Optimization of Poultry Feed Composition Using Hybrid Adaptive Genetic Algorithm and Simulated Annealing

Vivi Nur Wijayaningrum[1], Wayan Firdaus Mahmudy[1], Muhammad Halim Natsir[2]
[1]*Faculty of Computer Science, Brawijaya University*
[2]*Faculty of Animal Husbandry, Brawijaya University*
vivinurw@gmail.com

***Abstract*—The highest component in the production cost of the poultry industry is feed cost. The formation of an efficient feed composition is needed because of the increasing price of feed ingredients. Several types of software have been developed to help determine the feed composition, but the price of commercial feed formulation software is quite expensive for most organizations. Hybrid adaptive genetic algorithm and Simulated Annealing were used to calculate poultry feed formulations. This algorithm used a change mechanism of the control parameter in genetic algorithm adaptively to get better results. Simulated Annealing was applied to avoid a local optimum solution produced by the genetic algorithm. The results showed that hybrid adaptive genetic algorithm and Simulated Annealing is better than the classical genetic algorithm.**

***Index Terms*—Adaptive Genetic Algorithm; Livestock; Poultry Feed; Simulated Annealing**

I. INTRODUCTION

Consumption needs of livestock products, such as meat, milk, and eggs, have risen consistently over the years in some developing countries, such as Indonesia [1]. In Indonesia, poultry meat produced in a year is 1.285 million tons, representing 62% of the total meat production in the country. While the number of eggs produced is 1.2 million tons. However, the performance of the supply of feed ingredients in Indonesia is still largely done by imports, so the feed cost is based on the cost structure of imports [2].

The feed cost is an important factor in the production cost of the poultry industry, which ranges from 70% to 75% of the total production costs. The increase in feed costs has led to the need to establish an efficient feed composition in the poultry industry so that production can be increased. At the time of preparing the feed formulations, the needs of necessary nutrients of poultry should be fulfilled with a total feed cost as minimal as possible [3].

Some types of software have been developed to solve the problem of determining the feed composition, for example, *Brill Formulation* and *FeedLive*. In developing countries, the price of commercial feed formulation software is quite expensive for most organizations. In addition, the profits from investments using the software on a small scale are not comparable to the purchase price. The software is also inflexible because the database cannot be modified easily [4].

II. RELATED WORKS

Several techniques can be used as an alternative calculation to form a poultry feed formulation. Linear programming is used to establish the feed composition by using a mathematical model to minimize feed costs by considering the nutrient needs in broilers, the composition of the food available on the feed ingredients, and the availability limit of feed ingredients [5]. However, the application of Linear Programming in feed formulation problems is only done by reducing the cost of each feed ingredients to supply the feed requirements based on the average amount of each nutrient [6]. Genetic algorithms can also be used to solve optimization problems of feed cost on the determination of the poultry feed composition [3]. The advantages of genetic algorithm compared to Linear Programming is its ability to calculate the global minimum solutions [7]. Meanwhile, the drawback of genetic algorithms is its slowness to achieve convergence condition and it requires a long computation time to reach an optimal solution [8]. The determination of the composition of animal feed can also be done using Particle Swarm Optimization. The calculation process is done by forming particles with a number of dimensions as many as the selected feed ingredients. Each particle dimension stores the value which represents the number of feed ingredients used in the feed mixture [7]. However, Particle Swarm Optimization is easy to get caught up in local searches, causing a less precise measure to regulate the speed and direction search [9].

This research uses the genetic algorithm to solve the feed formulation problems. Some complex problems can be solved properly by the genetic algorithm [10]. One of the drawbacks on genetic algorithms is the initial value in the process that is usually formed randomly must be able to meet the limit values that have been determined [11]. The use of numerical methods can be used to determine the initial value by using Cramer's Rule, Gauss-Elimination and Gauss-Jordan [12]. The implementation of Cramer's Rule for the initialization process in the genetic algorithm can be used to solve the feed composition problems [13].

The determination of control parameters in genetic algorithm should also be determined properly because it can affect the performance of the genetic algorithm, which allows the premature convergence [14]. The premature convergence could be avoided by applying the local search algorithms, such as Simulated Annealing. In this study, the poultry feed composition problem is solved using a hybrid adaptive genetic algorithm and Simulated Annealing for adjusting the control parameters dynamically to obtain a better optimal solution.

III. RESEARCH METHODOLOGY

Determination of the feed composition is defined as the determination of the proportion of each feed ingredient used to meet the needs of nutrients (macro minerals, proteins, and amino acids) of any poultry (layers and broilers) by minimizing the total cost of feed ingredients and maximizing the nutrients in every feed ingredients, as shown in the Appendix.

