NCGA : Neighborhood Cultivation Genetic Algorithm for Multi-Objective Optimization Problems

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Abstract

In this paper, a new genetic algorithm for multi-objective optimization problems is introduced. That is called "Neighborhood Cultivation GA (NCGA)". In the recent studies such as SPEA2 or NSGA-II, it is demonstrated that some mechanisms are important; the mechanisms of placement in an archive of the excellent solutions, sharing without parameters, assign of fitness, selection and reflection the archived solutions to the search population. NCGA includes not only these mechanisms but also the neighborhood crossover. The comparison of NCGA with SPEA2 and NSGA-II by some test functions shows that NCGA is a robust algorithm to find Pareto-optimum solutions. Through the comparison between the case of using neighborhood crossover and the case of using normal crossover in NCGA, the effect of neighborhood crossover is made clear.

1 Introduction

Recently, the study of evolutionary computation of multi-objective optimization has been researched actively and made great progress [1, 2, 3, 4, 5]. The many approaches have been introduced and genetic algorithm (GA) is a main approach among them [1]. GA is one of simulations that imitate the heredity and evolution of creatures [6]. One of the goals of multi-objective optimization problems may be to obtain a set of Pareto-optimum solution [1]. Since the Pareto-optimum solution is a set, many trials should be needed for a single point search. On the other hand, the set can be derived in one trial with GAs, since GA is one of multi point search methods. That is the reason why GAs are focused in the field of multi-objective optimization problems. To apply GAs to multi-objective optimization problems, genetic operators and fitness function that keep the diversity of the solutions during the search should be prepared.

In this few years, several new algorithms that can find good Pareto-optimum solutions with small calculation cost are developped [1]. Those are NSGA-II [2], SPEA2 [3], NPGA-II [5] and MOGA [7]. These new algorithms have the same search mechanisms; those are preservation scheme of excellent solutions that are found in the search, allocation scheme of appropriate fitness values and sharing scheme without parameters.

We proposed the parallel model of multi-objective GA that is called DRMOGA [4]. In this model, we discussed the difference of the parallel models between single objective problems and multi-objective problems. We also proposed a neighborhood crossover and showed the effectiveness of the neighborhood crossover thorough the numerical examples.

In this paper, we propose a new GA for multi-objective optimization problems. That is called Neighborhood Cultivation GA (NCGA). NCGA not only includes the mechanisms of NSGA-II and SPEA2 that derive the good solutions but also the mechanism of neighborhood crossover. Through the numerical experiments, the effectiveness of NCGA is discussed. In the experiments, the results of NCGA are compared with those of NSGA-II, SPEA2 and non-NCGA (nNCGA).

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2 Multi-Objective Optimization Problems by Genetic Algorithms

In multi-objective optimization problems, there are several objectives. Usually these objectives cannot minimize or maximize at the same time since there is a trade-off relation ship between the objectives [1]. Therefore, one of the goals of multi-objective optimization problem is to find a set of Pareto-optimum solutions.

Genetic Algorithm is an algorithm that simulates creatures' heredity and evolution [6]. Since GA is one of multi point search methods, an optimum solution can be determined even when the landscape of the objective function is multi modal. Moreover, GA can be applied to problems whose search space is discrete. Therefore, GA is one of very powerful optimization tools and is very easy to use. In multi-objective optimization, GA can find a Pareto-optimum set with one trial because GA is a multi point search. As a result, GA is a very effective tool especially in multi-objective optimization problems. Thus, there are many researchers who are working on multi-objective GA and there are many algorithms of multi-objective GA. These algorithms of multi-objective GA are roughly divided into two categories; those are the algorithms that treat Pareto-optimum solution implicitly or explicitly [1]. The most of the latest methods treat Pareto-optimum solution explicitly.

The following topics are the mechanisms that the recent GA approaches have.

1) Reservation mechanism of the excellent solutions
2) Reflection to search solutions mechanism of the reserved excellent solutions
3) Cut down (sharing) method of the reserved excellent solutions
4) Assignment method of fitness function
5) Unification mechanism of values of each objective

These mechanisms derive the good Pareto-optimum solutions. Therefore, the developed algorithm should have these mechanisms.

