INDUSTRIAL AND HEALTHCARE WORKFORCE SCHEDULING FOR OCCUPATIONAL SAFETY, WORKLOAD, AND JOB SATISFACTION CONSIDERATION

BY

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ABSTRACT

Effective workforce scheduling is crucial in human resource management across various industries. It offers potential improvements in cost savings, operational efficiency, employee well-being, and retention. This dissertation is dedicated to advancing the field of workforce scheduling by introducing innovative mathematical models and analytical solutions tailored for both the manufacturing industry and the healthcare sector, emphasizing worker well-being, safety, and job satisfaction.

For industrial applications, our research focuses on the multifaceted benefits of job rotation in enhancing worker safety, promoting cross-training, and increasing job satisfaction. Two novel noise-safe job rotation scheduling models are introduced. The first model aims to ensure noise safety while optimizing production performance, considering worker-task skill matching within demand-driven manufacturing operations. This model can enhance a noise-safe work environment while maintaining promising operational performance. The second model incorporates skill development and personal attributes, including learning-forgetting rates and job boredom. This model addresses the complexities of balancing worker safety, skill development, and monotony-induced boredom. Such crucial aspects have a direct impact on production performance. Experiments showcase its capability to simultaneously achieve worker safety, multi-skill development, and reduced job monotony.

In healthcare applications, this dissertation highlights the vital role of nurses' job satisfaction in addressing the nursing shortage faced by hospitals worldwide. Two novel satisfaction-enhanced nurse scheduling models are presented. The first model seeks to accommodate individual nurse preferences for working slots and days off while ensuring equitable allocation of workload and preferred assignments. Building upon the first model, the second model incorporates a cost-effectiveness dimension to enhance practical applicability. Both models are validated using real-world data from hospitals in Thailand. The results highlight their effectiveness in generating more satisfactory and equitable work schedules within significantly reduced time compared to manually created schedules, with the second model offering cost-saving alternative scheduling plans.

This dissertation offers up-to-date workforce scheduling approaches for industrial and healthcare sectors, emphasizing the significance of workforce scheduling in driving positive changes in working conditions. The workforce scheduling models introduced in this dissertation can serve as valuable decision-support tools to enhance safety, job satisfaction, and operational performance in practice. Furthermore, this dissertation contributes significantly to the fields of occupational safety, industrial human resource management, and healthcare personnel management, providing guidelines for future research aiming to bridge the theoretical and practical gaps in workforce scheduling research.

Keywords: Workforce Scheduling Problem, Nurse Scheduling Problem, Job Rotation, Occupational safety, Job satisfaction

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Pavinee Rerkjirattikal

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LIST OF ABBREVIATIONS

Abbreviations	**Terms**
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ACS	Airline Crew Scheduling
BIP	Binary Integer Programming
CP	Constraint Programming
CPP	Crew Pairing Problem
CRP	Crew Rostering Problem
dBA	Decibel A
DND	Daily Noise Dose
GA	Genetic Algorithm
GP	Goal Programming
IP	Integer Programming
LGP	Lexicographic Goal Programming
LO	Lexicographic Optimization
LP	Linear Programming
MILP	Mix-Integer Linear Programming
NIOSH	National Institute for Occupational Safety and Health
NLP	Non-Linear Programming
NSP	Nurse Scheduling Problem
NRP	Nurse Rostering Problem
OSHA	Occupational Safety and Health Administration
PSP	Physician Scheduling Problem
RSP	Resident Scheduling Problem
SA	Simulated Annealing
SPL	Sound Pressure Level
SP	Stochastic Programming
TWA	Time-Weighted Average
WGP	Weighted-sum Goal Programming
WSP	Workforce Scheduling Problem

CHAPTER 1
INTRODUCTION

This chapter introduces the workforce scheduling problem (WSP) and its significance. It begins by defining the WSP, its goals, and challenges in Section 1.1. Section 1.2 discusses the general solution approaches to the WSP. Section 1.3 defines the specific applications of WSP within this dissertation. The scope of the dissertation, along with its objectives and significance, is outlined in Section 1.4 and Section 1.5, respectively. Finally, Section 1.6 offers an overview of this dissertation report.

1.1 The workforce scheduling problem

The workforce scheduling problem (WSP) involves assigning workers to shifts or tasks across a planning horizon while adhering to operational goals and constraints. These constraints usually encompass factors such as coverage requirements, worker skill limitations, legal work hours, and demand fulfillment. The objective is to optimize workforce utilization, skills, and worker well-being, thereby contributing to improved efficiency of human resources management. Effective workforce scheduling is substantial for organizations leveraging hourly human resources, such as manufacturers, retailers, airlines, and medical service providers.

WSP has gained significant attention in operations research due to its complexity and wide-ranging applications, including airline crew scheduling, retail staffing, healthcare staffing, manufacturing, and logistics. Although the core principles of WSP remain consistent, specific parameters, objectives, and constraints may vary by context. Common objectives found in the WSP literature include optimizing total labor costs, production performance, or service levels, enhancing workers' job satisfaction by accommodating their preferences, and identifying the optimal workforce size.

Effective workforce scheduling should address both organizational and worker perspectives. From an organizational standpoint, it aims to enhance productivity and service levels. Simultaneously, from a worker perspective, it seeks to meet individual preferences, ensuring job satisfaction and safety. Balancing these objectives, which are often conflicting, is a crucial challenge in WSP. Successful scheduling approaches provide proper allocation of workloads and rest allowances, enabling workers to perform tasks during preferred time slots. At the same time, the schedules should also meet operational requirements such as production or economic performance. Such desirable work conditions are essential for enhancing worker well-being, safety, job satisfaction, and long-term workforce retention, reducing costs associated with hiring and training new staff.

The complexity of WSP arises from the need to consider multiple stakeholders' perspectives and essential scheduling factors. Additionally, WSP is often a combinatorial and NP-hard problem, making it more challenging as the problem size increases. Consequently, selecting appropriate solution approaches for each problem nature is crucial. The following section outlines standard solution approaches applied to address WSP.

1.2 Solution approaches to the workforce scheduling problem

Solution approaches to WSP include a range of mathematical optimization and approximation techniques. The choice of method depends on the problem's characteristics, including the number of objectives, constraints, and nature of inputs.

For conventional WSP models with deterministic parameters, several mathematical optimization techniques are commonly employed. These include linear programming (LP), integer programming (IP), mixed-integer linear programming (MILP), and, in cases with non-linear conditions, non-linear programming (NLP). Multi-objective WSP models can be addressed using specialized methods like weighted-sum, lexicographic optimization, or goal programming (GP). For highly constrained WSP scenarios, constraint programming (CP) can find feasible solutions, even if they are not necessarily optimal. When dealing with uncertain or fuzzy parameters, techniques such as fuzzy optimization or stochastic programming (SP) can be applied to handle inherent uncertainty. While optimization techniques guarantee the best possible solution, they may take a substantial amount of time, depending on the complexity and the nature of the problem. Approximation techniques can be more beneficial for highly complex problems involving multiple quadratic equations or systems that cannot be mathematically represented.

Another category of WSP solution approaches involves approximation techniques, employing heuristic and metaheuristic algorithms to find near-optimal solutions, especially for large-scale and complex problems. Heuristic algorithms offer intuitive search strategies, delivering near-optimal solutions within reasonable computational time. However, they may not be suitable for highly complex problems and may not guarantee global optimality. Without careful design, heuristic algorithms can get trapped in local optima. They are also problem-specific and may not be adaptable to different problem types. Nonetheless, heuristic algorithms can be employed to obtain high-quality initial solutions, which can subsequently expedite the search for near-optimal solutions when combined with metaheuristic algorithms. Additionally, heuristic algorithms can be useful in real-time scheduling, where computational time takes precedence over optimality.

Metaheuristic algorithms are designed to tackle complex problems that heuristic algorithms alone cannot efficiently solve. These algorithms, characterized by diversification and intensification, generate diverse solutions and then intensify the search in local regions to exploit the best solutions. This iterative process converges towards optimality over time. Commonly used metaheuristic algorithms in WSP research include the ant colony optimization algorithm (ACO), artificial bee colony algorithm (ABC), genetic algorithm (GA), and simulated annealing (SA). GA is inspired by Darwinian evolution, involving reproduction, mutation, recombination, and selection processes. Due to its simplicity and efficiency, it is frequently applied in various optimization problems, including WSP. However, due to many genetic processes and parameter tuning involved, GA may get stuck in local optima if not carefully tuned. Therefore, GA is often enhanced with specialized diversification mechanisms or hybridized with exploitation-based metaheuristics, such as SA to improve performance. Refer to Chapter 2.2 for a detailed description of these approaches.

1.3 Applications of focus to the workforce scheduling problem

WSP is a versatile tool that finds applications in various industries, such as industrial, healthcare, transportation, and service sectors. However, this dissertation concentrates solely on the uses of WSP in industrial and healthcare systems. The primary focus of this dissertation is the development of workforce scheduling approaches that aim to improve workers' well-being and job satisfaction in both these domains.

Within industrial applications, WSP encompasses various sub-topics, including worker-to-task and job rotation scheduling. In worker-to-task scheduling, workers are assigned to specific tasks within a workday or for a period of time, with potentially different task assignments across the planning horizon. This class of problem aims to determine efficient production planning that optimally utilizes the workforce to meet operational cost or production efficiency performance. Another subtopic is job rotation scheduling, where workers are periodically rotated between multiple jobs within a workday. This scheduling strategy is primarily employed when occupational safety is of concern. Since this dissertation focuses on workers' well-being and job satisfaction, innovative approaches to job rotation scheduling are introduced, emphasizing mitigating occupational noise hazards, one of the most common occupational risks. Nevertheless, the proposed models can be adapted to address other hazards as needed. Henceforth, the WSP models proposed for industrial applications in this dissertation are called 'noise-safe job rotation scheduling.'

In healthcare applications, WSP offers several variants depending on the healthcare personnel involved, such as doctors, physicians, and nurses. This dissertation, however, primarily focuses on nursing staff. The reason is that nurses are extensively engaged in direct patient interactions, encompassing tasks such as preliminary screenings, patient care, and discharge preparations. The increasing demand for healthcare services has resulted in a shortage of nurses, leading to higher turnover rates due to the demanding workload and intricate shift patterns. Consequently, this dissertation aims to develop systematic nurse scheduling approaches to enhance nurses' well-being and job satisfaction. The proposed nurse scheduling models consider factors like nurses' skill levels, individual preferences, and scheduling fairness to distribute workload effectively, accommodate shift and day-off preferences, and ensure fair scheduling outcomes. The term' satisfaction-enhanced nurse scheduling' is used in this dissertation to refer to the proposed WSP model for healthcare applications. The proposed models can be adapted to accommodate other medical personnel having similar work patterns to nurses.

The subsequent subsections provide detailed explanations of noise-safe scheduling and satisfaction-enhanced scheduling, including their definitions, benefits, and challenges.

1.3.1 Industrial application (noise-safe job rotation scheduling)

This dissertation is centered around developing WSP solutions for industrial applications, focusing on improving occupational safety by mitigating noise hazards in the workplace. The proposed models are called 'noise-safe job rotation scheduling' models.

Workers in industries like metal, steel, and wood manufacturing often face excessive occupational noise levels due to their proximity to noisy machinery. This prolonged exposure can result in permanent noise-induced hearing loss (K.-H. Chen et al., 2020; Lie et al., 2016), elevated blood pressure (Gan & Mannino, 2018), cardiovascular problems (Li et al., 2019), psychological stress, communication challenges, reduced concentration (Themann et al., 2013), all of which adversely impact worker well-being, productivity, and increase the risk of accidents.

The National Institute for Occupational Safety and Health (NIOSH) recommends that workers should not be exposed to noise levels exceeding 85 decibels averaged over an 8-hour time-weighted average (TWA) (National Institute for Occupational Safety and Health, 2019). Workplaces with excessive noise levels should strictly follow the NIOSH hazard control guidelines as illustrated in Figure 1.1. While the ideal approach to mitigate noise hazards includes eliminating or substituting noisy machinery, these may not always be feasible or cost-effective. In such cases, administrative controls, such as job rotation scheduling, become a valuable supplementary measure to reduce hazard exposure. However, it is essential to note that employees should not rely solely on personal protective equipment as it is considered ineffective and burdensome for workers (Themann et al., 2013).

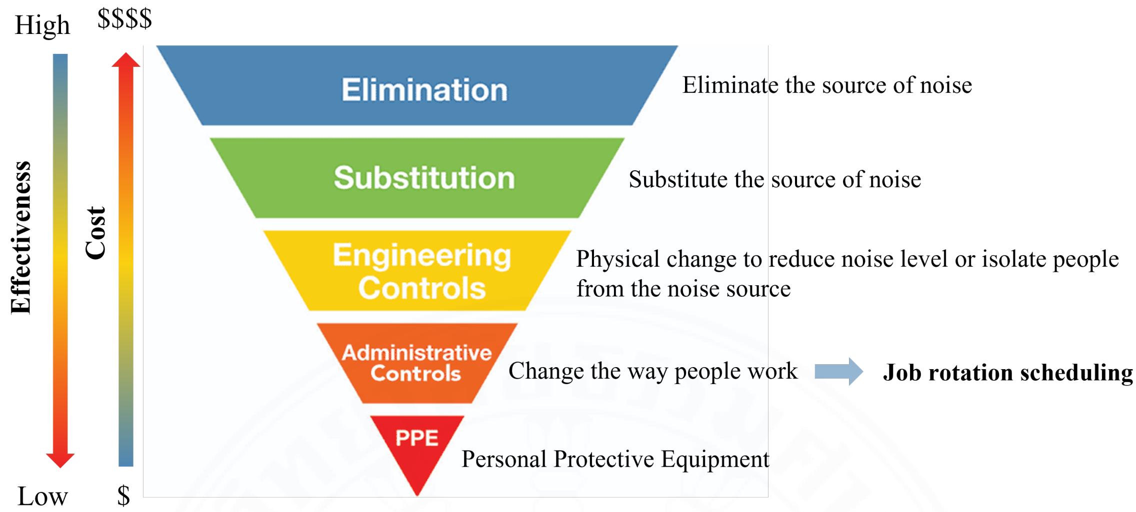

Figure 1.1 Hierarchy of occupational hazard controls adapted from National Institute for Occupational Safety and Health (2022).

Job rotation scheduling involves periodically assigning workers to tasks with varying hazard levels, ensuring that daily exposure to hazards remains within safe limits. This process is illustrated in Figure 1.2. While it offers benefits in mitigating hazard exposure, it also presents practical challenges. Determining the most appropriate assignments that maintain adequate system productivity requires careful consideration of worker and task skill levels. In addition, when workers are rotated multiple times during a workday, production can be lost due to relocation, skill deficiency, or setup times required for workers to adjust to new tasks. Additionally, in manufacturing facilities operating with minimal staff, workers are often required to work overtime during peak demand periods, posing additional challenges for job rotation in achieving worker safety during extended workdays and meeting the demand.

Job rotation also provides multifaceted benefits, including multi-skill learning, the reduction of job monotony, and improved job satisfaction. Rotating workers between tasks enables them to explore and acquire skills across multiple job roles, fostering personal development and opening up career opportunities. Simultaneously, rotation can help reduce the boredom from job monotony and boost motivation as workers engage in various tasks throughout the workday (Fernando & Dissanayake, 2019).

Determining the optimal rotation assignments, duration, and frequency is crucial, especially in a harsh work environment where safety is the priority. Frequent rotation is necessary to ensure worker safety, but it may disrupt the process of learning new skills.

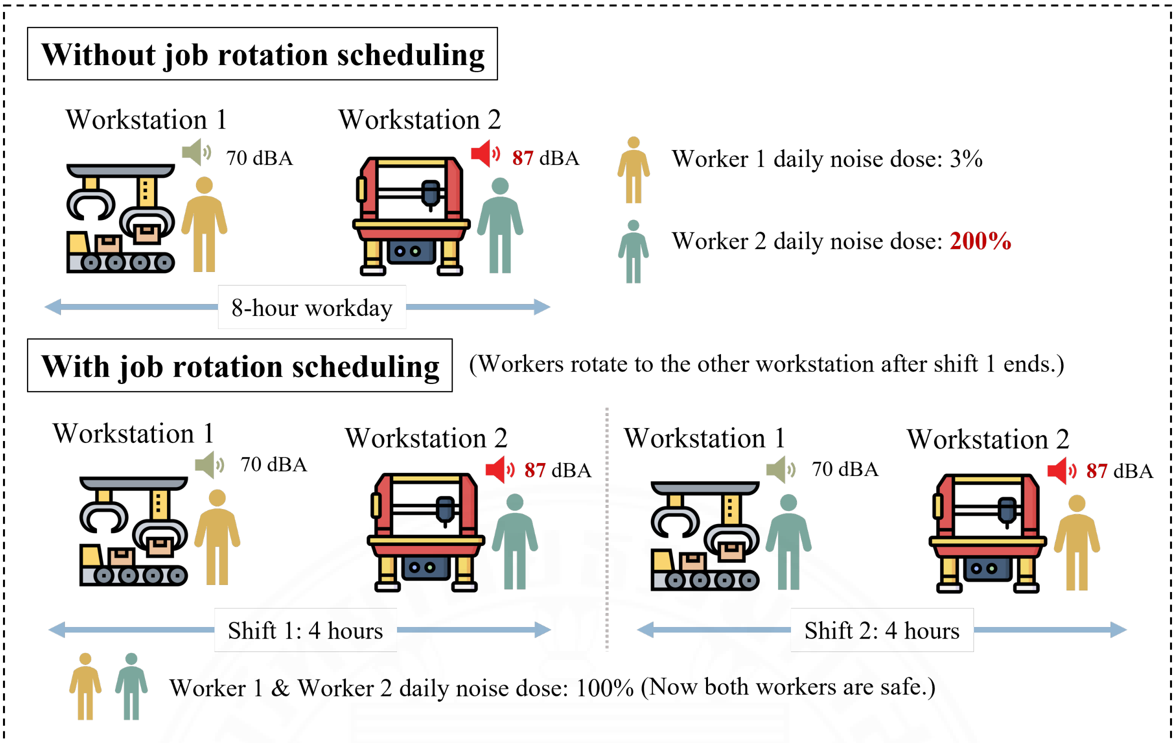

Figure 1.2 Example of job rotation for noise mitigation in manufacturing.

On the other hand, infrequent rotation may be preferred to maintain productivity, but it can hinder skill acquisition and lead to worker boredom. Moreover, extended periods away from certain tasks may result in skill forgetting. Finding the right balance between these factors remains a significant challenge in the job rotation scheduling domain, aiming for efficient outcomes that align with both management and worker needs.

In summary, job rotation offers valuable benefits besides worker safety, such as worker cross-training, reduced job monotony, and enhanced job satisfaction. Nevertheless, achieving these advantages while maintaining production and economic efficiency can pose challenges, as they often conflict with worker well-being objectives. To address these challenges, this dissertation introduces two noise-safe scheduling models that consider key scheduling factors such as worker skills, task requirements, demand fulfillment, and learning-forgetting-boredom patterns. Further details are provided in the subsequent chapters.

1.3.2 Healthcare application (satisfaction-enhanced nurse scheduling)

Hospitals typically require medical personnel, such as doctors, nurses, and physicians, to work irregular and extended hours due to their 24/7 operation. Shift work in healthcare involves factors like shift rotation, long hours, involuntary overtime, and insufficient rest due to consecutive workdays (Min et al., 2022). These conditions contribute to heightened risks of excessive fatigue (Min et al., 2021), circadian rhythm disorders (Ferri et al., 2016), job stress (Soewardi & Kusuma, 2019), and work-life imbalance (Navajas-Romero et al., 2020), which, in turn, lead to job dissatisfaction and turnover intentions among nurses (Lee & Jang, 2020).

Hospitals have been facing job dissatisfaction and high nurse turnover rates for decades. Studies have shown that poor work conditions, job stress, and burnout are strongly linked to nurses' intentions to leave their profession. For instance, in the United States, about 44,802 nurses (approximately 21%) have considered leaving their jobs due to heavy workloads and staffing issues (Koehler & Olds, 2022). Similarly, only 0.4% of nurses in China reported job satisfaction, with 70.7% considering resignation (Zhang et al., 2021). This trend is not unique to these countries, and it is also present in Thailand (Phuekphan et al., 2021). The nursing shortage persists despite the growing demand for medical services, necessitating hospital management to devise strategies to improve nurses' well-being, working conditions, and job satisfaction.

A well-designed work schedule is pivotal in enhancing nurses' job satisfaction and well-being, thereby reducing turnover rates. Research by Rizany et al. (2020) highlights a significant positive correlation between work schedule quality and nurses' job satisfaction. This can be achieved by maintaining proper nurse-to-patient ratios, ensuring an appropriate skill mix, and fair workload allocation. They also underscored that despite these research-supported findings, many practical work schedules still fall short in these aspects. Besides nurse-to-patient ratios and skill mixes, schedule quality can be further improved by considering nurses' preferences and ensuring scheduling fairness. Surveys indicate that nurses appreciate having some control over their work schedules, allowing them to specify preferred working slots (Cajulis et al., 2007). As suggested by Rizany et al. (2019), fairness in scheduling encompasses equitable workload distribution and preferred assignments.

In response to the challenging work conditions and the pressing nursing shortage, significant research efforts have focused on addressing solutions to the nurse scheduling problem (NSP), a branch of WSP within the healthcare sector. NSP aims to determine suitable nurse shift assignments while adhering to hospital and legal regulations regarding work hours, nurse requirements, and skill levels. An example of a weekly nurse schedule is provided in Figure 1.3, illustrating a three-shift rotation system with double-shift assignments on certain days.

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	M/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 1.3 An example of a weekly nurse schedule.

Nurse scheduling is a complex, time-consuming task typically overseen by the head nurse. It requires compliance with various hospital requirements, including adequate coverage, nurse competency, skill mix, and accommodating personal requests. Manual scheduling struggles to meet operational conditions and may overlook preferences and fairness. Optimization-based nurse scheduling models serve as valuable decision-support tools, addressing various objectives, such as cost minimization, quality improvement, and staffing optimization.

This dissertation primarily focuses on the development of satisfaction-enhanced nurse scheduling models. These models prioritize individual nurse preferences and scheduling fairness, aiming to create work schedules that enhance nurses' well-being and job satisfaction, thereby mitigating turnover intention. Challenges persist in comprehensively considering factors such as individual preferences for shifts and days off and ensuring fairness in workload and preferred assignments. Additionally, the economic impact of satisfaction-enhanced scheduling still requires further exploration.

In summary, systematic nurse scheduling approaches help head nurses generate satisfactory and fair work schedules while adhering to hospital regulations. These schedules are crucial in improving nurses' well-being and job satisfaction, addressing the ongoing nursing shortage crisis. To tackle these challenges, this dissertation proposes two satisfaction-enhanced nurse scheduling models, aiming to provide balanced workloads and preferred assignments while considering individual preferences and economic practicality. It also addresses differences in nurses' skill levels and investigates the economic performance of satisfaction-enhanced scheduling for enhanced application value.

This section outlines the challenges of noise-safe job rotation scheduling and nurse scheduling problems. Although these problems share similarities in coverage, skill requirements, and work hour regulations, they differ in the nature of assignments and shift work systems.

In noise-safe scheduling, workers are assigned specific tasks and shifts. This involves determining worker assignments for each task, shift, and workday. Typically, in manufacturing industries, a workday consists of a single 8-hour shift with overtime hours in some cases. Workers have a common day off each week during weekends when the factory is commonly closed. Therefore, shift and day-off preferences are less relevant, while task preferences can still be considered.

In nurse scheduling, nurses are assigned to specific shifts within a 24-hour workday, which may consist of 8-hour or 12-hour shifts, depending on the hospital's operational requirements. Nurses typically follow a rotating pattern that includes day and night shifts. They are also entitled to a certain number of days off each week, and this off-day pattern can vary over the planning horizon. The scheduling should consider nurses' preferences for their shifts and days off. However, task preferences are not within this scheduling context. Although some hospitals may assign nurses to specific roles and shifts independently, such an assignment system is not within the scope of the healthcare applications discussed in the dissertation. The following section will provide a detailed scope of this dissertation for each application.

1.4 Scope of this dissertation

This dissertation introduces innovative workforce scheduling approaches emphasizing worker well-being and job satisfaction in both industrial and healthcare applications. This section outlines the dissertation's scope and considerations for each application to provide clarity.

1.4.1 Industrial application (noise-safe job rotation scheduling)

This dissertation addresses the use of job rotation scheduling as an administrative hazard control measure and fostering multi-skill development among workers. Key aspects and their scopes are considered as follows:

- **Worker heterogeneity**: The models developed in this dissertation consider worker heterogeneity. Workers exhibit differences in skill levels, task efficiency, and task preferences. It is assumed that skilled workers can efficiently perform tasks at better production rates and handle a broader range of tasks. Additionally, worker variations in learning, forgetting, and boredom rates are considered.

- **Occupational noise hazard**: Noise is prevalent in heavy manufacturing industries. This dissertation focuses on noise as the main hazard, assuming uniform noise levels across workdays and planning horizons. Workers' perception of noise is uniform regardless of their demographic differences. Daily noise exposure level is calculated using established formulas from NIOSH standards.

- **Job satisfaction**: Workers' job satisfaction is influenced by various factors. This dissertation highlights the significance of safety perception, motivation, and organizational support for personal development as key contributors to job satisfaction. The positive impact of job rotation in reducing monotony-induced boredom, which is also associated with job satisfaction, is also considered. Additionally, this dissertation accounts for workers' task preferences as another contributor that increases job satisfaction and helps mitigate boredom from monotony.

- **Planning horizon**: The dissertation adopts a multi-workday planning horizon, allowing for scheduling decisions over an extended period. Throughout this planning horizon, the noise-safe scheduling models determine task assignments for each worker across shifts and workdays. The length of the planning horizon is adaptable to meet specific needs, whether on a weekly, bi-monthly, or monthly basis.

1.4.2 Healthcare application (satisfaction-enhanced nurse scheduling)

Within the healthcare system, this dissertation is dedicated to the development of nurse scheduling models aimed at enhancing nurses' job satisfaction. The key aspects and scopes are detailed below:

- **Nurse heterogeneity**: Nurses exhibit variations in skill levels and individual preferences. Incorporating skill heterogeneity into the models is essential, as it ensures a proper skill mix in each shift, a critical factor for maintaining operational quality. Additionally, nurses have different preferences for working shifts and days off, influenced by factors such as lifestyle, family dynamics, and personal choices. For instance, nurses with families may prefer morning to night shifts to align with their family commitments, while others may opt for afternoon and night shifts. Furthermore, some nurses may prefer weekdays off, while others prefer weekends. Accounting for these diverse preferences enables the creation of work schedules that effectively accommodate the individual needs and circumstances of nurses.

- **Job satisfaction**: In the context of satisfaction-enhanced nurse schedules, job satisfaction is influenced by the extent to which the schedule aligns with nurses' individual preferences and the fairness of assignments. Nurses find satisfaction in schedules that accommodate their shift and day-off preferences, aligning with their lifestyle needs. Furthermore, this dissertation acknowledges the significance of fairness in work schedules. The proposed satisfaction-enhanced nurse scheduling models aim to ensure both satisfactory and equitable work schedules, promoting job satisfaction across all dimensions.

- **Fairness**: The proposed models encompass fairness in two dimensions: equitable workload distribution (the number of assigned shifts) and preferred assignments. Focusing solely on one aspect of fairness, whether workload or preferred assignments, may result in schedules that are perceived as unfair from an overall perspective. Nurses may experience frustration and dissatisfaction if they receive equitable workloads but substantial deviations in preferred assignments. To address this, our proposed satisfaction-enhanced scheduling models incorporate considerations for fairness in both workload distribution and preferred assignments, ensuring a comprehensive perspective of fairness.

- **Planning horizon**: This dissertation adopts a multi-workday planning horizon, dividing workdays into multiple equal-length working shifts. For an entire planning period, the models determine optimal nurses' shift and day-off assignments, accommodating their individual preferences and ensuring equitable assignments. The length of shifts and the planning horizon are adaptable to accommodate the specific requirements of each hospital setting.

1.5 Dissertation objectives and significance

This dissertation has a twofold objective: to develop workforce scheduling approaches for both industrial and healthcare applications while emphasizing the enhancement of workers' well-being and job satisfaction. The key objectives and significance of each application are detailed below.

1.5.1 Industrial application (noise-safe job rotation scheduling)

1. **Development of noise-safe job rotation scheduling model**: The primary objective is to create a multiperiod noise-safe job rotation scheduling model that prioritizes worker safety and production performance. This model takes into account critical scheduling factors, including workers' skills, task skill requirements, production demand, and overtime assignments. The objective function is to minimize the total labor cost associated with workforce scheduling in harsh working environments.

