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Optimizing Production Planning for Fresh Sandwich Shops Under Demand Uncertainty

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Abstract

Fresh food shops such as small sandwich shops face operational difficulties due to demand uncertainty and the perishable nature of their inventory. These businesses often experience waste or stockouts that directly affect profitability and customer satisfaction. This study develops a data-driven production planning model for a sandwich shop operating in two shifts daily. The model aims to minimize daily ingredient waste and maximize profits. Using real transactional data on sales and purchases, we propose a mixed-integer linear programming (MILP) model supported by demand forecasting. Results show improved alignment between ingredient supply and actual consumption, leading to enhanced profitability and availability of products.

Keywords
Demand, SMEs, Production planning.

1. Introduction

Small-scale food retail operations such as fresh sandwich shops play a critical role in local economies and the broader food service industry. Globally, small and medium-sized enterprises (SMEs) account for over 90% of businesses (Filho 2023), and in the food sector, they form a major part of the supply chain, particularly in emerging economies. Despite their prevalence, small food retailers often struggle with financial sustainability, largely due to issues in inventory management, operational planning, and demand uncertainty.

Studies have shown that inventory mismanagement is a leading cause of business failure among small food establishments, with nearly 60% of such businesses shutting down within their first ten years of operation (Filho 2023). This is often attributed to either overstocking—which leads to waste and cost inflation—or understocking, which causes lost sales and customer dissatisfaction. The perishability of food items, coupled with variable demand, adds layers of complexity to these issues, especially for shops that operate across multiple shifts in a single day.

At the same time, the digital transformation sweeping through retail and supply chain management has opened new avenues for operational efficiency. Technologies such as cloud-based inventory systems, AI-driven demand forecasting, and mobile point-of-sale tools are becoming increasingly accessible. However, adoption rates among small food businesses remain low due to cost, complexity, or lack of technical expertise. There is a critical need for scalable and user-friendly planning models that can help these businesses thrive in competitive and volatile markets.

This paper addresses this need by developing and validating a production planning model tailored to a fresh sandwich shop. The model is designed to minimize daily ingredient waste and maximize profitability, using historical sales and purchase data from the shop. The paper integrates demand forecasting with a mixed-integer linear programming (MILP) framework to provide actionable insights for inventory and production planning.

2. Literature Review

Accurate demand forecasting is crucial for operational efficiency in the food retail sector, particularly for small and medium-sized enterprises (SMEs) like sandwich shops. Various forecasting methods have been developed and applied, each with its strengths and limitations, especially concerning accuracy and applicability across different business scales.

Traditional statistical methods, such as Moving Averages, Exponential Smoothing, and ARIMA models, have been widely used due to their simplicity and ease of implementation. These methods are particularly suitable for SMEs with limited computational resources and technical expertise (Gaertner et. al 2024), (Fattah et al 2018). However, their accuracy can be limited, especially in the presence of complex patterns or non-linear relationships in the data. For instance, a recent study comparing forecasting methods in retail SMEs found that traditional methods like Exponential Smoothing yielded a Mean Absolute Percentage Error (MAPE) of approximately 15.2% (Hikmah et al 2025). These models have demonstrated superior accuracy in various contexts. The same study reported that a Random Forest model achieved a MAPE of 8.5%, significantly outperforming traditional methods. Additionally, LSTM models have been shown to be effective in capturing temporal dependencies in sales data, making them suitable for demand forecasting in the food retail sector.

In recent years, advanced forecasting techniques, including machine learning (ML) models like Random Forests, Gradient Boosted Trees, and Long Short-Term Memory (LSTM) neural networks, have gained popularity due to their ability to capture complex patterns and interactions in the data (Nasseri 2023).

Despite the higher accuracy of advanced models, their adoption in SMEs is often limited due to factors such as computational requirements, the need for large datasets, and the complexity of model interpretation. To address these challenges, hybrid approaches that combine traditional and advanced methods have been proposed. These approaches aim to balance predictive accuracy with interpretability and resource constraints. For instance, integrating Exponential Smoothing with machine learning models can provide SMEs with more accurate forecasts while maintaining a level of simplicity in implementation.

