International Journal on Economics, Finance and Sustainable Development (IJEFSD)

e-ISSN: 2620 – 6269
p-ISSN: 2615 - 4021

Volume: 6 Issue: 12 | December 2024

https://journals.researchparks.org/index.php/IJEFSD

Article

Analysis and Optimization Strategies for Demand Forecasting Issues at Mixue

Chen Shihua[1*], Meng Xin[2], Li Wen[3]

1,2. PhD in Management. ALFA University College, Selangor, Malaysia,
3. Universidade Politécnica de Macau, Macao Polytechnic University, Master's Degree in Education
* Correspondence: 695618116@qq.com

Abstract: This study addresses demand forecasting challenges at MIXUE, a beverage chain, focusing on issues like high subjectivity and significant prediction errors that lead to market volatility and operational inefficiencies. Despite the critical role of the food and beverage industry in economic growth, MIXUE faces intense competition, emphasizing the need for accurate demand forecasting. This research aims to analyze historical sales data using time series analysis to identify patterns, optimize demand forecasting methods, and reduce data volatility. The study develops a demand forecasting model to align supply and demand, improve revenue management, and mitigate risks associated with uncertainty. Results highlight the importance of precise demand forecasting in enhancing operational efficiency, reducing costs, and maximizing profits. This research provides actionable insights for MIXUE to better anticipate market trends and strengthen its competitive position.

Keywords: Analysis, Optimization Strategies, Demand, Forecasting, Issues, MIXUE

Citation: Chen Shihua, Meng Xin, Li Wen. Analysis and Optimization Strategies for Demand Forecasting Issues at Mixue. International Journal on Economics, Finance and Sustainable Development (IJEFSD) 2024, 6(12), 383-396.

Received: 11th Sept 2024
Revised: 17th Oct 2024
Accepted: 24th Nov 2024
Published: 29th Dec 2024

1. Introduction

I. Current Status of Demand Forecasting

MIXUE does demand forecasting work on a regular basis to improve his understanding of the market. The prediction contains the overall number of products, popular variants, and monthly market demand for each item. MIXUE in P City currently requires its franchise stores to estimate sales volume and product kinds, which are then reported to the front warehouse (FDC) in Fuzhou. The front warehouse consolidates demand estimates from all P City retailers before reporting and summarizing them to the provincial distribution center. Finally, when the five central distribution centers aggregate and analyze demand from franchise stores around the country, the results are given to MIXUE Co., Ltd., which then develops the appropriate demand plan. This demand forecasting sequence is bottom-up, combining historical demand data with the experience judgment of relevant management professionals at all levels, predicting with a basic linear regression equation, and then integrating numerous parameters for reference. If there are logistical high seasons, such as holidays or the summer, managers at all levels will increase demand projection results to meet current market demand.

II. Issues with Demand Forecasting

A successful and appropriate demand forecasting system should incorporate a considerable quantity of historical data, external market information, and internal market dynamics from the outset. Effective and appropriate demand forecasting analysis can help P City MIXUE enhance production efficiency while also lowering inventory backlog and costs. According on the current demand forecasting models and the operational status of P City MIXUE, the following demand forecasting issues have been identified:

1. **Low accuracy of demand forecasting**

Currently, demand forecasting for raw materials at various franchise outlets operated by P City MIXUE is mostly based on material consumption statistics. Furthermore, the demand forecasting findings are changed based on the material demand orders provided by each franchisee and the subjective awareness of their managers. The accuracy of this demand forecasting is influenced by material classification errors and model choices. In comparison, the harm produced by selecting and tuning the demand forecasting model is far bigger. Material classification errors only influence one or two types of materials, which does not have a significant impact on overall inventory or capital requirements. However, flaws in model selection have a direct impact on the forecasting of a large number of materials, resulting in low accuracy in raw material demand forecasting. This eventually leads to inventory backlogs and stockouts in the warehouses of numerous franchise outlets under P City MIXUE. Furthermore, it generates delays and gaps in logistics distribution, which raises inventory costs, stockout costs, and logistics costs.

2. **Failure to thoroughly consider the dynamics and trends in the whole market.**

Based on MIXUE's existing demand forecasting system model, it is critical to gather and consider demand forecasting influencing elements in order to improve the scientificity and accuracy of forecasting findings. Any influencing factor or sudden occurrence can produce a variation in demand forecasting findings. Given the overall market changes, the examination of factors affecting demand forecasting must pay attention to historical data, key events, competition within the same industry, consumer behavior, and other aspects:

First, historical data. Historical data consists mostly of order data and sales data, which can be further classified into categories such as sales volume, sales unit price, gross profit, profit margin, and inventory amount. Collecting and understanding each store's historical data, as well as conducting horizontal analysis of previous product sales varieties and series specifications, followed by vertical analysis from major categories to individual product series, enables understanding and mastery of the sales patterns of each beverage series. Furthermore, using the aforementioned historical data, appropriate management professionals in the organization can forecast customer behavior and future sales trends.

