Multi-Criteria Genetic Algorithms for Solving Pig Food Problems

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Abstract— This paper presents an algorithm based on genetic algorithms (GAs) for multi-criteria problems to solve pig food problems. The proposed algorithm called Era-GAs scheme forms pig food formulations with the aim of finding the lowest cost under the conditions of the ingredient prices and pig's nutritional requirements such as energy, fat, protein, minerals, and vitamins. The requirements and the average price of pig food are primarily considered as multiple objectives for Era-GAs scheme. The simulation results of a proposed approach are compared with the traditional GAs. Experimental results indicate that Era-GAs scheme performs better in any environments. The advantage of the proposed approach is that it does not require any additional information about the problem.

Keywords-component; genetic algorithm; multi-criteria optimization; pig food problem

I. INTRODUCTION

Genetic algorithms are the well known stochastic search techniques based on the evolutionary concepts of natural selection on a population of behavioral strategies. GAs have been applied successfully to find acceptable solutions in a wide range of problem domains such as engineering, science, and business. One reason for GAs being attractive technique is the ability to search for optimal solutions in reasonable amounts of time. GAs are also be able to solve complex and difficult problems which are required higher computational.

In present, GAs have played an important role on multi-criteria optimization problems. Balazs Molnar in [2] applied GAs to solve the order picking process scheduling and planning in a warehouse. N.Suguna, and K.Thnushkodi had successfully applied GAs for multi-objective optimization problems to solve two problems of medical domain [12]. In [16], Xingdong Zhang and Marc P.Armstrong implemented a multi-objective genetic algorithm for corridor location problems. The research of Chih-Chao H., Liang-Cheng C., and Wai-Yi L. in [3] applied Multiobjiective GAs for water management. Also, S. Dehuri in [13] applied multi-object GAs for association rule mining and knowledge discover in databases. However, few researches have been applied GAs to solve the agricultural problems especial for food intake. Only researches in [4] applied GAs to simulate the pig growth model under a given feeding strategy.

In the pig farms, efficient and profitable pig production depends upon an understanding of the environment, heard, health, management, and nutrition. However, Food represents 60 to 70 percent of the total cost of pork production [9]. Therefore, in an industry, most farmers need to have pig food as cheap as possible. Energy, fat, protein, minerals, and vitamins must be provided and balanced to meet the standard of pig's nutritional requirements. Also, some pig farms have various kinds of pigs in the heard which need different nutritional programs. In this paper, a proposed algorithm for the pig food problem, called Era-GA scheme, employ the elite technique to enhance the efficiency of the solution. The concentration of this algorithm is to search for the best blending of the various ingredients at low price under pig's nutritional requirements and ingredient prices.

The paper is divided into six sections, including this introduction section. Section 2 provides an overview of the general multi-criteria genetic algorithms. Section 3 describes the motivation problem of pig food in detail. Section 4 presents the proposed algorithm, Era-GA scheme. The simulation setup and experimental results of the scheme are presented in section 5. The conclusion and future works are in the last section.

II. OVERVIEW OF GENERAL MULTI-CRITERIA GENETIC ALGORITHMS

The basic mechanism in GAs is a model of Darwinian evolution. Only good individuals of the population survive to the next generation while bad individuals are eliminated from the selection process. The fitness value of each element, which could be the objective of the solution, is used to distinct good and bad individuals from the population. GAs often apply to find the optimal solution to the problem by manipulating a population of solutions. The manners of problems need to be encoded in chromosomes for distinguishing good solutions from bad ones. In general, the way to discriminate good solutions from bad ones is called the fitness function. Once the problem is encoded in chromosomes with the fixed length, L, the genetic algorithm can be run. Often, the solution space can also be defined by looking at the strings that have 1's and 0's in specified places [10], thus the search space is formed by 2^L points. The genetic algorithm begins with generation 0 with the completely random

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population.

A variety scheme of genetic algorithms for multi-criteria problems has appeared in many different disciplines as in [1], [5], [6], [11], [13], [15]. They are very different from the “traditional genetic algorithms” proposed by Holland in 1975.

Currently, GAs for multi-criteria become popular for solving practical applications which is required to find the best solution among Pareto optima. A Pareto optimal set is the mathematical solution to a multi-objectives problem [12]. A solution is Pareto-optimal if no other solution can improve one object function without reducing at least one other objectives [8]. In [7] and [16], the definition of Pareto-optimality is defined as following.

Definition 1: Consider without loss of generality the following multi-objective optimization problem with a input decisions $x = (x_1,\ldots,x_m)$ in the decision space X and an objective $y = (y_1,\ldots,y_m)$ in the objective space Y.

Maximize $y = F(x)=(F_1(x_1,\ldots,x_m),\ldots, F_n(x_1,\ldots,x_m))$ (1)

A decision vector $a \in X$ is said to dominate a decision vector $b \in X$ (also written as $a \succ b$) if and only if:

$$\forall i \in \{1,\ldots,n\}: F_i(a) \geq F_i(b) \text{ and}$$
$$\exists i \in \{1,\ldots,n\}: F_i(a) > F_i(b). \quad (2)$$

Definition 2: The decision vector $a \in X$ is called Pareto-optimal if and only if a is nondominated regarding the whole decision of X.