2. **Development of noise-safe job rotation scheduling model considering learning-forgetting-boredom effects**: Another key objective is to develop non-linear multi-workday noise-safe job rotation scheduling models that consider the benefits of worker cross-training and motivation associated with job rotation. This model aims to minimize production delays arising from skill deficiencies and job dissatisfaction induced by the monotony of repetitive tasks. It also incorporates the impact of learning, forgetting, and boredom on worker productivity and job satisfaction.

The proposed models demonstrate the effectiveness of job rotation as an administrative hazard control measure. These models provide a solid foundation and practical demonstration of how organizations can enhance worker safety, job satisfaction, and overall well-being through the strategic use of job rotation. Additionally, they enable organizations to maintain satisfactory production performance and foster multi-skill development among workers, which contributes to increased worker flexibility and improved industrial workforce management in the long term.

1.5.2 Healthcare application (satisfaction-enhanced nurse scheduling)

1. **Development of satisfaction-enhanced nurse scheduling model**: This dissertation develops a multi-workday satisfaction-enhanced nurse scheduling model that prioritizes nurses' shift and day-off preferences while maintaining a balance between workload and preferred assignments. The goal programming technique is employed to handle multi-objectives associated with nurses' preferences and fairness aspects.

2. **Development of cost-effective and satisfaction-enhanced nurse scheduling model**: Another objective is to develop multi-workday nurse scheduling models that address multiple dimensions, including minimizing staffing costs, maximizing the fulfillment of shift and day-off preferences, and balancing workload and preferred assignments. The lexicographic optimization technique is employed to solve the model.

The proposed models offer practical and efficient decision-support tools for hospital nursing management. They facilitate nurse scheduling approaches to achieve improved shift work conditions for nurses that accommodate their personal needs, leading to enhanced job satisfaction and retention capabilities. A cost-effective variation to satisfaction-enhanced scheduling is also provided. These proposed models can mitigate the limitations associated with manual scheduling, saving time and effort for head nurses while generating more effective schedules.

1.6 Organization of the dissertation

This dissertation is structured into five chapters, each contributing to the understanding and development of workforce scheduling problems and solutions. The organization of the chapters is as follows:

- **Chapter 1** serves as an introduction to the concepts of WSP and outlines the specific applications emphasized in this dissertation. It provides an overview of the dissertation's scope, objectives, and significance and concludes by presenting the layout of the subsequent chapters.
- **Chapter 2** outlines the background of WSP and its variations as found in the existing literature. It reviews the range of solution approaches used to tackle WSP. The chapter also offers insights into existing noise-safe job rotation and satisfaction-enhanced scheduling approaches found in the literature, as well as highlights research gaps addressed in this dissertation.
- **Chapter 3** provides methods for the measurement and evaluation of occupational noise levels. It subsequently presents the development of two noise-safe job rotation mathematical models. Throughout the chapter, numerical examples, model validation procedures, and experimental results are presented to illustrate the application and efficacy of the models.
- **Chapter 4** describes the development processes of two satisfaction-enhanced nurse scheduling models. It outlines the utilization of hospital case data and offers a thorough analysis of experimental results, providing valuable insights into the application of these models in healthcare settings.
- **Chapter 5** serves as the conclusion of the research presented in this dissertation. It summarizes the key findings and contributions to both academia and practical applications. Additionally, this chapter acknowledges the limitations of the research and suggests potential directions for future research endeavors.

CHAPTER 2
LITERATURE REVIEW

This chapter reviews related literature on workforce scheduling and its real-world applications in Section 2.1. Section 2.2 discusses quantitative approaches to solving workforce scheduling problems, including exact and approximation techniques. Section 2.3 and 2.4 provide a literature review on noise-safe job rotation scheduling and satisfaction-enhanced nurse scheduling, respectively. Research challenges and gaps associated with each application are also presented.

2.1 Workforce scheduling problem and its variants

The Workforce Scheduling Problem (WSP) is a crucial research area focusing on efficiently allocating human resources to tasks. WSP aims to optimize worker assignments across shifts and days within a defined planning horizon while adhering to a set of constraints. These constraints may include skill requirements, allowable work hours, and safety regulations. The foundation of WSP is similar, with some objectives, parameters, or constraints that can differ based on the application domain. This section explores the diverse landscape of WSP applications and their significance within different industries.

Industrial applications

In industrial settings, WSP is often referred to as a labor scheduling problem, where the primary objective is to minimize workforce utilization while ensuring adequate staffing levels (Hung, 1994; Nanthavanij & Yenradee, 1999). Beyond cost minimization, this field has expanded to include objectives such as cost optimization (Castillo et al., 2009; Thompson & Goodale, 2006) and productivity enhancement (Moussavi et al., 2016; Nanthavanij et al., 2010). Recent research in industrial WSP increasingly focuses on worker-centric goals, emphasizing job satisfaction and preference-based assignments. Noteworthy efforts include models formulated to maximize workers' job satisfaction based on their preferred job and shift assignments (M. Akbari et al., 2013; M. Liu & Liu, 2019).

Healthcare applications

Within the healthcare sector, WSP is known as medical staff scheduling, encompassing various areas such as physician or nurse scheduling. These applications deal with complex scheduling requirements for different hospital departments, striving to balance workload, fulfill shift preferences, and adhere to legislative constraints such as work hour limitations. Like the other applications, healthcare WSP is typically developed to determine the minimum number of staff (P. S. Chen et al., 2016) and minimize the total staffing cost (Othman et al., 2015). Another objective commonly found in the emergency department is to minimize the patients' waiting time to maintain patients' satisfaction (Rashwan et al., 2018).

Transportation applications

Transportation systems tackle WSP for various industries, including airlines, railways, buses, trucks, and freight companies. Airline crew scheduling (ACS) is a prominent field within transportation, with two main components: Crew Pairing Problems (CPP) and Crew Rostering Problems (CRP). CPP optimizes crew utilization (Kornilakis & Stamatopoulos, 2002; Quesnel et al., 2017), while CRP focuses on preference-based scheduling, workload balance, and cost considerations (Quesnel et al., 2019; Zhou et al., 2020). Integrating these two sub-problems is essential for effective airline crew scheduling (Gomes & Gualda, 2015; Zeighami et al., 2020).

Service industry applications

The service industry extensively employs WSP in areas such as restaurants, retail, gas stations, and call centers. Objectives often include minimizing staffing costs, maintaining service quality, balancing full-time and part-time employees, and accommodating worker preferences. Noteworthy examples include retail worker scheduling models that aim to maximize profit while minimizing employee job dissatisfaction (Mac-Vicar et al., 2017). Similarly, gas station employee scheduling involves a two-stage approach, with the first stage allocating employees to stations and the second stage assigning shifts and days off while also considering worker preferences (Al-Yakoob & Sherali, 2007). Call center operations also utilize WSP to optimize agent scheduling (Dietz, 2011; Gans et al., 2015).

Recent advancements in WSP have increasingly focused on worker-centric objectives, emphasizing safety and job satisfaction. By integrating safety regulations and worker preferences, WSP can yield schedules that not only enhance employee well-being but also contribute to improved performance and higher retention rates, as highlighted by Krekel et al. (2019). However, it is important to acknowledge that WSPs are inherently complex and NP-hard problems due to their constraints and expansive solution space. The need to consider multiple aspects of WSP has made it even more challenging. While advanced optimization techniques can efficiently tackle WSP even in large-scale scenarios, highly complex problems may require approximation algorithms to yield practical solutions. The subsequent section offers an insightful overview of the existing quantitative solution approaches designed to address the multifaceted challenges posed by WSP.

2.2 Quantitative approaches to the workforce scheduling problem

WSP is a complex combinatorial problem that has been receiving extensive research attention due to its practical significance and human benefits. There are many approaches to solving the WSP, and the choice depends on the nature of the problems and inputs. This section categorizes solution approaches into optimization and approximation techniques.

2.2.1 Optimization approach

The optimization approach, often referred to as the exact technique, has its roots in LP, a concept introduced by Dantzig (1963). It involves formulating real-world problems as mathematical models that consist of crucial elements, including input parameters, objective functions, and constraints. In essence, optimization searches for combinations of variables that yield the best possible objective value while adhering to a set of constraints. Optimization is a powerful decision-support tool that has a wide range of applications in businesses and research, including economics, finance, logistics, and workforce scheduling.

LP and its extensions, such as binary integer programming (BIP) and MILP, have been effectively employed in addressing WSP. Numerous studies have demonstrated their utility in various contexts (Al-Rawi & Mukherjee, 2019; S. Y. Ang et al., 2019; Lorenzo-Espejo et al., 2021; Razali et al., 2018). WSP often involves multiple objectives, ranging from cost minimization to productivity improvement, safety enhancement, and worker satisfaction mirroring real-world scheduling processes. Several techniques have been proposed to tackle such multi-objective problems.

One straightforward approach is to optimize all objectives simultaneously, assuming equal importance. However, this method can be computationally expensive, especially when objectives conflict with each other. A more effective approach is the Pareto frontier, which identifies non-dominated solutions, allowing decision-makers to choose solutions aligned with their specific needs (Khorram et al., 2014). For example, Safaei et al. (2009) developed an approach to schedule maintenance workforce in a steel company to minimize job flow time and staffing requirements. Decision-makers can choose the Pareto solution depending on the allowable degree where job flow time can be sacrificed to limit the workforce employed. M. Liu and Liu (2019) proposed a workforce scheduling model to maximize the number of on-time jobs and workforce satisfaction level. Their findings suggest multiple solutions for decision-makers to select a suitable degree of trade-off between the two objectives.

Weighted-sum optimization is another technique where multiple objectives are transformed into a single objective function, with user-assigned weights representing their priorities. While this method is relatively straightforward, it can encounter incommensurability issues when objectives have different units, necessitating normalization. A similar concept, known as goal programming (GP), sets target values for each objective, aiming to minimize deviations from these targets. GP is known for its efficiency and practicality and has been widely used in WSP literature, such as Hasan et al. (2019), Kaçmaz et al. (2019), and Shuib and Kamarudin (2019).

Variations of GP include weighted-sum GP (WGP) and lexicographic GP (LGP), which allow decision-makers to specify objective values and priorities. For instance, Ighravwe et al. (2017) developed a WGP model for shift allocations in a process industry, where stakeholders assigned different weights to goals related to budgets, worker distribution, quality of work, and hiring-firing costs. Sundari and Mardiyati (2017) proposed an LGP model for nurse scheduling, prioritizing goals related to shift patterns, day-offs, and workload distribution. It is important to note that GP approaches may not produce Pareto-efficient solutions and may require normalization for objectives with different units (Jadidi et al., 2014).

Another strategy for handling multi-objective problems is lexicographic optimization (LO). In this approach, objectives are optimized iteratively, following their order of importance. Each objective's optimal value from one iteration serves as a boundary for the subsequent iteration until all objectives are optimized. This strategy enables decision-makers to focus on the most critical objective first, simplifying the problem and maintaining a reasonable solution time. For example, Barrera et al. (2012) employed LO to tackle a bi-objective crew scheduling problem, minimizing crew numbers first and then balancing workload. Wongwien and Nanthavanij (2017a) applied this approach to optimize a multi-objective ergonomic workforce scheduling problem, considering factors like the number of workers, person-job-fit score, and total worker changeover in a predefined order. They also extended their work to include worker job satisfaction as an additional objective, optimizing the model based on priority hierarchy Wongwien and Nanthavanij (2017b). Recent studies in the field have continued to utilize LO, as evidenced by works such as Bolsi et al. (2021), Mansini et al. (2023), and Vanheusden et al. (2022).

The approaches mentioned above are generally for linear problems. However, real-world problems often involve non-linear conditions that cannot be adequately represented using linear equations. These include scenarios related to chemical equilibrium, fluid flows, and worker learning forgetting. To address such complex non-linear systems, non-linear programming (NLP) techniques are employed. Solving NLPs is generally more complicated than LPs due to the significantly larger solution space. While commercial optimization tools supporting NLPs are available, practitioners often transform NLPs into LPs or resort to approximation techniques to manage computational complexity. The literature showcases instances of NLP usage in solving WSP, although less frequently than LP. For example, Abdel-Fattah Mansour (2011) proposed an NLP model to minimize workload variance among maintenance workers. They linearized the variance function and applied a genetic algorithm (GA) for problem resolution. Hewitt et al. (2015) addressed non-linear WSP by maximizing the number of finished goods while considering worker production rates with non-linear relationships to worker skill. Linearization techniques were employed to ensure manageable solution times with exact methods. Similarly, Jin et al. (2018) reformulated their workforce grouping and assignment models from NLP to MILP, reducing solution time and problem complexity. While linearization can reduce the computational burden of NLP, some accuracy might be lost due to linear approximations. Alternatively, researchers have opted for approximation techniques to solve NLP-WSP problems. These approaches include problem-specific heuristics (López B. & Nembhard, 2017), multi-objective particle swarm optimization (MOPSO), non-dominated sorting genetic algorithm II (NSGA-II) (Akhavizadegan, F. and Jolai, F. Jolai and Ansarifar, and Tavakkoli-Moghaddam, R., 2015), hybrid GA-SA (Azizi et al., 2010), Local Search (Ayough et al., 2021), and others.

In summary, the literature review showcases a variety of optimization techniques employed for addressing WSP. Each technique is suited to different problem formulations and specifications. Table 2.1 summarizes reviewed papers detailing their optimization-based solution approaches and applications to WSP, sorted in the order they appear in the section. The abovementioned techniques are primarily suited for handling deterministic problems with constant inputs and bounds. For situations involving uncertainties, stochastic programming or robust optimization may be more appropriate, although these topics are beyond the scope of this dissertation. For readers interested in further details, additional information can be found in references such as Ben-Tal et al. (2009) and Birge and Louveaux (2011). While optimization techniques effectively tackle WSP, challenges may arise when dealing with complex or exceptionally large problems. Some real-world problems may have conditions that cannot be represented as mathematical equations, rendering mathematical optimization unsuitable. Moreover, computational time can escalate significantly when applying optimization techniques to quadratic problems due to the multitude of feasible solution options.

Consequently, efforts have been made to develop approximation approaches to address such problems efficiently. Subsequent subsections will delve into various existing approximation approaches.

2.2.2 Approximation approach

The approximation approach is a trade-off between optimality, completeness, and accuracy, offering satisfactory solutions within significantly reduced solving times compared to optimization techniques. This approach can be broadly categorized into two main classes: heuristic algorithms and metaheuristic algorithms.

Heuristic algorithms are designed as intuitive problem-solving sequences tailored to specific problems, making them suitable for moderately complex tasks. While they are relatively fast, they can sometimes get trapped in local optima and sub-optimal solutions. In contrast, metaheuristic algorithms are problem-independent and equipped with complex strategies to avoid local optima to some extent. Often, heuristics are employed in conjunction with metaheuristics to provide initial solutions, enabling metaheuristics to converge to optimality more rapidly. Heuristic and metaheuristic approaches are flexible and capable of solving problems without the need for mathematical expressions, making them particularly well-suited for problems with conditions that cannot be mathematically expressed.

2.2.2.1 Heuristic algorithm

In the literature, heuristic algorithms have found extensive use in addressing WSP. For instance, McGinnis et al. (1978) proposed a two-stage heuristic algorithm for solving WSP under fluctuating workforce requirements, with the first stage determining shift allocation and the second stage performing shift assignments. Musliu (2006) developed heuristic methods for rotating workforce schedules that satisfy the given set of constraints. Becker (2020) proposed a decomposition heuristic algorithm for rotational workforce scheduling, which decomposed the problem into master and sub-problems to streamline the solution process. Nanthavanij et al. (2010) designed a heuristic approach for WSP with safety and productivity objectives, showcasing the trade-off between these two aspects and achieving compromising solutions. Additionally, Rodič and Baggia (2017) presented a heuristic algorithm for crew scheduling of airport ground staff, which they combined with agent-based simulation for validation and enhancement. Youssef and Senbel (2018) proposed a bi-level, shift-swapping heuristics algorithm for nurse scheduling problems.

Heuristic algorithms can also be effectively combined with optimization techniques to reduce solution space and help reach optimality more swiftly. For instance, Laesanklang

Table 2.1 A summary of papers utilizing optimization approaches to WSP

Authors	Approach	Application	Key points/ objectives
Al-Rawi and Mukherjee (2019)	LP	Construction	- Optimize project completion time and preferences and fairness.
S. Y. Ang et al. (2019)	LP	Security staff	- Optimize preference satisfaction in shifts and days off
Lorenzo-Espejo et al. (2021)	MILP	Maritime	- Optimize & fairly allocate consecutive days off and break time.
Razali et al. (2018)	LP	Retail	- Optimize staffing cost and preferences in shift and company policy.
Safaei et al. (2009)	Pareto	Industrial	- Optimize jobs flow time and no. of workers - Decision-makers can choose preferred solutions from the Pareto front
M. Liu and Liu (2019)	Pareto	Industrial	- Optimize worker job preferences and number of on-time jobs. - Decision-makers can choose preferred solutions from the Pareto front
Hasan et al. (2019)	GP	Industrial	- Optimize multiple operational goals for annualized hour flexibility schedule.
Kaçmaz et al. (2019)	GP	Industrial	- Optimize goals related to workload, worker skills, and desired assignments.
Shuib and Kamarudin (2019)	GP	Power plant	- Optimize preferred days off.
Ighravwe et al. (2017)	WGP	Industrial	- Optimize goals related to staffing/hiring/ firing costs and worker utilization.
Sundari and Mardiyati (2017)	LGP	Healthcare	- Optimize goals related to group preferences.
Barrera et al. (2012)	LO	Airline	- Combine timetabling and crew scheduling. - Optimize no. of crew and balance workload in a preemptive order.
Wongwien and Nanthavanij (2017a)	LO	Industrial	- Optimize cost, and productivity-based objectives in a preemptive order. - Consider worker hazard exposure level.
Wongwien and Nanthavanij (2017b)	LO	Industrial	- Optimize cost, productivity & preference objectives in a preemptive order. - Consider worker hazard exposure level.
Bolsi et al. (2021)	LO	Industrial	- Optimize production timeliness and cost objectives in a lexicographic order.
Mansini et al. (2023)	LO	Healthcare	- Optimize service level, employee idle time customer waiting time preemptively.
Vanheusden et al. (2022)	LO	Warehouse	- Optimize workload balancing objectives: max, minimax, variance & Gini coefficient.
Abdel-Fattah Mansour (2011)	NLP	Industrial	- Optimize man hours variance and cost. - Linearize NLP and solve with GA.
Hewitt et al. (2015)	NLP	Industrial	- Optimize production outputs. - Consider worker's learning-forgetting rates. - Linearize NLP and solve with optimization.
Jin et al. (2018)	NLP	Industrial	- Optimize system throughput. - Consider worker learning-by-doing and knowledge transfer in the assigned teams - Linearize NLP and solve with optimization.

and Landa-Silva (2017) developed a nurse scheduling solution for home healthcare that minimizes total monetary and penalty costs using MILP and introduced heuristics to decompose the problem into manageable size of sub-problems. Meanwhile, Éles et al. (2018) employed MILP for mobile workforce scheduling, minimizing total costs while maximizing task execution. The heuristic algorithm generated lists of potential tasks for each team, with MILP finalizing task assignments to achieve the most economical schedule.

One limitation of heuristic algorithms is their problem-specific nature, restricting their application to particular problems. In contrast, metaheuristic algorithms offer greater generality and can tackle more complex problems. Therefore, substantial research efforts have been invested in developing advanced metaheuristics.

2.2.2.2 Metaheuristic algorithm

Metaheuristic algorithms are problem-independent strategies for problem-solving that offer flexibility and adaptability to a wide range of real-world optimization problems. However, some degree of problem-specific modifications is required to achieve good performance. Similar to heuristic algorithms, they cannot guarantee optimality, but they often offer good enough solutions within a reasonable time. Most metaheuristic algorithms draw inspiration from nature or physical phenomena. For instance, GA is based on biological evolution, while SA is inspired by physics. In contrast, ACO and ABC are based on the swarming behavior of animals.

Among these algorithms, GA stands out as the most frequently employed and well-suited for solving variations of WSP. In the WSP literature, GA is demonstrated to be useful in many application domains such as workforce scheduling (Asensio-Cuesta et al., 2012; J. C. Chen et al., 2022; Turan et al., 2020), airline crew rostering and pairing (Demirel & Deveci, 2017; Deveci & Demirel, 2018; Shafipour-Omrani et al., 2022), healthcare personnel scheduling (Apornak et al., 2021; Rurifandho et al., 2022), and service staff scheduling (Ilk et al., 2018). Based on the principles of biological evolution, GA involves selection, reproduction (crossover), and mutation. The fitness of individuals is evaluated using a fitness function representing objective value. Fitness-based selection ensures fitter individuals have a higher chance of generating potentially fitter offspring. These offspring undergo mutation to obtain diversity and are reinserted into the population. These genetic operations iteratively repeat until the termination condition is met.

Since GA is a versatile problem-solving framework, many studies employ a heuristic for generating an initial population encompassing some problem-specific attributes. A well-designed initialization heuristic can enhance efficiency and accelerate the search for optimal solutions. However, GA has a tendency for premature convergence (Pandey et al., 2014). It also cannot always generate offspring that outperform their parents, resulting in sub-optimal solutions. To mitigate this, genetic operators and parameters can be fine-tuned, and hybridization with other metaheuristics is employed to improve solution quality. The combination of GA and SA, known as GA-SA, is particularly effective, as SA's ability to escape local optima complements GA's strengths.

SA is a metaheuristic that mimics the annealing process in metallurgy. In SA, a random solution close to the current one is selected, and then it chooses to accept or discard the random solution based on the acceptance probability. By probabilistically accepting worse solutions, SA can avoid being trapped in local optimal Eren et al. (2017). In most GA-SA algorithms, GA is first employed to generate a good enough solution, which becomes the initial solution for SA. Then, the solution is improved via SA procedures. The GA-SA algorithm's superiority over conventional GA or SA is demonstrated in many of the following works: Aroui et al. (2017), Rao et al. (2013), and Salahi et al. (2021).

In summary, approximation methods are applicable for solving complex and large-scale optimization problems like WSP. They provide near-optimal solutions within a reasonable time, making them suitable for computationally demanding problems such as NLP or those with mathematical expression limitations. While heuristic algorithms are designed to solve specific problems and provide initial solutions, metaheuristic algorithms offer more generality and flexibility. The effectiveness of approximation techniques in solving WSP is well-documented in the literature. This section has discussed various solution approaches to WSP in different applications. Table 2.2 summarizes reviewed papers detailing their approximation solution approaches and applications to WSP, sorted in the order they appear in the section. The following sections provide a literature review of noise-safe job rotation scheduling and satisfaction-enhanced nurse scheduling, two WSP applications covered in this dissertation.

2.3 Industrial application (noise-safe job rotation scheduling)

The previous sections have presented variations of WSP as discussed in the existing literature, as well as their solution approaches. This section delves into the safe job rotation scheduling research, which is the focus of the dissertation in industrial applications. Various research variants and essential scheduling factors used in mathematical model formulations in existing studies are also discussed.

Table 2.2 A summary of papers utilizing approximation approaches to WSP

Authors	Approaches	Application	Key points/ objectives
McGinnis et al. (1978)	Heuristic	Telecom	- Optimize idle time and day off allocation.
Musliu (2006)	Heuristic	General	- Minimize violations of workload & operational constraints.
Becker (2020)	Heuristic	General	- Constraint-satisfaction scheduling problem - Develop problem decomposition heuristics to solve the problem using less time.
Nanthavanij et al. (2010)	Heuristic	Industrial	- Safe scheduling considering productivity - Consider noise exposure & worker-job-fit.
Rodič and Baggia (2017)	Heuristic	Airline	- Optimize workforce & equipment utilization - Use system simulation to verify the result.
Youssef and Senbel (2018)	Heuristic	Healthcare	- Optimize fulfillment of nurses' preferred shift & day-off assignments. - Consider workload fairness among nurses.
Laesanklang and Landa-Silva (2017)	Heuristic	Healthcare	- Workforce scheduling & routing problem - Optimize cost and penalties for violating constraints and worker/client preferences. - Consider worker-client relationship, worker preferred location, clients' preferred skills.
Éles et al. (2018)	Heuristic	Mobile workforce	- Optimize operational costs & tasks completion. - Use the heuristic algorithm to reduce search space, accelerating MILP solving time.
Asensio-Cuesta et al. (2012)	GA	Industrial	- Ergonomic job rotation scheduling - Consider muscle group loading & worker skills.
J. C. Chen et al. (2022)	GA	Industrial	- Optimize total cost & project tardiness. - Consider worker multi-skill learning effects.
Turan et al. (2020)	GA	Military	- Minimize total salary cost for military. - Hybridize GA-simulation techniques to improve solution quality.
Demirel and Deveci (2017)	GA	Airline	- Determine legal crew pairing solutions. - GA is coupled with repairing heuristics to improve solution quality.
Deveci and Demirel (2018)	GA	Airline	- Optimize the total crew assignment costs. - Benchmark GA variants and other algorithms.
Shafipour-Omrani et al. (2022)	GA	Airline	- Optimize crew preferred assignments considering crew compatibility & seniority.
Ilk et al. (2018)	GA	Customer service	- Optimize staffing cost, and lost demand. - Consider omni service channels: phone, live chat, emails & social media.
Aroui et al. (2017)	GA-SA	Industrial	- Minimize workers overloading/fatigue. - GA-SA outperforms GA and SA alone.
Rao et al. (2013)	GA-SA	Industrial	- Optimize operation time and cost. - Demonstrate effectiveness of GA-SA
Salahi et al. (2021)	GA-SA	Procurement	- Minimize supply chain cost. - GA-SA outperforms GA and SA alone.

2.3.1 Variants of safe job rotation scheduling

Job rotation scheduling research predominantly addresses two primary hazards: ergonomics and noise. Ergonomic hazards encompass repetitive heavy muscle loading and awkward movements, potentially leading to musculoskeletal disorders. Researchers employ various indicators based on different body parts to assess and formulate mathematical models, including OCRA (Upper limbs), RULA (Upper limbs), REBA (Entire body), and LI (Lifting index). These models aim to optimize job rotations to reduce excessive muscle loading (Adem & Dağdeviren, 2020; Assunção et al., 2022; Moussavi et al., 2019) while considering differences in demographic characteristics of workers that influence the perception of ergonomic hazards such as age (Botti et al., 2020), gender (Battini et al., 2022), and physical abilities (Costa & Miralles, 2009). The evaluation of muscle group loading in ergonomic job rotation schedules is crucial to prevent the overuse of specific muscle groups.

In contrast, noise hazards remain relatively consistent across demographic groups. Industries such as agriculture, construction, mining, and manufacturing are particularly prone to violate the safe noise exposure standard of 85 dBA, which can result in hearing loss, cardiovascular issues, psychological stress, and decreased work ability index. These effects are gradual, asymptomatic, and often unnoticed, leading to delayed treatment. As a practical and cost-effective strategy, job rotation scheduling, which involves periodic rotations of workers between loud and quiet workstations throughout the workday can be useful. Several studies have highlighted the effectiveness of job rotation in reducing workers' daily noise exposure. For example, Tharmmaphornphilas et al. (2003) developed a job rotation model to minimize workers' daily noise exposure. Although the model can reduce overall workers' noise exposure levels, some are exposed to over-limit noise levels. Alternatively, some studies propose the inclusion of a daily noise limit constraint to ensure safety while pursuing additional objectives, such as optimizing workforce size (Asawarungsaengkul & Tuntitippawan, 2019; Yaoyuenyong & Nanthavanij, 2008) or enhancing overall system productivity.

Job rotation scheduling research also extends its focus beyond ergonomics and noise, addressing hazards such as heat stress (Srinakorn & Olapiriyakul, 2016), exposure to chemical substances (Maleki, 2019), and hand-arm vibration (Adem & Dağdeviren, 2020).

2.3.2 Productivity performance in safe job rotation scheduling

Numerous studies have demonstrated the promising effects of job rotation in alleviating excessive hazard exposure among workers. However, worker schedules that prioritize safety performance alone may not be practical or desirable for implementation in real-world settings due to productivity concerns. Multiple factors can lead to productivity loss when implementing job rotation, and it is essential to address them to achieve optimal job rotation outcomes.

In job rotation schedules, workers are assigned to rotate between different tasks throughout the workday, which potentially causes process discontinuity. Frequent rotations can result in significant productivity loss as workers require additional time to relocate and set up for new tasks. However, under harsh working conditions, frequent rotation may be necessary to prevent workers from being overly exposed to hazards. Therefore, finding a balance between worker safety and productivity is crucial to ensure that job rotation schedules benefit both workers and employers.

