Tabu Search Algorithms for Multimodal and Multi-Objective Function Optimizations

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Summary
The integration of genetic algorithms (GAs) and tabu search is one of the traditional problems in function optimization in the GA literature. However, most of the proposed methods have utilized genetic algorithms to explore global candidates and tabu search to exploit local optimal points. Unlike such methods so far, this paper proposes a new algorithm to directly store individuals into multiple tabu lists during GA-iterations. The tabu lists inhibit similar solution candidates from being selected so often. The proposed algorithm is so simple but strong that we can solve both multimodal and multi-objective problems in the same manner. This paper describes the basic idea, algorithms, and experimental results. One of the applications for this algorithm will be suitable for the recommendation of the grocery items among the retail businesses.

Key words:
Generic Algorithms, Tabu Search, Multi-modal Function Optimization, Multi-Objective Problems, Social System Simulation

1. Introduction

Hybrid genetic algorithms or the integration of genetic algorithms, simulated annealing, tabu search, and/or heuristics have been studied for long years to let GAs more powerful to solve complex optimization problems. Most of the conventional methods utilize GAs to explore global candidates and the other additional algorithms to exploit local optimal points. Unlike such conventional methods so far, this paper proposes new algorithms to directly store individuals into multiple tabu lists.

The Tabu lists have roles of (i) storing superior individuals in the previous generations, (ii) reusing the individuals as the elite, (iii) maintaining diversity of the population and (iv) inhibiting individual from converging local minima as is found in conventional Tabu search methods. Therefore, hence the optimization proceeds within the dynamical changes of the solution landscape, the Tabu-GA will be easier, more robust, and more powerful than the conventional hybrid methods.

The objectives of our research are to develop new GA-based methods that enable us to acquire simultaneously multiple feasible solutions for both problems; multimodal and multi-objective function optimization.

The basic idea of the algorithms is to store the best solutions of each generation into long-term and short-term tabu lists, which inhibit the individuals from being selected more than n times. The tabu lists or tabu constraints depress the possibility to local convergence in the early stages of the iterations. This enables the candidates to explore new solution spaces to get better and/or various solutions. The final results are accumulated in the long-term tabu list. This means that multiple peaks are obtained for multimodal problems and that Pareto optimal solutions are obtained for multi-objective problems.

When applying the methods to multimodal problems, in order not to converge into one peak, we first measure Hamming distances between the individuals of the current generation and the ones in the tabu lists, then omit the individuals within the distance *d*.

When applying the methods to multi-objective problems, in order to acquire the better Pareto optima, we prepare multiclass tabu lists, each of which contains solutions of each objective function.

This paper is composed following sections; in section 2, we survey related studies on hybrid methods in genetic algorithms. In section 3, we give the problem formulation and proposed algorithms. Then, we carry out intensive experiments to validate the effectiveness of the proposed methods in section 4 and 5; the objective functions include Rastrigin, FMS-parameter, and multi-objective function.

Finally, in section 6, concluding remarks and future works are described.

2. Related Studies

The hybridization of Genetic Algorithms with simulated annealing, tabu search, artificial neural networks and expert system aims at improving the performance of the searching capabilities to difficult problems (Costa,1995; Glover,1994; Glover,1995; Kitano,1990; Malek,1989; Mantawy,1999; Muhlenbein,1988; Muhlenbein,1992; Powel,1989; Ulder,1991).

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However, most of the studies in the literature have focused on the global search via GAs and the local search via the other methods. Fine tuning of the local search has been the main issue. On the other hand, we will focus on the selection process of GA iteration via multiple tabu lists.

We believe that GAs provide unique general ways to multimodal function Optimization. There also have been various studies (Echelman, 1991; DeJong, 1989; Goldberg, 1989; Goldberg, 1990; Tsutui, 1994a; Tsutui, 1994b). The proposed methods to keep the diversity of the population include (1) sharing methods, which utilize some sharing functions to avoid the convergence of similar individuals, (2) crowding methods, which constrain the replacements of new individuals, and (3) restrictions of crossover operations. However, these methods are difficult to apply to practical problems, because there are so many parameters to be tuned up.

About multi-objective function optimization problems, or problems to find Pareto optimal solutions, there have been various work to extend GAs (Cantu-Paz,1999; Coello,1999; Foncela and Fleming,1993; Hiroyasu,1999; Horn and Nafpliotis,1993; Schaffer,1985; Srinivas and Deb,1993; Tamaki,1996;). These studies include (1) methods to divide individuals into subgroups, each of which corresponds to each objective function, (2) methods to rank Pareto optimal individuals not to be covered by the other individuals, (3) combination of tournament and sharing methods and (4) methods to divide Pareto solutions to some ranges. These methods also have various parameters to be tuned up, therefore, difficult to apply.

