Title	不確実性のもとでのナーススケジューリングとリスケジューリング問題における職務満足度向上に関する研究
Author(s)	PAVINEE, RERKJIRATTIKAL
Citation	
Issue Date	2022-09
Type	Thesis or Dissertation
Text version	ETD
URL	http://hdl.handle.net/10119/18120
Rights	
Description	Supervisor:HUYNH NAM VAN, 先端科学技術研究科, 博士

Doctoral Dissertation

A Study of Nurse Scheduling and Rescheduling Problem under Uncertainty for Job Satisfaction Enhancement

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September 2022

Abstract

Nurses work around the clock in response to hourly medical demands. Their work characteristics include rotational shifts, strenuous workloads, and irregular work hours. Such conditions contribute to fatigue, burn-out, job dissatisfaction, and turnover intention. These are common causes of the intensified nursing shortage faced by hospitals worldwide. To improve nurse retention, hospital management must devise measures to enhance nurses' well-being, job satisfaction, and intention to stay.

Systematic scheduling strategies with proper workload assignment, meeting nurses' preferences and ensuring fairness are among the keys to achieving high job satisfaction. This dissertation develops two satisfaction-enhanced nurse scheduling models using mathematical optimization approaches. The first nurse scheduling model aims to maximize the fulfillment of nurses' individual preferences in shifts and days off. At the same time, deviations in workload and preferred assignments among nurses are minimized for scheduling fairness. Since cost-effectiveness is crucial for implementability, the second model encompasses cost minimization and job satisfaction maximization objectives. This model aims to ensure economic, satisfactory, and fair work schedules. Both models are validated using data collected from actual hospital cases in Thailand. The findings highlight the models' capability to promptly generate schedules that fulfill preferences and fairly allocate workload and desirable assignments among nurses. The proposed scheduling models can serve as practical decision-support tools for hospital management.

Hospital operations are dynamic in nature. Unexpected absences or variations in nursing demand emerge daily. Operational variations sometimes lead to mismatches between nursing demand and supply and schedule disruptions. For such cases, rescheduling is needed to maintain operational flow and service quality. This dissertation proposes a practical nurse rescheduling model to minimize the rescheduling penalty under uncertain demand and absenteeism. Under disruptions, the model repairs the original schedule while maintaining service quality and job satisfaction. In order to do so, the operational-related penalty is imposed to maintain an appropriate skill mix. At the same time, the satisfaction-related penalty minimizes undesirable rescheduling impacts via a human judgment shift change penalization. Differences among nurses' rescheduling impacts are also penalized to ensure rescheduling fairness throughout the planning period. The model is tested with multiple uncertain scenarios to verify its ability to handle uncertainties. The results indicate the model's effectiveness in promptly generating modified schedules with minimal rescheduling impacts, adequate service quality, and relatively fair.

Keywords: Nurse scheduling problem, Nurse rescheduling problem, Job satisfaction, Fairness, Mathematical optimization, Uncertainty

Dedicated to the loving memory of my dearest papa,

Surachai Rerkjirattikal
August 1951 - January 2022

whose dream was to live and cherish the end of this Ph.D. journey together,
who I know is smiling and feeling proud from somewhere above.

Acknowledgement

Pursuing a Ph.D. has been both a disheartening and pleasurable adventure. I certainly cannot accomplish this long and exhausting journey singlehandedly. Its completion is mainly thanks to all individuals who supported, motivated and challenged me along the way.

This journey would not be possible without the financial support from the National Electronics and Computer Technology Center (NECTEC), Japan Advanced Institute of Science and Technology (JAIST), and Sirindhorn International Institute of Technology (SIIT), Thammasat University through the dual doctoral degree scholarship program.

I would like to express my profound gratitude to my supervisor, Prof. Dr. Van-Nam Huynh, for the invaluable opportunity to be in his lab and for his intellectual guidance, encouragement, understanding and support. I am also grateful to my dissertation committee members, Prof. Dr. Youji Kohda, Prof. Dr. Takaya Yuizono, and Assoc. Prof. Dr. Eunyoung Kim, for their time and intellectual contributions. I am also thankful to Asst. Prof. Dr. Sun Olapiriyakul, my SIIT adviser, who paved the way for this Ph.D. journey with his support and guidance. I am also grateful for Dr. Thepchai Supnithi, my NECTEC adviser, who always encourages and guides me.

I thank all Huynh's lab members and friends, particularly Pun and Top, for always being there to keep me sane. Also, a special thanks to Sanggyu Nam, my significant other, who motivates and supports me.

Last but not least, I would like to dedicate this milestone to my family. Mom, my wonder woman, who always supports me, believes in me and loves me unconditionally. Dad, my guardian angel, who watched over me, inspired me, and who I wish could live to cherish the end of this journey together. Great, who is the hardest-working emergency nurse I have ever known. She inspired me to commence my research on the nurse scheduling problem and continuously provided essential insights. Gift, my dearest sister, who always cheers me up. Last, my dogs, Pumpkin, Pepper, and Pickle, for always being such great emotional supporters.

Pavinee Rerkjirattikal

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List of Abbreviations

CP	Constraint Programming
ED	Emergency Department
FSCP	Fair Shift Change Penalization
GA	Genetic Algorithm
GP	Goal Programming
HJSCP	Human Judgment Shift Change Penalization
KPI	Key Performance Indicator
LP	Linear Programming
MILP	Mixed-integer Linear Programming
NRP	Nurse Rostering Problem
NRRP	Nurse Rerostering Problem
NRSP	Nurse Rescheduling Problem
NSP	Nurse Scheduling Problem
OR	Operating Room
PSO	Particle Swarm Optimization
RO	Robust Optimization
SA	Simulated Annealing
SP	Stochastic Programming

Chapter 1

Introduction

This chapter firstly outlines the adverse effects of nurses' working conditions, and the need to emphasize nurses' job satisfaction in Section 1.1. Secondly, the significance of nurses' job satisfaction to nurse retention and its contributing factors are discussed in Section 1.2. Then, Section 1.3 and Section 1.4 provide extensive definitions and fundamentals of the nurse scheduling problem (NSP) and the nurse rescheduling problem (NRSP) , respectively. The scope of this dissertation and dissertation objectives and significance are given in Section 1.5 and Section 1.6. Finally, Section 1.7 outlines the overview of this dissertation report.

1.1 Problem Statement

Hospitals generally provide around-the-clock medical services to patients. There is a necessity for medical personnel, especially nurses, to work under the shift work system. The characteristics of shift work include shift rotation, prolonged work hours, involuntary overtime assignments, and inadequate rest allowance due to consecutive workdays [1]. Such work conditions results in higher risks of excessive fatigue [2], circadian rhythm disorders [3], job stress [4], and work-life imbalance [5]. These adverse physical and psychological impacts are known to induce job dissatisfaction and turnover intention among nurses [6].

Job dissatisfaction and turnover intention are the common causes of the ongoing nurse shortage faced by hospitals worldwide for decades. The shortage has become immense due to the coronavirus disease pandemic (COVID-19). Previous studies investigated the increasing nurses' intention to leave due to poor work conditions, job stress, and burn-out effects in many countries. In a survey by Koehler et al. [7], approximately 21% or about 44,802 nurses in the United States reported their turnover intention due to inappropriate workloads and staffing management. Zhang et al. [8] revealed that only 0.4% of 51,406 nurses in China were satisfied with their jobs. They also reported that 70.7% intended to resign. Similar results were identified in many other countries including Thailand [9], Australia [10], Turkey [11], and Ethiopia [12]. The findings from these studies have verified the growth in nurses' intention to quit their jobs on a global scale. The nursing supply in healthcare settings is deteriorating as a result. The findings indicate an immediate need for strategies that improve nurses' well-being, working conditions, and job satisfaction as remedies for the nursing shortage.

An improved job satisfaction level positively correlates with nursing retention, as indicated by many previous studies [13, 14, 15, 16]. It also increases organizational commitment [17], quality of care [18] and patients' satisfaction [19]. Considerable administrative measures can increase nurses' job satisfaction and thereby subside the intention to leave. For instance, the management can facilitate career development, provide adequate compensation, minimize workload pressures, ensure sufficient staffing, discourage mandatory overtime, adopt systematic scheduling practices, et cetera. A systematic scheduling practice is one of the important measures for job satisfaction enhancement. Shift works are inevitable in nursing practices due to the nature of hospital operations. A poorly designed schedule results in poor shift work conditions, leading to excessive work hours and fatigue. Such conditions not only result in adverse effects on the health and well-being of nurses but also on the medical service quality and patients' safety [20]. Proper management of shift work schedules is vital in mitigating poor working conditions and demanding workload assignments by allocating suitable workload amounts, rest allowance, and days off. Well-designed schedules are the key to enhancing nurses' well-being and job satisfaction. Thus, hospital management must implement appropriate scheduling measures to attain good working conditions and high job satisfaction under shift work schemes.

Failure to retain nurses results in not only the hospital's losses of skillful nurses but also contingency expenditure for replacement. NSI Nursing Solutions [21] estimated the average cost of nurse turnover, including recruitment, sign-on reward, training, and orienting fee, to be as high as $44,400 in 2022. Therefore, improving nurses' job satisfaction and retention should be the bottom line in effective nursing resource management. Many factors affect nurses' job satisfaction in positive and negative fashions. It is crucial that hospital management comprehensively understand them and tailor administrative policies accordingly. The following section discusses factors influencing job satisfaction and factors that can be achieved within the nurse scheduling scope.

1.2 Factors Influencing Nurses' Job Satisfaction

The importance of job satisfaction has been addressed by many studies, especially from the employee retention viewpoint. Job satisfaction is the extent to which employee is content, pleased, and comfortable with their job [22]. A high job satisfaction level substantially improves work performance, reduces job stress, decreases turnover intention, and creates a positive ambiance in the workplace [23]. Many aspects and assessments are used to evaluate job satisfaction in each research field. From the nurse scheduling viewpoint, job satisfaction can be defined as nurses' positive perceptions of work conditions and work schedules. Studies investigating factors influencing job satisfaction in nursing management have been well-documented in the literature. Their purposes are to understand the positive and negative effects of factors on job satisfaction. Their findings provide hospital management guidelines to devise managerial strategies for enhancing job satisfaction. This way, nurse retention can be improved and thereby subside the shortage predicament.

DeKeyser Ganz and Toren [24] pointed out that a well-designed nursing practice environment that promotes nurse engagement in management, staffing sufficiency, and positive relations among colleagues is essential for securing job satisfaction. O'Hara et al. [25] addressed the importance of supportive leadership to enhance job satisfaction among millennial nurses. Holmberg et al. [26] highlighted career advancements and incentives as factors influencing job satisfaction. However, the study also revealed that those factors were perceived as lacking in hospital practices. Shin et al. [27] pointed out a strong relationship between workload assignment to job satisfaction and intention to leave. Their findings also highlighted that voluntary overtime is associated with a higher risk of occupational injuries and job dissatisfaction. A survey by Rizany et al. [28] revealed a significant positive correlation between the quality of work schedule and nurses' job satisfaction. They addressed that the schedule quality can be improved by maintaining a proper nurse-to-patient ratio, an appropriate skill mix, and fair workload allocation. Their findings also suggested that work schedules in practice still lack these aspects.

In the past decade, the effects of job autonomy and organizational justice on job satisfaction have considerably attracted research attention. As addressed in Koning [29], Giles et al. [30], Choi and Kim [31], Mahoney et al. [32], and Li et al. [33], the perception of job control or so-called job autonomy is an essential factor that can improve job satisfaction and nurse retention. Job autonomy refers to the extent of authority in decision-making one is allowed in the workplace. There are two types of job autonomy: work method and schedule autonomy. Work method autonomy can be facilitated by authorizing nurses to provide independent nursing care based on their appropriate experience and permitting task refusals when they see fit [34]. Schedule autonomy is to authorize nurses to have an extent of control over their work schedule. It can be encouraged by permitting nurses to specify the preferred working slots that suit their needs [35]. Cajulis et a. [36]'s statistical survey revealed that nurses having control over their work schedule are less depressed and less strained, thus, more content. Their findings also suggested that work schedule autonomy corresponds to lower absenteeism.

Organizational justice refers to the employee perceptions of fairness in the workplace. It is another critical factor contributing to nurses' job satisfaction, and retention [37, 38]. Justice in an organization concerns monetary and non-monetary aspects, such as fair incentives, equal promotion opportunity, fair performance evaluation, and fair workload allocations. [39]. Nelson and Richard [40] clarified that the perception of distributive justice in the work schedule is vital to improved job satisfaction among nurses. Similar research findings were confirmed in the recent survey by Rizany et al. [41]. Their results indicated that implementing a systematic nurse scheduling method with the consideration of organizational justice positively affects nurse job satisfaction. The study also suggested that organizational justice can be attained by equitable workload allocation and favorable scheduling outcomes. Furthermore, an in-depth exploration of workplace injustice conducted by Skinner et al. [42] revealed that shift scheduling is the most frequently perceived unfair among nurses and adversely impacts their job satisfaction and work performance.

In summary, many factors contribute to improved nurses' job satisfaction, including work conditions, staffing adequacy, supportive leadership, job autonomy, organizational justice, et cetera. Unable to comprehend and facilitate them adversely affects overall job satisfaction. Accordingly, nurse retention capability and shortage issues deteriorate. Many measures can be employed to achieve higher job satisfaction among nurses, including providing adequate compensation, fostering career development, encouraging interpersonal relations, et cetera. In the nurse scheduling scope, the management can seek to implement a systematic scheduling method that properly and fairly allocates workload among nurses. Schedule autonomy can be encouraged by considering nurses' personal preferences and requests. Many individual preference factors, such as shift slots, days off, colleagues, shift pattern, et cetera, can be considered simultaneously for the best outcomes. In addition to fair workload allocation, fair distribution of favorable assignments can also be employed. A schedule with equitable workload distribution alone may not be a good indication of fairness from an overall perspective. When nurses receive work schedules that are tailored to suit their preferences with even distribution of the workloads and preferred assignments, their job satisfaction level can be significantly enhanced.

1.3 The Nurse Scheduling Problem (NSP)

In light of poor work conditions and intensified nursing shortage, considerable efforts have been made to develop approaches to the nurse scheduling problem (NSP). NSP is a variant of the personnel scheduling problem with nurses as the primary resource. Through mathematical optimization, NSP aims to determine the optimal nurse-shift assignments that fulfill operational objectives while complying with hospital regulations and staffing policies. An example of a one-week nurse schedule is displayed in Figure 1.1. In the figure, nurses are allocated to a three-shift rotation system with double-shift assignments on some workdays. In practice, nurse scheduling is a burdensome and time-consuming task overseen by the head nurse. Hospital requirements must be satisfied, including coverage, nurses' competency, appropriate skill mix, and personal requests. In manual scheduling, meeting all these conditions is already a challenging task, especially for moderate-to-large scale departments. Therefore, preferences and fairness factors are typically disregarded.

Nurse/Day	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total shifts
Nurse 1	M	M/A	O	N	N	A	A	7
Nurse 2	A/N	O	M/A	N	A	A	M	8
Nurse 3	A	M/A	N	O	M	M	N	8
...	...	...	...	...	...	...	...	...
Nurse N	N	O	M/A	N	A	M	A	7

M - Morning, A - Afternoon, N - Night, O - Day-off

Figure 1.1: Example of a weekly nurse schedule

In addition, manual scheduling allows schedulers to have complete control over nurse assignments. Oftentimes, they make subjective decisions depending on their relationship with each nurse. Skinner et al. [42] revealed that nurses with good relationships with the head nurses often receive better work schedules. They also suggested that work schedules are typically perceived as a means to control or discipline nurses. Nurses reported that they usually received non-preferred assignments without negotiation when they complained or spoke up about something at work. Furthermore, manual scheduling takes significant time to finalize the schedule. Therefore, the head nurses usually do not permit last-minute changes. Nurses with urgent requests must trade shifts with other nurses, causing difficulties and potential conflicts. Due to these difficulties, the attempt to effectively create a fair, satisfying, and flexible nurse schedule can be compromised in manual scheduling.

Mathematical modeling can eliminate these undesirable characteristics of manual scheduling. It enables the schedule to encompass more scheduling features such as hospital regulations, cost, preferences, requests, and fairness compared to the manually-made schedule. By doing so, the schedules can be promising from both management's and operation nurses' viewpoints. Job satisfaction-induced factors such as individual preferences and scheduling fairness can be incorporated as one of the desired objectives. Mathematical models treat nurses individually and equally, eradicating potential biases and punishments in manual scheduling. Compared to manual scheduling, the job-satisfaction-enhanced optimization models are more capable of constructing satisfying and fair work schedules, as demonstrated by the previous case studies [43, 44]. Mathematical optimization can also effectively handle urgent or last-minute requests and generate new schedules instantaneously. Single and multiple objectives can be employed when formulating NSP models. Decision-makers can maximize or maintain the level of job satisfaction while pursuing other objectives such as cost or service quality.

Nurse scheduling is one of the three stages of hospital human resource management, namely, staffing, scheduling, and rescheduling, as illustrated in Figure 1.2. Staffing is a strategic (long-term) plan to estimate and acquire the nursing capacity required six months to one year in advance. Scheduling is tactical (mid-term) plan executed one to three months in advance based on estimated staffing requirements. In the operational (short-term) stage, mismatches between planned and actual nursing demand may arise due to increased demand or urgent absences of nurses. As a result, understaffing occurs and adversely affects service quality and patients' safety. Under such events, nurse rescheduling must be made to ensure adequate staffing levels and serviceability.

1.4 The Nurse Rescheduling Problem (NRSP)

Nurse schedules are generated based on the estimated historical patient volume or forecasts. However, hospitals are highly dynamic in nature. Occasionally, emerging unanticipated daily events render a schedule disruption. In such cases, reassignment of nurses to maintain adequate care and service quality is necessary and unavoidable.

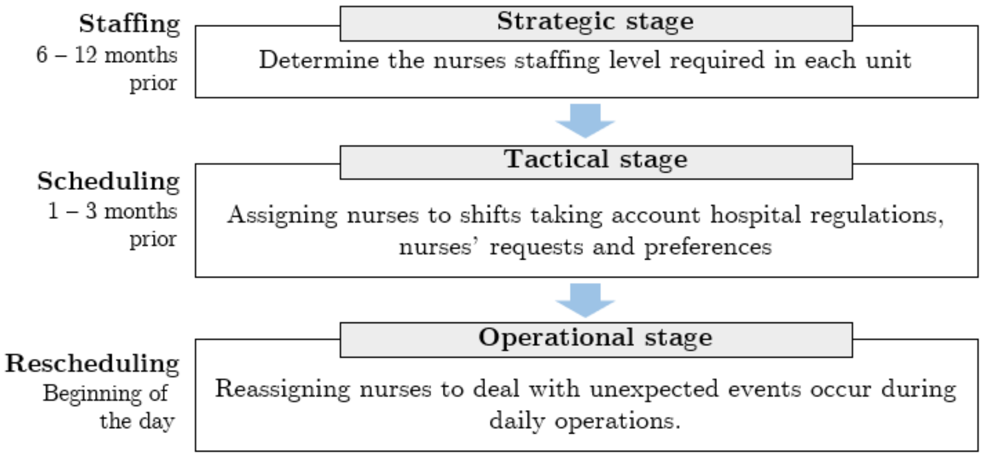


Figure 1.2: Nurses resource management procedures, adapted from Tohidi et al. [45].

Nurses adjust their personal matters and circadian cycle based on the original schedule. Frequent and illogical changes to the schedule may disturb their plan and induce job dissatisfaction. Therefore, nurse rescheduling decisions must be made carefully, promptly, and effectively. Such periodical and complicated tasks require computational decision support. Intuitive judgments may result in undesirable outcomes and lower job satisfaction levels among nurses. Approaches to the nurse rescheduling problem (NRSP) become a handy decision-support tool to determine modified schedules with minimal rescheduling impacts. Nevertheless, the research on NRSP receives little academic attention compared to the NSP literature. While in fact, they both are essential for the hospital management to execute in precedence.

Van den Bergh et al. [46] classified uncertainties in personnel (re)scheduling into three types: demand, capacity, and arrival. Demand uncertainty means that the expected demand differs from the actual demand. Meanwhile, capacity uncertainty represents deviations between planned and actual available staffing due to absenteeism, sick leave, et cetera. Uncertainty in arrival is the unpredictable workload or task arrival between intervals. The starting and ending task time is non-stationary based on its arrival time and duration. This type of uncertainty is generally considered in call-center, where agents are assigned upon calls. The nurse shift work considered in this dissertation has specified start and end duration. As a result, only demand and capacity uncertainty are considered since uncertainty in arrival impacts the starting time of specific tasks during the shift [47]. Under these two uncertain parameters, a schedule disruption can be triggered by the following scenarios: 1.) The actual demand for nurses is higher than the planned demand. 2.) Nurses' absences cause capacity shortages. 3.) Both increased demand and absenteeism occur concurrently.

Hospitals can neglect disruptions and allow understaffing. However, it is highly undesirable since understaffing negatively affects the safety and satisfaction of nurses and patients. Therefore, it is crucial to maintain an adequate staffing level. Many strategies are employed based on hospitals' policies. Substitutions can be made with nurses within the same department or the hospital or by employing external nurses. External resources can be costly, especially on such short notice, and quality of care can be compromised due to unfamiliarity in the work environment. Thus, instability of workflow still prevails. Internal resources are the most optimal alternatives in terms of functionality and economics. However, rescheduling internal resources should be thorough and appropriate. Otherwise, it can cause frustration, and nurses' job satisfaction may deteriorate.

Nurses' job dissatisfaction can easily be induced when being rescheduled. Therefore, rescheduling is not as simple as assigning any available nurse to fill the slot. Instead, it must be executed with even more thorough consideration in terms of service quality and nurses' job satisfaction. There are many types of rescheduling, such as shift changing, shift extensions, assigning nurses that are taking their day off to come to work, et cetera. Each type results in a different level of inconvenience. Therefore, vaguely assuming that all rescheduling types are equally penalized and aiming only to minimize the shift changes may not be ideal for maintaining job satisfaction. The example of rescheduling is illustrated in Figure 1.3. The absent nurses' slots are denoted as red crossed-out texts, and the rescheduled slots are highlighted in bold and green.

Nurse/Day	**Day 1**	**Day 2**	**Day 3**	**Day 4**	**Day 5**	**Day 6**	**Day 7**	**Total shifts**
Nurse 1	M	M/A	~~O~~ **N**	N	~~N~~	A	A	7
Nurse 2	A/N	O	M/A	N	A/**N**	A	M	9
Nurse 3	A	M/A	~~N~~	O	M	M	N	6
...	...	...	...	...	...	...	...	...
Nurse N	N	O	M/A	N	A	M	A	7

M - Morning, A - Afternoon, N - Night, O - Day-off, ~~N~~ - Absent

Figure 1.3: Example of nurse rescheduling

The figure shows that Nurse 3 and Nurse 1 are absent on Day 3 and Day 5, respectively. On Day 3, Nurse 1 is rescheduled from a day off to a night shift to fill the vacant slot. Although rescheduling from a day off to a workday is undesirable, Nurse 3 and Nurse N cannot be assigned more shifts as their shifts have reached the limit. On day 5, Nurse 2's shift is extended and spans from afternoon to night shifts. These are examples of how rescheduling can be done. The rescheduling decisions shown in this figure are not justified as the best alternatives.

Rescheduling is a challenging task since it concerns the consideration of many aspects. Poor rescheduling decisions can worsen the operational flow and nurses' job satisfaction. Nurses' skill levels should also be considered when rescheduling them. High service quality can be maintained by keeping an appropriate skill mix. Therefore, it is more desirable to aim for same-skill substitutions. Nurses with the same skills share the same duties and can function better as substitutions. Nurses' job satisfaction can be maintained by minimizing undesirable rescheduling impacts and distributing them evenly to achieve fairness across the entire planning horizon. Many disruptions occur during a planning period, and rescheduling may be required multiple times. Due to its high complexity, a practical, fast, and reusable computational support tool is necessary.

1.5 Scope of this Dissertation

This dissertation aims to develop the satisfaction-enhanced nurse scheduling, and rescheduling approaches accounting for multiple job satisfaction aspects, scheduling criteria, and uncertainties. For clarification, the scope of this dissertation is summarized below.

Nurse heterogeneity

For the practicality of the proposed scheduling and rescheduling approaches, this dissertation considers nurses' heterogeneity in skills and preferences. Nurses are classified into different skill levels based on their work experiences in practice. Hospitals always mandate a proper skill mix for high operational quality. Thus, scheduling and rescheduling approaches may be impractical without considering nurse skills. Furthermore, nurses have different preferences in working shifts and days off depending on their lifestyle, family status, and personal needs. For instance, night shifts may be undesirable for nurses with families or relationships. While some may prefer the night shift due to out-of-office hour compensation. Considering these aspects are crucial for developing practical scheduling and rescheduling approaches.

Job satisfaction

In nursing management, job satisfaction refers to nurses' positive perceptions of work conditions and schedules. Many factors contribute to job satisfaction, as discussed in Section 1.2. This dissertation considers factors that can be achieved within the scheduling scope, including work schedule, job autonomy, and organizational justice. Other factors such as supportive leadership or incentives should be achieved via other measures. Thus, they are out of the scope. In this dissertation, job satisfaction is determined by how well the schedule fulfills nurses' preferences and how fair the assignments are. Many preference factors include shifts, days off, colleagues, et cetera. However, this dissertation only considers the two preference factors: shifts and days off based on data availability. Incorporating nurses' preferences facilitates job autonomy, resulting in improved job satisfaction. In rescheduling, job satisfaction is maintained by ensuring nurses receive the least undesirable rescheduling impacts. Organizational justice is also included by ensuring the fairness of scheduling and rescheduling outcomes. The schedules must simultaneously be satisfactory and equitable to achieve job satisfaction in all aspects.

Fairness

Fairness in nursing management includes many aspects. This dissertation primarily focuses on scheduling fairness. Fair schedules mean equitable distribution of assignments in terms of workload (the number of shifts assigned) and preferable assignments. When considering fairness based on either workload or preferred assignments, the schedule may not be perceived as fair from an overall perspective. A schedule with an evenly distributed workload but high variations in preferred assignments is still unfair. This unfairness can lead to frustrations and job dissatisfaction. In this regard, this dissertation incorporates fairness in workload and preferred assignment distribution in the scheduling stage. In the rescheduling stage, fairness is considered the fair distribution of rescheduling impacts rendered to nurses throughout the planning period.

Planning horizon

This dissertation considers one month of a 28-day planning horizon in the scheduling stage. A workday is divided into multiple working shifts of equal length. The time span of shifts and planning horizon can be adjusted based on each hospital setting. In scheduling, the aim is to determine nurses' shift and day-off assignments across workdays on the planning horizon. Meanwhile, rescheduling reassigns nurses under a schedule disruption on a day-to-day basis. Thus, the planning horizon of nurse rescheduling is one day. However, the proposed rescheduling system facilitates decision-making for the entire 28-day period.

Operational uncertainty

This dissertation takes into account two operational variabilities: demand and capacity. The two uncertainties directly impact staffing levels, which are the key assessments for schedule feasibility. The demand uncertainty is the variations in patient volume that may result in more nurses required than planned. The capacity uncertainty is the variations between actual and planned staffing levels caused by the absences of nurses. Hereafter, the capacity uncertainty is referred to as the nurses' absenteeism. In this dissertation, uncertainties are known at the beginning of the workday and may or may not result in disruptions.

Scheduling disruption

Uncertainty in demand and absenteeism can trigger a schedule disruption in the following manner: 1.) The actual demand for nurses is higher than the planned. 2.) The absences of nurses cause insufficient capacity. 3.) Both high demand and nurses' absences coincide. Disruption is the violation of the coverage constraint or so-called understaffing. That is, the current nursing capacity is less than the actual demand. Schedule disruption is not known in advance and may often occur in a planning period. Once a schedule is disrupted, rescheduling decisions must be made to ensure an operational workflow.

1.6 Dissertation Objectives and Significance

Improved job satisfaction is essential for nurse retention and resolving the ongoing shortage predicament. A well-designed work schedule is one of the keys to improving nurses' well-being and job satisfaction. This dissertation proposes mathematical models for job-satisfaction enhanced nurse scheduling and rescheduling approaches. To achieve a high satisfaction level, the models consider comprehensive individual preference factors, fairness, cost, and feasibility under disruptions. Such multiple features cannot be obtained via manual scheduling. The proposed scheduling and rescheduling models can serve as prompt, efficient, and practical decision-support tools in hospital nursing management for tactical and operational stages.

The two satisfaction-enhanced NSP models encompass extensive job satisfaction factors to achieve satisfactory schedules in all aspects. The models ensure the fulfillment of nurses' shift and day-off preferences and fair distribution of workloads and preferred assignments. These aspects are essential to attain a satisfactory schedule. Critical scheduling criteria are incorporated for practicality, including hospital regulations and skill heterogeneity. Besides satisfaction enhancement, the application value of nurse schedules also relies on economic aspects, especially from the management standpoint. The second NSP model is proposed to minimize staffing costs in tandem with maximizing job satisfaction. Both models demonstrate that a systematic scheduling approach can achieve high nurses' job satisfaction. Hospitals can employ the models as another measure to improve job satisfaction and retention via satisfactory and fair work schedules.

Inherent uncertainties in daily hospital operations often disrupt the schedule. Immediate decisions must be made to preserve serviceability. This dissertation proposes a novel nurse rescheduling approach accounting for demand and absenteeism uncertainties. These two parameters directly affect the schedule feasibility. Disregarding one another would result in an inapplicable rescheduling approach. The proposed model aims to maintain nurses' job satisfaction and service quality. A human judgment shift change penalization (HJSCP) is employed to minimize the undesirable impacts on nurses. Rescheduling from a day-off to a workday is indeed more troublesome than changing from one shift type to another in the same workday. Assuming that all rescheduling types are the same and only minimizing the frequency is insufficient to sustain job satisfaction in rescheduling. The model also ensures nurses are exposed to similar rescheduling impacts across the planning horizon. Service quality is maintained by penalizing mismatches of nurses' skill assignments between the original and modified schedule. This penalization aims to maintain an appropriate skill mix for sufficient care quality. Rescheduling decisions are much more complicated than scheduling. Fast, efficient, and satisfactory outcomes cannot be achieved intuitively. This model provides computational support for hospitals to hedge against unanticipated day-to-day events.

