

COST OF FAIRNESS IN AGENT SCHEDULING FOR CONTACT CENTERS

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ABSTRACT. We study a workforce scheduling problem faced in contact centers with considerations on a fair distribution of shifts in compliance with agent preferences. We develop a mathematical model that aims to minimize operating costs associated with labor, transportation of agents, and lost customers. Aside from typical work hour-related constraints, we also try to conform with agents' preferences for shifts, as a measure of fairness. We plot the trade-off between agent satisfaction and total operating costs for Vestel, one of Turkey's largest consumer electronics companies. We present insights on the increased cost to have content and a fair environment on several agent availability scenarios.

1. Introduction. The number of interactions between customers and companies has been dramatically increasing for the last couple of decades. Many new technologies became interaction channels such as emails, chats, and even social media. As a result, traditional call centers evolved into massive multi-channel contact centers. Consequently, the workforce requirements and skillsets in contact centers have been steadily increasing [18].

Workforce management (WFM) has a large scope that typically covers forecasting workload, workforce scheduling, and tracking adherence. All these phases affect contact centers' efficiency significantly. Planners in contact centers start their WFM process according to *service level targets* considering the quality of service goals. WFM is critical because the average labor expenses of a contact center are more than 75% of total organization cost [25]. Currently, several widely-used WFM solutions exist. Based on ICMI [11], around 89% of contact centers use a WFM solution, where 61% use a complete WFM software. However, according to Creelman [5], 58% of users are not satisfied with WFM solutions. There are a number of causes for dissatisfaction, which are reported in [8, 5, 11, 29]. These studies highlight areas for improvement, including integration, employee engagement and satisfaction, fair schedules, long term agent requirements, adherence tracking, what-if analysis capabilities, and manual labor overseeing.

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One of the key problems within the broad scope of WFM, which has opportunities for improvement, is workforce scheduling. During scheduling, contact center managers seek cost-efficiency with a balanced agent assignment. A balanced assignment might involve rotating shifts within a week, which certainly provides more flexibility. However, considering operational tractability and management of transportation issues, agents are occasionally assigned the same shift during a week. That *adherence* is one of the key metrics that are followed by the company as irregularity is known to negatively affect work-life balance [9]. In shift assignment, agents are typically assigned a shift for all working days in the planning horizon. When adherence is in place, shift assignment problems can be solved in two steps: The first step is to assign shifts to agents with all financial and operational considerations, and the second step is to determine *off days* for agents. This approach is widely adopted in practice, where a *theoretical day* is solved assuming all agents are working. A theoretical day should have each time interval’s maximum call volume of the week, which can be created artificially or by choosing a *peak-demand day* that dominates other days for each interval.

With scheduling adherence in place, it becomes likely that some workers are *stuck* with shifts that are undesired, hence a need for *fairness* considerations in workforce scheduling [2, 12]. Especially in developing countries, transportation structure, work culture, and diverse technical skills make *fair schedules* a must, for employee engagement. Moreover, scheduling capabilities have to be agile in contact centers, meeting customer demand while responding to agents’ personal restrictions [24].

1.1. Our contribution. In this paper, we aim to address the problem of producing fair schedules for agents in the contact center of Vestel, which is one of the largest home and professional appliances manufacturing companies in Turkey. Exporting to over 150 countries around the world, Vestel has been the national export leader in the electronics sector for more than two decades [28]. In the contact center workforce plan we produce, our goal is to increase employee satisfaction as well as providing a cost-effective shift plan. We consider employee fairness, fair distribution of shifts, work flexibility of agents, shortages leading to loss of customer satisfaction, and transportation costs in our approach.

1.2. Related literature. Workforce scheduling is a complex problem for many industries. [3] present difficulties in workforce scheduling, especially in multi-channel environments. Service level targets, which is the key for contact centers, can be regulated by laws in some industries. For others, it is a measure of customer satisfaction, and in turn, expectation. Customer experience has a huge impact on profitability, and abandonment rates have a notable impact on customer satisfaction [17]. As a result, companies aim to improve their quality of service through better scheduling and management of the contact center workforce.

There is no standard approach for fairness modeling in workforce scheduling. Lin et al. [15] emphasize the importance of *equity* among workers, which is defined as the *average deviation from the mean number of assignments* for less preferred shifts. Blöchliger [2] presents a tutorial for modeling staff scheduling problems, where fairness is based on *deviation among assigned shift preferences*. Mohan [19] aims to maximize the *overall satisfaction* of a part-time workforce considering their restrictions and preferences. Wright and Mahar [30] suggest the use of both constraining and penalizing fairness measures. That is, they define both an upper bound for the number of undesired shifts assigned to each worker and an objective term that

minimizes the undesirability of assigned shifts. Jütte et al. [12] aim to *balance distribution of unpopular work* for railway crews. Unfair schedules reduce employee engagement, low engagement causes employee turnover, and turnover brings extra operational cost on companies [29]. On the other hand, creating fair schedules in a constricted environment is a challenging process. The trade-off between efficiency and agent satisfaction is the main motivation behind the survey in [29].

There are several verticals in workforce scheduling. Ernst et al. [6] present an entire breakdown of management of operations related to workforce scheduling and rostering in different industries. Van den Bergh et al. [26] present a broad survey on workforce scheduling settings, solution approaches, and considerations in workforce scheduling. Rocha et al. [22] propose a model to create cyclic schedules for employees, which is beneficial in ensuring regularity/adherence. Örmeci et al. [20] incorporate transportation planning into agent scheduling. Liu et al. [16] consider uncertain motivation effects based on processing times to provide a stochastic optimization approach.

A number of different solution approaches have been proposed for workforce scheduling. Castillo et al. [4] propose a heuristic approach to generate schedules by deciding on the start times of shifts. They use discrete-event simulation in order to evaluate these schedules, generating demand based on historical data from a real call center. The demand pattern they adopt is similar to the demand data that we present in the next section. Aligned with our assumptions, they do not optimize the operational decisions, such as break times, and emphasize the necessity of including workforce satisfaction to their model as a future direction. Lin et al. [15] work on managing workforce for the customer services department of a mobile communications company. They propose a complete decision support system with demand forecasting, a heuristic to schedule single-shift duties that satisfy day-off restrictions, and a mixed integer formulation to determine daily staff assignments to shifts. Despite being in a different industry, Wright and Mahar [30] formulate a bi-criteria integer scheduling model that minimizes cost and undesirability of assigned shifts for workers (nurses). Van Den Eeckhout et al. [27] present an exact approach to solve staffing problem with integrated demand that is generated from a project scheduling problem. Kletzander and Musliu [13] propose a general framework that can solve workforce scheduling problems with different constraints in a reasonable time.

We seek a fair and consistent shift assignment while minimizing the sum of the employee, understaffing, and transportation costs. We measure satisfaction by the desirability of assigned shifts, similar to [30] and [12]. We emphasize fairness by setting a lower bound on satisfaction, individually or collectively. To the best of our knowledge, no study in the literature considers both *shift preferences* for agents and *transportation costs* under *scheduling adherence*, which are pivotal aspects for Vestel, the consumer electronics company we consider.

1.3. Organization. The remainder of this paper is organized as follows. We elaborate on real-life challenges and present our problem with a mathematical formulation in Section 2. We present numerical results on problems motivated by real-life instances from the consumer electronics company in Section 3. We conclude and propose directions for future research in Section 4.

2. Problem description and mathematical formulation. In this section, we present the workflow for the company, shift assignment considerations, and our approach in addressing the inadequacies through a mathematical optimization model. Our model aims to minimize the operational costs such as agent costs, extra hours due to extended shifts, transportation costs, while avoiding understaffing as much as possible, subject to demand rotation, work hour, and agent satisfaction restrictions. Now we explain the problem and inputs for the mathematical model.

2.1. Workflow in contact centers and agent scheduling inputs. In the flow of operations, depending on the industry, there are different procedures that feed data to the models that manage the workforce [6]. In contact centers, *call forecasting* and *staffing* phases precede scheduling. Call forecasting is the phase in which demand volumes are estimated for intraday, days, and weeks. Staffing refers to the calculation of the number of agents that are required to provide a certain service level based on the demand volume from forecasts. Contact centers commonly use simple Erlang-C models or evaluated versions of the Erlang-C models to calculate staff requirements [14]. Thus, one of our inputs, demand, refers to the output of call forecasting and staffing in terms of the number of agents needed for each interval. Table 1 presents the inputs and outputs for this model.

TABLE 1. Model Inputs and Outputs.

