Optimal Nursing Home Shift Scheduling: A Two-Stage Stochastic Programming Approach

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***Abstract*— In this paper, we study a nursing home staff schedule optimization problem under resident demand uncertainty. We formulate a two-stage stochastic binary program accordingly, with objective to minimize the total labor cost (linearly related to work time) incurred by both regular registered nurses (RRNs) and part-time nurses (PTNs). As a significant constraint, we balance RRNs' total amount of work time with residents' total service need for every considered shift. Besides, we restrict feasible shift schedules based on common scheduling practice. We conduct a series of computational experiments to validate the proposed model. We discuss our optimal solutions under different compositions of residents in terms of their disabilities. In addition, we compare the total labor costs and an RRN scheduling flexibility index with the given optimal solution under different combinations of RRNs and PTNs. Our analysis offers an operational approach to set the minimum number of nurses on flexible shift schedules to cover uncertain the service needs while maintaining a minimum labor cost.**

***Index Terms*— Nurse scheduling, stochastic integer programming, demand scenario generation, Minimum Data Set (MDS)**

I. Introduction

With population aging and hospital overcrowding in the United States, demand for receiving care at nursing homes (often downstream facility after hospital discharge) is increasing rapidly. According to the Department of Health and Human Services, about 70 percent of the 76 million baby boomers will need some form of long-term care. About 13 million people may stay more than three years in a skilled nursing facility (or generically referred to a nursing home) [1].

Nursing homes are an essential component of the U.S. healthcare system. These facilities provide long-term care and rehabilitative care to the elderly and disabled, either physically or mentally. Most nursing homes have skilled nurses on duty 24 hours a day. Contrary to the increasing need for nursing care, there is a growing trend of skilled nurse shortage due to high nursing home staff turnover.

According to an American Nurses Association Annual Reports [2], above 40% of registered nurses (main workforce in nursing homes) expressed many workplace problems, such as burnout, stressful workplace, inconsistent staffing, as the reasons of high staff turnover. More than half of them complained about insufficient time with patients, and 54% of them reported that they had excessive workloads. While health service researchers have proposed effective staffing mechanisms (e.g., evidence-based nurse-resident ratio) to avoid the burnout issue of nursing home staff, it remains challenging to determine how cost-beneficial these mechanisms are at a particular nursing home, especially when dealing with fluctuating resident needs.

This work aims to develop a decision support tool to help nursing homes arrange their staff schedule at the operational level to maintain their financial viability while providing model care for their residents based on diverse needs. In addition, healthy continuing operations at each nursing home should not be ignored, which implies that each nursing home must follow labor guidelines on staffing and shift design, e.g., providing enough rest time for nurses between shifts. Overall, it is critical to nursing homes to develop work schedules to balance financial viability and staff friendliness under the requirement of delivering standard care.

In this paper, we present a two-stage stochastic programming model for designing an appropriate work schedule that assigns nurses to each shift, balancing the staff workload on a shift basis and fluctuating resident needs. The stochastic optimization problem we will present involves a binary decision on both stages, which makes solving it computationally expensive. Besides, To devise an appropriate shift-based work schedule, residents need prediction is of vital importance. Such speculation is challenging because nursing home managers need to consider various factors such as resident characteristics, nursing home facilities, and the environment. Furthermore, the time-varying nature inherent to some of the above factors, especially resident characteristics, adds additional complexity to modeling the service demand uncertainty. With a well-developed prediction model, we draw samples of shift-wise service demand over a two-week period (the typical duration of shift scheduling in a nursing home). We study the correlation between the two-week operating cost and the shift patterns (full-time registered nurses vs. part-time agency nurses, number of shifts for each full-time registered nurses).

Our main contribution in this paper is to develop a stochastic programming model for nursing home staff scheduling decision optimization under demand uncertainty. Note that there is a lack of decision support systems in the nursing home industry, especially towards operational scheduling. In addition, we utilize real-world nursing home clinical assessment data and established service demand classification system based on a long-term national nursing home time study. These add practical value to our optimal decisions. Finally, with studies in the operational context of a representative nursing facility, we demonstrate the viability of

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our presented sensitivity analysis in offering management insights into optimal schedule adjustment concerning case-mix percentage changes and staff hourly payment changes.

