# TOUR SCHEDULING AND ROSTERING

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## TOUR SCHEDULING AND ROSTERING IN SERVICE OPERATIONS

This article examines the process of scheduling individual workers to meet some form of time varying demand. This most often occurs in a service operation where the rate at which work presents itself varies significantly. Operations of this type include call centers, hospital emergency rooms, retail outlets, restaurants, and mail handling facilities.

In the *tour scheduling* process, the forecasted workload is converted into a schedule that specifies what shifts are to be staffed on each day by each employee over the course of a planning period, typically a week. The schedule is developed to meet the demand workload requirements at a minimum cost. The *rostering* process assigns the identified shifts to individual workers so as to best match individual preferences.

In this article, we first examine the problem of scheduling an inbound call center. This example illustrates the scheduling process and identifies some of the inherent issues involved in scheduling and rostering. We then discuss other environments where the same type of scheduling problems exist, and highlight some key differences in those environments.

## A CALL CENTER EXAMPLE

A *call center* is a facility used to provide interactive communications with customers. In a call center, customer service representatives (CSRs), or agents, interact with customers over the telephone. A *contact center* extends the notion of a call center to allow for other means of communication, including e-mails, faxes, and instant messages.

While call centers often deploy sophisticated telephony and computer equipment, and may require a large facility, the cost of the customer service agent is typically the most significant and controllable cost associated with call center operation [1]. Agent salaries typically account for 60–70% of the call center's total operating cost [2]. As such, effective capacity management is a critical success factor for efficient operations.

The workload presented to a call center, in terms of inbound calls, varies over the course of a week and over the course of a day. In order to efficiently staff the call center, the number of workers on duty must vary over the course of the week and the course of the day to match demand.

Call center managers are typically charged with providing a target level of overall service quality, most often specified based on some measure of caller wait time. The task of the call center manager is to develop a work schedule that assigns individual agents to work at specific time so as to achieve this service level goal at the lowest possible cost. In order to do this, call center managers must

- forecast the workload in terms of call volume;
- determine the number of agents required in each time period to meet the workload and achieve the service level target;
- package the agent level requirements into a set of shifts to which agents can be assigned;
- assign individual agents to tours taking into account the agent's availability and preferences.

Managers of small call centers may perform these tasks manually, but in most moderate to large call centers they receive automated support from a workforce management system (WMS).

*Wiley Encyclopedia of Operations Research and Management Science*, edited by James J. Cochran

## SCHEDULING MODELS

### The Two-Stage Scheduling Approach

**Overview.** The two-stage approach is a standard model for tour scheduling. In this approach, the staffing and scheduling decisions are made separately. Staffing requirements are developed based on the anticipated work in each time period. The staffing requirements are then used as an input to the scheduling model.

**Staffing Requirements.** The first step in the two-stage approach is to determine the staffing requirement, the number of workers required in each time period. Time periods are often 30 min in length, but in some cases 15 min intervals are used. In many environments, the number of workers required varies significantly over the course of the day.

In a call center, call volume tends to follow predictable patterns, with random variations superimposed. Consider daily call volumes shown in Fig. 1. In this call center, Mondays are in general the busiest day, Fridays are the slowest days, and the call center is closed on the weekends and holidays (such as Independence Day). The graph shows a 5-period moving average, which illustrates that over the course of a week call volume is roughly constant with no clear trend up or down.

Seasonality also applies within the day. Consider the fairly common pattern illustrated in Fig. 2. Call volume grows throughout the morning, peaking in midmorning then dropping off in the late morning and slowing further over lunch. A second smaller peak occurs in the afternoon. Overnight volume tends to be low. Figure 2 represents a Monday; other days have similar but slightly different patterns.

Staffing requirements are determined using a queueing model, an analytical model that estimates key queue parameters such as waiting time, based on the rate at which calls arrive, the average length of calls, and the number of agents available to service those calls. Because queueing models typically require a steady rate of call arrivals, the *rate* at which calls arrive is usually assumed to be constant for each 30 min period. In the SIPP (Stationary Independent Period by Period) method, each 30 time period is analyzed independently of all other periods using the average call volume for that period as illustrated in Fig. 3.