Inputs	Outputs
Demand for a Theoretical Day	Number of Agents in Each Shift
Scheduling/Planning Horizon	Total Employee Cost
Time Intervals and Possible Shifts	Total Shuttle Cost
Break Time Distribution Rules	Understaffed Hours
Shuttle (Transportation) Costs	Agent-Shift Assignments
Agent Wages and Undesirability Cost of Shifts	Total Satisfaction Score
Cost of Understaffing	Fairness Score Distribution
Shift Preference Scores of Agents	
Fairness Bounds	

Forecasted call volumes of a typical high-season week with the intraday distribution are given in Figure 1. We see that intraday distributions have very similar patterns, with a couple of exceptions. From the historical data of the contact center, we also see that national holidays have similar patterns and volumes of Sunday's. Although the working days and holidays have different patterns, we see peak intervals of each day are around noon, after which call volumes gradually decrease. We observe Monday, as the peak-demand day, have larger call volumes in all intervals and subsumes all other days. Therefore, we suggest using Monday as a theoretical day. If a plan suffices to cover Monday demand in a cyclic fashion, it guarantees the desired service level for the company we consider.

Regarding the *planning horizon*, it should be noted that our aim is to provide an agile solution at the operational level. Seasonal factors, vacation habits, and even student ratio of employees dramatically affect turnover ratio and assignment restrictions. Our model can dynamically be adjusted to reflect changes in external factors, yet it can also be used for longer term aggregate planning to shed light on strategic decisions. Below is a real-life scenario observed by the first author during his tenure at Vestel that motivates our model:

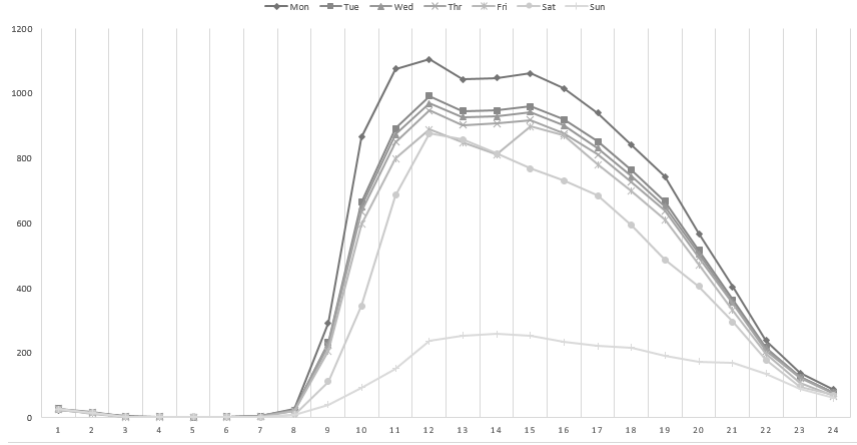


FIGURE 1. Forecasted Intraday Call Volumes

Call volumes are expected to increase mid-summer. To fill the gap between actual and needed agents, the company seeks mass recruitment just before the high-demand season. Meanwhile, student applications tend to increase before summer. The company usually ends up hiring more students with time restrictions and inexperienced agents. The regular workforce demands more vacations during the summer. Consequently, average service times increase drastically. Scheduling efficiency drops because of more restrictive working hours. Unscheduled vacation requests accumulate, forcing poor schedules, which lead to decreases in employee satisfaction. At the end of summer, while demand is still relatively high, students start leaving their jobs. Even regular workers tend to resign due to dissatisfaction, which creates a new challenge amid current employee fairness issues at that point.

To sum up, recruiting policy and assignment restrictions have significant impacts on long term planning, for which administration demands risk/crisis management plans. The model we propose in this study can be used for varying lengths of planning horizons to analyze the long term effects of solutions.

Next, we explain inputs related to shifts, such as possible shift structures, break time distribution rules, shuttle costs, and general undesirability measures for shifts. Table 2 presents a sample shift assignment for a day with *hourly* average number of effective agents. The shift structures, working time intervals for these 17 shifts, cost to denote general undesirability of these shifts can be read from Table 2. We assume the length of a time interval is one hour. A shift can start at the top of certain hours and lasts either 8 hours or 10 hours, except those starting after 14:30, which can last only 8 hours due to business rules. The undesirability cost is not only the cost for longer working hours but also a reflection of the shift inefficiency, based on experience. We also use this cost to penalize certain shifts in case the management does not prefer them during a planning horizon for any reason.

Agent requirements from call forecasting and staffing are shown at the bottom of the table together with average arrival and departure cost per agent for each time interval. These transportation costs are aggregated based on the shuttle traffic in the

company, hence a higher cost for less popular hours and directions. In estimating the shuttle cost of agents, we use \$2/person for common hours of arrival and departure, and \$6 to \$8 person for off-hours, depending on traffic. Contact centers provide a contractual taxi, a passenger van, or a large bus to pick up employees on a route, and each type of vehicle has a different cost. Aside from agents, in a contact center operation, there are many other types of employees: There is the administrative staff and office cleaners, who have a rigid shift structure using either 8:00am-4:00pm or 8:00am-6:00pm. Janitors, security staff cover 24 hours with a 3 shift structure, starting in the morning, early evening, or midnight. In our case study, the contact center shares the same campus with the production facilities. Therefore, the staff from around the factory, as well as a large body of production line workers in 3 shifts, share the same shuttles, hence have a huge impact on transportation costs. One of the limitations of our approach is that we consider average per-person cost, neglect distance and mode of transportation. However, it should be noted that this problem is expected to be solved separately at the operational level.

TABLE 2. Inputs and a Sample Assignment

			Working Time Intervals (1 Hour Interval)																							Undesirable Shift Cost		
Shifts			0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22		23	
#	Start Time	End Time	Number of Agents																									
1	08:00	16:00									46.0	38.2	38.2	30.8	30.8	38.2	38.2	46.0										\$0.00
2	08:00	18:00									7.0	5.8	5.8	5.8	4.7	4.7	5.8	5.8	5.8	7.0								\$10.00
3	09:00	17:00									0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0									\$0.00
4	09:00	19:00									12.6	10.5	10.5	10.5	8.5	8.5	10.5	10.5	10.5	12.6								\$10.00
5	10:00	18:00									0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0									\$0.00
6	10:00	20:00									13.7	11.4	11.4	11.4	9.2	9.2	11.4	11.4	11.4	13.7								\$10.00
7	11:00	19:00									0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0									\$0.00
8	11:00	21:00									11.2	9.3	9.3	9.3	7.5	7.5	9.3	9.3	9.3	11.2								\$10.00
9	12:00	20:00									0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		\$0.00
10	12:00	22:00									0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		\$10.00
11	13:00	21:00									0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		\$0.00
12	13:00	23:00									0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	\$10.00
13	14:00	22:00									0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		\$0.00
14	14:00	00:00									0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	\$0.00
15	15:00	23:00									0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	\$0.00
16	16:00	00:00									33.0	27.4	27.4	22.1	22.1	27.4	27.4	22.1	22.1	27.4	27.4	33.0						\$0.00
17	00:00	08:00	2.0	1.7	1.7	1.3	1.3	1.7	1.7	2.0																		\$0.00
Total Assigned Agents			2.0	1.7	1.7	1.3	1.3	1.7	1.7	2.0	53.0	56.6	68.2	69.7	66.6	80.0	77.5	85.6	73.5	70.9	67.3	51.8	41.3	27.4	27.4	33.0		
Required Agents			4.0	3.0	1.7	1.7	1.3	1.3	1.8	4.0	37.2	75.6	84.0	86.4	82.8	82.8	80.0	86.0	83.0	77.0	68.4	52.8	46.8	28.8	20.4	13.2		
Avg Arrival Cost			\$2	\$8	\$8	\$8	\$8	\$8	\$8	\$2	\$6	\$6	\$6	\$6	\$6	\$6	\$6	\$6	\$2	\$6	\$6	\$6	\$6	\$8	\$8	\$8		
Avg Departure Cost			\$2	\$8	\$8	\$8	\$8	\$8	\$8	\$2	\$6	\$6	\$6	\$6	\$6	\$6	\$6	\$6	\$2	\$6	\$6	\$6	\$6	\$8	\$8	\$8		

The break time usages is another key input that gets updated dynamically depending on the effective agent statistics in Table 2. The effectiveness expected for each shift is shown using bars in Table 3. For instance, towards the middle of each shift, more agents take lunch breaks, decreasing effectiveness down to 60-67%. As a rule of thumb, agents do not use breaks in their first or last hour of their shift. This also explains why the first hour effective agent count equals the total number of agents working in each shift in Table 2. The numbers that follow are less than or equal to that of the first hour, mostly due to break time usage. For example, in row 17 of Table 3, i.e., the 12:00am-8:00am shift, we show a bar to indicate 83.3%. That implies, usually each agent takes a break of 10 minutes in the second hour, $50/60 \approx 83.3\%$. In the solution provided in Table 2, there are two agents, each of which uses 10-minute breaks during their second hour. It is likely that they both work together for 40 minutes, one is off for 10 minutes, and the other one is off for 10 minutes. Therefore, the number of active agents show the rate of total agent minutes used divided by total minutes, which is $2 \times 50/60 = 1.7$.

