Multi-objective Optimization for Meal Planning using Multi-Island Genetic Algorithm

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Abstract. Food waste and food loss is becoming a big social problem in the world. The total amount of the household organic waste reached 2.7 million tons in 2019. The breakdown is that leftover is 27%, food thrown away before being eaten is 18%, and food scrap wasted during cooking is 55%. The main reason of throwing away food before being eaten is best-before date expiration. In this study, we aim to develop a recommender system for meal planning in a family. In practice, such recommender systems are required to not only extract user's preferences but also suggest meal plans on the basis of caloric intake, remaining amount of food and expiration dates. This boils down to a multi-objective optimization problem. This paper therefore presents a method of multi-objective optimization for meal planning and recommendation. We use a multi-island GA to deal with the optimization problem and propose a framework of content-based recommendation where the user can interactively rate the menu candidates. Moreover, we design the objective functions to minimize the amount of expired food and adjust caloric intake. Furthermore, we conduct a preliminary experiment to discuss the applicability of the proposed method.

Keywords: Recommendation System, Multi-objective Optimization, Multi-Island Genetic Algorithm, Meal Planning

1. INTRODUCTION

Food waste and food loss is becoming a big social problem in the world. The issue is dealt with in SDG 12.3, in order to realize a sustainable society. In Japan, 6.12 million tons of edible food is thrown away, equivalent to about 48 kilograms of waste per person every year. Moreover, the Japan's Ministry of Agriculture, Forestry, and Fisheries (MAFF) reported that the total amount of the household organic waste reached 2.7 million tons in 2019 [1]. The breakdown is that leftover is 27%, food thrown away before being eaten is 18%, and food scrap wasted during cooking is 55%. The main reason of throwing away food before being eaten is best-before date expiration.

As the super-aging society approaches, information and physical support for older adults are significant issue for maintaining their quality of life (QOL). Society 5.0 is a future vision of a human-centered society proposed by Government of Japan. The advanced society can comprehensively address the economic advancement and the resolution of social problems by a system that highly integrates cyberspace and physical space [2]. The cyber-physical systems can extend human capabilities, providing seamless connections between virtual space and real space. For example, smart devices and wireless sensor networks can provide the global and local measurement for gathering the environmental and individual information. Moreover, a huge amount of data is transferred and analyzed by using artificial intelligence techniques in order to derive information suitable for diverse users and situations. Furthermore, human friendly robots can support an individual informationally and physically through the physical interaction. The synthesis of technologies can be a prospective way to maintain and improve QOL in the aging society.

In this study, we aim to develop a recommender system for meal planning in a family. With the growth of cloud computing and artificial intelligence technologies in recent years, we can easily access to various information on the internet by using smart devices. However, due to excessive information, it is difficult to appropriately find and select valuable information. A recommender system can be an effective tool to address the problems in diverse fields. In the field of meal planning, many researchers have investigated effects of recommender systems in terms of appreciate dietary habit and personal health management. According to the prediction reported by World Health Organization, the global number of overweight adults, 18 years and older, has reached 1.9 billion in 2016 [3]. Most people are aware of the importance of dietary management in order to enhance overall well-being. However, many people don't attempt to improve their own habits because of troublesome tasks for meal planning and preparation. Furthermore, individual efforts to use up all veggies and food in the fridge should be required to reduce the food waste and loss. We therefore consider a multi-objective optimization in recommender system to systematically manage food in the fridge and plan the usage in order to reduce the waste.

In the related works, a diversity of recommendation techniques has been utilized for meal planning [4]. However, several challenging problems are still discussed in those studies. In practice, such recommender systems are required to not only extract user's preferences but also suggest meal plans on the basis of caloric intake, remaining amount of food and expiration dates. This boils down to a multi-objective optimization problem. Moreover, because quantities of ingredients necessary for recipe are different from each other, this extremely increase the complexity of meal planning. Although recommender systems use huge data set to deal with the above problem, the number of rating data given by the users is not so large because the users are required to rate the candidates in a narrow range of choices. Especially, in household meal planning, various users have different contents of a fridge and meal preferences. Therefore, it is very difficult to extract knowledge of commonly used recipe between meal plans and evaluate the similarity between users. This leads to sparsity and the cold-start problem in recommender systems.