MIXUE in City P's historical data is derived from frontline store operational data, which includes errors and omissions in orders when ordering as well as the collection of daily sales data after closure. Observing MIXUE franchise locations in City P, there are occasional instances of data disarray, which could be due to inconsistent, incomplete, or erroneous data entry from store staff. Inaccurate historical data will have an impact on demand forecasting in the following phase, making it impossible to correlate order quantities with actual demand, resulting in inventory accumulation and supply-demand mismatches, among other issues.

Second, big events. According to a study of current beverage industry sales data, Mixue Ice Cream City's products in City P may be broadly classified into two primary sales trends: summer and other seasons. For example, demand for ice cream and sundae series is significantly higher in the summer than in other seasons, whereas sales of other hot and cold beverages remain relatively stable throughout the year with no obvious seasonal characteristics, which is related to seasonal environmental conditions. Furthermore, certain time periods such as holidays and important events throughout the year will raise the store's sales figures. At the same time, unpredictable aspects like politics, economics, and natural calamities are inextricably linked to demand forecasting.

As a result, these unique data pieces should be given extra consideration when estimating demand. When estimating product demand, City MIXUE failed to take into account all conceivable aspects and instead used the same forecasting method consistently. During the summer and holidays, they just increase the demand projection numbers without completing thorough market research or examining past data. This might lead to an inventory backlog, putting strain on cash flow. When a huge amount of capital is tied up, it has an impact on the company's market marketing and new product development, slowing its growth process. If things are not sold within their shelf life, they go to waste. When supply falls short of demand over time, some customers will leave.

On the one hand, there's competition inside the industry. In light of the increasingly fierce competition within the same industry and region, factors such as order response time, service quality, logistics delivery timeliness, follow-up tracking services, and contingency mechanisms in special situations will all have an impact on the company's sales demand forecast. As a result, learning more about competitors in the same industry can assist improve the company's management and operational processes.

Nowadays, competitors' sales strategies and new offerings will have an impact on MIXUE's sales in P City. Furthermore, P City MIXUE currently lacks market research capabilities and is not particularly sensitive to environmental changes. When competitors use certain marketing techniques, the company fails to take suitable countermeasures, resulting in missed chances and blunders. In contrast, consider customer behavior. Consumers' personal tastes and spending power can be used as reference points for P City's MIXUE, which is strongly tied to retail sales. Therefore, if the needs of potential consumers are not foreseen in advance and sales plans are not altered properly, it will eventually lead to customer loss and a lack of market competitiveness.

3. Failure to Fully Consider the Target Customers' Directed Needs

Demand management analysis is a crucial area of concentration for relevant management personnel. Efficient demand management necessitates researching the directed demands of target consumers, assuring the capacity to swiftly discover, record, organize, and track, as well as dealing with changes in customer needs. To completely comprehend and appreciate client needs, a particular number of target customers and potential customers must be identified. As a result, P City MIXUE must work hard to develop its target and potential clients. Create client information files.

Only by fully understanding the consumer and putting ourselves in their position can we determine which product series best meets their needs and which do not. At the same time, we can have frequent interactions with clients to increase their loyalty and stickiness. Furthermore, knowing and assessing overall market demand as well as individual client wants, as well as improving market sensitivity, are critical for comprehending the overall industry's development trends. Mixue Ice Cream City's relevant departments in City P are now collecting demand through methods like as customer interviews, surveys, seminars, and franchisee ordering behavior analysis.

Improve communication and contact with clients. Communication is essential for understanding client needs in a fast and correct manner. Second, in order to increase the accuracy of client requests, relevant customer needs must be organized and customers with comparable needs must be categorized. At the same time, this can help find commonalities among consumers who have similar wants, resulting in a better understanding of specific product requirements.

Enhance research on specific target customers. Analyzing the order information, previous transaction data, and personal information of specific target consumers allows one to understand the pattern of their order volumes, resulting in a demand projection. Then, by aggregating and summarizing target customer demand projections from various locations of City P, a complete and accurate overall demand forecast value may be calculated. Of course, appropriate staff should thoroughly research the needs of certain target clients and avoid providing one-sided descriptions. For example, the age distribution of customers varies by location in City P, as do the types of items they require.

4. Inadequate consideration of the seasonal cycle of products

The beverage industry has distinct seasonal characteristics. The market demand for the beverage sector is often influenced by the seasons, holidays, climate conditions, local peculiarities, and times of day.

First and foremost, every spring, due to the end of the Chinese New Year, people's migration and mobility, and market changes, there is typically a low season from February to April. The beverage business as a whole is generally sluggish, and sales data are not promising, continuing to fall. Following that, when the weather warms, the beverage industry market rebounds, and sales figures continue to grow, particularly during the prime summer months of July to October. revenue during this quarter may account for 40% of annual revenue, making it the pinnacle.

