# A GENETIC ALGORITHM APPROACH TO OPTIMIZATION FOR THE RADIOLOGICAL WORKER ALLOCATION PROBLEM

# - DISCUSSIONS ON DIFFERENT HARD CONSTRAINTS -

Yan Chen,<sup>1</sup> Masakuni Narita,<sup>1</sup> Masashi Tsuji,<sup>1</sup> Sangduk Sa <sup>1,2</sup>

<sup>1</sup> Department of Nuclear Engineering, Hokkaido University, Sapporo, Japan,

#### INTRODUCTION

The worker allocation optimization problem in radiological facilities inevitably involves various types of requirements and constraints relevant to radiological protection and labor management. Some of these goals and constraints are not amenable to a rigorous mathematical formulation. Conventional methods for this problem rely heavily on sophisticated algebraic or numerical algorithms, which cause difficulties in the search for optimal solutions in the search space of worker allocation optimization problems.

Genetic algorithms (GAs) are stochastic search algorithms introduced by J. Holland in the 1970s based on ideas and techniques from genetic and evolutionary theories. The most striking characteristic of GAs is the large flexibility allowed in the formulation of the optimal problem and the process of the search for the optimal solution. In the formulation, it is not necessary to define the optimal problem in rigorous mathematical terms, as required in the conventional methods. Furthermore, by designing a model of evolution for the optimal search problem, the optimal solution can be sought efficiently with computational simple manipulations without highly complex mathematical algorithms.

We reported a GA approach to the worker allocation problem in radiological facilities in the previous study (2). In this study, two types of hard constraints were employed to reduce the huge search space, where the optimal solution is sought in such a way as to satisfy as many of soft constraints as possible. It was demonstrated that the proposed evolutionary method could provide the optimal solution efficiently compared with conventional methods. However, although the employed hard constraints could localize the search space into a very small region, it brought some complexities in the designed genetic operators and demanded additional computational burdens. In this paper, we propose a simplified evolutionary model with less restrictive hard constraints and make comparisons between the two models.

#### MODEL CONSTRUCTION

A simple test problem is specified as follows: a job is assumed to be accomplished when the required working time on the job is fulfilled. The predicted dose that a worker is exposed to is estimated by multiplying the Area Dose Rate (ADR) with the Working Time (WT):

Predicted Dose = ADR (mSv  $min^{-1}$ ) × WT (min).

- Input Conditions:
  - (A) 12 workers to be assigned to 5 jobs (each with one workplace) to accomplish the project.
  - (B) The Cumulative Dose for a worker before the assignment is CD[1-12] = 0.4, 2.2, 1.5, 0.7, 1.2, 0.0, 0.9, 0.0, 0.0, 0.2, 1.8, 0.0 mSv.
  - (C) The Area Dose Rate for a job is  $ADR[1-5] = 0.1, 0.02, 0.05, 0.04, 0.04 \text{ mSv min}^{-1}$ .
- Dose Limitations:
  - (D) Worker exposure should not exceed the Dose Limit, DL mSv. Here, DL is set to 5 mSv.
  - (E) Working assignments to a workplace should satisfy the Dose Constraint of that workplace, DC[1-5] = 5.0, 3.0, 4.0, 3.0, 4.0 mSv.
- Labor and Safety Constraints:
  - (F) The Working Time required to carry out a Job is JWT[1-5] = 120, 200, 360, 300, 100 minutes.

<sup>&</sup>lt;sup>2</sup> Present Address: Ministry of Science and Technology, Republic of Korea

- (G) The working time for a worker should be longer than 30 minutes, but should not exceed 120 minutes.
- (H) For special skill requirements, worker[1] is required to work at workplace[1] for more than 50 minutes, and worker[2] to work at workplace[3] for more than 80 minutes.
- (1) In this test model, workers [1-6] are set as skillful workers, and their total working time in workplace[3] should be more than twice as long as that of workers [7-12].
- (J) All the working times assigned to workers are integers.

## GA APPROACH

Genetic algorithms (GAs) are search and/or optimization algorithms based on the mechanisms of natural evolution. GAs maintain a population of a finite number of individuals during the evolutionary process. The evolutionary process is an iteration process which seeks better and better solutions from generation to generation. In each iteration, a new population is formed by applying genetic operators to the old population. Based on the fitness ranking, individuals can hand down their genes to the next generation by one of the following three genetic operators: reproduction, crossover, or mutation. After the evolutionary process approaches an equilibrium state, the best individual is considered as the optimal solution.

