Hybrid Modified Evolution Strategies and Linear Programming for Beef Cattle Feed Optimization

Tirana Noor Fatyanosa[1], Wayan Firdaus Mahmudy[1], and Marjuki[2]

[1]Faculty of Computer Science, Brawijaya University, INDONESIA
[2]Faculty of Animal Husbandry, Brawijaya University, INDONESIA

Abstract: The biggest obstacle faced by cattleman in cattle fattening is the high feed cost. Cattleman has to formulate cattle feed that meets the nutrient requirements of their cattle and minimize the feed costs. These problems belong to a class of constrained optimization. Various heuristic and deterministic algorithms have been used for solving the constrained optimization problems and applied to the feedstuffs composition. However, there is still some instability in finding mainly a reliable technique that can steadily discover solutions, which are truly near the global optimum of the problem. This paper proposes a combined Modified Evolution Strategies (MES) and Linear Programming (LP) method, named MESLP for optimizing the beef cattle feed. From this study, this novel method obtained a better result than either LP, Random Search, Genetic Algorithm, or Evolution Strategies with higher fitness and lower price.

Keywords: Evolution Strategies, Linear Programming, beef cattle feed

1. Introduction

The beef cattle feed formulation is complicated in a way that cattleman has to consider two constraints at once i.e. feed costs and nutrients content of the feed to meet the cattle requirements. The problems involved in feed formulation belong to a class known as constrained optimization. This class is optimizing an objective function either for minimization or maximization concerning some variables within which constraints exist.

Various algorithms of evolutionary computing and numerical methods had been used to solve the constrained optimization problems and applied to the fodder composition. Altun & Şahman [1] used PSO for optimizing the optimum feed on various animals, e.g. rabbit, broiler, cattle, and sheep. However, they did not put dry matter content of feedstuffs into the consideration. Even though it is a variable that must be assessed before the animal's diet can be legitimately computed. Furthermore, livestock needs to consume a specific amount of dry matter every day for health and production consideration [2]. Therefore, to address this matter, the dry matter content becomes one of the important variables in this study.

Wijayaningrum and Utaminingrum [3] presented Cramer's Rule, Gauss-Elimination, and Gauss-Jordan method to obtain the least feed-cost. The best result obtained from those methods was then used as one of the initial population in the Genetic Algorithm (GA) [4]. However, being different from that study which problem used an equality constraint, the current research uses inequality one because the nutrient requirement of beef cattle is a minimal and maximum need. Therefore, inequality constraints are employed (≥, ≤).

Numerical programming strategies, for example, Linear Programming (LP) has also been used for least cost rations optimization [5]–[8]. LP minimizes the feed cost using numerical equation. This method is quite accurate in a short time and can provide solutions to many equations. However, the disadvantage of this approach is with its strict limitation, it can only handle one objective function, and is unable to guarantee to find the global optima. In addition to that, it is also hard to determine balanced nutrition in the final solution [9]–[11].
The combination of the evolutionary algorithm and LP can be used to solve the combinatorial optimization problem. Cisty [12] used the combination of GA and LP for designing least-cost water distribution systems. The LP is used for improving each branch network composed of GA. The GALP has proved its robustness compared with other methods.

GA and ES have similarity in the way that both use an operator such as recombination, mutation, and selection, are included in the population-based algorithm, and also can deal with discrete, continuous and different optimization issues [13]–[15]. However, according to

Received: December 26th, 2017. Accepted: March 23rd, 2019
DOI: 10.15676/ijeei.2019.11.1.13

Hoffmeister & Bäck [13], ES accomplishes a higher convergence rate and are more efficient for solving the real-world problem than GA, as ES has a self-adaptation system. ES has been proven as a useful method for optimization. The experiment conducted by Garcia et al. [16]for several scenarios of video tracking system shows that ES can improve the outcomes from the most particular case to general circumstances. Furthermore, based on Khuluqi et al. [17], the ES can generate a better result than the manually evaluated amount generation process in the home textile industry for profit optimization.

In this study, a new hybrid using Modified ES and LP is proposed to determine the least-cost feed while maintaining nutritional balance. The LP is used to optimize the selected population in ES in a certain generation interval. The advantages of both methods are expected to be able to avoid the local optima and produce the highest fitness value with the lowest price.

2. Study of Literature

A. Evolution Strategies

Evolution Strategies is a method inspired by Darwin's natural evolution like the Genetic Algorithm (GA). Both ES and GA are included in the Evolutionary Algorithm. However, their reproductive operators are different. GA preference is to use the crossover and only uses mutations as reproduction support. While on ES, mutations are more widely used. ES is also supported by the existence of self-adaptation to control changes in standard mutation parameters. ES approach generates successive generations of models. Amid every generation, a group of models is produced by changing the parameters of the parents (mutation). For most of ES asexual reproduction is utilized. New individuals created without crossover or comparative systems are more pervasive in the field of genetic algorithms. Various examples are chosen, in light of their fitness values, while the fewer fit individuals are disposed of. The survivors then are utilized as parents and mutate to produce offspring. Mutation is a procedure which commonly prompts expanding fitness over generations. This fundamental ES structure, however, straightforward and heuristic in nature, has turned out to be capable and strong, generating a wide assortment of algorithms [18].

