Genetic Algorithm With Random Crossover and Dynamic Mutation on Bin Packing Problem

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Abstract—Bin Packing Problem (BPP) is a problem that aims to minimize the number of container usage by maximizing its contents. BPP can be applied to a case, such as maximizing the printing of a number of stickers on a sheet of paper of a certain size. Genetic Algorithm is one way to overcome BPP problems. Examples of the use of a combination of BPP and Genetic Algorithms are applied to printed paper in Digital Printing companies. Genetic Algorithms adopt evolutionary characteristics, such as selection, crossover and mutation. Repeatedly, Genetic Algorithms produce individuals who represent solutions. However, this algorithm often does not achieve maximum results because it is trapped in a local search and a case of premature convergence. The best results obtained are not comprehensive, so it is necessary to modify the parameters to improve this condition. Random Crossover and Dynamic Mutation were chosen to improve the performance of Genetic Algorithms. With this application, the performance of the Genetic Algorithm in the case of BPP can overcome premature convergence and maximize the allocation of printing and the use of paper. The test results show that an average of 99 stickers can be loaded on A3 + size paper and the best generation is obtained on average in the 21st generation and the remaining space is 3,500 mm^2.

Keywords—Bin Packing Problem, Genetic Algorithms, Dynamic Mutation, Random Crossover, Premature Convergence

I. INTRODUCTION

Companies in various industrial fields face the problem of cuts / patterns, for example in the paper, steel, textile and glass industries [1]. This problem can cause companies to be wasteful in the production process. For example, digital printing companies that use paper as one of the main raw materials. The use of good paper will save printing objects (photos, stickers, etc.) on printed paper. Optimization can help increase the ratio of the use of stock sheets, reduce preparation time and standardize process management [2].

Bin Packing Problem (BPP) is a type of problem that is similar in this case. BPP aims to package all goods into a minimum number of containers so that the total weight or capacity packed in it does not exceed capacity [3]. Examples of cases, such as printing stickers with various sizes on printed paper. So, how can you arrange the placement of stickers on printed paper so that more can be loaded and fewer areas of paper that are not used.

Several methods have been proposed to resolve BPP, including the use of Genetic Algorithms [4]. Characteristics of Algorithm Genetics is evolution, which means a process by which organisms develop better over time. Because of these characteristics, Genetic Algorithms carry out several repetitive generations until the best solutions are finally found. However, in this Genetic Algorithm we find the problem of premature convergence, which causes the optimal solution to be given because the results are too early *(local optimum)*.

Premature convergence is a condition that occurs when a population of Genetic Algorithms reaches a suboptimal state where genetic operators no longer produce offspring with better performance than parents [5]. For this reason, problems need to be solved, one of them is by modifying the parameters of Genetic Algorithm. The parameters that are often modified are crossover and mutation [6].

Research conducted by [7] proposed the development of crossover and mutation methods, namely Random Crossover and Dynamic Mutation. This development succeeded in overcoming premature convergence in the case of Traveling Saleman Problem (TSP). The final results obtained are also better than general crossover and mutations.

Based on some of the things previously explained, this study will apply the Random Crossover and Dynamic Mutation method to the BPP. An example of a BPP chosen is the allocation of stickers on printed paper. In this study, an interface will be developed that illustrates the Genetic Algorithm process on this issue. Premature convergence is expected to be overcome and also prove that Random Crossover and Dynamic Mutation can be applied to methods other than TSP.

II. PRELIMINARY RESEARCH

A. Genetic Algorithm

Genetic Algorithms are part of Evolutionary Algorithms that adopt evolutionary values, such as population, selection, crossover, mutation and so on. Genetic algorithms are similar to many other meta-heuristic algorithms that are population-based algorithm based algorithms. In other words, the population representation of answers will develop through an optimization process to move towards optimality of the problem [8]. The final result of this algorithm is a representation of the best or acceptable solution. To find out the flow of the Genetic Algorithm process can be seen in Figure 1.
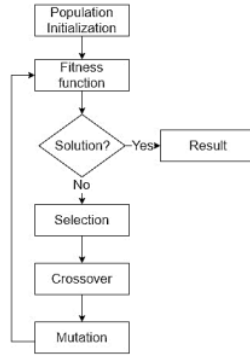
Fig. 1. Genetic algorithm process