For a highly constrained problem like the worker allocation problem in radiological facilities, various types of constraints including even mutually conflicting ones should be taken into account in the process of optimization. In the previous study, we presented an evolutionary model where the concepts of hard constraints and multiple fitness were introduced to search efficiently for the optimal solution. The constraints (D) for dose limits and the constraints (F) for labor power requirements were employed as hard constraints. The optimal solution was sought among feasible candidates defined as individuals that satisfy both of the hard constraints. However, the proposed genetic operations required complicated algorithms and even repair mechanisms to keep the feasibility of each individual in the evolutionary process. In this paper, we propose an evolutionary model that can seek the optimal assignment more efficiently with simpler genetic operations. The proposed model is outlined as follows:

**Chromosome:** The chromosomes of the individuals are specified by two dimension matrices whose entries, for example  $WT_{ij}$ , express the working time of the worker[j] at workplace[i].

Hard Constraints: For simplifying the genetic operations, only the constraints (F) are employed as hard constraints. Other constraints are treated as soft constraints. Weighting coefficients are assigned to the soft constraints in accordance with their priorities in the radiological protection and labor allocation. The first priority is given to the constraints (D) for dose limits to compensate for being removed from the hard constraints.

Evaluation Functions: Three types of fitness functions with different priorities are introduced in this model. 1) The total number of satisfied soft constraints is used as the principal fitness function; 2) The total sum of the weighted degree of violation of the unsatisfied soft constraints is defined as the secondary fitness function. 3) The total number of times required for workers to change workplaces during the project is employed as the third fitness function. A certain portion of individuals having low fitness are discarded from the population at every generation in the evolutionary process.

Mutation: The mutation defined here is much simpler than that in (2). The individual to be mutated is selected randomly. The mutation is performed by reassigning some workers' working times at some workplaces. For example, ith row is selected to be mutated, 2 entries in ith row are selected randomly, at least one of them is not zero. The working time is reassigned randomly in one of the following two ways: 1) assign a worker the maximum working time within the dose limit, and allocate the rest of the working time to the other; 2) redistribute the total working time of the two workers randomly between them.

Crossover: The parents are selected from the individuals and the row positions of the matrix chromosome for the crossover operation are determined randomly. A simple arithmetical crossover is applied to the selected rows of the parent chromosomes. In the crossover process, two offspring are born to maintain the number of the population during the evolutionary process. Since the genetic operators employed here always ensure the feasibility of the offspring, therefore the repair algorithms as defined in

(2) are not necessary.

#### RESULTS AND DISCUSSIONS

With the evolutionary model described above, the first feasible solution was found within 600 generations, and an equilibrium state was gradually reached after 15,300 generations. The results show that the labor allocation satisfies all other soft constraints except the special skill requirements. In addition, by virtue of the special skill requirements, the skilled workers, [1] and [2], are assigned to the specified workplaces with the maximum times allowed under dose limits. The number of times required for workers to shift workplaces can be reduced to 7 times. An optimal labor allocation is given in Table 1.

Individual													
Workplace	1	2	3	4	5	6	7	8	9	10	11	12	Total [min]
i	46	0	0	0	0	0	16	0	0	48	0	10	120
2	0	0	0	58	40	0	102	0	0	0	0	0	200
3	0	56	66	62	0	80	0	47	49	0	0	0	360
4	0	0	0	0	75	23	0	64	63	0	75	0	300
5	0	0	0	0	0	0	0	0	0	0	0	100	100

Table 1: Results of the present model.

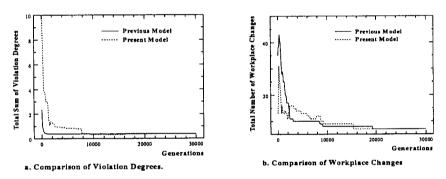


Figure 1: Comparisons between the two models.

For the purpose of comparison, the model proposed in (2) is also applied to the same problem. The results are almost the same as those of the model provided in this paper. The first feasible solution was found within 100 generations, and the best solution was found after 19,300 generations. The comparisons between the two models are shown in Fig.1.

From the comparisons, we found that the previously proposed model gave the first feasible solution very quickly, while the present model established the best solution faster than the previous one. As previous model employed more hard constraints than the present one, the search space became smaller. As a result, it was easier to find the first feasible solution. On the other hand, because of the much more strict restrictions of the previous model, it brought some complexities such as repair algorithms in designed genetic operators, which influenced the convergence efficiency.

### REFERENCES

- D.E.Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning. Reading, MA, Addison Wesley (1988).
- 2. Y.Chen, M.Narita, M.Tsuji, S.Sa, Health Phys. 70(2),180-186(1996).
- 3. Z.Michalewicz, G.A.Vignaux, M.Hobbs, ORSA J. Comput. 3, 307-316 (1991).
- 4. International Commission on Radiological Protection, ICRP37 (1983).