A Crossover in Simulated Annealing for Population Initialization of Genetic Algorithm to Optimize the Distribution Cost

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***Abstract*—Solving distribution problems have been an alluring topic for some academician. The determination of proper distribution network to provide a minimal cost is still difficult to resolve. This is because there are some difficult constraints to be addressed. As an algorithm, which typically offers a set of solutions in solving the problems, genetic algorithms (GA) has verified its power in solving complex combinatorial problems. The generation of a set of initial solutions (population) generally performed randomly in GA. In the large cases, it is becoming one of the drawbacks since the search space becomes too wide, so the probability to get stuck in a local optimum solution is also high. Therefore, simulated annealing (SA) is employed to generate the initial population for the GA. SA has been selected since it is able to avoid a local optimum solution. In this study, the process of finding new solutions using SA is improved by using the crossover process, which is commonly used in GA. This method has become novel because the crossover has the same principle of providing varied new solutions that still retain some of the properties of the parent solution. The result of the modification SA-GA proven to provide superior results than the existing algorithms.**

***Index Terms*—Genetic Algorithms; Crossover; Simulated Annealing; Multi-Level Multi-Product Distribution.**

I. INTRODUCTION

Distribution is the process of moving the product of a plant to the customers through multiple distributors [1]. Distributor in question is the perpetrator distribution, generally consists of central distributors, retailers, agents, and many others. The perpetrators have assumed the distribution levels in the distribution network (multi-level) with the highest level that is the central distributor, the lowest level that is the retailers and so on, as shown in Figure 1 [2], [3]. The problem is the distribution process cannot be performed randomly without considering some of the constraints that accompanying it. Some of the constraints that need to be considered carefully are such as the selection of the right vehicle from the number of vehicles available, the vehicle capacity limits and costs that followed, the distributor unit capacity limit on each level, the stock capacity of each distributor, and the capacity of the plant. If the solutions offered have already met these constraints, then the problem of the distribution network is solved at a minimal cost produced. The problems of distribution network will be more complex when a company produces more than one type of products (multi-product) [4], [5]. The products ordered by customers have a number of problems, which are uncertainty and each customer wants a different type of product [3].

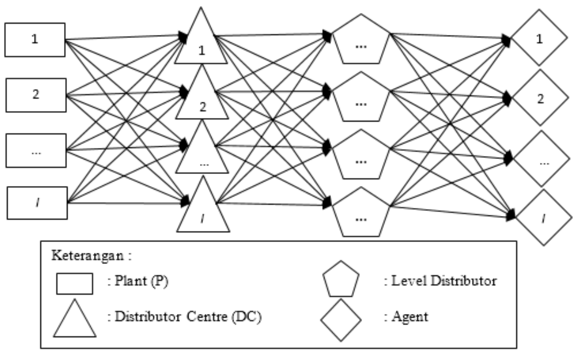

Figure 1: Distribution Network

Some researchers have resolved the distribution problems by acquiring minimum distribution costs, such as an approach to modeling the distribution problems into integer programming [6]. In this study, the distribution network used is the distribution network of two levels, in which the distribution of products from the plant to the customer that must go through a central distributor first. This study dealt with more than one type of product. The constraints involved in this study include the whole search for solutions in the distribution of resources among others, stock inventory, production, and transportation costs. Optimization model proposed in the study applies the integer programming and the solutions sought the help of special applications, such as LINGO and CPLEX. The advantage of this model is it finds the flow of the distribution and offers a variety of possibilities for decision support through analysis of available capacity on the distributor and the number of transportation units. According to researchers in the study, they stated that the weakness of the proposed model is that it is an intuitive approach and consistent with the standard form of the linear programming that is not very useful in practice because of the implementation of the differences in the size of the model.

As an algorithm capable of solving problems due to the complexity of combinatorial problems limit [7], genetic algorithms have also been used to solve distribution problems. In the completed study, a distribution network that uses a multi-level and one type of product has been adopted. The solution search was conducted by considering the constraints to find the minimal cost of distribution. The model proposed in that study can be applied in the real world due to its versatility with the way the data are used. The results obtained also provide the nearly optimal solution than the random search algorithms. In addition, a genetic algorithm was previously (GA-old) compared with the new genetic algorithm (GA-new) that uses a different operator, which is either a crossover, mutation or selection. The result of fitness is a value that indicates how well a candidate solution in a genetic algorithm, derived from genetic algorithms provide results that are less stable when it is executed as many as 10 times when compared with the GA-old and a random search on previous research. However, overall, based on the average fitness, the result given by GA-new has higher quality. Based on the quality of the results, it can be concluded that the model of the crossover operator one-cut-point, swap mutation, and selection elitism is highly recommended.

