EVOLUTIONARY METHODS FOR DESIGN, OPTIMISATION AND CONTROL
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PARALLEL EVOLUTIONARY MULTI-CRITERION OPTIMIZATION FOR MOBILE TELECOMMUNICATION NETWORKS OPTIMIZATION

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Abstract. In this paper, we propose a new type of parallel genetic algorithm model for multi objective optimization problems. That is called a "Master-Slave model with Local Cultivation model (MSLC)". To clarify the characteristics and effectiveness of this model, the proposed model and the various EAs are applied to solve an antenna arrangement problem of mobile telecommunication. Thorough this problem, advantages and disadvantages of these models are made clarified.

Key words: Parallel Distributed Algorithms, Evolutionary Multi-Criterion Optimization, Mobile Telecommunication Netoworks Optimization

1 INTRODUCTION

These days, most super computers are parallel computers. Evolutionally computations (ECs) are the applications that have parallelism implicitly.[1] Therefore, the models of parallel ECs are very important. However, there are few studies that are related to parallel models of GAs for multi objective optimization problems (MOPs).

In this paper, we propose a new model of parallel genetic algorithm model for multi objective optimization problems. That is called a "Master-Slave model with Local Cultivation model (MSLC)". This model is an expanded model of the original master slave model to parallel multi objective GAs to gain higher diversity of the solutions.

To clarify the characteristics and the effectiveness of these models, we applied them to an antenna arrangement problem of mobile telecommunication. Through this problem, advantages and disadvantages of these models are made clarified.

2 Parallel EMO

There are several models of Evolutional algorithms for Multi-criterion Optimization (EMO).[2] The parallel models of EMO are roughly classified into three categories; those are a master-slave population model, an island model, and a cellular model.

In an island model that is also called Distributed GA (DGA), a population is divided into sub populations. In each island, normal GA is performed for several iterations. After that, some individuals are chosen and moved to the other islands. This operation is called a migration. After the migration, GA operations are started again in each island. Since the network traffic is not huge and each island has the small number of individuals, an island model can gain the high parallel efficiency but cannot derive the good solutions.

To find good solutions in an island model, we developed a new model of an island model that is called a Divided Range Multi Objective Genetic Algorithm model (DRMOGA).[3] Though this is one of island models, this algorithm can keep the high diversity and can derive good solutions.

On the other hand, there are lots of studies of the master slave model. However, the most of them are very simple. In the following section, we introduced the new master slave model of EMO.

3 A Master-Slave model with Local Cultivation model

In this study, we propose a new master slave model for MOPs called a Master-Slave model with Local Cultivation (MSLC) model. The proposed model is expanded from the original master slave model to parallel multi objective GAs to gain higher diversity of the solutions. As the proposed model is one of the master slave models, there are a few master processes and several slave processes.

In this model, two individuals are randomly chosen and send to the slave. The most of GA operators are performed with a pair of two populations. It is important that the most of GA operators are practiced in slave processes. The master process mainly works on controlling the populations.

In MSLC, GA operations are modeled on minimal generation gap (MGG) model.[4] In the proposed model, all the individuals are gathered in a master slave and they are re-ranked. Therefore, the normal generation is existed and this is different point from the MGG model.

The followings topics are the features of this model.

- It is easy to take the load balancing.
- The increase of the number of slave processors does not effect to the parallel efficiency.
- This model has the mechanism to keep the diversity of the solutions.

The concept of this new master slave model of parallel MOGA is shown in Fig.1.

4 Antenna arrangement problem of mobile telecommunication

We applied the proposed algorithm to antenna arrangement problem. This problem is proposed by Herve etc .[5]

This is a problem to find a number of antennas and sites, types, and a configuration of power parameter of the antennas. The antenna arrangement problem is hard and complex combinatorial problem. At the same time, when there are several objectives, this problem is a multi-objective optimization problem.

We give a formulation of the problem as follow.

