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A 2 stage- Stochastic Programming Method to Optimum Nursing Home Shift Scheduling

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Abstract

In this study, we look at the problem of balancing the needs of nursing home staff with the needs of their patients. Stochastic binary programming is used to reduce total labour costs (which are directly proportional to work time) for both full-time and part-time registered nurses (RNs) (PTNs). For each assessed shift, we must balance the entire work time of RRNs with the overall service needs of residents. In addition, traditional scheduling practises restrict the number of feasible shift configurations. We conduct a series of computer simulations to test the proposed paradigm. There are many different combinations of residents with differing levels of handicap that we discuss. Overall labour expenses and RRN scheduling flexibility are also compared to the indicated best solution under different RRN and PTN combinations. In the face of shifting demand, our study proposes a viable technique for providing appropriate service coverage, while minimising labour expenses.

Index Terms

Nurse Scheduling, Stochastic Integer Programming, Demand Scenario Generation, Minimum Data Set (MDS).

1. INRODUCTION

Nursing home care is becoming more popular in the United States as the population ages and the number of hospital beds becomes congested. According to the Department of Health and Human Services, almost 70 percent of the 76 million baby boomers will need some type of long-term care. A nursing home or other kind of specialised care facility may be the last resting place for more than 13 million people [1].

There is no healthcare system in the United States that would be complete without nursing homes. These facilities offer long-term care and rehabilitation for the elderly and disabled, both physically and mentally. Nurses are on call 24 hours a day in most nursing homes. There is a scarcity of qualified nurses in nursing homes because the rate of staff turnover exceeds the rate of increase in demand for nursing care.

Over 40% of registered nurses (the core workforce in nursing homes) cited many work difficulties, such as burnout, a stressful environment, and unequal staffing as the reasons of high staff turnover, according to an American Nurses Association Annual Reports [2]. More than half of them complained about not having enough time to spend with patients, and 54% stated they were overburdened. Researchers have suggested efficient ways to staff nursing homes, such as a ratio of nurses to residents that is supported by scientific data. However, assessing whether these techniques are cost-effective may be challenging, particularly when dealing with continuously shifting resident demands.

For this project, we are developing a platform that may aid nursing homes in managing their operational staff schedules in order to maintain financial sustainability while providing model care for their patients with a wide range of needs. In addition, each nursing home must observe labour regulations on staffing and shift design, e.g., allowing adequate rest time for nurses between shifts, to ensure healthy continuous operations. Designing work schedules that balance financial viability with the need to provide high-quality care is critical for nursing homes.

Stochastic programming is used in this study to create an ideal work plan by allocating nurses to each shift in order to balance the workload on a shift-by-shift basis with the fluctuating needs of residents. The stochastic optimization problem we'll show you is computationally expensive to solve since it necessitates binary judgments at each stage. The prediction is also critical in creating an appropriate work schedule for shift-based shifts. Nursing home directors have a tough time guessing about these issues since they have to consider so many variables. Another complicating factor is that the time-varying nature of some of the aforementioned indicators, such as those of residents, makes it difficult to estimate service demand variability. An established prediction model allows us to gather data on the demand for services at various times within a two-week period (the common timeframe for nursing home staffing schedules); (the typical duration of shift scheduling in a nursing home). Two-week operating costs and shift patterns (full-time vs. part-time RNs and number of shifts for each full-time RN) are correlated, according to our findings (full-time registered nurses vs. part-time agency nurses, number of shifts for each full-time registered nurses).

Stochastic programming models for optimising nursing home staff scheduling decisions under variable demand are an important part of our contribution to this work. There are no decision support systems in the nursing home industry for operational scheduling. Our service demand classification approach is based on a long-term national nursing home time study, as well as real-world clinical assessment data. In this way, we may put our ideal judgements into action. Finally, we demonstrate the usefulness of our proposed sensitivity analysis in delivering management insights into the optimum schedule modification for case mix percentage adjustments and staff hourly payment changes by conducting operational tests in a sample nursing facility's operational environment.

Listed below is a breakdown of how the document is organised. On health services/outcomes research domains and operations engineering scheduling issues with different labour activities, we assess the relevant literature in Section 2. Here, we provide some context to the clinical examination outcomes. Our two-stage nursing home staff scheduling optimization task will benefit from these tools. Section 3 explains the two-stage approach in detail. The nursing home scheduling model's

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scenario set is also discussed in detail. In Section 4, we conduct computer experiments and analyse the results. Section 5 summarises our results and presents our next project.

