Employee Scheduling Problem for A Retail Store with Multiple Product Categories and Heterogeneous Employees

Kaan Apak
Kaan.Apak@ozu.edu.tr
Nazlı Can Daşdemir
Nazli.Dasdemir@ozu.edu.tr
Asena Ayşe Gevşek
Ayse.Gevsek@ozu.edu.tr
Deniz Ata Turhan
Ata.Turhan@ozu.edu.tr
Yağız Yüksel
Yagiz.Yuksel@ozu.edu.tr
Ömer Zorlubilek
Omer.Zorlubilek@ozu.edu.tr
Bachelor Student in Industrial Engineering
Faculty of Engineering
Özyeğin University
Istanbul, Turkey

Abstract

The employee scheduling problem is crucial for increasing profits in the retail business as labor costs are among the largest costs to companies. We propose a general analytic approach to solve a real-life motivated employee scheduling problem and apply our approach for a large retail store in Turkey. There are multiple product categories in the retail store and sales of each product category are affected whether there is an employee(s) responsible for the product category at that period. Our approach provides a suggestion engine for a multi-period employee scheduling problem where the objective is to maximize the profit while generating a shift schedule for part-time and full-time employees.

We start solving this problem by analyzing the past 12 months of sales data for a total of nine categories, taken from a large retail store company in Turkey. Then, we generate a contribution matrix for each category and each period via Arena capturing the stochasticity of both demand values and sales probabilities, conditional on the number and types of the employees working at that category and period. Following these, a deterministic integer linear programming model (ILP) is proposed to decide how many part-time and full-time employees should work at each category and each period to maximize the total profit. The ILP uses the contribution matrix generated by Arena, and also checks for legal working requirements, and it is solved by IBM ILOG CPLEX Optimization Studio version 20.1.0.

Keywords
Full Time employee, Part Time Employee, Retailing, Shift Scheduling, Workforce Scheduling

1. Introduction
Workforce scheduling is still important to achieving success in the retailing business as assigning qualified employees for the right product category, at the right time interval may increase business profits. However, it is still a complex problem as capturing the uncertainty in the demand of the customers and the effect of an employee on the sales is not obvious. In this paper, a real-life multi-period employee scheduling problem is studied for multi-product categories and heterogeneous employee types (i.e., part-time and full-time).

According to Yung et al. (2020), employee costs are one of the most significant expenses for retail stores, therefore a schedule that would result in the minimum possible cost and maximum revenue would result in better profitability and efficiency for the companies. Moreover, employee costs are equivalent to 8% to 20% of revenue, 30% of employees are responsible for serving customers directly in stores (Levy et al. 2013; Schmidt 2013, as cited in Talarico and Duque 2014). Zolfaghari et al. (2017) also underline the importance of employee management on productivity. Since the demand in retail stores fluctuates, and the excess labor cannot be stored or backlogged, the scheduling in the retail stores is different from manufacturing plants (Aggarwal 1982) so different approaches must be followed for manufacturing plants and retail stores due to increased uncertainty and labor constraints. Bard et. al (2003) emphasize the importance of the employee scheduling problem by pointing out that an optimized schedule will prevent excess costs or potential revenue losses, therefore enabling the company to compete with others in the market. Therefore, deciding on and quantifying the schedule requirements, and solving the employee scheduling problem is critical for retail stores to increase their profits and must be uniquely studied. In addition, several precautions were taken to regulate the Covid-19 pandemic, such as the limitations on the number of customers at the stores or local and country-level lockdowns. Global retail sales declined by 5.7% in 2020 as a result of changes in consumer behavior following the pandemic (Sabanoglu 2021). Moreover, approximately 40 million employees of the retail sector lost their jobs as the virus spread (Deloitte 2020). According to the Turkish Presidency of Strategy and Budget (2021), the retail sector makes up 13.7% of the employment in Turkey with 3.9 million people as of June 2021 and is responsible for 12.6% of the gross domestic product. Therefore, solving an employee scheduling problem for a retail store affects a large proportion of the population.

However, sales data are stochastic and the effect of an employee on the sales is not obvious. With this motivation, we first estimate the possible revenues for different employee numbers present by fitting distributions to customer arrival, receipt number, and sales data. Afterward, we use this estimation in the model to find an optimal shift schedule that would balance the employee costs and revenues to maximize profits.

The aim of this paper is to provide a suggestion engine tool by which the number of sales representatives to be employed in each product category and time period can be computed by analyzing the past sales data. The suggestion engine tool is developed and tested for one of Turkey's leading retailing business' stores. The existing system is based on intuition and the past experience of managers. In contrast to the current approach of the company's scheduling, a scientific and systematic model-based process is used to schedule the workload to increase the profit. A deterministic, single-objective ILP is solved to compute the optimal shift schedule for full-time and part-time employees while aiming to maximize the total profit.