These studies in the literature have common characteristics to improve GAs by adding capabilities of the diversity of populations, local and/or distributed search.

In this paper, we will propose a novel uniform method with multiple tabu lists.

3. Genetic Algorithm with Multiple Tabu-Lists

This section describes the genetic algorithm with multiple tabu-lists, which aims at implementing a fast, simple, and robust method to get optimal points for both multimodal and multi-objective problems. The algorithm is unique because we can process both problems within the same framework and without explicitly considering the existence of schematic structures of the problem representation. The main idea of the algorithm is that, (1) in each generation, one best individual generated by GA operation is stored into the tabu-lists to inhibit it from selecting specified times, and (2) solution candidates found in the previous generations will become tabus, and thus, the other candidates are explored in order to get better and divergent solutions.

3.1 Structures of the Tabu-Lists

We have two kinds of tabu-lists in general: long-term list with the length *m* and short-term list with the length *n*. The *m* and *n* are parameters of the algorithm and can be tuned against given problems. The tabu-lists have the following four roles: i) storing superior individuals in the previous generations, ii) reusing the individuals as the elite, iii) maintaining the diversity of the population, and iv) inhibiting individuals from converging local minima.

When solving multi-objective problems, the tabu-lists are extended to a multi-class so that each set of long-term and short-term tabu-lists is corresponds with (1) each objective function and (2) one Pareto optima. Furthermore, in the following sections, members of the long-term tabu list will be modified so that it only includes schematic information of the individuals. Using these tabu lists, we can simultaneously approach to multimodal and multi-objective problems.

Long-Term Tabu List

It contains best *m* individuals during all previous iterations. The individuals in the long-term tabu list do not have the same or similar genotype.

Short-Term Tabu List

It contains best *n* individuals during recent *n* iterations. The individuals in the short-term tabu list may have the same genotypes. The individuals only remain the *n* iteration, then are replaced in FIFO manner.

Multiclass Tabu List

When applying GAs to multi-objective problems, they reports that the optimization processes for one objective functions will be of use for generating the better Pareto optima. The multiclass tabu lists are prepared to correspond with each objective function. We also prepare another tabu list, which corresponds with the Pareto optima. The structures of the tabu lists are the same with the above long- and short-term tabu lists.

3.2 Algorithm of Tabu-GA for a multimodal function problem

After evaluating each individual by means of the objective function in each iteration, we store the best individual of the generation into both long-term and short-term tabu lists. When selecting parents candidate by the tournament selection method, we refer to the tabu lists in order not to select individuals with similar genotypes by means of the Hamming distance. The tabu constraint can be applied to only one parent to generate offspring. Using the tabu constraints, we also avoid to sconverge the individuals to local optima. The solutions are gradually accumulated into the long term tabu list. Thus, in case of a multimodal function, (respectively, a multi-objective function), multiple solutions (respectively, Pareto solutions) are obtained, simultaneously. The outline of the algorithm is shown in Fig.1.

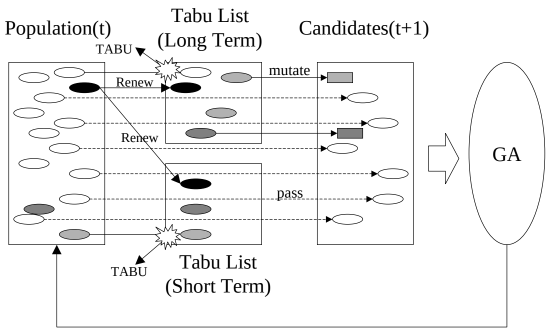

Fig.1: Tabu-GA.

1. Set H Empty, H which is a historical memory. Select $x^{now} \in X$ as an initial solution.
2. Choose $selection\_N(x^{now}) \subset N(H, x^{now})$, where $N(H, x^{now})$ is a set in $x \in X$ except in the neighborhoods of H.
3. Select $x^{next} = \max(c(H, x^{now}))$, $x^{next} \in selection\_N(x^{now})$, where $c(H, x^{now})$ is an objective function is a mapping of a set in $x \in X$ except in the neighborhoods of H.
4. Run GA.
5. If a condition of ending is true then end
6. Exchange x^{best} for x^{old} in H. Return to 2.

