A Comparison of Four Types of Evolution Strategies for Beef Cattle Feed Optimization

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***Abstract*—Beef cattle feed optimization is a multi-objective problem. For different weight of beef cattle, the required nutrition is also different. The feed also requires a balance of nutrients with a low price. This paper presents a comparison of four types of Evolution Strategies (ES) for beef cattle feed optimization. The results of our experiments suggest that the performance and robustness of ES (μ,λ), ES (μ/ρ,λ), and ES (μ+λ) are comparable, while ES (μ/ρ+λ) performs slightly worse. This fact together promotes ES (μ/ρ,λ) as the most robust for practical use. The experimental results show that the feed price obtained from ES (μ/ρ,λ) is 5524.465 with fitness value of 1.809861462.**

***Index Terms*—Beef Cattle Feed Optimization; Evolution Strategies.**

I. INTRODUCTION

The beef business can be separated into four main sectors: pedigree breeders, feedlot, cow-calf producers, and backgrounders [1]. Feedlot or cattle fattening is principally feeding beef cattle with balanced feed to provide balanced nutrient for beef production with consistent quantity and quality [2]. A balanced feed or ration is well-formulated feed, composed of two or more feedstuffs, contains all nutrients required by beef cattle's body.

Well formulated feed is required for better maintenance, growth, products synthesis (milk), and energy source for metabolic and physical activities (walking and feeding) [3]. Thus, formulated feed must be able to meet the needs of the cattle for nutrients according to its body weight, activity rate and productivity. The feed should not be underfed or overfed. Underfeeding causes production failure, while overfeeding causes higher feed wastage and cost. Both overfeeding and underfeeding have crucial monetary outcomes which reduce the feasibility of the farm.

Various techniques have been defined for the feed formulation: Pearson square method, trial and error method, Linear Programming [4], Nonlinear Programming [5], Particle Swarm Optimization [6], Genetic Algorithm [7], Evolution Strategies [9-10], and hybrid GA-SA [10].

Evolution Strategies (ES), with various types and modifications, has been utilized to solve the optimization problem. ES (1+1) is utilized by [11] to optimize the feature selection and consolidation of a music partition. They utilized the hybrid ES with local search with two scenarios and the ES with mutation modification. They found that the standard ES with mutation modification produces the best fitness to optimize parameter for the simple category.

The Fuzzy Clustering ES (FCES), Cooperative Co-Evaluation Strategy (CCES) and ES conventional with intermediate and discrete recombination were utilized by [12] for frequency modulation tone matching. The three algorithms were able to find the global optimum. The convergence of FCES was slow, but it was able to produce the best result. On the contrary, the convergence of CCES was faster.

The ES was also used by [13] to analyze the spectral. They claimed that ES was stable in the noisy data existence, and it did not need user input. Compared to the gradient based method, in the presence of local minima, ES was less sensitive. Jansen et al. [14] used ES (1+λ) with various offspring population size. The population size was determined based on the parent replacement by offspring's success rate. The right population size tuning to the problems complexity delivered promising results.

Adaptive population size was utilized by [15] at each generation. The determination of population size was based on the information gathered during the process. Various adaptive ES (μ/μ,λ) were developed by them. Their experimental results proved that the adaptive population size was better than certain population size.

This study is carried out to compare the four types of Evolution Strategies (ES) for beef cattle feed optimization. At the first step, the four types of ES were run with the same parameters. At the second step, the four types were compared by its average fitness, average price, convergence rate, time consumption, and standard deviation. At the third step, the different modified ES (μ/ρ+λ) were compared.

II. MATERIAL

This study used 12 feed ingredients (Table 1) as the independent variables and six nutrients: dry matter, protein, NEm, NEg, Calcium, Phosphorus and price as the dependent variables. The nutrition requirement for beef cattle was obtained from National Research Council [16] (see Table 2). The nutrients content of feed ingredients was obtained from Beef Magazine [17] and National Research Council [18] (see Table 2). The price data for feed ingredients was obtained from the local market price.

