Research Article

Evolutionary Algorithm with Roulette-Tournament Selection for Solving Aquaculture Diet Formulation

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The function of operators in an evolutionary algorithm (EA) is very crucial as the operators have a strong effect on the performance of the EA. In this paper, a new selection operator is introduced for a real valued encoding problem, which specifically exists in a shrimp diet formulation problem. This newly developed selection operator is a hybrid between two well-known established selection operators: roulette wheel and binary tournament selection. A comparison of the performance of the proposed operator and the other existing operator was made for evaluation purposes. The result shows that the proposed roulette-tournament selection is better in terms of its ability to provide many good feasible solutions when a population size of 30 is used. Thus, the proposed roulette-tournament is suitable and comparable to established selection for solving a real valued shrimp diet formulation problem. The selection operator can also be generalized to any problems related to EA.

1. Introduction

The evolutionary algorithms (EAs) family consists of genetic algorithm, Evolutionary Programming, Evolution Strategy, Genetic Programming, and hybrids of any EAs technique [1]. The success of an EA highly depends on its operators [2]. As a population-based metaheuristic search technique, one of the important operators used in an EA is selection or reproduction. Basically, the purpose of a selection operator is to choose more effective initial solutions to be used as parents for the following step which are crossover and mutation, and then the remaining worse solutions can be deleted [3]. Sivaraj and Ravichandran [4] reviewed several selection operators in the EA. The selection operators reviewed were, among others, roulette wheel [5, 6], deterministic sampling [7], linear ranking [8], binary tournament [9], and range selections [10]. Different selection mechanisms work well with different problems [4]. Thus, the most suitable selection operator has to be chosen in relation to a specific problem to increase the optimality of the expected solution.

The first selection operator introduced was roulette wheel selection (RWS), which was proposed in 1975 by Holland [11]. It has since been widely used in many applications of the EA, which includes scheduling [9, 12], spanning tree [13], menu planning [5], travelling salesman problem [14], and source allocation problem [15]. It has become one of the most prevalent selection operators, which is based on the concept of proportionality. Conceptually, the fitness value of each individual or potential solution in a population corresponds to the area of the roulette wheel proportions. When the roulette wheel is spun, a solution marked by the roulette wheel pointer is then selected. The higher fitness value with a bigger area is likely to have more chances of being chosen. The segment size and selection probability remain the same throughout the selection phase [16]. The advantage of this technique is that it gives no bias with unlimited spread [16, 17]. However, one of its disadvantages is that it cannot handle negative fitness values due to the proportionality concept [3, 18, 19]. In addition, it could not handle a minimization problem directly, but this limitation can be overcome by

transforming it into an equivalent maximization problem [20]. Furthermore, the other disadvantages of RWS are that when the population converges, it loses the selection pressure [21].

The competition among a group of parents is the basis for a tournament selection (TS) operator. Measurement of fitness of a potential solution is computed for all parents and the parent having the best fitness is then selected. The term "binary tournament" refers to the size of two in a tournament, which is the simplest form of tournament selection [3]. Binary tournament selection (BTS) starts by selecting two individuals at random. Then, fitness values of these individuals are evaluated. The one having more satisfactory fitness is then chosen. One advantage of the tournament selection is its ability to handle either minimization or maximization problems without any structural changes. In addition, the negative value is allowed without any restriction [18]. Despite the various selection operators being studied to improve the solution of a particular problem, there is still some potential for improvement in the solution based on selection procedures [22].

By using RWS algorithm, parents are selected based on a probability value. In this selection, the opportunity to obtain a good solution is quite high. However, parents with a high penalty value might also be selected. On the other hand, by using BTS, two parents are chosen at random; then the better parents will be chosen. In this case, the opportunity of choosing good parents is quite high, but if both selected parents are of low quality, then the low quality parent will be chosen. Therefore, by combining both RWS and BTS, the opportunity to obtain a good quality solution is higher since two phases of selection can be done. Therefore, this paper proposes an alternative selection operator that combines these two established selection operators, namely, RWS and BTS, with the expectation that the final solution is improved. In order to test this expectation, an EA-based genetic algorithm (GA) with the proposed combined selection procedures, known as roulette-tournament selection (RTS), is applied to a diet formulation problem for juvenile Whiteleg shrimp in the aquaculture industry. The Whiteleg shrimp problem is the focus of this study since this species is the most commonly cultured shrimp in Malaysia and in Asia; its production contributes to nearly 80 percent of the total shrimp production in Malaysia [23].

