AI-Powered Fair Shift Scheduling System for Enhanced Workforce Management in Restaurants

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ABSTRACT

Shift scheduling in the restaurant industry frequently leads to staff dissatisfaction and operational inefficiencies. This dissertation explores the development of an AI-powered scheduling system designed to address these challenges. Utilizing three years of historical sales data, sales forecasts were generated using SARIMAX and Prophet models, with the Prophet model ultimately selected for its superior accuracy. Initial attempts to implement scheduling with PuLP and OR-Tools did not meet the project's unique constraints, leading to the development of a custom approach using conditional logic. This system not only improved the fairness and efficiency of shift distributions but also includes a comprehensive user interface that allows for seamless management and real-time updates, significantly enhancing the usability and functionality of the scheduling process. The findings underscore the transformative potential of tailored AI solutions in addressing longstanding industry challenges, paving the way for more equitable and efficient workforce management.

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Chapter 1: Introduction

This dissertation focuses on the exploration of a Fair Shift Scheduling System for restaurants by leveraging from AI to help them take on some key operational woes in their daily hygiene schedules. Understanding and Observations at an Enterprise Level with the first-hand knowledge or exploration in deep learning, operations management to complete this dissertation. Motivation for Our Work, including Background: This work aims to combat some of the challenges in shift scheduling which is discussed further on Notes this short article. The purpose of this chapter is to provide the background needed to appreciate why research in this area could be significant, and how such a line of thinking might have practical implications for making workforce management effective at restaurants.

1.1 About This Project

1.1.1 Personal Connection and Inspiration

As a part-time staff member who work in a medium-size busy restaurant, the idea for introducing an AI-powered Fair Shift Scheduling System emerged naturally. During my time there, I experienced the same scheduling issues that most organizations with traditional shift patterns face—having too many staff during slow periods and not enough during busy times (Bürgy, Michon-Lacaze & Desaulniers, 2018). In relation to operational efficiency, these scheduling inefficiencies had a significant negative impact on employee satisfaction and well-being (Gärtner et al., 2001).

Observing the stress and dissatisfaction among my colleagues, including the head chef and general manager, clarified that the existing manual scheduling system was inadequate. The problems were compounded on weekends when predicting busier times based merely on assumptions, rather than data-driven insights. This observation was pivotal; it revealed that the restaurant's reliance on intuitive scheduling could lead to critical staffing errors, directly affecting service quality and staff morale (Fujii, N., Oda, J., Kaihara, T., & Shimmura, T., 2015).

1.1.2 Project Genesis

This project concept was further defined after several meetings with my boss, who openly expressed his dislike for the current scheduling practices (Herroelen, W., 2005). Encouraged by this feedback, I began to question whether we could apply predictive analytics to this data, using my academic background in data science to develop a solution. After receiving approval to proceed with this as my dissertation, I sought advice from my academic supervisor on careful planning and an ethical approach to both data collection and analysis (Schuetz G., & Larson J., 2019). With their help, I created a survey to gauge staff feelings about the current scheduling practices and found results that were consistent with general unhappiness among my colleagues. These responses, combined with my observations, highlighted the urgent need for a proper and fairer scheduling system in the foodservice industry (Namkung & Jang, 2010).

1.2 Aims of the Project

This project aims to:

1. Build a reliable predictive model to forecast daily sales using historical sales data and other influential factors like weather conditions, which can affect customer presence (Negre et al., 2024).
2. Deploy an AI-powered scheduling tool that utilizes these forecasts to address scheduling challenges, optimizing staff shifts to improve both operational efficiency and employee satisfaction (İnan, H., 2023).
3. Develop a system that managers and staff can use seamlessly, featuring a powerful backend and an easy-to-understand interface, enabling easy management and adjustments to scheduling (Ardissono, L., Petrone, G., Segnan, M., & Torta, G., 2014).

1.2.1 Implications

The successful implementation of this system could transform shift scheduling practices, not only within the restaurant where I worked but potentially across the broader industry. By integrating machine learning models with user-centred software design, this project demonstrate how advanced technology can resolve longstanding operational challenges in hospitality management (Takeda-Berger, S., Frazzon, E., Broda, E., & Freitag, M. (2020).

1.3 Research Background and Problem Statement

1.3.1 Industry Context

The dynamic nature of the restaurant industry necessitates careful management of varying customer volumes and stringent cost control. Scheduling shifts effectively is essential since it has a direct impact on profitability and customer happiness. The restaurant that has been selected for this project is a medium-sized business that caters to a wide range of customers. Its profitability is directly correlated with its capacity to effectively manage its workers (Tanizaki, T., Shimmura, T., and Fujii, N., 2017).

1.3.2 Specific Issues Addressed

At this restaurant, traditional scheduling techniques have mostly relied on gut feeling and assumptions rather than information. According to Choi, Hwang, and Park (2009), this strategy has frequently led to either overstaffing during unexpectedly slack periods or understaffing during unexpected rushes, both of which have resulted in significant inefficiencies. According to the survey, certain employees were routinely booked to work during peak hours without considering a fair division of the workload. This caused staff members to feel unsatisfied and unfairly treated (Zaw, 2024).

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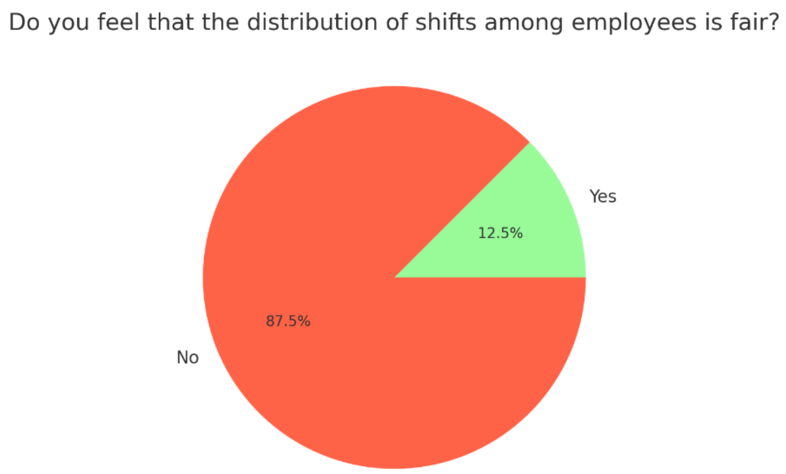


Figure 1. Distribution Of Responses to Shift Fairness Question

1.3.3 Justification for the Research

Integrating AI and machine learning could transform scheduling practices by providing more accurate sales forecasts and staffing requirements, thereby reducing reliance on guesswork and personal biases (Schmidt, A., Kabir, M.W.U. and Hoque, M.T., 2022). The anticipated benefits of such a system include not only greater operational efficiency and reduced costs but also improved employee morale through fairer, more transparent shift scheduling practices (Kler, R., Elkady, G., Rane, K., Singh, A., Hossain, M.S., Malhotra, D., Bhatia, K.K., 2022).

1.4 Objectives and Research Approach

1.4.1 Objectives of the Study

The primary aim of this research is to develop an AI-powered Fair Shift Scheduling System that optimizes staff shifts at a medium-sized restaurant based on predictive sales forecasts. This system aims to enhance operational efficiency and improve employee satisfaction by ensuring fair and data-driven shift distributions.

- **Specific Objectives**:
    1. **Develop Accurate Sales Forecasts**: Train and compare two advanced predictive models, SARIMAX and Prophet, to determine which more accurately forecasts daily restaurant sales using the same set of regressors (Schmidt, A., Kabir, M.W.U. and Hoque, M.T., 2022).
    2. **Implement a Dynamic Scheduling Algorithm**: Integrate the chosen model into a scheduling system that adjusts staff shifts in real-time based on forecasted sales data.
    3. **Evaluate System Impact**: Assess the impact of the scheduling system on operational efficiency and employee satisfaction through both quantitative metrics and qualitative feedback.

1.4.2 Research Approach

Data Collection: Gather historical sales data from the restaurant, supplemented with contextual data such as weather conditions and local events, which are known to affect sales. This comprehensive dataset serves as the basis for training the forecasting models (Seethapathy, K., 2024).

Model Development and Selection:

1. Train both SARIMAX and Prophet models using the collected data, applying the same regressors to ensure a fair comparison of their predictive capabilities (Serrano, A.L.M., Rodrigues, G.A.P., Martins, P.H.d.S., Saiki, G.M., Filho, G.P.R., Gonçalves, V.P., Albuquerque, R.d.O., 2024).
2. Evaluate each model's forecasting accuracy by comparing their predictions against actual sales data. The selection of the superior model is based on objective performance metrics, primarily focusing on the accuracy of the forecasts.

System Implementation:

1. Develop the backend of the scheduling system using FastAPI, chosen for its high performance and ease of integration with other technologies as discussed in the Complete Hands-on Guide to FastAPI with Machine Learning Deployment (2023).
2. Use MongoDB for managing and querying sales and scheduling data due to its flexibility and scalability (Chickerur, S., Goudar, A. and Kinnerkar, A., 2015).
3. Implement a user-friendly frontend with Vue.js, which facilitates real-time updates and interactions by the restaurant management and staff (Chen, J., 2023).

Anticipated Challenges

1. **Data Handling Challenges**: Efficiently managing and preparing large datasets to ensure data integrity and usability.
2. **Model Development Challenges**: Selecting and optimizing predictive models to achieve accurate sales forecasting.
3. **System Integration Challenges**: Ensuring smooth integration of various software components to create a cohesive system.
4. **Adoption and Training Challenges**: Encouraging user adoption and effectively training staff to utilize the new system.

1.5 Ethical, Legal, and Professional Considerations

1.5.1 Ethical Compliance

My research adhered to stringent ethical standards throughout, particularly in the handling and management of participant data and interactions. Prior to the distribution of any surveys, consent forms, or information sheets, these documents were reviewed and approved by my academic supervisor, ensuring alignment with the ethical standards prescribed in the UWE Bristol Handbook of Research Ethics.

- **Supervisor Approval**: The project's consent forms, and participant information sheets were approved by my supervisor, ensuring all materials were ethically sound before being distributed. This preliminary step was crucial for upholding the integrity and ethical standards of my research (UWE Bristol Handbook of Research Ethics, 2022).
- **Informed Consent Process**: Participants were provided with comprehensive details about the study through the Participant Information Sheet and a Data Protection Privacy Notice. These measures ensured participants were fully informed and consented voluntarily to the study, with clear information on their rights, including data privacy and the right to withdraw (UWE Bristol Handbook of Research Ethics, 2022).

1.5.2 Legal Aspects

The project strictly adhered to legal standards concerning data protection, ensuring compliance with national and international regulations such as the General Data Protection Regulation (GDPR).

- **Data Protection and Privacy**: All participant data was anonymized and securely managed to prevent unauthorized access, ensuring compliance with GDPR. The specifics of data handling were outlined in the consent form, which detailed the secure storage, access, and eventual deletion of data, reinforcing the legal protections in place (Willers, C., Lynch, T., Chand, V., Islam, M., Lassere, M. and March, L., 2022.).
- **Regulatory Compliance**: The legal framework for using predictive modelling in employment settings was thoroughly reviewed to ensure that the AI-powered scheduling system did not result in discriminatory practices, adhering to employment laws and the ethical use of employee information (Bodie, M.T., Cherry, M.A., McCormick, M.L. and Tang, J., 2016).

1.5.3 Professional Considerations

The research was conducted with a commitment to maintaining high professional standards, ensuring transparency, integrity, and respect for all participants involved.

- **Research Integrity and Transparency**: Regular audits and checks were performed to ensure that all stages of the research complied with both ethical and legal standards, maintaining the integrity of the research process (Obinna, A.J. and Kess-Momoh, J., 2024).
- **Accountability and Participant Respect**: All interactions with participants were conducted with the utmost respect and professionalism, ensuring participants felt valued and respected throughout the research process.

