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Research Article

A Dynamic Nurse Scheduling Approach Using Reinforcement Learning to Address Sudden Absences of an Unknown Nurse

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ABSTRACT

Creating work shift schedules for nurses can be a complex task, as it involves satisfying various requirements that can be difficult to reconcile. Although several studies have investigated the nurse scheduling problem, creating practical work schedules with numerous constraints and evaluation values can still be challenging. To address this issue, we have proposed a method for work revision that utilizes reinforcement learning to improve a constructive nurse scheduling system. In this article, we extend the proposed method to accommodate dynamic nurse scheduling, wherein work schedules are revised or rescheduled in response to sudden absences. Specifically, we demonstrate the effectiveness of our approach in creating feasible work schedules for an unknown nurse who may be absent at any given time, through computational experiments.

1. Introduction

Many studies have been conducted on the nurse scheduling problem[1], which involves creating work shift schedules for nurses. Despite this, in practical applications, adjustments are often necessary to incorporate various constraints and evaluation criteria, and the schedules produced may not always be practical, leaving many head nurses feeling overwhelmed[2]. To address this issue, we have proposed a method for work revision[3] that utilizes reinforcement learning[4] to improve a constructive nurse scheduling system[5]. While reinforcement learning (RL) has been extensively studied in various fields, to the best of our knowledge, its application to the nurse scheduling problem has not been reported.

In this article, we extend the proposed method to accommodate dynamic nurse scheduling, wherein work schedules are revised or rescheduled in response to sudden absences. Specifically, we demonstrate the effectiveness of our approach in creating feasible work schedules for an unknown nurse who may be absent at any given time, through computational experiments.

2. Constructive Nurse Scheduling System

2.1. *Characteristics*

The characteristics of the constructive nurse scheduling system[5] include:

1. Beginning with the earliest day in the scheduling period, the system generates a daily schedule.
2. The consideration of specific conditions can be incorporated into the priority calculation.
3. It does not consider the evaluation value of the shift schedule for the entire month.
4. The nurse scheduling problem is transformed into an N×N assignment problem by assigning priorities to each job *j* assigned to each nurse *n*. This transformation enables the efficient use of the Hungarian method for problem solving. Note that jobs are prepared for each nurse *n* by dividing the

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work shift w, including shifts that fall on holidays, of the relevant period by the number of nurses in their respective groups.

2.2. *Modification of Work Shifts*

The constructive scheduling system only takes into account the basic constraints that are required in a hospital with a large number of nurses, which could result in a feasible solution that does not satisfy the head nurse. Therefore, Kurashige et al.[5] proposed the following two procedures for actual modification.

(1) If a work shift for a nurse does not satisfy the head nurse, it can be manually exchanged with the work shift of another nurse. But such exchanges must meet all relevant constraints to be valid. If the exchange violates any constraints, a warning message will be displayed.

(2) To address situations where the head nurse's requirements are not satisfied, a manual exchange of a nurse's work shift is conducted with another nurse's shift designated as a replacement. It is important to ensure that the exchange satisfies all relevant constraints, and a warning message is displayed if it does not. Although the next solution displayed may not be satisfactory, this exchange and rescheduling process is repeated until a satisfactory solution is obtained.

The following sections will describe our proposed system [3], which employs RL to learn the exchange procedure.

3. Modification of Work Shifts Employing Reinforcement Learning

3.1. *Setting up the Problem for Reinforcement Learning*

The shift schedule generated by the constructive nurse scheduling system, in which shifts are assigned in sequential order from the first day, meets the shift constraints, such as the required number of nurses for each day. On the other hand, when the schedule of work shifts spanning the entire scheduling period, such as one month, is examined, there may be cases where nurse constraints, such as the maximum number of workdays, are not satisfied for individual nurses.

For this reason, the number of violations Vnw for work shift w is calculated as the number of days that exceed $UTnw$, which is the upper limit of the number of times work shift w is assigned to each nurse n based on the work schedule. A revision is then repeated according to the following Equation (1):

$$min \sum_n \sum_v V_{nw} \qquad (1)$$

The procedure for one revision is employed for the following steps:

(1) Choose a work shift w_0 to be exchanged, typically the one with the most violations.

(2) Determine the nurse n_0 with the most violations in the shift w_0.

(3) If the shift w_0 corresponds to the night shift, designate the shift w_0 with the most violations, whether it is an evening or late-night shift as w_0 for the nurse n_0.

(4) If there is a work shift that falls below the lower limit of the number of assignments for the nurse n_0, designate that work shift w_1 as the destination of the exchange shift. If there is no work shift that falls below the lower limit of the number of assignments for the nurse n_0, use a day shift without the upper and lower limits of the number of assignments as the exchange.

