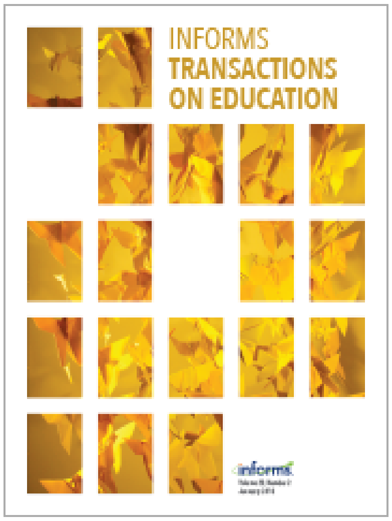

INFORMS Transactions on Education

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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INFORMS TRANSACTIONS ON EDUCATION
Articles in Advance, pp. 1–7
ISSN 1532-0545 (online)
https://pubsonline.informs.org/journal/ited

Case Article

Developing Data-Driven 24/7 Nurse Staffing and Shift Scheduling Plans

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Received: April 7, 2025
Revised: July 22, 2025; October 17, 2025
Accepted: November 27, 2025
Published Online in Articles in Advance: April 29, 2026

https://doi.org/10.1287/ited.2025.0139ca

Abstract. This case study offers a comprehensive hands-on approach to addressing hospital workforce planning challenges by integrating demand forecasting errors into mathematical programming. Structured around two interconnected projects—refined over a decade of experience—students develop data-driven 24/7 nurse staffing and shift scheduling plans that ensure continuous coverage while balancing cost, service quality, operational constraints, and nurse satisfaction. By employing time-series models to predict hourly patient volumes and integrating these forecasts into integer programming models, the case demonstrates how to construct 24/7 coverage matrices and incorporate auxiliary variables that allow for controlled deviations in staffing levels and service delays due to forecasting errors. Emphasizing multiobjective optimization and Pareto frontier analysis, the case effectively evaluates tradeoffs between overstaffing and understaffing. Designed for both undergraduate and graduate courses in healthcare management science or operations research, this case bridges theoretical concepts with real-world applications, thereby enhancing educators' ability to deliver effective decision-making training in healthcare operations.

Funding: This work was supported by the Division of Civil, Mechanical and Manufacturing Innovation [Grant CMMI-0928936].

Supplemental Material: The Teaching Note and supplemental material are available at https://www.informs.org/Publications/Subscribe/Access-Restricted-Materials.

Keywords: nurse staffing • workforce optimization • healthcare operations • integer programming • forecasting errors

1. Introduction

The healthcare sector is the largest employer in the United States, with more than 15 million workers providing care to a population of 332 million as of 2021 (Dowell 2020). Among these, registered nurses constitute the largest professional group, with nearly 3 million employees working across various healthcare settings (Bureau of Labor Statistics 2021). Healthcare services are labor intensive. Consequently, workforce planning is central to hospital operations and directly affects patient care quality, staff satisfaction, and financial sustainability. Hospitals must align nurse staffing levels with fluctuating patient demand while adhering to complex operational constraints. Understaffing can lead to patient safety risks, increased medical errors, and nurse burnout, whereas overstaffing results in excessive labor costs and resource inefficiencies. These challenges are further compounded by regulatory requirements that mandate minimum nurse coverage, as well as by the need to manage varying shift structures—including different start times, durations, and staffing mixes involving full-time and part-time nurses.

In operations research literature, the nurse staffing and shift scheduling problem has been studied extensively due to its direct impact on patient safety and operational efficiency (Ernst et al. 2004). This case study is based on the integrated nurse staffing and shift scheduling model developed in Kim and Mehrotra (2015) and Mehrotra et al. (2024). Kim and Mehrotra (2015) proposed a two-stage stochastic integer programming approach for nurse management in a large hospital, utilizing real patient data from a Hospital Medicine unit. Their work provides foundational insights into unifying staffing and shift scheduling decisions in the presence of uncertain patient volumes. This integration is critical to demonstrate the impact of demand uncertainty on 24/7 nurse staffing and shift scheduling plans—a key teaching component of our case study. The teaching notes in the case use some of the data and models from Mehrotra et al. (2024). As an alternative approach, Davis et al. (2014) presented a robust newsvendor model to determine optimal nurse staffing levels under demand uncertainty. However, our case is developed to demonstrate the challenges of solving both nurse staffing and shift scheduling problems using demand forecasting and mathematical programming tools.

