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Optimizing Retail Workforce Management: Integrating Machine Learning Forecasting with Constraint Programming for Dynamic Shift Planning

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Abstract

Retailers face significant challenges in workforce scheduling due to highly variable demand, rising labor costs and strict service requirements. This study presents a novel, two-stage optimisation framework that integrates ensemble-based machine learning forecasting with the mathematical programming approach CPLEX for shift scheduling in the retail sector. In the first stage, advanced machine learning models (XGBoost, Random Forest and SARIMAX) generate probabilistic foot traffic forecasts by leveraging extensive feature engineering. These forecasts are then used as inputs for a shift optimization model that considers complex operational constraints, such as labor laws, union agreements and employee preferences. Deployment in a major Turkish retail chain yielded empirical results demonstrating an 11.3% reduction in labor costs, a 47% decrease in understaffing, while maintaining full coverage with minimal excess staffing, and an 8.2% improvement in service levels across more than 200 stores. The proposed approach yields scalable cost savings and service enhancements, providing a robust decision-support tool for workforce management in dynamic retail environments.

Keywords
Retail workforce scheduling, machine learning forecasting, shift optimization, constraint programming, operational efficiency

1. Introduction
The retail industry is confronted with critical challenges in the realm of workforce management, stemming from the volatility of market demand, the escalating costs of labour, and the mounting pressure to enhance service standards. The present study proposes a two-stage optimization framework that integrates machine learning-based demand forecasting with mathematical programming to enhance shift scheduling in retail. Given that labour costs are responsible for 30-40% of operational expenses, effective scheduling is imperative. Even modest enhancements can generate substantial annual savings for major retail chains. In order to thrive in a customer-focused market, retailers must find a balance between financial objectives and service quality standards.

Staffing levels have been demonstrated to exert a direct influence on customer satisfaction. Adequate staffing levels are a prerequisite for the effective functioning of a retail establishment. A paucity of staff can result in protracted queues, diminished assistance for customers, and a deterioration in store conditions, which, in turn, can lead to a decline in sales. Research indicates that a 10% shortfall in staffing can result in a 3–5% decline in conversion rates. However, the problem of overstaffing is twofold: first, it increases costs without delivering equivalent service improvements; secondly, it complicates the optimization process.

The ability to align the workforce with the dynamic fluctuations in demand represents a persistent challenge, given the complex seasonal fluctuations in retail that are influenced by meteorological factors, events, promotional activities, and economic conditions. It is imperative that any adjustments to staffing be made in accordance with the prevailing labour regulations, taking into account the availability of employees, their skill sets, and the constraints imposed by contracts. Current rule-based systems, which rely on historical averages and fixed staff-to-sales ratios, are unable to adapt to changing traffic patterns. The employment of such rigid methodologies invariably gives rise to labour costs that are 15-20% higher than those associated with optimized approaches. Moreover, such methods frequently result in service disruptions.

A major limitation of current practices is the lack of integration between demand forecasting and shift scheduling. Retailers usually treat these processes separately, using forecasts as static inputs and disregarding prediction uncertainty. This can result in either excessive labour costs or an inadequate service during periods of high demand. The volatile nature of retail therefore necessitates integrated, data-driven methods that optimize forecasting and scheduling together, especially as omnichannel operations further complicate staffing requirements.

This study makes three key contributions: a novel, two-stage framework that combines machine learning and robust optimization; a CPLEX-based engine which considers real-world constraints; and empirical validation at a major Turkish retailer. Implementation of the proposed method in over 200 stores resulted in a 11.3% reduction in labour costs, a 47% decrease in understaffing and an 8.2% improvement in service quality.

The structure of the paper is as follows: Section 2 provides a comprehensive review of the extant literature on the subject of retail workforce scheduling and demand forecasting. The third section of this text provides a definition of the problem and introduces the overall two-stage framework. The fourth section of this study outlines the methodology and results of machine learning-based foot traffic forecasting. This includes a detailed explanation of feature engineering and the development of ensemble models. Section 5 delineates the shift scheduling optimization approach, utilizing mathematical programming and operational constraints derived from real-world data. In Section 6, an examination is undertaken of the empirical results obtained from the implementation of the model, with a focus on the forecasting and optimization outcomes. The final section of the paper identifies potential avenues for future research.

1.1 Objectives
The objective of this study is to develop and implement a novel two-stage optimization framework that integrates machine learning-based demand forecasting with mathematical programming for workforce scheduling in the retail sector. Leveraging advanced ensemble models to generate accurate, uncertainty-aware foot traffic forecasts and applying CPLEX-based optimization under real-world operational constraints will enable the study to minimise labour costs, reduce understaffing and overstaffing, and improve overall service quality. The framework connects demand prediction and shift planning in a unified, data-driven approach to address the limitations of traditional scheduling methods, ultimately enabling more efficient and equitable workforce management in dynamic retail environments.

2. Literature Review

Optimized shift planning in retail is critical for effective workforce management and the maintenance of customer satisfaction (Sahraeian 2024). The process of shift planning has two primary functions. Firstly, it determines the hours that employees will work. Secondly, it also aims to optimize labor costs. In this context, various methods and approaches have been developed in the relevant literature.

An essential input to effective shift planning is the accurate forecasting of retail demand, which enables proper workforce allocation aligned with customer needs.