1.5.4 Adherence to UWE Bristol Guidelines

Following the guidelines outlined in the UWE Bristol Handbook of Research Ethics, I ensured that all aspects of the research were reviewed and approved by the relevant ethics committees before proceeding.

1.6 Success Criteria, Expected Outcomes, and Code Availability

1.6.1 Evaluation Metrics

To effectively evaluate the success of the project, consider the following metrics:

- **Forecast Accuracy**: Compare the system-generated sales forecasts against actual sales data to evaluate the accuracy of the predictive models.
- **Feedback on Hypothetical Shift Schedules**: Gather qualitative feedback from coworkers on the hypothetical shift schedules created by the system to gauge perceived fairness and usability.
- **Management Feedback**: If possible, allow management to interact with the system and provide feedback on its usability and the practicality of the schedules it generates.

1.6.2 Anticipated Outcomes

While the system might not be implemented in a real-world setting immediately, anticipated outcomes include:

- **Proof of Concept**: Demonstrating that the system can effectively forecast sales and generate fair schedules based on those forecasts.
- **Potential for Future Implementation**: While the system is developed as a project, its success could encourage consideration for future real-world trials or inspire similar initiatives.
- **Academic Contributions**: The project contributes to the body of knowledge in applying AI to workforce management, offering a foundation for future research.

1.6.3 Code Availability

As for making the project code available:

- **GitHub Upload**: The project code and documentation will be uploaded to GitHub for public access to support transparency and enable future research. The repository will be linked to my GitHub profile, which can be accessed at https://github.com/SaiKaungUWE. Please check the profile for updates on the project availability.

1.7 Structure of the Dissertation

Chapter 1: Introduction

This chapter introduces the topic, defines the research problem, and sets the objectives of the study. It discusses the importance of the research and outlines the key questions to be addressed.

Chapter 2: Literature Review

Explores existing research on AI-powered shift scheduling systems and workforce management. It identifies the strengths and limitations of previous studies and highlights gaps that this dissertation will address.

Chapter 3: Methodology

Describes the research design and methodologies used, including data collection and analysis procedures. This chapter explains how the SARIMAX and Prophet models were used and outlines the use of CRISP-DM. Ethical considerations are also discussed here.

Chapter 4: Results

Presents the findings from the data analysis, assessing the performance of the predictive models and the scheduling system. It evaluates the system's accuracy, efficiency, and user satisfaction, supported by detailed data and visual aids.

Chapter 5: Discussion

Interprets the results in relation to the initial hypotheses and literature. It discusses the implications of the findings for the restaurant industry and suggests areas for future research.

Chapter 6: Conclusion and Recommendations

Summarizes the findings and draws conclusions. Offers recommendations for practical applications and further research, reflecting on the contribution of the study to the field.

Appendices

Includes supplementary materials such as data tables, code snippets, questionnaires, and consent forms.

Chapter 2: Literature Review

2.1 Chapter Introduction

Scheduling in the restaurant industry is burdened with challenges unlike anything other industries experience, mainly due to high spikes of customer demands and arguably getting more trade-off between efficiency and well-being. Lean scheduling methods, used by traditional systems and driven largely off managerial intuition produce inefficiencies as well dissatisfaction among the workforces. The evolution of shift scheduling with innovations in artificial intelligence (AI) and predictive analytics: a scoping review and instead assesses the quality of complex forecasting models and infrastructures required for them to work, with attention given to ethical implications introduced by these AI-powered systems.

2.2 Evolution of Shift Scheduling

Shift scheduling in the restaurant industry has undergone significant transformations over the years, evolving from rudimentary, manual methods to sophisticated, automated systems. These traditional methods, while straightforward, often led to suboptimal scheduling that did not account for complex variables such as employee preferences, peak hours, or unexpected fluctuations in customer flow (Lin, T.-C. and Lin, B.M.T., 2023).

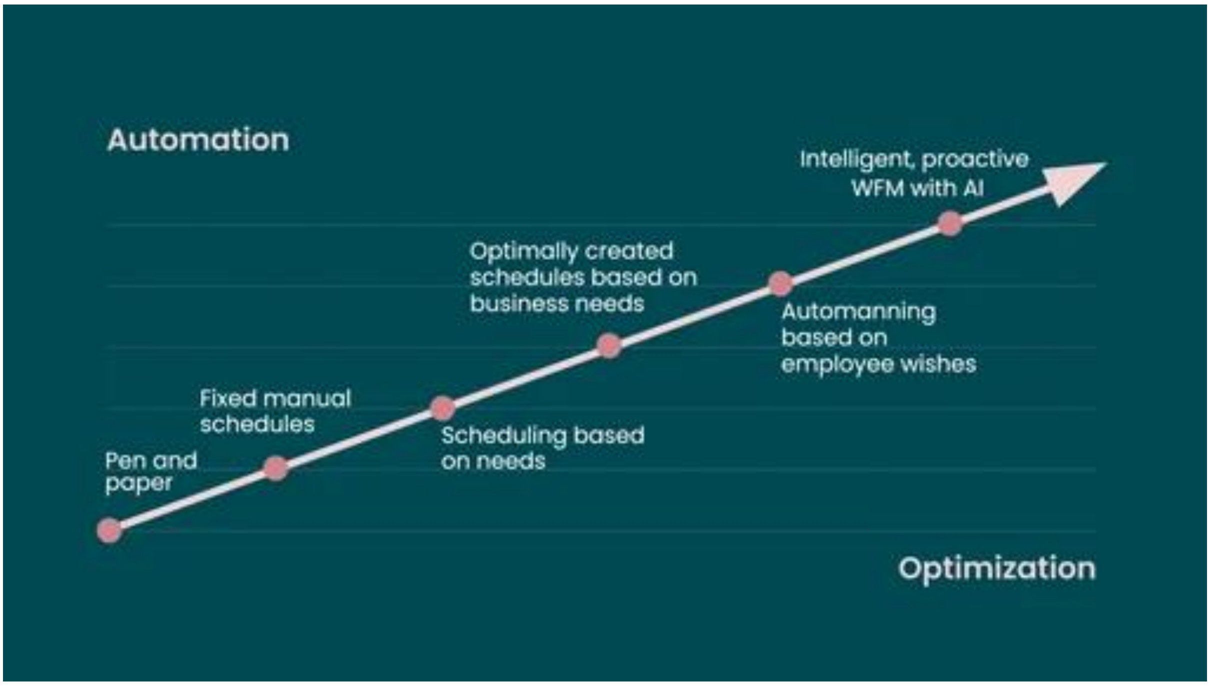


Figure 2. Evolution of work (Quinyx, 2023)

The industry gradually advanced into much more complex requirements which the manual scheduling process was simply not cut out to handle. However, as these procedures were very manual, they took a lot of time but also liable to human errors and biases which lead in labour wastage & lower employee satisfaction (Mundle, M.A. 2024). Automatic scheduling systems utilize algorithms to optimize staff deployment by analysing historical data and forecasting future needs (Riofrío-Valdivieso, A., Quinga-Socasi, F., Bustamante-Orellana, C. and Andrade-Chamorro, E., 2020).

In addition, the system can accommodate many other inputs such as employee skills and labor laws with individual availability to develop a schedule that serves both employer demand and preferences (Koole et al., 2008).

Figure 3. How to Optimize Workforce Scheduling (spicework, 2023)

The shift is also a reflection on wider changes to the workplace, showing businesses are leaning more heavily towards data-based decision making when enhancing operational efficiency and boosting corporate morale (Kavitha, D. & Chinnasamy, A., 2021).

2.3 Application of AI in Workforce Management

The adoption of Artificial Intelligence (AI) in workforce management, particularly for shift scheduling, represents a significant shift towards more data-driven and efficient practices. This section of the literature review explores the methodologies, effectiveness, and specific outcomes associated with the use of AI in this context.

2.3.1 Effectiveness of AI in Scheduling

Consider how AI-driven systems have transformed the landscape of workforce management. In Makkar, G. (2020), by leveraging precise data analytics, these systems optimize staffing by predicting needs based on variables like past sales and weather conditions. For example, Engel, R., Fernandez, P., Ruiz-Cortes, A., Megahed, A. and Ojeda-Perez, J., 2022 uncovered that AI integration boosted labor utilization by 30% without sacrificing service quality.

2.3.2 Methodologies in AI Deployment

The deployment of AI in workforce management typically employs advanced predictive models such as neural networks and decision trees. These models are chosen for their ability to handle large datasets and complex variables with significant accuracy. Zavvari, A., Jelodar, M.B. and Sutrisna, M., 2022, specifically noted the effectiveness of ensemble methods that combine predictions from multiple models to enhance accuracy and reliability in forecasting workforce needs.

2.3.3 Outcomes of AI Integration

Integrating AI into workforce management systems not only optimizes operational efficiency but also improves employee satisfaction. Saleh, S., & Gajendran, A. (2023) found that AI-driven scheduling systems contributed to a more transparent and equitable distribution of shifts, which significantly increased employee satisfaction levels. Moreover, according to Özder, E.H. and Gümüş, M., 2023, these systems reduce the managerial burden associated with manual scheduling, freeing up time for managers to engage in more strategic activities.

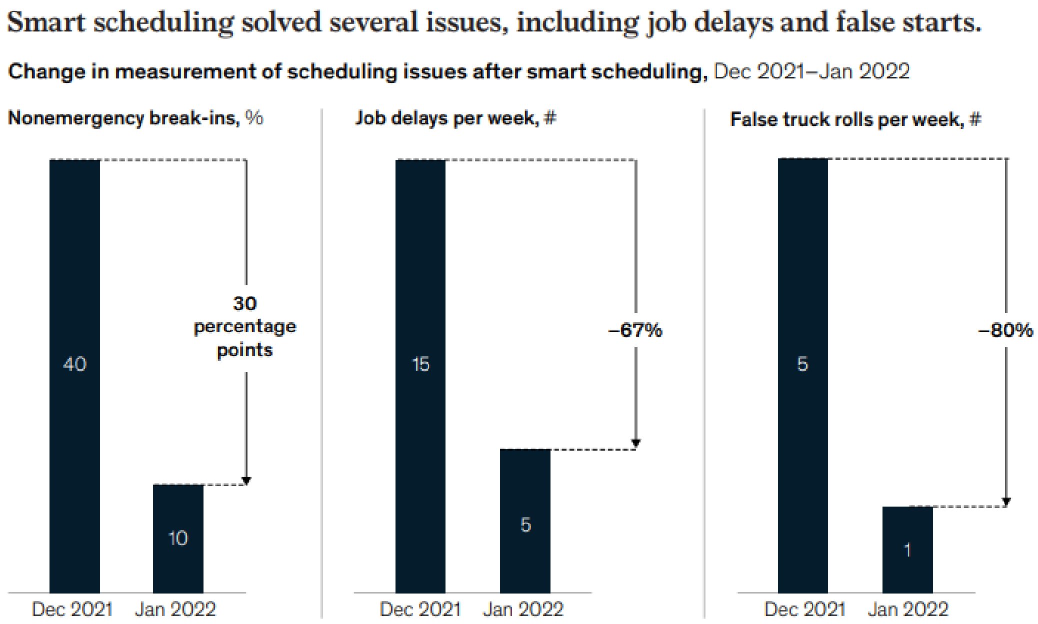


Figure 4. Smart scheduling solved several issues, including job delays and false starts (McKinsey & Company 2022)

2.4 Role of Predictive Modelling

AI-powered shift scheduling is based on predictive modelling as its core. These models help make use of demand forecast to staff proactively in line with the expected business volumes. In the earlier days, (Park, C.S.-Y., 2018) channelled time series forecasting models to predict customer activity leading to improved staff scheduling — a win-win in both service quality and reduced operational costs and less stressful job for employees during peak population times.

