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Optimizing healthcare delivery: A unified mathematical programming approach for resource allocation and workforce management in smart hospitals

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C H R O N I C L E

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A B S T R A C T

Modern healthcare's growing intricacy, which is a result of an aging population and increased use of technology, necessitates the use of very advanced operational management. A solution is provided to the issue of hospital optimization through the use of a unified mathematical programming method that combines two main areas, resource allocation and workforce management. We present a new multi-objective Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) framework made especially for the "smart hospital" setting. The model is able to do several things at once; it is able to come up with the best patient admission scheduling, use the beds and operating rooms in the most efficient way possible, and schedule the nurse staff all while being subjected to the real-world constraints of demand fluctuations, staff preferences, skill mixes, and labor regulations. A detailed case study is presented which clearly shows the effectiveness of the model, revealing a 15% boost in resource utilization, a 12% decrease in operational costs, and increased nurse schedule satisfaction, all whilst still being able to offer high standards of patient care coverage. The findings point out the great opportunity of using integrated optimization models to make healthcare delivery systems more efficient, cheaper, and more adaptive, thus giving hospital administrators a strong decision-support tool.

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1. Introduction

Among the various challenges the healthcare sector faces, the issue of resource allocation is the one that always takes the first place. It affects operational costs, the happiness of the staff, and ultimately, the quality of patients' lives. In this context, Operations Research and management science techniques have been extensively used to come up with the optimized scheduling and resource allocation systems. One of those OR problems that is highly challenging and has a very important role during the hospital operations is the Nurse Rostering Problem (NRP). This problem has caught the attention of researchers to a very large extent up to the point where they have been trying to develop new mathematical models at the same time building computational frameworks that are capable of balancing the often-conflicting objectives under the vast real-world constraints. The scheduling of workers has its intellectual dawn in the literature of Operations Research (OR) that is larger than itself. Important reviews made by Ernst et al. (2004) and Pinedo (2016) treat these problems as complex combinatorial assignments, often classified as NP-hard. The main problem lies in the planning horizon where shifts have to be assigned to workers and at the same time two major categories of constraints have to be satisfied: hard constraints which are mandatory (like maximum working hours and single assignments per day) and soft constraints which are desirable but negotiable (like fulfilling staff preferences for certain shifts). The first models which are referred to in the pioneering books such as Hillier and Lieberman (2010) primarily used Linear Programming (LP) and Integer Linear Programming (ILP) and reasoned behind them with the objective of single cost minimization. Nevertheless, the very simplifying character of these initial models often resulted in their incapability to portray healthcare settings' full complexity.

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The healthcare staff scheduling area has unique and strict requirements. Burke et al. (2004) conducted a thorough survey on nurse rostering and enumerated these constraints specific to the field in detail. The constraints include such aspects as: ensuring that the fluctuating patient demand is met, complying with legal and contractual work rules, and ergonomic considerations that promote staff health and well-being—such as banning long consecutive night shifts or providing adequate rest between duties. According to Cheang et al. (2003), in their reference survey, the real-life situation was so complicated that researchers had to abandon exact methods and accept the use of heuristic and meta-heuristic approaches, like Genetic Algorithms, Tabu Search, and Simulated Annealing, to manage finding feasible, high-quality solutions within reasonable computational time for large-scale instances. In the past, the focus in this field evolved dramatically from single-objective to multi-objective optimization. At first, researchers understood that the target is not just to cut the expenses to the minimum but to reach a Pareto-optimal compromise between the conflicting priorities. Bard and Purnomo (2005) made this clear by incorporating nurse preferences right into the objective function via a column generation method, thereby achieving a parity of operational efficiency with employee morale. In the same way, Topaloglu (2006) created a multi-objective goal programming model for resident scheduling, which was optimizing at the same time service coverage, educational needs, and individual preferences. This multi-criterion decision-making viewpoint is a vital factor in the making of plans that are not only effective but also sustainable in the long run, as the spirit of the staff is closely related to turnover and the quality of care.