Data of the nutrient needs of each type of poultry were obtained from the National Research Council [15], which contain the minimal needs of nutrients that must be met for each type of poultry. Data of feed ingredients were obtained from Animal Husbandry Department of East Java, Indonesia. The data consist of the price and nutrient content of each feed ingredient.

The development of adaptive genetic algorithm is to adjust the control parameters dynamically during the problem-solving process [16]. The conventional heuristic method can be used to set the control parameters in the genetic algorithm using fitness values as input and the output is the crossover rate and mutation rate value, which is changing adaptively at each generation. The fitness value of parent chromosomes and offspring chromosomes is compared in every generation to form a crossover and mutation operators adaptively [17]. The changes value of crossover rate and mutation rate are shown in Equation (1), Equation (2), and Equation (3).

$$\begin{aligned} cr_{(t+1)} &= cr_{(t)} + 0.05 \\ mr_{(t+1)} &= mr_{(t)} + 0.005 \end{aligned} \tag{1}$$

$$\begin{aligned} cr_{(t+1)} &= cr_{(t)} - 0.05 \\ mr_{(t+1)} &= mr_{(t)} - 0.005 \end{aligned} \tag{2}$$

$$\begin{aligned} cr_{(t+1)} &= cr_{(t)} \\ mr_{(t+1)} &= mr_{(t)} \end{aligned} \tag{3}$$

Equation 1 is used when the percentage of increase in the offspring chromosomes fitness value exceeds the parent chromosomes fitness value by 10% or more. Equation 2 is used when the percentage of decrease in the offspring chromosomes fitness value exceeds the parent chromosomes fitness value by 10% or more. Equation 3 is used when the percentage increase or decrease in the offspring chromosomes fitness value is ±10%. In these three equations, $cr_{(t)}$ and $mr_{(t)}$ is the crossover rate and mutation rate in the generation t, whereas $cr_{(t+1)}$ and $mr_{(t+1)}$ is the crossover rate and mutation rate in the generation t+1.

A. Chromosome Representation

Genetic algorithms have a population consisting of several possible solutions, where each possible solution is represented by a chromosome. Representation of the chromosome used will greatly affect the effectiveness of GA in the search space exploration [18].

In this study, real coded representation was used to represent the solution of feed formulation problems. Examples of chromosome representation used are shown in Figure 1.

Yellow Corn (x_1)	Soybean Meal (x_2)	Fine Bran (x_3)	Coconut Cake (x4)	Fish Oil (x5)
47.35	35.65	6.30	6.50	4.20

Figure 1: Example of a solution using real coded representation

Figure 1 shows that a chromosome that consists of five genes that describe a number of feed ingredients. The values contained in each of the genes state the percentage of feed ingredients used in the feed mixture. Those values are determined randomly, but they must fulfill the limit values for each type of feed ingredient. The limit value for the use of yellow corn is 60, soybean meal is 40, fine bran is 10, coconut cake is 15, and fish oil is 5. The total value of the genes in a chromosome must be equal to 100.

B. Fitness Function

The fitness value is used to describe the quality of the solutions produced by a chromosome. The calculation of fitness value is done by calculating the price of each feed ingredient used in the feed mixtures according to the percentage of use. The fitness function is shown in Equation (4) [13].

$$F = \frac{1000}{\sum_{i=1}^{N} \cos t_i + \sum_{j=1}^{M} \sum_{i=1}^{N} penalty_{ij} \times 1000} \tag{4}$$

In equation (4), 1000 is a constant number, *cost* is the total cost of feed ingredients used, the *penalty* is the total value given for any deficiency number of nutrients, N is a number of feed ingredients, and M is a number of nutrients.

C. Crossover

Crossover is a reproduction process that aims to produce offspring chromosome from two parent chromosomes. Crossover is able to exploit the solution obtained at this time to find a better solution [19]. Crossover method used in this study is a heuristic crossover that uses Equation (5) to form offspring chromosomes [20].

$$p_{new} = \beta\left(p_{mn} - p_{dn}\right) + p_{mn} \tag{5}$$

In equation (5), p_{mn} is the genes in the first parent chromosome, p_{dn} is the genes is the second parent chromosome, and β is the value chosen randomly in the interval [0, 1].

