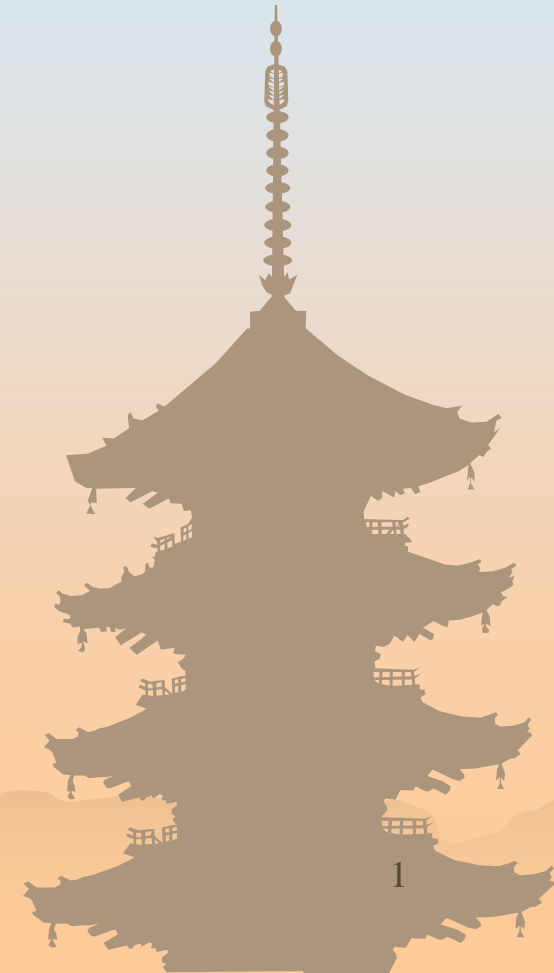


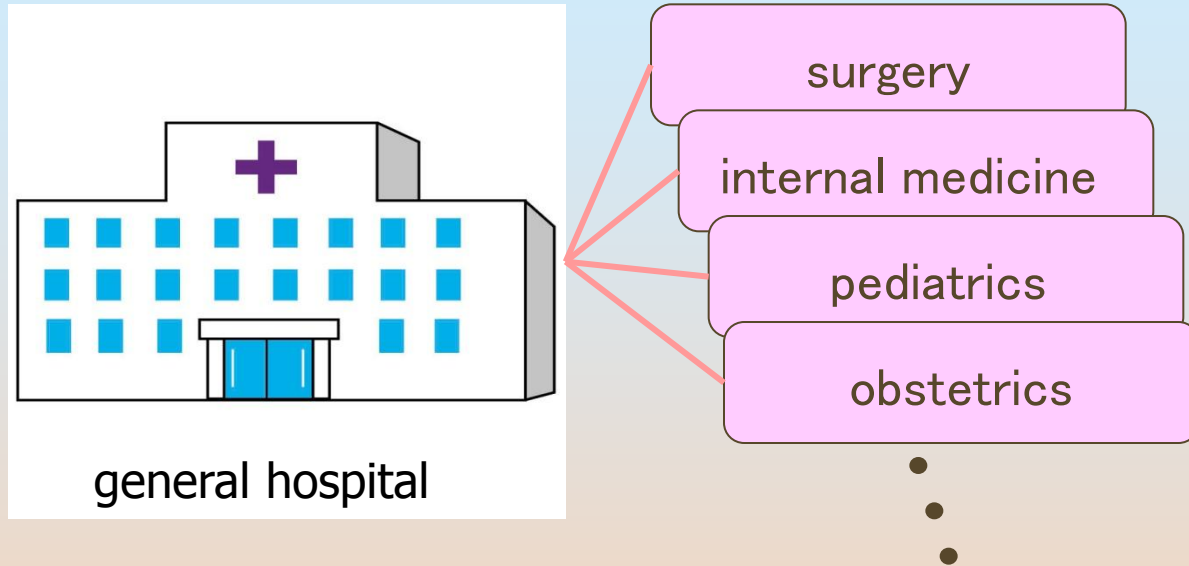
# Penalty Weight Adjustment in Cooperative GA for Nurse Scheduling



# 1. Introduction



# 1. Introduction

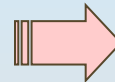


- ❁ General hospital consists of several sections.
- ❁ About 15–30 nurses belong to each section.
- ❁ A section director or a manager arranges a shift schedule of the nurses every month.

# 1. Introduction

many requirements

- requirements on the hope holiday.
- duty load in equality.
- the number of the night shift in equality.
- affinity between the nurses in the night shift.
- etc. . . . .



Veteran director requires one or two weeks.



Automatic Nurse Scheduling

- ❁ The nurse scheduling is very complex task, because the director consider many requirements for the scheduling.
- ❁ In our investigation, even veteran director spends **one or two weeks** for the nurse scheduling.
- ❁ This means a great loss of work force and time.
- ❁ Therefore, computer software for the nurse scheduling is strongly required recently.

# 1. Introduction

⚙️ We know there are actually several commercial software to generate nurse schedule. However, they are not used, because the optimized result is **dissatisfactory**.

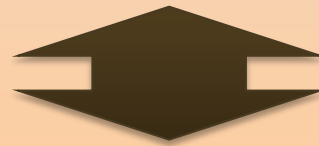
⚙️ We discuss the cooperative GA (CGA) to generate & optimize the nurse schedule.

⚙️ The conventional CGA searches solutions **only by**

**using crossover** operator, because it is considered as the only one operator keeping **consistency** of the population.

nurse A  
nurse B  
⋮  
nurse X  
⋮  
nurse V  
nurse W

D	S	H	M	H	⋯	D	D	M	S
S	M	D	D	H	⋯	H	M	S	H
⋮						⋮			
M	D	H	S	H	⋯	D	H	D	D
⋮						⋮			
S	M	D	D	H	⋯	S	H	H	M
D	D	H	M	S	⋯	S	R	D	H



⚙️ A **mutation** changing small parts of the population brings very important change to the population.

# 1. Introduction

⚙️ We have proposed an **effective mutation operator** activated depending on the optimization speed [19].

⇒ This requires some parameters to define itself.

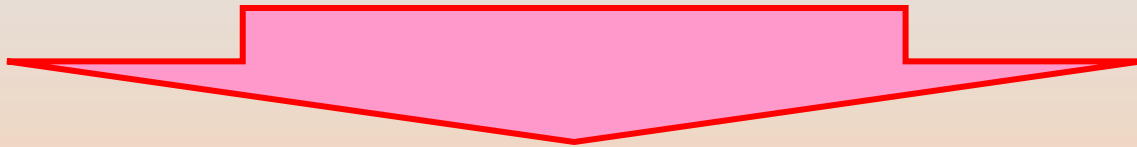
⚙️ We have proposed a mutation operator activated periodically, **Periodic Mutation** [20, 21].

