EVOLUTIONARY ALGORITHM APPROACH FOR SOLVING ANIMAL DIET FORMULATION

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ABSTRACT. One of the pillars in animal farming industries is formulation of food for the animal, which is also known as diet formulation. However, the feed component in the aquaculture industry incurs the most expensive operational cost, and has drawn many studies regarding diet formulation. Hence, this study aims to solve animal diet formulation problem with ratio constraint using evolutionary algorithm approach. Actual data with 14 ingredients and 18 nutrients were taken into consideration. The result shows that evolutionary algorithm provides feasible solution in all runs. Experimentation on what-if scenario has proven that this evolutionary model is robust as it can adopt to changes in the parameter.

Keywords: genetic algorithm, animal diet formulation, feed mix

INTRODUCTION

Evolutionary Algorithm (EA) is a population-based technique in the metaheuristics family. EA is widely used in many fields due to the robust adaptation to the environment (Fogel, 2000). The concept of EA is basically based on genetic algorithm (GA). Researchers who have employed EA in their studies include Bhanja et al. (2013) in solving network problem, Lim and Ramli (2014) for nurse scheduling problem, Hecker et al. (2013) for production planning, and Şahman et al. (2009) for animal diet formulation, to name a few.

In animal diet formulation, Furuya et al. (1997) is the pioneer in using EA with the aim to solve the nonlinear constraints which involved the ratio of ingredients. The study showed that EA is a good technique for diet formulation as a near optimal solution could be obtained even for a problem that has no apparent solution. In this research, Furuya et al. (1997) considered a minimum and maximum value of ingredient; however, almost all of the minimum values were considered as free value. Şahman et al. (2009) then continue Furuya et al. (1997) research using Genetic Algorithm (GA) to achieve least cost diet for livestock. Their GA experiments produced a good solution for this problem. However, the study by Şahman et al. (2009) did not consider a ratio constraint. Up till now, only these two papers address the use of EA in solving animal diet formulation. Hence, this paper combine both limitation in these two studies where EA models developed are considered on minimum and maximum value for nutrients and ingredients and take into account a ratio constraints between nutrients. For more details information on animal diet formulation, please refer to Rahman et al. (2010). Subsequently, the methodology and the mathematical model for our animal diet formulation is address in the next section.

METHODOLOGY

EA model developed in this study consists of initialization, roulette-wheel selection, average crossover (Rahman & Ramli, 2013), power mutation and steady state reproduction, as shown in Figure 1. In addition, elitism procedure is also inserted because it can increase GA performance as it prevents the loss of best found solution (López-Pujalte et al., 2002; Sharief et al., 2008). Power heuristics is also embedded in the methodology in order to obtain feasible solution by removing one or more ingredients from the list (Rahman & Ramli, 2014). In order to develop the model, objective function and the constraints involved in shrimp diet problem are illustrated in mathematical formulation in the next subsection. Meanwhile, for experimentation purposes, what-if analysis is also developed.