3 Neighborhood Cultivation Genetic Algorithm

3.1 Overall flow of Neighborhood Cultivation Genetic Algorithm

In this paper, we extend GA and develop a new algorithm that is called Neighborhood Cultivation Genetic Algorithm (NCGA). NCGA has a neighborhood crossover mechanism in addition to the mechanisms of GAs that are explained in the former chapter. In GAs, the exploration and exploitation are very important. By exploitation, an optimum solution can be found in a global area. By exploration, an optimum solution can be found around the elite solution. In a single object GAs, exploration is performed in the early stage of the search and exploitation is performed in the latter stage. On the other hand, in multi-objective GAs, both exploration and exploitation should be performed during the search. Usually, crossover operation helps both exploration and exploitation.

In NCGA, the exploitation factor of the crossover is reinforced. In the crossover operation of NCGA, a pair of the individuals for crossover is not chosen randomly, but individuals who are close each other are chosen. Because of this operation, child individuals which are generated after the crossover may be close to the parent individuals. Therefore, the precise exploitation is expected.

The following steps are the overall flow of NCGA where

P_t : search population at generation t
A_t : archive at generation t.

Step 1: Initialization: Generate an initial population P_0. Population size is N. Set $t = 0$. Calculate fitness values of initial individuals in P_0. Copy P_0 into A_0. Archive size is also N.

Step 2: Start new generation: set $t = t + 1$.

Step 3: Generate new search population: $P_t = A_{t-1}$.

Step 4: Sorting: Individuals of P_t are sorted with along to the values of focused objective. The focused objective is changed at every generation. For example, when there are three objectives, the first objective is focused in this step in the first generation. The third objective is focused in the third generation. Then the first objective is focused again in the fourth generation.

Step 5: Grouping: P_t is divided into groups which consists of two individuals. These two individuals are chosen from the top to the down of the sorted individuals.

Step 6: Crossover and Mutation: In a group, crossover and mutation operations are performed. From two parent individuals, two child individuals are generated. Here, parent individuals are eliminated.

Step 7: Evaluation: All of the objectives of individuals are derived.

Step 8: Assembling: The all individuals are assembled into one group and this becomes new P_t.

Step 9: Renewing archives: Assemble P_t and A_{t-1} together. Then N individuals are chosen from $2N$ individuals. To reduce the number of individuals, the same operation of SPEA2 (Environment Selection) is also performed.

Step 10: Termination: Check the terminal condition. If it is satisfied, the simulation is terminated. If it is not satisfied, the simulation returns to Step 2.

In NCGA, most of the genetic operations are performed in a group that is consisted of two individuals. That is why this algorithm is called "local cultivate". This scheme is similar to Minimum Generation Gap model (MGG) [8]. However, the concept of generation of NCGA is the same as simple GAs.

4 Numerical Examples

In this section, NCGA is applied to the some test functions. The results are compared with those of SPEA2 [3], NSGA-II [1] and non-NCGA (nNCGA). nNCGA is the same algorithm of NCGA except neighborhood crossover.

4.1 Test Functions

In this paper, we use two continuous functions and a knapsack problem. These problems are explained as follows. In these equations, f denotes an objective function and $g(g \geq 0)$ indicates a constraint.

$$ZDT4: \begin{cases} \min & f_1(x) = x_1 \\ \min & f_2(x) = g(x)[1 - \sqrt{\frac{x_1}{g(x)}}] \\ & g(x) = 91 + \sum_{i=2}^{10}[x_i^2 - 10\cos(4\pi x_i)] \\ & x_1 \in [0,1],\ x_i \in [-5,5],\ i = 2, \ldots, 10 \end{cases}$$

$$KUR: \begin{cases} \min & f_1 = \sum_{i=1}^{n}(-10\exp(-0.2\sqrt{x_i^2 + x_{i+1}^2})) \\ \min & f_2 = \sum_{i=1}^{n}(|x_i|^{0.8} + 5\sin(x_i)^3) \\ & x_i[-5,5],\ i = 1, \ldots, n,\ n = 100 \end{cases}$$

$$KP750-2: \begin{cases} \min & f_i(x) = \sum_{i=1}^{n} x_i \cdot p_{i,j} \\ s.t. & \\ & g(x) = \sum_{i=1}^{n} x_i \dot{w}_{i,j} \leq W_j \\ & p_{i,j}(\text{profit value}) \\ & w_{i,j}(\text{weight value}) \\ & 1 \leq j \leq 2 \end{cases}$$