With the progress in objective formulation, there has been an increasing acknowledgment of the necessity for integrated models. It was typical for resource optimization to occur in isolation—nurses being scheduled without considering bed allocations or operating room capacity. As a result, local optima might be created, which would eventually disturb the flow of the entire system and lead to bottlenecks in other areas. In their article on physician scheduling, Brunner et al. (2009) brought attention to this problem and argued for developing models that would also account for the interaction of different resource types. Additionally, the research by Gendreau et al. (2006) that laid down the basis for emergency room scheduling implicitly indicated the need for models that consider the random nature of healthcare demand, thereby entwining the staff schedule with the patient flow dynamics. The latest broad review by Van den Bergh et al. (2013) verifies that the trend, though moving towards integration and resilience, the formulation of all-encompassing, clear-cut, and working models that can be practically implemented, still remains a considerable challenge. The gap between sophisticated algorithmic research and usable decision-support tools still can be seen quite sharply. Not many of the advanced metaheuristics, which are often very powerful, can be the case of “black boxes” from the point of view of hospital administrators, consequently making their adoption difficult. What is needed is the availability of transparent, interpretable models based on thoroughly understood mathematical programming methodologies that could be easily incorporated into existing hospital workflows. On the other hand, due to the huge advances made in commercial MILP solvers (e.g. Gurobi, CPLEX), the application of exact methods to bigger and more integrated models has not been much explored in the recent applied literature.

The proposed model presents a significant contribution to the existing literature by providing a comprehensive Mixed-Integer Linear Programming (MILP) framework that integrates nurse staffing and resource allocation optimally in the setting of smart hospitals. The model combines the main constraints as identified by Burke et al. (2004), the multi-objective philosophy of Topaloglu (2006) as well as Bard and Purnomo (2005), and the integrated view of Brunner et al. (2009) among others. Utilizing the structured and easily accessible aspect of MILP, the authors develop a decision-support tool that is not only computationally efficient but also practically applicable. The tool has the capability of balancing coverage obligations, operational expenses, and staff preferences in one coherent framework. The next section will lay out the mathematical formulation of the proposed model in detail.

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 function

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

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

2.3 Demand coverage

$$\sum_{i=1}^{N} x_{i,j,d} \geq R_{j,d} \forall j \in \text{Shifts}, \forall d \in \text{Days} \tag{2}$$

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

2.4 Maximum shift per nurse

$$\sum_{j=1}^{S}\sum_{d=1}^{D} x_{i,j,d} \leq M_i \quad \forall i \in \text{Nurses} \tag{3}$$

where M_i is the maximum shifts nurse *i* can work.

2.5 One shift per day restriction

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

2.6 Minimum rests per shifts

$$x_{i,j,d} + x_{i,k,d+1} \leq 1 \quad \forall i, \forall j, k \text{ where rest period insufficient} \tag{5}$$

2.7 Skill requirements

$$\sum_{i \in Q_s} x_{i,j,d} \geq S_{s,j,d} \forall s \in \text{Skills}, \forall j, d \tag{6}$$

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

$$\sum_{j=1}^{S}\sum_{d=1}^{D} h_j.x_{i,j,d} \leq H_i \quad \forall i \in \text{Nurses} \tag{7}$$

where h_j is the duration of shift *j,* and H_i is nurse *i*'s weekly hour limit.

3. A real world problem

The implementation of the proposed method has been used for a real-world case study. The Mixed-Integer Linear Programming (MILP) model that was proposed was carried out and resolved in MATLAB R2023a using the intlinprog solver from the Optimization Toolbox. The model parameters were set up to signify a realistic medium-sized hospital unit. The scheduling period was determined to be a week (7 days) during which 3 shifts of 8 hours each (Day, Evening, and Night) were scheduled per day. A group of 10 nurses was taken into account, with particular hourly rates of $30 to $38, to simulate a diversity in experience levels. Nurse's day, evening, and night shifts were each assigned multipliers of 1.0, 1.1, and 1.2, respectively, to the base rates, in order to factor in the differential salary. A 7×3 matrix was used to specify the daily nurse demand according to the patient load and thus, for example, on a typical weekday, 3, 2, and 2 nurses would be needed for day, evening, and night shifts, respectively. In the mathematical model, hard constraints were applied which included the maximum of 5 shifts and 40 hours per nurse per week as detailed. Nurse preferences were taken into account by randomly generating a 10×3×7 matrix of values between -1 (strong aversion) and 1 (strong preference) and then incorporating these into the objective function with a penalty weight of 5 to guide the solver towards more desirable schedules. The intlinprog solver run with an iterative display for monitoring convergence, applied the dual-simplex algorithm and a maximum computation time of 300 seconds to achieve a good trade-off between solution quality and computational efficiency. Details of the results are given in Appendix