The mutation in Evolution Strategies is mostly taken from a normal distribution with a particular mutation sizes related to each issue parameter. One of the significant research in Evolution Strategies concerns the mechanized adjustment of the mutation sizes for the creation of new examples, a methodology, for the most part, alludes to as self-adaptation of mutation. Clearly, picking mutation sizes too high will create incapacitating mutations and guarantee that convergence to an adequately fit domain of parameter space obviated. Picking them too low prompts to small convergence rates and causes the calculation to get caught in local optima. For the most part, the mutation size must be selected within a little scope of values (evolution window) – particular to both the issue space and the distribution of current individuals on the fitness scene. ES calculations should in this manner modify mutation amid evolution in light of the improvement made on the current development way. Usually, this is finished by synchronously developing both issue parameters and the equivalent mutation sizes. ES has appeared to deliver significant outcomes in various cases [19].

B. The system of Linear Inequalities

The relationship between two linear expressions that may not be equal and are connected using the inequality symbols is called a linear inequality [20]. The inequality symbols consist of the less-than symbol (<), less than or equal to symbol (≤), greater-than symbol (>), and greater than or equal to symbol (≥). For example, the linear inequality $x < 5$ means that "x is less than 5". In this way, any number under five is a potential solution. Keep in mind that on the number line (see Figure 1), any number to one side (left) is not as much as a given number, and any number to another side (right) of that given number is larger. The '5' number is marked with an empty dot which means it does not involve the number 5.

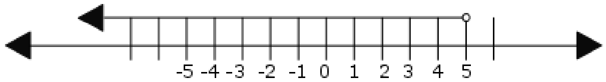

Figure 1. The number line for ‘less than’ symbols

Table 1. Beef cattle nutrition requirement used in the formulation

Body Weight (lb)	Average Daily Gain (lb)	Dry Matter Intake (kg/d)	Crude Protein (kg)	NEm (Mcal)	NEg (Mcal)	Ca (kg)	P (kg)
550	0.64	6.895	0.49	0.992	0.441	0.014	0.009
	1.77	7.303	0.716	1.345	0.772	0.026	0.014
	2.68	7.122	0.883	1.675	1.058	0.035	0.017
600	0.64	7.348	0.514	0.992	0.441	0.015	0.01
	1.77	7.802	0.741	1.345	0.772	0.027	0.014
	2.68	7.62	0.907	1.675	1.058	0.034	0.018
650	0.64	7.847	0.541	0.992	0.441	0.016	0.009
	1.77	8.256	0.76	1.345	0.772	0.026	0.014
	2.68	8.074	0.929	1.675	1.058	0.034	0.017
700	0.64	8.256	0.561	0.992	0.441	0.016	0.01
	1.77	8.754	0.77	1.345	0.772	0.026	0.014
	2.68	8.528	0.93	1.675	1.058	0.033	0.017
750	0.64	8.709	0.584	0.992	0.441	0.017	0.01
	1.77	9.208	0.783	1.345	0.772	0.026	0.015
	2.68	8.981	0.925	1.675	1.058	0.033	0.017
800	0.64	9.163	0.596	0.992	0.441	0.017	0.011
	1.77	9.662	0.783	1.345	0.772	0.026	0.014
	2.68	9.435	0.925	1.675	1.058	0.032	0.017

Table 2. Price and nutrition data

Ingredients	Price/kg	Nutrients					
		Dry Matter (%)	Crude Protein (%DM)	NEm (Mcal/kg)	NEg (Mcal/kg)	Ca (%DM)	P (%DM)
Urea	2000	99	281	0	0	0	0
Molasses Cane	1800	74.3	5.8	1.7	1.08	1	0.1
Rice Straw	150	91	4	0.93	0	0.23	0.08
Soybean Straw	200	88	5	0.95	0	1.59	0.06
Corn Hominy	2800	90	11.5	2.27	1.57	0.05	0.57
Rice Bran	2300	90.5	14.4	1.63	1.03	0.1	1.73
Fishmeal	6500	90	67.9	1.73	1.11	5.46	3.14
Corn Gluten Feed	2500	90	23.8	1.94	1.30	0.07	0.95
Coconut Meal	2800	92	21.5	1.44	0.86	0.21	0.65
Sugar Cane Bagasse	500	91	1	0.90	0.00	0.9	0.29
Wheat Shorts	2800	89	19	1.83	1.19	0.1	0.93
Tapioca Meal	2100	89	1	1.96	1.30	0.03	0.05

C. Linear Programming

Linear programming uses a mathematical model for finding the optimal solution of minimization or maximization problems declared using linear equations or linear inequalities. A linear program comprises of an arrangement of variables, a linear objective function showing the commitment of every variable to the preferred result, and an arrangement of linear constraints portraying the cut-off points on the estimations of the variables. The "appropriate response" to a linear program is an arrangement of values of the issue variables that yield outcomes in the best (biggest or smallest) estimation of the objective function but then is reliable with all the limitations. The formulation is the way toward deciphering a real-world issue into a linear program. Once an issue has been defined as a linear program, a computer program can be utilized to solve it. The answer to a linear program is simple. The hardest part of applying linear programming is planning the issue and deciphering the solution. A linear function can be described by the Eq. 1 [21].