ZDT4 was use by Zitzler and Deb [9]. There are 10 design variables and two objectives. This test function is a multi-model function. ZDT 6 was also used by Zitzler and Deb [9]. This is an unimodal and has a non-uniformly distributed objective space. KUR was Kursawa was used [10]. It has a multi-modal function in one component and pair-wise interactions among the variables in the other component. Since there are 100 design variables, it needs a high calculation cost to derive the solutions. KP750-2 is the 0/1 knapsack problem and it is a combinatorial problem [3, 11]. There are 750 items and two objects. The profit and weight values are the same as those of the Reference [11].

4.2 Parameters of GAs

In the former studies, some methods used the real value coding and made good results [12]. In this paper, to discuss the effectiveness of the algorithm, simple methods are applied for all the problems. Therefore the bit coding is used in the experiments. Similarly, one point crossover and bit flip are used for the crossover and mutation. The length of the chromosome is 20 bit per one design variable for the continuous problems and 750 bit for the knapsack problems. In the continuous problems, population size is 100 and the simulation is terminated when the generation is got over 250. In the knapsack problems, population size is 250 and the simulation is terminated when the generation is exceeded 2000.

4.3 Evaluation methods

To compare the results derived by each algorithm, the following evaluation methods are used in this paper.

4.3.1 Ratio of Non-dominated Individuals (RNI)

This performance measure is derived from comparing two solutions, which are derived by two methods. RNI is derived from the following steps. At first, two populations from different methods are mixed. Secondly, the solutions that are non-dominated are chosen. Finally, RNI of each method is determined as the ratio of the number of the solutions who are in chosen solutions and derived by the method and the total number of the solutions. By RNI, the accuracy of the solutions can be compared. Figure 1 shows an example of RNI. In this example, the results of method A and B are compared. This case figured out method B is superior to method A.

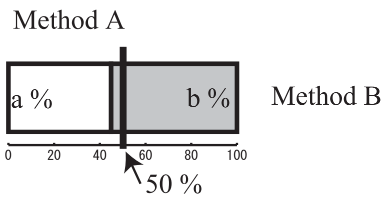

Figure 1: An example of RNI

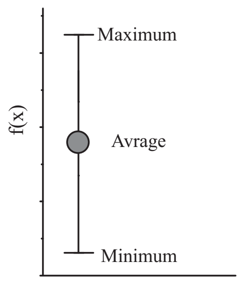

Figure 2: An example of MMA

4.3.2 Maximum, Minimum and Average values of each object of derived solutions (MMA)

To evaluate the derived solutions, not only the accuracy but also the expanse of the solutions is important. To discuss the expanse of the solutions, the maximum, minimum and average values of each object are considered. Figure 2 is an example of this measurement. In this figure, the maximum and minimum values of objective function are illustrated. At the same time, the medium value is pointed as a circle.

4.4 Results

Proposed NCGA, SPEA2, NSGA-II and NO-NC-NCGA (NCGA with no neighborhood crossover) are applied to test functions. 30 trials have been performed. The results are explained in the following sections. All the results are the average of 30 trials.

4.4.1 ZDT4

The results of RNI and MMA of ZDT4 are shown in Figure 3 and 4 respectively. Figure 5 indicates Pareto solutions in ZDT4. In this figure, all the Pareto-optimum solutions that are derived in 30 trials are figured out.

From figure 4, it is found that NCGA made the good results. SPEA2 is derived the wider solutions than the other methods. In the comparison of RNI, NSGA-II and NCGA are better than other methods and NCGA is slightly better than NSGA-II.