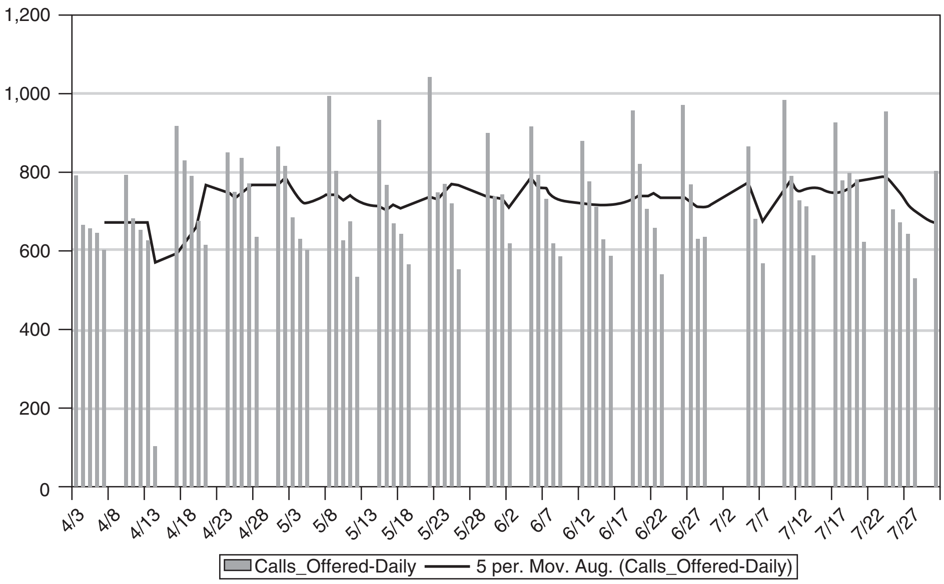


**Figure 1.** Calls offered daily.

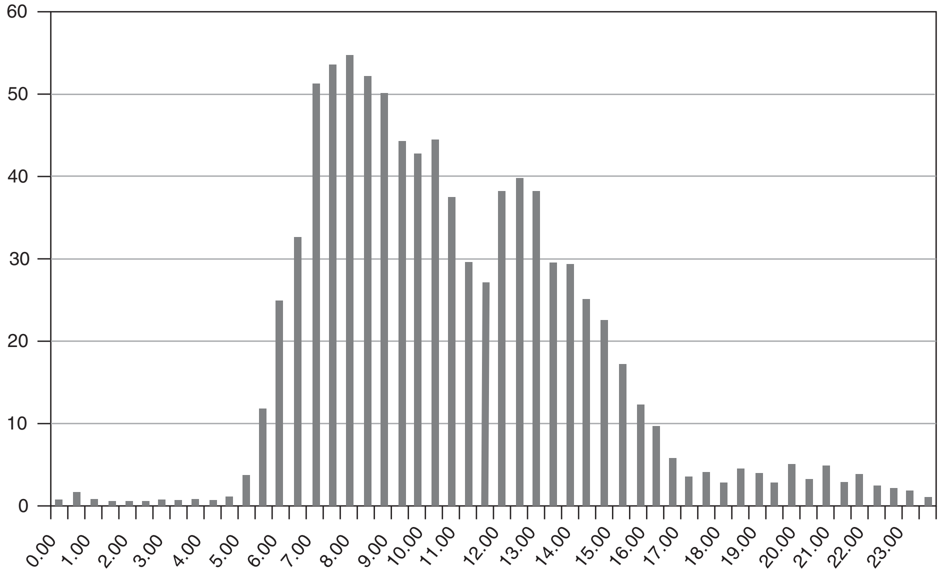


**Figure 2.** Average call volume.

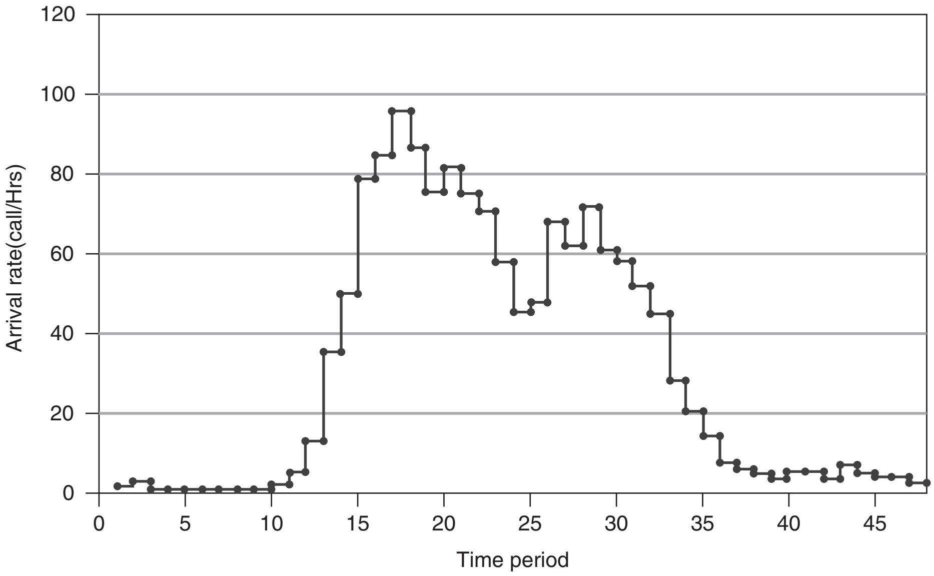


**Figure 3.** Arrival rates under SIPP.

The call center typically has a service level target, or a more formal service level agreement (SLA), that specifies the level of service to be provided in each period. For example, the SLA may specify that the average time on hold should be 30 s or less, or that 80% of calls should be answered within 15 s. The expected call volume and service level requirements are inputs to the queueing model and the number of agents