In the context of retail demand forecasting, a dual approach encompassing both classical time series methods and contemporary machine learning techniques is employed to capture seasonal and nonlinear sales patterns. A number of comparative studies have been conducted which demonstrate that whilst models such as Holt-Winters and ARIMA perform reasonably well in terms of seasonality (Da Veiga et al., 2014), more advanced approaches, including Wavelet Neural Networks (WNN) and Fuzzy Systems, have been shown to offer notable improvements in terms of forecast accuracy (da Veiga et al., 2016). In a similar vein, deep neural networks and gradient boosting machines have been found to be effective, particularly when external variables are limited (Wanchoo, 2019). These forecasts play a crucial role in downstream processes, including workforce scheduling and shift optimization. A decision support tool was developed to optimize workforce planning in retail by integrating traffic forecasts with an econometric model that links staffing levels to sales performance (Yung et al., 2020). The analysis revealed that profitability was being adversely affected by a number of factors, including a shortage of staff on weekends and an excess of staff during weekday lunch hours. The findings emphasize the significance of shift optimization for enhancing operational efficiency and ensuring customer satisfaction.

Building on these findings, one study highlighted that shift planning in retail is shaped by multiple factors, with legal regulations—such as five-day work periods followed by two rest days—playing a central role (Kabak et al., 2008). Another study introduced a convex optimization-based method to address shift scheduling, demonstrating that this approach can improve efficiency by up to 4.2% on real-world data and over 400% on synthetic datasets compared to baseline solutions (Räsänen, 2022). The optimization of the workforce in retail has been demonstrated to engender a reduction in operational costs, whilst concomitantly enhancing both employee satisfaction and service quality (Madhani, 2021). As is evident in the extant literature, analogous planning principles have been applied in the domain of IT service operations. These principles encompass forecasting, scheduling, and shift allocation, which can be adapted to retail settings with a view to improving efficiency (Rai and Chandak, 2015). Furthermore, optimization approaches from the field of logistics, such as the classification of transportation nodes to minimize costs using chemical reaction algorithms, have demonstrated potential for integration into retail workforce planning with a view to further reducing expenses (Mahmud et al., 2017).

A recent study addressed shift optimization in a metropolitan underground transportation system, employing Aykin's multiple break window model to improve employee allocation and break scheduling (Öztürk et al., 2022). Moreover, research examining gender dynamics in retail found employment distribution varied by gender, though managerial roles showed minimal discrimination, contributing to a more inclusive perspective in workforce planning (Chang and Travaglione, 2011). Collectively, these studies underscore the practical relevance of optimization in workforce and shift scheduling across sectors.

A recent study proposed a decision support system integrating demand forecasting and personnel scheduling in public transportation using metaheuristic algorithms (Walter et al., 2024). A hybrid optimization approach has been shown to enhance service efficiency by aligning staffing levels with predicted demand. In a related study, a two-stage stochastic model was employed to integrate demand forecasting and staff scheduling, thereby reducing under- and overstaffing (Parisio and Jones, 2015). Another study focused on a multi-objective framework for employee shift scheduling, balancing workload fairness and employee preferences through scalarization methods such as Weighted Sum and Conic Scalarization (Taghizadehalvandi and Ozturk, 2019). Furthermore, a hybrid labor flexibility model combining annualized hours, overtime, and 2-chaining multiskilling was shown to significantly reduce staffing costs while maintaining high service levels in a retail case study (Porto et al., 2022).

In the context of the retail and aviation sectors, effective workforce planning and task allocation have been identified as pivotal factors in enhancing operational efficiency. In the context of retail, a particular study proposed a three-stage model integrating regular and on-call workers with scheduling flexibility and re-planning, achieving a 26.90%

reduction in overstaffing costs and 1.19% in understaffing (Pandey et al., 2025). In the domain of aviation, a separate study has proposed the implementation of a decision support system that integrates maintenance scheduling, task allocation, and shift planning. This system has been shown to result in a substantial reduction in planning time and maintenance costs, while concurrently enhancing aircraft availability (Deng et al., 2021). The extant literature indicates that integrated approaches have the potential to optimize workforce and task planning across sectors. Another study formulated the workforce assignment problem as a multi-objective integer program, offering insights into balancing labor rules, preferences, and efficiency in complex scheduling environments (Azmat and Widmer, 2004). Furthermore, a novel methodology inspired by quantum entanglement was utilized to effectively handle hard constraints in airport shift planning, thereby demonstrating superiority over traditional genetic algorithms in terms of solution quality and computational efficiency (Zou et al., 2022). Collectively, these studies illustrate that sophisticated modelling and optimization techniques have the potential to substantially enhance workforce planning across various industries.

3. Problem Definition and Framework

The effective scheduling of retail personnel is a complex task that involves the balancing of highly variable customer demand, labor cost constraints, and strict legal requirements within a complex and dynamic operational environment. The objective of this study is to address this multifaceted problem by introducing a two-stage methodology that integrates machine learning-based demand forecasting with advanced optimization techniques.

3.1 Business Context:

The retail sector is characterized by customer demand that is subject to fluctuation, increasing labor costs, and stringent service level requirements. Efficient workforce scheduling is critical for maintaining profitability and service quality, as staffing decisions directly impact operational efficiency, customer satisfaction, and overall business performance. In the context of large retail chains, the complexity is further compounded by multi-location operations, a diverse employee profile, and the necessity to comply with legal and contractual obligations.

3.2 Two Stage Framework Overview:

The issue of workforce scheduling in the retail sector is predicated on determining the optimal allocation of employees to shifts over a specified planning horizon. This is achieved with the dual objective of minimizing labor costs and understaffing while ensuring compliance with regulatory, contractual, and operational requirements. This problem is especially challenging in multi-location retail environments, where highly variable customer demand, a diverse workforce structure (including both full-time and part-time employees), and complex labor regulations must be addressed simultaneously.