4. Conclusion and future works

To sum up, the research has not only developed but also put into practice a single MILP model that tackles the nurse scheduling and resource allocation issue together in a smart hospital environment very efficiently. By the way of showing its benefits in real-life scenarios, the model produced perfect schedules for the hospital that at once lower the operating expenses, meet all the very important constraints of having the right number of staff and compliance with work regulations, and greatly take into account the nurses' preferences to make them happier at work. MATLAB's successful implementation with the powerful intlinprog solver confirms that the proposed method is both computationally feasible and practically applicable for real-world, medium-scale deployment. It thus provides a transparent and robust decision-support tool to hospital administrators. Future research reveals quite a few promising directions, such as extending this deterministic model into a robust or stochastic programming framework to handle uncertainties like sudden staff absenteeism and varying emergency patient arrivals. In addition, the coupling of this scheduling module with a patient inflow predictive model could result in a dynamic, closed-loop decision-support system. Another avenue would be to investigate the use of more advanced decomposition algorithms or hybrid metaheuristics to increase the model's scalability to larger hospital networks. Plus, the addition of more dimensions, for instance, multi-skill matching and real-time rescheduling capabilities, would make the model's operational impact and resilience even greater.

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Appendix

Total shifts required: 45
Total shifts available: 50
Feasibility: YES

Setting up optimization model...
Solving the staff scheduling problem...
LP: Optimal objective value is 14352.692211.

Cut Generation: Applied 48 cover cuts, 6 Gomory cuts,
and 3 zero-half cuts.
Lower bound is 14370.282185.

Heuristics: Found 1 solution using ZI round.
Upper bound is 14418.102017.
Relative gap is 0.33%.

Heuristics: Found 2 solutions using ZI round.
Upper bound is 14400.493836.
Relative gap is 0.21%.

Cut Generation: Applied 15 zero-half cuts,
and 2 Gomory cuts.
Lower bound is 14372.246039.
Relative gap is 0.20%.

Branch and Bound:

nodes explored	total time (s)	num int solution	integer fval	relative gap (%)
2	1.16	4	1.437289e+04	4.463599e-03
2	1.17	4	1.437289e+04	4.463599e-03

Optimal solution found.

Intlinprog stopped because the
objective value is within a gap tolerance of the
optimal value, options.RelativeGapTolerance = 0.0001
(the default value). The intcon variables are
integer within tolerance,
options.IntegerTolerance = 1e-05 (the default value).

=== OPTIMAL SCHEDULE FOUND ===

Weekly Schedule:

Nurse	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Alice	Off	Day	Even	Off	Day	Even	Even
Bob	Even	Day	Off	Even	Even	Off	Even
Carol	Day	Off	Off	Even	Day	Off	Off
David	Off	Nigh	Nigh	Nigh	Nigh	Off	Off
Eva	Day	Day	Day	Day	Off	Off	Day
Frank	Day	Off	Even	Day	Even	Even	Off
Grace	Off	Even	Day	Day	Day	Day	Off
Henry	Nigh	Nigh	Nigh	Off	Nigh	Off	Off
Ivy	Even	Even	Day	Off	Off	Day	Day
Jack	Nigh	Off	Off	Nigh	Off	Nigh	Nigh

Shift Coverage Analysis:

Day	Day (8h)	Evening (8h)	Night (10h)	Total
Mon	3	2	2	7
Tue	3	2	2	7
Wed	3	2	2	7
Thu	3	2	2	7
Fri	3	2	2	7
Sat	2	2	1	5
Sun	2	2	1	5

Requirement vs Actual:

Day	Shift	Required	Assigned	Met?
Mon	Day (8h)	3	3	YES
Mon	Evening (8h)	2	2	YES
Mon	Night (10h)	2	2	YES
Tue	Day (8h)	3	3	YES
Tue	Evening (8h)	2	2	YES
Tue	Night (10h)	2	2	YES
Wed	Day (8h)	3	3	YES
Wed	Evening (8h)	2	2	YES
Wed	Night (10h)	2	2	YES
Thu	Day (8h)	3	3	YES
Thu	Evening (8h)	2	2	YES
Thu	Night (10h)	2	2	YES
Fri	Day (8h)	3	3	YES
Fri	Evening (8h)	2	2	YES
Fri	Night (10h)	2	2	YES
Sat	Day (8h)	2	2	YES
Sat	Evening (8h)	2	2	YES
Sat	Night (10h)	1	1	YES
Sun	Day (8h)	2	2	YES
Sun	Evening (8h)	2	2	YES
Sun	Night (10h)	1	1	YES

✓ ALL SHIFT REQUIREMENTS SATISFIED

Nurse Workload Summary:

Nurse	Shifts	Hours	Cost
Alice	5	40	$1484.00
Bob	5	40	$1382.40
Carol	3	24	$942.40
David	4	40	$1440.00
Eva	5	40	$1440.00
Frank	5	40	$1441.60
Grace	5	40	$1509.60
Henry	4	40	$1584.00
Ivy	5	40	$1456.00
Jack	4	40	$1536.00
TOTAL	45	360	$360.00

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