The dissertation aims to provide guidelines for practitioners and hospital management on how nurse schedules can be economical, satisfactory, and fair simultaneously through mathematical optimization approaches. Comparisons between the manually-made schedule and the proposed models regarding preference fulfillment, fairness, and cost-effectiveness are made. All scheduling models are validated using data collected from actual hospitals in

Thailand. The rescheduling model is validated using numerous scenarios to investigate its ability to handle uncertainties. The impact of HJSCP is also tested against minimizing shift changes to evaluate its performance in yielding more desirable rescheduling decisions. In addition, all proposed models are developed in a generic manner. Thus, they can be applied to other case studies or application domains with minor modifications.

In summary, the objectives of this dissertation are described as follows,

1. Develop a satisfaction-enhanced NSP model that minimizes the deviations between workload and fulfillment of shift and day-off preferences among the nurses using a goal programming approach. This NSP model ensures improved nurses' job satisfaction by fulfilling their preferences and providing equitable workload and preferred assignments while complying with hospital legislation.

2. Develop a cost-effective and satisfaction-enhanced NSP model that minimizes the total staffing cost and maximizes fulfillment of nurses' preferences while maintaining an equitable workload and preferable assignments using an ε-constraint approach. This model increases the application value of comprehensive satisfaction-enhanced NSP by incorporating an economic aspect. It shows that schedules can simultaneously be satisfactory and economical.

3. Develop a nurse rescheduling model under uncertain demand and absenteeism that minimizes the total scheduling penalty using a mixed-integer linear programming approach. To ensure practical and satisfactory updated schedules, the rescheduling penalty includes operational and satisfaction-related penalties via the human judgment shift change penalization. The model demonstrates that multiple uncertain factors can be handled simultaneously and that nurses' job satisfaction and service quality can be sustained under disruptions.

The significance of this dissertation is that it provides practical and efficient decision-support tools for tactical and operational stages in hospital resource management. The scheduling models can be employed to achieve better shift work conditions for nurses and improve their overall job satisfaction. As a result, nurse retention capability can be enhanced. The scheduling models can eliminate the drawbacks of manual scheduling and save time and effort for head nurses. In addition, the proposed rescheduling model helps make instantaneous and effective rescheduling decisions under uncertainties. It can promptly determine optimal nurse reassignments that sustain job satisfaction, service quality, and fairness under disruptions.

1.7 Organization of Dissertation

This dissertation consists of 5 chapters, organized as follows.

- **Chapter 1** introduces the nurses' working conditions and the importance of job satisfaction enhancement. Then, factors influencing nurses' job satisfaction are discussed, followed by the definitions of NSP, and NRSP, respectively. The scope of the dissertation and the objectives and significance are presented in the later sections. The chapter organization is outlined in the final section.

- **Chapter 2** provides an overview of the existing NSP and NRSP literature with identified research gaps. The last section summarizes the optimization-based approaches used to solve NSP and NRSP in the previous studies.

- **Chapter 3** presents the development of the two satisfaction-enhanced NSP mathematical models. The details of hospital datasets, model validation procedures, and experimental results are described at the end of each section.

- **Chapter 4** describes the proposed nurse rescheduling system and mathematical model development. The step-by-step details of the system are explained. The hospital case data, experimental results, and discussions are provided in the later sections.

- **Chapter 5** concludes the research outcomes achieved in this dissertation, followed by three-fold contributions, including academic, practical, and knowledge science contributions. The final section discusses dissertation limitations and possible research directions.

Chapter 2

Literature Review

This chapter provides an overview of literature related to the development of NSP and NRSP in Section 2.1 and Section 2.2, respectively. The research gaps in the existing NSP and NRSP literature are discussed. Modeling features and objectives of the existing studies and the proposed models are compared to clarify the originality of the models. In Section 2.3, mathematical optimization approaches to solving NSP and NRSP in the literature are presented.

2.1 The Nurse Scheduling Problem (NSP)

Nurses are indispensable resources in healthcare systems. They are the frontliners who engage with patients the most throughout their treatment. Therefore, nurses generally operate under a rotational shift work system to provide around-the-clock service to patients. Due to the continually growing demand, nurses have been working under demanding and strenuous conditions. Common work characteristics include mandatory overtime, consecutive long-hour workdays, and insufficient rest allowance. Such conditions adversely impact their well-being and job satisfaction and thus, result in the intention to leave. These factors are the common cause of the worsened nurse shortage issue. In light of this, considerable research efforts have been given to develop systematic nurse scheduling approaches. It is still of interest to the academic society due to its significance and immense human benefits.

The nurse scheduling problem (NSP), or so-called the nurse rostering problem (NRP) in the literature, is a variant of the personnel scheduling problem. It is one of the operations research applications in resource allocation, with nurses as the primary resource. NSP is known for its combinatorial nature, which is highly complicated and challenging to solve [48]. In principle, NSP aims to create a periodic (weekly, biweekly, or monthly) nurse-to-shift assignment, subject to a set of constraints such as hospital regulations and other hospital-specific requirements. The development of NSP was pioneered in 1973 by Maier-Rothe and Wolfe [49]. They invented an NSP mathematical model that utilizes the minimum number of nurses with respect to hospital regulations.

Over the past decades, the inclusion of nurses' preferences to improve job satisfaction has been considerably addressed in the literature. Many studies develop nurse scheduling approaches that positively affect job satisfaction through preference fulfillment. El-Adoly et al. [44] proposed a nurse scheduling method that considers shift and day-off preferences. They validated the model with an actual hospital case study in Egypt. Cetin and Sarucan [50]'s NSP model considered multiple factors influencing nurses' preferences, such as the desirable shift patterns, weekend day off allocation, and the balance between workload and day-night shifts. The preference factors considered in these studies are based on group preferences. The studies assumed all nurses favor specific shift patterns or shifts and days off. However, in reality, preferences differ for each individual. Therefore, the scheduling results based on group preferences may not be sufficient for satisfaction improvement at an individual level. Another type of NSP research addressed this matter and considered the individual shift and day-off preferences [51, 52, 53, 54, 55, 56]. Other aspects of individual preferences were also included besides shift and day-off preferences. Becker et al. [57] and Huang et al. [58] proposed an NSP model to fulfill and balance nurses' preferences on weekend day-offs. While the NSP developed by Hamid et al. [59] accounted for nurses' preferred co-workers. The model aimed to maximize compatibility among nurses working on the same shift.

Besides individual preferences, fairness is another desirable attribute commonly considered in the NSP literature. Regarding scheduling fairness, two significant aspects are generally addressed: 1.) balancing workload assignments and 2.) balancing preferred assignments. Thongsanit et al. [60], Al-Hinai et al. [61], Fugener et al. [62], and Mohammadian et al. [63] aimed to balance workload assignments among nurses without considering their individual preferences. Youssef and Senbel [64] formulated an NSP that accounts for maximizing nurses' shift and day-off preferences while ensuring a balanced workload distribution. Osman et al. [65] proposed an NSP approach for emergency department nurses that maximize the fairness in day-off allocation. Regarding preferences, most studies accounted only for either preferred shifts [66] or preferred day-off [67] balancing. While Lin et al. [68] developed an NSP algorithm to balance both nurses' preferred shifts and days off allocations. However, their model did not consider the balancing of workload assignments. Thus far, there is still no existing study that simultaneously accounts for fairness in workload and preferred assignment. Schedules that offer either a balanced workload or preferred assignment may not be an adequate indication of fairness from an overall perspective.

Achieving a high job satisfaction level is indeed vital. Still, the practicality of NSP relies on the economic aspect, especially from the management viewpoint. Scheduling approaches that maximize job satisfaction alone may not be desirable for implementation. NSP approach that ensures a cost-effective schedule while improving job satisfaction can be of value. The followings are examples of the studies that integrate cost-effectiveness into satisfaction-enhanced NSP formulation. J. Lim et al. [69] proposed an NSP model to minimize the total staffing cost while ensuring the fulfillment of nurses' shift preferences. Hamid et al. [70] developed a nurse scheduling approach that optimizes staffing cost and nurses' job satisfaction under workload balancing constraints. Later, they extended their proposed cost-effective NSP by considering nurses' preferred shifts and nurses' incompatibility [59]. To date, the inclusion of cost in the satisfaction-enhanced NSP context still has many potential improvements that can be made. In addition, the tradeoff between cost-effectiveness and job satisfaction has yet to be explored. This aspect can guide the management in terms of expenses in acquiring higher job satisfaction in scheduling. They can then control a proper level of job satisfaction without compromising cost.

2.1.1 Research Gaps in NSP Development

The previous studies provide fundamental guidelines for how job satisfaction and fairness can be integrated into an NSP. Table 2.1 summarizes the review of the satisfaction-enhanced NSP literature in chronological order. Comparisons are made regarding scheduling features considered in each study, including staffing cost, aspects of individual preferences, and scheduling fairness. Based on the literature review, this dissertation addresses the two significant research gaps in developing satisfaction-enhanced NSP to further improve its application value and practicality.

1. The consideration of comprehensive fairness, accounting for workloads, and individual preferences balancing is still lacking. In the current NSP literature, fairness is usually based on a single factor that offers either workload or satisfaction balancing. Schedules built upon single-aspect fairness may not be a good indication of overall job satisfaction. A schedule with a proportional workload but imbalanced preferred assignments allocation or vice versa can still be perceived as unfair. Hence

job dissatisfaction can be induced.

2. The consideration of the economic aspect in the comprehensive job satisfaction-enhanced NSP is still lacking. The existing NSP studies with cost consideration superficially regarded a single aspect of preferences or fairness. Therefore, the cost-effectiveness of the comprehensive job satisfaction- and fairness-enhanced NSP needs to be further explored. In addition, trade-offs between cost and job satisfaction have not been explored. Such findings play an important role in supporting decision-makers to accommodate cost and nurses' job satisfaction achievements.

This dissertation addresses these significant research gaps by proposing the two satisfaction-enhanced NSP models. The satisfaction-enhanced NSP Model I (Section 3.1) is the first satisfaction-enhanced NSP model to consider multi-aspect fairness. Model I is formulated using a goal programming NSP technique that considers comprehensive individual preferences and fairness factors. It optimizes the fulfillment of nurses' preferred shifts and days off while ensuring a balanced workload and favorable assignment allocation. Then, Model II (Section 3.2) is proposed to fulfill the second research gap by incorporating the cost element into the satisfaction-enhanced NSP. The bi-objective NSP model minimizes the total staffing cost and maximizes all nurses' minimum total preference score. In the model, decision-makers can prioritize the optimization of cost or job satisfaction based on their needs. The preference score is derived from the individual shift and day-off preferences. Scheduling fairness in a balanced workload and preferred assignment allotments is also assured.

In addition, the two proposed NSP models are developed to facilitate double-shift workday assignments. A shift work system is commonly found in Thailand and many other countries, including Indonesia, Australia, Chile, Brazil, Mexico, and Nepal. Additional constraints to control consecutive double-shift workdays are enforced to ensure a healthy work schedule and sufficient rest allowance. Most previous studies only facilitate a single-shift workday in their models. Those scheduling approaches may not function well for hospitals with a double-shift system. This dissertation adopts the suggestions from the recent review by Abdalkareem et al. [71], which suggested that specific work conditions in different countries should be considered in the NSP development to enhance its implementability. Finally, the usefulness of the proposed models is examined using actual hospital cases in Thailand. Datasets from both medium and large scales in Thailand are employed to bridge the theoretical and practical aspects of NSP research, as suggested by Petrovic [72].

Table 2.1: Summary of satisfaction-enhanced NSP literature review

Authors (year)	Scheduling features							
	Staffing cost	Individual preferences			Fairness			
		Shift	Day-off	Others	Workload	Shift preference	Day-off preferences	Others
Burke et al. (2012)[51]	-	✓	-	-	-	-	-	-
Lim et al. (2012)[69]	✓	✓	-	-	-	-	-	-
Lin et al. (2013)[53]	-	✓	✓	-	-	-	-	-
Wright & Mahar (2013)[52]	-	✓	✓	-	-	-	-	-
Michael et al. (2014)[67]	-	-	✓	-	-	-	✓	-
Agyei et al. (2015)[73]	-	-	-	-	✓	-	-	-
Cetin & Sarucan (2015)[50]	-	-	-	Weekend off	✓	-	-	Day-night shifts
Lin et al. (2015)[68]	-	✓	✓	-	-	✓	✓	-
Dumrongsiri & Chongphaisal (2018)[74]	-	✓	✓	-	✓	-	-	-
Huang et al. (2016)[54]	-	✓	✓	-	-	-	-	-
Thongsanit et al. (2016)[60]	-	-	-	-	✓	-	-	-
Widyastiti et al. (2016)[55]	-	-	✓	-	-	-	-	-
Ang et al. (2018)[66]	-	✓	-	-	-	✓	-	-
Al-Hinai et al. (2018)[61]	-	-	-	-	✓	-	-	-
El Adoly et al. (2018)[44]	✓	-	-	-	✓	-	-	-
Fugener et al. (2018)[62]	-	-	-	-	✓	-	-	-
Hamid et al. (2018)[70]	✓	✓	✓	-	✓	-	-	-
Youssef & Senbel (2018)[64]	-	✓	✓	-	✓	-	-	-
Becker et al. (2019)[57]	-	-	-	Weekend off	-	-	-	Weekend off
Mohammadian et al. (2019)[63]	-	-	-	-	✓	-	-	-
Osman et al. (2019)[65]	-	-	-	-	-	-	-	Day off

Authors (year)	Scheduling features							
	Staffing cost	Individual preferences			Fairness			
		Shift	Day-off	Others	Workload	Shift preference	Day-off preferences	Others
Svirsko et al. (2019)[56]	-	✓	-	-	-	✓	-	-
Hamid et al. (2020)[59]	✓	✓	-	Co-worker	-	-	-	-
Huang et al. (2021)[58]	-	-	-	Weekend off	-	-	-	Weekend off
The proposed NSP Model I	-	✓	✓	-	✓	✓	✓	-
The proposed NSP Model II	✓	✓	✓	-	✓	✓	✓	-

2.2 The Nurse Rescheduling Problem (NRSP)

The nurse rescheduling problem (NRSP), or the nurse rerostering problem (NRRP) in the literature, is to determine optimal nurse reassignments with minimal changes under schedule disruptions. Rescheduling is more a complicated task than scheduling. There is a need to consider additional factors beyond scheduling, such as the original schedule, previous rescheduling actions, and how each shift change affects nurses' satisfaction. Poor rescheduling decisions can worsen the schedule disruption and negatively impact the quality of care, patients' safety, nurses' satisfaction, and retention. Disruptions are unforeseeable and can arise multiple times in a planning horizon. When disruption occurs, rescheduling decisions must be made immediately to maintain sufficient nursing capacity and operational flow. Therefore, an effective and fast rescheduling decision-support tool is essential. An intuitive decision is inadequate to ensure proper, efficient, and satisfactory rescheduling actions. Nonetheless, computational support for rescheduling problems is currently lacking. Thus far, the scheduling problem has received more academic attention than the rescheduling problem, as addressed in a review paper by Clark et al. [75]. They also suggested that the consideration of nurses' satisfaction is crucial for rescheduling to be accepted in practice.

The NRSP was firstly introduced by Moz and Pato in 2003 [76]. They formulated the nurse rescheduling problem as a multi-commodity flow model to minimize the shift changes from the original schedule under unexpected absences. Real instances from a Lisbon hospital were employed to validate their model. 15 out of 16 instances can be solved within two hours. In 2007, they proposed a genetic algorithm (GA) approach to solve NRSP using the exact instances. GA outperformed the optimization model regarding solution time for all instances [77]. Later, Bäumelt et al. [78] proposed a parallel algorithm to solve the same instances from Moz and Pato. The algorithm generates the same solution quality more rapidly.

Bard and Purnomo [79] referred to rescheduling as the active scheduling. They proposed a cost minimization rescheduling model with multiple decision alternatives such as on-call nurses, float nurses, and overtime hours. Both uncertainties in nursing demand and supply were considered in their work. However, they were assumed deterministic, and all demand and supply profiles were known at the beginning of the period. Such an assumption is unrealistic since, in practice, uncertainty occurs daily and is not known in advance. Regarding absenteeism uncertainty, Kidata et al. proposed a heuristic NRSP approach to minimize the number of shift changes under single-day absent [80], and multi-day absent considerations [81] for nurses with different skill levels. They addressed that considering single- and multiple-day absences is crucial to meet the practical requirement.

Maenhout and Vanhoucke [82] were the first to incorporate preference and fairness in their rescheduling model. Their model aims to minimize the number of shift changes and rescheduling costs while satisfying nurses' preferences. Their follow-up study in 2013 [83] provided insights that it is unnecessary to consider the entire planning horizon when rescheduling. Instead, only previous and subsequent periods, and the period of the disruption itself, can be considered. They indicated that solution quality is relatively similar, but the computational time is significantly less. Their findings highlighted the effectiveness of problem decomposition in rescheduling problems. Nonetheless, their works assumed all absenteeism disruptions are deterministic and known in advance. Therefore, the proposed approaches may only be theoretically feasible since rescheduling generally involves stochastic variations.

Based on Maenhout and Vanhoucke's findings, Ingels and Maenhout [47] proposed a decomposed personnel rescheduling technique under uncertain demand and absenteeism. Their rescheduling model solves one disruption day at a time. As a result, the problem size is small and computationally tractable. Their work also exploited robustness in scheduling by utilizing reserved duties. They extended their scheduling model to account for employee substitutability considering heterogeneous skills such that substitution can be easily made in the rescheduling stage [84]. Their rescheduling model was the first to consider between-skill and within-skill substitution in rescheduling decisions. Their rescheduling models consist of multiple cost elements, including wage, shift change, preference, shift cancellation, and shortage.

Clark and Walker [85] stated that the existing NRSP papers focused more on methodology and problem-solving approaches. They reasoned that emphasizing how shift changes affect nurses and their job satisfaction is crucial for implementability. Their work was the first to introduce human judgment shift change penalization (HJSCP) instead of assuming fewer changes cause less disruption, as done by most previous studies. Based on common human judgment, being reassigned to work on the day was previously assigned as a day-off is evaluated as a worse disruptive change than vice versa. Therefore, their rescheduling models incorporated nurses' individual disruption penalty toward each shift change. They also examined the effects of individual-day and pattern rescheduling strategies on shift changes amount and fairness. The findings revealed that individual-day rescheduling causes minor changes for multiple nurses. In contrast, pattern rescheduling results in a substantial change for a single nurse. They discussed that pattern rescheduling might be more efficient in the number of changes, but its effect on fairness is questionable. Although they addressed the importance of fairness, there was no constraint or goal to control the spread of shift changes in their model and was left as points of improvement.

Regarding rescheduling fairness, Wolbeck et al. [86] was the first to propose a fair shift change penalization scheme (FSCP). Similar to Clark and Walker, they adopted the HJSCP and included additional dimensions. Their model penalizes three dimensions of shift change, including type, timing, and distribution. In shift change type, four types are of focus: 1.) No change 2.) Change from a day off to a workday 3.) Change to another shift type, and 4.) Change from a workday to a day off. In terms of timing, shift changes are penalized based on their urgency. In shift change distribution, individual shift change penalty scores are accumulated each time a disruption occurs. The differences between nurses' penalties are penalized to ensure that they were affected by similar rescheduling impacts throughout the planning period. Their findings highlighted that the FSCP could provide satisfactory and equitable shift changes compared to only minimizing shift changes.

Thus far, most existing studies mainly considered nurses' absenteeism in their rescheduling models. Three groups of absenteeism considerations are found in the literature as follows. The first group of studies assumed nurses are absent only for a single day [80, 82, 83, 85]. This assumption may not be a good representation of reality where nurses are periodically absent for consecutive days. The second group of studies made it possible by considering multiple-day absences [76, 77, 81, 86, 87]. The final group considered absenteeism more extensively. They accounted for the fact that employees are less likely to be absent if they have already been absent before [47, 84]. These studies evaluated the absenteeism probability of individual employees with a decreasing function of the number of days they were already absent. This is the most realistic approach to simulate absenteeism but has not been addressed in nurse rescheduling.

As opposed to absenteeism, demand uncertainty is seldom addressed in the current rescheduling literature. Batun and Karpuz [88] demonstrated the use of nurse scheduling and rescheduling techniques under demand uncertainty. Meanwhile, some studies incorporate demand and absenteeism uncertainties in their rescheduling models [47, 79, 84]. The studies enabled rescheduling models to hedge against uncertainties more realistically since demand and absence variations typically emerge in daily operations. Both directly affect nursing demand and supply and contribute to schedule disruptions. Therefore, rescheduling approaches that encompass both demand and absenteeism uncertainty are more effective and practical.

2.2.1 Research Gaps in NRSP Development

Table 2.2 summarizes the review of NRSP literature in chronological order. Comparisons are made in modeling features, uncertain parameters, facilitation of double-shift workday, and consideration of nurses' skills. The rationale behind a double-shift workday is that hospitals in Thailand and many other countries utilize the system. Existing rescheduling models considering only a single-shift workday system omitted some features of double-shift workday systems. In double-shift workday systems, shift extension can be used as another rescheduling alternative. This consideration is per Abdalkareem et al. [71]'s suggestion that scheduling and rescheduling approaches should consider work conditions and regulations for each country for practicality. Based on the literature review, two significant research gaps are identified in the existing NRSP.

1. The consideration of human judgment shift change penalization (HJSCP) and fair shift change penalization scheme (FSCP) with multiple uncertainties and other essential rescheduling features is still lacking. Clark and Walker [85], and Wolbeck et al. [86] were the pioneers in considering how each shift change type affects nurses' satisfaction. Their HJSCP and FSCP strategies provide promising results in sustaining job satisfaction and fairness. However, their models only accounted for absenteeism uncertainty. In addition, they did not consider nurses' skill heterogeneity when making rescheduling decisions. As a result, worsened quality of care may occur when not attempting to maintain an appropriate skill mix.

2. The consideration of rescheduling in a double-shift workday system has not been addressed in the previous rescheduling literature. Such a system exists in many countries but is generally disregarded. There is a need to facilitate differences in shift work conditions for each country to make NRSP models more practical and versatile. Under the double-shift workday system, shift extension can be utilized as another rescheduling alternative. This way, the undesirable off-to-work rescheduling pattern can be avoided.

This dissertation addresses these two substantial gaps as follows. A novel NRSP model (Chapter 4) is proposed to hedge against demand and absenteeism uncertainties utilizing internal substitutions. Variations in demand and absenteeism are typically inherent in hospitals' day-to-day operations. Still, most existing works only emphasize absenteeism. The proposed NRSP model minimizes the total rescheduling penalty derived from satisfaction-related and operational-related penalties.

In the satisfaction-related penalty, the HJSCP is employed to ensure rescheduling desirability. Each shift change type is penalized based on how inconvenient it is to nurses. Differ from Clark and Walker [85], and Wolbeck et al. [86], our model also considers nurses' individual preferences when making rescheduling decisions. Fairness is considered through cumulative individual rescheduling penalty scores and minimizing the differences between the minimum and maximum rescheduling impacts on nurses. This ensures that nurses are affected by similar rescheduling impacts throughout the planning horizon. In addition to job satisfaction, the proposed NRSP model maintains service quality via an operational-related penalization scheme to maintain an appropriate skill mix. These features assure that the rescheduling outcomes are efficient, desirable, and fair. Considering these features together improves the NRSP's application value significantly and has not been done before in any existing work. Since our model utilizes only internal substitutions, rescheduling cost is omitted because different costs typically incur from utilizing external resources such as part-time nurses.

Finally, the proposed NRSP model accommodates rescheduling under the double-shift workday system. In our NRSP model, shift extension can be used as another rescheduling alternative instead of assigning off to work. Shift extension is typical for hospitals with double-shift scheduling systems. To date, there is no existing computational support tool to address it in the literature.

Table 2.2: Summary of NRSP literature review

Authors (year)	**Rescheduling features**				**Uncertainty**	**Double-shift workday**	**Nurses' skill**
	No. shift change	**Cost**	**Preference**	**Fairness**			
Moz & Pato (2003) [76]	✓	-	-	-	A*	-	-
Bard & Purnomo (2005) [79]	-	✓	-	-	D&A	-	-
Moz & Pato (2007) [77]	✓	-	-	-	A*	-	-
Kitada et al. (2010) [80]	✓	-	-	-	A	-	✓
Clark and Walker (2011) [85]	✓*	-	✓	-	A	-	-
Maenhout & Vanhoucke (2011) [82]	✓	✓	-	✓	A	-	-
Maenhout & Vanhoucke (2013) [83]	✓	✓	✓	✓	A	-	-
Kitada et al. (2013) [81]	✓	-	-	-	A*	-	✓
Ingels & Maenhout (2015) [47]	✓	✓	✓	-	D & A**	-	-
Baumelt et al. (2016) [78]	✓	-	-	-	A*	-	-
Ingels & Maenhout (2017) [84]	✓	✓	✓	-	D & A**	-	✓
Wickert et al. (2019) [87]	✓	-	-	-	A*	-	✓
Batun & Karpuz (2020) [88]	-	✓	-	-	D	-	✓
Wolbeck et al. (2020) [86]	✓*	-	-	✓	A*	-	-
The proposed NRSP model	✓*	-	✓	✓	D & A**	✓	✓

✓* - Human judgment shift change penalization, A - Single-day absence, A* - Multiple-day absences, A** - Multiple-day absences with decreasing probability, D - Demand.

2.3 Optimization in NSP and NRSP

NSP and NRSP are branches of the operations research area in resource allocation. Both problems are known for their combinatorial nature, which is highly complex and challenging to solve. In the previous studies, NRP and NRSP are generally formulated as single- or multi-objective mathematical models subject to a subset of constraints. NSP and NRSP have different purposes and functions. Thus, their models cannot be used interchangeably. However, both problems can be developed and solved using mathematical programming techniques. There are various types of mathematical formulations and solution approaches. Each technique has its advantage and suits different types of problems.

The mathematical optimization approach, or mathematical programming, was firstly introduced in 1963 by a well-known mathematician, Gorge B. Dantzig [89]. He proposed a simplex method, a foundation for solving linear programming problems in various applications. Mathematical optimization aims to find the best solution to real-world problems by representing them as mathematical models encompassing multiple linear or quadratic equations. A mathematical model consists of three main components: input parameters, objective functions, and constraints. With these components, optimization finds combinations of variables that yield the extreme value of the objective function(s) subject to constraints. The objective function is to maximize or minimize one or more user-specified goals. Constraints define a feasible region enclosing feasible and optimal solutions. Optimization iteratively compares different choices and determines an alternative that yields the best outcome. It is a powerful decision-support tool that covers wide-range applications, including economics, finance, logistics, production scheduling, workforce scheduling, et cetera. To date, it has been widely utilized in businesses and research for its ability to guarantee optimality.

In the past, optimization techniques were known to be computationally expensive when applied to large-scale and highly complex problems. During the time, research efforts were given to developing approximation algorithms that acquire good-enough solutions within a shorter time. Some examples of the well-known meta-heuristics algorithms are the genetic algorithm (GA), particle swarm optimization (PSO) , simulated annealing (SA) , et cetera. With recent technological advancements, improved operating system efficiency enables open-source and commercial optimization tools to obtain optimal solutions significantly faster. These improvements substantially subside computation time issues of optimization approaches. Nowadays, optimization techniques can handle large-scale and complex problems more efficiently and rapidly. Thus, it becomes more favorable. The subsequent sections outline optimization approaches employed to solve NSP and NRSP in the existing literature.

Optimization-based NSP

Conventional optimization techniques such as linear programming (LP) or mixed-integer linear programming (MILP) are widely applied to formulate and solve NSP. Many studies have verified the effectiveness of those conventional techniques in solving NSP [44, 54, 90, 91]. These approaches suit for solving single-objective problems. However, in real-world problems, decision-makers may pursue multiple simultaneously. Most NSPs also frequently have many objectives such as satisfaction, cost, or service quality. For multi-objective problems, many techniques can be employed as follows.

The first approach optimizes all objectives simultaneously, assuming they are equally important. This technique may take a long computational time, especially under conflicting objectives. The model exhaustively seeks a solution that yields the best value for all objectives, which rarely exists. Pursuing a higher value of one objective always compromises the quality of others. In this case, the Pareto frontier concept can be applied to identify a set of non-dominated solutions. The Pareto front exhibits solutions that are superior to the rest in the solution spaces [92]. Then, decision-makers can decide on a solution along the front that suits their needs. Lin et al. [53] proposed a Pareto-based NSP model to provide insights into a trade-off between nurses' preferences and fatigue.

The second approach is to transform a multi-objective problem into a single-objective, with the single equation being the weighted summation of all objectives. In this technique, different weights of importance can be imposed on each objective based on decision-makers. The weighted-sum technique in NSP was demonstrated by Nahand et al. [93]. In their model, nurses' preferences, assignments, and penalty costs are scalarized and formulated into a single objective. Another technique with a similar concept is the well-known goal programming (GP) technique. It is one of the most widely applied techniques in NSP and other domains. In GP, each objective is given its goal or target value. Then, undesirable deviations from those values are minimized. GP allows decision-makers to determine the target value for each goal to satisfy their criteria. Weight of importance can also be given to each target goal, similar to the weighted-sum technique. The effectiveness of GP in solving NSP has been well-demonstrated by many studies [60, 61, 63, 66, 74, 94, 95]. However, the drawbacks are that the approaches cannot produce Pareto-efficient solutions. They also require scalarization for objectives with different units to prevent magnitude biases. Improper scalarization may lead to solutions that cannot represent their actual counterparts.