⇒ It brings almost same result as the earlier one.

Only one parameter is required.

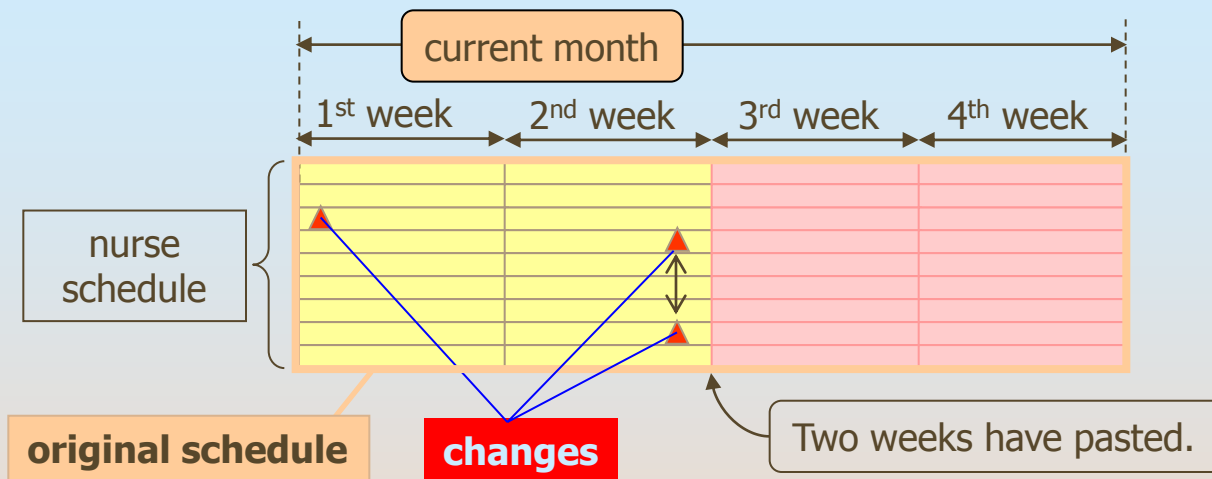
# 1. Introduction

- ❁ In the actual cases, there are the cases that nurses originally assigned to a rest are forced to attendance by means of emergency.
- ❁ There are also the cases that a nurse whom duty has been assigned originally takes a rest due to a disease.



- ❁ The shift schedule must be changed in the actual.

# 1. Introduction

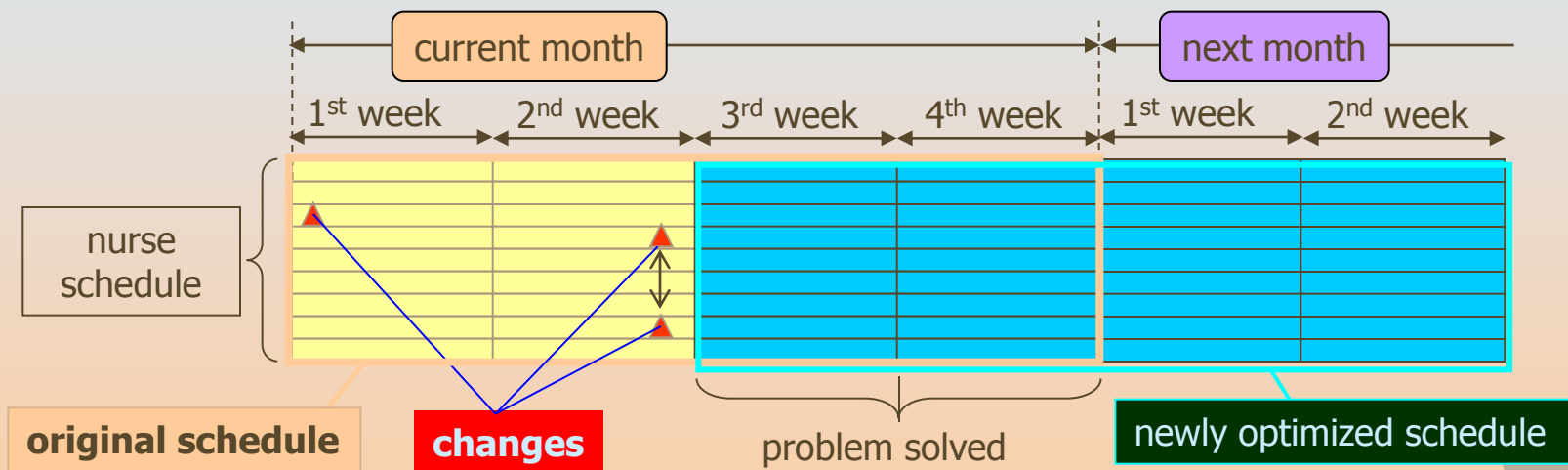


- ❁ By means of the **changes**, several **inconvenience** occurs, for example, imbalance of the number of the holidays/attendance.
- ❁ Such an **inconvenience** causes the fall of the nursing level of the whole nurse organization.
- ❁ The changed schedule should be re-optimized to **break off** the **inconvenience** as much as possible.



# 1. Introduction

- ❁ On the other hand, there is a requirement that the shift schedule already given does not want to change if possible.
- ❁ We define a penalty function to improve this confusion. It calculates the difference between the original and the optimized schedules.



- ❁ In this research, we treat the re-optimization of the coming four weeks (one month) including the remaining weeks of the current month and the several weeks of the next month.

# 1. Introduction

⚙ The re-optimization of such the changed schedule is difficult even by using the effective mutation operator.

⇒ We have proposed an **effective parallel mutation operator** for the re-optimization [23,24].

However, ...

⚙ The re-optimization is very hard task even by the parallel mutation, because the **solution space** of the nurse scheduling problem is **very complex**. There are many local minimum area in the solution space.

