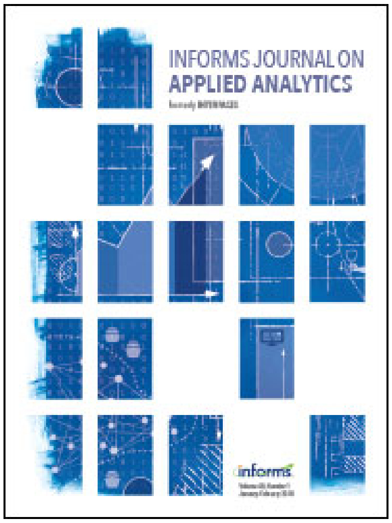


INFORMS Journal on Applied Analytics

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

Optimal Scheduling of Waitstaff with Different Experience Levels at a Restaurant Chain

Najmaddin Akhundov, Nail Tahirov, Christoph H. Glock

INFORMS JOURNAL ON APPLIED ANALYTICS
Vol. 52, No. 4, July–August 2022, pp. 324–343
ISSN 2644-0865 (print), ISSN 2644-0873 (online)
https://pubsonline.informs.org/journal/ijaa

Optimal Scheduling of Waitstaff with Different Experience Levels at a Restaurant Chain

Najmaddin Akhundov,[a] **Nail Tahirov,**[b] **Christoph H. Glock**[b,*]

[a] Department of Industrial and Systems Engineering, University of Tennessee, Knoxville, Tennessee 37996; [b] Institute of Production and Supply Chain Management, Technical University of Darmstadt, 64289 Darmstadt, Germany
*Corresponding author

Contact: nakhundo@utk.edu, https://orcid.org/0000-0002-8011-8097 (NA); nail.tahirov@pscm.tu-darmstadt.de, https://orcid.org/0000-0003-4287-7532 (NT); glock@pscm.tu-darmstadt.de, https://orcid.org/0000-0001-6006-0070 (CHG)

Received: January 19, 2021
Revised: July 20, 2021; December 20, 2021; March 22, 2022
Accepted: April 1, 2022
Published Online in Articles in Advance: June 23, 2022

https://doi.org/10.1287/inte.2022.1124

Abstract. Restaurants often face strong pressure to reduce costs. Managers regularly respond by hiring temporary or part-time workers and by trying to reduce the size of the workforce as much as possible, which makes it difficult to develop a personnel schedule that provides sufficient service to the customers. The problem gets even more complicated if (frequent) employee turnover and demand fluctuations occur and if employees have different experience levels. This paper presents mathematical models to support waitstaff scheduling at a restaurant chain based in Baku, Azerbaijan, taking into account the managerial requirements of the company. The problem we address is equivalent to a general tour scheduling problem that assigns waitstaff to work shifts throughout the week. We develop three integer programming models taking account of factors, such as employee types and experience levels, differences in the complexity of customer orders, and side tasks and responsibilities, to find the optimal number of employees together with the best tour for each of them. The models are solved to optimality, and the results are applied at a branch of the restaurant chain in Baku. Compared with the existing schedule, the optimized schedule enabled the restaurant to reduce overstaffing levels by approximately 40% and labor costs by 20% while keeping the same service standards.

History: This paper was refereed.

Keywords: tour scheduling • restaurant management • labor scheduling • weighted orders • employee skill levels

Introduction

Over the years, much research has been devoted to workforce scheduling. Within this area of investigation, studies generally address three types of workforce (or personnel) scheduling problems: *days-off scheduling*, *shift scheduling*, and *tour scheduling* (Loucks and Jacobs 1991). The days-off scheduling problem deals with determining the optimal staff size to satisfy the daily employee requirement per week and assigning predetermined consecutive free days to each staff member. Shift scheduling, in contrast, utilizes overlapping shifts to meet demand (especially for services that cannot be postponed or backlogged) within 24 hours. The combination of these two problems is referred to as tour scheduling, which has also been investigated frequently in the past (e.g., Baker 1976, Loucks and Jacobs 1991, Van den Bergh et al. 2013). One reason for the popularity of this research stream is the high labor costs that many restaurants have to deal with. Effective personnel scheduling has the potential to reduce costs and increase levels of customer service at the same time. However, in practice, it is difficult to determine optimal solutions that satisfy all relevant conditions, such as cost minimization, employee preferences, customer service quality, government regulations for employees, or individual workplace constraints (see Ernst et al. 2004). The complexity of the problems to be solved varies with the application area.

In the extant literature, restaurant or fast-food staff scheduling has been described as one of the most difficult problems because of shifts with varying working hours in length (e.g., from three to eight hours), different employee skill sets and experience levels (e.g., waiter, chef, cleaner, etc.), alternative forms of employment (e.g., part and full time), and the forecasting of short-term (daily) uncertain demand. Yet, in practice, personnel scheduling is the central part of restaurant operations. Moreover, rapid and high turnover of employees, especially at fast-food restaurants, also increases the complexity of the scheduling problem, as the availability of employees must be considered when preparing weekly schedules. Managers either spend long hours preparing weekly schedules, or they mostly use a previous week's schedule and reassign employees to the tours (shift and days off) based on their availability. This latter approach fails to balance understaffing and overstaffing, as the orders received in a specific time interval change over each week and month. An automated weekly schedule could help not only with improving effective staff management but also, with reducing the time that branch managers need to prepare staff schedules each week. Therefore, in today's competitive environment, one of the key techniques for restaurants to improve productivity is to apply optimized personnel scheduling. It helps to reduce overstaffing costs resulting from overemployment or inefficient scheduling. In addition, by proper scheduling, restaurants may increase customer satisfaction by ensuring high service levels and short waiting times (Godward and Swart 1994, Choi et al. 2009).

Despite a large stream of literature that develops models for personnel scheduling in restaurants, only a few works implemented their models in practice to gain insights into the benefits companies can obtain from staff scheduling models. Two related works are those of Love and Hoey (1990) and Choi et al. (2009), who applied their developed models at McDonald's restaurants in the Maryland area in the United States and at a single branch of a restaurant chain in Seoul, South Korea. Both works modeled both full-time and part-time employees and considered restaurant-specific unique settings. It should be noted that the distinctive working conditions encountered in each restaurant may require an individualized mathematical model, and applying the same model in different restaurants is often difficult, if not impossible. To the best of the authors' knowledge, to date, no study has considered employee experience levels and the weighting of orders for fairly distributing the workload among the restaurant waitstaff. Order weights may be determined by restaurant management, and they reflect the level of difficulty associated with the preparation of the order. Thus, considering order weights in personnel scheduling helps to ensure that some waitstaff are not overloaded with difficult orders, whereas other waitstaff only have to process easy ones. Moreover, waitstaff have thus far mainly been assumed to be inflexible, such that they can only serve a certain set of tables but not all of them, and further employee preferences in terms of availability have only rarely been addressed in this research stream so far. To close these research gaps, this study was undertaken to explore personnel scheduling and its implementation at a restaurant chain.

This paper proposes integer programming (IP) models for the optimal scheduling of employees with different tasks and different experience levels in a restaurant. The models were built based on the data provided by the MADO restaurant chain in Baku, Azerbaijan. The models were applied at a single branch of the restaurant chain, and changes in performance metrics and other details were recorded. Based on a guideline on the use of the model prepared by the authors (and provided in the appendix), the proposed optimization models were also applied to the remaining branches of the restaurant chain by trained staff of the restaurant. Using the proposed mathematical models, the company was able to reduce the total labor costs and overstaffing substantially. The models also helped to avoid understaffing situations completely, leading to higher levels of customer service. In addition, incorporating employee preferences into the model can also be expected to increase employee satisfaction.

The remainder of this paper is structured as follows. The next section reviews related literature and outlines the contributions of this work. We then introduce the restaurant setting and the managerial problems investigated in this paper followed by an explanation of our solution approach that includes both data processing and the development and solution of optimization models. Subsequently, we describe the implementation process and managerial implications. The last section summarizes the paper and outlines possible model extensions.

Related Literature

This section discusses related studies from two research streams. The first subsection gives an overview of works that consider the workforce as a key element of an aggregate production planning model. The second subsection then presents works that investigate workforce scheduling problems.

Aggregate Planning

Aggregate production planning establishes production plans for the medium-term future (i.e., for the next 3–18 months). Aggregate production plans may contain information on production quantities, inventory levels, backorder levels, and the size of the workforce depending on the specific planning situation the company faces.

The restaurant chain investigated in this paper faces an aggregate planning problem as well, as it has to determine the workforce size that is required to meet the demand forecast for the next year. The company's policy is to use a stable workforce, as this helps to improve customer service, enables waitstaff to gather experience at their job, and permits the company to implement a consistent scheduling policy throughout the year. This aggregate planning strategy has been referred to as a "level strategy" in the literature (e.g., Buxey 2003, Heizer et al. 2017). One of the main objectives of our model, therefore, is to determine the optimal number of waitstaff based on the monthly peak demand estimated from historical data. In the following, we briefly discuss a selection of related aggregate planning studies.

Jennings and Shah (2014), for example, proposed a strategic workforce planning model for a large-scale deployment of smart meters of a utility company supplying gas, electricity, and dual fuel. Their main contribution was to consider learning rates of the workforce during the performance of tasks. The developed multiperiod nonlinear programming model minimizes the sum of workforce, maintenance and service, and customer usage costs. Gomes da Silva et al. (2006) proposed a multicriteria mixed-integer programming model that optimizes the number of different types of workers, overtime hours, and inventory levels for multiple products. Sillekens et al. (2011) addressed aggregate planning with a flexible workforce for the automotive industry. They developed a mixed-integer programming model that minimizes the costs associated with production, holding inventory, changing capacity, paying the workers, and changing the workforce (hiring and firing).

Othman et al. (2012) investigated workforce planning for a job shop setting with multiple machine types grouped into different levels according to their complexity. The main objective of this study was to minimize hiring, firing, training, and overtime costs and to reduce the number of top-performing workers (with high skill and personality levels) laid off over all periods. Works that addressed similar aggregate planning problems are those of Hung (1999), Leung and Chan (2009), and Jamalnia et al. (2017) among others.

Workforce Scheduling

Workforce (or personnel) scheduling goes back to 1954 when George Dantzig (1954) presented his "D-framework." The D-framework prohibits understaffing and allows overstaffing at a cost, and it finds the best schedule by minimizing the total overstaffing cost. In 1979, Elbridge Keith (1979) developed the "K-framework," which basically minimizes both understaffing and overstaffing costs while assigning pseudocosts to understaffing. The "D-framework" is used more frequently in academic papers than the "K-framework." To build a road map for the application of scheduling in hospitality management, Thompson (1998a, b, 1999a, b) developed a four-stage method: (I) demand forecasting (Thompson 1998a), (II) converting demand into an employee requirement (Thompson 1998b), (III) employee scheduling (Thompson 1999a), and (IV) real-time monitoring of the schedule (Thompson 1999b).

Workforce scheduling has been investigated in various industries. Shahabsafa et al. (2018) studied an inmate assignment and scheduling problem to optimize operations of correctional institutions (CIs) in Pennsylvania. Their proposed hierarchical multiobjective mixed-integer model was capable of reducing staff, the total number and movements of inmates at the CIs, and waiting lists for treatment services. Miranda et al. (2018) investigated shift scheduling for the fare-collection staff of a subway. To minimize the total staffing cost and improve efficiency, the authors developed a two-stage (i.e., an integer programming and a simulation model) modeling approach. Their findings showed that a seven-day schedule reduces both costs and the staffing level.

