PRODUCTION AND OPERATIONS MANAGEMENT

POMS

Vol. 13, No. 4, Winter 2004, pp. 322–339
ISSN 1059-1478 | 04 | 1304 | 322$1.25

Real-Time Work Schedule Adjustment Decisions: An Investigation and Evaluation

Daesik Hur • Vincent A. Mabert • Kurt M. Bretthauer

Department of Management, College of Business Administration, Bowling Green State University, Bowling Green, Ohio 43403, USA

Department of Operations and Decision Technologies, Kelley School of Business, Indiana University, Bloomington, Indiana 47405, USA

Department of Operations and Decision Technologies, Kelley School of Business, Indiana University, Bloomington, Indiana 47405, USA

dhur@bgnet.bgsu.edu • mabert@indiana.edu • kbrettha@indiana.edu

Service managers often find that available worker capacity does not match with actual demand during a given day. They then must attempt to modify the planned work schedule to improve service and increase profitability. This study, which defines such a setting as the *real-time work schedule adjustment decision*, proposes mathematical formulations of the real-time adjustment and develops efficient heuristic approaches for this decision. The study evaluates the relative effectiveness of these heuristics versus experienced service managers, investigates the effect of the degree of schedule adjustment on profitability, and assesses the effect of demand forecast update errors on the performance of the schedule adjustment efforts. First, the results indicate that the computer based heuristics achieve higher profit improvement than experienced managers. Second, there is a trade-off between schedule stability and profitability so that more extensive schedule revisions (efficiency first heuristics) generally result in higher profitability. However, the incremental return on schedule changes is diminishing. Third, we find that active adjustments of work schedules are beneficial as long as the direction of demand change is accurately identified.

Key words: service operations; workforce schedule adjustment; goal programming; heuristics; simulation

Submissions and Acceptance: Received April 2003; revisions received April 2004 and August 2004; accepted August 2004.

1. Introduction

Service managers in such organizations as financial institutions (Mabert et al. 1979), health care organizations (Easton et al. 1992; Cayirli and Veral 2003; Mondschein and Weintraub 2003), postal services (Malhotra and Ritzman 1994), call centers (Green et al. 2003), emergency services (Mabert 1983), and quick service restaurants (Mabert and Showalter 1982) often expend significant effort and resources to forecast and schedule the appropriate number of workers to meet time-varying workloads. The process normally starts with short interval forecasts (e.g., hourly estimates within a day) that are developed two to four weeks in advance of the day of service, taking into account seasonal patterns and special events affecting workloads (Berry et al. 1979; Boyd and Mabert 1977; Andrews and Cunningham 1995; Mabert 1995). Based upon these estimates, full- and part-time personnel are scheduled to meet the expected workload. From initial scheduling to the day of service, updates can occur because of new information concerning changes in demand, availability of staff, and/or other factors. When the day of service arrives, actual demand can be measured early in the day and compared against what was forecasted. This comparison provides service managers with the opportunity to determine if a significant gap is present between the experienced workload so far and the scheduled staff capacity. If the gap is deemed large enough, service managers will attempt to make an immediate adjustment (within 15 to 30 minutes) to the staff schedule, using a set of the options listed in Table 1, all of which are quite common in many service organizations. This correction to the staff schedule is defined here as the *real-time work*

Table 1 Examples of Real Time Adjustment Options

Increase Capacity	Decrease Capacity
❑ Change station assignment	❑ Change station assignment
❑ Cancel or change breaks	❑ Send to break
❑ Early start	❑ Late start
❑ Late leave	❑ Early leave
❑ Call in (add a new shift)	❑ Cancel shift

schedule adjustment decision, and is the focus of this study.

Real-time schedule adjustment is an important concern in many labor-intensive, high-volume service organizations, such as quick service restaurants and call centers, because failure to correctly match capacity to demand can significantly reduce profitability and/or customer service. For instance, one percent of sales are lost for every six-second delay at the drive-thru in a typical *McDonald's* restaurant (Ordonez 2000). Therefore, in the quick service restaurant industry, real-time schedule adjustment is a common managerial practice (Schmenner 1998; Love and Hoey 1990; Hueter and Swart 1998). It is also reported that even the most accurate call center staff scheduling must be complemented by real-time schedule adjustment to achieve the target customer service level (Mabert 1991; Mabert 1995; Cleveland and Mayben 1997).

Although it is apparent that real-time schedule adjustments take place daily in many service organizations, there has been very little academic research to this end. To help understand the scope of this issue, it is useful to make an important operational distinction. The adjustment decision takes place in both front-line and back-office operations. Front-line operations involve those activities that deal with direct selling to customers and have an immediate impact on revenue. Examples include quick service restaurants (McDonald's and Burger King), catalog sales (Land's End and Eddie Bauer), and PC sales (Dell and Gateway) to name a few. Back-office operations are aftermarket support activities and include tasks like directory assistance (AT&T and MCI), technical support (Dell and Gateway), and utility billing (Cinery and Con Edison).

This study addresses the adjustment decision for front-line operations that impact revenue. This paper aims to: (1) propose a mathematical formulation of the real-time adjustment decision, develop efficient heuristic solution approaches, and evaluate the relative effectiveness of the heuristics versus experienced service managers, (2) investigate the relationship between the degree of schedule adjustment and profitability, and (3) evaluate the effect of demand forecast update errors on the performance of the schedule adjustment efforts.

While the adjustment decision occurs in many different institutional settings that reflect unique customs and procedures, the quick service restaurant industry was selected to test the proposed procedures. Specifically, this investigation was initiated with a data collection effort at the *McDonald's* franchise in Bloomington, Indiana (six restaurants), employing on-site observations, corporate document archival review, and structured interviews of corporate and unit managers. Various managerial goals associated with the adjustment process were identified, and based on this information, goal programming formulations and solution heuristics were developed. The authors conducted a series of experiments using the heuristics and actual service managers to address the research objectives discussed above.

Although this study focuses on quick service restaurants, the authors believe the suggested formulations and heuristics can be applied to other front-line service organizations with the following characteristics: (1) a high-volume of customer traffic, (2) a labor-intensive cost structure, (3) short service delivery time, (4) flexible workforce and shift structures that allow use of the options in Table 1, and (5) an automatic data collection system such as a point-of-sales system.

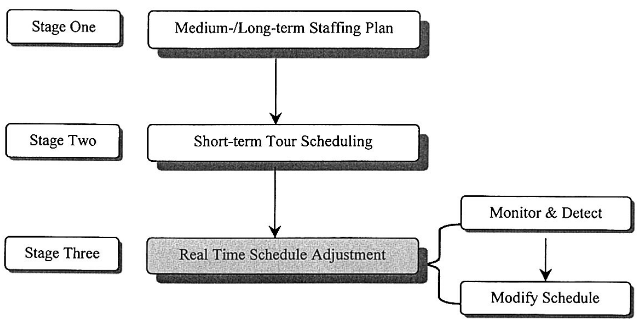
In the remaining sections of this paper, we present our study. To initiate the discussion, Section 2 reviews past literature on labor scheduling and real-time schedule adjustment and presents the research objectives. Section 3 describes the workforce management process at *McDonald's* as a backdrop for the following sections. Then Section 4 presents two versions of a preemptive integer goal programming formulation, with Section 5 discussing solution heuristics. Section 6 describes the experimental methodology and Section 7 reports the experimental results in detail with respect to the research questions. Finally, Section 8 outlines the managerial implications of the study and proposes future research directions.

2. Literature Review and Research Issues

2.1. Literature Review

Workforce staffing and scheduling can be seen as a three stage hierarchical process, as illustrated in Figure 1. While Stage One deals with deciding the size and composition of the workforce, Stage Two focuses upon assigning the staff to work tours covering a given time interval (e.g., one week). Stage Three concerns the process of modifying the work schedule while implementing it during a day. For the past three decades, numerous researchers have conducted extensive studies of the service workforce, primarily concentrating upon Stage One and Stage Two decisions. For example, Abernathy et al. (1973) and Ritzman et al. (1976) proposed a hierarchical methodology to address decisions in both Stages One and Two. Other

Figure 1 Hierarchical Workforce Management



researchers have focused on how to develop a "good" work schedule in advance of implementation (say one to two weeks). For instance, Mabert and Watts (1982), Morris and Showalter (1983), Easton and Rossin (1991), and Brusco and Jacobs (1998) developed heuristic tour scheduling approaches, while Brusco and Jacobs (2000) developed optimal models for continuous tour scheduling problems. In addition, Bechtold and Jacobs (1990), Thompson (1995) and Aykin (1996) proposed optimal shift scheduling approaches. Finally, several research works explicitly addressed the issue of differences between workers (work time availability, skill levels, preference, seniority, etc.) when performing tour scheduling (Love and Hoey, 1990; Loucks and Jacobs, 1991) and shift scheduling (Vakharia et al. 1992; Thompson 1997; Brusco and Johns 1998; Campbell 1999).

In Stage Three, the real-time schedule adjustment process is again broken down into two phases, *monitoring/detection* and *schedule adjustment*, that occur during the day of service. The first phase requires timely and accurate detection of forecast bias and appropriate revision of the forecast. Forecast bias detection can be facilitated by automatic monitoring tools such as simple cusum (Brown 1963), smoothed error (Trigg 1964), autocorrelation (Gardner 1983), planning charts (Wu et al. 1992), and threshold curves (Kimes 1989). Hur (2002) found planning charts and threshold curves more effective than cusum and smoothed error tracking signals in a high-volume service operation system. Once a forecast bias detection signal has been generated, the forecast can be updated using a 'partially known demand' forecasting model (Bodily and Freeland 1988; Kekre et al. 1990; Guerrero and Elizondo 1997). In particular, Thompson's (1999) business-volume-consistency (BVC) chart was developed to not only check whether actual demand counts are in line with the forecast, but also predict day-end business volume in real-time adjustment processes.

