Integrating Supply Chain Analytics to Improve Decision-Making

Master of Engineering Management
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Submitted in partial fulfillment of the requirements for the degree of
Master of Engineering Management

NAZARBAYEV UNIVERSITY

School of Engineering and Digital Sciences

In partnership with the
Graduate School of Business

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Supervised by
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May, 2025

DECLARATION FORM

We hereby declare that this report entitled "Integrating Supply Chain Analytics to Improve Decision-Making" is the result of our own project work except for quotations and citations which have been duly acknowledged. We also declare that it has not been previously or concurrently submitted for any other degree at Nazarbayev University.

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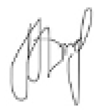

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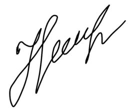

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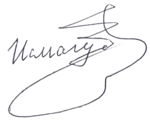

ABSTRACT

Small and medium-sized enterprises (SMEs) play an important role in any economy, but are particularly susceptible to the risks associated with challenges, such as supply chain disruptions, out of stock situations and changing customer demands. These challenges highlight the need for digital tools to help make more data-driven and flexible decisions. The purpose of this study is to demonstrate how the integration of supply chain analytics can enhance the resilience and adaptability of SMEs to changes in the market environment. The project uses an integrated approach combining methods of decision evaluation (ABC-XYZ analysis), demand forecasting (ARIMA, ARIMAX, exponential smoothing), and planning (programming models, scenario analysis). Unlike static approaches, the proposed model takes into account seasonality, uncertainty, and changing conditions, providing more accurate inventory planning and management. The results show that the use of analytics allows SMEs to adapt to fluctuations in demand, reduce costs, reduce the risks of stockouts or excess of goods, and improve overall operational efficiency. The study contributes to the development of practical strategies to increase the sustainability and competitiveness of SMEs in an unstable environment.

Keywords: SMEs, forecasting, planning, decision evaluation, demand, supply chain

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LIST OF ABBREVIATIONS

SME - Small and Medium Enterprises

ARIMA - AutoRegressive Integrated Moving Average

ARIMAX - AutoRegressive Integrated Moving Average with Exogenous Variables

MAE - Mean Absolute Error

MAPE - Mean Absolute Percentage Error

MAD - Mean Absolute Deviation

LP - Linear Programming

NLP - Non-Linear Programming

MIP - Mixed-Integer Programming

TSL - Target Stock Level

CV - Coefficient of Variation

WMS - Warehouse Management System

FMCG - Fast-Moving Consumer Goods

GDP - Gross Domestic Product

LSTM - Long Short-Term Memory

XGBoost - eXtreme Gradient Boosting

LightGBM - Light Gradient Boosting Machine

SARIMAX - Seasonal AutoRegressive Integrated Moving Average with Exogenous Variables

EOQ - Economic order quantity

1.Introduction

1.1 Problem statement

The supply chain is the most vital part of any business, and it encompasses every component of the business, from the sourcing of raw materials to the delivery of the end product to the customer. It directly impacts the profitability of the company since such factors as quality service, efficient delivery and clear pricing strategies contribute to improved customer satisfaction and retention (Wang & Jotikasthira, 2023). Effective supply chain management helps businesses to make sure that their product is of high quality and is delivered to the customer with no delays and shortage problems. However, companies struggle with optimizing supply chain decisions due to uncertainties in demand, logistics, and costs.

Based on industry-wide surveys conducted among U.S. manufacturing and supply chain sectors, approximately 55% of companies suffer from supply chain disruptions and more than 50% of them suffer from out-of-stock situations as well. Additionally, almost 30% of businesses still struggle with finding and retaining employees, and 20% are impacted by a lack of talent (Evans, 2023). Another study shows that 45% of small businesses in the United States have experienced supply chain disruptions (Lin et al., 2022). Moreover, serious disruptions lasting a month or longer occur on average once every 3.7 years, resulting in a loss of up to 45% of the company's annual profits over a decade (McKinsey & Company, n.d.).

Despite advancements in supply chain analytics, many businesses find it difficult to successfully incorporate data-driven decision-making tools to improve their supply chain. Also, even if they succeed in finding an application for those tools, their current supply chain models are reactive rather than proactive, meaning that tools will help with solving the consequences rather than the cause of the problem. For instance, while ABC-XYZ analysis and other inventory classification techniques offer organized prioritization, they are not integrated with forecasting and decision-evaluation models, which will help with the prediction of products of high priority. Previous research has demonstrated the integration of ABC classification with machine learning-based forecasting tools to support inventory optimization (Venkatesh & Sowmiya, 2024). However, the current study proposes using statistical forecasting tools such as ARIMA, ARIMAX, and Holt-Winters to make demand forecasts which could be then used to make decisions about inventory and production costs. Additionally, while optimization tools like scenario-based analysis and programming models provide strategic planning capabilities, they are not fully exploited to reduce supply chain interruption risks. To increase forecasting accuracy, optimize resource allocation, and boost operational efficiency, a comprehensive framework incorporating supply chain analytics technologies is desperately needed.

