Parallel Evolutionary Multi-Criterion Optimization for Block Layout Problems

Sinya WATANABE
sin@mikilab.doshisha.ac.jp

Tomoyuki HIROYASU
tomo@is.doshisha.ac.jp

Mitsunori MIKI
mmiki@mail.doshisha.ac.jp

Department of Knowledge Engineering and Computer Sciences
Doshisha University
1-3 Tatara Miyakodani Kyotanabe-shi, Kyoto, 610-0321, JAPAN

Abstract *In this paper, a parallel evolutionary multi-criteria optimization algorithm: DGA and DRMOGA are applied to block layout problems. The results are compared to the results of SGA and discussed. Because block layout problems are NP hard and can have several types of objectives, these problems are suitable to evolutionary multi-criterion optimization algorithms. DRMOGA is a DGA model that can derive good Pareto solutions in continuous optimization problems. However it has not been applied to discrete problems. In the numerical example, the Pareto solutions of the block layout problem with 13 blocks were derived by DGA, DRMOGA and SGA. It was confirmed that it is difficult to derive the solutions with any model, even if the problem has only one objective. It is also found that good parallel efficiency can be derived from both DGA and DRMOGA. The results of Pareto solutions of DGA and DRMOGA are almost the same. However, DRMOGA searched a wider area than that of DGA.*

Keywords: Genetic Algorithms, Multi-criterion problems, Parallel processing, Layout problems

1 Introduction

In real world problems, many problems with several types of objectives have been found. These kinds of problems are called multi-criterion or multi-objective problems. Since there are often trade-off relationship between the objective functions, a simple solution cannot be derived. Therefore, to find the final solution, the decision must be made. In the multi-criterion problems, some preferences have to be determined to do the decision making. It is said that the preferences can be expressed a priori, a posteriori or in an interactive way [1]. In the posteriori way, Pareto optimum solutions can derive the preferences. Since Pareto optimum solutions are assembly of the solutions, evolutionary algorithms (EAs) are often used to find Pareto solutions. EAs are the multi-points searching algorithms, and this point is suitable to find Pareto solutions.

There are several algorithms for finding Pareto optimum solutions in EAs. These algorithms are well summarized in some reviews [2,3,4]. These algorithms are called Evolutionary Multi-criterion Optimizations (EMOs). Among the algorithms, VEGA[5], MOGA[6], NPGA[7] and NSGA[8] are the typical approaches. These algorithms can all derive good Pareto optimum solutions. However, the calculation cost is high, since many iterations are required to calculate the values of objective functions and constraints. One of the solutions to reduce the calculation costs is to perform the multi criterion EAs in parallel processing.

There are few studies concerned with the proposition of the models of EAs in parallel. However there is one model where the evaluation parts are performed in parallel [9]. In this model, there is only population is called one population model or simple genetic algorithm (SGA). There is another model where the total population is divided into sub-populations and the multi objective optimization is performed in each sub-population [10]. This model is called sub-population model or distributed genetic algorithm model (DGA). We also proposed a new model of EA in parallel; that is called Divided Range Multi-Objective Genetic Algorithm (DRMOGA) [11]. In the DRMOGA, the population is sorted by the values of one objective. Then the population is divided into sub-populations with respect to the sorted values. The DRMOGA is applied to some test functions and it is found that the DRMOGA is an effective model for continuous multi-objective problems.

In this paper, the DGA and the DRMOGA are applied to discrete problems, and their effectiveness is discussed. Specifically, block layout problems were selected as discrete problems to examine. Block layout problems can be found in the setting problem of plant facilities or LSI layout problems. Because block layout problems are NP hard and can have several types of objectives, these problems are suitable to evolutionary multi-criterion optimization algorithms. However, most of the test functions that are used in the studies concerned with EMO are continuous problems. Specifically, parallel models of EMOs have not been applied to block layout problems, while some researchers focused on the single object problem of layout problems [12]. Therefore, the parallel model of EMOs are applied to block layout problems and discussed. In this paper, the parallel models of EMOs and the configuration of GAs for block layout problems are explained briefly.

2 Parallel EMO

In this chapter, the definition of Multi-criterion optimization problems is defined briefly. There are several models of Evolutional algorithms for Multi-criterion Optimization (EMO). The parallel models of EMO are roughly classified into two categories; those with a one population model and those with a sub-population model.