This paper contributes to the literature by capturing a real-life motivated employee scheduling problem by combining Arena simulations to obtain a revenue matrix based on the number and type of the employees and an ILP considering different legal working requirements and costs, different product categories that are affected by the employee number uniquely within a retail store. The literature review is in Section 2, whereas Section 3 explains the methodology and the proposed mathematical model. The dataset used, results and discussions are presented in Section 4. Conclusion and further research possibilities are mentioned in Section 5.

2. Literature Review

In this section, we first give a brief literature review by mentioning the most similar studies to ours and then present the differences and our unique contributions.

Workforce scheduling has been a popular research area and it has seen an increase in the number of research articles added to the literature during the last decade. The research done by Yung et al. (2020) shows that lack of employees on weekends and overworking during lunch hours on weekdays is one of the most common problems faced by many retail stores, which is due to the inflexible regulations for full-time employees. Kabak et al. (2006) propose a 2-stage model and a simulation work to determine the number of hourly employees in a retail store while taking into account store traffic, number of personnel, discount effect, and time period. The first stage, the sales response model, is to find the optimum staff size in each hour. At the second stage, a mixed-integer model tries to minimize the total number of staff while assigning full-time and part-time employees to shifts. Another two-stage stochastic programming approach is used by Parisio and Jones (2015) to schedule employees in retail stores. They focus on computing a weekly multi-skill staff schedule meeting an uncertain demand for sales personnel while satisfying all store and employee level constraints. The study utilizes a two-stage stochastic program, where the first stage is composed before the realization of demand by deciding on an employee schedule based on historical data. Afterward, when the demand becomes known at the second stage, and the numbers are either over, or under, a recourse action is taken. Recourse is a penalty function and punishes with extra cost to the problem. Zolfaghari et al. (2007) propose a model that works on flexiblesized shifts that start from various times and satisfy legal constraints. This approach creates more than 29,000 possible shifts and more than four million decision variables in the ILP. To handle these many possibilities and decision variables, the paper uses an efficient redundancy shift remover technique. This technique takes into consideration busy times of the service, which create a demand hump, it also compares other possible rules such as equal shift lengths or shifts starting at store opening and each shift being consecutive and not intersecting with each other. Veen (2014) built a different approach to workforce scheduling. The Five-stages approach used by Veen (2014) consists of forecasting, workload modeling, capacity planning, shift scheduling and shift rostering. In Veen's (2014) forecasting approach he combined various algorithms, one is Holt-Winters and Exponential Smoothing by Gelper et al (2010). In their research, Henao et. al (2015) show the potential of the multiskilled employees by determining the impact of multi-skilled employees.

The most significant difference between our paper and Kabak et. al (2006) is the representation of the effect of an additional employee on revenue. A parameter, percentage of increment, that is defined to limit impacts of staff size on sales by simulations with the result of the mathematical model by Kabak et al. (2006), while a simulation-based sales matrix demonstrates this trend in the case study of our paper. In our study, to validate the model and find appropriate parameters, various simulations are executed, and then the mathematical model is solved using the sales matrix as a parameter. Our research and Parisio and Jones (2016) are similar as in both scheduling problems, there are uncertain customer numbers that need to be forecasted or estimated and both use a mathematical model. However, Parisio and Jones (2016) use sophisticated forecasting methods and have a mixed-integer linear model whereas we use relatively simpler to implement simulations runs and an ILP. Zolfaghari et al. (2007)'s solution has similarities with our model, such that each shift length was decided by using each time period's sales data, and the periods are not intersecting as intersecting periods would create many more variables for the problem, complicating the calculation. Our study, however, differs from theirs as we propose an exact model that would neglect the employee preferences, shifts that start at different times, etc. whereas they include such parameters and propose heuristic algorithms to overcome the increased complexity of the new problem. Different from Veen (2014), Arena simulation is used to forecast invoice data in our research. Similar to Henao et. al, there are part-time and full-time employees, however in our study only the part-time employees are multi-skilled and they can change departments on the same day as well. Alvares et al. (2020) use a 4 module iterative algorithm to optimize shift schedule and break time to minimize overstaffing and understaffing costs. Similarly, overstaffing is also part of our model since the contribution matrix is used for calculating revenues. However, our study differs from theirs since in our model break times were not considered, and our proposed model is an ILP that is solved in one stage in contrast to their 2 staged stochastic model. Kacmaz et al. (2019) developed a model using goal programming method to develop a model that also considers employee preferences; although both our study and theirs focus on employee scheduling, they can consider multiple objectives where we only focus on maximizing profit.

To sum up, we extend the previous research made in employee scheduling by combining simulation runs to estimate the effect of employees on the revenue by creating a matrix and using it in our ILP, along with legal work constraints.

3. Methods

The problem in this paper is motivated by a real-life company. The aim is to determine how many and what types of employees (full-time or part-time) will work at each product category and at each time period such that the total profit is maximized.