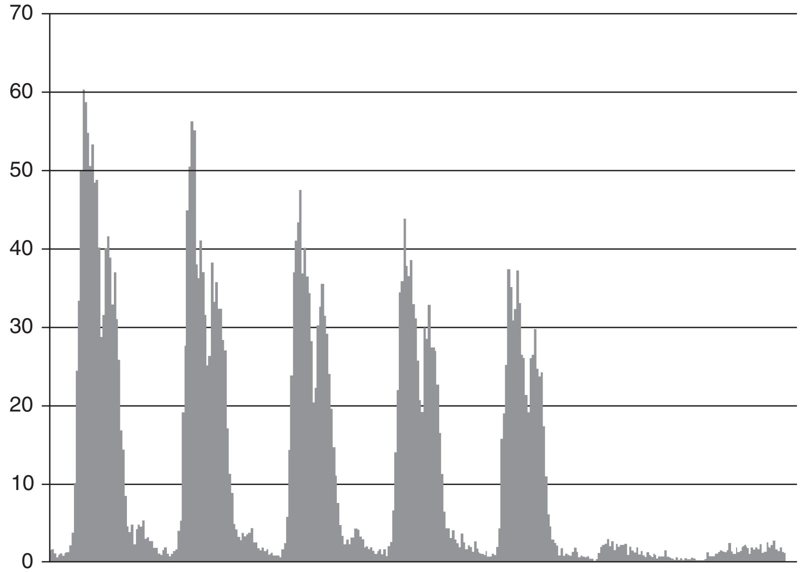


**Figure 4.** Minimum Agents required by 30 min period.

required per period is the output. Figure 4 graphically illustrates the output of the staffing requirements process.

**Tour Scheduling.** Once per period staffing requirements are defined, a tour schedule can be developed. The objective of the tour scheduling process is to determine the number of agents to assign to each possible schedule on each day so as to meet the minimum staffing requirements at the lowest possible cost. This implies minimizing the number of extra agents scheduled; that is, minimizing staffing above and beyond the minimum requirements.

A *shift* designates the specific time intervals, typically 30-min periods, during which an agent is on duty on a particular day. Consider the following simple example; a call center is open from 8:00 a.m. to 10:00 p.m., for a total of 28 half hour periods per day. Agents are scheduled to 9 h shifts, and breaks are not explicitly scheduled. A shift may start at any half hour period and lasts for 18 contiguous half hour periods. With these assumptions a total of 11 different shifts are possible, starting on each half from 8:00 a.m. to 1:00 p.m.

A schedule must further define the days of the week to be worked. Assume the call center is open seven days a week, but agents are only scheduled to work five days. Further assume that the scheduling policy is to give workers their two days off consecutively. This policy implies a total of seven different *day patterns*.

Given this relatively set of options, the scheduler has a total of 77 shift/pattern combinations (11shifts $\times$ 7 day patterns), which we will refer to as tours, to which agents can be assigned. The schedule covers 196 time periods (28 half hour periods per day $\times$ 7 days). Here, we assume that each agent works the same shift every day. If this restriction is relaxed then the number of tours may increase significantly.

**The Minimum Cost Schedule.** Given a set of time phased staffing requirements (Fig. 4), a set of available shifts and a set of day patterns, the scheduling problem can now be formulated as an optimization problem−assign agents to tours so as to meet the minimum staffing requirements at the lowest cost. This problem can be formulated as an integer program, a linear optimization problem where the decision variables can take on only integer values (See the section titled "Combinatorial Optimization/Integer Programming" in this encyclopedia). In this case, the decision variables are the number of agents to assign to each shift and day pattern, and since only whole agents can be assigned these numbers must be integers.

This model is an example of a *weighted set covering* problem. The basic formulation for solving this problem was first presented by George Dantzig in 1954 [3]. Dantzig looked at a similar problem, scheduling toll booth operators when the number of operators required was defined for each discrete time period.

In this model, a matrix is developed that maps tours to time periods. The matrix has $I$ rows, one for every time period in the planning horizon (often a week), and $J$ columns, one for each schedule (i.e., a shift and day pattern combination) to which an agent can be assigned. The cells in the matrix (denoted $a_{ij}$) are equal to 1 if the shift $j$ is "on" in time period $i$ and 0 otherwise. The cost associated with each schedule (denoted $c_j$) is a measure of the number of hours in the schedule. The decision variable (denoted $x_j$) specifies the number of agents assigned to each schedule $j$. The number of agents required in each period (denoted $b_i$) is the list of staffing levels defined in the staffing requirements step.

Mathematically, the model can be expressed as

$$\text{Minimize} \sum_{j \in J} c_j x_j$$

Subject to

$$\sum_{j \in J} a_{ij} x_j \geq b_i, x_j \geq 0, x_j \text{ integer } \forall I$$

This model seeks to minimize the number of agent/hours scheduled, subject to the constraint that the number of agents assigned in each period (found by summing up all the agents assigned to each schedule) must be greater than or equal to the number required in that period.

This model requires one decision variable for each tour a corresponding to the number of workers assigned, and one constraint for each time period. For the example outlined above, the model would contain 77 integer decision variables and 196 constraints.

**Flexible Scheduling and the Feasible Schedule Problem.** While integer programs are in general difficult to solve, the model outlined above is reasonably sized and can be solved to optimality without much difficulty. However, changing a few assumptions in this model formulation can quickly result in a much larger model.