2.1 Multi-Criterion Optimization Problems

In the optimization problems, when there are several objective functions, the problems are called the Multi-objective or Multi-criterion Optimization Problems: MOPs.

In general multi-objective optimization problems are formulated as follows:

$$min[f_1(x), f_2(x), \ldots, f_n(x)] \qquad (1)$$

$$subjecttog_i(x) \leq 0 \qquad (1, 2, \ldots, m) \qquad (2)$$

where $x \in F$ is the design variables and F is the domain that satisfies the constraints and is called the feasible domain.

Usually, there are trade off relations between the objective functions. Therefore there may be more than one optimum solution. In this case, the concept of the Pareto optimum solution is introduced in the multi objective optimization problems [13].

1. **Pareto dominant:**

   When $x^1 \in F$ and $x^2 \in F$ satisfy $f_i(x^1) \leq f_i(x^2)$ for all of the objective functions and f_i and satisfy $f_i(x^1) \in f_i(x^2)$ for some of the objective functions f_i, x^1 is dominant to x^2.

2. **Pareto optimum solutions:**

   When $x^1 \in F$ does not exist that dominant to x^0, x^0 is the Pareto optimum solution.

In real world problems, multi objective optimization problems are often found, such as the design problems. In these problems, the objective optimizations have a trade-off relationships. Usually, this relationship is not clear. Thus, when the relation can be grasped, the problem becomes easier for the designers. Deriving the Pareto optimum solutions is one of the goals in the multi objective optimization problems.

2.2 SGA

In GAs, there are several genetic operations. Among them, evaluation operation usually takes considerable computing time. Therefore, it can be said that it is efficient to perform evaluation operation in parallel. This is a single population model.

2.3 DGA

Distributed Genetic Algorithm (DGA) is one of the typical models of parallel genetic algorithms. In the DGA, the population is divided into sub-populations. In each sub-population, simple GA is performed for several iterations. After some iterations, some individuals are chosen and move to another island. This operation is called migration. The interval between iterations is called migration interval and the number of migrating individuals is determined by multiplying the number of individuals in the sub-population by migration rate. The migration keeps the diversity of the solutions even when there are few individuals in a sub-population. Since the network traffic is light, this model is very suitable to parallel processing. On the other hand, when this model is applied to multi-criterion problems, some wasteful calculation is produced, because some sub-populations might find the same Pareto solutions.

2.4 DRMOGA

Divided Range Multi-Objective Genetic Algorithm: DRMOGA was developed by Hiroyasu et al [11] and this is another model of parallel DGAs. This model is also suitable for parallel processing and can reduce the wasted calculation.

The flow of Distributed Range Multi-Objective Genetic Algorithm is explained as follows.

- **Step 1** The initial population (population size is N) is produced randomly. All the design variables that are derived from the individuals satisfy the constraints.

- **Step 2** The individuals are sorted by the values of focused objective function f_i . This focused objective function f_i is chosen in turn, and selected based on the loop iteration. N/m individuals are chosen in accordance with the value of this focused objective function f_i . As a result, there are m sub-populations.

- **Step 3** In each sub-population, the multi-objective GA is performed for some iterations. The multi-objective GA that is used in this paper is explained in the next section. At the end of each generation, the terminal condition is examined and the process is terminated when the condition is satisfied. If the terminal condition is not met, the algorithm proceeds to the next step.

- **Step 4** After the multi-objective optimization has been performed for k generations, all of the individuals are gathered (virtually). Then the algorithm jumps back to Step 2. This generation k is called the sort interval.

In this study, the distribution number, m, and the sort interval k are determined in advance. In Figure 1, the concept of the DR-MOGA is shown. In Figure 1, there are two objective functions. Individuals are divided into three by the value of the focused objective function f_1.

The sub-population of the DRMOGA is determined by the area with respect to the focused objective function. Therefore, the operation of dividing individuals can be same as

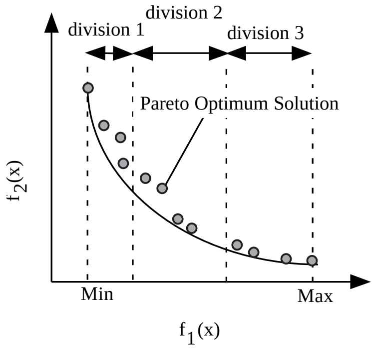

Figure 1: DRMOGA

the sharing. The derived Pareto optimum solutions of the DRMOGA might have the high diversity.