Objectives

We define two main objectives of the problem:

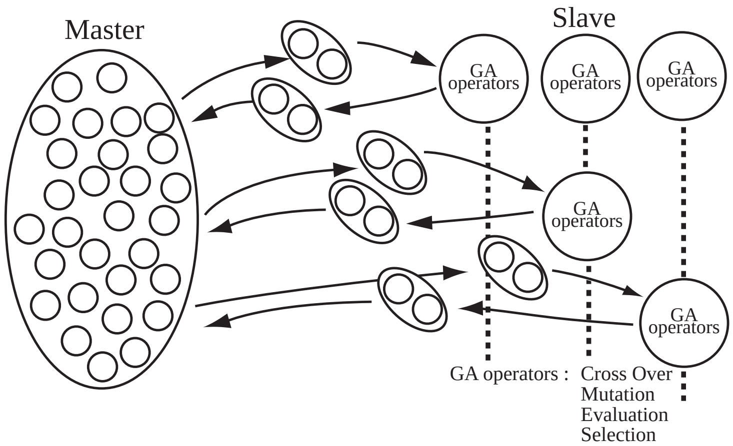

Figure 1: MSLC

- To maximize the cover the area
- To minimize the total cost of antenna

Constraints

We take account of three main constraints that have to be satisfied.

- Lower constrain of the area cover
- Lower constrain of the handover
- Upper constrain of the costs

The handover means that the ratio of overlapping borders between radio wave areas. The reason for setting this constrain is to make the continuous available.

5 Numerical Examples

To discuss the effectiveness and availability of parallel models in antenna arrangement problem, SGA[1], DGA, DRMOGA, and MSLC models are applied to the problem. In this numerical example, it is supposed that the antennas are in the square area and the area size of 50(m)$\times$50(m). Table.1 shows the used parameters of anntenas. In Table.1,the parameter of power means the radius of distance that radio wave of the antenna can reach.

Table 1: The kind of antenna power

Power(m)	Cost
10	100
15	250
20	500

To find the solutions, PC cluster consisted of 16 node of Pentium II 500MHz and 128M-byte memory is used. DGA and DRMOGA have 16 sub populations and each population is applied to one node.

5.1 Parameters and Cluster System

In this numerical example, the used parameters of GA are summarized in Table.1.

We have proved that number of sub populations (islands) has a dramatic effect on the solutions.[3] Therefore, in this study, the following 4 types of DGA and DRMOGA

[1]This algorithm is MOGA that is implemented by Fonseca and Fleming[1]

Table 2: Used parameters

	SGA	DGA	DRMOGA	MSLC
Population size	80			
Generations	100			
Crossover rate	1.0			
Mutation rate	0.0			
Migration interval (sort interval)	-	10		-
Migration rate	-	0.1	-	-

are applied. With these parameters, we discuss the influence of the number of sub populations to the derived solutions of these algorithms.

Table 3: Cases

Case	Number of sub populations
Case 1	2
Case 2	4
Case 3	8
Case 4	16

5.2 Performance Measures

In this study, two complementary measures are used to evaluate the trade-off fronts produced by the EAs. Those are *Cover Rate* and *Ratio of Non-dominated Individuals* : *RNI.*

Cover Rate (C): C is the index for the coverage of the Pareto optimum individuals. We derive $C(X)$ from the division space of objective domain. The division space is derived as follows; the area between the maximum and the minimum values of each object functions are divided into the certain number (N).

At first, $C_k(X)$ of one objective function(f_k) is mathematically formulated as follows.

$$C_k(X) = \frac{N_k}{N} \tag{1}$$

Where N_k is the number of the division area that has the Pareto optimum individuals. N is the division number.

$C(X)$ take the average of $C_k(X)$.

$$C = \frac{1}{M}\Sigma_{k=1}^{M} C_k \tag{2}$$

where M is number of the objectives.

The higher value of $C(X)$ means the larger the dominated volume in the objective domain. Hence, the better the solutions are derived in this case.

Ratio of Non-dominated Individuals (RNI): This performance measure is derived from comparing two Pareto solutions. RNI is derived from the following steps. At first, two populations from different methods are mixed. Secondly, mixed solutions are ranked again and the solutions whose rank is one are chosen. Finally, RNI of each methods 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 chosen solutions.

Table 4: RNI

	SGA	DGA	MSLC	DGA	SGA	DRMOGA	MSLC	DRMOGA
Case1	59%	41%	64%	36%	43%	57%	47%	53%
Case2	43%	57%	47%	53%	48%	52%	52%	48%
Case3	75%	25%	81%	19%	54%	47%	58%	42%
Case4	96%	4%	99%	1%	80%	20%	84%	16%

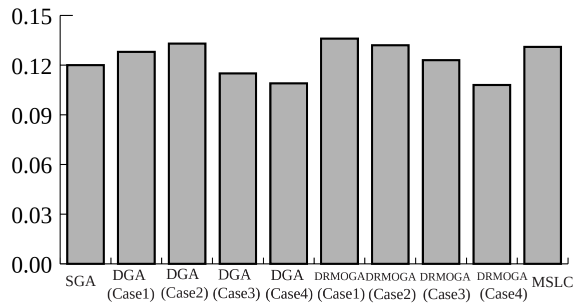

Figure 2: Cover rate

5.3 Experimental Results

The results of C are summarize in Fig.2 and the results of RNI are shows Table.4. Fig.3 shows one of the derived Pareto plots of each model.