The set of all Pareto-optimal points, denote by PS, is called Pareto Set. The set of all the Pareto objective vectors, $PF = \{F(x) \in R^m \mid x \in PS\}$, is called the Pareto front.

III. Pig Food Problems Considered

In this paper, the motivating problem considered in this paper can be found in the real farms which can be described as following to illustrate the problem.

In pig farm, as mention early, food represents 60 to 70 percent of the total cost of pork production, so many pig feeders need to concentrate on the ingredients blended in the pig food. Originally, they want to make pig foods with good quality level at the lowest prices as possible. The typically idea behind this is that a nutrition program should be provided to each type of pigs at the feeder with the quality feed at a cost-effective price. At a certain period of time the price of ingredients blended in pig food could fluctuate with seasonal conditions. Sometimes, they can be a shortage with economic constraints. Of course, the market price of these ingredients tends to be expensive. At one point of time with the price pressure, pig raisers might consider changing pig food formulations by replacing some ingredients under pig’s nutritional requirements.

TABLE I. The Example of the ingredients list at three different time frames.

Ingredients	**Price $/Kg.**		
	Time A	***Time B***	***Time C***
Broken Rice	0.318	0.26	0.24
Corn	0.26	0.26	0.27
Rice Bran	0.20	0.25	0.26
Soybean, full- fat	0.61	0.59	0.62
Soybean, 46 % fat	0.53	0.53	0.54
Palm oil	0.74	0.74	0.88
Rice oil	1.03	1.03	1.03
L-Lysine	1.97	1.73	1.81
DL-Methonine	3.64	5.21	5.27
L-Treonine	3.27	2.39	2.58
Calcium Carbonate	0.03	0.03	0.03
Salt	0.09	0.08	0.09
Dimonodicalcium phosphate- P18	0.75	0.73	0.74
Mondicalcium phosphate-P21	0.81	0.76	0.77
Maxilac	1.36	1.33	1.36
Nuklospray	1.01	1.08	1.06
Average price/kg	1.038	1.063	1.097

TABLE II. THE EXAMPLE OF NUTRIENTS NEEDED FOR PIGS.

Nutrients	Recommended Percent of Complete Diet					
	Weaned pigs up to 15 kg live weight		*Young growing pigs of 15 – 50 kg live weight*		*Growing pigs of 50 – 120 kg live weight*	
	Min	*Max*	*Min*	*Max*	*Min*	*Max*
Net Energy (C/Kg)	3500	4000	3220	3400	3000	3250
Protein (%)	20.0	24.0	18.5	21.0	18.0	22.0
Fat (%)	5.00	-	3.00	7.8	3.0	7.3
Fiber (%)	1.00	3.00	3.00	5.0	3.0	5.5
Calcium (%)	1.00	1.30	1.00	1.25	1.0	1.15
Total Phosphorus (%)	0.75	-	0.75	-	0.74	-
Bioavialablility of phosphorus used in Pig (%)	0.55	-	0.50	-	0.46	-
Salt (%)	0.40	0.70	0.30	0.5	0.30	0.55
Lysine (%)	1.50	-	1.20	-	1.10	-
Methionine + Cyteine (%)	0.90	-	0.72	-	0.65	-
Methionine (%)	0.45	-	0.36	-	0.32	-
Threonine (%)	0.91	-	0.74	-	0.67	-
Trytophan (%)	0.26	-	0.22	-	0.19	-
Lactose (%)	8.00	-	-	-	-	-

'-' means no limitation applied.

TABLE III. SOME FEED INGREDIENTS COMMONLY USED IN SWINE DIETS (AS-FED BASIS).

Ingredients	Energy KC/kg	Chemical Nutrition of Ingredients %														
		Salt	*Fiber*	*Calcium*	*Protein*	*Fat*	*Lysine*	*Bioavailability of phosphorus (%)*		*Methionine+ Cyteine*	*Methionine*	*Threonine*	*Trytophan*	*Veline*	*Linoleic*	*Lactose*
								Total	*Used in Pig*							
Broken rice	3500	0	1.0	0.03	7.6	1.2	0.27	0.18	0.04	0.3	0.2	0.28	0.09	0.50	0.39	0
Corn	3300	0	2.5	0.03	8.0	3.6	0.24	0.25	0.10	0.32	0.18	0.30	0.07	0.39	1.90	0
Rice Bran	2900	0.18	10.0	0.07	12.0	15.5	0.45	1.45	0.25	0.30	0.20	0.30	0.08	0.80	3.60	0
Soybeans, full-fat	3750	0	5.0	0.25	38.0	18.0	2.4	0.20	0.20	1.09	0	1.69	0.52	0	0	0
Soybean, 46 % fat	3750	0	5.0	0.25	38.0	18.0	2.40	0.20	0.20	1.09	0	1.69	0.52	2.10	0	0
Coconut oil	9000	0	0	0	0	100.	0	0	0	0	0	0	0	0	0	0
Palm oil	8000	0	0	0	37.0	98.0	0	0	0	0	0	0	0	0	0	0
Rice bran oil	8800	0	0	0	0	99.0	0	0	0	0	0	0	0	0	45.0	0
L-Lysine	4250	0	0	0	94.0	0	78.8	0	0	0	0	0	0	0	0	0
DL-Methonine	5280	0	0	0	58.0	0	0	0	0	98.5	98.5	0	0	0	0	0
L-Treonine	3700	0	0	0	73.5	0	0	0	0	0	0	98.5	0	0	0	0
Calcium Carbonate	0	0	0	38.0	0	0	0	0	0	0	0	0	0	0	0	0
Salt	0	98	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Dimonodicalcium phosphate- P18	0	0	0	24.0	0	0	0	18.00	12.60	0	0	0	0	0	0	0
Mondicalcium phosphate-P21	0	1.28	0	16.0	0	0	0	21.00	15.40	0	0	0	0	0	0	0
Maxilac	3370	0.35	2.0	0.5	38.0	1.0	2.55	0.60	0.42	1.11	0.57	1.51	0.47	0	0	0
Nuklospray	4000	1	1.0	0.5	26.0	10.0	1.56	0.70	0.63	0.74	0.34	1.08	0.33	0	0	41.0