Changes that can increase the size of the model include

- *Hours of Operation.* Expanding the hours of operation of the call center; in particular, moving to a 24-h operation.
- *Shift Options.* Adding more shifts; in particular, creating a more flexible scheduling environment that includes different shift lengths and/or part-time options.
- *Breaks.* Factoring break time into the schedule; in particular, explicitly including meal and/or rest breaks in the schedule.
- *Variable Shifts.* Creating tours that include different shifts on different days.

The call center, we looked at previously, operated from 8:00 a.m. to 10:00 a.m. leading to 11 different shifts, one starting on each half hour from 8:00 a.m. to 1:00 p.m. If we allow for continuous operation (24 h a day), we have 48 possible shift patterns; one for each half hour of the day. The result is a more than fourfold increase in the number of shifts.

The number of feasible tours will also increase if more flexible scheduling options are introduced. In the example stated earlier, we scheduled each agent five days per week with consecutive days off. That led to five feasible day patterns. If we relax the consecutive days off requirement, the result is a total of 21 day patterns (calculated as a combination; 7 choose 5) and the result is a total of 1008 schedules.

Now assume that in addition to five 8 h shifts, the call center offers employees the option of four 10 h shifts. This leads to 48 new shifts (one per half hour) and 35 day patterns (calculated as a combination; 7 choose 4.) The result is a total of 1680 schedules.

Now let us further assume that the call center allows for part-time workers. (Part-time staffing can be quite beneficial when trying to balance supply and demand.) Let us assume they allow for 8 h shifts 4 days a week. The result is another 1680 schedules.

So, if we assume we have a call center operating 24 h a day, 7 days a week (which has three basic scheduling options—five eights, four tens, and four eights), then agents can be assigned to any of 4368 schedules. The introduction of 24 h operation and moderately flexible scheduling has increased the number of integer decision variables from 77 to 4368.

The schedules described above do not explicitly account for breaks. Assume that the call center assigns agents to 9 h shifts, with a half hour lunch break and two 15 min coffee breaks. Further, assume that the call center wishes to explicitly schedule the lunch break, but not the rest breaks.

The call center may wish to have some flexibility in how breaks are scheduled. The shifts shown in Fig. 5 illustrate how adjusting when the lunch break occurs can lead to different schedules. If this flexibility is incorporated into the scheduling model, the model has a total of 21,840 integer decision variables.

The simple model with 77 decision variables developed in the previous section has now expanded to a model with more than 21,000 decision variables. Introduction of additional flexibility, such as more part-time options, would increase this number further. The calculations shown above account only for lunch breaks not rest breaks. If the call center wanted to explicitly schedule the rest break, they would need to plan based on 15-min periods, and incorporate the rest break options. This would have the effect of doubling the number of time periods, and therefore the number of constraints. The number of decision variables would increase significantly, perhaps by an order of magnitude or more.

While adding staffing flexibility greatly increases the size and complexity of the scheduling problem, there are significant benefits. In call centers with large peaks and valleys in the demand profile, it is difficult to fit supply to demand without creating significant overcapacity in other periods. Scheduling flexibility, in particular the use of part-time workers, allows call centers to better shape supply to meet the demand curve and reduce the cost of service delivery [4].

**The Complexity of Flexibility.** The example discussed above shows that the number of

| | S1 | S2 | S3 | S4 | S5 | S6 |
|---|---|---|---|---|---|---|
| 8:00 a.m. | 1 | 1 | 1 | 1 | 1 | 1 |
| 8:30 a.m. | 1 | 1 | 1 | 1 | 1 | 1 |
| 9:00 a.m. | 1 | 1 | 1 | 1 | 1 | 1 |
| 9:30 a.m. | 1 | 1 | 1 | 1 | 1 | 1 |
| 10:00 a.m. | 1 | 1 | 1 | 1 | 1 | 1 |
| 10:30 a.m. | 1 | 1 | 1 | 1 | 1 | 1 |
| 11:00 a.m. | | 1 | 1 | 1 | 1 | 1 |
| 11:30 a.m. | | | 1 | 1 | 1 | 1 |
| 12:00 a.m. | 1 | | | 1 | 1 | 1 |
| 12:30 a.m. | 1 | 1 | | | 1 | 1 |
| 1:00 a.m. | 1 | 1 | 1 | | | 1 |
| 1:30 a.m. | 1 | 1 | 1 | 1 | | |
| 2:00 a.m. | 1 | 1 | 1 | 1 | 1 | |
| 2:30 a.m. | 1 | 1 | 1 | 1 | 1 | 1 |
| 3:00 a.m. | 1 | 1 | 1 | 1 | 1 | 1 |
| 3:30 a.m. | 1 | 1 | 1 | 1 | 1 | 1 |
| 4:00 a.m. | 1 | 1 | 1 | 1 | 1 | 1 |

**Figure 5.** Example Shift Schedules with Breaks.

possible shifts, and therefore the number of integer variables in the optimization program can easily become very large. With explicit break scheduling, the number of decision variables can grow into the tens of thousands or more; test problems with millions of integer decision variables have been analyzed in the literature [5].