Unlike bias detection and forecast revision, the *adjustment* phase of Stage Three has received very little attention in the literature (Thompson 1999). Some researchers have suggested building flexibility strategies such as on-call work pools (Berman and Larson 1994) and action-time work-shift windows (Thompson 1996) to respond to changes. Recently, Hill et al. (2002) emphasized the need for research regarding information requirements, infrastructural processes, and economic consequences of real-time schedule control. While these researchers provide some insight and suggest scheduling alternatives, they do not directly address the issues associated with schedule adjustment decisions. This paper addresses this void in the literature.

2.2. Research Objectives

This paper focuses on three research objectives associated with the real-time schedule adjustment decision, identified from past literature and interviews with practicing service managers. The first research goal is to develop a mathematical formulation of the real-time adjustment decision and efficient heuristic solution approaches, and to evaluate the relative effectiveness of the heuristics versus experienced service managers. No research work has explored how a comprehensive set of adjustment options like those listed in Table 1 could be formulated within a mathematical model that generates the adjusted schedules quickly, say in 10 to 15 minutes. This is a challenging task, particularly when employees differ from one another in terms of their availability, work skills, and wage rates. Additionally, the practical viability of the heuristics would be reinforced when they outperform decisions made by experienced managers. Note that practicing managers at various service organizations routinely conduct real-time schedule adjustments and have developed their own rules of thumb through their years of experience. Past studies reported human decision-making is as good as (Hill 1983) or superior to (Nakamura and Salvendy 1988) computer based heuristics for operational planning problems. However, a human decision maker's performance is influenced by many factors, such as problem complexity, experiences, education, and analytical capability (Robinson and Swink 1995, Swink and Robinson 1997). Moreover, if different managers make decisions based on their own heuristic rules, it is difficult to expect consistent performance over time. Therefore, it is necessary to investigate how well the computer based solution methods measure up to experienced managers' performance, by answering the following research questions:

Q1: *Do computer-based heuristics achieve better adjustment performance than experienced managers' adjustment decisions?*

Q2: *When does the performance gap between experienced managers and computer based heuristics become substantial?*

The second research objective concerns the relationship between schedule adjustment and profitability. Proactive and complete modification of work schedules may improve customer service and, in turn, profitability of the organization. However, such active adjustment can result in worker dissatisfaction and increases managerial complexity. As will be discussed in Section 4.1, practicing managers consider multiple goals in schedule adjustments, but do not necessarily agree among themselves which goal is more important. In particular, junior managers tend to emphasize schedule stability and worker convenience rather than operational efficiency (labor cost and productivity). Such goal orientation may result in fewer schedule modifications and less profit improvement. Therefore, it is interesting to estimate the degree of profit reduction when employee and managerial convenience is emphasized over operational efficiency. Two additional research questions of interest address whether a schedule adjustment always brings about an increase in profitability, or if there is a diminishing return for adjustments, with changing levels of capacity gap:

Q3: *If worker and managerial convenience is emphasized over operational efficiency, to what extent does profitability decrease?*

Q4: *How much schedule adjustment is enough? Is there a saturation point where additional profit increase due to schedule adjustment becomes minimal?*

The third objective of this study aims to assess the effect of forecast update errors on the performance of real-time schedule adjustment decisions. Real-time schedule adjustment is based on the premise that managers can collect more accurate information on customer demand and labor availability during the day of service. Academic researchers have shown that more data collection over time improves decision quality in the setting of inventory control across the supply chain (Gavirneni et al. 1999; He et al. 2002). However, in reality, forecasting is rarely free from errors. If the forecast update is incorrect, the net benefit of real-time schedule adjustment may be reduced. Therefore, the final research question of interest is:

Q5: *What is the impact of demand forecast update errors on the performance of the schedule adjustment efforts?*

In order to address the above research goals, the next section describes the workforce management process at quick service restaurants and provides background information for the model formulation and subsequent experimental studies.

3. Workforce Management at Quick Service Restaurants

To provide the context of a front-line operation for this adjustment decision investigation, a field study was conducted at a *McDonald's* franchise consisting of six stores in the Bloomington, Indiana area. Workforce management at the *McDonald's* franchise follows a three-stage process as shown in Figure 1. In Stage One, managers routinely develop medium- and long-run staffing plans (recruiting and transfer), taking into account store expansion/closing and seasonal fluctuations of labor supply and customer demand over a year. At the time of this study, about 320 hourly employees (full and part time) and 30 salaried managers were employed across these six restaurants. Full-time and some part-time hourly employees are cross trained for all major workstations such as *Breakfast Grill*, *Grill*, *Drive-thru*, and walk-in *Counter*, while most part-time employees are trained on selected workstations, depending on their station preferences, legal requirements, and managers' discretion. Because of the difference in labor market supply characteristics, some restaurants employ almost a 100 percent part-time hourly staff, while other units have predominantly full-time hourly workers.

Stage Two starts with the generation of an hourly sales projection for the upcoming week using a modified five-period moving average model. The unit manager modifies the computer-generated sales projection by reflecting local special events. Projected sales are translated into target staffing requirements hour by hour according to the sales-to-staff conversion table. The conversion table is designed with a service target that has the average customer experiencing 3.5 minutes in the system (queue plus service). Each hourly staffing requirement is, in turn, disaggregated by specific workstations like grill or drive-thru window according to the positioning guide (or so-called *Floor Plan*). Updates are made to the workforce size (new hires and resignations), work time availability windows for employees, and skill ratings. Next, the computer system produces the "crew daily schedule report" for the planning horizon; inserting rest (meal) breaks if employees qualify. Tour scheduling aims to minimize the sum of absolute deviations between scheduled labor hours and target staffing requirements while satisfying employees' preferences for work times. Finally, the scheduling manager edits the computer-generated schedule for any changes, and then it is posted. It takes a scheduler an average of 2 to 6 hours per week per store to develop the upcoming weekly tour schedule. Once it is posted, updates can occur when turnover, employee illness, and absences are discovered. Employees are allowed to swap their shifts with one another under the master scheduler's approval.

Stage Three takes place during the day of service. At the observed restaurants, a day is divided into five work horizons for each of which a manager is assigned to run the restaurant operations. During 'prep time' (one hour before a work horizon starts), the manager computes, records, and monitors the gap between needed and available capacity in real-time, and makes real-time schedule adjustments if necessary. The need for real-time schedule control in these restaurants arises mainly from uncertain customer demand and unexpected worker absence or lateness. If the observed capacity gaps exceed pre-established threshold values (1 to 1.5 labor hours, amounting to \$100 to \$150 in sales), managers actively seek out the underlying causes by reviewing employee work schedules, customer traffic levels, and their interactions. Once the underlying causes are identified, managers revise the forecast and staff requirements for the rest of the day. If the causes are not identified, they are inclined to use a simple extrapolation technique based on the observed forecast errors during the early part of the day. With the newly estimated staff requirements, managers identify available capacity options such as those listed in Table 1, and decide the type and extent of actions that should be taken. When making adjustments the managers need to take into account worker skills, pay rate, worker availability, and the positioning guide in an attempt to achieve multiple goals associated with customer service, cost control, worker utilization, and schedule stability. Managers do not necessarily agree with one another on how to pursue the multiple goals. Interview data indicate that senior managers are disposed to emphasize proactive reduction of capacity gap and labor cost while junior managers are more concerned about schedule stability and worker dissatisfaction.

Based upon the operational data collected, the real-time adjustment decision involves the evaluation and selection of alternatives in an uncertain environment. The next section structures the decision process, recognizing the multiple dimensions (e.g., profit, employee morale, etc.) and constraints (e.g., worker skills, availability, etc.).

4. Problem Formulation

This section presents a mathematical formulation of the real-time schedule adjustment problem for settings with a heterogeneous workforce. As noted earlier, employees differ in their work-time availability, skill (productivity) levels, skill type (training), number of work hours a week available, and wage rates. Each employee is originally scheduled to work at most one shift per day (no split shifts are allowed). The assumptions of the formulation are: (1) managers have revised the workload forecast and established staffing requirements for the rest of day, and (2) managers have identified all employees who are willing to accept schedule changes. In this setting, managers need to modify the work schedule to meet the revised staffing requirement. For the scenario described above, we formulate the schedule adjustment decision as a shift and task assignment problem with multiple goals, employing two preemptive integer goal programming models, each representing different hierarchies of goals identified from experienced service managers.

The following notation will be used to formulate the models.

Indexes

i = employee

j = shift

k = workstation

t = time period

Constants and Parameters

r_{kt} = desired number of employees at station k during period t

c_{ij} = cost of employee i assigned to work shift j

a_{jt} = 1 if time period t is a work period in shift j, 0 otherwise

e_{ik} = relative efficiency or productivity index of employee i at workstation k

Employees

N = set of employees available to work

N_k = set of employees qualified for workstation k

Time Periods

T = set of remaining time periods in the schedule adjustment horizon

T_i^{RA} = real-time availability time window of employee i, $i \in N$, i.e., the set of time periods within which an employee's modified/adjusted shift can be scheduled within a day

t_i^L = last period of employee i's real-time availability time window, $i \in N$

Shifts

S = set of all shifts during a day

S_i = set of all shifts to which employee i can be assigned, $i \in N$.