Some companies tend to set strict times for lunch and mini-breaks. On the other hand, some companies restrict the total hours that an agent can be off duty. In our study, the company uses a hybrid approach; thus we project average effects of break rules using Table 3 to address the uncertainty.

TABLE 3. Break Time (Effectiveness) Factor

			Working Time Intervals (1 Hour Interval)																								
Shifts			0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	
#	Start Time	End Time	Concurrent Agent Distributions																								
1	08:00	16:00																									
2	08:00	18:00																									
3	09:00	17:00																									
4	09:00	19:00																									
5	10:00	18:00																									
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12	13:00	23:00																									
13	14:00	22:00																									
14	14:00	00:00																									
15	15:00	23:00																									
16	16:00	00:00																									
17	00:00	08:00																									

Another input to our model is the weekly work hour limit for each agent. In the company we consider, the upper bound on *legal working hours* is 45 hours, which implies an assignment of at most 50 hours with breaks per week for each agent. Thus, 8-hour shifts work for six days and use one day-off, while 10-hour shifts work for five days and take two days off.

Figure 2 shows the required number of agents and the number of agents in each shift for a sample day. Restrictions on contact centers preclude a perfect alignment of the required and working number of agents. As a result of this, overstaffing and understaffing occur. We consider *understaffing* as the cost of poor customer experience as a result of waiting time in line. However, instead of using a complicated function of waiting times in queue [7], we evaluate a Taguchi loss function of lost demand [23]. Most contact centers strategically set a service level and track their shortage from their target service level. Therefore, we assume the required number of agents in Table 2 is demanded for the desired service level.

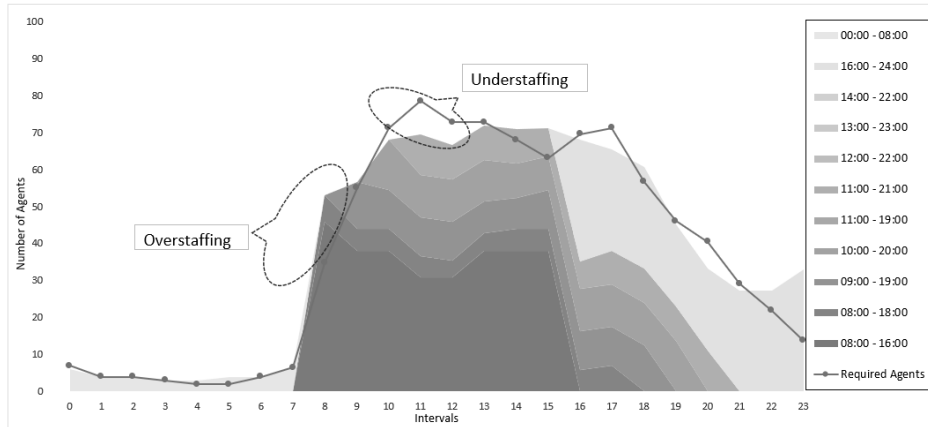


FIGURE 2. Required and Working Agents

The staffing calculation depends on a nonlinear Erlang-C function. When understaffing levels increase in an interval, waiting times increase exponentially in queues. Thus, overstaffing and understaffing calculations are also nonlinear. [21]

propose a 2-phase solution to staff scheduling in a retail shop. The second phase of this study tries to balance and improve understaffing and overstaffing occurrence in the weekly schedule with an iterative algorithm. In our mathematical model, we propose a simple formulation that penalizes the square of understaffing to demand ratio.

One of the unique considerations of our study is agent preferences. Agents work multiple days a week. A full-time agent is expected to work some hours, which is between the business' upper and lower weekly working time limits. In this model, we assume an agent works the same shift across a week. However, in the following week, agents can work another shift. This is referred to as *shift rotations*. In this model, our aim is to balance shift rotations for all agents from an employee satisfaction perspective. This way, we create shift rotations in which agents are expected to be more satisfied. From an employee standpoint, each shift has a different level of desirability. We categorize these in five priority levels. In our solution, we assume that these preferences increase exponentially. That is, a preferred shift has twice the preference score of the next preferred shift. Table 4 indicates the fairness scores of agents and priority degrees.

TABLE 4. Preference Scoring Sample

Preference Priority	Preference Score
First	8
Second	4
Third	2
Fourth	1
Not preferred	0

We collect the preferences of all agents with a survey to create scores in the model. They are allowed to prefer four shifts only and rank them. We observe that, while most agents prefer morning shifts, which are typical working shifts in any industry, there are some who prefer other shifts as well. Table 5 demonstrates a small section of the sample preference matrix for nine agents and eight shifts. In this table, agent 1 prefers shift 1, shift 2, shift 8 and shift 5, respectively; agent 1 has no interest in other shifts.

TABLE 5. Preference Matrix Sample

agents	shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 7	shift 8
agent 1	8	4	0	0	1	0	0	2
agent 2	8	4	0	0	0	0	2	1
agent 3	4	8	0	2	0	0	0	1
agent 4	4	2	0	1	0	0	8	0
agent 5	4	2	0	1	0	8	0	0
agent 6	2	1	8	4	0	0	0	0
agent 7	1	2	0	4	8	0	0	0
agent 8	0	0	1	2	4	0	0	8
agent 9	0	8	0	4	2	0	0	1

Next, we present our mixed integer nonlinear programming formulation that takes these inputs, and minimizes operational costs and provides a level of service for customers, while considering agent rotations and preferences.

2.2. Mathematical Model. According to the rules and objectives described above, we propose a mathematical model to solve the aforementioned issues. We present the list of parameters and variables in this model in Table 6 and Table 7, respectively.

TABLE 6. Model Parameters

Description	Parameter
Week Index in Planning Horizon	w
Shift Index	s
Time Interval Index in a Day	t
Agent Index	i
Individual Fairness Lower Limit	h
Overall Fairness Lower Limit	H
Weekly Cost Per Agent	c^{agent}
Cost Estimation for 1% of Understaffing	$c^{\text{understaff}}$
Cost of Shift Undesirability	$c_s^{\text{undesirable}}$
Average Per Person Arrival Shuttle Cost for Intervals	c_t^v
Average Per Person Departure Shuttle Cost for Intervals	c_t^v
Break Time Factor (Effectiveness) of Agent in Intervals of Shift	a_t^s
Demand in Intervals of Weeks	d_t^w
Agents' Preference Value of Shifts	p_{is}
Starting Interval Binary of Shifts	s_t^s
Ending Interval Binary of Shifts	e_t^s

TABLE 7. Decision Variables

Description	Notation
Binary Variable of Agents' Shift in Weeks	Y_{isw}
Individual Average Fairness Score Auxiliary Variable of Working Weeks	A_{iw}
Individual Average Weekly Fairness Score Variable	Z_i
Number of Agents Variable in Shifts of Weeks	X_s^w
Understaffed Level Variable in Intervals	U_t^w

Given the set of available shifts, break time distribution, agents and wages, demand distribution on a theoretical day, shift preferences, average shuttle and employee costs, the agent assignment problem decides which shifts to be used and which agents to be assigned to these shifts in order to minimize the total cost and maximize fairness while covering demands along consecutive weeks. Demand forecasts might differ from one week to another, however, we assume that shift assignments do not change within the weeks. Furthermore, we assume theoretical days are input for each week that subsumes other days. In the light of these, operational problems such as daily shift assignments, and management of deviations from the plan are out of our scope. We do not provide the assignment of day-offs as a part of the

solution. Since the solution covers theoretical days and theoretical days are potential bottlenecks of working weeks, day-offs can be assigned using the output of this model. In most cases, excluding the day horizon from the problem does not affect the efficiency of the solution. For only occasional call distribution scenarios, where demand is distributed somewhat evenly among the days, theoretical day solution may not be sufficient to solve the day-off assignment problem. For such occasions, a dummy volume can be added to the original theoretical day demand to address this issue.

2.2.1. Objective Definitions. The objective function consists of operational costs that are realized. However, different considerations are also included (e.g., understaffing). Thus we use a goal programming approach with a weighted sum of different objectives. In its basic form, the objective function is

$$\min C^{\text{employee}}(\mathbf{X}) + C^{\text{shuttle}}(\mathbf{X}) + C^{\text{understaff}}(\mathbf{X}) \quad (1)$$

Next, we elaborate on the components of this function. Let W be the set of weeks under consideration, indexed by w , S be the set of different shift types, indexed by s , and T be the set of time intervals in a day, indexed by t . Each shift type $s \in S$ has a number of X_s^w working agents for each week $w \in W$.