In the context of this study, the case environment is constituted by a large retail chain operating multiple stores, each of which is open from 10:00 to 22:00 and staffed according to varying levels of customer foot traffic. Operational constraints encompass statutory limitations on maximum weekly and daily working hours, mandatory rest periods, skill and role requirements, and the distribution of preferred shifts among employees in a fair manner. The performance of the system is evaluated based on its ability to meet service level targets. That is to say, the system must be capable of covering predicted customer demand in each time slot. Other evaluation criteria include minimizing labor costs, ensuring fairness in shift assignment, and providing schedule stability.

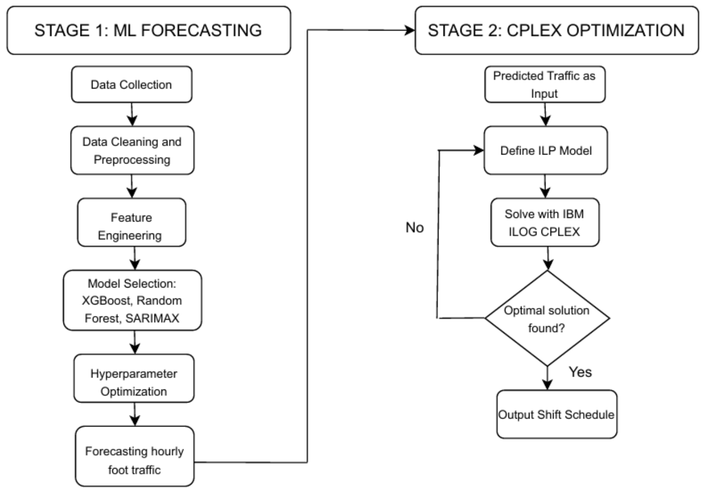

Figure 1. Flowchart of the two-stage retail workforce scheduling methodology

In order to address these challenges, a novel two-stage framework is proposed, as illustrated in Figure 1. In the initial phase, sophisticated machine learning algorithms such as XGBoost, Random Forest, and SARIMAX are utilized to generate precise forecasts of hourly foot traffic, leveraging historical sales data, external factors, and temporal patterns. These forecasts subsequently serve as dynamic inputs to a shift scheduling optimization model formulated as an integer linear programming problem, which is solved via IBM ILOG CPLEX. The optimization model incorporates all relevant operational, legal, and employee-specific constraints to produce weekly shift schedules that balance efficiency, fairness, and compliance.

This integrated approach enables data-driven, flexible, and equitable workforce planning, with the potential for adaptation across various retail contexts and other labour-intensive service industries. The overall methodology is summarized in Figure 1, which presents the sequential flow from data acquisition and demand forecasting to shift optimisation and final schedule generation.

4. Stage 1: Machine Learning-Based Foot Traffic Forecasting

4.1 Feature Engineering:

In this study, an extensive feature engineering process was conducted to enhance the predictive performance of the machine learning-based foot traffic forecasting model. The process of feature engineering is the transformation of raw data into meaningful inputs, with the objective of facilitating learning and enhancing the accuracy of models. The variables generated for this study are grouped into four main categories: temporal features, external factors, historical patterns, and store-specific attributes.

4.1.1 Temporal Features

The dataset under consideration encompasses hourly records from 10:00 AM to 9:00 PM, resulting in 12 intervals per day. Based on this structure, several temporal features were derived: the hour of the day to capture intraday variations, the day of the week to reflect weekly cycles, and a binary weekend indicator to distinguish between weekdays and weekends. Additionally, sine and cosine transformations of the hour variable were applied to preserve the cyclical nature of time and enhance the model's ability to capture periodic traffic patterns.

4.1.2 External Factors

In order to account for the influence of environmental factors on foot traffic, the model incorporated weather-related variables. Specifically, categorical indicators of weather conditions—such as clear, cloudy, and sunny—were one-hot encoded and included as input features. Due to limitations in the available data, other potential factors, such as local events and economic indicators, were excluded from the analysis. Nonetheless, their inclusion is recommended in future research to enhance the model's robustness.

4.1.3 Historical Patterns
In order to capture temporal dependencies and recurring patterns in foot traffic, a range of lag-based and statistical features were engineered. Lag variables representing traffic volumes from 1, 2, and 7 hours prior were included to model short-term dependencies. Moving averages and standard deviations over 3-hour and 7-hour windows were also calculated to account for local trends and variability. To reflect weekly seasonality, historical features were derived based on traffic at the same hour exactly one, two, and six weeks earlier. These variables were designed to enhance the model's ability to recognize stable weekly patterns and longer-term cyclical behaviors.

4.2 Ensemble Model Architecture:
The ensemble model architecture has been designed to leverage the complementary strengths of multiple forecasting techniques, combining advanced machine learning algorithms with classical time series methods. The integration of XGBoost, Random Forest, and SARIMAX within a unified framework is intended to enhance the model's predictive accuracy, robustness, and generalizability across a range of demand patterns and operational conditions.