Instability results from GA-new fitness [7] indicate that a given solution can still be repaired because they are stuck in a local optimum solution. This is caused by using a genetic algorithm that is still classical [8]. In contrast [9] which says that the preliminary determination in the process of the genetic algorithm is very important and can affect the solution. In general, the initial value of the genetic algorithm is randomly generated only [10], [11]. The use of random values has the disadvantage that if it is determined in the range of values that is large enough, then the process of finding solutions uses genetic algorithms to extend the computational time and the number of iterations that much.

Based on the problems described, the researchers are trying to raise the issue with the distribution of multi-level network using more than one type of products (multi-product). The algorithm used is a modification of a genetic algorithm used to find solutions more quickly with a relatively short time using a simulated annealing algorithm (SA). In a previous study, SA is also proven to be able to solve the other optimization problem [12]. This is because SA has the advantage to avoid the local optimum solution; hence, expecting a better solution obtained and nearly optimal.

II. Methodology

The data in this study is the simulated data generated based on the interview result with some experienced experts of distribution of several companies [7], [13]. Referring to the objective function, the variable cost of some products for every level distributors is also considered.

A. *Mathematical Formulation*

To model the distribution of multi-level multi-product problem and to make it easier to understand, it is formulated mathematically. Table 1 is the notations and necessary variables to solve the distribution problem. Based on the notations of the distribution of multi-level and multi-product that has been declared, the calculation of the total cost to be incurred is based on the formula in Equation (1).

$$Z = \sum_{l=0}^{L}\sum_{m=0}^{M}\sum_{n=0}^{N}\sum_{p=0}^{P}\left[\left(X_{lmnp}Cvb_{lmp}\right)+Cfx_{lmn}\right]St_l \qquad (1)$$

Besides formulating a mathematical model of distribution problems, there are also some constraint functions used as a prerequisite to represent a solution so as to provide optimal solutions. Equation 2 represents the number of each product shipped that must not exceed the order of the customer. Equation 3 is the constraint about the number of each product shipped that must be less than the capacity of the inventory on the distributor unit shipper and equation 4 represents the number of product unit shipped that must be less than the vehicle capacity.

Table 1
Notations in Distribution

Notations	Description
l	Level, $l \in L=\{1,2, \ldots, L)$
m	Distributor unit shipper
n	Distributor unit customer
v	Vehicle of distributor unit $v \in V=\{1,2, \ldots, V)$
p	Product, $p \in P=\{1,2, \ldots, P)$
X_{lmnp}	The number of product units to be shipped by the distributor unit shipper m to distributor unit customer n with p product
Cvb_{lmp}	Variable cost for each product p at distributor unit m at level l
Cfx_{lmn}	Fixed cost from distributor unit m to distributor unit n
St_l	Shipping the product if the value is 1, otherwise is not.
Or_{mp}	The number of order that shipped from distributor unit m for each product p
Cp_{mp}	The capacity of the stock owned by the distributor unit m for each product p
Vcp_{lmv}	The vehicle capacity of v owned by distributor unit m

$$\sum_{m=0}^{M}\sum_{p=0}^{P} X_{lmp} = Or_{mp} \qquad (2)$$

$$\sum_{m=0}^{M}\sum_{p=0}^{P} X_{lmp} \leq Cpc_{mp} \qquad (3)$$

$$\sum_{m=0}^{M}\sum_{v=0}^{V} X_{lmv} \leq Vcpc_{lmv} \qquad (4)$$

In this study, the distribution problem is solved using GA with modifications of SA. SA processes are used to improve the initial population of the GA, which is generally carried out randomly. The architecture of the proposed algorithm is shown in Figure 2.