Integer programs are difficult (i.e., time consuming) to solve to optimality, and the amount of time and other computer resources required grows in a nonlinear fashion with problem size. Call center scheduling problems of practical size can easily become intractable; that is, solving the problem to proven optimality cannot be accomplished in a reasonable time frame. (See the sections titled "NP-hard Network Flow Problems" and/or "Combinatorial Optimization/Integer Programming" in this encyclopedia for a more detailed discussion of integer programming and complexity theory.)

Given the benefits of increased staffing flexibility, more staffing options are desirable from a cost control perspective. But, given the increased complexity of the optimization problem, staffing flexibility is undesirable from a computational perspective. Finding a balance between these competing goals has been an active area of research. Researchers have developed many approaches, most of which can be put into two basic categories.

- *Implicit Break Scheduling.* In this approach, the scheduling problem is conceptually split into two components. Schedules are first developed without breaks. Breaks are then scheduled and assigned to schedules.
- *Heuristic Solutions.* Heuristic algorithms are designed to find *good* solutions quickly, but usually cannot solve a problem to optimality.

### Implicit Scheduling Models

A number of researchers have developed a modified formulation that includes an implicit definition of breaks. In the basic *implicit shift scheduling* approach, shifts are set up with no breaks, for a single day (i.e., no breaks within a day or between days). A separate set of decision variables is established that specifies the number of employees who are on break during any given time period. Shifts and breaks are essentially established separately, although constraints are established to ensure that the breaks will fit into schedule break windows. After the optimization is complete, a relatively straightforward procedure can be used to assign breaks to individual shifts. In models where this formulation can be applied, the implicit formulation will solve much faster than the explicit set covering approach; requiring between 25% and 50% of the computer time required to solve the basic set covering model [6]. Other models have been developed that increase flexibility and may solve even faster [7,8].

Implicit scheduling models were later extended to *implicit tour scheduling* models which can be applied to $24 \times 7$ operations where employees are scheduled across multiple days [5]. This model solves the scheduling problem for a week when the days worked are continuous, and all shifts are the same length. Under the conditions, the model dramatically reduces the number of decision variables required and creates integer programs that are quite tractable.

### Heuristic Solutions

A *heuristic* is a solution method that is designed to quickly find a solution that is "good" but not necessarily optimal (see the section titled "Heuristics and Metaheuristics" in this encyclopedia). Heuristics have the advantage that they can often solve a problem much faster than a method that is guaranteed to solve the problem to optimality. A key disadvantage is that not only do they typically not solve the problem to optimality but they usually cannot provide a meaningful estimate of the optimality gap.

Given the potential size of staff scheduling problem and the issue of intractability, heuristics are often employed to solve the problem. Many types of heuristics can be applied to this problem. With one type of heuristic, the scheduling problem is still formulated as an integer program, but heuristics are used to either reduce the size of the problem or to speed up the solution process. A second type of heuristic formulates the problem in a fundamentally different way. For the staff scheduling problem, this is most often done by formulating the problem as a discrete event simulation model and solving it using simulation-based optimization.

**Integer Programming Heuristics.** Given the inherent complexity of integer programs, the use of heuristics is fairly common (see the section titled “Heuristics and Metaheuristics” in this encyclopedia). One viable approach is to formulate the integer programming (IP) model as defined above and then to apply a heuristic algorithm, such as a genetic algorithm or simulated annealing, to search for a good solution to the IP. The Lagrangian heuristic has often been used to solve set covering problems [9] (see ***Relationship Among Benders, Dantzig–Wolfe, and Lagrangian Optimization***).

A second type of heuristic for solving the scheduling IP seeks to reduce the size of the problem by eliminating potential solutions. In this problem, a reasonable approach is to reduce the number of schedules that can be selected. A relatively simple method is to avoid explicit break scheduling, allowing supervisors to manage breaks off-line based on how conditions unfold over the course of the shift.

Another method for dealing with the large number of feasible schedules that can be assigned is to use some heuristic to reduce the set of available schedules to something much smaller. An example is presented in [10]. An initial set of 7,120 possible schedules is reduced to a *working set* of 100 or less using two different procedures; one that picks schedules that are the “most different,” and one that picks schedules at random. They find that scheduling against this small subset can yield solutions within a few agents of the optimal solution in much less time than required to solve the complete problem. They also find that for larger working subsets, a random selection performs nearly as well as the most different selection, and performs much faster.

**Simulation-Based Heuristics.** An alternate approach to solving the shift scheduling problem is to use a discrete event simulation model (see ***Introduction to Discrete-Event Simulation***). A simulation model generates and processes individual customers, calls in the case of a call center, according to the predefined probability distributions describing arrival rates, service durations, and other random factors. The simulation approach has the advantage of specifying a more realistic model of the operation; for example, by allowing for more realistic distributions of service times, varying and uncertain arrival rates, abandonment, and absenteeism.

Simulation models may be used to allow managers to evaluate policy or scheduling changes interactively. Saltzman and Mehrorta describe an application of simulation modeling to evaluate the impact that launching a priority support service would have on standard and priority customers in an IT support call center [11].