$$a_1x_1 + a_2x_2 + \cdots + a_nx_n \leq b \quad (1)$$

3. Data

The nutrients used in this study are dry matter, protein, NEm, NEg, Calcium, and Phosphorus. Those nutrient requirements for certain body weight and certain daily body weight gain of beef cattle is obtained from the National Research Council [22] (see Table 1). List of feed ingredients and their nutrient content data are obtained from Beef Magazine [23] and the National Research Council [22] (see Table 2). The ingredient price is based on the present local market price of the ingredients.

4. Methodology

A. *Mathematical Modelling*

In mathematical modeling, for example, there are m feed ingredients, $P_1, \ldots, P_m$, each of which contains n nutrients, $N_1, \ldots, N_n$, which are important for beef cattle growth. For example, a_j is the minimum daily requirement of a beef cattle for nutrient N_j; b_i is the feed price for feed ingredient P_i; c_{ij} is the amount of nutrient N_j owned by P_i. The problem to be solved is to provide cattle feed that meets the nutritional needs of cattle at a minimum price.

For example y_i is the amount of feed ingredient P_i purchased per day. The feed price per day can be written like Eq. 2.

$$b_1y_1 + b_2y_2 + \cdots + b_my_m \quad (2)$$

The amount of nutrient N_j contained in the feed ingredient can be written as Eq. 3.

$$c_{1j}y_1 + c_{2j}y_2 + \cdots + c_{mj}y_m. \qquad \mathrm{J} = 1, \ldots, n \quad (3)$$

The daily minimum requirement of a beef cattle must be fulfilled; it can be written like Eq. 4 below.

$$c_{1j}y_1 + c_{2j}y_2 + \cdots + c_{mj}y_m \geq a_j. \qquad \mathrm{j} = 1, \ldots, n \quad (4)$$

Since it is not possible for the amount of feed to be negative, the weight limit of each feed ingredients can be written as Eq. 5.

$$y_1 \geq 0, y_2 \geq 0, \ldots, y_m \geq 0 \quad (5)$$

From the mathematical model, we can find the minimum value for Eq. 2 which must satisfy the Eq. 4 and 5.

B. *Evolution Strategies*

ES (μ/ρ+λ) is used in this paper because based on the prior research [24], it produced a lower average fitness value than the other types. ES (μ/ρ+λ) uses the recombination and mutation to produce the offspring.

1. *Chromosome representation*

The chromosome comprises of the feed ingredients utilized as a part of the fodder formulation. Table 3 demonstrates the example of chromosome representation. Every gene is acquired from the feed amount for each ingredient. From Table 3, the amount of fresh ingredient for wheat shorts is 0.231 kg, tapioca meal is 0.752 kg, and coconut meal is 0.347 kg.

Table 3. Chromosome Representation

Wheat Shorts ($\mathbf{x_1}$)	Tapioca Meal ($\mathbf{x_2}$)	*Coconut Meal* (x_3)
0.231	0.752	0.347

2. Initialization population

This study uses random number generation which is the most commonly utilized strategy for all evolutionary algorithms to initialize the population. In ES, we also have to initialize the mutation strength (σ) which is raised in the range [0,1]. The example of the initial population is shown in Table 4.

Table 4. ES population

$P(t)$	x_1	x_2	x_3	σ_1	σ_2	σ_3	Fitness value
P_1	0.124	0.231	0.756	0.121	0.546	0.453	1.43633

3. Fitness Function

Eq. 6 shows the fitness function used in this study. Eq. 7 shows the total price calculation.

$$Fitness = \frac{10000}{total\ price + (total\ penalty * 10000)} \quad (6)$$

$$Total\ price = 2000x_1 + 1800x_2 + 150x_3 + 200x_4 + 2800x_5 + 2300x_6 + 6500x_7 + 2500x_8 + 2800x_9 + 500x_{10} + 2800x_{11} + 2100x_{12} \quad (7)$$

If the individual nutrient value is less than the nutrient requirements, then the penalty is awarded. The penalty is obtained from the difference between the nutrient requirements with the nutrient value obtained from the experiment. Some additional things affect penalties apart from the nutrient requirement such as the maximum limit of dry matter consumption per day. Because the beef cattle are unable to consume feed dry matter more than 4% of its body weight, then the penalty for dry matter intake is used. Furthermore, based on Hale & Olson [25], the suggested calcium to phosphorus proportion in ruminant weight control plans is 2:1. Therefore, the maximum calcium is 2% of dry matter, and the maximum phosphorus is 1% of dry matter. If the total calcium obtained from the experiment exceeds the maximum calcium, then the penalty will be awarded based on the difference between the obtained calcium and maximum calcium. This also applies to the phosphorus. Moreover, the use of urea and molasses are also restricted. According to [26] and [27], the quantity of urea should not exceed 1% DM and the amount of molasses is usually lower than 15% DM. Therefore, the penalty awarded if the total urea or total molasses exceeds the limits.

