Hierarchical Optimization Using Hierarchical Multi-competitive Genetic Algorithm and its Application to Multiple Vehicle Routing Problem

Shudai Ishikawa[1], Ryosuke Kubota[2] and Keiichi Horio[1]
[1]*Kyushu Institute of Technology, Kitakyushu, Japan*
[2]*Ube National College of Technology, Ube, Japan*

Keywords: Hierarchical Optimization, Genetic Algorithm, Multiple Vehicle Routing Problem, Multiple Solution Spaces.

Abstract: In this paper a new optimization technique which is effective for hierarchical optimization problem is proposed. This technique is an extension of the multiple-competitive distributed genetic algorithm (mcDGA). This method consists of two levels upper and lower. The solution space to be searched is determined at the upper level, and the optimum solution in a given solution space is determined at the lower level. The migration of the individual and competition is performed at the lower layer thereby optimal solution can be found efficiently. We apply the proposed hierarchical mcDGA to the mVRP to confirm the effectiveness. Simulation result shows the effectiveness of the proposed method.

1 INTRODUCTION

Some complex systems have hierarchical structure which is divided into multiple levels and optimization of such systems is known as hierarchical optimization. For example, suppose that the system is divided into two levels upper and lower. In the upper level, some solution spaces to be searched are determined and at the lower level, the optimal solutions are searched for each solution spaces which are determined in the upper level. Thus, optimal solutions at the lower level are reflected in the upper level. At the upper level, optimization is performed to determine the solution space to be searched based on the result of lower levels. By repeating this operation, the optimal solution of the whole system is obtained. The example of hierarchical optimization using multiple vehicle routing problem is shown in Figure 1. In this problem, a product is to be delivered to a customer by using a plurality of vehicles with minimized path of each vehicle. As shown in Figure 1, the allocation of customer for each vehicle is optimized at the upper level and the route is optimized at the lower level. In this situation, the problem of the hierarchical system, the searching space is reduced, and discovery of the solution is facilitated. However, when the optimal solution is not found at the lower level, it is difficult to find the optimal solution for the entire system. In addition, if much time is taken for calculation at the lower level, computational cost will be huge in amount.

The Vehicle Routing Problem (VRP) (Bernard and Hubert, 1959) is a problem that minimizes the delivery path between the distribution center and the customers. In recent years, the VRP has been attracted much attention and studied actively. Although the VRP is similar to the well-known Traveling Salesman Problem (TSP) (Flood, 1956), some constraints are taken into account in the VRP. For instance, the number of vehicles, the time windows (time scheduling), and the capacity of vehicles and so on (Laporte, 1992). Namely, the VRP is an extension of the TSP. In the VRP with multiple vehicles (mVRP), it is necessary to minimize the total delivery path of vehicles and therefore it is difficult to find the optimal solution because optimization of allocation for customers of each vehicle and the path of vehicles are performed at the same time. To facilitate the discovery of optimum solution, the method of determining the customer for each vehicle by clustering has been proposed (Sofge et al., 2002), (Nallusamy et al., 2009). In this method the discovery of the solution is facilitated because the solution space is reduced. However if some constraints such as the time window or the capacity of vehicles are added, this method cannot be applied. It is reported that this problem is solved by two interconnected Genetic Algorithms (GAs) (Potter and Bossomaier, 1995). In this method, at the upper level, a GA determines the allocation to customers of each vehicle and at the lower level a second GA for

Ishikawa S., Kubota R. and Horio K..
Hierarchical Optimization Using Hierarchical Multi-competitive Genetic Algorithm and its Application to Multiple Vehicle Routing Problem.
DOI: 10.5220/0005043202690274
In *Proceedings of the 11th International Conference on Signal Processing and Multimedia Applications* (SIGMAP-2014), pages 269-274
ISBN: 978-989-758-046-8