Suppose that they can find some ingredients in the area as shown in Table 1. Of course, each ingredient gives different chemical nutrition as shown in table 2 adapted from a series of Starter of Pig Recommendation, Kansas State University [10]. Pig raisers who understand the principle of table 2 can save the budget and get some other advantages. For example, phosphorus is one of the most expensive mineral added in pig diets. If the cost of Monodicalciumphospate (21 percent phosphorus) used in the pig feed is 0.81 dollar/kg, and Dimonodicalcium phosphate-P18 (18 percent phosphorus) is 0.75 dollar/kg. Most pig raisers might consider using the cheapest source of phosphorus by the following calculation.

1 Kilogram of Monodicalciumphospate-P21

Total Phosphorus is 21%, which is 0.21 Kg

Price is 0.81 dollar/Kg

Average price is 0.81/0.21= 3.86 dollar/kg

1 Kilogram of Dimonodicalcium phosphate-P18

Price is 0.75 dollar/Kg.

Total Phosphorus is 18 %, which is 0.18 Kg

Average price is 0.75/0.18 = 4.17 dollar/Kg

However, some nutrients are required only the minimum level such as the fat's requirement of young pigs. Of course, pig foods can be formulated in many different formulations of ingredients ratio. So, the problem appeared to the pig raisers is which formulation is the cheapest. Often, the pig raisers can make their pig foods mixed by their experiences. Suppose that the pig raiser has one food formulation of weaned pigs up to 15 kg live weight as shown in table 3. The average of pig food is changed due the difference of ingredient's price list. At time A in table 1, the calculations of net energy and protein are shown below:

$$\begin{aligned}\text{Net energy} &= (400*3500+350*3750+45*8000+\\ &\quad 4*4250+3*5280+0.5*3700+125*3370)/977.3\\ &= 3610.40 \text{ C/Kg}\end{aligned}$$

$$\begin{aligned}\text{Protein} &= (400*7.6+350*38+45*37+4*94+3*58+\\ &\quad 0.5*73.5+125*38)/977.3\\ &= 23.88\ \%\end{aligned}$$

The same calculation would apply to others nutrient. Then, the resulting of nutrients derived from the food formation is shown in table 4. It is shown that this formulation is unable to meet the pig's nutrient requirement. Total phosphorus, phosphorus used in pig, and salt are lower than the minimum requirement while there is no lactose in the formulation. Again, reformulating and evaluating a pig food formulation are needed to meet the nutrient levels.

TABLE IV. THE EXAMPLE OF NUTRIENTS NEEDED FOR PIGS.

Nutrients	**Nutrients derived from food formation**	**Nutrient Range**	
		Min	***Max***
Net Energy (C/Kg)	3610.40	3500.00	4000.00
Protein (%)	23.88	20.00	24.00
Fat (%)	11.58	5.00	-
Fiber (%)	2.46	1.00	3.00
Calcium (%)	1.06	1.00	1.30
Total Phosphorus (%)	0.74	0.75	-
Bioavialablility of Phosphorus used in Pig (%)	0.52	0.55	-
Salt (%)	0.37	0.40	0.70
Lysine (%)	1.62	1.50	-
Methionine+Cyteine (%)	0.96	0.90	-
Methionine (%)	0.46	0.45	-
Threonine (%)	0.93	0.91	-
Trytophan (%)	0.28	0.26	-
Lactose (%)	0	8.00	-

As the result, the monodicalciumphospate-P21 would be the cheapest source of phosphorus. However, ingredients used in the pig food are composed various chemical nutrition at different concentrations. That would be difficult for pig raisers to find the best formulations for pig feeds. Moreover, the nutrient's need for each pig can be changed and specified by pig feeder's objectives. Suppose the nutrient requirement of weaned pigs up to 15 kg live weight, young growing pigs of 15 – 50 kg live weight, and growing pigs of 50 – 120 kg live weight applied to the pig farm is shown in table 3. These nutrient requirements represent minimum and maximum levels.

Restrictive assumptions

1) The appearance of food such as form, color, test, and smell might be able to affect the quality of pig food, but only nutrient levels are concerned in the papers.

2) No limitation of ingredients used in pig food formulation and there is no perfect ingredient that can be fed to pigs by itself.

3) Some factors such as time, labors, and facilities for mixing and storing food in pig farms are not in the scope even though they are able to increase the average price of pig food.

4) No concerning of mycotoxins such as aflatoxins and ergots in the ingredients even though they might be able to diminish the nutritive value.