(5) Find the day d_0 that has the highest priority for the nurse n_0 among the days to switch from the shift w_0 to w_1

(6) Find out the group $g(j_0)$ in which the nurse n_0 is responsible for regarding the job j_0 that corresponds to the shift w_0.

(7) Find a nurse n_1 from the group $g(j_0)$ whose shift is w_1 on the day d_0. If there are multiple nurses that meet this condition, choose the one with the highest priority when exchanging the shift w_1 to w_0 on the day d_0.

(8) Exchange the shifts of the nurses n_0 and n_1 on d_0.

If there is no corresponding nurse in any of the procedures, the exchange cannot be carried out. Additionally, undoing a previous exchange is also not valid.

The problem of minimizing the number of violations is considered very challenging since the number of potential modifications depends on which work shift is being exchanged.

3.2. *RL Agent*

The proposed method applies Q-learning[6] to learn an appropriate exchange procedure. The state space of the RL agent consists of 4 dimensions: the previous exchange day (from day 1 to day 30), the sum of all violations committed by nurses for evening, late-night, and holiday shift, denoted as V_{nw} (w=1,2,3), to form a Markov decision process. A total of 4 actions are possible, corresponding to the exchange of holiday, evening, late-night, and night shift.

One episode is defined as a period in which the shift schedule reaches the target state or 100 steps have passed, and one step is defined as one exchange, including unsuccessful cases. The target state is defined as having no violations across all nurses and shifts, excluding violations of maximum holiday limits, which is equal to

$\sum_n \sum_v V_{nw} = 0$. The reinforcement signal $r_t = 10$ is only given when the target state is achieved, and the reinforcement signal $r_t = 0$ is given for all other steps. Each episode starts with the shift schedule being reset to its initial state prior to the sudden absence.

4. Dynamic Nurse Scheduling Approach Using Reinforcement Learning

When an assignment of work shift needs to be changed suddenly due to an absence or other unforeseen circumstances, the following procedure is used to secure an alternative nurse first. It may be considered to change to the night shift (which includes both evening and late-night shifts) if changing to the day shift cannot be avoided, but in this article, only changes to the holiday shift will be considered.

(1) Choose the original work shift w_0 of the absent nurse n_0 on the day of the absence d_A as the basis for the exchange, and mark the new work shift w_1 as a holiday.

(2) Find out the group $g(j_0)$ in which the absent nurse n_0 is responsible for regarding the job j_0 that corresponds to the shift w_0 on the day d_A.

(3) Find a nurse n_1 from the group $g(j_0)$ whose shift is w_1 on the day d_A. If there are multiple nurses that meet this condition, choose the one with the highest priority when exchanging the shift w_1 to w_0 on the day d_A. If no eligible nurse is found, select the nurse n_1 by attempting to shift the original work shift w_0 to the day shift, followed by the late-night shift, and then the evening shift, in that sequence.

(4) Exchange the shifts of the nurses n_0 and n_1 on the day d_A. Then, change the work shift of the nurse n_0 to a designated work shift so that the work shift of the nurse n_0 will not be exchanged anymore.

The exchange procedure is then obtained via RL using the same procedure as described in Section 3.1 following an absence. Nevertheless, in this scenario, the day with the highest priority is found following the absence date, d_A.

5. Computational Experiments

5.1. *Nurse Scheduling Problem*

Analogous to Kurashige et al. [5], we apply the extended method to a nurse scheduling problem. The scheduling problem was characterized by a system consisting of three shifts: day, evening, and late-night with a total of 23 nurses. The number of positions is classified into three categories: head nurse, deputy head nurse, and staff nurse. The nurses are divided

Table 1 Evaluation of Shift Pattern for 2 Days

Work shift on previous day	Work shift on the day			
	Day	Holiday	Evening	Late-night
Day	15	11	1	13
Holiday	23	17	3	0
Evening	0	12	5	0
Late-night	0	4	8	5

Table 2 Parameters for Experiments

Parameter	Value
α_Q	0.1
γ	0.9
τ	0.1

into two teams, and the skill level is further categorized into three levels: seasoned, experienced and novice. The other scheduling constraints are described below.

- Constraints on the number of nurses per shift as follows:
  (1) The minimum required number of nurses for the day shift on weekdays is 10 or more.
  (2) The minimum required number of nurses for the day shift for weekends and holidays is 5.
  (3) The minimum required number of nurses for the late-night shift is 5.
  (4) The minimum required number of nurses for the evening shift is 5.

Next, Table 1 shows the evaluation values of shift patterns for 2 days with M = 2.

5.2. *RL Agent*

The total number of violations in the state space of the RL agent is assumed to be in the range of [0, 2] and can take on 3 states.

The computational experiments were conducted using the parameters shown in Table 2. Additionally, all initial Q-values were set to 5.0 as optimistic initial values.

