NURSE SCHEDULING BY COOPERATIVE GA WITH VARIABLE MUTATION OPERATOR

Shin-ya Uneme, Hikaru Kawano and Makoto Ohki
Department of Information and Electronics, Graduate School of Engineering, Tottori University, Japan

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Abstract: This paper proposes an effective mutation operator for the cooperative genetic algorithm (CGA) to solve a nurse scheduling problem. The nurse scheduling is very complex task for a clinical director in a general hospital. Even veteran director requires one or two weeks to create the schedule. Besides, we extend the nurse schedule to permit the change of the schedule. This permission has explosively increased computation time for the nurse scheduling. We propose the new mutation operator to solve the problem. The CGA with the new mutation operator has brought surprising effective results.

1 INTRODUCTION

A general hospital consists of several sections such as the internal medicin department or the pediatrics department. About fifteen to thirty nurses are working in each section. A clinical director of the section arranges a shift schedule of all the nurses in the section every month. Constituting the nurse schedule (Ikegami 2001), or the nurse scheduling, is very complex task for the clinical director. In our investigation, even a veteran director needs one or two weeks for the nurse scheduling. Then, computer software for the nurse scheduling has recently come to be used in the hospital.

In conventional ways (Kawanaka 2002, Itoga, 2003) using the cooperative genetic algorithm (CGA), a crossover operator is only employed for the optimization, because it does not lose consistency between chromosomes. A mutation operator is considered to lose the consistency. In contrast, we have proposed an effective mutation operator for the CGA which does not lose consistency of the schedule (Ohki, 2007). The CGA with the mutation operator has brought surprising effective results which has never been brought by the conventional algorithm. On the other hand, Burke performs a lot of interesting studies about the nurse roster at the large hospital in the Europe (Burke 2004).

In this paper, we rearrange the nurse scheduling problem to permit the change of the schedule. This permission has complicated a problem and explosively increased computation time for the nurse scheduling. Now, we need a new technique to make the nurse scheduling speed up. We propose a new mutation operator to solve this problem.

2 OVERVIEW OF NURSE SCHEDULING

On the nurse scheduling, we have to consider many requirements (Ohki, 2007), such as duty load of each nurse, fairness of assignment of day time and night duty, intensiveness of night duty. We have arranged these many requirements for twelve penalty functions. These twelve penalty functions are summarized in one penalty function, *E(g)*, for performing a population.

In the CGA, the population represents the whole nurse schedule of one month as shown in Fig.1 (Ohki, 2007). Each individual is defined in a chromosome code which shows one-month schedule of a nurse. The individual consists of the duty symbols as shown in Fig.2. The duty sequence consists of thirty symbols, since one month includes thirty days in this practical example.

Initially, the population is randomly generated as satisfying the necessary number of nurses at every duty time slot. In this paper, the necessary number of nurses is specified as ten, six and five for the day time duty on a week day, Saturday and Sunday respectively, three for the semi night duty and three

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for the mid night duty respectively.

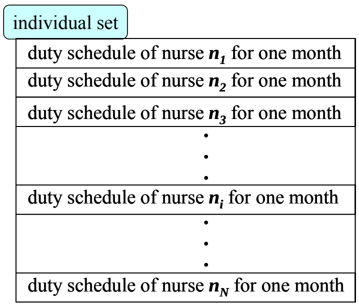


Figure 1: Population is composed of one-month schedules of each nurse.

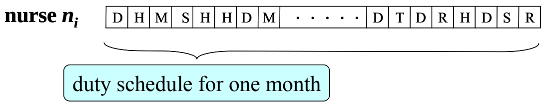


Figure 2: An individual coded in chromosome. The symbols, D, S, M, H, T, R denote daytime duty, semi-night duty, mid-night duty, given holiday, training and requested holiday respectively.