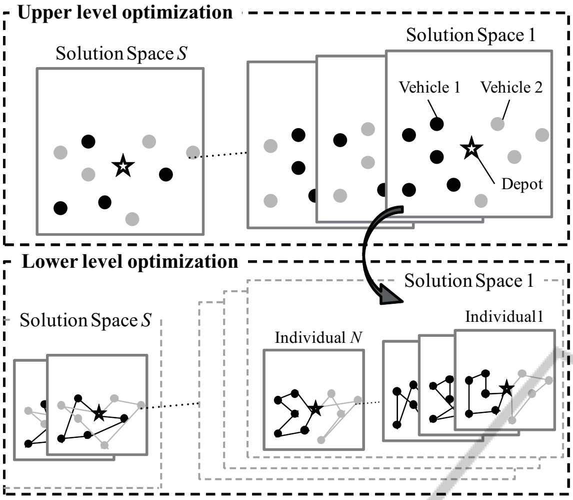

Figure 1: Conceptual diagram in case of mVRP to be the hierarchical structure.

each vehicle determines the shortest route of the customers allocated to the vehicles. This method is valid in solution search and difficult to set population size. If population size is too large, computational cost is more whereas if population size is too small, solution cannot be found stably at the lower level.

This proposed multi-space competitive distributed GA (mcDGA) (Ishikawa et al., 2011), competition is performed among different solution spaces, and the population size of the solution space is changed based on the result of the competition. The individual is added to the solution space which won the competition, and the individual is removed in loser. By repeating this process, the proposed method terminates the search of the solution space less likely to solution exists, and concentrates on the individuals for the solution space more likely solution exists. Namely, it is possible to improve the stability of finding optimal solution and reduce the computational cost.

This proposed hierarchical mcDGA is a stable and effective search method and we apply it to the mVRP a supposed hierarchical optimization problem. The proposed method performs not only the optimization of the individual but also the optimization of the solution space. Namely, in the proposed method, reducing the computational cost and improving the stability of discovery of the optimal solution in the lower level are expected. We apply the proposed method to the mVRP for two vehicles and try to show the effectiveness.

2 MULTIPLE-VEHICLE ROUTING PROBLEM

The multiple vehicle problem is an extension of the well-known vehicle routing problem, this problem consists of determining a set of routes for some vehicles. Generally, the prerequisites of the mVRP are as follows:

- The vehicles return to the depot after they leave the depot and visit customers.
- The positional coordinates of customers are given.
- The requirement of customers is filled by either vehicles visit only once.
- The distance of each delivery is calculated based on the Euclidean distance between customers.
- The total delivery distance is minimized.

In this paper, we consider two vehicles without its capacity.

3 GA AND MCDGA

3.1 GA

In nature the living things adapted by the environment, survive with high possibility and they have much opportunity to pass their genes on to their offspring. The GA, developed by John Holland in the 1960s (Holland, 1962), imitates the evolution of living things and this is one of powerful optimization algorithms. A problem to be solved and candidates for a solution are related to the environment and individuals respectively. The features of the GA are as follows: (1) a population that is a set of individuals is held (2) the individuals are evolved by genetic operators such as selection, reproduction, rearrangement and mutation (3) an evaluation of the environment is given to each individual and (4) the individuals whose evaluations are high survive with a high probability by selection and reproduction, whereas perturbation by rearrangement and mutation produces various kinds of individuals. In other words, in the GA, candidates for optimal solutions for the given problem are represented as coordinates in the solution space and the candidates search the optimal solution by re-genesis based on selection, reproduction, mutation and so on. The GA achieves local and global searches in the solution space by employing adequate genetic operators.

3.2 Multi-space Competitive Distributed GA

The mcDGA can be constructed as an extension of the DGA (Tanese, 1989) for multi-space solution search. Sub-populations are prepared in the corresponding solution spaces. Each sub-population searches an optimal solution in the corresponding solution space in accordance with the procedure of the GA. During the evolution, the mean value of the evaluations or the max value of the evaluations and so in each sub-population is calculated and their values are compared to each other. This operation is called "competition". The sub-populations are ranked based on the competition. The population sizes in the superior sub-populations increase, on the other hand, those decreases in the inferior ones. In particular, individuals are added in the sub-population with the highest evaluation and one individual is removed from the other sub-population. The individual to be added and to be removed is randomly chosen from each sub-population. This operation is called migration. The migration improves the search efficiency. The sub-population, which won the competition has the largest population size after the convergence and thereby it is easy to decide the correct solution space based on the population sizes. The GA and the DGA perform the parameter optimization. On the other hand, the mcDGA perform not only the parameter optimization(the solution) but also the model selection (solution space).