Firstly, the store is categorized according to products. For example, men's clothing, women's clothing, etc. There are also additional restrictions for some of the brands in a product category due to service level agreements signed between the retail store and the brand-owning company. For instance, X branded sneakers belong to the Young Active Sportswear category however due to the agreements X brand wants 2 sales representatives in the YAS category for every day between 10 am and 18 pm, which was ignored but can be added to the model by simply changing the parameters. The part-time and full-time employees issue different costs and have different legal labor restrictions. This project aims to maximize the profit by decreasing the excess salary costs and/or increasing sales and provides a systematic approach to monetize and translate the previously mentioned factors into a feasible working schedule.

In the real-life motivating problem, busy times and sales numbers are observed to fluctuate immensely during the rush hours and weekends and sales representatives would be prone to become overwhelmed and the demand in some periods could not be fulfilled. This would lead to missing sales at rush hours and overstaffing at empty hours, leading to unnecessary costs. To capture the real-life motivated problem's settings, the following assumptions are made in the suggestion engine.

- Part-time employees have less effect on revenue increase than full-time employees; therefore, part-time employees incur a "ghost cost" preventing the model from only scheduling part-time employees and to better represent the real-life conditions.
- Overtime costs, hiring and firing costs, and excused paid vacations, such as sick leaves, pregnancy costs are neglected.
- Shift scheduling for each week is independent of the other weeks.
- Full-time employees can work in certain product categories, but part-time employees can work in any product category.
- Extra pays during holiday seasons, and the bonus payments from employees' sales are neglected.
- All employees are employed by the retail store itself, all costs are issued to the company.
- Breaks can be taken at any time during the shift.
- The company can schedule the given number of employees to any product category without encountering an organizational problem.

There are also additional restrictions that are directly forced by the company and/or the law, such as the maximum and minimum working hours for a week for part-time employees and daily maximum working hours for full-time employees.

Firstly, the past data are used to calculate interarrival times and shopping probabilities. Using Arena input analyzer, we formed distributions for the inter-arrival times to the store and shopping probabilities (based on the number and the type of the employee(s)). A simulation model is developed on Arena to form a contribution matrix for each category, period, and number of employee(s), S_{clp}. This matrix, along with other parameters and decision variables, is used in our deterministic, linear integer model to obtain a shift schedule that would maximize the profit. The steps we used to solve this problem are given in Figure 1.

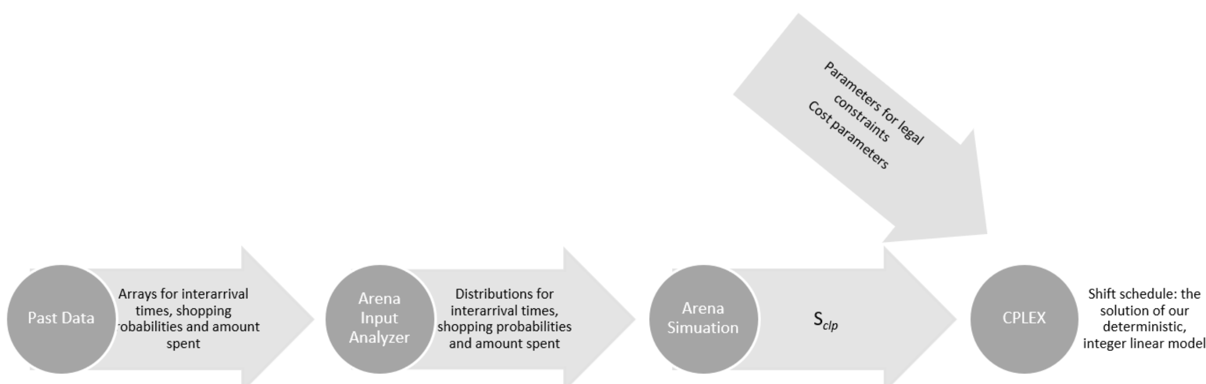

Figure 1: Methodology

Previous sales data are categorized with respect to customer arrivals per day, daily and the hourly number of receipts per product category, and daily and hourly amount spent (revenue generated) per product category. For each hour, the number of customer arrivals to a product category is estimated with respect to the ratio of the average number of receipts for that product category to the average receipt number for a whole day. The shopping probability is then calculated as the number of receipts over the number of arrived customers for each product category, and is estimated to differ based on the existence of an available employee; this is the same value for each product category in our model but can be differentiated as needed. The interarrival times are calculated straightforwardly, by dividing the average number of total arrivals by 60 for each hour. At this point, we divided a day into four time intervals that would include almost an equal ratio of one day's revenue, using the hourly average revenues. These intervals are 10:00-15:00, 15:00-17:00, 17:00-19:00 and 19:00-22:00. The 28 periods are then defined as four time intervals for each day of the week. With the arrays we got from these calculations on the past data, we used Arena Input Analyzer to form distributions for inter-arrival times, shopping probabilities, and the amount spent per customer that would be used in the next step. These distributions vary according to product category and period; product category and the presence of an available employee; product category, period, and the presence of an available employee, respectively. However, by only analyzing past data, it was not possible to estimate the effect of increasing the number of employees. We then modeled the system in Arena and ran many discrete event simulations with different numbers of employees using the above distributions for required nodes, added dynamically by a macro, to form the contribution matrix S_{clp}. S_{clp} shows the possible revenue value for each category-*l*, during each period-*p*, given c employees are working for that product category. Thus, in our problem, this effect was assumed to be deterministic but nonlinear and unique for each category and can be observed from the matrix S_{clp}. A simple illustration of the Arena model is given in Figure 2.