The paper is organized as follows. In Section 2, we review the relevant literature on health services/outcomes research areas and operations engineering scheduling problems with multiple work activities and stochastic demand. We present some background material related to the clinical assessment data. We will use these resourses to generate the scenarios for our two-stage nursing home staff scheduling optimization problem. In Section 3, we describe the two-stage model. We also describe the details of creating the scenario set for the nursing home scheduling model. We present computational experiments and discuss the results in Section 4. In section 5, we address our conclusions and point out our future work.

II. Literature Review

We first review relevant literature in health services/outcomes research areas. Much of the literature is focused on resource management and planning, which often reports real-world evaluation studies on experience-based staffing strategies (e.g., [3], [4]) and/or aggregate and one-size-fits-all policies (e.g., [5], [6]). These studies often simplify the service demand by assuming a homogeneous population of nursing home residents and neglecting the complexity in the service demand heterogeneity.

We next review relevant operations engineering literature on personnel staffing and scheduling. We focus on staffing and shift assignment optimization studies, which are the most pertinent to this paper. Venkataraman and Brusco [7] presented an optimal staffing and scheduling model for hospitals. The objective is to minimize total nursing labor costs. As an early attempt, the authors did not consider the uncertainty of the demand. Easton and Rossin [8] proposed a general staffing and scheduling model. The objective is to minimize wage costs plus labor shortage and surplus penalties. And the optimal solution is a probability distribution for the quantity of labor required but not a detailed schedule at every minimum time unit. The authors use the uncertainty of the labor requirement in their optimization model by assuming it comes from some simple distribution. Easton and Mansour [9] provided a unified formulation for both deterministic and stochastic labor scheduling problems and solves them by a distributed genetic algorithm that aims at minimizing the sum of labor expenses and expected opportunity costs. Although both approaches aim to solve problems over a one-week planning horizon, employee patterns are previously defined, and only a small set of stochastic scenarios is considered.

We then review relevant literature on nurse scheduling problems. Burke et al. [10] presented a review paper on nurse rostering problems. They categorize papers according to solution methods, constraints, and performance measures. This paper also provides tables with information on the planning period, the data used (i.e., real-world or theoretical), and the number of skills and their substitutability, etc. Wright and Bretthauer [11] solved a nurse scheduling optimization problem and a staff adjustment problem separately with deterministic resident demand. Maenhout and Vanhoucke [12] focused on integrated staffing and scheduling decision optimization. They used a Dantzig Wolfe decomposition approach to integrate nurse staffing and scheduling decisions in a deterministic setting. Bard and Purnomo [13] used an optimal staffing and scheduling model to compare alternative mechanisms for handling staff shortage. The authors incorporated the uncertainty that comes from a widely fluctuating demand. This model focus on satisfying nurse's individual preferences and design a daily schedule but not a shift-based schedule. More recently, Punnakitikashem et al. [14] studied an optimal staffing and assignment problem where the first-stage decision assigns each nurse to patients, and the second stage balances the workload for each nurse. Kim and Mehrotra [15] focused on integrated staffing and scheduling decision optimization, with demand prediction based on multiple-year patient volume data. Note that all the above nurse scheduling problems are applied to hospitals and emergency rooms.

Based on the above review, we conclude that to the best of our knowledge, there is no research focused on nursing home staff scheduling optimization under resident demand uncertainty. Besides, little work has utilized realistic clinical assessment data to determine time-based care needs. In our work, we utilize the Minimum Data Set (MDS), which is part of a federally mandated process for clinical assessment of all residents in Medicare or Medicaid certified nursing homes [16]. To convert the clinical assessment to time-based care needs, we adopt a national nursing home staff time measurement (STM) study, the Staff Time and Resource Intensity Verification (STRIVE) Project [17]. Data collected from the STRIVE study have been used to establish payment systems for Medicare and Medicaid funded nursing homes.

III. Mathematical Modeling

Our study formulated a two-stage stochastic binary program that integrates scheduling decisions with extra part-time agency nurse staffing decisions to hedge service demand uncertainty. We consider a standard-setting of nursing homes in practice. We assume that there are three eight-hour shifts per day in any feasible schedule, which is the most acceptable schedule for nurses' comfortable length of working hours. A morning shift is from 7 am to 3 pm; an evening shift is from 3 pm to 11 pm, and a night shift is from 11 pm to 7 am on the second day. We consider full-time and part-time employments over a 2-week schedule, which is the minimum working length that can be counted in the standard payroll system. In order to avoid nurses' burnout, we use practical nursing home scheduling rules to ensure enough break times.