Evolutionary computation techniques such as genetic algorithm (GA) and genetic programming (GP) are used as effective solutions to the common problems of recommender systems that can heuristically obtain suboptimal priorities for clustering and similarity evaluation for hybrid approaches based on the combination of content-based filtering and collaborative filtering [5]. In recommender systems, over-specialization is also an important problem to be solved. This can lead a situation that the recommender items are very similar to each other. However, the diversity of recommended items relevant to the user's interests should be preserved. GA is a heuristic search algorithm that can extend the search space and search new solutions by using various genetic operators. However, traditional GA has poor ability to maintain the diversity of population and easily bring the premature convergence. In multi-island GA, distributed multiple-populations are used for the diversification. Multi-island GA not only is strengthened in maintaining the diversity of the population capacity, but also has a better performance in finding the global optimal solution.

This paper presents a method of multi-objective optimization for meal planning and recommendation. Moreover, we used a multi-island GA to deal with the optimization problem and proposed a framework of content-based recommendation where the user can interactively rate the menu candidates. We designed the objective functions to minimize the amount of expired food and adjust caloric intake. Furthermore, we conducted a preliminary experiment to discuss the applicability of the proposed method.

This paper is organized as follows: section 2 explains the developed system, section 3 describes the details of the proposed approach, section 4 presents the discussion from the experimental results, and we finally summarize this paper and mention the future direction of this study in Section 5.

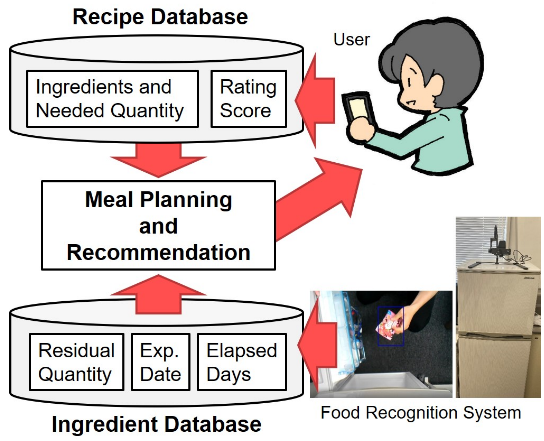


Fig. 1 Overview of the proposed system.

Table. 1 Recipe database.

ID	Recipe Name	Ingredients			Calorie intake
		Pork	Beef	· · ·	
1	Ginger Pork	200 g	0 g	· · ·	203 kcal
2	Stir-Fried Meat and Vegetable	100 g	0 g	· · ·	198 kcal
⋮	⋮	⋮	⋮	⋮	⋮
M	· · ·	· · ·	· · ·	· · ·	· · ·

Table. 2 Ingredient database.

ID	1	2	· · ·	*N*
Ingredient	Pork	Beef	· · ·	· · ·
Residual Quantity	400 g	200 g	· · ·	· · ·
Remaining Days to Exp. Date	3 days	3 days	· · ·	· · ·
Elapsed Days	2 days	0 days	· · ·	· · ·

2. MEAL PLAN RECOMMENDER SYSTEM

Figure 1 shows the proposed system. We use two databases in the recommender system: recipe database and ingredient database. The recipe database includes the data of ingredients and the needed quantities in each database. The recommender system can refer to the data to make a plan of meals corresponding to contents of a fridge. Table 1 shows a table of the recipe database. Furthermore, we developed a food recognition system for the management of food residual. Food and vegetables in the fridge are recognized by image processing devices and mattress pressure sensors, and the stock data and timestamps are transferred to the ingredient database. Table 2 shows an example of ingredient database.

Fig. 2 Example of traditional Japanese meal.

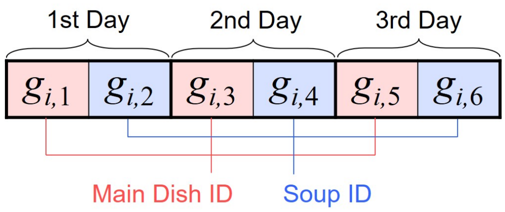


Fig. 3 Genotype in GA for meal planning.