The third technique is to handle each objective separately by its priority. This technique is referred to by various terms in the literature, including the pre-emptive optimization, the ε-constraint method, and the lexicographic optimization approach. It suits when decision-makers can distinctly define the importance of each objective. This dissertation hereafter refers to it as the ε-constraint approach. In the ε-constraint method, multiple objectives are optimized individually and iteratively based on their priority. The model is solved in multiple iterations, and each iteration is subject to one objective function. The optimal values are then formulated as the upper or lower bounds for the successive iterations. Many studies illustrated the use of ε-constraint in NSP. Hamid et al. [70] proposed an ε-constraint NSP that minimizes the staffing cost and then maximizes nurses' preferences. Di Martinelly et al. [96] developed a ε-constraint NSP to minimize the nurses' idle time, then maximize the affinity of the surgical team. Nasiri et al. [97] proposed a ε-constraint NSP to optimize the three objectives associated with nurses' preferences factors.

The final approach is constraint programming (CP) . Unlike other approaches, CP pursues feasible solutions rather than optimal solutions. It suits highly-constrained problems that are challenging to determine a solution that does not violate all constraints. In CP, constraints are classified into hard and soft constraints. Hard constraints are non-violable requirements such as hospital regulations and specific restrictions. Soft constraints are violable and subject to penalties such as personal preferences or desirable shift patterns. The goal of CP is to minimize the total violations of soft constraints. The examples of previous studies applying CP to solve NSP can be found in [98, 99, 100, 101].

Optimization-based NRSP

In the current literature, most NRSPs are formulated as single-objective problems. The most commonly found objective is to minimize the total number of shift changes. The other objective type is the weighted sum of several elements, including cost, shift change penalties, preferences, et cetera. Single-objective MILP is the most frequently employed to formulate and solve NRSP. Moz and Pato [76] was the first to demonstrate MILP in an NRSP context. They applied an optimization tool called CPLEX to solve their shift changes minimization NRSP model. Their model updated the entire schedule after the day that absences occurred. Based on the experiments, the optimization technique failed to generate an optimal solution within the two-hour time limit when nurses are absent on the first day of the schedule. That is, the planning period for rescheduling is 28 days long. They thus addressed the need for approximation algorithms. It is worth mentioning that this research was carried out using outdated operating systems. The current operating systems would easily handle such a problem scale within a significantly shortened time.

After that, Ingels and Maenhout [47, 84] applied the decomposition technique to decrease the size and complexity of the rescheduling problem. Their models determine rescheduling decisions for one disruption day at a time. As a result, they employed a simple MILP technique solved using an optimization software called GUROBI. The time required to solve each decomposed NRSP is as little as a split second. The more recent studies such as Wolbeck et al. [86] and Wickert et al. [87] also applied the same problem decomposition concept and MILP to formulate their NRSP models. Under different problem sizes (up to 110 nurses), the decomposed rescheduling models can generate results within less than 5 minutes. Their experimental findings ascertained the effectiveness of MILP in solving NRSP in terms of solution quality and execution time.

In summary, this chapter outlines the development of NSP and NRSP in the existing literature. Based on the review, the current satisfaction-enhanced NSP literature still lacks extensive consideration of well-round preferences and fairness factors. Most studies only offered preferences or fairness based on a single aspect. Such scheduling results may not be satisfactory when thoroughly evaluated. Furthermore, there is still a need to consider cost-effectiveness in the satisfaction-enhanced NSP context.

Regarding NRSP development, it is vital to address how each shift change decision affects nurses. Each shift change type should be evaluated based on human judgment rather than assuming that fewer shift changes are adequate. Thus far, the consideration of multi-limit uncertainties and nurses' skill heterogeneity in the HJSCP strategy has yet to be documented in the literature. In addition, no current work considers a double-shift workday system in their NRSP model. Such a system exists in many countries and can utilize shift extension as a rescheduling alternative. This way, an undesirable off-to-work rescheduling decision can be avoided.

The final section of this chapter provides a review of mathematical optimization approaches to solve NRP and NRSP in the literature. Mathematical optimization is a powerful problem-solving tool and is prevalent in the literature. Its effectiveness is well-proven in handling both NSP and NRSP models. Recent technological improvements decreased computational expensiveness issues. It can now handle the larger and more complex problems within a significantly lesser time. Therefore, this dissertation employs multiple mathematical optimization approaches to formulate and solve the proposed NSP and NRSP models. The next chapter outlines the development of the proposed satisfaction-enhanced NSP models. Hospital case data and experimental results for each model are also given.

Chapter 3

The Satisfaction-enhanced Nurse Scheduling Models

Well-designed nurse scheduling techniques play a substantial role in improving nurses' working conditions and retention prospects. Considering preferences and fairness in the work schedule renders satisfactory scheduling outcomes for nurses. With mathematical optimization, these desirable aspects can be achieved via NSP mathematical models while fulfilling hospital legislation. Chapter 1 provided a preface of systematic nurse scheduling approaches and their significance. In Chapter 2, an overview of the related works and points of improvement in NSP were discussed. Based on the review, the significance of the satisfaction-enhancement NSP can be improved by extensively incorporating multiple nurses' preferences and fairness factors. The inclusion of the economic aspect of the satisfaction-enhanced NSP with extensive preference and fairness is also lacking in the literature. Cost-effective and satisfaction-enhanced nurse schedules are more desirable and have more implementation potential from the management viewpoint.

This chapter presents the development of the two satisfaction-enhanced NSP models proposed in this dissertation. First, the mathematical formulation of Satisfaction-enhanced NSP (Model I) is described in Section 3.1. Then, the mathematical formulation of the cost-effective, satisfaction-enhanced NSP (Model II) is depicted in Section 3.2. The hospital dataset, experimental results, and discussions are also provided in each section.

3.1 Model I: The Satisfaction-enhanced NSP

Many factors positively affect job satisfaction, as previously discussed. This model considers the two satisfaction-inducing aspects: fulfilling preferred assignments and scheduling fairness to ensure satisfactory schedule outcomes. Although there are many aspects of individual preferences, this model emphasizes individual shifts and days off preferences due to data availability. Regarding fairness, this model aims to secure a fair workload and preferred assignments. The consideration of two fairness factors has not been addressed by any existing work. The satisfaction-enhanced features are formulated as the model's objectives as follows.

1. Minimize the deviations of nurses' shift assignments.
2. Minimize the deviations in the preferred shift assignments among nurses.
3. Minimize the deviations in the preferred day off assignments among nurses.

This proposed NSP model aims to provide an equitable distribution of workloads and the nurses' preferred shifts and days off assignments. The desirable schedule outcomes encompass the following attributes: 1.) All nurses should receive similar workloads that conform to hospital workload restrictions. 2.) All nurses should equally receive a certain amount of shifts and days off they prefer. Due to the need to fulfill hospital regulations, all nurses' preferences cannot be fulfilled. However, the model can ensure a desirable level of fulfillment for all nurses.

From the given specifications, the model consists of multiple goals, each with a definable target value. Therefore, a goal programming (GP) technique is employed to formulate and solve this proposed model. The usefulness of GP in solving multi-objective problems has been well demonstrated in the literature. Its main advantage is that it reflects how the management makes decisions in a real-world problem. GP allows decision-makers to incorporate their insights in determining the desired target for each goal. Once decision-makers assign the target values, the total undesirable deviations from those values are minimized. This model is suitable for general hospitals, where the target number of workload assignments is typically known. Then, management can allow nurses to participate in refining the preferences-related goals, encouraging the engagement of their job autonomy. The mathematical formulation of the model is displayed below.

3.1.1 Mathematical Model Formulation

This multi-objective, satisfaction-enhanced NSP model is formulated using the GP approach. The aim is to determine a work schedule that provides an equally distributed workload and preferable assignments. Without loss of generality, the assumptions and notations used in the model formulation are summarized below.

Assumptions

- The planning horizon is four weeks (28 days) long. Each workday consists of multiple same-length shifts.
- Nurses are classified into levels based on their work experience. The total number of nurses and the number of nurses with a particular skill level assigned in each shift must meet hospital requirements.
- The total amount of shifts assigned to each nurse must be within the limit.
- Each nurse must receive at least the minimum allowable days off each week.
- Morning shift cannot be assigned right after a night shift.
- The number of night shifts assigned per week must not exceed the limit.
- Night shifts cannot be assigned consecutively for certain days to ensure adequate rest.
- In the case of a double-shift workday system, there can be no more than certain days of consecutive double-shift workdays.

Indices

$\mathcal{N}$	Set of nurses; $\mathcal{N} = \{1, 2, \dots, \mathrm{N}\}$
$\mathcal{S}$	Set of shifts in a workday; $\mathcal{S} = \{1, 2, \dots, \mathrm{S}\}$
$\mathcal{K}$	Set of nurse skill levels; $\mathcal{K} = \{1, 2, \dots, \mathrm{K}\}$
$\mathcal{D}$	Set of days in planning horizon; $\mathcal{D} = \{1, 2, \dots, \mathrm{D}\}$

Input Parameters

R_{sd}	The total number of nurses required in shift s on the day d.
RL_{sk}	The minimum number of nurse with skill level k required in shift s.
N_k	A set of nurses that belong to skill level k; $\mathcal{N} = N_1 \cup N_2 \cup \ldots \cup N_K$
SK_{nk}	A binary parameter equals 1 if nurse n belongs to skill level k; 0 otherwise.
SP_{nsd}	A binary parameter equals 1 nurse n prefers to work in shift s on day d; 0 otherwise.

DP_{nd}	The preference score of nurse n towards taking a day-off on day d; $DP_{nd} \in \{1, \ldots, Q\}$
DS	The maximum number of shifts can be assigned to a nurse per day.
DO	The minimum number of days off a nurse must receive per week.
NS	The maximum night shifts can be assigned to a nurse per week.
TS	The maximum total shifts can be assigned to a nurse per month.
TS_{target}	The target number of shifts assigned to nurses
SP_{target}	The target number of preferred shifts
DP_{target}	The target preferred day-off preference scores

Decision Variables

X_{nsd}	$= 1$ if nurse n is assigned to work in shift s on day d; 0 otherwise.
Y_{nd}	$= 1$ if nurse n is assigned to take a day-off on day d; 0 otherwise.
TS_n^+,TS_n^-	The positive and negative deviations of the total number of shifts from the target for nurse n
SP_n^+,SP_n^-	The positive and negative deviations of the number of preferred shifts from the target for nurse n
DP_n^+,DP_n^-	The positive and negative deviations of the preferred day off scores from the target for nurse n

The proposed satisfaction-enhanced NSP model consists of 3 objectives, each derived as a GP goal. The first goal is to balance the number of shifts assigned to nurses subject to the workload target. The second and third goals aim to balance the individual preferences on shifts and days off, respectively. The description and formulation of each goal are shown below.

Goal 1: Workload balancing

This goal minimizes the deviations of workload assigned to each nurse from the target goal. At the same time, it aims to balance workload assignments among nurses. Underdeviation means the workload assigned is less than the target. Overdeviation means the workload assigned is more than the target. Both can be calculated using Equation (3.1). Both overworking and underworking result in undesirable scheduling outcomes. Therefore, the positive and negative deviations are included in the objective function.

$$\sum_{s=1}^{S}\sum_{d=1}^{D} X_{nsd} - TS_n^+ + TS_n^- = TS_{target} \quad \forall n \in \mathcal{N} \tag{3.1}$$

The justification of Equation (3.1) is explained as follows. Assume that the target workload of nurses (TS_{target}) is 24 shifts per month, and the total workload assigned to a nurse n is 22 shifts. By substituting those values, the equation becomes,

$$22 - TS_n^+ + TS_n^- = 24$$

For the equation to be valid, TS_n^+ cannot take any value other than 0. The model then assigns TS_n^+ as 0, meaning that the nurse n does not overwork. At the same time, the model assigns TS_n^- to 2 to justify the equation. The TS_n^- of 2 means the nurse n underworks by two shifts. The equation is valid by substituting those decision values, as shown below. The same computational logic is applied to the subsequent goal formulations.

$$22 - 0 + 2 = 24$$

Goal 2: Number of preferred shifts balancing

This goal aims to fulfill the nurses' individual shift preferences equitably. Nurses' preference for working in a shift s on the day d (SP_{nsd}) is represented as a binary value. The value of 1 represents the preferred shift, and 0 represents non-preferred. When shift assignment corresponds to the preferred slot, preferred shift assignments count as one. The deviations of the total number of preferred shift assignments of each nurse from the targeted preferred shifts (SP_{target}) are calculated in Equation (3.2). In this goal, only negative deviations are undesirable. Positive deviations mean nurses receive more preferred assignments than the target goal. Thus, the schedule outcome is more satisfactory.

$$(\sum_{s=1}^{S}\sum_{d=1}^{D} SP_{nsd} \cdot X_{nsd}) - SP_n^+ + SP_n^- = SP_{target} \quad \forall n \in \mathcal{N} \tag{3.2}$$

Goal 3: Preferred day off scores balancing

This final goal aims to fulfill nurses' days off preferences. The days off preferences are evaluated as scores (DP_{nd}), indicating how much nurses favor taking a day off on that particular day. Evaluating days off preferences as scores provides more flexible assignments. Nurses can choose multiple days that they prefer to take a day off. Each day is assigned a different score depending on the level of preferences. The scale can be adjusted based on the nurses' judgment. The preferred day off scores of each nurse that deviate from the targeted preferred day off scores (DP_{target}) are calculated in Equation (3.3). Only negative deviations are undesirable and included in the objective function. Positive deviations mean nurses received more preferred days off assignment than the target value. Thus, the schedule outcome is more desirable.

$$(\sum_{d=1}^{D} DP_{nd} \cdot Y_{nd}) - DP_n^+ + DP_n^- = DP_{target} \quad \forall n \in \mathcal{N} \tag{3.3}$$

Objective function

In GP, the summation of undesirable deviations from all goals is derived into a single objective function. In this model, each goal has a different magnitude. They must be normalized before summarizing them together to resolve the incommensurable issue. Normalization is to transfer different units of deviations of each goal into a standard unit to eliminate bias toward larger magnitude goals, as demonstrated in the GP formulation by Jadidi et al. [102]. The objective function of this satisfaction-enhanced NSP model (3.4) is to minimize the summation of normalized undesirable deviations, as shown below.

$$\min \left(\frac{(\sum_{n=1}^{N}(TS_n^+ + TS_n^-)}{TS_{target} \cdot N} \right) + \left(\frac{\sum_{n=1}^{N} SP_n^-}{SP_{target} \cdot N} \right) + \left(\frac{(\sum_{n=1}^{N} DP_n^-}{DP_{target} \cdot N} \right) \tag{3.4}$$

Constraints

Followings are a set of hard constraints that must be satisfied.

$$\sum_{n=1}^{N} X_{nsd} \geq R_{sd} \quad \forall s \in \mathcal{S}; d \in \mathcal{D} \tag{3.5}$$

$$\sum_{s=1}^{S} (X_{nsd} \cdot SK_{ns}) \geq RL_{sk} \quad \forall s \in \mathcal{S}; d \in \mathcal{D}; k \in \mathcal{K} \tag{3.6}$$

$$\sum_{s=1}^{S} X_{nsd} \leq DS \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \tag{3.7}$$

$$\sum_{d=d}^{d+6} Y_{nd} \geq DO \quad \forall n \in \mathcal{N}; d \in \mathcal{D}_1 \cup \mathcal{D}_8 \cup \mathcal{D}_{15} \cup \mathcal{D}_{22} \tag{3.8}$$

$$\sum_{s=1}^{S}\sum_{d=1}^{D} X_{nsd} \leq TS \quad \forall n \in \mathcal{N} \tag{3.9}$$

$$\sum_{s=1}^{S} X_{nsd} + Y_{nd} \geq 1 \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \tag{3.10}$$

$$X_{n,s=S,d} + X_{n,s=1,d+1} \leq 1 \quad \forall n \in \mathcal{N}; d \in \mathcal{D} - \{D\} \tag{3.11}$$

$$\sum_{s=S}\sum_{d=d}^{d+t} X_{nsd} \leq t \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \setminus \{D-t+1, ..., D\} \tag{3.12}$$

$$\sum_{s=S}\sum_{d=d}^{d+6} X_{nsd} \leq NS \quad \forall n \in \mathcal{N}; d \in \mathcal{D}_1 \cup \mathcal{D}_8 \cup \mathcal{D}_{15} \cup \mathcal{D}_{22} \tag{3.13}$$

$$\sum_{s=1}^{S}\sum_{d=d}^{d+f} X_{nsd} \leq 2f+1 \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \setminus \{D-f+1, ..., D\} \tag{3.14}$$

$$X_{nsd}, Y_{nd} \in \{0,1\} \tag{3.15}$$

$$TS_n^+, TS_n^-, SP_n^+, SP_n^-, DP_n^+, DP_n^- \in \mathbb{Z}_0^+ \tag{3.16}$$

Constraint (3.5) regulates that the number of nurses assigned to each shift meets the requirements. Constraint (3.6) ensures the number of nurses in each skill level meets the requirements. Constraint (3.7) restricts the number of shifts that can be assigned to nurses in a workday. Constraint (3.8) ensures nurses receive a certain amount of day(s) off per week. Constraint (3.9) ensures the number of total shifts assigned to nurses through the planning horizon does not exceed the limit. Constraint (3.10) prohibits shift assignment on any day off. Constraint (3.11) forbids a morning shift assignment after a night shift. Constraint (3.12) limits the number of consecutive night shifts to be less than t days. Constraint (3.13) limits the number of night shifts per week. Constraint (3.14) specifies that no more than f consecutive double-shift workdays are allowed to avoid accumulating fatigue. This constraint can be excluded if a double-shift workday is not permitted. Constraints (3.15) and (3.16) are the standard integrality and non-negativity constraints.

3.1.2 Hospital Case Data

The proposed model is validated using a case study of an operating room (OR) of a medium-sized private hospital with 200 beds capacity in Pathum Thani, Thailand. Data collection processes from December 2019 to February 2020 include a field survey, a questionnaire survey, and an interview with the head nurse. The OR department consists of 16 full-time registered nurses and one head nurse. The hospital uses a shift work rotation system with three 8-hour shifts in a workday. The shifts include morning shift (M): 8 AM - 4 PM, afternoon shift (A): 4 PM - 12 AM, and night shift (N): 12 AM - 8 AM. The head nurse only works the morning shifts. Nurses are classified into two levels based on their working experiences. Level-1 nurses have five or more years of working experience, and level-2 nurses have less than five years of experience. Nine level-1 nurses (including the head nurse) and eight level-2 nurses were employed.

In the hospital case, the head nurse manually devises monthly nurse schedules at the beginning of each month. The primary task is to assign a sufficient number of nurses to each shift across the planning horizon. The head nurse specified the scheduling task as burdensome. It usually requires about one week to generate a schedule that complies with all hospital regulations. The head nurse did not consider any nurses' preferences and fairness factors in the current scheduling process. In this model, a scheduling period of 28 days is assumed for the generality of the proposed model. The scheduling criteria, relevant hospital restrictions, and the three target goals specified by the head nurse are summarized in Table 3.1.

From Table 3.1, the hospital allows one shift per day and requires at least a day off per week for nurses. Nurses cannot work more than two night shifts per week. The total shifts per month must not exceed 24. The target number of shifts per month was specified per this restriction. The number of nurses required for morning, afternoon, and night shifts is 6, 6, and 2, respectively, for all days on the planning horizon. In addition, the head nurse specifies that the number of level-1 nurses must be at least half the total number of nurses to maintain sufficient service quality. There is no specified number of level-2 nurses in each shift. Thus, Table 3.1 only represents the number of level-1 nurses required in each shift.

Regarding individual preferences, nurses were asked to indicate their preferred shifts and day off across the 28-day planning period via a questionnaire survey. The mathematical model uses these data as input for shift and day off preference fulfillment goals. First, nurses were asked to fill the shifts they preferred to work each day throughout the 28-day time. An example of the first 14 days of shift preference data is shown in Table 3.2. It can be seen

Table 3.1: The hospital regulation parameters

Parameters	**Value**
Number of nurses required in each shift (R_{sd})	
Morning	6
Afternoon	6
Night	2
Number of level-1 nurse required in each shift (RL_{s1})	
Morning	3
Afternoon	3
Night	1
Allowable total shifts per month (TS)	24
Maximum daily shift (DS)	1
Minimum day off per week (DO)	1
Allowable night shifts per week (NS)	2
Target shifts assigned (TS_{target})	24
Target preferred shifts (SP_{target})	20
Target preferred day off score (DP_{target})	12

that nurses prefer night shifts less than morning and afternoon shifts. However, nurses must be present on night shifts per the coverage requirement. Therefore, fulfilling all shift preferences is challenging when conflicts exist. In this case study, the head nurse specified the target preferred shifts of 20. This means that out of the 24 shifts targeted to assign to nurses each month, nurses should receive about 20 preferred slots.

For the day off preferences, nurses identified their most and second-most preferred days off each week. A total of 8 days off preferences were specified across the planning period. The day-off preference data was then converted to scores using the Likert scales rather than the binary scales used by the previous studies [74, 63]. Different preference ratings provide more scheduling flexibility and a higher chance of maximizing the satisfaction of all nurses. In this case, the head nurse suggested that the most and second-most preferred days off are worth 3 and 1 points, respectively. The target preferred day-off score (DP_{target}) of 12 is achieved when nurses receive the most preferred day off every week throughout the 28-day planning period. The first 14 days of the day-off preference sheets are shown in Tables 3.3.

The following section presents experimental results, scenario analysis, and discussion. The effectiveness of the proposed model against the manually-made schedule is discussed.

Table 3.2: Nurses' preferred working shifts

Nurse	EXP	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14
1	1 (H)	M	M	M	M	M	M	M	M	M	M	M	M	M	M
2	1	M	A	A	A	M	M	M	A	A	A	N	A	A	A
3	1	M	M	M	M	M	N	M	M	M	M	M	M	M	A
4	1	A	A	A	A	A	M	A	A	A	A	M	N	M	M
5	1	M	M	A	A	A	A	N	A	A	A	A	A	M	M
6	1	A	A	A	A	A	N	A	A	A	A	A	M	M	M
7	1	M	M	M	M	M	A	A	A	A	A	A	A	N	A
8	1	A	A	A	A	A	A	M	M	M	M	M	M	M	M
9	1	A	A	M	M	M	M	A	A	A	A	N	A	A	N
10	2	M	M	M	M	M	M	M	M	M	M	M	M	M	M
11	2	A	A	A	A	A	N	A	A	A	N	M	M	M	M
12	2	M	M	A	A	A	M	M	M	M	M	N	A	A	A
13	2	M	M	M	M	M	A	A	A	A	A	N	A	A	A
14	2	A	A	A	A	A	A	A	M	M	M	M	M	M	M
15	2	A	A	A	N	A	M	M	M	M	M	M	A	A	A
16	2	M	M	M	M	M	A	A	A	A	A	A	A	N	A
17	2	N	A	A	A	A	M	M	A	A	A	A	N	A	A

EXP = Experience level, H = Head nurse, M = Morning shift, A = Afternoon shift, N = Night shift

3.1.3 Results and Discussion

This section presents the experimental results of scenario analysis. Different operational scenarios are employed to assess the practicality and robustness of the proposed model under different settings. Three following scenarios are used for model validation: 1.) the standard operation scenario, 2.) the extended capacity operation scenario, and 3.) the higher demand for experienced nurses scenario. For the standard operation scenario, the number of nurses required over the three shifts is 6, 6, and 2. In the extended capacity scenario, the morning shift capacity is assumed to be expanded to cope with the higher patient volume in the morning hours, as pointed out by the head nurse. The number of nurses required for each shift in the extended capacity operation is 9, 6, and 2.

The optimal schedules obtained from scenario analysis are compared to the manually-made schedule to evaluate their efficiency in preference fulfillment and fairness. Since this model is the first to incorporate fairness in both workload and preferred assignments, it cannot be compared with other existing models. It is worth noting that the scheduling requirements, such as the number of allowable shifts and forbidden shift patterns, are formulated as hard constraints according to the regulations of this hospital case. Therefore, the solution space is relatively tight, so sensitivity analysis cannot be performed. Therefore, only scenario analysis is performed for this case study. For other hospital cases, hard constraints can be reformulated as soft

Table 3.3: Nurses' preferred day off

Nurse	EXP	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14
1	1 (H)	-	1	-	-	-	-	3	-	1	-	-	-	-	3
2	1	-	-	3	-	-	1	-	-	1	-	-	3	-	-
3	1	1	-	-	-	3	-	-	-	3	-	-	-	1	-
4	1	-	1	-	-	-	-	3	3	-	-	1	-	-	-
5	1	-	-	-	-	-	3	1	-	1	-	-	-	3	-
6	1	-	-	-	3	-	1	-	-	-	1	3	-	-	-
7	1	-	3	-	-	1	-	-	-	1	-	-	-	-	3
8	1	1	-	-	-	-	3	-	1	-	-	-	3	-	-
9	1	-	1	-	-	-	-	3	-	3	-	-	-	-	1
10	2	-	1	-	-	3	-	-	-	-	1	-	3	-	-
11	2	-	-	1	-	-	-	3	-	-	-	1	-	-	3
12	2	3	-	-	-	-	-	1	-	-	3	-	-	1	-
13	2	3	-	-	1	-	-	-	-	3	-	-	1	-	-
14	2	-	3	-	-	-	1	-	1	-	-	-	-	3	-
15	2	1	-	-	-	3	-	-	-	1	-	-	-	-	3
16	2	-	-	1	-	-	3	-	-	-	1	-	3	-	-
17	2	3	-	-	-	-	1	-	3	-	-	-	1	-	-

constraints or goal equations so that constraint violations are allowed with some penalties, enabling the model to be more flexible.

Standard Operation Scenario

The proposed goal programming satisfaction-enhanced NSP is solved using Opensolver version 2.9.0, an add-in optimization tool in Microsoft Excel with a 2.3 GHz Dual-Core Intel Core i5-8300H operating system. Examples of the spreadsheet and OpenSolver interactive shell are shown in Appendix A. The standard operation scenario is identical to the actual operational setting of the hospital case. The number of nurses available is 17, with the number of nurses required for each shift on all workdays being 6, 6, and 2. The optimal nurse schedule can be acquired within 5 seconds. An example of the first 14 days of the nurse schedule under the standard operation scenario is shown in Table 3.4.

The total number of shifts, number of preferred shifts received, and the total day off preference score of all 17 nurses over the 28-day planning period are summarized in Table 3.5. The second-left column shows the actual total number of shifts assigned to nurses based on the manually created schedule from the month prior to the data collection. The details of deviation from the three goals are also given in the table. The experimental results indicate that the proposed model successfully achieves all desirable goals. Regarding the workload balancing goal, there are four nurses with 0 under deviations from the target of 24 shifts. The deviations from the target of other nurses are no more than two shifts. The workload assignments among nurses are relatively balanced. In the optimal schedule, five nurses receive fewer workloads, nine nurses receive more, and three receive no workload change. It is also worth mentioning that, in this case, the total allowable shifts (TS) and the target number of shifts assigned (TS_{target}) are specified as equally 24 by the head nurse. Therefore, TS_n^+ always equals zero and is excluded from Table 3.5. Both over and under deviations in shift assignments occur in cases where the target and allowable shifts are not equal.

Table 3.4: The nurse schedule outcome under the standard operation scenario

Nurse	**EXP**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**	**D11**	**D12**	**D13**	**D14**
1	1 (H)	M	M	M	O	M	M	O	M	M	O	M	M	M	O
2	1	M	M	O	N	M	A	M	A	A	M	N	O	A	A
3	1	M	M	O	M	N	A	M	M	M	M	M	M	O	A
4	1	A	A	A	O	A	M	A	M	M	N	O	N	M	M
5	1	M	M	N	A	A	O	N	A	N	A	A	A	O	A
6	1	A	A	A	A	O	N	A	M	A	A	O	M	A	M
7	1	M	M	M	M	O	A	A	N	M	A	A	A	N	O
8	1	A	N	A	A	A	O	M	M	M	M	M	O	M	M
9	1	N	A	M	M	M	M	O	A	A	O	A	A	A	N
10	2	M	O	M	M	M	M	M	M	O	M	M	M	M	M
11	2	A	A	O	A	A	N	O	A	A	N	O	M	M	M
12	2	O	N	A	A	N	M	M	N	M	O	N	A	A	A
13	2	O	M	M	M	M	A	A	A	O	A	A	A	M	N
14	2	A	O	N	A	A	A	A	O	N	M	M	M	O	M
15	2	A	A	A	N	O	M	M	O	O	M	M	A	A	O
16	2	O	O	M	M	M	A	A	A	A	A	A	O	N	A
17	2	N	A	A	O	A	O	N	O	A	A	A	N	A	A

EXP = Experience level, H = Head nurse, M = Morning shift, A = Afternoon shift, N = Night shift, O = Day off

Regarding the other two goals, the deviations from the target number of preferred shifts and target day off scores are negligible. Therefore, it can be concluded that the shift and day-off preferences are well-fulfilled and balanced. However, Nurse 2 is subject to moderate percent deviation across the two preference-related goals compared to other nurses. While Nurse 4 also receives the least number of preferred shifts. Typically, the individual preferences and the need to comply with hospital regulations are conflicting. Therefore, there may be cases where the preferences of one or a few individuals are compromised to achieve the overall maximum job satisfaction. Those nurses should be compensated by a rise in preferred shifts and day-off assignments during the next scheduling period to maintain fairness in the long run. Nevertheless, it is reasonable to conclude that the proposed model can satisfy all goals for the current optimal solution under this scenario.