Several job rotation models have been proposed to address this issue. Asawarungsaengkul and Nanthavanij (2008) developed a noise-safe job rotation model that aims to minimize the frequency of worker-location changeovers while ensuring noise safety. Similarly, Rerkjirattikarn et al. (2017) introduced a model that minimizes the overall setup time incurred by job rotation while maintaining noise safety.

In addition to rotation frequency, the impact of worker skill heterogeneity on system productivity is also significant, particularly for labor-intensive and highly manual industries. When workers are rotated to tasks without considering their competency and the skill requirements of the tasks, productivity and product quality may deteriorate. Therefore, considering workers' competencies is essential for achieving better productivity performance and practicality in job rotation scheduling. Some models, such as the one proposed by Wongwien and Nanthavanij (2012), formulate each worker's ability to perform specific tasks as a constraint to prevent workers from rotating to tasks they cannot perform. Alternatively, workers can be categorized into different skill levels, each capable of performing a different set of tasks with varying throughput, as demonstrated in Aryanezhad et al. (2009). Incorporating workers' skills into the job rotation model enables the optimization of a broader range of productivity performance metrics. For instance, Moussavi et al. (2018) introduced a job rotation model that minimizes the total production cycle time by considering variations in production time based on the assigned workers' competencies. Similarly, Mossa et al. (2016) developed a job rotation scheduling model aimed at maximizing the total production level, with units produced per period based on workers' skills.

Job rotation models can also be extended to meet production demand requirements, which are among the most crucial objectives, especially for demand-driven manufacturing operations. Neglecting demand fulfillment during the job rotation scheduling process can lead to inadequate production outputs, as constant worker rotations can result in production losses along the way, risking the loss of customer reliance and competitiveness. McDonald et al. (2009) proposed a job rotation model that facilitates worker multi-skill learning while ensuring customer demand fulfillment. Niakan et al. (2016) developed a noise-safe worker assignment model that guarantees demand fulfillment by employing worker hiring, firing, or training schemes. Rerkjirattikarn et al. (2018) extended their work to develop a noise-safe job rotation model that fulfills demand requirements by assigning workers to work overtime during peak-demand periods. Their research demonstrates that a well-designed job rotation schedule can achieve desirable worker safety and production requirements outcomes, even with extended work hours.

While incorporating overtime assignments in the job rotation model enhances its practicality and production performance, it is crucial to consider that overtime hours can adversely affect worker safety and the economic aspect of the schedule. Achieving safe and cost-effective scheduling outcomes with sufficient production levels to meet demand remains a challenge that has not been fully explored in the literature. An open research area remains in developing innovative approaches to balance worker safety, economic considerations, and production requirements in job rotation scheduling.

2.3.3 Job rotation scheduling and worker job satisfaction

Worker job satisfaction is a crucial factor that positively influences worker performance and turnover rates. One effective way to incorporate job satisfaction considerations into scheduling is by allowing a certain degree of job autonomy, such as considering workers' preferences. Multiple aspects of workers' preferences can be integrated into the scheduling model to encourage worker engagement in the scheduling process. This approach ensures that the scheduling outcome aligns with workers' needs while also meeting safety and productivity criteria.

Among the various aspects of worker preferences, task preferences and days off are commonly considered in industrial workforce scheduling, as evidenced by several studies. For example, in the model proposed by Diego-Mas et al. (2009), workers can specify tasks they prefer not to undertake, and the model penalizes violations of these task preferences. Similarly, Wongwien and Nanthavanij (2017b) developed a safe job rotation scheduling model that minimizes the number of times workers' job and partner preferences are violated while maintaining worker safety. In Adem and Dağdeviren (2020), a job rotation scheduling model was formulated to mitigate vibration exposure while taking into account workers' preferred days off. Additionally, Soriano et al. (2020) introduced a job rotation model aimed at minimizing the total scheduling penalty, which encompasses unsatisfied requested days off and vacation leaves.

These studies highlight the significance of taking worker job satisfaction and preferences into account in job rotation scheduling, as they contribute to enhanced worker engagement and overall scheduling outcomes. Another crucial aspect that further reinforces job satisfaction is motivation and the reduction of monotony-induced boredom, which will be discussed in detail below.

2.3.4 Job rotation scheduling as worker cross-training and motivator

Job rotation serves as an effective means of providing workers with cross-training opportunities, enabling them to acquire tacit knowledge through the performance of various job roles. This practice has been widely acknowledged for its capacity to enhance worker flexibility, personal development, and career prospects (Al-Zoubi et al., 2022; Muduli, 2017).

The literature often integrates the learning effect into models to monitor workers' skill development during job rotation. The learning effect is a time-dependent factor that evolves as workers repeat tasks, resulting in reduced task completion times and increased output efficiency within the same time frame. Each worker possesses a distinct learning ability, known as the learning rate, and the time needed to acquire a skill may vary accordingly. The learning curve of workers can be estimated using the log-linear equation initially proposed by T. P. Wright (1936). This equation can be used in its original form or approximated to a linear counterpart. For instance, Olivella et al. (2013) introduced a job rotation model that aims to maximize the total work performed while ensuring that the worker cross-training objective is met by the end of the period. Similarly, Jin et al. (2016) proposed a worker assignment model focused on minimizing makespan while considering the learning effect. To address concerns regarding the computational time required to solve the non-linear model, they devised a linearized learning curve to shorten the problem-solving time.

Rotating workers through multiple job roles allows them to acquire diverse skills. Nevertheless, workers' productivity may decline after acquiring new skills if they lack the opportunity to perform relevant tasks for a certain period. This phenomenon is commonly referred to as the forgetting effect, posing a challenge in designing job rotation schedules that balance the acquisition of new skills with the preservation of previously acquired ones. The concept of worker learning and forgetting was generalized in the job rotation schedule by Azizi et al. (2010). They developed a job rotation model aimed at minimizing production delays resulting from workers' lack of skill and boredom-induced lack of motivation. Integrating learning-forgetting and boredom involves a combination of numerous non-linear equations in the mathematical model, making it more complicated to solve. To address this complexity, they proposed a specialized metaheuristic algorithm, SAMED, which combines SA and GA. Its effectiveness has been demonstrated to surpass that of conventional SA and GA methods. In a subsequent study, Azizi and Liang (2013) extended their job rotation model with the concept of skill learning and forgetting to minimize costs associated with training, worker flexibility, and productivity loss. Furthermore, Chu et al. (2019) introduced an adaptive memetic differential search algorithm to solve a comprehensive worker assignment model, accounting for learning and forgetting, in a cellular manufacturing system. The model's goal is to minimize total training costs and workload imbalances among cells.

In addition to worker cross-training, many studies have explored the role of job rotation in reducing boredom and increasing motivation, an aspect known to reinforce job satisfaction and worker performance across various industries, including manufacturing (A. Akbari & Maniei, 2017; Kurtulu, 2010; Tirloni et al., 2021). Boredom is characterized by a significant lack of interest in current tasks, often resulting from repetitive exposure and varying among individuals based on personality (Fisherl, 1993). While some studies have examined the relationship between boredom and job rotation schedules, this aspect has not received as much attention as the learning and forgetting effects. Models proposed by Ayough et al. (2012) and Bhadury and Radovilsky (2006), for example, aim to minimize total staffing costs and boredom associated with assigning the same job to workers throughout the planning period.

More recent research has integrated the boredom effect with learning and forgetting in worker assignment models. Motivation is considered a key factor in recovering from boredom, as suggested by Azizi et al. (2010). They proposed that rotating workers with low motivation away from repetitive tasks can aid in their recovery from boredom, leading to improved production performance. Building upon this concept, Ayough et al. (2020, 2021) developed job rotation scheduling algorithms for U-shaped and lean manufacturing cells. Despite the numerous studies employing job rotation for cross-training and motivating workers in manufacturing systems, a comprehensive job rotation model that integrates worker safety, cross-training, motivation, and job satisfaction aspects remains unexplored in the literature.

2.3.5 Research gaps in noise-safe job rotation scheduling

Following an extensive literature review, two notable research gaps have been identified in the area of noise-safe job rotation scheduling:

1. Previous research has not delved into the effectiveness of noise-safe job rotation scheduling within a demand-driven manufacturing system that incorporates the use of overtime assignments. The inclusion of overtime hours introduces additional complexities in ensuring worker safety while meeting production demand requirements. Such an aspect is prevalent in manufacturing operations and has not been sufficiently emphasized. To address this research challenge, this dissertation proposes a novel noise-safe job rotation scheduling model with simultaneous consideration of worker-task skill matching, demand-driven production, and overtime assignments. Furthermore, it also investigates the impact of worker skills on worker safety.

2. To date, no research has combined the advantages of job rotation in maintaining occupational safety with its potential for facilitating cross-training and motivating workers. This consideration is based on practical aspects found in day-to-day manufacturing operations and can help expand the potential of job rotation for practical implementation. Still, it presents a challenge in determining the optimal rotation plan to avoid interrupting workers' learning processes while ensuring their safety and motivation. Addressing this research gap, this dissertation introduces a novel job rotation scheduling model, taking into account multiple essential factors, including noise safety, skill learning and forgetting, and monotony-induced boredom. Additionally, it accommodates the consideration of worker heterogeneity in terms of skills, learning-forgetting-boredom rates, and job preferences.

By addressing these research gaps, this dissertation aims to contribute valuable insights and practical solutions to the field of job rotation scheduling in industrial applications.

2.4 Healthcare application (satisfaction-enhanced nurse scheduling)

This section addresses an area of WSP, specifically focusing on personnel scheduling in healthcare applications. The medical staff scheduling literature can be categorized into subcategories based on the personnel they focus on, including physician scheduling problems (PSP), resident scheduling problems (RSP), and nurse scheduling problems (NSP). This dissertation primarily emphasizes nurse scheduling, recognizing the vital role that nurses play in healthcare systems as front-line workers who actively engage in patient care throughout the treatment process.

The increasing demand for healthcare services has subjected nurses to challenging and strenuous conditions, including mandatory overtime, prolonged consecutive workdays, and insufficient time for adequate rest and recovery. These conditions have had adverse effects on nurses' well-being and job satisfaction, contributing to retention challenges and the persistent issue of nurse shortages. A well-designed nurse schedule, one that balances workload, allows for adequate rest and respects nurses' autonomy in selecting their shifts or days off preferences, plays a pivotal role in enhancing their well-being and job satisfaction. Consequently, such scheduling practices can help alleviate retention issues. Given these implications on human well-being, extensive research efforts have been devoted to developing systematic approaches to nurse scheduling, making it a subject of ongoing interest within the academic community.

The nurse scheduling problem (NSP) or nurse rostering problem (NRP) represents a variant of personnel scheduling, with nurses being the primary resource. The fundamental objective of NSP is to generate a periodic nurse-to-shift assignment on a weekly, biweekly, or monthly basis while adhering to a set of constraints encompassing hospital regulations and staffing requirements. Pioneering research by Maier-Rothe and Wolfe (1973) led to the development of an NSP mathematical model aimed at creating schedules that utilize the minimum number of nurses while adhering to hospital regulations. In recent decades, scholarly literature has increasingly recognized the critical role of nurses' job satisfaction in reducing turnover intention through systematic scheduling approaches. Numerous studies have emphasized the significance of developing nurse scheduling methodologies that positively influence job satisfaction by accommodating group and individual preferences while ensuring fairness.

2.4.1 Group and individual preferences in nurse scheduling problem

The scheduling of nurses involves addressing their often challenging shift work patterns, which can significantly impact their well-being and their ability to manage personal and family responsibilities. To promote nurse well-being and job satisfaction, it is crucial to incorporate nurses' preferences when creating work schedules, allowing them to have a degree of control over their schedules. Doing so helps nurses to achieve a better work-life balance, which, in turn, leads to increased job satisfaction, improved performance, and enhanced retention rates. In the satisfaction-enhanced NSP research, preference consideration can be categorized into group and individual preferences.

Group preferences encompass the general desirable characteristics of nurse schedules, including workload distribution, rest allowance, equitable allocation of days off, and adherence to constraints related to shift patterns. These constraints may include avoiding consecutive night shifts followed by morning shifts or setting limits on the number of night shifts per week or consecutive nights, which can vary across hospitals and regions. Numerous studies have focused on addressing group preferences, aiming to create nurse schedules that prioritize nurses' overall well-being and work-related preferences. For instance, Çetin and Sarucan (2015) and Al-Hinai et al. (2018) introduced group preference-based nurse scheduling approaches that consider desirable shift patterns, such as incorporating rest days after night shifts, limiting consecutive night shifts, ensuring weekend day-off allocation, and balancing workload between day and night shifts as primary goals in their GP models. Similarly, Rahimian et al. (2017) developed a CP-based NSP that minimizes violations of schedule quality constraints, encompassing criteria such as the minimum and maximum number of shift assignments, consecutive working days, consecutive shift types, and forbidden shift patterns. Éles et al. (2018) proposed a multi-commodity network flow nurse scheduling approach that takes into account nurses' well-being in terms of work hours and the succession of healthy shift patterns. Their model was validated using a real hospital case in Egypt, demonstrating improvements in the quality of shift and day-off assignments compared to manually generated schedules.

While group preferences indeed enhance overall schedule quality, addressing individual preferences is equally vital for ensuring job satisfaction. Preferences are diverse and encompass many aspects that are influenced by personal needs and lifestyle. Typical yet essential aspects are individual shift and day-off preferences. This allows flexibility for nurses to choose working times that align with their preferences and lifestyles. Several works have focused on incorporating individual shift or days off preferences. For instance, P. D. Wright and Mahar (2013) developed an NSP model that minimizes undesirable shifts, overtime, and weekend assignments. Y. C. Huang et al. (2016) integrated shift and day-off preferences into their NSP model, resulting in more satisfactory schedules compared to manual approaches. Chiang et al. (2019) proposed a multi-objective NSP model to fulfill individual day-off requests, assigning scores to preferences given by nurses. Similar approaches can be found in works such as Becker et al. (2019), L. Huang et al. (2021), and Legrain et al. (2015). Other aspects of individual preferences were also considered.

In addition to shift and day-off preferences, other aspects of individual preferences have also been considered. For example, Z. Liu et al. (2018) developed a nurse scheduling model that accounts for preferences in shifts and roles (in-charged, dispensing, and treatment). Furthermore, Hamid et al. (2020)'s NSP model minimizes incompatibility among nurses assigned to the same shift while maximizing nurses' shift preferences.

When incorporating individual preferences into mathematical model formulations, these preferences can be expressed in binary form, indicating whether a particular shift or day off is preferred, or in numerical values representing the degree of preference that nurses have for specific shifts or days off. Models such as those proposed by C. C. Lin et al. (2015) and C.-C. Lin et al. (2014) collect nurses' preferences as ranks. Using different preference ranks allows for increased flexibility in fulfilling nurses' preferences and resolving potential conflicts among preferences. However, it is important to note that different hospitals may adopt varying policies for handling individual preferences. Therefore, NSP models should be designed to accommodate both preference representations or be easily adaptable to specific hospital policies.

2.4.2 Scheduling fairness in nurse scheduling problem

In addition to accommodating nurses' preferences, fairness plays a crucial role in determining overall nurse satisfaction with their work schedules. Within the existing literature, scheduling fairness typically revolves around two vital dimensions: balancing the workload and balancing preferred assignments.

Several studies have proposed NSP models to address workload variations among nurses while omitting their individual preferences. These works include those by Al-Hinai et al. (2018), Fügener et al. (2018), Mohammadian et al. (2019), and Thongsanit et al. (2016). Meanwhile, Youssef and Senbel (2018) formulated an NSP that considers nurses' shift and day-off preferences while ensuring a balance only in workload assignments. Osman et al. (2019) proposed an NSP approach that ensures nurses receive an equitable amount of day-offs.

Concerning fairness in preference assignments, most studies have typically concentrated on either achieving balance in the allocation of preferred shifts B. Y. Ang et al. (2018) or preferred day-offs Michael et al. (2014). However, C. C. Lin et al. (2015) developed an NSP algorithm that balances both nurses' preferred shifts and day-off allocations simultaneously. Nevertheless, their model did not address workload assignment balancing. This indicates a significant research gap, as there is still a need for approaches to address comprehensive aspects of scheduling fairness, including workload allocation and preferred shift and day-off assignments simultaneously. Prioritizing one aspect over the other may not fully capture fairness from a holistic perspective. For instance, schedules with an equitable workload distribution but significant discrepancies in preferred assignment allocation may lead to perceived unfairness among nurses, potentially resulting in job dissatisfaction. Therefore, considering all fairness aspects can significantly enhance nurses' satisfaction with their work schedules.

2.4.3 Cost-effectiveness in satisfaction-enhanced nurse scheduling problem

Job satisfaction is vital for nurse retention and service quality. Many studies have attempted to enhance nurse satisfaction through scheduling approaches, considering multiple aspects of preferences and fairness. However, the economic aspect is essential from a management perspective. A schedule with maximized job satisfaction may not be practically feasible as hospitals must also manage their expenses. Thus, there is a need for nurse scheduling that balances cost-effectiveness and job satisfaction, accommodating the needs of both hospitals and nurses.

Several studies addressed cost-effectiveness in satisfaction-enhanced nurse scheduling. For instance, J. Lim et al. (2012) proposed an NSP model that minimizes total staffing costs while meeting nurses' shift preferences and patient workload requirements. P. D. Wright and Mahar (2013) introduced centralized and decentralized NSP models, minimizing total regular and overtime wages and undesirable shift assignments, comparing cost reduction and overtime utilization of both policies. El Adoly et al. (2018) presented a nurse scheduling method that minimizes nurse assignment and overtime costs with constraints to improve schedule quality regarding workload and shift assignments. An actual hospital case in Egypt was used for model validation, and their model demonstrated its ability to decrease overtime cost and workload while providing more proper rest allowance. Hamid et al. (2018) developed a nurse scheduling approach optimizing staffing cost and nurses' job satisfaction under workload balancing constraints. They later extended their model accounting for nurses' preferred shifts and co-workers (Hamid et al., 2020).

However, despite these advancements, the inclusion of cost in the satisfaction-enhanced NSP context still holds potential for further improvements. For example, the trade-off between cost-effectiveness and job satisfaction still needs to be explored. This dissertation aims to provide valuable insights and guidance to management on allocating resources to achieve higher job satisfaction in scheduling without compromising cost considerations.

2.4.4 Research gaps in satisfaction-enhanced nurse scheduling

Based on the extensive literature review, this dissertation addresses two significant research gaps within the domain of satisfaction-enhanced nurse scheduling. These gaps are essential for further enhancing the practicality and applicability of satisfaction-enhanced NSP:

1. The current literature on nurse scheduling often fails to provide comprehensive fairness, as it primarily focuses on balancing individual workloads or preferences. This

approach leads to schedules that prioritize one aspect over the other and may not fully capture overall job satisfaction. To address this research gap, this dissertation proposes a GP nurse scheduling model that takes into account comprehensive individual preferences and fairness factors. The model aims to optimize nurses' preferred shifts and days off while ensuring equitable workload and preferred assignment distribution.

2. The integration of cost considerations within satisfaction-enhanced NSP is an area that requires further exploration. Current studies that incorporate cost tend to focus on singular aspects of preferences or fairness. Furthermore, the examination of trade-offs between cost and job satisfaction remains relatively unexplored. To address this gap, a bi-objective NSP model is introduced in this dissertation which minimizes the total staffing cost and maximizes all nurses' minimum total preference scores, which are derived from individual shift and day-off preferences. The model also ensures comprehensive fairness in balancing workload and preferred assignments.

Furthermore, the proposed nurse scheduling models are designed to accommodate double-shift workday assignments, which are common in various countries, including Thailand but often neglected in the existing nurse scheduling research. Additional constraints are introduced to control consecutive double-shift workdays, ensuring a healthier work schedule and sufficient rest. These models fill another crucial research gap addressed in Abdalkareem et al. (2021), which underscores the need to consider specific work conditions in different countries to improve the practicality of nurse scheduling approaches and bridge the gap between theoretical research and practical application.

CHAPTER 3
NOISE-SAFE JOB ROTATION SCHEDULING MODELS

This chapter presents the development of two noise-safe job rotation models proposed in this dissertation. Section 3.1 describes noise standards and calculations. Section 3.2 outlines the mathematical model for the noise-safe job rotation with skill and demand requirements. Section 3.3 covers the development of the noise-safe job rotation model considering learning-forgetting and the boredom effect. Each section includes the model validation process, experimental results, and discussions.

3.1 Noise standard and calculation

Noise represents a significant occupational hazard, especially in heavy industries such as wood and metal fabrication plants. Prolonged exposure to excessive noise can lead to temporary or permanent hearing impairment, physical stress, elevated blood pressure, and an increased risk of cardiovascular diseases. When noise levels rise within a workplace, it is mandatory to establish effective control measures to protect employees.

Various noise-measuring tools, including sound level meters and noise dosimeters, can be employed to assess the noise emitted from machinery. These instruments quantify the sound pressure level (SPL), usually expressed in decibel A (dBA) units, corresponding to the loudness perceived by the human ear. By correlating this data with the daily duration of exposure, the management can accurately evaluate the potential risk of excessive noise exposure for workers.

Occupational noise regulatory guidelines

- **Occupational Safety and Health Administration (OSHA):** Mandatory legally enforceable standard for noise exposure in the workplace is mandated at 90 dBA averaged over an 8-hour workday. OSHA also recommends implementing a hearing conservation program for workplaces where noise levels exceed 85 dBA over an 8-hour day.

- **National Institute for Occupational Safety and Health (NIOSH):** Recommended noise exposure limit is at 85 dBA over an 8-hour workday. A lower noise exposure limit aims to provide a safer working environment for workers. However, strictly adhering to this recommended threshold is not legally mandatory.

Exposure to noise levels at or above these defined thresholds significantly increases the risk of noise-induced hearing loss among workers. It is important to note that different countries and regions may adhere to distinct noise regulatory guidelines. This dissertation complies with the guidelines established by the Thailand Department of Labor Protection and Welfare, which has adopted the NIOSH noise exposure threshold. This ensures that our research is in harmony with internationally recognized standards for occupational noise exposure.

Noise exposure and permissible duration calculation

Given a noise exposure level in dBA, the reference exposure duration (T) in hours can be calculated using equations (3.1) - (3.3), as provided by the occupational noise guidebook published by the NIOSH (Chan, 1998):

$$T = \frac{8}{2^{(SPL-85)/3}} \tag{3.1}$$

Subsequently, the daily noise dose (DND), indicating the percentage of allowable noise exposure, can be calculated using the equation below. A noise dose exceeding 100% suggests that the worker has been exposed to noise levels exceeding the permissible threshold.

$$DND = 100 \cdot \left(\frac{C_s}{T_s} + \frac{C_{s+1}}{T_{s+1}} + ... + \frac{C_S}{T_S}\right) \tag{3.2}$$

Where:

- s is a set of shifts in a workday; $\mathcal{S}$ = {1, 2,. . . , S}
- C_s indicates the exposure duration of a specific SPL during the shift s.

The DND value can be converted to the Time-Weighted Average (TWA) value in dBA using the following equation:

$$TWA = 10 \cdot \log\left(\frac{DND}{100}\right) + 85 \tag{3.3}$$

Table 3.1 summarizes noise exposure levels and their recommended exposure duration according to the NIOSH's standard.

Table 3.1 Noise level and associated exposure duration as per NIOSH

Noise exposure level (SPL)	Recommended exposure duration (T)
82 dBA	12 hours
84 dBA	10 hours
85 dBA	8 hours
88 dBA	4 hours
91 dBA	2 hours
94 dBA	1 hour
97 dBA	30 minutes
100 dBA	15 minutes

The DND calculation is demonstrated with an example of an 8-hour workday. If a worker is exposed to 84 dBA noise level for 3 hours and 88 dBA for the next 5 hours, the recommended exposure duration (T) from Table 3.1 can be substituted into equations (3.2), and (3.3).

$$DND = 100 \cdot (\frac{3}{10} + \frac{5}{4}) = 155\%$$

$$TWA = 10 \cdot \log(\frac{155}{100}) + 85 = 87$$

The calculated DND value in this example exceeds the recommended threshold of 100%, with the TWA noise exposure level at 87 dBA. This underscores the need to control worker exposure duration near noise-emitting machines. In such cases, job rotation can be a useful strategy to mitigate prolonged exposure, supplementing personal protective equipment and other hazard control measures.

When applying the noise-safe concept to the mathematical model, a constraint can be imposed to limit the DND of workers to be within 100% or TWA within 85 dBA. Subsequently, the mathematical model can determine assignments that comply with the noise-safe requirements. However, in cases with extreme noise levels, such a constraint might be too strict, and the model may struggle to find assignments that strictly adhere to the guidelines. An alternative approach is to integrate the noise calculation as an objective function. In this scenario, the model focuses on minimizing the maximum noise level among workers. This method allows for a more flexible solution, especially in harsh working conditions, given that other hazard control measures are sufficient. Similar logic can be applied to address other occupational hazards as well.

3.2 The noise-safe job rotation scheduling model considering skill and demand requirements

Job rotation is an effective and cost-efficient strategy for controlling hazards, a practice widely adopted across diverse industries. While it effectively mitigates prolonged exposure to hazards, frequent rotation or rotation without considering worker-task skill requirements can potentially reduce production performance and system productivity. This is critical to prevent potential disruptions in production flow and to ensure that worker rotations align with the demands of each task, which ultimately safeguards both productivity and workers' health.

Addressing demand fulfillment in workforce scheduling is equally imperative, especially in demand-driven manufacturing systems, especially in demand-driven manufacturing systems. Neglecting to consider demand in the job rotation plan may lead to production shortfalls, resulting in the inability to meet customer demand. This is particularly important for demand-driven manufacturing systems or demand fluctuation situations. In response, management often resorts to assigning overtime hours to increase production capacity to the required level. However, while overtime can enhance production performance, it does come at the cost of prolonged exposure for workers, putting them at more risk.

This holistic approach to job rotation scheduling is particularly vital in labor-intensive industries with challenging working conditions. However, such a consideration has not been extensively explored in the existing literature. To address this challenge, this dissertation introduces a novel noise-safe job rotation model encompassing product demand, worker-task skill requirements, and overtime assignments. This model serves as a valuable decision-support tool, ensuring the demand and noise safety requirements are met throughout the planning horizon. The model can be employed as a supplementary hazard control measure, fostering a safer work environment for workers without requiring substantial investments. The mathematical formulation of the model is described below.

3.2.1 Mathematical model formulation

The noise-safe job rotation scheduling model considering skill and demand requirements is developed as an integer programming (IP) model. The objective is to minimize the total staffing cost, which encompasses both regular and overtime hourly wages. It is designed to ensure that the resulting schedule aligns with cost-saving operational goals while ensuring worker safety and sufficient production performance.

This model is tailored to accommodate manufacturing systems that engage workers with varying skill levels, with each task demanding distinct proficiency levels. This configuration is commonly observed in labor-intensive industries, where human labor is engaged in machine operations. The following are assumptions and notations used in the model formulation.

Assumptions

- Workers are categorized into three skill levels—entry, intermediate, and expert. Meanwhile, tasks are classified into three difficulty levels, with level 3 being the most challenging.
- Experts are proficient in performing all tasks, intermediates can handle levels 1 and 2 tasks, and entry-level workers manage only level 1 tasks.
- Steady-state production rates occur when workers perform the same task for consecutive shifts.
- Overtime is permitted for workers engaged in both morning and afternoon shifts.
- The planning horizon encompasses multiple workdays, each composed of various shifts, including morning, afternoon, and overtime. Shift and planning horizon lengths are adjustable based on different manufacturing operations.
- Workers can perform only one task during each shift, with job rotations allowed only at the end of a shift.
- The allocation of workers to tasks varies according to the demand level for each specific task.
- Labor costs encompass both regular and overtime shift wages, with these costs differing for each worker level.
- The permissible noise exposure is 85 dBA for a standard 8-hour workday (DND not exceeding 100%). The noise limit differs for an extended workday depending on the length of overtime hours.
- Workers must receive at least a specified amount of days off per week.

Indices

$\mathcal{W}$	Set of workers; $\mathcal{W}$ = {1, 2, . . . , W}
$\mathcal{K}$	Set of worker skill levels; $\mathcal{K}$ = {1, 2, . . . , K}
$\mathcal{T}$	Set of tasks; $\mathcal{T}$ = {1, 2,. . . , T}
$\mathcal{S}$	Set of shifts in a workday; $\mathcal{S}$ = {1, 2, . . . , S}
$\mathcal{D}$	Set of days in planning horizon; $\mathcal{D}$ = {1, 2, . . . , D}

Input parameters

ND_t	Noise dose received by a worker from performing task t for one shift.
Dem_t	Demand requirement of task t in units to be fulfilled at the end of the planning period.
E_{wkt}	A binary parameter: 1 if worker w with skill level k is eligible to perform task t, 0 otherwise.
PR_{kt}	Initial production rate of a worker with skill level k performing task t in units.
SR_{kt}	Steady-state production rate achieved when a worker with skill level k performs task t over consecutive shifts.
W_k	Regular daily wage of a worker with skill k.
O_k	Overtime wage of a worker with skill k.
DND	Maximum allowable daily noise dose.
WD	Maximum number of workdays that can be assigned to workers.
OT	Maximum number of overtime shifts that can be assigned to workers.