4 HIERARCHICAL MCDGA

In case of applying to the hierarchy problem with mcDGA, the system is divided into upper level and lower level. At the upper level, the allocation to customers of each vehicle is determined. At the lower level, the shortest route of a given allocation of customers in each vehicle is determined. In order to perform efficient search, the competition and the migration are conducted at the lower level. The solution which has determined at the lower level reflects to the upper level, and the new solution space will be determined based on the evaluation value of the solution at the lower level. The conceptual diagram and the simple flow of the hierarchical mcDGA are shown in Figure 1 and Figure 2. Generally, when GA is applied to both the upper level and the lower level, a large amount of computational cost is required. In addition, the discovery rate of the optimal solution at the lower level has a great influence on the discovery of optimal solution overall. However hierarchical mcDGA terminate the search of the solution space less likely to solution exists and also reduce the computational cost. Moreover the discovery rate of the optimal solution is improved by concentrating the individuals on the solution space more likely solution exists. Since it does not use a special method for genetic operators and representation of an individual, it is applicable to any hierarchical optimization problems.

5 SOLVING THE MVRP WITH HIERARCHICAL MCDGA

In case of solving mVRP with improved mcDGA, the representation of individuals is different from each other in the upper level and lower level. Therefore, different genetic operators are applied at the upper and lower level.

Representation. At the upper level the individuals are represented by a single genetic code with the vehicle number inserted into each gene and at the lower level the customer number inserted into each gene.

Fitness Function. Evaluation of the individuals is performed at only the lower layer, the evaluation function F is given by the follow;

$$F = \frac{1}{d_{max}}, \tag{1}$$

where, d_{max} is the maximum distance in all vehicles. This equation means the minimize The maximum distance of each vehicle.

Crossover. At the upper level a general crossover method which is used for the combinational optimization such as an one-point crossover and an uniform crossover is applied because the combination of the customer to be allocated to each vehicle. On the other hand, at the lower level, a crossover method which is devised for route optimization problems such as Partially Matched Crossover (PMX) (D.E.Goldberg, 1985), Cycle Crossover (CX) (I.M.Oliver, 1987) and Order Crossover (OX) (Davis, 1985) is applied. In this paper, an uniform crossover and PMX are applied at the upper level and lower level respectively.

Mutation. A normal mutation and gene sequence inversion are applied at the upper level and lower level respectively.