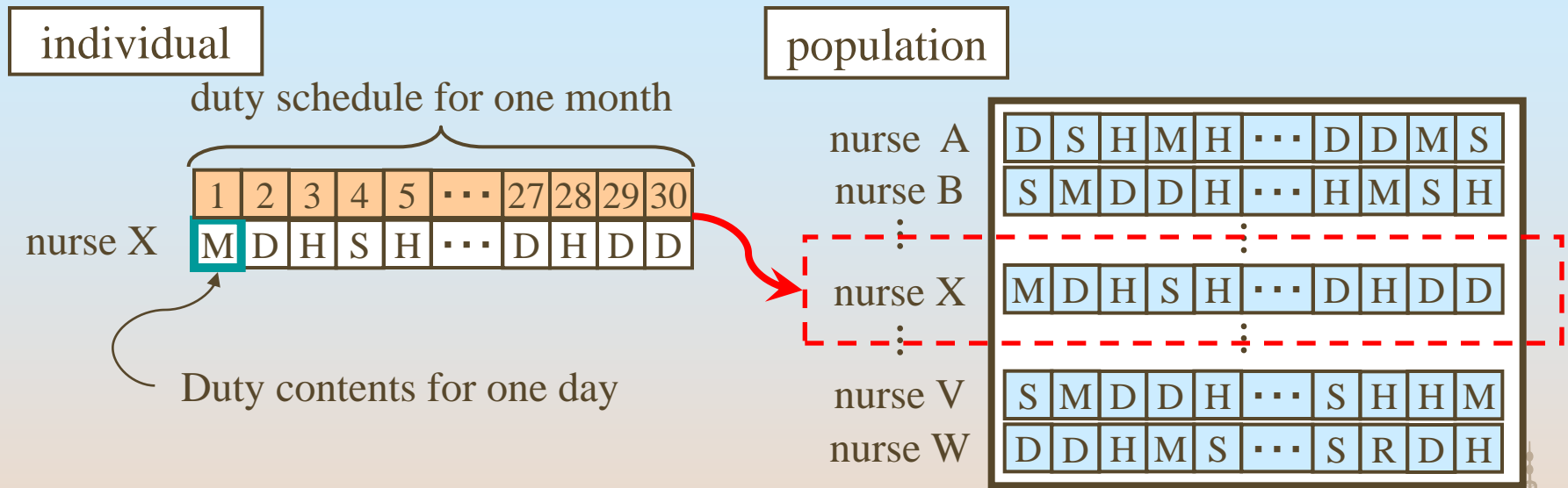
in this presentation, ...

⚙ We propose a technique to escape from such the local minimum area by using **Penalty weight Adjustment**.

## 2. Evaluation of Nurse Scheduling



# 2. Nurse Scheduling



- An individual consists of the sequence of the shift symbols.
- The individual shows the one-month schedule of the nurse X.
- Gathering all the individuals, the population is constructed.
- In CGA, the population does not contain two or more individuals giving the same nurse's schedule.

## 2. Nurse Scheduling

- The following two requirements have to be satisfied by means of the genotype coding and the genetic operations.

### (Strong Constraints)

- meeting, training and requested holiday must be accepted.
- the number of nurses at each shift interval must be secured.

- The following requirements are evaluated by penalty functions.

### (Weak Constraints)

- duty load depending on the duty pattern of consecutive 3 days. ( $F_1$ )
- 4 or more night shifts should not be assigned. ( $F_2$ )
- prohibited duty patterns. ( $F_3$ )
- fairness of the holidays and the night shifts assignment. ( $F_4, F_5$ )
- more than or equal to 6 consecutive duty days. ( $F_6$ )
- nursing levels must be kept at each shift interval. ( $F_7, F_8, F_9$ )
- unfavorable combinations in the night shift. ( $F_{10}$ )
- two or more new faces should not assigned to the midnight shift. ( $F_{11}$ )
- one or more expert or more skilled nurses must be assigned on day time. ( $F_{12}$ )
- difference between original schedule and optimized schedule. ( $F_{13}$ )

## 2. Nurse Scheduling

- Finally, the total penalty function  $E$  is defined by summarizing these **penalty functions** with **weights**.

$$E = \sum_{i=1}^M \sum_{k=1}^6 h_k F_{ki} + \sum_{j=1}^D \sum_{k=7}^{12} h_k F_{kj} + h_{13} F_{13} \quad (1)$$

# 3. Basic Algorithm of CGA



# 3. Basic Algorithm of CGA

## CGA (initialization)

D: day shift, S: semi-night shift, M: midnight shift  
R: requested holiday, H: holiday  
m: meeting, T: training

⚙️ CGA put the shift symbols randomly with keeping the number of nurses at the day time shift, the semi-night shift and the midnight shift as 6, 3 and 3 respectively.



# 3. Basic Algorithm of CGA

## CGA (basic algorithm)

	1	2	3	...	28	29
nurse A	D	S	M	...	D	M
nurse B	S	M	D	...	M	S
nurse C	M	H	R	...	S	H
⋮				⋮		
nurse V	S	M	D	...	H	H
nurse W	D	D	M	...	R	D

select  
parents

### crossover operator

Parent pair

D	S	M	...	D	M
M	H	R	...	S	H

crossover

Child pair

D	S	M	...	D	M
M	H	R	...	S	H
M	H	M	...	S	H
D	S	R	...	D	M

- Return the child pairs to the original position of the population.
- Evaluate new populations.
- Select best one.

⚙️ CGA searches good solution by basically using the crossover operator.

# 3. Basic Algorithm of CGA

## CGA (basic algorithm)

	1	2	3	...	28	29
nurse A	D	S	M	...	D	M
nurse B	S	M	D	...	M	S
nurse C	M	H	R	...	S	H
⋮				⋮		
nurse V	S	M	D	...	H	H
nurse W	D	D	M	...	R	D

select  
parents

crossover operator

Parent pair

D	S	M	...	D	M
M	H	R	...	S	H

crossover

Child pair

D	S	M	...	D	M
M	H	R	...	S	H
M	H	M	...	S	H
D	S	R	...	D	M

- Return the child pairs to the original position of the population.
- Evaluate new populations.
- Select best one.

- ⚙ The crossover operator selects **two individuals**, where one is selected by **roulette selection** manner and another is **randomly** selected.
- ⚙ By the **two-points crossover**, two child pairs are regenerated.

# 3. Basic Algorithm of CGA

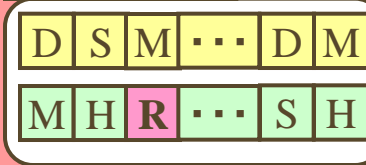
## CGA (basic algorithm)