Çakirgil et al. (2020) studied a multiskill workforce scheduling problem combined with a routing problem inspired by real-life operations of an energy distribution company. The authors formulated a mixed-integer programming model and a two-stage heuristic approach that optimize team formation, task-to-team assignment, and daily routes. Computational experiments showed that the mathematical model is not practical even for small-sized (10 tasks) instances, whereas the proposed metaheuristic approach is computationally efficient.

In a case study, Patrick et al. (2019) developed the optimal schedule of pathologists for the Department of Pathology and Laboratory Medicine at Ottawa Hospital. By extending the classical assignment problem, the authors minimized the total service time while satisfying a set of performance metrics defined by the department (including *idle time*, *back-to-back weeks*, *overloaded weeks*, and *consistent assignment within a week*). Bailey and Waddell (2020) investigated a workforce scheduling problem for tutors and students of an education center. The authors formulated a binary integer program to optimally assign both tutors and students to time slots while satisfying a set of *hard* (must) and *soft* constraints (preferred but not necessary) constraints. Their results show that the model is able to produce a consistent daily schedule and save working hours of the scheduler.

Further popular applications are the scheduling of airline crews (Cappanera and Gallo 2004, Casado et al. 2005, Chu 2007, Dück et al. 2012), nurses (Aickelin and Dowsland 2004, Aickelin and White 2004, Azaiez and Al Sharif 2005, Awadallah et al. 2011), call center agents (Atlason et al. 2004, Alfares 2007a), emergency ambulances (Sinreich and Jabali 2007, Frey et al. 2009, Erdoğan et al. 2010), railways (Alfieri et al. 2007, Elizondo et al. 2010), manufacturing personnel (Al-Yakoob and Sherali 2007, 2008; Alfares 2007b), and retail clerks (Kabak et al. 2008, Pastor and Olivella 2008).

There are only a few papers on workforce scheduling in restaurants that apply their model in a specific restaurant and report the achieved benefits. An early work in this area is the one by Love and Hoey (1990), who built a two-phase optimization model to solve a scheduling problem at McDonald's. The authors reported that within 1983–1990, their model was utilized by McDonald's and enabled them to reduce 80%–90% of the time spent by managers on weekly schedule preparation. Hueter and Swart (1998) used simulation to find an optimal server per customer ratio at Taco Bell Corporation. They used the integer programming model developed by Godward and Swart (1994) and solved the model with the network simplex method after using Lagrangian multipliers to eliminate capacity constraints. Their proposed schedule resulted in savings of $53 million for Taco Bell. Choi et al. (2009) considered both full-time and part-time employees and developed a weekly schedule that minimizes the total salary of employees. They used three overlapping shifts to satisfy demand in peak hours. Employee availability was not considered in the model. Therefore, the employees are assigned to the tours without considering their preferences.

We conclude that the distinct nature of the restaurant or fast-food industry (here, especially the hiring of part-time employees, the use of shifts with different working hours, high employee turnover, and the resulting difference in employee experience as well as variable and uncertain demand) make the workforce scheduling problem complex in this industry. In addition, restaurants often have further objectives besides the minimization of labor costs that need to be considered in the preparation of work schedules, such as meeting employee preferences for shifts or days off, minimizing the number of experienced staff laid off over time, or always meeting a minimum level of customer service, which makes it necessary to develop specific models and to validate their applicability in practice.

The paper at hand makes the following key contributions to the existing literature on waitstaff tour scheduling from an applied perspective. First, we consider two types of waitstaff (waiter and assistant waiter) with different experience levels. Second, we determine the workload of each type of waitstaff by weighting orders according to the level of difficulty associated with their preparation. This helps us to distribute the workload fairly among the restaurant staff. Finally, we incorporate the employees' preferences in terms of their availability while developing optimal weekly schedules. These features we encountered at MADO have not been considered in a waitstaff tour scheduling problem so far.

Restaurant Setting and Managerial Problems

This research addresses the personnel scheduling problem of MADO restaurants in Azerbaijan. Currently, MADO, a Turkey-based restaurant chain, serves traditional Turkish food in more than 12 countries across the globe, including Australia, Saudi Arabia, Cyprus, Hong Kong, South Korea, and Belgium. MADO is a table-based restaurant with working hours from 7:00 to 2:00 (in 24-hour time) seven days per week. Generally, sales happen either from customers sitting inside or from the showcase. A member of the waitstaff is assigned to customers at the tables and a salesman to the showcase. There are 68 waitstaff distributed between four branches relative to the size of the restaurants. The waitstaff are divided into two major classes: experienced waiters who are responsible for taking and delivering orders, who will be referred to hereafter as *waiters*, and novice waiters who are responsible for helping waiters to carry orders, preparing tables prior to customer arrival, and cleaning the restaurant in the early morning or late evening; these waiters will be referred to hereafter as *assistants*. Note that the term *waitstaff* will be used for referring to both types of waiters. A new employee starts as an assistant and over time, after getting sufficient experience, may level up to the highest level of waiter. There are two experience levels of an assistant and four experience levels of a waiter. The experience level affects service time, and as waiters or assistants get more experience over time, their experience level and salary increase. By adopting this strategy, the company aims to reduce employee turnover.

Unlike at most restaurants, waitstaff are not fixed to certain customers, and a customer may ask any nearby waitstaff for service. Prior to the optimization, this approach was used by the restaurant management with the intention of increasing customers' satisfaction, as they do not have to wait until fixed waitstaff become available. The restaurant serves customers through five departments—namely, bakery, kitchen, ice cream, bar, and pastry. Orders from those departments differ in terms of preparation time, service time, and size features. For example, the bar is close to the tables, and a drink can be prepared more quickly than a meal can be prepared in the kitchen. Moreover, in one go, waitstaff can serve four drinks using one tray, whereas waitstaff cannot show the same performance while serving orders (maximum of two orders) from the kitchen. Typically, a customer may have orders from multiple departments. Thus, as a demand metric, we considered the number of orders per time interval instead of the number of customers because the number of orders and the responsible departments have a strong impact on determining daily employee requirements and workload. Therefore, we assigned weights to each order based on the responsible department to consider this difference during staff assignment. Theoretically, all waiters and assistants are supposed to work six days a week, and it is fixed that they have to work at least five hours during their workdays. However, in case of high demand, the staff may work up to 10 hours, including two meals and five or six tea breaks. Furthermore, despite the fixed schedule, employees are allowed to come late or leave early after discussing their availability with management. The staff are allocated to one of three shifts (with each being 10 hours long): 07:00–17:00, 13:00–23:00, or 16:00–02:00. Once assigned to a certain shift, they work the same shift across the week.

Prior to this research, the branch managers used the same weekly schedule in all weeks regardless of customer numbers changing for each week and month. The only difference was staff-to-shift assignments, which were prepared considering the waitstaff's availability. It was also observed that in the restaurant, a huge variance in the number of customers per hour occurred, especially around noontime. This complicates the scheduling process, as assigning more waitstaff to peak time would increase the understaffing or overstaffing level in earlier or later hours. Put differently, if the manager assigns a sufficient number of waitstaff to the peak hour, then an hour before or later, they may encounter an overstaffing case. The reason is that the manager cannot assign waitstaff to work for only an hour per day, as they are full-time employees. As mentioned, the restaurants frequently encounter high employee turnover, including both waitstaff and managers. This case restaurant is no exception. The leave of branch managers has a substantial impact on operations because the current staff schedule relies on their experience and intuition. Therefore, the management board decided to use a waitstaff scheduling model that would be affected less in the aforementioned scenarios.

Solution Approach

Among the four branches of the restaurant chain in Baku, we picked the one with the highest demand rate and solved the scheduling problem. After completion of this project, we trained the managerial personnel to use our algorithms and showed them how it could be implemented in other branches. In this project, we avoided assumptions that simplify the problem too much and considered unique features of the restaurant chain along with other managerial requests. In general, we can divide the solution procedure into two phases: data preparation and development and solution of optimization models. Both steps are described in more detail in the following sections.

Data Preparation

The data required for this research were extracted from the restaurant's enterprise resource planning (ERP) software (LOGIX). As the restaurant branches in Baku just recently started to collect and store the data in the required format, only data for the past eight months (i.e., October 2018 to May 2019 inclusively) were available. Management is aware that the highest demand of every year occurs in May, which is used to find the optimal capacity in this research. The methodology used to process the data is similar to the framework suggested by Thompson (1998a, b, 1999a, b). The main steps we followed for generating the input parameters are forecasting the demand rate, standardizing service time, and finding the required labor force.

Forecasting the Demand Rate. As discussed in the previous section, the waitstaff of the case restaurant were originally not fixed to a customer or a certain table; instead, waitstaff may serve any customer as they are available. The demand rate was defined as the number of orders per hour, and it was obtained by evaluating past customer transactions. Orders within a one-hour time interval vary according to the time of the day, the day of the week, and the department. To observe and measure a preparation time for different orders, we conducted a standard time study at all departments of the restaurant for three months. Based on the data acquired from the time study and discussions with managers, we determined weights for the different types of orders per department (Table 1).

The weighted orders were then calculated per time interval and day of a week. Based on the calculated weighted orders, the demand rate was defined. Table 2 presents a sample demand rate for a week. The historical data were converted in the same fashion and used for testing various forecasting models. In the forecasting models, days were considered as the smallest period of a time series. Using the historical data, we calculated a seven-day moving average (F1), a linear trend projection based on the least-squares method (F2), and a linear trend associated with seasonal indices using the Holt–Winters multiplicative method (F3) (see Winters 1960, Glock 2021). The historical period covers eight months (240 days) with the data captured on a daily basis—that is, a period of the time series is a day (i.e., $t = 1, \ldots, 240$). Starting with the second week, we calculated daily forecasts using the F1, F2, and F3 models and evaluated their forecast accuracy with the help of the mean squared error (MSE) method. The MSE is the average of the squared differences between the forecasted values and the actual values, and it is a standard metric for evaluating forecasts. The obtained MSE values for the forecasting models are as follows: F1 = 198.20, F2 = 195.24, and F3 = 165.16. Our findings suggest that forecasting model F3 led to the

Table 1. The Weights for Different Types of Orders per Department of the Restaurant

Department	Weight
Pastry	1
Bakery	1
Ice cream	1
Bar	0.7
Kitchen	2

Table 2. The Sample Demand Rate per Service Time Interval for Each Day of a Week

Service time interval\days	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
7:00–8:00	2.3	11.8	0.0	2.0	16.2	2.6	18.4
8:00–9:00	17.3	12.3	32.3	40.5	22.8	20.6	65.8
9:00–10:00	66.5	38.3	44.0	27.5	34.8	54.6	29.0
10:00–11:00	34.8	30.8	36.0	43.3	58.2	60.8	114.0
11:00–12:00	44.5	46.0	75.5	49.5	95.4	138.0	156.0
12:00–13:00	105.5	95.3	95.5	93.0	106.2	91.8	146.8
13:00–14:00	119.0	165.3	145.5	138.5	153.4	154.0	174.0
14:00–15:00	140.0	117.0	128.5	161.5	135.2	166.6	214.6
15:00–16:00	151.3	137.0	137.5	137.3	176.0	196.2	228.4
16:00–17:00	123.3	124.0	114.3	135.5	167.4	182.0	201.0
17:00–18:00	139.8	134.5	117.0	137.8	127.4	187.2	214.4
18:00–19:00	129.3	124.3	131.3	117.0	159.0	191.2	203.2
19:00–20:00	122.3	140.3	116.3	170.8	176.8	161.8	191.6
20:00–21:00	127.5	122.3	133.0	150.8	177.8	151.2	159.6
21:00–22:00	105.3	96.8	103.8	120.5	133.8	169.4	147.2
22:00–23:00	58.3	80.3	57.3	119.8	101.4	106.0	87.6
23:00–00:00	26.0	39.8	30.8	42.0	66.0	70.8	47.8
00:00–01:00	6.5	15.0	5.5	7.3	17.4	20.0	12.6
01:00–02:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0

best forecast, and it was therefore used in our study and also by the case company for future demand prediction. Model F3 essentially consists of three main phases: the initialization of the procedure, the determination of the smoothing factors, and the actual forecasting. The first phase estimates initial seasonal indices, demand level, and trend. The second phase determines the appropriate smoothing factors (for the demand level, trend, and seasonality) that minimize the MSE. Finally, we implement the Holt–Winters multiplicative model to forecast next period (day of week) demand and allocate it to service time intervals. We refer the interested reader to the appendix, where model F3 is outlined in further detail.