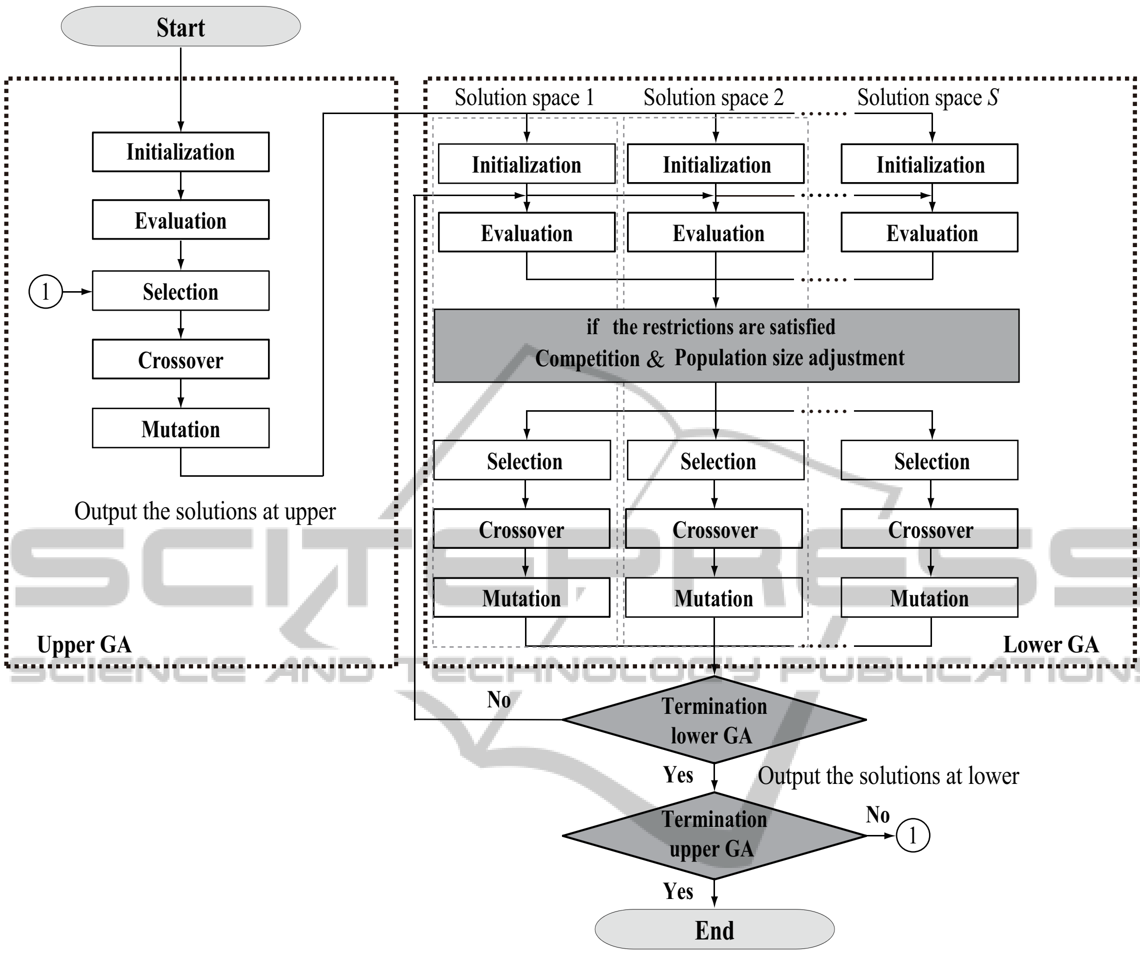

Figure 2: Flow of the hierarchical mcDGA.

6 SIMULATION AND RESULT

6.1 Simulation Setup

A computation experiment has been conducted to compare with two-level GA and confirm the efficiency of the proposed method. Table 1 shows the parameter of two-level GA and mcDGA used in computation experiment. These parameters were determined experimentally. In the two-level GA, population size set to 20 and 50, and the termination in the lower level set to 500 and 1000. i.e. we compared the experiments of four values for this proposed method. The number of customers set to 20. Parameter values for the hierarchical mcDGA are defined as follows. At the upper level, population size and terminate generation set to 10 and 30000 respectively. Crossover rate and mutation rate set to 0.8 and 0.3 respectively. At the lower level, initial population size set to 20 and 50 & terminate generation set to 500 and 1000. Crossover rate and mutation rate set to 0.8 and 0.1 respectively. In the competition, the maximum evaluation value of the solution space is compared. The migration is performed based on the update of the optimal solution and the generations. When the generation is more than 300 and the optimal solution of each solution space is updated, the migration is performed.

Table 1: Parameter of two-level GA and mcDGA.

		two-level GA	mcDGA
Upper level	Population size	10	
	Generation	30000	
	Crossover rate	0.8	
	Mutation rate	0.3	
Lower level	Population size	20, 50	adaptive
	Generation	500, 1000	1000
	Crossover rate	0.8	
	Mutation rate	0.1	