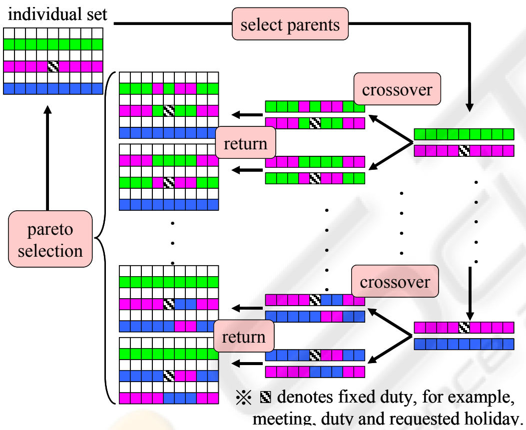


Figure 3: Basic optimization cycle of the CGA only employs with the crossover operator.

An overview of the optimization only with the crossover operator is shown by Fig.3. First, two hundreds pairs of the individual are selected as parents for the crossover. One of the pair is selected from the population under the roulette selection manner. The roulette selection gives an individual with higher penalty. This manner tends to select the worse individual. Another one of the parent pair is randomly selected from the population. Exchanging parts of the individuals divided at two points of the chromosome, two new pairs of individual are generated as children. This exchanging process does not exchange the fixed duties, such as the meeting, the training and the requested holiday. These child pairs are temporally returned to the original nurse position respectively. The temporal population with the children is performed by the penalty function. After all the temporal populations have been performed, one pair giving the smallest penalty is selected for the next generation.

3 EXTENSION OF NURSE SCHEDULING

In this research, we extend the nurse schedule problem to permit the change of the schedule. In fact, one or two changes appear in the past duty days of the current month. We consider the following cases:

(1) A certain nurse took a holiday on a duty date,
(2) A certain nurse worked in a holiday fixed day,
(3) Two nurse's shift were changed,
(4) Acertain nurse resigned from his/her job,
(5) A certain nurse increased newly.

When these rose in the past date, the number of day time, semi-night and mid-night duties of some nurses must be changed. Although these duty days must be fair for all nurses in the section, nursing level must be kept at each duty time slot. Then the director has to consider the change of the schedule.

In this paper, we asume that a change has been occurred in the past two weeks and handle the optimization of coming four weeks as shown in Fig.4. In the optimization of the four weeks, a new penalty function is defined as F_{13}. This penalty counts the differences between duty symbols on the 3rd and 4th weeks of the original schedule and them of the newly optimizaed schedule. Therefor, the total penalty function, $E(g)$, is defined as the summation of thirteen penalty functions.

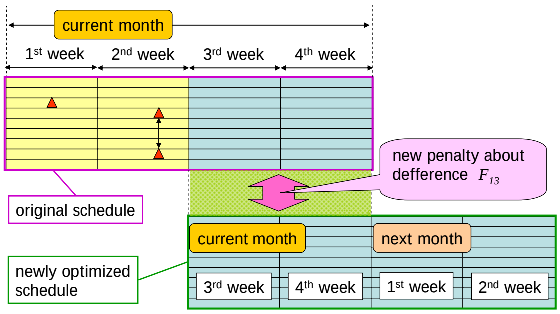


Figure 4: Permission of the change of the schedule in the past two weeks. The red triangle denotes the schedule change.

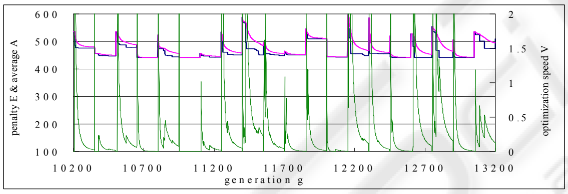
4 VARIABLE MUTATION OPERATOR

We have proposed the CGA with the mutation operator for the nurse scheduling in the manuscript (Ohki, 2007). When the conventional nurse scheduling is handled, the technique has given results good enough. On the other hand, the extension of the nurse scheduling to permit its change complicates the problem and explosively increases computation time. The conventional technique is not effective enough for the extended problem. Then we propose a new mutation operator.

