SUGISAKA MASANORI

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Research Article

Q-learning approach for Nurse Rostering: Addressing Variations in Work Patterns and Visualization of Results

Masato Nagayoshi[1], Hisashi Tamaki[2]
[1]*Niigata College of Nursing, 240 Shinnan-cho Joetsu, Niigata 943-0147, Japan*
[2]*Kobe University, 1-1 Rokkodai-cho, Nada-ku, Kobe, Hyogo 657-8501, Japan*

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ABSTRACT

Creating a duty roster that meets all the various requirements of nurse rostering is extremely challenging. Consequently, many researchers have studied nurse rostering. Despite these efforts, the shift schedules generated by these studies are often not practical in their initial form, as they require adjustments to accommodate various constraints and evaluation criteria. Thus, we have proposed a method for revising duty roster using Q-learning in a constructive nurse rostering. This paper explores the potential for developing a practical duty roster that accommodates nurses with varying duty plan valuations. This involves considering each nurse's lifestyle. Additionally, we visualize the duty plan valuations of the revised rosters we obtain.

1. Introduction

Many researchers have studied nurse rostering [1], which involves creating duty rosters for nurses. Despite these efforts, the duty rosters generated by these studies are often not practical in their initial form, as they require adjustments to accommodate various constraints and evaluation criteria. As a result, many chief nurses are still weighed down by the task of creating duty rosters. Thus, we have proposed a method for revising duty roster [2] by applying Q-learning [3] on a constructive nurse rostering [4].

This paper explores the potential for developing a practical duty roster that accommodates nurses with varying duty plan valuations. This involves considering each nurse's lifestyle. Additionally, we visualize the duty plan valuations of the revised rosters we obtain. Moreover, previous research on nurse rostering has overlooked the assessment of diverse work patterns.

2. Constructive Nurse Rostering

2.1. *Features of Constructive Nurse Rostering*

The features of the constructive nurse rostering [4] include the following:

1. The method generates a daily schedule, beginning from the first day.
2. It is possible to extend the priority calculation to account for additional criteria.
3. The method does not evaluate the overall value of the duty roster for the entire month.

2.2. *Revising Duty Roster*

The constructive rostering method addresses only the fundamental constraints needed in a hospital with many nurses, which may result in a feasible solution that does not meet the chief nurse's requirements. Consequently, Kurashige et al. [4] describe two methods for making practical adjustments.

1. A nurse’s shift that does not meet the chief nurse’s approval is manually swapped with the shift of another nurse.
2. A nurse’s shift that does not meet the chief nurse’s approval is replaced with a designated alternative

Corresponding author E-mail: nagayosi@niigata-cn.ac.jp, tamaki@al.cs.kobe-u.ac.jp

shift, and the schedule is adjusted accordingly

3. Revising Duty roster Using Q-learning

3.1. *Setting Up the Problem for Q-learning*

The shift constraints (for example, the number of required nurses for each day) are met by the duty roster generated by the constructive nurse rostering, which is generated sequentially from Day one. In contrast, when reviewing the duty roster for the entire scheduling period (such as one month), it may occur that individual nurse constraints (like a limited number of workdays) might remain unmet. Consequently, the violations *Inw* for work duty *w* is determined by counting the days on which the assignment of work duty *w* to each nurse *n* goes beyond *Unw,* the upper boundary. Revisions are then made iteratively as detailed below:

$$min \sum_{n} \sum_{v} I_{nw} \qquad (1)$$

The following steps outline the process for making a single revision.

(1) Pick a work duty w_S to be swapped, often the one with the highest number of violations.

(2) Identify the nurse n_S who has the most violations in the shift w_S.

(3) In the case that shift w_S is the nightshift, designate w_S as the shift (either the late or the overnight shift) with the higher number of violations for nurse n_S.

(4) When a work duty does not meet the minimum number of assignments for nurse n_S, swap it with the replacement shift w_D. If this is not the case, swap with the daytime shift that has no assignment constraints.

(5) Identify the day d_S that is most critical among the days when shift w_S is replaced by w_D for nurse n_S.

(6) Determine the group $g(j_S)$ in which nurse n_S is allocated for job j_S, scheduled for shift w_S.