2. LITERATURE REVIEW

To get started, let's take a look at some of the most influential studies in health care and outcomes research. Research in resource management and planning tends to concentrate on real-world assessments of experience-based staffing approaches (e.g., [3], [4]) and/or aggregate and one-size-fits-all policies (e.g., [5], [6]). (For instance, [5], [6]). Oversimplifying service demand by assuming all nursing home residents are the same is a common theme in these studies.

After that, we'll get into relevant operations research on human resource planning and management. Staffing and shift assignment optimization are two of the most important parts of our research. Hospital staffing and scheduling was revolutionised by Venkataraman and Brusco [7]. The goal is to lower the total cost of nursing labour. Although the writers made a first attempt, the ambiguity of demand was overlooked. Eastern and Rossin [8] provided an extensive personnel and scheduling model. As a result, wages will be reduced and there will be a reduction in overtime and penalties. Even though a probability distribution for the total amount of work is better than a detailed schedule at every minimum time unit, the best choice is still a probability distribution. Assuming there is a distribution of human resources, the authors use this uncertainty to their advantage in their model of optimization. Eastern and Mansour [9] developed an evolutionary method to tackle both deterministic and stochastic labour scheduling challenges, and they found that the overall labour expenditures and anticipated opportunity costs may be reduced by the system. Both strategies cover a limited set of stochastic scenarios, but both are focused on addressing problems within a one-week planning horizon.

In the next section, we review pertinent studies on nurse scheduling issues. Nurse Rostoring issues were reviewed by Burke et al. [10], who published a review paper on the subject. Methodologies, limitations, and performance measures used to address issues are used to categorise papers. Other tables provide information on the length of time it takes to plan, what data is used, and how many talents may be substituted for each other, among other things. Using deterministic resident demand, Wright and Bretthauer [11] solved both a nurse schedule optimization issue and a staff adjustment issue. It was Maenhout and Vanhoucke [12] who worked on optimising personnel and scheduling decisions together. In a deterministic situation, they used a Dantzig Wolfe decomposition approach to combine the options for nurse staffing and scheduling. Bard and Purnomo [13] utilised an optimal staffing and scheduling model to evaluate several options for coping with a staff shortage. Unpredictability was taken into consideration by the authors because of the always fluctuating market. In this technique, nurses are given the opportunity to design a daily schedule that is tailored to their individual needs, rather than a shift-based one. Punnakitikashem et al. [14] explored an optimal staffing and assignment problem in which the first-stage decision distributes each nurse to patients, while the second stage balances the workload for each nurse. [15] For Kim and Mehrotra [15], demand forecasts based on multiple-year patient volume data were the focus of their research on integrated staffing and scheduling decision optimization. Notably, hospitals and emergency rooms face all of the aforementioned scheduling issues with nurses.

To the best of our knowledge, there is no study on the optimization of staff schedules in nursing homes when the need for care is unpredictable. To add insult to injury, very little research has used clinical assessment data to determine time-based care needs. Each resident of a Medicare- or Medicaid-certified nursing facility [16] is evaluated using the Minimum Data Set (MDS), a nationally mandated method. STRIVE, a nationwide nursing home staff time measurement (STM) research project, is used to transform the clinical assessment into time-based care needs. Nursing homes funded by Medicare and Medicaid may now take use of data collected via the STRIVE study.

3. Methodology

Using stochastic binary programming in two phases that integrates scheduling choices with additional part-time agency nurse personnel decisions to hedge service demand uncertainty, we built our research. We look at how nursing homes are set up in practise and how they are regulated. We assume that in any feasible schedule, there are three eight-hour shifts per day, which is the most suitable schedule for the pleasant working hours of nurses. On the second day, afternoon shifts begin at 3 p.m. and night shifts begin at 11 p.m., with the morning shift being the longest. To determine whether an individual works full or part time, a two-week schedule is the minimal period of time. Nurses' burnout may be reduced by enforcing fair nursing home scheduling standards that allow for enough rest hours.

- **Model of Stochastic Binary Programming**

Look at the situation from a long-term perspective (2 weeks in our study). Three shifts are scheduled for each of the 14 days. There will be 42 shifts in the planning horizon at all times. We begin by scheduling regular registered nurses (RRNs) for shifts, and then we adjust the quantity of staffing with part-time nurses (PTNs) as we go along in our planning process (denoted by vector y). To denote whether or whether pattern incorporates time t, we'll use t a. The schedules of RRNs are structured in a certain way. Calculate RRN and PTN hourly rates using the formulae below. These prices are based on a variety of scheduling patterns.