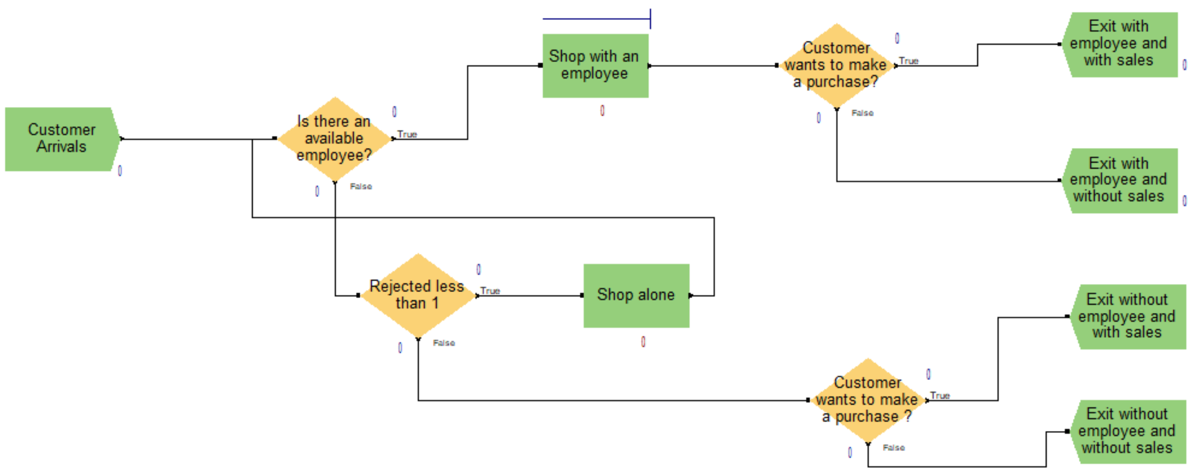

Figure 2: Arena Model for the Retail Store

A deterministic, single objective ILP was then created to decide how many part-time and full-time employees should work at which product categories during which periods to maximize the total profit. The model takes S_{clp}, legal working requirements and labor costs as inputs and outputs an optimized shift schedule that maximizes the profit. The model formulation is as follows.

Indices:

j	part-time employees	$j \in J$
k_l	full-time employees	$k_l \in K$
l	categories	$l \in L$
c	number of employee in categories	$c \in C$
p	working periods	$p \in P$
d	days	$d \in D$

Parameters:

$\mathbf{S}_{clp}$: total sales in category-***l*** when **c** employees work at period-*p*
$\mathbf{SP}_{pl,\min}$: minimum number of employees at period-*p* in category-*l*
$\mathbf{SP}_{pl,\max}$: maximum number of employees at period-*p* in category-*l*
$\mathbf{H}_{P,\max}$: maximum allowed number of working hours for part-time employee per week
$\mathbf{H}_{F,\max}$: maximum number of working hours for full-time employee per week
$\mathbf{H}_{\max}$: maximum number of working hours for any employee per day
$\mathbf{t}_p$: length of the period-*p*
$\mathbf{Cost}_{\text{part-time}}$: cost for part-time salesperson per hour
$\mathbf{Cost}_{\text{full-time}}$: cost for full-time salesperson per week to the employer
$\mathbf{Cost}_{\text{Ghost}}$: ghost cost for part-time salesperson per day

Decision Variables:
$part_{jlp}$:1 if part-time employee j works in category-*l* at period-*p*; 0 o.w.
$full_{k_l lp}$:1 if part-time employee k in employee subset-*l* works in category-*l* at period-*p*; 0 o.w.
p_j: 1 if part-time employee j works at any day; 0 o.w.
f_k: 1 if full-time employee k works on any day, 0 o.w.
n_{lp} : total number of employees in category-*l* at period-*p*

$$\textbf{max } Revenue - Cost_{PT} - Cost_{FT} - Cost_{Ghost} \quad \textbf{(1)}$$

The objective function (1) maximizes total profit, defined as the difference between revenue and the total cost of employees.

$$Revenue = \sum_p \sum_l S_{n_{lp}lp} \quad \textbf{(2)}$$
$$Cost_{PT} = \sum_j \sum_l \sum_p part_{jlp} * t_p * Cost_{PartTime} \quad \textbf{(3)}$$
$$Cost_G = \sum_j p_j * Cost_{Ghost} \quad \textbf{(4)}$$
$$Cost_{FT} = \sum_k f_k * Cost_{FullTime} \quad \textbf{(5)}$$

The equations (2), (3), (4), and (5) calculate the total revenue and the costs associated with part-time and full-time employees, respectively.