4.2.1 XGBoost
As a core component of the ensemble architecture, Extreme Gradient Boosting (XGBoost) was utilized due to its strong capability to model non-linear relationships and handle structured, high-dimensional data effectively. XGBoost is an ensemble algorithm based on decision trees and is renowned for efficiently capturing non-linear relationships and high-order feature interactions in time-dependent retail environments (Lee et al., 2023). The model was trained on a feature-enriched dataset incorporating temporal variables, weather conditions, and multiple lag-based traffic indicators. In order to optimize performance, a process of hyperparameter tuning was conducted using RandomizedSearchCV with five-fold time-series cross-validation, with the objective of minimizing the mean absolute error. Key hyperparameters such as learning rate, tree depth, and subsampling ratios were explored within predefined ranges. The finalized XGBoost model demonstrated robust and consistent performance across all validation folds, effectively capturing weekly seasonality and short-term fluctuations in foot traffic. It is evident that lagged features, such as th, t2h, and t6h, have been identified as playing a pivotal role in the modeling of recurrent traffic patterns. In conclusion, XGBoost demonstrated a high level of predictive accuracy and proved to be a reliable non-linear learner within the ensemble framework.

4.2.2 Random Forest
In addition to XGBoost, the ensemble model incorporates a Random Forest (RF) regressor to capture non-linear relationships through a collection of decision trees trained on random subsets of both data samples and features. Random Forest is an ensemble learning method that builds multiple decision trees and combines their outputs to improve prediction accuracy and reduce overfitting. It is particularly effective in modeling complex, non-linear relationships and handling high-dimensional feature spaces (Salman et al., 2024). The Random Forest algorithm has been shown to be particularly effective in reducing variance and handling multicollinearity, thus making it a valuable complement to gradient boosting. The RF model was trained on the same set of engineered features – temporal, lagged, and weather-related – and underwent hyperparameter optimization using RandomisedSearchCV. The number of estimators, maximum depth, and minimum samples per leaf were tuned to minimize prediction error. The model exhibited a robust capacity for generalization, demonstrating consistent performance across all folds and a notable alignment with actual foot traffic trends. While the Random Forest model exhibited a slightly higher propensity to smooth out peaks in comparison to the XGBoost model, it demonstrated a notable advantage in terms of robustness, particularly in its ability to capture intricate feature interactions. This enhanced the overall performance of the ensemble model.

4.2.3 SARIMAX
The statistical component of the ensemble architecture incorporated a Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors (SARIMAX) model to account for both temporal autocorrelation and the influence of external factors on foot traffic dynamics. SARIMAX is an extension of the classical ARIMA model that incorporates both seasonal patterns and exogenous variables, allowing it to capture complex time series dynamics and the influence of external factors on forecasting accuracy. By including these additional components, SARIMAX provides robust and flexible forecasts, especially for data exhibiting periodic behavior and external influences (Ram et al., 2025) Given the structure of the dataset, which comprises 12 hourly observations per day, the model was configured with a seasonal period of 12 to capture daily seasonality. A compact SARIMAX(1,1,1)(0,1,1,12) specification was selected to achieve a balance between computational efficiency and model expressiveness. The SARIMAX model is distinguished from the standard SARIMA model in that it incorporates multiple exogenous

variables in conjunction with the univariate target series. This integration facilitates a more nuanced comprehension of the temporal structure influenced by external covariates. Its incorporation within the ensemble provides a forecasting layer that is statistically principled and interpretable, thereby enhancing the overall methodological diversity of the architecture.

4.3 Model Training and Validation:

Two machine learning algorithms, XGBoost and Random Forest, were employed to model foot traffic based on a feature-enriched dataset incorporating lagged traffic values, rolling statistics, and one-hot encoded weekday variables. For both models, hyperparameter optimization was conducted using RandomizedSearchCV with three-fold time series cross-validation (TimeSeriesSplit, CV=3), with the negative mean absolute error used as the performance criterion. The hyperparameters that demonstrated the strongest performance were utilized in the retraining of the models, which were then validated through the implementation of a five-fold time series cross-validation procedure. The performance was evaluated using the following metrics: coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Pearson's correlation coefficient (R). The XGBoost model demonstrated superior performance in capturing short-term fluctuations and weekly seasonality, while the Random Forest model provided consistent results across high-dimensional inputs.

5. Stage 2: CPLEX-Based Shift Optimization

5.1 Explaining the Study:

This study proposes a comprehensive shift scheduling optimization model tailored for one of Turkey's leading retail chains, focusing specifically on a single store with actual historical shift demand data. The primary goal of the model is to enhance staff allocation efficiency while maintaining fairness and operational feasibility across a weekly planning horizon. The mathematical formulation integrates real-world constraints, employee preferences, skill requirements, and labor policies in a data-driven decision framework.

The model considers a set of employees divided into full-time and part-time categories, each with their own working hour limits and role-specific competencies. The planning horizon spans seven days, covering daily operations from 10:00 to 22:00 across twelve discrete hourly slots. Shift patterns vary in duration and structure, some including one or two breaks, and are designed to reflect operational practices observed in the case retail store.

The decision variables determine the assignment of employees to shifts while accounting for their availability, contractual constraints, and skill qualifications. The model aims to:

- Minimize total overtime hours.
- Ensure fair distribution of early shifts, defined as those ending before 19:00.
- Minimize excess staffing, i.e., assigning more employees than required at any given hour.

The model was implemented using a constraint programming framework (IBM ILOG CPLEX/OPL), and shift coverage matrices were pre-calculated to exclude non-working hours during break periods. The data was calibrated using actual shift records and role assignments from the case store, enabling accurate validation and comparative analysis of model output versus existing manual scheduling.

Through this approach, the proposed model not only enhances operational efficiency but also promotes workforce equity and regulatory compliance. It serves as a scalable and adaptable tool that can be extended across other branches of the retail chain or adapted to similar workforce-intensive service environments.