For better visualization, Figure 3.1 and 3.2 illustrate a comparison of

Table 3.5: Summary of goals deviations of the NSP model under the standard operation scenario

Nurse n	Actual Total Shift	G1: Working shifts balancing				G2: Preferred shifts assignments				G3: Score of preferred day-off assignments			
		Total shifts	TS_n^-	TS target	% Dev	Total preferred shifts	SP_n^-	SP target	% Dev	Total preferred day-off score	DP_n^--	DP target	% Dev
1	24	23	1	24	0.3	20	0	20	4.3	12	0	12	5.7
2	20	24	0	24	4.1	17	3	20	11.3	10	2	12	11.9
3	20	23	1	24	0.3	18	2	20	6.1	11	1	12	3.1
4	20	23	1	24	0.3	16	4	20	16.6	11	1	12	3.1
5	24	22	2	24	4.6	18	2	20	6.1	11	1	12	3.1
6	23	23	1	24	0.3	20	0	20	4.3	11	1	12	3.1
7	21	23	1	24	0.3	18	2	20	6.1	11	1	12	3.1
8	22	23	1	24	0.3	20	0	20	4.3	11	1	12	3.1
9	24	24	0	24	4.1	20	0	20	4.3	12	0	12	5.7
10	20	24	0	24	4.1	20	0	20	4.3	12	0	12	5.7
11	20	22	2	24	4.6	20	0	20	4.3	12	0	12	5.7
12	24	23	1	24	0.3	19	1	20	0.9	10	2	12	11.9
13	20	23	1	24	0.3	20	0	20	4.3	12	0	12	5.7
14	20	23	1	24	0.3	20	0	20	4.3	12	0	12	5.7
15	24	24	0	24	4.1	20	0	20	4.3	12	0	12	5.7
16	24	22	2	24	4.6	20	0	20	4.3	12	0	12	5.7
17	24	23	1	24	0.3	20	0	20	4.3	11	1	12	3.1
Average	22	23	0.9		1.9	19.2	0.8		5.6	11.3	0.6		5.4

% Dev = Percent deviation from the average value

the workload allocation between the actual and optimal schedules. The figures show that the optimal schedule allocates workload more evenly than the actual schedule. Figure 3.3 visualizes the spread of preferred shift assignments and the total day-off preference scores among all nurses of the optimal schedule. It can be seen that the fulfillment of preferences almost reached the target value in both goals with a relatively low spread among the nurses.

Extended Capacity Scenario

Based on the head nurse, there is a high patient volume frequently in the morning shifts. The current nursing capacity becomes inadequate on such occasions. In this scenario, the number of nurses required in each shift increases to 9, 6, and 2. That is, three more nurses are employed in the morning shifts. Therefore, the nursing capacity is extended from 17 to 20 to handle the higher demand. Three artificial nurses are added with synthetic shift and day-off preferences. The results are summarized in Table 3.6. The proposed approach successfully satisfied the workload balancing goal. The workload may be proportionally distributed more easily with the increased number of nurses. The shift assignment is relatively compatible with the nurses' preferences. Only one nurse with a preferred-shift deviation of 4, while other nurses' shift preferences are well satisfied.

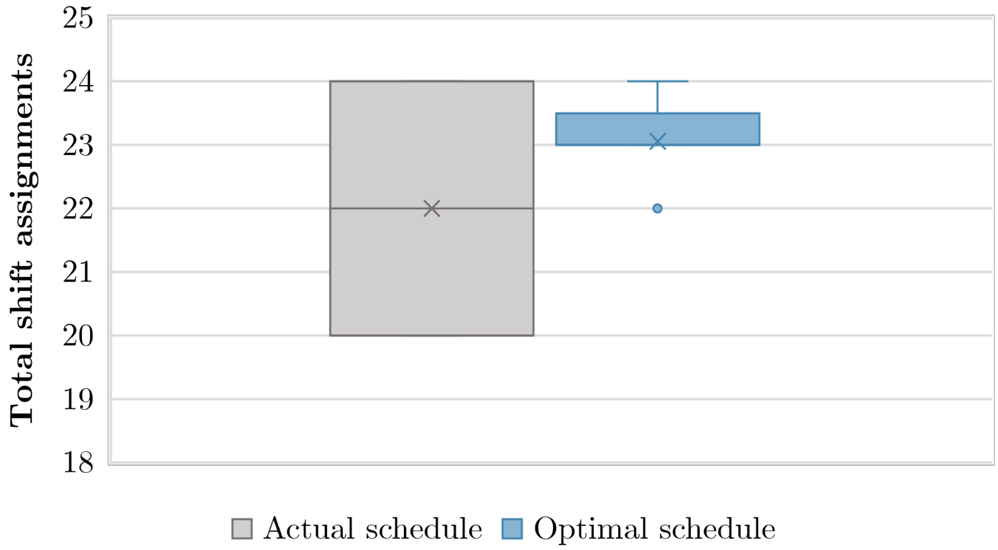


Figure 3.1: A comparison of the workload assignments between the actual and optimal schedules

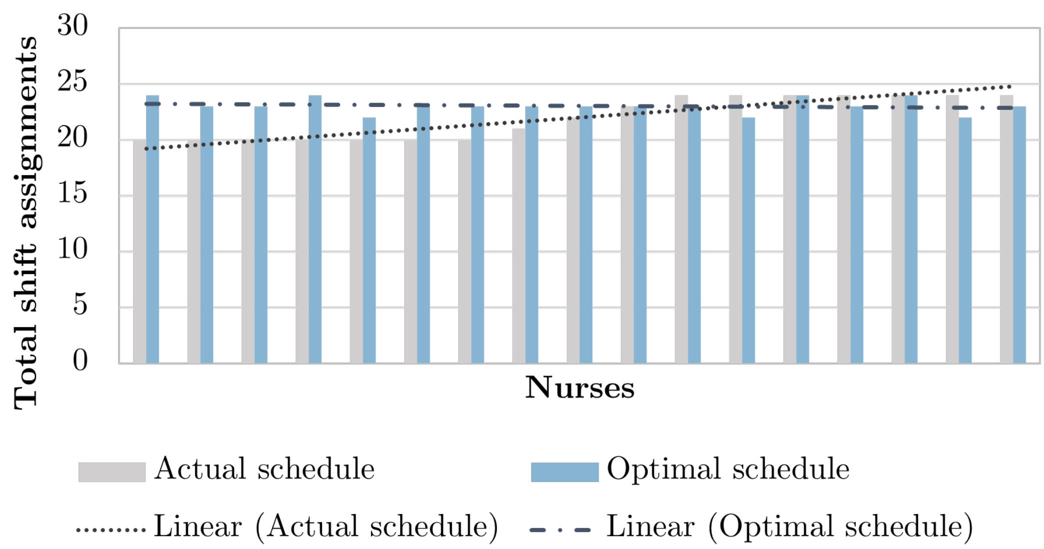


Figure 3.2: Workload assignments between the actual and optimal schedules by nurses

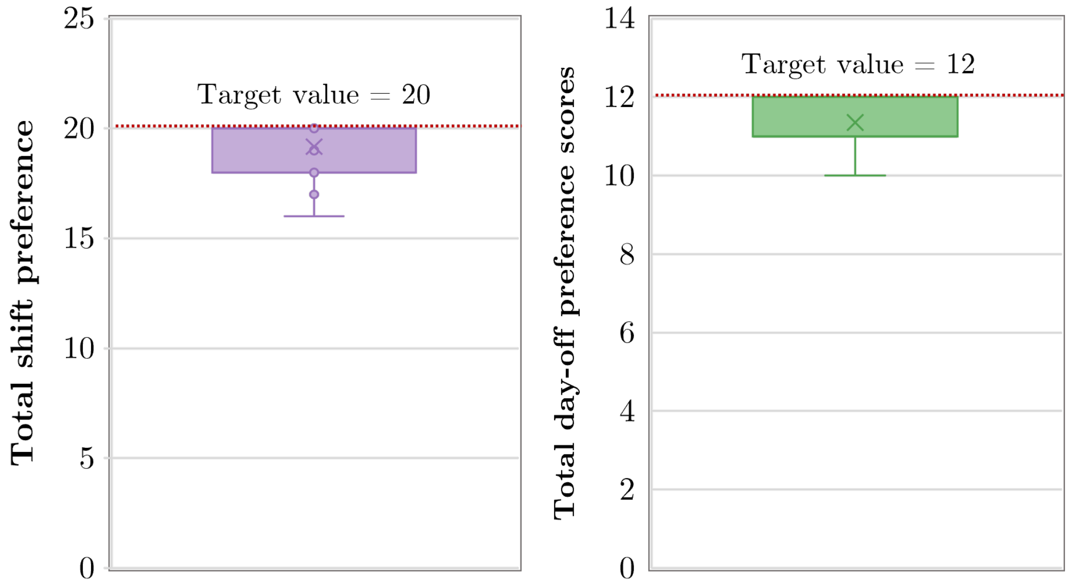


Figure 3.3: Distribution of shift and day-off preference fulfillment

The fulfillment of day-off preferences is still relatively consistent. However, it seems that some nurses' day-off preferences are compromised in order to cope with increasing demand in the morning shift. These nurses should be compensated to receive more preferred assignments in the next planning period. In terms of solving time, it takes only 5 seconds to generate an optimal solution. The computational performance is also tested using a larger scale problem. It has been found that the optimal schedule for 50 nurses can be achieved within 20 seconds.

Higher demand for experienced nurses scenario

This scenario assumes that more experienced nurses (level-1) are required on Monday and Tuesday mornings to cope with higher patient volume. The number of level-1 nurses required during these peak-demand periods increases from 3 to 5. The model is solved under the given parameters, and the results are summarized in Table 3.7. It can be seen that level-1 nurses are subject to more workloads in this scenario. Most of them received the maximum allowable shifts. The ability to fulfill level-1 nurse preferences is restricted by the increased number of level-1 nurses required during the peak-demand period. Especially in the day-off preference scores, level-1 nurses can no longer take a day off on Monday and Tuesday even if they prefer to do so. Compared to the other scenarios, the average percent deviations are higher

Table 3.6: Summary of goals deviations of the NSP model under the extended capacity scenario

Nurse n	Actual Total Shift	G1: Working shifts balancing				G2: Preferred shifts assignments				G3: Score of preferred day-off assignments			
		Total shifts	TS_n^-	TS target	% Dev	Total preferred shifts	SP_n^-	SP target	% Dev	Total preferred day-off score	DP_n^- -	DP target	% Dev
1	24	24	0	24	0.8	20	0	20	1.3	12	0	12	7.6
2	20	24	0	24	0.8	16	4	20	19.0	10	2	12	10.3
3	20	24	0	24	0.8	20	0	20	1.3	12	0	12	7.6
4	20	23	1	24	3.4	20	0	20	1.3	10	2	12	10.3
5	24	24	0	24	0.8	20	0	20	1.3	10	2	12	10.3
6	23	24	0	24	0.8	20	0	20	1.3	12	0	12	7.6
7	21	24	0	24	0.8	20	0	20	1.3	9	3	12	19.3
8	22	24	0	24	0.8	20	0	20	1.3	12	0	12	7.6
9	24	24	0	24	0.8	19	1	20	3.8	9	3	12	19.3
10	20	24	0	24	0.8	20	0	20	1.3	10	2	12	10.3
11	20	23	1	24	3.4	20	0	20	1.3	11	1	12	1.3
12	24	24	0	24	0.8	20	0	20	1.3	12	0	12	7.6
13	20	24	0	24	0.8	20	0	20	1.3	12	0	12	7.6
14	20	23	1	24	3.4	20	0	20	1.3	11	1	12	1.3
15	24	24	0	24	0.8	20	0	20	1.3	12	0	12	7.6
16	24	23	1	24	3.4	20	0	20	1.3	11	1	12	1.3
17	24	24	0	24	0.8	20	0	20	1.3	12	0	12	7.6
18	-	24	0	24	0.8	20	0	20	1.3	12	0	12	7.6
19	-	24	0	24	0.8	20	0	20	1.3	12	0	12	7.6
20	-	24	0	24	0.8	20	0	20	1.3	12	0	12	7.6
Average		23.8	0.2		1.3	19.7	0.3		2.3	11.2	0.8		8.4

% Dev = Percent deviation from the average value

for all goals.

In addition to the scenario analysis, a comparison of performance measures between the manually-made and optimal schedules is made. The optimal schedules can be compared against the manual schedule only on the workload balancing goal since preference-related goals were disregarded in the actual schedule. The comparison exhibits that the proposed model outperforms the actual schedule in terms of goal fulfillment and execution time. Table 3.8 summarizes the average and standard deviation of each objective goal for the manual schedule and optimal schedules under each scenario.

In the workload balancing goal, nurses work one shift more than the manual schedule on average. The optimal schedule yields a significantly lower standard deviation for all scenarios when compared to the manual schedule. A lower standard deviation suggests that the model provides a more balanced workload assignment than the manual schedule. In terms of shift preferences, nurses receive nearly the target shift preference of 20 on average, with a relatively low standard deviation except for the higher demand for level-1 nurses scenario. This is because the preference fulfillment

Table 3.7: Summary of goals deviations of the NSP model under the scenario with higher demand for level-1 nurses

Nurse n	Actual Total Shift	G1: Working shifts balancing				G2: Preferred shifts assignments				G3: Score of preferred day-off assignments			
		Total shifts	TS_n^-	TS target	% Dev	Total preferred shifts	SP_n^-	SP target	% Dev	Total preferred day-off score	DP_n^--	DP target	% Dev
1	24	22	2	24	4.6	20	0	20	6.3	12	0	12	23.6
2	20	24	0	24	4.1	19	1	20	0.9	9	3	12	7.3
3	20	24	0	24	4.1	19	1	20	0.9	4	5	12	58.8
4	20	24	0	24	4.1	17	3	20	9.7	4	5	12	58.8
5	24	24	0	24	4.1	19	1	20	0.9	12	0	12	23.6
6	23	24	0	24	4.1	17	3	20	9.7	10	4	12	3.0
7	21	24	0	24	4.1	20	0	20	6.3	12	0	12	23.6
8	22	24	0	24	4.1	19	1	20	0.9	10	2	12	3.0
9	24	24	0	24	4.1	20	0	20	6.3	6	9	12	38.2
10	20	23	1	24	0.3	20	0	20	6.3	7	2	12	27.9
11	20	22	2	24	4.6	20	0	20	6.3	11	1	12	13.3
12	24	22	2	24	4.6	15	5	20	20.3	12	0	12	23.6
13	20	22	2	24	4.6	16	4	20	15.0	12	0	12	23.6
14	20	23	1	24	0.3	19	1	20	0.9	11	1	12	13.3
15	24	22	2	24	4.6	20	0	20	6.3	12	1	12	23.6
16	24	22	2	24	4.6	20	0	20	6.3	10	1	12	3.0
17	24	22	2	24	4.6	20	0	20	6.3	11	0	12	13.3
Average	22	23.1	0.9		3.9	18.8	1.2		6.4	9.7	2		22.4

% Dev = Percent deviation from the average value

of level-1 nurses is restricted by the need to cope with increasing demand. In the day-off preference scores, similar results are also exhibited. In terms of execution time, the proposed model can generate optimal schedules within less than a minute. In this sense, the head nurse can efficiently deal with last-minute requests or changes in nurses' preferences and promptly generate the new finalized schedule.

3.1.4 Conclusion

This proposed satisfaction-enhanced NSP model is the first to consider fairness in workload and preferred assignment distribution. The model is developed as a nurse scheduling tool that can proportionally assign shifts to nurses while maximizing the fulfillment of their personal preferences on shifts and days off. The goal programming technique is employed to formulate the NSP model with three satisfaction-enhancement goals: 1) minimizing the unbalanced workload, 2) minimizing the unbalanced preferred shift assignments, and 3) minimizing the unbalanced preferred day off scores among the nurses. Data collected from an OR at a private hospital in Thailand is used to validate and examine the model's practicality.

Scenario analysis was performed to test the solution quality and com-

Table 3.8: A comparison of performance indicators between the manual and optimal schedules

	G1: No. of working shifts balancing		G2: No. of preferred shift assignments		G3: Score of preferred day-off assignments	
	Average	SD	Average	SD	Average	SD
Manual	22	1.84	-	-	-	-
Standard operation	23.0	0.64	19.17	1.24	11.32	0.68
Extended capacity	23.8	0.4	19.75	0.89	11.15	1.06
Higher demand for experienced nurses	23.1	0.94	18.82	1.60	9.70	2.78

SD - Standard deviation

putational time performance under different settings. Based on the experimental results, the schedules obtained from the proposed model outperform the manually-made schedule in all target goals and execution times. The optimization nurse scheduling model can effectively and promptly generate a satisfactory and fair monthly work schedule. The ability to handle large-scale problems is verified by using a problem instance with 50 nurses and a 28-day planning horizon. It only took 20 seconds to generate an optimal solution for the problem instance. Therefore, it is reasonable to conclude that the proposed model is a handy decision-support tool that can be executed with Microsoft Excel.

From a theoretical perspective, the model strengthens the existing NSP literature by incorporating multiple job satisfaction-enhancement factors based on individual preferences and fairness. In addition, the model is developed generically. Therefore, it can be altered to suit other hospital settings or application areas. Constraints and regulations can be relaxed to handle scheduling in emergencies. Adaptations can be made to consider other scheduling attributes such as staffing cost, task heterogeneity, and nurses' affinities to meet the administration policies.

To this end, this model provides promising scheduling outcomes for fulfilling nurses' shift and day-off preferences and ensuring fairness. Nonetheless, the economic aspect is still necessary for practical implementation. Schedules that perform well in the economic and job satisfaction aspects are indeed more favorable from the management viewpoint. Therefore, an extension is made to this model by incorporating staffing cost as another objective in Model II. The following section describes the mathematical formulation and validation of Model II.

3.2 Model II: The Cost-effective and Satisfaction-enhanced NSP

The previous section describes the satisfaction-enhanced NSP Model I development using a goal programming technique. The aim is to provide a work schedule that fulfills nurses' shift and day-off preferences while balancing the workload and preferred assignment distribution. Nonetheless, the practical implication value of NSP relies on the economic aspect as well. Thus, an extension is made to the concept of Model I by incorporating the economic factor. This section presents the development of Model II, a cost-effective and satisfaction-enhanced NSP. Similar to Model I, preferences and fairness are extensively considered—shift and day-off preferences, fair workload, and preferable assignments. This model is formulated as a bi-objective optimization model encompassing the following objectives.

1. Minimize the total staffing cost.
2. Maximize the minimum nurses' job satisfaction score.

The second objective derives the job satisfaction score from nurses' shift and day-off preferences. With these two objectives, schedule outcomes can simultaneously be economical and satisfactory. Thus, it is desirable for both nurses and the management. From the management viewpoint, the two objectives have different priorities. Indeed, management seeks an alternative that yields a minimum cost first, then maximizes satisfaction. Therefore, the ε-constraint technique is employed as the solution approach.

In most multi-objective problems, it is rare to find a single solution that yields the best values of all objectives. Typically, an optimal value of an objective can be achieved by compromising the others. An ε-constraint technique, so-called pre-emptive or lexicographic optimization in the literature, is another effective technique in solving multi-objective problems. ε-constraint technique allows decision-makers to define the level of importance of each objective. The model is then solved sequentially under one objective at a time, ordered by its priority. Each objective is imposed as a constraint in the subsequent iterations. By doing so, the best value of the most important objective can be obtained before optimizing other less important objectives.

In the weighted-sum or GP approach, all objectives are formulated into a single equation. Determining appropriate objective weights that ensure the original problem's equivalence can be more challenging and time-consuming than solving it sequentially in some cases. In ε-constraint, normalization or weight of importance is not required since each objective is handled separately. In addition, ε-constraint decomposes a multi-objective problem into a sequence of single-objective problems. Therefore, the computational time required is less than straightforwardly handling multiple objectives simultaneously.

3.2.1 Mathematical Model Formulation

This proposed NSP model aims to generate economic, satisfactory, and fair nurse schedules. The model is formulated as a bi-objective MILP and solved with the ε-constraint technique. Without loss of generality, the assumptions and notations used in the model formulation are summarized below.

Assumption

- The planning horizon is four weeks (28 days). Each workday consists of multiple shifts of the same length.
- Nurses are classified into levels based on their working experience. The total number of nurses and nurses with a particular skill level in each shift must meet the requirements.
- The total shifts assigned to each nurse must not exceed the monthly limit.
- Each nurse must receive at least the minimum allowable day-offs per week.
- Night shifts cannot be followed by the morning shift of the subsequent day.
- There can be no more than a certain amount of consecutive night shift assignments.
- In case a double-shift workday is allowed, there can be no more than two consecutive double-shift workdays.

Indices

$\mathcal{N}$	Set of nurses; $\mathcal{N} = \{1, 2, \dots , \mathrm{N}\}$
$\mathcal{S}$	Set of shifts in a workday; $\mathcal{S} = \{1, 2, \dots, \mathrm{S}\}$
$\mathcal{K}$	Set of nurse skill levels; $\mathcal{K} = \{1, 2, \dots, \mathrm{K}\}$
$\mathcal{D}$	Set of days in planning horizon; $\mathcal{D} = \{1, 2, \dots, \mathrm{D}\}$

Input Parameters

R_{sd}	The total number of nurses required in shift s on the day d.
RL_{sk}	The minimum number of nurse with skill level k required in shift s.
N_k	A set of nurses that belong to skill level k; $\mathcal{N} = N_1 \cup N_2 \cup \ldots \cup N_K$
SK_{nk}	A binary parameter equals 1 if nurse n belongs to skill level k; 0 otherwise.
SP_{ns}	The preference score of nurse n towards working in shift s; $SP_{ns} \in \{1, \ldots, Q\}$
DP_{nd}	The preference score of nurse n towards taking a day-off on day d; $DP_{nd} \in \{1, \ldots, Q\}$
Q_{nd}	A binary parameter equals 1 if nurse n requests to take a day-off on day d; 0 otherwise.
C_s	Cost of assigning a shift type s to a nurse
DS	The maximum number of shifts can be assigned to a nurse per day.
DO	The minimum number of days off a nurse must receive per week.
TS	The maximum total shifts can be assigned to a nurse per month.
Gap_{WL}	The limit of differences between the total shifts assigned among nurses
$BigM$	A large positive value for formulating conditional equations

Decision Variables

X_{nsd}	= 1 if nurse n is assigned to shift s on day d; 0 otherwise.
Y_{nd}	= 1 if nurse n is assigned to take a day-off on day d; 0 otherwise.

Auxiliary Variables

This section provides definitions of auxiliary variables derived from computations of decision variables used in formulating objective functions and constraints for ease of understanding.

TPC_n	The total preference score of nurse n, calculated by the summation of the total shift and day off preference scores

$$TPC_n = \sum_{s=1}^{S} \sum_{d=1}^{D} (X_{nsd} \cdot SP_{ns}) + \sum_{d=1}^{D} (Y_{nd} \cdot DP_{nd}) \qquad \forall n \in \mathcal{N} \tag{3.17}$$

TPC_{min} The minimum total preference score among all nurses

$$TPC_{min} = \min_{n \in \mathcal{N}} \{TPC_n\} \tag{3.18}$$

WL_n The total shifts assigned to nurse n across the planning period.

$$WL_n = \sum_{s=1}^{S} \sum_{d=1}^{D} X_{nsd} \qquad \forall n \in \mathcal{N} \tag{3.19}$$

Objective Functions

The proposed cost-effective and satisfaction-enhanced NSP model consists of two objectives as follows.
1.) Minimize the total staffing cost.

$$\min \sum_{n=1}^{N} (\sum_{s=1}^{S} (\sum_{d=1}^{D} X_{nsd}) \cdot C_s) \tag{3.20}$$

2.) Maximize the minimum total preference score among all nurses.

$$\max \ TPC_{min} \tag{3.21}$$

The second objective is formulated using the MAXIMIN technique, which simultaneously maximizes the total preference scores and minimizes the differences in scores among nurses. This MAXIMIN technique increases the quality of the worst nurse's schedule. The gap between the upper and lower bound decreases as a result. This method has been widely used as one of the fairness enhancing measures in personnel scheduling literature as discussed by Wolbeck [103].

Constraints

The following are hard constraints that must be fulfilled.

$$\sum_{n=1}^{N} X_{nsd} \geq R_{sd} \quad \forall s \in \mathcal{S}; d \in \mathcal{D} \tag{3.22}$$

$$\sum_{n=1}^{N} (X_{nsd} \cdot SK_{nk}) \geq RL_{sk} \quad \forall s \in \mathcal{S}; d \in \mathcal{D}; k \in \mathcal{K} \tag{3.23}$$

$$\sum_{s=1}^{S} X_{nsd} \leq DS \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \tag{3.24}$$

$$\sum_{d=d}^{d+6} Y_{nd} \geq DO \quad \forall n \in \mathcal{N}; d \in \mathcal{D}_1 \cup \mathcal{D}_8 \cup \mathcal{D}_{15} \cup \mathcal{D}_{22} \tag{3.25}$$

$$WL_n \leq TS \quad \forall n \in \mathcal{N} \tag{3.26}$$

$$\sum_{s=1}^{S} X_{nsd} \leq BigM \cdot (1 - Y_{nd}) \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \tag{3.27}$$

$$\sum_{s=1}^{S} X_{nsd} + Y_{nd} \geq 1 \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \tag{3.28}$$

$$Q_{nd} \leq Y_{nd} \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \tag{3.29}$$

$$|WL_n - WL_{n'}| \leq Gap_{WL} \quad \forall n \in \mathcal{N}; n \neq n' \tag{3.30}$$

$$X_{n,s=S,d} + X_{n,s=1,d+1} \leq 1 \quad \forall n \in \mathcal{N}; d \in \mathcal{D} - \{D\} \tag{3.31}$$

$$\sum_{s=S} \sum_{d=d}^{d+t} X_{nsd} \leq t \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \setminus \{D - t + 1, ..., D\} \tag{3.32}$$

$$\sum_{s=1}^{S} \sum_{d=d}^{d+f} X_{nsd} \leq 2f + 1 \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \setminus \{D - f + 1, ..., D\} \tag{3.33}$$

$$X_{nsd}, Y_{nd} \in \{0, 1\} \tag{3.34}$$

$$TPC_n, TPC_{min}, WL_n \in \mathbb{Z}_0^+ \tag{3.35}$$

Constraint (3.22) regulates that the total number of nurses assigned to shifts must meet the coverage requirements. Constraint (3.23) ensures the number of nurses in each skill level assigned in each shift meets the minimum requirements. Constraint (3.24) limits the number of daily shifts assigned to nurses. Constraint (3.25) ensures that nurses receive at least a certain amount of days off per week. Constraint (3.26) regulates that nurses' total number of shifts per month must be within the limit. Constraints (3.27) and (3.28) specify that no shift assignment is made on any day-off. Constraint (3.29) guarantees that the requested day off of nurses is fulfilled. Constraint (3.30) limits the differences between total shift assignments (WL_n) between all nurses to ensure workload fairness. Constraint (3.31) forbids morning shift after a night shift succession. Constraint (3.32) restricts the number of consecutive night shifts to be less than t days. Constraint (3.33) restricts that no more than f consecutive double-shift workdays are allowed to avoid accumulating fatigue. This constraint can be excluded if double-shift workdays are not allowed. Constraints (3.34) and (3.35) are the standard integrality and non-negativity constraints.

In this model, staffing cost minimization must be achieved before maximizing the minimum total preference score. With ε-constraint, the problem is decomposed into two sequential optimization problems. In the first iteration, the model is solved under the cost minimization objective (3.20) subject to Constraints (3.22) - (3.35). The optimal total staffing cost ($Cost^*$) is obtained. In the second iteration, an ε-constraint (3.36) is imposed as the upper bound of staffing cost. The model is then solved under the maximization of the minimum total preference score objective (3.21) with respect to Constraints (3.22) - (3.36). The ε-constraint technique ensures that the economic performance of the schedule outcomes is not compromised for improved job satisfaction.

$$\sum_{n=1}^{N}\left(\sum_{s=1}^{S}\left(\sum_{d=1}^{D} X_{nsd}\right) \cdot C_s\right) \leq Cost^* \tag{3.36}$$

3.2.2 Hospital Case Data

The case study used for model validation is the Emergency Department (ED) at a large-scale public hospital with 800 beds capacity in Pathum Thani, Thailand. The data collection procedures, including questionnaire survey and interview, were conducted from March to June 2021. The hospital case employs 40 ED nurses, including one head nurse. A 3-shift rotation system is used; morning shift (M): 8 AM - 4 PM, afternoon shift (A): 4 PM - 12 AM, and night shift (N): 12 AM - 8 AM. The head nurse only works during morning or afternoon shifts. Nurses are classified into five levels, with level 5 being the most experienced (more than ten years of employment). There are 10, 11, 7, 9, and 3 nurses with skill levels 1 - 5, respectively.

Like the previous hospital case, the head nurse manually creates a monthly nurse schedule prior to the beginning of each month. The manually-made schedule is subject to the hospital regulations and the requested day-offs without considering any individual preferences. Depending on request conflicts, the scheduling task usually requires about 3 - 7 days to complete. In terms of fairness, the head nurse attempted to distribute the workload as evenly as possible. However, no indicator is used to define how fair the schedule is. From an interview with the head nurse, hospital regulations for using as input parameters are summarized in Table 3.9. Similar to the previous model, the planning horizon is 28 days long.

Table 3.9: The regulation-related parameters

Parameters	**Value**
Cost of assigning a shift s to nurses (C_s) ($)	
Morning	23.66
Afternoon	31.84
Night	32.42
The number of required nurses in shift s (R_{sd})	
Morning	13
Afternoon	12
Night	9
The number of nurses with skill level k required in shift s (RL_{sk}) (ordered from level 1 - 5, respectively)	
Morning	3, 3, 2, 2, 1
Afternoon	3, 3, 2, 2, 0
Night	2, 2, 1, 1, 0
Maximum shifts per month (TS)	26
Maximum daily shift (DS)	2
Minimum day off per week (DO)	1
Allowable gap of workloads assigned between nurses (Gap_{WL})	3

Table 3.9 displays the costs of assigning nurses to each shift converted from Thai Baht to US Dollar. The afternoon and night shifts span across out-of-office hours and have higher pay rates. In this wage system, nurses are automatically paid overtime hours when they work during afternoon or night shifts. Nurses are paid the same shift wage regardless of their experience levels. However, they receive a position allowance based on levels. This dissertation only focuses on the cost incurred by assigning shifts to nurses. Thus, position allowance is excluded. The total number of nurses required across the three shifts is different. Morning shifts require the most nurses, followed by afternoon and night shifts. The minimum requirement for nurses with skill levels 1 - 5 in each shift s is also displayed.

It is worth noting that this hospital's regulations differ from those of the previous hospital. This hospital permits more monthly shift assignments and employs double-shift workdays. Also, the hospital does not limit the number of night shifts per week. Instead, the hospital restraints that no more than three consecutive night shifts and two double-shifts workdays are allowed. Therefore, the value of t in Constraint (3.32) is 3, and f in Constraint (3.33) is 2 for this hospital case.