The organization of the paper is as follows. Section 2 elaborates issues related to diet formulation and heuristic techniques. In Section 3, the materials and methodology of the proposed evolutionary model are discussed. In Section 4, the results and the comparative evaluation of proposed and established model are presented. The final section concludes the paper along with some recommendations for future work.

2. Diet Formulation and Heuristics

Diet formulation is a problem to find the best quantities of appropriate ingredients that are able to fulfil decision-making criteria at a low cost. Diet formulation can be categorised into four techniques, namely, algebraic, optimization technique, heuristic technique, and integrated technique [1]. Among these techniques, the heuristic and integrated techniques can be considered relatively new efforts in solution techniques, especially in diet formulation problems. On the other hand, the integrated technique, such as genetic algorithm (GA) based might offer potential solutions for feed mix problems.

EA is classified as metaheuristics which is a higher level of heuristics [24]. Furuya et al. [25] conducted a research 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 their research, Furuya et al. [25] considered a minimum and maximum value of ingredient; however, almost all of the minimum values were considered a free value.

In a study conducted by Şahman et al. [26], GA was used to achieve the least cost diet for a livestock. Their GA experiments produced a good solution for a problem with a few constraints, which obtained a zero penalty function value. The problems with many constraints resulted in some penalty value. However, the study by Şahman et al. [26] did not consider a ratio constraint. More recently, Pathumnakul et al. [27] proposed a search-based heuristics algorithm to solve several small-scale problems involving four to ten ingredients in each problem. They showed that the proposed heuristics technique is good at finding the best solution with a good computation time compared to the exact method.

Since the success of EA highly depends on its operators and selection is one of the important operators used in EA, therefore, the selection of the operators has to be further investigated to find the most appropriate selection technique for our problem. Previous works have motivated us to search for a new selection procedure, which suits the aquaculture formulation problem to increase the optimality of the solution.

One of relatively new selection techniques is queen bee selection. This selection technique chooses the fittest chromosome as parent one and then randomly chooses another chromosome as parent two. The idea of queen bee selection is the injection of a bee's characteristic into the selection operator. The incorporation of a queen bee selection operator has been done since 2003 by Jung. The idea was then modified by Azeem and Saad [28]. Other versions of a queen bee operator were also introduced by Karci [29], Xu et al. [30], and Lu and Zhou [31]. The basic idea in these research works is that the least total penalty in the population is chosen as a queen bee, which is then crossed over with any drone as its couple. The queen bee concept can increase the exploitation in EA but somehow increases the opportunity fall into a premature convergence [30, 32], caused by the selection mechanism that takes only the fittest chromosome and eliminates the less fit chromosome [4].

Even though there are many selection mechanisms that have been proposed in the literature, roulette wheel selection (RWS) and tournament selection are favourable to many researchers because they are simple and have been proven to produce an acceptable solution [3]. RWS is a classic selection operator in the proportional type. Conceptually, the fitness

value of each individual in the population corresponds to the area on the roulette wheel proportion.

Another one favourable selection operator is tournament selection that is based on competition among a group of parents [3, 33]. However, the disadvantages of tournament selection are that it does not guarantee reproduction of best solution [34].