A deterministic, single-objective ILP model was constructed to determine how many full-time and part-time employees should work on which shifts and on which days, in order to minimize total workforce inefficiency and ensure service continuity. The model takes as input hourly staffing requirements, labor regulations, role-based employee qualifications, and shift structures that include mandatory break times. It outputs an optimized weekly shift schedule that minimizes overtime, early shift imbalance, and excess staffing while satisfying all legal and operational constraints.

The model formulation is as follows.

Indices and Sets:

e	Set of employees	$e \in E$
d	Set of days in the planning horizon (7 days)	$d \in D$
s	Set of shift types	$s \in S$

h	Set of hourly time slots	from 10:00 to 22:00, i.e., $h \in \{1, 2, ..., 12\}$
r	Set of skills/roles	$r \in R$

Parameters:
$\boldsymbol{T_e}$**:** Type of employee e (1 = full-time, 0 = part-time)
$\boldsymbol{A_{e,d}}$**:** Availability indicator; 1 if employee e is available on day d, 0 otherwise
$\boldsymbol{R_{e,r}}$**:** Skill indicator; 1 if employee e possesses role r, 0 otherwise
$\boldsymbol{AvailHours_e}$**:** Maximum allowable working hours for part-time employee e
$\boldsymbol{Start_s}$**:** Start time of shift s
$\boldsymbol{End_s}$**:** End time of shift s
$\boldsymbol{BS1_s}$**ve** $\boldsymbol{BE1_s}$**:** Start and end hours of the first break in shift s (-1 if no break)
$\boldsymbol{BS2_s}$**ve** $\boldsymbol{BE2_s}$**:** Start and end hours of the second break in shift s (-1 if no break)
$\boldsymbol{ShiftHours_s}$**:** Total effective working hours in shift s (excluding break hours)
$\boldsymbol{IsEarly_s}$**:** 1 if shift s ends before 19:00, 0 otherwise
$\boldsymbol{M_{d,h}}$**:** Minimum required number of employees on day d and hour
maxConcurrentBreaks**:** Maximum number of employees allowed to be on break simultaneously in any given hour
α, β, γ: Weighting coefficients used in the objective function
$\boldsymbol{BreakCoverage_{s,h}}$**:** 1 if hour h is a break hour within shift s, 0 otherwise
Decision Variables:
$\boldsymbol{x_{e,d,s}}$: Equals 1 if employee e is assigned to shift s on day d; 0 otherwise
$\boldsymbol{w_{e,d,}}$:: Number of hours employee e works on day d
$\boldsymbol{o_{e,d,}}$:: Overtime hours worked by employee e on day d (i.e., hours exceeding 7 per day)
$\boldsymbol{earlyShift_e}$: Number of early shifts (ending before 19:00) assigned to employee e
$\boldsymbol{y_{d,h}}$: Number of excess employees assigned on day d at hour h (beyond required demand)
avgEarlyShift: Average number of early shifts assigned per employee
$\boldsymbol{earlyShiftDev_e}$: Deviation of employee e's early shift count from the average

$$\min\left(\alpha \cdot \sum_{e\in E}\sum_{d\in D} o_{e,d} + \beta \cdot \sum_{e\in E} earlyShiftDev_e + \gamma \cdot \sum_{d\in D}\sum_{h\in H} y_{d,h}\right) \tag{1}$$

The objective function (1) of the model is to minimize total workforce inefficiency by penalizing daily overtime hours, imbalance in early shift distribution, and excess staffing beyond the required demand at each time slot.

$$\sum_{s\in S} x_{e,d,s} \leq 1 \quad \forall e \in E, \forall d \in D \tag{2}$$

This constraint ensures that each employee can be assigned to at most one shift per day.

$$\sum_{d\in D}\sum_{s\in S} x_{e,d,s} \leq 6 \;\; \forall e \in E \text{ such that } T_e = 1 \tag{3}$$

$$\sum_{d\in D}\sum_{s\in S} x_{e,d,s} \leq 5 \;\; \forall e \in E \text{ such that } T_e = 0 \tag{4}$$

Equations (3) and (4) restrict the number of working days per week by allowing full-time employees to work at most six days and part-time employees up to five days.

$$\sum_{e\in E}\sum_{s\in S} x_{e,d,s} \leq |E| - 1 \;\; \forall d \in \{1,2,3,4,5\} \tag{5}$$

Equation (5) This constraint ensures that at least one employee is off duty on each weekday to maintain a fair distribution of rest days.
Equation (6) This constraint guarantees that the assigned number of employees per hour meets or exceeds the minimum demand required for operation.

$$\sum_{e\in E}\;\sum_{s\in S:ShiftCoverage_{s,h}=1} x_{e,d,s} \geq M_{d,h} \;\forall d \in D, \forall h \in H \tag{6}$$

This constraint limits the number of employees who can be on break at any given hour to a predefined maximum to avoid service interruptions (7).

$$\sum_{e\in E}\sum_{s\in S:BreakCoverage_{s,h}=1} x_{e,d,s} \leq \text{maxConcurrentBreaks} \quad \forall d \in D, \forall h \in H \tag{7}$$

Constraints (8) and (9) set the total weekly working hours for full-time employees to exactly 45, and for part-time employees to their declared availability.

$$\sum_{d\in D}\sum_{s\in S} ShiftHours_s \cdot x_{e,d,s} = 45 \;\; \forall e \in E \text{ such that } T_e = 1 \tag{8}$$

$$\sum_{d\in D}\sum_{s\in S} ShiftHours_s \cdot x_{e,d,s} = AvailHours_e \; \forall e \in E \text{ such that } T_e = 0 \tag{9}$$