3. MULTI-ISLAND GENETIC ALGORITHM FOR MEAL PLANNING

3.1. Setting

We focused on the development of recommender system for planning three days' home-cooked Japanese dinners. Figure 2 shows a traditional home-style Japanese meal. Traditional Japanese meals are usually made of a few different dishes. In this study, we assumed the traditional meals mostly consist of rice, main dish and soup, and that rice is the staple for most Japanese. The purpose of the recommender system is therefore to find an optimal combination of main dish and soup in each meal.

We applied genetic algorithm to the solution of the combinatorial optimization problem. Evolutionary computation (EC) has been applied to various types of optimization problem. EC has three different historical streams: genetic algorithm (GA), evolutionary programming (EP), and evolution strategy (ES). GA has mainly been used for combinatorial problems [6]. To deal with the meal planning problem, we defined the genotype composed of recipe IDs for main dishes and soups as shown in Fig. 3. In the figure, $g_{i,j}$ is j-th recipe ID of i-th individual in GA population. The odd-numbered genes are represented as main dish IDs, and the even-numbered genes are represented as soup IDs.

3.2. Multi-objective Optimization for Meal Planning

The main genetic operator is a crossover, and the fitness proportional selection such as a roulette wheel selection is used as a selection strategy. In the crossover and the mutation, the worst candidate is removed in each generation. The searching processes are repeated until the terminal condition is satisfied.

In this study, we proposed the objective functions to minimize the amount of expired food and adjust caloric intake. The recommended daily calorie intake is 2000 calories a day for women and 2500 for men. We therefore set 2200 calories as a criteria value to evaluate personal daily calorie intake. The objective of calorie intake is to minimize the difference between caloric amount of a recommended meal plan and the criterion. The objective function is given by

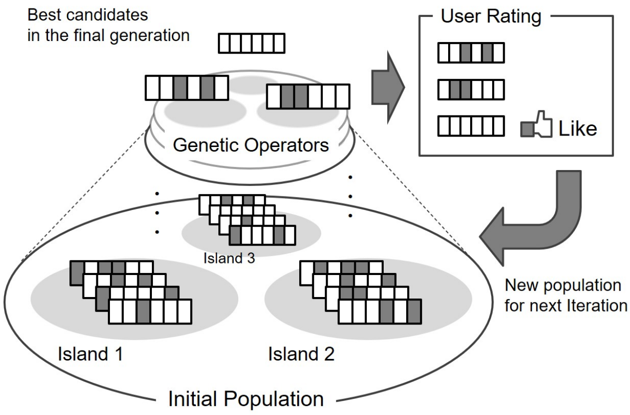


Fig. 4 Multi-island genetic algorithm for meal planning.

$$x_i = \left| 1 - \frac{1}{C} \sum_{j=1}^{6} c_{i,j} \right| \quad (1)$$

where C is the amount of personal calorie intake for three meals ($C = 2200$), and $c_{i,j}$ is calorie intake on j-th recipe. Moreover, to reduce the amount of expired food, we define the objective function as follows:

$$y_i = 1 - \frac{1}{W} \sum_{j=1}^{6} \sum_{k \in R_{i,j}} w_{j,k} \quad (2),$$

$$z_i = \sum_{j=1}^{6} \sum_{k \in R_{i,j}} e_{i,j,k} \quad (3),$$

$$e_{i,j,k} = \begin{cases} 0 & \text{if } d_{i,j,k} - D_k < 0 \\ w_{j,k} \cdot \left(d_{i,j,k} - D_k \right)^2 & \text{otherwise} \end{cases} \quad (4)$$

where W is the total quantity of ingredients on i-th candidate, $R_{i,j}$ is a set of ingredient IDs for j-th recipe on i-th meal plan, $w_{j,k}$ is the quantity of k-th ingredient for j-th recipe, $d_{i,j,k}$ is the elapsed date of k-th ingredient for j-th recipe on i-th meal plan, and D_k is the remaining days to the expiration date. To achieve the multiple objectives, the fitness value of candidate solution is calculated by

$$f_i = x_i + y_i + z_i \quad (5).$$

This results in a minimization problem.

3.3. Interactive GA with Island Model

Figure 4 shows the processing flow of recommender system with multi-island GA for meal planning. In the island model, it has been argued that having multiple subpopulations helps to preserve genetic diversity because each island can potentially follow a different meal planning through the search space.