Decision variables

X_{wktsd}	= 1 if worker w with skill k is assigned task t in shift s on day d, otherwise 0.
Y_{wktd}	= 1 if worker w with skill k performs task t in both morning and afternoon shifts on day d, otherwise 0.
Z_{wktd}	= 1 if worker w with skill k performs task t in morning, afternoon, and overtime shifts on day d, otherwise 0.
A_{wkd}	= 1 if worker w with skill k is scheduled for at least one shift on day d, otherwise 0.

Objective function

The objective function aims to minimize the total labor cost, which comprises both regular and overtime wages. It can be mathematically expressed as:

$$\min \sum_{w=1}^{W}\sum_{k=1}^{K}\sum_{d=1}^{D}(W_k \cdot A_{wkd}) + \sum_{w=1}^{W}\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{s=S}\sum_{d=1}^{D}(O_k \cdot X_{wktsd}) \tag{3.4}$$

Constraints

$$\sum_{t=1}^{T} X_{wktsd} \leq 1 \quad \forall w \in \mathcal{W}; k \in \mathcal{K}; s \in \mathcal{S}; d \in \mathcal{D} \tag{3.5}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S} X_{wktsd} \leq S \cdot A_{wkd} \quad \forall w \in \mathcal{W}; k \in \mathcal{K}; d \in \mathcal{D} \tag{3.6}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S-1}(ND_t \cdot X_{wktsd}) + \frac{o}{r}\sum_{t=1}^{T}\sum_{s=S}(ND_t \cdot X_{wktsd}) \leq DND \quad \forall w \in \mathcal{W}; k \in \mathcal{K}; d \in \mathcal{D} \tag{3.7}$$

$$2 \cdot \sum_{t=1}^{T}\sum_{s=S} X_{wktsd} - \sum_{t=1}^{T}\sum_{s=1}^{S-1} X_{wktsd} \leq 0 \quad \forall w \in \mathcal{W}; k \in \mathcal{K}; d \in \mathcal{D} \tag{3.8}$$

$$\begin{aligned} PR_{kt} \cdot (&\sum_{w=1}^{W}\sum_{k=1}^{K}\sum_{s=1}^{S-1}\sum_{d=1}^{D} X_{wktsd} + \frac{o}{r} \cdot \sum_{w=1}^{W}\sum_{k=1}^{K}\sum_{s=S}\sum_{d=1}^{D} X_{wktsd}) + \\ &\sum_{w=1}^{W}\sum_{k=1}^{K}\sum_{d=1}^{D}[(SR_{kt} - PR_{kt}) \cdot (Y_{wktd} + Z_{wktd})] \geq Dem_t \quad \forall t \in \mathcal{T} \end{aligned} \tag{3.9}$$

$$Y_{wktd} \leq 0.5 \cdot \sum_{s=1}^{S-1} X_{wktsd} \quad \forall w \in \mathcal{W}; k \in \mathcal{K}; t \in \mathcal{T}; d \in \mathcal{D} \tag{3.10}$$

$$Y_{wktd} + 1 \geq \sum_{s=1}^{S-1} X_{wktsd} \quad \forall w \in \mathcal{W}; k \in \mathcal{K}; t \in \mathcal{T}; d \in \mathcal{D} \tag{3.11}$$

$$Z_{wktd} \leq 0.5 \cdot \sum_{s=S-1}^{S} X_{wktsd} \quad \forall w \in \mathcal{W}; k \in \mathcal{K}; t \in \mathcal{T}; d \in \mathcal{D} \tag{3.12}$$

$$Z_{wktd} + 1 \geq \sum_{s=S-1}^{S} X_{wktsd} \quad \forall w \in \mathcal{W}; k \in \mathcal{K}; t \in \mathcal{T}; d \in \mathcal{D} \tag{3.13}$$

$$\sum_{d=1}^{D} A_{wkd} \leq WD \quad \forall w \in \mathcal{W}; k \in \mathcal{K} \tag{3.14}$$

$$X_{wktsd} \leq E_{wkt} \quad \forall w \in \mathcal{W}; k \in \mathcal{K}; s \in \mathcal{S}; t \in \mathcal{T}; d \in \mathcal{D} \tag{3.15}$$

$$\sum_{s=S} \sum_{d=1}^{D} X_{wktsd} \leq OT \quad \forall w \in \mathcal{W}; k \in \mathcal{K} \tag{3.16}$$

$$X_{wktsd}, Y_{wktd}, Z_{wktd}, A_{wkd} \in \{0, 1\} \tag{3.17}$$

Constraint (3.5) ensures that each worker is allocated to a single task at any given time. Constraint (3.6) prevents shift assignment on designated days off. Constraint (3.7) is the DND calculation equation derived from equation (3.2), which is the summation of the proportion of actual exposure duration and the recommended duration associated with noise levels exposed throughout a workday. The second term indicates noise levels received during overtime shift of length o, proportional to a regular length shift r. This constraint is key to the noise-safe job rotation strategy as it restricts workers' total daily noise dose, including regular and overtime hours, to be within permissible limits. Constraint (3.8) restricts overtime eligibility to workers engaging in both morning and afternoon shifts. Constraint (3.9) guarantees fulfillment of task demands. Constraints (3.10) and (3.11) identify whether workers are consecutively assigned the same task during regular shifts. Constraints (3.12) and (3.13) determine whether workers are assigned the same task during overtime shifts.

Constraint (3.14) limits the number of workdays per planning period. Constraint (3.15) ensures alignment between worker skills and task skill requirements. Constraint (3.16) limits the number of overtime assignments in a planning period. Constraint (3.17) is the standard integrality constraint.

3.2.2 Numerical example

In this section, a numerical example is presented to demonstrate the practical application of the proposed model. The example considers a manufacturing system comprising ten workers and seven tasks. The workforce is categorized into three experience levels: five entry-level workers, three intermediate-level workers, and two experts. The smaller number of experts reflects the actual challenges of acquiring and training highly skilled workers.

The planning horizon of seven workdays (one week) is assumed, which is a typical duration for short-term scheduling in manufacturing plants. Each workday consists of two 4-hour shifts, labeled as Morning (M) and Afternoon (A), as well as a 2-hour overtime shift (O). This numerical example emphasizing matching worker skills with task requirements represents labor-intensive, small and medium-sized enterprises (SMEs), which generally utilize semi-skilled and skilled laborers operating with machines.

Realistic wage rates for industrial workers in Thailand are used, converting them from Thai Baht to US dollars as detailed in Table 3.2.

Table 3.2 Wages for workers at different skill levels

Worker level	Entry	Intermediate	Expert
Regular daily wage (W_k)($)	11.23	12.35	15.08
Overtime shift wage (O_k)($)	4.23	4.62	5.65

The tasks are categorized into three levels based on complexity, with level 3 representing the most complex tasks. Table 3.3 provides values for the worker-workstation capability index (E_{wkt}), noise levels, and noise doses associated with each task. Additionally, Table 3.4 summarizes the initial production rate, steady-state production rate, and demand requirement of each task.

Table 3.3 Job difficulty index, worker level capability index, and noise levels

Tasks	Difficulty index	Worker capability index			Noise level (dBA)	Noise dose per 4-hour shift (%)
		Entry	Intermediate	Expert		
T1	1	1	1	1	87	79.4
T2	1	1	1	1	79	12.5
T3	2	0	1	1	80	15.7
T4	2	0	1	1	86	63
T5	2	0	1	1	84	39.7
T6	3	0	0	1	86	63
T7	3	0	0	1	81	13.8

Table 3.4 Tasks' initial and steady-state production rates and demand requirements

Tasks	Difficulty index	Initial production rate (units/ shift) (PR_{kt})			Steady-state production rate (units/ shift) (SR_{kt})			Demand (units)
		Entry	Intermediate	Expert	Entry	Intermediate	Expert	
T1	1	90	110	120	110	125	145	2,700
T2	1	110	130	140	120	140	170	2,900
T3	2	0	100	120	0	120	140	1,800
T4	2	0	100	120	0	120	130	1,700
T5	2	0	150	165	0	165	180	1,900
T6	3	0	0	90	0	0	110	1,000
T7	3	0	0	100	0	0	120	1,200

3.2.3 Results and discussion

This section presents the empirical findings of the proposed job rotation model, examining its effectiveness in mitigating excessive noise exposure while meeting operational demands. To analyze the impact of worker skill on noise safety, three scenarios featuring different worker skill compositions are considered: 1) Normal skill mix, 2) Medium skill mix, and 3) High skill mix, as detailed in Table 3.5. 'The Normal skill mix' scenario represents typical manufacturing operations, where entry-level workers make up the majority, while expert-level workers are typically fewer in number. In contrast, the 'High skill mix' scenario includes the highest number of experts, allowing us to explore the impact of a more proficient workforce on job rotation and worker safety. The model is solved using OpenSolver version 2.9.0, an optimization tool add-in for Microsoft Excel, running on a 2.3 GHz Dual-Core Intel Core i5-8300H processor for all analyses. The model efficiently produces optimal job rotation schedules for all scenarios within a minute.

Table 3.5 Worker skill composition of each scenario

Worker level	Entry	Intermediate	Expert
Scenario 1: Normal skill mix	5	3	2
Scenario 2: Medium skill mix	4	3	3
Scenario 3: High skill mix	3	3	4

The impact of job rotation on labor cost, safety, and productivity

This initial analysis focuses on exploring the impact of job rotation on labor cost, safety, and productivity. This examination compares schedule outcomes between non-rotation and job rotation plans under the 'Normal-skill mix' scenario. The non-rotation plan represents a productivity-focused scheduling strategy that prioritizes worker-task skill matching but does not explicitly consider safety considerations. The comparative results can be found in Table 3.6.

Table 3.6 Performance comparison between non-rotation and job rotation plan

Key performance indicators (KPIs)	Non-rotation plan	Job rotation plan
Total labor cost ($)	747.19	827.72
Maximum/minimum DND	1.98/ 0.25	0.99/ 0.71
Average DND (SD)	0.87 (0.54)	0.89 (0.07)
Frequency of DND exceeding 1.0	24	0
Total regular shifts assigned	112	120
Total overtime shifts assigned	11	15
Total steady-state production units achieved	1,165	225

As indicated in Table 3.6, the non-rotation plan results in workers experiencing DND levels nearly double the safe limit of 1.0. Over the 7-day planning period, workers exceeded the safe DND threshold on 24 occasions. Although the average DND appears almost the same for both rotation and non-rotation plans, the non-rotation plan exhibits a wider spread of DND, indicated by a significantly higher SD and range. This means that, in the non-rotation plan, some workers are exposed to minimal DND levels, while others experience almost double the DND limit. Consequently, the non-rotation plan has a lower DND average than the rotation plan, where the range of DND is smaller, resulting in a higher average.

However, the non-rotation plan performs better when considering economic and productivity aspects. It requires fewer overtime assignments to meet the same demands, leading to reduced labor costs. Additionally, higher production rates are achieved through work continuity, as less production is lost due to workers needing to rotate and adapt to different tasks.

In contrast, under the proposed job rotation scheduling approach, the cost increases to $827.72, or approximately 10%. Nevertheless, all workers' DND levels remain within the safe limit throughout the planning period. The noise-safe schedule employs more regular shifts and overtime hours to fulfill demand due to the disruption in process continuity caused by job rotation, resulting in a significantly lower steady-state production rate. These results highlight the inherent trade-offs between safety and cost and between safety and production performance. They also demonstrate the model's capability to ensure worker safety while meeting demand requirements despite the additional total labor cost. The findings offer insights for decision-makers seeking to implement a job rotation scheduling plan.

It is crucial to emphasize that this model strictly adheres to noise safety standards, ensuring that exposure remains within the permissible limit. However, meeting this standard may be challenging in some scenarios, particularly in manufacturing systems with extremely high noise levels. For such cases, there is flexibility to adjust the noise consideration by either raising the DND limit or treating it as an additional objective function. This adaptation allows the model to generate a job rotation plan that balances worker safety with other operational requirements. Subsequently, supplementary measures such as engineering controls or personal protective equipment can be introduced to mitigate noise exposure levels effectively. Moreover, the constraint related to demand requirements can also be modified by introducing violation penalties, making the model more adaptable to fluctuations in demand.

The impact of worker skill composition on job rotation performance

The proposed job rotation model is applied to three different worker skill composition scenarios to assess how varying worker skills influence job rotation safety and operational performance. The outcomes of the job rotation model are assessed across these scenarios and are summarized in Table 3.7.

Table 3.7 Performance of job rotation scheduling under different worker skill composition scenarios

Key performance indicators (KPIs)	Scenario 1: Normal skill mix	Scenario 2: Medium skill mix	Scenario 3: High skill mix
Total labor cost ($)	827.72	803.91	798.08
Maximum/minimum DND	0.99/ 0.71	0.99/ 0.67	0.99/ 0.65
Average DND (SD)	0.89 (0.070)	0.87 (0.085)	0.85 (0.086)
Frequency of workers with DND > 0.9	42	36	28
Total regular shifts assigned	120	120	118
Total overtime shifts assigned	15	8	5

The results reveal that, despite the higher wages paid to expert workers, the scenario with a larger proportion of expert-level workers (Scenario 3) is more cost-effective. Scenario 3 demonstrates a cost reduction of approximately 3.6% compared to Scenario 1. This cost-saving can be attributed to the higher production rates of expert workers, requiring fewer shifts and less overtime to meet the same demand.

Regarding noise exposure, all scenarios maintain the maximum DND values within the safe limit. However, as more expert-level workers are incorporated, the average DND and the frequency of workers exposed to DND levels exceeding 0.9 decreases. On average, Scenario 1 has the highest DND values due to the lower spread of noise exposure levels. This indicates that workers are almost equally exposed to high noise levels, as evidenced by a lower range and SD. In contrast, Scenario 3 exhibits the lowest average DND due to a greater spread of noise exposure levels among workers, and the frequency of workers with DND exceeding 0.9 is lower than that of the two scenarios.

These findings suggest that a workforce with a higher proportion of expert workers (Scenario 3) can enhance noise safety by achieving the required production rates more efficiently, meeting the same demand within less time, and thereby reducing the risk and duration of excessive noise exposure. To provide a more detailed insight into how worker skills affect job rotation schedules, work schedules for scenarios 1 and 3 are provided in Tables 3.8 and 3.9.

Table 3.8 Job rotation schedule under Scenario 1: Normal skill mix

Level	Workers	Daily task assignment for Morning, Afternoon, Overtime shifts (DND)							Total shifts	
		D1	D2	D3	D4	D5	D6	D7	Regular	Overtime
Entry	1	T1, T2, - (0.919)	T1, T2, - (0.919)	T2, T1, - (0.919)	T1, T2, - (0.919)	T2, T1, - (0.919)	T2, T1, - (0.919)	DAY OFF	12	0
	2	T2, T1, - (0.919)	T2, T1, - (0.919)	T1, T2, - (0.919)	DAY OFF	T1, T2, - (0.919)	T1, T2, - (0.919)	T1, T2, - (0.919)	12	0
	3	T1, T2, - (0.919)	T2, T1, - (0.919)	DAY OFF	T2, T1, - (0.919)	T1, T2, - (0.919)	T2, T1, - (0.919)	T1, T2, - (0.919)	12	0
	4	T2, T1, - (0.919)	T1, T2, - (0.919)	T2, T1, - (0.919)	T1, T2, - (0.919)	DAY OFF	T2, T1, - (0.919)	T1, T2, - (0.919)	12	0
	5	T1, T2, - (0.919)	T1, T2, - (0.919)	T1, T2, - (0.919)	T1, T2, - (0.919)	DAY OFF	T2, T1, - (0.919)	T1, T2, - (0.919)	12	0
Interme-diate	6	T4, T3, T5 (0.986)	T4, T3, T5 (0.986)	T4, T3, - (0.787)	DAY OFF	T4,T3,T5 (0.986)	T4, T3, - (0.787)	T4, T2, - (0.755)	12	3
	7	T4, T3, T5 (0.986)	DAY OFF	T3, T4, - (0.787)	T5, T5, T5 (0.992)	T4, T3, - (0.787)	T3, T4, - (0.787)	T5, T5, T3 (0.872)	12	3
	8	T4, T3, T5 (0.986)	DAY OFF	T3, T4, - (0.787)	T5, T5, T5 (0.992)	T4, T3, T5 (0.986)	T4, T3, - (0.787)	T4, T3, - (0.787)	12	3
Expert	9	T5, T5, T5 (0.992)	DAY OFF	T6, T2, T7 (0.854)	T3, T6, - (0.787)	T5, T7, T6 (0.910)	T5, T5, - (0.794)	T7, T6, - (0.828)	12	3
	10	T6, T7, T7 (0.928)	T6, T7, T7 (0.928)	T6, T7, - (0.828)	T6, T7, - (0.828)	DAY OFF	T7, T7, T4 (0.712)	T6, T3, - (0.787)	12	3
								Total labor cost ($)	827.72	

Table 3.9 Job rotation schedule under Scenario 3: High skill mix

Level	Workers	Daily task assignment for Morning, Afternoon, Overtime shifts (DND)							Total shifts	
		D1	D2	D3	D4	D5	D6	D7	Regular	Overtime
Entry	1	T2, T1, - (0.919)	DAY OFF	DAY OFF	T1, T2, T2 (0.981)	T2, T1, - (0.919)	T2, T1, - (0.919)	T2, T1, - (0.919)	10	1
	2	T1, T2, - (0.919)	T2, T1, - (0.919)	T1, T2, - (0.919)	DAY OFF	T1, T2, - (0.919)	T1, T2, T2 (0.981)	T1, T2, - (0.919)	12	1
	3	T1, T2, - (0.919)	T2, T2, T1 (0.647)	DAY OFF	T2, T1, - (0.919)	T1, T2, - (0.919)	T2, T1, - (0.919)	T1, T2, - (0.919)	12	1
Interme-diate	4	T3, T1, - (0.951)	T4, T3, - (0.787)	T2, T1, - (0.919)	T3, T1, - (0.951)	DAY OFF	T1, T2, - (0.919)	T2, T4, - (0.755)	12	0
	5	T1, T2, - (0.919)	T1, T2, - (0.919)	T1, T2, - (0.919)	T1, T2, - (0.919)	DAY OFF	T2, T1, - (0.919)	T1, T2, - (0.919)	12	0
	6	T4, T2, - (0.755)	T4, T3, - (0.787)	T4, T3, - (0.787)	DAY OFF	T4, T3, T5 (0.986)	T3, T1, - (0.951)	T4, T3, - (0.787)	12	1
Expert	7	T4, T3, - (0.787)	T6, T2, - (0.755)	T1, T7, - (0.992)	T5, T5, - (0.794)	T4, T3, - (0.787)	DAY OFF	T5, T5, - (0.794)	12	0
	8	DAY OFF	T1, T2, - (0.919)	T7, T4, - (0.828)	T5, T5, - (0.794)	T4, T2, - (0.755)	T7, T3, T6 (0.671)	T4, T3, - (0.787)	12	1
	9	DAY OFF	T6, T7, - (0.828)	T5, T5, - (0.794)	T7, T6, - (0.828)	T5, T5, - (0.794)	T5, T5, - (0.794)	T6, T7, - (0.828)	12	0
	10	T4, T2, - (0.755)	T6, T7, - (0.828)	T5, T5, - (0.794)	T6, T7, - (0.828)	DAY OFF	T6, T7, - (0.828)	T6, T7, - (0.828)	12	0
								Total labor cost ($)	798.08	

The numerical example employed to validate the model reflects the typical scale of SME manufacturing plants. In all scenarios, the model efficiently generates optimal 7-day job rotation schedules for 10 workers handling 7 tasks in just 0.02 seconds. This computational efficiency extends to larger workforce sizes of 30 workers, with a solution time of 2 seconds. These results underscore the model's applicability to larger manufacturing environments, demonstrating its capacity to swiftly create job rotation schedules without substantial time or financial investments.

From a practical standpoint, the model is developed in a generic manner, making it easily adaptable to a range of scenarios with minimal adjustments. Decision-makers can fine-tune the model by modifying its size, input parameters, or planning horizon to align with the specific needs of their manufacturing operations. Furthermore, certain constraints, like those related to noise safety or demand requirements, can be modified or relaxed to enhance flexibility in generating job rotation schedules.

3.2.4 Conclusion

This section introduces a novel noise-safe job rotation scheduling model, which addresses the intricate interplay of essential scheduling factors, encompassing safety, worker skill, productivity, and demand requirements. The model takes into account aspects like aligning worker skills with specific tasks, demand-driven production, and overtime considerations, factors that have not been extensively explored in existing literature. Formulated as an integer programming problem, the model seeks to minimize the overall labor cost associated with employing workers of various skill levels during regular and overtime hours.

To validate the model, a numerical example is used to represent labor-intensive SMEs with heterogeneous workforces and tasks of varying complexities. When compared to a non-rotation plan, the job rotation schedule generated by the proposed model demonstrates a notable improvement in workforce safety. Although this is accompanied by a slight increase in labor costs due to process disruptions caused by job rotations, it underlines the inherent trade-off between cost and worker safety. Nevertheless, the model can produce job rotation schedules that effectively meet both demand and safety requirements while maintaining costs at a minimal level within a negligible time.

Furthermore, scenario analyses are conducted under scenarios varying the numbers of entry-level and expert workers in the rotation plan. These analyses emphasize the role of worker skill and expertise in simultaneously achieving better cost management, boosting productivity, and enhancing worker safety. The findings suggest that including more expert workers in the rotation plan can efficiently fulfill demand requirements using fewer regular and overtime shifts, resulting in a more cost-effective and safer job rotation strategy. This sheds light on the importance and positive effects of worker development and retention programs on worker safety and production performance.

Finally, the proposed model is developed in a generic manner and can be applied to other manufacturing cases with minor modifications. However, a limitation of our model is its suitability for manufacturing cases with combinations of high and low noise levels. In manufacturing systems with excessive noise levels, the model may fail to generate feasible solutions. In such instances, decision-makers should consider relaxing the safety constraint and implementing alternative noise control measures such as engineering controls or personal protective equipment.

3.3 The noise-safe job rotation scheduling model with learning-forgetting and boredom effects

As demonstrated in the previous section, job rotation scheduling is a highly effective strategy for reducing excessive noise exposure, meeting demand requirements, and maintaining cost efficiency. This approach is a widely adopted practice in various industries, not only addressing safety concerns but also for worker cross-training, enhancing versatility and proficiency in performing different job functions. In addition, engaging in multiple tasks across a workday can motivate workers, reducing monotony-induced boredom, which can also reinforce job satisfaction. However, the challenge lies in balancing safety and skill development, especially when frequent rotations are required to ensure worker well-being and maintain non-monotonous work environments.

To maximize the benefits of job rotation, it is essential to address a fundamental issue: the potential deterioration of skills when workers are away from specific tasks. Achieving this balance is crucial for ensuring the best outcomes in terms of safety, worker satisfaction, and productivity.

In addition to optimizing system productivity, it is equally important to consider the human element in workforce scheduling. Worker heterogeneity, including factors like skill levels, task preferences, and cognitive abilities related to learning, forgetting, and boredom, plays a vital role in scheduling effectiveness. While various aspects of workforce heterogeneity have received substantial attention in job rotation scheduling, their integration with safety considerations remains relatively unexplored in the existing literature.

This dissertation introduces a novel approach to job rotation scheduling, where safety, cross-training, and the management of boredom are simultaneously considered. This integration represents the primary contribution of this dissertation. The proposed model serves as a useful decision-support tool for stakeholders implementing job rotation strategies, enabling the creation of safe work schedules that not only accommodate worker skill development but also address individual preferences. The subsequent sections provide the mathematical model formulation and validation.

3.3.1 Mathematical model formulation

The noise-safe job rotation scheduling model, which takes into account worker learning-forgetting and boredom effects, is formulated as a non-linear programming (NLP) model due to the exponential nature of skill learning-forgetting and boredom curves. The primary objective is to minimize the total production delay resulting from worker skill deficiencies and boredom. The assumptions and notations employed in the model formulation are summarized below.

Assumptions

- Workers are heterogeneous in skills, learning, forgetting, boredom, and task preferences.
- The planning period consists of multiple days, with each workday divided into multiple shifts of the same length.
- The permissible noise exposure follows NIOSH standards of 85 dBA for a standard 8-hour workday (DND not exceeding 100%). However, the noise limit may vary for workdays longer than 8 hours.
- Workers can perform only one task per shift and can rotate to other tasks at the end of each shift.
- The frequency of job rotation influences worker skill development, forgetting, and boredom, directly impacting system productivity.
- Workers must receive at least a specified amount of days off per week.

Indices

$\mathcal{W}$	Set of workers; $\mathcal{W}$ = {1, 2, ... , W}
$\mathcal{T}$	Set of tasks; $\mathcal{T}$ = {1, 2,..., T}
$\mathcal{S}$	Set of shifts in a workday; $\mathcal{S}$ = {1, 2, ..., S}
$\mathcal{D}$	Set of days in planning horizon; $\mathcal{D}$ = {1, 2, ..., D}

Input parameters

TP_{wt}	A binary parameter: 1 if worker w prefers task t, 0 otherwise
ND_t	Noise dose received by a worker from performing task t for one shift.
$Delay_t^{max}$	Maximum production delay of task t.
SK_{max}	Maximum skill level of workers in which they can produce a unit of product using the exact time as the standard production time
V_{max}	Maximum satisfaction level of workers.
β_w	Learning slope of worker w.
γ_w	Forgetting slope of worker w.
τ_w	Boredom slope of worker w.
H	Length of a work shift in hours.
DND	Maximum allowable daily noise dose.
WD	Maximum number of workdays that can be assigned to workers.

Decision variables

X_{wtsd}	= 1 if worker w is assigned task t in shift s on day d, otherwise 0.
A_{wd}	= 1 if worker w is scheduled for at least one shift on day d, otherwise 0.

Auxiliary variables

S_{wtsd}	Skill level of worker w for task t in shift s on day d.
S_{wtsd}^{Rem}	Skill remnant of worker w for task t in shift s on day d.
S_{wtsd}^{BD}	Skill before departure of worker w for task t in shift s on day d.
V_{wsd}	Satisfaction level of worker w in shift s on day d.
U_{wsd}	Satisfaction level restoration w in shift s on day d.
W_{wtsd}	Working duration of worker w on task t in shift s on day d.
D_{wtsd}	Departure duration of worker w on task t in shift s on day d.

Worker skill learning and forgetting effect

Worker skill learning and forgetting represent the human cognitive ability to acquire and retain skills over time through repetitive learning and subsequent forgetting. Workers who repeatedly perform the same task may experience a learning phenomenon, resulting in reduced task processing times. On the other hand, when there are gaps between consecutive operations, the forgetting effect can lead to longer task processing times than usual. This fundamental mechanism of skill acquisition and decay serves as the foundation for various learning and forgetting models discussed in the literature.

Numerous attempts have been made to quantify the industrial learning and forgetting effect. This dissertation utilizes the skill learning and deterioration curve from a highly-cited article on worker cross-training job rotation schedules by Azizi et al. (2010). Their scheduling model incorporates critical characteristics influencing learning and forgetting rates in human-paced operations. These characteristics encompass individual variations in skill acquisition and deterioration, steady-state performance levels (maximum and minimum), and the exponential nature of skill improvement and deterioration. This exponential pattern and its variations, such as log-linear and hyperbolic patterns, have been previously employed to construct various learning and forgetting models for both manual and cognitive tasks, representing worker performance changes during the learning and forgetting phases.

The relationships between worker skill levels and the learning and forgetting rates used in this safe job rotation scheduling model are derived from the work of Azizi et al. (2010) and described by the following equations. The learning phenomenon depends on the initial/remaining skill level and the duration of task engagement, while the forgetting phenomenon is influenced by the duration of departure from the task and the skill level attained before the interruption.

$$S_{wtsd} = SK_{max} - [(SK_{max} - S^{Rem}_{wtsd}) \cdot e^{(\beta_w \cdot W_{wtsd})}] \tag{3.18}$$

$$S^{Rem}_{wtsd} = S^{BD}_{wtsd} \cdot e^{(\gamma_w \cdot D_{wtsd})} \tag{3.19}$$

$$S^{BD}_{wtsd} = [S^{BD}_{wt,s-1,d} \cdot (1 - X_{wtsd})] + [S_{wt,s-1,t} \cdot (1 - X_{wtsd})] \tag{3.20}$$

In industrial settings, defining worker skills can be approached in various ways. In this dissertation, SK_{max} is described as the ability to produce a unit of product within the standard time. Meanwhile, SK^{BD}_{wt} signifies the time worker w takes to produce one unit before moving on from a specific task t. Alternatively, skill can also be viewed as the theoretical maximum number of units a worker can produce within a single working period, as discussed by Pérez-Wheelock et al. (2022).