2.5 Comparative Analysis of Predictive Models

The most important in the changing landscape of shift scheduling is how efficient are our forecasting models, SARIMAX and Prophet. As the nature of the industry and data characteristics are changing, each model has its own advantages to predict staffing needs — however there is a great variation in real-world applications.

2.5.1 SARIMAX: Detailed Application and Performance

The ability to add external variables of SARIMAX makes it a strong model, especially in industries where demand is determined not only by the basics. In retail, for example, Arunraj, N.S., Ahrens, D. and Fernandes, M (2016) have shown that SARIMAX was able to predict sales during promotions periods where information on holidays and marketing campaigns served as explanatory variables. Because the model can account for seasonality and exogenous variables it is particularly well suited to forecasting complex circumstances, where many factors influence an outcome (Ampountolas, A., 2021).

2.5.2 Prophet: Flexibility and User Accessibility

In an environment with a lower amplitude of seasonality, such as where Prophet excels in rapid deployment and easy use. Once again, considering industries like hospitality (Jha, B.K. and Pande, S., 2021) where demand patterns are prone to non-regular events and significant impacts on its trend and seasonality. This framework provides automated detection for changing trends or seasonality as a part of the package ideally suited such domains. Prophet is preferred by small businesses due to lower computational needs and increased access (Sharma, K., Bhalla, R. and Ganesan, G., 2022)

2.5.3 Comparative Studies and Model Selection

Previous comparative research has identified the conditions under which each model excels. For example, a comprehensive analysis by André Luiz Marques Serrano et al., (2024) compared SARIMAX and Prophet in a multi-industry study and found that SARIMAX provided better accuracy in environments with well-defined seasonal patterns and known external influences. On the other hand, Prophet was indicated for its adaptability in scenarios with rapid demand fluctuations and less historical data (Stefenon, S.F., Seman, L.O., Mariani, V.C., and Coelho, L.d.S., 2023).

2.5.4 Impact of Regressors on Model Accuracy

The most critical component, weather attributes as regressors have been reported to increase forecast accuracy by a significant amount in utility companies for the staff arrangements needed during emergency repairs of extreme weather events using SARIMAX (Bahrami, A., Shahidehpour, M., Pandey, S., Zheng, H., Alabdulwahab, A. and Abusorrah, A., 2023). Also, (Liu, Y., Feng, G., Chin, K.S., Sun, S. and Wang, S., 2022) stated that the prediction performance of Prophet significantly improves by using public holidays together with local events as regressors for tourism recommendation application to forecast surges more accurately in visitors.

2.6 Implementation of Trained Models in System Architecture

In this article, we will take a deeper look at the possibilities of combining trained forecasting models within web applications and show how important is to have modern technology stack in service (FastAPI + Vue.js, and MongoDB). Based on a review of the academic literature, this discussion considers how these technologies work and function.

2.6.1 FastAPI as Backend

Chowdary, M.N., Sankeerth, B., Chowdary, C.K. and Gupta, M., (2022) particularly praises its asynchronous capabilities and automatic API documentation, which streamline the development process in dynamic settings where rapid adjustments and real-time data processing are essential.

2.6.2 Vue.js for Frontend

The capability of Vue.js for providing real-time updates and proper integration with the backend, which can make a significant difference in user experience when dealing with data driven applications. Nation, J., Bowman, M., Daily, M., Lister, T.A., Sohi, J., Storrie-Lombardi, L.J. and Street, R.A., (2022) notes that this responsiveness significantly improves user experience and operational efficiency, allowing for immediate reflections of data changes in the user interface.

2.6.3 MongoDB for Database Management

When it comes to handling large volumes of unstructured data, MongoDB's flexible data model is well-suited for AI-driven applications that require quick data retrieval and storage. According to Reddy, B.A., Reddy, G.S., Lokesh, K., S.B., and M.R., (2024), the database accommodates the high variability and volume of data typical in these applications, supporting quick scalability and flexible data management.

2.6.4 Case Studies and Practical Implementations

Mukesh, S.J., Ashwin, S., Subash Rao, S. and Elavarasi, J., (2023are compelling in terms of validating the effectiveness of these technologies during real-world use-cases i.e. operational workflows with clinical data references.

2.7 Use of Optimization Tools and Logic in Shift Scheduling

2.7.1 Development and Application of PuLP and Google OR-Tools

This article we have shared PuLP and Google OR-Tools is able to solve scheduling shifts, it shows research that can be useful in facing those challenge.

- **PuLP**: Being capable to model linear and integer programming problems, it allows for the solution of more sophisticated shift scheduling with an easy integration into Python’s data processing libraries (Vladimir Popović et al., 2021).
- **Google OR-Tools**: With a rich collection of solvers, Google OR-Tools is particularly adept with complex scheduling constraints to ensure compliance and cost-saving. Manion Anderson et al., (2021) highlights its application in achieving cost-effective and compliant staffing solutions.

2.7.2 Use of Conditional Logic in Custom Shift Scheduling Algorithms

Scholarly articles detail how tailored algorithms using conditional logic enhance shift scheduling responsiveness and precision.

- **Custom Algorithms**: Two-level decomposition algorithm is proposed by Doi, T. and Nishi, T., (2014) for custom shift scheduling to reduce costs without destroying fairness of the problem. This algorithm was implemented to solve master problems and subproblems iteratively, via conditional logic in a price-based optimization framework, accounting for constraints such as labour laws (work time directives) or the working preferences of workers that are critical factors within creating fair and practical shift schedules

2.8 Integration Challenges and Solutions

A recent study sheds light the challenges of integrating AI for predictive maintenance within production environments. It emphasizes the importance of seamless data integration to ensure the efficient flow of information, which is often hindered by data silos that require AI systems to operate across various technical and organizational boundaries without the need for deep technical knowledge of the data sources (Marco Franke et al., 2024) and S. Youn et al., (2019). (D. Walker et al., 2019) emphasizes the importance of involving employees in development and rollout phases, improving acceptance and easing the transition.

2.9 Impact on Operational Efficiency and Employee Satisfaction

Studies show that AI-based scheduling systems were able to increase operational efficiency by accurately determining staffing levels and lowering the cost of human labour (Elhalid, O.B. and Isık, A.H., 2024). Additionally, these have been proved to boost the morale of employees through even-handed and transparent distribution of shifts thereby resulting into higher job contentment as well as lower turnover (Hee Jun Ryu et al., 2023).

2.10 Research Gaps and Future Directions

We focus on addressing critical gaps in current literature related to the application of predictive models and operational strategies concerning AI-driven shift scheduling. Every single gap identified results from an explicit discrepancy between theories and general literature, on the one hand, and observations in the operational setting of this study. Such variations have large effects on the practical application and efficacy of these technologies, making it clear that a more specific approach would be advantageous in structuring research to close these gaps effectively.

2.10.1 Efficacy of Weather and Holiday Regressors

Literature often points to weather conditions and holidays as key sales drivers in the restaurant industry, but my analysis of this target firm showed differently. This contrasts with other studies which have linked sales increase with certain weather patterns or holidays as I found no significant positive correlation, and even negative correlations (decreases) on holidays – likely why restaurant are unavailable for purchase. This study seeks to explore under what specific circumstances these commonly cited factors affect sales, providing a tailored analysis of their real impact on forecasting accuracy.

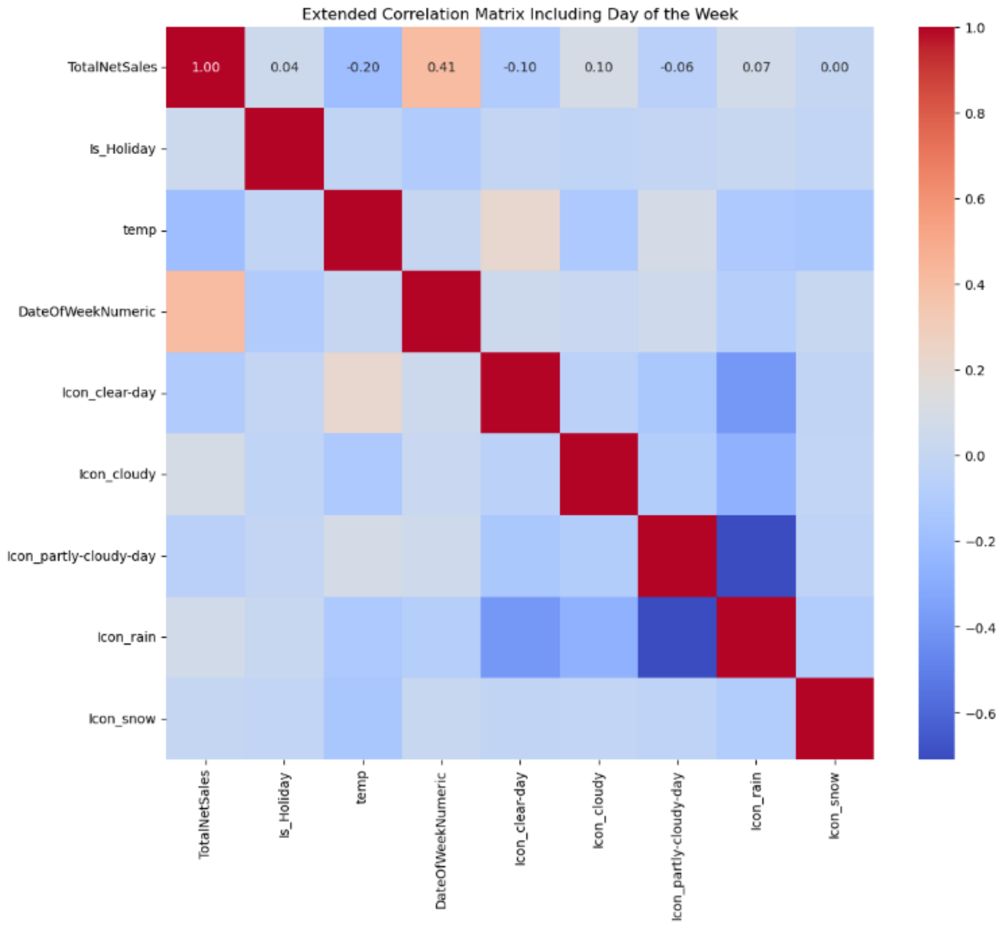


Figure 5. Correlation Matrix: Date of Week, Temperature, and Weather Conditions

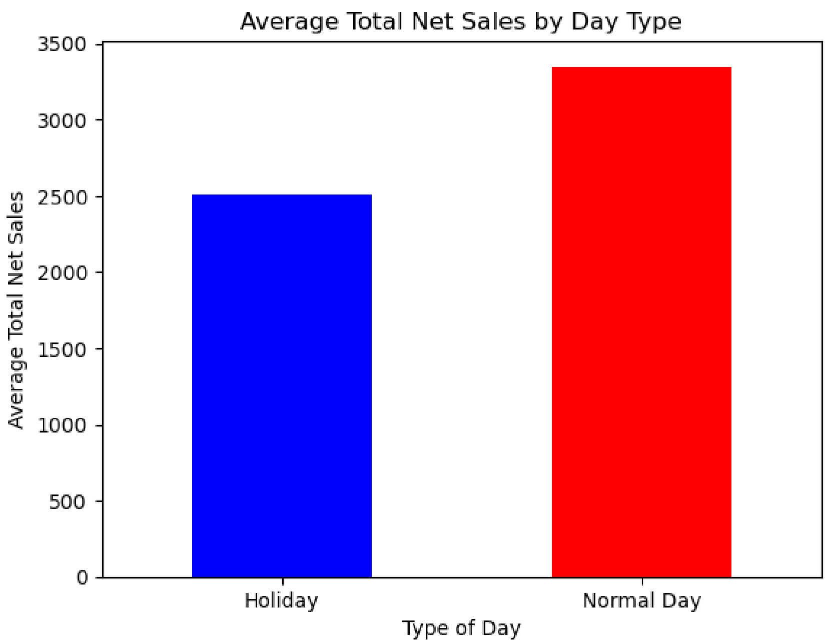


Figure 6. Average Total Net Sales by Day Type

2.10.2 Operational Needs vs. Staffing Requirements

Specifications Most of the academic literature on company growth bases required operating hours on forecasted sales. My approach, however, puts an emphasis on the actual of staff required per shift. This focus on practical staffing needs, rather than merely operational hours.