A. A Two-Stage Stochastic Binary Programming Model

Consider the problem over a planning horizon (2 weeks in our study). For 14 days, each day contains three shifts. The overall planning horizon will be 42 shifts long. Along the planning horizon, we make decisions at two stages: shift scheduling for regular registered nurses (RRN) at the first stage (denoted by vector $\mathbf{x}$) and staffing level adjustment with part-time nurses (PTN) at the second stage (denoted by vector $\mathbf{y}$). We will use τ_a^t to denote whether pattern $a \in \mathcal{A}$ contains time t. Each RRN is assigned to a scheduling pattern. Let c_a^r and c_t^p be the hourly rates for the payment of RRN and PTN, respectively. These rates are assumed to be variable with different scheduling patterns.

Set of Indices:

$\mathcal{R}$: set of RRNs, $i^r \in \mathcal{R}$.
$\mathcal{P}$: set of PTNs, $i^p \in \mathcal{P}$.
$\mathcal{T}$: set of shifts, $t \in \mathcal{T}$.
$\mathcal{A}$: set of scheduling patterns, $a \in \mathcal{A}$.
Ω: set of scenarios $\omega \in \Omega$.

Model Parameters:

c_a^r: staffing payment for a RRN assigned to pattern a.
c_t^p: per shift payment rate for a PTN called in to cover shift t.
τ_a^t: 1 if scheduling pattern a contains shift t, and 0 otherwise.
l^t: working time at shift t (480 minutes in our study).
ω: random scenarios, $\omega \in \Omega$.
$d^t(\omega)$: service demand (in minutes) required in shift t for scenario ω.
$p(\omega)$: probability of scenario ω.

Decision Variables:

$x_{i^r a}$: 1 if RRN i^r is assigned to scheduling pattern a, and 0 otherwise. *First-stage decision variables*.
$y_{i^p}^t(\omega)$: 1 if PTN i^p is scheduled for shift t; and 0 otherwise, for each scenario $\omega \in \Omega$. *Second-stage decision variables*.

$$\min_{\mathbf{x}} \quad \left\{ \sum_{a\in\mathcal{A}} \sum_{i^r\in\mathcal{R}} c_a^r x_{i^r a} + Q(\mathbf{x}) \right\} \tag{1}$$

subject to

$$\sum_{a\in\mathcal{A}} x_{i^r a} = 1 \quad \forall i^r \in \mathcal{R}, \tag{2}$$

$$\sum_{i^r\in\mathcal{R}} \sum_{a\in\mathcal{A}} \tau_a^t x_{i^r a} \geq 1 \quad t \in \mathcal{T}, \tag{3}$$

$$\sum_{j=t}^{t+2} x_{i^r a} \tau_a^t \leq 1 \quad \forall i^r \in \mathcal{R}, a \in \mathcal{A}, t = 1, \ldots, 40, \tag{4}$$

$$x_{i^r a}(\tau_a^t - \tau_a^{t+21}) = 0 \quad \forall i^r \in \mathcal{R}, a \in \mathcal{A}, t = 1, \ldots, 21, \tag{5}$$

$$\sum_{t=1}^{21} \sum_{a\in\mathcal{A}} x_{i^r a} \tau_a^t \leq 5 \quad \forall i^r \in \mathcal{R}, \tag{6}$$

$$x_{i^r a} \in \{0, 1\} \quad \forall i^r \in \mathcal{R}, a \in \mathcal{A}, \tag{7}$$

$$Q(\mathbf{x}) \triangleq \sum_{\Omega} [p(\omega) \cdot \min_y q(\mathbf{x}, \omega)], \tag{8}$$

where for each $\omega \in \Omega$,

$$q(\mathbf{x}, \omega) = \sum_{t\in\mathcal{T}} \left(\sum_{i^p\in\mathcal{P}} c_t^p y_{i^p}^t(\omega) \right) \tag{9}$$

subject to

$$\sum_{i^p\in\mathcal{P}} y_{i^p}^t(\omega) \geq d^t(\omega)/l^t - \sum_{i^r\in\mathcal{R}} \sum_{a\in\mathcal{A}} \tau_a^t x_{i^r a} \ \forall t \in \mathcal{T}, \tag{10}$$

$$\sum_{t=1}^{21} y_{i^p}^t(\omega) \leq 3 \quad \forall i^p \in \mathcal{P}, \tag{11}$$

$$\sum_{t=22}^{42} y_{i^p}^t(\omega) \leq 3 \quad \forall i^p \in \mathcal{P}, \tag{12}$$

$$\sum_{k=t}^{t+2} y_{i^p}^t(\omega) \leq 1 \quad \forall i^p \in \mathcal{P}, t = 1, \ldots, 40, \tag{13}$$

$$y_{i^p}^t(\omega) \in \{0, 1\} \quad \forall i^p \in \mathcal{P}, t \in \mathcal{T}. \tag{14}$$