Standardization of Service Time. To calculate a standard for service time, the available eight-month data were examined. The ratio of waitstaff (waiters and assistants) to weighted orders was calculated for peak hours separately for both staff groups. Similar to the work by Choi et al. (2009), after the order count per server (OCS) was calculated, the standard for the waiters and the assistants was set to 95% of the peak hour order count. The calculation of OCS for both waiters and assistants is as follows:

$$OCS_{waiter} = \frac{1}{31}\left(\sum_{d=1}^{31} c_d/w_d\right) \times \alpha$$

$$OCS_{assistant\ waiter} = \frac{1}{31}\left(\sum_{d=1}^{31} c_d/a_d\right) \times \alpha,$$

where c_d, w_d, and a_d denote the number of customers, waiters, and assistants, respectively, and α (0.95) represents the service level. The standard numbers of weighted orders per waiter and assistant were determined as 141 and 45 on average, respectively. After discussions with management, the average time was divided between waiters and assistants relative to their experience levels. These standards were set constant for each month (Table 3).

After the weekly weighted demand has been calculated, it is used as an input along with other given restaurant settings. This includes the number of waitstaff from each category and experience level and the number of waitstaff required for other tasks (OTs). OTs are a set of tasks carried out by waitstaff that are not directly related to customer orders, such as cleaning, preparation of dishes, helping in the kitchen, and so on. The branch investigated in this paper required three assistants at 07:00–08:00, one assistant at 08:00–09:00, four assistants at 00:00–01:00, and two assistants at 01:00–02:00 for preparation and cleaning tasks.

Optimization Models

Three deterministic IP models were formulated to find the optimal labor capacity for each waitstaff type and experience level as well as the best tour (shift and day off) within a week. The first model (Model 1)

Table 3. The Hourly Weighted Order Capacity for Each Type of Waitstaff

Waitstaff type	Order capacity per hour
Waiter level 1	112.2
Waiter level 2	132.0
Waiter level 3	151.8
Waiter level 4	171.6
Assistant level 1	36.0
Assistant level 2	54.0

Table 4. The Optimal Number of Waitstaff Found by Model 1

Waitstaff type	Optimal number of waitstaff
Waiter level 1	4
Waiter level 2	0
Waiter level 3	1
Waiter level 4	0
Assistant level 1	6
Assistant level 2	6
Total	17

is solved on a yearly basis to find the number of employees that is sufficient to cover demand during the busiest week of the year. By doing so, we minimize waitstaff hiring and firing costs within a year, which was requested by management. Note that lead time occurs for the hiring of waitstaff, which is why this model has a longer planning horizon than the other two. The other two models (Model 2 and Model 3) are solved on a weekly basis to generate a weekly waitstaff schedule based on historical demand patterns for that week and employee availability. The demand requirement and employee availability matrix is updated weekly to generate a new schedule.

The objective function of Model 1 (A.1) we aim to minimize has four terms (see the appendix). The first and second terms denote the total hourly labor costs of waiters and assistants, respectively. The next two terms are used to penalize the use of less experienced waitstaff when there is a waiter or assistant with higher experience. Constraints (A.2) and (A.3) ensure that the number of waiters and assistants is sufficient to carry all orders. On the right-hand side (RHS) of these constraints, hourly order weights are used instead of order count (see the Standardization of Service Time section). Constraints (A.4) and (A.5) are added to make sure that there is sufficient staff for cleaning and other tasks. They also ensure that there is a minimum number of staff required by the management, even if there is no customer inside the restaurant within a specific time interval. The next constraints, (A.6) and (A.7), ensure that assigned waiters and assistants do not exceed the number of available waitstaff. Furthermore, the remaining two constraints, (A.8) and (A.9), are used to store the optimum number of waiters and assistants. Additionally, they determine the number of nonassigned waiters (N_u^w) and assistants (N_v^a) from each experience level.

Model 2 is a modified version of Model 1 (see the appendix). Once the optimal staff size has been found by Model 1, that output becomes an input parameter for Model 2 (see Table 4). Then, Model 2 is used weekly to obtain optimal schedules for regular months. The objective of Model 2 is to optimally allocate the total number of weekly required waiters and assistants over the shifts. Related constraints ((A.11) and (A.12)) of Model 2 are used for limiting the total number of assigned waiters and assistants to the number available in the restaurant.

To support the branch manager's decision-making process, we also proposed Model 3 (see the appendix), which assigns employees to the shifts in accordance with their preferences. The major input parameter of this model is the employee preference matrix that is based on a waitstaff availability table (see Table 5).

Each employee is asked to fill the query (Table 5) before the start of each week. This table is then considered as a reward matrix in the objective of Model 3. The objective of Model 3 is to maximize the sum of the employees' preference values by choosing the most favorable employee-to-tour assignment. The first two constraints of Model 3, (A.14) and (A.15), guarantee that the total number of assigned waiters and assistants is equal to the optimal solution found by Model 2. Finally, Constraints (A.16) and (A.17) make sure that every employee is assigned to one shift only.

Implementation

All models were implemented in MATLAB and solved on a Personal Computer (PC) with an Intel-i7-6700 Central Processing Unit (CPU), 3.40 Gigahertz (GHz) and 12 GB Random Access Memory (RAM), under Windows 8 x64. The use of MATLAB was requested by management, as they had experience with the use of this software. Although the run time of the MATLAB solver is longer than those of alternative solvers, we were able to solve the model in a reasonably short time by slightly modifying the model (i.e., Model 1 was modified to Model 2, and Model 2 was solved with the proposed algorithm; see the Optimization Models section for

Table 5. A Waitstaff Availability Query Filled by Each Waitstaff Member Before the Start of Each Week

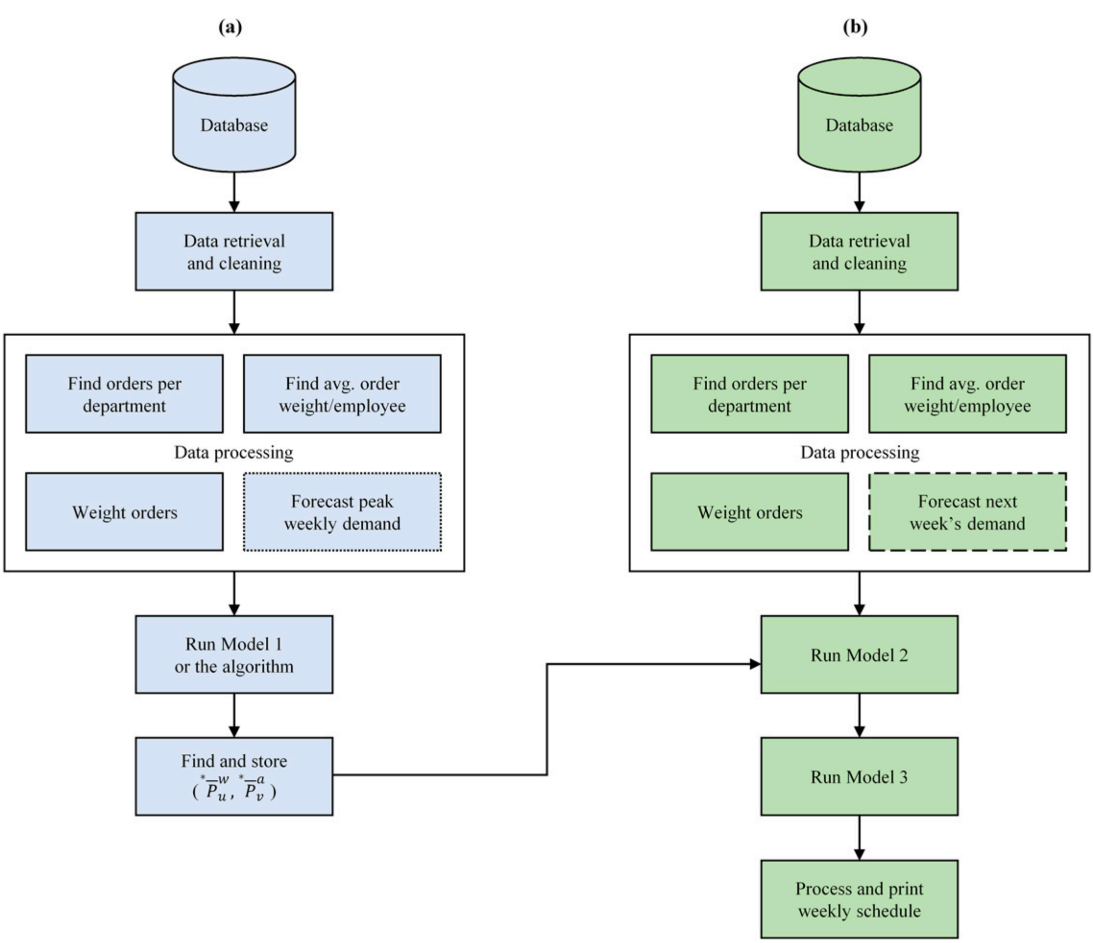
Service periods\days	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
07:00–08:00	0	1	0	2	1	1	2
09:00–10:00	1	1	1	1	1	1	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
01:00–02:00	0	0	0	2	2	2	0

Note. 0 = unavailable, 1 = available, and 2 = preferred.

details) without sacrificing optimality. Regarding the solution time, Model 1 had a substantial run time (more than two hours) compared with that of the other models (less than two minutes). Although this run time seems acceptable given that the model would be run only once per year, we still tried to reduce the run time to facilitate its use in other contexts. We, therefore, developed an algorithm (see pseudocode in the appendix) that was used jointly with Model 2 and that obtained the optimal output in a relatively very short time, around five minutes. In addition, we benchmarked our proposed algorithm against the MATLAB solver for 20 instances in which only the weekly demand (i.e., the sum of weighted orders) changes, with the other parameters remaining constant. Note that we generated those instances randomly (i.e., in the range of 5,688–7,921) and that the range was inspired by the practical data we had gathered. The results showed that the proposed algorithm significantly outperforms the MATLAB solver (156 versus 7738 CPU seconds on average) (see Table A.1). The general process flows of the proposed models are depicted in Figure 1.