(7) Identify a nurse n_D in group $g(j_S)$ who has shift w_D on day d_S. If multiple nurses qualify, pick the one with the highest priority for swapping shift w_D to w_S on day d_S.

(8) Swap the shifts of nurses n_S and n_D on day d_S.

If no suitable nurses are available in any of the procedures, the exchange is invalid. Additionally, it is invalid to reverse a prior exchange.

Reducing the number of violations is complex due to the varying adjustments that can be made depending on the work duty being swapped.

3.2. *Setting for Q-learning*

In order to learn a suitable exchange procedure, Q-learning [3] is used in the proposed method. The state space of the Q-learning agent is defined by four dimensions: the previous exchange days (ranging from 1 to 30), the total number of violations for the late shift, the overnight shift, and the leave shift (represented as I_{nw} for *w*=1,2,3). The agent can take one of four actions: exchanging the late shift, the overnight shift, the leave shift, or the nightshift.

One step is defined as one exchange, even if they are unsuccessful. One episode lasts until the duty roster meets the goal or 100 steps have been taken. The goal is achieved when the combined violations of all nurses and shifts is zero, noted as $\sum_{n} \sum_{v} I_{nw} = 0$ (not including violations caused by an excessive number of leave shifts). A positive reinforcement signal of $r_t = 10$ is awarded only when the goal is achieved, whereas a reinforcement signal of $r_t = 0$ is provided at all other steps. Each episode begins with the duty roster in its starting condition.

4. Experimentation

4.1. *Problem Specification*

The proposed method addresses a nurse rostering problem similar to that of Kurashige et al. [4]. First, a system with three-shift (the daytime shift, the late shift, and the overnight shift) is implemented, with a total of 23 nurses, one of whom is the chief nurse. The positions are classified into 3 categories (chief nurse, deputy chief nurse, and general nurse), there are 2 teams (Team 1 and Team 2), and the skill levels are categorized into 3 types (advanced, skilled, and beginner). The additional constraints are outlined below.

- Shift-specific nurse allocation limits:
  1. A minimum of 10 nurses is needed for the daytime shift on weekdays.
  2. 5 nurses are necessary for the daytime shift on weekends and holidays.
  3. The overnight shift requires 5 nurses.
  4. The late shift requires 5 nurses.

Next, Table 1 presents duty plan valuations spanning 2 days.

Table 1. Duty plan valuations spanning 2 days.

shift on preceding day	shift for the current day			
	daytime	late	overnight	leave
daytime	15	1	13	11
late	0	5	0	12
overnight	0	8	5	4
leave	23	3	0	17

We explore the potential for developing a revised duty roster under three different scenarios:

- Case A: All nurses have the duty plan valuations detailed in Table 1.
- Case B: Only Staff 6, the advanced nurse from Team 1, has duty plan valuations incorporating shifts from the late to the overnight, as shown in Table 2.
- Case C: Only Staff 5, the advanced nurse from Team 1, has duty plan valuations for nurses who prefer the nightshift, as shown in Table 3.
- Case D: Only Staff 4, the advanced nurse from Team 1, has duty plan valuations for nurses who prefer longer vacation time, as shown in Table 4.
- Case E: Staff 6, 5, 4, the advanced nurses from Team 1, have duty plan valuations shown in Table 2, 3, 4, respectively.

Table 2. Duty plan valuations spanning 2 days, incorporating shifts from the late to the overnight.

shift on preceding day	shift for the current day			
	daytime	late	overnight	leave
daytime	15	1	13	11
late	0	2	8	7
overnight	0	8	5	4
leave	23	3	0	17

Table 3. Duty plan valuations spanning 2 days for nurses who prefer the nightshift.

shift on preceding day	shift for the current day			
	daytime	late	overnight	leave
daytime	10	4	15	11
late	0	5	0	12
overnight	0	8	5	4
leave	18	8	0	17

Table 4. Duty plan valuations spanning 2 days for nurses who prefer longer vacation time.

shift on preceding day	shift for the current day			
	daytime	late	overnight	leave
daytime	10	1	13	16
late	0	5	0	12
overnight	0	8	5	4
leave	18	8	0	17

Table 5. Q-learning parameter

Parameter	Value
Learning rate α_Q	0.1
Discount rate γ	0.9
Temperature τ	0.1

4.2. *Setting for Q-learning*

In the state space of the Q-learning agent, the number of violations can range from 0 to 2, resulting in 3 possible states.