4. Recombination, mutation, and selection

We use the discrete recombination which produces offspring from two parents by randomly copying a selected element from each parent [28]. The offspring are then mutated by using the Eq. 8-13. Where $N(0,1)$ denotes the normal distribution with 0 as an average and 1 as a standard deviation; σ denotes sigma value; τ'denotes global learning rate; τ denotes individual learning rate; n is chromosome length; r_1, r_2 are a random number between 0 and 1.

$$\tau' = \frac{1}{\sqrt{2n}} \quad (8)$$

$$\tau = \frac{1}{\sqrt{2\sqrt{n}}} \quad (9)$$

$$N(0,1) = \sqrt{-2.\,ln\, r_1}\, \sin 2\pi r_2 \quad (10)$$

$$\eta = \tau' \cdot N(0,1) \quad (11)$$

$$\sigma' = \sigma \cdot \exp(\eta + \tau \cdot N(0,1) \quad (12)$$

$$x' = x + \ \sigma'\, N(0.1) \quad (13)$$

The selection used in this study is the elitist selection. This type of selection is used to track the good solutions during the ES search process.

C. Modified Evolution Strategies

There are two types of modifications used in this paper, modification to avoid negative results and modification of the initial population. There are four methods used to prevent negative results as follows.

1. ES without modification.
2. The negative value does not change but the fitness is given a small value or given a negative value.
3. The gene will be directly assigned a value of 0 if it is negative.
4. The random injection will be done if the gene contains a negative value.

For the second modification, LP will be used to generate the initial population. The steps of ES initialization using LP are described as follows.

1. Randomly generated initial population.
2. Select individuals randomly as many as maximum selected individuals to be repaired using LP.
3. Choose one gene from a randomly selected individual as a constraint on the LP. The gene selection is intended so that the results of the LP is different between each individual.
4. Perform the LP process.
5. Change the selected individuals with the results from LP.
6. Perform steps 2-5 to the maximum of selected individuals.
   Use the initialization from steps 1-6 as the initial population on ES.

D. Hybrid MESLP

For more details, see Figure 2 for the flowchart of MESLP.

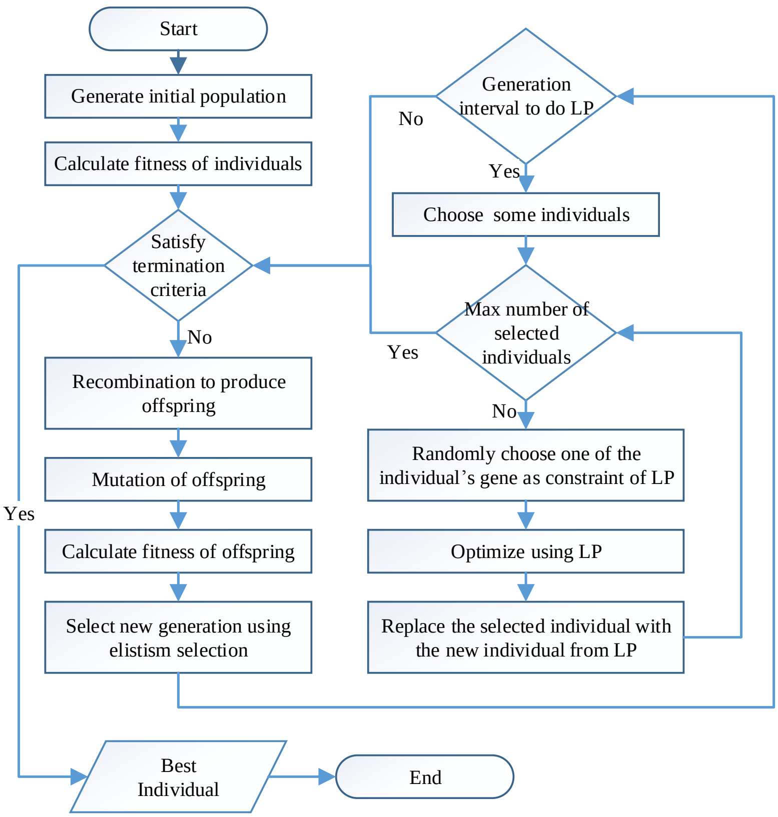

Figure 2. Flowchart of MESLP

The idea of hybrid MESLP can help us to obtain the best result and avoid being trapped in local optima. Here are the steps of our proposed algorithm.

1. When the ES process reaches a certain generation, choose some of the individuals in the population to be optimized by LP. Table 5 shows an example of the selected individual.

Table 5. Example of selected individual

x_1	x_2	x_3	x_4	x_5	x_6
0.039	0.511	1.219	0.341	0.001	0.84
x_7	x_8	x_9	x_{10}	x_{11}	x_{12}
0.0	0.106	0.0	0.026	0.002	0.981

2. Randomly choose one of the individual's genes as one of the LP constraint (the genes value will not change). For example, x_1 is the selected gene then the LP constraint for x_1 becomes $x_1 = 0.039$, while the other constraint for each gene remains greater than or equal to zero.
3. Optimize using LP and replace the chosen individual with the new individual obtained from LP.