	1	2	3	...	28	29
nurse A	D	S	M	...	D	M
nurse B	S	M	D	...	M	S
nurse C	M	H	R	...	S	H
⋮				⋮		
nurse V	S	M	D	...	H	H
nurse W	D	D	M	...	R	D

select  
parents

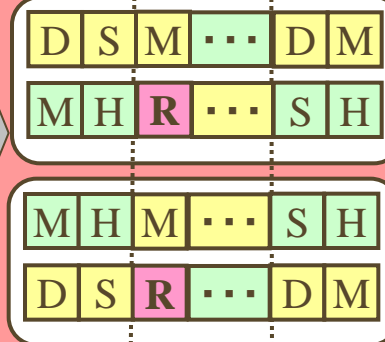
crossover operator

Parent pair



crossover

Child pair



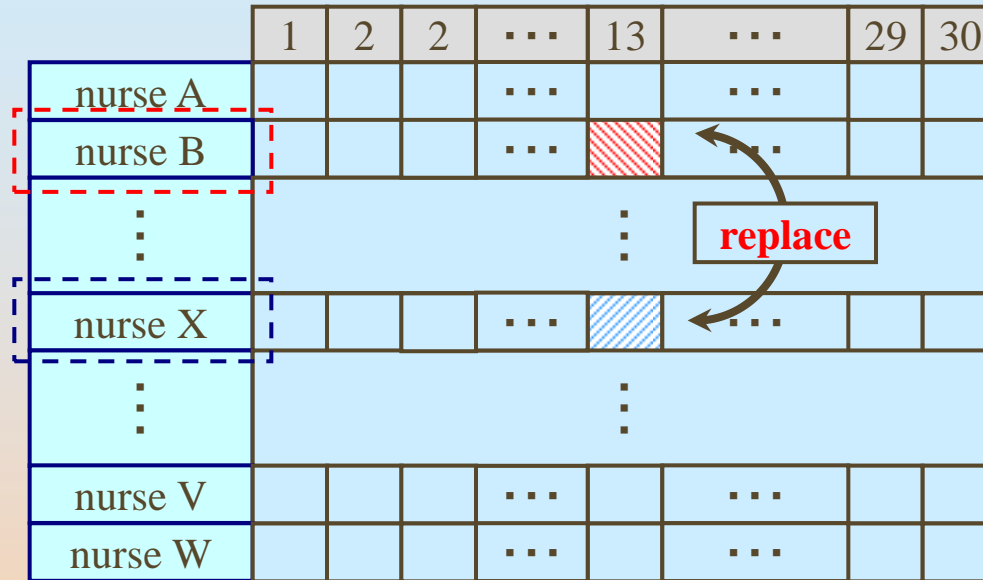
- Return the child pairs to the original position of the population.
- Evaluate new populations.
- Select best one.

- ⚙️ Setting these child pairs back to the original positions of their parent pair, the population is **evaluated** by the penalty,  $E$ .
- ⚙️ This procedure is applied to **100 parent pairs** in 1 generation cycle.

# 3. Basic Algorithm of CGA

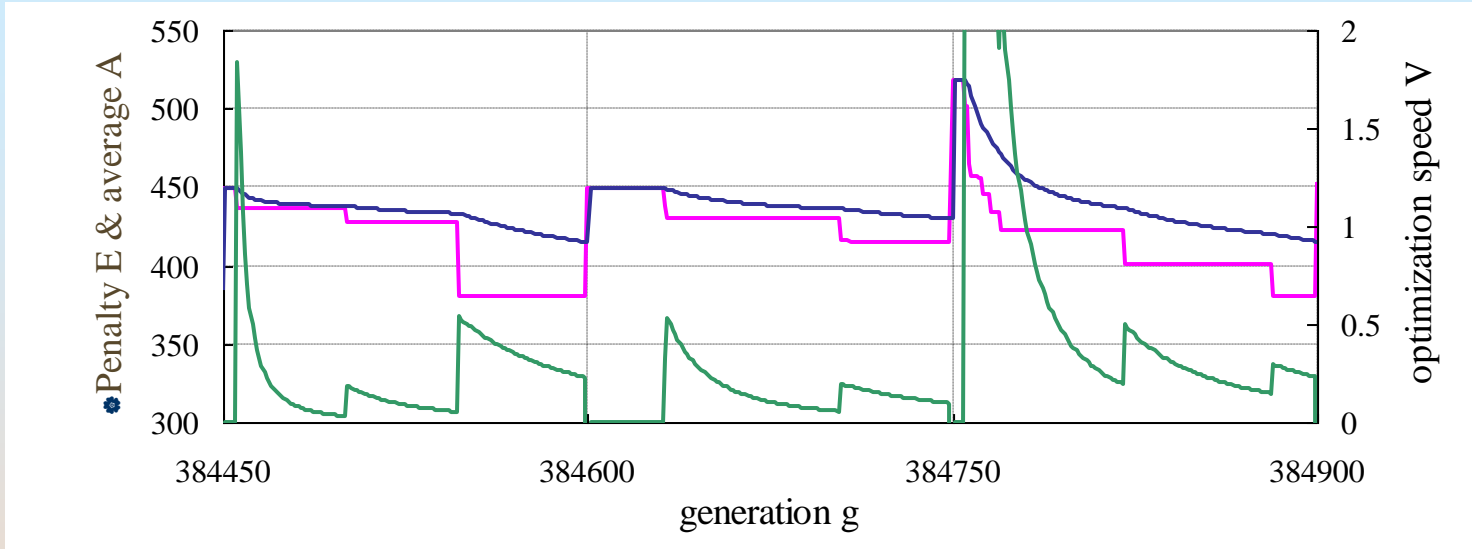
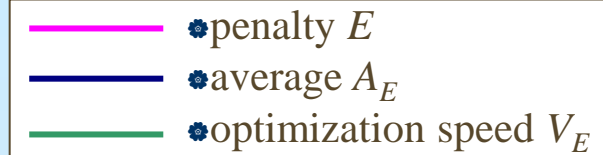
CGA (mutation operator)

	1	2	2	...	13	...	29	30
nurse A				...		...		
nurse B				...		...		
⋮					⋮			
nurse X				...		...		
⋮					⋮			
nurse V				...		...		
nurse W				...		...		



- ① Randomly select one of shift dates.
- ② Randomly select two nurses. If one of them or both two are fixed shift, return to ①.
- ③ Replace these two shifts.

# 3. Basic Algorithm of CGA



- Average value  $A_E$  of the penalty  $E$  for  $N_g$  generation cycles after mutation:

$$N_g = g - g_{prim}, \quad (2)$$

$$A_E(g) = \frac{1}{N_g} \sum_{i=0}^{N_g-1} E(g-i). \quad (3)$$

- Optimization Speed  $V_E$ :

$$V_E(g) = A_E(g-1) - A_E(g) \quad (4)$$

- When the optimization speed  $V_E$  becomes less than a **speedo-threshold**  $\varepsilon_E$ , the mutation is activated.

$$V(g) < \varepsilon_E.$$

- The optimization sometimes does not advance for several generation cycles right after the mutation. Then, the mutation is prohibited for **guard interval**  $\underline{G}_G$  generation cycles right after the mutation.

- When the mutation is executed  $N_M$  times, the optimization finishes.