Second, due to the influence of holidays such as Chinese New Year, Labor Day, summer vacation, National Day, and Christmas abroad, each store will stock up ahead of time to prepare for these important days. During this time, their items' sales volume will fluctuate significantly. Weather and time of day can also have an impact on product sales. For example, sunny weather, rising temperatures, and midday hours can contribute to a surge in beverage sales; meanwhile, severe weather such as wind and rain, as well as periods when people are at work or school, result in more P City MIXUE's manufacturing and sales strategy for items to satisfy seasonal demand fluctuations change at different seasons.

Because of the large variations in market demand between peak and off-peak seasons, organizations in mature markets must ensure that they do not run out of stock or can respond promptly to any exceptional conditions during management and decision-making. At the same time, inventory control should strive to decrease reasonable inventory capacity in order to reduce the accumulation of working capital. P City MIXUE will maintain a safety stock of freshly developed items throughout peak seasons. However, in circumstances of acute stock shortages, the uncertainty and unpredictability of such new products may cause inventory backlogs.

Currently, P City's MIXUE and its connected outlets mostly use the following ways to meet seasonal product orders: First, inventory is used to correct supply and demand imbalances. Produce a specific quantity of products as inventory reserves for emergencies. City MIXUE reserves a fixed number of popular materials ahead of time before the off-peak or peak season begins, in order to fulfill increased product demand during the peak season. To some extent, this can ease concerns like as material shortages and logistics delivery timeliness that arise during the peak season's focused ordering periods. MIXUE can respond fast due to its early creation and relative wealth of experience when compared to other companies in the same industry.

Pre-stocking a particular quantity of goods allows it to satisfy client requests while also serving as a good model. However, due to market instability, it is unable to effectively monitor inventory dynamics, resulting in increased inventory costs due to stockpiling, as well as waste of related materials. Second, adjust manufacturing capacity to fulfill order volumes. Basic operations can be maintained assuming that MIXUE's existing raw material production firms, such as Henan Daki Food Co., Ltd., can meet the cargo needs of the current 22,000 franchise outlets. When seasonal ordering demands increase, it poses a considerable challenge to the original production cycle, forcing either a reduction or an increase in capacity within the existing production cycle.

MIXUE's relevant management personnel enhanced efficiency by extending working hours and decreasing waiting times in order to adapt production capacity. Third, use external forces to fulfill order demands. External collaboration can be sought for particular products in order to outsource or totally subcontract them to other companies for processing, which can help to shorten production cycles and boost capacity.

MIXUE's demand forecasting and related departments face substantial challenges as a result of the seasonal ordering cycle. As we all know, the seasonal ordering cycle necessitates mastery and prediction of market demand projection data from clients, as well as some level of demand cycle planning and analytical abilities. Furthermore, effective coordination is required to meet the demands of the ordering cycle while minimizing inventory expenditures.

2. Materials and Methods

Materials

This study focuses on demand forecasting for MIXUE, a beverage chain operating in City P. The primary materials used include:

Historical Sales Data: Daily and monthly sales records from MIXUE franchise stores in City P, including order quantities, sales volume, and inventory levels.

Operational Data: Information related to product variants, pricing, gross profit, and supply chain logistics from MIXUE's front warehouse (FDC) in Fuzhou and the provincial distribution center.

Market Data: External data such as seasonal trends, competitor activity, consumer behavior, and key market events influencing demand.

Demand Forecasting Models: Basic linear regression models currently in use, alongside more advanced methods developed during this study, such as time series analysis.

Methods

Data Collection and Cleaning

1 Collection: Gathered historical sales and operational data from MIXUE franchise outlets, consolidated by the FDC in Fuzhou and the provincial distribution center.
2 Cleaning: Addressed inconsistencies in historical data by identifying and correcting errors, such as incomplete records, duplicate entries, and outliers. Missing values were imputed using statistical methods like interpolation.

Exploratory Data Analysis (EDA)

1 Conducted descriptive analysis to identify trends and patterns in sales and inventory data.
2 Visualized historical sales performance using charts to observe seasonality, demand spikes, and trends over time.

Model Development

1 Baseline Model: Evaluated the performance of the existing linear regression model used by MIXUE.
2 Advanced Models: Implemented time series analysis methods, including:
   a. Autoregressive Integrated Moving Average (ARIMA)
   b. Seasonal Decomposition of Time Series (STL)
   c. Long Short-Term Memory (LSTM) networks for capturing complex demand patterns.
   d. Selected the best-performing model based on evaluation metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

Market Dynamics Analysis

1 Incorporated external market factors such as consumer behavior, industry competition, and significant events.
2 Conducted scenario analysis to assess the impact of market volatility and sudden occurrences on demand forecasting accuracy.

Optimization of Demand Forecasting

1 Developed an integrated model combining historical data, market factors, and machine learning algorithms to enhance forecasting accuracy.
2 Proposed adjustments to the forecasting system, including automated data collection and model fine-tuning for high-demand periods (e.g., holidays).