D. Mutation

Mutation aims to maintain genetic diversity in the population. This mutation process provides a new genetic structure in the population by modifying some parts of chromosomes randomly. Mutation method used in this study is a random mutation. Random mutation works by raising or lowering the value of the selected genes with a small random number. Equation (6) is used to form the offspring chromosome $C = [x'_1, x'_2, ..., x'_n]$.

$$x'_i = x'_i + r\left(\max_i - \min_i\right) \quad (6)$$

In Equation (6), r is the value chosen randomly in the interval [-0.1, 0.1], while the max_i and min_i are the range values of the variable x_i.

E. Selection

Selection is a mechanism of selecting random chromosome in a population based on its evaluation function, in this case, is the fitness value. The higher fitness value, the greater the chances of a chromosome to be selected [19].

This study uses a combination of elitism and tournament selection. Elitism selection works by sorting all the chromosomes from the highest to the lowest fitness value, then choosing a number of top chromosomes according to the population size. Tournament selection selects a number of chromosomes randomly from the population and then compares the fitness value of those chromosomes. Chromosomes with the highest fitness value will be chosen to move on to the next generation.

IV. Results and Discussion

Some tests have been conducted to determine the parameter values in genetic algorithm and Simulated Annealing to produce an optimal solution. In the genetic algorithm, the parameter testing consists of the population size testing, the generation number testing, and the testing of crossover rate (*cr*) and mutation rate (*mr*) combinations. While in Simulated Annealing, the parameter testing consists of the iteration number testing and the testing of temperature in decreasing rate.

In each testing type, there are several different types of testing scenarios. The population size tested are 100, 200, 300, 400, 500, and 600. The generation number tested are 100, 200, 300, 400, 500, and 600. The *cr* and *mr* combination tested is 0.1 and 0.9, 0.2 and 0.8, 0.3 and 0.7, 0.4 and 0.6, 0.5 and 0.5, 0.6 and 0.4, 0.7 and 0.3, 0.8 and 0.2, and 0.9 and 0.1. This combination carried out in order to obtain a fair result. The iteration number tested in Simulated Annealing are 5, 10, 15, 20, 25, and 30. The temperature decrease rate tested are 0.95, 0.90, 0.85, 0.80, 0.75, and 0.70. The testing carried 20 times for each type of test scenarios. Figure 2 to Figure 6 shows the results of the parameters testing contained in the genetic algorithm and Simulated Annealing.