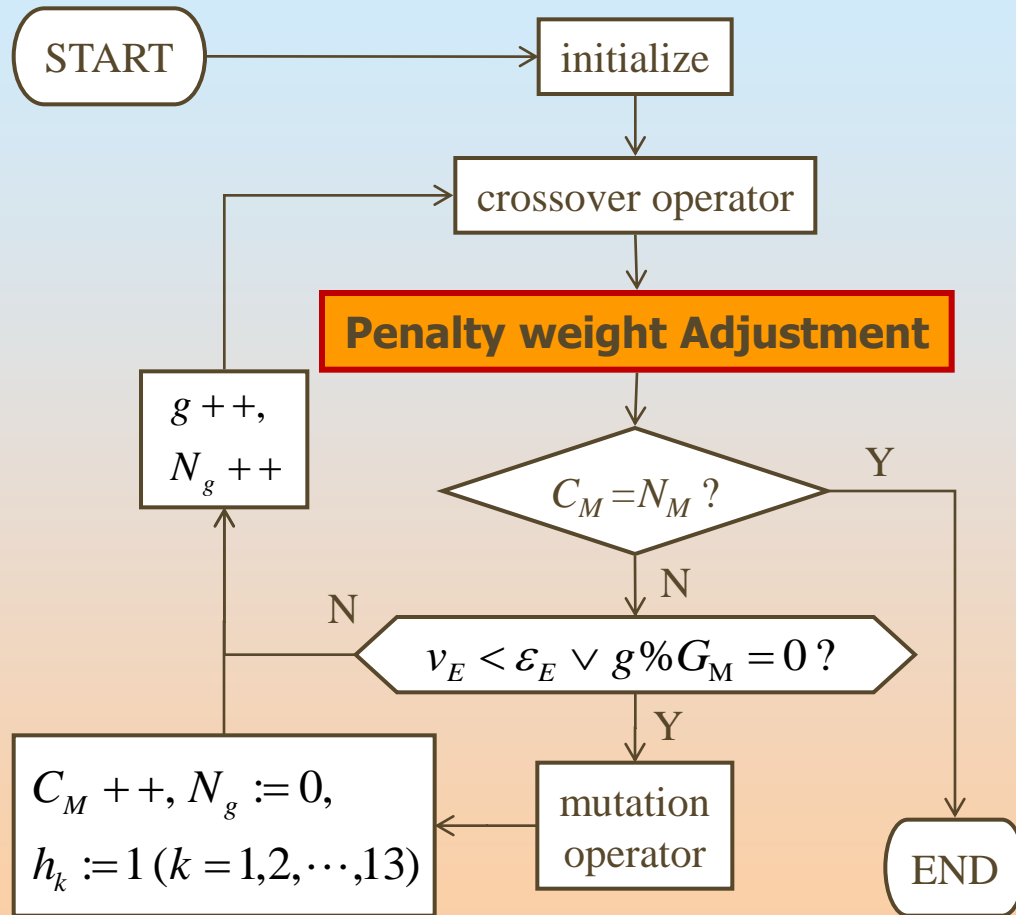
# 4. Penalty Weight Adjustment



# 4. Penalty Weight Adjustment

- ✿ Re-optimization of the schedule is very hard task even by the parallel computing and then requires very long computing time.
- ✿ We consider that this problem is caused by the complexity of the solution space. (There are many local minima.)
- ✿ When the optimization is caught in a local minimum, some penalties stagnate decreasing as still greater value.
- ✿ If the shape of the **solution space** can be deformed, the searching point can **escape** from the local minimum.
- ✿ The shape of the solution space is defined by  $E$ .
- ✿ By **changing the penalty weights**, the shape of the solution space is deformed.

# 4. Penalty Weight Adjustment



Optimization flow with the Penalty weight Adjustment



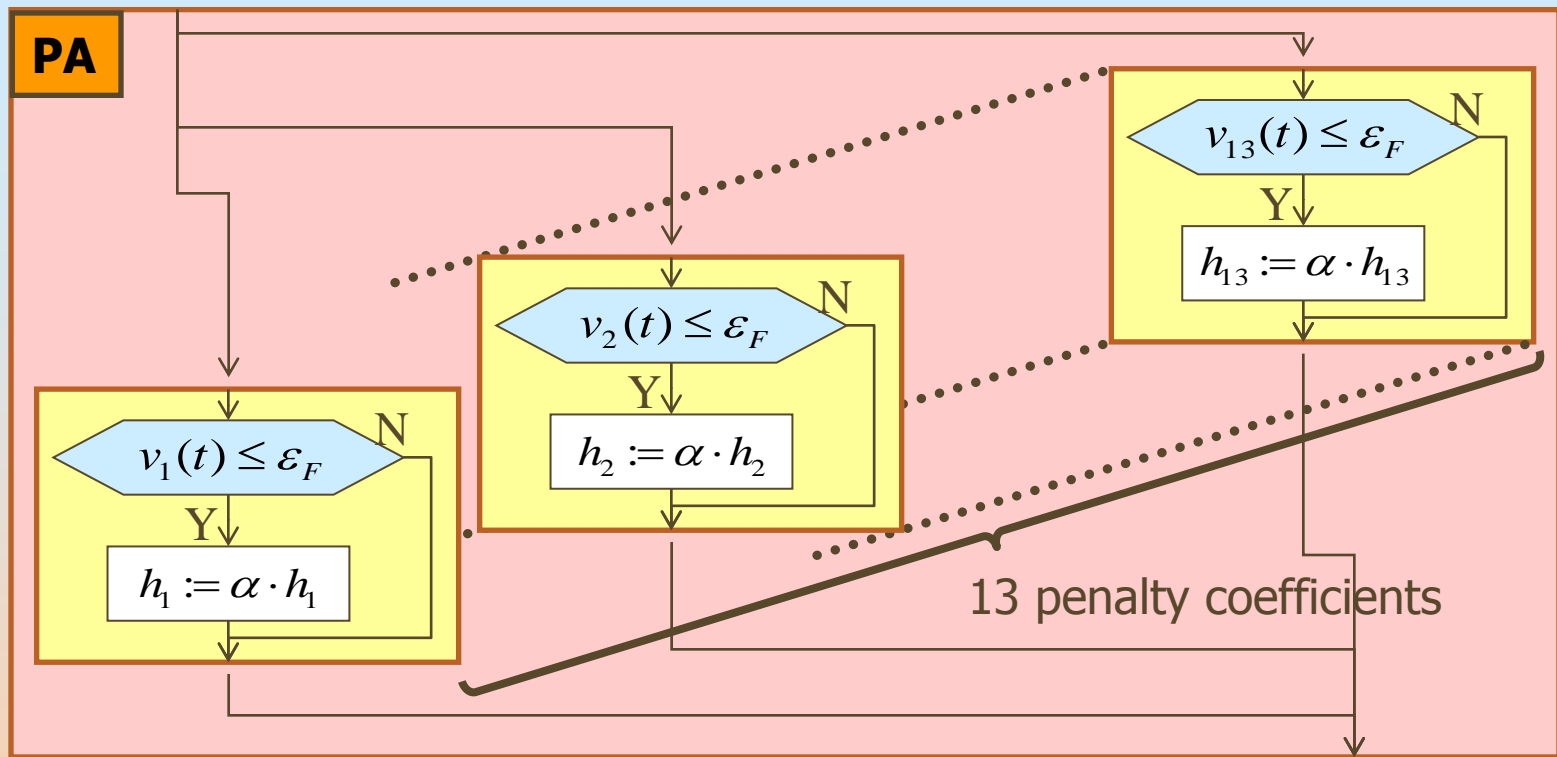
# 4. Penalty Weight Adjustment

- Initially, all penalty weights  $h_1 \dots h_{13}$  are initialized to 1.
- Decreasing speed**,  $v_k$ , of the  $k$ -th penalty is defined as