In addition to hospital regulations, nurses' preferences data regarding the preferred shifts and days off were acquired via a questionnaire survey. The questionnaire design for preferences data in this research was revised. In the data collection of Model I (Section 3.1.2), nurses were asked to fill their preferred shift slots across a 28-day planning horizon and eight of their most and second-most preferred days off. The process was rather inconvenient for nurses to define 28 preferred shift slots and 8 preferred days off slots. Most nurses did not have specific shift preferences for every day. They filled similar shift preference patterns across the 28-day slots. In this research, nurses were asked to only rank the most to least preferred working shifts and the three most to least day-of-the-week they prefer to take days off. This way, they only had to specify 6 slots. The process was less complicated and less time-consuming. Examples of the questionnaire survey questions are below.

1. Please specify the order of your shift preferences by filling in morning, afternoon, and night shifts in the following spaces.
   (a) Most preferred shift: ______________________
   (b) Second-most preferred shift: ______________________
   (c) Third-most preferred shift: ______________________
2. Please specify your three most preferred days of the week to take days off by filling in the day of the week (E.g., Monday – Sunday).
   (a) Most preferred day to take a day off: ______________
   (b) Second-most preferred day to take a day off: ______________
   (c) Third-most preferred day to take a day off: ______________

The shift and day-off preferences for 40 ED nurses obtained from the questionnaire survey are summarized in Table 3.10 and Table 3.11, respectively. For this hospital case, the nurses' shift preferences are converted into scores of 3, 2, and 1 for the first, second, and third-most preferred shift types, respectively, as displayed in Table 3.10. An example of how to interpret the table is as follows. Nurse 1 prefers to work the morning shift most, followed by afternoon and night shifts, while Nurse 2 prefers the night shift most, followed by afternoon and morning shifts.

In Table 3.11, the three-most preferred day-of-week that nurses wish to take days off are summarized. Similar to the shift preference scores, the day-off preferences (DP_{nd}) scores are specified for first, second, and third-most preferred slots as 3, 2, and 1, respectively. From the table, Nurse 1 prefers taking a day off on Sunday, Saturday, and Friday, ordered by preference level. Thus, the DP of Nurse 1 equals 3, 2, and 1 for Sunday, Saturday, and Friday. The DP_{nd} of the other non-preferred days are assigned 0 points.

The survey captures nurses' general shift and day-off preferences. The collected preference data are used as inputs in the optimization model for maximizing their total preference scores. In case nurses have specifically requested days off, they can specify their requested days off (Q_{nd}), which are guaranteed to be fulfilled by Constraint (3.29).

Table 3.10: Nurses' shift preferences data

Nurse (Skill)	**Shift**	**Shift Preference Score (SP_{ns})**	**Nurse (Skill)**	**Shift**	**Shift Preference Score (SP_{ns})**
1	M	3	21	M	3
(5)	A	2	(2)	A	1
	N	1		N	2
2	M	1	22	M	1
(5)	A	2	(2)	A	3
	N	3		N	2
3	M	1	23	M	3
(5)	A	2	(2)	A	2
	N	3		N	1
4	M	3	24	M	1
(4)	A	2	(2)	A	2
	N	1		N	3
5	M	1	25	M	2
(4)	A	2	(2)	A	3
	N	3		N	1
6	M	2	26	M	1
(4)	A	1	(2)	A	2
	N	3		N	3
7	M	3	27	M	3
(4)	A	1	(2)	A	2
	N	2		N	1
8	M	1	28	M	1

Nurse (Skill)	Shift	Shift Preference Score (SP_{ns})	Nurse (Skill)	Shift	Shift Preference Score (SP_{ns})
(4)	A	2	(2)	A	2
	N	3		N	3
9	M	3	29	M	3
(4)	A	2	(2)	A	2
	N	1		N	1
10	M	1	30	M	1
(4)	A	2	(2)	A	2
	N	3		N	3
11	M	3	31	M	2
(4)	A	2	(1)	A	3
	N	1		N	1
12	M	1	32	M	2
(4)	A	2	(1)	A	3
	N	3		N	1
13	M	3	33	M	1
(3)	A	2	(1)	A	2
	N	1		N	3
14	M	2	34	M	3
(3)	A	1	(1)	A	2
	N	3		N	1
15	M	2	35	M	1
(3)	A	3	(1)	A	2
	N	1		N	3
16	M	2	36	M	2
(3)	A	3	(1)	A	3
	N	1		N	1
17	M	1	37	M	3
(3)	A	2	(1)	A	2
	N	3		N	1
18	M	3	38	M	2
(3)	A	2	(1)	A	3
	N	1		N	1
19	M	1	39	M	2
(3)	A	2	(1)	A	3
	N	3		N	1
20	M	3	40	M	3

Nurse (Skill)	Shift	Shift Preference Score (SP_{ns})	Nurse (Skill)	Shift	Shift Preference Score (SP_{ns})
(2)	A	1	(1)	A	2
	N	2		N	1

Table 3.11: Nurses' day off preferences data

Nurse (Skill)	Preference rank	Day-of-week	Nurse (Skill)	Preference rank	Day-of-week
1	1^{st}	Sun	21	1^{st}	Thu
(5)	2^{nd}	Sat	(2)	2^{nd}	Wed
	3^{rd}	Fri		3^{rd}	Mon
2	1^{st}	Sun	22	1^{st}	Sat
(5)	2^{nd}	Sat	(2)	2^{nd}	Fri
	3^{rd}	Fri		3^{rd}	Thu
3	1^{st}	Thu	23	1^{st}	Sat
(5)	2^{nd}	Wed	(2)	2^{nd}	Fri
	3^{rd}	Mon		3^{rd}	Mon
4	1^{st}	Sat	24	1^{st}	Fri
(4)	2^{nd}	Fri	(2)	2^{nd}	Sat
	3^{rd}	Thu		3^{rd}	Sun
5	1^{st}	Sat	25	1^{st}	Sun
(4)	2^{nd}	Fri	(2)	2^{nd}	Sat
	3^{rd}	Mon		3^{rd}	Fri
6	1^{st}	Fri	26	1^{st}	Sun
(4)	2^{nd}	Sat	(2)	2^{nd}	Sat
	3^{rd}	Sun		3^{rd}	Fri
7	1^{st}	Sun	27	1^{st}	Thu
(4)	2^{nd}	Sat	(2)	2^{nd}	Wed
	3^{rd}	Fri		3^{rd}	Mon
8	1^{st}	Tue	28	1^{st}	Sat
(4)	2^{nd}	Wed	(2)	2^{nd}	Fri
	3^{rd}	Mon		3^{rd}	Thu
9	1^{st}	Sat	29	1^{st}	Sat
(4)	2^{nd}	Fri	(2)	2^{nd}	Fri
	3^{rd}	Thu		3^{rd}	Mon
10	1^{st}	Sat	30	1^{st}	Fri
(4)	2^{nd}	Fri	(2)	2^{nd}	Sat

Nurse (Skill)	Preference rank	Day-of-week	Nurse (Skill)	Preference rank	Day-of-week
	3^{rd}	Mon		3^{rd}	Sun
11	1^{st}	Sat	31	1^{st}	Sun
(4)	2^{nd}	Fri	(1)	2^{nd}	Sat
	3^{rd}	Mon		3^{rd}	Fri
12	1^{st}	Fri	32	1^{st}	Sun
(4)	2^{nd}	Sat	(1)	2^{nd}	Sat
	3^{rd}	Sun		3^{rd}	Fri
13	1^{st}	Sun	33	1^{st}	Thu
(3)	2^{nd}	Sat	(1)	2^{nd}	Wed
	3^{rd}	Fri		3^{rd}	Mon
14	1^{st}	Sun	34	1^{st}	Sat
(3)	2^{nd}	Sat	(1)	2^{nd}	Fri
	3^{rd}	Fri		3^{rd}	Thu
15	1^{st}	Thu	35	1^{st}	Sat
(3)	2^{nd}	Wed	(1)	2^{nd}	Fri
	3^{rd}	Mon		3^{rd}	Mon
16	1^{st}	Sat	36	1^{st}	Fri
(3)	2^{nd}	Fri	(1)	2^{nd}	Sat
	3^{rd}	Thu		3^{rd}	Sun
17	1^{st}	Sat	37	1^{st}	Sun
(3)	2^{nd}	Fri	(1)	2^{nd}	Sat
	3^{rd}	Mon		3^{rd}	Fri
18	1^{st}	Fri	38	1^{st}	Sun
(3)	2^{nd}	Sat	(1)	2^{nd}	Sat
	3^{rd}	Sun		3^{rd}	Fri
19	1^{st}	Sun	39	1^{st}	Thu
(3)	2^{nd}	Sat	(1)	2^{nd}	Wed
	3^{rd}	Fri		3^{rd}	Mon
20	1^{st}	Sun	40	1^{st}	Sat
(2)	2^{nd}	Sat	(1)	2^{nd}	Fri
	3^{rd}	Fri		3^{rd}	Thu

The following section describes the experimental results, and the effectiveness of the proposed model compared to the manually-made schedule is also discussed.

3.2.3 Results and Discussion

The proposed cost-effective and satisfaction-enhanced NSP is solved using the GUROBI optimizer version 9.1.2 coded in Python and a 2.3 GHz Dual-Core Intel Core i5-8300H operating system. The source code of this model in Python can be found in the Appendix B. The model can obtain optimal values of both objectives within less than a minute. Table 3.12 shows the example of nurse schedule outputs for 40 nurses and 28-day workdays. To examine the trade-off between cost and nurses' job satisfaction, the model is solved using the epsilon constraint method. Under the cost-prioritized scheme, the model minimizes the staffing cost first and then maximizes job satisfaction subsequently. Under the job-satisfaction-prioritized scheme, the model maximizes the minimum total satisfaction score first, before minimizing the total staffing cost.. The key performance indicators (KPIs) , including staffing cost, distribution of workload, preferences of the actual, and optimal schedules of the two objective schemes, are summarized in Table 3.13.

Table 3.12: An example of nurse schedule output

Nurses	**D1**	**D2**	**D3**	**D4**	**D5**	**. . .**	**D24**	**D25**	**D26**	**D27**	**D28**	**Total shifts (WL_n)**
1	O	M	M	M	M	. . .	M	M	M	O	M	24
2	M	A	N	N	A/N	. . .	A	A	A/N	O	O	24
3	N	N	O	O	A/N		N	O	O	M/N	N	25
4	M	O	M	M	O	. . .	M	M	O	M/A	M/A	23
5	A	A	N	A	O	. . .	N	A/N	O	O	A/N	25
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
36	A	M	O	A	O	. . .	A	A	O	O	M/A	24
37	M	M	M	M	M	. . .	M	M	M	O	O	22
38	A	A	A	A	A	. . .	N	A	A	M/A	O	24
39	A	O	A	O	A	. . .	O	O	A	A/N	A	25
40	M	O	M	M	M/N	. . .	M	M	O	O	M	23

M = Morning shift, A = Afternoon shift, N = Night shift

As shown in Table 3.13, the optimal schedules in both settings show good improvements compared to the manual schedule in terms of all KPIs. When using the proposed model under the cost-prioritized scheme, the total staffing cost decreases by almost 13% or about $4,000 for the entire scheduling period of one month. Regarding workload distribution, nurses work on an average of 27 shifts per month with a standard deviation of 4.44 in the actual schedule. The range between the minimum and maximum workloads is as high as 19. Meanwhile, the proposed model decreases the average shift assignments and

Table 3.13: A comparison of key performance indicators (KPIs) between the actual, and optimal schedules from the proposed model

Key Performance Indicators (KPIs)	**Actual schedule**	**Optimal schedules**	
		Cost-prioritized scheme	**Job-satisfaction-prioritized scheme**
Total staffing cost ($)	31,465.3	27,482.3	28,845.0
Total shifts (WL_n)			
Min - Max	17 - 36	22 - 25	23 - 26
Range	19	3	3
Average	27.3	23.8	24.7
Standard deviation (SD)	4.44	0.98	1.2
Total Satisfaction score (TPC_n)			
Min - Max	-	80 - 81	85 - 85
Range	-	1	0
Average	-	80.3	85
Standard deviation (SD)	-	0.4	0

distributes them more evenly, as indicated by the substantial reduction in standard deviation to 0.98 and range to 3.

In terms of the total preference score, the manual schedule did not consider nurses' preferences. Therefore, the scores cannot be assessed. However, the experimental results highlight the proposed model's capability to fulfill nurses' shift and day-off preferences. The total preference score for each nurse is not equivalent, depending on the number of shifts and days off he/she is assigned each month. More shifts and days off allocation contribute to the higher total preference score. In the cost-prioritized scheme, nurses are assigned 24 shifts per month and receive about 8 days off on average. If nurses receive all of the most-preferred assignments, the total preference score becomes 96. The average total preference score in the cost-prioritized scheme of 80 indicates that approximately 83% of the most-preferred preferences are fulfilled. In addition, the standard deviation and range of the score are nominal, exhibiting a fair preferred assignments distribution. Hence, it is reasonable to conclude that the model effectively and fairly satisfies nurses' shift and day-off preferences.

Nurses equally receive total preference scores as high as 85 in the job-satisfaction-prioritized scheme, indicating a more satisfactory and fair schedule. However, the total staffing cost is increased to $ 28,845 or approximately 5%. This finding reveals a trade-off between the staffing cost and the satisfaction enhancement. It can provide decision-makers with guidelines regarding how the total staffing cost is compromised to achieve higher and equitable job satisfaction among nurses. The management can then establish the objectives hierarchy that serves their policies best.

For better visualization, Figure 3.4 and 3.5 illustrate the distribution of the workload allocations of the manual and the optimal schedules under the cost-prioritized scheme. It can be seen that the distribution of workload from the optimal schedule spreads more consistently than the actual schedule. Figure 3.6 shows a frequency histogram of the total preference score distribution among nurses.

The proposed model can effectively provide cost-effective, satisfactory, and fair scheduling outcomes based on the experimental results. The time complexity of the model is evaluated by solving the model to generate a 28-day schedule under multiple department sizes of 20 - 100 nurses. The optimal solution can be generated within a minute for all instances. With less than a minute of solving time, the scheduling process can be more responsive to any last-minute changes in requests or preferences when employing this model.

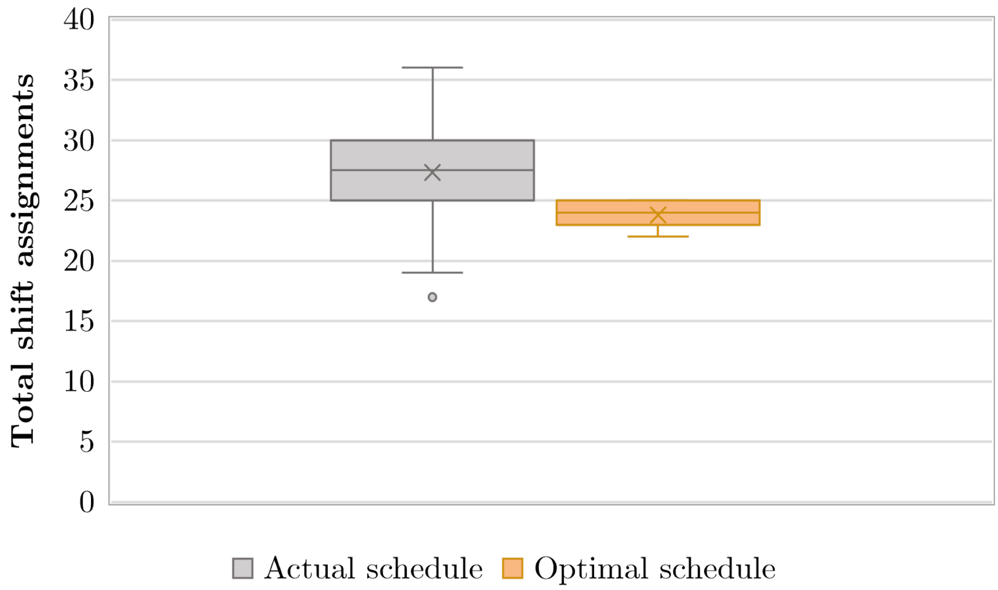


Figure 3.4: A comparison of workload distribution among nurses between actual and optimal schedules

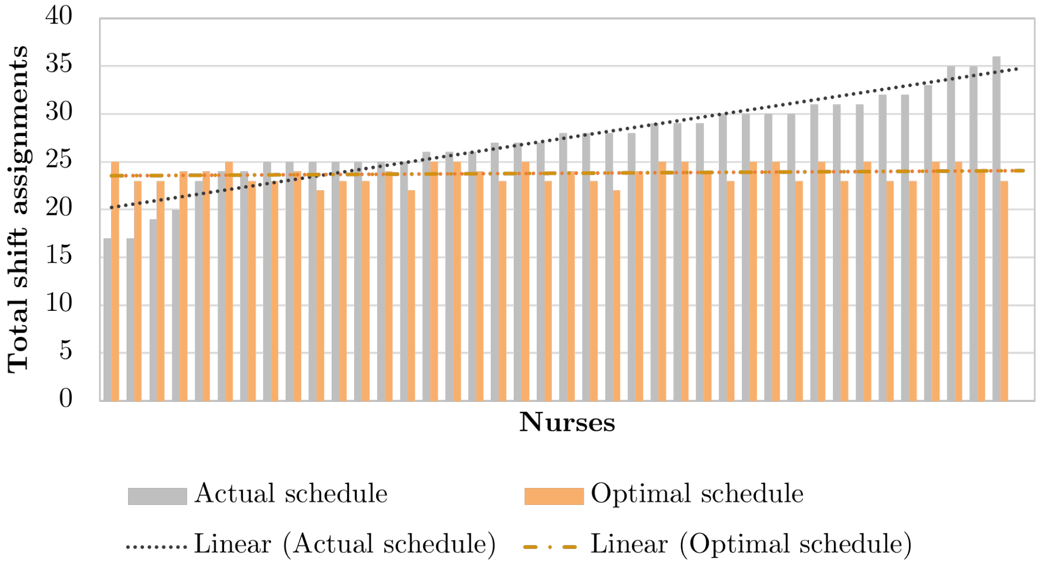


Figure 3.5: Workload assignments between the actual and optimal schedules by nurses

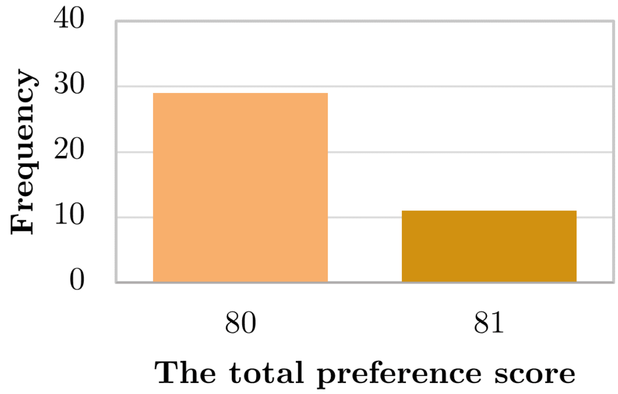


Figure 3.6: Distribution of the total preference score among nurses of the optimal schedule under the cost-prioritized scheme

3.2.4 Conclusion

This proposed NSP model is the first to consider multiple job satisfaction factors and cost-effectiveness simultaneously. The model aims to generate a cost-saving schedule that satisfies the nurses' shift and day-off preferences while ensuring an equitable workload and preferred assignment distribution.

The NSP model with cost and job satisfaction objectives is formulated and solved using an ε-constraint technique. Data from an actual hospital case of an ED at a large-scale public hospital in Thailand is used for model verification. The results indicate that the model can provide a more cost-saving and satisfaction-enhanced scheduling solution than manual scheduling. Based on the trade-off analysis, the result also exhibits that high and equitable total preference scores among nurses can be acquired at the expense of additional cost. This finding can help the management determine suitable objective priorities that accommodate their goals. In addition, the time required to generate a monthly schedule for the hospital case is only less than a minute. The scheduling can be much more responsive to any urgent requests.

This chapter illustrates the development of the two proposed satisfaction-enhanced NSP models. In the first model (Model I), a new formulation of satisfaction-enhanced NSP with the consideration of fairness in workload and preferred assignment distributions. This multi-limit fairness aspect has yet to be addressed in any existing literature. A goal programming satisfaction-enhanced NSP is proposed to minimize the deviations of workload, preferred shift, and day-off assignments among the nurses. The model aims to provide a balanced workload and preferred shifts and days off assignments among the nurses. The model is validated using a case of OR in a medium-scale private hospital in Thailand. The results show the model's ability to generate a promising outcome in preference fulfillment, workload, and preferred assignment distributions compared to the actual schedule in multiple scenario settings. The computational time required to solve the model is relatively low, even for a large-scale instance of 50 nurses.

The second model (Model II) is the first NSP to incorporate an economic aspect into the NSP with comprehensive satisfaction-enhanced factors, especially regarding fairness in both workload and favorable assignments. The NSP model is formulated with cost minimization and satisfaction objectives and solved with the ε-constraint technique. A case of an ED at a large-scale public hospital in Thailand is employed for model validation. The results indicate that the model can reduce staffing expenditure while equitably fulfilling nurses' shift and day-off preferences compared to the manual schedule. The two proposed NSP models only took a little time to generate satisfactory and fair scheduling outcomes. Thus, it can be concluded that they are practical decision-support tools that can be employed in hospitals without a significant investment.

The scheduling outcomes acquired from the models can be used as the mid-term scheduling strategy. The staffing requirements used in the models are derived from hospitals' estimations. In the daily operational stage, a schedule disruption may occur due to mismatches in the nursing supply and demand from uncertainties. The head nurses must instantaneously reschedule nurses to maintain operational flow and service quality under disruptions. However, effective rescheduling decisions are challenging to be made intuitively. To maintain high job satisfaction, the head nurse must consider the effects of rescheduling on nurses and equitably distribute rescheduling impacts across the planning period. Thus computational support is essential for determining swift and systematic decisions. In the subsequent chapter, the development of the nurse rescheduling model for satisfaction-enhancement proposed in this dissertation is presented.

Chapter 4

The Nurse Rescheduling Model under Uncertain Demand and Absenteeism

Chapter 1 introduced the satisfaction-enhanced NSP and NRSP and their relative importance in improving nurses' working conditions. The chapter also outlined the significance of effective human resource management against hospital uncertainty. Chapter 2 discussed an overview of the literature review related to NSP and NRSP. Chapter 3 described the development and demonstrated the effectiveness of the two proposed satisfaction-enhanced NSP models. Those models can be employed in the tactical resource management stage. This chapter illustrates the development of the proposed NRSP model to hedge against demand and absenteeism uncertainties in the operational phase.

Staffing capacity used in the scheduling stage is based on historical data estimations or forecasts. Even with accurate forecast strategies, unanticipated events in daily operations often occur and lead to schedule disruptions. Unforeseen circumstances include variations in patient volume or abrupt absences of nurses that may lead to staffing deficiencies. Under disruptions, rescheduling is required to sustain viable operations. The nurse rescheduling problem (NRSP) is to determine optimal nurse reassignments to repair the disrupted schedule with minor modifications. Any alteration of the original schedule may affect nurses' personal plans, causing frustration and job dissatisfaction. Therefore, minimizing rescheduling slots is the most common objective in NRSP.

This NRSP model adopted the human judgment shift change penalization (HJSCP) that considers the effect of rescheduling types on nurses. A minimum number of shift changes may not be a suitable indication of the rescheduling result. For example, in nurses' opinions, assigning shifts to a nurse taking a day off is worse than changing shift types of two nurses. The HJSCP sustains nurses' job satisfaction by determining the least undesirable impact modifications. In the proposed NRSP model, HJSCP is derived as an aspect of job satisfaction-related penalties. In addition, the model also considers nurses' skill levels when rescheduling them. Nurses with the same skill level share the same responsibilities and duties. Thus, they are more suitable for substitutions of the absent ones. Same-skill substitutions are desirable but cannot always be achieved. Sometimes available nurses are of different skills. Different-skill substitutions should be permitted but only as necessary. Therefore, the operational-related penalty is introduced to address nurses' skill levels in substitutions and maintain an appropriate skill mix.

The proposed NRSP is formulated as a MILP to minimize the total rescheduling penalties, including satisfaction-related and operational-related penalties. Satisfaction-related penalties keep the undesirable impacts of shift changing at a minimum. Each shift change type is subject to a different penalty score based on its unpleasant effect on nurses. The operational-related penalty penalizes deviations in the number of nurses in each skill level assigned between the original and modified schedules. The details of each penalization type are summarized below.

1. The satisfaction-related penalties ordered by undesirability
    (a) Changing from a day off to a workday
    (b) Extending from a single- to a double-shift workday
    (c) Changing from one shift type to another within the same workday
    (d) Changing from a workday to a day off
2. The operational-related penalty
    (a) Deviations of the number of nurses assigned in each skill level between the original and modified schedules.

The proposed nurse rescheduling framework is illustrated in Figure 4.1. The original nurse schedule obtained from solving the NSP Model II in Chapter 3.2 is used as an input in the rescheduling system. This rescheduling system mimics the nurse rescheduling process in practice. In actual hospitals, the head nurse evaluates the feasibility of the schedule under operational variations at the start of a workday. Then, the head nurse determines the necessary rescheduling actions accordingly. A planning horizon of 28 days is assumed to be the same as the original schedule. The 28-day planning horizon is decomposed into 28 sub-problems, each for one workday. Operational variabilities for each day are simulated and assumed to be known at the beginning of each workday. Then the original schedule's feasibility is assessed. The NRSP model is solved to generate an updated schedule if a disruption occurs. These procedures repeat until the last day of the schedule. The problem decomposition is practical and decreases the size of uncertain scenarios and problem scales. It significantly improves problem tractability and reduces solution time. The pseudo-code of the proposed rescheduling system is displayed as follows.

Inputs: The original schedule, days in planning horizon
For all days in the planning horizon, $d \in \mathcal{D}$:

1. Generate operational variability scenario: demand for nurses in each shift and nurses' absenteeism.
2. Assess the feasibility of the initial schedule under the simulated scenario. If the schedule is feasible, go to Step 4. Otherwise, go to Step 3.
3. Solve the NRSP model.
4. Update the current schedule.
5. Proceed to the next day and repeat Step 1 until the last day $\mathcal{D}$.

Detailed descriptions of each procedure in the system are given in the following sections.

4.1 Operational Variability Simulation

The original nurse schedule is evaluated one day at a time, similar to what is done in practice. The ad hoc operational variability scenario of demand and absenteeism uncertainty is generated for a particular day and assumed to be known at the beginning of the day. The simulation process of demand uncertainty in shift s of day d (Dem_{sd}) and nurse n's absenteeism of day d (a_{nd}) are described in the succeeding sections.

4.1.1 Demand Uncertainty

Demand is the number of nurses required in each shift and workday to provide sufficient care to patients. Depending on data availability, demand can be

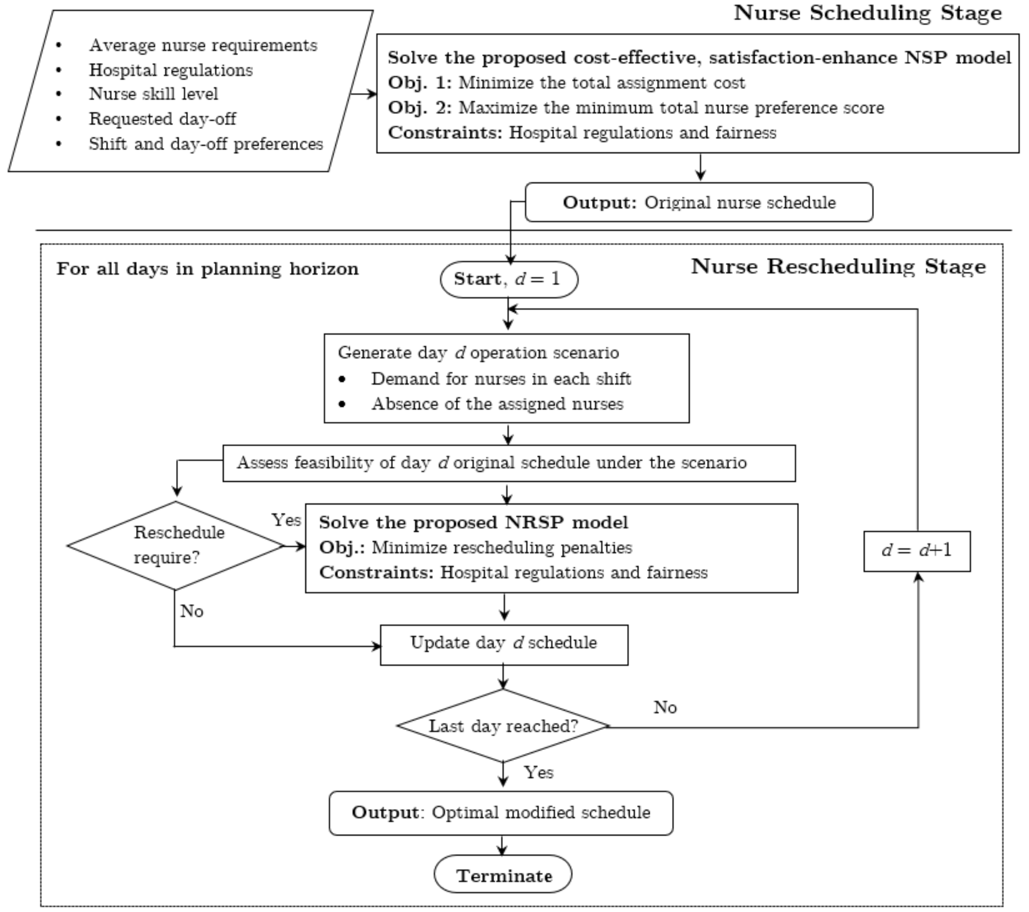


Figure 4.1: The proposed nurse rescheduling conceptual framework

derived directly from the staffing requirement data or converted from patient volume using the regulated nurse-to-patient ratio. There are many techniques to generate demand uncertainty scenarios based on the nature of the data. According to the literature, the following methods are typically employed to simulate the patient volume (PV_{sd}) or the demand for nurses (Dem_{sd}) in each shift s, day d.