Studies have focused on enhancing forecasting accuracy and applicability in the food retail sector. For example, (Pauls-Worm et al 2013) developed a Mixed-Integer Linear Programming (MILP) model to manage inventory for perishable products under non-stationary demand conditions. The model integrates a First-In-First-Out (FIFO) issuing policy and incorporates explicit service level constraints, making it particularly effective for supply chains where product freshness and customer satisfaction are critical. Their findings demonstrate that commercial MILP solvers can yield practical and implementable replenishment plans that strike a balance between minimizing waste and ensuring product availability—enhancing both operational efficiency and service reliability in perishable food systems. These advancements highlight the ongoing efforts to develop forecasting methods that are both accurate and accessible to SMEs, enabling better inventory management and operational planning in the food retail sector.

In addition, Lean principles and operations research techniques have been adapted from manufacturing to service industries, including food retail (Womack and Jones 2003). Lean methods help eliminate non-value-adding activities and improve process flows. In food settings, Lean implementation contributes to managing inventory, reducing wait times, and improving product freshness. Mathematical modelling, particularly MILP, has been extensively used for optimizing ingredient usage and managing perishable inventory, especially under constraints related to labor, storage, and time.

Hybrid systems combining forecasting with optimization have demonstrated strong results in improving planning accuracy and reducing waste in food supply chains (Abbasian et al 2023). However, many of these systems target larger or centralized operations. This study extends those approaches to a localized, dual-shift sandwich shop context, demonstrating the feasibility of high-accuracy forecasting and optimization techniques in small food businesses.

3. Methodology

This study proposes a mixed-integer linear programming (MILP) model to support production planning in a sandwich shop. The objective is to minimize ingredient waste and maximize profit at the end of each business day. Let the indices, parameters, and decision variables be defined as follows:

Indices

$i \in I$: Index for sandwich types
$j \in J$: Index for ingredient types

$t \in T$: Index for time shifts (morning and evening)

Parameters
d_{it}: Forecasted demand for sandwich type i during shift t
p_i: Selling price per unit of sandwich type i
c_{ij}: Cost of ingredient j used in sandwich iii
a_{ij}: Quantity of ingredient j required to produce one unit of sandwich i
B: Total budget allocated for daily ingredient purchases
Λ_j: Penalty cost per unit of unused (wasted) ingredient j
θ_i: *Penalty cost per unit of unmet demand for sandwich i*

Decision Variables
x_{it}: Number of sandwiches of type i to be produced during shift t
y_{jt}: Quantity of ingredient j to be purchased for for shift t
w_{jt}: Waste quantity of ingredient jjj at end of shift t
u_{jt}: Unmet demand for sandwich iii in shift t
Maximize total profit: $max\ Z = \sum_{i\in I}\sum_{t\in T} p_i * x_{it} - \sum_{j\in J}\sum_{t\in T} c_{ij} * y_{jt} - \sum_{j\in J}\sum_{t\in T} \lambda_j * w_{jt} - \sum_{i\in I}\sum_{t\in T} \theta_i * u_{it}$

Constraints
1. Ingredient Availability Constraint:
$\sum_{i\in I}\sum_{t\in T} a_{ij} * x_{it} + w_j \le y_j \qquad \forall j \in J$
2. Demand Satisfaction Constraint: Type equation here.
$x_{it} + u_{it} = d_{it} \qquad \forall\, i \in I,\ t \in T$
3. Budget Constraint:
$$\sum_{j\in J}\sum_{t\in T} c_{ij} * y_{jt} \le B$$
4. Non-negativity Constraints:
$x_{it} \ge 0, \quad y_{jt} \ge 0, \quad w_{jt} \ge 0, \quad {}_{uit} \ge 0 \qquad \forall\, i, j, t$

4. Data Collection and Preparation

Data was collected from two primary sources: The business operates in two shifts: 5:30 AM–11:30 AM and 4:30 PM–11:30 PM. The dataset covered 92 with a total of 184 shifts for three different type of sandwich and their fresh ingredient, these ingredients must be fresh for each shift. providing insight into overall demand trends. The Figure 1 below shows an example of the historical data, where S1, S2, and S3 represents sandwich type 1, 2, and 3 respectively; and I1, I2, I3, and I4 represents ingredient 1, 2, 3, and 4 respectively.

