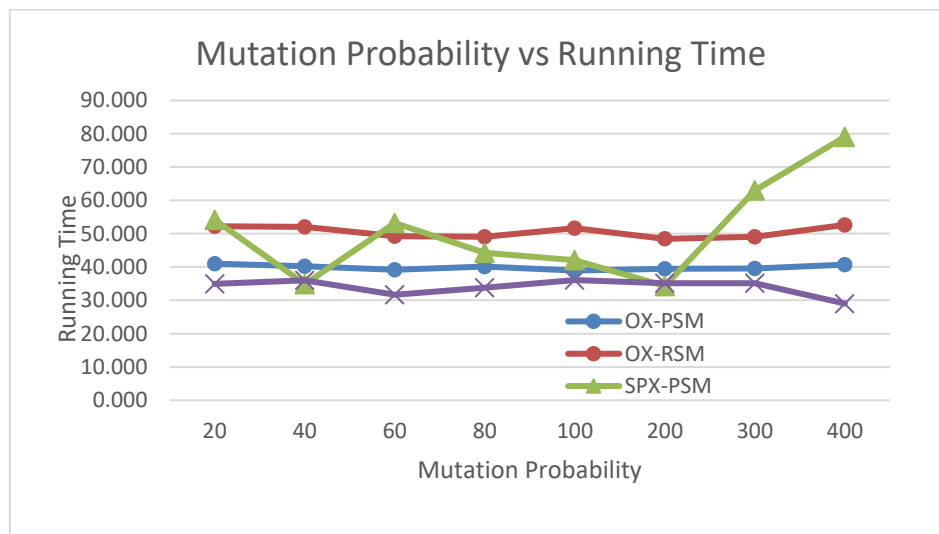
Figure 3. Mutation Probability vs Running Time of the Experiment.

From table 3 and figure 2, it can be seen that in the four combinations of crossover and mutation operators, smaller mutation probability tends to result in smaller minimum fitness values as well. Also, for all mutation probabilities, the combination of OX-PSM always result in smaller fitness values compare to other combination of crossover techniques and mutation operators. The smallest minimum fitness value is achieved by the combination of OX and PSM with mutation probability 1:20, while the combination of OX-RSM with mutation probability 1:400 results on the highest minimum fitness value.

From table 3 and figure 3, it can be seen that for all mutation probabilities, the running time of SPX-RSM combination is always shorter than other combinations of mutation and crossover technique. The running time of the SPX-PSM combination tends to be unstable compared to other combinations of mutation operators and crossover techniques which are quite stable. The shortest running time is found on the combination of SPX cross-over operator and RSM mutation operator with a mutation probability of 1: 400. On the other hand, the longest-running time is found on the combination of SPX cross-over operator and PSM mutation operator with a 1: 400 mutation probability.

5. Conclusion

From the above discussion, it can be concluded that the combination of Order Crossover-Partial Shuffle Mutation operator with mutation probability 1:20 gives the lowest minimum fitness value compared to other combinations of crossover technique and mutation operator. Besides, the running time of the combination of OX-PSM is quite stable in any mutation probability. Therefore, the combination of OX-PSM can be recommended as the model of decision making in teacher placement problem that considers the following factors: the distance of teacher's residence to school, and gender as well as teachers' age.

Further research to embed the model in a decision support system is encouraged. Another possible research development involves other determinant factors in the case of teacher placement.

6. Acknowledgments

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