IV. Proposed Algorithm

A. Problem Formulation

One pig farm might has m kinds of pig which are defined as a set of P = $\{p_1, p_2, p_3,\ldots,p_m\}$. The pig raiser has some ingredients used in pig food formulation denoted as K = $\{k_1, k_2, k_3, \ldots, k_n\}$, where n is the maximum number of ingredients. At a certain period of time (called Time A), prices of all ingredients are listed in the set of $Price^A = \{price^A{}_1, price^A{}_2, price^A{}_3, \ldots, price^A{}_n\}$. Also, each individual k_p has its own nutrition detail which are formed in the vector of $(w^p{}_1, w^p{}_2, w^p{}_3, \ldots, w^p{}_j)$, where j is the number of chemical nutrition concerned with the pig food problems. Let X is a set of input parameters or pig food formulations for a specific kind of pig in P. As mention in the previous section, there are standard of pig's nutritional requirements for each type of pigs which are considered as multi-objectives for the problems. These requirements are strictly represented within the set of ordered pairs called NutritionBound = $\{[l_1, u_1], [l_2, u_2], \ldots, [l_j, u_j]\}$, i.e., $[l_1, u_1]$ is the pair of lower and upper limit of nutrition w_1. Let's all members of X are formed by the same sequence of ingredients listed in K, so an individual chromosome of the problem can be formed as following. Each individual of pig food formulation $x_i \in X$ is be represented by a sequence of $<x^i{}_1\ x^i{}_2\ x^i{}_3 \ldots x^i{}_n>$, in which $x^i{}_d$ is the amount of ingredient k_d, $0 < d \leq n$. However, if $x^i{}_d = 0$, it implies that no k_d added into the formulation. The general multi-criteria optimization for pig food problems can be defined as following:

$$F(x_i)=(AvgPrice(x_i),F_1(x_i), F_2(x_i), \ldots, F_j(x_i)) \quad (3)$$

where $AvgPrice(x_i)$ is the average price of x_i which is shown below:

$$Avg\,Price(x_i) = \frac{(price_1 x_1^i + price_2 x_2^i + ... + price_n x_n^i)}{\sum_{k=1}^{n} x_k^i} \quad (4)$$

And

$$F_1(x_i) = w^1{}_1 x^i{}_1 + w^2{}_1 x^i{}_2 + w^3{}_1 x^i{}_3 + \ldots + w^n{}_1 x^i{}_n = \sum_{k=1}^{n} w_1^k x_k^i\ ,$$

$$F_2(x_i) = w^1{}_2 x^i{}_1 + w^2{}_2 x^i{}_2 + w^3{}_2 x^i{}_3 + \ldots + w^n{}_2 x^i{}_n = \sum_{k=1}^{n} w_2^k x_k^i\ ,$$

…

$$F_j(x_i) = w^1{}_j x^i{}_1 + w^2{}_j x^i{}_2 + w^3{}_j x^i{}_3 + \ldots + w^n{}_j x^i{}_n = \sum_{k=1}^{n} w_j^k x_k^i \quad . (5)$$

The objective functions of the pig food problem are shown below:

$$Min(AvgPrice(x_i), i=1,2,\ldots, M \text{ and } x_i \in X) \quad (6)$$

,where

$F_1(x_i) \geq 0$, and $F_1(x_i)$ is in the range of $[l_1, u_1]$
$F_2(x_i) \geq 0$, and $F_2(x_i)$ is in the range of $[l_2, u_2]$
…
$F_j(x_i) \geq 0$, and $F_j(x_i)$ is in the rang of $[l_j, u_j]$. (7)

B. Problem encapsulation and fitness functions

As seen in the previous section, a pig food formulation xi is formed in a sequence of $<x^i_1\ x^i_2\ x^i_3 \ldots x^i_n>$ where any x^i_d is a weight of ingredient w_d which it can be used to find AvgPrice(x_i) and $F_1(x_i)$, $F_2(x_i)$, $F_3(x_i)$, …, $F_j(x_i)$. As the result, the form of $xi = <x^i_1\ x^i_2\ x^i_3 \ldots x^i_n>$ is suitable for representing the problem. In the Era-GA scheme, the weighted function is applied to each individual to obtain a single cost, which is assigned as a fitness value for each individual x_i of the population. The weighted sum of x_i can be written mathematical function as follows:

$$weight(x_j) = \sum_{j=0}^{n} g(x_j^i) \text{ ,where } g(x_j^i) = \begin{cases} 1, l_i \leq x_j^i \leq u_i \\ 0, otherwise \end{cases}. \quad (8)$$

The maximum value of weigth(x_j) is equal to the number of nutrition considered in the pig food problem. However, in (6) the average price of any x_j is also one of the main objectives. So, it is applied with the weighted sum of each individual x_i as an index for sorting all members of the population as seen in Fig. 1.

C. Era-GAs scheme design

As shown in Fig. 1, a set of parameters is initialized in the first era, such as population size (M) for each era, mutation rate (p_m), crossover rate (p_c), immigration rate (Img_rate), maximum generation (Max_Gen), and maximum era (Max_Era). Then, an initial population of pig food formulations is generated in a complete random. Create a new population for the next generation based on fitness value by randomly applying two operators, crossover operator and mutation operator.