B. Bin Packing Problem

One type of problem that can be overcome by Genetic Algorithms is the Bin Packing Problem (BPP). BPP is a case involving a number of objects or materials that must be inserted into as few containers as possible. Such as the case of the allocation of 2 (two) dimensions, cargo on container trucks, and others. Following this, Figure 2 is an example of a BPP case in a 2 (two) dimension field.
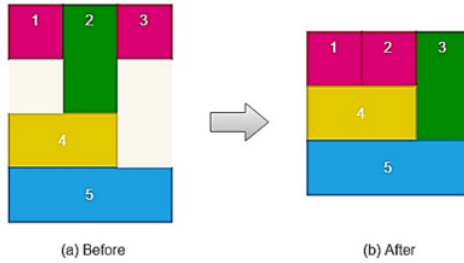

(a) Before   (b) After

Fig. 2. Bin packing problem process

Figure 2(a) is before the BPP process and Figure 2(b) is after the process has ben completed. BPP is solved by various methods proposed by many researchers. In fact, it is known that the bin packaging problem is Non-deterministic Polynomial-time Hard (NP-Hard) [9].

C. Premature Convergence

Premature convergence is an event where the Genetic Algorithm process is no longer able to find the best solution. This situation makes the solution stuck to the optimum locale. Figure 3 is an illustration of premature convergence.
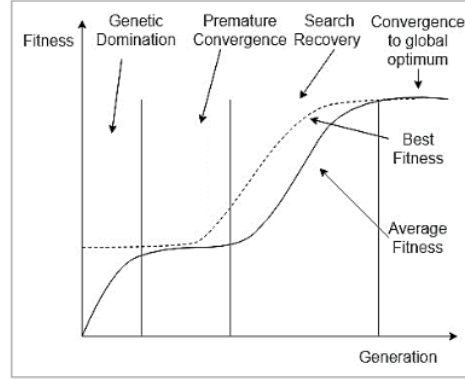

Fig. 3. Premature convergence illustration

At the beginning of generation, the fitness value obtained does not change. This is known as premature convergence (fitness value is too early to stop). Then, after subsequent generations fitness values rise until convergence occurs at the best point.

D. Random Crossover and Dynamic Mutation

The research conducted by [7] has been tested for improved crossover and mutation. The trial showed better results compared to current crossover and mutation methods. In a crossover, the algorithm first produces a random intersection, and the length of the crossover part is half of the individual length. According to the starting position and the fixed length of the crossover section, this algorithm might produce a second intersection, thus breaking the boundaries of the number of fixed intersections and increasing population diversity.

The original individual length is n, and the length of the crossover part is m, their relationship satisfies equation 1.

$$m = \left\lceil \frac{n}{2} \right\rceil \tag{1}$$

In Random Crossover method, the crossover intersection points are different, and the results of the exchanged parts A with B are also different. The probability of mutations is dynamically generated, the size varies because it is influenced by changes in population stability. When the population is unstable, the probability of mutations can be very small, when the population is almost stable for local solutions, the probability of mutations will increase. The formula for calculating the current mutation probability is in equation 2.

$$P_2 = \left(1 - \frac{C_{ave} - C_{min}}{C_{min}} \right)^k \tag{2}$$

Step 1: Through the state of the population of the last generation, calculate the sum of all the individual characteristics of the current generation.

Step 2: Use population size n and C_{all} to calculate the average of individual characters and be represented as a C_{ave}.

Step 3: Find the most optimal individual in the current population and record its characteristics as C_{min}.

Step 4: Calculate the probability of a current mutation P_2 and the results are stored for genetic processes. The

formula for calculating the current mutation probability. At the same time, k is an assumed coefficient to regulate the amplitude of the probability change.

E. Literature Review

The Genetic Algorithm Research conducted by [7] discusses the parameters that can overcome premature convergence. They propose the latest crossover and mutation techniques to reduce premature convergence and improve the final results of solutions, namely Random Crossover and Dynamic Mutation. After testing, the simulation results show the speed convergence and optimal solutions. This proposal is clearly better than traditional Genetic Algorithms, Adaptive crossover probability Genetic Algorithms and improved genetic selection algorithms.