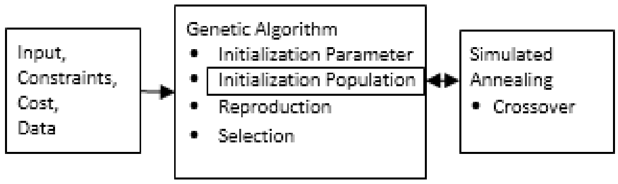

Figure 2: Architecture of SA-GA

B. *Simulated Annealing (SA)*

The iron crystallization process is a process of imitation performed by simulated annealing. It begins with a warm iron and followed by lowering the temperature gradually until the iron is transformed into crystalline that forms SA work process in general [14]. As one of the local search algorithms, SA has the ability to escape from local optimum solution, especially when juxtaposed with other algorithms. SA working process is generally described in Figure 3.

For the description of the structure of the solution, Figure 4 is the illustration for one segment solution. The number of segments for a solution depends on the number of levels required upon order. Each of the columns contained in the solution is a representation of the number of product units to be shipped to the distributor unit customer.

```
Initial temperature T=T_0 dan solution x_0
Set last Temperature T_f, maximum iteration N,best
X_b
While (T≥T_f)
  For N
    Calculate f(x_t)
    Search current solution x_t+1 = crossover(x_t)
    Calculate f(x_t+1)
    IF f(x_t+1)< f(x_t)THEN
       Accept current solution (x_t=x_t+1)
       x_b = x_t+1
    ELSE IF f(x_t+1)> f(x_t)
       Accept solution if the probability
       p=1/[exp((f(x_t+1)- f(x_t))/T)] bigger than
       variable u in range [0,1]
    END IF
  END For
Update T=T*α
END WHILE
Return x_b as best solution
```

Figure 3: Pseudocode of SA

<table>
<tr><td colspan="17">Level l</td></tr>
<tr><td colspan="15">m</td><td>. .</td><td>M</td></tr>
<tr><td colspan="7">v</td><td>. .</td><td colspan="7">V</td><td></td><td></td></tr>
<tr><td colspan="3">n</td><td>. .</td><td colspan="3">N</td><td></td><td colspan="3">n</td><td>. .</td><td colspan="3">N</td><td></td><td></td></tr>
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<tr><td>30</td><td></td><td>122</td><td></td><td>22</td><td></td><td>51</td><td></td><td>101</td><td></td><td>25</td><td></td><td>35</td><td></td><td>55</td><td></td><td></td></tr>
</table>

Figure 4: Solution Representation of one-segment

In Figure 4, the value in the first column is 30. The meaning of it is at the initial level *l*, the distributor unit *m* using its vehicle *v* to ship 30 product units of product type *p* to distributor unit customer *n*. The value in the other columns also has the same meaning. The length of the chromosome is obtained from the multiplication of the number of the type of products ordered by each distributor customer and the number of vehicles distributor unit shipper. Solutions have been normalized so that it meets some limits of the calculated energy distribution problems to find out how well is the solution. Based on the theory of annealing, the less energy, the better solution or particle formation is derived so that the problem of distribution, the lower cost, is the better solution to provide a solution and distribution costs searched using equation (1).

SA process used in the study has a novelty. To search the current solutions, this study implements the crossover process, which is commonly used in GA. This is applied because inserting the crossover process in SA as the initial population of the GA generated a better result than SA, in general. There are several models of crossover capable of solving distribution problems in the previous studies, such as one cut point that scrambles the number of genes to get the position as a point deduction, then both parents were elected cut on selected and displacement cross the position [15]. Two cut points that choose 2 positions of genes randomly at the same time, and then transfer crossly the first parent genes at the center position to the middle position holding on the other parent. Extended Intermediate that works by replacing certain values in the range specified by the variables obtained at random between 0 to 1 is usually called α [16]

C. Genetic Algorithm

A genetic algorithm is implemented to solve distribution problems, because of its natural properties of individual biological natural selection provide solutions that can solve some complex problems [17]. The process of GA begins with chromosome representation, reproduction, evaluation, and selection to obtain the quality solution. Regarding the high value of fitness of the individual on the next generation, it has a higher probability to be selected again as a solution [18].