The development of worker skill proficiency is influenced by their learning and forgetting rates. A higher learning rate and longer task engagement result in more effective skill development. However, when workers switch between tasks, their proficiency in previously assigned tasks can decline due to the forgetting effect. In our specific scenario, worker skill

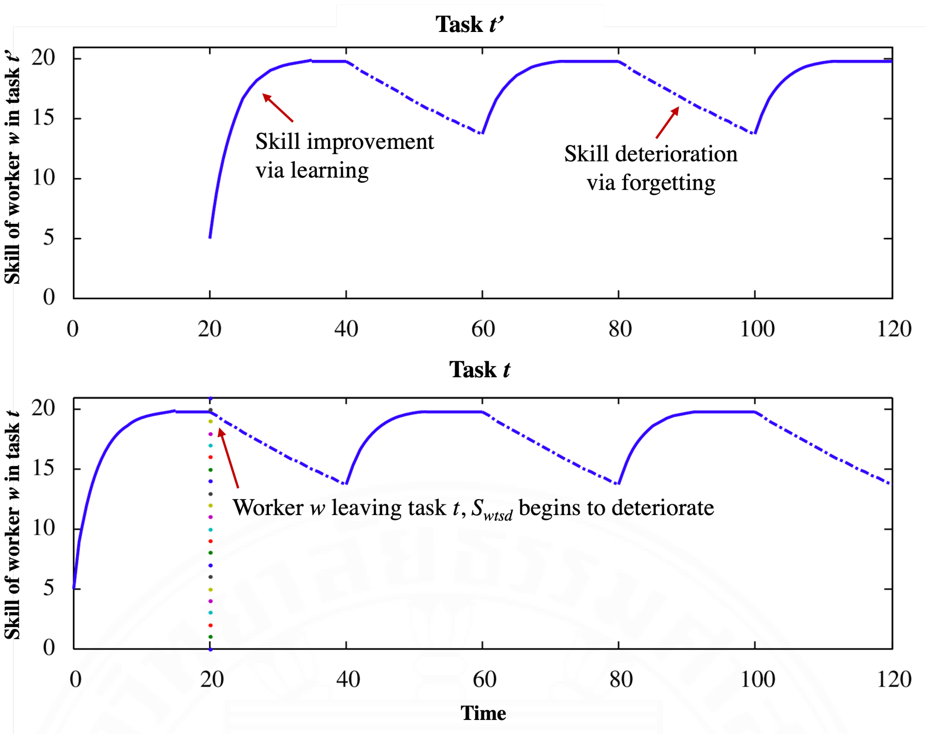

Figure 3.1 Illustration of worker skill improvement and deterioration between two tasks, adapted from Azizi et al. (2010).

proficiency varies based on individual learning and forgetting rates, yet it remains within the predefined minimum and maximum skill proficiency limits. The variation of worker skill variation due to the learning-forgetting effect is illustrated in Figure 3.1. While excessive worker rotation can negatively impact overall productivity, insufficient rotation may hinder the scheduling plan's ability to address issues like job dissatisfaction due to monotony and noise exposure among workers.

Worker job satisfaction, task preference, and boredom effect

Job rotation serves a multifaceted purpose, addressing not only excessive hazard exposure and promoting multi-skill development but also preventing the issue of worker boredom. Monotonous, repetitive tasks can deteriorate motivation and job satisfaction, negatively impacting production performance, as extensively discussed in previous studies.

This dissertation considers a manufacturing scenario that features highly repetitive processes, where worker job satisfaction and production performance are significantly influenced by worker task preferences and the emergence of boredom resulting from task monotony. Worker task preference refers to the attitudes workers hold toward specific tasks, with some being preferred and others less so. Boredom manifests when workers engage in repetitive tasks.

Job satisfaction levels decrease according to the individual boredom slope when performing the same task over time. The following equations illustrate the relationship between worker satisfaction levels, boredom slope, and worker task preference.

$$V_{wsd} = V_{max} - (V_{max} - V_{w,s-1,d}) \cdot e^{\tau_w \cdot (\sum_{t=1}^{T} D_{wtsd} + U_{wsd})} \tag{3.21}$$

$$U_{wsd} = [\sum_{t=1}^{T} D_{wt,s-1,d} \cdot (1 - \sum_{t=1}^{T} (X_{wstd} \cdot X_{w,s-1,td}))] + [U_{w,s-1,d} \cdot \sum_{t=1}^{T} (X_{wstd} \cdot TP_{wt})] \tag{3.22}$$

Based on these equations, when workers are rotated to tasks they prefer, their job satisfaction levels can be effectively restored. However, if workers are assigned to tasks they do not prefer, the presence of a non-restoration variable (U) prevents the restoration of their satisfaction levels.

In this model, the maximum and minimum threshold satisfaction levels of workers are defined. The assumption is that variations in worker satisfaction levels within these defined thresholds have a direct influence on productivity. Workers with higher job satisfaction can perform tasks with higher productivity. Conversely, when workers lack sufficient skill proficiency and job satisfaction, their productivity rates fall below the standard rate. This leads to delays in achieving production targets, and such productivity delays are considered as the additional time in minutes required to reach production targets.

Objective function

The objective is to minimize the total production delay resulting from the lack of skill proficiency and boredom-induced motivation. It is calculated as a weighted sum of the skill proficiency and motivation factors for each worker-task combination, multiplied by the maximum delay for the respective task.

$$\min \sum_{w=1}^{W} \sum_{t=1}^{T} \sum_{s=1}^{S} \sum_{d=1}^{D} \left[\left[\left(\frac{SK_{max} - S_{wtsd}}{SK_{max}} \right) + \left(\frac{V_{max} - V_{wsd}}{V_{max}} \right) \right] \cdot Delay_t^{max} \cdot X_{wtsd} \right] \tag{3.23}$$

Constraints

$$\sum_{t=1}^{T} X_{wtsd} \leq 1 \qquad \forall w \in \mathcal{W}; s \in \mathcal{S}; d \in \mathcal{D} \tag{3.24}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S} X_{wtsd} \cdot ND_t \leq DND \quad \forall w \in \mathcal{W}; d \in \mathcal{D} \tag{3.25}$$

$$\sum_{d=1}^{D} A_{wd} \leq WD \quad \forall w \in \mathcal{W} \tag{3.26}$$

$$S_{wtsd} = SK_{max} - [(SK_{max} - S_{wtsd}^{Rem}) \cdot e^{(\beta_w \cdot W_{wtsd})}] \quad \forall w \in \mathcal{W}; t \in \mathcal{T}; s \in \mathcal{S}; d \in \mathcal{D} \tag{3.27}$$

$$S_{wtsd}^{Rem} = S_{wtsd}^{BD} \cdot e^{(\gamma_w \cdot D_{wtsd})} \quad \forall w \in \mathcal{W}; t \in \mathcal{T}; s \in \mathcal{S}; d \in \mathcal{D} \tag{3.28}$$

$$S_{wtsd}^{BD} = [S_{wt,s-1,d}^{BD} \cdot (1 - X_{wtsd})] + [S_{wt,s-1,t} \cdot (1 - X_{wtsd})] \quad \forall w \in \mathcal{W}; \quad t \in \mathcal{T}; s \in \mathcal{S}; d \in \mathcal{D} \tag{3.29}$$

$$V_{wsd} = V_{max} - (V_{max} - V_{w,s-1,d}) \cdot e^{\tau_w \cdot (\sum_{t=1}^{T} D_{wtsd} + U_{wsd})} \quad \forall w \in \mathcal{W}; s \in \mathcal{S}; d \in \mathcal{D} \tag{3.30}$$

$$U_{wsd} = [\sum_{t=1}^{T} D_{wt,s-1,d} \cdot (1 - \sum_{t=1}^{T}(X_{wstd} \cdot X_{w,s-1,td}))] + [U_{w,s-1,d} \cdot \sum_{t=1}^{T}(X_{wstd} \cdot TP_{wt})] \quad \forall w \in \mathcal{W}; s \in \mathcal{S}; d \in \mathcal{D} \tag{3.31}$$

$$W_{wtsd} = [(W_{wtsd} + X_{wtsd}) \cdot X_{wtsd}] \cdot H \quad \forall w \in \mathcal{W}; t \in \mathcal{T}; s \in \mathcal{S}; d \in \mathcal{D} \tag{3.32}$$

$$D_{wtsd} = [(D_{wtsd} + 1) \cdot (1 - X_{wtsd})] \cdot H \quad \forall w \in \mathcal{W}; t \in \mathcal{T}; s \in \mathcal{S}; d \in \mathcal{D} \tag{3.33}$$

$$X_{wktsd}, A_{wkd} \in \{0, 1\} \tag{3.34}$$

$$S_{wktsd}, S^{Rem}_{wktsd}, S^{BD}_{wktsd}, V_{wsd}, U_{wsd}, W_{wtsd}, D_{wtsd} \in \mathbb{R}^{+} \tag{3.35}$$

Constraint (3.24) restricts that each worker is allocated to a single task at any given time. Constraint (3.25) ensures that daily noise exposure of workers remains within the defined limit. Constraint (3.26) guarantees that workers receive a certain number of days off per planning period. Constraint (3.27) calculates the skill level of workers. Constraint (3.28) Computes the remnant skill for the task after the worker is reassigned. (3.29) determines the task skill level that the worker has gained before being rotated from the task. Constraint (3.30) calculates the worker satisfaction levels. Constraint (3.31) limits the restoration of job satisfaction for workers assigned to non-preferred tasks. Constraints (3.32) and (3.33) keep track of workers' working duration and departure duration for each task. Constraints (3.34) and (3.35) are the standard integrality constraints.

This proposed noise-safe job rotation model incorporates skill learning-forgetting dynamics and the impact of boredom-induced job dissatisfaction. The model involves various parameters, including noise exposure levels, skill learning/forgetting rates, and job satisfaction levels, some of which are represented as exponential functions. Due to the problem's complexity and non-linearity, obtaining optimal solutions using exact techniques may not be practical within a reasonable time. As a result, the use of heuristic techniques is proposed. The following sections include details of the heuristic techniques, numerical examples, and a comparison of computational performance across different solution methods.

3.3.2 Heuristic solution approaches

This section provides an overview of the heuristic and metaheuristic algorithms applied to the proposed model. The two main algorithms employed in our study are the randomized greedy algorithm (RGA) and the well-known genetic algorithm (GA).

3.3.2.1 Initialization algorithm

Both RGA and GA initiate their operations with the same initialization algorithm, as depicted in Figure 3.2. This initialization step is essential for constructing initial noise-safe job rotation schedules that are both feasible and of relatively high quality. This initial schedule serves as the starting point for RGA and GA, guiding them in the search for improved solutions and expediting the path to a near-optimal solution.

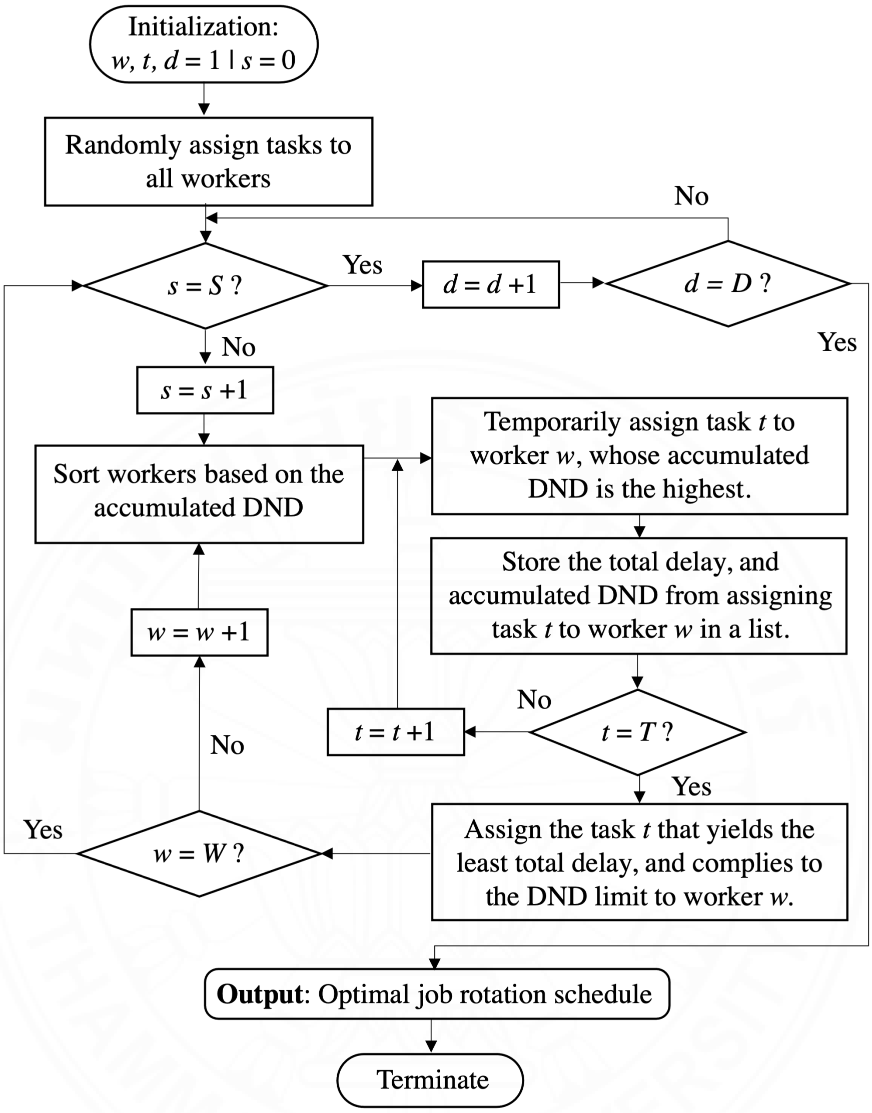

Figure 3.2 Flowchart of the initialization algorithm

The algorithm begins by randomly assigning tasks to workers without considering their skill proficiency or job satisfaction. Subsequently, workers are sorted in descending order based on their accumulated noise dose values. The algorithm then assigns tasks to workers to minimize delay, giving priority to those with the highest accumulated noise dose while ensuring that the assigned tasks comply with the noise restriction. These worker-task assignment processes repeat for all shifts in a workday until the last workday. Upon completion, the algorithm generates an optimal job rotation schedule with noise safety.

3.3.2.2 Randomized greedy algorithm (RGA)

RGA is a heuristic optimization algorithm used to solve combinatorial optimization problems. It operates by making a sequence of choices by selecting the locally optimal option at each step aiming to find a globally optimal solution. Unlike traditional greedy algorithms, RGA introduces randomness by occasionally selecting sub-optimal solutions in certain iterations rather than consistently opting for the locally optimal choice. This element of randomization enables RGA to avoid becoming trapped in local optima. The procedures involved in RGA are outlined as follows.

For each iteration, denoted as i and continuing until the predefined maximum number of iterations (I) is reached, the following steps are executed:

1. Generate several random initial populations using the initialization algorithm as described in Section 3.3.2.1.

2. Identify a subset of members characterized by relatively low total production delay values. Randomly select a member from this defined subset and record the result along with the total production delay for the current iteration.

3. Repeat steps 1 - 2 until the iteration I is reached.

RGA is a versatile approach applicable to a wide range of optimization problems. While its implementation is relatively simple, it can effectively strike a balance between exploration and exploitation, which marks its ability to escape local optima and potentially find better solutions. Consequently, RGA is often used for problems that are computationally expensive, like NLP, and when a reasonably good solution is accepted.

3.3.2.3 Genetic algorithm (GA)

GA is a metaheuristic optimization technique inspired by the principles of natural selection, where individuals with higher fitness levels have a better survival chance and propagating their genetic traits. It proves to be a powerful tool for solving problems characterized by large search spaces, combinatorial optimization challenges, and complex, multi-dimensional objective functions. Given the nature of this noise-safe job rotation model, GA is employed as the primary solution approach, with an equipped initialization algorithm for generating the initial population.

In this model, the fitness value for GA is defined as the reciprocal of the total production delay, calculated using Equation (3.23). This choice prioritizes minimizing adverse productivity effects arising from skill and job satisfaction deficiencies. Therefore, solutions with lower delays are favored during the selection process. The GA algorithm can be described through the following steps.

For each generation (g), continuing until a predetermined maximum number of generations (G) is reached, the following steps are executed:

1. Generate a set of random initial populations using the initialization algorithm described in Section 3.3.2.1.

2. Evaluate the fitness value of each chromosome using the following equation:

$$\text{Fitness value} = \frac{1}{\text{Total production delay}} \tag{3.36}$$

3. Select parents from the initial population (with a size of P) using the roulette wheel selection method, where the probability of each chromosome's selection is directly proportional to its fitness value.

4. Apply crossover operations at specified rates and crossover points to the selected parents to generate offspring.

5. Verify the feasibility of each offspring chromosome, ensuring that all tasks are allocated and workers' DND levels remain within the defined limits. If necessary, reassign tasks to infeasible chromosomes.

6. Introduce mutations to offspring chromosomes at a predefined mutation rate, randomly altering some of the genes. Subsequently, validate the feasibility of the mutated chromosomes and adjust them as required.

7. Combine the parent and offspring populations and repeat steps 1 - 6 until reaching generation G.

Over multiple generations of GA, the quality of the solutions typically improves. Nevertheless, GA may sometimes become trapped in local optima. This can be influenced by various factors, such as the diversity and size of the initial population, crossover points, and mutation rates, among others. Thus, parameter tuning and algorithm modifications are often necessary to ensure that the generated solutions are near-optimal, if not globally optimal. In this model, SA is employed as an additional step to evaluate and improve the performance of GA. The rationale is that if the GA solution is locally optimal, SA, an algorithm specially designed for escaping local extreme points, is expected to further enhance it. The details of SA are presented in the following subsection.

3.3.2.4 Simulated annealing (SA)

SA is a metaheuristic algorithm inspired by the metal annealing process, known for its capability to escape local optima by introducing perturbations, which may initially degrade solutions but ultimately lead to improved results (Gallo et al., 2019). SA is fundamentally a hill-climbing algorithm but differs in that it probabilistically accepts sub-optimal solutions rather than strictly selecting the best one. The algorithm integrates a temperature parameter ($Temp$) as part of the probability calculation, which gradually decreases as the algorithm progresses. The slower cooling rate can lead to a higher chance of getting an optimal solution, but the solution time can be long. The SA process is described below.

For each iteration, i, until the predetermined maximum number of iterations (I) is reached, the following steps are performed:

1. Set the solution obtained from GA as the current solution (S^{cur}), and calculate the total delay.

2. Randomly generate a new solution (S^{new}), and calculate the total delay. Regenerate if the solution is infeasible.

3. Compare the total delay of S^{new} with that of S^{cur}. If it is less, proceed to step 6; otherwise, go to step 4.

4. Calculate the probability of acceptance (p) using the following equation and generate a random number (r) in the range (0,1):

$$p = \exp\left(\frac{-[f(S^{new}) - f(S^{cur})]}{Temp}\right) \tag{3.37}$$

   If $r < p$, go to step 5; otherwise, proceed to step 6.

5. Update the current solution by setting $S^{cur} = S^{new}$.

6. Decrease the temperature value ($Temp$) at a predetermined cooling rate.

7. Repeat steps 2 - 8 until the final iteration I is reached.

In this model, SA was applied after GA to evaluate and potentially refine the best solution obtained. If SA cannot find an improved solution, then it can be concluded that the GA solution is good enough, if not globally optimal.

3.3.3 Numerical example

This numerical example represents a manufacturing system characterized by a diverse set of tasks, each demanding distinct skills. The number of available workers corresponds to the number of tasks. Essential parameters, including the learning, forgetting, and boredom slopes of the workers, are derived from the comprehensive study conducted by Azizi et al. (2010), and these values are presented in Table 3.11. Furthermore, this model considers workers' task preferences and non-preferred tasks are listed in the same table.

Table 3.11 Workers learning, forgetting, boredom slopes, and non-preferred tasks

Workers	Learning slope (β)	Forgetting slope (γ)	Boredom slope (τ)	Non-preferred tasks
1	-0.20	-0.12	0.15	3
2	-0.23	-0.15	0.17	5
3	-0.19	-0.20	0.14	4
4	-0.30	-0.25	0.21	5
5	-0.21	-0.08	0.17	1, 3
6	-0.22	-0.13	0.13	9
7	-0.18	-0.10	0.11	9
8	-0.25	-0.15	0.21	5
9	-0.18	-0.21	0.11	-
10	-0.17	-0.27	0.12	3

In this scenario, we consider manufacturing plants adhering to a 5-day workweek structure, with each workday divided into two 4-hour shifts. Thus, the constraint (3.26) is excluded from the model, as workers are granted weekends off. However, the model can be easily adapted to accommodate alternative operational schedules. Decision-makers have the flexibility to modify shift lengths and planning horizons, extending them to either a 7-day workweek or an entire month while ensuring the reinstatement of Constraint (3.26) to guarantee sufficient rest days for workers. Still, it is important to note that for extended planning periods, particularly in the case of a combinatorial NLP problem like this, the computational time required for a solution may become substantial. In such instances, it may be advisable to decompose the planning period into weekly.

Over the 5-day job rotation cycle, workers are assigned tasks considering their competencies, preferences, and noise exposure limits. They encounter varying noise exposure levels while carrying out these tasks. Detailed information regarding the noise levels experienced by workers during each task and the maximum allowable delays for each task are provided in Table 3.12. The noise dose is computed based on the duration of exposure during the 4-hour shift.

Table 3.12 Noise levels, noise dose and maximum production delays for each task

Tasks	Noise levels (dBA)	Noise dose per shift	Maximum production delay ($Delay_t^{max}$) (minutes)
1	70	0.016	30
2	86.5	0.707	30
3	87	0.79	29
4	65	0.005	15
5	80	0.15	20
6	87	0.79	30
7	82	0.25	27
8	78	0.099	39
9	71.5	0.022	29
10	85	0.5	30

3.3.4 Results and discussion

This section presents the experimental results, which aimed to assess the effectiveness of the proposed model and solution approaches and to explore the impact of different job rotation plans on productivity delay. Three solving approaches are used in the analyses: NLP for exact optimization, RGA, and GA for approximate solutions. Additionally, a comparison is made between a job rotation and a non-rotation plan to understand the influence of skill and satisfaction factors and the necessity of rotating workers based on noise exposure limits.

Comparison of solution approaches

NLP, RGA, and GA are applied to solve the problem, and their computational efficiency for various problem sizes ranging from 5 - 60 workers within a 5-day planning period is investigated. Table 3.13 presents the results, including total production delay and solving times.

Table 3.13 Comparison of results and solving time between solution approaches

Problem sizes (worker-task)	Total production delay (minutes)			Solving time (seconds)			Percentage of excess total production delay compared to GA		
	NLP	RGA	GA	NLP	RGA	GA	NLP	RGA	GA-SA
5w-5t	581.6	406.0	402.0	48	0.1	105.1	45%	1.0%	0%
6w-6t	651.0	517.4	506.4	199.8	0.3	984.2	29%	2.2%	0%
7w-7t	810.8	578.1	568.6	400.2	0.6	1,836.3	43%	1.7%	0%
8w-8t	1,018.7	690.6	673.8	1,021.8	0.6	1,292.6	51%	2.5%	0%
9w-9t	1,106.1	821.4	802.6	1,575	0.8	1,896.0	38%	2.4%	0%
10w-10t	-	907.6	890.7	-	1.0	2,439.9	-	1.9%	0%
20w-20t	-	1,834.4	1,801.4	-	2.3	3,658.9	-	1.8%	0%
30w-30t	-	2,762.4	2,714.1	-	4.2	3,606.0	-	1.8%	0%
40w-40t	-	3,692.2	3,606.5	-	6.8	3,607.4	-	2.4%	0%
50w-50t	-	4,616.4	4,521.9	-	9.7	3,608.1	-	2.1%	0%
60w-60t	-	5,561.9	5,448.2	-	13.2	3,621.7	-	2.1%	0%

It can be observed that NLP is efficient for cases with up to 9 workers and 9 tasks within the 5-day scheduling period, but it showed limitations beyond this scale. The limitations of NLP may arise from the complexity and non-convexity of the problem, leading to convergence on local optima. Meanwhile, GA and RGA exhibited robustness across all problem sizes, even reaching up to 60 workers and 60 tasks. GA consistently produced solutions with the lowest delay for all instances, while RGA, providing slightly higher delays, offered significantly shorter computational times. RGA stands as a practical choice when prompt solutions are needed, especially for large-scale problems. Additionally, SA is applied after GA to evaluate and improve the performance of GA. However, SA consistently fails to improve upon GA solutions, indicating that GA solutions are likely near-optimal if not optimal. Despite RGA's speed and practicality, GA consistently produced solutions with minimal delay, making it a robust choice for solving complex job rotation scheduling challenges.

The impact of job rotation on safety, skill learning, and production delay

This section examines the effects of implementing the proposed job-rotation scheduling approach to reduce noise exposure, comparing it with a scenario where noise control measures are neglected. GA is applied to address the problem of 5 workers and 5 tasks over a 5-day planning period in both scenarios. The results are presented in Table 3.14.

Without noise exposure control, workers are assigned the same task for the entire planning period. The schedule primarily focuses on skill development objectives, resulting in reduced production delay. This non-rotation plan results in some workers engaging in loud tasks and being exposed to noise levels well above the permissible daily limits. It also leads to a gradual decline in workers' job satisfaction due to the boredom effect.

In contrast, the implementation of noise exposure control involves regular worker rotation among tasks to ensure safety regarding noise exposure. This rotation efficiently reduces the average DND of workers and provides opportunities for multi-skill development while mitigating boredom-induced job dissatisfaction. Because skill development contributes to less production delay, workers assigned to quiet tasks are not rotated, as in the case of worker 3. However, if minimizing boredom becomes the priority, workers will be rotated frequently at the end of each shift to mitigate the boredom effect, but with the potential compromise of continuous skill development.

Table 3.14 Comparisons of production delays caused by skill learning-forgetting and boredom between rotation and non-rotation plans

Scheduling plans	Total production delay (minutes)	Delay due to skilll learning-forgetting (minutes)	Delay due to boredom (minutes)
Non-rotation plan	341.5	126.3	215.2
Job rotation plan	402.0	265.1	136.9

Table 3.14 presents the total production delay from each rotation plan. Despite the positive effects of job rotation in mitigating noise exposure and boredom, it incurs a substantial production delay (402 minutes) compared to the non-rotation plan (341.5 minutes). This total delay is further categorized into delay attributed to skill learning-forgetting and delay due to boredom. Job rotation plans cause disruptions in production operations and the learning process. Thus, the delay due to skill-learning-forgetting increases, while the delay due to boredom is less than the non-rotation plan due to a non-monotonous work environment from frequent rotation. In contrast, the non-rotation plan experiences less delay from the skill learning-forgetting effect but incurs more delay due to the monotony of performing the same task throughout the entire planning period.