Table. 3 Parameters in multi-island GA.

Parameter	Description	Value
N	size of population in each island	20
I	number of islands	10
T	maximum number of generations	20
U	maximum number of user rating	20
η	update ratio	0.5
θ	criteria value	0.5
α	coefficient value	0.05
β	offset value	0.01

Table. 4 Properties of dataset.

Parameter	Description	Value
K	size of ingredient set	53
M	size of recipe set (main dish)	329
S	size of recipe set (soup)	51

In the proposed approach, we use the best candidates in each island as a recommended items to the user. The items are suboptimal solutions of meal planning generated by the genetic operator. However, the fitness function does not include any element to measure personal preference regarding the recommended plans. We therefore developed the recommender system where the user can interactively rate the menu candidates from which the duplicated candidates are removed. The user is required to rate each candidate by using binary input ("Like" or "No") as the user's preference. After the rating, new populations in each island are created on the basis on the rating results. Then the selection probability of n-th recipe on the selected plan is updated by

$$p_n \to p_n + (1 - p_n)\eta \tag{6}$$

Moreover, the probabilities of others are updated based on the degree of ingredient similarity with those of the selected recipe. The similarity is measured by cosine distance, and the probability is updated as follows:

$$s_{n,m} = \frac{\mathbf{w}_n \cdot \mathbf{w}_m}{|\mathbf{w}_n||\mathbf{w}_m|} = \frac{\sum_{k=1}^{K} w_{n,k} \cdot w_{m,k}}{\sqrt{\sum_{k=1}^{K} w_{n,k}^2} \cdot \sqrt{\sum_{k=1}^{K} w_{m,k}^2}} \tag{7}$$

$$p_m \to (1-\eta) \cdot p_m + \eta \cdot s_{n,m} \quad \text{if } s_{n,m} > \theta \tag{8}$$

where K is the maximum number of ingredient ID, η is the update ratio, and θ is a criteria value. Furthermore, the general process of island model is based on migration selection and replacement. In the migration, the selected individuals are probabilistically transferred to subpopulations, replacing the worst individuals.

In order to renew the population, there are two major kinds of generation models. The first one is discrete generation model, and the second one is continuous generation model. We apply a steady-state genetic algorithm (SSGA) as a continuous model of generation because we have to consider not only the diversity of recommendation and but also the personalization through the iteration. In the SSGA, only the worst candidate is replaced with a candidate solution generated by crossover and mutation. The former is elitist crossover that a new individual is generated by combining genetic information between an individual selected randomly and the worst one, and the latter is adaptive mutation. The occurrence probability of the mutation is given by

$$q_i = \alpha \cdot \frac{f_i - f_{best\,i}}{f_{worst} - f_{best}} + \beta \tag{9}$$

where q_i is the probability for i-th individual, α is a coefficient value, and β is an offset value. The adaptive mutation can perform local search and global search because the probability is multiplied by a coefficient calculated based on the fitness value of selected individual. Table 3 shows the hyperparameters of the proposed method, and Table 4 presents the properties of dataset. We referred to recipe websites run by Kikkoman Corp., Ajinomoto Co., Inc, and COOKPAD Inc. in order to create the recipe database [7-9].

Table. 5 Content of a fridge in the simulated environment.

Ingredient	Residual Quantity	Remaining Days to Exp.	Elapsed Days
chicken thigh	400 g	3 days	2 days
sliced pork	400 g	3 days	1 day
sausage	100 g	20 days	19 days
cabbage	400 g	14 days	1 day
onion	400 g	30 days	2 days
carrot	200 g	7 days	2 days
potherb mustard	100 g	5 days	0 day
green onion	100 g	7 days	6 days
Shimeji	150 g	7 days	1 day
Enokitake	200 g	5 days	1 day
tofu	200 g	7 days	2 days
potato	400 g	30 days	10 days
bell pepper	100 g	7 days	2 days
maitake	100 g	6 days	2 days
Elingi	100 g	7 days	0 day
cherry tomato	100 g	7 days	2 days
paprika	100 g	10 days	2 days
Chinese chive	100 g	10 days	2 days
Japanese radish	400 g	10 days	6 days
egg	200 g	14 days	2 days
lettuce	250 g	5 days	1 day
thin fried tofu	100 g	7 days	1 day
Komatsuna	200 g	7 days	2 days
ginger	50 g	14 days	6 days

4. EXPERIMENTAL RESULTS

4.1. Condition

This section presents an experimental example to discuss the applicability of the proposed approach. In the experiment, we predefined a simulated condition as shown in Table 5. The list of foods and vegetables in the table is represented as content of a household refrigerator. Each ingredient has different expiration date. As the

Table. 6 Fitness values of the best candidates in each island during recommendation and user ratings.