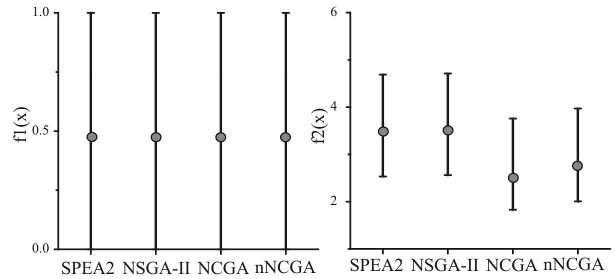

Figure 3: Max-Min values of ZDT4

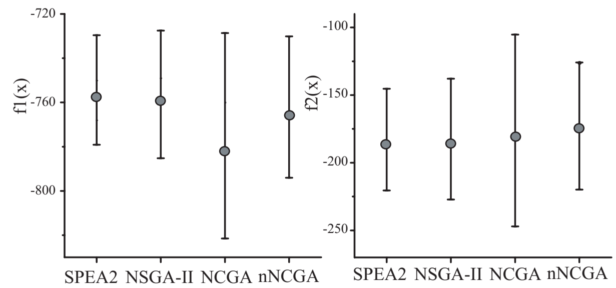

Figure 6: Max-Min values of KUR

4.4.2 KUR

In this problem, there are 100 design variables. Therefore, a lot of generations should be needed to derive the solutions. The results of RNI and MMA are shown in figure 6 and 7. Figure 8 indicates Pareto solutions in KUR. In this figure, all the Pareto-optimum solutions that are derived in 30 trials are figured out.

It is clear from the figure 7 that NCGA derived better solutions than the other methods. The solutions of NCGA are also wider spread than those of the other methods. In this problem, the mechanism of neighborhood crossover acts effectively to derive the solutions. That is to say the neighborhood crossover is an operation to find the solutions that have the diversity and high accuracy.