The case introduces interconnected time-series forecasting and integer programming models to expose students to the challenges of 24/7 nurse staffing and shift scheduling operations. Unlike static models or manual scheduling (Nurre and Weir 2017), our approach addresses hourly patient demand while incorporating all nurse staffing and scheduling–related constraints—such as shift structures, nurse work-life balance, continuity of care, service quality, and controlled demand violations to account for forecasting errors. Refined and implemented over the past decade in both master's-level healthcare analytics and undergraduate healthcare engineering courses, this case is valued for its real-world applicability and its integration of multiple course concepts into a single, practical problem.

Based on student feedback, the workload has been modularized into two distinct projects: one focused on demand forecasting and the other on workforce optimization, allowing students to progressively build their analytical capabilities while maintaining real-world relevance. By engaging with this case, students gain hands-on experience with time-series forecasting, integer programming, modeling techniques to incorporate forecasting errors, and evaluating tradeoffs in complex nurse staffing and shift scheduling decisions using AMPL/Python.

In the remainder of this document, we first describe the intended audience for the case in Section 2. In Section 3, we lay out the teaching objectives of the case, and in Section 4, we highlight the gap in the literature. Section 5 describes the components of the case, Section 6 discusses our classroom experience and student feedback, and Section 7 concludes the case discussion.

2. Intended Audience

The case is designed for students in operations research, healthcare management science, and analytics courses covering forecasting, workforce planning, scheduling, and mathematical programming. Students can have minimal to no background in optimization and forecasting techniques.

Undergraduate Students: This case can be used to teach forecasting algorithms and the formulation of integer programming models. Students learn to define constraints and implement basic nurse staffing and shift scheduling solutions, gaining exposure to the challenges of healthcare operations, mathematical modeling techniques, and sensitivity analysis using AMPL and Python.

Graduate Students: The case can be used to engage students in advanced topics such as forecasting integration, scenario analysis, and multiobjective decision making. Master's students can analyze tradeoffs between cost minimization and service quality, balance understaffing and overstaffing caused by forecasting errors, and apply Pareto frontier analysis, thus gaining practical insights into the complexities of 24/7 nurse staffing and shift scheduling. With appropriate simplifications, PhD students can use this case to explore two-stage stochastic integer programming models.

Healthcare practitioners can also benefit from the case by gaining useful insights into the impact of data-driven decision making on nurse staffing and shift scheduling operations.

3. Teaching Objective

This case is intended to provide hands-on experience in designing data-driven 24/7 nurse staffing and shift scheduling plans by integrating forecasting and optimization models. Students will understand the challenges posed by forecasting errors and shift scheduling in nurse staffing decisions. The key teaching objectives are as follows:

1. **Demand Forecasting:** Analyze historical patient arrival data using various time-series models (e.g., moving averages, exponential smoothing, regression) and assess forecast accuracy. Students will also identify seasonal trends and select relevant performance metrics to evaluate the forecasts. Finally, learn how predictive analytics impacts prescriptive decisions.

2. **Mathematical Programming for Staffing and Shift Scheduling:** Develop a base integer programming model that determines the optimal nurse staffing and shift scheduling plan, including the required mix of registered (i.e., full-time) and agency (i.e., part-time) nurses, by incorporating varying shift structures, nurse work-life balance, and both operational and quality-of-service constraints.

3. **Incorporate Forecasting Errors in Optimization:** Use auxiliary variables (shortfall and surplus) to relax strict demand coverage constraints due to forecasting errors. This approach enables controlled demand violations and service delays while effectively balancing trade-offs through Pareto frontier analysis.

4. **Practical Implementation:** Employ mathematical modeling tools such as AMPL and Python to build,

solve, and analyze real-world optimization models, thereby enhancing technical proficiency and decision-making skills.

4. Related Literature

There are many case studies developed to teach mathematical modeling techniques in nonhealthcare settings. For example, Beliën et al. (2013) introduce an energy supply game-based tutorial that motivates students to learn integer programming. Rao et al. (2020a, b) describe a hands-on approach to teach discrete optimization modeling for production planning. Winch and Yurkiewicz (2014a, b) use a class scheduling setting to teach linear programming, whereas Saltos and Maldonado (2022a, b) employ a high-school timetable scheduling problem to effectively demonstrate integer programming modeling and implementation techniques. Some case studies in mathematical programming education have underscored the effectiveness of integer programming for workforce planning (Ernst et al. 2004). Sharkey et al. (2020a, b) presented a workforce optimization case for airport immigration control that dealt with fixed shift durations amid variable passenger arrivals, mainly focusing on illustrating that there is no single true mathematical model.