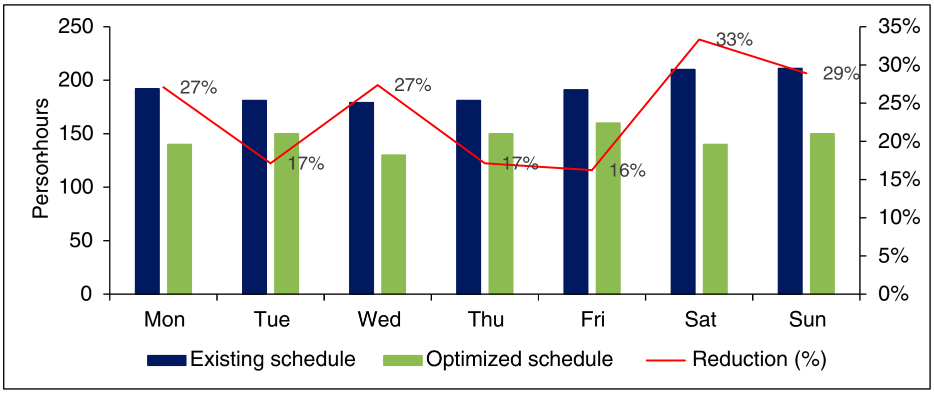
The application process consists of two general phases: data manipulation and development of the optimized weekly schedule. The first phase derives weekly average weighted orders from raw data and from the processed data, and the second phase generates a detailed weekly personnel schedule. An Excel interface was added to the MATLAB program to improve usability (see a sample view of the interfaces in the appendix). Once the data had been changed to the proper format, the IP models were implemented, and then, the results were compared with those of the previously used schedule for estimating the cost reduction. The results are presented in Table A.2 with the differences denoted by Δ. The average reduction in staff ranged between 1.6 and 3.7 (average 2.4) when changing from the existing to the optimized schedule. For certain service periods, the Δ adopts a positive value, implying an increase in staff size. This increase in staff size results from the constraints imposed on the optimization problem by management to ensure the completion of other tasks. That is, each day, six employees need to be present between 00:00 and 2:00 for cleaning in the evening time, and four are required for cleaning and

Figure 1. (Color online) The General Process Flow of the Proposed Models Consists of Two Parts



Notes. (a) Process flow of finding the optimal employee count (i.e., running once per year). (b) Weekly scheduling procedure.

Figure 2. (Color online) Comparison of the Total Person-Hours of the Existing (Blue) Against the Optimized (Green) Schedule per Day of the Week



Note. The red line indicates the percentage reduction of person-hours per day of the week.

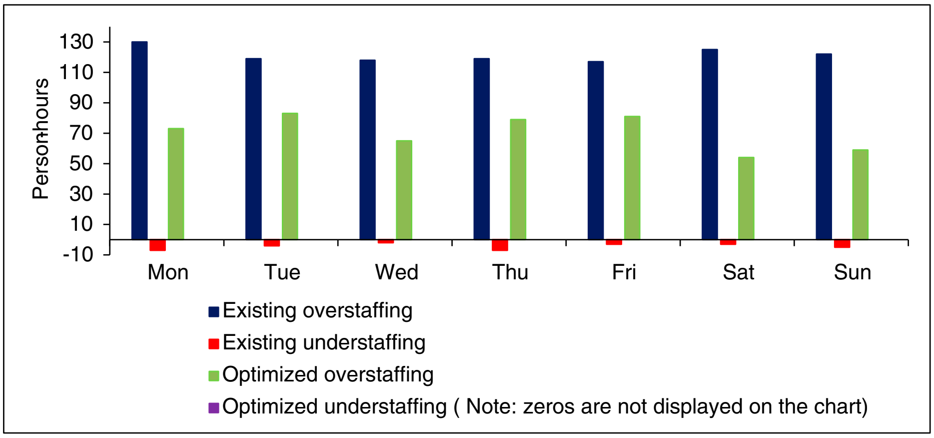
preparation tasks at 07:00–09:00. When they are scheduled, they have to be present in adjacent hours to complete their 10 shift hours. Figure 2 illustrates the graphic summary of the total person-hours per day and savings after implementation of the IP model.

In the existing schedule, understaffing occurred in certain hours, which are marked red in Figure 3. This happened despite the overtime employment of assistants in the existing schedule. After the application of the optimization model, the number of staff was reduced from 22 to 17 in this branch. This improvement reduced overstaffing (marked in green in Figure 3) significantly. At the same time, all understaffed hours were eliminated despite the reduction in staff.

The results are presented in Table A.3. The new schedule was able to reduce the labor force in the branch by approximately 23% (i.e., from 22 to 17) (Table 4) while keeping the same service quality as before. The optimal schedule requires at least five waiters to be available each week. In the previous section, it was explained that in the current restaurant settings, it is not possible to erase overstaffing completely. However, overstaffing can be reduced by optimally allocating tours to waitstaff members. In this project, overstaffing was reduced from 850 to 494 hours while decreasing the total work hours in a week from 1,320 to 1,020 hours (see Table 6, which reports the major improvements).

Note that the results shown in Table 6 are expected benefits predicted by our model for the month with the highest demand (May). In May, the existing schedule was still in practice at our partner company. Using May's data, we presented a comparison between the existing schedule and the optimal schedule to the management. Upon their approval, the new schedule was implemented in the following months.

Figure 3. (Color online) The Levels of Overstaffing and Understaffing (Blue and Red, Respectively) in Terms of Person-Hours of the Existing Vs. the Optimized Schedule (Green and Purple, Respectively)



Note. Because optimized understaffing was eliminated completely, it is not displayed on the chart.

Table 6. The Expected Weekly Improvements Resulting from Our Proposed Approach for a Single Branch of the Restaurant Chain

	Existing schedule	New schedule	Reduction, %
Scheduled hours	1,320	1,020	23
Overstaffing hours	850	494	42
Understaffing hours	31	0	100
Labor cost	—[a]	—	21

[a]The labor costs (wages) were excluded owing to confidentiality.

Sensitivity Analysis

Analyzing the historical demand data provided by the company, we can see that there is a huge variance in hourly demand (see Figure 4). Order counts may increase strongly, especially on holidays. According to the management, the demand reaches its yearly peak usually in May, which is confirmed by the data provided to us (see Figure 5). Even though we did not receive any data for the summer months, management informed us that demand drops during the summer break as people leave the capital. Based on this information, we can proceed on the assumption that if we are able to cover the entire demand during May, then the waitstaff will also be sufficient to serve all customers during the other months.

As mentioned before, to avoid employee turnover, the restaurant's management wanted to keep the waitstaff constant throughout the year. At the same time, it was required to eliminate understaffing completely. Therefore, we selected the month with the highest demand (May) and solved the scheduling problem to find the optimal waitstaff number. To evaluate the robustness of the solution, we changed the hourly (i.e., service time interval) demand by ±30% and applied the optimization model anew to monitor changes in waitstaff count. Figure 6 illustrates the changes we observed.

As shown in Figure 6, for a demand increase of up to 5%, the waitstaff our model had identified are still optimal. However, if the demand increases by 10% or more, there is a need for at least one additional waitstaff member. Such high demand increases as assumed in this sensitivity analysis were not observed at our partner company. One reason is that the highest demand was encountered when all tables in the restaurant were filled, such that a further increase in demand was not possible. If the demand decreases by 5%, then it would be possible to cover the demand with a waitstaff size reduced by one (in this case, an assistant waiter). A further 5% decrease in the demand would reduce the required waitstaff size by one further employee. The number of required waitstaff decreases gradually up to a 20% reduction in the demand. Then, it becomes steady for another demand reduction of 5% before decreasing by one more employee. From our analysis, we conclude that the size of the waitstaff is sufficient throughout the year for the current restaurant setting.

In the project at hand, our approach to the problem was to identify the optimal waitstaff number for the busiest month and to keep this number constant throughout the year. Even though this constraint was requested by management in our case, it is clear that this practice may lead to high levels of overstaffing for less busy months. In the next step, we therefore investigate the overstaffing levels that result from our approach by solving the scheduling problem for each

Figure 4. (Color online) The Distribution of Demand per Service Time Interval over the Available Eight Months

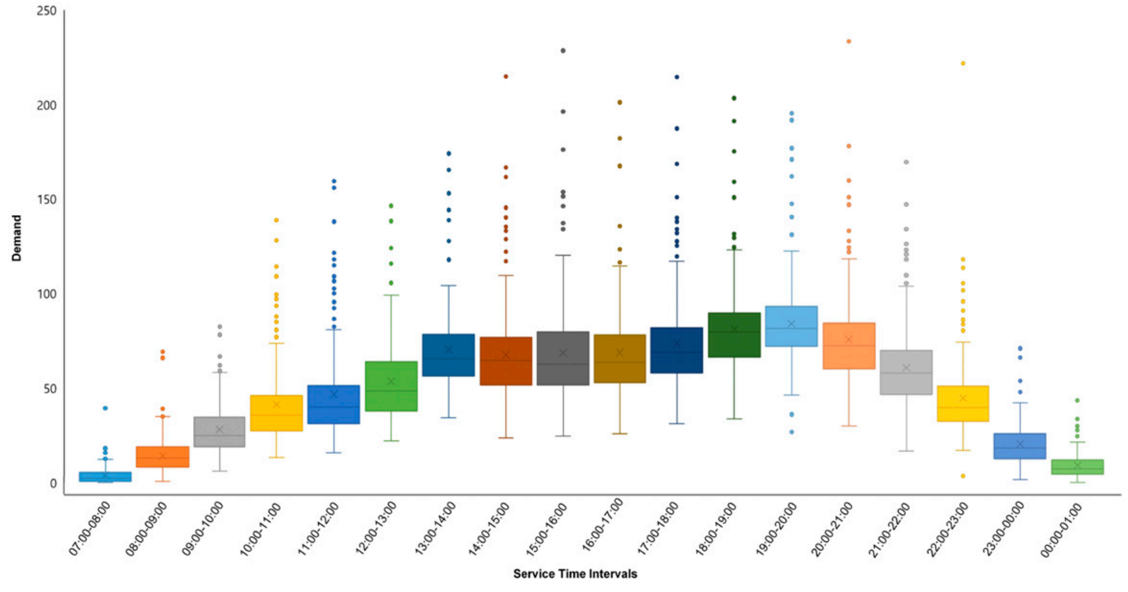
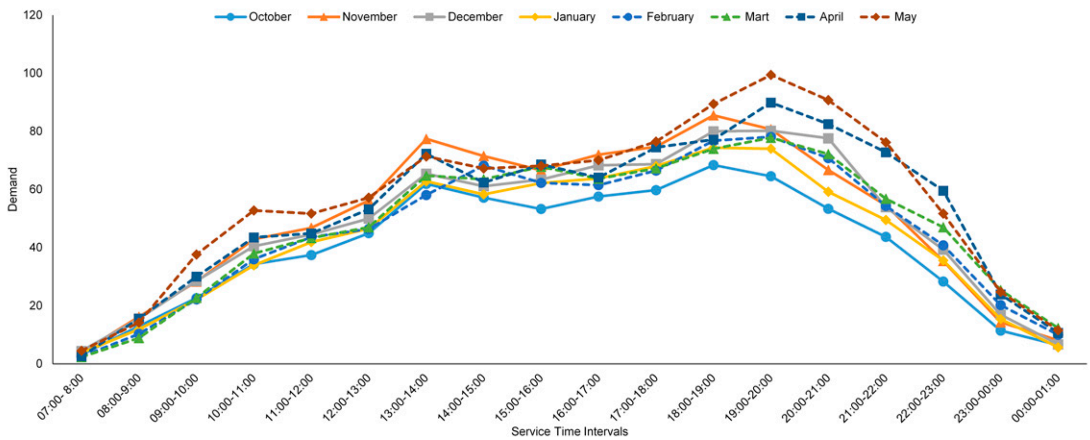


Figure 5. (Color online) The Average Demand per Service Time Interval for Each Month



month individually. Figure 7 shows results (waitstaff numbers and overstaffing levels) for each month for the case in which employee turnover is allowed.

Compared with May, customers could be served in April and November with a waitstaff size reduced by two, even though demand in these two months is just slightly lower than that in May. The reduction in waitstaff would extend to one employee from the waiters and one from the assistants group. Even larger reductions in waitstaff would be possible for January, February, and March. Given that demand in seven of eight months could be covered with a smaller waitstaff number than that required in May, the company could consider implementing specific measure for handling the demand peak in May, such as the employment of temporary workers. Even though such a measure is not fully compatible with its current employment philosophy, it would help to save personnel cost during the remaining months of the year.