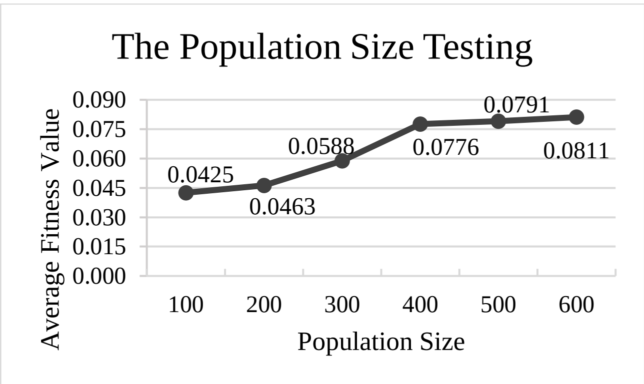

Figure 2: The result of population size testing

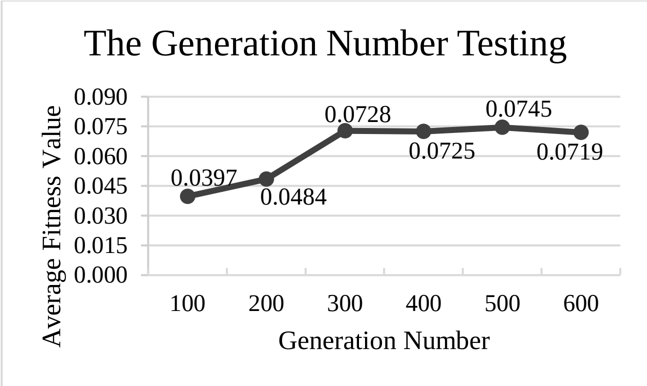

Figure 3: The result of generation number testing

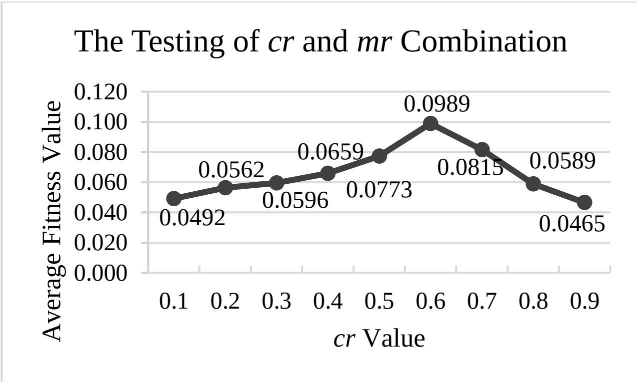

Figure 4: The result of testing of *cr* and *mr* combination

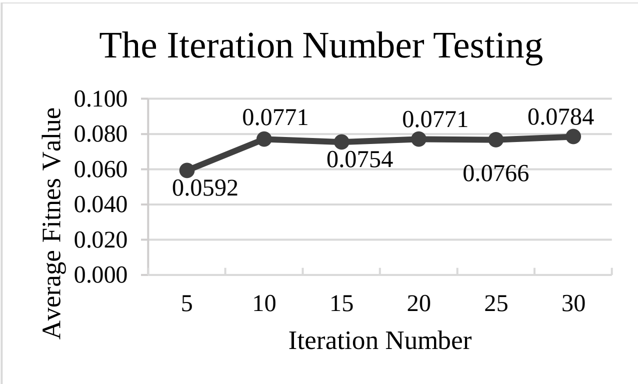

Figure 5: The result of iteration number testing

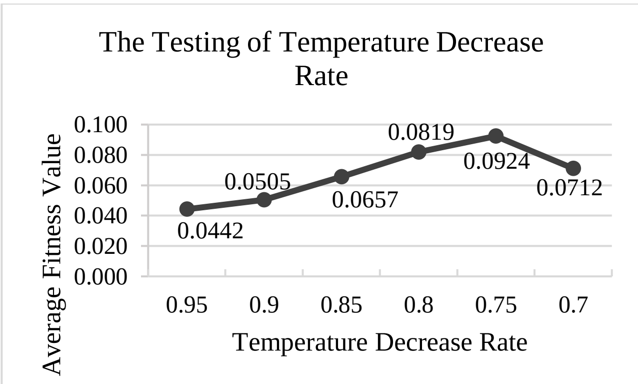

Figure 6: The result of testing of temperature decrease rate

Based on the testing results shown in Figure 2 to Figure 6, it can be seen that the optimal parameters to obtain optimal results are the population size is 400, the generation number is 300, crossover rate is 0.6, mutation rate is 0.4, the iteration number in Simulated Annealing is 10, and the temperature decrease rate is 0.75.

Table 1 shows an example of the optimal poultry feed composition for broiler starter produced by using the optimal parameters that have been obtained from the test results.

Table 1
Results of Poultry Feed Composition Using Optimal Parameters

Feed Ingredients	Percentage
Yellow Corn	47.34
Soybean Meal	32.76
Fine Bran	8.57
Coconut Cake	10.45
Fish Oil	0.88

By using the optimal parameters that have been obtained from these testing, the performance of the hybrid adaptive genetic algorithms and Simulated Annealing was compared with the classical genetic algorithm. The comparisons results of the fitness value generated from these two algorithms are shown in Table 2. The comparison shows that the hybrid adaptive genetic algorithm and Simulated Annealing give better results with higher fitness value than the classical genetic algorithm.

Table 2
Comparison of the Fitness Value

Trial Number	Classical Genetic Algorithm		Hybrid Adaptive Genetic Algorithm and Simulated Annealing	
	Fitness	Time (ms)	Fitness	Time (ms)
1	0.0560	927	0.0851	3216
2	0.0523	908	0.0859	3281
3	0.0527	919	0.0779	3205
4	0.0660	970	0.0885	3276
5	0.0509	925	0.0757	3333
6	0.0522	996	0.0815	3263
7	0.0586	929	0.1020	3303
8	0.0513	960	0.0789	3245
9	0.0682	971	0.0739	3211
10	0.0597	963	0.0837	3257
Average	0.0568	946.8	0.0833	3259

V. CONCLUSION

The parameters contained in the genetic algorithm and Simulated Annealing to obtain optimal results are as follows: population size is 400, the generation number is 300, crossover rate is 0.6, the mutation rate is 0.4, the iteration number in Simulated Annealing is 10, and the temperature decrease rate is 0.75. By using the optimal parameters, the hybrid adaptive genetic algorithm and Simulated Annealing proved to provide better results than the classical genetic algorithm, with less additional computational time.

In future research, a modification to the fitness function will be carried out by considering the price of feed ingredients. The prices of feed ingredients are nonlinear, which means that there will be a discount on the purchase of feed ingredients in large quantities. In addition, the consideration of the amount of feed ingredient used should also be taken into account if there are two compositions of feed ingredients with the same price, but the number of feed ingredients is different.

APPENDIX

Each type of feed ingredients has different price and nutrient content.