$$A_k(g) = \begin{cases} \frac{1}{N_g} \sum_{h=0}^{N_g-1} \sum_{i=1}^M F_{ki}(g-h) & (k \leq 6) \\ \frac{1}{N_g} \sum_{h=0}^{N_g-1} \sum_{j=1}^D F_{kj}(g-h) & (k > 6) \end{cases} \quad (5)$$

$$v_k = A_k(g-1) - A_k(g). \quad (6)$$

# 4. Penalty Weight Adjustment



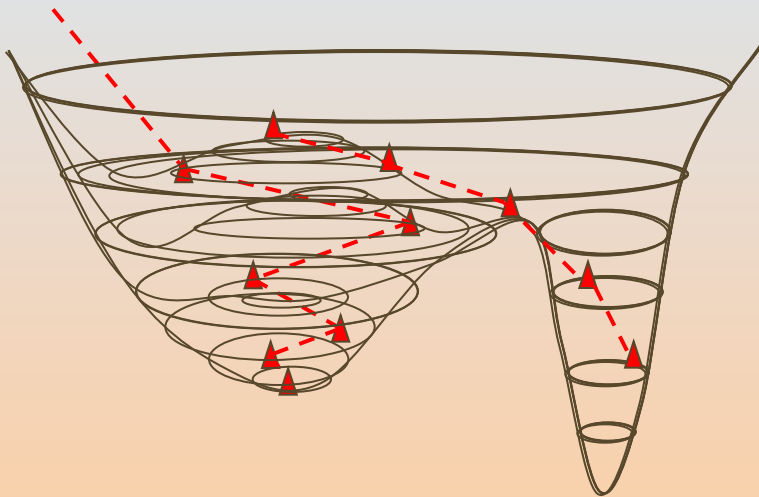
⚙ When the **decreasing speed**,  $v_k$ , becomes less than or equal to a **speed threshold**  $\epsilon_F$ , the penalty weight  $h_k$  is increased by multiplying with  $\alpha$ . ( $\epsilon_F=0.01$ ,  $\alpha=1.01$ )

⚙ When the mutation is activated, all penalty weights are initialized to 1.

# 4. Penalty Weight Adjustment

## ★ Effect of Penalty Weight Adjustment

Optimization stagnates...  $\Rightarrow$  caught in a wide local minimum region



Valley of the local minimum upheaves



Searching point escapes from the local minimum area.

# 5. Practical Experiment of Nurse Scheduling



# 5. Practical Experiment of NS

- The number of nurses : 23
- We suppose that two weeks have passed. In the past two weeks, two changes (one emergency attendance, one unplanned absence) exists.
- Guard interval  $G_G$  : 50.
- Speed threshold  $\varepsilon_E$  : 0.01.
- Mutation number  $N_M$  : 500. (PA1)
- Mutation period  $G_M$  : 2000 (GM)