1.2 Research objectives

The capstone project has five main objectives:

- To utilize the existing inventory classification method (ABC-XYZ) in finding out the products of high priority for a chosen company.
- To evaluate the effectiveness of forecasting models (Holt-Winters, ARIMA, and ARIMAX) using MAE, MSE, RMSE, and MAPE metrics, and to select the most accurate model for the partner company in the construction retail sector.
- To use scenario-based analysis in supply chain planning and the mitigation of risks in the operations of the company.
- To develop an integrated supply chain analytics framework that combines planning, forecasting, and decision optimization tools to improve decision-making.
- To validate the proposed framework based on the actual data of the chosen company.

1.3 Expected outcomes

1. A suggested supply chain analytics framework that enhances decision-making by combining planning, forecasting, and decision optimization tools.

2. Recommendations for an organization on how to integrate a suggested framework into decision-making in supply chain operations.

1.4 Company information

The selected partner for this project operates as a mid-sized business from Astana, Kazakhstan which delivers construction and energy-related products to customers. The company supports business and individual clients in the regional market by delivering high-quality materials through its staff of 110 workers. The organization aims to enhance its operations by implementing supply chain analytics to create efficient system architecture that delivers transparent information processing and achieves exceptional customer satisfaction in its supply chain operations.

The company supports inventory management using the Smartzapas system that operates with 1C accounting platform integration. The data collection system combines real-time capabilities for stock information as well as sales information and procurement updates. The company conducts demand forecasting analysis by examining past sales patterns together with seasonal patterns and market environmental factors so they refactor their predictions monthly for basic inventory and weekly for popular product lines. Target Stock Levels (TSL) run automatically as a computation function adjusted to account for historical demand averages along with supplier lead times and seasonal patterns as well as risk buffers which help prevent supply chain breakdowns.

The operational inventory process at the company starts with sales forecasting then moves into warehouse space allocation followed by material acquisition and products get prepared before instant stock monitoring across all sales outlets. Through ongoing surveillance and flexible operational changes the company works toward reducing out-of-stock items and maximizing its warehouse efficiency and market reaction speed.

1.4.1 General information

The chosen company is a company based in Astana, specializing in the supply and distribution of construction and energy-related products. Due to a non-disclosure agreement (NDA), its name cannot be revealed and it will be referred to as "the company" hereafter. The company employs 110 staff members and plays a key role in providing high-quality materials to businesses and individuals. With a strong focus on efficiency and customer satisfaction, the company integrates modern technologies into its operations to streamline processes and improve service delivery.

1.4.2 Company’s method of forecasting demand

To predict demand for its products, the company relies on a combination of historical sales data analysis, seasonal trends, and current market conditions. This data-driven approach helps the company anticipate customer needs and maintain optimal stock levels.

Sales data is automatically collected through integrated accounting software (1C) and the inventory management system Smartzapas. These tools allow for real-time monitoring of sales and help in identifying demand patterns. Additionally, the company uses Smartzapas as its primary forecasting tool, which employs automated algorithms to analyze past sales trends and predict future demand.

The frequency of demand forecasting updates depends on the product category. General forecasts are updated monthly, while high-demand products undergo weekly reviews to ensure that stock levels align with actual sales trends. This dynamic approach enables the company to minimize stock shortages and optimize procurement planning.

1.4.3 Company’s method for computing Target Stock Level (TSL)

The chosen company determines the required stock levels using automated calculations within the Smartzapas system. This system is integrated with 1C and applies advanced algorithms to compute the Target Stock Level (TSL).

Several factors are considered when determining TSL, including:

- **Average demand from previous periods** – historical sales data helps to estimate expected sales.
- **Seasonality** – adjustments are made based on seasonal demand fluctuations.
- **Supplier lead times** – the time required for restocking from suppliers is factored into calculations.
- **Risk management** – potential delays and supply chain disruptions are considered.

- **Current demand trends and competition** – real-time market conditions influence stock adjustments.

To manage inventory efficiently, the company relies on Smartzapas, which operates on the 1C platform. This software ensures real-time inventory monitoring and provides recommendations for stock replenishment. By continuously analyzing turnover rates and excess inventory levels, the chosen company assesses the effectiveness of its stock management strategy. Regular evaluations help the company reduce storage costs while maintaining an optimal balance between supply and demand.

This structured approach enables the company to efficiently manage its supply chain, ensuring product availability while minimizing unnecessary stock accumulation.