Research conducted by Bala and Sharma [10] applied Genetic Algorithms to the Traveling Salesman Problem (TSP) to find the optimal solution. The crossover operator with a cycling technique is used to avoid the problem of missing and duplicate integers from traditional crossover operators. Mutation and crossover operators play an important role in the work of Genetic Algorithm. Here, Genetic Algorithm is applied to problems to show the performance of a new single point operator, two points and uniforms. The experimental results show that the new one-point crossover operator outperformed the other two crossover operators. Experiments also illustrate that Genetic Algorithms provide better results with low mutation rates.

The research conducted by [11] proposed an optimization of the BPP Genetic Algorithm (GABP) in the metal framework by changing the crossover and mutation parameters. The results obtained are almost the same as Hybrid-GA. An interesting finding is that when bin is greater than a constant, for example, 0.96, the algorithm shows performance that is similar to the heuristic algorithm, such as First Fit (FF) and Best Fit (BF).

Research conducted by [12] discusses the problem of cutting and packaging on rectangular objects, such as clothing, metal materials, and others. Then the researcher combined several algorithms, such as Best-Fit + Same Adjacency (BF + SA), Heuristic for Rectangular Packing (HRP), and Layer-based heuristic and Genetic Algorithms (LH + GA). As a result, LH + GA has the fastest time in the process. This combination is in accordance with the rational layout problems of rectangular objects in the field of engineering, such as the wood, glass and paper industries, and ship building industry, textile and leather industries.

The research conducted by [13] discuss how to maximize the ratio of paper use and reduce production costs. Then, Genetic Algorithms are selected and compiled by the appropriate supporting operators. As a result, the combination of Genetic Algorithms and horizontal line search algorithms can meet the requirements for production standards, and can be used for mass production in cutting patterns.

The research conducted by [14] proposed a framework for the application of Genetic Algorithms to 2-dimensional BPP and identified problems in path recombination and hill-climbing mutation. The results of sequence optimization decide which items will be placed before the others, making the given greedy placement strategy produce the best results.

The research conducted by [15] in this study, a detailed and comprehensive survey of various approaches was applied to prevent premature convergence in Genetic Algorithm with its advantages and disadvantages. It was concluded that many studies used reproductive operator Genetic Algorithms to deal with premature convergence. It has been shown in many literature that by applying crossover and mutation in the right way can avoid premature convergence.

III. RESEARCH METHODS

This study uses an experimental research method combining Genetic Algorithms with Random Crossover and Dynamic Mutation parameters in the case of sticker allocation in printed paper. Experimental experiments were carried out on modified crossover parameters and mutations. The results of these algorithm experiments are compared with Genetic Algorithms with parameters in general. Each experiment uses the same data. The various experiments conducted in this study include:

- Data collection. At this stage the data is collected from SOLEGRAFIK printing. The data obtained is printing paper and some certain size stickers.

- Process. In this part of the process, the implementation of Genetic Algorithms is carried out with general parameters and also Random Crossover and Dynamic Mutation parameters in the test data.

- Analysis. At this stage, the results of the process will be analyzed to determine whether the method applied has succeeded in improving premature convergence and improving the final results.

- Result. In this process a representation of the solution will be displayed and compared to determine its performance, then it will be displayed in tables and graphs.

A. Data Collection

Data collection methods used in this study were observations and observations on SOLEGRAFIK printing. collection obtained from printing is in the form of printing paper size and sticker size.

B. Model Design and Testing

In this research a Genetic Algorithm design was made using Random Crossover and Dynamic Mutation which had been done in previous studies. For this study, it will be tested on the case of sticker printing on A3 + size paper. Then this design will be applied and tested to determine its performance. First, collect datasets from SOLEGRAFIK printing for test data. Second, the Genetic Algorithm process with general parameters will be tested. Beginning with the process of forming chromosomes until mutations and the results will be stored. Third, the proposed algorithm process will be tested, the results will be saved again. Finally, the two test results will be compared to determine the best.

The dataset to be used in this study design was obtained from SOLEGRAFIK printing. The dataset used is A3+ size paper and several sizes in the following table.