3 Formulation of Layout Problems and Configuration of Genetic Algorithm

3.1 Formulation of Block Layout Problems

In this paper, parallel GA models are applied to 2D Block layout problems. It is assumed that all of the blocks are rectangles and there are two objectives as follows:

$$f_1 = \sum_{\substack{i=1 \\ i \neq j}}^{n} \sum_{j=1}^{n} c_{ij} d_{ij} \quad (3)$$

$$f_2 = \textbf{Total Area} S \quad (4)$$

where
n :number of blocks
c_{ij}:flow from block i to block j
d_{ij}:distance from block i to block j .

These objectives are often found in block layout problems. The first objective function is the weighted distance and second one is the area. In [12], a trade-off relationship was found between these 2 objectives. This paper also assumes that three lines of the base on which the blocks are layout have been determined in advance. The block are numbered at first and the blocks are packed in accordance with these numbers. The concept of this packing method is shown in Figure 2.

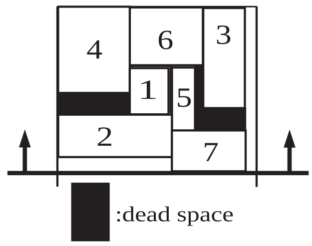

Figure 2: Packing Method

3.2 Expression of Solutions

In this paper, a block packing method is used. In this method, the chromosome has two kinds of information; those are block number and the direction of a block layout. An example is shown in Figure 3.

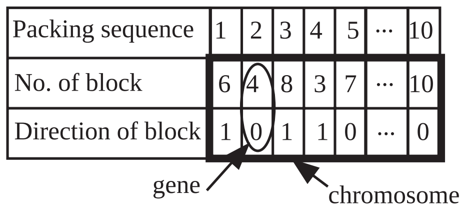

Figure 3: Coding of block layout problems

When the direction number is equal to 0, the block is placed in horizontal way and when it is 1, the block is placed in vertical way.

3.3 Configuration of Genetic Algorithm

In each sub-population of the DRMOGA, the serial genetic algorithm is performed. In the GA, there are several genetic operations; those are selection , crossover and mutation.

3.3.1 Selection

In the selection operation, there are several strategies. First of all, all of the individuals that are rank 1 are preserved. When the number of the individuals has excessed the maximum population size, the number of individuals is shrunk by roulette selection. The fitness value for roulette selection of each individual is determined by the sharing operation in this case. When the number of the individuals has not excessed the population size, the rest of the individuals are determined by the roulette selection. The fitness value for roulette selection of each individual is determined by the ranking in this case.

3.3.2 Crossover

In this paper, the PMX method is used in crossover operation [14]. PMX was originally developed for TSP problems.

3.3.3 Mutation

In this paper, 2 bit substitution method is used in mutation operation. In the mutation operation, 2 bits are selected arbitrarily and these bits are substituted.

4 Numerical Examples

To discuss the effectiveness of parallel models in block layout problems, SGA, DGA and DRMOGA models were applied to layout problems that have 13 blocks [15]. To find the solutions, a PC cluster with Pentium II 400MHz nodes and 128M byte memory was used. DGA and DRMOGA have 4 sub-populations and each population is applied to one node.

The PMX method was used for the crossover operator and 2 bit substitution method was used in mutation operation. Each subpopulation had 400 individuals. Therefore, there were totally 1600 individuals. When the generation exceeded the 300 generation, simulations were terminated. Migration interval or sort interval were 5, 10, 15 and 20.

In Figure 4, 5 and 6, the derived individuals of SGA, DGA and DRMOGA were shown in the respective objective fields. The migration or sorting interval of these figures is 10. In this example, the 1600 individuals are used. In these figures, the best 100 solutions are shown.

Because of the second object function, there are only weak Pareto solutions. For objective function f_2, the layout which does not have any