- **Demand Scenario Generator**

Shift-specific service demand generators are used in the following formulation in order to construct the scenario set To better understand the complex service needs of NH residents, we first developed a computer simulation decision platform that incorporated multi-source information and knowledge, including real NH data (i.e, Minimum Data Set 3.0 [16]) from our partnering local NH provider in Tama Bay area, patient classification system (e.g. [17]) adopted by the CMS, and existing NH staffing time study (i.e., STRIVE project [18]). A project like STRIVE [18] is an example. Individual lengths of stay (LOS) for NH patients are calculated by taking into account their various discharge options, such as home discharge or re-hospitalization. As a result of their various unique features (e.g. ADL), each resident's daily service needs might be somewhat variable over their stay (e.g., ADL). NH patients were divided into a variety of service need groups using the RUG-IV patient classification approach [17], and each service need group included persons with similar resource use levels. With the help of the earlier STRIVE project [18], we calculated daily nursing staff time (measured in minutes) required for NH residents in each service need category to better understand their service requirements. Real-time needs for facility and resident services may be produced as a consequence of this simulation for a varied population of inhabitants.

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Greystone Healthcare, based in Tampa, Florida, serves as our industrial partner and provides us with de-identified electronic health information of residents to evaluate the planned work. Detailed information on each resident's health status is gathered, as are records of admissions and discharges, including demographics, diagnosis and long-term conditions (e.g., physical limitation and cognitive impairment).

The original cohort from this data set is used in the baseline scenario. There are a total of 710 persons to consider. Inhabitants are mostly old and suffering with a range of serious illnesses. Moreover, the activities of daily living (ADL) score is further examined to show the needed functional help of each resident. A higher ADL score indicates that the person has a greater need for functional assistance. There are a total of 16 possible ADL points. Ten percent of residents are functionally independent and have ADL values no higher than 1, while fifteen percent of residents are very dependent (with ADL values more than 10) and so need considerable functional assistance. To explain the arrivals of NH residents, the negative binomial distribution (NB(r, p)) is recommended since it has the best fit compared to other parametric distributions (estimated parameters $r = 4.95$ and $p = 0.64$). According to the estimated model, the actual arrival data's p-value indicates that it has a reasonable goodness-of-fit (e.g., Chi-square test). A ratio of 2:1:1 was used to produce the facility-wide service demand (in minutes) for each shift throughout the scheduling horizon using our simulations of daily demand.

4. Experimental results

At the outset of our numerical trials, we determine the baseline setting before moving on to the case-mix setting. We use Python to develop the mathematical model and the Gurobi MIP solver to resolve the produced cases. Each stochastic programming problem has 150 possible solutions. Personal computers with Intel i5-6200U processors and 8GB of RAM are used for all of our research.

- **Scenario Description**

It was decided that the nursing home's capacity would be 500, which is large enough to accommodate all conditions, but small enough to avoid overcrowding (large enough for any scenarios since the optimal capacity varies when arrival rate changes). In addition to the baseline setting, we additionally take into consideration two rather harsh nursing home situations. Table I lists the characteristics of the three case-mixing configurations. One alternative scenario is that the majority of the population is heavily reliant. We refer to this as the HD setting. The vast majority of the population is self-sufficient. We refer to it as the LD setting. The LOS for each simulated individual varies according to the self-development LOS models used in the construction of scenarios for the two distinct contexts. The daily hourly demand fluctuates to about the same degree around various demand measurements because to different ADL distributions. Here is a breakdown of each of the three parameters' 150 possible service demand scenarios:

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Table 1 Patients' ROT and LOS during the analysis

	Emergent			Elective				
				Ordinary			Day Surgery	
	# patients	ROT (hours)	LOS (days)	# patients	ROT (hours)	LOS (days)	# patients	ROT (hours)
DRG								
290	1	2.05	2	417	2.39	4	2	1.25
others	46	2.16	11	237	2.34	8	125	1.46
URG								
A	39	2.14	12	11	3.08	17	4	2.02
B	5	2.29	8	71	2.52	7	17	1.46
C	3	2.42	2	285	2.28	6	38	1.45
D	0	0	0	115	2.33	4	31	1.36
E	0	0	0	82	2.51	5	15	1.45
F	0	0	0	53	2.44	3	11	1.48
G	0	0	0	37	2.46	3	12	2.19

