Parallel Evolutionary Multi-Criterion Optimization for Block Layout Problems

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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. It is said that block layout problems are NP hard problems and there are several types of objectives. Therefore, it can be said that the block layout problems are suitable to evolutionary multi-criterion optimization algorithms. DRMOGA is one of the DGA models. This model can derive good Pareto solutions in continuous optimization problems. However it has not applied to discrete problems. In the numerical example, the Pareto solutions of the block layout problem who has 13 blocks are derived by DGA, DRMOGA and SGA. Then it is confirmed that it is difficult to derive the solutions with any model, even in 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 same. However, DRMOGA searched wider area than that of DGA.*

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

1 Introduction

In the real world problems, it is often found the problems that have several types of objective functions. These kinds of problems are called multi-criterion or multi-objective problems. Since there are often trade-off relationship between the objective functions, it can not derive the simple solution. Therefore, to find the final solution, the decision making should be needed. 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 assembles of the solutions, evolutionary algorithms (EAs) are often uses to find Pareto solutions. EAs are the multi points searching algorithms, so to have high compatibility to find Pareto solutions at one trial.

There are several algorithms to find 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. Like this way, there are several models of multi criterion EAs and they can derive the good Pareto optimum solutions. However, it needs the high calculation cost, since it needs a lot of iterations to calculate the values of objective functions and constrains. One of the solutions to reduce the calculation costs is to perform the multi criterion EAs in parallel processing.

There are not so many studies that concerned with the proposition of the models of EAs in parallel. There is a model where the evaluation parts are performed in parallel [9]. In this model, there are only one population and this model 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 the new model of EA in parallel; that is called Divided Range Multi-Objective Genetic Algorithm (DRMOGA) [11]. The DRMOGA is one of the divided population models and a population is divided into sub populations. In the DRMOGA, the population is sorted with 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 effective model for continuous multi-objective problems.

In this paper, the DGA and the DRMOGA are applied to discrete problems, and their effectiveness and their availability are discussed. Especially, block layout problems are selected as discrete problems. Block layout problems can be found in setting problem of plant facilities or LSI layout problems. It is said that block layout problems are NP hard problems and there are several types of objectives. Therefore, it can be said that the block layout problems are suitable to evolutionary multi-criterion optimization algorithms. However, the test functions that are used in the studies that are concerned with EMO are almost continuous problems. Especially, parallel models of EMOs have not 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. The discussion is performed through the numerical example that has 13 blocks.

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 are one population model and 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.

The multi objective optimization problems are formulated as follows. In general,

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

$$subjectto g_i(x) \leq 0 \qquad (1, 2, \dots, m) \qquad (2)$$

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 the optimum solution is not only one. 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 the real world problems, the multi objective optimization problems are often found, such as the design problems. In these problems, the objective optimizations have the trade off relationships. Usually, these relation is not clear. Thus, when the relation can be grasped, the problem turns easily for the designers. Then, the 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 a lot of time. Therefore, it can be said that it is efficient to operate evaluation operation in parallel. This is one of the one population models.

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 the other island. This operation is called migration. The interval of iterations is called migration interval and the number of migrate individuals is determined by multiple individuals of sub population and migration rate. The migration keeps the diversity of the solutions even when there are not so many individuals in a sub population. Since the network traffic is not so heavy, this model is very suitable to parallel processing. On the other hand, when this model is applied to multi-criterion problems, some calculation wastes are produced, because some sub populations might find the same Pareto solutions.

2.4 DRMOGA

Divided Range Multi-Objective Genetic Algorithm: DRMOGA is 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 calculation waste.

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

- **Step 1** Initial population (population size is N) is produced randomly. All the design variables that are shown with 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 turned with the loop. Then, the individuals of number N/m are chosen in accordance with the value of this focused objective function f_i . As the result, there exist m sub populations.

- **Step 3** In each sub population, the multi-objective GA has been performed for some iterations. The multi-objective GA that is used in this paper is explained in the next section. The end of each generation, the terminal condition is examined and the process is terminated when the condition is satisfied. When the terminal condition is not satisfied, the process progress into 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 process is going back to Step 2. This generation k is called the sort interval.

In this study, the number of distribution m and the sort interval k is determined in advance. In Figure 1, the concept of the DRMOGA 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.

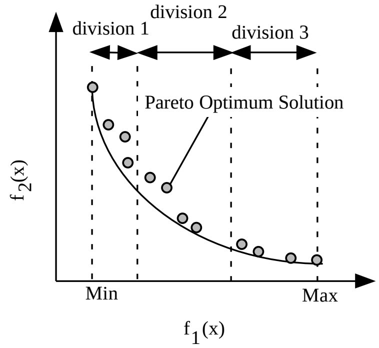

Figure 1: DRMOGA

The sub population of the DRMOGA is determined by the area with respect to the focused objective function. This mechanism is supposed to functions as the sharing. Therefore, 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 supposed that all of the blocks are rectangles and there are two objectives as follows,

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

$$f_2 = \textbf{Total Area} S \tag{4}$$

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 find in block layout problems. First objective function is the weighted distance and second one is the area. It is said that there is trade off relationship [12]. This paper also assumes that three lines of the base on which the blocks are layout have been determined in advance. When the order of the blocks are determined, the blocks are packed in accordance with the order. The concept of this packing method is shown in Figure 2.