Figure 3.3 illustrates the impact of job rotation, learning and forgetting rates, and boredom on workers' skill development and job satisfaction via worker 1's task assignments. The figure shows the changes in worker 1's skill level during the transition between tasks 1 and 3. As the worker shifts from task 1 to task 3, the skill for task 1 decreases due to

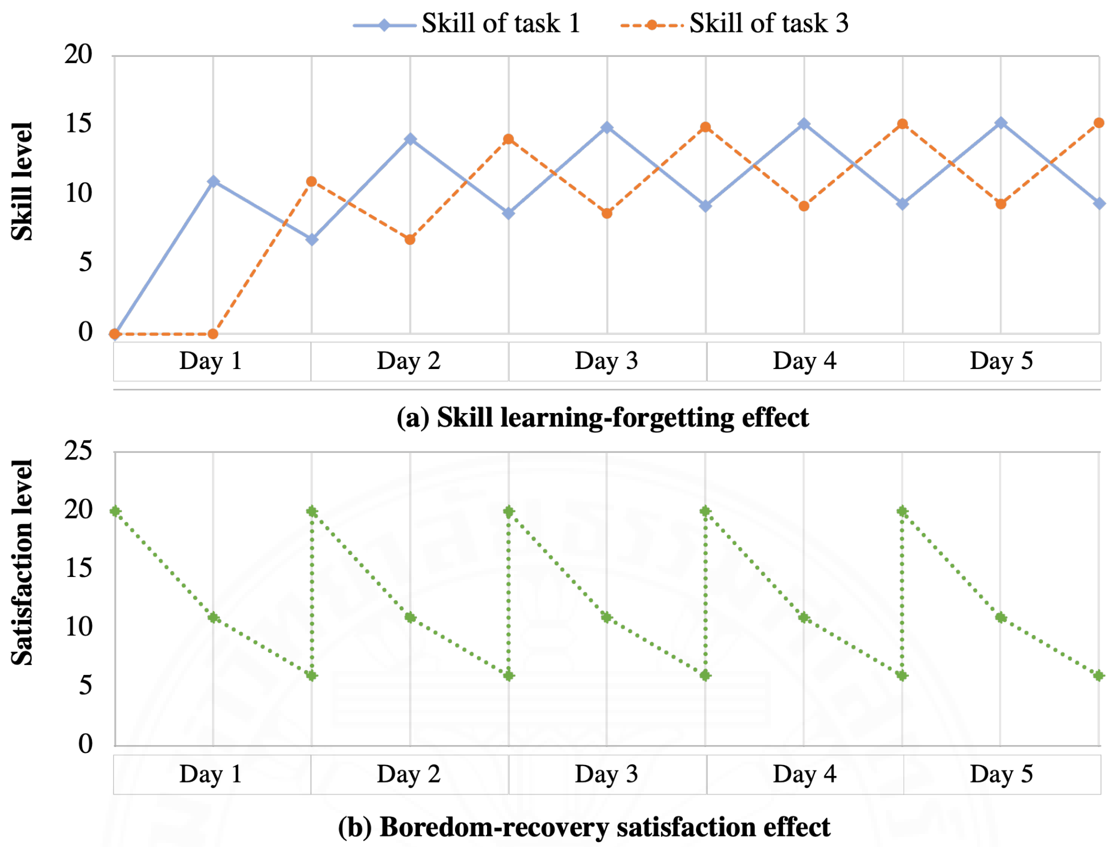

Figure 3.3 Impact of job rotation on worker 1's skill learning, forgetting, and job satisfaction.

the forgetting effect, while the skill for task 3 increases due to the learning effect. However, the worker's job satisfaction remains low as task 3 is not their preferred task, resulting in a continued decline in satisfaction until returning to task 1.

3.3.5 Conclusion

This section introduces a novel noise-safe job rotation scheduling approach, which considers workers' skill learning and forgetting rates, as well as their boredom-related job satisfaction. The simultaneous consideration of safety management, cross-training, and job satisfaction in job rotation scheduling constitutes a significant academic contribution of this dissertation.

This proposed job rotation model serves as a decision-support tool aiming to minimize production delays caused by skill deficiency and job dissatisfaction while simultaneously ensuring worker safety by limiting noise exposure. Given its complexity and NP-hard nature, exact optimization may not always be feasible. Therefore, RGA and GA algorithms are employed as alternative solutions with a problem-specific initialization algorithm to generate initial solutions for both. Additionally, SA is employed to enhance GA solutions, leveraging its ability to escape local optima. Experimental results indicate that NLP is viable for small-scale problems while RGA efficiently delivers comparable solutions within a reasonable computational time for all problem sizes. GA achieves optimal solutions for all problem sizes but at a substantial computational time, rendering it less suitable for large-scale manufacturing systems. However, for those prioritizing solution quality over computation time, GA remains a viable choice. The findings from SA experiments suggest that the solutions produced by GA are of sufficiently high quality, if not globally optimal. With GA, decision-makers can consider decomposing the planning horizon into multiple weekly plans instead of monthly.

The experiment underscores that job rotation can reduce noise exposure while promoting worker multi-skill development among workers. Without job rotation, workers continuously develop skills for a specific task, but some are exposed to extreme noise levels, and the associated boredom-induced job dissatisfaction contributes to production delays. Under job rotation, noise exposure and delays due to boredom decrease, though production delays increase due to skill development interruptions. Over time, these delays can decrease as workers acquire proficiency in multiple tasks. For better efficiency, noise levels at tasks should be reduced using supplemental controls, leading to less frequent rotation, improving process continuity, and reducing production delays. In summary, this model demonstrates that job rotation can effectively mitigate hazards, foster multi-skill development, and alleviate monotony-related boredom. However, it may take time for workers to acquire the necessary skills for productive operations.

In practice, this model serves as a theoretical foundation for job rotation implementation, demonstrating three-fold benefits: reducing occupational injuries, facilitating multi-skill learning, and mitigating boredom. However, the model is particularly suitable for manufacturing cases with varying noise levels. For more flexibility, the noise limit constraint can be relaxed given that decision-makers supply other noise hazard controls. In addition, methods for evaluating workers' learning, forgetting, and boredom rates should be further explored. Although this model was originally tailored for handling noise hazards, it can be adapted for other occupational hazards with minor adjustments to hazard assessments and limits. The assessment of learning, forgetting, and boredom-related dissatisfaction can also be customized to specific cases.

To summarize, this chapter has introduced the development of two novel noise-safe job rotation scheduling models. The first model incorporates critical scheduling parameters such as matching workers to tasks, demand-driven production, and overtime assignments

– an area relatively unexplored in the context of safe job rotation scheduling. A numerical example representing SME manufacturing systems has been utilized to validate its efficacy in meeting operational and safety requirements with a marginal increase in total labor costs. The results emphasize the trade-off between worker safety and cost and underscore the importance of including more experts in the rotation plan, highlighting the significance of worker skill development and retention.

The second model extends the benefits of job rotation by integrating workers' skill learning, forgetting rates, and boredom-related job satisfaction into noise-safe job rotation scheduling. This integration constitutes a novel contribution to the field. The model's objective is to minimize production delays due to skill deficiency and job dissatisfaction with many proposed solution approaches to address its complexity. Numerical examples representative of manufacturing scenarios with tasks demanding distinct skill sets have been employed for model validation. The results highlight that the model effectively mitigates workplace hazards, encourages multi-skill development, and alleviates monotony-induced boredom.

Both noise-safe job rotation models serve as decision-support tools for utilizing job rotation scheduling as an administrative hazard control strategy in manufacturing facilities. They have been designed in a generic manner, enabling easy adaptation with minor modifications to various manufacturing scenarios. Furthermore, they can be applied to manage other hazards, such as ergonomics, heat, or vibration, by adjusting hazard evaluations and limits. However, it is important to note that both models are equipped with strict hazard constraints, making them suitable for manufacturing systems with varying noise levels. For systems with extreme hazards, relaxing noise limits may be necessary to implement the models, provided that additional hazard controls are employed to ensure worker safety.

CHAPTER 4
SATISFACTION-ENHANCED NURSE SCHEDULING MODELS

Nurses are invaluable resources in healthcare premises, which are facing strenuous working and demanding conditions, prompting them to leave the profession and leading to nurse shortage issues. Ensuring their well-being and job satisfaction becomes paramount in healthcare human resource management. A satisfied nurse not only provides better care but also stays committed to the profession.

This chapter presents the development of the two satisfaction-enhanced NSP models proposed in this dissertation. Section 4.1 presents the mathematical formulation of satisfaction-enhanced NSP Model I, while Section 4.2 outlines the mathematical formulation of the cost-effective, satisfaction-enhanced NSP Model II. Additionally, each section includes details on the hospital dataset, experimental results, and discussions relevant to the respective model.

4.1 The satisfaction-enhanced NSP (Model I)

Numerous factors have a positive influence on job satisfaction, as discussed earlier. This model encompasses two essential aspects to enhance nurse job satisfaction via scheduling: 1) Fulfilling their preferred shifts and days off. and 2) Equitably distributing workload and preferred assignments among nurses.

While individual preferences encompass various dimensions, this model emphasizes personal preferences for shifts and days off. In terms of fairness, the model aims to establish equal workload distribution and preferred assignments. This model fills a gap in existing research by simultaneously considering two fairness factors with comprehensive individual preferences.

The model encompasses three objectives: minimizing discrepancies in the allocation of shifts to nurses, minimizing variations in their preferred shifts, and minimizing variations in their preferred day-off assignments. Each objective has adjustable target values to meet the requirements of different healthcare facilities. In practice, hospitals often set specific shift quotas for nurses while attempting to accommodate preferred assignments and maintaining equitable workloads. Therefore, a goal programming (GP) technique is chosen to formulate and solve this proposed model. GP transforms objectives into goals with target values that can be defined by hospital management.

GP is an effective solution approach for addressing multi-objective problems, as well-documented in the literature. It reflects real-world decision-making and allows decision-makers or stakeholders to contribute their insights into setting desired targets for each objective. This results in an optimal solution that aligns with the collective needs of the healthcare facility.

In GP, model objectives are formulated into goals with target values specified by hospital management. The objective function of GP is to minimize the total undesirable deviations from these specified target values. The adaptability of this approach makes it particularly suitable for scheduling tasks in hospitals, where the allocation of shifts to nurses is typically predetermined. Then, hospital management can actively involve nurses in refining preferences-related goals, thus fostering their perception of job autonomy. The mathematical formulation of the model is described below.

4.1.1 Mathematical model formulation

This satisfaction-enhanced NSP model is formulated as a GP model. Its primary objective is to create a well-balanced work schedule that equally distributes the workload and preferable tasks. Without loss of generality, model formulation adheres to the following key assumptions and notations.

Assumptions

- The planning horizon is four weeks (28 days), with each workday consisting of multiple shifts of uniform length.
- Nurses are categorized based on experience levels, and shift assignments must adhere to hospital regulations regarding nurse quantity and skill prerequisites.
- Shift allocations per nurse follow the defined hospital limits.
- Each nurse is guaranteed a minimum number of weekly days off.
- Scheduling morning shifts immediately following night shifts is prohibited.
- Weekly night shift assignments are limited as defined.
- Consecutive night shifts are limited to ensure adequate rest.
- In the case of double-shift workdays, the number of consecutive double-shift workdays is restricted within the defined limit.

Indices

$\mathcal{N}$	Set of nurses: $\mathcal{N} = 1, 2, \ldots, N$.
$\mathcal{S}$	Set of shifts in a workday: $\mathcal{S} = 1, 2, \ldots, S$.
$\mathcal{K}$	Set of nurse skill levels: $\mathcal{K} = 1, 2, \ldots, K$.
$\mathcal{D}$	Set of days in the planning horizon: $\mathcal{D} = 1, 2, \ldots, D$.

Input parameters

R_{sd}	The total number of nurses required in shift s on day d.
RL_{sk}	The minimum number of nurse with skill level k required in shift s.
N_k	The set of nurses belonging to skill level k: $\mathcal{N} = N_1 \cup N_2 \cup \ldots \cup N_K$
SK_{nk}	A binary parameter: 1 if nurse n belongs to skill level k, 0 otherwise.
SP_{nsd}	A binary parameter: 1 if nurse n prefers to work in shift s on day d, 0 otherwise.
DP_{nd}	The preference score of nurse n for taking a day-off on day d: $DP_{nd} \in \{1, \ldots, Q\}$
DS	The maximum number of shifts that can be assigned to a nurse per day.
DO	The minimum number of days off a nurse must receive per week.
NS	The maximum number of night shifts that can be assigned to a nurse per week.
TS	The maximum total shifts that 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 shift assignments.
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^-	Positive and negative deviations of the total number of shifts from the target for nurse n.
SP_n^+, SP_n^-	Positive and negative deviations of the number of preferred shifts from the target for nurse n.
DP_n^+, DP_n^-	Positive and negative deviations of the preferred day-off scores from the target for nurse n.

The proposed satisfaction-enhanced NSP model encompasses three objectives formulated as GP goals. The first goal aims to evenly distribute shifts among nurses while adhering to workload targets. The second and third goals focus on balancing individual preferences for shifts and days off. The description and formulation of each goal are provided below.

Goal 1: Balancing shift assignments

This goal is to achieve a balance in shift assignments, minimizing deviations for each nurse from the target while ensuring equitable distribution of workloads among nurses. Deviations below the target represent under-assignment, while deviations exceeding the target indicate over-assignment. These deviations can be calculated using Equation (4.1). The objective function includes positive and negative deviations because over- and under-assignment are undesirable.

$$\sum_{s=1}^{S}\sum_{d=1}^{D} X_{nsd} - TS_n^+ + TS_n^- = TS_{target} \quad \forall n \in \mathcal{N} \tag{4.1}$$

Equation (4.1) can be explained as follows: Consider a scenario in which the designated target workload for nurses (TS_{target}) is 24 shifts per month, while the actual workload assigned to a nurse n is to 22 shifts. Substituting these values, the equation becomes,

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

For the equation to remain valid, TS_n^+ must be set to 0, indicating that nurse n does not exceed the workload limit. Simultaneously, TS_n^- is set to 2 within the model, signifying that nurse n is under-assigned by two shifts. The equation's validity is confirmed by substituting these decision values, as demonstrated below. This computational logic is applied to subsequent goal formulations.

$$22 - 0 + 2 = 24$$

Goal 2: Balancing preferred shift assignments

This goal is to equitably fulfill nurses' individual shift preferences. Each nurse's preference for working in shifts s on day d (SP_{nsd}) is expressed as a binary value, with 1 representing a preferred shift and 0 indicating otherwise. When a shift assignment aligns with a nurse's preference, it contributes to the count of preferred shift assignments. Deviations in the total number of preferred shift assignments for each nurse from the designated target (SP_{target}) are computed using Equation (4.2). In this goal, only negative deviations are considered in the objective function because positive deviations indicate that nurses receive more preferred assignments than the target, resulting in a more satisfactory schedule outcome.

$$(\sum_{s=1}^{S}\sum_{d=1}^{D} SP_{nsd} \cdot X_{nsd}) - SP_n^+ + SP_n^- = SP_{target} \quad \forall n \in \mathcal{N} \tag{4.2}$$

Goal 3: Balancing preferred day off scores

This final goal is to accommodate nurses' preferences for days off. We use scores to express days off preferences (DP_{nd}), reflecting the degree of their preference for taking a day off on specific days. This scoring approach offers enhanced assignment flexibility, enabling nurses to indicate multiple preferred days for time off. It also helps handle preference conflicts among nurses. Each day is assigned a different score based on individual preferences, and these scores can be adjusted based on the nurses' judgment. Deviations in preferred day off scores for each nurse from the designated target scores (DP_{target}) are quantified using Equation (4.3). Similar to the second goal, only negative deviations are considered in the objective function, as positive deviations indicate an excess of preferred day-off assignments, resulting in a more preferable schedule outcome.

$$(\sum_{d=1}^{D} DP_{nd} \cdot Y_{nd}) - DP_n^+ + DP_n^- = DP_{target} \quad \forall n \in \mathcal{N} \tag{4.3}$$

Objective function

In a GP model, the objective function is the summation of the total undesirable deviations from all goals. As each goal in the model may have a different magnitude, it is necessary to normalize these deviations before summing them to avoid incommensurability issues. The normalization process standardizes deviations from each goal into a uniform unit, thus preventing any bias towards goals with larger magnitudes.

The objective function for this satisfaction-enhanced NSP model seeks to minimize the sum of normalized undesirable deviations, as presented below.

$$\min\left(\frac{(\sum_{n=1}^{N}(TS_n^{+}+TS_n^{-})}{TS_{target}\cdot N}\right)+\left(\frac{\sum_{n=1}^{N}SP_n^{-}}{SP_{target}\cdot N}\right)+\left(\frac{(\sum_{n=1}^{N}DP_n^{-}}{DP_{target}\cdot N}\right) \tag{4.4}$$

Constraints

$$\sum_{n=1}^{N}X_{nsd}\geq R_{sd} \quad \forall s\in\mathcal{S};d\in\mathcal{D} \tag{4.5}$$

$$\sum_{s=1}^{S}(X_{nsd}\cdot SK_{ns})\geq RL_{sk} \quad \forall s\in\mathcal{S};d\in\mathcal{D};k\in\mathcal{K} \tag{4.6}$$

$$\sum_{s=1}^{S}X_{nsd}\leq DS \quad \forall n\in\mathcal{N};d\in\mathcal{D} \tag{4.7}$$

$$\sum_{d=d}^{d+6}Y_{nd}\geq DO \quad \forall n\in\mathcal{N};d\in\mathcal{D}_1\cup\mathcal{D}_8\cup\mathcal{D}_{15}\cup\mathcal{D}_{22} \tag{4.8}$$

$$\sum_{s=1}^{S}\sum_{d=1}^{D}X_{nsd}\leq TS \quad \forall n\in\mathcal{N} \tag{4.9}$$

$$\sum_{s=1}^{S}X_{nsd}+Y_{nd}\geq 1 \quad \forall n\in\mathcal{N};d\in\mathcal{D} \tag{4.10}$$

$$X_{n,s=S,d}+X_{n,s=1,d+1}\leq 1 \quad \forall n\in\mathcal{N};d\in\mathcal{D}-\{D\} \tag{4.11}$$

$$\sum_{s=S}\sum_{d=d}^{d+t}X_{nsd}\leq t \quad \forall n\in\mathcal{N};d\in\mathcal{D}\setminus\{D-t+1,\ldots,D\} \tag{4.12}$$

$$\sum_{s=S}\sum_{d=d}^{d+6} X_{nsd} \leq NS \qquad \forall n \in \mathcal{N}; d \in \mathcal{D}_1 \cup \mathcal{D}_8 \cup \mathcal{D}_{15} \cup \mathcal{D}_{22} \tag{4.13}$$

$$\sum_{s=1}^{S}\sum_{d=d}^{d+f} X_{nsd} \leq 2f+1 \qquad \forall n \in \mathcal{N}; d \in \mathcal{D} \setminus \{D-f+1,...,D\} \tag{4.14}$$

$$X_{nsd}, Y_{nd} \in \{0,1\} \tag{4.15}$$

$$TS_n^+, TS_n^-, SP_n^+, SP_n^-, DP_n^+, DP_n^- \in \mathbb{Z}_0^+ \tag{4.16}$$

Constraint (4.5) ensures that the number of assigned nurses per shift meets the requirements. Constraint (4.6) guarantees that the specified nurse numbers for each skill level are met. Constraint (4.7) restricts the assignment of shifts for nurses within a workday. Constraint (4.8) mandates a minimum number of days off per week for nurses. Constraint (4.9) ensures that the total shifts assigned to nurses across the planning horizon remain within specified limits. Constraint (4.10) prevents shift assignments on designated days off. Constraint (4.11) prohibits scheduling morning shifts following night shifts. Constraint (4.12) limits consecutive night shifts to be fewer than t days. Constraint (4.13) restricts the number of night shifts per week. Constraint (4.14) enforces a maximum of f consecutive double-shift workdays, which can be omitted if double-shift workdays are not allowed. Constraints (4.15) and (4.16) are standard integrality and non-negativity constraints.

4.1.2 Hospital case data

The validation of the proposed model is conducted through a case study in the operating room (OR) of a medium-sized private hospital with a capacity of 200 beds located in Pathum Thani, Thailand. Data collection for this case study was carried out between December 2019 and February 2020, employing a comprehensive approach that included a field survey, a questionnaire survey, and an interview with the head nurse. It is important to note that the data collection procedures were conducted in accordance with the requirements of The Human Research Ethics Committee of Thammasat University and the hospital. The name of the hospital, along with raw data, is confidential and cannot be publicized. Therefore, only anonymized and processed data can be included.

The OR department consists of 16 full-time registered nurses, including one head nurse. The operational structure follows a shift work rotation system with three 8-hour shifts: morning shift (M) from 8 AM to 4 PM, afternoon shift (A) from 4 PM to 12 AM, and night shift (N) from 12 AM to 8 AM. The head nurse only works during morning shifts. The department's nurses are categorized into two experience levels: nine level-1 nurses (including the head nurse) and eight level-2 nurses.

In the current hospital scheduling process, the head nurse manually generates monthly nurse schedules at the beginning of each month. The primary objective is to allocate an adequate number of nurses to each shift within the planning horizon. However, the head nurse characterizes this scheduling task as demanding, often requiring up to a week to create a schedule that complies with all hospital regulations. The current scheduling process does not take into account nurses' preferences or fairness considerations.

For the generality of the proposed model, a scheduling period of 28 days is assumed. The specific scheduling criteria, relevant hospital constraints, and the three target goals specified by the head nurse are summarized in Table 4.1.

Table 4.1 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

From Table 4.1, the hospital stipulates a maximum of one shift per day for each nurse and requires a minimum of one day off per week for every nurse. Nurses are also restricted to a maximum of two night shifts per week. The total number of monthly shifts is limited to 24, and the target number is set in accordance with this restriction. The hospital specifies that the required number of nurses for morning, afternoon, and night shifts is 6, 6, and 2, respectively, for all days within the planning horizon. Additionally, the head nurse specifies that the number of level-1 nurses must constitute at least half the total number of nurses to maintain the desired service quality. However, no specific number of level-2 nurses is specified for each shift. Therefore, Table 4.1 only displays the required number of level-1 nurses for each shift.

In terms of individual preferences, nurses were asked to indicate their preferred shifts and days off over the 28-day planning period through a questionnaire survey. The mathematical model uses this preference data as input to fulfill shift and day-off preferences. An example of the shift preference data for the first 14 days is presented in Table 4.2. It can be observed that nurses exhibit a lower preference for night shifts compared to morning and afternoon shifts. However, given the coverage requirements, they must still be assigned to night shifts. Consequently, fulfilling all shift preferences becomes complicated when conflicts arise. In this case study, the head nurse has established a target of 20 preferred shifts. This implies that out of the 24 shifts assigned to nurses each month, approximately 20 of these should align with their preferences.

Table 4.2 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

In terms of day-off preferences, nurses were requested to specify their most preferred and second-most preferred days off each week, resulting in a total of specified 8 day-off preferences over the planning period. A Likert scale was employed to assign preference ratings, offering enhanced scheduling flexibility and increasing the likelihood of accommodating nurses' preferences. Based on the head nurse's recommendation, the most preferred and second-most preferred days off were assigned 3 and 1 points, respectively.

The target preferred day-off score (DP_{target}) of 12 is met when nurses are assigned their most preferred day off every week throughout the 28-day planning period. The day-off preference sheets for the first 14 days can be found in Tables 4.3.

The following section discusses experimental results, scenario analysis and further explores the effectiveness of the proposed model compared to manually generated schedules.

Table 4.3 Nurses' preferred day-off scores

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	-	-

4.1.3 Results and discussion

This section presents the experimental results of scenario analysis to assess the practicality and robustness of the proposed model under different operational settings. Three scenarios are used for model validation: 1) Standard operation, 2) Extended operation capacity, and 3) Higher demand for experienced nurses.

In the standard operation scenario, the number of nurses required for each of the three shifts is 6, 6, and 2, respectively. In the extended capacity scenario, the capacity of the morning shift is expanded to accommodate a higher patient volume during the morning hours, as indicated by the head nurse. The number of nurses required for each shift in the extended capacity operation is 9, 6, and 2.

The efficiency of the optimal schedules obtained from scenario analysis is compared to the manually-made schedule, evaluating their performance in preference fulfillment and fairness. As this model is the first to incorporate fairness considerations in both workload and preferred assignments, direct comparisons with existing models are not feasible. It is important to note that scheduling requirements, such as allowable shifts and prohibited shift patterns, are formulated as hard constraints based on the regulations of the hospital case. Thus, this case study relies solely on scenario analysis. In alternative hospital cases, hard constraints can be reformulated as soft constraints or goal equations, allowing for limited constraint violations with associated penalties, thereby enhancing model flexibility.

Scenario 1: standard operation

The proposed satisfaction-enhanced NSP is solved using Opensolver version 2.9.0, an optimization tool add-in in Microsoft Excel, operating on a 2.3 GHz Dual-Core Intel Core i5-8300H processor. The standard operation scenario replicates the actual operational setting of the hospital case. In this scenario, there are 17 nurses available, with 6, 6, and 2 nurses required for each shift on all workdays. The optimal nurse schedule can be obtained within 5 seconds. An example of the nurse schedule for the first 14 days under the standard operation scenario is provided in Table 4.4.

Table 4.4 Nurse schedule 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

The summarized results for the 28-day planning period encompass the total shifts, preferred shifts received, and day-off preference scores for all 17 nurses, as shown in Table 4.5. The table's second-left column presents the actual total shifts assigned to nurses based on the schedule manually created for the prior month. Detailed deviations from the three goals are also provided in the table. The experimental findings demonstrate the achievement

Table 4.5 Summary of deviations from goals in Scenario 1

Nurse n	Actual total shift	G1: Balancing shift assignments				G2: Balancing preferred shift assignments				G3: Balancing preferred day off scores			
		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

of all desired goals.

In the workload balancing goal, most nurses deviate by no more than two shifts from the target of 24 shifts, with four nurses exhibiting zero deviations. This indicates a relatively balanced distribution of shift assignments. In the optimal schedule, five nurses receive fewer workloads, nine receive more, and three receive no workload change. It is also worth mentioning that the total allowable shifts (TS) and the targeted shifts (TS_{target}) are both set at 24 by the head nurse, resulting in TS_n^+ being zero and excluded from Table 4.5. Deviations in shift assignments, both over and under, are observed when target and allowable shifts are unequal.

Regarding the other two goals, deviations from the target number of preferred shifts and day-off scores are negligible. Consequently, it can be inferred that shift and day-off preferences are effectively met and balanced. However, Nurse 2 experiences a moderate percent deviation across the two preference-related goals, while Nurse 4 receives the fewest preferred shifts. To address this, nurses with compromised preferences should be compensated with increased preferred shifts and day-off assignments in subsequent schedules to maintain fairness over time. Nevertheless, it is reasonable to conclude that the proposed model satisfactorily fulfills all goals within this scenario's optimal solution.

For enhanced visualization, a comparison of workload allocation between the actual and optimal schedules is illustrated in Figures 4.1 and 4.2. These figures demonstrate the optimal schedule's more even workload distribution compared to the actual schedule. Additionally, Figure 4.3 visually depicts the spread of preferred shift assignments and total day-off preference scores among all nurses in the optimal schedule. It can be seen that preferences are nearly aligned with target values in both goals, exhibiting a relatively low spread among nurses.