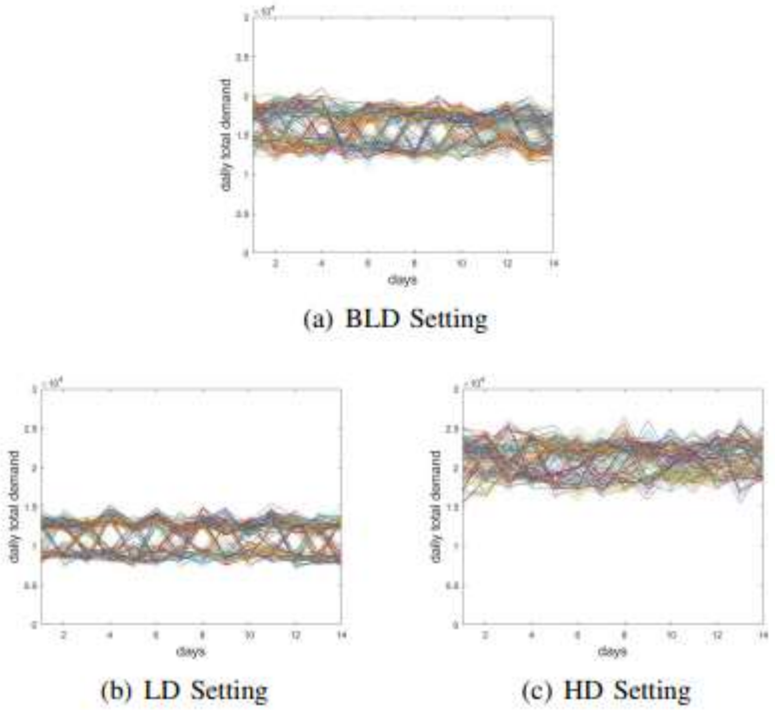

Figure 1 Demand on a daily basis for each of three cases mixing settings

RRNs (contractual full-time nurses) and PTNs (contractual part-time agency nurses) were paid first (part-time agency nurses). According to a national wage study, a nursing

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home must pay each RRN a basic salary plus F&A. Since RRNs work longer hours than PTNs, the compensation package they get has a higher per-hour value but a lower pay rate. PTNs' running costs must also include any additional expenditures that may be necessary (such as transportation). The hourly pricing for each RRN has been set at $11 because of the reasons outlined above. This rate is derived from the skilled nursing facility prospective payment mechanism (PPS). As a result, we calculated that the hourly rate for each PTN should be 1.5 times the RRN hourly rate. One to ten is a popular setting for the RRN-to-resident ratio in the real world. For a nursing facility with 500 residents, we set the baseline number of RRNs at 50. The tables below provide a breakdown of the data. Keep in mind that the price is expressed in tens of thousands.

5. CONCLUSION AND FUTURE WORK

Two different types of nursing staff, notably RRNs and PTNs, are the focus of our study as we attempt to optimise the scheduling of nursing home shifts. Each RRN is allocated a shift pattern based on a two-stage stochastic binary algorithm. In the case of a service supply shortfall, the programme describes the steps to be followed, including which shifts should be filled by PTNs. The RRN and PTN ratio should be utilised to create the nursing home's RRNs and PTNs, in our opinion. A lower RRN staffing level and more PTNs may help reduce labour expenses and provide schedule flexibility in nursing homes with high functional independence. Nursing institutions that have a large number of patients who are reliant on them might consider expanding the number of registered nurses (RNs) in order to reduce labour costs and help nurses cope with the stress of caring for them. In the future, we want to use Benders decomposition-based solution approaches with accurate convexification of the binary recourse in the formulation to improve the efficiency of the solution. For example, we can better justify the use of an individual demand generator by taking into account concerns regarding consistent nurse-resident assignments and a balanced workload for the nurses using this model. Nursing facilities that are plagued by high turnover of nursing staff and complaints from residents about inadequate patient-centeredness are likely to find the provided management insights more appealing. A Bayesian stochastic programming approach will be shown to deal with the temporal non stationarity in the uncertain service demand throughout numerous staff scheduling periods, and it will include the notion of rolling-horizon staff scheduling.

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