1) Chromosome Representation and Population Initialization

The encoding process of chromosome representation is essential in the process of GAs due to the correct coding of the solution and in accordance with the issue would provide the correct solution, as expected [19]. The structure of chromosomes in the process of genetic algorithm has a similar structure of the solution in Figure 4. The solutions used in the representation of these chromosomes are not generated randomly in general of GA, but using solution results that have been processed using simulated annealing algorithm. The solutions are as numerous as the population obtained from the SA into a set of solutions used as the initial population in the process of GA.

2) Fitness Function

The fitness calculation process is applied to each chromosome/individual whose function is to guide the quality of the individual. The main goal of this study is to minimize the distribution costs, but based on the theory of GA, a fitness function is contrary to the goal; therefore, it is declared in Equation 5.

$$fitness = \frac{1}{Z} \tag{5}$$

Where Z is derived from equation 1 that interprets the search of distribution costs.

3) Reproduction

Reproduction is a process of accumulating new individuals (children) through two genetic operators, crossover, and mutation. The purpose of reproduction is that more diverse individuals are produced, it provides the possibility of another better solution [20]. The crossover rate (cr) in crossover operator and the mutation rate (mr) in mutation operator are the determinant variables of the number of children produced. The models of crossover in this step use the same models as the crossover process in SA.

a) Crossover

The crossover process generates new individuals by exchanging the information on the two parent individuals selected randomly. The number of children produced is acquired from the multiplication of population size (popSize) and crossover rate (cr). In this study, using three models of crossover, they are one-cut-point, two-cut-point, and extended intermediate. One-cut-point is a model used one point to cut the gene of a chromosome then crosses the gene value of the first parent from the first gene until the gene before the cut point to the other side of the cut point on the second parent. Two-cut-point is the same as one-cut-point but using two points to cut the gene. The third is extended intermediate. It uses a random variable α to give the change of the gene value.

b) Mutation

Mutation is the new individual's search process by varying one individual parent. There are several methods in mutation:

They are swap, insertion, and simple random mutation. The first is swap mutation that selects two positions of genes, which is randomly selected then the value is directly exchangeable [21]. The second is the insertion that performs randomly to determine the two positions of genes on the chromosome that have been randomly selected earlier. The value of the second position that has been selected is inserted before the first elected positions. The last is the simple random mutation using a random number *r* that has a range as a trigger for the change in the real value of the gene.

4) Selection

This step involves the selection of individuals who survive to the next generation. The resistance of individuals triggered by the fitness value generated to prove the quality of the solution. Some models of selection have been used before, such as roulette wheel by applying the cumulative probability of all individuals [7]. There is also an elitism selection model, which has also been used in other studies and the two studies use the same distribution case study. The method works elitism by doing the sorting of the fitness value of the individual in descending popularity. Another selection model used is a binary tournament that chooses individual parents (usually two) randomly and compared the fitness value.

III. Experimental Result

Some testing applied to get the optimal solution under the conditions of the stochastic genetic algorithm (GA). The tests were carried out as GA parameters testing, the best model of genetic operators, the best selection model, the best crossover model in the novelty of SA-GA, and the best percentage of hybridization of the SA-GA-VaNS.

A. GA Parameters Testing

The average fitness value obtained from testing executed is ten times the size of assuming to represent the solutions offered for considering that the stochastic nature of the genetic algorithm gives the quality solution.

1) Population Size

As the multi-population algorithm, GA is able to solve various kinds of optimization and complex problems. The test population size in Figure 7 uses the number of generation 300, *cr* 0.5 and 0.5 *mr*. Those chosen parameters were used because they were able to solve the multi-level distribution problems using the same model of crossover, mutation, and selection [13].

The tested population size in Figure 7 used the average fitness (line graph). It shows that the size of the population provides different solutions. The chosen population size is indicated at 60. The size below 60 displays that the solution is not too good, while the larger populations give results that are not too significant [22].

2) Generation Number

To obtain quality solutions with the computing time that is not too long, there is a need to consider generating the experiment by selecting a point that started the converging conditions. It means that the solutions on the greater number of generations do not have much difference. Figure 8 is the illustration of the test results using the best size of the population before it is 60, using cr and mr combinations is the same as the previous test.