Therefore, since both RWS and tournament selection have their drawback, it is possible to further explore this hybrid technique. Previously, Wiles et al. [35] combined both RWS and binary tournament selection mechanism. In their work, two candidates were chosen using a roulette wheel selection. Then, of these two individuals, the fittest individual became the parent, as in a tournament. Then the same process was done to select parent two. In this paper, we replicated Wiles et al. [35] procedure slightly, where we initially selected several individuals using the RWS. Then in the second phase, two individuals were again randomly selected from the list of the selected individuals. The fittest individual became parent one. Parent two was selected using the same process where two individuals were again randomly selected from the list of the selected individuals and the fittest parent was chosen. In other words, a two-phase selection process was employed here. By combining these two selection techniques, we hope the performance of the selection process could be improved.

In this study, instead of the new proposed roulette-tournament selection, another two types of selection were carried out, that is, RWS and queen bee. The RWS was adopted as a controlled selection operator as previous research in the human diet has shown that a good result can be obtained by using the RWS operator in hybrid GA [5]. The queen bee selection was adopted to experiment and find the most appropriate selection with shrimp formulation.

3. Materials and Method

3.1. Data Collection. The main concern of this study is to introduce a new selection operator named roulette-tournament selection as an operator in EA. To develop the EA model, a diet formulation for juvenile Whiteleg shrimp was considered. The diet formulation problem must satisfy the required constraints at a minimum cost. The problem of shrimp production consists of several constraints, which include 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. The nutrient range is classified into three types: single nutrient, a combination of nutrients, and a ratio between two nutrients. In this problem, a list of selected ingredients in specific quantities that satisfy the required constraints at the end of the problem shrimp process is identified. The ingredient mix represents the diet formulation for the shrimp.

Primary data were collected through interviews with experts. Interviews with commercial manufacturers of shrimp feed and farmers were also conducted to understand the current scenario of shrimp feed in Malaysia. Meanwhile, secondary data were taken from two reports published by the National Research Council (NRC). The first report was titled
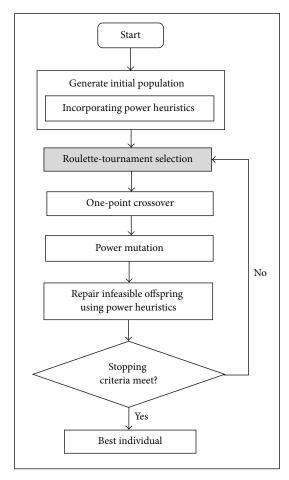

FIGURE 1: Evolutionary model.

United States-Canadian Table of Feed Composition [36] and the second report *Nutrient Requirement of Fish and Shrimp* [37]. Other secondary data were taken from the literature and website proposed by the experts.

3.2. Model Development. The evolutionary model consists of initialization, roulette-tournament selection, one-point crossover, power mutation, and steady-state reproduction (see Figure 1). In addition, an elitism operator is also inserted because it can increase the EA performance as it prevents the loss of the best-found solution [38, 39]. A repair operator named power heuristics [1] is also developed for this problem. However, this paper specifically focuses on the roulette-tournament selection operator, as highlighted in Figure 1.

The roulette-tournament selection operator introduced in this study is a combination of RWS operator and binary tournament selection. The operator starts with the same steps as RWS, where several solutions are chosen at this phase. Then, in the second phase of selection, the binary tournament operator takes place by choosing two solutions as parents. As in the binary tournament, two solutions are randomly picked from all selected solutions, and the fitter parents will be chosen as parent one. The same step is repeated to find parent two. Algorithms 1 and 2 describe the algorithm for RWS and

```
While population size < pop_size do
        Generate pop_size random number r
        Calculate cumulative fitness, total fitness (Pᵢ) and sum of proportional fitness (Sum)
        Spin the wheel pop_size times
        If Sum < r then
            Select the first chromosome, otherwise, select jth chromosome
        End If
End While
```

ALGORITHM 1: Algorithm for roulette wheel selection.

```
For chromosome i = 1 to pop_size
        Choose two chromosomes randomly from all population
        If fitness chromosome 1 > fitness chromosome 2
            Select chromosome 1, otherwise, select chromosome 2
        End If
End For
```

ALGORITHM 2: Algorithm for binary tournament selection.