Evaluation of Results

1 Compared forecasted demand with actual sales data to measure the accuracy and reliability of the optimized models.
2 Analyzed inventory performance to assess improvements in stock management, cost reduction, and revenue enhancement.

Implementation Recommendations

1 Provided actionable insights and a step-by-step framework for MIXUE to adopt the optimized forecasting methods.
2 Suggested ongoing monitoring and periodic updates to the forecasting system to adapt to changing market conditions.

This methodology ensures a comprehensive approach to identifying and addressing demand forecasting challenges, ultimately enhancing MIXUE's operational efficiency and competitive position.

3. Results and Discussion

Analysis of the Causes of Demand Forecasting Issues

The aforementioned problems can be summarized by analyzing P City MIXUE's actual operations and demand projections. A full investigation of the reasons of these problems is provided below:

(i) Prediction methods are rather straightforward.

P City MIXUE only adopts a simple moving average method for demand forecasting, depending on the subjective assessment of relevant managers from the logistics, sales, and marketing departments based on their own experience, resulting in a simple experience-weighted approach. This is then utilized to purchase raw supplies for franchise locations. This simplistic demand forecasting method fails to take into account consumer demand for beverages as well as internal market considerations. It is based exclusively on sales data from a week, month, or even longer ago. Predicted outcomes frequently fail to match real demand in the beverage business. Furthermore, the future period anticipated by this method is brief, and it is mainly based on recent historical data from the retailers. However, the demand for beverages at franchise stores is affected by various factors, both directly and indirectly.

Demand Forecasting Optimization Strategy

(A) Establishment of Demand Forecasting Model

The time series Yt was examined, which comprises the long-term trend Tt, seasonal variation St, cyclical variation Ct, and irregular variation It. Multiplicative formula for time series

$$(Yt = Tt * St * Ct * It)$$

was used to construct a seasonal trend model. The specific operational process is as follows:

1 The central moving average method was used over N (one cycle) periods to create a model that captures both long-term and cyclical change patterns.
2 To reduce long-term and cyclical fluctuations, the Stlt time series was created by dividing the matching central moving average by all original time series data.
3 The adjusted seasonal index St was calculated by removing non-normal effects from the Stlt obtained in step 2 using the monthly average approach.
4 The moving average data Tt, which reflects both long-term and cyclical fluctuations, was employed as an independent variable. A time-varying analysis method was used to build a dynamic forecasting model that was appropriate for this data, yielding the long-term change trend data Tt.
5 Based on a movement. Based on this, an analysis was carried out to calculate the cycle variation index Ct and synthetic forecast values. Among them, using the trend model built in step 4, St+l can be substituted by the same period's seasonal index, and Ct+l can be forecasted semi-quantitatively, that is, from the perspective of Ct+l, to determine the value of Ct+l. In this section, we did not distinguish between long-term trends and cyclical changes, but rather integrated the two, naming it the "trend-cyclical" component and expressing it using.

Using this model's capability, we may generate forecast values that are influenced by seasonality and trends, bringing them closer to the real values.

(2) Demand Forecast Based on Actual Sales Volume from 2018-2020

Because of the company's wide range of fast-moving consumer items, we will focus our investigation on ice cream, which has a reasonably high sales volume. On this basis, we can use the past data to anticipate our sales volume for a specific period in the future, which will serve as a reference for our warehouse inventory reserves. The specific operational procedure is as follows:

Using the company's management system, collected and arranged previous data to acquire actual sales data for ice cream raw materials over a period of 36 months, from January 2018 to December 2020. This contains the outbound time and quantity of each order, as well as the monthly sales (in tons), as illustrated in Table 1.

Table 1. Sales volume data breakdown

Years and months	Sales volume	Years and months	Sales volume	Years and months	Sales volume
2018/1	70.2	2019/1	98.7	2020/1	119.4
2018/2	83.5	2019/2	112.35	2020/2	131.34
2018/3	69.6	2019/3	97.5	2020/3	110.4
2018/4	70.8	2019/4	94.5	2020/4	112.5
2018/5	72.3	2019/5	100.5	2020/5	119.4
2018/6	72.9	2019/6	105.3	2020/6	126.6
2018/7	82.5	2019/7	112.5	2020/7	135.6
2018/8	81.6	2019/8	105.6	2020/8	129.6
2018/9	85.8	2019/9	118.8	2020/9	132.9
2018/10	89.4	2019/10	123.3	2020/10	139.5
2018/11	76.2	2019/11	108.3	2020/11	126.3
2018/12	78.3	2019/12	107.7	2020/12	128.4

At the same time, a time series chart was created for the sales data from January 2018 to December 2020, as shown in Figure 1.

Figure 2 depicts a scatter plot of historical sales from 2018 to 2020 generated with EXCEL software. This chart shows that the monthly sales data are seasonal and have an upward trend. The supply volume fluctuates within the same month, although the amplitude does not change dramatically, demonstrating the product's seasonal features.