At the first stage, each nurse is assigned to one scheduling pattern a in advance, ensured by constraint (2). Constraint (3) ensures that there must be at least one RRN for every shift t. At the second stage, PTNs are staffed and assigned to shifts to cover residents' demand for each scenario, by constraint (10). The objective (1) aims to minimize the sum of RRN shift assignment cost and expected PTN schedule adjustment cost. For the mathematical expression of the latter cost, please refer to the second-stage objective (8) and (9)

We further incorporate practical scheduling constraints in the formulation. Every week, each RRN cannot work over five shifts (i.e., 40 hours), ensured by constraint (6); and each PTN cannot work over three shifts (i.e., 24 hours), ensured by constraints (11) and (12). In addition, for management convenience and service quality, the shift scheduling of each RRN often repeats itself from week to week. Finally, each nurse who works in the morning/evening/night shift cannot work until the next morning/evening/night shift, ensured by constraints (4) and (13).

B. Demand Scenario Generator

To generate the scenario set Ω for the above formulation, we develop a shift-specific facility-wide service demand generator. We first developed a computer simulation decision platform in characterizing the heterogeneous service demand of NH residents by utilizing multi-source information and knowledge, including real NH data (i.e., Minimum Data Set 3.0 [16]) of our partnering local NH provider in the Tama Bay area, patient classification system (e.g., [17]) adopted by the CMS, and existing NH staffing time study (i.e., STRIVE project [18]). We develop the arrival process and individual length-of-stay (LOS) for NH residents incorporating their characteristics and further considering their multiple discharge dispositions, such as community discharge and re/hospitalization. During his/her stay, each resident may require significantly different daily service demands due to their varied individual characteristics (e.g., ADL). We considered the RUG-IV patient classification system [17] to categorize NH residents into multiple services need groups, and each service needs group comprised residents with similar resource usage level. To further quantify service demands for NH residents from each service need group, we incorporated STRIVE project [18] from existing NH studies to quantify the required daily staff-time (in minutes) of nursing staff for NH residents in each service need group. The developed simulation is capable of generating the resident-level service demand of each individual as well as the facility-level service demand of a heterogeneous population of residents over time.

For the actual simulation model parameterization, we utilize de-identified electronic health records of residents from our industrial collaborator, Greystone Healthcare, based in Tampa, Florida, to evaluate the performance of the proposed work. The data set contains details of admission and discharges records, and rich resident-level health assessment information, including but not limited to socio-demographic, clinical diagnoses, chronic conditions, and functional performances (e.g., physical limitation and cognitive impairment).

In the baseline setting, we utilize the original cohort from this data set. We consider a total of 710 residents. Most of the residents are frail and have multiple chronic conditions. Moreover, the activities of daily living (ADL) score is further considered to represent the required functional assistance of each resident. An ADL score ranges from 0 to 16, and a higher ADL value indicates a higher level of functional assistance required by the resident. In the baseline scenario, 10% of residents are functionally independent and have ADL values no more than 1; 15% of residents are highly dependent (with ADLs greater than 10) and thus require significant functional assistance. For the resident arrival process, negative binomial distribution i.e.,NB(r, p), is considered to model the arrivals of NH residents (with estimated parameters of $r = 4.95$ and $p = 0.64$) since it exhibits the best goodness-of-fit as compared to other parametric distributions. The p-value of goodness-of-fit (e.g., Chi-square test) is 0.3, which indicates that the estimated model has a satisfactory goodness-of-fit to the real arrival data. In the end, we divide the simulated daily demand into morning, evening, and night shifts by a ratio of 2:2:1 to generate the facility-wide service demand (in minutes) at each shift over the scheduling horizon.

IV. Numerical Experiments

In our numerical experiments, we first solve the baseline setting mentioned above and then perform sensitivity analysis concerning the case-mix setting. We implement the proposed mathematical model in Python and solve the resultant instances with the Gurobi MIP solver. We consider 150 scenarios for each stochastic programming instance to solve. We run all the experiments on a personal computer with an Intel i5-6200U at a 2.3-GHz processor with 8-GB RAM.

