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Optimal Nursing Home Service Scheduling under Covid-19 Related Probabilistic Staff Shortage: A Two-Stage Stochastic Programming Approach

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Abstract

Maintaining an appropriate staffing level is essential to providing a healthy workplace environment at nursing homes and ensuring quality care among residents. With the widespread Covid-19 pandemic, staff absenteeism frequently occurs due to mandatory quarantine and providing care to their inflicted family members. Even though some of the staff show up for work, they may have to perform additional pandemic-related protection duties. In combination, these changes lead to an uncertain reduction in the quantity of care each staff member able to provide in a future shift. To alleviate the staff shortage concern and maintain the necessary care quantity, we study the optimal shift scheduling problem for a skilled nursing facility under probabilistic staff shortage in the presence of pandemic-related service provision disruptions. We apply a two-stage stochastic programming approach to our study. Our objective is to assign staff (i.e., certified nursing aids) to shifts to minimize the total staffing cost associated with contract staff workload, the adjusted workload for the changing resident demand, and extra workload due to required sanitization. Thus, the uncertainties considered arise from probabilistic staff shortage in addition to resident service need fluctuation. We model the former source of uncertainty with a geometric random variable for each staffer. In a proof-of-the-concept study, we consider realistic COVID-19 pandemic response measures recommended by the Indiana state government. We extract payment parameter estimates from the COVID-19 Nursing Home Dataset publicly available by the Centers for Medicare and Medicaid Services (CMS). We conclude with our numerical experiments that when a skilled nursing facility is at low risk of the pandemic, the absenteeism rate and staff workload increase slightly, thus maintaining the current staffing level can still handle the service disruptions. On the other hand, under high-risk circumstances, with the sharp increase of the absence rate and workload, a care facility likely needs to hire additional full-time staff as soon as possible. Our research offers insights into staff shift scheduling in the face of uncertain staff shortages and service disruption due to pandemics and prolonged disasters.

Keywords
Staff scheduling, Nursing home, Covid-19, Stochastic programming, Health care delivery

1. Introduction

Nurses and aides constitute a significant workforce in nursing home (NH) facilities. They are responsible for caring for the frail and vulnerable elderly residents by providing 24/7 personal care and assistance with their daily living activities, such as toileting and bathing. Since early 2020, the COVID-19 outbreak has stressed NH facilities nationwide and worldwide both to their leadership and frontline caregivers. The Indiana State Department of Health provides strong evidence that the COVID-19 pandemic, since its outbreak, has targeted almost all 770 long-term care communities in Indiana – home to 38,000 residents. By the end of 2020, nearly 5000 COVID-19 deaths were reported in 532 nursing facilities across Indiana. These deaths accounted for almost three-quarters of the total long-term care deaths and more than one-quarter of the total deaths the state reported. Most long-term care facilities are skilled nursing facilities (SNFs). These SNFs had to respond to outbreak threats quickly. They had to adjust to a plethora of federal and state guidance, make rapid changes in daily operations of care delivery, and implement new guidelines to safeguard residents and workers [1]. Moreover, frontline staffers face changes to their personal lives due to the closure of schools and childcare facilities, changes to mass transportation schedules, financial strain, and risk perception among their family members. Finally, it is difficult for SNFs to maintain their care quantity and quality due to additional resident isolation, family member distress, as well as intensive mandated sanitation.

Accurate prediction of nursing staff absenteeism, proactively identifying at-risk staff, and timely interventions on them are of great importance to mitigate or prevent absenteeism, and more importantly, maintain quality of care. Absenteeism is one of the most common causes of workforce shortage and significantly affects NH care delivery. NH staff often have low salaries and employment benefits but demanding work assignments and environment [2, 3]. The recent COVID-19 pandemic has hammered NHs nationally and internationally and considerably exacerbated the NH caregiver absenteeism and short-term shortage. For example, 83 NH residents were evacuated from an NH at Riverside, CA, recently after nursing staff failed to show up for two days [4]. Thirty-one deaths were recently discovered in a Quebec NH with only two nurses left to care for a 150-bed residence after the remaining staff had fled during the pandemic outbreak [5]. Several reasons have contributed to the rising absenteeism. First, caregivers who were tested COVID-19 positive had to self-quarantine and were not able to work. Second, the pandemic outbreak led to a significant shortage of medical supplies (e.g., personal protective equipment, oxygen tanks). Thus, many caregivers were worried about being infected and failed to show up at work with/without notice.