III. METHODOLOGY

Evolution Strategies (ES) are the variant of an evolutionary algorithm which has been initiated since early 1960s by students at the Technical University of Berlin. ES were then developed further in the 1970s by Ingo Rechenberg and HansPaul Schwefel [19]. ES have a tendency to be utilized for exact analyses that are hard to show scientifically. The framework to be advanced is really developed and ES are utilized to locate the ideal parameter settings. ES simply focus on interpreting the basic systems of a natural development for specialized optimization issues [20]. There are four types of ES, namely ES (μ,λ), ES (μ/ρ,λ), ES (μ+λ), and ES (μ/ρ+λ) [19]..

Table 1
Price and nutrition of feed ingredients

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	0.83	0	0.23	0.08
Soybean Straw	200	88	5	0.85	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	1.3	0.07	0.95
Coconut Meal	2800	92	21.5	1.44	0.86	0.21	0.65
Sugar Cane Bagasse	500	91	1	0.81	0	0.9	0.29
Wheat Shorts	2800	89	19	1.63	1.06	0.1	0.93
Tapioca Meal	2100	89	1	1.75	1.16	0.03	0.05

Table 2
Nutrition requirement of beef cattle

Body Weight (lb)	Average Daily Gain (lb)	Dry Matter Intake (kg/d)	Crude Protein (kg)	NEm (Mcal)	NEg (Mcal)	Ca (kg)	P (kg)
300	0.5	3.583	0.331	3.07	0.42	0.011	0.006

A. ES Types

ES(μ,λ) is the type of ES which produces offspring using mutation without recombination. The selection in ES(μ,λ) is obtained only from offspring, the individual parent in the population is not involved [20]. Figure 1 shows the flowchart of ES(μ,λ). ES (μ/ρ,λ) produces offspring using mutation and recombination. The selection process in ES (μ/ρ,λ) is obtained from offspring, without involving the parents [20]. Figure 2 shows the flowchart of ES (μ/ρ,λ).

ES(μ+λ) uses mutation without recombination to produce offspring. The new generation in ES(μ+λ) is selected from offspring and the parents [20]. Figure 3 shows the flowchart of ES(μ,λ). ES (μ/ρ+λ) uses mutation and recombination to produce offspring. The selection process in ES (μ/ρ+λ) is obtained from offspring and parents [20]. Figure 4 shows the flowchart of ES (μ/ρ+λ). Table 3 shows the comparison of four types of ES.

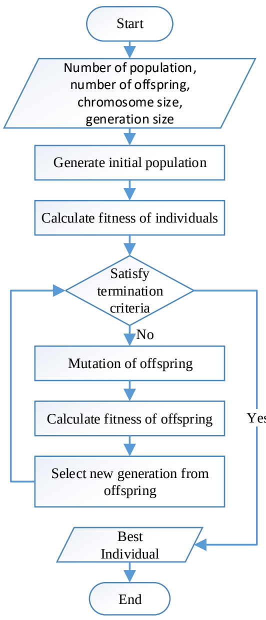

Figure 1: Flowchart of ES (μ,λ)

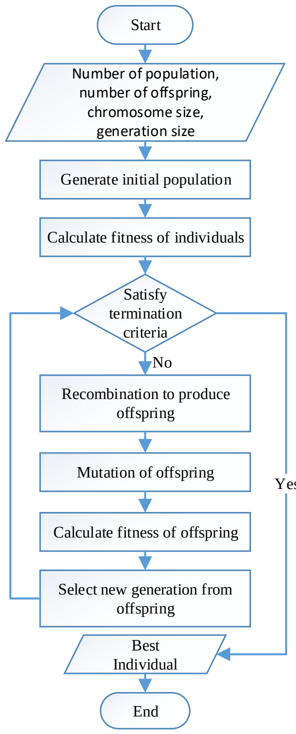

Figure 2: Flowchart of ES (μ/ρ,λ)

Table 3
Four ES types comparison

ES Type	Recombination	New generation source
ES (μ,λ)	No	Offspring
ES (μ/ρ,λ)	Yes	Offspring
ES (μ+λ)	No	Offspring and parents
ES (μ/ρ+λ)	Yes	Offspring and parents