Despite these studies, existing approaches do not account for constraints specific to hospital operations—such as nurse work-life balance, continuity of care, and other relevant factors—thereby limiting their direct applicability to healthcare settings.

In healthcare workforce planning, comprehensive reviews by Blöchliger (2004), Van den Bergh et al. (2013), Erhard et al. (2018), and Mehrotra et al. (2024) have documented a wide array of nurse scheduling methods and highlighted key challenges such as 24/7 operations, demand variability, and potential staffing flexibilities. Pachamanova et al. (2022a, b) demonstrated the use of predictive analytics in the operations of hospital observational units, highlighting the challenges involved in translating data analytics into actual medical decision making. Shechter (2023a, b) presents an in-class role-playing exercise to demonstrate optimal shift scheduling for pediatricians in a hospital, yet that approach did not incorporate forecasting-driven demand estimation. Hans and Nieberg (2007) demonstrate an in-class game to expose students to the complexity of managing an operating room in a hospital. In contrast, our case builds on the foundational research on staffing and shift scheduling models by demonstrating the impact of forecasting on integer programming models. This holistic approach not only enhances the pedagogical framework for teaching nurse staffing and shift scheduling but also more accurately mirrors the dynamic and complex nature of real-world healthcare operations.

Diamant (2024) describes an MBA-level course that combines prescriptive and predictive analytics for students with nontechnical backgrounds. Other teaching cases have integrated forecasting and optimization via simulation techniques—often in staff-scheduling or job-assignment contexts (Kopcso and Pachamanova 2017a, b; Gorman 2023a, b). Grossman and Özlük (2009) present a scenario-analysis exercise that links simulation and optimization for inventory management, whereas Weltman and Tokar (2019) demonstrate an in-class Monte Carlo workshop that tackles a classic transportation problem under demand uncertainty.

By contrast, our case emphasizes integer-programming techniques that embed forecast error directly into the optimization model. Implementing a fully simulation-based framework typically requires students to master simulation concepts and demands four to five weeks of coursework. The present case is designed for students with minimal—or no—background in optimization, forecasting, or simulation, yet still achieves the goal of integrating forecasts into nurse-staffing and scheduling decisions within a one- to two-week project.

5. Case Components

This case is structured into two interrelated components that together cover the full spectrum of nurse workforce planning: *Hourly Demand Forecasting* and *Workforce Optimization for Nurse Staffing and Shift Scheduling*.

The first component introduces hourly demand forecasting, focusing on real-world data-driven prediction techniques. The second component presents workforce optimization models for nurse staffing and shift scheduling, incorporating operational constraints such as patient-to-nurse ratios, shift duration, balancing nurse work-life, and hospital-specific staffing policies. Students extend their optimization model to account for forecasting errors and strike a balance between overstaffing and understaffing while violating the demand coverage constraint. Each component builds on the previous one, progressively introducing complexity while maintaining a real-world application focus. Students will use AMPL and Python for mathematical modeling and optimization, gaining hands-on experience with forecasting, integer programming, and multiobjective decision making in healthcare operations.

5.1. Hourly Demand Forecasting

Accurate demand forecasting is the cornerstone of an effective nurse staffing and shift scheduling plan. In this component, students work with real hospital patient arrival data to predict hourly patient volumes—a critical input for subsequent workforce planning decisions. The forecasting task involves dynamically generating predictions for future planning periods. For example, students generate four-hour-ahead forecasts for three distinct shifts (e.g., forecasts made at 3:00 a.m. for the 7:00 a.m. shift, at 7:00 a.m. for the 11:00 a.m. shift, and at 3:00 p.m. for the 7:00 p.m. shift), thereby enabling management to make timely short-term resource reallocation decisions.

Students are introduced to a variety of time-series forecasting methods. For example, they begin with *moving averages and exponential smoothing* to capture short-term trends and inherent seasonality in the patient volume data. They then explore *regression-based forecasting* techniques that incorporate external factors such as weekday effects and seasonal patterns, along with autoregressive components, to improve predictive accuracy. Students calibrate models using training data sets spanning different durations (e.g., 6 months, 1 year, 18 months, and 2 years) and validate performance on out-of-sample data.

Forecast accuracy is evaluated using standard error metrics, including mean absolute deviation (MAD), root mean squared error (RMSE), and mean absolute percentage error (MAPE). Students also assess forecast uncertainty by conducting residual analysis—examining autocorrelation functions (ACF) and Q–Q plots to ensure that forecast errors exhibit properties of white noise. Such analysis not only validates the model's fit but also highlights opportunities to refine the forecasting model (e.g., by adjusting the model order or incorporating seasonality indicators).

