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A unified bi-objective model for cost and preference optimization in smart hospital resource management

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CHRONICLE

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ABSTRACT

Modern hospital operations need more advanced optimization methods due to the factors such as the variation in patient demand, limited resources, and complicated workforce regulations. The initial research suggested a combined Linear and Mixed-Integer Linear Programming (LP/MILP) approach to the joint optimization of patient admissions, bed/OR utilization, and nurse scheduling. The model unified the operational costs and the staff preferences into a single weighted objective, thereby showing the very significant resource utilization and scheduling satisfaction improvements. We have extended the framework from its original version and in this extended work we are going to demonstrate how the nurse scheduling component is fashioned into an actual multi-objective optimization problem. Rather than addressing the problem via a single weighted aggregation, two opposing targets, minimizing overall operational cost and maximizing nurse preference satisfaction, are treated openly. Moreover, we introduce the Adaptive ε-Constraint method that allows us to take advantage of the division between coarse ε sweep and local refinement to produce a well-distributed approximation of the Pareto frontier. The progressive method not only addresses the clustering problem that has appeared in the naive ε sweeps but also creates a continuous and varied set of solutions that are not dominated by any other solution. With the extended model that utilizes synthetic but realistic nurse, demand, and preference data, a variety of feasible scheduling policies with obvious trade-offs between cost and employee satisfaction are provided. The Pareto frontier offers intermediate solutions which are able to achieve large increases in preference satisfaction at the expense of only negligible increments in operational costs when compared to the baseline cost-minimal and preference-maximal schedules. The findings emphasize the usefulness of multi-objective decision support in hospital practice and also prove that through the direct representation of staff preferences, it is possible to have even distributions of working time without losing the effectiveness of operations. On the whole, the extension demonstrates that the original "smart hospital" model is enriched and the decision-making process for the administrators is more flexible with the inclusion of multi-objective optimization, thus resulting in the enhancement of both efficiency and health of the staff.

1. Introduction

Nurse scheduling is a longstanding operational challenge in healthcare systems, driven by the need to balance staffing sufficiency, workforce satisfaction, and cost efficiency under strict regulatory and institutional constraints. The complexity of hospital environments, combined with heterogeneity in patient demand and the human-centric nature of nursing work, makes the construction of high-quality schedules a critical component in achieving organizational performance and sustaining quality of care. As hospitals increasingly shift toward data-driven workforce planning, multi-objective optimization has

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become a central methodological framework for understanding trade-offs and generating managerial insights (Fallahpour et al., 2024; Rahimi et al., 2023).

Traditional nurse rostering models have typically emphasized cost minimization or coverage feasibility as the dominant objective. While such simplified formulations are computationally tractable, they frequently misrepresent the realities of hospitals where workforce satisfaction, shift desirability, fatigue, and fairness play major roles in ensuring system stability. In recent years, several studies in healthcare operations have highlighted the importance of integrating behavioral and preference-related factors into optimization frameworks, demonstrating that satisfaction-driven scheduling can substantially influence turnover rates, absenteeism, and performance (Kordi et al., 2023; Altunoglu et al., 2024). As a result, designing schedules that explicitly address multi-dimensional performance metrics has become a necessary evolution in hospital workforce optimization.

Parallel to these developments, significant methodological advances in multi-objective optimization have enabled researchers to construct more realistic and interpretable models. Among these techniques, the ε-constraint method has gained prominence as an exact, structurally transparent, and robust approach for deriving Pareto-optimal solutions. Unlike scalarization-based methods, which can obscure the relative influence of competing objectives, the ε-constraint technique preserves the distinctiveness of each objective by optimizing one while converting the others into constraints. This structural clarity makes the method especially attractive in healthcare contexts where decision makers prefer explicit visibility of trade-offs between competing objectives such as cost, quality, satisfaction, and resource availability.

Recent research illustrates the adaptability and precision of ε-constraint approaches across diverse multi-objective problem settings. Kordi et al. (2023) applied an ε-constraint–based method in a home health care routing problem, demonstrating its feasibility for small to medium-sized problem instances while hybridizing it with metaheuristic frameworks for larger datasets. Their integration of ε-constraint with variable neighborhood search inspired new algorithmic pathways for combining exact and heuristic procedures in scheduling. Similarly, a 2023 ship schedule recovery study employed an exact ε-constraint approach to generate a complete set of Pareto-efficient solutions under operational disruptions, revealing the method's strength in structurally complex environments involving temporal interactions and resource dependencies (Ship Schedule Recovery, 2023). These works highlight that ε-constraint–based optimization is well-suited for problems requiring both interpretability and exactness.