2.10.3 Limitations of Conventional Optimization Tools

My use of PuLP and Google OR-Tools revealed their inadequacy for my restaurant's unique scheduling needs, prompting the development of a custom solution with conditional logic with pandas. This story is a lesson in the limitations of widely recommended tools in unique scenarios and highlights the necessity for more adaptable and customizable solutions.

2.10.4 Exploration of Custom Logic over Standard Tools

By using unique logic rather than conventional tools, I learned to design tailored AI-powered solutions that are accurate and flexible for exact operational requirements. Use third-party tools only when built-in solutions are not enough; consider custom approaches instead.

2.11 Conclusion

This review highlights the role of AI in shift scheduling with models like SARIMAX and Prophet, and the importance of custom solutions where standard tools fall short. My findings support the tailored deployment of predictive technologies in hospitality, advocating for specialized approaches to integration and application.

Chapter 3: Methodology

3.1 Research Design and Framework

3.1.1 CRISP-DM Methodology Overview

This work adheres to the CRISP-DM (Cross Industry Standard Process for Data Mining) process, a well-established and widely used data-driven research methodology. We use CRISP-DM because it has a more structured method to problem solve that fits well into many different pieces of the chain, including business understanding (e.g., what should we be predicting), data preparation, modelling and deployment making it an ideal fit for complex problems such as scheduling demand at restaurants.

3.1.2 Business Understanding

The primary business challenge addressed by this project centres on Inefficient and bias shift scheduling inside a restaurant. They focus on problems related to those areas and their implications such as high turnover, operational costs, fatigue of staff for opportunities—in particular the unfair shift allocation issues causing overstaffing or understaffing. To do this, we want to create an AI based scheduling system designed for the efficient and unbiased distribution of shifts.

3.1.3 Data Understanding

To tackle these challenges, several types of data were identified as crucial:

- **Sales Data**: Using historical sales data from the restaurant helps to model demand patterns and peak times.
- **Staff Satisfaction Survey**: Responses from staff currently working will yield qualitative information on the satisfaction and perceived fairness of current scheduling practices.
- **Weather Data**: Historical weather data is used to predict any day wise external factors, which might affect the business of a particular restaurant.
- **Chef Interviews**: Best Information of top cook will assist in converting forecasted income into a real labour requirement which is used to create the model predictions, Head Chef (2024)

3.2 Data Collection and Preparation

3.2.1 Data Gathering

Data collection was meticulously carried out from multiple sources to ensure a comprehensive dataset:

- **Sales Data**: 3 years of historical sales data from the restaurants point-of-sale (POS) system and directly acquired. The General Manager allowing access to the system and copying all data on a USB stick.

Business Sheet for 14/03/2021 from 08/03/2021 to

Sales

[redacted]	110	Week No.		1	Business	Sheet	Boparan	Restaurants v 1.0
	08/03/2021	09/03/2021	10/03/2021	11/03/2021	12/03/2021	13/03/2021	14/03/2021	
NET SALES	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Sun**	**TOTAL**
Eat In	57.57	0	0	0	0	0	0	57.57
Takeaway	0	198.68	179.07	221.28	365.34	535.13	375.99	1875.49
OOR	39.15	852.38	1195.75	906.09	2372.61	1578.07	956.45	7900.5
Retail	0	0	0	0	0	0	0	0
Kiosk Eat In	33.48	0	0	0	0	0	0	33.48
Kiosk Take Away	0	0	0	0	0	0	0	0
Total Net Sales	**695.57**	**1051.06**	**1374.82**	**1127.37**	**2737.95**	**2113.2**	**1332.44**	**10432.4**
Budget	969.83	1185.19	1128.66	1317.75	1654.49	2692.88	1501.27	10450.07
Variance (Net Sales - Budget)	**-274.26**	**-134.13**	**246.16**	**-190.38**	**1083.46**	**-579.68**	**-168.83**	**-17.67**
Forecast	650	650	700	750	2000	1700	650	7100
Variance (Net Sales - Forecast)	**45.57**	**401.06**	**674.82**	**377.37**	**737.95**	**413.2**	**682.44**	**3332.4**
Last Year	0	0	0	0	0	0	0	0
Variance (Net Sales - Last Year)	**695.57**	**1051.06**	**1374.82**	**1127.37**	**2737.95**	**2113.2**	**1332.44**	**10432.4**

GP	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Sun**	**TOTAL**
GP %								76.39%
Theo %								78.04%
Variance (GP - Theo)								**-1.64%**
Cost of Sales								2467.76
Theo Cost								2295.99

Figure 7. Example raw data of weekly sale

- **Weather Data**: From the visual crossing weather services, that provided historical weather data as CSV files. It refers to a period where the data range was matched precisely with that in sales data so as not to upset temporal analysis
- **Holiday Data**: Pulling from the holiday's python package via further back-end processing during cleaning, to match sales and weather data dates while including major public holidays that may prompt restaurants into action.

3.2.2 Data Cleaning and Preprocessing

The raw data collected were extensive and required substantial cleaning and preprocessing to be usable for analysis:

- **Initial Cleaning**: This includes extracting and cleaning the data from 167 Excel files using Python scripts as it would take way too long to open each file independently and prepare a new excel sheet. And we also have to ignore the data which do not use for sales.
- **Revaluation and Challenges**: Once the data was pre-processed, it underwent new scrutiny for any inconsistencies like null values or outliers This was followed by a second pass script to correct the specific variances highlighted in the assessment.
- **Final Cleaning Processes**: The pandas' library had our backs when it came to wrapping up data prep. It was used for re-arranging the cleaned data into a proper single time-series format that made sense to be analysed. Also, we integrated the holiday data by creating new columns with whether it was a holiday or not and which type of holiday using our own functions to leave the dataset fully ready for modelling afterwards.

No	Date	DateOfWeek	EatÂ In	TotalNetSales	Forecast	VarianceÃ,Â (N	Is_Holiday	Holiday_Name	temp	feelslike	conditions	description	icon
1	17/05/2021	Mon	1318.37	2118.92	2500	933.34	0		10.6	9.5	Rain, Partially cloudy	Partly cloudy throughout the day with rain.	rain
2	18/05/2021	Tue	1779.13	2255.63	2500	846.74	0		10.2	9.2	Rain, Partially cloudy	Partly cloudy throughout the day with rain.	rain
3	19/05/2021	Wed	2033.29	2713.71	2500	1069.98	0		10.3	9.2	Rain, Partially cloudy	Partly cloudy throughout the day with a chance of rain throughout the day.	rain
4	20/05/2021	Thu	2145.98	3019.6	2800	1043.05	0		10	9.3	Rain, Partially cloudy	Partly cloudy throughout the day with rain.	rain
5	21/05/2021	Fri	3511.22	5420.47	3500	2817.46	0		9.4	6.4	Rain, Overcast	Cloudy skies throughout the day with a chance of rain throughout the day.	rain
6	22/05/2021	Sat	4096.35	5407.81	6500	1141.8	0		9.7	7.9	Rain, Partially cloudy	Partly cloudy throughout the day with a chance of rain throughout the day.	rain
7	23/05/2021	Sun	2387.7	2603.24	2500	-239.29	0		8	5.6	Rain, Partially cloudy	Partly cloudy throughout the day with rain.	rain
8	24/05/2021	Mon	2034.94	2716.83	2500	1690.78	0		8.3	6.2	Rain, Partially cloudy	Partly cloudy throughout the day with a chance of rain throughout the day.	rain
9	25/05/2021	Tue	1602.34	2377.33	2500	1364.75	0		9	7.1	Rain, Partially cloudy	Partly cloudy throughout the day with rain.	rain
10	26/05/2021	Wed	1639.54	2661.54	2500	1811.66	0		9.8	8.9	Rain, Partially cloudy	Partly cloudy throughout the day with early morning rain.	rain
11	27/05/2021	Thu	1991.85	2882.54	2850	1981.75	0		12.7	12.6	Rain, Partially cloudy	Clearing in the afternoon with early morning rain.	rain
12	28/05/2021	Fri	3416.29	5789.69	3750	4478.27	0		13.2	13.2	Rain, Partially cloudy	Partly cloudy throughout the day with rain.	rain
13	29/05/2021	Sat	3870.7	4955.62	6850	4145.92	0		15.7	15.7	Partially cloudy	Partly cloudy throughout the day.	partly-cloudy-day
14	30/05/2021	Sun	1397.15	1784.58	3000	1403.15	0		14.3	14.2	Clear	Clear conditions throughout the day.	clear-day
15	31/05/2021	Mon	2421.58	2949.36	3500	2949.36	1	Spring Bank Holi	14.9	14.5	Partially cloudy	Partly cloudy throughout the day.	partly-cloudy-day

Figure 8. Example of final cleaned data

3.3 Model Development and Selection

3.3.1 Model Selection

SARIMAX and Prophet was shortlisted due to their inherent capabilities in time-series forecasting. We evaluated the adequacy of each model with respect to predicting customer behaviour changes and handling eventual sales volume fluctuations Vivin Nur Aziza et al. (2023).

- As it can also incorporate external regressors well, SARIMAX was the preferred choice. While this model is very good at including factors like weather and holidays in the forecast, essential for sales prediction of an industry such as hospitality (Arunraj et al., 2016).
- Prophet showed robust handlings of missing data as well automatically detecting trend changes, which makes it appropriate for the swift moving environment that is representative in restaurants field (Fatima, S.S.W., Rahimi, A. and Hayat, K., 2023).

3.3.2 Training Process

- **Data Preparation**: Preprocessing of sales data needed for both models to mix around different regressors. This included creating dummies for sales data, other categorical variables such as weather conditions and holiday events.
- **Parameter Tuning**:
    - **S**ARIMAX Parameters were selected using the AIC criterion to identify the best p, d, q combinations for improving seasonality and exogenous information integration.

      Best SARIMAX parameters: (3, 1, 0, 1, 0, 1, 7)
      Best AIC: 19313.167326467923

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                 y   No. Observations:                 1128
Model:             SARIMAX(3, 1, 0)x(1, 0, [1], 7)   Log Likelihood               -9313.975
Date:                           Fri, 14 Jun 2024   AIC                          18641.950
Time:                                   20:32:04   BIC                          18677.141
Sample:                               05-17-2021   HQIC                         18655.247
                                    - 06-17-2024
Covariance Type:                             opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept    107.3837     17.277      6.215      0.000      73.522     141.246
ar.L1         -0.3773      0.029    -12.827      0.000      -0.435      -0.320
ar.L2         -0.2685      0.029     -9.202      0.000      -0.326      -0.211
ar.L3         -0.1878      0.031     -6.117      0.000      -0.248      -0.128
ar.S.L7        0.9171      0.014     64.507      0.000       0.889       0.945
ma.S.L7       -0.4681      0.027    -17.165      0.000      -0.522      -0.415
sigma2      9.897e+05   3.31e+04     29.879      0.000    9.25e+05    1.05e+06
===================================================================================
Ljung-Box (L1) (Q):                   0.26   Jarque-Bera (JB):               702.59
Prob(Q):                              0.61   Prob(JB):                         0.00
Heteroskedasticity (H):               0.93   Skew:                             0.38
Prob(H) (two-sided):                  0.48   Kurtosis:                         6.79
===================================================================================
```

Figure 9. SARIMAX result after AIC criterion

- **Prophet Parameters** were adjusted for seasonality, with additional regressors for holidays configured to model their impact accurately.

3.3.3 Regressors Used

- **Standard Regressors**: Predict for common variables such as day of week effects, temperature and public holiday. These are well-documented in forecasting literature for their impact on sales (Negre et al., 2024).