Rating Steps	Island 1 Mean, SD	Island 2 Mean, SD	Island 3 Mean, SD	Island 4 Mean, SD	Island 5 Mean, SD	Island 6 Mean, SD	Island 7 Mean, SD	Island 8 Mean, SD	Island 9 Mean, SD	Island 10 Mean, SD
1	2.26 ± 0.80	1.57 ± 0.48	1.88 ± 0.73	2.42 ± 0.48	1.93 ± 0.69	2.26 ± 0.49	1.69 ± 0.63	2.29 ± 0.54	1.71 ± 0.58	2.65 ± 0.58
2	1.98 ± 0.66	1.46 ± 0.39	1.64 ± 0.41	2.13 ± 0.16	1.26 ± 0.28	1.87 ± 0.40	1.34 ± 0.37	1.94 ± 0.38	1.75 ± 0.58	1.70 ± 0.48
3	1.33 ± 0.29	1.47 ± 0.61	1.36 ± 0.60	2.26 ± 0.23	1.14 ± 0.07	1.34 ± 0.39	1.34 ± 0.30	1.70 ± 0.39	1.71 ± 0.38	1.26 ± 0.19
4	1.07 ± 0.12	1.16 ± 0.12	1.00 ± 0.14	1.65 ± 0.48	1.07 ± 0.12	1.08 ± 0.18	1.11 ± 0.09	1.38 ± 0.26	1.06 ± 0.18	1.09 ± 0.06
5	0.99 ± 0.14	1.09 ± 0.10	1.10 ± 0.78	1.70 ± 0.47	0.94 ± 0.06	0.95 ± 0.11	1.01 ± 0.28	1.07 ± 0.22	0.85 ± 0.12	1.01 ± 0.02
6	0.78 ± 0.02	1.19 ± 0.25	0.76 ± 0.04	1.20 ± 0.44	0.83 ± 0.08	0.83 ± 0.06	0.79 ± 0.06	1.07 ± 0.78	0.93 ± 0.60	1.03 ± 0.19
7	0.75 ± 0.02	1.15 ± 0.17	0.71 ± 0.01	0.86 ± 0.34	0.71 ± 0.02	0.72 ± 0.01	0.72 ± 0.02	0.84 ± 0.11	0.84 ± 0.44	0.87 ± 0.00
8	1.43 ± 0.83	1.24 ± 0.78	0.71 ± 0.09	0.79 ± 0.23	0.69 ± 0.01	0.69 ± 0.01	0.69 ± 0.01	0.68 ± 0.02	0.76 ± 0.10	0.85 ± 0.00
9	0.85 ± 0.29	0.91 ± 0.23	0.68 ± 0.01	0.68 ± 0.02	0.67 ± 0.00	0.67 ± 0.00	0.68 ± 0.00	0.66 ± 0.01	0.76 ± 0.17	0.84 ± 0.00
10	0.72 ± 0.07	0.76 ± 0.14	0.72 ± 0.13	0.66 ± 0.00	0.66 ± 0.00	0.67 ± 0.01	0.67 ± 0.00	0.64 ± 0.00	0.84 ± 0.27	0.76 ± 0.09
11	0.66 ± 0.00	0.66 ± 0.00	0.66 ± 0.01	0.65 ± 0.00	0.65 ± 0.00	0.66 ± 0.00	0.67 ± 0.00	0.64 ± 0.00	0.70 ± 0.09	0.65 ± 0.02
12	0.65 ± 0.02	0.66 ± 0.00	0.65 ± 0.00	0.65 ± 0.00	0.65 ± 0.00	0.64 ± 0.01	0.66 ± 0.00	0.63 ± 0.00	0.64 ± 0.01	0.64 ± 0.01