S_i^0 = set of all shifts whose start and end times are the same as those of employee i's planned shift for the day, $i \in N$ (e.g., two shifts may start and end at the same time, but have a break at different times)

Workstations

M = set of all workstations

M_i = set of workstations for which employee i is qualified, $i \in N$

Decision Variables

X_{ij} = 1 if employee i is assigned to shift j, 0 otherwise, $i \in N$, $j \in S_i$

U_{ikt} = 1 if employee i is assigned to work at station k during period t, 0 otherwise, $i \in N$, $k \in M_i$, $t \in T_i^{RA}$

h_{kt}^{+} = number of surplus employees at workstation k during period t, $k \in M$, $t \in T$

h_{kt}^{-} = number of employees short at workstation k during period t, $k \in M$, $t \in T$

W_i = 1 if employee i's planned shift is changed, 0 otherwise, $i \in N$

V_{ikt}^{-} = 1 if employee i is released from station k at the end of time period t, 0 otherwise, $i \in N$, $k \in M_i$, $t \in T_i^{RA}$

V_{ikt}^{+} = 1 if employee i is newly assigned to station k at the beginning of time period $t + 1$, 0 otherwise, $i \in N$, $k \in M_i$, $t \in T_i^{RA}$

4.1. Objective Functions

Extensive interviews with managers at the observed restaurants revealed that profit maximization and schedule stability are the major operational goals at the restaurants. Managers assume that profit maximization is equivalent to the achievement of the target customer service level (i.e., "average experience time" = 3.5 minutes) with minimum labor cost. The target customer service level is established so as to maximize profit by *McDonald's Corporation* and built into the target staffing guideline. The staffing guideline establishes the number of workers required for the expected transactions during the period. Practicing managers accept this approach because it is easy for front-line managers and employees to understand and implement on a daily basis. The target customer service level and minimum labor cost are expressed by three operational goals, as shown in equations (1) to (3), representing surrogate measures for profit maximization in the objective function. Equation (1) indicates that managers seek to minimize the sum of the number of employees short from target staffing requirements. Equation (2) minimizes direct labor costs associated with the shift assignment. Equation (3) attempts to maximize the sum of "effective" number of employees (productivity) by assigning workers to workstations at which they perform best.

Schedule stability is considered important as well because excessive schedule modification increases managerial burden/complexity and worker dissatisfaction. Therefore, managers try to avoid shift changes and task rotations, as represented in equations (4) and (5). Equation (4) minimizes the number of workers whose planned shifts are modified. In this study, a shift change is defined as a change in either start or end time of a shift. Finally, equation (5) suggests that the total number of task rotations (as opposed to the number of shift changes) scheduled during the day should be minimized.

$$\text{Minimize} \sum_{t \in T} \sum_{k \in M} h_{kt}^{-} \quad \text{(Minimize labor shortage)} \tag{1}$$

$$\text{Minimize} \sum_{i \in N} \sum_{j \in S_i} c_{ij} X_{ij} \quad \text{(Minimize direct labor cost)} \tag{2}$$

$$\text{Minimize} -\sum_{i \in N} \sum_{k \in M_i} \sum_{t \in T_i^{RA}} e_{ik} U_{ikt} \quad \text{(Maximize overall productivity)} \tag{3}$$

$$\text{Minimize} \sum_{i \in N} W_i \quad \text{(Minimize shift changes)} \tag{4}$$

$$\text{Minimize} \sum_{i \in N} \sum_{k \in M_i} \sum_{t \in T_i^{RA}} (V_{ikt}^{-} + V_{ikt}^{+}) \quad \text{(Minimize task rotations)} \tag{5}$$

We also note that managers have different preferences toward goals (1) to (5). Senior or salaried managers are compensated based upon restaurant profitability so that they tend to be very proactive about schedule adjustment and focus on labor cost reduction, whereas junior or unsalaried managers typically are more concerned about schedule stability and worker dissatisfaction. To reflect such goal incongruence, we propose two general policies, labeled an *efficiency first* (EF) policy and a *convenience first* (CF) policy. Both policies give top priority to minimizing labor shortages (i.e., meeting staff requirements) because it is necessary not only to achieve the target service level, but also to prevent employee burn out resulting from high work intensity. In addition, shift assignment (equations (2) and (4)) is considered more critical than task assignment (equations (3) and (5)). They, however, differ in prioritizing the goals of each assignment problem.

Equation (6) below shows a general form of the objective function, where ω_i represents the weight associated with the ith priority goal. The *efficiency first* policy places higher priority on profit maximization in shift and task assignments, as shown in Equation (7a). For shift assignment, the policy emphasizes minimum labor cost over minimum number of shifts adjusted (i.e., $\omega_2 \gg \omega_3$). The focus of the station assignment is first on maximizing effective capacity rather than minimizing task assignment changes (i.e., $\omega_4 \gg \omega_5$).

$$\omega_1\left\{\sum_{t \in T} \sum_{k \in M} h_{kt}^{-}\right\} + \omega_2\left\{\sum_{i \in N} \sum_{j \in S_i} c_{ij} X_{ij}\right\} + \omega_3\left\{\sum_{i \in N} W_i\right\} + \omega_4\left\{-\sum_{i \in N} \sum_{k \in M_i} \sum_{t \in T_i^{RA}} e_{ik} U_{ikt}\right\} + \omega_5\left\{\sum_{i \in N} \sum_{k \in M_i} \sum_{t \in T_i^{RA}} (V_{ikt}^{-} + V_{ikt}^{+})\right\} \tag{6}$$

$$\omega_1 \gg \omega_2 \gg \omega_3 \gg \omega_4 \gg \omega_5 \tag{7a}$$

In contrast, the *convenience first* policy emphasizes less managerial intervention and more employee convenience, as shown in weight structure (7b) below. This policy determines shift assignments such that the number of adjusted shifts is minimized at the expense of potentially higher labor cost ($\omega_3 \gg \omega_2$). Additionally, a higher emphasis is placed on minimizing the number of worker transfers between stations than on maximizing effective capacity in station assignment ($\omega_5 \gg \omega_4$).

$$\omega_1 \gg \omega_3 \gg \omega_2 \gg \omega_5 \gg \omega_4 \tag{7b}$$

4.2. Constraints

Although the two policies have different objective functions, they have to satisfy a common set of constraints. Constraint (8) establishes staffing requirements by workstation for the rest of the day while allowing either labor shortage or surplus to occur at a workstation. Constraint (9) requires that each worker i be assigned to a shift in S_i. Note that S_i can be defined to include shifts representing all the options in Table 1, including shifts of zero length, such as canceling a shift or not asking an employee who is on call to come in. Recall that we assume an employee works only one shift per day. Constraint (10) requires that a worker be assigned to one of the workstations if the worker is scheduled to work during time period t. Note that constraints (9) and (10) ensure that no employee is assigned to work more than one task during a given time period (i.e., $\sum_{k \in M_i} U_{ikt} \le 1 \ \forall i \in N, \ t \in T_i^{RA}$). Constraints (11), (12), and (13) count adjusted shifts and worker transfers between stations. Finally, constraints (14) and (15) enforce integrality and non-negativity constraints.

$$\sum_{i \in N_k} e_{ik} U_{ikt} + h_{kt}^- - h_{kt}^+ = r_{kt} \quad \forall k \in M, \ t \in T \tag{8}$$

$$\sum_{j \in S_i} X_{ij} = 1 \quad \forall i \in N \tag{9}$$

$$\sum_{j \in S_i} a_{jt} X_{ij} - \sum_{k \in M_i} U_{ikt} = 0 \quad \forall i \in N, \ t \in T_i^{RA} \tag{10}$$

$$\sum_{j \in S_i^0} X_{ij} + W_i = 1 \quad \forall i \in N \tag{11}$$

$$U_{ik(t+1)} - U_{ikt} + V_{ikt}^- - V_{ikt}^+ = 0 \quad \forall i \in N, \ k \in M_i, \ t \in T_i^{RA} \backslash t_i^L \tag{12}$$

$$V_{ikt}^- + V_{ikt}^+ \le 1 \quad \forall i \in N, \ k \in M_i, \ t \in T_i^{RA} \backslash t_i^L \tag{13}$$

$$X_{ij} \in \{0, 1\} \quad \forall i \in N, \ j \in S_i, \ U_{ikt} \in \{0, 1\} \quad \forall i \in N, \ k \in M_i, \ t \in T_i^{RA} \tag{14}$$

$$W_i \in \{0, 1\} \quad \forall i \in N, \ V_{ikt}^-, V_{ikt}^+ \in \{0, 1\} \quad \forall i \in N, \ k \in M_i, \ t \in T_i^{RA}$$

$$h_{kt}^-, h_{kt}^+ \ge 0 \quad \forall k \in M, \ t \in T \tag{15}$$

In sum, we propose two goal programming models using the two general policy objective functions and the constraints described above. First, the *efficiency first preemptive goal program* (EFPGP) minimizes objective function (6) subject to constraints (7a) and (8) to (15). Similarly, the *convenience first preemptive goal program* (CFPGP) minimizes objective function (6) while meeting constraints (7b) and (8) to (15).

4.3. Preprocessing

The assignment formulation for the real-time adjustment decision is possible because all options in Table 1 can be included in set S_i, the alternative shift schedules to which employee i can be assigned. The set S_i allows the model formulation to handle a wide variety of different scheduling policies while still remaining quite general. To identify S_i given employee i, we need to find the employee's real-time availability window (T_i^{RA}), which is jointly determined by his/her normal availability window, maximum tolerable change in shift times, and initial work schedule. Once the time window is found, all shifts of set S are enumerated to search for those that are in the time window while satisfying shift length restrictions. For the test problems discussed in Section 6, the average size of S_i is 50. The size of S_i is a function of availability window, shift length flexibility (limitation on shift length), break time flexibility, and degree of worker tolerance (how many hours they are willing to adjust).