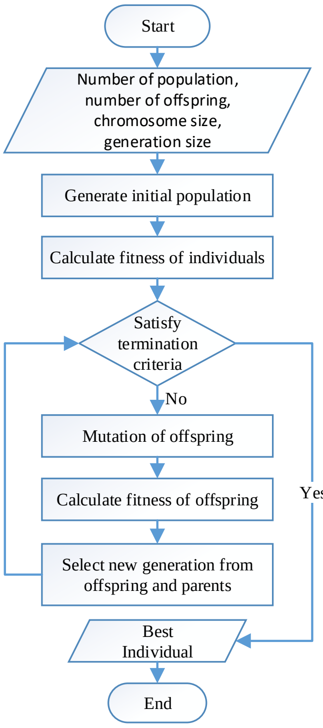

Figure 3: Flowchart of ES (μ+λ)

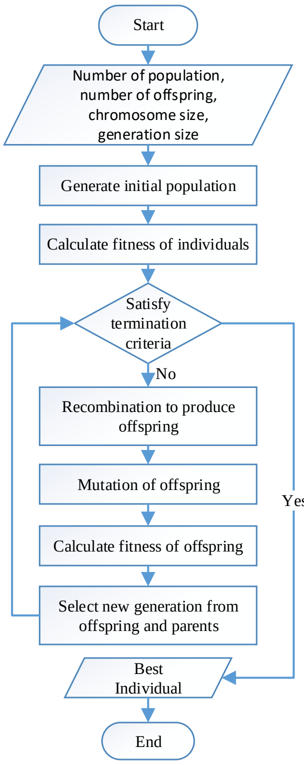

Figure 4: Flowchart of ES (μ/ρ+λ)

B. *Chromosome Representation*

The number of gene in the chromosome equals to the number of feed ingredient used in this study for feed formulation. Each gene in chromosome represents a number of feed ingredients in a kilogram. For example, the amount of rice straw is 0.985 kg, corn hominy is 0.563 kg, and fishmeal is 0.232. Then, the chromosome representation can be written as shown in Table 4.

Table 4
Chromosome representation

Rice Straw (x_1)	Corn Hominy (x_2)	Fishmeal (x_3)
0.985	0.563	0.232

C. *Initial Population and Initial Mutation Strength*

Initial population and initial mutation strength (σ) of ES are randomly generated in the range of [0,1]. The number of σ equals to the number of gene in the chromosome. Table 5 shows the example of initial population and initial mutation strength.

Table 5
ES' population

$P(t)$	x_1	x_2	x_3	σ_1	σ_2	σ_3
P_1	0.985	0.563	0.232	0.224	0.782	0.535

D. *Fitness Function*

The fitness function used in this study was done by calculating the price of each feed ingredient and calculating the penalty (see Eq. (1)). The number 10,000 was a constant number so that the fitness value was not too small. If the nutrient fulfillment by ES was less than the minimum nutrient requirement, then the penalty was awarded. The calculation of penalty was based on the difference between the nutrient fulfillment by ES and the minimum nutrient requirement.

$$Fitness = \frac{10000}{\sum_{i=1}^{N} price_i + \left(\sum_{j=1}^{M} \sum_{i=1}^{N} penalty_{ij} * 10000\right)} \quad (1)$$

where: M = number of nutrients
N = number of ingredients

IV. EXPERIMENTAL RESULT

For each ES type, ES (μ,λ), ES (μ/ρ,λ), ES (μ+λ) and ES (μ/ρ+λ), a graph is presented to demonstrate performance by the *fitness* value, Figure 5-8. Each graph demonstrates the ES type's convergence rate. Each line on the fitness value graphs demonstrates the best fitness and average fitness from ten runs. Beef cattle with a weight of 300 lb and daily weight gain of 0.5 lb was used in this paper (see Table 1). This paper used intermediate recombination from two parents, elitist selection, and random injection mutation from previous research [8].

A. *ES (μ,λ)*

The fitness value chart for ES (μ,λ) is presented in Figure 5. The best feed composition obtained from ES (μ,λ) is shown in Table 6. For this type of ES, the average value always changed because of the selection process which only the offspring for the next generation were chosen. From Figure 5, the best fitness and average value were almost intersecting. This indicates that the value obtained from ES (μ,λ) is good..