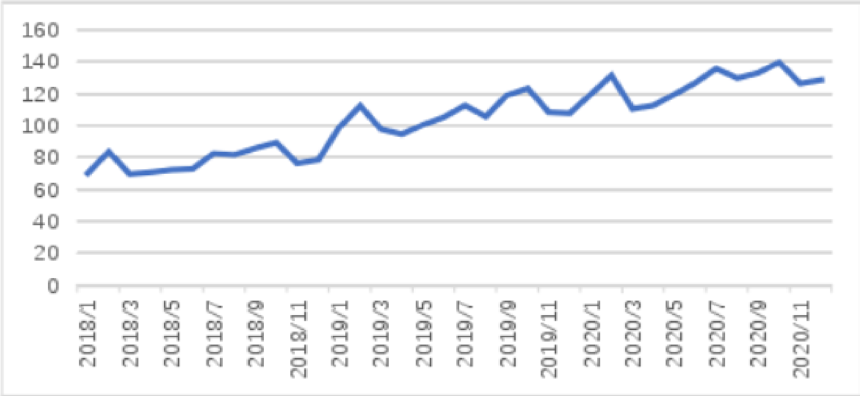

Figure 1. Ice cream sales data

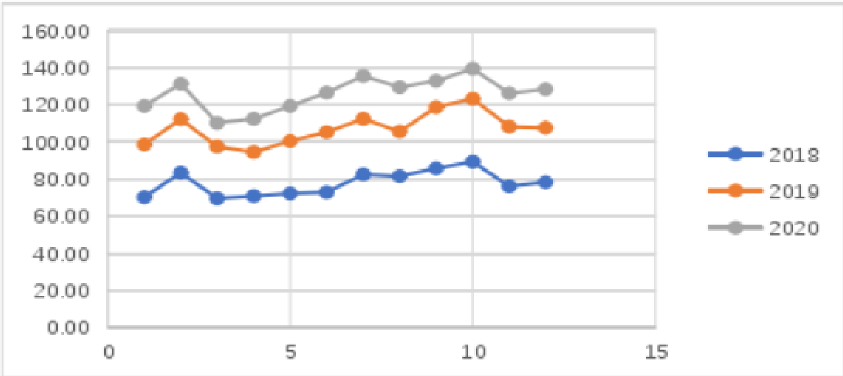

Figure 2. Time series diagram of Atom sales

Determine the seasonal ratio using Table 2.First, we apply the moving average method to eliminate random fluctuations and seasonal variations in product sales. Because product sales are calculated monthly, we take the sales across 12 quarters as a single period and apply the moving average to minimize seasonal changes.

For example, the moving average of the first 12 items is:

$$\sum_{t=1}^{12}\frac{Y_t}{12}=(70.2+83.5+69.6+70.8+72.3+72.9+82.5+81.6+85.8+89.4+76.2+78.3)/12$$
$$=77.76$$

And so on, see Table 2 for the results.

Table 2. Quarterly ratio value

Year	Month	Serial number	Demand	Moving average	Centered moving average	Seasonal ratio
2018	1	1	70.20			
	2	2	83.50			
	3	3	69.60			
	4	4	70.80			

	5	5	72.30			
	6	6	72.90	77.76		
	7	7	82.50	80.13	78.95	1.05
	8	8	81.60	82.54	81.34	1.00
	9	9	85.80	84.86	83.70	1.03
	10	10	89.40	86.84	85.85	1.04
	11	11	76.20	89.19	88.01	0.87
	12	12	78.30	91.89	90.54	0.86
2019	1	13	98.70	94.39	93.14	1.06
	2	14	112.35	96.39	95.39	1.18
	3	15	97.50	99.14	97.76	1.00
	4	16	94.50	101.96	100.55	0.94
	5	17	100.50	104.64	103.30	0.97
	6	18	105.30	107.09	105.86	0.99
	7	19	112.50	108.81	107.95	1.04
	8	20	105.60	110.40	109.60	0.96
	9	21	118.80	111.47	110.93	1.07
	10	22	123.30	112.97	112.22	1.10
	11	23	108.30	114.55	113.76	0.95
	12	24	107.70	116.32	115.43	0.93
2020	1	25	119.40	118.25	117.28	1.02
	2	26	131.34	120.25	119.25	1.10
	3	27	110.40	121.42	120.83	0.91
	4	28	112.50	122.77	122.10	0.92
	5	29	119.40	124.27	123.52	0.97
	6	30	126.60	126.00	125.13	1.01
	7	31	135.60	126.59		
	8	32	129.60	126.12		
	9	33	132.90	127.87		
	10	34	139.50	129.79		
	11	35	1269.30	131.27		
	12	36	128.40	132.05		

Because N=12 is an even number, a two-item moving average is required to change the direction of the trend values. Applying a two-item moving average to the twelve-item moving average yields the centered moving average, Tt, which excludes seasonal and erratic oscillations. For example, in a centered moving average series, the starting value is the average of the first 12 months, then the average of the next 12 months, and so on. See Table 2 for the results.(77.76 + 80.13) / 2 = 78.95. By dividing the statistical time series sales data Yt by the centered moving average Tt, the trend cycle component can be removed, yielding the seasonal ratio, Yt/Tt = StIt.