Antenna arrangement problem is a difficult problem to find the pareto solutions, because the number of combinations are large and this problem also has some constraints.

From these results, it is obvious that the results of MSLC are better than those of the other methods. MSLC can get the better values of $Cover\ rate$ and RNI. In MSLC, all of the good solutions that are found in the searching process are preserved and the local selection is performed. These are the reasons that MSLC can better solutions than SGA.

In the most cases (except Case 2), DGA cannot get better solutions than SGA, DGA and MSLC. In DGA, the solutions are strongly affected by the number of subpopulations. In DGA, Case 2 can derive very good solutions, but other cases (especially in Case 3, 4) can't at all. From Fig.3, it is found that the solution of Case 4 of DGA is the worst solution of all.

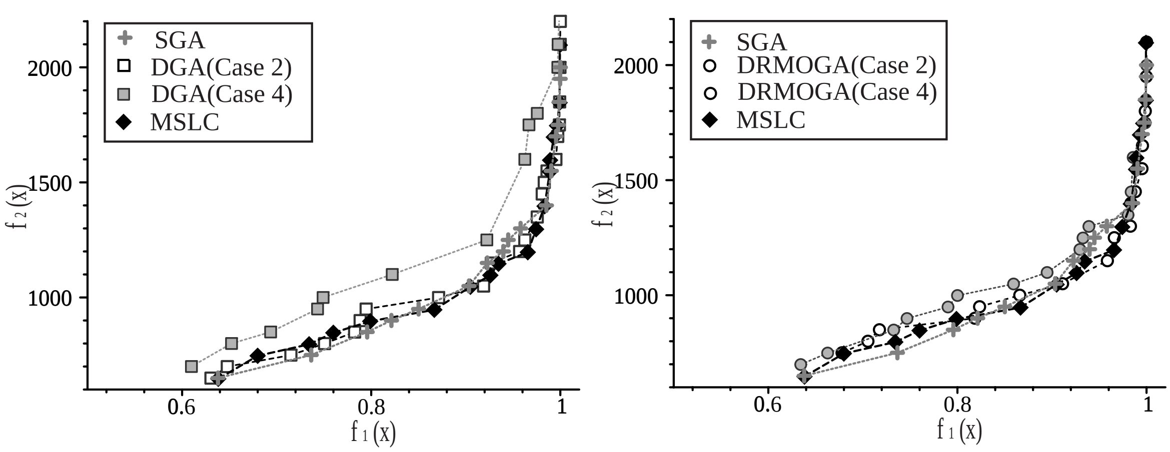

Figure 3: Pareto optimum individuals

On the other hand, when the results of DRMOGA are compared with those of SGA and MSLC. We can see that the results of DRMOGA have not been affected by the number of subpopulations. From Fig.3, the solutions of DRMOGA in any cases are not so different. DRMOGA cannot derive good solution in Case 4, since the number of subpopulation is too small. However, comparing to the results of DGA, those of DRMOGA are better. From the results of DGA and DRMOGA, there is the optimum number of subpopulations in these methods, and the solutions are strongly affected by this parameter.

6 Conclusions

We proposed a new parallel model of EMO: That is called a Master-Slave model with Local Cultivation model (MSLC). This model has mechanism to keep the diversity of the solutions and to preserve all of the good solutions that are found in the searching process. Therefore, it is possible to derive the good Pareto solutions. In the numerical examples, MSLC and the several EAs are applied to antenna setting problems. Through the numerical examples, the following are clarified.

- DRMOGA and MSLC can get better solutions than those of DGA.
- MSLC can get better solutions than those of SGA.
- The number of sub populations effects the solutions in island models (DGA, DRMOGA).
- The effect of the number of sub population of DGA is stronger than that of DRMOAG.

The searching ability of the proposed model was almost better than that of SGA and DGA in numerical examples.

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