$$\sum_l \sum_p part_{jlp} * t_p \leq H_{P,max} \quad ,\forall j \quad \textbf{(6)}$$
$$\sum_l \sum_p full_{k_l lp} * t_p \leq H_{F,max} \quad ,\forall k \quad \textbf{(7)}$$
$$\sum_l \sum_{p \in P_d} full_{k_l lp} * t_p \leq \mathrm{H}_{max} \quad ,\forall d, k \quad \textbf{(8)}$$
$$\sum_l \sum_{p \in P_d} part_{jlp} * t_p \leq \mathrm{H}_{max} \quad ,\forall d, j \quad \textbf{(9)}$$

The constraints given above limit the working hours. The upper and lower bounds for working hours per part-time employee per week are shown in (6), and weekly upper bounds for per full-time employee are given in (7), and finally, the maximum working hours in a day per employee are given in (8) and (9).

$$\sum_l part_{jlp} \leq 1 \quad ,\forall j, p \quad \textbf{(10)}$$

Constraints that limit the part-time employees as working in at most one category at any period are given in (10).

$$part_{jlp} \leq p_j \quad ,\forall j, l, p \quad \textbf{(11)}$$
$$full_{k_l lp} \leq f_k \quad ,\forall k, l, p \quad \textbf{(12)}$$

An employee can be assigned to a period only if they are hired; this is ensured by the constraints (11) and (12).

$$SP_{lp,min} \leq n_{lp} \quad ,\forall l, p \quad \textbf{(13)}$$
$$SP_{lp,max} \geq n_{lp} \quad ,\forall l, p \quad \textbf{(14)}$$
$$n_{lp} = \sum_j part_{jlp} + \sum_k full_{k_l lp} \quad ,\forall l, p \quad \textbf{(15)}$$

The lower and upper bounds of the number of employees in category-*l* at period-*p* are calculated by (13) and (14), constraint set (15) gives the total number of employees who work at category-*l* during period-p.

$$part_{jlp}, full_{k_l lp}, f_k, p_j \in \{0,1\} \quad ,\forall j, k, l, p \quad \textbf{(16)}$$
$$n_{lp} \geq 0 \quad ,\forall l, p \quad \textbf{(17)}$$

The binary and nonnegativity constraints are given with the constraint set (16) and (17).

This model can be implemented and solved easily, even for larger instances due to its linear and deterministic nature; however, one limitation is that obtaining the S matrix requires many simulations runs on Arena which might take.

4. Results and Discussion

4.1 Data

A brief description of the data used for our base case is given in this subsection. The data is real-life 2019 data from one of Turkey's leading retail stores.

The sets J and K represent employees, assuming that the store has 135 full-time and part-time employees to assign for a week. The set K is divided into 9 to represent subsets which include 15 employees for each product category (e.g., 1st 15 employees' set, k1, is for category 1 (1={1, 2, …, 15}.), and employees in a subset can only work in the category of their subset. 9 categories are considered in total for this paper, which are labeled as follows: accessories L0, child L1, men L2, men's shoes L3, home L4, YAS (Young active sports) L5, women L6, women's shoes L7, cosmetics L8, and FMC is ignored by the company's request. The set C is used in the S_{clp} matrix to represent the number of employees who work in the given category. The periods were enumerated starting from Monday to Sunday, where a day is split into 4 parts (eg. the first period on Monday is p=1, the first period on Tuesday is p=5, and so on.) and each day is represented as P_d where d is from the set D, the set of days in a week, starting from Monday to Sunday. Numerical values of problem parameters are given in table 1.

Table 1 Parameter Values

Parameter Name	Value	Unit
$SP_{pl,\ min}$	0	# of employees
$SP_{pl,max}$	15	# of employees
$H_{P,max}$	34	Hours
$H_{F,max}$	45	Hours
H_{max}	8	Hours
t_p	Varying to p	Hours
$Cost_{part\text{-}time}$	20	TL/Hour
$Cost_{full\text{-}time}$	1062.5	TL/Week
$Cost_{Ghost}$	175	TL

4.2 Results

The model is solved with IBM ILOG CPLEX Optimization Studio 20.1.0 on a computer with Windows 10, AMD Ryzen 5 5600x 3.7 GHz 16 GB RAM and runs for 20 minutes 7 seconds for the base case, with an optimality gap of 0.000604101%. The optimal number of employees for each product category and period is shown in Table 2. More employees are scheduled to busier periods (3, 7, 11…) and to product categories where the existence of an employee makes a significant difference on the revenue (L3, L4). Detailed analysis of the solutions and visual demonstrations are given below.