2. Literature review

In today's dynamic business environment, a company's success depends on its ability to effectively manage supply chain challenges. To address these challenges, there are three categories of interconnected tools, each responsible for a specific part of the supply chain: decision evaluation frameworks, forecasting models and planning tools. Here, decision evaluation tools help identify and prioritize key inventory, forecasting methods predict future demand, and planning tools minimize and mitigate potential risks.

2.1 Decision evaluation tools

The volatile nature of demand presents a continuous management issue for supply chains which triggers predictive mismatch and increased inventory expenses and inefficient resource utilization according to Abolghasemi et al. (2020). Organizations in the supply chain industry implement diverse classification systems which provide support for executives of the companies to make a decision while maintaining sustainability in inventory systems. Inventory classification methods used in this field is ABC-XYZ classification through ABC analysis valuable products gain precedence based on their financial worth so they get appropriate organizational attention. Basically, the ABC method operates in a way of categorizing products into diverse categories to evaluate overall value to the company, where A-class items contribute the most to revenue, B-class items contribute moderately, and C-class items have the lowest impact. Meanwhile, XYZ analysis evaluates inventory based on demand volatility, where X-class items have stable demand, Y-class items experience moderate fluctuations, and Z-class items show high unpredictability.

The use of XYZ analysis helps organizations categorize inventory based on stable demand patterns to distinguish between frequently used profitable products versus unpredictable products (Orelma, 2024; Álvarez-Rodríguez et al., 2020). Hospitals successfully use this technique to preserve vital medical product supplies alongside decreasing their storage of less important medical supplies according to Yu et al. (2021). Moreover, integration of modern inventory classification systems like ABC-XYZ in logistics leads to improved warehouse management and improved transportation route planning while improving supplier coordination (Aubakirova 2024, Villacis et al. 2024).

The ABC-XYZ classification produces an efficient data-based system for inventory management under changing demand patterns. Businesses endorsing high-value continuous needs items and implementing strategic inventory assessment through diverse criteria will attain lower costs and better forecasts and supply chain resilience and adaptability. The inclusive strategy creates operational efficiency while increasing service quality and promotes sustainable business practices and ethical measures. The combination of such an integrated approach gives organizations better abilities to handle market uncertainties as they optimize resource usage for enduring competitive dominance in today's dynamic business environment.

2.2 Forecasting methods

The unpredictable nature of demand in supply chains leads to inefficiencies in forecasting, inventory management, and production planning. To address these challenges, organizations increasingly rely on data-driven analytics to improve decision-making and optimize operations. One widely used forecasting method is the Holt-Winters exponential smoothing model, which effectively captures trend and seasonality across various industries, making it an essential tool in supply chain analytics (Lindfors, 2021). In the retail sector, Holt-Winters has been successfully applied to Walmart sales data, demonstrating its accuracy in short-term demand forecasting. The study by Lindfors (2021) compared Holt-Winters with ARIMA and machine learning models, showing that Holt-Winters achieved MAPE values between 5% and 15%, outperforming machine-learning approaches over a 12-week forecasting period. Similarly, in the furniture industry, Holt-Winters was used to forecast sales from 2019 to 2023, with projections reaching $12.9 billion by 2026, helping businesses optimize inventory levels and procurement strategies (İnce & Taşdemir, 2024).

In agriculture, Holt-Winters has been used to predict abaca fiber production trends, with findings showing that the multiplicative model provided the most accurate forecasts, achieving a MAPE of 5.84% (Pleños, 2022). Similarly, the model was applied in food production to forecast jam and sherbet demand, demonstrating its effectiveness in managing seasonal supply chain fluctuations (Tirkeş et al., 2017). Beyond demand forecasting, Holt-Winters contributes to inventory optimization. A study on sports retail businesses integrated Holt-Winters with ABC analysis and the 5S methodology, leading to an 84.57% reduction in excess inventory costs and a savings of $21,500 USD (Amasifén-Pacheco et al., 2020). The model also outperformed ARIMA in manufacturing demand forecasting, achieving lower MAPE values (3.13% to 9.75%), improving production planning and reducing shortages (Bhatnagar et al., 2020).

Holt-Winters has also been implemented in transportation and logistics, particularly in air travel demand forecasting. A study on Hasanudin Airport used the model to predict passenger departures, accurately identifying seasonal peaks in July and October, which allowed for better resource planning and staffing (Nurhamidah et al., 2020). The application of supply chain analytics through Holt-Winters forecasting enhances decision-making by providing reliable demand predictions and optimizing resource allocation. Businesses that implement advanced forecasting models benefit from reduced costs, improved supply chain resilience, and better operational efficiency, making data-driven analytics a crucial component in the modern supply chain.