A. *Scenario Description*

We set the nursing home's capacity to be 500 (large enough for any scenarios since the optimal capacity varies when arrival rate changes). In addition to the baseline setting on the case mixing, we consider two rather extreme settings to a representative nursing home. We summarize the characteristics of the three case-mix settings in table I. One alternative setting is that the majority of residents are highly dependent. We call it the *HD setting*. The other one is that most of the residents are functionally independent. We call it the *LD settting*. Note that in the generation of scenarios for the two alternative settings, the LOS for each simulated individual varies according to the self-development LOS models. Table II represents the statistics summary description of the simulated 150 demand scenarios for each of the three settings. Because of different ADL distributions, the daily demand that is counted by hours fluctuates to almost the same degree around various demand means. Figure 1 illustrates the 150 scenarios of service demand for each of the three settings.

TABLE I

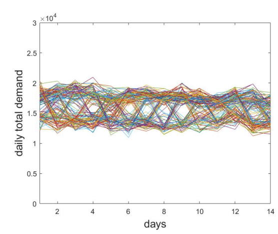
Demand scenario generation settings

Setting	ADL distribution
BLD	10%(0-1),75%(2-10),15%(11-16)
LD	90%(0-1),10%(2-16)
HD	10%(0-10),90%(11-16)

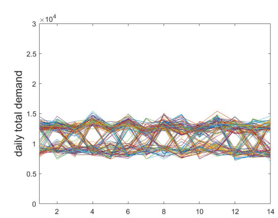
TABLE II

Summary statistics of demand scenarios (in hours)

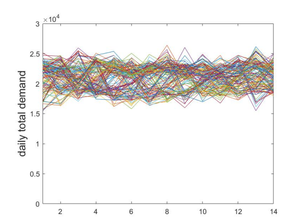
	BLD	LD	HD
mean	266.9	187.5	351.7
standard error	36.5	35.8	34.7
minimum	183.0	116.4	257.1
maximum	349.4	257.3	440.0



(a) BLD Setting



(b) LD Setting



(c) HD Setting

Fig. 1. Daily Demand under the three Case-mixing Settings

B. *Baseline Experimentation*

First, we set up the payment for RRNs (full-time contracted nurses) and PTNs (part-time agency nurses). According to the nation-wide wage study [18], a nursing home needs to pay a basic salary and F&A to each RRN. So the package to each RRN, factoring the amount of hours worked, tends to have a higher per-hour value but a lower pay rate than PTNs. In addition, accessory payments (like transportation) for PTNs need to be considered operational costs. Because of the reason we listed above, we set an hourly rate for paying each RRN to be $11. The source of this rate is the skilled nursing facility prospective payment system (PPS). Accordingly, we set an hourly rate for paying each PTN to be 1.5 times RRN hourly rate under the baseline setting. In practice, the ratio of RRNs to residents is 1 to 10, and it is often set relatively constant. Thus, for a nursing home of 500 residents, we set the number of RRNs to be 50 in the baseline. The following tables show the results. Note that the cost is counted in thousands of dollars.

TABLE III
TOTAL LABOR COST (IN THOUSANDS) UNDER THE BLD SETTING

RRNs \ PTNs	10	20	25	30
40	Infeas.	Infeas.	Infeas.	46.7
50	Infeas.	46.1	45.2	45.2
60	47.8	46.1	45.2	45.2

Table III represents the total labor cost under different combinations of RRNs and PTNs staffing levels under the BLD setting. Infeasible means that the combination can not cover the resident demand, leading to an understaffing situation. From the table, we can see that the lowest labor cost with the minimum number of total nurses appears at the combination of 50 RRNs and 25 PTNs.

Next, we set the number of RRNs to be 50 to check the RRN shift pattern distribution in the optimal schedule with respect to the PTN staffing level, i.e., different numbers of RRN shifts scheduled to cover the resident needs in a combination of some given PTN staffing level.

TABLE IV
RRN SHIFT PATTERN DISTRIBUTION UNDER THE BLD SETTING

PTNs	2 shifts	4 shifts	6 shifts	8 shifts	10 shifts
20	0	0	2	23	25
25	0	1	11	15	23
30	0	1	10	17	22

Table IV suggests the schedule flexibility under the BLD setting, i.e., RRN shift pattern distribution over a two-week schedule in the optimal solution. For example, when the number of PTNs is 20, half of the RRNs work ten shifts in the two-week schedule. We can see from the table that hiring more PTNs can reduce the number of RRNs working on too many shifts.