Each agent costs c^{agent} weekly to the company, i.e., wages. Beyond this, shift s have $c_s^{\text{undesirable}}$ cost parameters. Each $c_s^{\text{undesirable}}$ description reflects extra hours cost or inefficiency from the perspective of the management for that specific shift s . Therefore, the cost associated with employees is

$$C^{\text{employee}}(\mathbf{X}) = \sum_{w \in W} \sum_{s \in S} (c^{\text{agent}} + c_s^{\text{undesirable}}) X_s^w. \quad (2)$$

A shift starts where s_t^s binary is equal to 1 and ends where e_t^s binary is equal to 1, at which point there also is a shuttle requirement for agent transportation. We define c_t^v cost for arrival shuttles as average per person cost and $c_t'^v$ cost for departure shuttles as average per person cost. Cost of shuttles differ depending on time and direction of transport. We assume shuttle costs as average per person prices for any number of agents. Thus, we consider X_s^w , the number of agents in calculating shuttle costs. We describe arrival and departure shuttle costs function as

$$C^{\text{shuttle}}(\mathbf{X}) = \sum_{w \in W} \sum_{t \in T} \sum_{s \in S} X_s^w s_t^s c_t^v + \sum_{w \in W} \sum_{t \in T} \sum_{s \in S} X_s^w e_t^s c_t'^v. \quad (3)$$

Agents cost and shuttle cost are the all operational costs of the contact center which we deal with. Beyond these costs, there are understaffing and overstaffing situations to be minimized. Overstaffing creates unnecessary workforce in terms of demand covering. C^{employee} is enough to prevent overstaffing. However, understaffing situations create cost to company because of dropping customer satisfaction. Model aims to cover all d_t^w demand with a U_t^w understaffing deficiency. This deficiency prevents infeasibility and redundant expenses in interval $t \in T$ of week $w \in W$. We define $c^{\text{understaff}}$ as cost coefficient for unsatisfied service levels. Understaffing effects queue lengths gradually. When demand is low, even a small understaffing affects the waiting time of customers in queue significantly. Thus, we use the understaffing to demand ratio in our formulation. To reflect these gradually growing effects of understaffing to demand ratio, we simply penalize the square of that ratio. The

final cost component in our objective function is

$$C^{\text{understaff}}(\mathbf{X}) = \sum_{w \in W} \sum_{t \in T} c^{\text{understaff}} (100U_t^w / d_t^w)^2. \quad (4)$$

Note that this is the only nonlinear term in the proposed formulation. Because this is a convex function, a commercial solver can handle the minimization of this function efficiently.

2.2.2. *Constraints.* Next, we explain the constraints that are considered in our mathematical model.

$$\sum_{s \in S} a_t^s X_s^w + U_t^w \geq d_t^w \quad \forall t \in T, w \in W \quad (5)$$

$$\sum_{w \in W} \sum_{s \in S} p_{is} Y_{isw} = \sum_{w \in W} A_{iw} \quad \forall i \in I \quad (6)$$

$$Z_i - M(1 - \sum_{s \in S} Y_{isw}) \leq A_{iw} \leq M \sum_{s \in S} Y_{isw} \quad \forall i \in I, w \in W \quad (7)$$

$$A_{iw} \leq Z_i \quad \forall i \in I, w \in W \quad (8)$$

$$\sum_{s \in S} Y_{isw} \leq 1 \quad \forall i \in I, w \in W \quad (9)$$

$$\sum_{i \in I} Y_{isw} = X_s^w \quad \forall s \in S, w \in W \quad (10)$$

$$Y_{isw} + Y_{ik(w+1)} \leq 1 \quad \forall i \in I, (s, k) \in \Omega, w \in W, w+1 \in W \quad (11)$$

$$\begin{aligned} Y_{isw} &\in \{0, 1\} \quad \forall i \in I, s \in S, w \in W \\ X_s^w &\geq 0 \quad \forall s \in S, w \in W \\ A_{iw} &\geq 0 \quad \forall i \in I, w \in W \\ U_t^w &\geq 0 \quad \forall t \in T, w \in W \end{aligned} \quad (12)$$

Each agent $i \in I$ works in one shift $s \in S$. Y_{isw} is decision variable for shift assignment. When agent i works in shift s within week w , Y_{isw} equals to 1 and otherwise equals to 0. The required number of agents for each interval is satisfied in constraints (5). Constraints (6) are the calculation of weekly individual fairness scores of all agents from their preference scores of working shifts. (7) and (8) calculate Z_i average fairness scores of agents in their working weeks and shifts. Each agent i has a preference value for each shift s . p_{is} indicates these preference values of all agent for all shifts. When agent i is assigned to shift s , agent also gets an average Z_i fairness score from multiplication of Y_{isw} assignment and p_{is} preference for all weeks that agent assigned to any shift. (9) ensures that any agent can only work in one shift at most. (10) ensures each assigned agent contributes as a worker to X_s^w . In (11), we define workable shifts in consecutive weeks. Next, we explain the set definition used for this constraint. (12) includes nonnegativity or binary requirements for decision variables.

In shift transitions across the weeks, agents must rest at least 11 hours according to labor legislation. Thus, after working in some of the shifts, the agents are not allowed to work in particular shifts. For example, when an agent works for shift 16, which ends midnight, that agent cannot work for shifts that start earlier than 11:00am (e.g., shifts 1, 2, 3, 4, 5, and 6) for the following week. In order to define workable shifts in consecutive weeks, we define set Ω that consists of pairs of shifts,

where the first shift cannot be followed by the second shift in the following week. Based on Table 2,

$$\Omega = \{(16, 1), (16, 2), (16, 3), (16, 4), (16, 5), (16, 6), (15, 1), (15, 2), (15, 3), (15, 4), (14, 1), (14, 2), (14, 3), (14, 4), (14, 5), (14, 6), (13, 1), (13, 2), (12, 1), (12, 2), (12, 3), (12, 4), (10, 1), (10, 2)\}$$

2.2.3. Additional Constraints on Fairness. We additionally have fairness goals that are competing against the minimum cost goal described in the objective function. We define the following two approaches in modeling fairness goals:

- P1: has minimum individual fairness levels for each agent,
- P2: has minimum overall fairness levels for all agents.

P1 (Individual Fairness Level): We want fair schedules for all agents. Therefore, we do not want Z_i , individual fairness, to fall under level of h for any agent at the end of the planning horizon. Therefore, we add the following constraint for P1:

$$Z_i \geq h \quad \forall i \in I \quad (13)$$

P2 (Overall Fairness Level): The second approach is to collectively increase fairness. We do not want overall fairness level to fall under a level of H . We add the following constraint for P2:

$$\sum_{i \in I} Z_i \geq H \quad (14)$$

3. Results. In this section, we present the instances we use in our model. For different problem sets, we examine the outcomes of all problems and analyze these results to provide further insights. Next, we provide a brief summary of input data¹.

3.1. Data Instance from Vestel Contact Center.

Demand: We solve this model for a real call volume sample from Vestel. We use only peak day volumes for each week. Demands are processed weekly and interval based, as shown in Figure 3. Demand volume increases from week 1 to week 4 due to seasonality at the beginning of summer.

Shifts: We describe 24 intervals and 17 possible shifts for a day. Table 8 indicates all shifts with break time factors for each hour and undesirability cost. a_t^s break time factors are the multiplier of the concurrent workforce in intervals. When an agent's shift is off, a_t^s is equal to zero for these off intervals. We define undesirability cost as a multiplier of the working agent in the same shift. We only set undesirability costs for longer shifts where agents get extended time pay.

Shuttles: In our model, the employer provides shuttles for all agents. If at least one agent starts or ends a shift in one hour interval, there must be a shuttle assigned. Average shuttle costs vary for intervals within a day. Table 9 indicates average arrival and departure shuttle costs per person for each interval. As mentioned before, the cost is lower for intervals that are used by other employees.

¹All the input presented in this paper, except cost figures, are based on real data from Contact Center Operations of Vestel. Cost figures are adjusted to reflect the overall behavior, but are multiplied by constants to protect privacy.