Arrange and combine the seasonal ratio data into a table, as illustrated in Table 3. Calculate the average values for the same month from 2018 to 2020. By removing the erratic fluctuation element, it is possible to calculate the average seasonal index for that month from 2018 to 2020. The seasonal index St can then be obtained by calculating the average for each month. Finally, divide the seasonal index for each month by 12 to obtain the matching seasonal index for that month.

Table 3. Seasonal index values for each month

Year Month	1	2	3	4	5	6	7	8	9	10	11	12
2018							1.05	1.00	1.03	1.04	0.87	0.86
2019	1.06	1.18	1.00	0.94	0.97	0.99	1.04	0.96	1.07	1.10	0.95	0.93
2020	1.02	1.10	0.91	0.92	0.97	1.01						
Seasonal index average	1.04	1.14	0.96	0.93	0.97	1.00	1.04	0.98	1.05	1.07	0.91	0.90
Overall average	1.00											
Seasonal index	1.04	1.14	0.96	0.93	0.97	1.00	1.04	0.98	1.05	1.07	0.91	0.90

Divide the actual sales volume (Yt) by the seasonal indicator (S). This enables the calculation of sales volumes without the seasonal component, and a scatter plot is used to depict the original actual sales data and the actual sales data with the seasonal component separated, as shown in Figure 3.

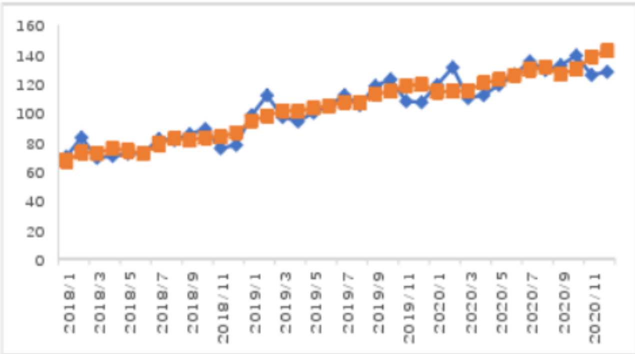

Figure 3. Separate seasonal component sales

After studying and evaluating the seasonal indicators, we discovered that they follow a clear linear tendency. We used EXCEL data regression analysis to analyze sales quantities by season and time series. We used the least squares method to create a linear regression formula between the time index and the sales quantity by season, as shown below: where Tt represents the regression forecast value and t represents the time index. To better portray the changes in this trend, we merged the sales volumes after removing seasonal effects using this regression model to produce the scatter plot displayed in Figure 4.

Figure 4. Seasonally adjusted monthly sales estimates

The regression prediction value Tt+i was obtained using the simple linear regression formula. The predicted value was multiplied by the seasonal index St+l to obtain the final predicted value, which represents the forecast value for the period t+l.

Sales Demand Forecast

Table 4 shows how the sales quantity for the next year is estimated using EXCEL, regression models, and seasonal indices. Figure 5 depicts a scatter plot created by comparing the final forecast findings to actual sales data.