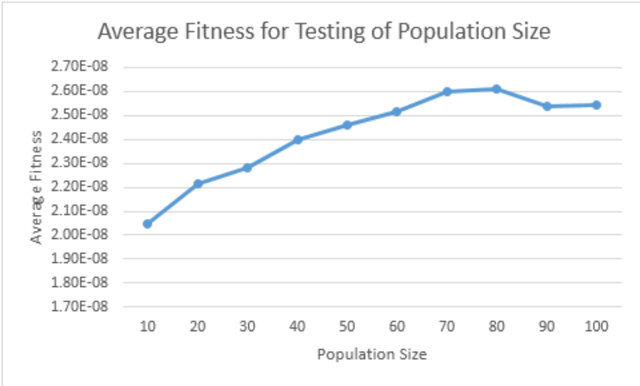

Figure 5: Testing of population size

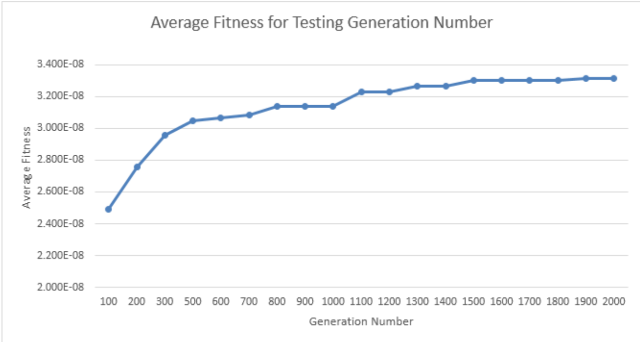

Figure 6: Testing of generation number

Figure 8 shows the line graph of the average fitness for each number of the tested generation. The start point of convergence is 1100. This is because the average fitness before 1100 point still increases significantly, but the average fitness after the point does not provide the significant change. In addition, using the generation number that exceeds the point is actually to spend more computing time [23].

3) Testing Combination of Crossover rate (cr) and Mutation rate (mr)

The next testing is the combination of cr and mr value. It shows which combination that gives the great solution based on the total children produced by the reproduction process and describes how far the exploitation and the exploration. The result of this test using the best population size and generation number in the earlier tests is shown in Figure 9. The 0.8 of cr and 0.2 mr are the best combination of the crossover process that explores more new solutions [24].

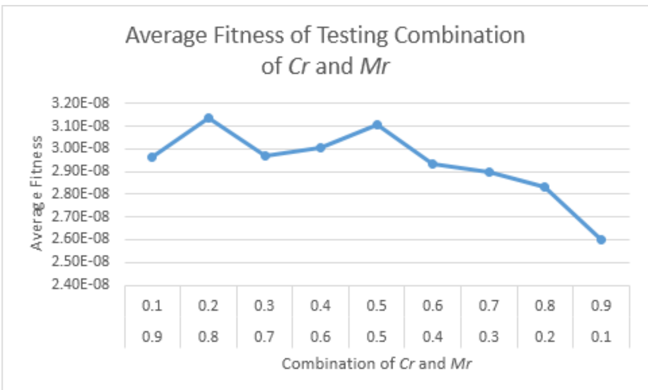

Figure 7: Testing combination of cr and mr

B. Testing of Suitable Genetic Operators

This test aims to find a model that provides a better solution than the other models. This is because there are two kinds of genetic operators in the reproduction process, and there are two tests, namely for the operator's crossover and mutation.

1) Crossover Model

The first test is the genetic operator of crossover model to find the best solution of crossover model. The one cut point, two cut point, and extended intermediate models were tested in this session. Using the best parameters of GA tested before, Table 2 is the result of each crossover model in GA. Referring to Table 2, the two-cut-point is the best crossover model.

Table 2
Suitable crossover model

No.	Crossover Model	Average *Fitness*	Average Cost
1	One cut point	2.54088E-8	39583805
2	**Two cut point**	**3.07092E-8**	**32679440**
3	Extended Intermediate	2.49052E-8	40537165

2) Mutation Model

The genetic operators tested next are the models of mutation. Swap, insertion, and simple random are the models tested. The results of each mutation model are shown in Table 3. Based on the average fitness and the average cost, swap mutation gives the best solution.