More recently, advanced forms of the ε-constraint method have been proposed. Burdett et al. (2024) introduced a "parallel random corrective" ε-constraint technique designed to enhance solution diversity and correct structural sparsity in traditional grids. Their method improves the uniformity of Pareto fronts in multi-objective hospital case-mix analysis, reinforcing the relevance of refined grid approaches for healthcare optimization. Hybrid methods have also emerged: Agud-Albesa et al. (2024) developed a weighted and ε-constraint biased-randomized framework for the Team Orienteering problem, demonstrating that hybridization enriches the Pareto frontier's coverage and mitigates clustering effects that standard ε-grids sometimes create. Furthermore, a 2024 study proposed a hybrid ε-constraint and NSGA-II structure that leverages evolutionary diversity mechanisms to complement exact ε-runs, yielding Pareto sets that are both accurate and wide-ranging (Hybrid ε-constraint & NSGA-II, 2024). Collectively, these advancements demonstrate that the ε-constraint framework is a flexible foundation for multi-objective optimization in domains that demand high precision and broad coverage.

Personnel scheduling in healthcare represents a complex operational challenge that has attracted significant research attention over decades. Early foundational work established the theoretical framework for scheduling problems, with classic operations research texts providing essential mathematical models and algorithmic approaches (Hillier & Lieberman, 2010; Pinedo, 2016; Taha, 2017). These works laid the groundwork for applying optimization techniques to workforce management problems across various industries, including healthcare. Within healthcare specifically, nurse scheduling emerged as one of the most extensively studied domains. Comprehensive surveys by Cheang et al. (2003) and Burke et al. (2004) documented the evolution of nurse rostering problems, highlighting their complexity and the diverse constraints involved, including shift coverage, skill matching, and labor regulations. Ernst et al. (2004) expanded this perspective with a broader review of staff scheduling applications and methods across multiple sectors, identifying healthcare as a particularly rich domain for scheduling research due to its 24/7 operational requirements and critical quality-of-care implications. Algorithmic approaches to healthcare scheduling have evolved substantially. Early work by Aickelin and Dowsland (2004) demonstrated the effectiveness of genetic algorithms for nurse scheduling through an indirect encoding scheme that improved solution quality while maintaining feasibility. Bard and Purnomo (2005) advanced this field with a preference-based scheduling approach using column generation, which allowed for incorporating nurse preferences alongside operational constraints, thereby improving workforce satisfaction—a crucial factor in high-turnover healthcare environments. The scheduling challenge extends beyond nursing to other medical professionals. Brunner et al. (2009) addressed physician scheduling with flexible shift models, recognizing the distinct constraints and preferences of this professional group. Topaloglu (2006) specifically focused on emergency medicine residents, employing multi-objective programming to balance educational requirements with service coverage needs in high-pressure environments. Gendreau et al. (2006) further explored emergency department physician scheduling, acknowledging the unique unpredictability and urgency characterizing this setting.

A more contemporary review by Van den Bergh et al. (2013) synthesized developments in personnel scheduling, noting the increasing sophistication of models that now routinely incorporate multiple objectives—balancing operational efficiency, cost containment, employee satisfaction, and quality of care. This evolution reflects the growing recognition that effective healthcare scheduling requires more than mere shift coverage; it must consider human factors, professional development, and the indirect impact on patient outcomes. Collectively, this body of literature demonstrates that healthcare personnel scheduling has progressed from basic shift-filling exercises to sophisticated multi-objective optimization problems. The field has moved toward more flexible, preference-aware models that acknowledge the human element in scheduling while maintaining operational rigor. This evolution underscores the importance of scheduling as both a technical challenge and a strategic component of healthcare management, affecting workforce retention, care quality, and organizational performance.