1) Crossover operator

Two parents are selected from the mating pool, an intermediate approach to separate only best parents who will produce offspring from the current population. If selected parents are x_i and x_j, then two-point crossover is applied by randomly selecting two points on both parents. Everything between the two points is swapped between the parents. The possible result of two-point crossover is represented in Fig. 2.

2) Mutation operator

Due to the size of chromosomes used for this particular problem, the mutation operation in this approach creates three new offspring from an existing member. The technique is that one random member of the current population is chosen with two mutation points. Suppose x_i is the chosen member and two mutation points are 3 and 7. The possible results of mutation operator are shown in Fig. 3.

D. Migration phase

New offspring created from two-point mutation and two-point crossover are evaluated by fitness function. Then, both offspring and current parents are sorted based on their fitness value. Each individual with bad fitness cost is eliminated, so the rest of the population is transferred to the next generation. It needs to run several generations until it gets the maximum number of generations (Max_Gen). The best members of the current era are found. As shown in Fig. 1, the elite technique is applied, so some of these winners found so far migrate to the next era. The numbers of immigrating members are controlled by Img_rate. The population of the following era is derived from two parts, selected members of the previous era and its own initial random population with the size of M.

E. Parameters adjusting phase

At the beginning of Era-GAs, the amount of each ingredient is randomly chosen. The range of the each decision of input is automatically set in the wide range. For instance, the range of first ingredient (k_1) in the food formulation is set to be $[0, \infty)$. During first few eras, Era-GAs monitor the range of each ingredient derived from all of the best winner populations. For example, at the end of exploration of the first era the boundary of k_1 can be adjusted to a new limit, [$lower_1$, $upper_1$] which is obtained by observing the first manipulating the range of ingredient of k_1 during the exploration. The $lower_1$ and $upper_1$ are obtained by the following calculation.

$min_1=min(x^i_1$ where $i=1,2,\ldots,M)$
$max_1= max(x^i_1$ where $i=1,2,\ldots,M)$

$$lower_1 = min_1 - \alpha\,(max_1 - min_1) \quad (9)$$

$$upper_1 = max_1 + \alpha\,(max_1 - min_1) \quad (10)$$

TABLE V. THE EXAMPLE OF NUTRIENTS NEEDED FOR PIGS.

Ingredients used in pig food	Amount (Kg)	% in Food	Time A		Time B		Time C	
			$/Kg	*Cost (S)*	*$/Kg*	*Cost ($)*	*$ /Kg*	*Cost ($)*
Broken Rice	400	40.93	0.318	127.2	0.26	104	0.24	96
Soybean, full-fat	350	35.81	0.61	213.5	0.59	206.5	0.62	217
Palm oil	45	4.6	0.74	33.3	0.74	33.3	0.88	39.6
L-Lysine	4	0.41	1.97	7.88	1.73	6.92	1.81	7.24
DL-Methonine	3	0.31	3.64	10.92	5.21	15.63	5.27	15.81
L-Treonine	0.5	0.05	3.27	1.635	2.39	1.195	2.58	1.29
Monodiphospate P21	24	2.46	0.81	19.44	0.76	18.24	0.77	18.48
Calcium Carbonate	13	1.33	0.03	0.39	0.03	0.39	0.03	0.39
Salt	3	0.31	0.09	0.27	0.08	0.24	0.09	0.27
Maxilac	125	12.79	1.36	170	1.33	166.25	1.36	170
Others Minerals and vitamins	9.8	1.0	4.72	46.256	4.72	46.256	4.72	46.256
Total	977.3	100%	-	630.791	-	598.921	-	612.336
Average price per kilogram (Dollars/Kg)			0.645		0.613		0.627	