Table 2: Optimal Number of Employees Per Category Per Period

Periods	Product Categories									Periods	Product Categories								
	L1	L2	L3	L4	L5	L6	L7	L8	L9		L1	L2	L3	L4	L5	L6	L7	L8	L9
1	1	3	5	3	1	2	1	1	1	15	2	10	14	10	4	6	3	1	2
2	1	8	14	10	4	7	3	1	3	16	1	7	10	6	3	4	1	1	1
3	2	10	14	10	4	6	3	1	2	17	1	3	5	3	1	2	1	1	1
4	1	7	10	6	3	4	1	1	1	18	1	8	14	10	4	7	3	1	3
5	1	3	5	3	1	2	1	1	1	19	2	10	14	10	4	6	3	1	2
6	1	8	14	10	4	7	3	1	3	20	1	7	10	6	3	4	1	1	1
7	2	10	14	10	4	6	3	1	2	21	1	9	13	10	3	0	3	3	1
8	1	7	10	6	3	4	1	1	1	22	4	15	15	9	7	2	9	7	2
9	1	3	5	3	1	2	1	1	1	23	6	11	15	1	13	1	10	8	3
10	1	8	14	10	4	7	3	1	3	24	3	14	14	13	9	8	5	5	2
11	2	10	14	10	4	6	3	1	2	25	1	9	13	10	3	0	3	3	1
12	1	7	10	6	3	4	1	1	1	26	4	15	15	9	7	2	9	7	2
13	1	3	5	3	1	2	1	1	1	27	6	11	15	1	13	1	10	8	3
14	1	8	14	10	4	7	3	1	3	28	3	14	14	13	9	6	6	5	2

As expected, the model allocated more employees to busy intervals, i.e., periods starting from 15.00 to 19.00. The average number of employees at periods starting at 10:00 during weekdays are represented by WD P1, similarly during weekends are represented by WE P1 and so on, on the x-axis in Figures 3 and 4.

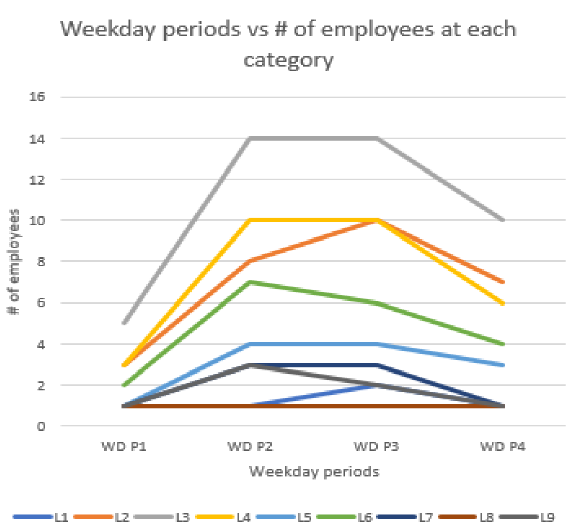

Figure 3
Average # of employees on periods of WDs

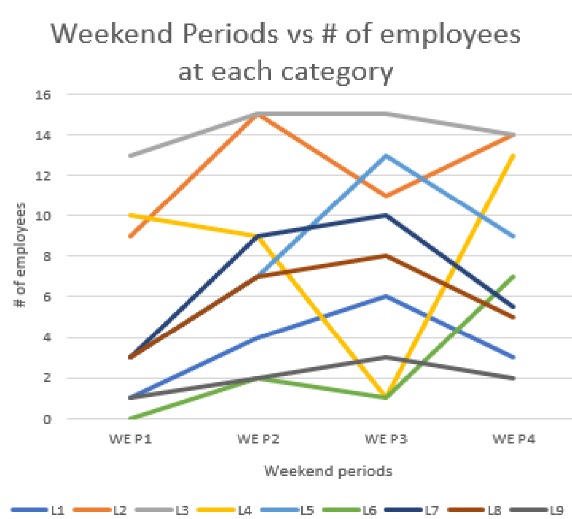

Figure 4
Average # of employees on periods of WEs

Since more customers visit the stores on the weekends, the model schedules more employees to generate any possible revenue. In Figure 5, D1 represents the Mondays, D2 Tuesdays, etc., on the x-axis, and the average number of employees is given on the y axis.

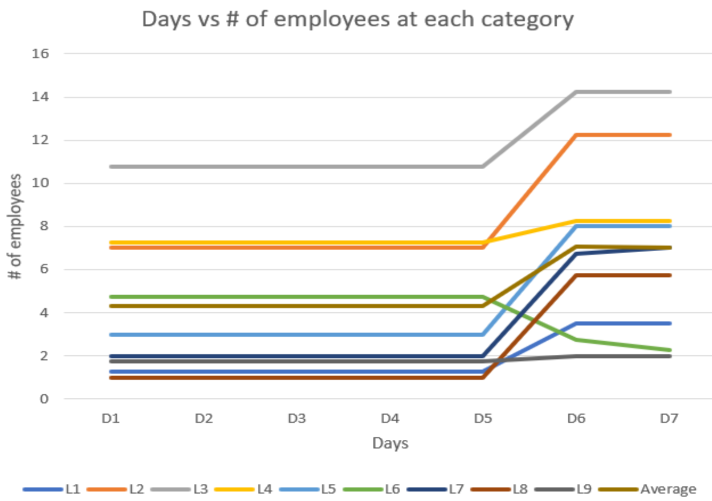

Figure 5 Average # of employees on each day

The model must decide between hiring a part-time employee versus a full-time employee since there is a trade-off between the flexibility and costs of both employees. Using part-time employees allows a more flexible schedule while issuing higher costs. Since full-time employees are paid a fixed amount, regardless of their working hours, therefore are more cost-effective, the model tries to utilize them as much as possible during the weekdays. Part-time employees are assigned to weekends more, rather than the weekdays to generate more revenue. The average number of full-time and part-time employees for each day are given in Figure 6 and Figure 7, respectively.