BTS, respectively. The step-by-step procedure of obtaining the roulette-tournament selection operator is then shown in Algorithm 3. The hybridization of this operator will merge the advantages from both RWS and binary tournament.

To develop the hybrid model, the objective function and the constraints involved in the shrimp diet problem are illustrated in the mathematical formulation in the next subsection.

3.3. Development of the EA Model of Shrimp Diet Formulation. The performance of the proposed EA model with the new selection operators was tested using real data of the aquaculture diet formulation problem. Further explanation about this problem can be found in Rahman et al. [40] and Saxena and Chandra [41]. 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 14 ingredients and 18 nutrients. The following are the objective function and constraints involved in this problem [1].

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

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

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 firstly reduce the penalty function value based on all the identified constraints. The constraints consist of the ingredient range, the ingredient (ration) weight, the number of ingredients, the single nutrient

range, the combination of nutrients range, and the ratio of nutrients.

(i) Ingredient Range. The ingredient range should be equal to zero or within the minimum and maximum requirement of each ingredient. The minimum and maximum requirement is different for each ingredient:

$$X_i = 0$$
$$\text{or } L_{X_i} \le X_i \le U_{X_i} \qquad (2)$$
$$\forall X_i,$$

where L_{X_i} is the lower bound of ingredient i, U_{X_i} is the upper bound of ingredient i, X_i is the the weight of the ith ingredient.

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

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

where Y is a weight predefined by the user in the user interface.

(iii) Number of Ingredients. Total number of selected ingredients should be at most 14:

$$n \le 14. \qquad (4)$$

(iv) Single Nutrient Range. The general model for a single nutrient range is the total nutrient k in the final ration which should be within the permitted range of that nutrient:

$$L_{N_k} \le \sum_{i=1}^{n} N_{k_i} X_i \le U_{N_k}, \qquad (5)$$

```
While population size < pop_size do
        Generate pop_size random number r
        Calculate cumulative fitness, total fitness (P_i) and sum of proportional fitness (Sum)
        Spin the wheel pop_size times
        If Sum < r then
            Select the first chromosome, otherwise, select jth chromosome
        End If
End While
For chromosome i = 1 to pop_size
        Choose two chromosomes randomly from list of selected chromosome
        If fitness chromosome 1 > fitness chromosome 2
            Select chromosome 1, otherwise, select chromosome 2
        End If
End For
```

ALGORITHM 3: Algorithm for roulette-tournament selection.

where L_{N_k} is the lower bound of nutrient k, U_{N_k} is the upper bound of nutrient k, and N is the total value of nutrient k.

(v) Combination of Nutrients Range. Two nutrient combinations are considered in this study, that is, the combination of methionine and cysteine and the combination of phenylalanine and tyrosine:

$$L_{N_{k(ij)}} \leq \sum_{i=1}^{n} N_{k(ij)} X_i \leq U_{N_{k(ij)}}, \qquad (6)$$

where $L_{N_{k(ij)}}$ is the lower bound of combination nutrient i and j and $U_{N_{k(ij)}}$ is the upper bound of combination nutrient i and j.

(vi) Ratio of Nutrients Range. The ratio of the nutrients should be within the allowable range:

$$L_{\text{ratio}} \leq \frac{\sum_{i=1}^{n} N_{k_i}}{\sum_{i=l}^{n} N_{k_j}} \leq U_{\text{ratio}}, \qquad (7)$$

where L_{ratio} is the lower bound of ratio between nutrient i and j and U_{ratio} is the upper bound of ratio between nutrient i and j.

The fitness calculation for the EA is primarily based on a penalty value for each constraint. There are two types of constraint: hard and soft constraints. In this study, hard constraints are the ingredient (ration) weight, the number of ingredients, and the protein range constraint. For soft constraints, different penalty values are given for different constraints based on in-depth discussion with the experts. These values are chosen based on the priority concept where a higher value represents a higher priority level. For equally important constraints, the same value is given. Thus, a penalty value of 20 is given when each ingredient constraint is violated except for the two most important ingredients, where the penalty value of 30 is given. This is because all of the ingredients having equally the same priority except the two most important ingredients that have a higher protein level. A penalty value of 40 is given for single nutrient; except for

amino acids, the penalty value is 30. A penalty value of 20 is given for a combination of nutrients and 20 for the ratio of nutrient. The reason is that single nutrient is the most important constraint to be fulfilled, followed by nutrients combination and nutrient ratio.