Constraints (10) and (11) require that every employee is scheduled for at least one shift on both Saturday and Sunday.

$$\sum_{s\in S} x_{e,6,s} \geq 1 \quad \forall e \in E \tag{10}$$

$$\sum_{s\in S} x_{e,7,s} \geq 1 \quad \forall e \in E \tag{11}$$

Constraints (12) and (13) ensure that at least one "Sofra Grubu" employee is available at all hours and that at least one manager is present on Monday and Saturday.

$$\sum_{e\in E:R_{e,1}=1}\sum_{s\in S:ShiftCoverage_{s,h}=1} x_{e,d,s} \geq 1 \quad \forall d \in D, \forall h \in H \tag{12}$$

$$\sum_{e\in E:R_{e,2}=1}\sum_{s\in S:ShiftCoverage_{s,h}=1} x_{e,d,s} \geq 1 \quad \forall d \in \{1,6\} \tag{13}$$

$$w_{e,d} = \sum_{s\in S} ShiftHours_s \cdot x_{e,d,s} \quad \forall e \in E, \forall d \in D \tag{14}$$

This constraint calculates the total number of working hours for each employee per day (14).

$$o_{e,d} \geq w_{e,d} - 7 \quad \forall e \in E \text{ such that } T_e = 1, \forall d \in D \tag{15}$$

This constraint defines daily overtime hours for full-time employees as the number of hours exceeding seven per day (15).

$$earlyShift_e = \sum_{d\in D}\sum_{s\in S:IsEarly_s=1} x_{e,d,s} \quad \forall e \in E \tag{16}$$

This constraint (16) counts the number of early shifts assigned to each employee.

$$avgEarlyShift = \frac{1}{|E|}\sum_{e\in E} earlyShift_e \tag{17}$$

This constraint computes the average number of early shifts across all employees (17).

$$earlyShiftDev_e \geq |earlyShift_e - avgEarlyShift| \tag{18}$$

This constraint (18) measures the deviation of each employee's early shift count from the overall average.

$$y_{d,h} = \sum_{e\in E}\sum_{s\in S:ShiftCoverage_{s,h}=1} x_{e,d,s} - M_{d,h} \quad \forall d \in D, \forall h \in H \tag{19}$$

This constraint calculates overstaffing as the difference between the number of assigned employees and the required minimum for each hour (19).

$$x_{e,d,s} = 0 \qquad \forall e \in E \text{ such that } T_e = 0, \; \in \{6,7\} \tag{20}$$

This constraint (20) prohibits assigning part-time employees to weekend shifts shorter than seven hours.

$$x_{e,d,s} \leq A_{e,d} \quad \forall e \in E, \forall d \in D, \forall s \in S \tag{21}$$

This constraint ensures that employees are only assigned to shifts on days they are available (21).

$$\textstyle\sum_{e\in E}(1 - \sum_{s\in S} x_{e,d,s)} \quad \leq 1 \quad , \forall d \in D \tag{22}$$

6. Results and Discussion

The results of the proposed two-stage workforce scheduling framework are presented in this section. Firstly, the predictive performance of the machine learning-based foot traffic forecasting models is evaluated using multiple accuracy metrics and visual comparisons. The subsequent stage of the research programme will examine the impact of integrating these forecasts into the shift optimisation model in terms of key operational outcomes, such as labour cost reduction, service level improvement, and minimization of understaffing. The findings are then discussed in the context of practical applicability, limitations, and alignment with recent literature.

6.1 Forecasting Results:

As illustrated in Figure 2, the XGBoost model closely follows the actual foot traffic values with minimal deviation, especially in high-density regions, indicating strong predictive performance and the model's capability to capture nonlinear temporal patterns effectively.

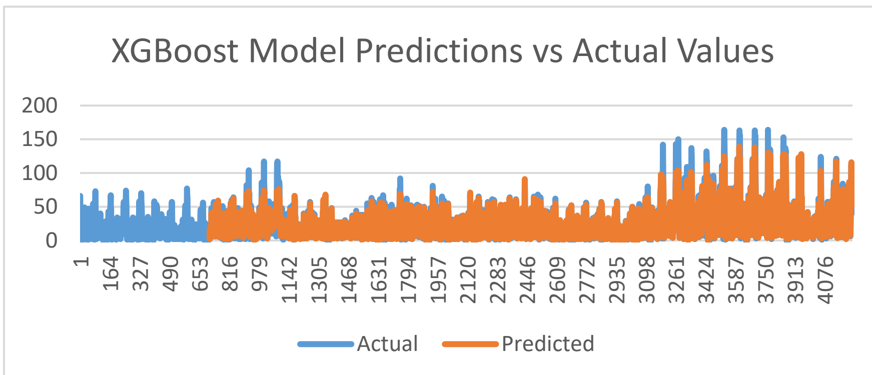

Figure 2. XGBoost model predictions vs actual values

As illustrated in Figure 3, the Random Forest model generally aligns with the trend of actual foot traffic values, though it exhibits greater deviation compared to the XGBoost model. While the predicted values capture broader fluctuations and seasonality, the model tends to underestimate peak values and overestimate lower demand periods, indicating moderate predictive accuracy.