The experimentation was conducted using the parameters shown in Table 5. Additionally, Q-values are initialized to 5.0 for all starting conditions.

4.3. *Results*

During the learning process over 20 simulations, we tracked the average number of steps required to achieve the task and the average total number of violations for Cases A, B, C, D and E. The findings are shown in Figs. 1 and 2, respectively.

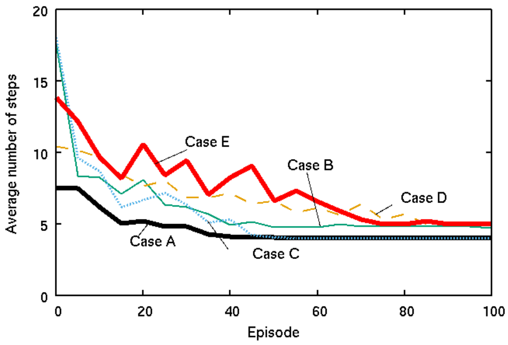

Fig. 1. The average number of steps required to achieve the task for Cases A, B, C, D and E.

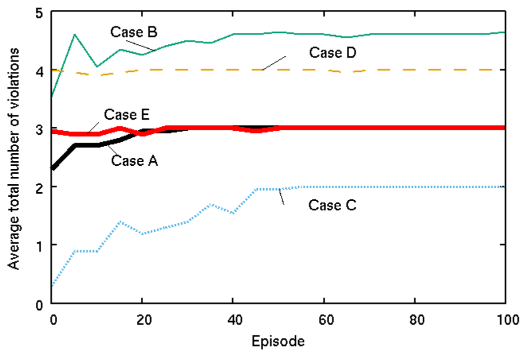

Fig. 2. The average total number of violations to achive the task for Cases A, B, C, D and E.

Figs. 1and 2 illustrate the following observations: (1) In all cases, the goal state was reached after approximately 5 steps. (2) In Case B, the number of violations was lower than in Case A. (3) In Case E, the number of violations was the same as in Case A. (4) In Cases B and D, the number of violations was higher than in Case A.

From these observations, it can be confirmed that, although the number of violations varies from case to case, a feasible revised roster was obtained in all cases.

Figs. 3, 4, 5, 6 and 7 display the average duty plan valuations for each nurse for each day, including the average valuations of the preceding day and the current day, the current day and the next day, as well as the overall average duty plan valuations in the revised duty roster for Cases A, B, C, D and E. In Fig. 4, the red box on the 24th, 25th, and 26th days for Staff 6 denote the average duty plan valuations for the overnight shift, late shift, and overnight shift, respectively.

Based on Figs. 3 to 7, the following can be observed:

(1) In all cases, the overall average of the duty plan valuations shows little difference, ranging from 13.9 to 14.2.

(2) In Case B, the overall average of the duty plan valuations is higher than in Case A.

(3) In Cases C, D, and E, the average value of nurse with particularly different duty plan valuations is lower than in other cases.

This likely occurred because the average duty plan evaluation for these nurses decreased when the valuation for the "leave shift to daytime shift" pattern, which typically has the highest score of 23, was set lower, as well as the valuation for the most common "daytime shift to daytime shift" pattern, which usually has a score of 15, was also set lower. These adjustments were made to accommodate preferences for the nightshift or longer vacation time. Based on the above, it is considered necessary to present a concrete method for setting duty plan valuations that allows each nurse to standardize the valuation while also considering their own lifestyle when determining their duty plan valuations.

While further experimentation is necessary, assigning duty plan valuations based on each nurse's preferences will allow them to achieve a work style that aligns with their lifestyle. Additionally, it will assist them in understanding the duty roster creation process.

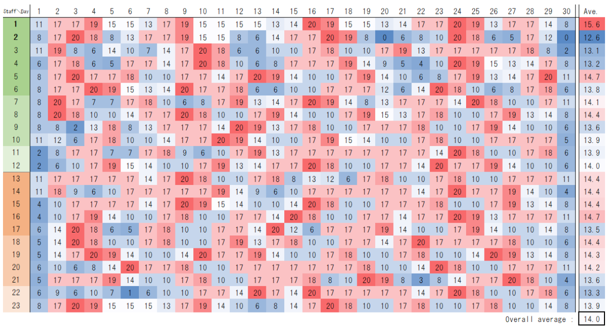

Fig. 3 Average duty plan valuations in the revised roster for Case A.