Another way to use simulation is to perform *simulation-based optimization*; a process whereby simulation is used to evaluate the schedule, and a search algorithm is used to look for better schedules (see the section titled “Simulation Optimization” in this encyclopedia). A drawback of simulation-based optimization is that it is in general impossible to determine if a solution is optimal. Instead of finding a known optimal solution, or a solution known to be within a specified percentage of optimal, the simulation optimization algorithm typically searches until it is unable to find a better solution for some designated length of time.

A common approach to simulation-based scheduling is to use an analytical method to create a rough cut schedule. The rough cut schedule is then evaluated using the simulation model. Changing the original schedule, often using randomized changes, generates new schedules, which can then be simulated. One approach uses a simple *greedy* heuristic to generate a first cut schedule for a call center with variable arrival rates [12]. A simulation model then searches for better schedules, evaluating similar schedules using a meta-heuristic search technique known as *variable neighborhood search* (VNS). Other metaheuristics include genetic algorithms, simulated annealing or Tabu search (see the section titled "Heuristics and Metaheuristics" in this encyclopedia). Other models use simulation and cutting planes to develop a schedule for a call center where agents have different skill sets [13,14].

### Joint Staffing Models

The basic set covering model splits staffing requirements and shift scheduling into two separate and distinct steps. Joint staffing models combine these two steps into a one optimization problem.

The basic set covering model implicitly makes several important assumptions that are relaxed in joint scheduling models. First, by taking as an input the number of agents required in every time period, the model implicitly assumes that service level requirements are strict in every interval. In call centers with short interval peaks (such as the call centers represented in Figs 2 and 4), staffing to satisfy the peak arrival rate may result in excess capacity in other periods. In response to this issue, some call centers seek to achieve their service level targets over an extended period; perhaps a day, week, or even a month. This is often referred to as a *global service constraint*.

A second issue is the implicit assumption that arrival *rates* are known prior to the scheduling process. While the standard queueing model used when setting staffing requirements assume that the time between call arrivals is random, the models assume the average rate at which those calls arrive is known. In many situations this is not the case, and arrivals are considered to be *doubly stochastic*; customers arrive randomly with an average rate that itself is random [15,16].

These limitations can be addressed in *joint staffing and scheduling models*; models that integrates the staffing requirement and the shift scheduling steps into one optimization problem. The simulation models discussed above are inherently joint staffing and scheduling models, but the approach can also be applied to optimization models [17,18]. Some models use a piecewise linear approximation to the service level curve; allowing for the calculation of a global service level based on the per period staffing decision [19,20].

## ROSTERING

The final step in the scheduling process is rostering. *Rostering* is the process of assigning individual agents to schedules defined in the shift scheduling process. The rostering process must consider employee preferences (e.g., I prefer to start after 10:00 a.m.), employee restrictions (e.g., I cannot work on Thursdays), management policies (e.g., all employees must work one weekend day a month), and potentially union or contract restrictions (e.g., agents must have two consecutive days off.)

While extremely important in practice, the rostering process has received limited attention in academic research, perhaps because the process is not one that has not traditionally been highly automated. The process used at New Brunswick Telephone (NBTel) is described in Ref. 21, a case where an automated heuristic was used to improve the process. The article highlights the rostering process (referred to as the shift assignment problem in this article) and identifies many of the issues.

The input to the rostering process is the set of schedules defined in the shift scheduling process. The output is the assignment of specific individuals to all of the schedules. The objective of the process is to match employee preferences as closely as possible. Agent preferences are not all considered equal, and preferences are often evaluated relative to worker seniority with higher levels of seniority given first choice.

Agent preferences cover a range of attributes; for example, days worked per week, starting time, length of lunch break, specific days off, or length of shift. Agent preferences may be soft (e.g., I would prefer not to start before 8:00 a.m.), or hard (e.g., I cannot work on Sundays). An agent's skill level forms another hard constraint; agents cannot be assigned to shifts that require skills they do not possess.

In smaller call centers, agent preferences can be tracked by supervisors informally and rostering can be done in a manual fashion. In larger call centers with hundreds or even thousands of agents, a manual process is not practical and call centers typically utilize an *agent self-service* module within the WMS.

The self-service module typically allows agents to indicate their hard constraints and express their preferences. An agent may, for example, indicate hours or days of the week for which they are unavailable. The system may be configured to forward this entry to a supervisor for confirmation. They may also enter a request to take a week of vacation into the WMS. The WMS may use a set of configurable rules to evaluate the request. The request may be denied, approved, or forwarded to a supervisor for evaluation and dispensation.

When it comes to shift assignment, assignments are often handled via a bidding process. Agents may use the self-service module to bid on schedules they find desirable. The WMS will typically utilize some rule set to attempt to meet agent preferences to the extent possible. Agent bids are often weighted based on agent seniority. The rules by which bids are evaluated are often complex, and a heuristic is used to balance multiple criterion (see the section titled “Heuristics for Multiple Objectives” in this encyclopedia). The heuristic used at NBTel is described in Ref. 21. The heuristic utilized at NBTel first tries to ensure that all schedules are assigned to a qualified agent; it then seeks to satisfy agent requests in order of seniority. If at the end of the run, shifts remain unassigned, the application performs a series of two and three way swaps to allocate these unassigned shifts seeking to ensure that a qualified agent is assigned to every scheduled shift.