5. Result and Discussion

In this study, the parameters are determined as follows:

- μ is 500; λ is 25μ.
- The length of the chromosome is determined based on the number of feed ingredients used. As this paper uses 12 feed ingredients (see Table 2), then the chromosome length is 12.
- 18 beef cattle (see Table 1).

Based on [29] and [30], the heuristic and stochastic method always generate a different solution in each run. Therefore, in this study, the testing is run ten times.

A. Negative Gen Modification Results

Negative gene modification testing is performed to select the best negative gene modification for ES (μ/ρ+λ). There are four methods tested, ES without modification, the fitness value is given a small value if it is a negative value (Modification 1), the gene will be directly assigned a value of 0 if it is a negative value (Modification 2), and random injection will be performed if the gene contains a negative value (Modification 3).

Based on Table 6, although ES without modification and Modification 1 produce the best average fitness value, but based on Table 7, both produce negative genes in the final solution (invalid). Therefore, ES without modification and Modification 1 cannot be used in the next experiment and modification method that can be utilized are Modification 2 and Modification 3. From Table 6, the average fitness value, average price, and standard deviation from Modification 3 outperformed Modification 2. So, in this study, Modification 3 is used in the next test.

Table 6. Modification method comparison

Modification Method	Average Fitness	Average Price (IDR)	Average Computation Time (s)	Standard Deviation
Without Modification	5.841E+13	-223145	801729	7.69E+13
Modification 1	1.26E+14	-187856	446908	1.30E+14
Modification 2	0.0436398	229111	427668	0.00012
Modification 3	0.0436703	228973	730842	6.2E-05

Table 7. Comparison of best optimization results for each modification method

Ingredients	Without Modification	Modification 1	Modification 2	Modification 3
Urea	14.909	10.429	1.504	1.504
Molasses Cane	-18.632	9.378	28.47	24.669
Rice Straw	26.888	20.332	57.596	58.573
Soybean Straw	39.041	28.712	8.152	7.142
Corn Hominy	-44.467	-96.839	0.0	0.0
Rice Bran	177.222	141.758	39.615	40.806
Fishmeal	-128.159	-98.253	0.0	0.0
Corn Gluten Feed	88.747	150.772	0.0	0.0
Coconut Meal	1.198	0.076	0.0	0.0
Sugar Cane Bagasse	0.69	4.751	0.0	0.0
Wheat Shorts	6.276	0.394	0.0	0.0
Tapioca Meal	3.1	6.459	34.701	36.663
Fitness Value	1.71799E+14	3.43597E+14	0.043761684	0.043768915
Total Penalty	29.2159	14.3034	0.0	0.0
Total Price	-292159	-143034	228510	2284723

B. LP Initialization method results

In this hybridization scheme, initialization is done by generating individuals from the LP processes of selected individuals. The test is performed ten times. In this test, the number of selected individuals is 10% to 100% of the total population. Based on Table 8, the percentage of 10% of selected individuals is the highest average fitness value and lowest average price, although in terms of time it takes longer than the other percentage of selected individuals. So in this study, the percentage of selected individuals 10% is used for subsequent testing.

Table 8. Percentage of selected individual comparison

Percentage of Selected Individual	Average Fitness	Average Price (IDR)	Average Computation Time (s)	Standard Deviation
10%	0.043721475	228716.02	690.5888	7.75E-06
20%	0.043720916	228719.235	688.556	8.24E-06
30%	0.043721079	228720.12	717.3041	1.02E-05
40%	0.043718205	228734.43	737.5912	7.66E-06
50%	0.043715773	228746.78	730.5081	5.8E-06
60%	0.043711062	228770.44	736.6948	9.71E-06
70%	0.043716023	228744.475	704.9002	7.79E-06
80%	0.043716528	228742.835	704.4758	8.39E-06
90%	0.043714393	228754.02	704.9778	1.03E-05
100%	0.043713975	228756.17	697.5881	6.48E-06

C. Generation Interval Comparison

In this section, we compare the generation interval of LP optimization after processed using ES. The selected population size used in this comparison is 10% from μ (50). Based on the comparison of average fitness values, average prices, and standard deviations in Table 9, the interval of every 10 generations is produced the highest fitness value. So, in this study, the interval of every 10 generations is used in the next test. The high standard deviation demonstrates that the outcome tends to close to the average fitness which causes a high-quality result. Based on Figure 3, from the 10th generation interval, the average fitness value decreases until the 60th generation interval. After that, the graph is fluctuating but not too high. This is likely due to the longer interval generation; the more unoptimized the LP helps ES pass local optima. The generation interval is shown to affect the result. The more frequent the LP process is done, the higher the fitness value obtained. It can be concluded that LP can exploit the area around the solutions produced by ES. The LP proves to help ES to get the global optima faster.