Next, we analyze how changes in the service level affect the required waitstaff. The service level, in the context of our study, describes the percentage of customers served. In the case of the company we worked with, understaffing should be eliminated completely, leading to a 100% service level. Figure 8 shows overstaffing and understaffing levels for each month if lower service levels are used.

As shown in Figure 8, understaffing levels are (very) much lower than overstaffing levels if a lower service level is used, and in most cases, they are zero. Based on this result, the company could consider using a lower service level for weekly waitstaff scheduling to further decrease its personnel cost.

Managerial Implications

The results of our study may guide managers facing similar workforce scheduling problems in the restaurant industry. In the following, we outline possible implications that may be crucial for practitioners aiming to optimize workforce scheduling.

The time required for developing and implementing the proposed model was four months. Data processing was the most time-consuming part, as were frequent changes requested by management during the course of the project.

To ensure high service quality, restaurants need to plan their workforce effectively in light of uncertain

Figure 6. (Color online) The Optimal Waitstaff Number for Different Changes in Hourly Demand

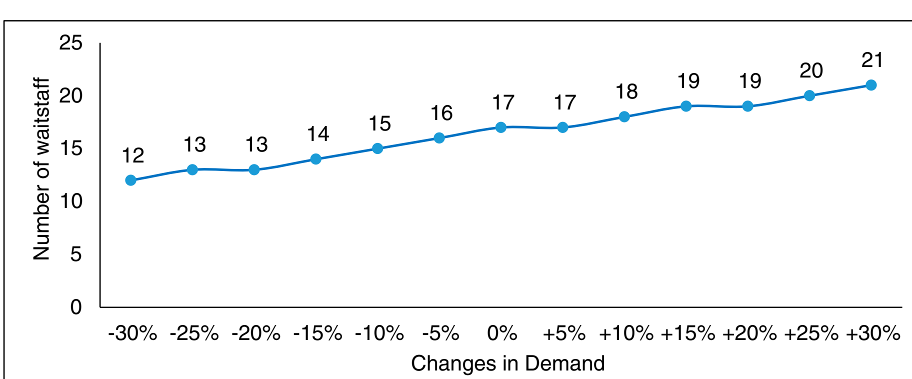
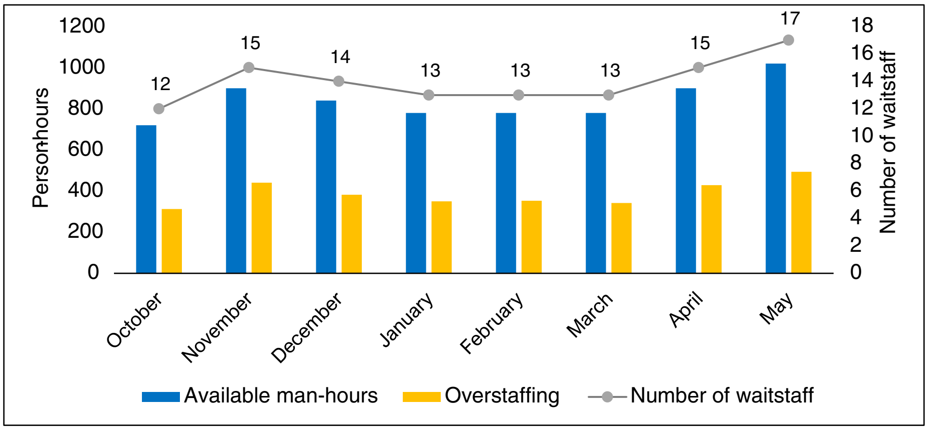


Figure 7. (Color online) The Available Person-Hours, Waitstaff Number, and Overstaffing for the Case of an Individual Optimization per Month



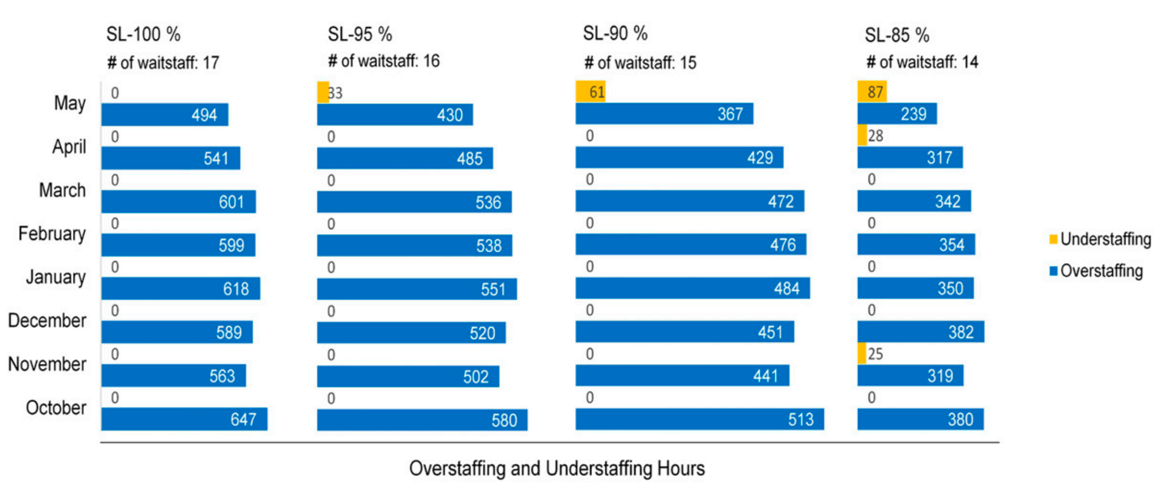
demand. In practice, many restaurants react to uncertainty by either maintaining more full-time than part-time employees or by employing full-time staff only. This leads to overstaffing in many situations. To provide a better planning outcome, mathematical programming can be used to develop optimal daily/weekly workforce schedules.

In this context, our study outlined possible implications that result from applying a waitstaff scheduling model considering several requirements defined by the case company. Before optimized employee schedules were used, there were complaints from customers about low service levels resulting from understaffing. At the same time, team leaders reported overstaffing at certain hours. There was a dispute among managers with respect to whether new waitstaff were needed. Our project showed that the problems occurred as a result of poor scheduling. The restaurant used to rely heavily on the branch manager's experience for determining daily and weekly schedules. A successful application of the models developed in this paper showed that an optimal weekly schedule cannot only solve this problem but also, generate further benefits in terms of cost savings and more effective personnel management.

The application of the optimal schedules helped the restaurant management in various respects (these and the following results were reported to us in a follow-up interview with the management).

- Managers spent less time on preparing weekly schedules.
- Understaffing was completely eliminated.
- Overstaffing decreased by 42%.
- Labor cost decreased by 21%.
- Meal and tea breaks could be arranged by comparing required and assigned staff.
- Staff absence permissions and replacements could be easily managed.
- Workload was fairly distributed among the staff.

Figure 8. (Color online) The Optimal Waitstaff Number as well as Overstaffing and Understaffing Levels per Month for Different Service Levels



In addition, the proposed model helped management to predict the number of waitstaff from each category and experience level needed for a new branch of the restaurant that is supposed to open soon. After assigning the optimal number of staff to each of the four restaurants, the remaining experienced workforce could be assigned to the new fifth restaurant.

This optimized schedule can also be expected to lead to an increase in waitstaff morale for two reasons. First, we tried to achieve a fair allocation of workload among waitstaff, with the benchmark being the ratio of the total number of customers to the total number of waitstaff. Our model produces a more stable workload ratio throughout the week compared with the existing schedule. A second aspect we considered was employee availability, which we tried to respect when assigning waitstaff to shifts. At the end of the project, we did not conduct a questionnaire-type study to evaluate employee satisfaction. However, based on the positive feedback we received from the branch managers, we concluded that employee satisfaction increased significantly.

We also expect increased customer satisfaction as a result of an improvement in service times. Leaving the quality of food aside, service time has a strong impact on customer satisfaction. Service times depend on the number of waitstaff available in the restaurant at a given hour. For setting a customer satisfaction target, we processed past data and analyzed the total number of waitstaff and the total number of customers in the restaurant for each hour. After discussing the findings with the management team, we decided on the target ratio of the total number of waitstaff to the total number of customers. In the modeling part, the parameters used for establishing the required number of waitstaff were found by using this target ratio and historical demand patterns. By solving the optimization model, the resulting weekly schedules were generated while considering this detail in order to ensure customer satisfaction.

After a successful application of the models in one of the restaurant branches, the models were applied in three other branches by management using adjusted input data. To this end, we prepared a guideline for the restaurant management and provided all necessary files to them (see the appendix).

Conclusion

In this study, mathematical models were developed and implemented to solve the scheduling problem of a restaurant chain in Baku, Azerbaijan. The developed models were integrated into the restaurant's ERP program and complemented with an easy-to-use user interface. With the application of a new workforce scheduling method, it was shown that the same amount of workload could be carried by a lower number of employees using the optimized schedule. By using the models, more efficient daily and weekly schedules were produced based on past data. The profitability of the branch we investigated is expected to increase, as monthly labor costs could be lowered by more than 20%. The reduction of overstaffing helped to reduce overall labor costs. In addition, eliminating understaffing likely improved service quality and decreased the number of lost customers. The models also helped to eliminate the burden of preparing new weekly schedules because of employee turnover.

This research consolidated factors affecting employee performance in the developed models—namely, the order's relative weight, different waitstaff types and experience levels, and other tasks regularly carried out. As a result of using the models, employee morale and productivity were reportedly (according to management of the MADO) increased owing to a more fairly distributed workload among employees. The major limitation of this research is that it did not consider the occurrence of exceptionally high demand rates when a special event (race, carnival, concert, etc.) takes place in the city. However, managers could still address this special case by properly scaling order weights in the models for that specific day.

A possible extension of this study could be to give the restaurant more flexibility in adjusting the staff size by permitting short-term hiring and firing of employees. Provided that such an action is legal and compatible with the company's employment philosophy, this could further reduce labor costs by adjusting the staff size to the period's customer demand. It should be noted that this may increase solution times because of more decision variables that would have to be considered in the models to represent the multiperiod planning horizon. The employment of part-time staff could also be considered, which would add more flexible shifts to the models and could therefore help to further reduce overstaffing. Finally, changes in the experience levels of the waitstaff over time could be considered also in future studies. Such changes could reduce the overall number of waiters needed at a restaurant and may also influence the assignment of waitstaff to restaurants to avoid an imbalance in the workforce (in which older restaurants have mainly experienced waiters, whereas newer restaurants employ inexperienced ones). We leave these and other interesting extensions for future research.

Acknowledgments

The authors thank Kamran Mashadiyev for giving them permission to access the data of MADO Azerbaijan, which were crucial for conducting this research. The authors also thank the editors and the anonymous referees for their constructive comments that helped to improve this manuscript substantially.

Appendix

Nomenclature

Sets.

I Set of service time intervals; index $i \in I \equiv \{1, \ldots, 19\}$

S Set of shifts; index $s \in S \equiv \{1, \ldots, 70\}$*

D Set of week days; index $d \in D \equiv \{1, \ldots, 7\}$

U Set of waiters' experience levels; index $u \in U \equiv \{1, 2, 3, 4\}$

V Set of assistant waiters' experience levels; index $v \in V \equiv \{1, 2\}$

G Set of index for waiters $g \in G \equiv \{1, ., \textit{total number of waiters}\}$

H Set of index for assistant waiters $h \in H \equiv \{1, ., \textit{total number of assistant waiters}\}$

Shift means 10 consecutive hours; it includes two meal breaks and several tea breaks. The first shift ($s = 1$) starts at 7:00 and takes Monday off; the last shift ($s = 70$) starts at 16:00 and takes Sunday off.