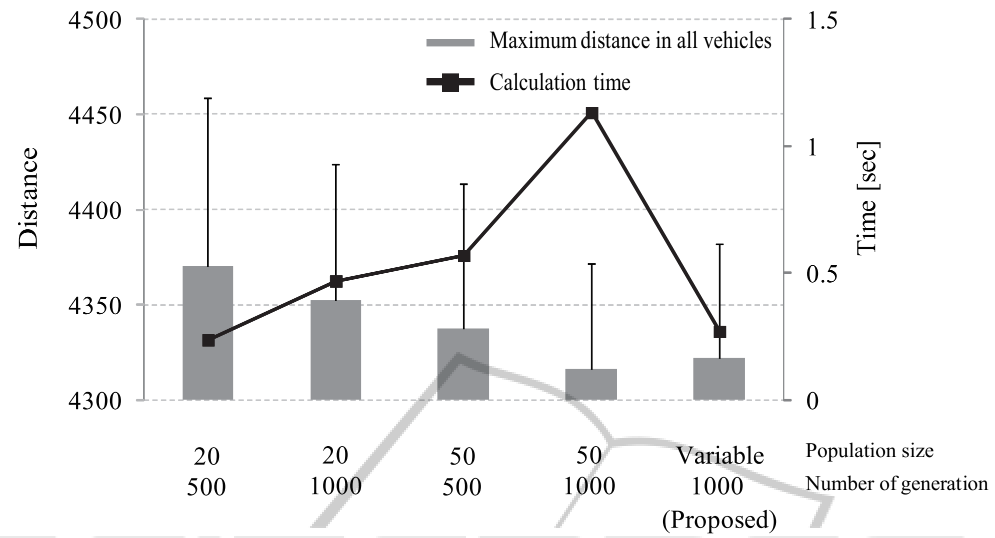

Figure 3: The result of simulation. The gray bar shows the maximum distance in all vehicles. The black dots show the calculation time.

When the generation is 300 to 500, the population size in the solution space of the upper half of the evaluation value is increased and the population size in the solution space of the lower half of the evaluation value is decreased, i.e. the solution space searched got narrows to half. Then, minimum and maximum population size of each solution spaces set to 0 and 30, respectively. When the generation is more than 500, the population size of the solution space which is increased the highest evaluation value, and the population size of the other solution space is decreased. Then, maximum population size of solution space set to 50. Namely, the solution space to be searched is narrowed to one. Then, minimum and maximum population size of each solution spaces set to 0 and 50 respectively.

6.2 Result and Discussion

The trial is performed 10 times. Figure 3 and Figure 4 show the result of the experiments.

In Figure 3, the bar graph shows the distribution and the average of the maximum distance of the vehicles , and line graph shows the calculation time which is required for one generation respectively. From Figure 3, If population size and generation are set to 20 and 500 respectively then calculation time is very short and stability of finding the solution is poor. On the other hand, If population size and generation are set to 50 and 1000 respectively, then calculation time is very long and stability of finding the solution is good. This proposed method is able to find the solution in short calculation time at the lower layer. Figure 4 is the best solution of the problem handled in this paper. The black stars and the light gray stars show the customer of vehicle 1 and vehicle 2 respectively. The black line and the light gray line show the route of each vehicle. From this result, it is shown that the probability of the discovery of the optimal solution has improved by collecting the individual to the solution space having high evaluation value. In other word, the competition and the migration at the lower level is effective in finding the optimal solution. Also it is shown that the proposed method is able to reduce the calculation time due to migration of individuals of small evaluation value to search solution space. Figure 5 shows the image of competition and migration. In Figure 5, the black and white ball show the winner and loser solution space respectively at the lower level. The number in each circle shows population

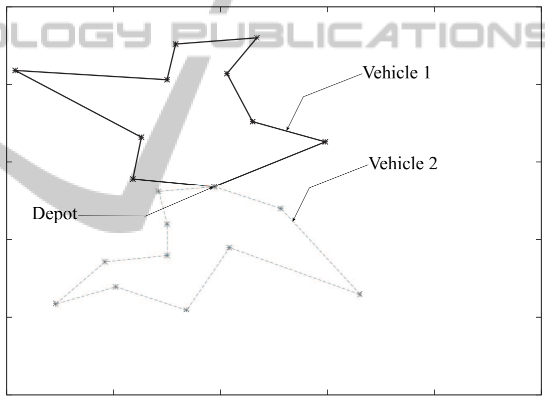

Figure 4: The best solution of this simulation. The black stars and the light gray stars show the customer of vehicle 1 and vehicle 2 respectively. The black line and the light gray line show the route of each vehicle.