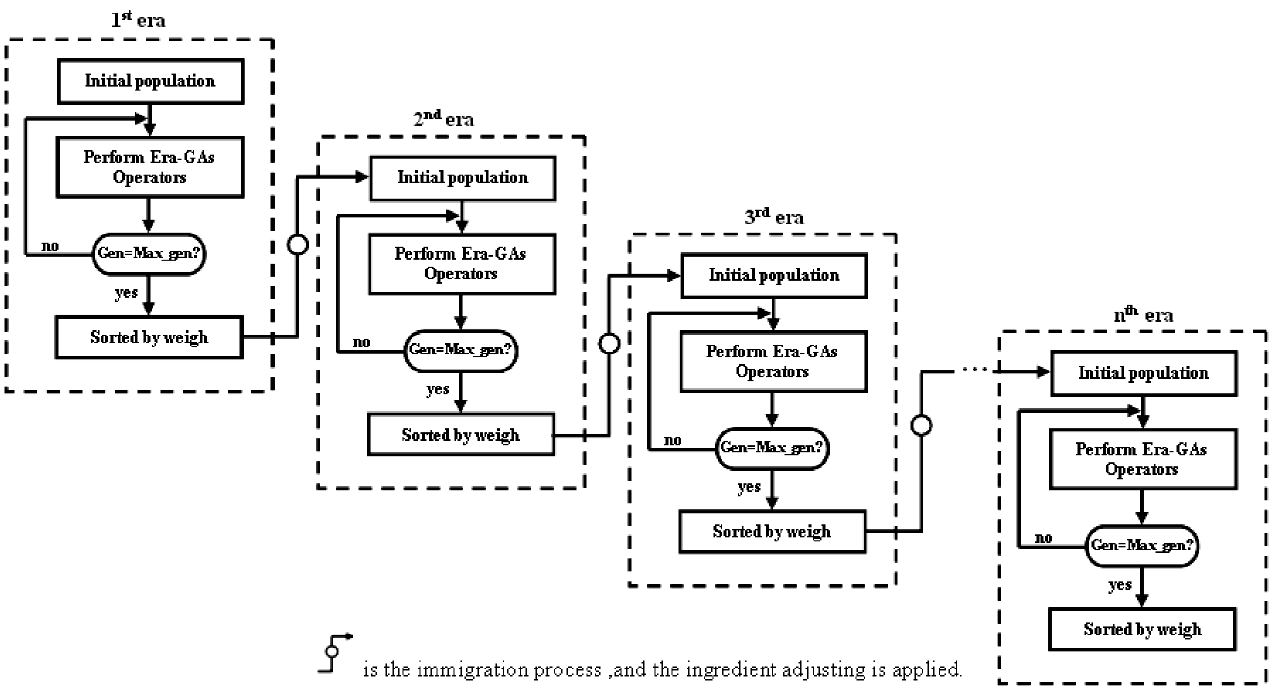

Figure 1. Conceptual of Era-GAs scheme for multi-objectives problem

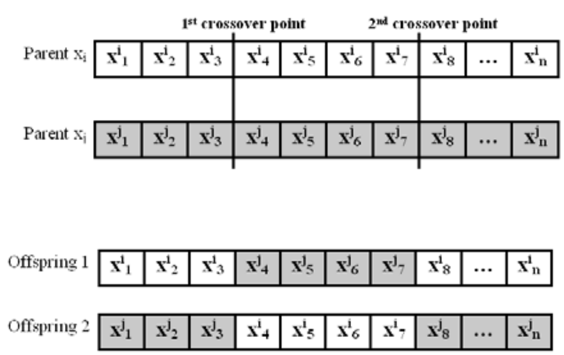

Figure 2. Example of two-point crossover

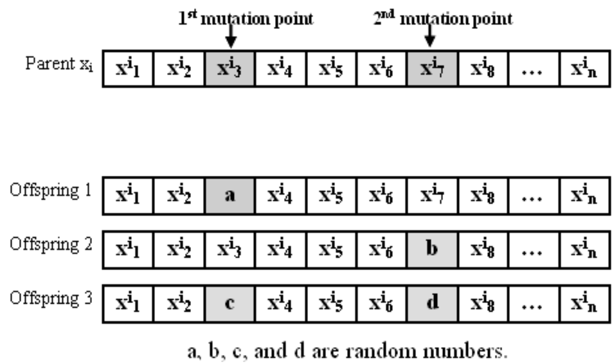

Figure 3. Example of two-point mutation

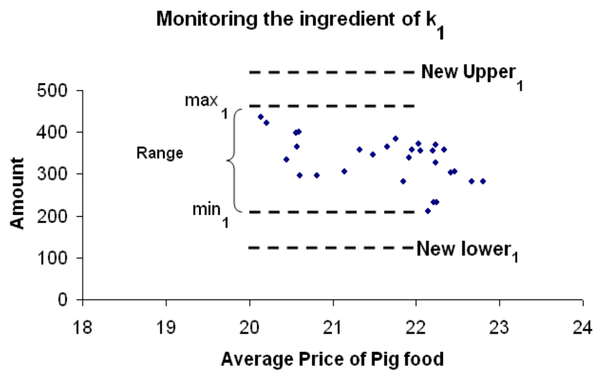

Figure 4. Example of manipulation the ingredient k_1

However, quick adjustments are possible to bear Era-GAs into the bad solutions, so the parameter $\alpha = 0.2$ is set. It is used in the calculation to ensure that exploration and exploitation of the search are balanced. As the result, the range of ingredient x_1 is limited into the smaller bound which is helpful for following eras because the size of all feasible solutions is becoming smaller. Consider when boundaries of all ingredients have manipulated, the algorithm will be more effective finding the solutions. For example, at the beginning of the process the range of k_1 in the pig food formulation is set to be $[0,\infty)$. If $min_1 = 200$ and $max_1 = 450$, then $lower_1 = 200-0.2(450-200) = 150$ and $upper_1 = 480+0.2(450-200) = 500$. Then, the new boundary of k_1 is changed to [150,500], as seen in Fig. 4.

V. THE SIMULATION AND EXPERIMENTAL RESULTS

A. Simulation Setup

The simulation has implemented more than 4000 lines of Java program. It is run on a Pentium(R) D CPU 2.80 GHz, 2 GB of RAM, IBM PC. The simulation has been tried several of runs with different values of the population size (M), mutation probability (pm), and crossover probability (pc), to find which values would steer the search towards the best solution. Also, some constraints of nutrient requirements are set for the simulation. Table 6 summarizes the simulation of Era-GA parameters which are obtained from the experiments.

From the experimental result, the fixed Era-GA parameters are the crossover probability pc = 0.95, mutation probability pm = 0.05. The initial population size (M) = 400, and maximum generation (Max_Gen) for each era = 200, as in table 6. In addition, several other quantitative control parameters and qualitative control variables must be specified in order to completely specify how to execute the Era-Gas scheme. The simulation is applied to three kinds of pigs under three main sets of constraints, the ingredients pricing as previously shown in table 1, nutrients needed for pigs as in table 3, and the chemical nutrition of ingredients listed in table 2. The summary of data setting for Era-GAs simulation is listed in table 7.