5. Solution Heuristics

Realistic size schedule adjustment problems have thousands of integer variables and constraints and generally require a great deal of computing time to obtain proven optimal solutions to the goal programming subproblems. Considering that real-time schedule adjustment should be carried out during a short time window, such as 15 to 30 minutes, it is essential to quickly generate new work schedules. Therefore, in this study, we introduce the following heuristic solution approaches:

LB: *Sequential Mixed Integer Programming* (*MIP*) *with Loose Bounds*

BDA: *Build-Drop-Assign with Greedy Search*

The LB approach adopts a sequential approach to the preemptive goal programming models, and accelerates the LP based branch and bound process by relaxing the optimality criteria. The BDA heuristic starts from the initial work schedule, and modifies it via heuristic search rules. Each solution approach has two variations according to its managerial goal orientations, namely, efficiency first (EF) and convenience first (CF). Therefore, a total of four heuristic solution methods are developed for evaluation, as shown in Table 2.

5.1. LB Heuristic: Sequential MIP with Loose Bounds

It is not easy to select the weight coefficients (ω_i) given the different units of measure (labor hours, cost, number of shift changes and task rotations) for the five objective functional forms in equation (6). The loose bound (LB) approach solves the efficiency first and convenience first goal programs EFPGP and CFPGP by using a sequential procedure (Hillier and Lieberman 2001). Specifically, the first priority goal is optimized given a set of constraints without consideration of the other goals. Then, a constraint stating that this optimal objective function value cannot be exceeded is added to the constraints of the second MIP problem, and the second goal is optimized. Such sequential optimization is continued until the last goal is optimized.

The LB approach successively solves the five MIP subproblems with relatively loose optimality criteria. Loose optimality criteria are achieved by objective value tolerances (percent gap = 3%, absolute gap = 0.01 for 1st subproblem, absolute gap = 0.9 for the other four subproblems). The time limit per subproblem is 5 minutes, allowing a maximum of 25 minutes for each test problem. In addition, solution time is shortened for the task assignment subproblems (4th and 5th priority goals) by fixing the shift assignment schedule as the one obtained from the 3rd subproblem. This method makes the second and third priority goal constraints redundant and eliminates all shift related variables and constraints. As a result, the task assignment subproblems become simpler to solve.

We also considered a tight bound approach (percent gap = 0.1%, absolute gap = 0.001, solution time limit = 1 hour per subproblem), and found that the quality of solution can be slightly improved, but at the cost of significantly greater computing time. For instance, using the test problems discussed in the next section (STORE A), the efficiency first approach with the above mentioned tight optimality criteria achieved a 0.4% increase in profitability but took 28.5 times longer to solve (7,950 seconds per problem) than the loose bound heuristics. Therefore, the remainder of the paper focuses on the loose bound heuristics.

Table 2 Summary of Heuristic Solution Methods

Solution approach	Goal orientation: Efficiency first (EF)	Convenience first (CF)
LB Heuristics (LB)	LB_EF	LB_CF
Build-Drop-Assign (BDA)	BDA_EF	BDA_CF

5.2. BDA Heuristic: Build-Drop-Assign with Greedy Search

The BDA heuristic, described in more detail below, modifies a given work schedule through the use of priority based selection rules, and aims to achieve a given hierarchy of managerial goals. First, the BUILD module attempts to eliminate any capacity shortages, and then the DROP module is called to reduce any unnecessary surplus labor hours. The resulting shift assignment schedule is fed to the ASSIGN module, from which the task assignment schedule is determined. The following notation is used to present the steps required for each module.

CANDIDATE: the set of workers available for shift and task assignment

BEST_SHIFTS: incumbent shift assignment schedule

BEST_ASSIGN: incumbent task assignment schedule

MIN_COST: direct labor cost associated with BEST_SHIFTS

MIN_SHORT: labor shortage achieved by BEST_SHIFTS

MIN_SURPLUS: labor surplus achieved by BEST_SHIFTS

MIN_CHANGES: shift changes required to obtain BEST_SHIFTS

BUILD

Step 1. *From the given work schedule, identify candidate workers for capacity increase and sort in ascending order of hourly wage* (*ties are broken first by overall productivity, second by the number of assignable shifts, and finally lexicographically*.)

Step 2. *Select the lowest paid worker from CANDIDATE and identify the shifts assignable to that worker. For each of these shifts, calculate the labor shortage assuming the shift is adopted but the other shifts of BEST_SHIFTS remain unchanged.*

Step 3. *Select the shift that minimizes labor shortage and update BEST_SHIFTS and CANDIDATE only if it reduces MIN_SHORT. Otherwise, remove the worker from CANDIDATE.*

Step 4. *If MIN_SHORT is zero or if CANDIDATE is empty, then terminate BUILD and go to the DROP module. Otherwise, go to STEP* 2.

DROP

Step 1. *Identify candidate workers for capacity decrease and sort in descending order of wage rate* (*ties are broken first by the number of assignable shifts, second by overall productivity, and finally lexicographically*).

STEP 2. *Select the highest paid worker from CANDIDATE and identify all shorter shifts assignable to the selected worker (including a "cancel shift" option). For each shift, compute labor cost, labor shortage, and shift changes assuming that the shorter shift is adopted and that the other shifts of BEST_SHIFTS remain unchanged.*

STEP 3. *Select the shift that minimizes labor cost and update BEST_SHIFTS and CANDIDATE only if labor cost is reduced while MIN_SHORT is not increased (In the case of BDA CF, MIN_CHANGES should not be increased). If no shift meets these conditions, remove the worker from CANDIDATE.*

STEP 4. *If MIN_SURPLUS is zero or if CANDIDATE is empty, then terminate DROP and go to the ASSIGN module. Otherwise, go to STEP 2.*

ASSIGN

The ASSIGN module sets the staffing requirements for each period equal to the number of employees scheduled in BEST_SHIFTS, which is available after a single pass of the BUILD and DROP modules. In addition, the module initializes CANDIDATE by assigning the workers only in BEST_SHIFTS to this set. The efficiency first BDA heuristic (BDA_EF) determines task assignments period by period to maximize overall productivity as follows:

STEP 1. *From the set CANDIDATE, select the workers who are available to work the earliest "unassigned" time period in BEST_SHIFTS.*

STEP 2. *Select the task with the largest capacity shortage and, from the workers identified in Step 1, assign the most productive worker to the task. Update BEST_ASSIGN. Repeat this process until every worker identified in Step 1 is assigned to a task.*

STEP 3. *If the task assignments for the last period of the day have been determined, then terminate ASSIGN. Otherwise, go to STEP 1.*

The convenience first BDA heuristic (BDA_CF) determines task assignments worker by worker, rather than period by period, to minimize task rotations as follows:

STEP 1. *From the set CANDIDATE, select the worker with the highest overall productivity.*

STEP 2. *From the worker's shift start time, assign the worker to the task that he/she performs best. If the task is fully staffed, the worker is assigned to the next best performing task. Repeat this process until the worker's shift end time. Update the sets BEST_ASSIGN and CANDIDATE.*

STEP 3. *If CANDIDATE is empty, then terminate the ASSIGN module. Otherwise, go to STEP 1.*

6. Experimental Methodology

To address the research issues posited earlier in the paper, this study conducts experiments that employ a variety of experimental factors. First, a set of test problems are designed based upon factors such as store type and workload gap. Test problems are solved using both computer based heuristics and human decision makers (experienced managers). Solutions (i.e., modified work schedules) from both the heuristics and the managers are used in a computer simulation to evaluate the impact of the modified schedules on profitability of the restaurants.

Three major performance measures are collected in the experiments: (1) percent shift changes, (2) task rotations per worker, and (3) percent Earnings after Labor (EAL) increase. Percent shift changes is a percentage computed from the ratio of the number of workers whose shifts are changed to the number of all workers available for schedule adjustments. Task rotations per worker is computed as the ratio of total number of station changeovers to the number of workers scheduled in a revised half-day schedule. Earnings after Labor (EAL), defined as sales revenue minus direct labor cost, is estimated from computer simulation. Percent EAL increase measures the percentage EAL improvement due to schedule adjustment as compared to the base case of no adjustment action (NO ACTION).

6.1. Test Problems

The test problems represent diverse schedule adjustment scenarios, generated using two different store environments (STORE A and STORE B) and various levels of workload gap (WORKLOAD GAP). The characteristics of STORE A and STORE B, representing two staff configurations, are given in Table 3. STORE B has a higher proportion of part-time workers and more action times in its work schedules. Action time is the time when a shift or break started or finished (Thompson 1996). In addition, STORE B has more scheduled workers within the adjustment horizon, and almost twice as many call-in employees available when compared to STORE A. Both stores have the same overall storewide skill ratings and hourly wage rates, and all workers are cross-trained. In addition, a shift length of at least three hours is guaranteed, while changes in start time, end time, and shift length are limited to two hours. Eight initial work schedules per store are considered. WORKLOAD GAP indicates the difference between the actual workload and the initially predicted workload, measured by the mean percent deviation. X% Gap is implemented such that the initial half-hourly sales projections are changed by X%, implying the demand change would persist throughout the remainder of the day. For each test problem, it was assumed that the real-time schedule

Table 3 Store Environments

	STORE A		STORE B	
Workforce composition	Full-time = 13		Full-time = 5	
	Part-time = 29		Part-time = 45	
	Total 42		Total 50	
	Time window	No. of workers	Time window	No. of workers
Permanent work-time availability	Opening–Closing	13	Opening–Closing	5
	Opening–16:00	12	Opening–16:00	16
	10:00–20:00	5	10:00–20:00	13
	14:00–Closing	12	14:00–Closing	16
Cross-training	All trained to three major stations and average skill rating = Good			
	Outstanding (120%), Excellent (110%), Good (100%), Need Improvement (80%)			
Wage rates	Store-wide average rate = \$6.60/hour			
	Opening and closing time premium = \$0.25–\$0.50			
	Multi-skilled and higher productivity workers are paid higher			
Shift length restriction	Minimum 3 hours			
Shift change restriction	Maximum start time change = 2 hours			
	Maximum end time change = 2 hours			
	Maximum shift length change = 2 hours			
Number of variables	$\sum_i \lvert S_i\rvert + \lvert N\rvert + 2\cdot\lvert M\rvert\cdot\lvert T\rvert + 3\lvert N\rvert\cdot\lvert M\rvert\cdot\lvert T\rvert$ (maximum)			
	STORE A = 5,057, STORE B = 6,288 (average)			
Number of constraints*	$2\cdot\lvert M\rvert + \lvert M\rvert\cdot\lvert T\rvert + \quad\cdot\lvert M\rvert\cdot\lvert T\rvert + 2\cdot\lvert M\rvert\cdot\lvert M\rvert\cdot\lvert T\rvert$ (maximum)			
	STORE A = 2,810, STORE B = 3,369 (average)			

* Excluding non-negativity and integrality constraints.

adjustment was carried out only once per day, at 1:00 PM.