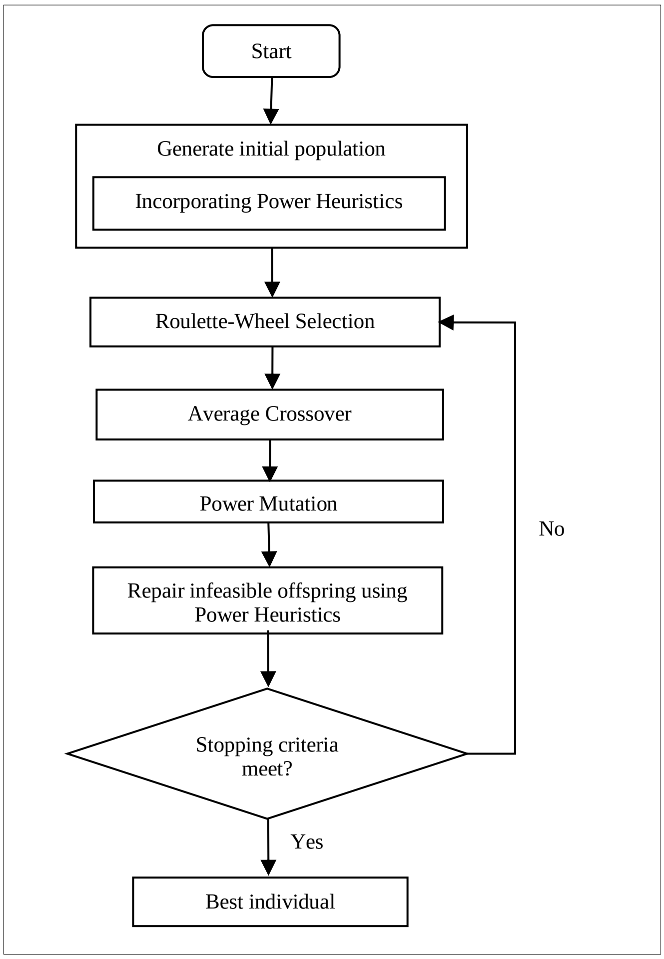

Figure 1. Evolutionary Model

Development of the EA Model

The performance of the proposed EA model is tested using real data for an aquaculture type of animal diet formulation problem. In this problem, the aim is to satisfy all the nutritional needs of farmed shrimps at a minimum cost. The minimization problem takes into account fourteen ingredients and eighteen nutrients. Several constraints on shrimp diet were considered including total ingredient weight, nutrient range, and ingredient range. These were defined through interview session with farmers, manufacturers, experts and also from literature review and websites. Nutritional range is classified into three; single nutrient, combination of nutrients, and ratio between two nutrients. The following are the objective function and constraints involved in this problem.

The objective function of the cumulative feed cost is defined as summation of the weight for all ingredient times the cost in one kg for each ingredient:

$$f(s) = \min \sum_{i=1}^{n} (X_i \times C_i), \quad (1)$$

where C_i is the cost of ingredient i,

X_i equals the weight of the ith ingredient,

s is cumulative cost in a string of chromosome, and

n is the number of ingredient

However, the aim of this study is to first reduce the penalty function value based on all identified constraints. The constraints consist of ingredients' range, ingredient (ration) weight, number of ingredients, single nutrient's range, combination nutrients' range, and ratio of nutrients.

- Ingredients' range:

Ingredients range should be equal to zero or within the minimum and maximum requirement of each ingredient. Minimum and maximum requirement is different on each ingredient.

$$X_i = 0 \text{ or } L_{Xi} \leq X_i \leq U_{Xi} \quad \text{for all } X_i, \quad (2)$$

where L_{X_i} = lower bound of ingredient i,

U_{X_i} = upper bound of ingredient i,

X_i = the weight of the ith ingredient.

- Ingredient weight:

The summation of all selected ingredients should be equal to the weight predefined by user (Y).

$$\sum_{i=1}^{n} X_i = Y, \quad (3)$$

where Y is a weight predefine by user in user interface.

- Number of ingredient:

Total number of selected ingredients should be at most 14.

$$n \leq 14. \tag{4}$$

- Single nutrients' range:

The general model for a single nutrients range is total nutrient *k* in the final ration should be within the permitted range of that nutrient.

$$L_{N_k} \leq \sum_{i=1}^{n} N_{ki} X_i \leq U_{N_k} \tag{5}$$

where L_{N_k} = lower bound of nutrient *k*,

U_{N_k} = upper bound of nutrient *k*,

N = total value of nutrient *k*.

- Combination nutrients' range:

Two nutrient combinations are considered in this study. They are the combination of methionine and cysteine, and the combination of phenylalanine and tyrosine.

$$L_{Nk(i+j)} \leq \sum_{i=1}^{n} N_{k(i+j)} X_i \leq U_{Nk(i+j)}, \tag{6}$$

where $L_{Nk\,(i+j)}$ = lower bound of combination nutrient $i+j$,

$U_{Nk\,(i+j)}$= upper bound of combination nutrient $i+j$.

- Ratio nutrients' range:

The ratio of the nutrients should be within the allowable range.

$$L_{ratio} \leq \frac{\sum_{i=1}^{n} N_{ki}}{\sum_{i=1}^{n} N_{kj}} \leq U_{ratio}, \tag{7}$$

where L_{ratio} = lower bound of ratio between nutrient *i* and *j*,

U_{ratio} = upper bound of ratio between nutrient *i* and *j*.

Fitness calculation for the EA is basically based on penalty value for each constraint. There are two types of constraint; hard and soft constraints. In this study, hard constraints are ingredient (ration) weight, number of ingredient, and protein range constraint. Meanwhile, for soft constraints, different penalty values are given for different constraints based on in depth discussion with experts. A penalty value of 20 is given for violating each ingredient constraint, except for the two most important ingredients. A penalty value of 40 is given for single nutrient, except for amino acids, the penalty value is 30, 20 for combination of nutrients, and 20 for ratio of nutrient.

RESULT AND DISCUSSION

In our experiments, EA parameters were set as follow: size of a population is 60, number of generation is 200, crossover rate is 0.60, and power value for power mutation is 0.25. Table 1 illustrates the simulated results of the EA model. From the Table, we summarize the best so far penalty, average penalty, standard deviation and average run time (in second) taken to produce the best-so-far solution. These values are used as an indicator to evaluate the performance of the proposed EA model.