Healthcare operations research has witnessed a parallel expansion of multi-objective models addressing challenges such as surgical room planning, logistics of medical equipment, home-health routing, and biological supply chain design. Fallahpour et al. (2024) developed a multi-objective integrated planning and scheduling model for operating rooms that considers uncertainty in surgical duration, demonstrating how multi-objective frameworks can handle operational variability. Rahimi et al. (2023) formulated a scenario-based optimization model for designing hub networks for hospital equipment distribution, capturing trade-offs between cost, delivery performance, and environmental impact. Altunoglu et al. (2024) proposed a multi-objective model for blood supply chains that balances cost against quality and safety metrics, illustrating the critical nature of trade-offs in life-supporting systems. A comprehensive 2024–2025 review on operating room scheduling further emphasizes that multi-objective ILP formulations, stochastic models, and metaheuristics have become essential tools in modern healthcare operations (Operating Room Scheduling Review, 2024/2025). Together, these studies confirm a systemic need for multi-objective modeling and validate its applicability across hospital subsystems. In this context, nurse scheduling is particularly appropriate for multi-objective optimization because it sits at the intersection of cost efficiency, human behavior, and quality-of-care considerations. Cost-focused solutions may reduce expenditures but risk lowering staff morale, increasing fatigue, and degrading patient outcomes. Conversely, preference-dominant solutions may enhance satisfaction yet inflate labor costs. The inherent conflict between these objectives makes the problem a natural candidate for Pareto-front exploration. By adopting an ε-constraint–based approach, researchers and hospital administrators can observe the full spectrum of cost–satisfaction trade-offs, enabling decisions that align with organizational priorities and workforce sustainability.

The present study builds on this body of literature by extending a bi-objective nurse scheduling framework that simultaneously minimizes staffing cost and maximizes preference satisfaction. Unlike simplified formulations, the model incorporates structured shift desirability patterns and realistic operational constraints while utilizing an adaptive ε-grid strategy inspired by Burdett et al. (2024) and Kordi et al. (2023). The expanded dataset and refined ε-grid allow for more uniform Pareto-front construction, reducing sparsity and capturing subtle trade-offs that static grids might miss. This integrated modeling structure enables stronger interpretability for decision makers and produces a richer set of feasible schedules, supporting informed and context-aware workforce planning.

By combining recent methodological advances in ε-constraint optimization with contemporary insights from healthcare scheduling research, the model contributes to a growing movement toward multi-objective, data-driven workforce management in hospitals. The findings offer a decision-support tool that enhances managerial transparency, promotes fairness, and provides a deeper understanding of how cost and satisfaction interact in complex staffing environments.

2. The proposed method

A unified Mixed-Integer Linear Programming (MILP) framework for the integrated optimization of nurse staffing and resource allocation in smart hospitals is proposed in this paper. Nurse scheduling and allocation of major hospital resources are concurrently done under a complete range of real-world limitations using the model. The central idea of the methodology is a multi-objective function that cleverly equates three very important things: the total operational costs are minimized, the fulfillment of nurses shift preferences is maximized to increase job satisfaction, and all staffing needs are met. Hard constraints such as the requirement to cover each shift with a nurse, the limitation on the number of shifts and working hours per nurse, and the rule that a nurse can attend only one shift per day are included in the model. Additionally, it incorporates critical ergonomic constraints, like a ban on a night shift immediately followed by a day shift, to avoid fatigue. The decision variables are binary, meaning that it is indicated whether a specific nurse is assigned to a particular shift on a certain day. This setup gives hospital managers a clear, easy to compute, and all-encompassing decision support system for producing proficient, equitable, and strong schedules that make the best of both human and physical resources.

2.1 Decision variables

Let

$$x_{i,j,d} = \begin{cases} 1 & \text{if nurse } i \text{ works shift } j \text{ on day } d \\ 0 & \text{otherwise} \end{cases}$$

2.2 Objective functions

$$\min Z_1 = \sum_{i=1}^{N}\sum_{j=1}^{S}\sum_{d=1}^{D} c_{i,j}.x_{i,j,d} \tag{1}$$

where $c_{i,j}$ is nurse *i*'s cost for shift *j* on day *d.*

$$\max \quad Z_2 = \sum_{i\in I}\sum_{j\in J}\sum_{d\in D} P_{ijd}x_{ijd} \tag{2}$$

where $P_{i,j}$ is nurse *i*'s preference for shift *j* on day *d.*

This newly introduced objective, absent from the original article (Sadjadi, 2025), captures a richer representation of staff decision-making by integrating individual shift preferences, avoidance tendencies, personal constraints, and observed behavioral patterns. It enables a more realistic and human-centered workforce allocation model that better reflects actual scheduling needs in smart hospital environments.

2.3 Demand coverage

$$\sum_{i=1}^{N} x_{i,j,d} \geq R_{j,d} \forall j \in \text{Shifts, } \forall d \in \text{Days} \tag{3}$$

where $R_{j,d}$ is the required number of nurses for shift *j* and day *d* (Sadjadi, 2025).