Learning Objectives:

- Apply and evaluate different time-series forecasting methods to predict hourly patient volumes.
- Understand how forecast uncertainty, as measured by error metrics and residual analysis, impacts nurse staffing and shift scheduling decisions. Specifically, provide insights into the strictness of demand coverage constraints derived from the varying imperfections in the forecasting models.
- Prepare and integrate forecasting outputs as inputs for subsequent optimization models that rely on the required patient-nurse ratios.

Teaching Suggestions:

- Provide students with the patient demand data set and guide them through model calibration and parameter estimation using tools such as R and Python.
- Encourage experimentation with multiple forecasting techniques and error metrics and facilitate hands-on sessions where students plot ACF and Q–Q plots to verify that residuals behave like white noise.
- Initiate discussions on how improvements in forecast accuracy (e.g., via adjusting model parameters or incorporating seasonality) can enhance the reliability of subsequent nurse staffing and shift scheduling decisions.

5.2. Workforce Optimization for Nurse Staffing and Scheduling

Building on the demand forecasts, students develop a nurse staffing and shift scheduling model that ensures 24/7 coverage while balancing cost and service quality. The base mixed-integer linear programming model addresses the following:

- **24/7 Hourly Demand Constraints:** To ensure the continuity of care, each hour's staffing level must meet or exceed the nurse demand computed from the forecast.
- **Shift Structures:** Shifts are restricted to start at 7 a.m., 11 a.m., and 7 p.m. Students choose between an 8-hour shift and a 12-hour shift. A 12-hour shift, which is preferred by nurses, is costed at $20 per hour, compared with $25 per hour for an 8-hour shift.
- **Operational Constraints:** The model incorporates internal staffing policies such as patient-nurse ratios. The staffing plan balances the mix of registered nurses with alternatives such as floating or agency nurses, accounting for differences in cost structures.
- **Nurse Work-Life Balance:** Nurses typically work the same shift throughout the week and adhere to work-hour limitations (each nurse must work between 36 and 40 hours per week)—fostering routine and improved team coordination. Nurses working a full-time shift are scheduled with a one-hour lunch break after the first four hours.

5.2.1. Accounting for the Forecasting Errors.

To address the challenge posed by forecasting errors, the base optimization model with all operational constraints is extended to introduce auxiliary variables—shortfall and surplus—to relax strict demand coverage constraints. This allows for controlled demand violations and service delays while balancing nurse overstaffing and understaffing. For instance, the nurse shortfall in any hour is constrained to be less than two, allowing the model to tolerate minor deviations from the ideal staffing level. This approach not only mirrors real-world tradeoffs between additional staffing costs and service quality but also offers an approach to integrate forecasting errors into optimization modeling.

For instructors who want to more closely demonstrate the link between forecasting errors and optimization, the teaching notes provide detailed alternatives, including robust optimization, a min-max formulation, and an average-cost variant. These techniques incorporate scenario-based analyses of different demand realizations—derived from the empirical distribution produced by the forecasting component—and adjust the optimization model accordingly.

Learning Objectives:

- Formulate and solve complex mathematical programming models for nurse staffing and shift scheduling, ensuring continuous 24/7 coverage. Students learn to use optimization packages such as AMPL and Gurobi (codes provided in the online appendix).

- Learn the use of overstaffing and understaffing auxiliary variables to formulate a controlled demand violation constraint.
- Analyze the tradeoffs between staffing costs and service levels using multiobjective optimization.
- Apply sensitivity analysis—such as varying the maximum allowed nurse shortfall and testing alternative shift options (e.g., an 8-hour shift starting at 3 p.m.)—to assess the robustness of the staffing and shift scheduling plans.

Teaching Suggestions:

- Start with a base optimization model that employs a coverage matrix for the given shift types and then progressively incorporate additional constraints (e.g., weekly work-hour limits, alternative shift options, different nurse mix options).
- Assign group projects that simulate real-world decision making in hospital staffing. For example, have students iteratively reduce the available nurse count until the model becomes infeasible and then discuss the implications of their recommendations.
- Encourage extensions by exploring variations such as allowing controlled demand violations or patient service delays to account for forecasting errors. This approach prompts students to critically evaluate the impact of forecasting on workforce optimization.

6. Classroom Experience

This case study has been implemented in advanced undergraduate and master's-level courses, such as healthcare engineering and healthcare analytics, over the past decade. Initially, we assigned an integrated project involving both forecasting and workforce optimization. After two to three iterations, we observed that many students underperformed because errors in their forecasting code negatively impacted integration with the optimization models. In a later quarter-long capstone project, we experimented with an integrated simulation-based approach, but the undergraduate team could not build an adequate simulator and, as a result, had too little time to master the core forecasting and optimization techniques.