4. Updating the tabu lists to keep the diversity

To avoid the solutions to converge to one peak for a multimodal function, we extend the tabu constraint, where the distance of an individual in the tabu list and a new candidate is less than d. We employ the following distance measures.

Hamming distance

It represents the difference of bits in the two genotypes.

$$d_H(\mathbf{a},\mathbf{b}) = \sum_{i=1}^{n} |\mathbf{a_i} - \mathbf{b_i}|$$

Schema matching

It represents the similarity of schemas contained in the two genotypes.

$$d_S(\mathbf{a},\mathbf{b}) = \sum_{i=1}^{n} |\, schema(\mathbf{a})_\mathbf{i} - schema(\mathbf{b})_\mathbf{i} \,|$$

Norm

It represents the difference of the values of phenotypes, or function values of the two individuals.

$$d_N(\mathbf{a},\mathbf{b}) = \sum_{i=1}^{n} \|\, ptype(\mathbf{a}) - ptype(\mathbf{b}) \,\|$$

We implement the following tabu list updating methods in order to keep the diversity of the individuals. Although the parameters depend on the characteristics of the problem domain, we could not find the remarkable difference among them from our intensive experiments. One point we should mention is that, in case of the schema tabu, the threshold value to detect the schemas is very sensitive to get good solutions.

Genotype tabu

When selecting individuals generated by specific GA operations via the tournament selection method, compare them with the ones in the tabu list. If the fitness value of the selected individual is low and the distance between the genotype of the selected individual and the genotype in the tabu list is within d_H by means of Hamming distance, then the one in the tabu list remains.

Schema tabu

If the same schema is kept for a long duration in the iteration, it might be a part of the candidate of global and/or local optima. We detect the schemas by (1) representing the current individuals to a matrix form and (2) finding the convergence of the phenotypes by measuring each locus with a given threshold value. If the fitness of the best individual of the generation is low and the distance between the detected schema and the schema in the tabu list is within d_S, then the schema in the tabu list remains.

Phenotype tabu

The method is the same with the above one, except the distance d_N of the detected schema and the schema in the tabu list is evaluated by the phenotype of the individuals.

4.1 Algorithm of Tabu-GA for multi-objective functions problem

When applying our algorithm to multi-objective problems, we prepare multiclass tabu lists: the ones for each objective function and a tabu list for Pareto optima. Thus, the number of the tabu lists is m+1, where m is the number of the objective Functions. The Pareto optima are evaluated by the ranking method. Each offspring is evaluated by each tabu list. The individuals are selected by the tournament selection by means of each objectives and Pareto optima.

Genetic operations are applied to all the individuals. The outline of the algorithm for multi-objective functions is shown in Fig.2.

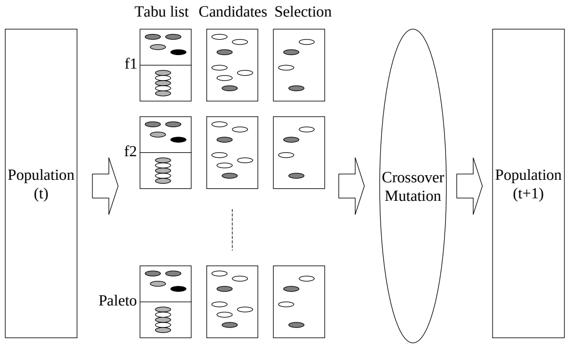

Fig.2: Multi-objective Tabu-GA.

5. Experiments

To validate the effectiveness of the proposed method, we carry out numerical experiments on various test functions, which include very difficult multimodal functions.

5.1 Experimental Set Up and Objective Functions

We compare the proposed method with Simple GA with the tournament selection method. Simple GA is also modified so that it processes both multimodal and multi-objective functions. We employ the following functions as the test bed.

- Sin function

$$\max \quad : \quad f_{\sin}(x) = \frac{a_1 \sin(2\pi x + a_2)}{a_3(x + a_4)}$$

$$a_i : const.$$

- Rastrigin function

$$\min \quad : \quad f_{ras}(x) = nA + \sum_{i=1}^{n} x_i^2 - A\cos(2\pi x_i)$$

$$i = 1,2,3,\ldots,n \quad A = 10.$$

- FM sound parameters function

$$\max \quad : \quad f_{fms,i}(x,y) = x_i \sin(2\pi y_i t + f_{fms,i+1})$$

$$i = 1,2,3,\ldots,n.$$

- Multi-objective function

$$\min \quad : \quad f_1(x) = \frac{x_1^2}{4}$$

$$\min \quad : \quad f_2(x) = x_1(1 - x_2) + 5$$

$$s.t. \qquad 1 \le x_1 \le 4, \quad 1 \le x_2 \le 2.$$

Table 1: summarizes the experiment parameters.