Without adequate allocation of frontline caregivers, NH resident outcomes (e.g., re-hospitalization, morbidity, and mortality rates) and the facility's overall service quality have been significantly undermined [6, 7]. Therefore, intelligent NH staff shift scheduling becomes even more critical than usual times. In this paper, we develop a two-stage stochastic programming model to hedge staff absenteeism-related uncertainty in addition to the regular resident service need fluctuation. We focus on the scheduling task of assigning appropriate workload to currently employed certified nursing assistants (CNAs). If needed, the decision also involves adding part-time CNAs to the schedule. We construct realistic scenarios based on CDC's weekly report on COVID-19 pandemic status in assisted living facilities [8]. This report characterizes the infection rate and increased work demand with nursing homes at either low or high risk of the COVID-19 pandemic. Our scheduling optimization research will enable us to develop a data-enabled decision support system for NH human resource analytics and management, especially under prolonged emergencies that cause significant supply-side uncertainty.

2. Literature Review

Burke et al. [9] conducted a literature review on nurse rostering problems. They categorized the available research papers according to solution methods, constraints, and performance measures. Their work also included discussions about the planning period, data, skills, and substitutability. Wright and Bretthauer [10] solved a nurse scheduling optimization problem and a staff adjustment problem separately with deterministic resident demand. Maenhout and Vanhoucke [11] focused on integrated nurse staffing and scheduling decision optimization. The authors used a Dantzig-Wolfe decomposition approach to integrate staffing and scheduling decisions in a deterministic setting. Bard and Purnomo [12] developed an optimal staffing and scheduling model to compare alternative mechanisms for handling staff shortage. The authors incorporated uncertainty that arises from a widely fluctuating demand. This model was intended to satisfy nurses' individual preferences and design a daily (not shift-based) schedule. Recently, Punnakitikashem et al. [13] studied an optimal staffing and assignment problem where the first-stage decision assigns each nurse to patients. The second stage balances each nurse's workload. Kim and Mehrotra [14] focused on integrated staffing and scheduling decision optimization, with demand prediction based on patient volume data. Jiang et al. [15] focused on nursing home staff scheduling optimization under resident demand uncertainty. The authors offered management insights into optimal schedule adjustment while concerning case-mix percentage changes and staff hourly payment changes. We concluded a lack of literature focusing on NH shift scheduling under uncertainties both from resident demand and staff availability through the above review.

3. A Two-Stage Stochastic Scheduling Model with Pandemic Responses

Our planning procedure comprises three parts: when the COVID-19 comes, we analyze the current issue that may harm the nursing home's care delivery. We give an estimation of the risk level of the nursing home. We combine with the possible solution method, a two-stage stochastic programming model to hedge staff absenteeism-related uncertainty and the regular resident service need fluctuation. Our outputs are the scheduling task of assigning appropriate workload to currently employed certified nursing assistants. And least number of CNAs to hire if needed. Our goal is to provide a data-enabled decision support system for NH human resource analytics and management, especially under prolonged emergencies that cause significant supply-side uncertainty.

This paper focuses on nursing home shift scheduling optimization under potential absenteeism and extra workload during the pandemic. We present a two-stage stochastic programming formulation for optimal scheduling, which involves designing the schedules for full-time certified nursing assistants (FNAs) and adjusting the schedule with part-time certified nursing assistants (PNAs). We use $\mathcal{F}$ to denote the set of FNAs. We use P to represent the number of our total available PNAs. Our objective function is to minimize the total labor cost (with hourly payment and raising the amount c^f) and the surplus cost incurred by FNAs and PNAs. In the formulation, we balance FNAs' total working time with residents' total service time needed in each shift t in the shift set $\mathcal{T}$. Each shift is l hours long. We use $\mathcal{A}$ to denote the set of scheduling patterns. Each FNA has to pick a pattern a.

Our first-stage decision $\mathbf{x}$ is the schedule from a set of feasible schedules that are assignable to each FNA. Our second-stage decisions $\mathbf{y}_+$ describes how many added working hours, realized by adding PNAs to the staff; and $\mathbf{y}_-$ describes how many canceled working hours. Then we use x_a^f as a binary variable for every FNA f. If FNA f is assigned to scheduling pattern a at the beginning of the staff scheduling period, the value is 1, and 0 otherwise. We use Ω to denote the uncertainty space. For each scenario $\omega \in \Omega$ with probability $p(\omega)$, we use $y_+^t(\omega)$ to represent the total amount of resident need (in hours) that need to hire PNAs to satisfy at shift t (i.e., service supply shortage); and use $y_-^t(\omega)$ to represent the total amount of available staff time that exceeds the actual resident need (in hours) at shift t, making some staffers idle (i.e., service supply surplus).