As a result, in the subsequent six to seven iterations, we deployed the case as two separate but interrelated projects conducted sequentially in two weeks—one focusing on forecasting and the other on workforce optimization and modeling techniques to account for forecasting errors. A few years ago, we experimented with allowing students the flexibility to choose shift start times, which simplified work-life balance constraints. However, to better illustrate the computational complexity involved in generating realistic staffing and shift scheduling plans, we now provide specific constraints on shift start times.

Student feedback indicates that undergraduates appreciate the manageable scope of the forecasting and basic staffing models, even though they find the project somewhat time-consuming. In contrast, master's students—often concurrently enrolled in optimization courses—report that the integrated approach is both challenging and highly relevant to real-world applications. Some students noted that they valued the healthcare context of the case more than the optimization modeling and coding aspects. Overall, the case effectively bridges theoretical coursework with practical healthcare workforce planning, offering valuable insights into the challenges posed by imperfect forecasts within optimization models. Students have remarked the following:

- "It's comprehensive, covers many concepts in class."
- "Apply all knowledge learned in class in a comprehensive way."

We have observed that a staged approach—introducing forecasting models first and then gradually integrating optimization components—facilitates a deeper understanding. The use of real hospital data and hands-on implementation via AMPL and Python further enhances learning outcomes. Based on our experience in two different courses—an undergraduate course in healthcare engineering and a master's course in healthcare analytics, each delivers separate projects for the individual case components. The case can also be extended to PhD-level courses, such as a stochastic optimization course to teach two-stage stochastic integer programming, and can serve as a comprehensive capstone project where a second-year or beyond PhD student builds an integrated simulation tool for generating nurse staffing and shift scheduling plans based on historical patient volume data, as suggested by classroom experience.

7. Conclusion

This case study presents an integrated approach to 24/7 nurse staffing and shift scheduling by combining forecasting, mathematical optimization, and decision analysis. It offers a realistic setting of healthcare workforce planning, addressing the challenges of demand forecasting errors and complex operational constraints. Students develop robust demand forecasts from historical data and incorporate these forecasts into integer programming models that account for varying shift structure, nurse work-life balance, and both operational and quality-of-service constraints.

The case reinforces key concepts in time-series forecasting and optimization, challenging students to evaluate tradeoffs between cost efficiency and service quality using multiobjective techniques such as Pareto frontier analysis. Classroom experiences demonstrate that the case enhances technical proficiency and prepares students for real-world decision making in healthcare operations. Overall, this case serves as an effective pedagogical tool for bridging theoretical optimization methods with practical workforce planning, making it a valuable addition to curricula in operations research, healthcare management, and analytics.

This case also aligns well with nurse-patient assignment models that incorporate nurse and patient preferences and expertise. However, student feedback suggests that adding these elements can diminish the learning experience by requiring substantial additional time. Instructors who wish to integrate staffing and assignment models, or to use simulation-based scenario analysis, should do so only if the course offers at least four to five weeks for the project and if students already have some background in simulation. Likewise, master's students will benefit from having completed an optimization course in advance; this prior knowledge allows them to focus on extensions rather than spending excessive time on the base model. Finally, we recommend assigning the case to teams rather than individuals, because collaborative work fosters more diverse thinking and richer solutions.

Appendix. List of Supplementary Material Provided with the Case

A.1. Data Files

`PatientVolume.csv`: Hourly patient-volume data from January 1, 2022, to June 30, 2025.

`WeeklyDataforShiftScheduling.csv`: Hourly forecasted patient-volume data for the next seven days.

A.2. Teaching Notes

Section 1 (TN): Sample project description, pointers for student discussion, typical student responses, and teaching suggestions and plans for the forecasting component.

Section 2 (TN): Sample project description, pointers for student discussion, typical student responses, and teaching suggestions and plans for the workforce-optimization component.

A.3. Code

Section 1.2 (TN): R and Python scripts for the forecasting exercise.

Section 2.2 (TN): AMPL and Python scripts for the standalone workforce-optimization exercise.

`integrated forecasting and optimization models.ipynb`: A Python notebook that performs both the forecasting and optimization tasks in a single workflow. The optimization component uses the Gurobi solver, which requires a license.

`ForecastingPatientVolume.Rmd`: An R Markdown file that performs only the forecasting tasks of the case.

`OneDayShift.mod` and `OneDayShift.dat`: AMPL model and data file for running the optimization base model.

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