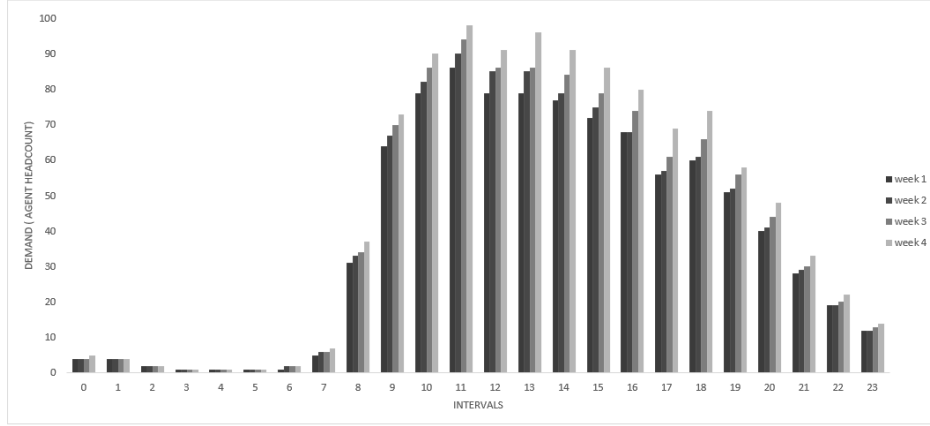


FIGURE 3. Demand Volumes

TABLE 8. Shift Descriptions

	Working Time Intervals (1 Hour Interval)																							Undesirable Shift Cost	
Shifts	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22		23
#	Break Time Factors of Intervals																								
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.67	0.67	0.83	0.83	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	\$0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.83	0.83	0.83	0.67	0.67	0.83	0.83	0.83	1.00	0.00	0.00	0.00	0.00	0.00	\$10.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.67	0.67	0.83	0.83	1.00	0.00	0.00	0.00	0.00	0.00	0.00	\$0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.83	0.67	0.67	0.83	0.83	0.83	1.00	0.00	0.00	0.00	0.00	\$10.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.67	0.67	0.83	0.83	1.00	0.00	0.00	0.00	0.00	0.00	\$0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.83	0.67	0.67	0.83	0.83	0.83	1.00	0.00	0.00	0.00	\$10.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.67	0.67	0.83	0.83	1.00	0.00	0.00	0.00	0.00	\$0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.83	0.67	0.67	0.83	0.83	0.83	1.00	0.00	0.00	\$10.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.67	0.67	0.83	0.83	1.00	0.00	0.00	0.00	\$0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.67	0.67	0.83	0.83	0.83	1.00	0.00	\$10.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.67	0.67	0.83	0.83	1.00	0.00	0.00	\$0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.83	0.67	0.67	0.83	0.83	1.00	\$10.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.67	0.67	0.83	0.83	1.00	0.00	\$0.00
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.83	0.67	0.67	0.83	0.83	1.00	\$0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.67	0.67	0.83	0.83	1.00	\$0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.83	0.83	0.67	0.67	0.83	0.83	\$0.00
17	1.00	0.83	0.83	0.67	0.67	0.83	0.83	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	\$0.00

TABLE 9. Shuttle Costs

Intervals	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Avg Arrival Cost	\$2	\$8	\$8	\$8	\$8	\$8	\$8	\$8	\$2	\$6	\$6	\$6	\$6	\$6	\$6	\$6	\$2	\$6	\$6	\$6	\$6	\$8	\$8	\$8
Avg Departure Cost	\$2	\$8	\$8	\$8	\$8	\$8	\$8	\$8	\$2	\$6	\$6	\$6	\$6	\$6	\$6	\$6	\$2	\$6	\$2	\$6	\$2	\$8	\$8	\$8

Agents: We assume that the company can employ at most 150 agents to handle all call demands. All agents do not necessarily work all weeks. Contact centers hire employees gradually when requirements increase from week to week. On the other hand, we observe that employers use excess workforce on other tasks, hence no penalty incurred for overstaffing aside from the regular agent cost.

Preference Scores: Each agent specifies four shifts out of 17 as preferred shifts. We project real preference orders of an agent group of the consumer electronics manufacturer. We assign scores of 8, 4, 2, 1 for preferred shifts of each agent. Average preference scores for each shift are shown in Figure 4. Most agents prefer early shifts (Shift 1 and Shift 2), which start at 8:00am. Some evening and night shifts (Shift 16 and Shift 17) are also relatively popular shifts among agents.

Other parameter values used in our numerical study are shown in Table 10.

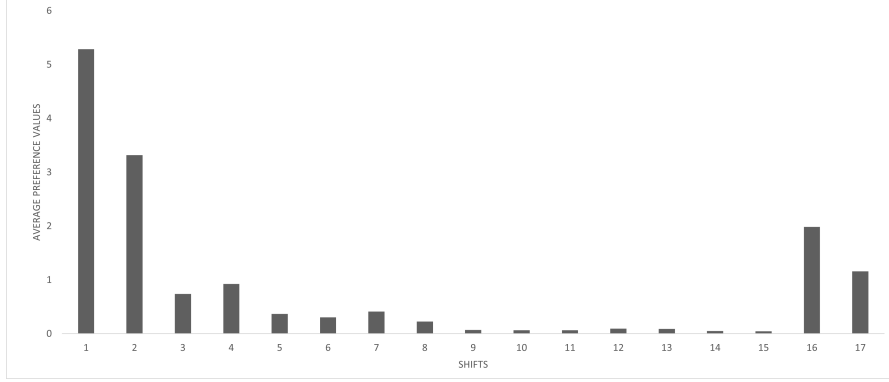


FIGURE 4. Preference Scores

TABLE 10. Parameter Values

Description	Parameter	Value
Number of Weeks	$ W $	4
Number of Shifts	$ S $	17
Number of Time Intervals	$ T $	24
Number of Agent	$ I $	150
Agent Cost	c^{agent}	\$200
Understaffing Coefficient	$c^{\text{understaff}}$	\$10

3.2. Results and Sensitivity Analysis: Bounded Individual Fairness. As explained in Section 2.2.3, P1 is the problem in which *individual* fairness levels are constrained by a lower bound. For different runs, while keeping all parameters and data constant, we solve the model using different lower bounds on fairness values (h). We run the model for $h \in \{0, 1, 2, 3, 4, 6, 7, 8\}$ and obtain nine solutions. We observe the objective value, overall fairness level, and fairness distribution for every h value. Agents receive average Z_i fairness scores from their assignments based on their preference scores. Z_i can be fractional as it is divided by the number of weeks.

Table 11 shows the number of agents within fairness ranges for all runs. Column headers denote the h value input to the optimization model. Total satisfaction score, which is the sum of assigned shift preference scores for all agents and optimal objective values are given as cost at the bottom row of this table. Note that, despite their similarity as a measure, for constraint bounds, we use the term *fairness*, whereas for assigned preferences, we prefer a different term, *satisfaction*. In each column, we present the average fairness distribution, breaking into intervals of length 1. For instance, for $h = 0$, Z_i scores of 83 agents are in range of $[0 - 1)$ and 19 agents' scores are in range of $[1 - 2)$. As lower bound h increases, individual fairness levels of agents naturally increase due to the hard constraint introduced to the model. Increased fairness scores imply more schedules become fair for all agents.

Figure 5 shows the distribution of agents in all available shifts. We see that when h increases, there is less diverse shift assignments. Especially in the mid-day shifts (shift-numbers 3 to 15), we see the number of assignments diminishes for greater

TABLE 11. Fairness Distribution

Z_i Range/ h	0	1	2	3	4	5	6	7	8
[0-1)	83	0	0	0	0	0	0	0	0
[1-2)	19	62	0	0	0	0	0	0	0
[2-3)	35	68	120	0	0	0	0	0	0
[3-4)	8	9	14	89	0	0	0	0	0
[4-5)	3	8	12	61	130	0	0	0	0
[5-6)	0	1	3	0	14	81	0	0	0
[6-7)	0	2	1	0	6	68	149	0	0
[7-8)	0	0	0	0	0	0	1	77	0
[8]	2	0	0	0	0	1	0	73	150
Total Satisfaction Score	178	289	370	519	640	824	904	1123	1200
Cost (in \$1000)	139	139	139	139	140	143	157	522	618

h values. On the contrary, the number of shift 1, shift 2, and shift 16 assignments increase. We see that the assignment distribution reflects the preference distribution on the right-hand side of the table.