```python
# Fill missing values for exogenous variables if necessary
data['feelslike'].ffill(inplace=True)
data['Is_Holiday'].fillna(0, inplace=True)

# Standardize the exogenous variables
scaler = StandardScaler()
data[['feelslike', 'Is_Holiday']] = scaler.fit_transform(data[['feelslike', 'Is_Holiday']])

# Define exogenous variables
exog_vars = ['feelslike', 'Is_Holiday']
```

Figure 10. Screenshot of creating some standard regressors

- **New Regressors**: Identifying the pre-Christmas surge as an important predictor, it has been added as a custom holiday in Prophet and implemented with "is_numpy = False" for SARIMAX.

```
# Add Pre-Christmas two weeks before 25th December each year
data['year'] = data['ds'].dt.year
pre_christmas_start = pd.to_datetime(data['year'].astype(str) + '-12-11')
pre_christmas_end = pd.to_datetime(data['year'].astype(str) + '-12-24')

pre_christmas = pd.DataFrame({
    'holiday': 'Pre-Christmas',
    'ds': [pd.date_range(start, end) for start, end in zip(pre_christmas_start, pre_christmas_end)],
    'lower_window': 0,
    'upper_window': 1,
}).explode('ds').drop_duplicates()

# Combine regular and special holidays
holidays = pd.concat([holidays, pre_christmas], ignore_index=True)
```

Figure 11. Adding pre-Christmas feature

3.3.4 Model Comparison and Evaluation

Statistical Equations and **Performance Metrics**:

The SARIMAX model uses the following general form for its equation:

“SARIMAX (p, d, q) × (P, D, Q) s\=(1−i\=1∑pϕiLi) (1−Ld) (1−i\=1∑PΦiLsi) Yt \=ϵt+i\=1∑qθiLi+i\=1∑QΘiLsiϵt”

Here, ϕ, Φ, θ, Θ are parameters of the model, *L* is the lag operator, ϵt is the error term, xkt represents exogenous variables, and βk are the coefficients for the exogenous variables Hyndman, R.J. and Athanasopoulos, G., (2018).

The Prophet model incorporates growth and seasonality components, mathematically represented as:

“y(t)=g(t)+s(t)+h(t)+ϵt"

where g(t) models non-periodic changes (trend), s(t) captures periodic changes such as weekly and yearly seasonality, h(t) models’ irregular effects of holidays and events, ϵt is the error term that is normally distributed Lyla, Y., (2019).

3.3.5 Validation Techniques:

We proceeded as normal and calculated the RMSE, MAE, and MAPE for each of the models on a cross-validation basis over multiple forecast horizons.

The chosen one: Prophet fared much better than SARIMAX with lower accuracy measure values so all in favour of predicting restaurant industry's dynamic sales patterns. Will display the result in Chapter 4: Results Performance metrics and Comparative analysis of the selected models

3.4 System Development: Backend Operations

3.4.1 Backend Initialization and Forecast Management

Upon initialization of the backend system with Model-View-Controller (MVC), the first file that runs is __init__.py, which is responsible for setting up the environment and invoking the main functionalities. One of the important functions generate_and_save_forecasts () defined in prediction_service.py as part of this initialization process. This role is very important to get the system working in according to readiness for operations.

- **Forecast Generation**: The trained Prophet model was serialized to a. file with the help of joblib library for persistence. This trained modal is then stored to be loaded into FastAPI application when a request for forecast arises. The generate_and_save_forecasts () function, looks for weather and forecast data already exists up to henceforth two weeks. New forecasts are generated automatically if any data is incomplete or outdated.

- **Translation to Staff Needs**: The forecasts can then be translated into the number of staff required on each day, using expected volume of sales as a baseline (Head Chef 2024)

The system stores the generated forecasts and staffing needs in MongoDB with the following structure:

```
_id: ObjectId('66c5603b60afb29b3bf75a7d')
date : "2024-08-30"
forecast : 4113
staff_needed : 5
```

```
_id: ObjectId('66c5606160afb29b3bf75a7e')
date : "2024-08-31"
forecast : 3486
staff_needed : 4
```

Figure 12. Document structure of forecasts and staffing

3.4.2 Dynamic Shift Scheduling

Concurrently with forecast management, the generate_shift () function actively monitors the database for upcoming scheduling requirements. This function ensures that:

- **Shift Planning**: If shifts are not already planned or if updates are required due to changes in forecasts, the function dynamically generates new shift schedules.

- **Constraint Handling**: The function respects multiple non-operational constraints, such as enforcing the no-consecutive assignments policy on staff or handling availability and working hour restrictions while keeping active during some critical operational hours that cannot be left unmanned.

Previous efforts with optimization libraries such as PuLP and Google OR-Tools were unable to return feasible solutions due to highly complex constraints but have since been replaced by the conditional logic that creates shifts. This logic ensures compliance with all specified operational requirements.


```
_id: ObjectId('66c79f90684db5ff7b36a570')
▸ username : Object
  email : "person6@gmail.com"
  role : "BOH Team Member"
▸ shift : Array (25)
```