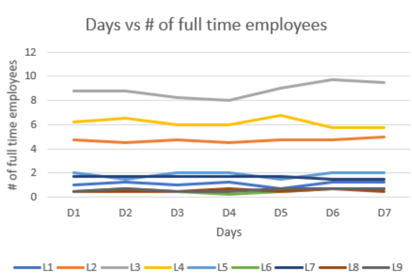

Figure 6
Average # of employees on periods of WDs

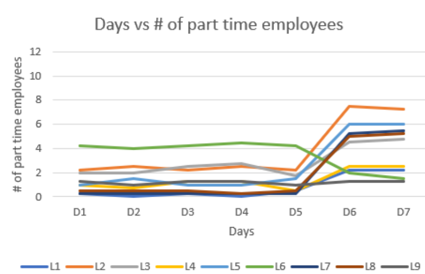

Figure 7
Average # of employees on periods of Wes

The average increase in profits with each additional employee converges as the number of employees increases since the labor costs start to balance the revenues. Ideally, we expect the model not to employ more than the number of employees where the additional revenue does not increase more than the added labor costs. A numeric calculation is performed on the S_{clp} matrix to decide on the number of employees where the additional profit converges. There is a 0.7 correlation between the numerically calculated values and the model's output for the number of employees for the first six locations, which suggests that our model works in line with the expectations. However, the correlation drops to 0.4 when all locations are included since the revenue does not change significantly with respect to the number of employees present for the last three categories; the model prioritizes other product categories. High correlation and less assigned number of employees suggest that with a higher capacity, more revenue could be generated as represented in Figure 8.

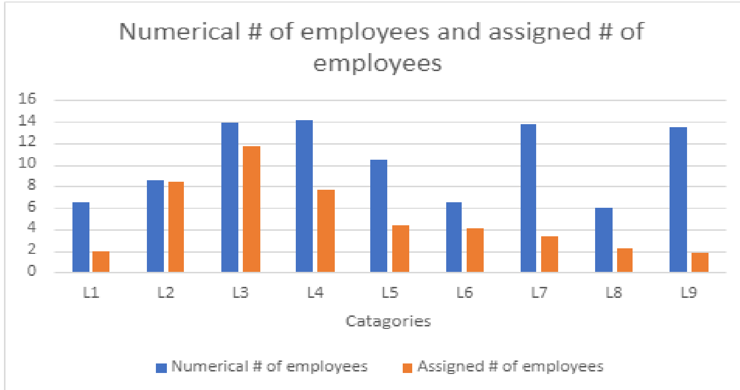

Figure 8 Numerical and assigned # of employees

5. Conclusion and Future Work

This paper focuses on solving an employee scheduling problem to maximize profit. The first step lies in understanding the effect of one additional employee in each time interval and each individual category on overall revenue and representing this complex integrity as a matrix obtained by Arena simulations. This 3-dimensional matrix output is later used as a parameter in our deterministic ILP to maximize the total profit while satisfying working restrictions. The unique contribution of this paper is its unique use of programmable macros on simulation runs used to estimate the effect employment level has on revenue. This information is combined with part-time and full-time employees which can work in different product categories, are issued different costs and all have legal working requirements to abide by. An ILP is solved with the help of a commercial solver to present the optimal shift schedule of the existing situation.

Different working constraints such as working in consecutive periods and paid vacations can be added to better represent real-life scenarios. The model can be extended by adding other types of employees, product categories or different objectives as well. Additionally, employee preferences can be added to the model to achieve a better objective value.

Acknowledgements

We would like to thank our advisor Dr. Elvin Çoban for her time and support during our project.

References

Aggarwal, S. C. A focussed review of scheduling in Services. *European Journal of Operational Research*,(1982, February) Retrieved January 27, 2022,from https://www.sciencedirect.com/science/article/abs/pii/03772217829006
37.

Álvarez, E. Ferrer, J., Muñoz, J., Henao, C.,Efficient shift scheduling with multiple breaks for full-time employees retail industry case, *Computers & Industrial Engineering*, vol. 150, 2020.

Bard, J., Binici, C., de Silva, A., Staff scheduling at the United States Postal Service, *Computers & Operations Research*, Volume 30, Issue 5 , Pages 745-771, 2003.

Deloitte, The retail evolution's great acceleration, Available: https://www2.deloitte.com/us/en/pages/consumer-business/articles/retail-recession.html, Accessed on Jan 30, 2022 .