Distribution fitting

Distribution fitting is the most straightforward technique. It determines the statistical distribution and corresponding parameters that best fit the data. When the patient volume or nursing requirement follows a known statistical distribution, it can be randomly generated using the corresponding statistical distribution and parameters. The distribution fitting cannot be used when data does not follow any probability distribution. In the literature, demand uncertainty is typically expressed with Poisson distribution [47, 84, 104], and Normal distribution [105, 106].

Forecasting

Instead of estimating demands based on historical data, time-series forecasting methods can be applied to obtain demand predictions. The commonly used approaches are the autoregressive model (AR), the moving average model (MA), and the autoregressive integrated moving average (ARIMA). Among the long-term time-series forecasting models, ARIMA is most frequently applied. Its accuracy and effectiveness are widely demonstrated in the previous scheduling studies [107, 108, 109, 110].

Patient volume of the hospital case study

The patient volume data from January 2016 to May 2021 is obtained from a public hospital emergency department in Thailand. The same hospital as that was employed to validate Model II. The data is aggregated into each shift type and fed into the Input Analyzer of the ARENA simulation software to determine its statistical distribution. The patient volume of all shifts seem to be normally distributed, as illustrated in Figure 4.2. The associated parameters rounded into integers and the given nurse-to-patient ratio are summarized in Table 4.1.

Table 4.1: The distribution of patient volume and the regulated nurse-to-patient ratio

Shifts	**Distribution of patient volume**	**Nurse-to-patient ratio**
Morning	NORM(17, 5)	1:2
Afternoon	NORM(34, 8)	1:3
Night	NORM(30, 7)	1:4

As illustrated in the figure and table, the demand for nurses in the morning is the lowest, followed by the night and afternoon shifts. As suggested by the hospital, the nurse staffing for the morning, afternoon, and night shifts are 13, 12, and 9, respectively. The morning shift has the least patient volume on average but is the most staffed because patient acuity differs in each shift. Therefore, the hospital regulates different nurse-to-patient ratios for each shift. Assume an example of patient volume for shift s of the day d (PV_{sd}) is 20, 33, and 32, respectively. The demand for nurses in each shift

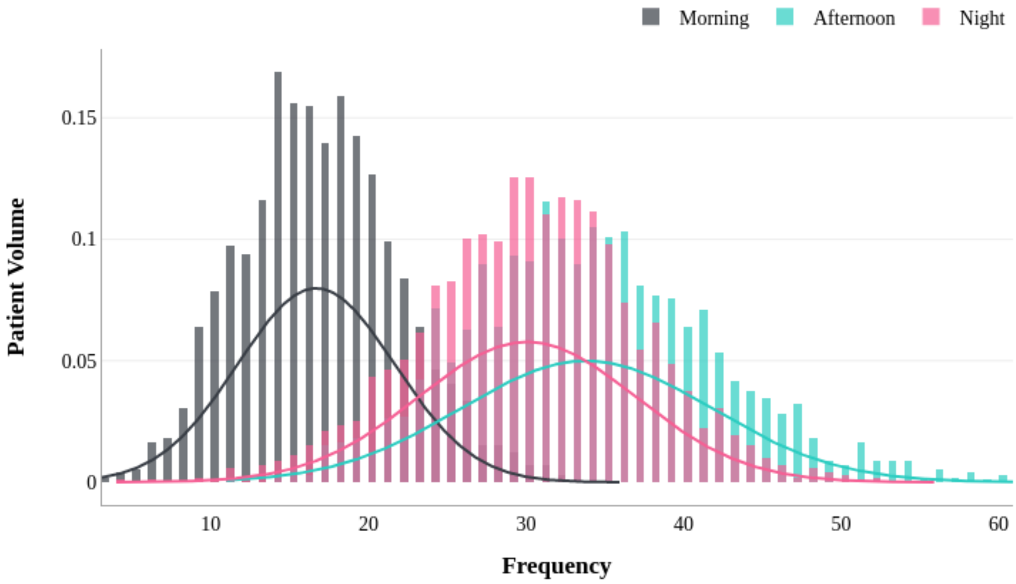


Figure 4.2: Distribution of patient volume by shift

s of the day d (Dem_{sd}) can be calculated by dividing the patient volume by the corresponding nurse-to-patient ratio as follows,

$$Dem_{M,d} : \lceil 20/2 \rceil = 10$$
$$Dem_{A,d} : \lceil 33/3 \rceil = 11$$
$$Dem_{N,d} : \lceil 32/4 \rceil = 8$$

4.1.2 Absenteeism Uncertainty

Absenteeism is unplanned employee absences excluding authorized leaves and paid time off. It occurs from urgent personal matters or illnesses and can span multiple days. Absenteeism is precarious in hospital settings since it may cause understaffing, poor service quality, and jeopardize patients' safety. Therefore, immediate substitutions must be made should the absences cause understaffing.

The consideration of absenteeism is typically found in the rescheduling literature. One commonly used technique is to simulate absenteeism via the Bernoulli distribution as demonstrated by many previous studies [47, 84, 87, 111, 112]. The Bernoulli distribution is a probability distribution that models random experiments with binary outcomes (E.g., yes or no, true or false, success or fail). In absenteeism simulation, the outcomes are absent and not absent. In the Bernoulli distribution, if the baseline probability of a nurse being absent ($a_{nd} = 1$) equals p, then the probability of not absent ($a_{nd} = 0$) becomes 1 - p . The probability density function (f) of the Bernoulli Distribution over the possible absence of any nurse n on the day d (a_{nd}) can be represented as follows.

$$f(a_{nd}; p) = \begin{cases} p & \text{for } a_{nd} = 1 \\ 1 - p & \text{for } a_{nd} = 0 \end{cases} \quad \forall n \in \mathcal{N} \tag{4.1}$$

In this research, nurses have the same baseline probability of absence (p) at the beginning. Later, their likelihood of absence changes if they are absent. The probability of the absence of each nurse (p_{nd}) on the day of consideration is calculated based on the following formula, derived from Ingels and Maenhout [47], and Barmby [113]:

$$p_{nd}\,(a_{nd} = 1) = p \cdot q^{days\,absent_{nd}} \quad \forall n \in \mathcal{N} \tag{4.2}$$

From Equation (4.2), the baseline absent probability p is multiplied with a decreasing function that has the maximum value of one. The value of function $q^{days\,absent_{nd}}$ decreases by the number of absent days a nurse n had before the day d. If the nurses have never been absent before, the function equals 1, then p_{nd} equals p. This equation corresponds to the assumption that nurses are less likely to be absent if they have already been absent. Based on their empirical study, Ingels and Maenhout [47] used the value q of 0.8158 under p of 2.44%. Using this q value, p_{nd} becomes approximately 0 if nurses have been absent for 28 days.

For each day, the likelihood of absence for each nurse p_{nd} is calculated based on their total absent days and the baseline probability p. Then absenteeism of each nurse (a_{nd}) is simulated via Bernoulli distribution. The Bernoulli process is similar to spinning a roulette wheel. If the simulated absent probability falls into the absence region, then a_{nd} equals 1; otherwise, 0. If a nurse n appears to be absent, the number of absent days is generated according to the corresponding probability. Given the planning horizon of 28-day, the number of absent days can span between 1 - 28 days. Similar to Wolbeck et al. [86], one day absent happens most frequently. The probability of other absent days decreases as the number of days increases.

The nurses' absenteeism is simulated at the beginning of the day d for all days in the planning horizon using the following steps. Figure 4.3 illustrates the overall simulation procedures.

Inputs: Today = d, Nurses' initial absenteeism (a_{nd}), Baseline absent probability (p), Nurses' accumulated absent days ($Absent\,days_{nd}$), q
For all nurses that are not currently absent ($a_{nd} = 0$):

Step 1: Random a nurse absent value (v_{nd}) (between 0 - 1).

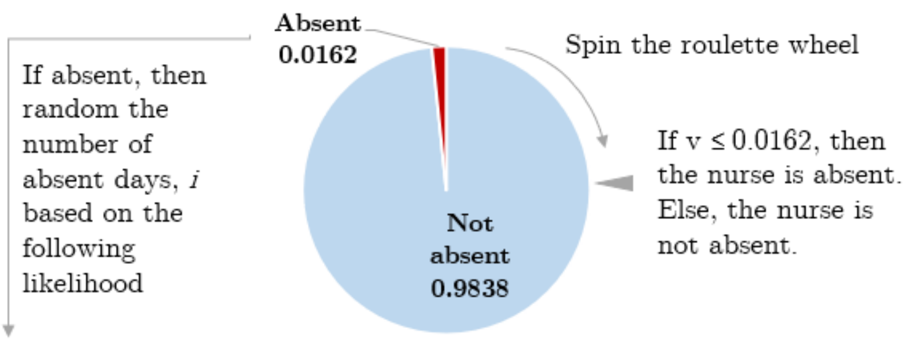
Step 2: If $v_{nd} \leq p \cdot q^{days\,absent_{nd}}$, update a_{nd} equals 1, go to Step 3. Else, a_{nd} remains 0, go to Step 5.

Step 3: Random the number absent days (i).

Step 4: Update the value of a_{nd} as 1 for day d to day $d + i - 1$.

Step 5: Go to the next nurse and repeat Step 1 until the last nurse $\mathcal{N}$

Example: Baseline absent probability (p) = 2.44%, Absent days = 2
Absent probability (p_{nd}) = 0.0244 * 0.8158^2 = 0.0162



Absent days, i	1 day	2 days	3 days	4 days	...	28 days	Total
Probability	50%	15%	10%	8%	...	0.0005%	100%

Figure 4.3: The simulation of absenteeism uncertainty

The procedures in this section simulate the day d's demand for nurses in each shift (Dem_{sd}) and the absenteeism of all nurses (a_{nd}). Then, the following procedure evaluates whether the original schedule of the particular day is feasible under the simulated operational variability. The detail of the feasibility assessment is outlined in the next section.

4.2 Feasibility Assessment

The previous section described the demand and absenteeism scenario simulation processes for each workday d. This section outlines the feasibility assessment of the original schedule under the given scenario. The process verifies whether the current nursing supply is sufficient. As previously stated, a schedule disruption is driven by these possibilities 1.) The actual nursing demand is higher than planned. 2.) The absences of nurses cause a shortage in the nursing supply. 3.) Both increased demand and absences occur together. These scenarios result in mismatches between nursing supply and demand and disrupt the original schedule. The NRSP model is then solved to obtain a viable nurse schedule. The feasibility assessment procedure under the example of operational variability is demonstrated below.

An example of a day d's initial schedule with five nurses and the associated number of nurses required in each shift (R_{sd}) is given in Table 4.2. The coverage constraint is met in the example. If there is no absence or rising demand, this schedule is feasible. The algorithm can proceed to the next workday.

Table 4.2: The original nurse schedule of the day d

	Nurse's original assignments (X_{nsd})		
Nurse (n)	**Morning**	**Afternoon**	**Night**
1	1	0	0
2	0	1	1
3	1	1	0
4	0	0	1
5	0	1	0
No. of nurses required (R_{sd})	2	3	2
No. of nurses assigned ($\sum_{n=1}^{N} X_{nsd}$)	2	3	2

The following scenarios illustrate how the feasibility is assessed under various conditions of operational variability.

Scenario 1 illustrates a scenario where Nurse 1 is absent and two nurses are required for all shifts. From Table 4.3, Nurse 1's a_{1d} is updated as 1. All shift assignments of the nurse become 0 since he/she is absent. As a result, the number of nurses assigned is lower than the demand for the morning shift. The coverage constraint is violated, and the original schedule becomes infeasible. For this scenario, the algorithm proceeds to solve the NRSP model.

Table 4.3: The feasibility assessment under Scenario 1

Nurse (n)	**Absence** (a_{nd})	**Nurse assignments** (X_{snd}) **Morning**	**Afternoon**	**Night**
1	**1**	**0**	**0**	**0**
2	0	0	1	1
3	0	1	1	0
4	0	0	0	1
5	0	0	1	0
No. of nurses required (R_{sd})		2	3	2
No. of nurses assigned ($\sum_{n=1}^{N} X_{nsd}$)		**1**	3	2
Actual demand for nurses (Dem_{sd})		2	2	2
Coverage constraint violation?		TRUE	FALSE	FALSE
Rescheduling required?		**YES**		

Scenario 2 illustrates a scenario where Nurse 1 is absent and nursing demand for the morning shift decreases. From Table 4.4, the demand for nurses in the morning shift lessens from 2 to only 1 nurse. Although Nurse 1 is absent, the original schedule is still feasible due to the lower demand. Rescheduling is not required in this scenario, and the algorithm can proceed to the next workday.

Table 4.4: The feasibility assessment under Scenario 2

Nurse (n)	**Absence** (a_{nd})	**Nurse assignments** (X_{snd}) **Morning**	**Afternoon**	**Night**
1	**1**	**0**	**0**	**0**
2	0	0	1	1
3	0	1	1	0
4	0	0	0	1
5	0	0	1	0
No. of nurses required (R_{sd})		2	3	2
No. of nurses assigned ($\sum_{n=1}^{N} X_{nsd}$)		**1**	3	2
Actual demand for nurses (Dem_{sd})		**1**	2	2
Coverage constraint violation?		FALSE	FALSE	FALSE
Rescheduling required?		**NO**		

Scenario 3 displays a scenario without any absence, but the actual demand for the morning shift increases. From Table 4.5, the demand for nurses in the morning shift raised from 2 to 3. Although no nurse is absent, the coverage constraint is violated due to increased demand. Rescheduling is required in this scenario. The algorithm proceeds to solve the NRSP model.

Table 4.5: The feasibility assessment under Scenario 3

Nurse (n)	**Absence** (a_{nd})	**Nurse assignments** (X_{snd}) **Morning**	**Afternoon**	**Night**
1	0	1	0	0
2	0	0	1	1
3	0	1	1	0
4	0	0	0	1
5	0	0	1	0
No. of nurses required (R_{sd})		2	3	2
No. of nurses assigned ($\sum_{n=1}^{N} X_{nsd}$)		2	3	2
Actual demand for nurses (Dem_{sd})		**3**	2	2
Coverage constraint violation?		TRUE	FALSE	FALSE
Rescheduling required?		**YES**		

Scenario 4 depicts a scenario without any absence, but the actual demand for the afternoon shift rises. From Table 4.6, the demand for nurses in the afternoon shift increased from 2 to 3. The coverage constraint is not violated in this scenario because the shift was overstaffed. Rescheduling is required not required in this scenario. The algorithm can then iterate to the next workday.

4.3 Mathematical Model Formulation

When the original schedule of any workday is infeasible, the rescheduling is required to generate a viable schedule under the uncertain scenario. The proposed NRSP model is formulated as a MILP to minimize the total rescheduling penalty, including operational- and job satisfaction-related penalties.

The operational-related penalty penalizes deviations in the number of nurses assigned for each skill level from the modified and original schedules. This type of penalty is to maintain an appropriate skill mix and operational quality after rescheduling. Nurses can function as a better substitute for the

Table 4.6: The feasibility assessment under Scenario 4

Nurse (n)	**Absence** (a_{nd})	**Nurse assignments** (X_{snd}) **Morning**	**Afternoon**	**Night**
1	0	1	0	0
2	0	0	1	1
3	0	1	1	0
4	0	0	0	1
5	0	0	1	0
No. of nurses required (R_{sd})		2	3	2
No. of nurses assigned ($\sum_{n=1}^{N} X_{nsd}$)		2	3	2
Actual demand for nurses (Dem_{sd})		2	**3**	2
Coverage constraint violation?		FALSE	FALSE	FALSE
Rescheduling required?		**NO**		

same-skill nurses since they share the same duties. Different-skill substitutions are permitted but should be avoided if possible. The satisfaction-related penalty penalizes each of the four types of shift changes differently based on their undesirability. Each nurse's penalty is calculated and accumulated after each disruption. Differences in nurses' rescheduling penalty scores are penalized to ensure nurses are subject to a similar rescheduling impact across the planning period. Without loss of generality, the assumptions and notations used in the NRSP formulation are summarized below.

Assumptions

- The rescheduling planning horizon is one day. Each day consists of multiple shifts of the same length.
- In each shift, the total number of nurses assigned must meet the actual demands.
- Mismatches in the number of nurses assigned for each skill level between the original and modified schedules are subject to operational-related penalties.
- The number of daily shifts assigned to each nurse must not exceed the limit.
- Rescheduling to morning-after-night shift pattern is prohibited.
- No shift can be assigned to the absent nurses.

Indices

$\mathcal{N}$	Set of nurses; $\mathcal{N}$ = {1, 2, ... , N}
$\mathcal{S}$	Set of shifts in a workday; $\mathcal{S}$ = {1, 2,..., S}
$\mathcal{K}$	Set of nurse skill levels; $\mathcal{K}$ = {1, 2, ..., K}
d	The day under consideration in rescheduling stage; $d \in \mathcal{D}$

Input Parameters

X_{nsd}	= 1 if nurse n is assigned to shift s on day d in the original schedule; 0 otherwise.
Y_{nd}	= 1 if nurse n is assigned to take a day-off on day d in the original schedule; 0 otherwise.
a_{nd}	= 1 if nurse n is absent on day d; 0 otherwise.
Dem_{sd}	The actual demand for nurses in shift s on day d
N_k	A set of nurses that belong to skill level k; $\mathcal{N} = N_1 \cup N_2 \cup \ldots \cup N_K$
SK_{nk}	A binary parameter equals 1 if nurse n belongs to skill level k; 0 otherwise.
SP_{ns}	The preference score of nurse n towards working in shift s; $SP_{ns} \in \{1, \ldots, Q\}$
DS	The maximum number of shifts can be assigned to a nurse per day.
$P_n^{'}$	Penalty score of nurse n accumulating from the previous disruptions
PO^{+}	Penalty cost for employing more nurses from each skill level in the modified schedule than in the original schedule.
PO^{-}	Penalty cost for employing less nurses from each skill level in the modified schedule than in the original schedule.
P^{Type1}	Penalty cost incurred from Type 1 rescheduling (off-to-work).
P^{Type2}	Penalty cost incurred from Type 2 rescheduling (extending shifts).
P^{Type3}	Penalty cost incurred from Type 3 rescheduling (changing shifts).
P^{Type4}	Penalty cost incurred from Type 4 rescheduling (work-to-off).
F	Penalty cost incurred from the range of satisfaction-related penalty.
$BigM$	A large positive number used for formulating conditional linear equations

Decision Variables

$X_{nsd}^{'}$	= 1 if nurse n is assigned to shift s on day d in the modified schedule; 0 otherwise.
$Y_{nd}^{'}$	= 1 if nurse n is assigned to take a day-off on day d in the modified schedule; 0 otherwise.

Auxiliary Variables

This section outlines auxiliary variables derived from the value of decision variables. Variables representing rescheduling types are subjected to penalty costs in the objective function. Definitions and calculations of the variables are shown below.

Operational-related penalty maintains the service quality of the modified schedule by penalizing deviations in the number of nurses assigned in each skill level from the original schedule. In the original schedule, nurses are assigned based on the regulated skill mix to ensure service quality. Therefore, mismatched skill assignments from the original schedule mean the skill mix is disrupted. Moreover, nurses with the same skill have the same responsibility and duties and can function better as substitutions. Still, same-skill substitution is not always an available option. Thus, the deviations from skill assignments are allowed and subjected to penalties. The operational-related penalties can be determined as follows.

O^-_{sk}	The negative deviation of nurses with skill level k assigned in shift s from the original schedule
O^+_{sk}	The positive deviation of nurses with skill level k assigned in shift s from the original schedule

The number of positive (O^+_{sk}) and negative (O^-_{sk}) deviations of nurse assignments for skill level k in shift s from the original schedule are determined with Equation 4.3. The negative deviations are more undesirable and, thus, penalized with a higher penalty score.

$$\sum_{n=1}^{N}(X'_{nsd} \cdot SK_{nk}) - \sum_{n=1}^{N}(X_{nsd} \cdot SK_{nk}) - O^+_{sk} + O^-_{sk} = 0 \quad \forall s \in \mathcal{S}; k \in \mathcal{K} \quad (4.3)$$

Satisfaction-related penalties ensure a satisfactory modified schedule by penalizing each shift change type based on its undesirability perceived by human judgment. Nurses' shift preferences are also incorporated to penalize if nurses are assigned to the less preferred shifts in the modified schedule. The four rescheduling types ordered by their undesirability are 1.) off-to-work, 2.) shift extension, 3.) shift changing, and 4.) work-to-off. Each shift change type can be expressed in mathematical equations as described below.

- Type 1 and Type 4: changing between a workday and a day off

V_{nd}^{Type1} Binary variables representing the off-to-work rescheduling pattern
= 1 if nurse n is rescheduled to work on the day d instead of taking a day off; 0 otherwise.

V_{nd}^{Type4} Binary variables representing the work-to-off rescheduling pattern
= 1 if nurse n is rescheduled to take a day off on the day d instead of working; 0 otherwise.

The variables V_{nd}^{Type1} and V_{nd}^{Type4} are calculated using Equation (4.4) and (4.5) using Y_{nd} as inputs. Y_{nd} equals 1 if the nurse was assigned to take a day off in the original schedule, and 0 otherwise. The decision variables $Y_{nd}^{'}$ determine the nurses' day off assignments in the modified schedule.

$$Y_{nd} - Y_{nd}^{'} - V_{nd}^{Type1} + V_{nd}^{Type4} + a_{nd} = 0 \quad \forall n \in \mathcal{N} \tag{4.4}$$

$$V_{nd}^{Type1} + V_{nd}^{Type4} \leq 1 \quad \forall n \in \mathcal{N} \tag{4.5}$$

Based on the equations, three possible cases are as follows.
Case 1: $Y_{nd} = 1$ and $Y_{nd}^{'} = 0$, or the off-to-work pattern. V_{nd}^{Type1} equals 1 and V_{nd}^{Type4} equals 0 to satisfy the equations.
Case 2: $Y_{nd} = 0$ and $Y_{nd}^{'} = 1$, or the work-to-off pattern. V_{nd}^{Type4} becomes 1 and V_{nd}^{Type1} becomes 0 to satisfy the equations. For the absent nurses ($a_{nd} = 1$), V_{nd}^{Type4} becomes 0.
Case 3: $Y_{nd} = Y_{nd}^{'}$, no change in the workday or the day off. V_{nd}^{Type1} and V_{nd}^{Type4} are 0.

- Type 2: shift extension

This shift change type is firstly introduced in this dissertation. It is only possible for hospitals with double-shift workday system. For hospitals that do not allow double-shift workdays, this shift change type can be discarded.

V_{nd}^{Type2} Binary variables to determine the extension of shifts within the same workday d.
= 1 if nurse n's total shift assignments of the day d in the modified schedule is more than that of original schedule; 0 otherwise.

The variable V_{nd}^{Type2} can be computed using an introduced auxiliary binary variable h_{nd} with the following equations.

$$\frac{\sum_{s=1}^{S} X_{nsd}}{2} \geq h_{nd} \quad \forall n \in \mathcal{N} \tag{4.6}$$

$$\sum_{s=1}^{S} X_{nsd} - 1 \leq h_{nd} \quad \forall n \in \mathcal{N} \tag{4.7}$$

$$\sum_{s=1}^{S} X'_{nsd} + \sum_{s=1}^{S} X_{nsd} - 2 - (2 \cdot h_{nd}) \leq V_{nd}^{Type2} \quad \forall n \in \mathcal{N} \tag{4.8}$$

Equations (4.6) and (4.7) firstly determine an auxiliary binary variable h_{nd}. It takes value of 1 for nurses who received two shifts in the original schedule. Shift extension for those nurses is not possible since the number of shifts has reached the limit. Therefore, Equation (4.8) enforces V_{nd}^{Type2} as 0 for such cases. V_{nd}^{Type2} takes the value of 1, if the total shifts assigned in the modified schedule is more than the original schedule ($\sum_{s=1}^{S} X'_{nsd} \geq \sum_{s=1}^{S} X_{nsd}$).

- Type 3: changing of shift type

V_{nd}^{Type3} Integer variables to determine the number of times shift type changing within the same workday occurs for nurse n in the workday d.

The variable V_{nd}^{Type3} can be calculated using a newly introduced binary variable v_{nsd} and the following equations. The variable v_{nsd} counts every slot that the assignments in the original schedule and modified schedule are different.

$$v_{nsd} \geq X_{nsd} - X'_{nsd} \quad \forall n \in \mathcal{N}; \forall s \in \mathcal{S} \tag{4.9}$$

$$v_{nsd} \geq X'_{nsd} - X_{nsd} \quad \forall n \in \mathcal{N}; \forall s \in \mathcal{S} \tag{4.10}$$

$$\sum_{s=1}^{S} v_{nsd} - 1 = V_{nd}^{Type3} \quad \forall n \in \mathcal{N} \tag{4.11}$$

Equations (4.9) and (4.10) are the linear counterparts of v_{nsd} equals the absolute of X_{nsd} - X'_{nsd}. For any nurse n and shift s that $X_{nsd} \neq X'_{nsd}$, v_{nd} equals to 1. Then, Equation (4.11) computes V_{nd}^{Type3}.

All types of satisfaction-related penalties have been defined. The total satisfaction-related penalty score (P_n) for each nurse can be computed as,

$$\begin{aligned} P_n = P_n^{'} + (P^{Type1} \cdot V_{nd}^{Type1}) + (P^{Type2} \cdot V_{nd}^{Type2}) + (P^{Type3} \cdot V_{nd}^{Type3}) \\ +(P^{Type4} \cdot V_{nd}^{Type4}) + (Q \cdot (1 - Y_{nd}^{'}) - \sum_{s=1}^{S} SP_{ns} \cdot X_{nsd}^{'}) \quad \forall n \in \mathcal{N} \end{aligned} \tag{4.12}$$

The parameter $P_n^{'}$ is the input accumulating satisfaction-related penalty score. In the first disruption, $P_n^{'}$ of all nurses equal 0. Then, total P_n occurs during the current disruption becomes $P_n^{'}$ in the following disruption. The final term of the Equation (4.12) penalizes when nurses are assigned to the shifts that they less preferred in the modified schedule. It is worth noting that only shift preferences are considered in this NRSP model because the model mainly reschedules nurses to shifts and rarely reschedule day off for nurses.

Objective Function

The objective of the proposed NRSP model is to minimize the total rescheduling penalty. The first term is the total operational-related penalty, and the second term is the total satisfaction-related penalty. The third term is the gap between the minimum and maximum satisfaction-related penalty among nurses to ensure rescheduling fairness. The objective function is defined in the Equation (4.13).

$$\min \sum_{s=1}^{S} \Big((\sum_{k=1}^{K} O_{sk}^{+} \cdot PO^{+}) + (\sum_{k=1}^{K} O_{sk}^{-} \cdot PO^{-}) \Big) + \sum_{n=1}^{N} P_n + F \cdot (P_{max} - P_{min}) \tag{4.13}$$

Constraints

$$\sum_{n=1}^{N} X_{nsd}^{'} \geq Dem_{sd} \quad \forall s \in \mathcal{S} \tag{4.14}$$

$$BigM \cdot (1 - a_{nd}) \geq \sum_{s=1}^{S} X_{nsd}^{'} \quad \forall n \in \mathcal{N} \tag{4.15}$$

$$\sum_{s=1}^{S} X_{nsd}^{'} \leq DS \quad \forall n \in \mathcal{N} \tag{4.16}$$

$$\sum_{s=1}^{S} X'_{nsd} \leq BigM \cdot (1 - Y'_{nd}) \quad \forall n \in \mathcal{N} \tag{4.17}$$

$$\sum_{s=1}^{S} X'_{nsd} + Y'_{nd} \geq 1 \quad \forall n \in \mathcal{N} \tag{4.18}$$

$$\sum_{s=1}^{S} X'_{nsd} + V_{nd}^{Type1} \leq 2 \quad \forall n \in \mathcal{N} \tag{4.19}$$

$$X'_{n,s=S,d} + X_{n,s=1,d+1} \leq 1 \quad \forall n \in \mathcal{N}; d \neq \mathcal{D}_{28} \tag{4.20}$$

$$X_{n,s=S,d-1} + X'_{n,s=1,d} \leq 1 \quad \forall n \in \mathcal{N}; d \neq \mathcal{D}_{1} \tag{4.21}$$

$$X'_{nsd}, Y'_{nd} \in \{0, 1\} \tag{4.22}$$

$$O^{+}_{sk}, O^{-}_{sk}, V_{nd}^{Type1}, V_{nd}^{Type2}, V_{nd}^{Type3}, V_{nd}^{Type4} \in \mathbb{Z}^{+}_{0} \tag{4.23}$$

Constraint (4.14) ensures the number of nurses assigned in the modified schedule meet the actual demand. Constraint (4.15) regulates no shift can be assigned to any absent nurses. Constraint (4.16) limits total shifts assigned to nurses in a workday. Constraints (4.17) and (4.18) determine nurses' day off. Constraint (4.19) forbids double-shift assignments in the off-to-work rescheduling type. Constraints (4.20) and (4.21) restrict that any night shift cannot be followed by a morning shift in the modified schedule. Constraints (4.22) and (4.23) are the standard integrality and non-negativity constraints.

4.4 Hospital Case Data

The hospital instance of an ED at a large-scale public hospital in Thailand is employed. The same hospital case as the one used for Model II's validation. The schedule of 40 nurses across a 28-day planning period obtained from solving the Model II in Chapter 3.2 is used as the input original schedule. The regulations and penalty scores for each type of rescheduling are summarized in Table 4.12.

Table 4.12: Summary of input parameters for the rescheduling model

Parameters	**Value**
Maximum daily shift (DS)	2
Penalty cost for overstaffing nurses from each skill level (PO^+)	5
Penalty cost for understaffing nurses from each skill level (PO^-)	20
Penalty cost incurred from Type 1 rescheduling (off-to-work) (P^{Type1})	40
Penalty cost incurred from Type 2 rescheduling (extending shifts) (P^{Type2})	20
Penalty cost incurred from Type 3 rescheduling (changing shifts) (P^{Type3})	10
Penalty cost incurred from Type 4 rescheduling (work-to-off) (P^{Type4})	5
Penalty cost incurred from the range of satisfaction-related penalty (F)	10

The demand for nurses is derived from the patient volume data, with the regulated nurse-to-patient ratio at the hospital case study as described in Table 4.1. The hospital cannot disclose the absence rate and nurses' illness data. Therefore, the absenteeism of nurses is simulated using the absent probability of 2.44%, similar to Ingels and Maenhout [47, 84]. Their study adopted the absent probability from the statistical analysis of employee absences conducted by an organization in Belgium. The absent rate is similar to the findings from the United States (3.2 %) [114], and Europe (3 - 6%) [115].