# 5. Practical Experiment of NS

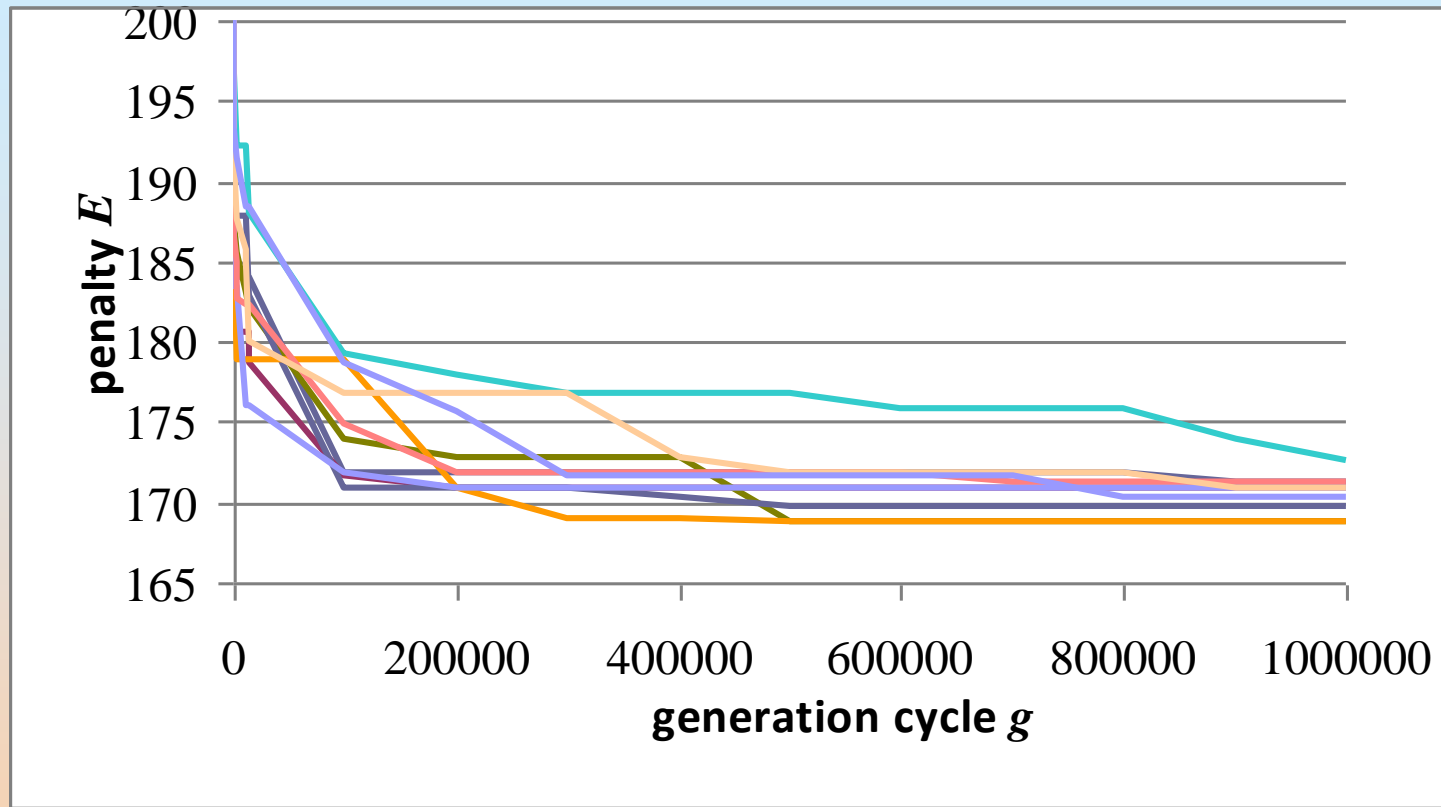


Fig.5: Ten optimization progresses when the periodic mutation is applied. The optimization is executed for 1,000,000 generation cycles. (GM)

⚙️ This result is almost same as the result given by CGA with the mutation depending on the optimization speed.

# 5. Practical Experiment of NS

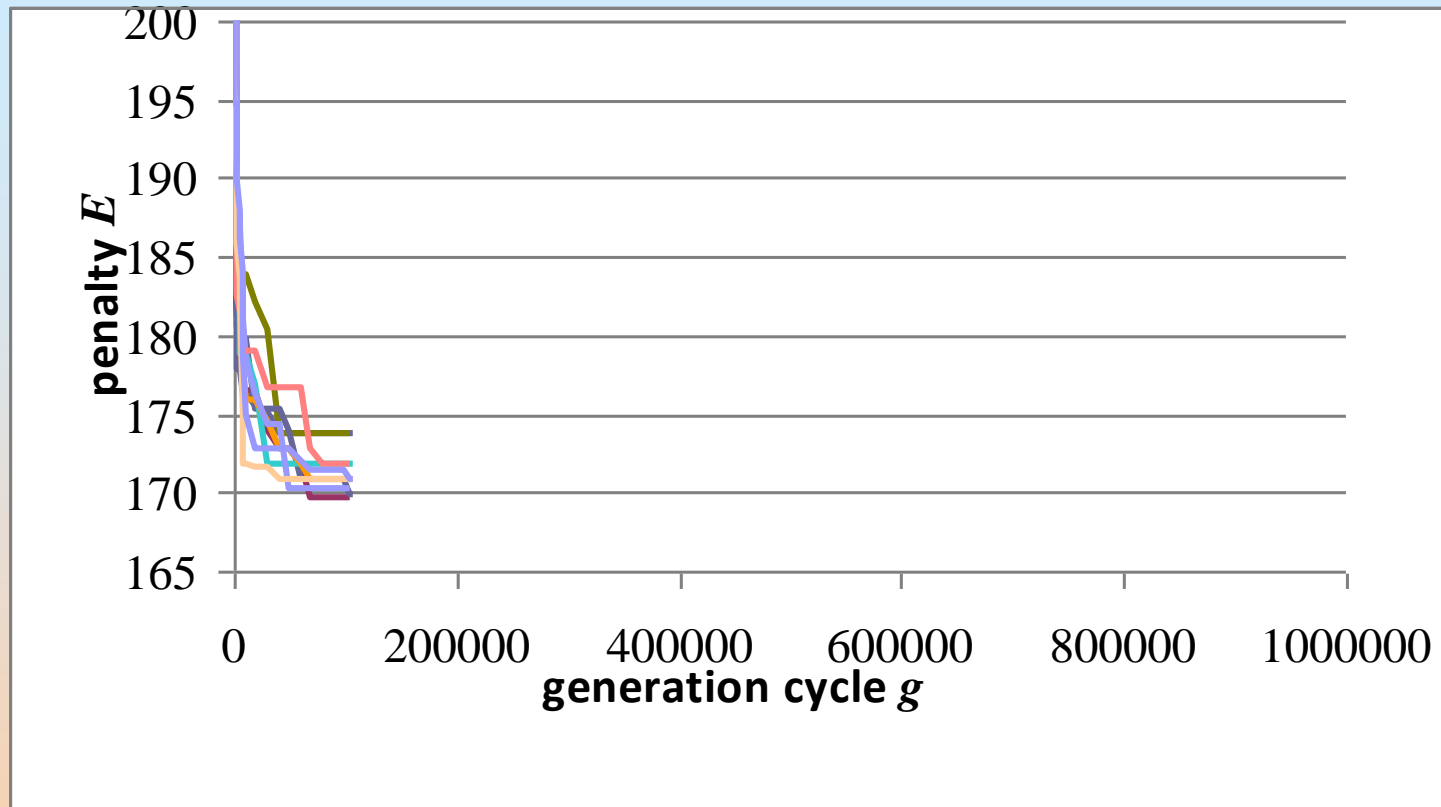


Fig.6: Ten optimization progresses when the mutation depending on the optimization speed with the **Penalty weight Adjustment** is applied. (PA1)

⚙️ The mutation period has been shorten by PA. Then the optimization has been accelerated.