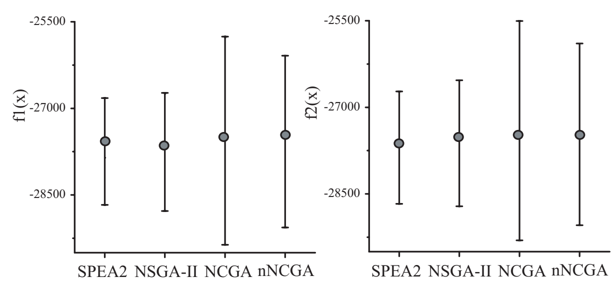

Figure 9: Max-Min values of KP750-2

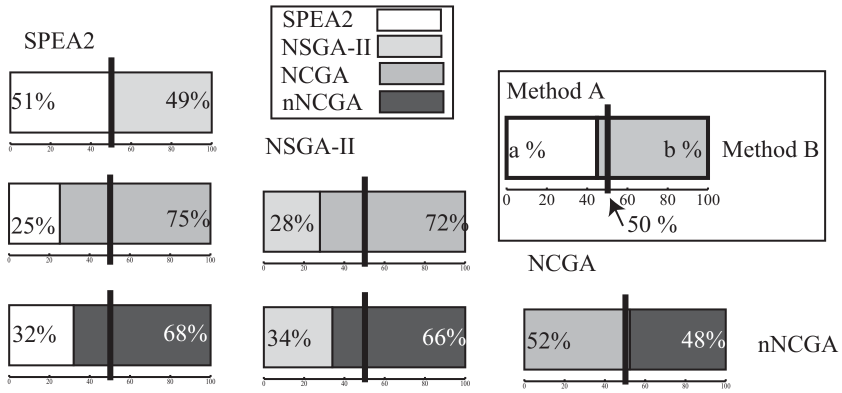

Figure 4: RNI of ZDT4

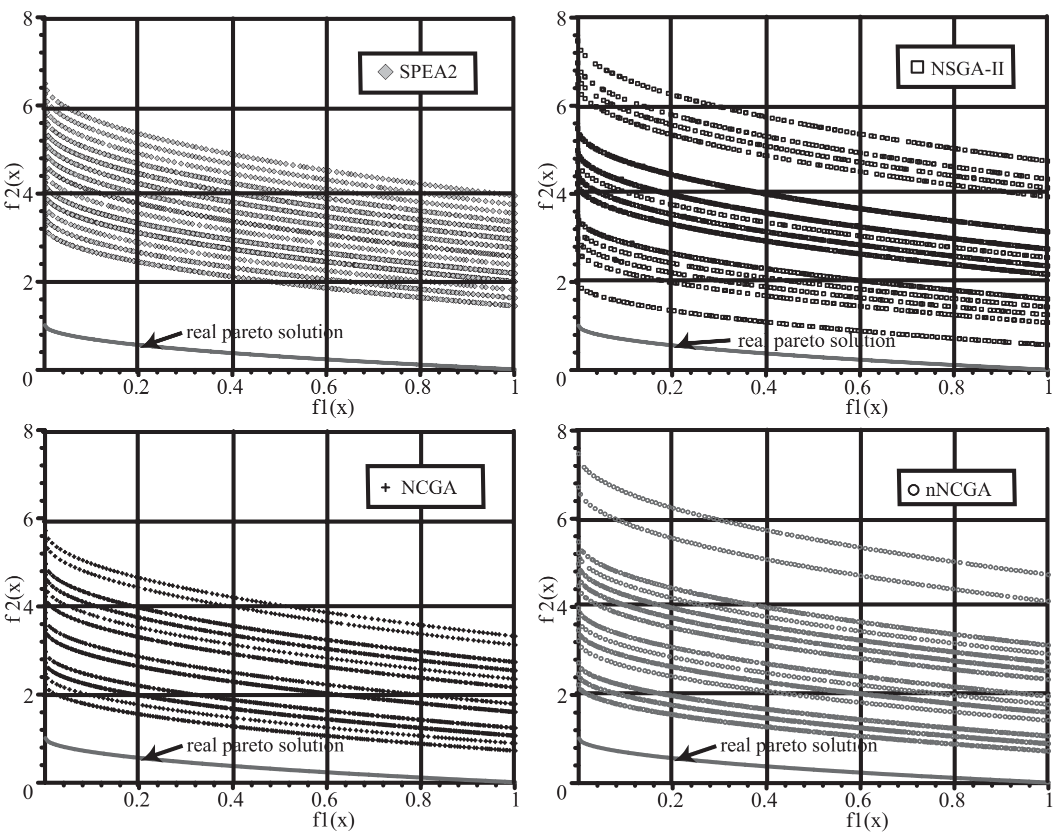

Figure 5: Pareto optimum individuals(ZDT4)