2.4 Maximum shift per nurse

$$\sum_{j=1}^{S}\sum_{d=1}^{D} x_{i,j,d} \leq M_i \quad \forall i \in \text{Nurses} \tag{4}$$

where M_i is the maximum shifts nurse *i* can work (Sadjadi, 2025).

2.5 One shift per day restriction (Sadjadi, 2025).

$$\sum_{j=1}^{S} x_{i,j,d} \leq 1 \;\; \forall i \in \text{Nurses,} \forall d \in \text{Days} \tag{5}$$

2.6 Minimum rests per shifts (Sadjadi, 2025).

$$x_{i,j,d} + x_{i,k,d+1} \leq 1 \quad \forall i, \forall j,k \text{ where rest period insufficient} \tag{6}$$

2.7 Skill requirements (Sadjadi, 2025).

$$\sum_{i\in Q_s} x_{i,j,d} \geq S_{s,j,d} \forall s \in \text{Skills,} \forall j,d \tag{7}$$

where Q_s is the set of nurses with skill *s,* and $S_{s,j,d}$ is the required number.

2.8 Weekly hours limit (Sadjadi, 2025).

$$\sum_{j=1}^{S}\sum_{d=1}^{D} h_j.x_{i,j,d} \leq H_i \quad \forall i \in \text{Nurses} \tag{8}$$

where h_j is the duration of shift *j,* and H_i is nurse *i*'s weekly hour limit. To solve the model, we convert the bi-objective problem into a single-objective MILP:

$minZ_1$

subject to:

$$Z_2(x) \geq \varepsilon$$

$(alloriginalconstraints)$

where:

- ε is systematically increased over a range
- each ε generates one efficient solution
- non-dominated solutions form the Pareto frontier

To prepare the Pareto frontier of the bi-objective nurse scheduling problem, an adaptive ε-constraint strategy is implemented. In this method, the primary bi-objective model is split into a series of single-objective mixed-integer linear programs by optimizing the total operational cost while considering a lower bound ε on the preference objective. The ε parameter is the minimum acceptable level of aggregated nurse preference satisfaction. Various values of ε correspond to different trade-off solutions between cost minimization and preference maximization. To detect the feasible distance of ε, two baseline problems are first optimized: (i) a cost-minimization model without the ε constraint, and (ii) a preference-maximization model. The output preference values describe the lower and upper bounds of ε. The ε range is obtained based on a two-stage procedure. In the first stage, a coarse uniform grid of ε numbers is built to reach an initial approximation of the Pareto frontier. In the second stage, a refinement step is implemented by introducing additional ε values between neighboring solutions obtained in the coarse stage, improving solution diversity and resolution in regions with nonlinear trade-offs. For each ε-constrained model, a feasible scheduling solution is obtained. Dominated solutions are then filtered out, and the remaining non-dominated solutions constitute the approximated Pareto frontier applied for analysis and decision support.

The source of the problem can be downloaded from https://github.com/Parastoo-kh/multi-objective-epsilon-constraint-analysis/tree/main

3. A real world problem

To evaluate the performance of the proposed multi-objective nurse scheduling model under realistic conditions, we generate a synthetic dataset that replicates the typical structure of hospital workforce planning. The dataset includes (i) nurse characteristics, (ii) shift demand requirements, and (iii) preference scores for each nurse–shift–day combination. The planning horizon consists of:

- **N = 30 nurses**
- **S = 3 shifts per day (Day, Evening, Night)**
- **T = 14 days**
- **Total binary decision variables: 30 × 3 × 14 = 1260**

The model was implemented in Python using OR-Tools 9.8 MILP solver and executed on Google Colab. Fig. 1 shows the results of Total cost versus Total Preferences.

