Multi-Objective Tour Guide Shift Scheduling

Sarah Crowson [a], Gabriel Griffin [a], Jacob Holzberger [a], Callie Warren [a]
[a] School of Industrial and Systems Engineering, University of Oklahoma

12/12/2025

Abstract

Staff scheduling is a well understood problem within optimization. However, due to complex availability factors, it is rarely applied to shift scheduling within the tour guide industry. Our data comes from a survey recording the availability and shift preferences of University of Oklahoma Tour Guide staff. This is used to create a model optimizing individual utility constrained by employee availability and management need. As each student's schedule, shift limits, and tour guide experience is different, we must consider different utility functions to meet the needs of employer and employee. A multi-objective optimization framework is considered to balance competing goals between managers and employees. We will show that in cases where preferences and availability are similar, alternative feasible solutions that do not directly trade between objectives are few. Due to this, in most instances there exists a one to one tradeoff between shifts covered and unwanted shifts. A Pareto Frontier is provided to Decision makers to allow schedules to change based on preference.

1 Introduction

Student workers are pivotal to the functioning of a public research university. However, due to their student status, work scheduling must first respect their class schedule. The overall goal is to fill the required shift slots without creating schedule conflicts. A schedule that balances student needs and employer requirements is essential to the function and morale of a work environment. (Shafique and Al Haddi (2022)).

Staff scheduling problems are an optimization problem commonly applied to a vast array of industries (Ernst et al. (2004)). Utilizing these tools for tour guides could lead to improvement of employee satisfaction and therefore return on investment of outreach and recruitment for the university.

2 Literature Review

Multi-objective optimization is used in many cases to make decisions where conflicting goals are inherent to the problem. When given a Pareto Frontier, the set of non-dominated solutions, Decision Makers (DM), can visually identify solutions that meet the criteria they find most important.

Background/Significance: Shafique and Al Haddi (2022) presents a study whose goal was to show the significance of flexible workweek options on employee morale. They provide motivation for the importance of employee satisfaction.

ε-Constraint Methods: ε-Constraint is a method for multi-objective optimization in which a singular objective is chosen, and all others are constrained by a value ε. By varying the value of ε, Mesquita-Cunha et al. (2023) and Mavrotas (2009) identify techniques for selecting the range of ε values considered.

Staff Scheduling Applications: In relation to staff scheduling, these journals help us understand models, applications, and approaches to solving scheduling problems within the scope of tourism. Ernst et al. (2004) Wanga and Huanga (2014) Perera et al. (2018)

3 Problem and Methods

3.1 *Problem*

Similarities to the call center scheduling type as described in Ernst et al. (2004) are shown here. However, we will not be considering demand as a factor for shift scheduling, since the shifts have been set. Though knowledge of exact tasks is not necessary *a priori*, tour guide shift attendance may vary due to daily demand.

Each day contains four different shifts within two categories: "Tour" (9 AM and 2 PM) and "Coverage" (lunch and afternoon). These shifts do not overlap, meaning a guide could, in theory, work all four shifts in a singular day. Each tour guide has one requirement of working at least one Tour shift a week. Rookie, Veteran, and Team leader (TL) are individual classifications, and each shift should have at least one TL to ensure proper training and function.

The output of our work will be a schedule that minimizes the amount of shifts that are left unassigned as well as the number of unwanted shifts for tour guides. This guarantees that each shift will have enough workers to function and train younger members.

3.2 *Model*

The model considered is a bi-objective integer linear programming problem and the two objectives represent the conflicting perspectives as discussed in 3.1. One is the managerial need to have fully staffed shifts with competent workers, and the other is the tour guides' desires to work preferred shift times and weekly shift quantities.

Table 1: Notation.

Sets and Indices	
T	set of tour guides
S	set of shifts
L	set of tour guides qualified to be a shift lead $L \subseteq T$
N	set of tour guides with no preferred number of shifts $N \subseteq T$
C	set of coverage shifts $C \subseteq S$
Parameters	
d_s	number of tour guides needed on shift $s \in S$
m_t	max number of shifts tour guide $t \in T$ works per week
w_t	preferred number of shifts for tour guide $t \in T$
a_{st}	$= \begin{cases} 1 & \text{if } t \in T \text{ is available for } s \in S \\ 0 & \text{otherwise} \end{cases}$
p_{st}	$= \begin{cases} 1 & \text{if } t \in T \text{ prefers to work shift } s \in S \\ 0 & \text{otherwise} \end{cases}$
Decision Variables	
x_{st}	$\begin{cases} 1 & \text{if } t \in T \text{ works } s \in S \\ 0 & \text{otherwise} \end{cases}$
y_s	open slots for shift $s \in S$
u_t	unwanted shifts for tour guide $t \in T$