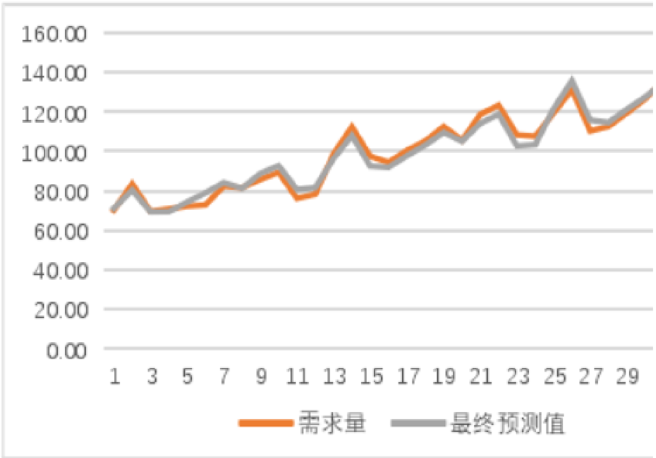

Figure 5. Graph comparing actual and predicted data

Table 4. 2021.1-2023.6 sales forecast

Year	Month	Sales volume	Moving average	Centered moving average	Season Ratio	Season Index	Eliminate seasonal impact on sales volume	Regression Prediction	predicted value
2021	1	70.20				1.04	67.51	68.48	71.20
	2	83.50				1.14	73.21	70.50	80.41
	3	69.60				0.96	72.78	72.52	69.35
	4	70.80				0.93	76.02	74.54	69.42
	5	72.30				0.97	74.49	76.56	74.30
	6	72.90	77.76			1.00	72.61	78.58	78.89
	7	82.50	80.13	78.95	1.05	1.04	79.00	80.60	84.18
	8	81.60	82.54	81.34	1.00	0.99	82.91	80.62	81.31
	9	85.80	84.86	83.70	1.03	1.05	81.80	84.64	88.77
	10	89.40	86.84	85.85	1.04	1.07	83.48	86.66	92.80
	11	76.20	89.19	88.01	0.87	0.91	83.77	88.68	80.66
	12	78.30	91.89	90.54	0.87	0.90	87.03	90.69	81.59
2022	1	98.70	94.39	93.14	1.06	1.04	94.93	92.71	96.40
	2	112.35	96.39	95.39	1.18	1.14	98.51	94.73	108.05
	3	97.50	99.14	97.76	1.00	0.96	101.97	96.75	92.52
	4	94.50	101.96	100.55	0.94	0.93	101.46	98.77	91.99
	5	100.50	104.64	103.30	0.97	0.97	103.55	100.79	97.82
	6	105.30	107.09	105.86	1.00	1.00	104.88	102.81	103.22
	7	112.50	108.81	107.96	1.04	1.04	107.72	104.83	109.49
	8	105.60	110.40	109.60	0.96	0.98	107.30	106.85	105.16
	9	118.80	111.47	110.93	1.07	1.05	113.27	108.87	114.19
	10	123.30	112.97	112.22	1.10	1.07	115.14	110.89	118.75
	11	108.30	114.55	113.76	0.95	0.91	119.06	112.91	102.70
	12	107.70	116.32	115.43	0.93	0.90	119.71	114.93	103.39

2023	1	119.40	118.25	117.28	1.02	1.04	114.84	116.95	121.59
	2	131.34	120.25	119.25	1.10	1.14	115.16	118.96	135.68
	3	110.40	121.42	120.83	0.91	0.96	115.45	120.98	115.69
	4	112.50	122.77	122.10	0.92	0.93	120.79	123.00	114.56
	5	119.40	124.27	123.52	0.97	0.97	123.02	125.02	121.34
	6	126.60	126.00	125.13	1.01	1.00	126.09	127.04	127.55

Prediction Error Calculation

Table 4 shows how the sales quantity for the next year is estimated using EXCEL, regression models, and seasonal indices. Figure 5 depicts a scatter plot created by comparing the final forecast findings to actual sales data.

Table 5. Statistical table of prediction error

Years and months	actual value	predicted value	absolute error	MAE	MSE
2021.7	135.6	134.79	0.81	0.135	14
2021.8	129.6	129	0.6		
2021.9	132.9	139.6	6.7		
2021.10	139.5	144.69	5.2		
2021.11	126.3	124.74	1.55		
2021.12	128.4	125.19	3.21		

Reliability and Validity Analysis of Sales Volume Forecast Values

After analyzing sales volume forecasts from January 2021 to June 2023 using SPSS, the Cronbach's α coefficient is 0.716, showing the scale's relative reliability. Furthermore, the KMO value of 0.763 indicates that the validity of the scale is good, and the practicality of this data is rather high.

Analysis of Sales Volume Forecast Effectiveness

The time series analysis method can be used to anticipate ice cream sales volume. Based on the actual and predicted sales volume of ice cream before and after.

Table 6. Error comparison before and after optimization

	mean absolute value（MAE）	mean square error（MSE）
Before optimization	4.45	24.6
After optimization	0.135	14

Using time series analysis, it is possible to produce reliable forecasts of market demand for MIXUE in City P and evaluate them based on the projected outcomes, thereby validating the process and establishing a foundation for inventory management in City P.

4. Conclusion

The comparison study of demand prediction values and actual sales data from January 2021 to June 2023 found other faults to be small and within the error range. Comparing the two datasets revealed this. However, demand projection values and actual sales data in June 2021, February, March, July, September, October, November, and December 2022, and February and March 2023 were inaccurate, causing data swings. Lack of precision hampered demand forecasts. This is due to uncontrollable occurrences, particularly the pandemic. MIXUE, a beverage firm in City P, has demand forecasting challenges such high subjectivity and significant prediction errors, which are important to its operation. Inconsistent demand forecasts and sales may cause market volatility. To reduce market volatility and boost profits, these flaws must be identified and fixed quickly, coupled with appropriate optimization measures. Create a demand forecasting model first. Next, use past sales data to forecast demand. According to an ancient saying, "Food is the deity of the populace." The food and beverage industry drives national economic growth. The MIXUE beverage chain in P City faces stiff competition. Thus, by reviewing MIXUE's demand prediction in P City, understanding its current state, identifying obstacles, analyzing the underlying causes, and developing appropriate optimization strategies, we can reduce demand forecasting risks. Benefits will increase while reducing data volatility and costs. Time series analysis dominates demand forecasting. It uses statistical analysis of previous time series data to uncover operational patterns and predict the future. P City's MIXUE can predict market trends, capitalize on opportunities, and manage revenue with accurate and efficient demand forecasting. More accurate demand forecasting can align demand planning with the supply-demand relationship, guiding enterprise production, increasing revenue, and addressing uncertainty-related risks, resulting in efficient enterprise operational management. Therefore, demand forecasting is crucial.