It should be noted that the assumptions of a persistent demand gap and once-per-day adjustment are not necessary for the suggested goal programming formulation and heuristic solution approaches. In other words, the suggested formulation and heuristics can be utilized to make multiple adjustments under differing demand change scenarios. The primary reason for the two assumptions is to help the field managers more easily understand and analyze the test problems. In addition, this persistent demand shift is not uncommon in reality. For example, a major culprit of forecast errors in this industry is the weather, which tends to influence sales during the entire day. Moreover, managers often use simple extrapolation methods to update forecasts when they do not know the cause of demand changes.

6.2. Computer Implementation of the Heuristics

The BDA heuristic was programmed using *Microsoft EXCEL 2000 Visual Basic for Applications,* while the LB heuristics were implemented using the *ILOG CPLEX Callable Library* (Version 7.0). Since the *CPLEX Mixed Integer Optimizer* allows custom configuration of its parameters, a pilot computational study was conducted to identify parameter values that performed well for the test problems (preprocessor = on; node selection = best estimate search; variable selection = maximum infeasibility; MIP emphasis = optimality). In addition, to help find a feasible integer solution quickly, each goal programming subproblem wrote the best integer solution into a file, which was read and used as a starting integer solution by the next subproblem. All problems were solved on a Pentium III (600 Mhz) IBM PC-compatible computer.

6.3. Data Collection from Experienced Managers

To address the relative effectiveness of human decision makers versus computer based approaches, 16 experienced operations managers were recruited from the observed restaurants by different ranks (store manager, first assistant manager, second assistant manager, and master swing manager). Participating managers had an average of seven years of managerial work experience in the quick service restaurant industry. Eight of the sixteen participants were randomly assigned to STORE A, whereas the rest were assigned to solve the problems based upon STORE B characteristics. Each manager was given 15 minutes to read the task description and a short case on the store to which he or she was assigned.

A single work schedule for the day was given to the manager, who was asked to revise the work schedule one time for the remainder of that day. The daily activity report showed actual customer transactions up to 1:00 PM. For example, in the case of '+30%' demand gap, the report showed approximately a 30% increase in sales over the initial projections, and the managers were told that these data represented a 30% upward shift in customer traffic, and that such a shift would persist for the rest of day. Then, the managers were asked to estimate the new capacity requirements, and adjust the work schedule to obtain the required capacity. Fifteen minutes were given to the manager to complete each case. All managers solved the assigned problems during the given time.

6.4. The Quick Service Restaurant Simulator

Percent shift changes and task rotations per employee were collected by inspecting the work schedules revised by each solution method. Recognizing that staff adjustments occurring in practice face uncertain outcomes, computer simulation was used to determine the impact on profitability of the schedule adjustment decisions for both the heuristic and manager solutions. The *Quick Service Restaurant (QSR) Simulator* used in this study is a discrete event simulation model and was designed to imitate daily restaurant operations by incorporating opening and closing of the restaurant, customer arrival, queuing, blocking, reneging, order placement, payment, food processing, order assembly and presentation, and real-time work schedule adjustment. It was programmed in *Visual Basic* and used the support routines of Law and Kelton (2000) to control list-processing tasks and to gather statistical data.

Each simulation run corresponds to a single day's operation, and a daily work schedule is randomly selected from the eight schedules before starting each run. Stores open at 6:00 AM and close at 11:00 PM. Real-time schedule adjustment by each solution method occurs at 1:00 PM. We assume that the size of the demand gap is identified at 1:00 PM based on actual sales data collected up to that point in time. Only wages to be paid for the rest of day were computed because labor costs incurred before 1:00 PM are a sunk cost. Sales revenues were accumulated from 1:00 PM to the last customer being served. Finally, half-day Earnings after Labor was obtained by subtracting labor cost from accumulated half-day sales revenue.

The customer order process follows a non-stationary Poisson process given a series of mean half-hour customer arrival rates since empirical data corroborated an exponential interarrival time distribution. Customer order class (binomial, walk-in:drive-thru = 50%:50%) and intended purchase (multinomial, average = $3.5) are determined upon arrival to the system. Orders are routed through three serial service stations, including order placement/payment, food preparation, and order assembly and presentation, where service times are exponentially distributed. The maximum number of work-in-progress orders in the stations is limited to eight for each customer class, reflecting physical limitations of the drive-thru lane and a maximum of two work-in-progress policy at the walk-in cashier. The mean service time of a station is estimated as a function of staff size, based upon the sales-to-staff guideline and 210-second service time target. Customer impatience for delayed service is modeled by reneging. If the actual waiting time of a customer in the queue exceeds his/her randomly generated tolerable limit, then the customer reneges and leaves the queue. Otherwise, s/he places an order and waits until the order is presented. No reneging occurs after the order is placed. The tolerable waiting time distributions were estimated based upon data collected from the sixteen managers. A uniform distribution was used for drive-thru customers (Uniform(0.5 min, 5 min)) and a truncated exponential distribution was used for walk-in customers (min(1.5 min, exponential (3.72)). The estimated distributions are consistent with data reported in the literature (Hueter and Swart 1998).

7. Experiments and Analysis of Results

7.1. Comparison of Human Decision Makers and Computer Based Heuristics

To evaluate the relative performance of the proposed computer heuristics (LB_EF, and BDA_EF) and human decision-making (MGMT), 64 test problems were generated based upon eight initial work schedules per store, two store types (STORE A and STORE B), and four levels of workload gap (WORKLOAD GAP = −30%, −15%, +15%, +30%). To obtain earnings after labor, the revised schedules were then simulated under the same level of workload gaps upon which the schedules were adjusted. The performance differences between LB_EF and MGMT and BDA_EF and MGMT were tested at a 5% significance level using a repeated measures ANOVA and paired sample *t*-tests. The experimental results are similar for STORE A and STORE B, so we report only the data for STORE A, as shown in Table 4.

Research Question Q1: *Do computer-based heuristics achieve better adjustment performance than experienced managers' adjustment decisions*?

For all levels of workload gaps at both STORE A and STORE B, LB_EF made more shift changes and greater profit improvement than experienced managers (MGMT). The differences in both shift changes and profitability were statistically significant at $\alpha = 5\%$. On the other hand, the difference in shift changes between BDA_EF and MGMT is not significant at STORE A (significant at STORE B), but BDA_EF yields more profit improvement (statistically significant) than experienced managers for all levels of workload gaps at both stores. It was also observed that managers scheduled more task rotations than the heuristics. The tenable explanation is that managers had more control over task rotation in practice and, thus,

Table 4 Experienced Managers versus Computer Heuristics: STORE A

		Solution method				
	Workload gap	MGMT (A)	LB_EF (B)	BDA_EF (C)	(B)-(A)	(C)-(A)
Mean percent shift change[1]	−30%	53.2	54.4	47.0	1.2	−6.2
	−15%	33.7	48.8	25.2	15.1*	−8.5*
	+15%	27.5	56.7	44.0	29.2*	16.5*
	+30%	39.6	56.6	61.2	17.0	21.6*
	Total	38.5	54.1	44.3	15.6*	5.8
Mean task rotations[2]	−30%	1.8	1.0	1.6	−0.8*	−0.2*
	−15%	2.0	1.1	1.8	−0.9*	−0.2
	+15%	2.1	1.0	2.0	−1.1*	−0.1
	+30%	2.3	1.0	1.9	−1.3*	−0.4
	Total	2.1	1.0	1.8	−1.0*	−0.3*
Percent EAL increase versus no action[3]	−30%	5.9	7.4	6.4	1.5*	0.5*
	−15%	1.7	2.9	2.5	1.2*	0.8*
	+15%	−0.2	2.3	2.4	2.5*	2.6*
	+30%	2.8	6.6	7.1	3.8*	4.3*
	Total	2.6	4.8	4.6	2.3*	2.0*

[1] Mean percent shift change = average of the percent ratios of shift changes made by solution method over shifts available for adjustment.
[2] Mean task rotations = average number of task rotations per employee made by solution method.
[3] Percent EAL increase versus no action = (Half day EAL − Half Day $EAL_{NO\ ACTION}$)/Half Day $EAL_{NO\ ACTION}$ × 100.
* Statistically significant at $\alpha = 5\%$.

they had a tendency to emphasize assigning people with the right skills and did not spend much time attempting to reduce task rotations when solving the test problems. Based on the above findings, we may conclude that computer based heuristics resulted in greater profit improvement than the experienced managers.