# 5. Practical Experiment of NS

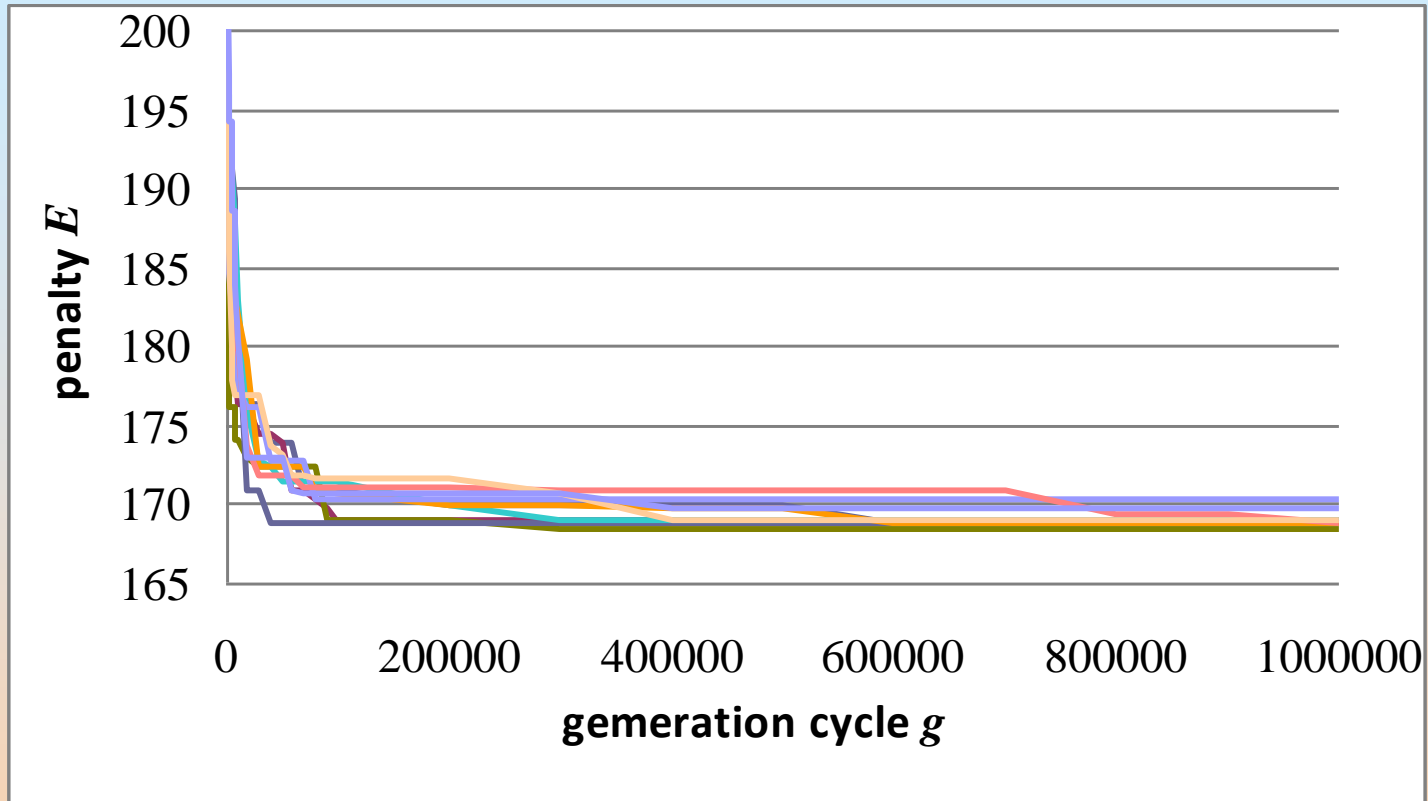


Fig.9: Ten optimization progresses when the mutation depending on the optimization speed with the **Penalty weight Adjustment** is applied. The optimization is executed for 1,000,000 generation cycles. (PA2)



# 5. Practical Experiment of NS

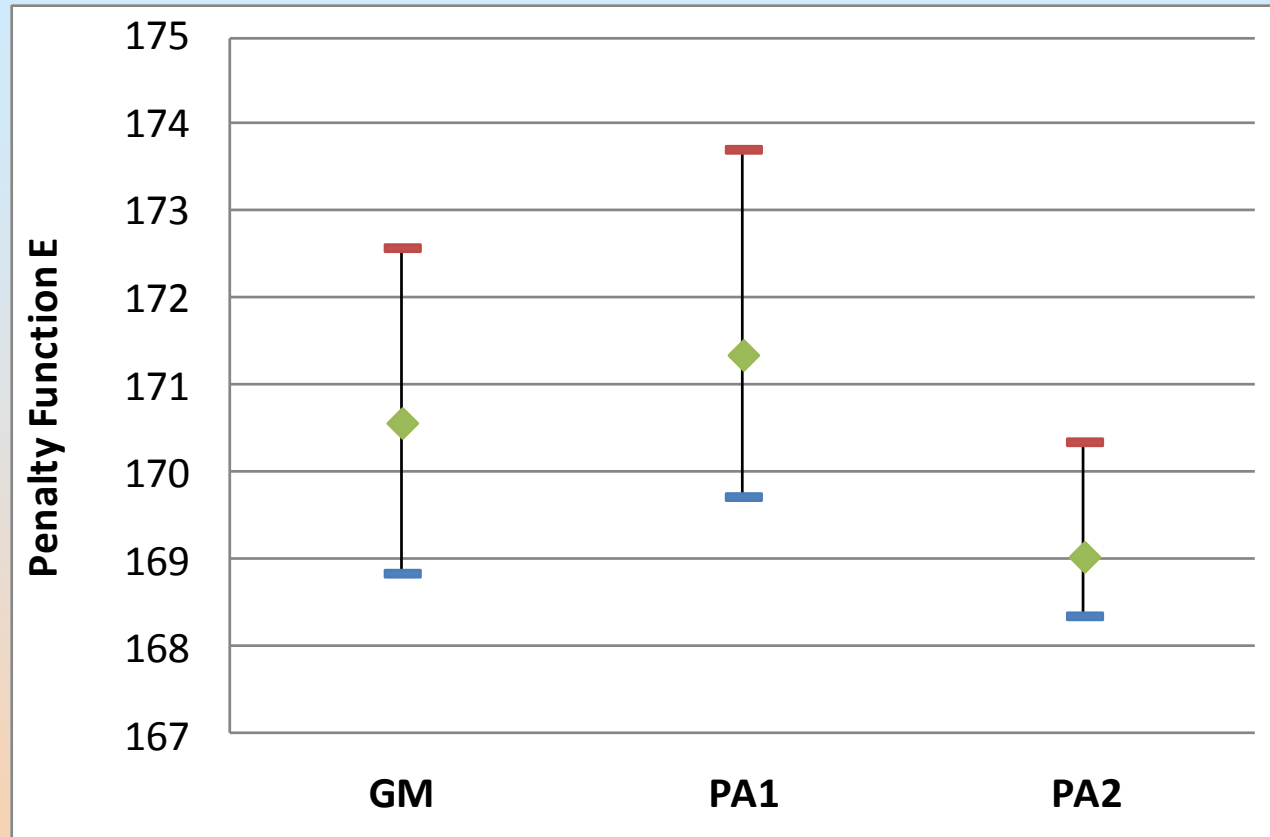


Fig.9: Comparison of the optimization results between the **periodic mutation (GM)** and the mutation depending on the optimization speed with the **Penalty weight Adjustment (PA1, PA2)**.

# 5. Conclusion



# 5. Conclusion

- ❁ In this research, we have treaded the nurse scheduling by using **CGA**.
- ❁ We have handled the case when the shift schedule has been changed in the middle of a month.
- ❁ The nurse scheduling including such changes become **difficult**, and the enormous generation cycles has been necessary to provide a good schedule.
- ❁ To improve the difficulty, we have proposed the mutation operator depending on the optimization speed and the Penalty weight Adjustment.
- ❁ CGA with **PA accelerates the optimization** of the nurse schedule, because it can search solution space effectively.

Thank you very much  
for your kind attention!

Ask me **symply!**  
(Do not ask a complex question!)