Table 1. Performance of the EA Model

Best-so-far penalty	Average penalty	Standard Deviation	Average Run Time (minutes)
300	520.6667	126.5166	202

In 30 runs, a best-so-far penalty of 300 is obtained with the average penalty of 520.6667. This shows that a few soft constraints are violated with the penalty value of 520.6667. However, all hard constraints are satisfied. The total cost of 100 kg ingredients mix for the proposed EA model is RM 175.86.

What-if analysis

What-if analysis was conducted as part of a comparative evaluation on the solutions. This analysis considers a 'what if' question that will lead to what can happen when a variable is changed. In this analysis, a scenario of when the total ingredient weight is increased is experimented. Hence, the proposed EA model is evaluated to see the impact on the changes of the parameter obtained including the penalty value and processing time. The scenario is:

What if the total ingredient weight is increased by 500 kg and the price of each ingredient remains?

This scenario describes the situation where the total ingredient weight is increased by 500 kg and the price of each ingredient remains the same. Practitioners especially farmers tend to buy more than 100 kg of feed for shrimp depending on their farm sizes. In this case, 500 kg is reasonable to be considered for evaluation purposes. Table 2 shows the analysis for this scenario, where the best so far penalty value obtained is 330.

Table 2. Performance of the EA Model for 500 kg ingredient mix

Best-so-far penalty	Average penalty	Standard Deviation	Average Run Time (minutes)
330	602.0000	146.3481	196

The average penalty value is raised to 602.0000 and the standard deviation is increased to 146.3481. On average, the run time is about the same which is about 196 minutes. In 10 runs, the best-so-far penalty for the solution is 330 with no infeasible solution obtained. This solution satisfies all the hard constraints, but a few of the soft constraints are violated with average penalty of 602.0000. The total ingredient weight for this solution is 500.0774 kg and the total cost is RM1173.504. Since the total ingredient weight is five times the original value, the total cost is also approximately five times more. Therefore, we can say the performance of this model variant is stable and it can adopt changes in the total ingredient weight.

CONCLUSION

The proposed EA model is able to obtain a feasible solution for shrimp diet formulation. Further investigation on the model was carried out with what-if analysis on a different scenario. The result obtained from the experimentation shows that the performance of the model can adopt changes in total ingredient weight. Therefore, the proposed model is applicable for shrimp and other aquaculture diet formulation.

REFERENCES

Bhanja, U., Mahapatra, S., & Roy, R. (2013). QoT aware evolutionary programming algorithm for transparent optical networks. *International Journal for Light and Electron Optics*, *124*(23), 6391-6399.

Fogel, D. B. (2000a). Introduction to evolutionary computation. In T. Bäck, D. B. Fogel, & Z. Michalewicz (EDs.), *Evolutionary Computation 1: Basic algorithms and operators* (pp. 1-3). Bristol and Philadelphia: Institute of Physics Publishing.

Furuya, T., Satake, K., & Minami, Y. (1997). Evolutionary programming for mix design. *Computers and Electronics in Agriculture, 18*, 129-135.

Hecker, F. T., Hussein, W. B., Paquet-Durand, O., Hussein, M. A.,& Becker, T. (2013). A case study on using evolutionary algorithms to optimize bakery production planning. *Expert Systems with Applications*, *40*(17), 6837-6847.

Lim, H. T. & Ramli, R. (2014). Enhancements of evolutionary algorithm for the complex requirements of a nurse scheduling problem. *AIP Conf. Proc. 1635*, 615; http://dx.doi.org/10.1063/1.4903645.

López-Pujalte, C., Bote, V. P. G. and Anegón, F, d., M. (2002). A test of genetic algorithms in relevance feedback. *Information Processing and Management, 38*, 793–805.

Rahman, R. A., Chooi-Leng, A., & Ramli, R. (2010). Investigating Feed Mix Problem Approaches: An Overview and Potential Solution. Paper presented at *International Conference on Computer and Applied Mathematics (ICCAM 2010)*. October 27-29, 2010. Paris, France.

Rahman, R. A. & Ramli, R. (2013). Average Concept of Crossover Operator in Real Coded Genetic Algorithm. Proceeding of the *International Conference of Management and Artificial Intelligence (ICMAI 2013)*. April 8-9, 2013, Bangkok, Thailand.

Rahman, R. A. & Ramli, R. (2014). Power Heuristics for Handling Constraint in Evolutionary Algorithms. *AIP Conf. Proc. 1635*, pp 647-650.

Şahman, M. A., Çunkaş, M., İnal, Ş., İnal, F., Coşkun, B., & Taşkiran, U. (2009). Cost optimization of feed mixes by genetic algorithms. *Advances in Engineering Software, 40*, 965-974.

Sharief, S., Eldho, T., & Rastogi, A. (2008). Elitist GA Based Evolutionary Algorithm for Groundwater. The *12th International Conference of International Association for Computer Methods and Advances in Geomechanics (IACMAG)*. Goa, India.