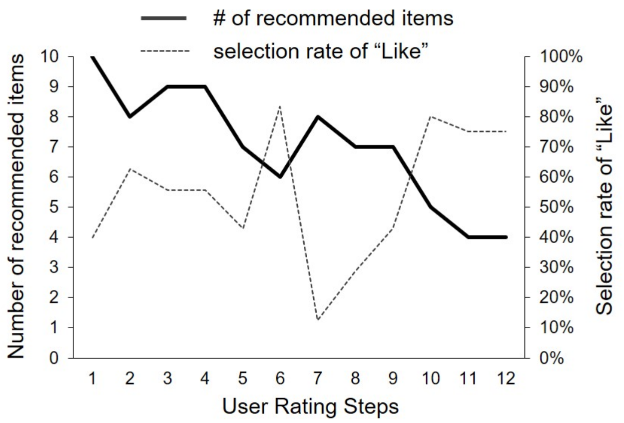


Fig. 5 Number of recommended items and selection rate of "Like" in each user rating.

purpose is to recommend plans of three days' home-cooked Japanese dinners, the expiration dates of chicken thigh, sausage, and green onion are close on the initial condition. We conducted the experiment on the simulated environment and the questionnaire survey on the degree of satisfaction as to recommended items while using the recommender system.

4.2. Experimental Result on Simulated Condition

In the experiment, the subject is required to rate the recommended items. The maximum number of items presented to the user is 10, and the maximum number of the user's rating is 20. Before each user rating phase, meal plans are optimized by the genetic operator of the proposed multi-island GA. The maximum number of generations is 20. When one of the best candidates overlaps with others, the item is automatically removed from the list of meal plans for the user.

Table 6 shows the results of fitness values of the best candidates in each island. As the meal planning is attributed to the minimization problem, the fitness values converge through the rating steps. The subject was satisfied with the recommended plan in the 12th rating. Although the fitness values among the individuals vary widely in the initial step, the items become gradually similar in contents. Figure 5 shows the number of recommended items and selection rate of "Like" in each user rating. The number of items gradually decrease in the result. This results in personalization in the recommendation system. Moreover, we find that the number of items partially increases with decreasing the selection rate of "Like". This indicates that the proposed method can deal with the problem of trade-off between specialization and diversity.

Table. 7 Content of a fridge in the simulated environment.

Ingredient	Residual Quantity before	Residual Quantity after
chicken thigh	400 g	0 g
sliced pork	400 g	250 g
sausage	100 g	0 g
cabbage	400 g	80 g
onion	400 g	60 g
carrot	200 g	115 g
potherb mustard	100 g	100 g
green onion	100 g	0 g
Shimeji	150 g	150 g
Enokitake	200 g	200 g
tofu	200 g	50 g
potato	400 g	200 g
bell pepper	100 g	100 g
maitake	100 g	100 g
Elingi	100 g	20 g
cherry tomato	100 g	100 g
paprika	100 g	100 g
Chinese chive	100 g	100 g
Japanese radish	400 g	400 g
egg	200 g	150 g
lettuce	250 g	250 g
thin fried tofu	100 g	100 g
Komatsuna	200 g	200 g
ginger	50 g	50 g

Table 7 shows the food consumption resulting from the best meal plan. In the result, there is no food that reaches its expiration date. This is because the close-to-date ingredients are preferentially selected in the early days.

4.3. Questionnaire Survey

In the questionnaire survey, the subjects were required to score their satisfaction with the recommended plans when they rated the presented items. The subjects consisted of three male university students. The subjects were prenotified of the simulated condition. We used 10-point scale questionnaire.