```
_id: ObjectId('66c79f90684db5ff7b36a571')
▾ username : Object
    first : "Ms"
    second : "Staff_3"
  email : "person3@gmail.com"
  role : "Grill Chef"
▾ shift : Array (26)
  ▾ 0: Object
      date : "2024-08-12"
      time : "09:00 - 15:00"
  ▾ 1: Object
      date : "2024-08-15"
      time : "15:00 - 21:00"
  ▾ 2: Object
      date : "2024-08-16"
      time : "09:00 - 15:00"
  ▾ 3: Object
      date : "2024-08-17"
      time : "15:00 - 21:00"
```


Figure 13. Document structure of generated shift

3.4.3 CRUD Operations and Security Measures

The backend also facilitates comprehensive CRUD operations for managing staff data:

- **Data Management**: All staff data, from personal information to scheduling preferences are managed through a series of FastAPI API endpoints. In my case, it is Create Read Update and Delete for staff information.
- **Security**: Finally, to store for example database passwords in a secure way the system is using more advanced hashing algorithms by utilizing CryptContext package.

3.5 Front-End Development

3.5.1 Main Features of the Front-End Interface

On the other hand, designing front-end of scheduling system maintaining Requisite User experience level along with considering. The main features of the front-end interface include:

3.5.1.1 Login Portal:

Access Control: A user must sign in at the website to proceed into the portal. The secure orchestration through this login process, with credential verification against the backend via API requests.

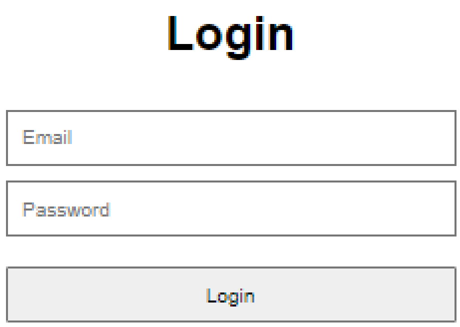


Figure 14. Login form

3.5.1.2 Staff Management Interface

CRUD Operations: Add new staffRead Existing Records and show them with listDelete entries when there is need It employs APIs for interfacing with back-end so that we can do real-time updates into the MongoDB database. This is what delivers real time accuracy of the staff roster.

3.5.1.3 Forecast Generation and Staff Need Interface

Sales and Staffing Forecast: If there are no forecast data is displaying, Managers may generate a sales forecast weekly on the same tab or click update button to refresh all their forecast simultaneously. The results are presented in an easy-to-understand interface which makes this detail useful to managers for scheduling

3.5.1.4 Schedule Interface:

Shift Display: Displays the shifts of that week, based on forecasts already made. The scheduler is running as a backend that automatically generates this schedule based on operational demands and constraints.

19 Aug - 25 Aug

	Mon 2024-08-19	Tue 2024-08-20	Wed 2024-08-21	Thu 2024-08-22	Fri 2024-08-23	Sat 2024-08-24	Sun 2024-08-25
Mr Staff_4	-	-	-	15:00 - 21:00	-	15:00 - 21:00	15:00 - 21:00
Mr Staff_6	15:00 - 21:00	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00	15:00 - 21:00	15:00 - 21:00	-
Ms Staff_3	-	-	-	09:00 - 15:00	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00
Mr Staff_10	-	09:00 - 15:00	15:00 - 21:00	09:00 - 15:00	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00
Ms Staff_9	-	09:00 - 15:00	09:00 - 15:00	-	09:00 - 15:00	09:00 - 15:00	-
Mr Staff_2	15:00 - 21:00	15:00 - 21:00	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00	09:00 - 15:00	-
Ms Staff_5	09:00 - 15:00	-	09:00 - 15:00	09:00 - 15:00	09:00 - 15:00	09:00 - 15:00	15:00 - 21:00
Ms Staff_8	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00	15:00 - 21:00	-	09:00 - 15:00	15:00 - 21:00
Mr Staff_7	09:00 - 15:00	-	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00	09:00 - 15:00	-
Mr Staff_1	09:00 - 15:00	09:00 - 15:00	09:00 - 15:00	-	15:00 - 21:00	15:00 - 21:00	15:00 - 21:00

Figure 15. Schedule Interface

3.5.1.5 Personal Shift Access for Staff:

Individual Shift View: Unlike the management interfaces, this view is simplified and focuses solely on the shift information relevant to the individual staff member, ensuring that they have easy access to their work schedule.

02 Sep - 08 Sep

	Mon 2024-09-02	Tue 2024-09-03	Wed 2024-09-04	Thu 2024-09-05	Fri 2024-09-06	Sat 2024-09-07	Sun 2024-09-08
Ms Staff_3	09:00 - 15:00	09:00 - 15:00	15:00 - 21:00	15:00 - 21:00	-	09:00 - 15:00	09:00 - 15:00

Figure 16. Personal Schedule Interface

3.5.2 Interaction with the Back end

The front-end interfaces are tightly coupled with the back-end system and make sure these interfaces facilitate in seamless data exchange real time updating. A set of API endpoints given by FastAPI to interact with that interaction:

- **Data Retrieval and Submission**: If a user creates forecast or updates employee details at the front-end, then an API call will be made to the back end. It makes a request to the backend where it updates my MongoDB database accordingly and sends back what I should render on the front end.
- **Real-Time Updates**: The Vue.js framework that enables dynamic updates, as soon as the back-end processes new data (e.g., a new sales forecast), the front-end is updated automatically without re-loading.

3.6 Ethical, Legal, and Professional Considerations in Methodology

The following section outlines the ethical and legal guidelines followed during this research for participant safety & data integrity.

3.6.1 Ethical Compliance

- **Approval and Oversight**: Approval was obtained from the university ethics committee, which is governed by UWE Bristol Handbook of Research Ethics (2021) ensuring that all participant materials complied with high ethical standards.
- **Informed Consent**: All participants were provided with complete information sheets, consent forms to assure informed voluntary involvement.

3.6.2 Legal Compliance

- **Data Protection and Privacy**: Adherence to GDPR and other relevant laws ensured stringent data privacy and security measures were implemented, as detailed in participant consent forms (Willers et al., 2022).
- **Regulatory Compliance**: Legal analysis checks ensure compliance with Employment and anti-discrimination laws, preventing biases from occurring in AI applications (Bodie et al., 2016).

3.6.3 Managing Ethical Challenges

- **Monitoring and Adaptation**: The ethical standards were constantly monitored, adapted in correlation to issues that arose throughout the project with input of participants.

3.7 Limitations of the Methodology

This section discusses the inherent limitations in the research methodology that could affect the findings and interpretations of the study.

- **Data Dependencies**: The research leaned heavily on historic sales data, manually input holiday schedules and weather information. Access to this data, however qualitative and quantitative it was, proved essential yet extrapolating trends can create bias especially in new activities not experienced by historical data.
- **Model Biases**: While Prophet shows some improvement in accuracy, this is subject to too many regressors and limitations from data quality. Prior data-based dependencies:

Past patterns may not map to new consumer behaviour UVPs or changes in the operating environment, which can lead that model astray.

- **Tool Limitations**: Optimization tools, such as PuLP and OR-Tools were tried initially for scheduling, but the constraints so complex that did not fit well to our project's specific requirements due to restaurant specific operational needs. The final implementation relied on simpler conditional logic to generate shifts, which, while effective, may not offer the optimization depth that more sophisticated algorithms could provide.
- **Software and Integration Challenges**: FastAPI with MongoDB helped streamline data processing, application operation. However, getting the forecasting model integrated into a real-time system which is being used by humans in day-to-day fire operations proved more difficult and hackier as the data needed for updating was often not available yet.
- **Generalizability**: Results are not generalizable beyond the specific conditions and operational setting of our medium-sized restaurant, because we did only one controlled experiment in it. Therefore, the findings may not be readily generalizable to other restaurant types or sizes and perhaps even more inappropriate for translation into practice outside of the industry.

Chapter 4: Results

4.1 Presentation of Findings

4.1.1 Sales Distribution Analysis:

A histogram illustrating the distribution of total net sales. This visual helps identify the most common sales figures and outliers in the dataset.

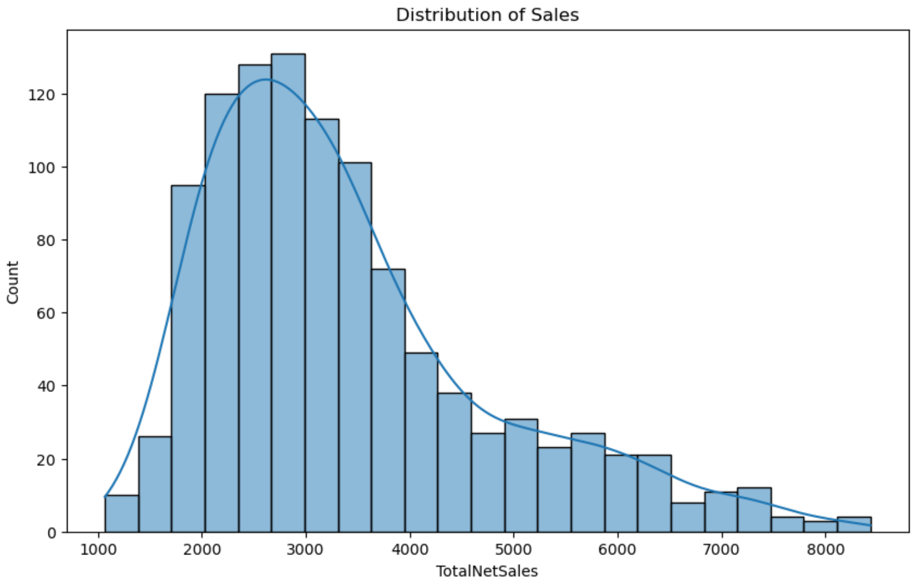


Figure 17. Distribution of Sales

4.1.2 Temperature and Sales Relationship:

Scatter plot showing how sales figures correlate with temperature changes, providing a preliminary view of external factors influencing sales.

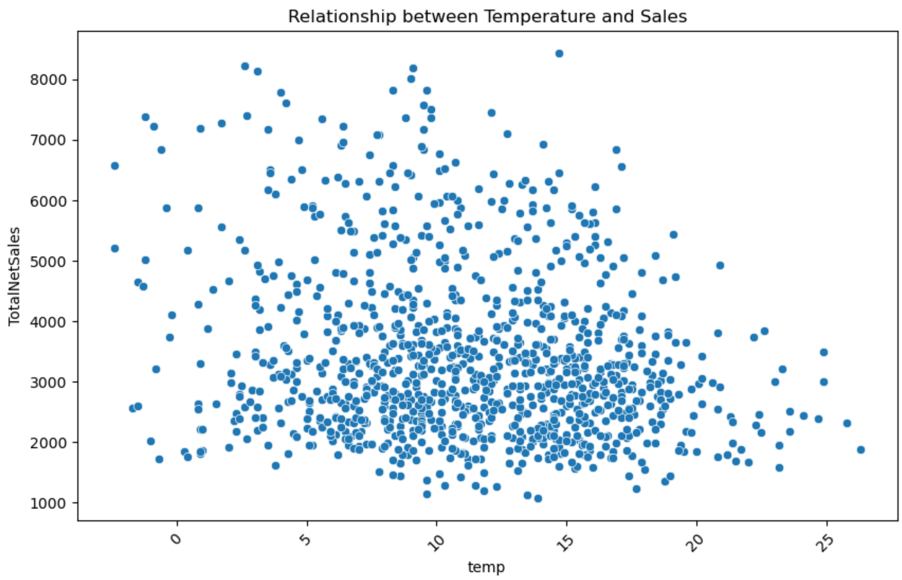


Figure 18. Relationship between Temperature and Sales

4.1.3 Correlation Matrix:

Correlation matrix that includes day of the week and weather conditions, offering insights into various factors that might affect sales figures.

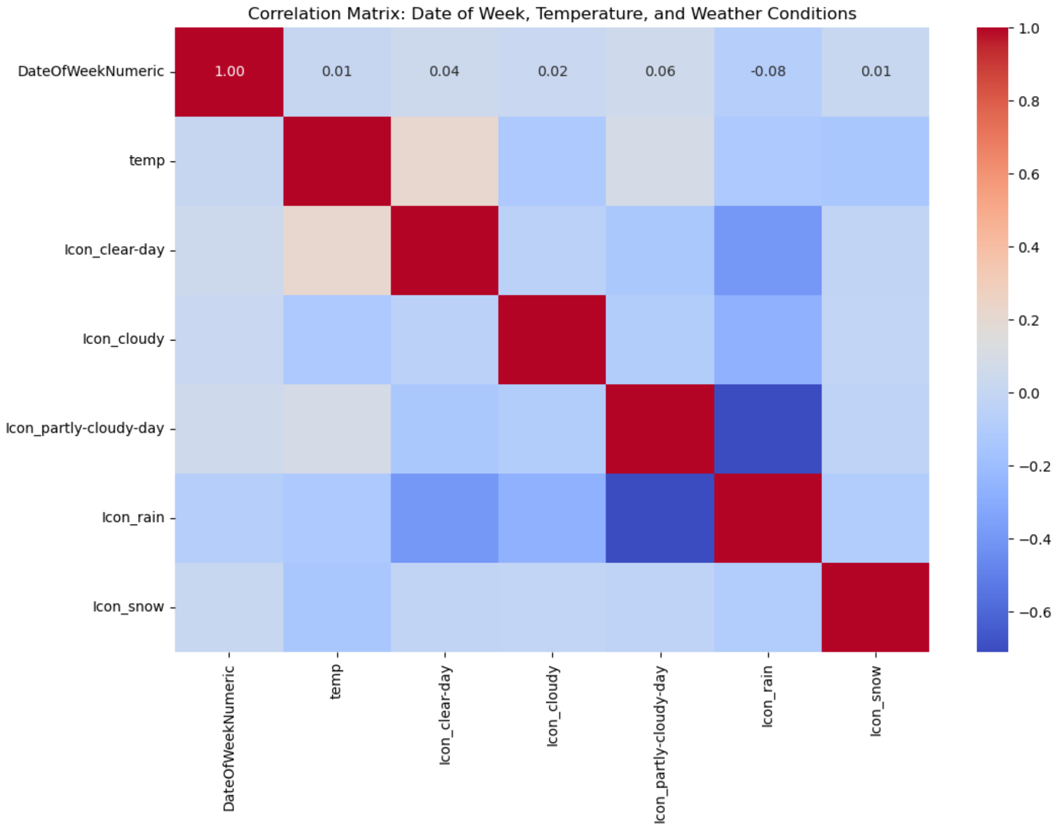


Figure 19. Correlation Matrix

4.1.4 Trend and Seasonality Analysis:

Plots from the Prophet model detailing trends, holiday effects, and day-of-the-week patterns that influence sales dynamics.