Table 6
Best feed composition from ES (μ,λ)

Urea	Molasses Cane	Rice Straw	Soybean Straw	Corn Hominy	Rice Bran
0.036	0.718	1.458	0.12	0.001	1.024
Fishmeal	**Corn Gluten Feed**	**Coconut Meal**	**Sugar Cane Bagasse**	**Wheat Shorts**	**Tapioca Meal**
0.0	0.007	0.001	0.001	0.0	0.727

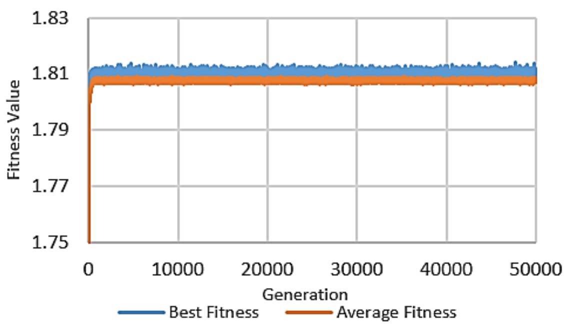

Figure 5: Fitness value chart for ES (μ,λ)

B. *ES (μ/ρ,λ)*

The fitness value chart for ES (μ/ρ,λ) is presented in Figure 6. The best feed composition obtained from ES (μ/ρ,λ) is shown in Table 7. Based on Figure. 6, the line for best fitness and average fitness intersect each other. This shows the results from ES (μ/ρ,λ) is good.

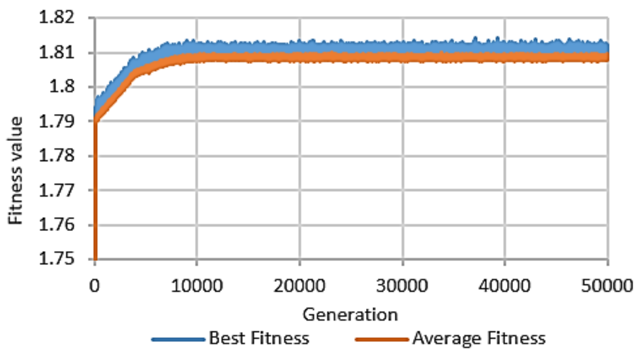

Figure 6: Fitness value chart for ES (μ/ρ,λ)

Table 7
Best feed composition from ES (μ/ρ,λ)

Urea	Molasses Cane	Rice Straw	Soybean Straw	Corn Hominy	Rice Bran
0.036	0.715	1.471	0.107	0.001	1.018
Fishmeal	Corn Gluten Feed	Coconut Meal	Sugar Cane Bagasse	Wheat Shorts	Tapioca Meal
0.0	0.008	0.003	0.0	0.001	0.731

C. *ES (μ+λ)*

The fitness value chart for ES (μ+λ) is presented in Figure 7. The best feed composition obtained from ES (μ+λ) is shown in Table 8. Because ES (μ+λ) uses the selection from offspring and parent, ES (μ+λ) saves the best solution from the first generation until the last generation. This resulted in a straight convergence line until the end of the generation.

Table 8
Best feed composition from ES (μ+λ)

Urea	Molasses Cane	Rice Straw	Soybean Straw	Corn Hominy	Rice Bran
0.036	0.614	1.355	0.224	0.00	1.007
Fishmeal	Corn Gluten Feed	Coconut Meal	Sugar Cane Bagasse	Wheat Shorts	Tapioca Meal
0.0	0.029	0.001	0.003	0.002	0.807

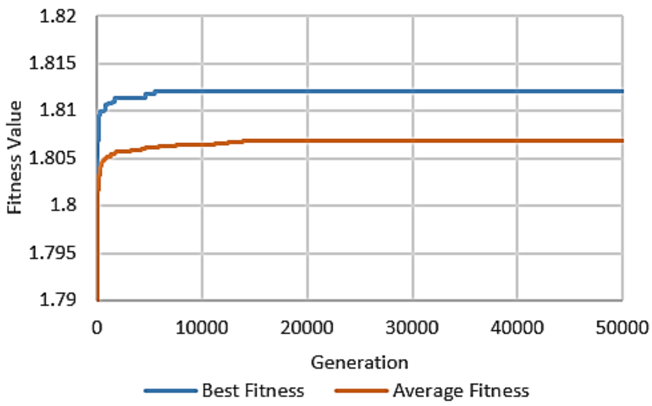

Figure 7: Fitness value chart for ES (μ+λ)

D. *ES (μ/ρ+λ)*

The fitness value chart for ES (μ/ρ+λ) is presented in Figure 8. The best feed composition obtained from ES (μ/ρ+λ) is shown in Table 9. This type of ES selected the best solution in each generation from offspring and parent. As the result, the line from a generation when it converges was straight until the last generation. The graph line from the best fitness and average fitness did not intersect each other. This indicates that the value is not too good.