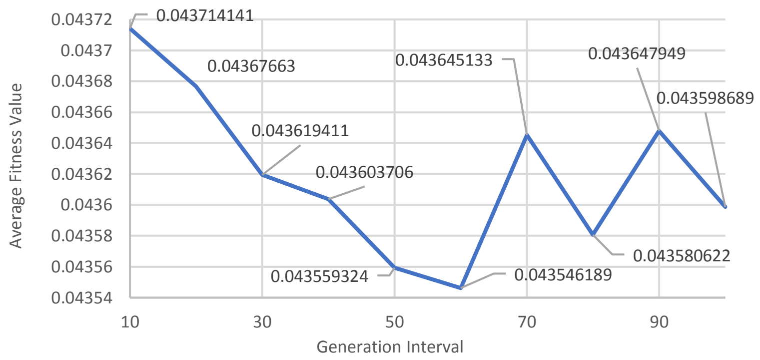

Figure 3. Average fitness value comparison for each generation interval

Table 9. Generation interval comparison

Generation Interval	Average Fitness	Average Price (IDR)	Average Computation Time (s)	Standard Deviation
10	0.043714141	228752.675	720.9634	7.8056E-06
20	0.04367663	228939.685	718.1555	3.0385E-05
30	0.043619411	229241.93	716.9948	5.444E-05
40	0.043603706	229260.4	722.4072	0.00010266
50	0.043559324	229525.715	722.4688	0.00014454
60	0.043546189	229642.3	720.9477	0.00018071
70	0.043645133	229095.895	741.7057	2.4448E-05
80	0.043580622	229384.12	742.4123	0.00014404
90	0.043647949	229093.815	742.4561	3.4522E-05
100	0.043598689	229291.38	662.9525	6.9736E-05

D. Selected Population Size Comparison

In this section, we compare the percentage of selected population size to be repaired by LP after processed using ES. The number of selected population size is based on the percentage of the total population, 10% to 100% of the total population. In this test, we compare the average fitness value, price, time, and standard deviation.

Based on the comparison of average fitness values, average prices, and standard deviation from Table 10, the percentage of selected population 30% is the best. Therefore, in this study, the percentage of the selected population of 30% is used in subsequent tests. In Figure 4, the percentage of the selected population from 10% to 90% of charts tend to be stable. However, at 100% selected population size, the graph decreases drastically. The decline in the graph is because the use of LP in ES is too excessive. The diversity of the population then becomes low. It can be seen from the high standard deviation of 100% selected population size. A high standard deviation indicates that the fitness value of each individual spreads and is not close to the average fitness, so the resulting average fitness value tends to be lower.

Table 10. Percentage of selected population size comparison

Percentage of Selected Population Size	Average Fitness	Average Price (IDR)	Average Computation Time (s)	Standard Deviation
10%	0.043706246	228796.38	715.8095	1.3236E-05
20%	0.04371269	228761.32	734.2557	1.7923E-05
30%	0.043714896	228739.365	736.3785	9.6558E-06
40%	0.043705202	228800.115	755.7909	9.1989E-06
50%	0.043714141	228752.675	720.9634	7.8056E-06
60%	0.043711635	228756.455	756.532	9.9933E-06
70%	0.04370898	228768.335	766.1894	1.1788E-05
80%	0.043704615	228802.55	730.4656	1.6775E-05
90%	0.043705945	228774.245	730.308	1.2874E-05
100%	0.043540147	229501.345	723.3013	2.9656E-05

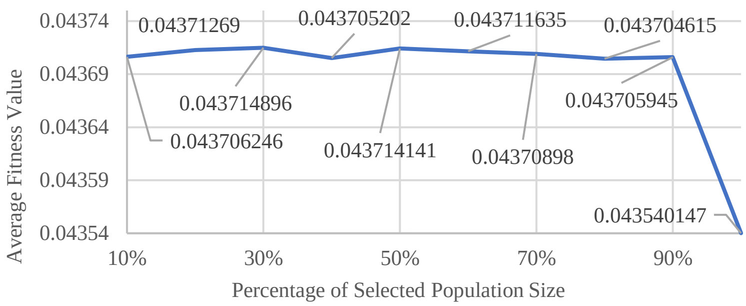

Figure 4. Average fitness value comparison for each selected population size

E. Comparison with other methods

The MESLP is compared with the LP, random search, genetic algorithm, and ES (μ/ρ+λ). For stochastic optimization methods such as random search, genetic algorithm, MESLP and ES (μ/ρ+λ), we compare the average of fitness values, average prices, and standard deviation. As for the LP, the test is performed only once and compared with the average results in random search, genetic algorithm, ES (μ/ρ+λ), and MESLP. The MESLP, Genetic Algorithm, and Random Search are done for 600 seconds or 10 minutes and run ten times.

Parameters used for Genetic Algorithm are population size of 400, the crossover rate of 0.6, the mutation rate of 0.4, heuristic crossover, random mutation, and elitist selection. As for the random search algorithm, individuals are generated at intervals 0 and 100. The lower limit 0 is chosen so that the weight of the feed produced is not negative. While the upper limit of 100 is due to the ES test results, the weight of feed produced does not exceed the value of 100.