Function	Parameters
Sin	TGA(MM,20,3,1,H 0.9)
Rastrigin	TGA(MM,50,10,3,H 0.9)
FMS-parameters	TGA(MM,50,10,3,N 0.2)
Multi-objective	TGA(MO,50,5,3,N 0.2)

where TGA(MM, i, m, n, d) shows the characteristics of Tabu-GA, MM/MO shows multimodal or multi-objective, i is the number of individuals, m is the length of long tabu lists, n is the length of short tabu lists, and d is the distance of individuals: H/Hamming; N/Norm. Common methods of them are Tournament Selection and Uniform Crossover.

5.2 Experiments in Tabu-GA

To each test function, we have applied both Simple GA and Tabu-GA. General observations have suggested that (1) Individuals generated by simple GA with conventional elitist strategies loose their population diversity, and then rapidly converge to local optima, (2) On the other hand, the tabu-GA has the more wider searching area, and escapes the individuals from local optima, thus, it finds global optima more often.

5.3 Sin Function

The cases of the sin function are summarized in Fig.3. The proposed method works better than Simple GA with the sharing method, that is, many peaks are simultaneously obtained. The remarkable point is that the change of the number of the tabu list size easily controls the number of multiple solutions compared with the sharing method. The effect of the tabu list size is shown in Table 2. The tabu size of the upper Figure is three, and the lower Figure is ten. Both Figures certainly show that tabu lists can get the diversity depending on the size. Where the population size is 20, the mutation rate is 0.005.

5.4 Rastrigin Function

Fig.4 shows the landscape of Rastrigin function, which is converted to the maximization problem. Simple GA with or without hill climbing techniques cannot generate optima of such functions with many peaks. The proposed method finds the optima faster than simple GA. The result is shown in Fig.4.

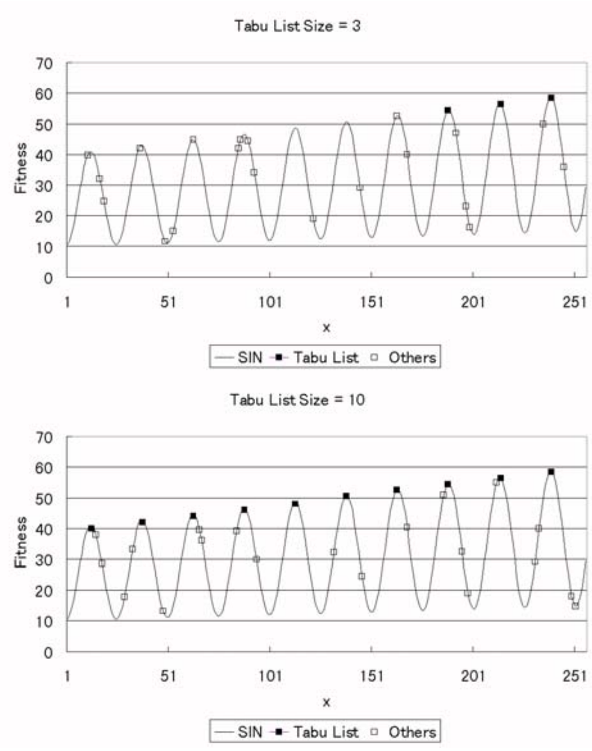

Fig.3: Sin function.

Table 2: Effect of Tabu List's Size on SIN Function.

Tabu List Size	The Number of Generation to Converge	The Number of Multimodal Solutions
3	36	3
7	95	7
10	187	10

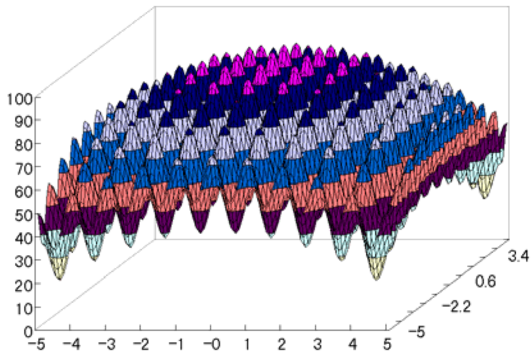

Fig.4: Rastrigin function (f, x_1, x_2).