Table 9
Best feed composition from ES (μ/ρ+λ)

Urea	Molasses Cane	Rice Straw	Soybean Straw	Corn Hominy	Rice Bran
0.033	0.584	1.056	0.305	0.064	0.986
Fishmeal	Corn Gluten Feed	Coconut Meal	Sugar Cane Bagasse	Wheat Shorts	Tapioca Meal
0.012	0.17	0.01	0.218	0.017	0.684

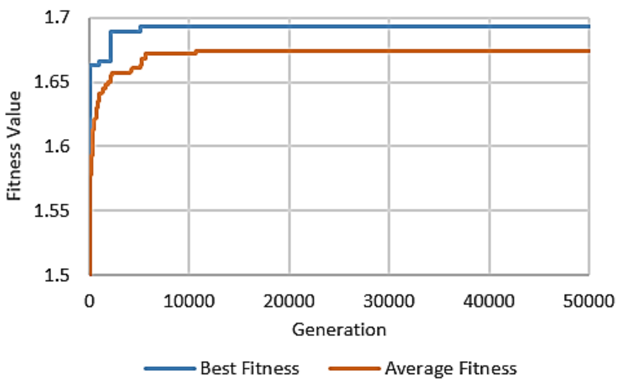

Figure 8: Fitness value chart for ES (μ/ρ+λ)

E. *Comparison of four types of ES*

Table 10 shows the nutrition fulfillment by all the four types of ES. It was clear that all four types of ES were able to find the cattle feed composition with zero penalties for cattle with a weight of 300 lb and daily weight gain of 0.5 lb. From Figure 9, the lines for ES (μ,λ), ES (μ/ρ,λ), and ES (μ+λ) intersected each other, while the result of ES (μ/ρ+λ) was rather far below.

From the fitness comparison, Table 11 shows that ES (μ+λ) and ES (μ/ρ+λ) found the best fitness at the fewer number of generations in respect of ES (μ,λ) and ES (μ/ρ,λ). Furthermore, ES (μ,λ), ES (μ/ρ,λ), and ES (μ+λ) produced higher best fitness value than ES (μ/ρ+λ). The computation time for ES (μ+λ) was faster than ES (μ,λ), ES (μ/ρ,λ), and

ES (μ/ρ+λ).

Table 10
The nutrition fulfillment by all four types of ES

ES Type	Dry Matter	Crude Protein	NEm	NEg	Cal-cium	Phos-phorus
ES (μ,λ)	3.584	0.331	5.492	2.685	0.011	0.018
ES (μ/ρ,λ)	3.583	0.331	5.49	2.684	0.011	0.018
ES (μ+λ)	3.583	0.331	5.476	2.677	0.012	0.018
ES (μ/ρ+λ)	3.641	0.361	5.647	2.801	0.014	0.02