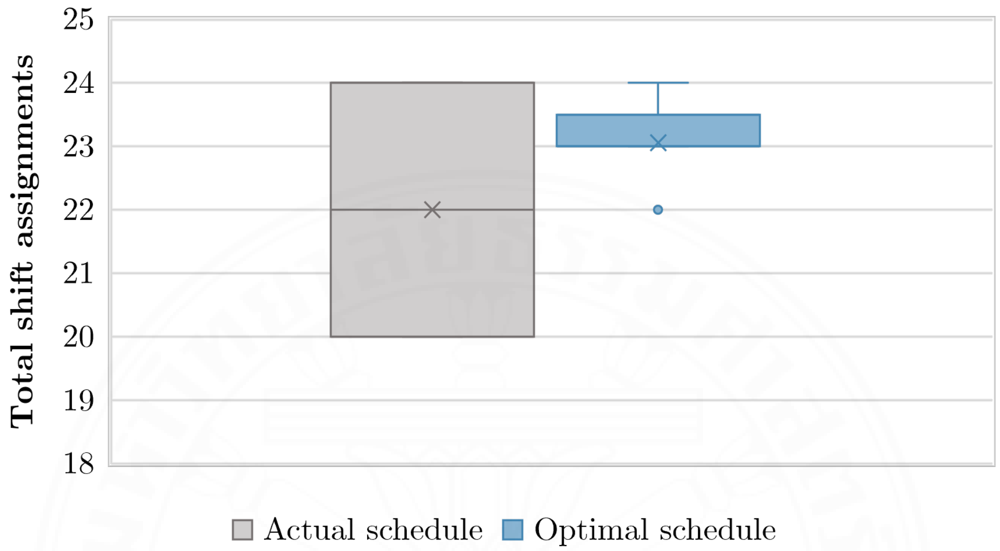

Figure 4.1 A comparison of the workload assignments between the actual and optimal schedules

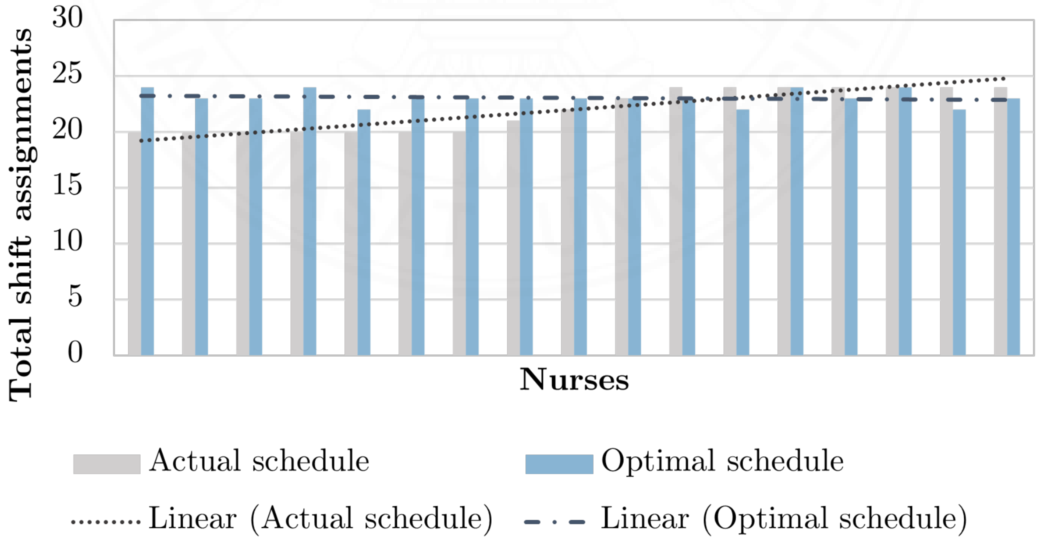

Figure 4.2 Workload assignments between the actual and optimal schedules by nurses

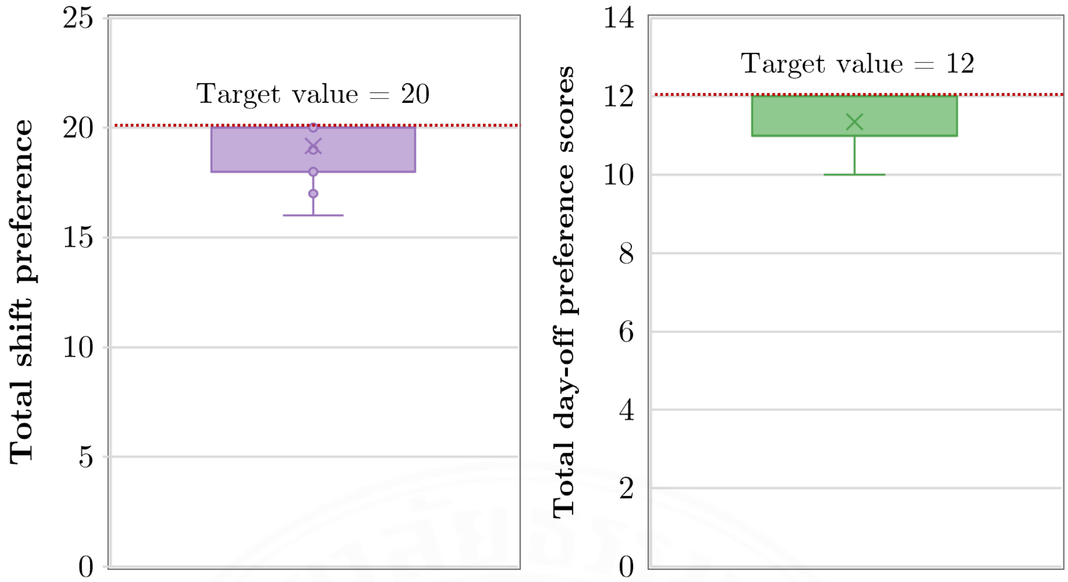

Figure 4.3 Distribution of shift and day-off preference fulfillment

Scenario 2: Extended operation capacity

According to the head nurse's speculation, periods of high patient volume frequently occur during morning shifts, resulting in an occasional inadequate nursing capacity of 17. In this scenario, the required nurse count for each shift is increased to 9 for the morning, 6 for the afternoon, and 2 for the night shifts. This adjustment results in a total nursing capacity of 20, allowing the healthcare facility to manage heightened demand better. Three artificial nurses are introduced to accommodate the expanded capacity, each equipped with synthetic shift and day-off preferences.

The summarized results of this scenario are provided in Table 4.6. The proposed approach effectively achieves the workload balancing goal. With the augmented nursing staff, the workload distribution becomes more proportional and manageable. Furthermore, the shift assignments align relatively well with the nurses' preferences. While most nurses' shift preferences are satisfactorily met, one nurse experiences a preferred shift deviation of 4, highlighting a potential area for improvement. The fulfillment of day-off preferences remains relatively consistent. However, some nurses' day-off preferences are compromised to accommodate the increased demand during morning shifts. These nurses should be considered for compensation through additional preferred assignments in the upcoming planning period.

Regarding computational efficiency, generating an optimal solution takes only 5 seconds. This computational performance is further validated through testing with a larger-scale problem, demonstrating that the optimal schedule for 50 nurses can be generated within 20 seconds. This quick solution time underlines the model's applicability to more extensive healthcare facilities, enhancing its practicality in real-world settings.

Table 4.6 Summary of deviations from goals in Scenario 2

Nurse n	Actual total shift	G1: Balancing shift assignments				G2: Balancing preferred shift assignments				G3: Balancing preferred day off scores			
		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

Scenario 3: Higher demand for experienced nurses

This scenario investigates the implications of an increased need for more experienced nurses (level-1) during the demanding morning shifts on Monday and Tuesday. To address the heightened patient volume, the required count of level-1 nurses during these peak-demand periods is raised from 3 to 5. The computational model is solved using the given parameters, and the results are summarized in Table 4.7. The results show that level-1 nurses bear heightened workloads in this scenario. Most of them are assigned the maximum allowable shifts. The fulfillment of level-1 nurse preferences encounters limitations due to the augmented necessity for level-1 nurses during the peak-demand period, particularly in the day-off preference scores, as level-1 nurses cannot take a day off on Monday and Tuesday, even if they prefer. Compared to the other scenarios, the average percent deviations are higher for all goals.

Table 4.7 Summary of deviations from goals in Scenario 3

Nurse n	Actual total shift	G1: Balancing shift assignments				G2: Balancing preferred shift assignments				G3: Balancing preferred day off scores			
		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

Comparison to the manually-devised schedule

In addition to the scenario analyses, a comparative assessment of performance metrics is conducted between manually constructed schedules and the optimal schedules generated by the proposed computational model. This evaluation focuses exclusively on the workload balancing objective since preference-related goals were omitted from the original manual schedule. The comparison highlights the superiority of our proposed model in achieving goals and its computational efficiency.

Table 4.8 presents the average and standard deviation of each targeted goal for the manually made and optimal schedules across the various scenarios. For the workload balancing goal, it is observed that nurses, on average, engage in one additional shift compared to the manual schedule. The optimal schedule consistently yields a substantially lower standard deviation across all scenarios when compared to the manual schedule, underscoring the model's capacity to establish a more equitable and balanced workload allocation than the manual schedule.

In terms of shift preferences, nurses, on average, are assigned nearly the target shift preference of 20 with a relatively low standard deviation. This is except for the scenario involving higher demand for level-1 nurses. In this scenario, the constraint on fulfilling the preferences of level-1 nurses stems from the imperative of managing escalating demand. A similar trend is observed in the context of day-off preference scores.

In terms of computational efficiency, the proposed model can generate optimal schedules in less than a minute, even when dealing with larger departments encompassing 50 nurses. This efficiency enables the head nurse to address spontaneous requests, accommodate nurses' preferences, and promptly generate a desirable final schedule.

Table 4.8 A comparison of performance indicators between the manual and optimal schedules

	G1: Balancing shift assignments		G2: Balancing preferred shift assignments		G3: Balancing preferred day-off scores	
	Average	SD	Average	SD	Average	SD
Manually-devised	22	1.84	-	-	-	-
Scenario 1: Standard operation	23.0	0.64	19.17	1.24	11.32	0.68
Scenario 2: Extended capacity	23.8	0.4	19.75	0.89	11.15	1.06
Scenario 3: Higher demand for experienced nurses	23.1	0.94	18.82	1.60	9.70	2.78

SD - Standard deviation

4.1.4 Conclusion

This section presents a novel nurse scheduling model designed to enhance job satisfaction by accommodating nurses' shift and day-off preferences while ensuring a fair distribution of workloads and preferred assignments. Employing the GP technique, the model incorporates three key satisfaction-enhancement goals: balancing shift assignments, balancing preferred shift assignments, and balancing preferred day-off scores among nurses. Data collected from an OR at a private hospital in Thailand is used to validate and assess the model's practicality.

Scenario analyses were performed to evaluate solution quality and computational performance across various settings. The experimental results clearly demonstrate that the schedules generated by our proposed model outperform manually created schedules in all targeted goals and execution times. This optimization-based nurse scheduling model efficiently delivers satisfactory and equitable monthly work schedules. Furthermore, we demonstrated the model's scalability by successfully solving a large-scale instance involving 50 nurses and a 28-day planning horizon in just 20 seconds. As a result, the proposed model serves as a practical decision-support tool well-suited for implementation within standard platforms commonly used by nurses, such as Microsoft Excel.

From a theoretical perspective, the model significantly enriches the existing literature on NSP by integrating multiple job satisfaction-enhancement factors, including comprehensive individual preferences and fairness considerations. Furthermore, the model's generic structure allows customization to various hospital settings or applications. It can be adapted to handle emergencies by relaxing certain constraints and regulations. Potential extensions could encompass additional scheduling attributes, such as staffing cost, task heterogeneity, and nurses' affinities, in alignment with broader administrative policies.

It is worth noting that while this model demonstrates promising outcomes in fulfilling nurses' preferences and ensuring fairness, practical implementation must also consider economic aspects. Schedules that comply with both economic and job satisfaction requirements can be particularly desirable from a managerial perspective. To address this, an extension of the model is proposed with the integration of staffing cost as an additional objective to further enhance its practical utility. The subsequent section outlines the mathematical formulation and validation of this extended model.

4.2 The cost-effective and satisfaction-enhanced NSP (Model II)

The previous section describes the development of the satisfaction-enhanced NSP (Model I), designed to create work schedules that balance workload and preferred assignments while accommodating nurses' shift and day-off preferences. While the model demonstrates promising and satisfactory scheduling outcomes, the practicality of NSPs also relies on economic considerations. To address this, the foundational concept of Model I is extended by integrating the consideration of staffing cost. This section introduces the formulation and development of the cost-effective and satisfaction-enhanced NSP (Model II).

Similar to Model I, the design principles of Model II uphold the importance of preferences and fairness—specifically, shift and day-off preferences, equitable workload distribution, and desirable assignments. This model incorporates a bi-objective optimization approach with the objectives of minimizing the total staffing cost and maximizing the minimum total preference score among all nurses. The total preference score is derived from the fulfillment of nurses' shift and day-off preferences. This dual-objective formulation ensures that the generated schedules are both economically viable and satisfactory—qualities that are advantageous from both nurses' and management's perspectives. However, the priorities of these two objectives differ from a managerial standpoint. Typically, cost-effectiveness takes precedence over job satisfaction. To address this priority distinction, we employ a lexicographic optimization technique as our solution approach.

The lexicographic optimization technique, also known as preemptive optimization, is a valuable approach for solving multi-objective problems. Unlike other methods that aim to find a single solution that optimizes all objectives simultaneously, lexicographic optimization allows decision-makers to assign priority levels to each objective. The model is then solved iteratively, tackling one objective at a time based on its assigned priority. The optimal solution from each iteration becomes a constraint for subsequent iterations. This methodology enables us to optimize the most important objective first and subsequently fine-tune other less critical objectives. Unlike approaches such as weighted-sum or goal programming, lexicographic optimization does not require normalization or weight assignment, as each objective is handled separately. The problem is effectively decomposed into a sequence of single-objective problems, reducing computational complexity. This sequential approach leads to reduced computational time compared to the simultaneous handling of multiple objectives.

4.2.1 Mathematical model formulation

This NSP Model II aims to generate cost-effective nurse schedules that can accommodate nurses' individual preferences and ensure scheduling fairness. The model is formulated as a bi-objective MILP, and the lexicographic optimization technique is applied as the solution approach. Without loss of generality, the assumptions and notations used in the model formulation are summarized below.

Assumptions

- The planning horizon spans four weeks (28 days), with each workday consisting of multiple shifts of uniform length.
- Nurses are categorized based on experience levels, and shift assignments must conform to hospital regulations regarding nurse quantity and skill prerequisites.
- Shift allocations per nurse adhere to the prescribed limits set by the hospital.
- Each nurse is guaranteed a minimum number of weekly days off.
- Scheduling morning shifts immediately following night shifts is prohibited.
- Weekly night shift assignments are limited as defined.
- Consecutive night shifts are limited to ensure adequate rest.
- In the case of double-shift workdays, the number of consecutive double-shift workdays is restricted within the defined limit.

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 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: 1 if nurse n belongs to skill level k, 0 otherwise.
SP_{ns}	The preference score of nurse n for working in shift s: $SP_{ns} \in \{1, \dots, Q\}$
DP_{nd}	The preference score of nurse n for taking a day-off on day d: $DP_{nd} \in \{1, \dots, Q\}$
Q_{nd}	A binary parameter: 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 on the differences between 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 introduces auxiliary variables used in formulating objective functions and constraints.

TPC_n The total preference score of nurse n, calculated as the sum of the total shift and day-off preference scores:

$$TPC_n = \sum_{s=1}^{S}\sum_{d=1}^{D}(X_{nsd} \cdot SP_{ns}) + \sum_{d=1}^{D}(Y_{nd} \cdot DP_{nd}) \qquad \forall n \in \mathcal{N} \tag{4.17}$$

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

$$TPC_{min} = \min_{n \in \mathcal{N}}\{TPC_n\} \tag{4.18}$$

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

$$WL_n = \sum_{s=1}^{S}\sum_{d=1}^{D} X_{nsd} \qquad \forall n \in \mathcal{N} \tag{4.19}$$

Objective functions

The proposed cost-effective and satisfaction-enhanced nurse scheduling approach (Model II) encompasses the following two objectives.

1.) Minimize the total staffing cost:

$$\min \sum_{n=1}^{N}(\sum_{s=1}^{S}(\sum_{d=1}^{D} X_{nsd}) \cdot C_s) \tag{4.20}$$

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

$$\max\ TPC_{min} \tag{4.21}$$

The second objective is derived using the MAXIMIN technique, which seeks to simultaneously maximize the total preference scores and minimize the deviation of scores among nurses. The technique is widely recognized for its capacity to enhance fairness and has been prominently featured in the personnel scheduling literature as discussed in Wolbeck (2019). Through MAXIMIN, fairness is achieved by improving the quality of the least-preferred schedule outcome, effectively narrowing the gap between the upper and lower bounds.

Constraints

$$\sum_{n=1}^{N} X_{nsd} \geq R_{sd} \quad \forall s \in \mathcal{S}; d \in \mathcal{D} \tag{4.22}$$

$$\sum_{n=1}^{N} (X_{nsd} \cdot SK_{nk}) \geq RL_{sk} \quad \forall s \in \mathcal{S}; d \in \mathcal{D}; k \in \mathcal{K} \tag{4.23}$$

$$\sum_{s=1}^{S} X_{nsd} \leq DS \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \tag{4.24}$$

$$\sum_{d=d}^{d+6} Y_{nd} \geq DO \quad \forall n \in \mathcal{N}; d \in \mathcal{D}_1 \cup \mathcal{D}_8 \cup \mathcal{D}_{15} \cup \mathcal{D}_{22} \tag{4.25}$$

$$WL_n \leq TS \quad \forall n \in \mathcal{N} \tag{4.26}$$

$$\sum_{s=1}^{S} X_{nsd} \leq BigM \cdot (1 - Y_{nd}) \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \tag{4.27}$$

$$\sum_{s=1}^{S} X_{nsd} + Y_{nd} \geq 1 \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \tag{4.28}$$

$$Q_{nd} \leq Y_{nd} \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \tag{4.29}$$

$$|WL_n - WL_{n'}| \leq Gap_{WL} \quad \forall n \in \mathcal{N}; n \neq n' \tag{4.30}$$

$$X_{n,s=S,d} + X_{n,s=1,d+1} \leq 1 \quad \forall n \in \mathcal{N}; d \in \mathcal{D} - \{D\} \tag{4.31}$$

$$\sum_{s=S} \sum_{d=d}^{d+t} X_{nsd} \leq t \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \setminus \{D - t + 1, ..., D\} \tag{4.32}$$

$$\sum_{s=1}^{S} \sum_{d=d}^{d+f} X_{nsd} \leq 2f + 1 \quad \forall n \in \mathcal{N}; d \in \mathcal{D} \setminus \{D - f + 1, ..., D\} \tag{4.33}$$

$$X_{nsd}, Y_{nd} \in \{0, 1\} \tag{4.34}$$

$$TPC_n, TPC_{min}, WL_n \in \mathbb{Z}_0^+ \tag{4.35}$$

Constraint (4.22) enforces that the assigned number of nurses for each shift meets the required staffing level. Constraint (4.23) guarantees the fulfillment of the specified nurse numbers in each skill level. Constraint (4.24) restricts the assignment of shifts for nurses within a workday. Constraint (4.25) mandates a minimum number of days off per week for nurses. Constraint (4.26) ensures that the total shifts assigned to nurses across the planning horizon remain within specified limits. Constraints (4.27) and (4.28) events shift assignments on designated days off. Constraint (4.29) guarantees the fulfillment of nurses' requested day off. Constraint (4.30) promotes workload fairness by limiting the differences in total shift assignments (WL_n) among all nurses. Constraint (4.31) prohibits scheduling morning shifts following night shifts. Constraint (4.32) limits consecutive night shifts to be fewer than t days. Constraint (4.33) enforces a maximum of f consecutive double-shift workdays, which can be omitted if double-shift workdays are not allowed. Constraints (4.34) and (4.35) are the standard integrality and non-negativity constraints.

For this problem, attaining the minimum staffing cost takes precedence before maximizing the minimum total preference score. By employing the lexicographic method, the problem is decomposed into two sequential single-objective optimization problems. In the initial iteration, the model optimizes the objective of minimizing staffing cost (4.20) while adhering to Constraints (4.22) - (4.35), obtaining the optimal total staffing cost ($Cost^*$). Subsequently, in the second iteration, an additional constraint (4.36) is introduced as an upper limit on the staffing cost.

$$\sum_{n=1}^{N}(\sum_{s=1}^{S}(\sum_{d=1}^{D} X_{nsd}) \cdot C_s) \leq Cost^* \tag{4.36}$$

The objective of the model in the second iteration is to maximize the minimum total preference score (4.21) while complying with Constraints (4.22) - (4.36). The lexicographic approach guarantees that enhancements in total preference scores are achieved without compromising the economic feasibility of the schedule outcomes.

4.2.2 Hospital case data

The model validation features a case study conducted at an Emergency Department (ED) within a large-scale public hospital with an 800-bed capacity in Pathum Thani, Thailand. Data collection from March to June 2021 involved questionnaire surveys and interviews. It is important to note that the data collection procedures were conducted in accordance with the requirements of The Human Research Ethics Committee of Thammasat University and the hospital. The name of the hospital, along with raw data, is confidential and cannot be publicized. Therefore, only anonymized and processed data can be included.

The nursing staff comprises 40 registered nurses, including a head nurse. Hospital operations adhere to a 3-shift rotation: morning shift (M) from 8 AM to 4 PM, afternoon shift (A) from 4 PM to 12 AM, and night shift (N) from 12 AM to 8 AM, with the head nurse exclusively assigned to morning shifts. Nursing staff are categorized into five levels, denoted as levels 1 through 5. Level 5 signifies more than ten years of experience, with the staff distribution being 10, 11, 7, 9, and 3 nurses for levels 1 through 5, respectively.

Similar to the previous section's hospital case, the head nurse manually constructs a monthly nurse schedule before each month's commencement. This schedule aims to ensure comprehensive nurse coverage across all shifts and days during the planning horizon while adhering to hospital regulations and accommodating requested time off. Due to the intricate regulations and the department's scale, individual preferences are not considered. The manual scheduling process typically spans 3 to 7 days, contingent upon request conflicts. Regarding scheduling fairness, the head nurse aims to distribute duties as evenly as possible. However, there exists no specific metric for evaluating this fairness. The hospital regulations data gathered from an interview with the head nurse are summarized in Table 4.9 and serve as input parameters for the model. The planning horizon of 28 days is assumed for the generality of the model.

Table 4.9 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 levels 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 shifts (DS)	2
Minimum day off per week (DO)	1
Allowable gap of workloads assigned between nurses (Gap_{WL})	3

Table 4.9 presents shift assignment costs converted from Thai Baht to US dollars. Afternoon and night shifts offer higher pay rates to compensate for out-of-office hours, and nurses receive automatic overtime compensation for these shifts. The hospital adheres to uniform shift wages for all experience levels, accompanied by an additional position allowance. However, this study focuses solely on the shift assignment costs to nurses. Thus, the position allowance is omitted.

Nurse allocation across the three shifts is influenced by patient volume, leading to varying staffing requirements. Morning shifts are the busiest and require the highest number of nurses, followed by afternoon and night shifts. Additionally, the minimum staffing levels for nurses of skill levels 1 to 5 in each shift s are specified.

It is important to highlight that the regulations of this hospital differ from those of the previous hospital case. It adopts a double-shift workday scheme, allowing for increased monthly shift assignments. In contrast to the previous case, there is no limit on weekly night shifts. Instead, regulations permit a maximum of three consecutive night shifts and two double-shift workdays per week. Consequently, Constraint (4.32) is bounded by 3, while Constraint (4.33) is set to 2 for this specific hospital case.

Nurse shift and day off preferences were gathered through a questionnaire survey.

The survey design used during the data collection for Model I (Section 4.1.2) required nurses to outline preferred shift allocations across a 28-day planning horizon and indicate their most-preferred eight days off. However, this process proved cumbersome and time-consuming, as many nurses did not have a specific shift preference for all days in the planning period. As a result, the questionnaire was revised to rank working shifts from most to least preferred and identify the three most to least favored day-of-week to take days off. This streamlined approach requires only six preference indications, resulting in a more straightforward and less time-consuming process. However, it is worth noting that preference collection can be adapted to accommodate different hospital regulations if the model is applied to other hospital cases. Below are several examples of the questionnaire survey questions.

Please indicate your preferences for shifts and days off by filling in the corresponding information below:

1. Shift Preferences: Please rank your shift preferences from most preferred to least preferred among morning, afternoon, and night shifts.
   (a) Most preferred shift: ______________________________
   (b) Second-most preferred shift: ______________________________
   (c) Third-most preferred shift: ______________________________
2. Days Off Preferences: Rank your three most-preferred days of the week for taking a day off (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 of the 40 ED nurses, as gathered from the questionnaire survey, are summarized in Table 4.10 and Table 4.11, respectively. In this hospital case, shift preferences of nurses are converted into scores: 3, 2, and 1 for their first, second, and third-most preferred shifts, respectively, as shown in Table 4.10. This table is interpreted as follows: for instance, Nurse 1 prioritizes the morning shift, followed by afternoon and night shifts, while Nurse 2 favors night shifts most, then afternoon and morning shifts.

Table 4.11 outlines the three most preferred days of the week for nurses' desired days off. Similar to shift preferences, scores (DP_{nd}) are assigned to first, second, and third-most preferred days with values of 3, 2, and 1, respectively. For instance, Nurse 1 prefers taking days off on Sunday, Saturday, and Friday, corresponding to scores of 3, 2, and 1, respectively. Days not among the preferred options receive a score of 0.

While the survey captures nurses' general shift and day-off preferences, it is noteworthy that they may vary based on monthly holidays. In such instances, the questionnaire from Model I may be more suitable, as it can comprehensively capture preferences for all days within the planning period. In Model II, nurses' requested days off are accommodated (Q_{nd}) using the Constraint (4.29) in cases when they need to attend to personal matters.

Table 4.10 Nurses' shift preferences

Nurse (Skill)	Shifts	Shift preference score (SP_{ns})	Nurse (Skill)	Shifts	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
(4)	A	2	(2)	A	2

Nurse (Skill)	Preference rank	Day-of-week	Nurse (Skill)	Preference rank	Day-of-week
	N	3		N	3
9 (4)	M A N	3 2 1	29 (2)	M A N	3 2 1
10 (4)	M A N	1 2 3	30 (2)	M A N	1 2 3
11 (4)	M A N	3 2 1	31 (1)	M A N	2 3 1
12 (4)	M A N	1 2 3	32 (1)	M A N	2 3 1
13 (3)	M A N	3 2 1	33 (1)	M A N	1 2 3
14 (3)	M A N	2 1 3	34 (1)	M A N	3 2 1
15 (3)	M A N	2 3 1	35 (1)	M A N	1 2 3
16 (3)	M A N	2 3 1	36 (1)	M A N	2 3 1
17 (3)	M A N	1 2 3	37 (1)	M A N	3 2 1
18 (3)	M A N	3 2 1	38 (1)	M A N	2 3 1
19	M	1	39	M	2

Nurse (Skill)	Preference rank	Day-of-week	Nurse (Skill)	Preference rank	Day-of-week
(3)	A N	2 3	(1)	A N	3 1
20 (2)	M A N	3 1 2	40 (1)	M A N	3 2 1

Table 4.11 Nurses' day off preferences

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

Nurse (Skill)	Preference rank	Day-of-week	Nurse (Skill)	Preference rank	Day-of-week
	3^{rd}	Mon		3^{rd}	Thu
9 (4)	1^{st} 2^{nd} 3^{rd}	Sat Fri Thu	29 (2)	1^{st} 2^{nd} 3^{rd}	Sat Fri Mon
10 (4)	1^{st} 2^{nd} 3^{rd}	Sat Fri Mon	30 (2)	1^{st} 2^{nd} 3^{rd}	Fri Sat Sun
11 (4)	1^{st} 2^{nd} 3^{rd}	Sat Fri Mon	31 (1)	1^{st} 2^{nd} 3^{rd}	Sun Sat Fri
12 (4)	1^{st} 2^{nd} 3^{rd}	Fri Sat Sun	32 (1)	1^{st} 2^{nd} 3^{rd}	Sun Sat Fri
13 (3)	1^{st} 2^{nd} 3^{rd}	Sun Sat Fri	33 (1)	1^{st} 2^{nd} 3^{rd}	Thu Wed Mon
14 (3)	1^{st} 2^{nd} 3^{rd}	Sun Sat Fri	34 (1)	1^{st} 2^{nd} 3^{rd}	Sat Fri Thu
15 (3)	1^{st} 2^{nd} 3^{rd}	Thu Wed Mon	35 (1)	1^{st} 2^{nd} 3^{rd}	Sat Fri Mon
16 (3)	1^{st} 2^{nd} 3^{rd}	Sat Fri Thu	36 (1)	1^{st} 2^{nd} 3^{rd}	Fri Sat Sun
17 (3)	1^{st} 2^{nd} 3^{rd}	Sat Fri Mon	37 (1)	1^{st} 2^{nd} 3^{rd}	Sun Sat Fri
18 (3)	1^{st} 2^{nd} 3^{rd}	Fri Sat Sun	38 (1)	1^{st} 2^{nd} 3^{rd}	Sun Sat Fri
19	1^{st}	Sun	39	1^{st}	Thu

Nurse (Skill)	Preference rank	Day-of-week	Nurse (Skill)	Preference rank	Day-of-week
(3)	2^{nd} 3^{rd}	Sat Fri	(1)	2^{nd} 3^{rd}	Wed Mon
20 (2)	1^{st} 2^{nd} 3^{rd}	Sun Sat Fri	40 (1)	1^{st} 2^{nd} 3^{rd}	Sat Fri Thu

The next section presents the experimental results and discusses the efficacy of the proposed model in comparison with the manually made schedule.

4.2.3 Results and discussion

This section presents the outcomes of the proposed cost-effective and satisfaction-enhanced NSP (Model II), which was solved using the GUROBI optimizer version 9.1.2, implemented in Python, on a 2.3 GHz Dual-Core Intel Core i5-8300H operating system. The model can achieve optimal values for both objectives in less than a minute.

An illustrative nurse schedule output for a scenario involving 40 nurses and a 28-day work cycle is displayed in Table 4.12. The model's performance is assessed under varying objective priorities to discern the impact of each objective on the other. Under the cost-prioritized scheme, the model minimizes staffing costs before maximizing job satisfaction. Conversely, the job-satisfaction-prioritized scheme maximizes the minimum satisfaction score before minimizing total staffing costs. The model's performance is evaluated using key performance indicators (KPIs) encompassing staffing costs, workload distribution, and preferences for both actual and optimal schedules under the two objective schemes. These findings are summarized in Table 4.13. This comprehensive analysis sheds light on the trade-offs between the two key objectives of the model.

As presented in Table 4.13, the optimal schedules in both settings demonstrate substantial improvements compared to the manual schedule across all key performance indicators (KPIs). Under the cost-prioritized scheme, the proposed model leads to a significant reduction of nearly 13% in total staffing costs, equivalent to approximately \$4,000 in savings for the one-month scheduling period.

Regarding workload distribution, the actual schedule assigns an average of 27 monthly shifts for nurses, with a standard deviation of 4.44 and a wide range of 19 shifts between the minimum and maximum. In contrast, the optimal schedule achieves a more balanced distribution of shift assignments, evidenced by the significant reduction in the average (24),

Table 4.12 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, O = Off day

Table 4.13 Comparison of KPIs of the actual and optimal schedules

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

standard deviation (0.98), and range (3) of shifts.