Parameters.

P_u^w number of waiters with experience level u

P_v^a number of assistant waiters with experience level v

C_u^w employee cost for a waiter with experience level u

C_v^a employee cost for an assistant waiter with experience level v

R_{id}^w minimum number of waiters required at interval i of day d

R_{id}^a minimum number of assistant waiters required at interval i of day d

E_{id}^w extra number of waiters required (for other tasks)at interval i of day d

E_{id}^a extra number of assistant waiters required (for other tasks) at interval i of day d

W_{id} weight of orders at interval i of day d

A_u^w average weight of orders completed by a waiter with experience level u per hour

A_v^a average weight of orders performed by an assistant waiter with experience level v per hour

a_{isd} binary variable; one if interval i is a part of shift s at day d, zero otherwise

T_{gsu}^w availability of waiter g with experience level u for shift s; $\equiv \{2 - \textit{prefer},\ 1 - \textit{available},\ 0 - \textit{not available}\}$

T_{hsv}^a availability of assistant waiter h with experience level v for shift s; $\equiv \{2 - \textit{prefer},\ 1 - \textit{available},\ 0 - \textit{not available}\}$

M_u^w big M value for priortizing the utilization of a more experienced waiter; $M_1^w \geq M_2^w \geq M_3^w \geq M_4^w$

M_v^a big M value for priortizing the utilization of a more experienced assistant waiter; $M_1^a \geq M_2^a$

Decision Variables.

x_{su} number of waiters with experience level u assigned to shift s

y_{sv} number of assistant waiters with experience level v assigned to shift s

N_u^w number of nonutilized waiters with experience level u

N_v^a number of non utilized assistant waiters with experience level v

α_{gsu} binary variable; one if waiter g with experience level u is assigned to shift s, zero otherwise

β_{hsv} binary variable; one if assistant waiter h with experience level v is assigned to shift s, zero otherwise

$\overline{P}_u^w$ optimal number of waiters with experience level u

$\overline{P}_v^a$ optimal number of assistant waiters with experience level v

Model 1

$$Min\ Z = \sum_s \sum_u x_{su}.C_u^w + \sum_s \sum_v y_{sv}.C_v^a - \sum_u N_u^w.\ M_u^w - \sum_v N_v^a.\ M_v^a \tag{A.1}$$

s.t.

$$\sum_s \sum_u a_{isd}.x_{su}.A_u^w \geq W_{id} + E_{id}^w.\frac{\sum_u A_u^w}{|U|} \qquad \forall i, d \tag{A.2}$$

$$\sum_s \sum_v a_{isd}.y_{sv}.A_v^a \geq W_{id} + E_{id}^a.\frac{\sum_v A_v^a}{|V|} \qquad \forall i, d \tag{A.3}$$

Figure A.1. (Color online) Sample Input View of the User Interface, Where White Cells Are Filled/Updated by the User to Optimize the Weekly Schedule

white cell	→ user input

Estimated Demand for Each Service Time Interval								
From:	To:	M	Tu	W	Th	Fr	Sa	Su
7:00	8:00	3.5	2.6	2.7	1.8	4.2	1.7	1.2
8:00	9:00	8.8	9.2	11.4	10.5	13.0	6.6	7.5
9:00	10:00	16.0	15.2	15.0	15.2	13.7	16.7	18.9
10:00	11:00	21.9	17.3	16.8	19.2	24.9	26.5	44.3
11:00	12:00	24.2	20.9	24.3	25.8	27.8	41.0	52.4
12:00	13:00	50.7	43.4	39.7	47.3	43.9	47.9	55.6
13:00	14:00	68.4	64.6	78.8	63.3	64.6	62.8	72.1
14:00	15:00	65.9	56.2	57.8	60.5	59.8	77.5	94.4
15:00	16:00	65.0	61.3	58.1	59.3	73.3	84.8	85.1
16:00	17:00	62.8	71.7	59.4	72.8	74.3	86.1	106.8
17:00	18:00	78.6	84.2	68.6	75.7	73.8	108.1	100.4
18:00	19:00	79.2	90.0	66.6	76.7	80.4	90.5	108.7
19:00	20:00	74.8	80.5	77.3	76.7	77.9	88.9	93.5
20:00	21:00	74.0	76.7	70.5	74.8	77.1	81.1	82.7
21:00	22:00	74.7	61.2	59.2	67.1	67.7	91.6	73.7
22:00	23:00	50.7	57.4	42.7	50.8	57.5	66.7	58.3
23:00	0:00	26.3	29.1	24.6	26.8	41.8	56.3	33.6
0:00	1:00	11.0	10.0	10.6	9.6	8.1	17.1	22.4
1:00	2:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Minimum Number of Waiter Required by Management								
From:	To:	M	Tu	W	Th	Fr	Sa	Su
7:00	8:00	0	0	0	0	0	0	0
8:00	9:00	0	0	0	0	0	0	0
9:00	10:00	0	0	0	0	0	0	0
10:00	11:00	0	0	0	0	0	0	0
11:00	12:00	0	0	0	0	0	0	0
12:00	13:00	0	0	0	0	0	0	0
13:00	14:00	0	0	0	0	0	0	0
14:00	15:00	0	0	0	0	0	0	0
15:00	16:00	0	0	0	0	0	0	0
16:00	17:00	0	0	0	0	0	0	0
17:00	18:00	0	0	0	0	0	0	0
18:00	19:00	0	0	0	0	0	0	0
19:00	20:00	0	0	0	0	0	0	0
20:00	21:00	0	0	0	0	0	0	0
21:00	22:00	0	0	0	0	0	0	0
22:00	23:00	0	0	0	0	0	0	0
23:00	0:00	0	0	0	0	0	0	0
0:00	1:00	0	0	0	0	0	0	0
1:00	2:00	0	0	0	0	0	0	0

Minimum Number of Assistant Required by Management								
From:	To:	M	Tu	W	Th	Fr	Sa	Su
7:00	8:00	1	1	1	1	1	1	1
8:00	9:00	1	1	1	1	1	1	1
9:00	10:00	1	1	1	1	1	1	1
10:00	11:00	1	1	1	1	1	1	1
11:00	12:00	1	1	1	1	1	1	1
12:00	13:00	1	1	1	1	1	1	1
13:00	14:00	1	1	1	1	1	1	1
14:00	15:00	1	1	1	1	1	1	1
15:00	16:00	1	1	1	1	1	1	1
16:00	17:00	1	1	1	1	1	1	1
17:00	18:00	1	1	1	1	1	1	1
18:00	19:00	1	1	1	1	1	1	1
19:00	20:00	1	1	1	1	1	1	1
20:00	21:00	1	1	1	1	1	1	1
21:00	22:00	1	1	1	1	1	1	1
22:00	23:00	1	1	1	1	1	1	1
23:00	0:00	1	1	1	1	1	1	1
0:00	1:00	1	1	1	1	1	1	1
1:00	2:00	1	1	1	1	1	1	1

Waitstaff Type	Restaurant Has
Waiter Level 1	4
Waiter Level 2	0
Waiter Level 3	1
Waiter Level 4	0
Assistant level 1	6
Assistant level 2	8

$$\sum_s \sum_u a_{isd}.x_{su} \geq R^w_{id} \qquad \forall i,\, d \tag{A.4}$$

$$\sum_s \sum_v a_{isd}.y_{sv} \geq R^a_{id} \qquad \forall i,\, d \tag{A.5}$$

$$\sum_s x_{su} + N^w_u = P^w_u \qquad \forall u \tag{A.6}$$

$$\sum_s y_{sv} + N^a_v = P^a_v \qquad \forall v \tag{A.7}$$

$$\sum_s x_{su} = \overline{P}^w_u \qquad \forall u \tag{A.8}$$

$$\sum_s y_{sv} = \overline{P}^a_v \qquad \forall v. \tag{A.9}$$

Slack Variables.

The last two terms of the objective function (A.1) are for penalizing the use of less experienced staff when there is a waiter/assistant with higher experience. This part of the model gives priority to keeping more experienced staff in case the company decides to reduce the number of hired staff. This can be achieved by sorting the M^w_u and M^a_v parameters in decreasing order:

$$M^w_1 \geq M^w_2 \geq M^w_3 \geq M^w_4$$
$$M^a_1 \geq M^a_2.$$

This will put weights on slack variables N^w_u and N^a_v to control preferences of employees with higher levels.

Model 2

$$Min\ Z = \sum_s \sum_u x_{su}.C^w_u + \sum_s \sum_v y_{sv}.C^a_v \tag{A.10}$$

$s.t.$

$$\sum_s x_{su} = {}^*\overline{P}^w_u \qquad \forall u \tag{A.11}$$

$$\sum_s y_{sv} = {}^*\overline{P}^a_v \qquad \forall v. \tag{A.12}$$

In addition, the same four constraints of Model 1—(A.2)–(A.5)—${}^*\overline{P}^w_u$, ${}^*\overline{P}^a_v$ represent the optimal values of the decision variables obtained from Model 1.

Model 3

$$Max\ Z = \sum_g \sum_s \sum_u \alpha_{gsu}.T^w_{gsu} + \sum_h \sum_s \sum_v \beta_{hsv}.T^a_{hsv} \tag{A.13}$$

$s.t.$

$$\sum_g \alpha_{gsu} = x^*_{su} \qquad \forall s, u \tag{A.14}$$

$$\sum_h \beta_{hsv} = y^*_{sv} \qquad \forall s, v \tag{A.15}$$

Figure A.2. (Color online) Sample Output View of the User Interface Comprising the Weekly Waitstaff Schedule (Here for Monday) and the Assignment of Waitstaff to the Working Hours and Waitstaff's Day Off

Weekly Waitstaff Schedule

Waitstaff and level	DOW | Service time interval	7 8	8 9	9 10	10 11	11 12	12 13	13 14	14 15	15 16	16 17	17 18	18 19	19 20	20 21	21 22	22 23	23 24	24 1	1 2
Waiter 3	Monday	1	1	1	1	1	1	1	1	1	1									
Waiter 1 (A)	Monday	1	1	1	1	1	1	1	1	1	1									
Waiter 1 (B)	Monday							1	1	1	1	1	1	1	1	1	1			
Waiter 1 (D)	Monday										1	1	1	1	1	1	1	1	1	1
Assistant 2 (E)	Monday	1	1	1	1	1	1	1	1	1	1									
Assistant 2 (F)	Monday		1	1	1	1	1	1	1	1	1	1								
Assistant 2 (H)	Monday						1	1	1	1	1	1	1	1	1	1				
Assistant 2 (I)	Monday							1	1	1	1	1	1	1	1	1	1			
Assistant 2 (J)	Monday								1	1	1	1	1	1	1	1	1	1		
Assistant 2 (K)	Monday										1	1	1	1	1	1	1	1	1	1
Assistant 2 (L)	Monday										1	1	1	1	1	1	1	1	1	1
Assistant 1 (M)	Monday	1	1	1	1	1	1	1	1	1	1									
Assistant 1 (N)	Monday										1	1	1	1	1	1	1	1	1	1
Waiter Assigned	Monday	2	2	2	2	2	2	3	3	3	4	2	2	2	2	2	2	1	1	1
Assistant Assigned	Monday	2	3	3	3	3	4	5	6	6	9	7	6	6	6	6	5	4	3	3
Waiter Required	Monday	1	1	1	1	1	1	2	2	1	1	2	2	2	2	2	1	1	1	1
Assistant Required	Monday	1	1	1	2	2	3	4	4	4	4	5	5	4	4	4	4	2	1	1

#	Waitstaff	Working hours	Day-Off
1	Waiter 3	Working hour# 1	6
2	Waiter 1 (A)	Working hour# 1	3
3	Waiter 1 (B)	Working hour# 7	5
4	Waiter 1 (C)	Working hour# 9	1
5	Waiter 1 (D)	Working hour# 10	4
6	Assistant 2 (E)	Working hour# 1	4
7	Assistant 2 (F)	Working hour# 2	2
8	Assistant 2 (G)	Working hour# 4	1
9	Assistant 2 (H)	Working hour# 6	2
10	Assistant 2 (I)	Working hour# 7	5
11	Assistant 2 (J)	Working hour# 8	4
12	Assistant 2 (K)	Working hour# 10	3
13	Assistant 2 (L)	Working hour# 10	7
14	Assistant 1 (M)	Working hour# 1	7
15	Assistant 1 (N)	Working hour# 10	6

Working hours	Hours
Working hour# 1	7:00 - 17:00
Working hour# 2	8:00 - 18:00
Working hour# 3	9:00 - 19:00
Working hour# 4	10:00 - 20:00
Working hour# 5	11:00 - 21:00
Working hour# 6	12:00 - 22:00
Working hour# 7	13:00 - 23:00
Working hour# 8	14:00 - 00:00
Working hour# 9	15:00 - 01:00
Working hour# 10	16:00 - 02:00

Note. DOW, day of week.

$$\sum_s \alpha_{gsu} = 1 \qquad \forall g, u \tag{A.16}$$

$$\sum_s \beta_{hsv} = 1 \qquad \forall h, v. \tag{A.17}$$

x^*_{su}, y^*_{sv} represent the optimal values of the decision variables obtained from Model 2.