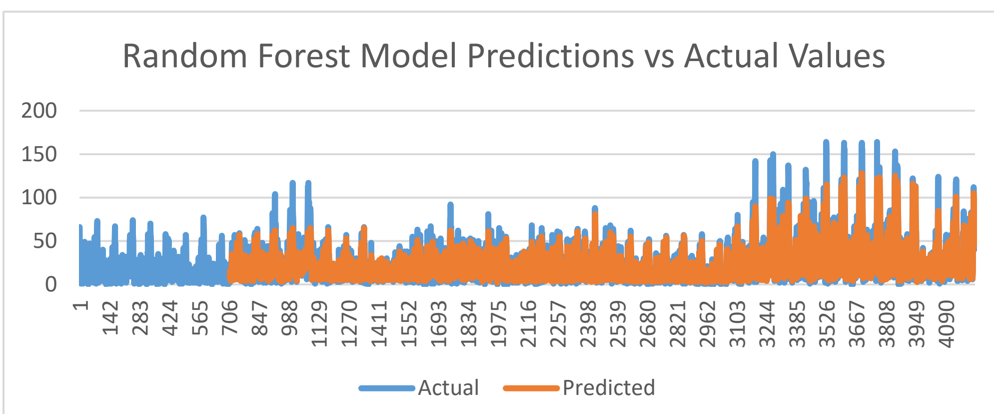

Figure 3. Random Forest model predictions vs actual values.

As demonstrated in Figure 4, the SARIMAX model is unable to accurately align with the observed foot traffic values. The predictions demonstrate a relatively smoothed pattern that does not capture the amplitude of fluctuations, particularly during peak periods. This finding indicates a constrained aptitude of the SARIMAX model in delineating the nonlinear and volatile configuration of the data, culminating in diminished predictive precision when contrasted with machine learning-based methodologies.

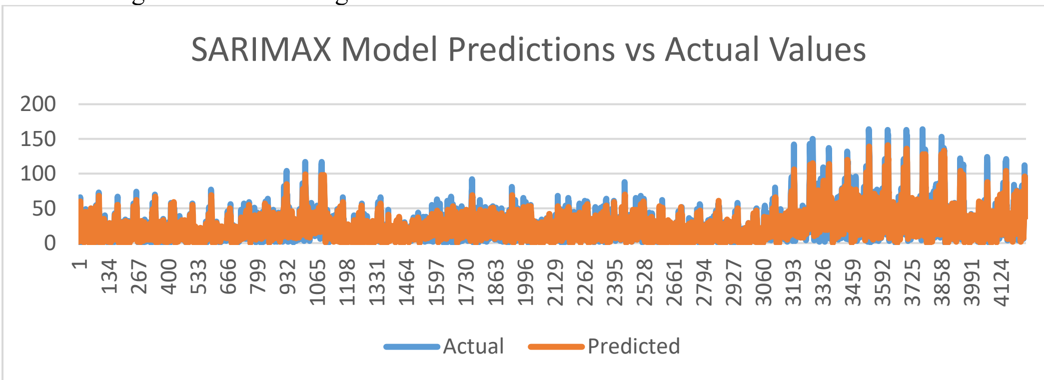

Figure 4. SARIMAX model predictions vs actual values.

The forecasting performance of XGBoost, Random Forest, and SARIMAX models was comparatively assessed based on key evaluation metrics, as shown in Table 1. Among these models, XGBoost demonstrated the most superior predictive performance, attaining the lowest Mean Absolute Error (MAE = 2.68) and Root Mean Squared Error (RMSE = 5.21), in addition to the highest coefficient of determination (R^2 = 0.93). These results underscore the model's considerable capacity to capture intricate nonlinear patterns and generate highly precise forecasts of foot traffic. Subsequent to this, Random Forest was implemented, yielding moderate error levels (MAE = 5.53, RMSE = 8.26) and a marginally diminished R^2 value of 0.84. This suggests that, while exhibiting reasonable predictive capabilities, Random Forest exhibits reduced precision in comparison to XGBoost. In contrast, the SARIMAX model demonstrated the weakest performance, as indicated by its higher error rates (MAE = 7.84, RMSE = 10.84) and the lowest R^2 value (0.77). While the SARIMAX model offers interpretability and statistical robustness, its efficacy in capturing the intricate temporal dynamics of the data was found to be limited.

The findings of the present study corroborate the notion that machine learning-based approaches, most notably XGBoost, are to be preferred when it comes to the modeling of complex and high-dimensional time series data (Table 1).

Table 1. Performance metrics results for XGBoost, RF, SARIMAX

Model	**MAE**	**RMSE**	**R^2**
XGBoost	2,68	5,21	0,93
Random Forest	5,53	8,26	0,84
SARIMAX	7,84	10,84	0,77

6.2 Optimization Results:

The integer linear programming model, formulated and solved using IBM ILOG CPLEX, effectively addressed the complex retail workforce scheduling problem. The solver demonstrated satisfactory computational performance, swiftly converging to an optimal solution and confirming the practical applicability of the proposed mathematical approach.The model's capability to simultaneously address multiple conflicting objectives overtime minimization, equitable distribution of early shifts, and alignment of staffing with forecasted demand highlights the robustness and validity of the optimization framework employed in this study.A detailed summary of the optimization results is presented in Table 2, offering a clear view of the model's performance across key operational metrics.