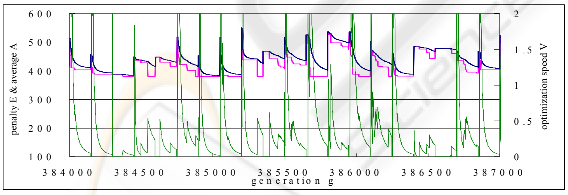
We have examined the extended nurse scheduling using the conventional mutation. The conventional mutation operator whose mutation interval is defined as 150 generations works most effective. Since the mutation interval is fixed, the mutation is executed at the same frequency anytime. When the optimization stagnates long time, the mutation should be executed. In contrast, when the optimization goes steadily, the mutation should not be executed. An optimization speed is defined as follows to explain progress of the optimization,

$$A(g)=\frac{1}{N_g}\sum_{i=0}^{N_g-1}E(g-i), \qquad (1)$$

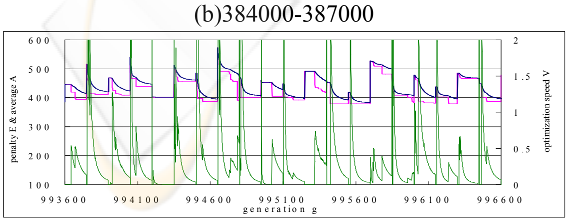
$$V(g)=A(g-1)-A(g), \qquad (2)$$



(a)10200-13200



(b)384000-387000



(c) 993600-996600

Figure 5: The total penalty function, $E(g)$, the average, $A(g)$, and the optimization speed, $V(g)$ in the beginning (a), the middle (b) and the end (c) of the optimization using the conventional mutation operator respectively.

where N_g denotes the number of generations for average. Examples of the value of the total penalty function, $E(g)$, the average, $A(g)$, and the optimization speed, $V(g)$, are shown in Fig.5. Though the optimization goes well, the mutation is executed too early in some cases. In some other cases, though the optimization has already stagnated, the mutation is executed too late.

We propose the variable mutation operator to improve such an obstruction. The new operator mutates the schedule when the optimization speed satisfies the following condition,

$$V(g)<\varepsilon,$$

where ε denotes a threshold value. This condition means that the optimization has stagnated.

In some cases, the optimization does not advance for several generations after the mutation, as shown in Fig.5. The mutation does not work during G_g generations after the mutation is executed once. We call such generations the guard interval. The mutation is executed in the appropriate generation by means of such a technique.

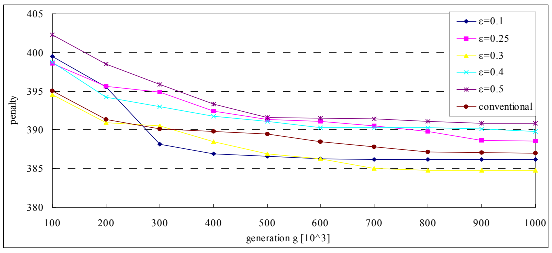
5 PRACTICAL EXPERIMENTS

Here, we set a problem as follows. Let the number of nurses and the number of duty days be twenty-three and twenty-eight respectively. We handle a case when one change has been occurred in the past two weeks. This situation is one of typical and practical case in Japanese hospital which we have investigated.

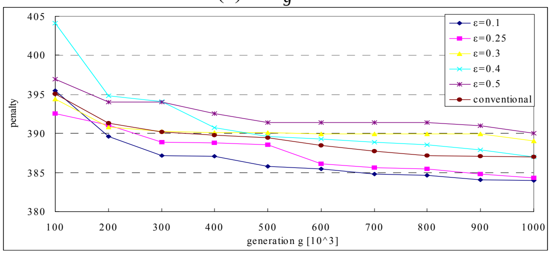
First, we have considered about the guard interval. We tried the extended nurse scheduling by using the variable mutation operator under several conditions as shown in Fig.6. This result shows that the guard interval can be easily decided in wide range. Here, we decide it as fifty.