Pseudocode of the Algorithm

Step 1. Run Model 2 by replacing $({}^*\overline{P}^w_u, {}^*\overline{P}^a_v)$ with (P^w_u, P^a_v) on the RHS of Constraints (A.11) and (A.12). Then, check feasibility.

a. If a feasible solution is available, go to Step 2; otherwise, undo the last modification in capacity (not applicable in the beginning) and proceed to Step 1(b).

b. If a feasible solution is available, go to Step 3; otherwise, undo the last modification in capacity (not applicable in the beginning) and terminate.

Step 2. Decrease the available capacity of the least-experienced assistant waiter (P^a_v) by one, and go to Step 1(a).

Step 3. Decrease the available capacity of the least-experienced waiter (P^w_u) by one, and go to Step 1(b) (Figures A.1 and A.2 and Tables A.1–A.3).

Implemented Forecasting Model F3 (Holt–Winters Multiplicative Method)

Phase 1: Initialization of Parameters.

1. Estimation of initial seasonality indices for each period of the seasonal cycle (i.e., day of the week).

a. Starting with Thursday of the first week, calculate a seven-day centered moving average for each period.

b. Divide the actual demand observations by the respective centered moving averages calculated in Step 1(a) to obtain initial seasonality indices.

2. Normalization of seasonality indices.

a. Average initial seasonality indices from Step 1(b) for each period of the seasonal cycle (e.g., for all Mondays, Tuesdays, and so on).

b. Normalize the indices from Step 2(a) to ensure that the sum of the indices equals seven. To this end, divide seven by the sum of the seasonality indices, and multiply each index by this value.

3. Projection of initial level and trend values.

a. Deseasonalize the time series by dividing each demand observation by the corresponding seasonality index from Step 2(b).

b. Use the deseasonalized data set from Step 3(a), and use the method of Holt (2004) for forecasting linear trends (see also Phase 3).

Phase 2: Optimization of Smoothing Factors.

In the second phase, using the Excel solver, we determine the optimal values for the smoothing factors (i.e., level α, trend β, and seasonality γ) to minimize the forecast error (MSE) with $\alpha, \beta, \gamma \in [0.001, 0.50]$. The results returned by Excel are $\alpha = 0.2$, $\beta = 0.06$, and $\gamma = 0.08$.

Phase 3: Implementation.

1. Use Holt–Winters triple-exponential smoothing formulas to forecast the next period (day of week) demand:

- $\hat{a}_t = \alpha\left(\frac{x_t}{\hat{F}_{t-P}}\right) + (1-\alpha)(\hat{a}_{t-1} + \hat{b}_{t-1})$
- $\hat{b}_t = \beta(\hat{a}_t - \hat{a}_{t-1}) + (1-\beta)\hat{b}_{t-1}$
- $\hat{F}_t = \gamma\left(\frac{x_t}{\hat{a}_t}\right) + (1-\gamma)\hat{F}_{t-P}$

Table A.1. The Algorithmic Performance (in Terms of Solution Time and Optimality Gap) of the Proposed Algorithm Against the MATLAB Solver for 20 Random Instances

	CPU, seconds		
No.	Algorithm	MATLAB	Gap,[a] %
1	143	7,295	0.00
2	183	7,775	0.00
3	139	7,322	0.00
4	168	8,181	0.00
5	132	7,275	0.00
6	192	8,271	0.00
7	162	7,472	0.00
8	161	7,926	0.00
9	131	7,854	0.00
10	149	8,278	0.00
11	142	7,458	0.00
12	147	8,033	0.00
13	136	7,466	0.00
14	195	7,778	0.00
15	171	7,206	0.00
16	139	7,822	0.00
17	188	7,396	0.00
18	136	8,023	0.00
19	185	8,046	0.00
20	125	7,891	0.00
Average	156	7,738	

[a]The gap represents the relative optimality gap—that is, the difference between the optimal (MATLAB) and the best (algorithm) objective value divided by the best objective value.

INFORMS Journal on Applied Analytics, 2022, vol. 52, no. 4, pp. 324–343, © 2022 INFORMS

Table A.2. The Number of Assigned Waitstaff of the Existing Schedule and the Difference (Δ) Between the Number of Assigned Waitstaff of the Optimized Schedule and the Existing Schedule per Service Period and Day

	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
Service periods	exist. assn.	Δ	exist. assn.	Δ	exist. assn.	Δ	exist. assn.	Δ	exist. assn.	Δ	exist. assn.	Δ	exist. assn.	Δ
7:00–8:00	3	2	3	3	3	2	3	3	4	3	4	2	4	3
8:00–9:00	4	1	4	2	4	1	3	3	5	2	5	1	5	2
9:00–10:00	4	1	4	2	4	1	3	3	5	2	5	1	5	2
10:00–11:00	5	0	6	0	6	−1	5	1	6	1	7	−1	7	0
11:00–12:00	5	0	6	0	6	−1	5	1	6	1	7	−1	7	0
12:00–13:00	6	−1	6	0	6	−1	5	1	6	1	7	−1	7	0
13:00–14:00	9	−3	10	−3	9	−3	9	−2	10	−2	10	−4	11	−3
14:00–15:00	9	−3	10	−3	8	−2	9	−2	10	−2	10	−4	11	−3
15:00–16:00	10	0	10	0	9	1	10	0	11	1	11	−2	12	−1
16:00–17:00	19	−5	18	−3	18	−5	18	−3	19	−3	21	−7	21	−6
17:00–18:00	16	−7	15	−6	15	−7	15	−6	15	−6	17	−9	17	−9
18:00–19:00	15	−6	14	−5	14	−6	15	−6	14	−5	16	−8	16	−8
19:00–20:00	15	−6	14	−5	14	−6	15	−6	14	−5	16	−8	16	−8
20:00–21:00	14	−5	12	−3	12	−4	13	−4	13	−4	14	−6	14	−6
21:00–22:00	14	−5	12	−3	12	−4	13	−4	13	−4	14	−6	14	−6
22:00–23:00	14	−5	12	−3	12	−4	13	−4	13	−4	14	−6	14	−6
23:00–00:00	10	−2	8	0	9	−2	9	−1	9	−1	11	−3	10	−3
00:00–01:00	11	−3	9	−1	10	−3	10	−2	10	−2	11	−3	11	−4
01:00–02:00	9	−5	8	−3	8	−5	8	−3	8	−4	10	−5	9	−5
Average		−2.7		−1.6		−2.6		−1.6		−1.6		−3.7		−3.2

Note. exist. assn., existing assignment.

Table A.3. The Optimal Number of Waitstaff Scheduled After Application of the IP Models

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Shift 1							
Waiters	1	1		1	1	1	1
		1	1	1	1	1	1
Assistants		1	1	1	1	1	1
	1		1	1	1	1	1
	1	1		1	1	1	1
	1	1	1		1	1	1
	1	1	1	1	1		1
Total	5	6	5	6	7	6	7
Shift 2							
Waiters	1	1	1	1	1		1
Total	1	1	1	1	1	0	1
Shift 3							
Waiters	1	1	1	1	1	1	
Assistants	1		1	1	1	1	1
	1	1	1		1	1	1
	1	1	1	1	1		1
Total	4	3	4	3	4	3	3
Shift 4							
Waiters	1	1		1	1	1	1
Assistants		1	1	1	1	1	1
	1	1		1	1	1	1
	1	1	1	1		1	1
	1	1	1	1	1		1
Total	4	5	3	5	4	4	5
Total							
Waiters	4	5	3	5	5	4	4
Assistants	10	10	10	10	11	9	12
Total waitstaff	14	15	13	15	16	13	16

Table A.4. Ratios of Service Time Intervals

Service time intervals	Ratios
7:00 –8:00	0.08
8:00 –9:00	0.32
9:00 –10:00	0.44
10:00 –11:00	0.56
11:00 –12:00	0.90
12:00 –13:00	1.10
13:00 –14:00	1.57
14:00 –15:00	1.59
15:00 –16:00	1.74
16:00 –17:00	1.57
17:00 –18:00	1.58
18:00 –19:00	1.58
19:00 –20:00	1.61
20:00 –21:00	1.53
21:00 –22:00	1.31
22:00 –23:00	0.91
23:00 –00:00	0.48
00:00 –01:00	0.13
01:00 –02:00	0.00

- $\hat{x}_{t,t+\tau} = (\hat{a}_t + \tau\,\hat{b}_t)\hat{F}_{t+\tau-P}$,

  where

  x_t: demand observation (actual demand) in period t,

  $\hat{x}_{t,t+1}$: forecast for time $t+1$ made at time t,

  a: level component,

  b: linear trend component,

  F_t: multiplicative seasonal index for period t, and

  P: number of time periods (in our case, seven) after which the seasonal cycle starts repeating itself.

2. Allocate the forecast value to the service time intervals (07:00–02:00).

   a. Divide the forecast value by 19 (i.e., number of service time intervals in a day).

   b. Multiply the obtained value by the ratios of each service time interval derived from historical data, shown in Table A.4.

The Guideline

This guideline was prepared for the restaurant management to apply the proposed optimization approach in other branches of the restaurant chain. All necessary files were provided to the management. It is required to follow these six easy steps to generate weekly schedules for other branches.

Step 1. Analyze the past data, and find the week with the highest demand throughout a year.

Step 2. Run the MATLAB script "wo_calculation.m" to compute weighted orders for that week by using the weekly demand file as an input.

Step 3. Run the MATLAB script "opt_staff.m" (Model 1) to find the optimal number of waitstaff for the week with the highest demand by using the weighted orders as an input. For getting results faster, the alternative MATLAB script "opt_staff_v2.m" can be used, which produces the same result as "opt_staff.m" but uses the algorithm provided in the appendix.

Step 4. Based on the historical data, use the forecasting model ("HWM_forecast.xls") to estimate demand for each day of the upcoming week. Run the MATLAB script "wo_calcuation.m" to compute weighted orders for that week by using the weekly demand file as input.