TABLE VI. SUMMARIZE THE FIXED PARAMETERS SETUP FOR THE SIMULATION OF THE ERA-GA SCHEME.

Constant	Detail	Value
MaxNumOfIngredients	Maximum number of ingredients	16
NumOfIngredients	Number of ingredients used in pig feed	13,14
NumOfNutritions	Number of chemical nutrients concerned in pig feed	10, 13, 14
Max_Era	Maximum number of eras	2,…,10
Max_Gen	Maximum number of generations of each era	200
M	Population size	200,…,400
pc	Crossover probability (pc)	0.95
pm	Mutation probability (pm)	0.05
Img_rate	Immigration rate	0.05-1.0
L	Fixed length of chromosome	14

TABLE VII. SUMMARIZE OF DATA SETTINGS FOR SIMULATION.

No. of Test	Type of pig	No. of chemical nutrition need in pig food formulation	No. of ingredients used in pig food (input parameters)
1	Weaned pigs up to 15 kg live weight	14	13
2	Young growing pigs of 15 – 50 kg live weight	13	10
3	Growing pigs of 50 – 120 kg live weight	13	14

B. Experimental Results

The objective of this simulation is to minimize the price of pig food while balancing the chemical nutrition to meet the standard of pig's nutritional requirements. From the experiments, there are several parameter settings of the Era-GAs scheme which affect the algorithm performance as described below.

1. Immigration Rate

The experimental result is shown in Fig. 5, it is seen that at any time when immigration rate is approximately 2.5-5% the Era-GAs scheme is able to form the cheapest pig food. As the graph shown, when the immigration rate is higher than 5%, the quality of the solution is decreased because the numbers of initial population of successive eras are bigger which is possible to degrade the efficiency and quality of the Era-GAs.

2. Number of Eras

The simulation has tried several of runs with different numbers of eras to find which the minimum number of eras gives the best solutions. From the experiments, when the number of eras is equal to 5, the simulation gives acceptable solutions as in the Fig. 6.

3. Number of Generations

Since the smaller population size helps in reducing the computational time [14], the simulation had tried several numbers of generations to find which numbers tend to generate the best results. When the numbers were increased the Era-GAs had a better result. The obtained result was in Fig.7. A considerable point in the figure is that when the number of generations was about 200 the quality of an Era-GAs of all tests is acceptable.

4. Parameters Adjusting

From the experiments in Fig. 8, it is clearly shown that, at any period of time, when Era-GAs performs without parameters adjusting phase, the average price of pig's formulation is more expensive than the average price derived from Era-GAs scheme.

C. *Comparison Era-GAs to Traditional GA*

In most GA-setup there are two operations to perform during one generation, crossover, and mutation. Briefly justifications for common GA with standard setup are: crossover probability pc = 0.95, mutation probability pm = 0.05, the initial population size (M) = 400, and maximum generation (Max_Gen) = 400. The common GA has defined the fitness function as it is appeared in Era-GAs scheme. However, in the Era-GAs, the number of initial populations and number of generations tends to become larger than traditional GA. From the experience results, Era-GAs gives best results when Max_Gen = 5, so the total initial number of populations is 5x400=2000 and the total number of generations is 5x200 = 1000. Since traditional GA is done by executing in one time, for making the fare comparison, the traditional GA is repeated 5 runs. The best of all designates to be the result of traditional GA. However, from experimental results, Era-GAs yield better solutions than the traditional GA in any environments as shown in Fig. 8.

VI. CONCLUSION AND FUTURE WORK

This paper presents the algorithm called Era-GAs scheme at the aim of forming the best blending of various ingredients at the lowest prices under the multi-criteria, pig's nutritional requirements and the ingredients prices. A number of experiments used in this paper are from the real world. The results of simulation confirm that in most cases the proposed approach is found to be satisfactory. The Era-GAs scheme is appropriate for the events in which the pig feeders want to make pig food at the lowest cost under the standard of pig's nutritional requirements. In most cases the proposed approach is found to be satisfactory. Fig 8 shows that the Era-GA can find the cheapest price of pig food formulations which is better than any formulations generated by traditional GA. From the experiments, there are three significant factors involved in efficiency of Era-GAs scheme; immigration rate, number of eras, and number of generation. Also, parameter adjusting phase is an important phase in improving the quality of the Era-Gas. The resulting in Fig. 5 showed that the best immigration rate for Era-GAs is approximately 5%. Moreover, the Era-GAs needs to run at least 5 eras with 200 generations of each era to get the best results. Some restrictive assumptions do apply: 1) no limitation of ingredient used in forming pig food formulation 2) Time, labors, and facilities for mixing and storing food in pig farms are not in the scope, and 3) no concerning of negative properties of ingredients such as aflatoxins and ergots which can diminish the nutritive value. Future researches will investigate in these restrictive and compare with the other well-known algorithm approaches.