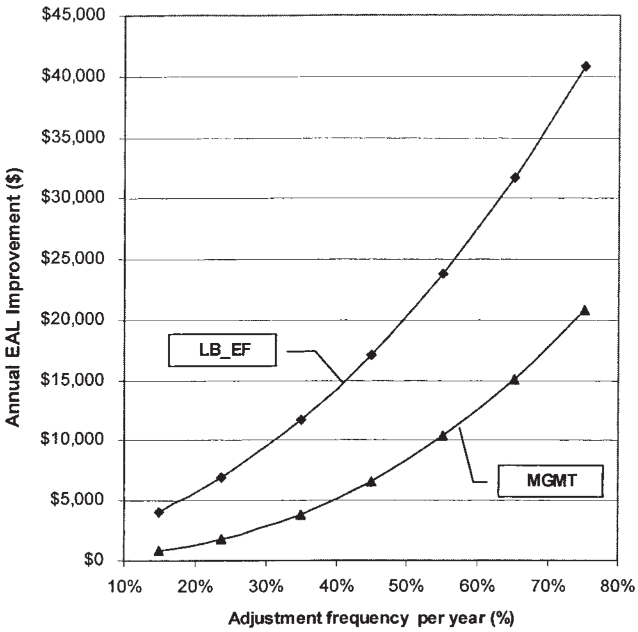
In addition, the difference in shift changes between LB_EF and BDA_EF was insignificant at both stores but, overall, LB_EF achieved slightly higher and statistically significant profit improvement than BDA_EF at both stores. Note that LB_EF consistently scheduled fewer task rotations than BDA_EF, implying that the "Assign" module of BDA_EF was relatively ineffective. Both LB and BDA heuristics proved computationally very efficient. BDA solved the test problems in less than a minute, while LB_EF took an average of 4 to 5 minutes, suggesting either of the heuristics is a viable alternative.

Research Question Q2: *When does the performance gap between experienced managers and computer based heuristics become substantial*?

First, a test problem becomes more complex when the workload gap gets bigger. Therefore, we conducted a repeated measures ANOVA to evaluate whether the large workload gap (i.e., −30 or +30%) would induce a greater performance gap between managers and computer heuristics than the small gap (i.e., −15% or +15%). The differences in shift changes and task rotations between MGMT and LB_EF were not significantly affected by the size of the workload gap. However, the profitability gap between MGMT and LB_EF was greater and statistically significant when the workload gap was larger. Second, an investigation was conducted to determine if managers adjusted work schedules differently when the workload gap was positive (i.e., +15% and +30%). The repeated measures ANOVA found results similar to those above. That is, the profitability gap between MGMT and LB_EF was greater and statistically significant when capacity was increased, although the differences in shift changes and task rotations were insignificant. In summation, these findings lead us to conclude that the performance gap between managers and heuristics is closely associated with problem complexity, measured in the size and direction of workload gap. The greater and positive workload gap increases problem complexity, which in turn makes problem-solving more challenging to managers.

Finally, it is useful to estimate the practical significance of computer based heuristics in an average restaurant. For a given schedule adjustment approach, annual EAL improvement (versus No Action) is extrapolated at a quick service restaurant with annual revenue of $2 million, and presented in Figure 2 as a function of the percentage of days where the schedule is adjusted. The frequency of schedule adjustment during a year varies widely across the observed restaurants. Given the portion of adjusted days in a year, it was assumed that 80% of them were equally divided between + 15% or −15% gap, with the remaining 20% at either +30% or −30% gap, based upon data obtained from the restaurants. When a moderate amount of adjustment occurs, say 35% to 45% annually, LB_EF can increase earnings by approximately $8,000 to

Figure 2 Annual EAL Improvement Over No Action ($)—STORE A



$12,000 per store more than what experienced managers can achieve, as estimated from Figure 2.

7.2. The Extent of Schedule Adjustment and Profitability

RESEARCH QUESTION Q3: *If worker and managerial convenience is emphasized over operational efficiency, to what extent does profitability decrease?*

To address this question, the same test problems from the prior section were solved and simulated again using convenience first solution approaches such as BDA_CF and LB_CF heuristics. The performance differences between LB_EF and LB_CF and BDA_EF and BDA_CF were tested at a significance level of 5% using a repeated measures ANOVA and paired sample *t*-tests. The experimental results are similar for STORE A and STORE B, so we report only the data for STORE A, as shown in Table 5. The efficiency first heuristics, as expected, achieved greater profit improvement at the expense of more schedule disruption. When excess capacity existed (WORKLAD GAP = −15%, −30%), the convenience first heuristics did not initiate schedule changes and resulted in a statistically significant loss of profitability (the same results as the case of No Action). When the workload gap was positive (+15%, +30%), LB_EF made more shift changes and task rotations and achieved higher profit improvement than LB_CF. All differences are significant at α = 5%. Similar conclusions can be drawn regarding BDA_EF versus BDA_CF, but the gaps between the two approaches were generally smaller than those of LB_EF and LB_CF. Although the profit gap between the efficiency first and convenience first heuristics was statistically significant, it was relatively small when the workload gap was positive. In fact, slightly higher profitability (0.3% to 1.05%) was obtained at the cost of substantially more schedule changes (14% to 38%). This finding motivates the following:

RESEARCH QUESTION Q4: *How much schedule adjustment is enough? Is there a saturation point where additional profit increase due to schedule adjustment becomes minimal?*

To address this question, consider the following constraint in addition to the efficiency first goal programming model (6), (7a) and (8) to (15):

$$\sum_{i \in N} W_i \le \delta \cdot n(N) \tag{16}$$

The parameter δ is the percent allowed schedule change, representing the proportion of the staff whose

Table 5 Efficiency First versus Convenience First Approaches: STORE A

		Solution method					
	Workload gap	LB_CF (A)	LB_EF (B)	BDA_CF (C)	BDA_EF (D)	(B)-(A)	(D)-(C)
Mean percent shift change[1]	+15%	13.3	56.7	27.5	44.0	43.4*	16.5*
	+30%	23.5	56.6	48.7	61.2	33.1*	12.5*
	Total	18.4	56.65	38.1	52.6	38.25*	14.5*
Mean task rotations[2]	+15%	0.5	1.0	1.4	2.0	0.5*	0.6*
	+30%	0.5	1.0	1.3	1.9	0.5*	0.6*
	Total	0.5	1.0	1.35	1.95	0.5*	0.6*
Percent EAL increase versus no action[3]	+15%	1.2	2.3	2.0	2.4	1.1*	0.4*
	+30%	5.6	6.6	6.9	7.1	1.0*	0.2
	Total	3.4	4.45	4.45	4.75	1.05*	0.3*

[1] Mean percent shift change = average of the percent ratios of shift changes made by solution method over shifts available for adjustment.
[2] Mean task rotations = average number of task rotations per employee made by solution method.
[3] Percent EAL increase versus no action = (Half day EAL − Half Day $\text{EAL}_{\text{NO ACTION}}$)/Half Day $\text{EAL}_{\text{NO ACTION}}$ × 100.
* Statistically significant at α = 5%.

shifts are allowed to change and n (N) represents the total number of employees available to work. Therefore, constraint (16) sets an upper bound on the percentage of shifts changed. The experiment considered the six cases of $\delta = 0\%, 20\%, 40\%, 60\%, 80\%$, and 100% (0% represents the case of no adjustment). The same test problems as in the prior section with constraint (16) added were solved using LB_EF. Figure 3 provides the profit improvement profile over the various levels of δ for workload gaps of -30%, -15%, 15%, and 30%. In every workload scenario, one observes that increasing schedule adjustment increases profitability. However, the incremental return resulting from a higher δ substantially decreases, and the profile curve starts to taper off at approximately $\delta = 60\%$. This finding confirms the existence of diminishing returns from schedule adjustment and suggests that changing more than 60% of the workers' shifts provides little additional improvement in profitability.

In sum, convenience first heuristics generate fewer schedule adjustments and less profitability given a capacity gap. Therefore, it is necessary for managers to understand the opportunity cost of fewer schedule adjustments. However, it appears that incremental returns to schedule modifications tend to decrease. Regardless of the level of capacity gaps, 50% to 60% of worker shift changes suffice to achieve the majority of profit improvement. Therefore, when a capacity shortage exists, managers who are concerned about excessive schedule adjustment may need to adjust the work schedule with convenience first heuristics, without incurring considerable profit reduction.

7.3. Impact of Demand Forecast Update Errors

In the prior evaluations it was assumed that the workload forecast is updated without error, which is rarely true in real-world operations. Because the estimation process is not perfect, some schedule adjustments may turn out to be not necessary, of the wrong magnitude, or in the wrong direction, resulting in a negative impact upon performance. Therefore, Research Question Q5 focuses on this issue: *What is the impact of demand forecast update errors on the performance of the schedule adjustment efforts?*

To address the robustness of the proposed real-time schedule adjustment approach in the presence of forecast update errors, an experiment was conducted where two workload gap factors were considered. Actual workload gap (ACTUAL GAP) represents the actual percent change in demand, while expected workload gap (EXPECTED GAP) denotes the managers' projection of the mean workload gap based on the actual observations early during the day of service. Forecast revision errors are represented by the differences between the two gaps (ACTUAL − EXPECTED) for all combinations evaluated. This experiment considered seven levels of EXPECTED GAP (-45%, -30%, -15%, 0%, $+15\%$, $+30\%$, $+45\%$), for each of which the work schedules were modified via the LB_EF heuristic. The 0% level of EXPECTED GAP corresponds to the no adjustment case. The modified work schedules were evaluated through the use of the QSR simulator under seven levels of true demand change scenarios (ACTUAL GAP = -45%, -30%, -15%, 0%, $+15\%$, $+30\%$, $+45\%$). Table 6 reports the