Gelper, S., Fried, R., Croux, C., Robust Forecasting with Exponential and Holt-Winters Smoothing. Journal of Forecasting, vol. 29, no. 3, pp. 285-300, 2010.

Henao, C., Muñoz, J., Ferrer, J., The impact of multi-skilling on personnel scheduling in the service sector: A retail industry case, J*ournal of the Operational Research Society*. vol. 66, no. 12, pp. 1949-1959, 2015.

Kabak, Ö., Ülengin, F., Aktaş, E., Önsel, Ş., & Topcu, Y. I. (2006, January 13). Efficient shift scheduling in the retail sector through two-stage optimization. *European Journal of Operational Research*. Retrieved November 27, 2021.

Kaçmaz Ö, Alakaş H., Eren T. Shift Scheduling with the Goal Programming Method: A Case Study in the Glass Industry. *Mathematics*. 2019; 7(6):561., 2019.

Parisio, A., and Neil Jones, C. A two-stage stochastic programming approach to employee scheduling in retail outlets with uncertain demand. *Omega*, *53*, 97–103., 2015.

Sabanoglu, T. Coronavirus: impact on the retail industry worldwide - Statistics & Facts Available:https://www.statista.com/topics/6239/coronavirus-impact-on-the-retail-industry-worldwide/#dossierKeyfigures.

Talarico, L. and Maya Duque, P. A. An optimization algorithm for the workforce management in a retail chain, Computers & Industrial Engineering, 82, pp. 65–77, 2015.

Turkish Presidency of Strategy and Budget (2021), 2022 Annual Presidency Program (in Turkish), Available: https://www.sbb.gov.tr/wp-content/uploads/2021/10/2022-Yili-Cumhurbaskanligi-Yillik-Programi-26102021.pdf.

Van der Veen, E., (2014). From sales data to workforce schedules, *Proceedings of the International Conference of the Practice and Theory of Automated Timetabling*, vol. 10., York, United Kingdom, August 2014.

Yung, D., Bucarey, V., Olivares, M., & Christiansen, M.Labor planning and shift scheduling in retail stores using customer traffic data. SSRN Electronic Journal.,2020, Available at SSRN: https://ssrn.com/abstract=3695353.

Zolfaghari, S., El-Bouri, A., Namiranian, B., & Quan, V. Heuristics for large scale labour scheduling problems in the retail sector. INFOR: *Information Systems and Operational Research*, 45(3), 111–122., 2007.

Biographies

Kaan Apak studies industrial engineering at Özyeğin University and is minoring computer engineering. Kaan has already worked on earthquakes, preparing an evacuation plan and became part of the Kyoto World Tsunami Awareness summit. At the moment, Kaan is working on two projects, one to generate a new system for preventing violence to women, and one on managing dialysis patients in case of disaster in the Humanitarian Operations & Disaster Management Research Lab in Özyeğin University. He is also a long term intern at Borusan CAT Data Analytics Department.

Nazlı Can Daşdemir will achieve a bachelor's degree in Industrial Engineering from Özyeğin University. Her past experience includes internships in supply chain management at Assan Foods and product management at Group Renault. She is currently working as a long term Customer Relations Management intern at KIA Turkey. Her research interests include customer relations, mathematical modelling under uncertainty, and humanitarian logistics.

Asena Ayşe Gevşek has been studying Industrial Engineering since 2018 and double majoring in Computer Science at Özyegin University from 2019. She has interned at ICRON, a supply chain solutions company in their platform department. She has worked in a project to create a fair distribution of Covid-19 vaccines in the Humanitarian Operations & Disaster Management Research Lab in Özyeğin University. Her research interests are education technologies and humanitarian relief systems. Following her graduation, she wants to pursue an academic career and research on providing equal opportunities and required aid to people in need.

Deniz Ata Turhan is set to graduate from Özyeğin University Industrial Engineering department at the end of this following semester. His past experiences include short internships at Vestel Head Quarters in Logistics Department as logistics planner trainee and at Bosch Powertrain Solutions in Quality Management and Methods department as quality planning trainee. In addition, he has worked in Grammer A.Ş. as material planning engineer, and he is currently working part-time at Bosch Powertrain Solutions in Quality Management and Methods department as quality management and planning engineer.

Yağız Yüksel has been studying Industrial Engineering at Özyeğin University since 2017. Yağız is interested in operations research algorithms, programming heuristics algorithms and inventory management. Yağız is working at Sampa Automotive at their operational excellence department as a long term intern.

Ömer Zorlubilek, is a Bachelor of Science student in Özyeğin University Industrial Engineering Program as well as having minor studies in Entrepreneurship. He has worked on a grant subsidised TÜBİTAK Project under Dr Ali Ekici on the subject of Integrated Solution Method and Applications for Inventory Routing Problem. He spent a period of 5 months carrying on his studies in Hochschule Pforzheim in Germany where he worked on both engineering and business. He has worked in several different companies of differing arrest from cost analysis in Group Renault to human resources in Turkish Presidency Bureau. He is currently serving as the Özyeğin University Student Council Vice-President.