Table 3
Suitable Mutation Model

No.	Mutation Model	Average *Fitness*	Average Cost
1	**Swap Mutation**	**3.18331E-8**	**31484625**
2	Insertion Mutation	2.83421E-8	35348305
3	Simple Random Mutation	2.36457E-8	42419490

C. Testing of Suitable Selection Model

The next test is to find the best selection model for the distribution problem. Table 4 is the detailed results of each of the models compared. Based on the average fitness and the average cost produced, elitism is the best model.

Table 4
Suitable Selection Model

No.	Selection Model	Average *Fitness*	Average Cost
1	**Elitism Selection**	**3.13905E-8**	**31994380**
2	Roulette-wheel Selection	1.15668E-8	86463140
3	Binary Tournament	2.81680E-8	9498236.1

D. Testing of Suitable Crossover Model in SA

This study generated the novelty in SA inserted in crossover model, which then provides the near optimal solution. There are some types the crossover model, such as crossover model in GA (one-cut-point, two-cut-point, and extended intermediate) to be tested. The test result of each crossover model in SA and non-crossover model (Default SA) are shown in Table 5. Referring to Table 5, the two-cut-point is the best crossover model for the novelty of SA because it gives the minimum of average fitness and the average cost.

Table 5
Suitable crossover model in SA

No.	Genetic Model	Average *Fitness*	Average Cost
1	Default SA	3.04718 E-8	32986800
2	One cut Point	3.03270 E-8	33128140
3	**Two cut point**	**3.08961 E-8**	**32469120**
4	Extended Intermediate	2.92032 E-8	34317775

E. Analysis and Discussion

After several tests, the next step is analyzing the quality result of the novelty SA for initialization of GA. Before analyzing, to acquire the best results, some tests must be performed due to the stochastic of GA, such as the parameters, the operators model of reproduction, and selection model. Due to the proposed algorithm that has a novelty by inserting the crossover model in SA, a test was also performed to find the best model crossover used to get the excellence solution. Table 6 is the list of the test result. Based on Table 6, the result of the proposed algorithm can be compared with the classical genetic algorithm (GA) and random search, as shown in Table 7. The overall algorithms are executed for 4 minutes so they could be compared fairly.

Table 6
The best test result

No.	Genetic Model	Test Result
1	Genetic Parameters :	
	Population size	60
	Number of generation	1100
	Cr	0.8
	Mr	0.2
2	Genetic Operators :	
	Crossover	Two-cut-point
	Mutation	Swap Mutation
	Selection	Elitism Selection
3	Crossover in SA :	
	Crossover	Two-cut-point

With reference to Table 7, the SA-GA as the proposed algorithm was compared to the random search and classical GA. SA-GA gives a better result than the others. To know the toughness of the SA-GA, the deviation in the percentage of random search and classical GA were calculated and showed in Table 8. The deviation of random search is 27.66%, which shows that the differences in results with SA-GA algorithm are higher than the classical GA. Although the deviation of classical GA is only 2.78%, which means there is a small difference with SA-GA, although the difference in cost is quite high. The difference in cost shown in Table 8 is 12246295 (rupiahs).

Table 7
The result of overall algorithms in 4 minutes

No.	Algorithms	Average *Fitness*	Average Cost
1	Random Search (RS)	2.25098E-8	44439825
2	Classical GA	3.02533E-8	33125360
3	Modifikasi SA-GA	3.11047E-8	32272095

Table 8
The deviation of each algorithm based on SA-GA

No.	Algorithms	SA-GA (%)	Difference (Rp)
1	Random Search	27.66	12246295
2	Classical GA	2.78	931830

IV. CONCLUSION

Multi-level, multi-product distribution problems can be solved using genetic algorithms. By using the best parameters and best model of genetic operators and selection in the testing process, the cost obtained is minimal. To minimize the computing time and increase the quality of the solution, the genetic algorithm optimized using a modified simulated annealing to repair the population initialization has been developed. An additional test on the model of crossover used in simulated annealing as a novelty was conducted. The result was surprising because it has the difference in deviation of random search 27.66% and classical GA 2.78%, which has the difference in cost that quite high.

Despite the increase in SA-GA that affords a promising result than the classical algorithm, the results obtained still do not reach the global optimum solution. This is because there are no more search narrows to reach a global point. Therefore, for further development of this research, it is suggested that the research focuses on the hybridization of the algorithm proposed in this algorithm with variable neighborhood search (VNS) that applied global and local search to repair the result of GA.

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