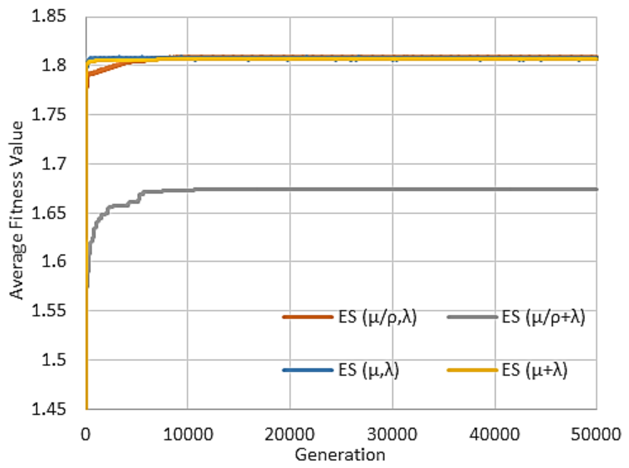

Figure 9: Comparison of four types of ES

Table 11
Comparison of best fitness

ES Type	The best fitness found at t-th generation	Best Fitness	Best Price	The time required to produce the best fitness (ms)
ES (μ,λ)	47687	1.814026049	5512.6	149000000
ES (μ/ρ,λ)	37114	1.814254024	5511.55	111000000
ES (μ+λ)	5504	1.812023429	5518.45	11800000
ES (μ/ρ+λ)	5142	1.692734782	5907.6	19900000

Table 12 shows the average fitness comparison. ES (μ+λ) and ES (μ/ρ+λ) converged faster than ES (μ,λ) and ES (μ/ρ,λ). Furthermore, ES (μ,λ), ES (μ/ρ,λ), and ES (μ+λ) produced higher average fitness value and lower average price than ES (μ/ρ+λ).

Table 12
Average fitness comparison

ES Type	Best Average Fitness found at t-th generation		Best Average Fitness
ES (μ,λ)	26629		1.809233015
ES (μ/ρ,λ)	23138		1.809861462
ES (μ+λ)	14514		1.806837983
ES (μ/ρ+λ)	10616		1.673621522
ES Type	**Average Price**	**Standard Deviation**	**Average Time (ms)**
ES (μ,λ)	5524.04	0.000583637	60910000
ES (μ/ρ,λ)	5524.465	0.001095282	53380000
ES (μ+λ)	5534.425	0.003814135	31380000
ES (μ/ρ+λ)	5907.915	0.013081598	44990000

In this experiment, the standard deviation of all ES types were also compared. The standard deviation indicated the variability of the result. If the standard deviation is low, the results are clustered close together or close to the mean value. If the standard deviation is high, the results are spread widely and the variability is high. The low standard deviation tends to produce a high-quality result.

From Table 12, the standard deviation value for ES (μ,λ), ES (μ/ρ,λ), and ES (μ+λ) were lower than ES (μ/ρ+λ). This indicates that the results from ES (μ,λ), ES (μ/ρ,λ), and ES (μ+λ) are close to mean value, which leads to higher average fitness value. Otherwise, the result from ES (μ/ρ+λ) is spread widely, so it tends to produce lower fitness value.

F. Comparison of Modified ES (μ/ρ+λ)

a. ES (μ/ρ+λ) Modification Schema

From the prior comparison between four types of ES, ES (μ/ρ+λ) produced the worst result than the other type of ES. Therefore, we tried to improve the ES (μ/ρ+λ) using the following modifications.

1. As the prior ES (μ/ρ+λ) used intermediate recombination from two parents, then we compared with intermediate recombination from three parents (ES1).
2. If the chromosome contains a negative value, the fitness value is change to a negative value (ES2).

b. Comparison Result of Modified ES (μ/ρ+λ)

Based on Table 13, the amount produced by ES (μ/ρ+λ) and ES2 can meet the nutrient requirement for beef cattle. However, ES1 failed to meet the nutrient requirement. The calcium produced by ES1 was less than the minimum calcium required by beef cattle.

Table 13
The nutrition fulfillment by ES (μ/ρ+λ) and its modification

ES Type	Dry Matter	Crude Protein	NEm	NEg	Cal-cium	Phos-phorus
ES (μ/ρ+λ)	3.641	0.361	5.647	2.801	0.014	0.02
ES1	3.584	0.38	5.484	2.733	0.007	0.013
ES2	3.591	0.335	5.561	2.753	0.016	0.015

Based on the fitness value comparison from Table 14 and 15, and Figure 10, it is clear that the best fitness value and the best average fitness value are obtained by ES2. In contrast, ES1 proves to get the lowest fitness value. However, ES2 requires a longer generation to converge and longer computation time than ES (μ/ρ+λ) and ES1. Furthermore, the standard deviation for ES2 is slightly higher than ES (μ/ρ+λ) and ES1.