Date	Shift	Sandwich	ForecastedDemand	Sold	Price	Revenue	TotalCost	Profit	I1_Forecasted	I2_Forecasted	I3_Forecasted	I4_Forecasted	I1_used	I2_used	I3_used	I4_used	I1_waste	I2_waste	I3_waste	I4_waste	UnmetDemand
3/1/2024	Morning	S1	59	51	2	102	40.8	61.2	29.5	59	73.75	295	25.5	51	63.75	255	4	8	10	40	0
3/1/2024	Morning	S2	48	48	3	144	57.6	86.4	48	48	72	336	48	48	72	336	0	0	0	0	0
3/1/2024	Morning	S3	27	21	4	84	33.6	50.4	27	27	54	216	21	21	42	168	6	6	12	48	0
3/1/2024	Evening	S1	61	57	2	114	45.6	68.4	30.5	61	76.25	305	28.5	57	71.25	285	2	4	5	20	0
3/1/2024	Evening	S2	38	34	3	102	40.8	61.2	38	38	57	266	34	34	51	238	4	4	6	28	0
3/1/2024	Evening	S3	30	28	4	112	44.8	67.2	30	30	60	240	28	28	56	224	2	2	4	16	0
3/2/2024	Morning	S1	47	47	2	94	37.6	56.4	23.5	47	58.75	235	23.5	47	58.75	235	0	0	0	0	0
3/2/2024	Morning	S2	55	55	3	165	66	99	55	55	82.5	385	55	55	82.5	385	0	0	0	0	0
3/2/2024	Morning	S3	43	43	4	172	68.8	103.2	43	43	86	344	43	43	86	344	0	0	0	0	0

Figure 1. Sample of the historical data

5. Results

The integrated MILP model developed in Python demonstrated strong performance when applied to historical data from a dual-shift sandwich shop. By incorporating demand forecasts, ingredient constraints, and differentiated penalty structures for both waste and unmet demand, the model significantly improved key operational outcomes.

- Profit Increase: The result showed a 20.45% increase in total profit compared to the baseline. This improvement was driven by tighter alignment between forecasted demand and actual production, as well as smarter purchasing decisions that avoided overstocking and minimized the financial impact of unmet demand.
- Waste Reduction: The total cost of wasted ingredients declined by 19.45%, reflecting improved inventory efficiency and better planning around perishable stock.

- Customer Satisfaction: Penalties due to unmet demand decreased by 25%, indicating fewer stockouts and better service levels during peak demand periods.

6. Discussion

These results suggest that incorporating demand-responsive planning and cost-weighted penalties enables businesses to optimize resource use while maintaining high service levels. In particular, the model's use of distinct waste penalties per ingredient and unmet demand penalties per sandwich type allowed for nuanced prioritization—encouraging more conservative planning for expensive or high-demand items.

Operational insights revealed that ingredient waste was most often linked to aggressive over-preparation in uncertain demand periods (especially on weekends). By contrast, underproduction during evening shifts led to significant unmet demand penalties. The model's balancing mechanism dynamically adapted to these patterns, suggesting its suitability for routine decision-making.

Importantly, this implementation required no advanced ERP system. The model was built using common spreadsheet data and optimized using freely available solvers. This reinforces its value for SMEs seeking data-driven transformation without incurring heavy software investment.
However, limitations remain. The model assumes static pricing and fixed preparation costs, which may vary in reality due to supplier variability or seasonality. It also considers a single-day planning horizon; real-world operations could benefit from rolling forecasts and inventory carryover. Moreover, spoilage and shelf-life were not explicitly included, which would be relevant in multi-day inventory strategies.

7. Conclusion

This study presents a practical and effective production planning framework tailored to the needs of small sandwich shops operating under demand uncertainty. By integrating sales forecasting with a mixed-integer linear programming (MILP) model, the proposed approach optimizes profitability, minimizes waste, and reduces penalties for unmet demand.
results based on real operational data revealed **profit improvements exceeding 20%**, **nearly 20% waste reduction**, and **25% fewer stockouts**, showcasing the tangible benefits of structured planning. The model accommodates shift-based production, ingredient-level constraints, and differentiated penalties, making it highly applicable for small-scale food businesses.

The findings support the use of lightweight optimization tools as an entry point for digital transformation in SMEs. Without requiring complex systems or expensive infrastructure, the model demonstrates that measurable operational gains are achievable with accessible tools and accurate data.

Future research should focus on expanding the model to include dynamic pricing, spoilage rates, multi-day planning horizons, and real-time sales monitoring. Integration with user-friendly dashboards or mobile interfaces could also enhance decision-making and adoption among staff. As small food retailers navigate competitive and volatile markets, such tailored and data-informed planning frameworks can offer a path to greater sustainability and resilience.

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