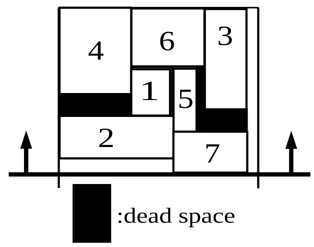

Figure 2: Packing Method

3.2 Expression of Solutions

In this paper, the 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.

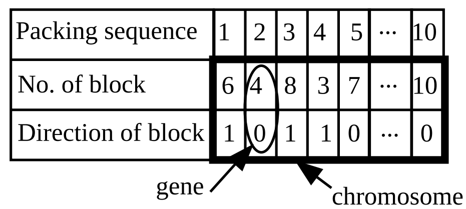

Figure 3: Coding of block layout problems

When the number of direction 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, genetic algorithm is performed. In GA, there are several genetic operations; those are selection , crossover and mutation.

3.3.1 Selection

In the selection operation, there are some strategies. First of all, all of the individuals that are rank 1 are preserved. When the number of the individuals are excessed the population size, the number of individuals are shrunk by roulette selection. The fitness value for roulette selection of each individual is determined by the sharing in this case. When the number of the individuals is 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, PMX method is used in crossover operation [14]. PMX is originally developed for TSP problems.

3.3.3 Mutation

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

4 Numerical Examples

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

PMX method is used in crossover operator and 2 bit substitution method are used in mutation operation. Each sub population has 400 individuals. Therefore, there are totally 1600 individuals. When the generation excesses the 300 generations, simulations are terminated. Migration interval or sort interval is 5, 10, 15 and 20.

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

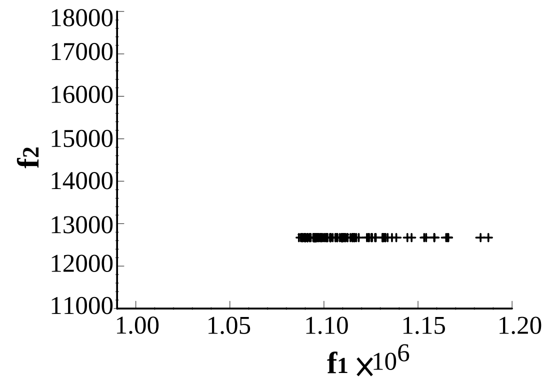

Figure 4: Results of SGA

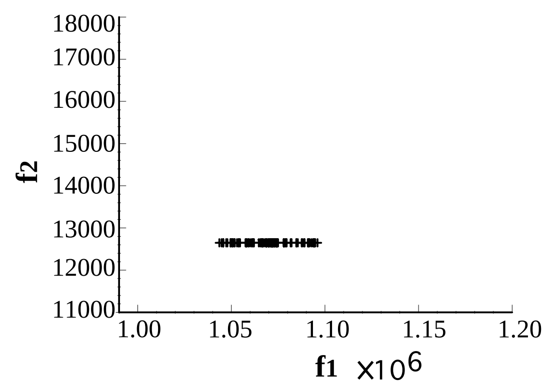

Figure 5: Results of DGA

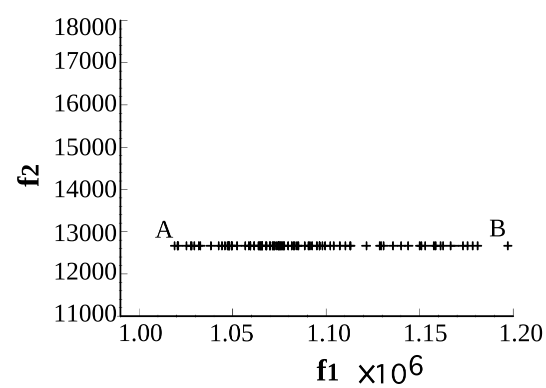

Figure 6: Results of DRMOGA

Because of the second object function, there are only weak Pareto solutions. For objective function f_2, the layout which does not have any dead space is the optimum. Among three models, it is found that the DRMOGA searched in wider area compared to the results of the other models. This result is the same as that of 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

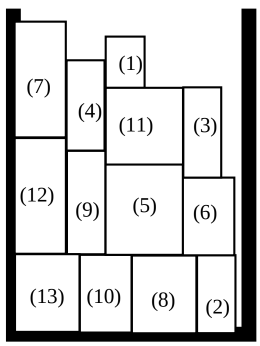

Figure 7: Derived Layout (A)

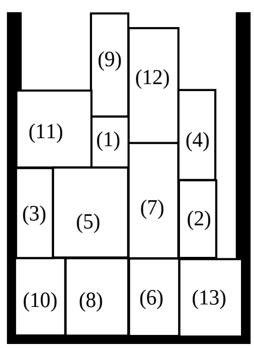

Figure 8: Derived Layout (B)

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 migration or sorting interval is equal to 20, DGA takes 183.7 [s] and DRMOGA takes 185.6 [s], while SGA takes 726.3 [s]. Therefore, the parallel efficiencies of both DGA and DRMOGA are almost 100%. Compared to DGA, the network traffic of DRMOGA is bigger. However, there are not so big differences between the DGA and DRMOGA. In this case, only small number of Pareto solutions derived. Therefore, the same individuals do 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. It is said that block layout problems are NP and there are several types of objectives. Therefore, it can be said that the block layout problems are suitable to evolutionary multi-criterion optimization algorithms.

In this paper, two types of parallel models are 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 DDRMOGA are both high.
- The solutions of DGA have higher accuracy and diversity.
- DRMOGA searched in 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 to the results. The effect of these parameters should be examined.

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