Based on Table 11, MESLP produces the highest average fitness value and the lowest average price compared to LP, random search, genetic algorithm, and ES (μ/ρ+λ). Moreover, the standard deviation of MESLP is the lowest. Higher standard deviation indicates the results of the experiment spread out and far from the average fitness, leading to a low average fitness. In contrast, a lower standard deviation shows that the resulting fitness value is close to the average of fitness, so the resulting average fitness value is higher. This proposed method proves to avoid the local optima and help to find the global optima. The LP is assisting ES to expand the search area and reach the global optimum in the area corresponding to the constraints of the problem.

Table 11. Methods comparison

Methods	Average Fitness	Average Price (IDR)	Standard Deviation
LP	0.041409556	241490.15	-
Random Search	0.029106822	338935.305	0.001679
Genetic Algorithm	0.043466986	230054.245	0.000231
ES (μ/ρ+λ)	0.043636606	229160.720	3.26E-05
MESLP	0.043722611	228712.465	1.04456E-05

F. *The best amount of feed from MESLP*

Table 12 shows the best composition of cattle feed ingredients obtained from MESLP. It is concluded that MESLP could fulfill beef cattle's daily nutrient requirement. The feed price obtained from MESLP is 228615.05 with the fitness value of 0.043741652 and zero penalties.

Table 12. The best amount of feed from MESLP

Urea	Molasses Cane	Rice Straw	Soybean Straw
1.504	23.457	55.611	10.206
Corn Hominy	Rice Bran	Fishmeal	Corn Gluten Feed
0.0	40.947	0.0	0.0
Coconut Meal	Sugar Cane Bagasse	Wheat Shorts	Tapioca Meal
0.0	0.0	0.0	37.535

6. Conclusion

In this study, LP is used to improve the quality of the ES' solution. The main purpose of the work is to obtain the highest fitness value with the lowest price for beef cattle feed. MESLP gives better results than LP, random search, genetic algorithm, and ES (μ/ρ+λ). MESLP can produce the highest average fitness with the lowest average price. The best result is possible because the individual which has been grouping by ES, at a certain generation the LP start to exploit the area and uncover the global optimum. The LP help ES escaping from local optima. Therefore, it is concluded that the best fitness with the lowest price and the global optima can be efficiently achieved by using MESLP. For further research, the subpopulation can be used to overcome the slow rate of convergence and add diversity. Furthermore, the other hybridization schemes of modified ES and LP need to be investigated.

7. References

[1]. A. A. Altun and M. A. Şahman, "Cost optimization of mixed feeds with the particle swarm optimization method," *Neural Comput. Appl.*, vol. 22, no. 2, pp. 383–390, Feb. 2013.

[2]. David Wieland, "Understanding dry matter intake," 2002.

[3]. V. N. Wijayaningrum and F. Utaminingrum, "Numerical Methods for Initialization in Fodder Composition Optimization," in *IEEE International Conference on Advanced Computer Science and Information Systems*, 2016.

[4]. V. N. Wijayaningrum, W. F. Mahmudy, and M. H. Natsir, "Optimization of Poultry Feed Composition Using Hybrid Adaptive Genetic Algorithm and Simulated Annealing," *J. Telecommun. Electron. Comput. Eng.*, vol. 9, no. 2–8, pp. 183–187, 2018.

[5]. T. Rehman and C. Romero, "Multiple-Criteria Decision-Making Techniques and Their Role in Livestock Ration Formulation," *Agric. Syst.*, vol. 15, pp. 23–49, 1984.

[6]. P. Lara and C. Romero, "An interactive multigoal programming model for determining livestock rations: An application to dairy cows in Andalusia, Spain," *J. Oper. Res. Soc.*, vol. 43, no. 10, pp. 945–953, 1992.

[7]. F. Zhang and W. B. Roush, "Multiple-objective (goal) programming model for feed formulation: An example for reducing nutrient variation," *Poult. Sci.*, vol. 81, pp. 182–192, 2002.