Given that the manual schedule did not account for nurses' preferences, the scores cannot be evaluated. The experimental results underscore the model's efficacy in accommodating nurses' shift and day-off preferences. In the cost-prioritized scheme, nurses are assigned an average of 24 monthly shifts, with approximately 8 days off. If all assignments align with nurses' most-preferred slots, the total preference score can reach 96. The average total preference score of 80 in the cost-prioritized scheme suggests that around 83% of the most preferred preferences are fulfilled. Moreover, the small standard deviation and range of the score reflect a relatively equitable distribution of preferred assignments. Therefore, it is reasonable to conclude that the model effectively and equitably addresses nurses' shift and day-off preferences. It is important to note that total preference scores vary among nurses based on the number of shifts and days off allocated. A higher allocation of shifts and days off contributes to a correspondingly higher total preference score.

In the job-satisfaction-prioritized scheme, nurses can achieve total preference scores as high as 85, indicating a more satisfactory and equitable schedule. However, this comes with a corresponding increase in total staffing costs to $28,845, representing an approximate 5% increment. This finding highlights the trade-off between staffing costs and the enhancement of job satisfaction. These results can provide decision-makers with valuable insights into balancing staffing costs and attaining higher and more equitable job satisfaction among nurses, enabling them to tailor objectives to align with their policies.

For enhanced visualization, Figures 4.4 and 4.5 illustrate the distribution of workload allocations in both the manual and optimal schedules under the cost-prioritized scheme. The optimal schedule exhibits a more consistent workload distribution than the actual schedule. Additionally, Figure 4.6 presents a frequency histogram depicting the distribution of total preference scores among nurses.

Based on the experimental findings, the proposed model effectively yields cost-effective, satisfactory, and equitable scheduling outcomes. The model's time complexity is evaluated by generating 28-day schedules for varying department sizes, ranging from 20 to 100 nurses. Remarkably, the optimal solutions are obtained within a minute for all instances. This rapid solving time enables the scheduling process to be highly responsive to last-minute changes in requests or preferences when employing the proposed model.

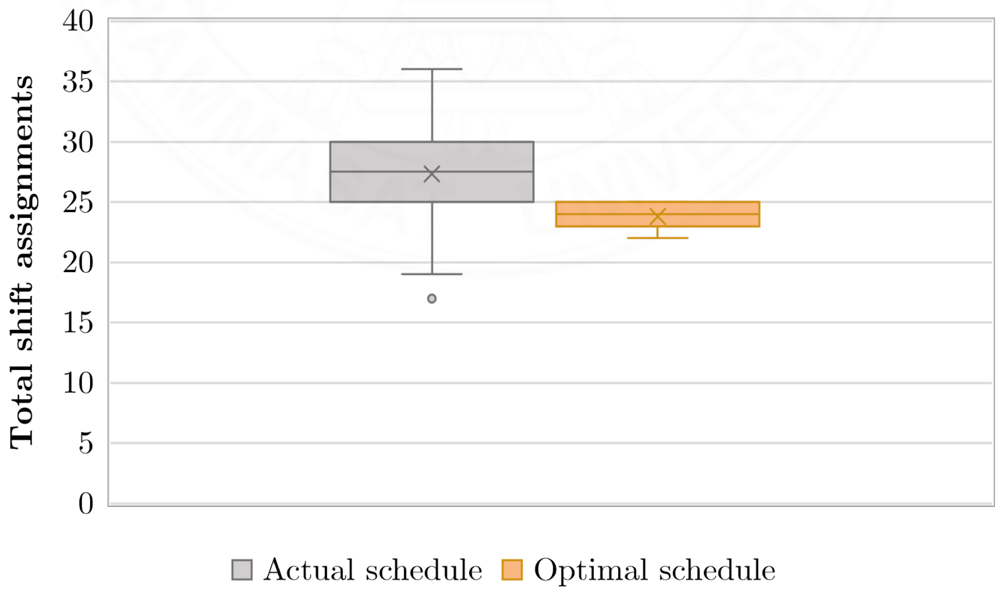

Figure 4.4 A comparison of workload distribution among nurses between actual and optimal schedules

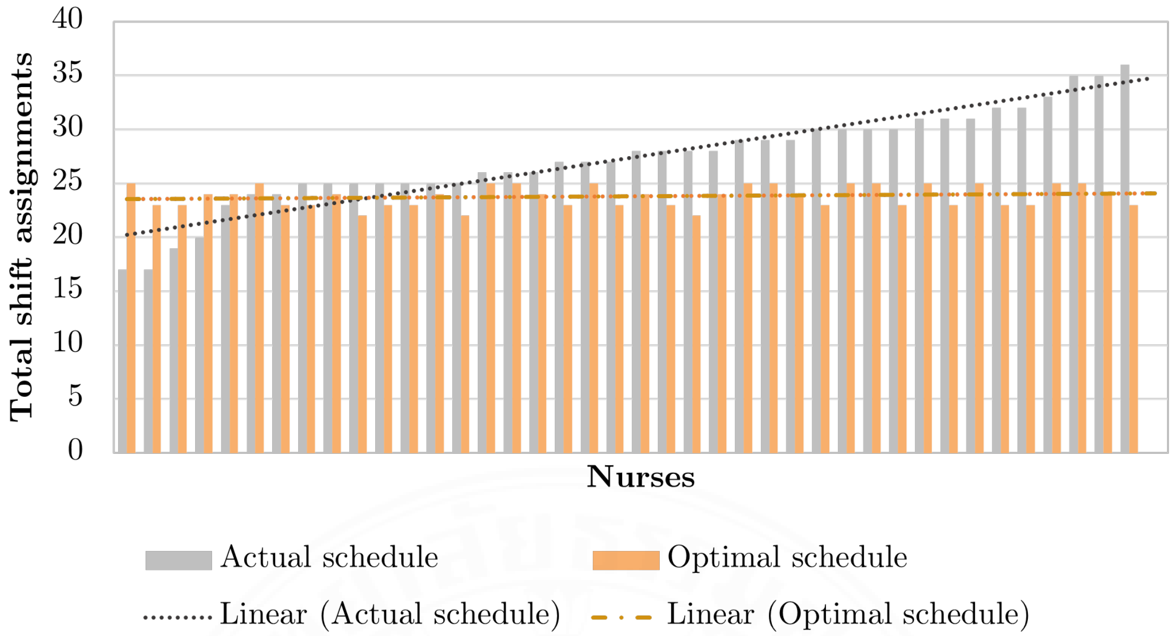

Figure 4.5 Workload assignments between the actual and optimal schedules by nurses

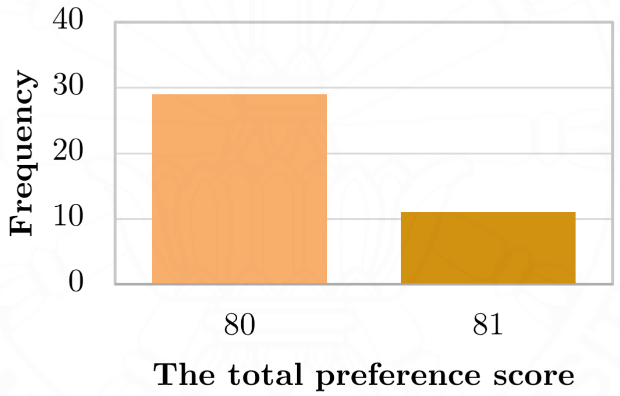

Figure 4.6 Distribution of the total preference score among nurses of the optimal schedule under the cost-prioritized scheme

4.2.4 Conclusion

The proposed cost-effective and satisfaction-enhanced NSP (Model II) represents a pioneering approach that simultaneously considers multiple job satisfaction factors and economic aspects. The objective is to generate a cost-efficient schedule aligned with nurses' preferences for shifts and days off while ensuring an equitable workload and preferred assignment distribution. The model is proposed as a bi-objective MILP and solved with the lexicographic optimization approach using the data collected from an actual hospital case of an ED at a large-scale public hospital in Thailand.

The experimental findings underscore the model's ability to enhance cost savings and job satisfaction, surpassing outcomes achievable through manual scheduling. Moreover, the trade-off analysis highlights the potential for achieving higher and more equitable total preference scores among nurses by incurring incremental costs. This insight can help decision-makers strategically prioritize objectives that align with their organizational goals. In addition, the model can generate a monthly schedule for varying department sizes of 20 to 100 nurses within one minute, highlighting its responsiveness in accommodating urgent scheduling requirements.

To summarize, this chapter presents the development of the two satisfaction-enhanced NSP models. Model I introduces a novel NSP approach that integrates fairness aspects in workload and preferred assignment distributions, an unexplored aspect in the existing literature. Employing a goal programming technique, the model aims to balance workload, preferred shifts, and day-off assignments among nurses. The model demonstrates its efficacy in generating satisfactory scheduling outcomes through a case study of an OR department in a medium-sized private hospital in Pathum Thani, Thailand. The findings show that the model successfully fulfills nurses' preferences while ensuring equitable workload and preferred assignment allocations, surpassing the performance of the actual schedule across various operational scenarios.

Model II presents a significant advancement by incorporating an economic perspective into the NSP alongside comprehensive satisfaction-enhanced factors. This model adopts the lexicographic optimization technique to minimize costs while maximizing the fulfillment of nurses' shift and day off preferences. The model's validation using a real-world case from an ED at a large-scale public hospital in Pathum Thani, Thailand, showcases its capacity to reduce staffing expenses while equitably accommodating nurses' shift and day-off preferences. Both proposed NSP models exhibit efficient computation times, promptly generating satisfactory and equitable scheduling outcomes for instances of varying sizes. The NSP models introduced in this chapter serve as practical decision-support tools that can be seamlessly integrated into hospital scheduling processes, offering enhanced efficiency and fairness without substantial software investment.

CHAPTER 5
CONCLUSION AND FUTURE WORK

5.1 Concluding remarks

This dissertation presents innovative workforce scheduling approaches to improve well-being and job satisfaction in industrial and healthcare contexts. The contributions of this work span both academic and practical dimensions, providing fundamental concepts and valuable decision-support tools for researchers and practitioners.

In industrial applications, the significance of job rotation scheduling is emphasized as a means to reduce excessive hazard exposure and achieve multifaceted benefits. Two job rotation scheduling models have been developed to address worker noise safety, productivity, skill development, and job satisfaction. The first model addresses critical scheduling factors such as safety, worker-task skill alignment, productivity, and demand requirements. It serves as a comprehensive scheduling approach, ensuring worker safety and efficient production in demand-driven manufacturing operations. The second model explores the advantages of safe job rotation in promoting worker multi-skill development and reducing production losses due to monotony-induced boredom. Numerical examples have validated and demonstrated the efficiency of both proposed models in achieving worker safety, productivity, and multi-skill development objectives. These models establish the groundwork for future research and serve as theoretical validation for practical implementations, underscoring the essential role of job rotation scheduling in industrial workforce management.

In healthcare applications, the proposed satisfaction-enhanced nurse scheduling models address the critical issue of nurse shortages by focusing on job satisfaction and fairness. These models provide a guideline for hospitals to create efficient and satisfactory work schedules that align with nurses' individual preferences and operational requirements. Data collected from actual hospital cases are used to validate the models against manually created schedules. Results showcase their capability to generate more satisfactory and fair nurse schedules within negligible time. These proposed satisfaction-enhanced nurse scheduling approaches can serve as practical decision-making tools, assisting head nurses in generating schedules that accommodate nurses' personal needs while maintaining economic performance. Hospitals can integrate these models into their scheduling processes by tailoring objective functions and constraints to ensure cost-effectiveness, satisfaction, and equitable work schedules. Positive scheduling outcomes are anticipated to play a pivotal role in nurse retention, thereby mitigating the challenges posed by nurse shortages prevalent in hospitals.

Furthermore, our workforce scheduling models are versatile and adaptable to various application domains. In the manufacturing sector, the models can be adjusted to accommodate different occupational hazards or expanded to account for multiple hazards simultaneously. Meanwhile, our nurse scheduling models can also be applied to personnel scheduling with around-the-clock work patterns. These models provide a robust framework for addressing scheduling challenges while optimizing multiple dimensions of worker well-being.

While experiments have showcased the efficacy of the proposed models, there remains scope for further enhancement and fine-tuning to facilitate their seamless implementation into real-world scenarios. This dissertation serves as a foundation for ongoing progress in workforce scheduling research, supplementing the knowledge that future studies can build upon.

In conclusion, this dissertation underscores the importance of workforce scheduling and its potential to drive positive transformations in the work environment. The methodologies and findings documented herein are believed to benefit researchers and practitioners alike in their pursuits to enhance safety, satisfaction, and productivity across various sectors, including manufacturing and healthcare. This work provides significant academic contributions to the fields of occupational safety and industrial human resource management, and healthcare personnel management. It can be used as a basis for future research in these areas.

5.2 Dissertation contributions

This section outlines the academic and practical contributions of this dissertation in the field of workforce scheduling for industrial and healthcare applications.

5.2.1 Academic contribution

All model formulations and experimental findings have been documented in conference proceedings and international journal articles. This dissertation provides an up-to-date understanding of noise-safe job rotation scheduling and satisfaction-enhanced nurse scheduling fields and strengthens their practical application value.

Practitioners and researchers can use the proposed models as guiding principles to enhance workforce scheduling approaches, promote employee well-being, and improve job satisfaction. These holistic approaches can be incorporated into future research to advance these study areas further. Significant academic contributions to the fields of occupational safety, industrial human resource management, and healthcare personnel management are described below.

Occupational safety and industrial human resource management

This dissertation presents novel insights into workforce scheduling, focusing on occupational safety and industrial human resource management. Workforce scheduling is a fundamental aspect of human resource management, encompassing the efficient allocation of workers to tasks and time slots to optimize operational objectives. Job rotation scheduling is a branch of workforce scheduling that assigns workers to specific time slots and various tasks. Rotating workers through multiple tasks can reduce excessive hazard exposure and provide safer working conditions. Workers' safety is essential to industrial human resource management, especially for labor-intensive industries with harsh working environments.

The first noise-safe job rotation model considers crucial scheduling factors, such as safety, skill, productivity, and demand requirements, which have yet to be simultaneously accounted for in existing literature. This model integrates worker-task skill matching, demand-driven production, and overtime assignments. The experimental results validate the model's ability to ensure worker safety even during extended work hours while maintaining the necessary production levels to meet production demand. Additionally, our findings underscore a valuable insight: the presence of expert workers within the system positively influences worker safety, emphasizing the importance of worker development programs in human resource management.

Moreover, the second noise-safe job rotation model explores the multifaceted benefits of job rotation, including hazard exposure mitigation, worker cross-training, and job satisfaction enhancement. This simultaneous consideration of these vital aspects remains unexplored in the existing literature, contributing toward seamlessly integrating occupational safety measures with industrial human resource management. The model generates job rotation schedules that not only protect workers from excessive noise exposure but also foster their horizontal skill development, addressing the challenges posed by trade-offs between safety and multi-skill development. It addresses the challenges associated with trade-offs between safety and multi-skill development. Moreover, this model accounts for the forgetting effect and monotony-induced job dissatisfaction, enhancing its practical applicability.

The proposed noise-safe job rotation models offer a foundation for advancing workforce scheduling research in industrial sectors, aiming to enhance worker well-being while maintaining production competitiveness. They supplement industrial human resource management knowledge by ensuring improved worker safety and fostering professional development. While the models primarily focus on noise control, they can be extended to various occupational hazards such as ergonomics, heat, vibration, or chemical substances. By adjusting hazard evaluations and limits, the models can accommodate diverse work environments and multi-limit occupational hazards.

Healthcare personnel management

In healthcare personnel management, our dissertation contributes to existing knowledge on nurse scheduling approaches to enhance job satisfaction. The nurse shortage issue emerges due to demanding and shift work conditions, which poses a significant challenge in healthcare personnel management. We propose novel NSP models encompassing the consideration of comprehensive satisfaction-enhancing factors, with particular emphasis on multiple fairness aspects to ensure satisfactory and fair work schedules for nurses as a means to subside their intention to leave.

The NSP Model I incorporates nurses' shift and day preferences alongside considerations for fairness in workload distribution and preferred assignment allocations. This approach enriches the previous NSP models that only focus on fairness in either workload or desirable assignments, resulting in schedules that may not be perceived as fair. Model I ensures that nurses' workloads and preferred assignments are distributed equally. The model was tested using data collected from an actual hospital case study and effectively produced satisfactory and equitable scheduling outcomes.

In addition, this dissertation introduces NSP Model II, which builds on Model I by including cost minimization as an objective. This considers the importance of the economic dimension of nurse scheduling, making it a more practical and cost-effective solution. Experimental results demonstrated a trade-off between cost and job satisfaction, enhancing understanding for researchers or practitioners to develop approaches that offer more promising solutions in both economic and satisfaction-enhance aspects.

These NSP models have been developed to enhance the job satisfaction and working conditions of healthcare personnel, with a particular focus on nurses. The models prioritize individual preferences and fairness factors, which are crucial for the overall well-being of nurses and can be a foundation for future research to accommodate for comprehensive factors. Although this dissertation mainly focuses on nurse scheduling, the models can be adapted to other medical personnel scheduling research with minor modifications.

5.2.2 Practical contribution

This section describes the practical contributions of this dissertation within the domains of human resource management for manufacturing and healthcare sectors. It also discusses the practical implementation and implications for other application domains.

Enhancing worker safety in manufacturing industries

This dissertation emphasizes the importance of job rotation scheduling for the safety of workers in manufacturing industries. The proposed model considers workers' diverse skills and the skill requirements of their tasks. This makes the model adaptable for use in manufacturing systems requiring worker-task skill matching under demand-driven production conditions to ensure worker safety and productivity.

Furthermore, this research demonstrates that employers can leverage job rotation to foster multi-skill development and boost worker motivation while maintaining job safety and satisfaction. The study highlights that well-designed job rotation scheduling programs can effectively achieve these fundamental pillars of human resource management.

The proposed job rotation models can serve as valuable decision-support tools for manufacturing industries aiming to enhance worker well-being and skill development. Decision-makers seeking to implement job rotation within their workplace can utilize these models as practical guidelines, customizing them as necessary to align with the specific requirements of their manufacturing settings.

Enhancing nurses' job satisfaction in healthcare

This dissertation underscores the critical role of enhancing nurses' job satisfaction as a crucial solution to address the ongoing nurse shortage issue. Thoughtfully designed nurse scheduling approaches enable decision-makers to consider workload allocation, nurses' job satisfaction factors, and fairness while complying with hospital regulations and economic requirements.

The proposed satisfaction-enhanced NSP models account for nurses' diverse personal preferences in shifts or days off, aligning them with individual lifestyles. Such a consideration encourages nurses to have some degree of job autonomy and allows them to design work schedules to suit their needs. Furthermore, the models ensure scheduling fairness in both workload distribution and preferred assignment allocation, enhancing their practicality for real-world implementation.

This dissertation also demonstrates that balancing cost minimization and job satisfaction enhancement through our nurse scheduling approach is possible, even though trade-offs between these aspects may exist. Our model allows decision-makers to customize objective goal values or priorities to reflect their preferences and operational needs.

These proposed models can be seamlessly integrated into hospital scheduling processes as decision-support tools. Hospital administration can tailor model components to align with their operational systems. For instance, the input and regulations-related parameters can be adjusted based on the scale of departments, desired planning period, or operational requirements. Hospitals can efficiently utilize the proposed NSP models to generate high-quality work schedules that positively affect nurses' well-being and job satisfaction. This enables head nurses to allocate their time and effort to other critical administrative tasks.

Enriching workforce sustainability development

This dissertation underscores the pivotal role of workforce sustainability development and introduces scheduling approaches to foster the achievement of workforce sustainability goals. Based on the work by Karakhan et al. (2020), various dimensions of workforce sustainability are recognized, including:

1. **Nurturing:** The extent to which the workplace offers support, education, and training to facilitate employee growth.
2. **Diversity:** The extent to which the workplace embraces an inclusive workforce, encompassing differences in ethnicity, background, demographics, and cultural diversity.
3. **Equity:** The extent to which the workplace ensures equal treatment, accommodates needs fairly and evaluates employees without biases.
4. **Health and well-being:** The extent to which the workplace prioritizes a safe working environment, emphasizing employees' physical and mental well-being and satisfaction.
5. **Connectivity:** The extent to which the workplace encourages relationships, collaborations, and employee interactions.
6. **Value:** The extent to which the workplace acknowledges, appreciates and respects employees for their contributions, work performance, and commitment.
7. **Community:** The extent to which the workplace nurtures team bonding, fostering acceptance and support among employees.
8. **Maturity:** The extent employees share competency, responsibility, and accountability in problem-solving and decision-making processes.

This dissertation actively contributes to nurturing, equity, and health and well-being attributes. The proposed job rotation model, which considers multi-skill development, provides comprehensive training opportunities for workers, nurturing their career growth.

Addressing equity, the proposed nurse scheduling models offer guidelines for achieving enhanced fairness in the workplace through improved workforce scheduling practices. Ultimately, all proposed models promote health and well-being by enhancing many key aspects of worker safety, well-being, work-life balance, and overall job satisfaction.

Practical implementation

All proposed models were implemented using widely accessible tools, primarily Microsoft Excel, and for those who prefer coding, Jupyter Notebook or Google Colab. Microsoft Excel, a user-friendly office tool familiar to professionals in various sectors, serves as a convenient platform for model implementation. By utilizing optimization solvers like OpenSolver (free) or Gurobi (commercial license required) within Microsoft Excel, these models can efficiently generate job rotation or nurse schedules for medium- to large-sized manufacturing plants or hospital departments. Although implementing the scheduling models in Microsoft Excel does not demand extensive coding skills, a basic understanding of spreadsheet and solver manipulation is required. This approach provides a cost-effective solution for companies with Microsoft Office subscriptions, eliminating the need for dedicated scheduling software.

In the experiments, OpenSolver and Gurobi integrated with Microsoft Excel can swiftly generate job rotation and nurse schedules with negligible processing time for most scenarios. However, for complex problems involving aspects like worker learning and forgetting, it may be advisable to consider alternative solving approaches, such as heuristics or metaheuristics. These advanced methods may not be fully supported within Microsoft Excel's environment.

Additionally, for those who prefer a more programming-oriented approach, Jupyter Notebook or Google Colab, open-source platforms supporting multiple programming languages, can also be employed for model implementation. In Jupyter Notebook or Google Colab, the optimization technique can be implemented through the Gurobi or CPLEX optimization library. Heuristics and metaheuristic approaches such as RGA or GA offer flexibility and the capability to handle more complex and larger problems. These approaches can be effectively applied to the job rotation model involving the worker learning-forgetting aspect. GA may take longer to generate optimal solutions due to its multiple genetic operators required in each generation. Decision-makers can employ other metaheuristics that offer shorter solution times based on their specific needs.

Implications for other application domains

The workforce scheduling models presented in this dissertation are designed to be versatile decision-support tools that can be adapted for scheduling processes across different sectors with minimal modifications.

Noise-safe job rotation models can be readily applied to industries sharing similar scheduling patterns. These models accommodate the rotation of workers among multiple tasks within a workday or over specific periods, enhancing safety, multi-skill development, and work motivation. Managers can customize the model to address specific hazard controls or learning-forgetting aspects relevant to their context. The hazard control constraints can be adjusted to accommodate specific occupational hazards encountered in various settings.

The proposed nurse scheduling models can be implemented in different hospital departments or other hospitals requiring only parameter adjustments such as shift lengths, planning periods, or specific hospital regulations. Furthermore, their versatility extends to scheduling other personnel working around the clock, including physicians, security guards, gas station attendants, and hotel front staff. For instance, challenges in staffing hotel front desks share similarities with nurse scheduling, encompassing concerns such as staffing coverage, schedule quality, staffing cost, and fairness.

The proposed workforce scheduling models incorporate a standard set of constraints frequently encountered in personnel scheduling problems, encompassing work-hour or days off requirements and staffing coverage criteria. For around-the-clock work systems, it is advisable to include forbidden shift pattern constraints to ensure that staff receive sufficient rest. The consideration of differences in skill levels and skill requirements can be tailored to match the specific demands of various job natures. Decision-makers can include or omit specific constraints or conditions to align with the unique requirements of their applications.

In conclusion, the versatility of these workforce scheduling models renders them handy decision-support tools with applicability across a wide range of sectors. Whether mitigating noise hazards or enhancing job satisfaction, their capabilities empower practitioners and researchers to address scheduling challenges in diverse domains while optimizing operational efficiency and employee well-being.

5.3 Limitations and future works

While the experiments confirm the effectiveness of the proposed scheduling approaches, there exist limitations and avenues for future research and improvement.

5.3.1 Noise-safe job rotation scheduling approaches

While both noise-safe job rotation models have demonstrated their effectiveness in ensuring worker safety, productivity, job satisfaction, and skill development, they still possess inherent limitations that warrant further refinement for practical application.

Firstly, these models are primarily designed to address noise hazard exposure and may not consider other potential occupational hazards in the work environment. Future research should focus on extending the models to account for multiple occupational hazards simultaneously, enhancing workplace safety comprehensively. This may involve considering factors such as heat stress, vibration, and ergonomic risks, ensuring a more holistic approach to worker safety.

The current models are equipped with strict noise constraints and are most suitable for systems involving combinations of tasks with varying noise levels. They may encounter limitations when applied to scenarios where all tasks consistently have high noise levels, potentially resulting in infeasible schedules. Future enhancements could involve reformulating strict noise constraints as objectives, allowing more flexibility in handling hazards. Alternatively, noise limits can be relaxed when other hazard control measures are readily implemented.

Another critical aspect is the estimation of worker learning, forgetting, and boredom rates. These parameters are derived from theoretical estimates by the existing literature, which may not fully align with their influences on real-world worker production performance. Future research can aim to improve the estimation of these values, making them more reflective of actual worker dynamics and their influence on production performance.

Regarding model evaluation, the efficiency of the job rotation models is assessed by comparing scenarios with rotation and without rotation in terms of safety and productivity performance. To rigorously test the models, they can be benchmarked against other existing models in the literature or employ system simulation to evaluate their effectiveness.

Furthermore, while job rotation models provide valuable insights, their practical implementation in real-world cases remains limited due to their complexity and potential disruptions to production processes. Finding cooperative cases for implementation can be challenging. Therefore, there is a need for further refinement of these models to ensure their practicality and ease of implementation in industrial settings. Future research efforts should focus on bridging the gap between theory and practice by conducting real-world case studies to gain insights into job rotation's potential impacts and benefits.

In conclusion, future research should address these limitations, expand the applicability of job rotation models to diverse hazards, improve parameter estimation, and prioritize practical implementation. This will provide actionable insights for enhancing workplace safety, productivity, and worker well-being in real-world manufacturing environments.

5.3.2 Satisfaction-enhanced nurse scheduling approaches

While both NSP models demonstrate efficiency, they have limitations that warrant further exploration for improved practicality and fairness. The current models primarily focus on assigning nurses to shifts, which may not fully encompass the complexities of nurse-team or nurse-role allocations, as seen in some hospitals. Future research should delve into these aspects to enhance the models' capabilities.

In terms of fairness, the current models address it within a single planning horizon but may fall short of ensuring long-term fairness. Continuous use of the models can lead to situations where some nurses consistently receive less preferred assignments. To address this, future research should incorporate historical assignments into the scheduling process, prioritizing nurses who have received less favorable assignments in the past. Additionally, the models assume fairness for all nurses regardless of their levels, whereas nurses with different levels may have varying work-hour contracts. Future research can employ hierarchical fairness models to align with practical considerations, ensuring fairness only among nurses with similar levels and conditions.

The satisfaction-enhanced models proposed primarily consider individual preferences for shifts and days off. Nevertheless, there is potential for further refinement by incorporating additional preference aspects, such as nurse affinities or preferences for specific shift patterns when working two daily shifts. By doing so, the working atmosphere can be improved by catering to specific scheduling preferences. This can make scheduling approaches enhance overall job satisfaction among nurses more efficiently.

Finally, while our models were developed under deterministic assumptions of parameters, they do not consider inherent uncertainties in hospital operations, such as patient volume fluctuations or sudden nurse absences. To address this, future research can introduce uncertainty considerations during the scheduling stage. This proactive approach can minimize understaffing risks and mitigate adverse rescheduling impacts, resulting in more resilient and less disruptive nurse schedules.

In summary, the current satisfaction-enhanced nurse scheduling models provide a solid foundation but offer areas for further refinement. Exploring nurse-team assignments, long-term fairness considerations, individual preferences, and uncertainty handling can further enhance the practicality and effectiveness of these scheduling approaches.

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