Next, we have considered about the threshold, ε. The variable mutation operator with the guard interval, 50, and the threshold, 0.1, has given the best result as shown in Fig.6, (d). We have tried several thresholds less than 0.1 as shown in Fig.7. This result shows that the threshold can be easily decided in wide range less than 0.1. The variable mutation operator with any values of threshold has given better results than the conventional one.

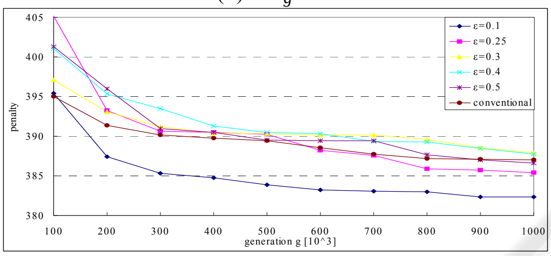
Finally, we have examined the extended nurse scheduling using the variable mutation operator. The mutation is executed in appropriate generations as shown in Fig.8. This means that the variable mutation operator works effectively.



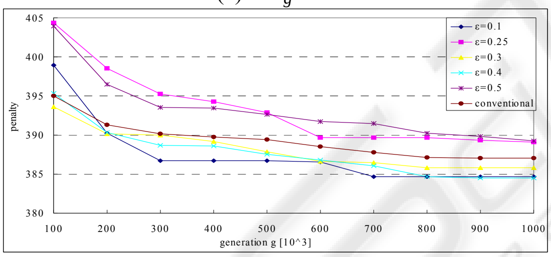
(a) $G_g = 10$



(b) $G_g = 20$



(c) $G_g = 30$



(d) $G_g = 50$

Figure 6: Comparison among optimization results with several values of the guard interval. We have tried the optimization under each condition ten times. We took average of each ten trials.

6 CONCLUSION

In this paper, we have extended the nurse scheduling problem to permit the change of the schedule. This extension complicates the problem and explosively increases computation time. To improve this difficulty, the new mutation operator with variable interval is proposed. The variable mutation operator has several parameters which can be defined in wide range. This means that the new technique possesses high versatility.

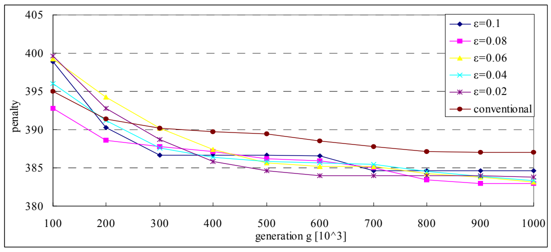
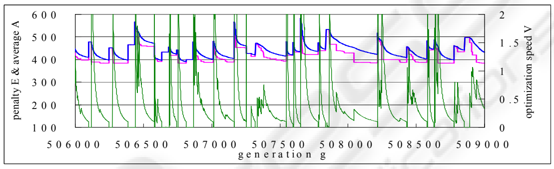
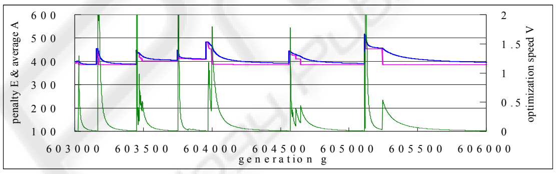


Figure 7: Results of the variable mutation operator with the threshold less than 0.1. We have tried the optimization under each condition ten times. We took average of each ten trials.



(a) $g \in [506000, 509000], \quad \varepsilon = 0.07$



(b) $g \in [603000, 606000], \quad \varepsilon = 0.01$

Figure 8: The total penalty function, $E(g)$, the average, $A(g)$, and the optimization speed, $V(g)$, of the optimization using the variable mutation operator respectively.

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