$$\min \quad \sum_{s \in S} y_s \tag{1}$$

$$\text{s.t.} \quad \sum_{t \in T} \Big(\sum_{s \in S} p_{st} x_{st} + u_t \Big) \le \varepsilon \tag{2}$$

$$\sum_{t \in T} x_{st} + y_s = d_s \qquad \forall s \in S \tag{3}$$

$$\sum_{s \in S} x_{st} \le m_t \qquad \forall t \in T \tag{4}$$

$$x_{st} \le a_{st} \qquad \forall s \in S, \ t \in T \tag{5}$$

$$\sum_{s \in S} x_{st} - u_t \le w_t \qquad \forall t \in T \setminus N \tag{6}$$

$$\sum_{t \in L} x_{st} \ge 1 \qquad \forall s \in S \setminus C \tag{7}$$

$$x_{st} \in \{0, 1\} \qquad \forall s \in S, \ t \in T \tag{8}$$

$$y_s \in \mathbb{Z}_{\ge 0} \qquad \forall s \in S \tag{9}$$

$$u_t \in \mathbb{Z}_{\ge 0} \qquad \forall t \in T \tag{10}$$

The objective function (1) minimizes uncovered shifts. (2) limits the number of unwanted shifts for all tour guides. (3) ensures that covered and uncovered shifts meet that shift's tour guide demand. (4) limits guides' shifts to a maximum. (5) ensures guides are available for shifts they take. (6) measures the number of shifts a guide works past their preferred amount. (7) ensures each shift has a TL. (8),(9), and (10) limit domain of decision variables.

3.3 *Solving Techniques*

As outlined in (2), we utilize the ε constraint method to solve a bi-objective integer linear programming problem. The constrained objective will be the tour guides' preferences and the managerial needs will be optimized. The lower and upper bounds are nontrivial and equal to the lexicographically optimal main and constrained objectives solved in both orders (Mavrotas (2009)). Due to the small size between constrained objective values at optimal and lexicographically optimal for the main objective, it is unnecessary to determine a more efficient represent of the Pareto Frontier. The range considered will be every integer between the minimum and maximum ε.

4 Case Study

Since tour guide scheduling requires flexibility and shift times are often stochastic, multiple methodologies have been created to improve tour guide shift allocation (Perera et al. (2018)), (Wanga and Huanga (2014)). However, since the shift times in our study are predetermined, we will be developing a new optimization strategy.

In order to maintain a functioning office it is critical that each shift quota is met, even though this can impede individual tour guide requests. On the other hand, frequently violating these requests can lead to complaints and lower employee retainment. The push and pull between these two factors leads us to believe that figuring out the objective function interaction will be beneficial for tour guide managers, especially at the University of Oklahoma.

5 Results and Discussion

The upper and lower bound of ε are solved as [0,16] (Fig 1). In other words, when no tour guide works any shift they don't want and no more shifts than they want, sixteen shifts are left uncovered, giving a lower bound to the possible tour guide objective as zero. When there are as many shifts covered as possible, all but two, there are at most sixteen shifts covered by tour guides that are unwanted, either because of their time, day, over preferred amount of shifts, or a combination of factors, giving an upper bound of sixteen to ε.

Order	Manager	Tour Guides
Manager → Tour Guides	2	16
Tour Guides → Manager	16	0

Figure 1: Lexicographically Solved Objective Values

Solving ε for every integer in range $[0, 16]$ gives the Pareto Frontier in Figure 2. It highlights an interesting relationship between unmet shifts and unwanted shifts. It appears that for most instances, the only option to cover an additional shift is to make someone work it who does not want to. In other words there are no alternative feasible schedules which do not increase unwanted shifts. This is likely due to extremely similar preference and availability responses from tour guides. Most useful is that near the manager optimal, there do seem to be alternative feasible schedules which do not increase the number of uncovered shifts.