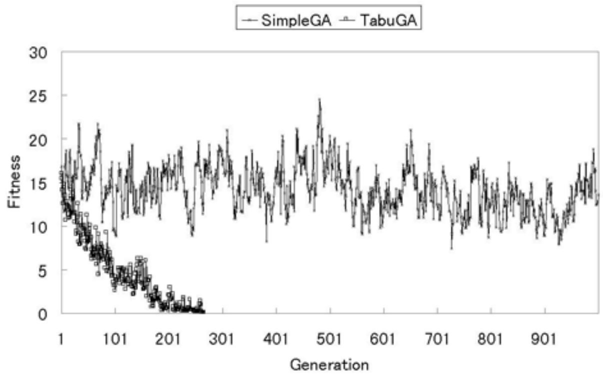

Fig.5: Tabu-GA results of Rastrigin function

5.5 FMS Parameter Function

FMS parameter function was introduced by (TsuTsui93) to show the effectiveness of their folking GA method. The landscape is shown in Fig.6 with parameters n=6, and y_2-y_3, which is also converted to the maximization problem. As shown in the Figure, searching optima in the y_2-y_3 space is a complex multimodal problem.

Fig.7 shows the iteration processes by Simple GA, Simple GA with the elitist strategy, and the tabu-GA. Ten cases of Simple GA and the tabu-GA are all averaged in the Figure.

Simple GA fails to find the optimal solution after 1,000 iterations with 50 individuals, Simple GA with the elitist strategy finds the optimal solution two times from the ten trials. About the other eight cases, the solution rapidly converges to local optima. The Figure plots the results of the three cases out of the eight trials. On the other hand, the proposed method always finds the optima in the ten trials.

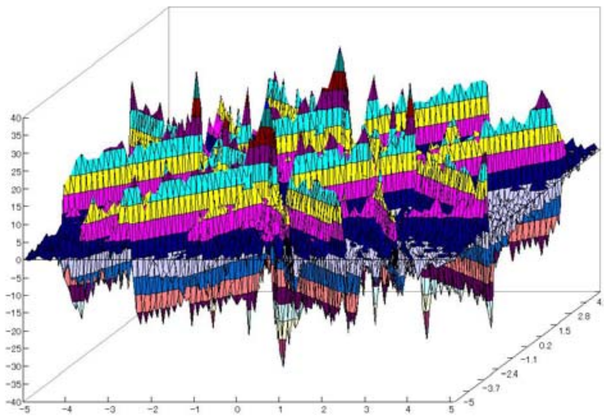

Fig.6: FMS function (f, y_2, y_3).

Fig.8 shows the final stage of the iteration. Similar to the sin function case, we get three local optima as marked A, B, and C in the Figure. Among the three C is the global minimum. Please note that the tabu list contains these local optima, which are hardly obtained by conventional GAs.

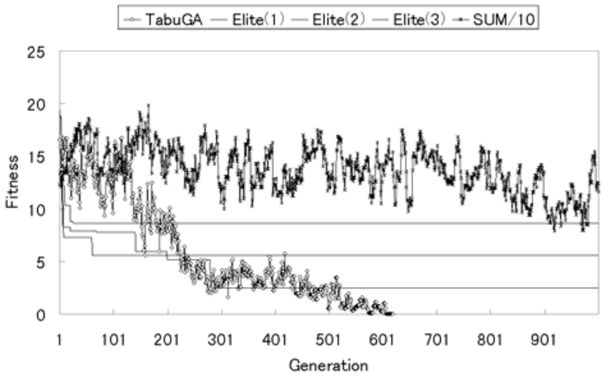

Fig.7: Tabu-GA results of FMS function.

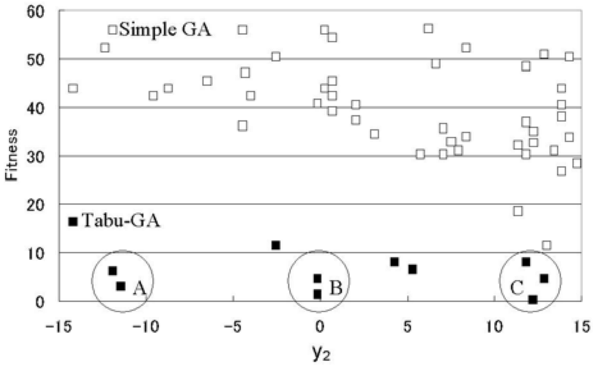

Fig.8: Individuals of FMS function.