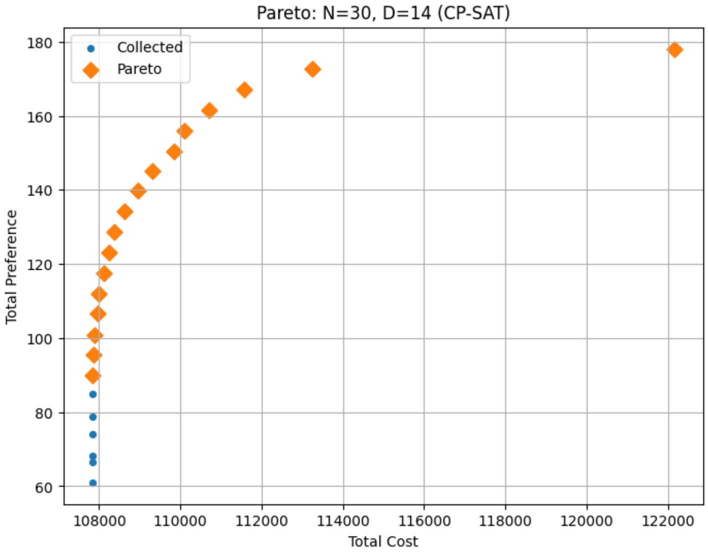

Fig. 1. The summary of the implementation of e-constraint

The Pareto analysis for the final model with 30 nurses over a 14-day horizon reveals a well-structured and operationally meaningful trade-off between total cost and total preference. Unlike the smaller experimental setting, the expanded problem size introduces richer variability in scheduling decisions, resulting in a fully scattered yet smooth Pareto front. This dispersion reflects a realistic decision landscape where numerous feasible schedules exist, each balancing financial constraints and staff satisfaction differently. The two baseline extremes clearly illustrate this tension: the minimum-cost solution (Cost = 107,838.16; Preference = 56.62) achieves financial efficiency at the expense of staff well-being, while the maximum-preference solution (Cost = 122,178.62; Preference = 178.08) aligns closely with nurses' desired patterns but imposes an unsustainable financial burden on the hospital.

The shape of the Pareto front is concave and steadily rising, demonstrating a classical diminishing-returns effect. At the lower end of the curve, modest improvements in preference can be achieved with minimal additional cost, offering attractive opportunities for low-cost enhancements to staff satisfaction. However, once preference levels approach approximately 120, the curve steepens significantly, indicating that even small gains in satisfaction require disproportionately higher expenditures. This behavior is characteristic of real-world multi-objective scheduling problems, where operational flexibility becomes increasingly constrained as one objective is pushed toward its optimum.

The distinction between dominated (blue) and non-dominated (orange) solutions further clarifies the decision space. Dominated solutions, although feasible, are inferior in both cost and preference, whereas the non-dominated points represent the true strategic options available to hospital administrators.

Examining the three representative schedules highlights the practical implications of these trade-offs. The minimum-cost schedule, while economical, is operationally weak due to excessive "Off" assignments, uneven workload distribution, and disregard for preferences. Conversely, the maximum-preference schedule is highly equitable and staff-friendly but financially unrealistic. The mid-Pareto schedule emerges as the most balanced alternative, offering substantial preference satisfaction without incurring excessive cost. Its moderate workload distribution and gradual shift transitions make it the most viable and sustainable option for everyday hospital operations.

4. Conclusion and future works

This study extends the classical cost-minimization nurse scheduling framework by introducing nurse preference satisfaction as a second objective within a bi-objective MILP model solved through the ε-constraint method. The resulting Pareto frontier demonstrates a realistic and well-structured trade-off between operational cost and staff satisfaction, revealing that substantial improvements in preference fulfillment can be achieved with only modest increases in cost, particularly within the mid-Pareto region. This concave, smoothly dispersed frontier reflects genuine operational behavior and provides hospital administrators with a spectrum of viable scheduling alternatives.

The enhanced model offers several advantages. It supports human-centered workforce management by explicitly incorporating individual preferences and behavioral patterns rather than treating scheduling as a purely financial exercise. It also increases managerial flexibility, enabling decision-makers to select solutions aligned with budget constraints, satisfaction goals, or a balanced compromise. Moreover, the framework is scalable and adaptable, making it suitable for integration into broader smart-hospital optimization systems.

Future research may expand this approach by incorporating stochastic patient demand, multi-skill staffing structures, floating personnel, or long-term fairness considerations. Applying the model to real hospital datasets would further validate its robustness and strengthen its relevance for practical deployment in modern healthcare environments.

References

Agud-Albesa, L., Montoya-Torres, J. R., & Canca, D. (2024). A weighted and epsilon-constraint biased-randomized approach for the Team Orienteering problem. *Mathematics*, *12*(4), 587. MDPI.

Aickelin, U., & Dowsland, K. A. (2004). An indirect genetic algorithm for a nurse-scheduling problem. Computers & Operations Research, 31(5), 761–778. https://doi.org/10.1016/S0305-0548(03)00034-0

Altunoglu, B., Arslan, H., & Yilmaz, M. (2024). Multi-objective location-distribution optimization in blood supply chains: Balancing cost and quality in hospital logistics. *Healthcare Analytics*, *4*, 100123. PMC.