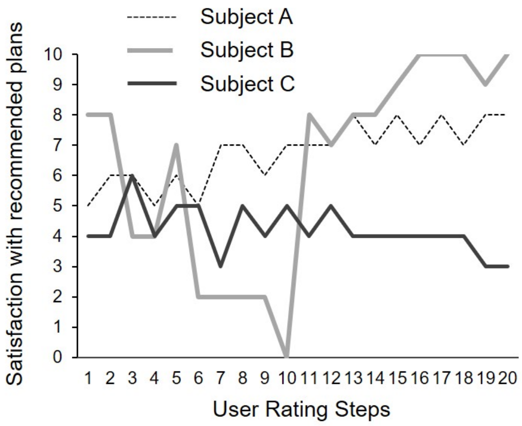


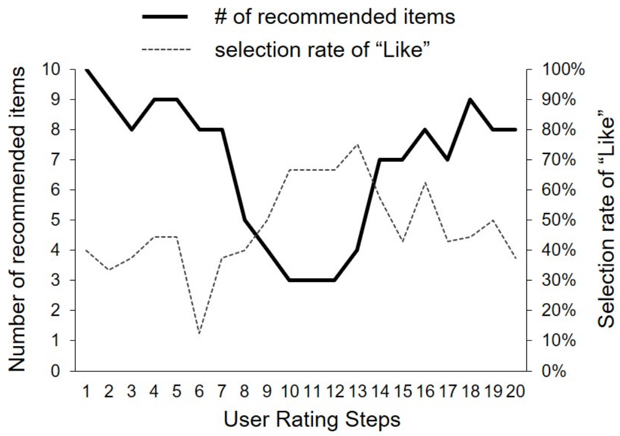
Fig. 6 Questionnaire results.

Figure 6 shows the questionnaire results, and the number of recommended items and the users' selection rates of "Like" are presented by Fig 7. According to the questionnaire results, the satisfaction of the subject A and B is improved by the recommender system. The satisfaction of the subject A gradually increases with each user rating, whereas the subject B seems to get great satisfaction from the items at the 11th rating step. In Fig. 7 (b), there is no meal plan at the 10th user rating that the subject B likes. On the other hand, the satisfaction of the subject C has tended to decline in Fig. 6. In the Fig. 7 (c), the number of items is consistently high through the recommendation while the selection rate of "Like" is decreasing clearly. This indicates that the subject C was not able to find any meal plan that he liked.

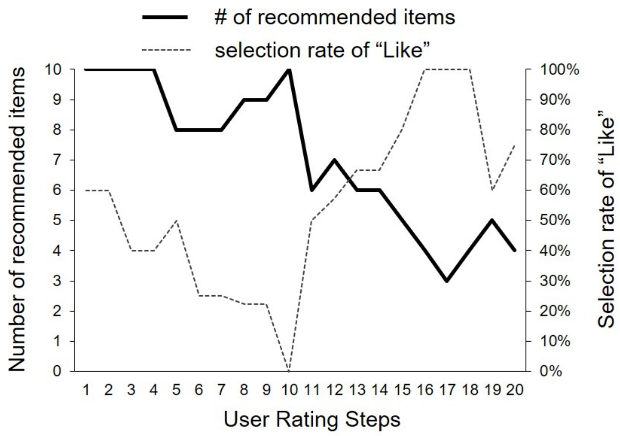
5. SUMMARY

In this paper, we propose a method of meal planning recommendation based on multi-objective optimization using the multi-island GA. To address common problem in recommender systems, such as personalization and diversification, the system includes the process to interactively search optimal items through user rating. Moreover, we define the objective functions to minimize the amount of expired food and adjust caloric intake. In the experiment, we show some experimental results to discuss the applicability of the proposed approach.

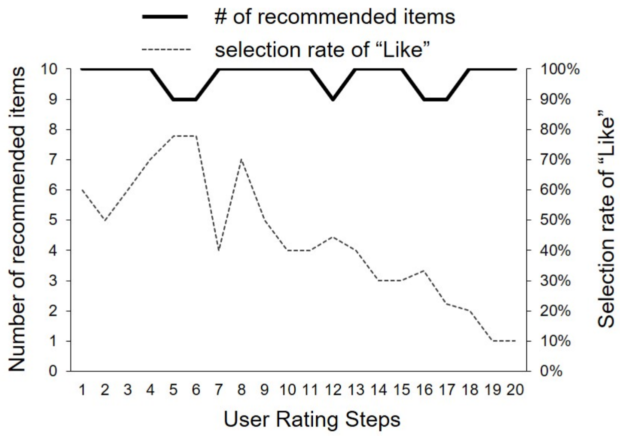
In the future work, we intend to conduct additional experiments by using real data and discuss the effectiveness in more detail. In addition, we will improve the system on the basis of the results of this study.



(a) result of subject A



(b) result of subject B



(c) result of subject C

Fig. 7 Number of recommendation items and selection rate of "Like" in each user rating.

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