4.5 Result and Discussion

The proposed NRSP is solved using the GUROBI optimizer version 9.1.2 coded in Python and a 2.3 GHz Dual-Core Intel Core i5-8300H operating system. The source code of this model in Python can be found in the Appendix C. The rescheduling system can generate the modified schedule for the 28-day planning period within 10 seconds. The system is tested with 100 28-day demand and absenteeism scenarios to verify the model's capability against various uncertain scenarios. That is 2,800 1-day scenarios in total. Each scenario has different intensity of disruptions. The minimum and maximum disruptions are 7 and 21 out of 28 workdays, respectively, with 14 disruption days on average. Out of 100 scenarios, the system cannot generate the entire 28-day modified schedule for only 1 of them. This is because the scenario contains a workday where many nurses are absent at the same time while the demand for nurses increases for all shifts. Therefore, the NRSP model fails to generate a feasible solution utilizing only internal substitutions. In this case, the hospital management may seek to employ external resources such as float and part-time nurses or allow understaffing based on the hospital's policies.

An example of the 1-day rescheduling result is shown in Table 4.13. Based on the table, Nurses 3 and 28 are absent. The demand for the morning, afternoon, and night shifts are 13, 16, and 7, respectively. Three nurses are assigned for shift extension, and three are assigned for shift changing within the same workday. Regarding the operational-related penalty, positive (highlighted in blue) and negative (highlighted in pink) deviations of the nurses' skill assignments from the original schedule are 4 and 2, respectively.

Table 4.13: Example of a 1-day rescheduling result

		Original schedule (X_{nsd})				**Modified schedule** (X'_{nsd})				
Nurse	**Skill**	**M**	**A**	**N**	**O**	**M**	**A**	**N**	**O**	
1	5	1	0	0	0	1	0	0	0	
2	5	0	1	0	0	0	1	0	0	
3	5	0	0	1	0	0	0	0	1	Absent
4	4	1	0	0	0	0	1	0	0	Type 3
5	4	0	1	0	0	1	1	0	0	Type 2
6	4	1	0	0	0	1	1	0	0	Type 2
7	4	1	0	0	0	1	0	0	0	
8	4	0	0	1	0	0	0	1	0	
9	4	1	0	0	0	0	1	0	0	Type 3
10	4	0	0	1	0	0	0	1	0	
11	4	0	0	0	1	0	0	0	1	
12	4	0	1	0	0	1	1	0	0	Type 2
13	3	1	0	0	0	1	0	0	0	
14	3	0	0	0	1	0	0	0	1	
15	3	0	1	0	0	0	1	0	0	
16	3	0	1	0	0	0	1	0	0	
17	3	0	0	1	0	0	0	1	0	
18	3	1	0	0	0	1	0	0	0	
19	3	0	0	1	0	0	0	1	0	
20	2	1	0	0	0	1	0	0	0	
21	2	1	0	0	0	1	0	0	0	
22	2	0	1	0	0	0	1	0	0	
23	2	1	0	0	0	0	1	0	0	Type 3
24	2	0	0	1	0	0	0	1	0	
25	2	0	1	0	0	0	1	0	0	
26	2	0	0	1	0	0	0	1	0	
27	2	0	0	0	1	0	0	0	1	
28	2	0	1	0	0	0	0	0	1	Absent

29	2	0	0	0	1	0	0	0	1	
30	2	0	1	0	0	1	1	0	0	Type 2
31	1	0	1	0	0	0	1	0	0	
32	1	0	0	0	1	0	0	0	1	
33	1	0	0	1	0	0	0	1	0	
34	1	1	0	0	0	1	0	0	0	
35	1	0	0	0	1	0	0	0	1	
36	1	0	1	0	0	0	1	0	0	
37	1	1	0	0	0	1	0	0	0	
38	1	0	1	0	0	0	1	0	0	
39	1	0	0	1	0	0	1	0	0	Type 3
40	1	1	0	0	0	1	0	0	0	
Total assigned		13	12	9	6	13	16	7	8	
Level 5 assigned		1	1	1		1	1	0		
Level 4 assigned		4	2	2		4	5	2		
Level 3 assigned		2	2	2		2	2	2		
Level 2 assigned		3	4	2		3	4	2		
Level 1 assigned		3	3	2		3	4	1		

M - Morning shift, A - Afternoon shift, N - Night shift, O - Day-off

The effect of human judgment shift change penalization on rescheduling desirability

In most existing rescheduling models, the primary aim is to minimize the number of shift changes. However, Clark and Walker [85], and Wolbeck et al. [86] stated that fewer shift changes do not always imply less rescheduling impacts. In their model, each shift change type is penalized differently based on its inconvenience. This penalization is so-called the human judgment shift change penalization (HJSCP). In the proposed NRSP model, HJSCP is adopted as a part of the satisfaction-related penalty. In this section, the effects of employing the HJSCP against minimizing shift changes are analyzed regarding the total number of shift changes, impacts on nurses, and the ability to maintain skill mixes.

The NRSP model is solved under the same penalty scores for all four shift change types. The comparison of the 1-day rescheduling results between minimizing the number of shift changes (denoted as SC) and the HJSCP is shown in Table 4.14 under the same 1-day scenario as in Table 4.13. In the SC, the total shift changes are 5, most of which are from the off-to-work rescheduling type. When employing the HJSCP, more changes are made from assigning shift extensions and shift changing instead of off-to-work assignments. Regarding the operational-related penalty, SC results in fewer negative skill deviations. That is, more same-skill substitutions are utilized than the HJSCP. The positive skill deviations incurred in SC and HJSCP are from assigning more nurses to handle higher demand than in the original schedule. Table 4.15 summarizes the total rescheduling penalties and impacts for the entire 28-day planning period between SC and HJSCP.

Table 4.14: A comparison of 1-day rescheduling outcomes between SC and HJSCP

Nurse	**Skill**	**Original schedule**	**SC**	**HJSCP**
1	5	M	M	M
2	5	A	A	A
3	5	N	Absent	Absent
4	4	M	M	A
5	4	A	A	M/A
6	4	M	M/A	M/A
7	4	M	M	M
8	4	N	N	N
9	4	M	M	A
10	4	N	N	N
11	4	O	N	O
12	4	A	A	M/A
13	3	M	M	M
14	3	O	O	O
15	3	A	A	A
16	3	A	A	A
17	3	N	N	N
18	3	M	M	M
19	3	N	N	N
20	2	M	M	M
21	2	M	M	M
22	2	A	A	A
23	2	M	M	A
24	2	N	N	N
25	2	A	A	A
26	2	N	N	N
27	2	O	A	O
28	2	M	Absent	Absent

29	2	O	A	O
30	2	A	A	M/A
31	1	A	A	A
32	1	O	A	O
33	1	N	N	N
34	1	M	M	M
35	1	O	O	O
36	1	A	A	A
37	1	M	M	M
38	1	A	A	A
39	1	N	N	A
40	1	M	M	M
Total shift changes			5	8
Off-to-work			4	0
Shift extension			1	4
Shift changing			0	4
Work-to-off			0	0
Negative skill deviations			1	2
Positive skill deviations			4	4

M - Morning shift, A - Afternoon shift, N - Night shift, O - Day-off

Table 4.15: A comparison of 28-day rescheduling penalties and impacts between SC and HJSCP

	Penalty score	No. of shift changes		Impacts of penalty	
		SC	**HJSCP**	**SC**	**HJSCP**
Off-to-work	40	30	5	1,200	200
Shift extension	20	9	14	180	280
Shift changing	10	14	40	140	400
Work-to-off	5	0	0	0	0
Total satisfaction-related penalty		53	59	1,520	880
Negative skill deviations	20	26	38	520	760
Positive skill deviations	5	21	21	105	105
Total operational-related penalty		47	59	625	865

From Table 4.15, SC results in 53 total shift changes. However, more than half of them are off-to-work assignments—such a rescheduling type leading to adverse impacts on nurses' job satisfaction. When employing the HJSCP, shift changes increase to 59 times, and the off-to-work assignments are less utilized. Still, the increase is within an acceptable range. When calculating each rescheduling type as the satisfaction-related penalty scores, SC results in nearly twice the undesirable rescheduling impacts of the HJSCP. These outcomes exhibit that fewer shift changes are not a good indication of rescheduling quality. More shift changes contributed from lower impact rescheduling types are required to achieve more desirable rescheduling results. Regarding the operational-related penalty, SC performs better in ensuring same-skill substitutions. The negative skill deviations in SC and HJSCP are 26 and 38 times, respectively, implying that same-skill substitutions cannot always be achieved. Nonetheless, the inclusion of the operational-related penalty facilitates same-skill substitutions better, thus, resulting in fewer negative skill deviations. Without the operational-related penalty, negative skill deviations increase to 57 times for the HJSCP in this scenario.

The fairness performance in rescheduling

Nurses should be subject to similar impacts throughout the planning period for a desirable rescheduling outcome. Therefore, the proposed NRSP model includes a penalty in the range of the satisfaction-related penalty among nurses in the objective function. This penalization aims to avoid rescheduling the same nurses repetitively. To verify the fairness performance, the NRSP model is solved by discarding the fairness element from the objective function. The summary of fairness performance between with and without fairness consideration settings is shown in Table 4.16.

Table 4.16: A comparison of fairness performance between with and without fairness consideration NRSP settings

	Satisfaction-related penalty	
	With fairness consideration	**Without fairness consideration**
Total	951	945
Average	23.8	23.6
SD	12.3	19.9
Min	10	0
Max	45	72
Range	35	72

From Table 4.16, the total and average satisfaction-related penalty increase slightly when considering fairness. This is because of the need to ensure all nurses are subject to rescheduling impacts. The standard deviation of the with fairness setting is relatively lower than without, indicating fairer distribution of rescheduling impacts. For better visualization, the distribution of the satisfaction-related penalty among nurses is illustrated in Figure 4.4. When fairness penalization is discarded, there is a nurse receiving undesirable rescheduling impact as high as 72, while some nurses are not rescheduled. With the fairness consideration, all nurses are rescheduled at least once, and the maximum rescheduling penalty decreases to 45. When considering fairness, the differences in the satisfaction-related penalty among nurses appear to be smaller.

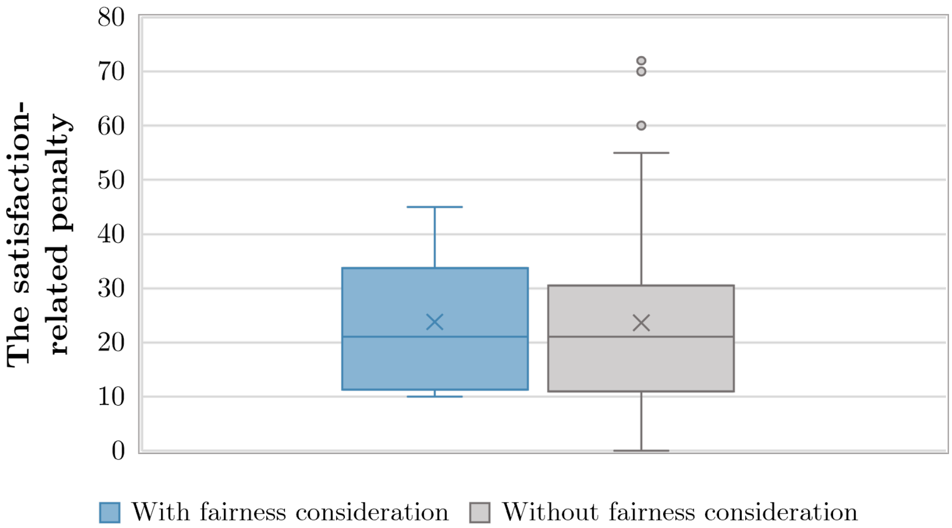


Figure 4.4: A comparison of the distribution of satisfaction-related penalty between solving the NRSP model with and without rescheduling fairness consideration

The results show that including fairness consideration results in a fairer distribution of rescheduling impacts. However, there are still rather significant differences between the satisfaction-related penalty scores among nurses. Enhanced rescheduling fairness can be achieved by raising the weight of the range penalty (F). With F being 20, the range and standard deviation of the satisfaction-related penalty decrease significantly to 22 and 5.5, respectively. However, shift changes have increased considerably from 59 to 111 times. The findings exhibit trade-offs between ensuring fairness and keeping the rescheduling penalty low. More rescheduling actions are required to ensure all nurses are subject to similar rescheduling impacts. However, the essence of rescheduling is to keep the rescheduling frequencies and impacts as little as possible. Therefore, achieving absolute fairness within a single planning period is difficult. In this regard, the current nurses' penalty scores should be considered when rescheduling them for the subsequent periods. Rescheduling nurses with high penalty scores should be avoided in the next planning period to ensure long-term rescheduling fairness.

4.6 Conclusion

This chapter proposes a novel satisfaction-enhanced NRSP model to hedge against uncertain demand and absenteeism. The objective of the model is to minimize the total rescheduling penalty derived from the satisfaction-related and operational-related penalties. The satisfaction-related penalty consists of three aspects: 1.) desirability, 2.) individual preferences, 3.) rescheduling fairness. In the first aspect, the human judgment shift change penalization (HJSCP) is employed to minimize undesirable rescheduling impacts rather than minimizing the number of shift changes. Four rescheduling alternatives are considered: off-to-work, shift extension, shift changing, and work-to-off. Each rescheduling type is subject to different penalty scores depending on its inconvenience. This NRSP model is the first to include shift extension as another rescheduling alternative. Shift extension is possible for the double-shift workday system, a typical shift work system found in Thailand and many other countries. To the best of our knowledge, no existing rescheduling model addresses this. The second aspect is to penalize when nurses are assigned to less preferred shifts in the modified schedule. Finally, the gap between maximum and minimum satisfaction-related penalty scores among nurses is penalized to ensure nurses are subject to similar rescheduling impacts. Regarding the operational-related penalty, mismatches of the assignments of nurses' skills between the original and modified schedules are penalized for maintaining an appropriate skill mix. At the same time, this penalization also aims for same-skill substitution to ensure seamless operations since same-skill nurses can function better as substitutions for the absent ones.

The proposed NRSP model is validated using the original schedule derived from solving the NSP Model II under simulated uncertainties. The 100 28-day (2,800 1-day scenarios) demand and absenteeism scenarios are simulated using actual patient volume data collected from the ED at a large-scale public hospital in Thailand. The model can generate repaired schedules for almost all scenarios except the worst-case scenario. The effectiveness of the

HJSCP is verified against the minimizing number of shift changes. HJSCP results in slightly higher shift changes (SC) but significantly less undesirable rescheduling impacts. The findings highlight that number of shift changes is not a good indication of rescheduling quality. Regarding operational-related penalties, both SC and HJSCP have relatively high negative skill deviations but are still significantly lower than without the penalty. Finally, the fairness performance is evaluated by comparing with and without fairness consideration settings. The results exhibit a trade-off between achieving high rescheduling fairness and keeping undesirable impacts at a minimum. A high level of fairness throughout the planning period can be achieved at the expense of rescheduling desirability. In this regard, it is better to have somewhat fair rescheduling impacts in the current period and avoid rescheduling nurses with high penalty scores in the next planning horizons.

To this end, the proposed NRSP model is the first to incorporate the HJSCP with the consideration of nurses' individual preferences and skill mix under uncertain demand and absenteeism. Furthermore, the model is the first to utilize shift extension as another rescheduling alternative. The model can generate repaired schedules for the whole 28-day planning period within 10 seconds. Hospital management can employ this NRSP model to help make prompt, efficient, and desirable rescheduling decisions. However, the management should also consider achieving robustness in the original schedules to make them more resilient. When the original schedule is less disrupted, rescheduling is less often. Thus fewer undesirable impacts incur. Accurate demand and absenteeism forecasting techniques are also helpful for increasing the schedules' robustness.

Chapter 5

Conclusion

In this chapter, the first Section 5.1 provides an overview of the NSP and NRSP research conducted in this dissertation. Then, the three-fold dissertation contributions, including academic contributions, practical contributions, and contributions to knowledge science, are expressed in the Section 5.2. Finally, the limitations of the research, along with possible research directions, are described in Section 5.3.

5.1 Concluding Remarks

Strenuous shift work conditions adversely affect nurses' health, well-being, and work-life balance. Such working conditions induce job dissatisfaction and intention to leave. These are the common causes of hospitals worldwide facing the intensified nurse shortage issue. In light of this, hospital management must employ countermeasures emphasizing enhancing nurses' well-being and job satisfaction. Many measures can improve nurses' job satisfaction, including providing reasonable incentives, fostering self-development, adopting systematic scheduling practices, et cetera.

In nursing practice, shift work is inevitable due to its around-the-clock nature. However, schedule desirability can be achieved by integrating vital satisfaction-enhanced factors. This dissertation develops systematic nurse scheduling and rescheduling approaches taking into account individual preferences and fairness for satisfaction enhancement. Mathematical optimization techniques enable the models to encompass multiple desirable factors and operational goals simultaneously.

Thus far, the existing satisfaction-enhanced NSP studies only offer single-aspect fairness in their scheduling model. The first NSP model (Model I) is proposed to generate monthly schedules that fulfill nurses' individual preferences in shifts and days off. At the same time, the model aims to provide equitable workload and preferred assignment distribution. The multi-objective NSP model is formulated using a goal programming approach. A real dataset from a medium-scale private hospital operating room in Thailand is used for model validation. The findings indicate the model's capability to generate a more satisfactory and fair work schedule compared to the manual schedule for all operational scenarios.

Besides satisfaction enhancement, cost-effectiveness is another desirable factor from the management viewpoint. To date, there is no consideration of cost and comprehensive satisfaction-enhanced factors in the literature. Therefore, the concept of Model I is extended to incorporate the economic aspect. The second NSP model (Model II) is proposed with the cost minimization and satisfaction enhancement objectives. A bi-objective model is formulated as a MILP and solved with an ε-constraint. Data collected from a large-scale hospital in Thailand is used for model validation. The result highlights the model's ability to promptly generate cost-saving, satisfactory and fair work schedules compared to the manually-made schedule. A trade-off analysis between cost and job satisfaction is also performed. The result reveals that higher and equally distributed job satisfaction scores among nurses can be achieved at the expense of higher costs. This finding provides insights for the management to determine the importance of objectives that suit their needs. Both NSP models require less than a minute of solving time, even for large-scale problems. Thus, they are responsive to any last-minute requests and can regenerate new schedules promptly.

The proposed NSP models are the mid-term resource management plan. Nursing requirements are based on the hospitals' estimations. On daily operations, higher patient volume or absences of nurses may lead to the deficiency of nursing supply. An NRSP model is proposed to assist decision-making under schedule disruptions from uncertain demand and absenteeism. The proposed NRSP model is the first to employ the HJSCP under multi-limit uncertain parameters and consider nurses' heterogeneous skills. In addition, the model is the first to facilitate the shift extension rescheduling alternative, which is possible for a double-shift workday system. The HJSCP penalizes undesirable rescheduling actions to minimize rescheduling impacts on nurses. The nurses' preferences and rescheduling fairness are also incorporated to ensure the desirability of the modified schedule. The operational-related penalty is employed to maintain an appropriate skill mix and serviceability. The model is validated against 2,800 daily demand and absenteeism scenarios. The demand is derived from actual patient volume data from the same hospital case in Model II. Based on the experiment, the NRSP model can promptly generate efficient and satisfactory rescheduling outcomes for almost all scenarios, except the worst-case scenario. The proposed model performs significantly better in rescheduling desirability than minimizing the number of shift changes. The result indicates that fewer shift changes do not indicate rescheduling quality.

To this end, this dissertation proposes the novel nurse scheduling and rescheduling models for satisfaction-enhancement as decision-support tools in mid and short-term plans. Both scheduling models show promising results in fulfilling nurses' shift and day-off preferences and providing equitable workload and favorable assignments. The rescheduling model can generate rescheduling outcomes with minimal inconvenience and sustain service quality under various uncertain demand and absenteeism scenarios. The results exhibit the models' effectiveness in generating promising and satisfactory scheduling and rescheduling outcomes within a minute.

5.2 Dissertation Contributions

This section outlines the three-fold contributions of this dissertation: academic contribution, practical contribution, and contribution to knowledge science.

5.2.1 Academic Contribution

This dissertation strengthens the existing satisfaction-enhanced NSP literature by proposing novel NSP models encompassing comprehensive satisfaction-enhanced factors, especially in terms of multiple fairness aspects. The NSP Model I is the first to incorporate nurses' shifts and days preference and fairness in workload and preferred assignment allocations. This model enriches the existing NSP studies that predominantly emphasize only offering fairness in either workload or desirable assignments. Schedules generated based on single-aspect fairness may not be perceived as fair. The Model I ensures equitable distribution of workload and favorable assignments among nurses for more satisfactory scheduling outcomes. Thus far, no existing satisfaction-enhanced NSP research simultaneously incorporates cost-effective and comprehensive job satisfaction factors. The economic aspect is essential to strengthening the application value of NSP. Therefore, NSP Model II is proposed as the extension of Model I, including the cost minimization aspect. Furthermore, this model is the first to examine the trade-off between cost and job satisfaction. The proposed NSP models expand the boundaries of the existing works in terms of achieving an economical, satisfactory, and fair work schedule.

Regarding NRSP literature, the proposed novel NRSP model is the first to consider uncertain demand and absenteeism with human judgment shift change penalization. The model accounts for satisfaction- and operational-related penalties for rescheduling outcomes that maintain nurses' job satisfaction and service quality. The HJSCP ensures rescheduling renders the minimal undesirable rescheduling impacts to nurses and fairly distributes them throughout the entire planning period. Nurses' skill levels are also considered to ensure the utilization of same-skill nurses for seamless operations. In addition, the model also accommodates rescheduling in a double-shift workday system. By doing so, shift extension can be utilized as another rescheduling alternative. To the best of our knowledge, the integration of these essential rescheduling aspects has not been addressed in the existing literature. The novel NRSP model provides theoretical guidelines for future satisfaction-enhanced NRSP development. In this regard, our proposed NRSP helps reinforce the usefulness of NRSP research and strengthens its potential to be implemented in practice.

Finally, all model formulations and experimental findings have been documented in the conference proceedings and international journal articles as supplemental to the existing satisfaction-enhanced NSP and NRSP domains. This dissertation provides up-to-date NSP and NRSP fundamentals, taking new and substantial aspects into account to strengthen their application values. Researchers and practitioners can use the proposed models as guidelines to further improve the quality of NSP and NRSP future research.

5.2.2 Practical Contribution

This dissertation addresses the significance of job satisfaction enhancement as a countermeasure for the nurse retention issue. It demonstrates that higher nurses' job satisfaction can be achieved and sustained via the proposed systematic satisfaction-enhanced scheduling and rescheduling approaches.

Practical use for the hospital resource management

The proposed satisfaction-enhanced NSP models fulfill nurses' individual preferences and ensure scheduling fairness while satisfying hospital regulations. In addition, this dissertation exemplifies that cost minimization can be achieved in tandem with nurses' job satisfaction. The proposed NSP models can be employed as decision-support tools for hospital scheduling processes. The hospital management can tailor objective functions, constraints, and problem sizes to accommodate their needs. Legal work hours or other constraints can be relaxed or modified to handle emergencies without reformulating the model. Hospitals can employ the proposed NSP models to promptly generate efficient and satisfactory work schedules for their mid-term plan. The models eliminate undesirable characteristics of manual scheduling and help the head nurse save time. Therefore, they can utilize their time and effort on other critical administrative tasks.

Uncertainties are inherent in hospitals' daily operations, especially in emergency departments. Variations in patient volume and nurses' sudden absences are inevitable and often cause schedule disruptions. This dissertation also demonstrates how to hedge against schedule disruptions via the proposed NRSP model. Under disruptions, the hospital management can utilize the proposed NRSP model to help make instantaneous short-term rescheduling decisions that cause minimal undesirable impacts to nurses and simultaneously sustain serviceability. The model also provides a relatively fair distribution of rescheduling impacts among nurses.

Practical implementation

Regarding practical implementation, the proposed NSP and NRSP models were constructed using two standard tools, Microsoft Excel and Jupyter Notebook. Microsoft Excel is a general tool that head nurses are familiar with in their daily life. With OpenSolver, a free add-in optimization tool in Microsoft Excel, the proposed NSP models can create nurse schedules for moderate-to-large scale problems without any coding background and large-sum investments. OpenSolver in Microsoft Excel can generate a monthly nurse schedule for 50 nurses within 20 seconds with our proposed model. Alternatively, hospitals without a Microsoft Office subscription can use the Jupyter Notebook or Google Colab. Both are open-source software supporting dozens of programming languages. This dissertation built the NSP and NRSP models on Jupyter Notebook using Gurobi Python API. Its effectiveness in solving the proposed NSP and NRSP to obtain high-quality original and modified schedules quickly is promising. With Gurobi Python API, the time to generate a 28-day schedule for 100 nurses is still within a minute. Therefore, the head nurse can promptly handle last-minute requests and regenerate new schedules. However, implementing the Jupyter Notebook may require user interface design since most nurses do not have a coding background.

Practical implications to other applications

All proposed models are developed in a generic manner. They can be applied as decision-support tools for scheduling and rescheduling processes in different hospital cases with minor modifications. In addition, the models can be applied to schedule or reschedule other personnel applications with similar around-the-clock shift work patterns, such as doctors, convenience store workers, gas station workers, hospitality staff, and security staff. A review by Rocha et al. [116] pointed out that hospitality personnel scheduling problems share similarities to the nurse scheduling problem in terms of staffing coverage, schedule quality, staffing cost, and fairness. However, it is worth noting that the scope of our models is within the personnel-to-shift assignments. They do not support personnel-to-task or personnel-to-team assignments.

Our proposed models encompass a set of constraints that are generally found in any personnel scheduling problem, including the daily and monthly work hour restrictions, day-off requirements, and staffing level requirements. The forbidden shift pattern constraints are highly recommended in the around-the-clock shifts to maintain sufficient rest for the staff. The consideration of heterogeneous skills and the skill mix is optional, depending on the nature of the job. Other constraints or conditions can be discarded or included when implementing the models in other applications.

5.2.3 Contribution to Knowledge Science

This dissertation demonstrates how systematic nurse scheduling and rescheduling procedures can enhance the nurses' job satisfaction. This dissertation contributes to knowledge science by knowledge creation. The dissertation findings enrich the existing NSP and NRSP knowledge with the proposed novel satisfaction-enhanced nurse scheduling and rescheduling models encompassing new and multiple essential aspects. In addition, this dissertation commences knowledge co-creation between researchers, hospital management, head nurses, and operation nurses. Effective, novel, practical nurse satisfaction-enhanced scheduling, and rescheduling approaches are created and conveyed through cooperative research and discussions. Finally, this dissertation enhances the understanding of hospital management and nurses of how mathematical optimization can help facilitate their scheduling and rescheduling processes.

5.3 Limitations and Future Works

The limitations of the proposed satisfaction-enhanced NRP and NRSP models and possible points of improvement are summarized below.

1. More aspects of individual preferences such as nurses' affinities or double-shift patterns can be included for more desirable scheduling outcomes. Future research can schedule nurses with good relationships together to improve the working atmosphere. Regarding double-shift pattern preferences, some nurses prefer working morning-afternoon or afternoon-night consecutively, while others prefer morning-rest-night.

2. Regarding fairness, the proposed models only considered fairness for a single planning horizon. It is challenging to generate scheduling or rescheduling decisions that are the most satisfactory and entirely fair. There are still nurses who receive less desirable work schedules and are subject to more rescheduling impacts than the others. These nurses must be compensated by considering the current scheduling and rescheduling outcomes in the subsequent periods. By doing so, fairness can be achieved in the long run.

3. The proposed NSP and NRSP models vaguely assumed absolute fairness for all nurses. However, different levels of nurses may be subject to different work requirements and contracts in some hospitals. It may be irrational to aim for absolute fairness for nurses with different classes and conditions. Future works can employ hierarchical fairness to ensure fairness within the same-level nurses as suggested in Huang et al. [58] for more practical fairness consideration.

4. The consideration uncertainties can be included in the scheduling stage to improve the robustness of the schedules. Stochastic programming (SP) or robust optimization (RO) approaches can be employed to formulate NSP to minimize potential understaffing risks or rescheduling impacts. By doing so, nurse schedules can be more resilient and robust. As a result, fewer schedule disruptions may occur in the operational stage. Thus, rescheduling tasks are less frequent and less complicated.

5. The proposed NRSP assumes that nurses are always willing to take over the shift. In practice, nurses may refuse, and the head nurse must find other available nurses. In this regard, future works can include the chance of refusal in the NRSP to strengthen its practicality. The future NRSP model can choose nurses with a high refusal chance as a last resort. Furthermore, the model should be able to handle refusals and promptly regenerate a new schedule utilizing other nurses. This will provide substantial decision support under rushed and stressful circumstances.

6. Our proposed NRSP model omitted the rescheduling cost due to the wage system in the hospital case where all nurses receive the same shift wage. Therefore, reassigning any nurse to a vacant slot would cost the same. However, future works can consider cases where each nurse level costs differently. In addition, the future model that utilizes external rescheduling resources, including on-call nurses, part-time nurses, or float nurses, should take account the rescheduling costs. Each type of resource incurs a different cost for such cases. Thus, cost minimization can be imposed as another objective or a rescheduling penalty.

7. Future works can extend the proposed NRSP by including external resources as rescheduling alternatives. Depending on hospitals' policies, other department nurses, float nurses, or external nurses can be rescheduled to fill vacant slots. The proposed NRSP model only considers internal substitutions. As a result, the model fails to generate a feasible solution under the worst-case scenario where internal nurses are no longer available. Although such a scenario is unlikely to occur, being able to handle it makes the NRSP more functional. Nevertheless, the penalty cost should be suitably defined so that the model utilizes external resources as a last resort.