It was concluded from the experiments that ES2 is able to provide the nutrient requirement for beef cattle with higher fitness value and lower price than ES (μ/ρ+λ) and ES1. However, ES2 is still not able to exceed the fitness value and price obtained by ES (μ/ρ,λ).

Table 14
Comparison of best fitness

ES Type	The best fitness found at t-th generation	Best Fitness	Best Price	The time required to produce the best fitness (ms)
ES (μ/ρ+λ)	5142	1.692734782	5907.6	19900000
ES1	1852	1.694917567	5823.8	7155037
ES2	10214	1.757554435	5682.55	28100000

Table 15
Average fitness comparison

ES Type	Best Average Fitness found at t-th generation		Best Average Fitness
ES (μ/ρ+λ)	10616		1.673621522
ES1	8746		1.668568751
ES2	18709		1.731416064
ES Type	Average Price	Standard Deviation	Average Time (ms)
ES (μ/ρ+λ)	5907.915	0.013081598	44990000
ES1	5968.44	0.014645154	38796054
ES2	5765.45	0.023543484	62460614

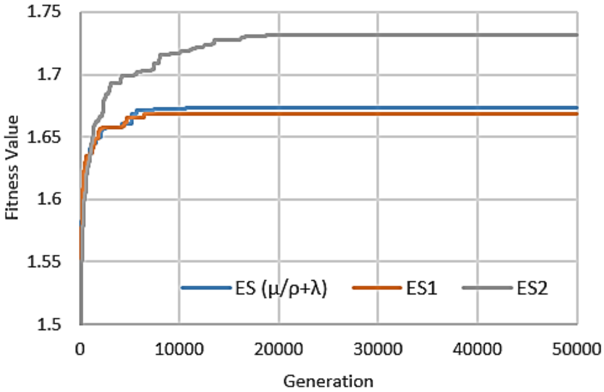

Figure 10: Comparison of modified ES (μ/ρ+λ)

V. CONCLUSION

Four types of ES for beef cattle feed optimization were tested in this experiment. All the ES were capable of finding the composition with zero penalties. ES (μ,λ) and ES (μ/ρ,λ) were both computationally expensive and found the best average fitness after the long generation. However, it produced the highest average fitness with the lowest average price, compared with the other two types. In contrast, whilst both the ES (μ+λ) and ES (μ/ρ+λ) were computationally inexpensive and faster to converge than ES (μ,λ) and ES (μ/ρ,λ).

Because ES (μ/ρ+λ) produced lower fitness compared with other types, we modified the ES (μ/ρ+λ) using intermediate recombination from three parents (ES1) and changed the fitness value to a negative value if the chromosome contained negative value (ES2). This comparison yielded the conclusion that ES2 was able to surpass the ES (μ/ρ+λ) and ES. However, it still could not exceed the fitness value and price obtained by ES (μ/ρ,λ). Our experiments conclude that ES (μ/ρ,λ) produced highest average fitness value and lowest price. This is due to the use of the recombination process which helps the ES to explore new areas of the search space. Furthermore, the selection process in ES (μ/ρ,λ) which was obtained from offspring, resulted in a more diverse individual. This high diversity enables the ES to explore larger search space, makes it possible to avoid the premature convergence and achieve the global optimum.

ES most generally addresses the issue of black-box optimization in the continuous domain [21]. The continuous domain usually consists of maximizing or minimizing an objective function. Beef cattle feed optimization is a maximization, constrained, and multimodal optimization problem. So, its objective function is to produce a solution with higher fitness value. The four types of ES have given different results in this case and has evidenced ES (μ/ρ,λ) as the best. The best ES type depends on the problem and domain. Different problems and domain can lead to different results as the dimensional search space is different. Based on our experiments, we observed that the choice of ES type is important to performance in terms of convergence speed and solution reliability.

Furthermore, distinctive variants of Evolution Strategies were tested to solve both unimodal and multimodal optimization problems by [22]. They found that the probability of Niching [κ(μ/ρ,λ)] ES (NES) of discovering the global optimum or very good local optimum is higher than ES (μ/ρ,λ). NES not only able to solve the unimodal, but also multimodal optimization problem which closes to Pareto optimal front. So, for further research, it needs to compare the ES (μ/ρ,λ) and NES for beef cattle feed optimization.

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