TABLE I.   STICKER AND PAPER DATASET

Label	Sticker size (mm)	Paper size (mm)
A	48x150	
B	20x40	480x325
C	88x75	

D	50x70	

In this study, label A stickers will be combined with label stickers B. Then also with label C stickers will be combined with label stickers D. Chromosomes (individuals) consist of 2 types of stickers that have a size of width (w), height (h) and quantity (q). Each sticker can have a normal orientation or a 90° rotation. There are limits to chromosome formation, ie each sticker size does not exceed the length and width of the printed paper.

1	88x75mm
2	50x70mm
3	75x88mm
4	70x50mm
...	...
n	nxn

(a) Sticker

1	150x48mm
2	48x150mm
3	20x40mm
4	40x20mm
...	...
n	nxn

(a) Sticker CD

Fig. 4. Chromosome formation

The probability of mutations is adjusted, seeing from the biggest fitness as the main reference. For this case, the formula for the original dynamic mutation changes to equation 3.

$$P_2 = \left(1 - \frac{C_{max} - C_{ave}}{C_{max}}\right)^k \qquad (3)$$

Previously in equation 2, C_{min} was considered the best individual. However, in this case the formula is changed to C_{max} as the best individual and and applied to equation 3.

C. Research Steps

The steps planned in this study are illustrated in Figure 5.

Literature review

Identification of problems

Formulation of the problem
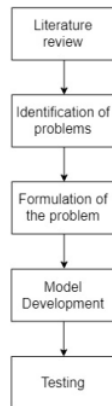
Model Development

Testing

Fig. 5. Research steps

IV. RESULTS AND DISCUSSION

The application designed in this study was built using the PHP programming language. In this study an application prototype was developed that applies genetic algorithms with general parameters and modification parameters. This prototype will display sticker layout information on printed paper according to the data entered. For more details, see in Figure 6.

Fig. 6. Application workflow

The purpose of this test is to determine the performance level of the algorithm under study. In the general algorithm the general parameters and modification parameters will be included in the same data, namely the sticker size and the size of the printing paper. Table 2 below is the data tested.

TABLE II. DATA TESTING GENETIC ALGORITHM PROCESSES

Label	Sticker 1 (mm)	Sticker 2 (mm)	Paper size (mm)
AB	20x40	48x150	480x325
CD	88x75	50x70	

In Table 2, the data of the two stickers will be combined and allocated to 1 (one) of the same printed paper. In the next process, the test data is processed following the data in the testing initialization. For initialization of generation, population, and chromosome lengths, use the data in Table 3.

TABLE III. TEST INITIALIZATION DATA

Generation	Population	Chromosome length
100	50	Sticker 1 + Sticker 2

In Table 3, loops are carried out 100 times with each generation having a population size of 50 chromosomes. Each chromosome has a total gene length of the number of items sticker 1 and sticker 2.

The algorithm testing process is performed on 4 (four) genetic algorithm scenarios as follows:

- Using general parameters
- Using Random Crossover
- Using Dynamic Mutation
- Using Random Crossover and Dynamic Mutation

Some of these algorithmic test scenarios are conducted to see the effect of each parameter on the final results obtained. Then, to be more detailed, 3 (three) indicators of the test results are applied in each scenario as follows:

- Sticker quantity
- Processing time
- Premature Convergence

If the quantity of stickers obtained is more and more, the better. If the processing time is faster, the better. Whereas, for premature convergence seen from the best generation. If the best generation is obtained not earlier, but in the middle and at

the end, then there is the same value following it in several generations, then premature convergence has occurred.

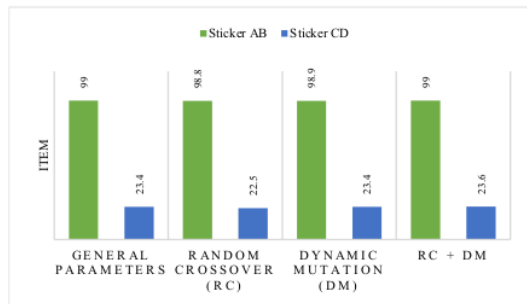The use of random crossover and dynamic mutation was adjusted in this case of BPP.