3.4. Model Evaluation. Instead of roulette-tournament selection, another two selection techniques were also run for evaluation purposes. They are RWS and queen bee selection. The performance of these three models was then evaluated based on the best-so-far solution and also the number of feasible solutions obtained. Standard deviation and average penalty value were also evaluated.

4. Results and Discussions

At first, the RWS model was tested and reported. The process flow is as shown in Figure 2 with the controlled operators of standard one-point crossover and power mutation. Then, the experimentation was altered when the RWS operator was replaced by the queen bee selection (QBS) operator. The QBS concept is mainly about finding the least penalty value in each generation to obtain the best-so-far solution faster based on the penalty value obtained. The experimentation was again altered when the RWS operator was replaced by the roulette-tournament (RTS) operator. The concept of a roulette-tournament is about combining the advantages of both the RWS and the tournament selection to obtain the efficient selection performance towards achieving the best solution. Figure 2 exhibits the generic process flow.

Experimentations of EA with three selection operators, that is, roulette wheel selection (RWS), queen bee selection (QBS), and roulette-tournament selection (RTS), were conducted. These selection operators were tested while other EA operators remained the same. These controlled operators were initialization with the incorporation of power heuristics, one-point crossover, and power mutation. The parameter values used in this experimentation are shown in Table 1.

The parameters value for each property was obtained through various experimentations based on solution quality.
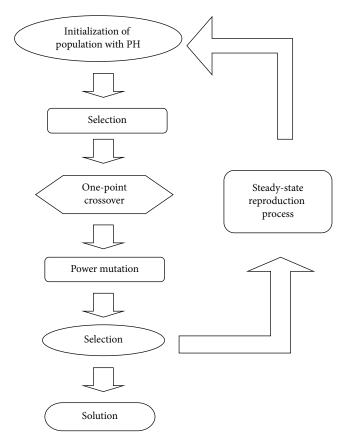
FIGURE 2: The process flow of EA model.

TABLE 1: Parameters value.

Properties	Value
Crossover probability	0.60
Power mutation index	0.25
Generation number	200
Number of runs	30

For example, various values were tested in 30 runs for crossover probability and the value with best-so-far penalty was chosen as parameter value. By using a population size of 30, the simulated results of all EA models are illustrated in Table 2. From the table, we summarize the best-so-far solution, average fitness, and standard deviation from all models. These values are used as an indicator to evaluate the performance of the EA models.

From Table 2, the RTS model offered the worst solution with 460 fitness value, while the RWS produced the best solution. However, from 30 runs, the RTS produced only 5 infeasible solutions compared to the RWS with 6 infeasible solutions and QBS with 16 infeasible solutions. The standard deviation of the RWS was the lowest, followed by the RTS model and the QBS model. A standard deviation shows the deviation or dispersion of the data from the mean. A lower standard deviation indicates that the model produces a stable solution, which means it is always approaching the mean.
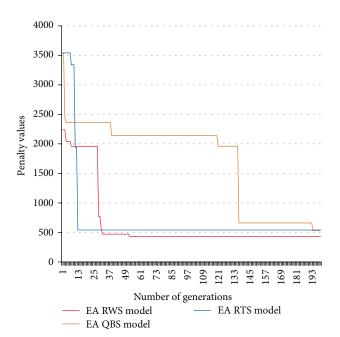

FIGURE 3: Sample solutions of all three models with different selection operators.

The same experimentation with the same parameters value was run, but this time the population size was increased to 60 while the other parameters were controlled. The results of the experiments are depicted in Table 3.