REFERENCES

[1] R. Zhang, "Research on the Improvement of Demand Forecasting Methods for Fast-Moving Consumer Products at M Maternal and Infant Company," M.S. thesis, Shanghai Univ. of Finance and Economics, Shanghai, China, 2020.

[2] Q. Deng, "Research on Demand Forecasting in the Supply Chain of Company L," M.S. thesis, Univ. of International Business and Economics, Beijing, China, 2021.

[3] X. Xie, "Research on Finished Goods Inventory Management of Y Clothing Company," M.S. thesis, Xiamen Univ., Xiamen, China, 2017.

[4] J. Ruan, "Optimization of the Distribution System of Z Cold Chain Logistics Company in Zhoukou City," M.S. thesis, Hebei Univ. of Science and Technology, Hebei, China, 2021.

[5] Research Group of the Gannan Prefecture Central Branch of the People's Bank of China and C. Guo, "Comparative Study on Forecasting Methods for Time Series Indicators of Deposits and Loans: An Empirical Forecast Based on Data from Gannan Prefecture," Gansu Finance, no. 3, pp. 52–57, 2016.

[6] M. Seyedan and F. Mafakheri, "Predictive Big Data Analytics for Supply Chain Demand Forecasting: Methods, Applications, and Research Opportunities," Journal of Big Data, vol. 7, no. 1, p. 53, 2020.

[7] N. Li, et al., "From Demand Forecasting to Inventory Ordering Decisions for Red Blood Cells Through Integrating Machine Learning, Statistical Modeling, and Inventory Optimization," Transfusion, vol. 62, no. 1, pp. 87–99, 2022.

[8] Z. H. Kilimci, et al., "An Improved Demand Forecasting Model Using Deep Learning Approach and Proposed Decision Integration Strategy for Supply Chain," Complexity, vol. 2019, no. 1, Article ID 9067367, 2019.

[9] H. Abbasimehr, M. Shabani, and M. Yousefi, "An Optimized Model Using LSTM Network for Demand Forecasting," Computers & Industrial Engineering, vol. 143, Article ID 106435, 2020.

[10] L. Suganthi and A. A. Samuel, "Energy Models for Demand Forecasting—A Review," Renewable and Sustainable Energy Reviews, vol. 16, no. 2, pp. 1223–1240, 2012.

[11] M. Seyedan, F. Mafakheri, and C. Wang, "Order-Up-to-Level Inventory Optimization Model Using Time-Series Demand Forecasting with Ensemble Deep Learning," Supply Chain Analytics, vol. 3, Article ID 100024, 2023.

[12] J. M. Chandran and M. R. B. Khan, "A Strategic Demand Forecasting: Assessing Methodologies, Market Volatility, and Operational Efficiency," Malaysian Journal of Business, Economics and Management, vol. 2024, pp. 150–167, 2024.

[13] F. Olaoye, K. Potter, and B. Klinton, "Big Data Analytics in Retail: Optimizing Inventory and Demand Forecasting," unpublished.

[14] M. Q. Raza and A. Khosravi, "A Review on Artificial Intelligence-Based Load Demand Forecasting Techniques for Smart Grid and Buildings," Renewable and Sustainable Energy Reviews, vol. 50, pp. 1352–1372, 2015.

[15] Y. Barlas and B. Gunduz, "Demand Forecasting and Sharing Strategies to Reduce Fluctuations and the Bullwhip Effect in Supply Chains," Journal of the Operational Research Society, vol. 62, no. 3, pp. 458–473, 2011.

[16] S. Gattinoni, "Supply Chain Planning: Inventory Optimization Through the Demand Forecasting Tools and Algorithm," unpublished, 2022.

[17] H. Hu, S. Gong, and B. Taheri, "Energy Demand Forecasting Using Convolutional Neural Network and Modified War Strategy Optimization Algorithm," Heliyon, vol. 10, no. 6, Article ID e13010, 2024.

[18] K. Li, et al., "A Data-Driven Strategy to Forecast Next-Day Electricity Usage and Peak Electricity Demand of a Building Portfolio Using Cluster Analysis, Cubist Regression Models, and Particle Swarm Optimization," Journal of Cleaner Production, vol. 273, Article ID 123115, 2020.

[19] J. Pascual, et al., "Energy Management Strategy for a Renewable-Based Residential Microgrid with Generation and Demand Forecasting," Applied Energy, vol. 158, pp. 12–25, 2015.

[20] S. R. Gayam, "AI for Supply Chain Visibility in E-Commerce: Techniques for Real-Time Tracking, Inventory Management, and Demand Forecasting," Distributed Learning and Broad Applications in Scientific Research, vol. 5, pp. 218–251, 2019.