Given the difficulty of expressing, much less satisfying agent preferences, the resulting assignments may not satisfy all agents’ desires. A common way to address this issue is for the WFM to provide automated support for a *shift swapping* process. Shift swapping is a process whereby two or more agents may agree to trade shifts. The WFM system may support this process in various ways. It may allow agents to view the detailed schedule to identify potential swaps. It may also provide automated workflow support for the swapping process. For example, the system may allow one agent to request a swap with another agent, prompting a message to the effected agent. If that agent accepts the swap, a message may be sent to the supervisor seeking approval.

### Real-Time Control

Service environments, in general, and call centers, in particular, are subject to significant uncertainty in both the demand for and supply of labor. Call center volume often varies significantly from forecast, and staff absenteeism is a common problem. The implication is there even a well developed schedule may prove inadequate when implemented.

Real-time control refers to the actions managers make during the course of the day to adjust capacity to better match realized demand. Real-time control actions can be short-lived changes that affect capacity for only a short period of time, such as rescheduling breaks, or longer-term changes that affect capacity for an hour or more, such as sending employees home, or calling in additional workers. An overview of real-time control, focused on the hospitality industry, is provided in Ref. 22. An overview of the literature associated with real-time schedule adjustments is provided in Ref. 23. In this article, the authors study the applicability of real-time control heuristics in the quick service restaurant industry.

When applied to call centers, much of the research on real-time control addresses the issue of when to take action, and focuses on determining when a statistically significant deviation from forecast has occurred [24,25]. Other papers focus on updating agent schedules [26].

### Real-World Challenges

While a substantial body of academic research addresses the workforce scheduling problem, the literature often deals with models that are highly simplified versions of reality. Stated another way, workforce management application vendors, and call center managers face a reality far more complex than that addressed in the academic literature. Assumptions made about the statistical distributions of call arrivals, talk times, and caller's willingness to wait are often inaccurate. Agents are heterogeneous with differing skills, productivities, and scheduling preferences. Agent absenteeism is a chronic problem in many call centers. Performing scheduling and rostering sequentially may create schedules that cannot be staffed given agent availability constraints. In many real-world applications, call center managers make substantial manual changes to system generated schedules.

There is a subset of the literature that attempts to quantify, and in some cases address, these complexities. Issues related to how statistical distributions in real-world call centers differ from those assumed in standard models are addressed in Ref. 16. The design of a commercial workforce management application is described in Ref. 27. A series of papers examine issues related to implementing call center solutions at L.L. Bean [28–31]. Heterogeneous agent skills and sophisticated skills based routing greatly complicate the agent scheduling problem, and while assumed away in many scheduling models, this is an area of active research (See Ref. 1 for a more detailed discussion.)

## SCHEDULING AND ROSTERING IN OTHER ENVIRONMENTS

The bulk of this document looks at scheduling and rostering in call center environments. The techniques and models discussed here are also applicable to a range of other environments such as airline ticket counters, airline crews, hospitals, emergency services, restaurants, retail outlets, or mail facilities. The methods discussed here apply to any operation characterized by a time varying requirement for personnel. Ernst *et al*. give an overview of scheduling and rostering applications across a range of applications, highlighting some of the key issues that arise in various environments [9]. Call Centers are a common application for scheduling and rostering models, and as discussed in this article, call centers are characterized by significant uncertainty in workload. Other notable application areas are listed below.

### Transportation Systems

Scheduling and rostering is an important aspect of transportation systems, such as airlines. Many models have been developed to look at airline crew scheduling [9]. One important difference with airline models, in particular, is the spatial aspect of the models. Airline crew schedules are driven by point to point transportation links which move the crew from one location to another. Crews have home locations that they must eventually return to, and leaving a crew at a remote location creates an additional cost. Other transportation applications, such as bus systems, subways, and other public transport systems, are less focused on the starting and ending location of the crew as they tend to be confined to a narrow geographical area. Transportation scheduling staff requirements are also less uncertain and more controllable than those in a call center. The transportation schedule tends to drive the staff schedule.

### Health Care

Many models have been developed to analyze staffing issues in health-care delivery, most notably nurse scheduling. Much of this work has focused on allocating weekday and weekend shift in accordance with work regulations. Another interesting aspect of health-care models is the ability to substitute higher skilled workers for lower skilled requirements; that is, assigning an Registered Nurse (RN) when only an Licensed practical nurse (LPN) is required.

### Emergency Services

Staffing is an important issue in emergency services such as police, fire, or ambulance services. Spatial issues are also important in emergency services, in particular, ambulance services where the response time are critical and driven in large part by the distance between the incident and the responding crew. Ambulance services also create a demand profile that is highly uncertain.

## Retail

Scheduling and rostering is an important characteristic in retail operations of all types. Retail scheduling applications tend to be similar to call center models, although staffing levels are often defined exogenously rather than via a queueing model approach.