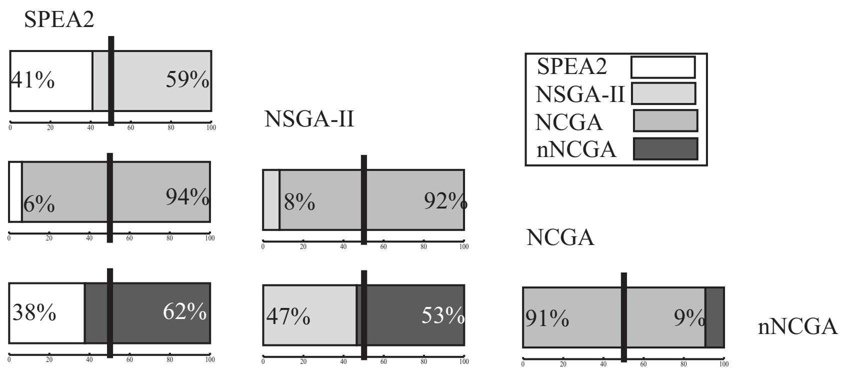

Figure 7: RNI of KUR

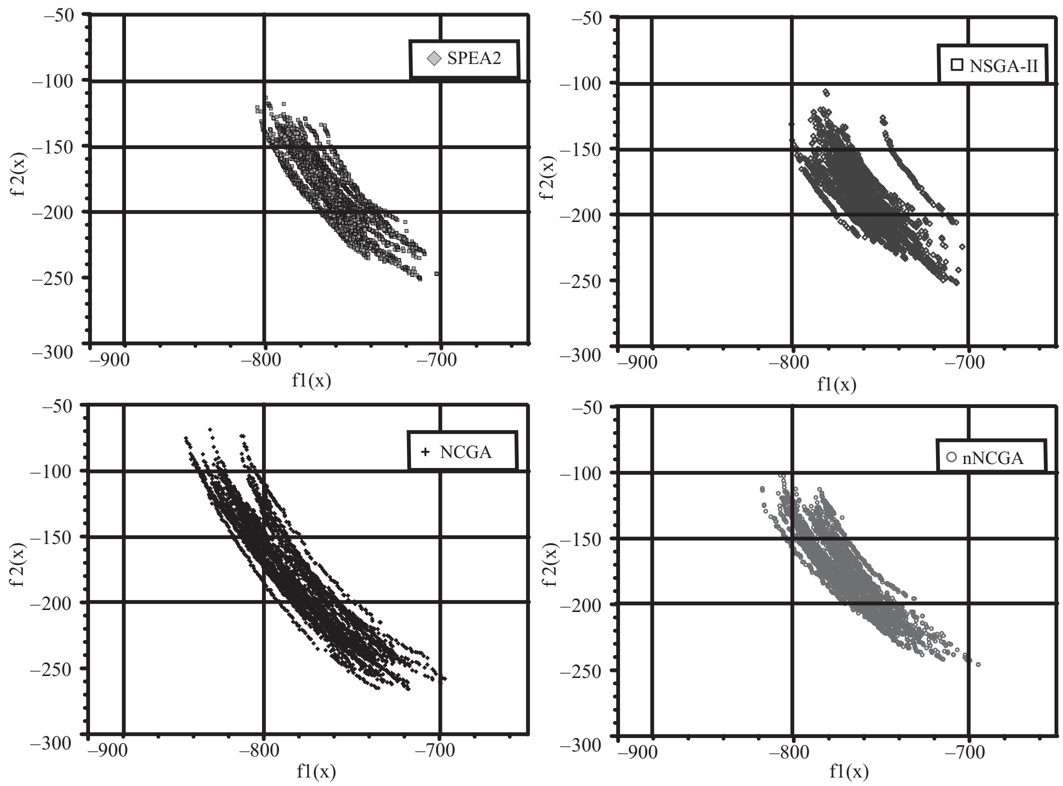

Figure 8: Pareto optimum individuals(KUR)