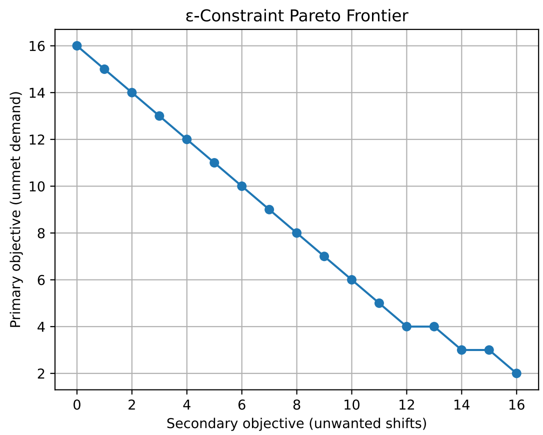
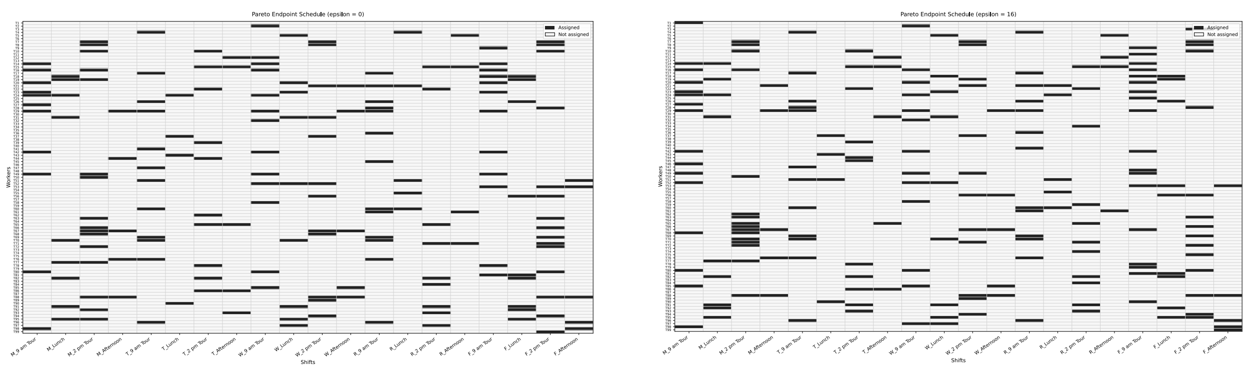


Figure 2: Pareto Frontier of Tour Guides v. Manager Objective



(a) $\varepsilon = 0$

(b) $\varepsilon = 16$

Figure 3: Binary schedules at the two Pareto endpoints.

The graphs (3) represent schedules found at the endpoints of ε values considered. These are the two extremes, meaning the manager could pick any non-dominated point in between these two outputs depending on their preference for objective tradeoffs. The Y-axis represents each Tour Guide and the X-axis represents each available shift. Note that this data could be formatted differently to fit the manager's needs.

6 Conclusion

Utilizing models such as the ε - Constraint Method, user input analysis, and constraint commands lead to finding optimal schedule solutions for the manager's preferences of minimizing unmet demand and unwanted shifts. This analysis leaves room for flexibility within schedule choice, which could differ based on weekly need or employee variability.

Taking into account given individual preference, the Pareto Frontier provides seventeen optimal solutions for the manager to pick from. For instance, an option with a higher unmet demand value may value the preference of student workers, while minimizing this value on the opposite end of the spectrum creates a higher emphasis on need for full shifts. With all of this in mind, a full range of non-dominated solutions is being presented for the manager of the tour guide office to utilize and personalize for their specific needs. In future work we would like to understand and quantify how the differences between availability and preference might change how many non-dominated solutions exist, and produce interactive methods for managers to create schedules.

References

Ernst, A. T., H. Jiang, M. Krishnamoorthy, and D. Sier (2004, 2). Staff scheduling and rostering: A review of applications, methods and models. *European Journal of Operational Research 153*(1), 3–27.

Mavrotas, G. (2009, 7). Effective implementation of the ϵ-constraint method in Multi-Objective Mathematical Programming problems. *Applied Mathematics and Computation 213*(2), 455–465.

Mesquita-Cunha, M., J. R. Figueira, and A. P. Barbosa-Póvoa (2023, 4). New constraint methods for multi-objective integer linear programming: A Pareto front representation approach. *European Journal of Operational Research 306*(1), 286–307.

Perera, D., C. Rathnayaka, S. Dilan, L. Siriweera, and W. H. Rankothge (2018, 7). Sustainable tourism: Application of optimization algorithms to schedule tour plans. *IEEE Region 10 Humanitarian Technology Conference, R10-HTC 2018-December.*

Shafique, F. M. and M. Al Haddi (2022, 10). Enhancing Employee Morale by Providing Felxible Workweek Options: A Success Story in Sharjah. *Society of Petroleum Engineers - ADIPEC 2022*.

Wanga, H.-L. and M.-C. Huanga (2014, 1). Application of Genetic Algorithm to Guide Scheduling Problem. , 21–26.