Fig. 7. Analysis of sticker quantity

Of the four test scenarios, the best average quantity for AB label stickers is 99 stickers. These results in Figure 7, are obtained from testing general parameters and Random Crossover with Dynamic Mutation. Whereas on CD label stickers, the best results are obtained from Random Crossover with Dynamic Mutation testing, the average quantity obtained is 23.6 stickers.
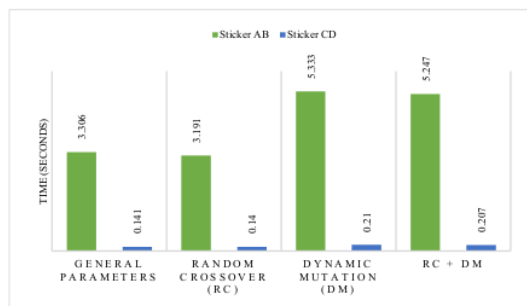

Fig. 8. Analysis of time process

Figure 8 shows the four test scenarios, the fastest average time for label AB stickers is 3,191 seconds on Random Crossover testing. The same thing happened to CD label stickers, Random Crossover testing had the fastest time, which was 0.14 seconds.
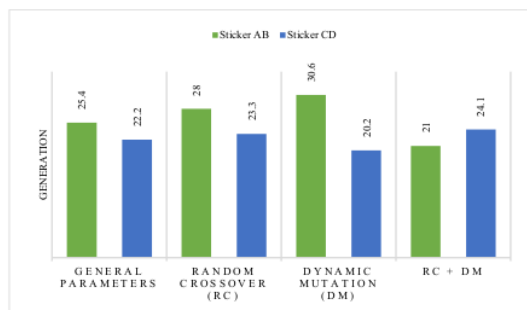

Fig. 9. Analysis of premature convergence

Based on Figure 9 and the four test scenarios, the average generation of the best label AB stickers is the 21st generation in Random Crossover testing with Dynamic Mutation. While

on CD label stickers, Dynamic Mutation testing is the best with the best generation average obtained in the generation 20.2nd.

TABLE IV. INDICATOR TEST RESULTS

Testing Indicator	General Parameters	Random Crossover (RC)	Dynamic Mutation (DM)	RC + DM
Sticker Quantity	AB			AB, CD
Processing Time		AB, CD		
Premature Convergence			CD	AB
Total	1	2	1	3

In Table 4 can be seen the average results obtained by each test. For sticker quantity indicators, testing with general parameters and Random Crossover with Dynamic Mutation is the best for AB label stickers and CD label stickers. The maximum amount that can be allocated is an average of 99 and 23.6 stickers. In the process time indicator, testing with Random Crossover is the fastest, both for AB label stickers and CD label stickers. The fastest time obtained is an average of 3,191 seconds and 0.14 seconds. Finally, the premature convergence indicator on Random Crossover testing with Dynamic Mutation is the best for AB label stickers. The best average results can be obtained in the 21st generation. CD label stickers have the lowest premature convergence performance on Dynamic Mutation testing. The best average results were obtained in the 20th test. This is the fastest (initial) generation that produces the best allocation.

V. CONCLUSION

Based on the research that has been done, the genetic algorithm model with modifications to the Random Crossover and Dynamic Mutation parameters can be applied in the case of a two-dimensional Bin Packing Problem. This can be seen in the results of testing the quantity of AB label stickers obtained in the same amount as the general parameters, namely 99 stickers. The same event is also on a CD label sticker. Most stickers that can be loaded occur when modifying the two parameters. The advantage of applying Random Crossover and Dynamic Mutation is that it can prevent premature convergence. In testing, the results of general testing obtained the best average results in the 25th generation. Meanwhile, the Random Crossover random crossover test obtained the best average yield in the earlier generation, namely the 21st generation with the remaining free space of 3,500mm².

However, the processing time obtained from Random Crossover testing with Dynamic Mutation was longer. In fact, the fastest processing time is obtained from testing that applies Random Crossover only. So prevention of premature convergence is successful, but does not make the entire processing time faster. For further research, the use of Random Crossover with Dynamic Mutation is expected to be combined with other methods. This is done with the hope that sticker allocations are more orderly and maximal. Or modification of this parameter is applied in the case of genetic algorithms other than bin packing problems so that they can be universal.

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