## REFERENCES


1. Aksin Z, Armony M, Mehrotra V. The modern call-center: a multi-disciplinary perspective on operations management research. Prod Oper Manage 2007;16(6):665–668.
2. Gans N, Koole G, Mandelbaum A. Telephone call centers: tutorial, review, and research prospects. Manuf Serv Oper Manage 2003;5(2):79–141.
3. Dantzig GB A comment on Edie's "Traffic Delays at Toll Booths". J Oper Res Soc Am 1954;2(3):339–341.
4. Robbins. TR. Managing service capacity under uncertainty [Unpublished PhD Dissertation]. Pennsylvania State University; 2007. 235p. Available at: http://personal.ecu.edu/robbinst/.
5. Brusco MJ, Jacobs LW. Optimal models for meal-break and start-time flexibility in continuous tour scheduling. Manage Sci 2000;46(12):1630–1641.
6. Bechtold SE, Jacobs LW. Implicit modeling of flexible break assignments in optimal shift scheduling. Manage Sci 1990;36(11):1339–1351.
7. Thompson GM. Improved implicit optimal modeling of the labor shift scheduling problem. Manage Sci 1995;41(4):595–607.
8. Aykin T. Optimal shift scheduling with multiple break windows. Manage Sci 1996;42(4):591–602.
9. Ernst AT, Jiang H, Krishnamoorthy M, *et al*. Staff scheduling and rostering: a review of applications, methods and models. Eur J Oper Res 2004;153(1):3.
10. Henderson WB, Berry WL. Heuristic methods for telephone operator shift scheduling: an experimental analysis. Manage Sci 1976;22(12):1372–1380.
11. Saltzman RM, Mehrotra V. A call center uses simulation to drive strategic change. Interfaces 2001;31(3):87.
12. Robbins TR. A simulation based scheduling algorithm for call centers with uncertain arrival rates. Proceedings of the 2008 Winter Simulation Conference; Miami (FL). 2008. pp. 2884–2890.
13. Avramidis AN, Gendreau M, L'Ecuyer P, *et al*. Simulation-based optimization of agent scheduling in multiskill call centers. 5th Annual International Industrial Simulation Conference (ISC-2007); Delft, The Netherlands. 2007.
14. Atlason J, Epelman MA, Henderson SG. Optimizing call center staffing using simulation and analytic center cutting-plane methods. Manage Sci 2008;54(2):295–309.
15. Jongbloed G, Koole G. Managing uncertainty in call centers using Poisson mixtures. Appl Stoch Models Bus Ind 2001;17:307–318.
16. Brown L, Gans N, Mandelbaum A, *et al*. Statistical analysis of a telephone call center: a queueing-science perspective. J Am Stat Assoc 2005;100(469):36–50.
17. Koole G, van der Sluis E. Optimal shift scheduling with a global service level constraint. IIE Trans 2003;35:1049–1055.
18. Thompon GM. Labor staffing and scheduling models for controlling service levels. Nav Res Logist 1997;44(8):719–740.
19. Robbins TR, Harrison TP. Call center scheduling with uncertain arrivals and global service level agreements. Eur J Oper Res 2010. In press.
20. Robbins TR. Addressing arrival rate uncertainty in call center workforce management. 2007 IEEE/INFORMS International Conference on Service Operations and Logistics, and Informatics; Penn State University, Philadelphia (PA). 2007. 6p.
21. Thompson GM. Assigning telephone operators to shifts at new Brunswick telephone company. Interfaces. 1997;27(4):1–11.
22. Thompson GM. Labor scheduling, part 4. Cornell Hotel Restaur Adm Q 1999;40(3):85–96.
23. Hur D, Mabert VA, Bretthauer KM. Real-time work schedule adjustment decisions: an investigation and evaluation. Prod Oper Manage 2004;13(4):322–339.
24. Shen H, Huang JZ. Interday forecasting and intraday updating of call center arrivals. Manuf Serv Oper Manage 2008;10(3):391–410.
25. Weinberg J, Brown L, Stroud JR. Bayesian forecasting of an inhomogeneous Poisson process with applications to call center data. J Am Stat Assoc 2007;102(480):1185–1198.
26. Mehrotra V, Ozlük O, Saltzman RM. Intelligent procedures for intra-day updating of call

center agent schedules. Prod Oper Manage 2009;19(3):353–367.

27. Fukunaga A, Hamilton E, Fama J, *et al*. Staff scheduling for inbound call centers and customer contact centers. Eighteenth National Conference on Artificial Intelligence; Edmonton, Alberta, Canada. 2002. Edmonton.
28. Andrews B, Parsons H. Establishing telephone-agent staffing levels through economic optimization. Interfaces 1993;23(2):14.
29. Andrews BH, Cunningham SM L.L. Bean improves call-center forecasting. Interfaces 1995;25(6):1.
30. Andrews BH, Parsons HL. L.L. Bean chooses a telephone agent scheduling system. Interfaces 1989;19(6):1.
31. Quinn P, Andrews B, Parsons H. Allocating telecommunications resources at L. L. Bean, Inc. Interfaces 1991;21(1):75.