The considered pandemic responses include 1) raising wages to retain staff during the pandemic and 2) implementing infection prevention and control measures to minimize the disease transmission. We let δ be the raised wage amount per hour. We let $\alpha \in [0,1]$ be the percentage increase of the work time to carry out the infection prevention measures. Let τ_a^t denote whether scheduling pattern a contains shift t. Let c_+^p, c_-^p denote the unit penalty cost for surplus and shortage on the service time. We let $r^f(\omega)$ be the shift that until FNA f can provide service; let $\gamma_f^t(\omega)$ represent the presence for each f at shift t; let $d_t(\omega)$ be the service time required in shift t for scenario ω.

In the following formulation, equation (1) is the overall two-stage objective function; and equation (7) is the second-stage expected recourse function. Constraint (2) ensures that every FNA has to pick one schedule pattern a; constraint (3) ensures that there must be at least one FNA for each shift; constraint (4) ensures that every FNA can not work for two consecutive shifts; constraint (5) shows every FNA's work capacity; constraint (9) ensures the work time of FNAs and PNAs to meet each resident's required service time; constraint (10) ensures the work time of FNAs will not exceed the resident demand; constraint (11) specifies the total amount of available work time of PNAs. Note that we assume off individualized scheduling restrictions due to the lack of data on individual scheduling requests.

$$\min\ z = \min\left\{(c^f + \delta) \sum_{f\in\mathcal{F}} \sum_{t\in\mathcal{T}} \sum_{a\in\mathcal{A}} l\tau_a^t x_a^f + Q(\mathbf{x})\right\} \tag{1}$$

subject to:

<u>schedule set up:</u>

$$\sum_{a\in\mathcal{A}} x_a^f = 1, \forall f \in \mathcal{F}, \tag{2}$$

$$\sum_{f\in\mathcal{F}} \sum_{a\in\mathcal{A}} \tau_a^t x_a^f \geq 1, \forall t \in \mathcal{T}, \tag{3}$$

$$\sum_{j=t}^{t+1} x_a^f \tau_a^t \leq 1 \quad \forall f \in \mathcal{F}, a \in \mathcal{A}, t = 1, \ldots, |\mathcal{T}| - 1, \tag{4}$$

$$\sum_{t=1}^{|\mathcal{T}|} \sum_{a \in \mathcal{A}} x_a^f \tau_a^t \leq 10, \quad \forall f \in \mathcal{F}, \tag{5}$$

domain constraints:

$$x_a^f \in \{0,1\}, \forall f \in \mathcal{F}, a \in \mathcal{A}; \tag{6}$$

the second stage objective function is:

$$Q(\mathbf{x}) = \sum_{\omega \in \Omega} \left[p(\omega) \min_{\mathbf{y}_+, \mathbf{y}_-} q(\mathbf{x}, \omega) \right], \tag{7}$$

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

$$q(x, \omega) = \min_{\mathbf{y}_+, \mathbf{y}_-} \sum_{t \in \mathcal{T}} \left((c_+^p + \delta) y_+^t(\omega) + c_-^p y_-^t(\omega) \right), \tag{8}$$

subject to:

supply and demand:

$$y_+^t(\omega) \geq (1 + \alpha) d_t(\omega) - \sum_{f \in \mathcal{F}} \sum_{a \in \mathcal{A}} l \tau_a^t x_a^f \gamma_f^t(\omega), \forall t \in \mathcal{T}, \tag{9}$$

$$y_-^t(\omega) \geq \sum_{f \in \mathcal{F}} \sum_{a \in \mathcal{A}} l \tau_a^t x_a^f \gamma_f^t(\omega) - (1 + \alpha) d_t(\omega), \forall t \in \mathcal{T}, \tag{10}$$

$$\sum_{t \in \mathcal{T}} y_+^t(\omega) \leq 40P, \tag{11}$$

domain constraints:

$$y_+^t(\omega), y_-^t(\omega) \in \mathbb{Z}^+, \forall t \in \mathcal{T}. \tag{12}$$

We coded the above mathematical model in pyomo and solved the generated instances with the Gurobi MIP solver.

4. Numerical Experiments

In our numerical experiments, we first solved the baseline setting and then performed case studies assuming the nursing home is at low and high risks. We generated 200 scenarios for each stochastic programming instance. We ran the experiments on an Intel i5-6200U PC with a 2.3-GHz processor and 8-GB RAM.

4.1 Instance Generation

We utilized historical clinical assessment data to determine time-based service needs (in hours per shift) in the usual time. We developed 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]). Our partnering local NH provider in the Tampa Bay area, patient classification system adopted by the CMS, and existing NH staffing time study (i.e., STRIVE project). We developed 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 to categorize NH residents into multiple services need groups, and each service needs group comprised residents with similar resource usage level. [17] 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 NH residents in each service need group.