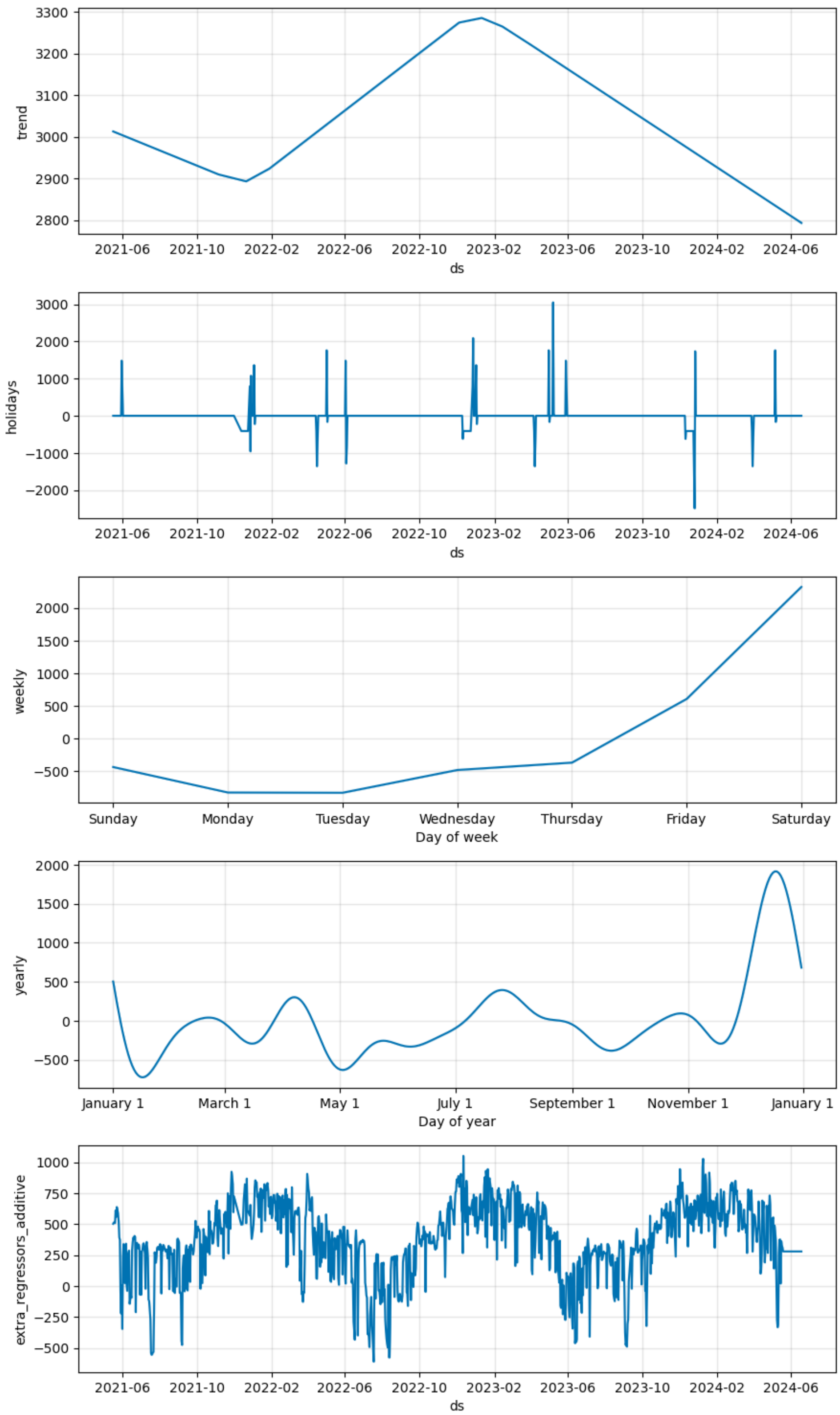


Figure 20. Trend and Seasonality Analysis

4.2 Forecast Accuracy Results:

4.2.1 Comparative Forecast Performance:

SARIMAX vs Prophet These values are presented in tables and graphs that detail key metrics — RMSE, MAE, and MAPE — for multiple testing scenarios to understand how the two models perform compared with each other. These accuracy metrics are important because they show comparatively how much each model is good at predicting the sales accurately.

4.2.1.1 Forecasting statistical details of SARIMAX

Test MSE: 982107.2386307776,	Test R^2: 0.509462602826336
Test MAE: 750.0349619577463,	Test MAPE: 25.13%
Test RMSE: 991.0132383731196,	Test SMAPE: 23.24%

4.2.1.2 Forecasting statistical details of Prophet

Average RMSE: 562.8761870682736	Average MAPE: 0.16868683028472303
Average MAE: 461.3745746369076	R-squared: 0.79

4.2.2 Accuracy Metrics Comparison:

- **Root Mean Square Error (RMSE)**: A lower RMSE value is better, Prophet has an RMSE nearly half that of SARIMAX (562.88 vs 991.01), implying its predictions are quite close to the true values.
- **Mean Absolute Error (MAE)**: It is the mean of the absolute value of errors however larger error means bringing more punishment as opposed to smaller ones. In contrast, Prophet can do much better (with MAE of 461.37 against SARIMAX's 750.03.
- **Mean Absolute Percentage Error (MAPE)**: This measures the average percentage error. Prophet's MAPE is 0.169% (or 16.87% if not a decimal error in reporting), significantly lower than SARIMAX's 25.13%, indicating that Prophet's errors are smaller as a percentage of actual values.
- **R-squared (R^2)**: This is a measure of the proportion of the variance in your response variable that can be explained by your model. The better values are typically higher (closer to 1.0). The R^2 of Prophet (0.79) is much higher than SARIMAX at 0.51, implying that the model using Prophet can explain more variance in the sales data compared to SARIMAX.

4.2.3 Model Selection Visualization:

The following plots show how Prophet did way better in predicting sales across the years, month wise. These are about the adaptability of it to sales trends and seasonal fluctuations, this is why Prophet was chosen over SARIMAX.

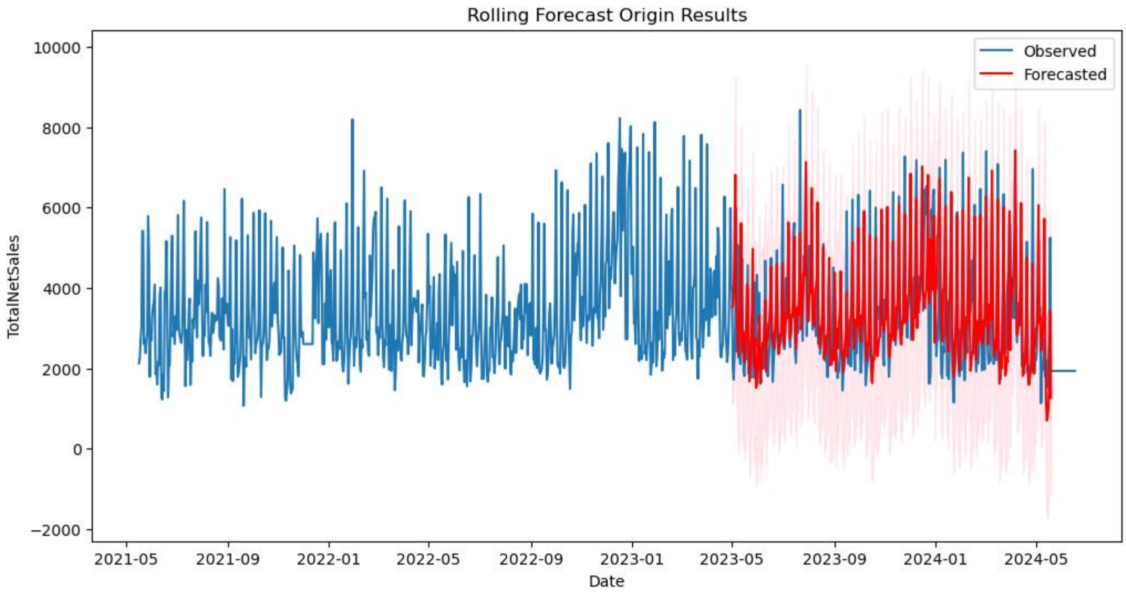


Figure 21. Forecasting with SARIMAX MODEL

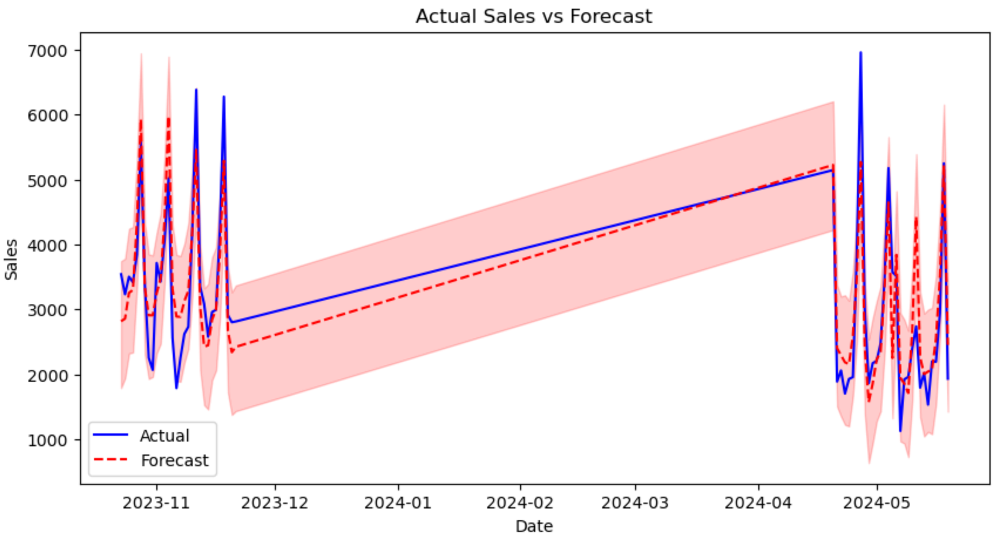
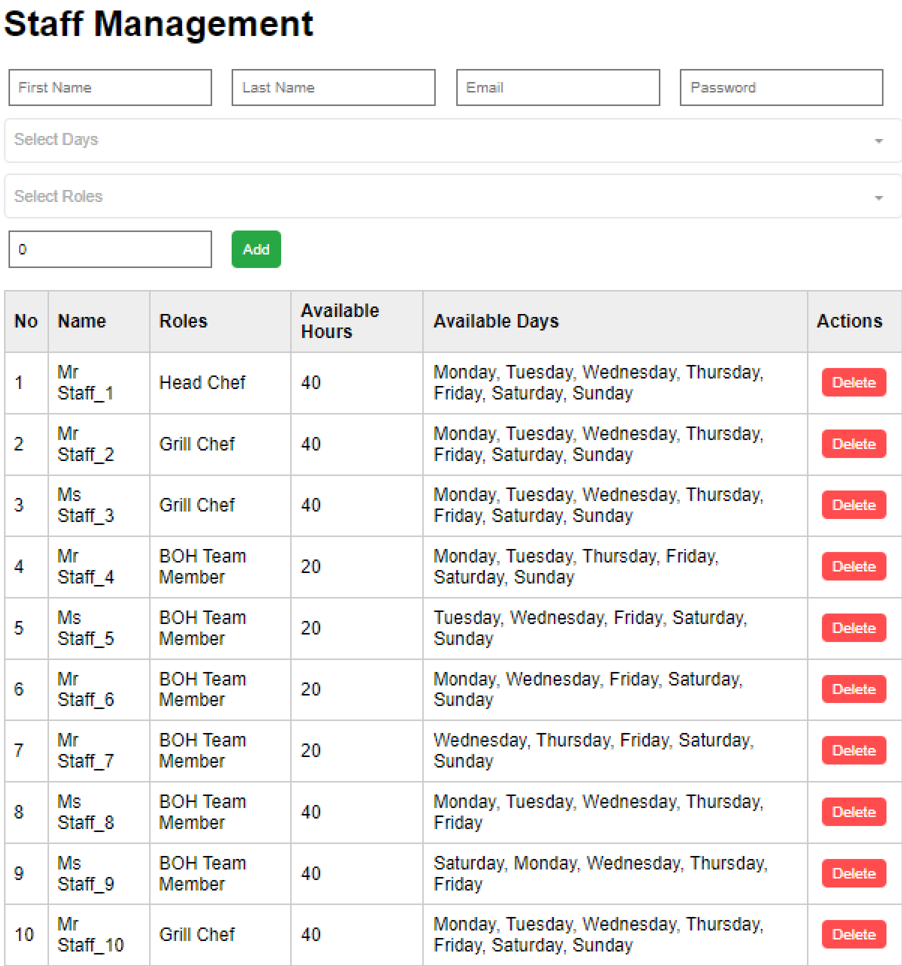


Figure 22. Forecasting with Prophet MODEL

4.3 System Utilization Results:

Interface Utilization: Screenshots and user flow diagrams from the system demonstrate its functionality and ease of use.



Staff Management

First Name | Last Name | Email | Password

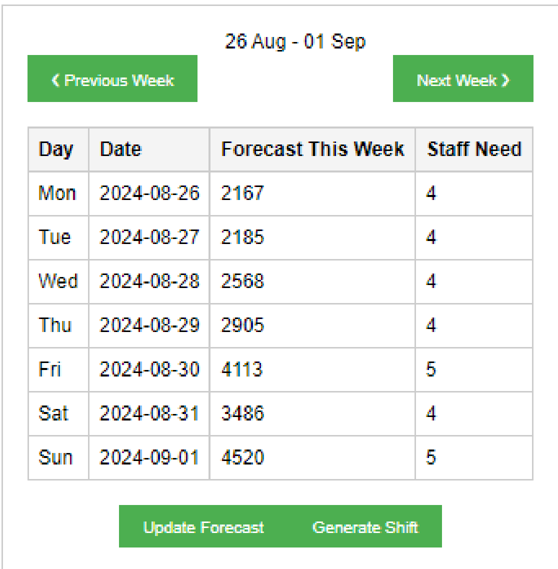
Select Days

Select Roles

0 | Add

No	Name	Roles	Available Hours	Available Days	Actions
1	Mr Staff_1	Head Chef	40	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday	Delete
2	Mr Staff_2	Grill Chef	40	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday	Delete
3	Ms Staff_3	Grill Chef	40	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday	Delete
4	Mr Staff_4	BOH Team Member	20	Monday, Tuesday, Thursday, Friday, Saturday, Sunday	Delete
5	Ms Staff_5	BOH Team Member	20	Tuesday, Wednesday, Friday, Saturday, Sunday	Delete
6	Mr Staff_6	BOH Team Member	20	Monday, Wednesday, Friday, Saturday, Sunday	Delete
7	Mr Staff_7	BOH Team Member	20	Wednesday, Thursday, Friday, Saturday, Sunday	Delete
8	Ms Staff_8	BOH Team Member	40	Monday, Tuesday, Wednesday, Thursday, Friday	Delete
9	Ms Staff_9	BOH Team Member	40	Saturday, Monday, Wednesday, Thursday, Friday	Delete
10	Mr Staff_10	Grill Chef	40	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday	Delete

Figure 23. Staff Management Interface



26 Aug - 01 Sep

❮ Previous Week | Next Week ❯

Day	Date	Forecast This Week	Staff Need
Mon	2024-08-26	2167	4
Tue	2024-08-27	2185	4
Wed	2024-08-28	2568	4
Thu	2024-08-29	2905	4
Fri	2024-08-30	4113	5
Sat	2024-08-31	3486	4
Sun	2024-09-01	4520	5

Update Forecast | Generate Shift

Figure 24. Sale and Staffing Forecast

19 Aug - 25 Aug

	Mon 2024-08-19	Tue 2024-08-20	Wed 2024-08-21	Thu 2024-08-22	Fri 2024-08-23	Sat 2024-08-24	Sun 2024-08-25
Mr Staff_4	-	-	-	15:00 - 21:00	-	15:00 - 21:00	15:00 - 21:00
Mr Staff_6	15:00 - 21:00	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00	15:00 - 21:00	15:00 - 21:00	-
Ms Staff_3	-	-	-	09:00 - 15:00	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00
Mr Staff_10	-	09:00 - 15:00	15:00 - 21:00	09:00 - 15:00	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00
Ms Staff_9	-	09:00 - 15:00	09:00 - 15:00	-	09:00 - 15:00	09:00 - 15:00	-
Mr Staff_2	15:00 - 21:00	15:00 - 21:00	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00	09:00 - 15:00	-
Ms Staff_5	09:00 - 15:00	-	09:00 - 15:00	09:00 - 15:00	09:00 - 15:00	09:00 - 15:00	15:00 - 21:00
Ms Staff_8	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00	15:00 - 21:00	-	09:00 - 15:00	15:00 - 21:00
Mr Staff_7	09:00 - 15:00	-	15:00 - 21:00	15:00 - 21:00	09:00 - 15:00	09:00 - 15:00	-
Mr Staff_1	09:00 - 15:00	09:00 - 15:00	09:00 - 15:00	-	15:00 - 21:00	15:00 - 21:00	15:00 - 21:00

Figure 25. Schedule Interface

Figure 26. Individual Staff's Schedule Interface

Chapter 5: Discussion

5.1 Interpretation of Results

5.1.1 Forecast Model Efficacy:

In this part of the interview, we were exploring why Prophet outperformed SARIMAX in terms of accuracy: flexibility and its capability to promptly adapt with changing trends during training gave it a tremendous boost over the predictions. These results reinforce the research hypothesis that more flexible models in dynamic environments such as restaurants can improve scheduling accuracy.

5.1.2 System Utilization Insights:

In this edition we take a closer look at how the AI-driven scheduling system enhanced operational efficiency and employee satisfaction. We discuss the findings as they relate to cost reduction and improved employee morale, providing clear examples of how modern predictive analytics tools add tangible value in workforce management.

5.2 Comparison with Literature

5.2.1 Alignment and Contrasts with Existing Studies:

The discovered results were matched up to the review of literature and mapped established ones in Chapter 2, as well as highlighted any gaps. For instance, literature would tell you that SARIMAX is generally good at incorporating external regressors but the results from this project show Prophet as a better model for the setting of restaurant sales since it gives superior performance within their nuggets.

5.2.2 Discussion of New Insights:

This contribution is new to the growing research in AI-based shift scheduling, especially regarding how predictive models behave under real-world conditions. These insights contribute to a deeper understanding of the areas in this scientific literature that have noted gaps and specifically on how these models can be put into practice within an established medium sized restaurant.

5.3 Implications

5.3.1 Theoretical and Methodological Implications:

In theory, the study expands current models covering workforce management that utilise new advanced types of predictive analytics. In terms of methods, the research also shows that real-world data is sufficient to train prediction models and offers a template for similarly implementing in other industries.

5.4 Recommendations

5.4.1 Applications of Findings:

According to the results, other restaurants or service industries may want to investigate utilising AI scheduling systems. Moni et al. (2022) have illustrated a compelling case for using Prophet models with solid backend systems such as FastAPI and MongoDB to handle real-time data that was the basis of other applications constructed in this study.

5.4.2 Future Research Directions:

Additional work could investigate the incorporation of other types of data, such as live customer feedback or more detailed weather information, to improve forecast precision. In addition, replication in diverse restaurant types or regions.

5.4.3 Changes in Practice or Policy:

Policymakers and industry leaders might consider guidelines for the ethical use of AI in employee scheduling to prevent potential biases and ensure transparency in shift assignments.

Chapter 6: Conclusion

6.1 Summary of Findings

The study has successfully illustrated the accuracy of advanced forecasting models, especially Prophet in scheduling shifts within restaurant business as shown previously for the Model 2, significant improvements in terms of accuracy measurement were obtained when performing dynamic forecasts with Prophet in fluctuating market landscapes (André Luiz Marques Serrano et al., (2024). Number four, integrating these models into a web-based application with FastAPI in the backend and Vue.js, and MongoDB that has been successful in automating & streamlining staff scheduling operations. The above integration has helped optimize operations for a medium-size restaurant, proving that machine learning can be combined with modern web technologies in practice.

6.2 Contributions