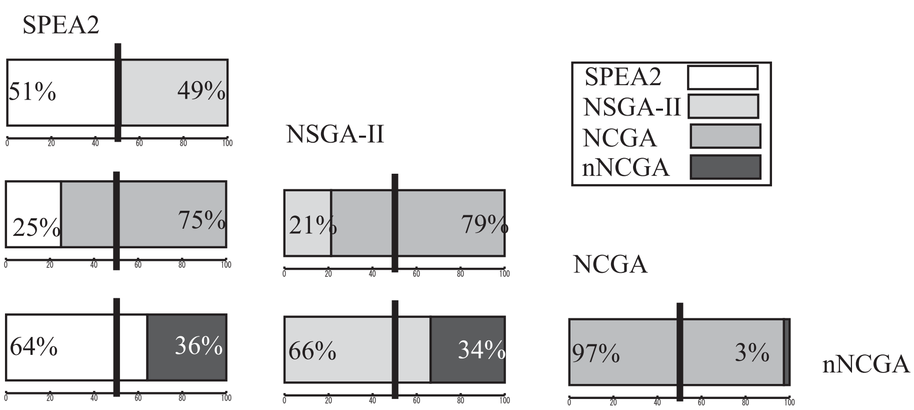

Figure 10: RNI of KP750-2

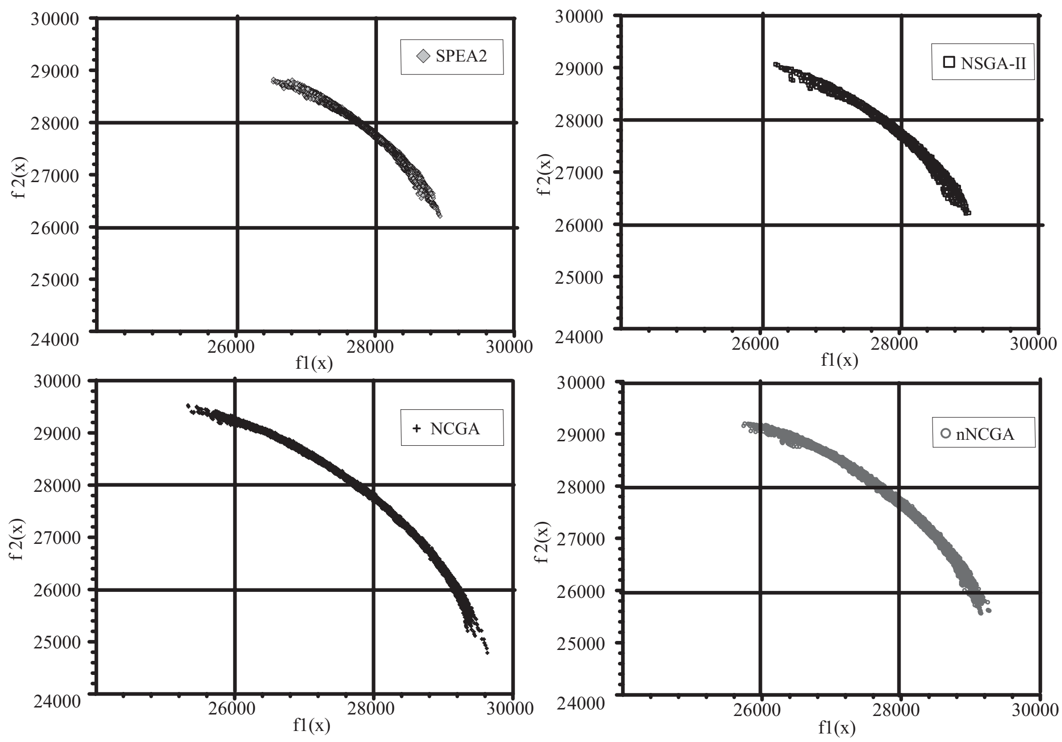

Figure 11: Pareto optimum individuals(KP750-2)

4.4.3 KP750-2

KP750-2 is the knapsack problem and it is very difficult to search the real Pareto-optimum solutions. The results of RNI and MMA are shown in figure 9 and 10. Figure 11 indicates Pareto solutions in KP750-2. In this figure, all the Pareto-optimum solutions that are derived in 30 trials are figured out.

From figure 9, NCGA found the wide spread solutions compared to the other methods. According to figure 10, the accuracy of the solutions of NCGA is better than those of the other methods. It is also concluded that the neighborhood crossover affects the good results in this problem.

5 Conclusion

In this paper, a new algorithm for multi-objective problems is proposed. The proposed algorithm is called "Neighborhood Cultivation Genetic Algorithm (NCGA)". NCGA has not only important mechanism of the other methods but also the mechanism of neighborhood crossover selection.

To discuss the effectiveness of the proposed method, NCGA was applied to test functions and results were compared to the other methods; those are SPEA2, NSGA-II and nNCGA (NCGA with no neighborhood crossover). Through the numerical examples, the following topics are made clear.

1) In almost all the test functions, NCGA derived the good results. Compared to the other method, the results are superior to the others. From this result, it can be noted that the proposed NCGA is good method in multi-objective optimization problems.

2) Comparing to NCGA using neighborhood crossover and NCGA using random crossover, the former is obviously superior to the latter in all problems. Therefore, the results emphasize that the neighborhood crossover acts to derive the good solutions.

3) Comparing to SPEA2 and NSGA-II, two methods have almost the same ability to find Pareto optimum solutions.

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