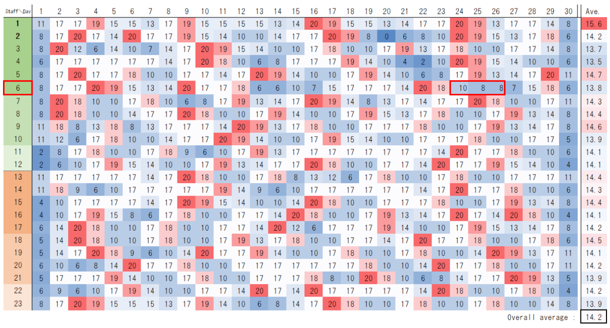

Fig. 4 Average duty plan valuations in the revised roster for Case B.

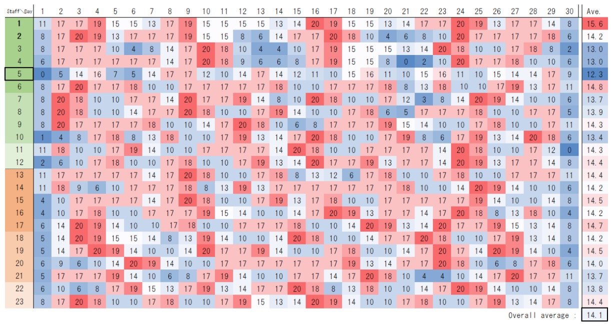

Fig. 5 Average duty plan valuations in the revised roster for Case C.

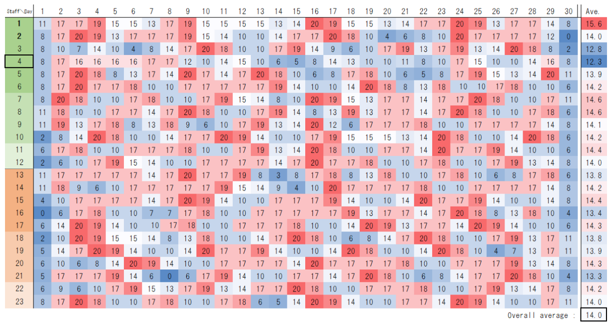

Fig. 6 Average duty plan valuations in the revised roster for Case D.

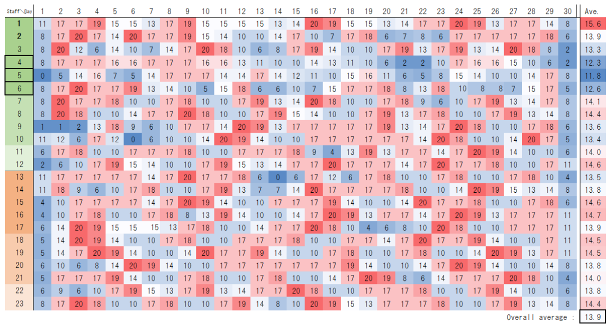

Fig. 7 Average duty plan valuations in the revised roster for Case E.

5. Conclusion

This paper explored the potential for developing a practical duty roster that accommodates nurses with different duty plan valuations. This involves considering the lifestyle of each nurse. Additionally, we visualized the duty plan valuations of the revised rosters. We compared the overall averages of the duty plan valuations in the four cases to that of a typical case. In all cases, the overall average of the duty plan valuations shows little difference.

Upcoming projects will aim to validate the proposed method's effectiveness in cases where nurses assess a greater diversity of duty plan valuations and other relevant factors.

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Authors Introduction

Dr. Masato Nagayoshi

He is an Associate Professor of Niigata College of Nursing. He graduated from Kobe University in 2002 and received Master of Engineering from Kobe University in 2004 and Doctor of Engineering from Kobe University in 2007. IEEJ, SICE, ISCIE member.

Dr. Hisashi Tamaki

He is a Professor, Graduate School of Engineering, Kobe University. He graduated from Kyoto university in 1985 and received Master of Engineering from Kyoto University in 1987 and Doctor of Engineering from Kyoto University in 1993. ISCIE, IEEJ, SICE, ISIJ member.