Feed Ingredients	Price (Rp)	Feed Ingredients	Price (Rp)
Cotton seed meal	2500	Vegetable oil	12000
Rubber seed meal	4500	Pollard	2300
Peanut meal	3000	Buckwheat	6000
Soybean meal	5900	Skimmed milk	30000
Coconut cake	3500	Snail flour	6500
Fine bran	2500	Chicken feather meal	5000
Corn bran	4000	Meat meal	5000
FOKA	2000	Blood meal	5000
Wheat	20000	Dried cassava flour	2400
Rumen content hydrolysis	2500	Fishmeal (Ancovetta)	7500
Yellow corn	5000	Fishmeal (Herring)	8000
Limestone	1100	Fishmeal (Manhaden)	8500
Clamshell	6000	Leucaena glauca flour	4500
Meat & Bone Meal	5000	Bone meal	6000
Groats	6000	Molasses (bit)	10000
Fish oil	150000	Molasses (sugar cane)	15000
Coconut oil	11500		

Feed Ingredients	ME (kcal/kg)	Crude Protein (%)	Fat (%)	Crude Fiber (%)	Calcium (%)	Phosphorus (%)	Sodium (%)	Pottasium (%)	…	Tyrosine (%)	Valine (%)
Cotton seed meal	2100	42	4.8	12	0.18	0.33	0.03	1.2	…	0.7	2
Rubber seed meal	2159	24.2	3.45	9.8	0.11	0	0	0	…	0	0
Peanut meal	2200	42	1.9	17	0.2	0.2	0.07	1.2	…	1.8	2.2
Soybean meal	2240	42	0.9	6	0.29	0.65	0.03	1.2	…	0.7	2.3
Coconut cake	2200	18.5	2.5	15	0.2	0.57	0.04	1.1	…	0.56	0.98
Fine bran	1630	8	8	12	0.12	0.21	0.07	1.7	…	0.68	0.91
Corn bran	2950	10.6	6	5	0.04	0.15	0.06	1.2	…	0.4	0.7
FOKA	2700	14	1.8	10.1	2.25	1	0.1	1.1	…	0.63	0.84
Wheat	2980	10.7	2.1	2.1	0.05	0	0	0	…	0	0
Rumen content hydrolysis	2000	16.2	2.3	25.4	0.38	0.55	0	0	…	0	0
Yellow corn	3370	8.54	2.61	4.76	0.02	0.1	0.02	0.28	…	0.41	0.4
Limestone	0	0	0	0	38	0	0	0	…	0	0
Clamshell	0	0	0	0	37	0	0	0	…	0	0
Meat & Bone Meal	2190	52	10	2.8	10	5.1	0.7	1.45	…	1.2	2.36
Groats	3390	8.9	4	3	0.03	0.4	0	0	…	0.09	0
Fish oil	8450	0	100	0	0	0	0	0	…	0	0
Coconut oil	8600	0	100	0	0	0	0	0	…	0	0
Vegetable oil	8950	0	100	0	0	0	0	0	…	0	0
Pollard	1300	15	4	10	0.14	0.32	1.2	1.1	…	0.6	0.51
Buckwheat	3250	10	2.8	2	0.03	0.1	0.01	0.35	…	0.7	0.53
Skimmed milk	2510	33	0.9	0.2	1.3	1	0.5	1.5	…	0.82	2.4
Snail flour	4906	61	6.1	4.5	2	0	0	0	…	0	0
Chicken feather meal	2310	85	2.5	1.5	0.32	0.32	0	0	…	0	0
Meat meal	2957	57	12	0	5.96	0	0	0	…	0	0
Blood meal	2750	85	1.1	1	0.15	0.32	0.32	0.09	…	1.8	6.5
Dried cassava flour	2970	1.5	0.7	0.9	0.18	0.09	0.06	0.01	…	0.2	0.35
Fishmeal (Ancovetta)	2830	65	4	1	4	2.6	0.8	0.7	…	2	3.4
Fishmeal (Herring)	2640	72	10	1	2	1.5	0.5	1.1	…	2.1	3.5
Fishmeal (Manhaden)	2650	54	9	1	5.5	2.8	0.3	0.7	…	2	3.4
Leucaena glauca flour	828	18.9	5.9	16.3	0.05	0	0	0	…	0	0
Bone meal	818	12	3	2.3	26	13.5	0	0	…	0	0
Molasses (beet)	1980	6.5	0.2	0	0.16	0.2	1.2	2	…	0	0
Molasses (sugar cane)	1960	3	0.1	0	0.9	0.1	0.17	1.5	…	0	0

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