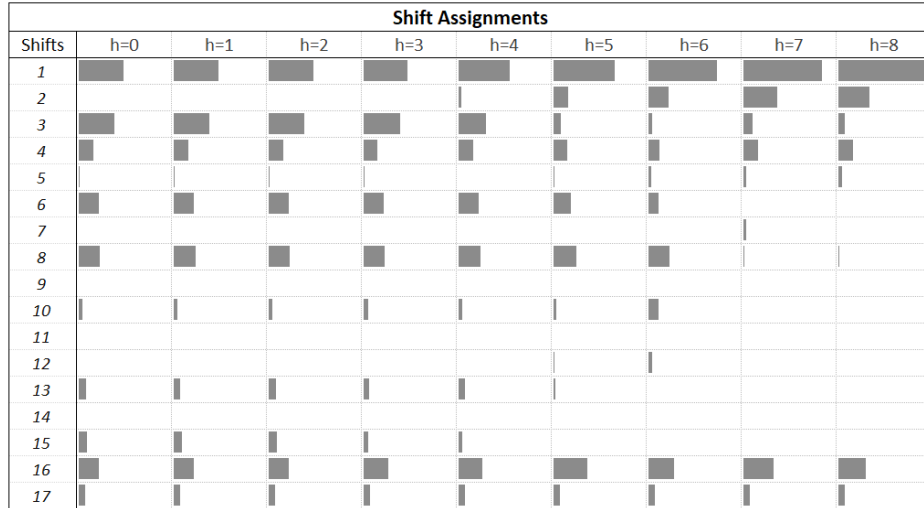


FIGURE 5. Distribution of Agents in Shifts

Figure 6 depicts the objective function value and fairness bound relationship. The objective function value is the total cost and total satisfaction value indicates the sum of all preference scores for assigned shifts of agents. When we increase individual fairness lower bound, total satisfaction also increases almost linearly. When h is between 0 and 6, we see the objective value stays around \$140 K, with no major change. However, when h exceeds 6, the objective value increases significantly. Especially when the bound goes from 6 to 7, the cost triples. Note that the number of agents is limited to 150. Workforce, shuttles, and undesirability cost expectations are around \$132 K. We know the excess cost occurs due to understaffing, which

leads to unsatisfied customers. When h is greater than 6, demand cannot be covered within an acceptable service level. Although the results are as expected, this analysis shows how much room there is to the individual fairness bound, without a sacrifice from the overall costs.

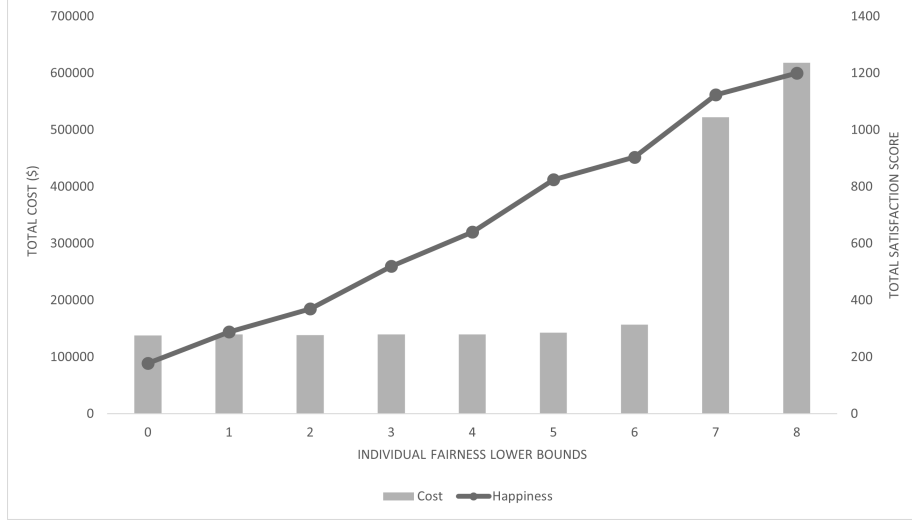


FIGURE 6. Cost and Fairness Values for P1

We also present two additional measures on covering the demand in Figure 7. We report the total understaffed hours in equation (15) and total working hours in equation (16).

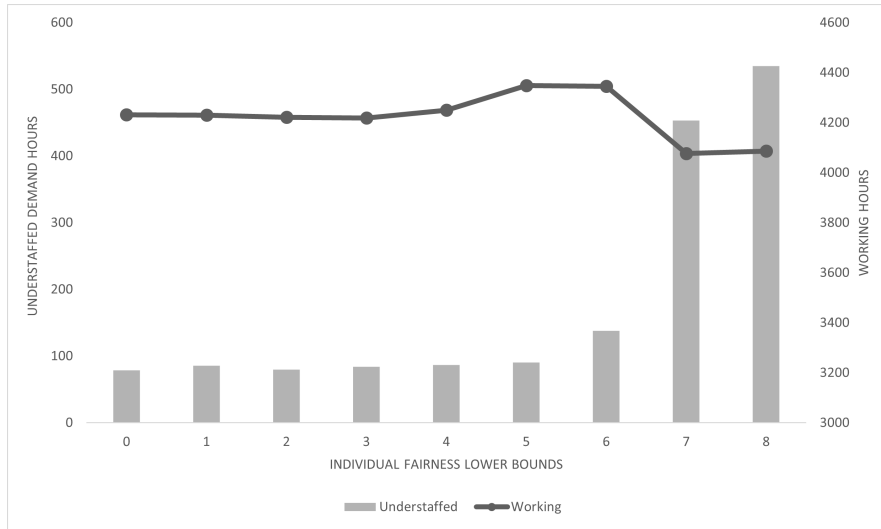


FIGURE 7. Total Understaffed and Working Hours for P1

$$\text{Total Understaffed Hours} = \sum_{t \in T} \sum_{w \in W} U_t^w \quad (15)$$

$$\text{Total Working Hours} = \sum_{s \in S} \sum_{t \in T} \sum_{w \in W} a_t^s X_s^w \quad (16)$$

Figure 7 shows that total working hours slightly increases when h increases up to 4. Similarly, during this zone, there is no significant change for total understaffed hours. We can infer that increasing the individual fairness lower bound from 0 to 4 has no significant effect on either required workforce level or service level. When h moves from 4 to 5, we see a slight increase in both total working hours and total understaffed hours. For $h = 6$, we do not observe a drastic change in total working hours, however, we see that total understaffed hours increases significantly. Individual fairness lower bound starts to force the model to assign some agents to less efficient but preferable shifts for $h = 6$. When h is greater than 6, we see total working hours decrease drastically. The solution becomes infeasible for some agents in some weeks due to fairness lower bound. The model enforces off-weeks for certain agents. Total understaffed hours also increase because of these unassigned weeks.

3.3. Results and Sensitivity Analysis: Bounded Overall Fairness. Next, we consider the bound for the overall fairness of agents, denoted by H . In P2, we do not consider the distribution of individual shifts and fairness levels. This means we do not consider the fairness of schedules, but only an overall fairness score. For P1, we observe that the lower bound on fairness *mostly* has no significant effect on the objective function value. Therefore, we use the overall satisfaction level in P1 where h is greater than 4. We observe that the overall satisfaction scores are respectively 640, 824, 904, 1123, and 1200 where $h \in \{4, 5, 6, 7, 8\}$ in P1. Therefore, we use these as overall fairness bounds in P2, to see if there is a more desirable distribution of that satisfaction. We also know that the result for $h = 8$ represents the solution where all agents are at the maximum possible satisfaction level. Therefore, we run instances for $H \in \{640, 824, 904, 1123\}$ in P2 to compare the results with P1. Figure 8 shows the objective function value and fairness bound relationship.

Table 12 compares the cost of achieving these overall satisfaction levels in P1 and P2. The bottom row highlights the percentage of the cost difference between P2 and P1. We can compare P1 to P2 by looking at H values $\in \{640, 824, 904, 1123\}$ in Figure 8 and h values $\in \{4, 5, 6, 7\}$ in Figure 6. As expected, more flexibility in P2 pushes the objective function back, especially in tighter scenarios where bounds are larger.

TABLE 12. Comparison of P1 and P2

Overall Fairness Score	640	824	904	1123
P1 Cost (\$1000)	140	143	157	522
P2 Cost (\$1000)	139	139	141	304
(P1 Cost - P2 Cost) / P2 Cost	0.7%	2.3%	10.9%	71.5%

We observe the cost difference is worthwhile where the overall fairness score is greater than 824. P2 is more cost-effective than P1 in this aspect. The gap between objective costs (bottom row of the table) significantly increases for higher overall fairness scores. We know that the difference between P2 and P1 problems

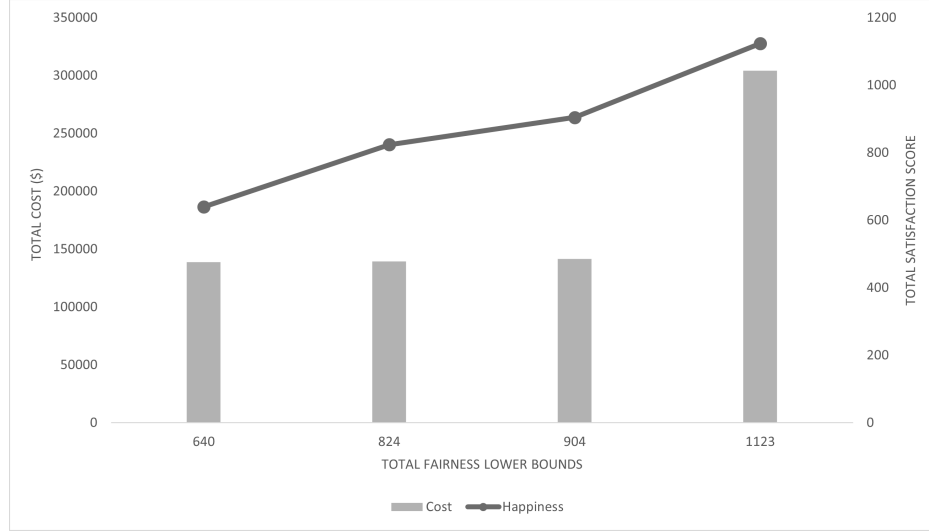


FIGURE 8. Cost and Fairness Values for P2

is the consideration of fairness with regard to individual fairness distributions. We summarize the key result here as follows.