Figure 3 **Diminishing Returns to Schedule Adjustment**

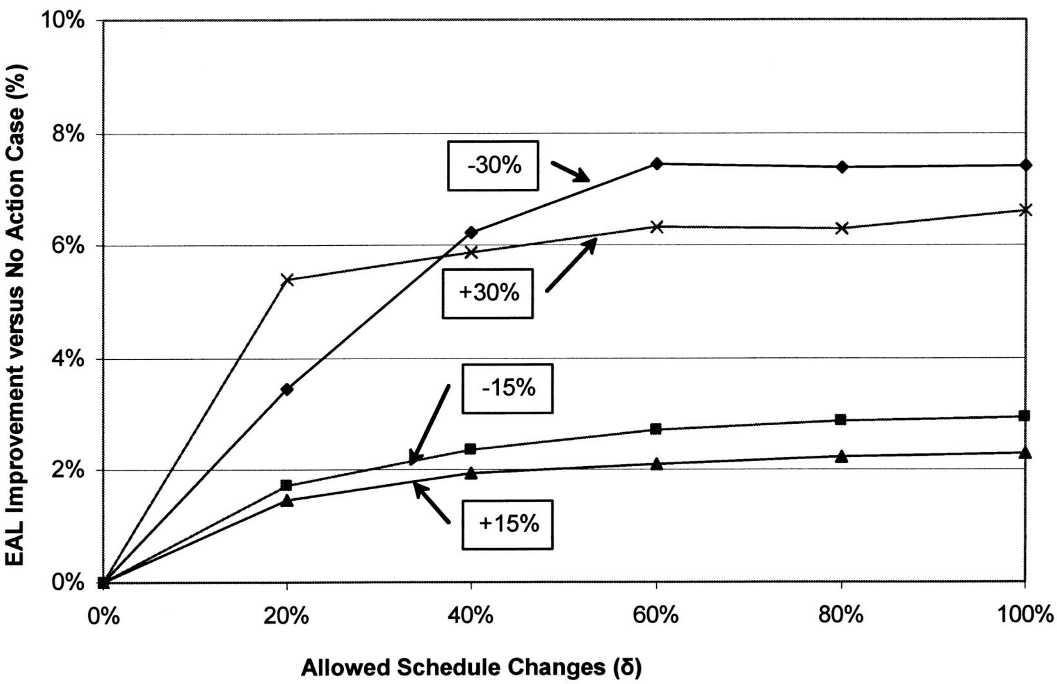


Table 6 EAL Percent Difference Between Expected and Actual[1]: STORE A

	Actual workload gap						
Expected workload gap	−45%	−30%	−15%	0%	+15%	+30%	+45%
−45%	0.0	1.5	2.2*	0.5	−6.4*	−12.6*	−17.8*
−30%	−2.3*	0.0	1.7	1.2	−4.5*	−10.3*	−15.8*
−15%	−6.9*	−3.3*	0.0	2.0	−1.0	−5.2*	−10.3*
0%	−11.6*	−6.8*	−2.7*	0.0	−2.3*	−5.8*	−10.5*
+15%	−16.7*	−10.6*	−5.5*	−0.8	0.0	−0.8	−3.4*
+30%	−22.4*	−14.9*	−8.8*	−3.3*	−1.1	0.0	−0.8
+45%	−28.9*	−19.8*	−12.9*	−6.7*	−3.5*	−1.0	0.0

[1] EAL Percent Difference $= (\text{EAL}_{\text{Expected GAP}} - \text{EAL}_{\text{Actual GAP}})/\text{EAL}_{\text{Actual GAP}} \times 100$.
* Statistically significant at $\alpha = 5\%$.
Adjustment was made using the LB_EF heuristic based on the EXPECTED GAP.

percent difference in EAL between the various combinations of expected and actual workload gaps at STORE A. The significance of the deviations are tested using ANOVA and paired sample *t*-tests ($\alpha = 5\%$). The results for STORE B were similar to those for STORE A and omitted here.

The EAL percent difference shows that in most cases the store experienced reduced profits because of forecast update error. In the case of a positive ACTUAL GAP, the highest EAL improvement was achieved when the ACTUAL GAP was equal to EXPECTED GAP (accurate forecast revision). For instance, when the actual demand gap was 15%, the maximum EAL improvement was obtained when the adjustments were made based on a 15% expected demand increase. As expected, the greater the difference between the EXPECTED and ACTUAL GAP, the larger the reduction in profitability. In the case of a negative ACTUAL GAP, under-forecasting (e.g., ACTUAL GAP = −15%, EXPECTED GAP = −45%) did not lead to large lost sales, but labor cost reduction was large enough to offset the modest change in lost sales, ultimately increasing EAL (2.2%). Such findings can be attributed to the fixed service standard policy employed in the target staffing guideline. As discussed earlier, the 210-second service standard may be optimal for the peak-level demand, but suboptimal for lower levels of customer traffic. For lower demand levels, the 210-second service standard tends to overstaff the restaurant so that a moderate level of demand surge (workload gap < +15%) can be absorbed without a real-time schedule adjustment.

With the direction of the workload change accurately estimated, reduction in profit caused by inaccurate estimation of the magnitude is relatively small and often statistically insignificant, in particular if the magnitude of forecast update error is less than 15%. However, statistically significant profit differences exist when the direction of the workload imbalance is incorrectly estimated. For example, when actual demand was greater than the initial forecast (ACTUAL GAP > 0%), significant profit loss would be experienced if managers expected a decreasing trend (EXPECTED GAP < 0%). Likewise, they would be able to increase EAL if they expect a slowdown of customer traffic (EXPECTED GAP < 0%), when actual demand proved to be lower than the initial forecast (ACTUAL GAP < 0%). In sum, as long as managers can correctly identify the *overall direction* of the demand change (e.g. 'busy' or 'slow') and the error size is not substantial (less than 30%), the real-time schedule adjustment is relatively robust to forecast update errors.

8. Discussion and Future Studies

8.1. Discussion

This paper proposed a methodology for structuring the real-time schedule adjustment decision for front-line operations using quick service restaurants as a demonstration vehicle. The methodology involved the development of a mathematical formulation of the real-time schedule adjustment decision based upon a field study, and proposed efficient heuristic solution approaches. A series of experimental studies were conducted to evaluate the relative effectiveness of the heuristics and experienced service managers, to investigate the trade-off between profit improvement and schedule stability, and to test the sensitivity of the schedule adjustment efforts when revised workload forecast estimates are inaccurate.

As a result, this study made a number of noteworthy observations. First, experienced managers' decisions were effective, but computer based heuristic approaches could provide further improvements in profitability, particularly in the case of larger or positive workload gaps. The suggested decision support approaches may not only reduce managerial time burden but also decrease inconsistency in decision-making among managers. As suggested in a study by

Bowman (1963) decades ago, establishing a more consistent process can improve performance.

Second, this study identified the diversity of goal orientation among managers and evaluates its impact on profitability. Convenience first heuristics generated fewer schedule modifications and produced less profit improvement, particularly in case of capacity surplus. When capacity shortages occur, profit reduction in return for few schedule disruptions was statistically significant, but practically minimal. It was noted that limiting the percentage of workers whose shifts are allowed to change to about 50% to 60% was sufficient to attain near maximum profit improvement. Therefore, when considering the schedule stability versus profitability tradeoff, the degree of schedule changes made may range from no adjustment up to this saturation point of the profit profile curve (Figure 3). Within this range, managers may choose one of multiple solutions generated by the heuristics. In particular, when service capacity needs expansion, the convenience first heuristics are an attractive alternative for those who are concerned about worker dissatisfaction and managerial burden. Alternatively, the efficiency first heuristics with the constraint (16) and an acceptable level of δ can generate schedules more satisfactory to practicing managers.

Third, the study confirms the value of accurate workload estimates for the real-time schedule adjustment decision and suggests the importance of determining the direction (rather than magnitude) of demand changes. To do so, managers must monitor POS sales data and actively search for the qualitative 'clues' from employees, customers, and other media within a very short time window. Thompson's (1999) business-volume-consistency chart may be a useful quantitative tool to keep track of sales during a day. To help improve predictability, managers should identify the causes of any changed conditions at the end of the day, and keep an event logbook that is routinely updated (event characteristics, impact on sales, duration, etc.). This would be a useful and quick reference data source to assist in making a no-adjustment/adjustment decision.

8.2. Recommendations for Future Studies

This study represents the first reported investigation of a mathematical model of the front-line real-time work schedule adjustment decision. While providing useful insights into this complex management task and proposing a useful methodology, the paper has several limitations, requiring further research efforts in the future. First, while the proposed goal programming model contains the primary objectives of interest to management, it does not explicitly consider profit maximization directly in its objective function, but instead pursues surrogate goals, as did the experienced decision makers. For example, the target customer service goals were developed to take into account profitability and represent a surrogate profit measure. As research studies on customer tolerance and reneging behaviors has progressed (Zohar et al. 2003), it would be interesting to explicitly model profitability by taking into account customer impatience as a function of service capacity. For example, Goodale et al. (2003) suggested a market-utility based shift scheduling formulation, which may be useful to real-time schedule adjustment research. Additionally, the back-office formulation needs to be investigated to determine its primary objectives. Second, this paper does not fully investigate the negative effect of excessive schedule adjustment. For example, frequent schedule disruption may break smooth work flow, and lower worker morale, which in turn may reduce worker productivity as well as worker's willingness to accommodate schedule changes. Furthermore, lowered morale might increase worker absenteeism or turnover so that management may have to adjust schedules more frequently. The relationship between schedule disruption and worker morale has been the topic of study in organizational behavior (O'Connor et al. 1982). Interdisciplinary research efforts are necessary to address this issue. Finally, more case studies on various high-volume, labor-intensive quick service organizations such as call centers are necessary to further understand the issues associated with real-time schedule adjustment. In particular, the call center industry has been growing fast recently and already has appropriate infrastructure and technology in place such as sophisticated data tracking/forecasting and agent scheduling software (Pinedo et al. 2000), which would facilitate the implementation of real-time schedule adjustment.

Acknowledgments

We would like to express our appreciation to Roland Long for his support during the study and acknowledge the insightful and thorough comments and suggestions of the three anonymous referees, which greatly improved the content and presentation of the paper. Daesik Hur was supported in part by CBA Summer Research Grant of Bowling Green State University.