Table 3 shows that the result of the RTS model was improved with 340 penalty values, while other models remained the same. The RWS model produced no infeasible solution, while the performance of newly introduced RTS model was comparable with only two infeasible values obtained. Meanwhile, the queen bee performed the poorest with nine infeasible solutions obtained. The standard deviation of the RTS was the lowest, followed by the RWS and the QBS models. However, among these three models, the RWS model is still the best in terms of best-so-far, average penalty, and a number of infeasible solutions.

The experiments showed that the best-so-far penalty and the infeasible solution could be reduced by increasing the population size especially for the RTS. The performance of the newly introduced RTS operator is comparable to the RWS in terms of the least number of infeasible solutions obtained. Figure 3 shows a sample solution of these three models.

Figure 3 shows sample solutions obtained from all the three EA models of the RWS, QBS, and RTS. The red colour graph represents the RWS model. This model, at first, showed a gradual decrease in penalty value, and then by generation 30 a sharp decrease in penalty occurred. The penalty value was then slowly decreasing until around generation 53, where the least penalty value was obtained with the best-so-far penalty being below 500. In the process of running until generation 200, some good penalty values were also obtained. However, the penalty values that were greater than the least penalty value obtained in generation 53 do not appear in the graph as the inclusion of the elitism procedure kept the least penalty value in each generation. The termination criterion in this

TABLE 2: The results of EA models with 30 population sizes.

Model	Best-so-far penalty	Average penalty	Standard deviation	Number of infeasible solutions
Roulette-tournament (RTS)	460	699.60	129.47	5/30
Roulette wheel (RWS)	300	554.58	127.15	6/30
Queen bee (QBS)	410	687.14	145.52	16/30

TABLE 3: The results of EA models with 60 population sizes.

Model	Best-so-far penalty	Average penalty	Standard deviation	Number of infeasible solutions
Roulette-tournament (RTS)	340	700.36	131.70	2/30
Roulette wheel (RWS)	300	547.00	134.63	0/30
Queen bee (QBS)	410	660.48	141.37	9/30

TABLE 4: Sample solutions for three different EA models.

Ingredient	Minimum (kg)	Maximum (kg)	RWS model	QBS model	RTS model
X_1	5	10	0	9.3987	10.3201
X_2	15	50	0	43.2535	28.7322
X_3	3	5	5.1456	4.8377	0
X_4	5	50	30.0305	0	23.6823
X_5	30	40	39.3687	0	19.8341
X_6	5	15	0	11.0613	0
X_7	5	15	0	0	11.7725
X_8	2	5	0	0	0.0615
X_9	15	60	0	0	0
X_{10}	5	15	0	12.3407	0
X_{11}	5	15	11.5438	10.6669	0
X_{12}	3	5	5.3695	4.3561	0.4605
X_{13}	3	5	3.4875	0	4.3874
X_{14}	3	5	5.4861	4.3561	0.3427
Total weight (kg)			100.4317	100.4952	99.5933
Total cost (RM)			238.13	134.29	220.08

research was based on a user-identified generation number; therefore, the process was kept on running until generation 200 was reached.

The brown colour line shows a sample solution obtained from the QBS model, where it shows a sharp decrease in the penalty value in some points around generation 2, 40, 120, and 132. The best-so-far penalty of about 500 was obtained around generation 195. On the other hand, the blue colour graph of the RTS model shows only decreases in the penalty values at the early generation. Around generation 14, the least penalty values were obtained where the best-so-far penalty was about 500. In the process of running until generation 200, some good penalty values were also obtained. However, the penalty values that were greater than the least penalty as in generation 14 do not appear in the graph as the inclusion of the elitism procedure kept the best penalty value in each generation. Based on these three sample solutions, the RWS appears to give the least penalty value, while the QBS gives the highest penalty. Our newly proposed RTS gives quite a good solution.

Further experimentation on real case of aquaculture diet formulation was conducted using those three selection operators. They are the roulette wheel, queen bee, and roulette-tournament selections. The experimentations were run using the same parameters including the number of ingredients, type of ingredients, price of ingredients, ingredient weight, and EA parameters such as population size and generation number.