[8]. T. N. Fatyanosa, F. Utaminingrum, and M. Data, "Linear Programming Initialization Method of Evolution Strategies for Beef Cattle Feed Optimization," *J. Telecommun. Electron. Comput. Eng.*, vol. 10, no. 1–4, pp. 153–158, 2018.
[9]. S. A. Rahman and F. E. Bender, "Linear Programming Approximation of Least-Cost Feed Mixes with Probability Restrictions," *Am. J. Agric. Econ.*, vol. 53, no. 4, p. 612, Nov. 1971.
[10]. M. Nabasirye, J. Y. T. Mugisha, F. Tibayungwa, and C. C. Kyarisiima, "Optimization of input in animal production: A linear programming approach to the ration formulation problem," *Int. Res. J. Agric. Sci. Soil Sci.*, vol. 1, no. 7, pp. 221–226, 2011.
[11]. A. M. Olatunde and M. Afolayan, "Nigeria Oriented Poultry Feed Formulation Software Requirements," *J. Appl. Sci. Res.*, vol. 4, no. 11, pp. 815–821, 2006.
[12]. M. Cisty, "Hybrid genetic algorithm and linear programming method for least-cost design of water distribution systems," *Water Resour. Manag.*, vol. 24, no. 1, pp. 1–24, 2010.
[13]. F. Hoffmeister and T. Bäck, "Genetic Algorithms and evolution strategies: Similarities and differences," in *Parallel Problem Solving from Nature*, Berlin/Heidelberg: Springer-Verlag, 1991, pp. 455–469.
[14]. G. Thierauf and J. Cai, "Structural optimization based on Evolution Strategy," in *Advanced computational methods in structural mechanics*, Barcelona: CIMNE, 1996, pp. 266–280.
[15]. G. Thierauf and J. Cai, "A two level parallel evolution strategy for solving mixed-discrete structural optimization problems," in *2Ist ASME Design Automation Conference*, 1995, pp. 17–21.
[16]. J. Garcia, O. Perez, A. Berlanga, and J. M. Molina, "Video tracking system optimization using evolution strategies," *Int. J. Imaging Syst. Technol.*, vol. 17, no. 2, pp. 75–90, 2007.
[17]. M. Al Khuluqi, W. F. Mahmudy, and A. Rahmi, "Profit Optimization Based on Total Production in Textile Home Industry Using Evolution Strategies Algorithms," *International Journal of Social and Local Economic Governance*, vol. 2, no. 2. pp. 109–117, Sep-2016.
[18]. D. Wierstra, T. Schaul, T. Glasmachers, Y. Sun, J. Peters, and J. Schmidhuber, "Natural Evolution Strategies," *J. Mach. Learn. Res.*, vol. 15, pp. 949–980, 2014.
[19]. H.-G. Beyer, "Toward a theory of evolution strategies: Self-adaptation," *Evol. Comput.*, vol. 3, no. 3, pp. 311–347, 1995.
[20]. M. Dugopolski, "Linear Equations and Inequalities in One Variable," in *Algebra for College Students*, New York: McGraw-Hill Education, 2000, p. 84.
[21]. M. E. McDill, "Chapter 11: Basic Linear Programming Concepts," *Forest Resource Management*, 2012.
[22]. National Research Council, *Nutrient Requirements of Beef Cattle*, Seventh Re. Washington, DC: The National Academies Press, 2000.
[23]. R. L. Preston, "2016 Feed Composition Tables," *Beef Magazine*, Minneapolis, Minnesota, p. 18,21-22,29,34, Mar-2016.
[24]. T. N. Fatyanosa, W. F. Mahmudy, and Marjuki, "A Comparison of Four Types of Evolution Strategies for Beef Cattle Feed Optimization," *J. Telecommun. Electron. Comput. Eng.*, vol. 10, no. 1–8, pp. 165–171, 2018.
[25]. C. Hale and K. Olson, "Mineral Supplements for Beef Cattle," Columbia, 2001.
[26]. A. DiCostanzo, "Fine-Tuning Protein Nutrition of Feedlot Cattle," in *Minnesota Cattle Feeder Days Proceedings Report B-437*, 1996, pp. 24–30.
[27]. M. F. Fuller, *The Encyclopedia of Farm Animal Nutrition*. Wallingford, Oxfordshire: CABI Publishing Series, 2004.
[28]. J. F. Ramírez and O. Fuentes, "Spectral Analysis Using Evolution Strategies," in *IASTED International Conference on Artificial Intelligence and Soft Computing*, 2002.
[29]. W. F. Mahmudy, R. M. Marian, and L. H. S. Luong, "Real Coded Genetic Algorithms for Solving Flexible Job-Shop Scheduling Problem - Part I: Modelling," *Adv. Mater. Res.*, vol. 701, pp. 359–363, May 2013.

[30]. D. Novitasari, I. Cholissodin, and W. F. Mahmudy, "Hybridizing PSO With SA for Optimizing SVR Applied to Software Effort Estimation," *Telkomnika (Telecommunication Comput. Electron. Control.*, vol. 14, no. 1, pp. 245–253, 2016.

Tirana Noor Fatyanosa was born in Balikpapan, East Kalimantan, Indonesia in 1991. She received her bachelor and master's degree in information technology from Brawijaya University, Indonesia, in 2013 and 2017, respectively. Her research interests include the Evolutionary Algorithm, Optimization Algorithm, Artificial Intelligence, Data Mining, and Knowledge Discovery.

Wayan Firdaus Mahmudy was born in Gresik, East Java, Indonesia. He obtained a bachelor degree in mathematics from Brawijaya University, Indonesia, master's degree in information technology from Institut Teknologi Sepuluh November (ITS), Indonesia, and completed his Ph.D. in Manufacturing Engineering at University of South Australia. Wayan is currently a lecturer at Faculty of Computer Science, Brawijaya University.

Marjuki was born in Jombang, East Java, Indonesia in 1963. He obtained a bachelor degree in animal nutrition from Brawijaya University, Indonesia, master's degree in animal nutrition from Wageningen Agriculture University, and completed his Ph.D. in Ruminant Animal Nutrition at Brawijaya University. Marjuki is currently a lecturer at Faculty of Animal Husbandry, Brawijaya University.