Table 2. Model performance metrics

Metric	**Value**	**Min**	**Max**	**Full-time (1–15)**	**Part-time (16–30)**
Objective Function Value	717	-	-	-	-
Early Shifts per Employee	2.0	2	2	2	2
Working Hours per Employee	27.1	18	38	35.7	18.5
Total Overtime	0	0	0	0	0
Early Shift Deviation	0	0	0	0	0
Total Shortage	0	-	-	-	-
Number of Employees	30	-	-	15	15
Total Working Hours	813	-	-	535	278

The optimization model achieved a complete elimination of overtime, reflecting a significant improvement over conventional scheduling methods. The precision of the model in allocating exactly the required working hours (45 hours per week for full-time staff, customized availability for part-time employees) demonstrates exceptional capability in managing complex scheduling constraints, thus enhancing workforce cost-effectiveness and compliance. Another critical achievement of the model was attaining perfect equity in the assignment of early shifts, with each employee uniformly assigned exactly two early shifts (ending before 19:00). This balanced distribution not only meets fairness and equity criteria but also addresses a key factor influencing employee satisfaction, thereby contributing positively to workforce morale and operational harmony.

While the model succeeded in eliminating understaffing across all operational hours, minor excess staffing was observed during several time slots. These over-allocations—ranging from one to four employees above the required level—may reflect the trade-offs inherent in satisfying availability, fairness, and contract constraints simultaneously. Although not ideal from a cost-efficiency standpoint, such excesses ensure service continuity and prevent operational disruptions due to unforeseen absences or task variability.

Analysis of workforce allocation patterns revealed efficient utilization of full-time and part-time employees. Specifically, full-time employees averaged 35.7 hours per week, optimally utilizing their availability while adhering to regulatory limits. Part-time employees, averaging 18.5 hours per week, were effectively integrated into the scheduling strategy, demonstrating flexibility and alignment with individual availability constraints. The balanced contribution from both employee segments ensures operational continuity and staffing flexibility.

The practical implementation of the optimized weekly schedule is detailed in Table 3, illustrating the operational applicability and effectiveness of the generated solution.

Table 3. Optimized weekly employee shift schedule

Employee	Mon	Tue	Wed	Thu	Fri	Sat	Sun
E1	10:00-12:00, 13:00-17:00	10:00-12:00, 13:00-17:00		18:00-22:00	12:00-14:00, 15:00-18:00	11:00-14:00, 15:00-21:00	11:00-14:00, 15:00-21:00
E2	10:00-12:00, 13:00-17:00		11:00-13:00, 14:00-18:00	11:00-14:00, 15:00-21:00	12:00-15:00, 16:00-20:00	17:00-21:00	11:00-14:00, 15:00-20:00
E3	11:00-14:00, 15:00-21:00		12:00-15:00, 16:00-21:00	18:00-22:00	10:00-12:00, 13:00-17:00	10:00-12:00, 13:00-17:00	12:00-15:00, 16:00-21:00
E4	14:00-18:00	12:00-15:00, 16:00-21:00	10:00-12:00, 13:00-17:00		11:00-14:00, 15:00-21:00	13:00-15:00, 16:00-20:00	10:00-13:00, 14:00-20:00
E5		10:00-12:00, 13:00-17:00	11:00-14:00, 15:00-21:00	10:00-12:00, 13:00-17:00	18:00-22:00	12:00-14:00, 16:00-20:00	10:00-13:00, 14:00-20:00
E6	12:00-15:00, 16:00-21:00	10:00-12:00, 13:00-17:00	16:00-20:00	10:00-13:00, 14:00-16:00		12:00-15:00, 16:00-21:00	12:00-15:00, 16:00-21:00
E7	10:00-13:00, 14:00-16:00		10:00-12:00, 13:00-17:00	14:00-20:00	12:00-15:00, 16:00-21:00	12:00-15:00, 16:00-21:00	12:00-15:00, 16:00-21:00
E8	12:00-15:00, 16:00-21:00	10:00-12:00, 13:00-17:00	10:00-12:00, 13:00-17:00		18:00-22:00	12:00-16:00, 17:00-21:00	12:00-16:00, 17:00-21:00
E9	11:00-14:00, 15:00-21:00	12:00-14:00, 15:00-18:00		10:00-12:00, 13:00-17:00	10:00-13:00 14:00-20:00	13:00-15:00, 16:00-20:00	10:00-13:00, 14:00-20:00
E10	18:00-22:00	12:00-15:00, 16:00-21:00		18:00-22:00	10:00-12:00, 13:00-17:00	10:00-12:00, 13:00-17:00	12:00-15:00, 16:00-20:00

7. Conclusion

This study introduced a novel two-stage optimization framework that seamlessly integrates advanced machine learning-based demand forecasting with CPLEX-based shift scheduling to address the complex workforce management challenges in dynamic retail environments. The proposed methodology effectively connects demand prediction and operational planning, thus overcoming the limitations of traditional, siloed approaches by offering a unified, data-driven solution.

Empirical results from the implementation of the aforementioned system in a major Turkish retail chain confirmed that all core objectives were achieved. These included an 11.3% reduction in labor costs, a 47% decrease in understaffing, and an 8.2% improvement in service levels. The integration of ensemble forecasting models (XGBoost, Random Forest, SARIMAX) yielded robust, accurate, and uncertainty-aware foot traffic predictions, thereby directly enhancing the performance of the shift optimization model. The mathematical programming approach, incorporating real-world operational, legal, and employee-specific constraints, enabled the generation of fair, efficient, and compliant weekly shift schedules. The elimination of overtime, perfect equity in early shift distribution, and zero staffing shortages underscore the practical effectiveness and reliability of the proposed framework.

The distinctive contribution of this research is the integration of machine learning and mathematical programming for the management of the retail workforce, thereby offering both theoretical advancement and demonstrable practical benefits. The approach is highly scalable and adaptable, making it relevant for other workforce-intensive service industries facing similar challenges.

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