8. Future works can explore the use of our NSP and NRSP models with different lengths of the planning period. In our NSP models, we assumed a general 28-day planning horizon. When applied in practice, the number of days can be adjusted based on the month of interest. In addition to generating a monthly schedule, the models can be used to generate quarterly, half-yearly, or yearly schedules. An index representing months ($\mathcal{M}$ = {1,..., M}) can be introduced so that users can regulate workload and day-off assignments for each month. For a longer planning horizon, the fairness constraint can be imposed for each month and the entire period. Therefore, long-term fairness can be ensured. However, it is worth noting that a more extended planning horizon would lead to larger problem size. Thus, optimization approaches may not be able to solve the models in a reasonable time for some problem sizes. In such cases, meta-heuristic algorithms such as the genetic algorithm or simulated annealing can be employed to generate near-optimal solutions within less time.

   Regarding the NRSP model, the planning horizon can be adjusted to several days or to cover the entire month. However, an empirical study by Maenhout and Vanhoucke [83] revealed that it is sufficient to consider the disrupted period and the periods before and after. A longer planning horizon in rescheduling does not improve the solution quality.

9. Organizational culture in hospital management plays an important role in dictating how it hedges against uncertainty. For example, some hospitals employ staffing buffers that can be called to fill sudden vacant slots, such as on-call nurses. Some hospitals employ float nurses that can substitute nurses in all departments across the hospital. Meanwhile, sudden shift changes are expected in some hospitals and are generally accepted as measures to handle unexpected events—our rescheduling model suits such organizational culture.

   Thus far, we have not explored the use of our rescheduling model under other organizational cultures. This is another point of improvement where our rescheduling framework can also be extended to suit different organizational cultures. However, for hospitals that do not allow sudden changes to the original schedule, it is suggested that they should emphasize improving the schedule robustness and the accuracy of demand and absenteeism forecasting. Robust schedules are more resilient against disruptions. This way, disruptions do not occur as often, and sudden changes can be decreased.

Publications

International Conference Proceedings

- Pavinee Rerkjirattikal, Van-Nam Huynh, Sun Olapiriyakul, and Thepchai Supnithi. A Framework for a Practical Nurse Scheduling Approach: A Case of Operating Room of a Hospital in Thailand. In: Spohrer J., Leitner C. (eds) Advances in the Human Side of Service Engineering. AHFE 2020. *Advances in Intelligent Systems and Computing*, vol 1208. Springer, Cham, 2020.

- Pavinee Rerkjirattikal, Raveekiat Singhaphandu, Van-Nam Huynh, and Sun Olapiriyakul. Job-Satisfaction Enhancement in Nurse Scheduling: A Case of Hospital Emergency Department in Thailand. In: Honda K., Entani T., Ubukata S., Huynh VN., Inuiguchi M. (eds) Integrated Uncertainty in Knowledge Modelling and Decision Making. IUKM 2022. *Lecture Notes in Computer Science*, vol 13199. Springer, Cham, 2022.

International Journals

- Pavinee Rerkjirattikal, Van-Nam Huynh, Sun Olapiriyakul, and Thepchai Supnithi, A Goal Programming Approach to Nurse Scheduling with Individual Preference Satisfaction, *Mathematical Problems in Engineering*, vol. 2020, Article ID 2379091, 11 pages, 2020.

- Pavinee Rerkjirattikal, Van-Nam Huynh, and Sun Olapiriyakul, A Nurse Rescheduling Approach under Uncertain Demand and Absenteeism for Job Satisfaction Enhancement (**to be submitted**)

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Appendix A

NSP Model I: Microsoft Excel Spreadsheet

B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
Morning	**Nurse**	**EXP**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**	**D11**	**D12**	**D13**	**D14**
No. Required	**1**	1	1	1	1	0	1	1	0	1	1	1	1	1	1	0
6	**2**	1	1	1	0	0	1	1	1	0	0	1	0	0	0	0
	3	1	0	0	1	1	1	0	1	1	0	0	1	1	1	0
	4	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0
	5	1	1	1	0	0	0	0	0	1	0	0	0	0	0	
	6	1	0	0	0	0	0	0	0	0	0	0	0	1	1	
	7	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0
	8	1	0	0	0	0	0	0	1	0	1	1	1	1	0	
	9	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0
	10	2	1	0	1	1	0	1	0	1	1	1	1	0	1	
	11	2	0	0	0	0	0	0	0	0	0	0	0	1	1	
	12	2	0	1	0	0	0	1	1	1	1	0	0	0	0	0
	13	2	0	1	1	1	1	0	0	0	0	0	0	0	0	0
	14	2	0	0	0	0	0	0	0	0	1	1	1	1	0	
	15	2	0	0	0	0	0	1	1	1	0	1	1	0	0	0
	16	2	1	1	0	1	1	0	0	0	0	0	0	0	0	0
	17	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Afternoon	**Nurse**		6	6	6	6	6	6	6	6	6	6	6	6	6	6
No. Required	**1**	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	**2**	1	0	0	0	0	0	0	0	0	1	0	0	0	1	
	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	
	4	1	0	0	1	1	1	1	1	0	0	1	0	0	0	
	5	1	0	0	1	0	1	0	0	0	1	1	1	1	0	0
	6	1	1	1	0	1	0	1	1	1	1	0	0	0	0	0
	7	1	0	0	0	0	0	1	1	1	0	1	1	1	0	0
	8	1	1	1	1	1	1	0	0	0	0	0	0	0	1	0
	9	1	1	1	0	0	0	0	0	1	0	1	1	1	1	0
	10	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	11	2	1	1	0	1	1	0	0	1	1	0	0	0	0	0
	12	2	0	0	1	1	0	0	0	0	0	0	1	1	0	0
	13	2	0	0	0	0	0	1	1	1	0	1	0	1	1	
	14	2	1	0	0	0	1	1	1	0	0	0	0	0	0	0
	15	2	1	1	1	0	0	0	0	0	0	0	0	1	1	0
	16	2	0	0	0	0	0	1	1	1	1	0	1	0	0	
	17	2	0	1	1	1	1	0	0	0	1	1	1	0	1	

Figure A.1: A part of Model I Microsoft Excel spreadsheet (a)

No. shift/day	Nurse	EXP	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14
	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	0
	2	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1
	3	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1
	4	1	1	0	1	1	1	1	1	0	1	1	0	1	1	1
	5	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1
	6	1	1	1	1	1	0	1	1	1	1	0	0	1	1	1
	7	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0
	8	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1
	9	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1
	10	2	1	1	1	1	0	1	1	1	1	1	1	0	1	1
	11	2	1	1	0	1	1	1	0	1	1	1	0	1	1	1
	12	2	0	1	1	1	1	1	1	1	1	0	1	1	0	1
	13	2	0	1	1	1	1	1	1	1	0	1	1	1	1	1
	14	2	1	0	1	0	1	1	1	1	1	1	1	1	0	1
	15	2	1	1	1	1	0	1	1	1	1	1	1	1	1	0
	16	2	1	1	0	1	1	1	1	1	1	0	1	0	1	1
	17	2	1	1	1	1	1	0	1	0	1	1	1	1	1	1

Morning	Nurse	EXP	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14
	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	0
	2	1	1	1	0	0	1	1	1	0	0	1	0	0	0	0
	3	1	0	0	1	1	1	0	1	1	0	0	1	1	1	0
	4	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	5	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1
	6	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1
	7	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0
	8	1	0	0	0	0	0	0	1	0	1	1	1	1	0	1
	9	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0
	10	2	1	0	1	1	0	1	0	1	1	1	1	0	1	1
	11	2	0	0	0	0	0	0	0	0	0	0	0	1	1	1
	12	2	0	1	0	0	0	1	1	1	1	0	0	0	0	0
	13	2	0	1	1	1	1	0	0	0	0	0	0	0	0	0
	14	2	0	0	0	0	0	0	0	0	1	1	1	1	0	1
	15	2	0	0	0	0	0	1	1	1	0	1	1	0	0	0
	16	2	1	1	0	1	1	0	0	0	0	0	0	0	0	0
	17	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0

Figure A.2: A part of Model I Microsoft Excel spreadsheet (b)

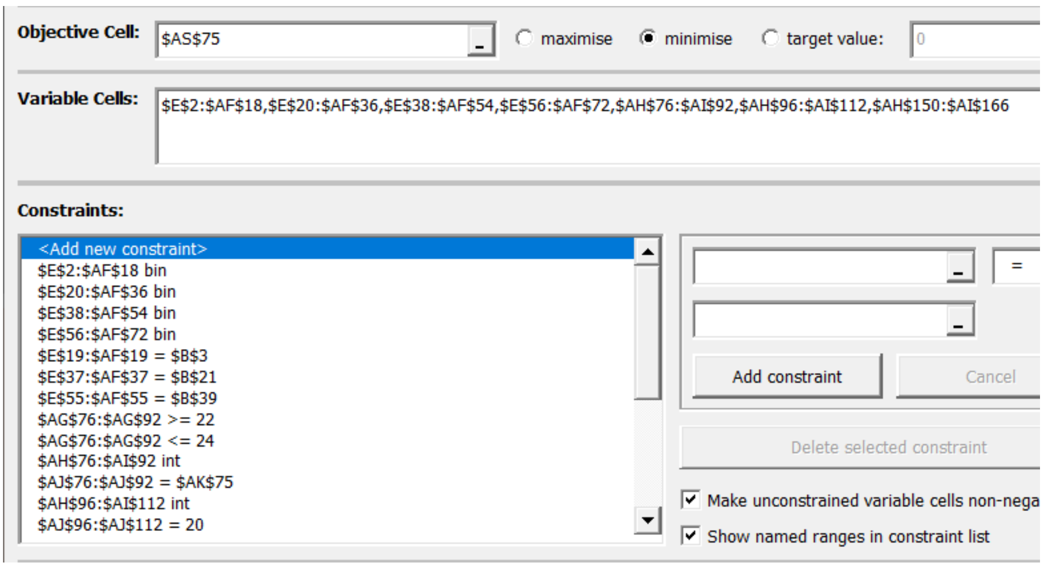

Figure A.3: OpenSolver interactive shell

Appendix B

NSP Model II Source Code

The source code of the proposed cost-effective and satisfaction-enhanced NSP (Model II) developed in Python language using the GUROBI Python API and implemented with Jupyter Notebook is shown below.

```

# Importing important libraries
import gurobipy as gp
from gurobipy import GRB
import pandas as pd
import numpy as np
import os

# Parameters setting
## A case of 40 nurses and 28 days planning period
nurses = list(range(1,40+1))
nurses = [str(x) for x in nurses]
shifts = ["M","A","N"]
skills = ["K1","K2","K3","K4","K5"]
days = ["Mon1","Tue2","Wed3","Thu4","Fri5","Sat6","Sun7","
    Mon8","Tue9","Wed10","Thu11","Fri12","Sat13","Sun14","
    Mon15","Tue16","Wed17","Thu18","Fri19","Sat20","Sun21","
    Mon22","Tue23","Wed24","Thu25","Fri26","Sat27","Sun28"]
week_begin = ["Mon1","Mon8","Mon15","Mon22"]

# Processors of input parameters
## Total nurse requirements per day (R[s,d])
df = pd.read_excel("phase1_nsp_inputs.xlsx", index_col=None,
    sheet_name="tot_requirement")
df["Day"] = df["Day"].replace(np.nan)
df = df.set_index(["Day","Shift"])
as_dict = df.to_dict(orient="index")
for k in as_dict.keys():
    as_dict[k] = as_dict[k]["Amount"]
req_tot = as_dict
```

```
## Requirements for nurses in each skill level (RL[s,k])
df = pd.read_excel("phase1_nsp_inputs.xlsx", index_col=None,
    sheet_name="shift_skill_requirement")
df["Level"] = df["Level"].replace(np.nan)
df = df.set_index(["Shift","Level"])
as_dict = df.to_dict(orient="index")
for k in as_dict.keys():
    as_dict[k] = as_dict[k]["Amount"]
req_skill = as_dict


## Nurses" skill level (SK[n,k])
df = pd.read_excel("phase1_nsp_inputs.xlsx", index_col=None,
    sheet_name="nurse_skill")
df = df.set_index(["Nurse"])
as_dict = df.to_dict(orient="index")
tmp_dict = {}
for nurse in as_dict.keys():
    for skill in as_dict[nurse].keys():
        tmp_dict[(str(nurse),skill)] = as_dict[nurse][skill]
nurse_skill_set = tmp_dict

## Nurses" day-off requests (Q[n,d])
df = pd.read_excel("phase1_nsp_inputs.xlsx", index_col=None,
    sheet_name="nurse_dayoff_requests")
df = df.set_index(["Nurse"])
as_dict = df.to_dict(orient="index")
tmp_dict = {}
for nurse in as_dict.keys():
    for day in as_dict[nurse].keys():
        tmp_dict[(str(nurse),day)] = as_dict[nurse][day]
Q = tmp_dict

## Nurses" shift preferences (SP[n,s])
df = pd.read_excel("phase1_nsp_inputs.xlsx", index_col=None,
    sheet_name="nurse_shift_pref")
df["Nurse"] = df["Nurse"].replace(np.nan)
df["Nurse"] = df["Nurse"].astype(int)
df["Nurse"] = df["Nurse"].astype(str)
df = df.set_index(["Nurse","Shift"])
as_dict = df.to_dict(orient="index")
for k in as_dict.keys():
    as_dict[k] = as_dict[k]["SP"]
SP = as_dict

## Nurses" day off preferences (DP[n,d])
```

```python
df = pd.read_excel("phase1_nsp_inputs.xlsx", index_col=None,
    sheet_name="nurse_dayoff_pref")
df["Nurse"] = df["Nurse"].replace(np.nan)
df["Nurse"] = df["Nurse"].astype(int)
df["Nurse"] = df["Nurse"].astype(str)
df = df.set_index(["Nurse","Day"])
as_dict = df.to_dict(orient="index")
for k in as_dict.keys():
    as_dict[k] = as_dict[k]["DP"]
DP = as_dict

#Regulations-related parameters
REG = 16
TS = 26
DS = 2
DO = 1
Gap_WL_LB = -3
Gap_WL_UB = 3
cost_reg = {
    ("M"): 810,
    ("A"): 1090,
    ("N"): 1110
}

#Declaring a model
m = gp.Model("Model_II_NSP")

#Decision variables
## x[n,s,d]
x = m.addVars(nurses,shifts,days,vtype=GRB.BINARY)
## y[n,d]
y = m.addVars(nurses,days,vtype=GRB.BINARY)

#Auxiliary variables
## WL[n]
total_nurse_WL = m.addVars(nurses, vtype=GRB.CONTINUOUS)
WL_cal = m.addConstrs(total_nurse_WL[nurse] == gp.quicksum(x[
    nurse,shift,day] for shift in shifts for day in days) for
    nurse in nurses)

## TDP[n]: Total day off preference score of nurse n
total_nurse_DP = m.addVars(nurses, vtype=GRB.CONTINUOUS)
DP_calculator = m.addConstrs(total_nurse_DP[nurse] == gp.
    quicksum(DP[nurse, day]*y[nurse, day] for day in days) for
     nurse in nurses)

## TSP[n]: Total shift preference score of nurse n
total_nurse_SP = m.addVars(nurses, vtype=GRB.CONTINUOUS)
```

```
SP_calculator = m.addConstrs(total_nurse_SP[nurse] == gp.
    quicksum(x[nurse,shift,day]*SP[nurse, shift] for shift in
    shifts for day in days) for nurse in nurses)

## TPC[n]: Total preference score of nurse n
TPC = m.addVars(nurses, vtype=GRB.CONTINUOUS)
TPC_calculator = m.addConstrs(TPC[nurse] == total_nurse_DP[
    nurse] + total_nurse_SP[nurse] for nurse in nurses)

## TPC_min: The minimum total preference score among all
    nurses
TPC_min = m.addVar(name="TPC_min")
TPC_min_constr = m.addGenConstrMin(TPC_min, TPC)

#Objective functions
## Calculating nurses' total shift type per month since the
    cost of each shift type is different
shift_nurse_per_type = m.addVars(nurses,shifts,vtype=GRB.
    CONTINUOUS)
shift_type_per_month_cal = m.addConstrs(shift_nurse_per_type[
    nurse,shift] ==  gp.quicksum(x[nurse,shift,day] for day in
     days) for nurse in nurses for shift in shifts)

nurse_total_cost = m.addVars(nurses,vtype=GRB.CONTINUOUS)
tot_cost_per_nurse = m.addConstrs(nurse_total_cost[nurse] ==
    gp.quicksum(shift_nurse_per_type[nurse,shift] * cost_reg[
    shift] for shift in shifts) for nurse in nurses)

##Total staffing cost (higher priority than TPC_min)
total_cost = gp.quicksum(nurse_total_cost[nurse] for nurse in
     nurses)
m.setObjectiveN(total_cost, index=0, priority=2, reltol=0.0)

#The minimum TPC (weight = -1 means maximization)
m.setObjectiveN(TPC_min, index=1, weight=-1, priority=1)

m.ModelSense = GRB.MINIMIZE

#Constraints
coverage = m.addConstrs((gp.quicksum(x[nurse,shift,day] for
    nurse in nurses) >= req_tot[day,shift] for day in days for
     shift in shifts))

skill_coverage = m.addConstrs((gp.quicksum(x[nurse,shift,day
    ]*nurse_skill_set[nurse,skill] for nurse in nurses) >=
    req_skill[shift,skill] for skill in skills for shift in
    shifts for day in days))

```

```
WL_limit = m.addConstrs((total_nurse_WL[nurse] <= TS for
    nurse in nurses))

DS_limit = m.addConstrs((gp.quicksum(x[nurse,shift,day] for
    shift in shifts) <= DS for nurse in nurses for day in days
    ))

Day_off_1 = m.addConstrs((gp.quicksum(x[nurse,shift,day] for
    shift in shifts) <= 999999*(1-y[nurse,day]) for nurse in
    nurses for day in days))

Day_off_2 = m.addConstrs((gp.quicksum(x[nurse,shift,day] for
    shift in shifts) + y[nurse,day] >=  1 for nurse in nurses
    for day in days))

Req_day_off = m.addConstrs((Q[nurse,day] <= y[nurse,day] for
    nurse in nurses for day in days))

No_M_after_N = m.addConstrs((x[nurse,shifts[2],day] + x[nurse
    ,shifts[0],days[days.index(day)+1]]<=  1 for nurse in
    nurses for day in days[0:-1]))

DO_limit = m.addConstrs((y[nurse,day] + y[nurse,days[days.
    index(day)+1]] + y[nurse,days[days.index(day)+2]]+ y[nurse
    ,days[days.index(day)+3]] + y[nurse,days[days.index(day)
    +4]] + y[nurse,days[days.index(day)+5]] + y[nurse,days[
    days.index(day)+6]] >=  DO for nurse in nurses for day in
    week_begin))

WL_fairness1 = m.addConstrs((total_nurse_WL[n] -
    total_nurse_WL[n_prime]  <=  Gap_WL_UB for n in nurses for
     n_prime in nurses if n != n_prime))

WL_fairness2 = m.addConstrs((total_nurse_WL[n] -
    total_nurse_WL[n_prime]  >=  Gap_WL_LB for n in nurses for
     n_prime in nurses if n != n_prime))

consecutive_night_limit = m.addConstrs((x[nurse,shifts[2],day
    ] + x[nurse,shifts[2],days[days.index(day)+1]] + x[nurse,
    shifts[2],days[days.index(day)+2]] + x[nurse,shifts[2],
    days[days.index(day)+3]]  <= 3 for nurse in nurses for day
     in days[0:-3]))

shifts_per_day = m.addVars(nurses,days,vtype=GRB.CONTINUOUS)
shift_per_day_cal = m.addConstrs(shifts_per_day[nurse,day] ==
     gp.quicksum(x[nurse,shift,day] for shift in shifts) for
    nurse in nurses for day in days)
consec_doubleshift_limit = m.addConstrs((shifts_per_day[nurse
    ,day] + shifts_per_day[nurse,days[days.index(day)+1]] +
```

```
    shifts_per_day[nurse,days[days.index(day)+2]] <= 5) for
    nurse in nurses for day in days[0:-2])

# Optimize
m.write("ModelII_NSP.rlp")
m.Params.Seed = 1
m.optimize()
```

Appendix C

NRSP Model Source Code

The source code of the proposed NRSP model developed in Python language using the GUROBI Python API and implemented with Jupyter Notebook is shown below.

```
# Importing important libraries
import pandas as pd
import numpy as np
import os
import gurobipy as gp
from gurobipy import GRB
import pickle

# Parameters setting
## A case of 40 nurses and 28 days planning period
nurses = list(range(1,40+1))
nurses = [str(x) for x in nurses]
shifts = ["M","A","N"]
skills = ["K1","K2","K3","K4","K5"]
today_index = 0 # 0 means the first day of the days list
days = ["Mon1","Tue2","Wed3","Thu4","Fri5","Sat6","Sun7","
    Mon8","Tue9","Wed10","Thu11","Fri12","Sat13","Sun14","
    Mon15","Tue16","Wed17","Thu18","Fri19","Sat20","Sun21","
    Mon22","Tue23","Wed24","Thu25","Fri26","Sat27","Sun28"]
today = [days[today_index]]

# Processors of input parameters
## The original schedule (obtained from solving Model II)
## x_nsd
with open("x_nsd.pkl", "rb") as tf:
    x_nsd = pickle.load(tf)
##y_nd
import pickle

with open("y_nd.pkl", "rb") as tf:
```

```
    y_nd = pickle.load(tf)

## Total nurse requirements per day (R[s,d])
df = pd.read_excel("phase1_nsp_inputs.xlsx", index_col=None,
    sheet_name="tot_requirement")
df["Day"] = df["Day"].replace(np.nan)
df = df.set_index(["Day","Shift"])
as_dict = df.to_dict(orient="index")
for k in as_dict.keys():
    as_dict[k] = as_dict[k]["Amount"]
req_tot = as_dict

## Nurses" skill level (SK[n,k])
df = pd.read_excel("phase1_nsp_inputs.xlsx", index_col=None,
    sheet_name="nurse_skill")
df = df.set_index(["Nurse"])
as_dict = df.to_dict(orient="index")
tmp_dict = {}
for nurse in as_dict.keys():
    for skill in as_dict[nurse].keys():
        tmp_dict[(str(nurse),skill)] = as_dict[nurse][skill]
nurse_skill_set = tmp_dict

## Nurses" shift preferences (SP[n,s])
df = pd.read_excel("phase1_nsp_inputs.xlsx", index_col=None,
    sheet_name="nurse_shift_pref")
df["Nurse"] = df["Nurse"].replace(np.nan)
df["Nurse"] = df["Nurse"].astype(int)
df["Nurse"] = df["Nurse"].astype(str)
df = df.set_index(["Nurse","Shift"])
as_dict = df.to_dict(orient="index")
for k in as_dict.keys():
    as_dict[k] = as_dict[k]["SP"]
SP = as_dict

#Regulations-related parameters and penalties
DS = 2
P_Op_plus = 5
P_Op_minus = 20
P_Type1 = 40
P_Type2 = 20
P_Type3 = 15
P_Type4 = 5
Big_M = 999999 #formulating conditional linear equations

# Declaring a model
m = gp.Model("Model_NRSP")

# Decision variables
```

```
## x'[n,s,d]
x_prime_nsd = m.addVars(nurses,shifts,today,vtype=GRB.BINARY)
## y'[n,d]
y_prime_nd = m.addVars(nurses,today,vtype=GRB.BINARY)

# Auxiliary variables
## Operational-related penalties
O_sk_plus = m.addVars(shifts,skills, vtype=GRB.CONTINUOUS)
O_sk_minus = m.addVars(shifts,skills, vtype=GRB.CONTINUOUS)
O_sk_equation = m.addConstrs(((gp.quicksum(x_prime_nsd[nurse,shift,day]*nurse_skill_set[nurse,skill] for nurse in nurses for day in today)) - (gp.quicksum(x_nsd[nurse,shift,day]*nurse_skill_set[nurse,skill] for nurse in nurses for day in today)) - O_sk_plus[shift,skill] + O_sk_minus[shift,skill] == 0 for skill in skills for shift in shifts))
shift_O_sk = m.addVars(shifts,vtype=GRB.CONTINUOUS)
Total_O_sk_per_shift = m.addConstrs(shift_O_sk[shift] == gp.quicksum(O_sk_plus[shift,skill] * P_Op_plus for skill in skills) + gp.quicksum(O_sk_minus[shift,skill] * P_Op_minus for skill in skills) for shift in shifts)
Total_O_sk = gp.quicksum(shift_O_sk[shift] for shift in shifts)

## Satisfaction-related penalties
# Type 1 & Type 4 penalties
V_type1_nd = m.addVars(nurses,today, vtype=GRB.BINARY)
V_type4_nd = m.addVars(nurses,today, vtype=GRB.BINARY)
Vtype1_type4_cal1 = m.addConstrs(y_nd[nurse,day] - y_prime_nd[nurse,day] - V_type1_nd[nurse,day] + V_type4_nd[nurse,day] == -a_nd_today_dict[nurse] for nurse in nurses for day in today)
Vtype1_type4_cal2 = m.addConstrs(V_type1_nd[nurse,day] + V_type4_nd[nurse,day] <= 1 for nurse in nurses for day in today)

# Type 2 penalty
V_type2_nd = m.addVars(nurses,today, vtype=GRB.BINARY)
h_nd = m.addVars(nurses,today, vtype=GRB.BINARY)
VT2_cal1 = m.addConstrs(gp.quicksum(x_nsd[nurse,shift,day] for shift in shifts)*0.5 >= h_nd[nurse,day] for nurse in nurses for day in today)
VT2_cal2 = m.addConstrs(gp.quicksum(x_nsd[nurse,shift,day] for shift in shifts) -1 <= h_nd[nurse,day] for nurse in nurses for day in today)
VT2_cal3 = m.addConstrs(gp.quicksum(x_prime_nsd[nurse,shift,day] for shift in shifts) + gp.quicksum(x_nsd[nurse,shift,day] for shift in shifts) -2 -2*h_nd[nurse,day] <= V_type2_nd[nurse,day] for nurse in nurses for day in today
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    )

# Type 3 penalty
V_type3_nd = m.addVars(nurses,today, vtype=GRB.CONTINUOUS)
v = m.addVars(nurses,shifts,today, vtype=GRB.BINARY)
VT3_cal1 = m.addConstrs(v[nurse,shift,day] >= x_nsd[nurse,
    shift,day] - x_prime_nsd[nurse,shift,day] for nurse in
    nurses for shift in shifts for day in today)
VT3_cal2 = m.addConstrs(v[nurse,shift,day] >= x_prime_nsd[
    nurse,shift,day] - x_nsd[nurse,shift,day] for nurse in
    nurses for shift in shifts for day in today)
VT3_cal3 = m.addConstrs(gp.quicksum(v[nurse,shift,day] for
    shift in shifts) -1 == V_type3_nd[nurse,day] for nurse in
    nurses for day in today)

# Rescheduled shift Preferences
RSP = m.addVars(nurses, vtype=GRB.CONTINUOUS)
RSP_cal = m.addConstrs(RSP[nurse] == 3 * (1-y_prime_nd[nurse,
    today[0]]) - gp.quicksum(SP[nurse,shift]*x_prime_nsd[nurse
    ,shift,day] for shift in shifts for day in today) for
    nurse in nurses)

# Total satisfaction-related penalty (P[n])
P_n = m.addVars(nurses, vtype=GRB.CONTINUOUS)
P_n_this_period = m.addVars(nurses, vtype=GRB.CONTINUOUS)
P_n_this_period_cal = m.addConstrs(P_n_this_period[nurse] ==
    (P_Type1*V_type1_nd[nurse,day]) + (P_Type2*V_type2_nd[
    nurse,day]) + (P_Type3*V_type3_nd[nurse,day]) + (P_Type4*
    V_type4_nd[nurse,day]) + RSP[nurse]  for nurse in nurses
    for day in today)
P_n_cal = m.addConstrs(P_n[nurse] == p_prime[nurse] +
    P_n_this_period[nurse] for nurse in nurses)
Total_P = gp.quicksum(P_n[nurse] for nurse in nurses)

# Objective function
Total_penalty = Total_O_sk + Total_P
m.setObjective(Total_penalty)
m.ModelSense = GRB.MINIMIZE

# Constraints
Coverage = m.addConstrs(gp.quicksum(x_prime_nsd[nurse,shift,
    day] for nurse in nurses) >= today_demand[shift,day] for
    shift in shifts for day in today)

Day_off_1 = m.addConstrs((gp.quicksum(x_prime_nsd[nurse,shift
    ,day] for shift in shifts) <= Big_M*(1-y_prime_nd[nurse,
    day]) for nurse in nurses for day in today))

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Day_off_2 = m.addConstrs((gp.quicksum(x_prime_nsd[nurse,shift,day] for shift in shifts) + y_prime_nd[nurse,day] >=  1 for nurse in nurses for day in today))

Absent_con = m.addConstrs(Big_M*(1-int(a_nd_today_dict[nurse])) >= gp.quicksum(x_prime_nsd[nurse,shift,day] for shift in shifts) for nurse in nurses for day in today)

total_daily_shift= m.addConstrs(gp.quicksum(x_prime_nsd[nurse,shift,day] for shift in shifts) <= DS for nurse in nurses for day in today)

#For comparing with tomorrow, exclude the last day
No_M_after_N_tomorrow = m.addConstrs((x_prime_nsd[nurse,shifts[2],day] + x_nsd[nurse,shifts[0],days[days.index(day)+1]]<=  1 for nurse in nurses for day in today if day != days[-1]), name = "No_M_after_N_tmr")

#For comparing with yesterday, exclude the first day
No_M_after_N_yesterday = m.addConstrs((updated_x_nsd[nurse,shifts[2],days[days.index(day)-1]] + x_prime_nsd[nurse,shifts[0],day] <=  1 for nurse in nurses for day in today if day != days[0]), name = "No_M_after_N_yesterday")

# Optimize
m.write('NRSP_model.rlp')
m.Params.Seed = 1
m.optimize()
```