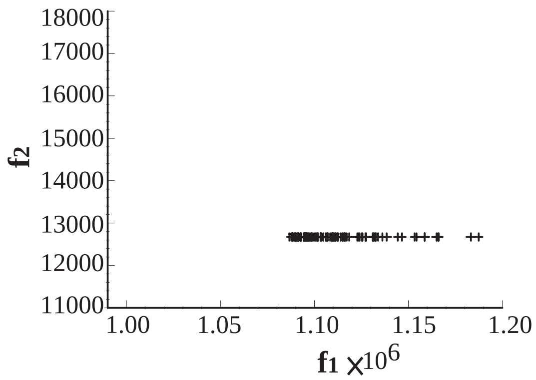

Figure 4: Results of SGA

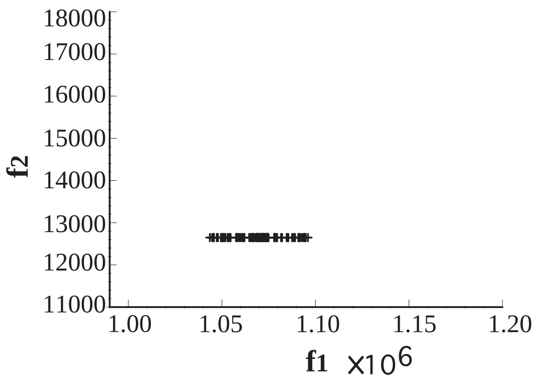

Figure 5: Results of DGA

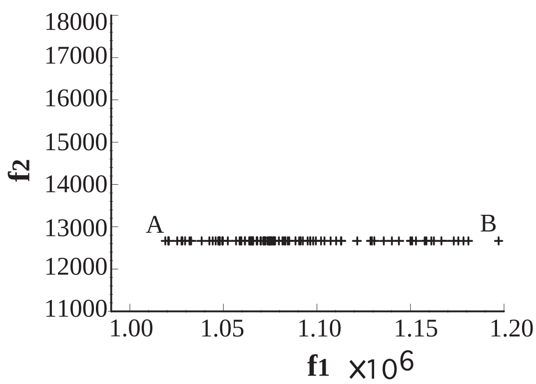

Figure 6: Results of DRMOGA

dead space is the optimum. Among three models, it was found that the DRMOGA searched in wider area compared to the results of the other models. This result is the same as those of [11] whose test functions are the continuous problems. Therefore, it can be said that DRMOGA can search efficiently in discrete problems.

The examples of layouts of point A and B in Figure 6 are shown in Figure 7 and Figure 8. Though, the values of f_2 are the

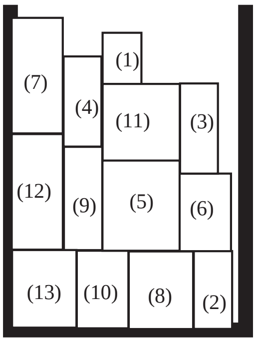

Figure 7: Derived Layout (A)

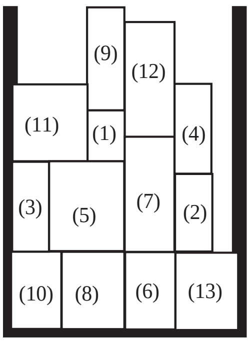

Figure 8: Derived Layout (B)

same, it is found that there are several layouts are derived. Therefore, it is very useful to use multi-criterion optimization for block layout problems.

When the migration or sorting interval is equal to 20, DGA takes 183.7 secs and DRMOGA takes 185.6 secs, while SGA takes 726.3 secs. Therefore, the parallel efficiencies of both DGA and DRMOGA are almost 100%. Compared to DGA, the network traffic of DRMOGA is higher. However, the differences between the traffic for DGA and DRMOGA was not very large. In this case, only small number of Pareto solutions were derived. Therefore, the same individuals did not existed in the sub-populations of DGA and the calculation wastes do not occur. It can be said that when a large number of Pareto solutions are derived, DRMOGA is also useful in block layout problems.

5 Conclusions

Block layout problems can be found in setting problem of plant facilities or LSI layout problems. Because block layout problems are NP hard and can have several types of objectives, these problems are suitable to evolutionary multi-criterion optimization algorithms.

In this paper, two types of parallel models were compared, and results are examined. Those two models are sub-population model (DGA) and divided range multi-objective genetic algorithm model (DRMOGA).

Through the numerical example that has 13 block and whose objectives are layout area and weighted distance, the following things are clarified.

- We used PMX method in crossover and 2 bit substitution method in mutation. These operations can not derive good Pareto solutions.
- The parallel efficiencies of DGA and DRMOGA are both high.
- The solutions of DGA have higher accuracy and diversity.
- DRMOGA searched a wider area.

The following future trials should be needed.

- The problems that have other types of objectives are discussed.

- The number of individuals or migration interval is the parameters and these parameters might affect the results. The effect of these parameters should be examined.

acknowledgement

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