This research has taken standard forecasting models and adapted them, using new regresses identified by localized data analysis to meet specific operational needs, that significantly advances methodological process in this field. The paper also presents an architecture to deploy these models in the real-world scenario and provides state-of-the-art comparisons, which can be justified for other researchers working on technology-based workforce management studies.

6.3 Limitations

Some limitations in this study are using the historical sales figures to predict future market transitions or macroeconomic impacts, which could make it hard for us to use the same forecast and methodology across various industries or at different times of higher turbulence due to external factors. Reliability: The system used some external APIs for real-time weather & this is not in favour of the reliability as if these external sources become unavailable it leads to Unreachability which forces technical loss, this might affect either forecast or System Robustness. PuLP and OR-Tools also allegedly tried for schedule optimization to no ware, as they cannot handle the complex constraints necessary in effective shift planning such that a chef is available at opening and closing or an employee does not work same day repetitive slots.

6.4 Future Research

Future studies could examine real-time data analytics to enable shift scheduling adjustments, which may increase operational agility and effectiveness. Alternative algorithms or hybrid models may offer more accurate future forecasts, or improved performance for distinct operational conditions. These developments of the user interface in addition to extensive usability testing could mean that human users will find it ideal, and they can set their preferences, enhancing general usability for all stakeholders leading receive wide end-user adoption consequent operational impact.

Reflection on the AI-Powered Fair Shift Scheduling System Project

7.1 Project Insights and Achievements

This project originated from a deep-seated need to address the inefficiencies and unfairness inherent in traditional shift scheduling within the restaurant where I worked. The successful development and integration of the AI-powered scheduling system using the Prophet model represent a significant achievement. The model's ability to adapt to dynamic sales patterns based on historical data and external factors like weather and holidays was a key discovery. It proved more effective than the SARIMAX model, which was initially considered but later set aside due to its complexity and less satisfactory performance under our specific conditions.

7.2 Challenges and Struggles

The journey was not without its challenges. One of the most significant hurdles was the initial failure of standard optimization tools like PuLP and Google OR-Tools, which could not accommodate the unique scheduling needs of our restaurant's operational environment. This necessitated the development of a custom scheduling logic, a task that was both demanding and enlightening. Implementing this custom logic required a deep dive into conditional programming and iterative testing, which, while time-consuming, was critical for achieving a functional and effective scheduling system.

7.3 Practical Takeaways and Personal Growth

The project was instrumental in highlighting the practical limitations of conventional tools and the necessity for bespoke solutions in specific settings. Developing the custom logic for shift scheduling provided me with a profound appreciation for the nuances of practical software application in a business context. It underscored the importance of flexibility and creativity in problem-solving, especially when standard solutions fall short.

The process of integrating predictive analytics with real-world applications also offered valuable lessons in the practical challenges of applying theoretical models in a dynamic industry. This experience has sharpened my problem-solving skills and deepened my understanding of how data science can be applied to improve everyday business operations.

7.4 Reflections on Project Impact

Reflecting on the project's impact, even though the journey was challenging, it was immensely rewarding. The system developed has the potential to revolutionize how staffing is managed not just in the restaurant I worked in but potentially in the broader industry. The success of this project has motivated me to continue exploring AI and machine learning applications in operational contexts, with a focus on developing solutions that are both innovative and practically applicable.

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Appendices

Appendix A: Survey Instruments

Survey Questions and answers that use to Analyse the staff satisfaction

Question	Person 1	Person 2	Person 3	Person 4	Person 5	Person 6	Person 7	Person 8
1. How satisfied are you with your current work schedule?	3	5	4	2	3	2	3	3
4. Do you feel that the distribution of shifts among employees is fair?	Yes	No	No	No	No	No	No	No
5. On a scale of 1-5, how fairly do you think shifts are assigned during peak hours?	2	3	4	1	2	2	3	2
6. Do you believe some roles are consistently scheduled more favourably than others?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7. How adequately do you think scheduling system accommodates the demands of your specific role?	2	4	4	3	4	1	3	3
8. In your role, do you feel your workload during your shifts is reasonable?	Yes	No	Yes	Yes	Yes	No	No	Yes
9. Do you feel that you have sufficient time to complete your tasks effectively?	No	No	Yes	No	No	No	Yes	No
11. Are there any times or days you prefer not to work, but are often scheduled anyway?	No	Yes	No	Yes	No	Yes	Yes	Yes
13. On a scale of 1-5, how supported do you feel by management in terms of scheduling flexibility?	3	3	5	3	3	1	3	3
17. Do you feel that the differences in workload between roles are justified based on the responsibilities of each role?	Yes	No	Yes	Yes	Yes	No	No	No
18. In times when your workload is lighter, would you be willing to assist others whose workload is heavier?	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes

Appendix B: Transcription of Interviews

Full transcriptions of interviews with restaurant staff, originally recorded and later converted from audio to text format using Google Cloud Speech-to-Text services. These transcriptions offer detailed insights into staff experiences and perspectives regarding shift scheduling practices within the restaurant. For access to the transcribed .srt files, please visit my GitHub repository: GitHub Profile. The files are stored under the repository specifically dedicated to this project's resources.

Appendix C: Project Timeline

- **Timeline Description:** Provides a revised timeline of the project's tasks, with accurate dates of key activities from initial data collection to final project submission:
  - Data Collection: March 8 - March 29
  - Comprehensive Data Cleaning: March 29 - April 19
  - Modelling and Model Refinement: April 30 - May 31
  - System Development and Testing: May 31 - July 27
  - Revision Based on Feedback and Final Submission: June 28 - Aug 28

Appendix D: Supervisor Meeting Notes

30/04/2024	Meeting absent by me.
07/05/2024	Initial discussion about the project concept. Suggestions received on conducting surveys, including necessary preparations for ethical considerations.
28/05/2024	Focus on ethical aspects of the research, including a review of sample consent forms and information sheets. Initiated the process of filling out the Ethical Review Record.
04/06/2024	Discussions centered on data cleaning and maintaining data ethics throughout the project.
11/06/2024	Guidance provided on preparing the literature review, including advice on appropriate structuring and content inclusion.
18/06/2024	Discussed data science methodologies, specifically the application of CRISP-DM. Reviewed the draft literature review.
25/06/2024	Conversation about conducting interviews with the head chef, leading to advice on creating another consent form and the recommendation to use text-to-transcript tools like NVivo for interview data.
02/07/2024	Presentation of the initial back-end setup, with feedback and discussions on its configuration and ethical handling.
16/07/2024	Review of the prototype design on Figma, with a discussion focusing on the selection of front-end technologies suitable for the project's data science aspects.
23/07/2024	Guidance received on dissertation writing and the structuring of findings.

Appendix E: Ethical Approval and Project Documentation

This appendix includes copies of all ethical approval certificates, participant information sheets, and consent forms used in the study, demonstrating adherence to the ethical standards of the University of the West of England. To ensure privacy and data protection, all raw data associated with this project will be securely deleted two months after the project's completion. Comprehensive documentation, including scripts for data cleaning, additional data analysis visualizations, model development, and the prototype interface, is available on my GitHub repository for ongoing access and transparency. Visit GitHub Profile to access these resources.