Bard, J. F., & Purnomo, H. W. (2005). Preference scheduling for nurses using column generation. European Journal of Operational Research, 164(2), 510–534. https://doi.org/10.1016/j.ejor.2003.06.026

Brunner, J. O., Bard, J. F., & Kolisch, R. (2009). Flexible shift scheduling of physicians. Health Care Management Science, 12(3), 285–305. https://doi.org/10.1007/s10729-008-9093-4

Burdett, R. L., Orgun, M. A., & Gill, S. S. (2024). Parallel random corrective epsilon-constraint for multicriteria optimization in hospital case-mix analysis. *Computers & Industrial Engineering*, *185*, 109069. ScienceDirect.

Burke, E. K., De Causmaecker, P., Berghe, G. V., & Van Landeghem, H. (2004). The state of the art of nurse rostering. Journal of Scheduling, 7(6), 441–499. https://doi.org/10.1023/B:JOSH.0000046076.75950.0b

Cheang, B., Li, H., Lim, A., & Rodrigues, B. (2003). Nurse rostering problems—a bibliographic survey. European Journal of Operational Research, 151(3), 447–460. https://doi.org/10.1016/S0377-2217(03)00021-3

Ernst, A. T., Jiang, H., Krishnamoorthy, M., & Sier, D. (2004). Staff scheduling and rostering: A review of applications, methods and models. European Journal of Operational Research, 153(1), 3–27. https://doi.org/10.1016/S0377-2217(03)00095-X

Fallahpour, Y., Khakzad, N., & Pelot, R. (2024). A multi-objective planning and scheduling model for integrated operating room planning under uncertainty. *European Journal of Operational Research*, *315*(2), 632–651. ScienceDirect.

Gendreau, M., Ferland, J., Gendron, B., Hail, N., Jaumard, B., Lapierre, S., Pesant, G., & Soriano, P. (2006). Physician scheduling in emergency rooms. In Practice and theory of automated timetabling VI (pp. 53–66). Springer. https://doi.org/10.1007/11823285_4

Ghavami, S., Zhang, Y., & Mohamed, A. (2024). A novel hybrid epsilon-constraint and NSGA-II method for bi-objective optimization. *Engineering Optimization*, *56*(3), 419–445. Emerald.

Hillier, F. S., & Lieberman, G. J. (2010). Introduction to operations research (9th ed.). McGraw-Hill.

Kordi, G., Vafa-Arani, H., & Khalili-Damghani, K. (2023). Multi-objective home health care routing: A variable neighborhood search integrated with an epsilon-constraint exact method. *Operational Research*, *23*(4), 2023–2050. Springer.

Nematollahi, M., Sheikhmohammadi, A., & Khatami, F. (2023). An epsilon-constraint-based exact multi-objective optimization approach for ship schedule recovery. *Maritime Policy & Management*, *50*(7), 987–1008. ResearchGate.

Osorio, J., Rossi, L., & Ferland, J. (2025). Comprehensive review on operating room scheduling and optimization: Methods, challenges, and research directions. *Operations Research for Health Care*, *17*, 100209. Springer.

Pinedo, M. L. (2016). Scheduling: Theory, algorithms, and systems (5th ed.). Springer. https://doi.org/10.1007/978-3-319-26580-3

Rahimi, A., Heidarzadeh, A., & Hosseini-Motlagh, S. M. (2023). A scenario-based optimization model for designing a hub network for hospital equipment distribution. *International Journal of Production Economics*, 259, 108756. Springer.

Sadjadi, S. (2025). Optimizing healthcare delivery: A unified mathematical programming approach for resource allocation and workforce management in smart hospitals. *Healthcare Engineering*, *1*(3), 87-92.

Taha, H. A. (2017). Operations research: An introduction (10th ed.). Pearson.

Topaloglu, S. (2006). A multi-objective programming model for scheduling emergency medicine residents. Computers & Industrial Engineering, 51(3), 375–388. https://doi.org/10.1016/j.cie.2006.08.002

Van den Bergh, J., Beliën, J., De Bruecker, P., Demeulemeester, E., & De Boeck, L. (2013). Personnel scheduling: A literature review. European Journal of Operational Research, 226(3), 367–385. https://doi.org/10.1016/j.ejor.2012.11.029