5.6 Optimization of a Multi-objective Function

Conventional GAs including the simple GA only process single objective functions or multi-objective functions which are represented by the linear combination of each Function. On the contrary, the proposed method with multiclass tabu lists stores divergent Pareto optima in the long term tabu lists. Using the intrinsic property of divergent search ability of the method, it also searches for the better Pareto solutions.

Fig.9 shows the results of the proposed method and the conventional method with population ranking. The Figure suggests that Tabu-GA generates the better solutions. The upper graph of Fig.9 shows the case with the length 5 long term tabu lists and the lower graph of the Figure shows the case where the length of the long term tabu lists is 20. Each iteration is 300. The Figure suggests that we can control the frontier line of Pareto optima by changing the length of the tabu lists.

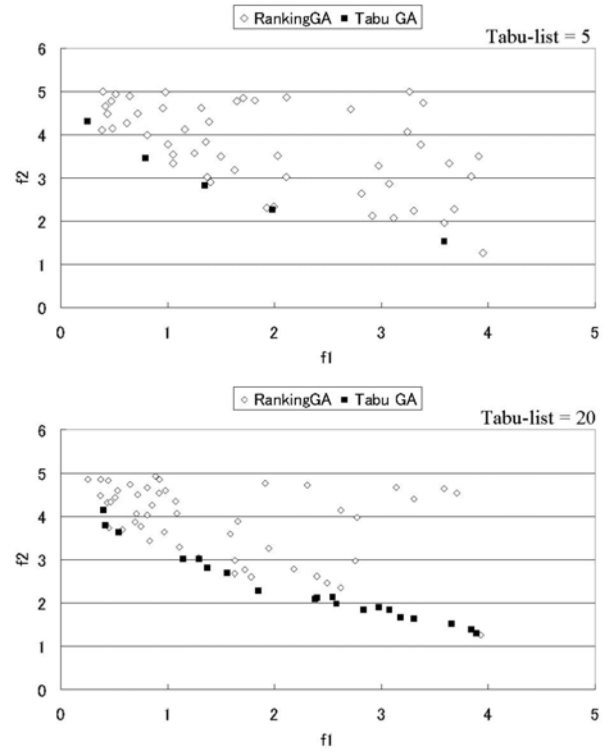

Fig.9: Multi-objective optimization

5.7 Results of Experiments

Table 3 shows the results of some multimodal experiments, where SGA is Simple-GA, three values are Best/Ave/Success, Best is the best iteration in ten executions, Ave is the average iteration of successful executions in them, and Success is the number of successful executions in them. Although the simple GA with elite seems better than Tabu-GA to solve FMS parameters function, it fails at eight times in ten executions to get the optimum solution, while Tabu-GA succeeds at all times to do it.

Table 3: Results of Multimodal Experiments.

Function	SGA	SGA with elite	Tabu-GA
Rastrigin	829/829/1	141/497/5	73/264/10
FMS-parameters	-/-/0	126/282/2	143/608/10

Table 4 shows the results of some multi-objective experiments, where Pareto is the number of Pareto optima and (n) is the tabu list size. While Ranking Selection GA gets six Pareto solutions on the frontier line of Pareto optima, Tabu-GA can get flexible and diverse Pareto solutions depending on a tabu list size.

Table 4: Results of Multi-objective Experiments.

Method	Pareto
Ranking Selection	6
Tabu-GA (5)	5
Tabu-GA (10)	9
Tabu-GA (20)	16

6. Concluding Remarks

This paper has described a novel method to directly store individuals into multiple tabu lists during GA-iterations.

Although both the basic idea and the algorithm are very simple, the experimental results have suggested that the method is powerful and robust against very wide class of problems. Because, the proposed method only focuses on the population diversity and the selection process, and it does not depend on the variety of genetic operations, we will tune the method up to apply the other difficult class of problems. Our future works include to improve the proposed method to GA hard domains and to apply it to large scale problems. One of the applications for this algorithm will be suitable for the recommendation of the grocery items among the retail businesses. There used to be simple inventory activities such as controlling the quantity and the timing of the items for the ordering. This is not only for covering the customers' demand but controlling the losses for the items. But in this retail business such kind of the small profits and quick returns, it is necessary to improve a purchase mark to gain gross margin more than before. For this algorithm that we discussed in this paper, to figure out the recommended items for the local optimized solution will fit the clients' demand changing drastically.

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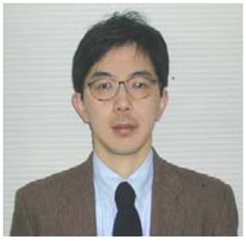

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