5.3. *Results*

We conducted 50 simulations to observe the average number of required steps for accomplishing the task and the average of the total number of violations when accomplishing the task in the occurrence of a sudden absence on day, evening and late-night shift, as illustrated in Figures 1 and 2, respectively. Here, the day of absence and which nurse would be absent were randomly selected.

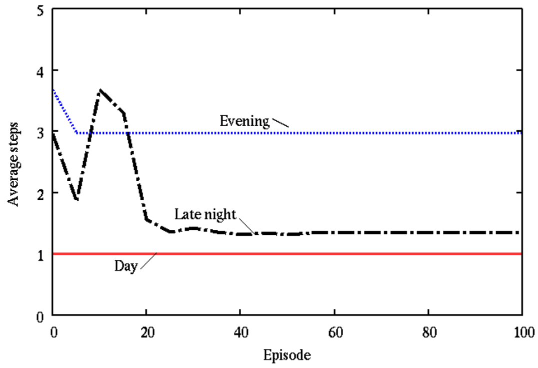

Figure 1 Required steps for accomplishing the task.

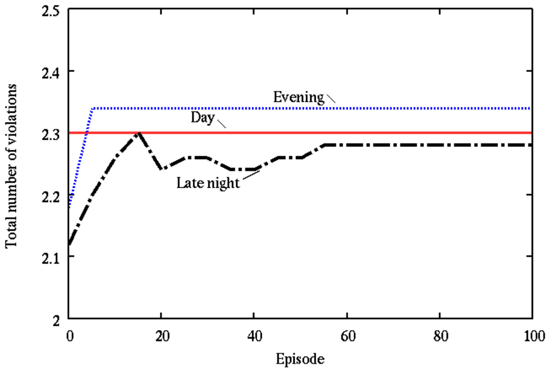

Figure 2 Average of the total number of violations when accomplishing the task.

Figures 1 and 2 demonstrate that (1) the target state was achieved in a few steps for day and late-night shift absences, (2) the task required 100 steps only once during an evening shift absence because the target state could not be reached, and (3) the number of violations did not increase much from the initial number of 2.

In the evening shift, the target state could not be reached and there was no alternative nurse available for the 17th nurse's absence on the 28th day. This situation could not be resolved without increasing the number of violations, excluding violations of maximum holiday limits, in the current month only, since the absence occurred late in the month. In practical terms, it is often necessary to secure an alternative nurse while taking into account the work shift schedule for the following month.

Then, an exchange procedure acquired that reached the maximum number of steps and the resulting modified shift schedule are shown in Figures 3 and 4, respectively, in case of the 15th nurse's absence during the late-night shift on the 13th day. The right-hand columns of

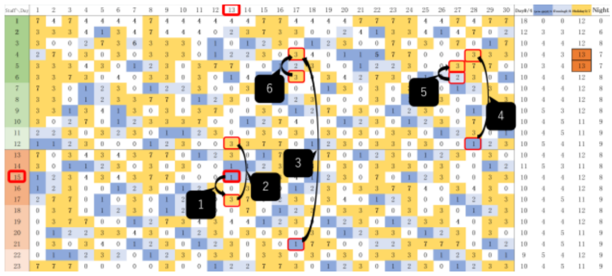

Figure 3 An acquired exchange procedure.

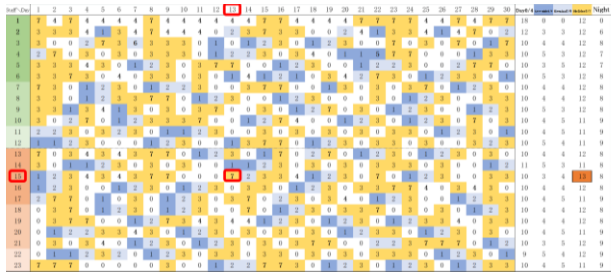

Figure 4 A resulting modified shift schedule.

Figures 3 and 4 display the number of assignments for each work shift, in which marked with color to signify violations.

Figures 3 and 4 illustrate that (1) our approach was successful in managing sudden absences through six exchanges, (2) the number of violations of the maximum holiday limits decreased from 2 to 1 after six exchanges.

We confirmed from Figures 1, 2, 3 and 4 that the effectiveness of our approach in creating feasible work schedules for an unknown nurse who may be absent at any given time other than during the designated work shift, except for absences occurring at the end of the month in this task.

6. Conclusion

In this article, we extended the proposed method to accommodate dynamic nurse scheduling, wherein work schedules are revised or rescheduled in response to sudden absences. Through computational experiments, we confirmed the effectiveness of our approach in creating feasible work schedules for an unknown nurse who may be absent at any given time other than during the designated work shift, except for absences occurring at the end of the month.

Our future projects include responding to sudden absences during designated work shifts and clarifying the rules for creating shift schedules, among other tasks.

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