Table 4 shows a sample solution for each of the EA model where seven ingredients were selected for the RWS model, eight ingredients for the QBS model, and nine ingredients for the RTS model. The zero value means that the ingredient is not included in the combination of diet. Table 5 shows the composition of nutrient values in each corresponding solution. In every model, some soft constraints which are ingredients range and nutrients range were violated but all hard constraints were satisfied. This sample solution shows that the total cost for the ingredient mix of QBS model is the lowest with RM 134.29, whereas RWS and RTS obtained RM 238.13 and RM 220.08, respectively. However, since the total

TABLE 5: Nutrient values for three different EA models.

Nutrients	Minimum	Maximum	RWS model	QBS model	RTS model
Crude protein, %	38.00	45.00	41.5328	43.2310	41.5534
Lipid, %	0.08	0.18	5.7381	4.4771	5.8115
Fibre, %	0	4.00	3.5017	6.0078	4.7898
Ash, %	0	15.0	10.2398	9.4372	10.4196
Calcium, %	0	2.30	1.9881	1.8679	1.3983
Phosphorus, %	0.30	0.70	1.1629	1.1469	1.0050
Arginine, %	2.2	2.32	2.1570	2.6589	2.7407
Histidine, %	0.6	0.84	0.9648	1.0541	1.0184
Isoleucine, %	1.0	1.33	5.7968	5.0654	2.2921
Leucine, %	1.7	2.16	7.3826	6.8225	3.6547
Lysine, %	1.55	1.65	2.4929	2.5920	2.8756
Methionine, %	0.7	0.96	0.8836	0.5765	0.9273
Phenylalanine, %	1.4	1.6	1.6745	2.0093	1.9787
Threonine, %	1.3	1.44	0.3844	0.4175	0.4533
Tryptophan, %	0.2	0.32	1.4556	1.5453	1.7018
Valine	1.4	1.6	2.0589	2.1667	2.2159
Methionine + cystine, %	1.0	1.44	1.3544	1.1757	1.4684
Phenylalanine + tyrosine, %	2.7	7.1	2.6158	3.0639	3.1231
Calcium : phosphorus, %	0.7692	0.7692	1.7096	1.6287	1.3913

cost is greater, but with fewer constraints violated, the RWS is still more relevant to be chosen as the best solution.

As a whole, the RWS model with roulette wheel selection operator is still the best selection operator compared to the other two operators, especially in terms of the best-so-far penalty. The performance of the newly introduced RTS model with roulette-tournament selection operator is comparable with RWS in terms of the least number of infeasible solutions obtained and total cost of ingredients.

5. Conclusion

The performance of EA-based GA model with different selection operators was described. In this paper, we extend the EA selection operator by introducing the RTS. The combination of both RWS and BTS in two phases of selection could produce a comparable solution with other established selection operators. The result shows that the RWS is still the best suitable selection operator to the diet formulation problem in terms of best-so-far solution and number of feasible solutions obtained. However, the result also shows that our proposed RTS operator is better in terms of its ability to provide many good feasible solutions when a population size of 30 is used. Thus, it is suitable and comparable to be used in problems with real value encoding. Furthermore, the experimentation shows that a better result could be obtained by increasing the population size since EA is a population-based technique. For future research, this study could be improved by comparing the results of the proposed RTS with a binary tournament selection.

Competing Interests

The authors declare that they have no competing interests.

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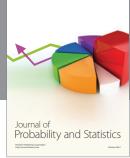
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[41] P. Saxena and M. Chandra, "Animal diet formulation models: a review (1950–2010)," in *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources*, D. Hemming, Ed., p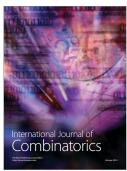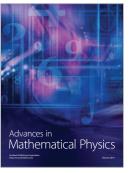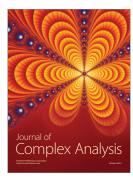p. 1–9, CABI, London, UK, 2011.