We followed a report of the US Department of Health and Human Services [1] on estimating the extra workload and amount of raising wages during the pandemic. According to this report, several states provided direct or indirect financial support to nursing home staff by increasing wages to boost retention during the COVID-19 pandemic. Thus, we assumed δ to be \$2 per hour at low-risk facilities and \$4 per hour at high-risk facilities. Also, from the report mentioned above, the extra workload of direct and indirect care time was mainly caused by 1) additional precaution and training to reduce both airborne and contact exposure to the virus and the need to isolate residents to prevent the infection from spreading; 2) the need for staff to help deliver meals to rooms and assist residents individually at mealtimes increased due to the suspension of group dining; 3) need to move residents to single rooms or for cohorting purposes. For our case study, we assumed α to be 0.2 in low-risk facilities and 0.4 in high-risk facilities.

The report also informed three reasons for the absenteeism: 1) nursing assistant burn-out, 2) infection by COVID-19 and, 3) being sent to take care of the infected and cohort residents so that the FNA will not serve for the current schedule. For every scenario ω, we used $r^f(\omega)$ as a random variable to represent the shift FNA would need to leave the scheduled working zone because of the above reasons. We assume this random variable follows a geometric distribution, i.e., Geo($1/r^f$). Because in this case study, the scheduling period is 14 days, identical to the often required quarantine period. Thus, we assumed that s/he would not return to the staff before the end of the scheduling period once the FNA left. Table 1 summarizes these three key model parameters. Table 2 shows the change of available FNAs on average for 14 days using the geometric distribution samples.

Table 1: Parameters under different risk modes

Parameters\Risk level	Baseline	Low	High
δ	0	2	4
α	0	0.2	0.4
r^f	60	45	30

Table 2: Available FNAs on average under different risk modes

Risk level\Day	1	2	3	…	12	13	14
Baseline	50	49	49	…	45	44	44
Low	49	49	48	…	39	38	38
High	50	45	45	…	35	32	32

4.2 Case Study

In Table 3, we report the scheduling solution and NH total labor cost in different modes. We set our baseline staffing level to be 50 FNAs and 20 PNAs for a 710-resident nursing home. We set the primary payment to be $11 per hour.

Table 3: Results under different risk mode

Parameters\Risk level	Baseline	Low	High	High (+21 FNAs)
FNA Staffing hours	3360	3584	Infeasible	6164
PNA Staffing hours	336	435	Infeasible	512
Total cost	42504	54007	Infeasible	100540

Based on the results in Table 3, we can conclude that when the nursing home is at low risk of the pandemic, staff absence and workload have a slight increase, and it is sufficient to continue to use 50 FNAs to handle the situation. However, under high-risk conditions, when the absence rate or the workload increases sharply, solving the instance reports infeasible, which means using the current numbers of FNAs and PNAs cannot meet the hard constraints. The result suggests that the nursing home should hire more FNAs as early as possible to meet resident demand and keep operating. In our test instance, adding 21 more FNAs at the beginning of the scheduling period would be enough.

5. Conclusions and Future Work

This paper studies a nursing home shift scheduling optimization problem with two nursing staff types, namely FNAs and PNAs, considering the uncertainty of resident service need and CNA absenteeism under the pandemic situation. We formulated a two-stage stochastic program to determine the optimal shift scheduling pattern assignment for each FNA. Besides, the stochastic programming model can suggest the recourse action to take, i.e., when to call in PNAs to cover the shortage, when the NH administrator needs to hire more CNAs.

In the future, we are interested in examining how exogenous decisions affect the CNA staffing level. For example, suppose an NH is in the understaffing condition. In that case, CNAs need to perform more duties or in a more intensive manner than under normal circumstances, which may lead to further CNA burn-out and increased absence rate. In return, an increased absence rate would lead to exacerbated understaff. We plan to model the above interplay mathematically and incorporate it into our optimal staff scheduling model. For this, we plan to conduct survey-based retrospective studies to understand better caregiver absenteeism at different pandemic phases, e.g., reopening, disease rebound. The follow-up can also help us examine the effects of interventions/mitigation measures implemented at the NHs on absenteeism. For example, workshops during the pandemic recovery phase help NH caregivers cope with the economic downturn's potential stress. Finally, to address temporal dependency (i.e., non-stationarity) on the uncertain service demand and CNA drop-out rate over multiple staff scheduling periods, we plan to apply a Bayesian stochastic programming approach that can incorporate the notion of rolling-horizon for optimal staff scheduling under a stochastic programming framework. The above two future research items together will prepare us to develop a data-enabled decision support system for NH human resource analytics and management, especially under emergencies that cause significant supply uncertainty challenging to be dealt with by NH administrators.

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