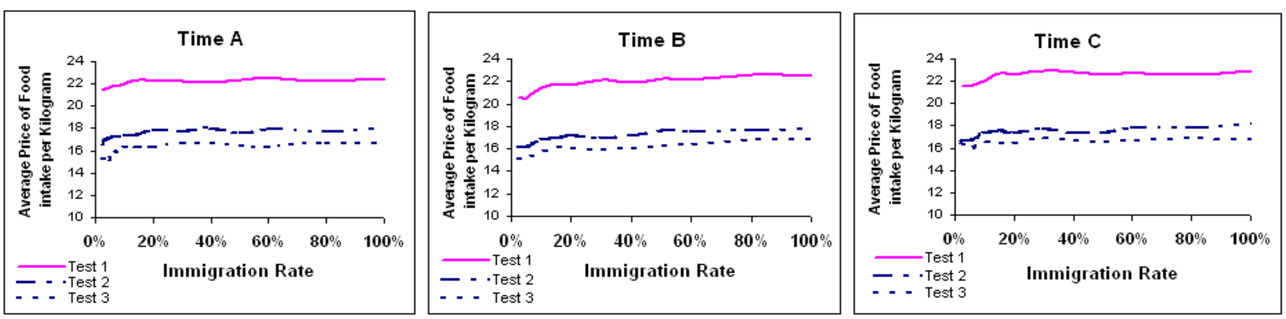

Figure 5. Immigration rate

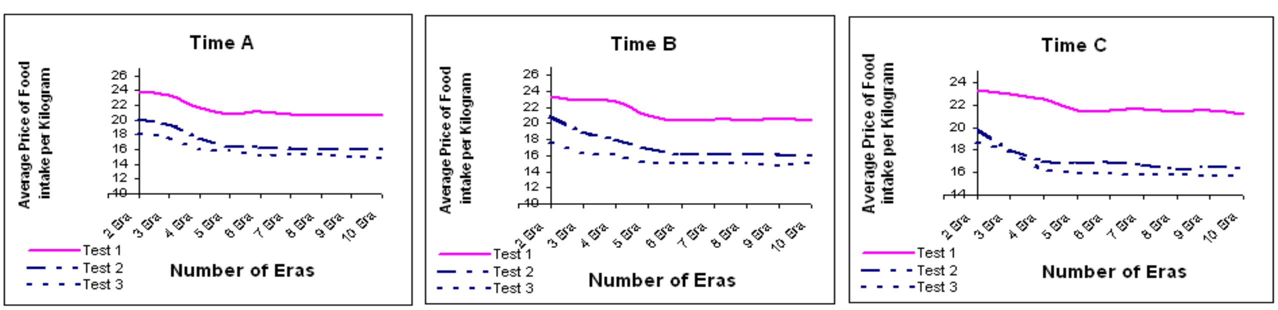

Figure 6. Number of eras

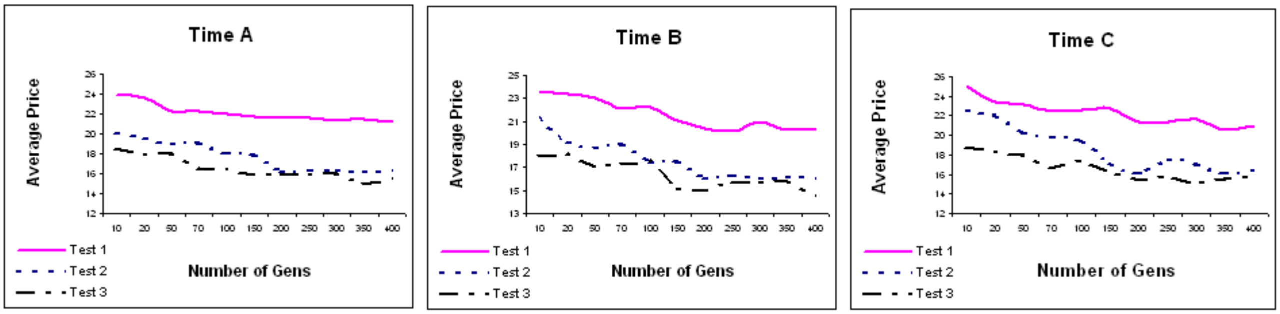

Figure 7. Number of generations (Gen), number of era = 5

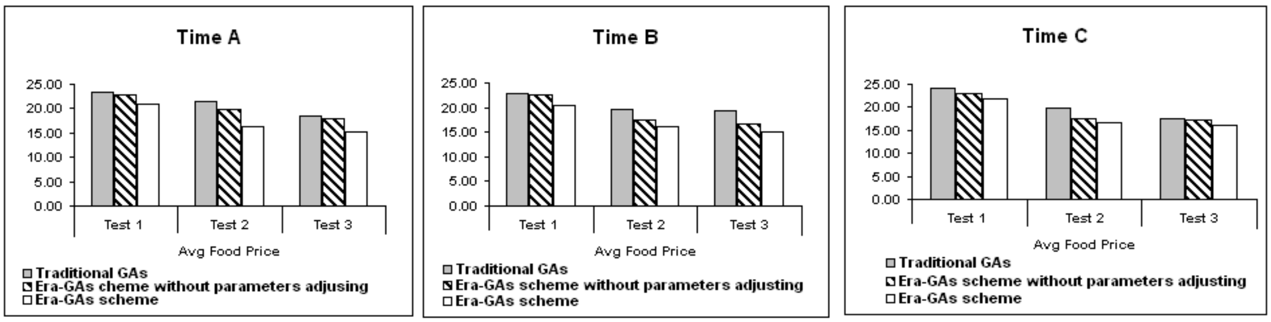

Figure 8. Comparison to traditional GA

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