Step 5. Run the MATLAB script "weekly_schedule.m" (Model 2) to find weekly schedules for this week by using the weighted orders as input.

Step 6. Run the MATLAB script "shift_assignment.m" (Model 3) to assign employees to the shifts by using the employee availability matrix and weekly schedules as inputs.

References

Aickelin U, Dowsland KA (2004) An indirect genetic algorithm for a nurse-scheduling problem. *Comput. Oper. Res.* 31(5): 761–778.

Aickelin U, White P (2004) Building better nurse scheduling algorithms. *Ann. Oper. Res.* 128(1-4):159–177.

Alfares HK (2007a) A simulation approach for stochastic employee days-off scheduling. *Internat. J. Model. Simulation* 27(1):9–15.

Alfares HK (2007b) Operator staffing and scheduling for an IT-help call centre. *Eur. J. Indust. Engrg.* 1(4):414–430.

Alfieri A, Kroon L, van de Velde S (2007) Personnel scheduling in a complex logistic system: A railway application case. *J. Intelligent Manufacturing* 18(2):223–232.

Al-Yakoob SM, Sherali HD (2007) Mixed-integer programming models for an employee scheduling problem with multiple shifts and work locations. *Ann. Oper. Res.* 155(1):119–142.

Al-Yakoob SM, Sherali HD (2008) A column generation approach for an employee scheduling problem with multiple shifts and work locations. *J. Oper. Res. Soc.* 59(1):34–43.

Atlason J, Epelman MA, Henderson SG (2004) Call center staffing with simulation and cutting plane methods. *Ann. Oper. Res.* 127(1-4):333–358.

Awadallah MA, Khader AT, Al-Betar MA, Bolaji AL (2011) Nurse rostering using modified harmony search algorithm. Panigrahi BK, Suganthan PN, Das S, Satapathy SC, eds. *Internat. Conf. Swarm Evolutionary Memetic Comput. 2011*, Lecture Notes in Computer Science, vol. 7077 (Springer, Berlin, Germany), 27–37.

Azaiez MN, Al Sharif SS (2005) A 0-1 goal programming model for nurse scheduling. *Comput. Oper. Res.* 32(3):491–507.

Bailey MD, Waddell LA (2020) Daily tutor scheduling support at Hopeful Journeys Educational Center. *INFORMS J. Appl. Anal.* 50(5):287–297.

Baker K (1976) Workforce allocation in cyclical scheduling problems: A survey. *J. Oper. Res. Soc.* 27:155–167.

Buxey G (2003) Strategy not tactics drives aggregate planning. *Internat. J. Production Econom.* 85(3):331–346.

Çakirgil S, Yücel E, Kuyzu G (2020) An integrated solution approach for multi-objective, multi-skill workforce scheduling and routing problems. *Comput. Oper. Res.* 118(2020):104908.

Cappanera P, Gallo G (2004) A multicommodity flow approach to the crew rostering problem. *Oper. Res.* 52(4):583–596.

Casado S, Laguna M, Pacheco J (2005) Heuristical labour scheduling to optimize airport passenger flows. *J. Oper. Res. Soc.* 56(6):649–658.

Choi K, Hwang J, Park M (2009) Scheduling restaurant workers to minimize labor cost and meet service standards. *Cornell Hospitality Quart.* 50(2):155–167.

Chu SCK (2007) Generating, scheduling and rostering of shift crew-duties: Applications at the Hong Kong International Airport. *Eur. J. Oper. Res.* 177(3):1764–1778.

Dantzig GB (1954) Letter to the editor: A comment on Edie's traffic delays at toll booths. *J. Oper. Res. Soc. Am.* 2(3):339–341.

Dück V, Ionescu L, Kliewer N, Suhl L (2012) Increasing stability of crew and aircraft schedules. *Transportation Res. Part C Emerging Techn.* 20(1):47–61.

Elizondo R, Parada V, Pradenas L, Artigues C (2010) An evolutionary and constructive approach to a crew scheduling problem in underground passenger transport. *J. Heuristics* 16(4):575–591.

Erdoğan G, Erkut E, Ingolfsson A, Laporte G (2010) Scheduling ambulance crews for maximum coverage. *J. Oper. Res. Soc.* 61(4):543–550.

Ernst AT, Jiang H, Krishnamoorthy M, Sier D (2004) Staff scheduling and rostering: A review of applications, methods and models. *Eur. J. Oper. Res.* 153(1):3–27.

Frey L, Hanne T, Dornberger R (2009) Optimizing staff rosters for emergency shifts for doctors. *IEEE Congress Evolutionary Comput. 1999* (IEEE, Trondheim, Norway), 2540–2546.

Glock C (2021) *Production and Supply Chain Management: An Introduction* (Kindle Direct Publishing, Hesse, Germany), 52–54.

Godward M, Swart W (1994) An object-oriented simulation model for determining labor requirements at Taco Bell. *Proc. 26th Conf. Winter Simulation 1994* (IEEE, San Diego, CA), 1067–1073.

Gomes da Silva C, José F, João L, Samir B (2006) An interactive decision support system for an aggregate production planning model based on multiple criteria mixed integer linear programming. *Omega* 34(2):167–177.

Heizer J, Render B, Munson C (2017) *Operations Management: Sustainability and Supply Chain Management* (Pearson, Boston).

Holt CC (2004) Forecasting seasonals and trends by exponentially weighted moving averages. *Internat. J. Forecasting* 20(1): 5–10.

Hueter J, Swart W (1998) An integrated labor-management system for Taco Bell. *Interfaces* 28(1):75–91.

Hung R (1999) Scheduling a workforce under annualized hours. *Internat. J. Production Res.* 37(11):2419–2427.

Jamalnia A, Yang J-B, Xu D-L, Feili A (2017) Novel decision model based on mixed chase and level strategy for aggregate production planning under uncertainty: Case study in beverage industry. *Comput. Indust. Engrg.* 114(2017):54–68.

Jennings MG, Shah N (2014) Workforce planning and technology installation optimisation for utilities. *Comput. Indust. Engrg.* 67(2014):72–81.

Kabak Ö, Ulengin F, Aktas E, Önsel S, Topcu I (2008) Efficient shift scheduling in the retail sector through two-stage optimization. *Eur. J. Oper. Res.* 184(1):76–90.

Keith EG (1979) Operator scheduling. *AIIE Trans.* 11(1):37–41.

Leung SCH, Chan SSW (2009) A goal programming model for aggregate production planning with resource utilization constraint. *Comput. Indust. Engrg.* 56(3):1053–1064.

Loucks JS, Jacobs FR (1991) Tour scheduling and task assignment of a heterogeneous work force: A heuristic approach. *Decision Sci.* 22(1):719–738.

Love RR, Hoey JM (1990) Management science improves fast-food operations. *Interfaces* 20(2):21–29.

Miranda J, Rey PA, Saure A, Weber R (2018) Metro uses a simulation-optimization approach to improve fare-collection shift scheduling. *Interfaces* 48(6):529–542.

Othman M, Bhuiyan N, Gouw GJ (2012) Integrating workers' differences into workforce planning. *Comput. Indust. Engrg.* 63(4):1096–1106.

Pastor R, Olivella J (2008) Selecting and adapting weekly work schedules with working time accounts: A case of a retail clothing chain. *Eur. J. Oper. Res.* 184(1):1–12.

Patrick P, Montazeri A, Michalowski W, Banerjee D (2019) Automated pathologist scheduling at the Ottawa Hospital. *INFORMS J. Appl. Analytics* 49(2):93–103.

Shahabsafa M, Terlaky T, Gudapati NVC, Sharma A, Wilson GR, Plebani LJ, Bucklen KB (2018) The inmate assignment and scheduling problem and its application in the Pennsylvania Department of Corrections. *Interfaces* 48(5):467–483.

Sillekens T, Koberstein A, Suhl L (2011) Aggregate production planning in the automotive industry with special consideration of workforce flexibility. *Internat. J. Production Res.* 49(17):5055–5078.

Sinreich D, Jabali O (2007) Staggered work shifts: A way to downsize and restructure an emergency department workforce yet maintain current operational performance. *Health Care Management Sci.* 10(3):293–308.

Thompson GM (1998a) Labor scheduling part 1: Forecasting demand. *Cornell Hotel Restaurant Admin. Quart.* 39(5):22–31.

Thompson GM (1998b) Labor scheduling part 2: Knowing how many on-duty employees to schedule. *Cornell Hotel Restaurant Admin. Quart.* 39(60):26–37.

Thompson GM (1999a) Labor scheduling part 3: Developing a workforce schedule. *Cornell Hotel Restaurant Admin. Quart.* 40(1):86–96.

Thompson GM (1999b) Labor scheduling part 4: Controlling workforce schedules in real time. *Cornell Hotel Restaurant Admin. Quart.* 40(3):85–96.

Van den Bergh J, Beliën J, Bruecker PD, Demeulemeester E, Boeck LD (2013) Personnel scheduling: A literature review. *Eur. J. Oper. Res.* 226(3):367–385.

Winters PR (1960) Forecasting sales by exponentially weighted moving averages. *Management Sci.* 6(3):324–342.

Verification Letter

Ramiz Kazimov, Deputy Director at Mado Azerbaijan, Babak Avenue 90, Khatai District AZ1025, Baku, Azerbaijan, writes:

"I am pleased to confirm that we are currently using the optimization models proposed in 'Optimal Scheduling of Staff with Different Experience Levels at a Restaurant Chain' authored by Akhundov, Tahirov, and Glock to optimize the staff scheduling operations of our company. Prior to the application of the proposed models, branch managers developed staff schedules by relying on their experience and intuition, which often led to situation where we had too much or too little staff available. This impacted our business negatively in different ways. First, the employees were not happy with the situation, as they were either too busy during their shifts or because they did not have enough to do and felt bored. Second, customers at times complained about poor service because of staff shortages, and third, we lost profit because of overstaffing and unsatisfied customers leaving our branches.

"The mathematical models developed in the paper enabled us to find the optimal number of waiters based on the highest monthly demand. The models thus also support our objective to vary the size of the staff as little as possible to avoid costs connected with the hiring and laying off of waiters. Clearly, this also supports us in maintaining a workforce of experiences employees that enables us to increase customer satisfaction. Finally, the model also permits assigning waiters optimally over the week by considering staff preferences.

"Altogether, the models proposed by the authors enabled us to improve personnel scheduling in our company by reducing labor cost and overstaffing to a certain extent. One important outcome from our point of view is also that the models helped us to avoid understaffing situations completely, which helped us to improve customer service. We also found the managerial insights suggested in the paper useful in planning our future restaurant operations."

Najmaddin Akhundov is a graduate assistant and PhD candidate at the University of Tennessee, Knoxville. He received his MSc degree in systems design engineering from the University of Waterloo, Canada in 2015 and his BSc in industrial engineering from Baku Engineering University, Azerbaijan in 2011. He has worked on several optimization projects from diverse application areas, which include but are not limited to power systems, maintenance, invasive species, and logistics.

Nail Tahirov is a PhD candidate at the Institute of Production and Supply Chain Management at the Technical University of Darmstadt, Germany. His educational background is in industrial engineering. He has been involved in many consultancy projects and corporate education initiatives. His primary research interests include omnichannel supply chains, the optimization of forward and reverse distribution systems, and inventory control problems.

Christoph H. Glock is the head of the Institute of Production and Supply Chain Management at the Technical University of Darmstadt, Germany. His research interests include inventory management, supply chain management, warehousing, sustainable production, and human factors in logistics systems. His work has appeared in various international journals, such as *IISE Transactions*, *Decision Sciences*, *OR Spectrum*, *European Journal of Operational Research*, and *Journal of Business Logistics*.