C. Sensitivity Analysis

Our results offer management insights for the case where nursing home faces a subdued working environment where the majority of residents are functionally independent. Our results show the labor cost is reduced by increasing the PTN staffing level. From table V, we can see that the lowest labor cost with a minimum number of total nurses appears at a combination of 40 RRNs and 20 PTNs. Here we set our RRN level to be 40 to check the scheduling flexibility in the optimal solution with respect to different PTN staffing levels.

TABLE V
TOTAL LABOR COST (IN THOUSANDS) UNDER THE LD SETTING

RRNs \ PTNs	5	10	15	20
40	Infeas.	34.6	34.6	33.1
50	35.8	34.6	34.6	33.1
60	35.8	34.6	34.6	33.1

TABLE VI
RRN SHIFT PATTERN DISTRIBUTION UNDER THE LD SETTING

PTNs	2 shifts	4 shifts	6 shifts	8 shifts	10 shifts
10	0	0	11	8	31
15	3	2	3	4	28
20	9	2	2	2	25

Table VI suggests the schedule flexibility under LD setting with 40 RRNs. Our results show that hiring more PTNs can help to change the working shifts distribution; hence can increase RRN schedule flexibility. In this case, RRNs can choose to take rests and pick their suitable work schedules. Our results indicate that in the LD setting, nursing homes can consider hiring more PTNs and fewer RRNs to increase schedule flexibility and reduce total labor costs. Our results give the management insight for the case where the nursing home faces an intense working environment where the majority of residents need a significant assistant. Our results show the RRN staffing level determines the labor cost.

TABLE VII
TOTAL LABOR COST (IN THOUSANDS) UNDER THE HD SETTING

RRNs \ PTNs	20	30	40	50
40	Infeas.	Infeas.	Infeas.	64.3
50	Infeas.	Infeas.	60.7	60.7
60	57.9	57.9	57.9	57.9

From table VII, we can see that the lowest labor cost with a minimum number of total nurses at a combination of 60 RRNs and 20 PTNs. Here we set our RRNs level to be 60, and we check the flexibility of the optimal schedule based on different numbers of PTNs to cover the resident's needs. From table VIII, we can see that the staffing level of PTNs will not affect working shift distribution. Our results indicate, in this case, where each RRN provides his or her maximum working time within a reasonable range of working time. Our results indicate that under the HD setting, nursing homes should consider hiring more RRNs to help reduce nurse work burden and total labor costs.

TABLE VIII

RRN SHIFT PATTERN DISTRIBUTION UNDER THE LD SETTING

PTNs	2shifts	4shifts	6shifts	8shifts	10 shifts
20	0	0	0	0	60
30	0	0	0	0	60
50	0	0	0	0	60

V. CONCLUSIONS AND FUTURE WORK

In this paper, we study a nursing home shift scheduling optimization problem with two nursing staff types, namely RRNs and PTNs. We formulate the problem as a two-stage stochastic binary program to determine the assignment of shift scheduling pattern for each RRN here and now. The program also offers the recourse action to take, i.e., for what shifts to call in PTNs to cover the service supply shortage. Our results suggest that the nursing home should design the RRNs and PTNs based on the case mixing condition and make adaption based on the standard resident nurse ratio. We suggest that for nursing homes having high functional independence, a lower RRN staffing level and more PTNs can help reduce labor costs and increase schedule flexibility. However, for nursing homes with high dependent residents, increasing the staffing level of RRNs will be a more effective way to reduce the labor cost and help nurses reduce the work burden.

In the future, we plan to improve the solution efficiency with the adaption of Benders decomposition based solution approaches with proper convexification of the binary recourse in the formulation. We will also incorporate the concerns on nurse-resident consistent assignment and nurse workload balance in the model, which can better justify the use of the self-developed shift-wise individual demand generator. The incorporation of the above two concerns will likely make the offered management insights more appealing to nursing homes that often suffer from nursing staff turnover and resident complaints on low patient-centeredness. Finally, to address temporal nonstationarity in the uncertain service demand over multiple staff scheduling periods, we will consider a Bayesian stochastic programming approach that can incorporate the notion of rolling-horizon staff scheduling into a stochastic programming framework.

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