Remark 1. For an overall gain of $1123 - 640 = 483$ points in satisfaction, the company has to spend $\$304,000 - \$139,000 = \$165,000$. For a **fair** distribution of that same satisfaction, the company has to spend an extra $\$522,000 - \$304,000 = \$218,000$. This is, increased agent satisfaction comes with a cost, but a **fair** increase costs twice as much. The tendency of cost figures in this case study also reflects that for narrower margins, increased satisfaction might be inexpensive, even free. However, a fair distribution of satisfaction is always pricier.

In Table 13, we report distribution of individual satisfaction levels for P2. As expected, the satisfaction distribution of individuals is scattered. We observe that, in this approach, more agents are reaching the highest satisfaction score, compared to P1. However, while more agents are assigned to their preferred shifts in P2, some agents have dramatically lower satisfaction scores. P1 avoids these lower satisfaction scores of individuals. However, P2 uses these cost savings coming from unsatisfied agents to assign some agents to their favorite shifts.

Figure 9 shows total working hours are almost flat. There is a slight increase, followed by a decrease. During the slight increase in total working hours, understaffed hours also increases at a slow pace. We can infer that increasing the overall fairness lower bound from 640 to 904 has a slight effect on required workforce level and service level. When H increases to 1123, we see a jump in total understaffed hours and a slight decrease in total working hours. At this point, overall fairness lower bound forces an assignment to less efficient but more preferred shifts. Similar to P1, we observe that the model creates enforced off-weeks for certain agents. However, the decrease in total working hours is insignificant in P2 compared to the drastic change in P1.

TABLE 13. Fairness Distribution for P2

Z_i Range/ H	640	824	904	1123
[0-1)	23	16	17	0
[1-2)	10	7	6	2
[2-3)	25	9	7	3
[3-4)	5	4	2	0
[4-5)	19	17	7	11
[5-6)	11	6	3	0
[6-7)	17	20	12	1
[7-8)	2	5	12	0
[8]	38	66	84	133
Cost (in \$1000)	139	139	141	304

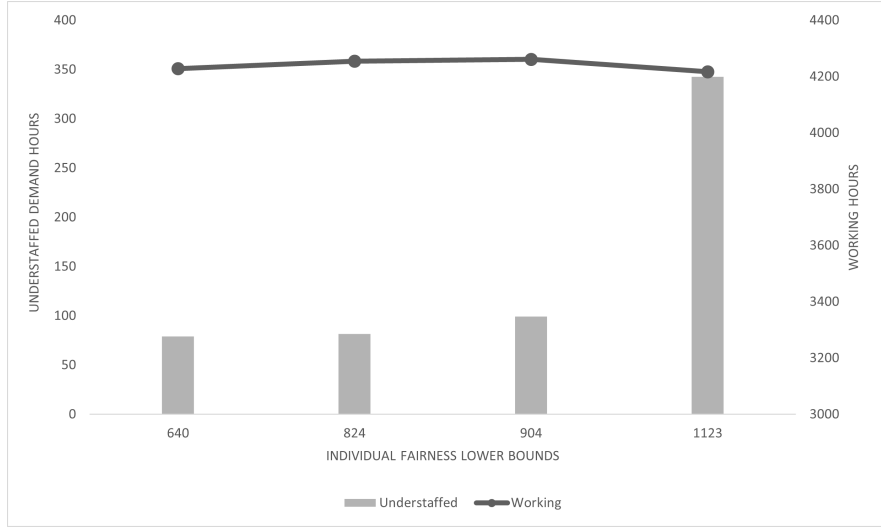


FIGURE 9. Total Understaffed and Working Hours for P2

3.4. Restrictive Scenarios. In this section, we introduce the availability of agents to our problem. The availability of agents can be limited by legal restrictions or personal reasons. Based on real-life instances, we divide agents into 5 groups according to their availability: unrestricted agents, pregnant agents, student agents, disabled agents, and distant agents. Unrestricted agents have no limitations. Working hours of pregnant agents are restricted by labor laws. Pregnant agents are not allowed to work more than 8 hours in a day, and in their work time, the company has to keep a medical doctor. Within all available shifts, only shift 1 and shift 3 are workable shift for pregnant agents because of this labor law. The company follows a similar policy for disabled agents too. Students have to be off during the daytime. Distant agents are the ones that live in another city, hence they travel only during certain hours based on shuttle availability. Table 14 shows shifts that can be assigned to agents in different groups.

TABLE 14. Available Shifts for Agent Groups

Shifts	Unrestricted	Pregnant	Disabled	Student	Distant
1	•	•	•		•
2	•		•		•
3	•	•	•		
4	•				
5	•		•		
6	•				
7	•				
8	•				
9	•				
10	•				
11	•				
12	•				
13	•				
14	•				
15	•			•	
16	•			•	•
17	•			•	•

We consider four scenarios: high restriction, medium restriction, low restriction, and no restriction. Each one uses 150 agents. In the high restriction scenario, group populations are distributed as highly restrictive. In the medium restriction scenario, the group populations are similar to the actual distribution of agents in Vestel. Low restriction scenario has fewer, and no restriction scenario has no restrictions. Number of agents in each group are given in Table 15.

TABLE 15. Number of Agents in Groups

Scenario	Unrestricted	Pregnant	Disabled	Student	Distant
high restriction	30	20	20	20	60
med. restriction	90	10	10	10	30
low restriction	120	5	5	5	15
no restriction	150	0	0	0	0

In Table 16, we present the cost of these four scenarios, with no fairness consideration. We see the medium restriction and low restriction scenarios have no effect on the total cost. However, the high restriction scenario is 14% more expensive than others. Similar to earlier results on fairness restrictions, we conclude that agent availability for a certain interval can be tolerated from a cost standpoint. On the other hand, exceeding some critical points dramatically increases the total cost.

TABLE 16. Cost of Restriction

	no rest.	low rest.	medium rest.	high rest.
total cost (\$1000)	139	139	139	159
cost gap	-	0%	0%	14%

3.5. Restrictive Scenarios with Bounded Individual Fairness. We introduce restrictive scenarios for P1 to observe results for a more realistic scenario. In P1, we assume best frontier solutions are for $h \in \{4, 5, 6\}$. We combine these h bounds with agent restriction scenarios. Total costs for scenarios are given in Table 17. We see that when restriction levels increase, tolerance to individual fairness bounds decreases, leading to fast-paced cost increases.

TABLE 17. Cost of Fairness Levels with Restriction in \$1000

	no rest.	low rest.	med. rest.	high rest.
h=4	140	140	140	193
h=5	143	144	155	224
h=6	157	160	176	243

For long term planning, Table 17 can assist on decision making for available scenarios. When the main goal is cost minimization, we see that the contact center has to spend at least \$138 K operating cost. Generally, operations have tolerance for extra costs to conform to their other goals. We approach the problem as a multi-objective model [1]. We increase the cost tolerance that can be borne by the company, and present up to two solutions with best fairness bounds and agent restrictiveness scenarios in the *efficient frontier* in Table 18. Higher tolerance levels to agent restrictiveness relieve contact centers in their human resource management policies. Decreases in tolerance reduce recruiting options of contact centers and responsiveness in seasonal changes when demand suddenly increases. Thus, we assume that a higher level of tolerance to restrictive scenarios is a better option in practice for the same cost.

TABLE 18. Efficient Solutions for Fairness Levels with Restriction

Cost Tolerance	Acceptable Cost (\$1000)	Solution 1	Solution 2
0%	139	h=0—medium rest. scenario	N/A
1%	140		
2%	141		
3%	143	h=4—medium rest. scenario	h=5—no rest. scenario
4%	144		
5%	146		
10%	153		
15%	160	h=5—medium rest. scenario	h=6—low rest. scenario

Table 18 is quite useful from a managerial standpoint. Contact centers can figure out their budget, individual fairness level targets, and recruitment policies. Depending on how the contact center currently operates in terms of restricted agent groups, the management can evaluate their options as “set individual fairness lower bound to a certain value and expect a certain percentage of increase in costs unless a certain level of sacrifice is made in restrictions.” This high-level approach also helps contact center management with the current and long term planning strategies.