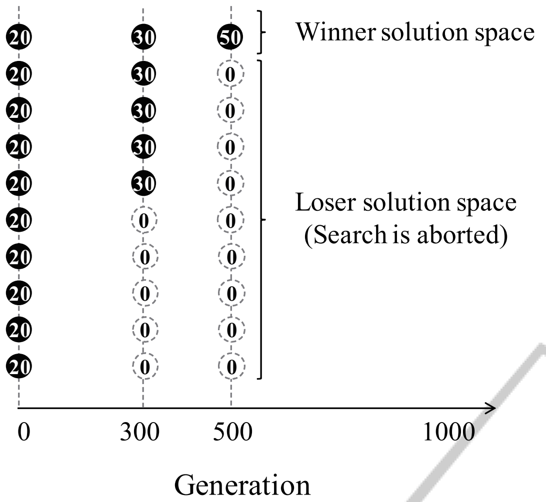

Figure 5: Image of the competition and the migration. The black and white ball show the winner and loser solution space at the lower level, respectively. The number in each circle shows the population size of each solution space. The number of balls is equal to the number of solution space to be searched.

size of each solution space. Let t be a calculation time per one generation. If population size and the terminate generation are set to 20 and 1000 respectively and the competition and the migration are not performed then total calculation time T_u will be calculated as below.

$$T_u = 20 \times 10 \times 1000 \times t, \quad (2)$$
$$= 2.0 \times 10^5 t. \quad (3)$$

On the other hand, in the proposed method, the total calculation time T_p is given by follows.

$$T_p = (20\times10\times300+30\times5\times200+50\times1\times500)t, \quad (4)$$
$$= 1.15 \times 10^5 t. \quad (5)$$

From the above equations, the calculation time can be significantly reduced in the proposed method was confirmed. From above results, it was shown that the proposed method is able to find the solution in short calculation time.

7 CONCLUSION

A new optimization method is proposed which is effective for hierarchical optimization problem also an extension of the multiple-competitive distributed genetic algorithm (mcDGA). This method consists of two levels upper and lower. The solution space to be searched is determined at the upper level, and the optimum solution in a given solution space is determined at the lower level. The migration of the individual and competition is performed at the lower layer thereby optimal solution can be found efficiently. We applied the proposed hierarchical mcDGA to the mVRP to confirm the effectiveness and this method has shown good discovery accuracy and short computation time. Although the experimental validation is limited in this paper, it is not important for our study. Because we are aim to construct a generic optimization technique for any problem. In the future, we will not only consider timing and rules of migration but also apply the mcDGA for other problems, (e.g. traffic signal control, digital signal processing, image processing, etc).

REFERENCES

Bernard, D. G. and Hubert, R. J. (1959). The truck dispatching. *Management Science*, 6:80–91.

Davis, L. (1985). Applying adaptive algorithms to epistatic domains. *Proceeding of the International Joint Conference on Artificial Intelligence, IEEE Computer Society Press, Los Angeles*, pages 162–164.

D.E.Goldberg (1985). Alleles loci and the tsp. *Proceedings of the First International Conference on Genetic Algorithms and Their Application, Lawrence Erolaum, New Jersy*, pages 154–159.

Flood, M. M. (1956). The traveling-salesman problem. *Oper. Res.*

Holland, J. (1962). Outline for a logical theory of adaptive systems. *J. of the Association for Computing*.

I.M.Oliver, D.J.Smith, J. H. (1987). Proceedings of the second international conference , lawrence erolaum, new jersy. *A Study of Permutation Crossover Operator on the TSP*, pages 224–230.

Ishikawa, S., Misawa, H., Kubota, R., Tokiwa, T., Horio, K., and Yamakawa, T. (2011). Multi-space competitive dga for model selection and its application to localization of multiple signal sources. *Journal of Advanced Computational Intelligence Intelligent Informatics*, 15(9):1320–1328.

Laporte, G. (1992). The vehicle routing problem: An overview of exact and approximate algorithms. *European Journal of Operational Research*, 4:61–75.

Nallusamy, R., Duraiswamy, K., Dhanalaksmi, R., and Parthiban, P. (2009). Optimization of multiple vehicle routing. *International Journal of Engineering Science and Technology*, 1(3):129–135.

Potter, T. and Bossomaier, T. (1995). Solving vehicle routing problems with genetic algorithms. *IEEE international conference on evolutionary computing*.

Sofge, D., Schultz, A., and Jong, K. D. (2002). Evolutionary computational approaches to solving the multiple traveling salesman problem using a neighborhood attractor schema. *Lecture notes in computer science*, 2279:51–60.

Tanese, R. (1989). Distributed genetic algorithm. *Proc. of the Int. Conf. on Genetic Algorithms*, pages 434–439.