References

Abernathy, W. J., N. Baloff, J. C. Hershey, S. Wandel. 1973. A three-stage manpower planning and scheduling model—A service sector example. *Operations Research* **21**(3) 693–711.

Andrews, B. H., S. M. Cunningham. 1995. L.L. Bean improves call-center forecasting. *Interfaces* **25**(6) 1–13.

Aykin, T. 1996. Optimal shift scheduling with multiple break windows. *Management Science* **42**(4) 591–602.

Bechtold, S. E., L. W. Jacobs. 1990. Implicit modeling of flexible break assignments in optimal shift scheduling. *Management Science* **36**(11) 1330–1351.

Berman, O., R. C. Larson. 1994. Determining optimal pool size of a temporary call-in work force. *European Journal of Operational Research* **73**(1) 55–65.

Berry, W. L., V. A. Mabert, M. Marcus. 1979. Forecasting teller window demand with exponential smoothing. *Academy of Management Journal* **22**(1) 129–137.

Bodily, S. E., J. R. Freeland. 1988. A simulation of techniques for forecasting shipments using firm orders-to-date. *Journal of Operational Research Society* **39**(9) 833–846.

Boyd, K, V. A. Mabert. 1977. A two-stage forecasting approach at Chemical Bank of New York for check processing. *Journal of Bank Research* **8**(2) 101–107.

Bowman, E. H. 1963. Consistency and optimality in managerial decision making. *Management Sciences* **9**(2) 310–321.

Brown, R. 1963. *Smoothing, forecasting, and prediction of discrete time series.* Prentice Hall, Englewood Cliffs, New Jersey.

Brusco, M. J., L. W. Jacobs. 1998. Personnel tour scheduling when starting-time restrictions are present. *Management Science* **44**(4) 534–547.

Brusco, M. J., L. W. Jacobs. 2000. Optimal models for meal-break and start-time flexibility in continuous tour scheduling. *Management Science* **46**(12) 1630–1641.

Brusco, M. J., T. R. Johns. 1998. Staffing a multi-skilled workforce with varying levels of productivity: An analysis of cross-training policies. *Decision Sciences* **29**(2) 499–515.

Campbell, G. M. 1999. Cross-utilization of workers whose capabilities differ. *Management Science* **45**(5) 722–732.

Cayirli, T., E. Veral. 2003. Outpatient scheduling in health care: A review of literature. *Production and Operations Management* **12**(4) 519–549.

Cleveland, B., J. Mayben. 1997. *Call center management: On fast forward.* Call Center Press, Annapolis, Maryland.

Easton, F. F., D. F. Rossin. 1991. Sufficient working subsets for the tour scheduling problem. *Management Science* **37**(11) 1441–1451.

Easton, F. F., D. F. Rossin, W. S. Borders. 1992. Analysis of alternative scheduling policies for hospital nurses. *Production and Operations Management* **1**(2) 159–174.

Gardner, E. S. 1983. Automatic monitoring of forecast errors. *Journal of Forecasting* **2**(1) 1–21.

Gavirneni S., R. Kapuscinski, S. Tayur. 1999. Value of information in capacitated supply chains. *Management Science* **45**(1) 16–24.

Goodale, J. C., R. Verma, M. E. Pullman. 2003. A market utility-based model for capacity scheduling in mass services. *Production and Operations Management* **12**(2) 165–186.

Green, L. V., P. J. Kolesar, J. Soares. 2003. An improved heuristic for staffing telephone call centers with limited operating hours. *Production and Operations Management* **12**(1) 46–61.

Guerrero, V. M., J. A. Elizondo. 1997. Forecasting a cumulative variable using its partially accumulated data. *Management Science* **43**(6) 879–889.

He, Q., E. M. Jewkes, J. Buzacott. 2002. The value of information used in inventory control of a make-to-order inventory-production system. *IIE Transactions* **34**(11) 999–1013.

Hill, A. V. 1983. An experimental comparison of human scheduler and heuristic algorithms for the traveling salesman problem. *Journal of Operations Management* **2**(4) 215–223.

Hill, A. V., D. A. Collier, C. M. Froehle, J. C. Goodale, R. D. Metters, R. Verma. 2002. Research opportunities in services process design. *Journal of Operations Management* **20**(2) 189–202.

Hillier, F. S., G. J. Lieberman. 2001. *Introduction to operations research.* McGraw-Hill, New York, New York.

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

Hur, D. 2002. A comparative evaluation of forecast monitoring system in service organizations. *Proceedings of Decisions Sciences Institute Conference.*

Kekre, S., T. E. Morton, T. L. Smunt. 1990. Forecasting using partially known demands. *International Journal of Forecasting* **6**(1) 115–125.

Kimes, S. E. 1989. Yield management: A tool for capacity-constrained service firms. *Journal of Operations Management* **8**(4) 348–363.

Law, A. M., W. D. Kelton. 2000. *Simulation modeling and analysis (3rd edition),* McGraw-Hill, New York, New York.

Loucks, J. S., F. R. Jacobs. 1991. Tour scheduling and task assignment of a heterogeneous work force: A heuristic approach. *Decision Sciences* **22**(4) 719–738.

Love, R. R., J. M. Hoey. 1990. Management science improves fast-food operations. *Interfaces* **20**(2) 21–29.

Mabert, V. A. 1983. Planning police communications support. *AIIE Transactions* **15**(4) 313–319.

Mabert, V. A. 1985. Short interval forecasting of emergency phone call (911) work loads. *Journal of Operations Management* **5**(3) 259–271.

Mabert, V. A. 1991. Ohio Valley National Bank. *Cases in manufacturing and service systems management.* Prentice-Hall, Inc., Englewood Cliffs, New Jersey.

Mabert, V. A. 1995. PSI Energy's call center. Unpublished case study, Indiana University.

Mabert, V. A., C. A. Watts. 1982. A simulation analysis of tour-shift construction procedures. *Management Science* **28**(5) 520–532.

Mabert, V. A., M. Showalter. 1982. Forecasting for service products in *Handbook of Forecasting (Chapter 24).* S. Wheelwright and S. Makridakis (eds.), John Wiley and Co., New York, New York.

Mabert, V. A., R. Fairhurst, M. Kilpatrick. 1979. Chemical Bank's encoder daily shift scheduling system. *Journal of Bank Research* **10**(3) 173–180.

Malhotra, M. K., L. P. Ritzman. 1994. Scheduling flexibility in the service sector: A postal case study. *Production and Operations Management* **3**(2) 100–117.

Mondschein, S. V., G. Y. Weintraub. 2003. Appointment policies in service operations: A critical analysis of the economic framework. *Production and Operations Management* **12**(2) 266–286.

Morris, J. G., M. J. Showalter. 1983. Simple approaches to shift, days-off and tour scheduling problems. *Management Science* **29**(8) 942–950.

Nakamura, N., G. Salvendy. 1988. An experimental study of human decision-making in computer-based scheduling of flexible manufacturing system. *International Journal of Production Research* **26**(4) 567–583.

O'Connor, E. J., L. H. Peters, C. J. Rudolf, A. Pooyan. 1982. Situational constraints and employee affective reactions: A partial field replication. *Group and Organization Studies* **7**(4) 418–428.

Ordonez, J. May 18, 2000. An efficiency drive: Fast-food lanes, equipped with timers, get even faster. *Wall Street Journal.*

Pinedo, M., S. Seshadri, G. Shanthikumar. 2000. Call centers in financial services: Strategies, technologies and operations in *Creating value in financial services—Strategies, operations and technologies.* E. Melnick, P.R. Nayyer, M. Pinedo, and S. Seshadri (eds.), Kluwer Academic Publishers, Boston, Massachusetts, 357–388.

Ritzman, L. P., L. J. Krajewski, M. J. Showalter. 1976. The disaggregation of aggregate manpower plans. *Management Science* **22**(11) 1204–1214.

Robinson, E. P., M. L. Swink. 1995. A comparative model of facility network design methodologies. *Journal of Operations Management* **13**(3) 169–181.

Schmenner, R. W. 1998. A worker-paced line flow process and a service factory: Burger King Restaurant, Route 37, Noblesville, Indiana in *Plant and service tours in operations management.* Prentice Hall, Englewood Cliffs, New Jersey, 140–161.

Swink, M. L, E. P. Robinson. 1997. Complexity factors and intuition-based methods for facility network design. *Decision Sciences* **28**(3) 583–614.

Thompson, G. M. 1995. Improved implicit optimal modeling of the labor shift scheduling problem. *Management Science* **41**(4) 595–607.

Thompson, G. M. 1996. Controlling action times in daily workforce schedules. *Cornell Hotel and Restaurant Administration Quarterly* **37**(2) 82–96.

Thompson, G. M. 1997. Assigning telephone operations to shifts at New Brunswick Telephone Company. *Interfaces* **27**(4) 1–11.

Thompson, G. M. 1999. Labor scheduling: Part 4. Controlling work-force schedules in real-time. *Cornell Hotel and Restaurant Administration Quarterly* **40**(3) 85–96.

Trigg, D. W. 1964. Monitoring a forecasting system. *Operational Research Quarterly* **15** 271–274.

Vakharia, A. J., H. S. Selim, R. R. Husted. 1992. Efficient scheduling of part-time employees. *Omega* **20**(2) 201–213.

Wu, L. S-Y., J. R. M. Hosking, J. M. Doll. 1992. Business planning under uncertainty: Will we attain our goal? *International Journal of Forecasting* **8**(4) 547–557.

Zohar, E., A. Mandelbaum, N. Shimkin. 2002. Adaptive behavior of impatient customers in tele-queues: Theory and empirical support. *Management Science* **48**(4) 566–583.