3.6. Computational Aspects. We mainly focus our attention on the managerial aspects, but now we present the solution times for a commercial solver to show our

model is useful in practice. We run all our instances using GUROBI 8.0 [10] with a gap tolerance of 1% on a 3.6 GHz Intel i7 Quad-core Computer with 16 GB RAM running a Linux operating system. For the described instances, the model solution times are given in Table 19 .

TABLE 19. Solution Times for Instances

Restrictions	Preferences	Bound	Time (sec)
		h for P1 H for P2	
None	Individual – P1	0	3
		1	7
		2	17
		3	1257
		4	117
		5	126
		6	49
		7	14
		8	5
	Overall – P2	640	12
		824	18
		904	16
		1123	10
Low		0	5
		4	20
		5	30
		6	20
Medium	Individual – P1	0	3
		4	12
		5	14
		6	9
High		0	2
		4	7
		5	9
		6	6

It can be seen that all practical instances can be solved within half an hour. This shows why this approach is successful and used in practice to plan multiple weeks in Vestel in less than half an hour.

4. Conclusions and future work. We study a contact center workforce planning model. Our model aims to increase employee satisfaction in contact centers as well as providing a cost-effective shift plan. We include elements such as increasing employee fairness, distributing shifts fairly, incorporating work flexibility of agents, and shuttle service costs of agent transportation in the plan. In addition, we define the shortage of meeting demand as a loss function. We present several instances to provide sensitivity analysis results for fairness bounds. We also create instances that reflect agent restrictions in reality. We provide an approach to how employee satisfaction and working flexibility should be evaluated in the long-term. This approach affects the recruitment policies of Vestel’s contact center. Our approach is effective in incorporating the availability and preferences of agents into a workforce plan. We present a set of instances for Vestel only, therefore our insights might only be relevant to a contact center of their size with similar restrictions and cost

figures. However, our approach and mixed integer nonlinear model can be applied to any contact center.

One of the main shortcomings of this approach is that the problem is solved at a strategic level for multiple weeks. Management of operations and deviations that include day-offs, no-shows, sudden demand changes, special events, and trainings are out of the scope of this model. We do not consider skill structure in the model, but it can be included in the formulation. In this case, demanded skills should be input separately, and demand coverage constraints have to be updated to ensure coverage in every skill type.

As a related future study, performance metrics of agents can be included in the planning model. Experience levels and capabilities of agents affect their performance. Besides, agent performance can vary in different time windows of a day. For a multi-skill environment, including the performance of agents into the assignment phase, similar to the preference scores of our model, would lead to different results. Another topic, which we consider in a narrower perspective in this study, is the loss function of a customer. We use a simple formulation to estimate the cost of understaffing in an interval. The sensitivity and accuracy of this loss function could depend on customer type and impatience characteristics of customer groups. A more extensive formulation could be useful in practice on the accuracy of cost estimation.

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REFERENCES

- [1] H. P. Benson, [An outer approximation algorithm for generating all efficient extreme points in the outcome set of a multiple objective linear programming problem](#), *Journal of Global Optimization*, **13** (1998), 1–24.
- [2] I. Blöchliger, [Modeling staff scheduling problems. A tutorial](#), *European Journal of Operational Research*, **158** (2004), 533–542.
- [3] P. Brucker, R. Qu and E. Burke, [Personnel scheduling: Models and complexity](#), *European Journal of Operational Research*, **210** (2011), 467–473.
- [4] I. Castillo, T. Joro and Y. Y. Li, [Workforce scheduling with multiple objectives](#), *European Journal of Operational Research*, **196** (2009), 162–170.
- [5] D. Creelman, Top trends in workforce management: How technology provides significant value managing your people (2014), <http://audentia-gestion.fr/oracle/workforce-management-2706797.pdf>, 2014.
- [6] A. T. Ernst, H. Jiang, M. Krishnamoorthy and D. Sier, [Staff scheduling and rostering: A review of applications, methods and models](#), *European Journal of Operational Research*, **153** (2004), 3–27.
- [7] R. Fink and J. Gillett, Queuing theory and the Taguchi loss function: The cost of customer dissatisfaction in waiting lines, *International Journal of Strategic Cost Management*, 17–25.
- [8] D. Fluss, Workforce management: Better but not good enough, <https://www.destinationcrm.com/Articles/Columns-Departments/Scouting-Report/Workforce-Management-Better-but-Not-Good-Enough-90113.aspx>, 2013.
- [9] L. Golden, [Irregular work scheduling and its consequences](#), *Economic Policy Institute Briefing Paper*, **1**, No. 394, 41 pp.
- [10] Gurobi, *Gurobi Optimizer 8 Reference Manual*, Gurobi Optimization, Inc., 2020.
- [11] ICMI, *The State of Workforce Management*, Technical report, International Customer Management Institute, 2017.
- [12] S. Jütte, D. Müller and U. W. Thonemann, [Optimizing railway crew schedules with fairness preferences](#), *Journal of Scheduling*, **20** (2017), 43–55.
- [13] L. Kletzander and N. Musliu, [Solving the general employee scheduling problem](#), *Computers & Operations Research*, **113** (2020), 104794, 13 pp.

- [14] G. Koole and A. Mandelbaum, [Queueing models of call centers: An introduction](#), *Annals of Operations Research*, **113** (2002), 41–59.
- [15] C. K. Y. Lin, K. F. Lai and S. L. Hung, [Development of a workforce management system for a customer hotline service](#), *Computers & Operations Research*, **27** (2000), 987–1004.
- [16] M. Liu, X. Liu, F. Chu, E. Zhang and C. Chu, [Service-oriented robust worker scheduling with motivation effects](#), *International Journal of Production Research*, 1–24.
- [17] J. Lywood, M. Stone and Y. Ekinici, [Customer experience and profitability: An application of the empathy rating index \(ERIC\) in UK call centres](#), *Journal of Database Marketing & Customer Strategy Management*, **16** (2009), 207–214.
- [18] J. Manyika, S. Lund, M. Chui, J. Bughin, J. Woetzel, P. Batra, R. Ko and S. Sanghvi, *Jobs lost, jobs gained: Workforce transitions in a time of automation*, *McKinsey Global Institute*.
- [19] S. Mohan, [Scheduling part-time personnel with availability restrictions and preferences to maximize employee satisfaction](#), *Mathematical and Computer Modelling*, **48** (2008), 1806–1813.
- [20] E. L. Örmeci, F. S. Salman and E. Yücel, [Staff rostering in call centers providing employee transportation](#), *Omega*, **43** (2014), 41–53.
- [21] R. Pastor and J. Olivella, [Selecting and adapting weekly work schedules with working time accounts: A case of a retail clothing chain](#), *European Journal of Operational Research*, **184** (2008), 1–12.
- [22] M. Rocha, J. F. Oliveira and M. A. Carravilla, [Cyclic staff scheduling: optimization models for some real-life problems](#), *Journal of Scheduling*, **16** (2013), 231–242.
- [23] R. K. Roy, *Design of Experiments Using the Taguchi Approach: 16 Steps to Product and Process Improvement*, John Wiley & Sons, 2001.
- [24] R. Schalk and A. Van Rijckevorsel, [Factors influencing absenteeism and intention to leave in a call centre](#), *New Technology, Work and Employment*, **22** (2007), 260–274.
- [25] G. Smart, What contributes to the cost of a contact center?, <https://www.niceincontact.com/blog/what-contributes-to-the-cost-of-a-contact-center-1>, 2010.
- [26] J. Van den Bergh, J. Beliën, P. De Bruecker, E. Demeulemeester and L. De Boeck, [Personnel scheduling: A literature review](#), *European Journal of Operational Research*, **226** (2013), 367–385.
- [27] M. Van Den Eeckhout, M. Vanhoucke and B. Maenhout, [A decomposed branch-and-price procedure for integrating demand planning in personnel staffing problems](#), *European Journal of Operational Research*, **280** (2020), 845–859.
- [28] Vestel, Towards New Horizons: 2019 Annual Report, <http://www.vestelinvestorrelations.com/en/financials/annual-reports.aspx>, 2019.
- [29] WorkForceSoftware, New Survey: The 6 Most Critical Workforce Management Issues of 2017, <https://www.workforcesoftware.com/blog/6-workforce-management-issues-2017/>, 2017.
- [30] P. D. Wright and S. Mahar, [Centralized nurse scheduling to simultaneously improve schedule cost and nurse satisfaction](#), *Omega*, **41** (2013), 1042–1052.

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