Moreover, demand volatility can cause forecasting errors and complicate inventory management. It may impose unnecessary costs and due to this, it is one of the most important challenges in supply chain management (M. Abolghasemi et al., 2020). Researchers have conducted many studies to find out the best-performing tool for forecasting demand and the results may vary for different conditions. Some of those widespread statistical tools used for forecasting are ARIMA and ARIMAX, which utilize historical data to predict future values. ARIMA (AutoRegressive Integrated

Moving Average) was first introduced by Box and Jenkins in 1976 and due to this, is often referred to as the Box-Jenkins model. It is best suited for working with stationary data, the data with mean and variance that stay the same over the period. Otherwise, differencing is applied to make data stationary by subtracting the previous observations from the current observation.

Overall, the model consists of three stages: identification, estimation, and diagnostic checking. In the identification phase, the appropriate model parameters are identified based on the given data. Then the model is fitted to the data and the coefficients are estimated. In the end, in diagnostic checking, the model is assessed on how well it fits the data by verifying that the model's residuals are random. If the last stage fails, the model is revised and new coefficients are estimated. Once the model passes the last stage, it can be used to forecast the time series. However, some external variables might influence the given data such as in the case of supply chain, marketing spending, or inflation in the country. In such cases, the ARIMAX (AutoRegressive Integrated Moving Average with Exogenous Variables) model is used, where external factors are used as input to predict a given time series. ARIMAX has the same three stages as ARIMA and a transfer function that identifies the relationship between the input and outputs and helps to achieve better forecasting performance (Durka & Pastorekova, 2012).

ARIMA is often used in the industry of healthcare. For instance, one of the research papers identified that ARIMA could have been used during COVID-19 pandemic in order to predict the number of COVID-19 cases (Ospina et.al., 2023), in this particular research data for Brazil was used and it was identified that results obtained from the ARIMA model were close to real values which shows that it is an effective model for forecasting. Apart from the healthcare industry, ARIMA can also be used in supply chain management. One of the research studies conducted in this field revealed that both Holt-Winters Exponential Smoothing (HWES) and ARIMA can be used for supply chain forecasting, however, they should be used in different scenarios (Abolghasemi et al., 2024). For instance, ARIMA performs better in the markets where it is difficult to make predictions, HWES, on the other hand, can be used in the markets with seasonalities and trends.

There was also research conducted in the assembly industry. This research compared ARIMAX with machine learning methods (Gonçalves et al., 2021). It concluded that ARIMAX gives accurate predictions during the initial (or launch) stage of the life-cycle of a component. In addition, ARIMAX gives better forecasts than machine-learning models when there is not enough data for training. This research also stated that accurate forecasts can have a number of benefits including cost minimization due to less stockouts and better safety stocks. Another paper analyzed the effectiveness of different linear and non-linear models for predicting demand for after-market spare parts (Chien et al., 2023). The conclusion that was made suggests that the ARIMA model may not be very accurate for this industry. So, the best model that can be used is ensemble forecasting which is a combination of different forecasting models.

In one of the researches where different models were used to forecast volatile demand series for a fast-moving consumer goods company in Australia, ARIMAX performed well and displayed the lowest MASE among all the models such as exponential smoothing with price covariate, dynamic linear regression, support vector regression, artificial neural networks. Moreover, it minimized the inventory costs and maintained high fill rates compared to other tools (M. Abolghasemi, et al., 2020). Nevertheless, this study has its own limitations such as using only one covariate (price) and focusing only on FMCG data. Another study that tried to address the challenge of predicting the fluctuating demand utilized ARIMA and ARIMAX models for forecasting clothes sales. As a result, ARIMAX outperformed ARIMA with lower MAPE and RMSE values with predictions being almost close to the real demand values. This helped businesses to optimize their inventory and production planning and improve operational efficiency (Anggraeni, Vinarti, & Kurniawati, 2015).

Those tools are also used to forecast economic factors such as GDP per capita influenced by employment rate (Durka & Pastorekova, 2012) and daily traffic influenced by holidays (Cools et al., 2009). Studies show that in some cases simple models like ARIMA forecast better than ARIMAX and in some circumstances, the performance of ARIMAX is high due to considering different factors in calculations. Overall, most studies highlighted the strong forecasting capabilities of ARIMAX compared to other statistical and machine learning tools, making it a good solution for problems of demand unpredictability and low inventory performance in the supply chain.

2.3 Planning tools

To further reinforce the benefits of forecasting tools and create a strategic plan, the planning models are necessary. In the scope of this work, programming models and scenario-based analysis were chosen for planning purposes, as these tools create a basis for short-term and long-term plans of the company.

Programming models are mathematical models utilized to solve optimization problems by determining the best possible set of variables within a set of constraints that allow maximizing or minimizing an objective function (Castillo et al., 2001). Depending on the nature of objective function and constraints, these models can be linear (linear programming, LP), non-linear (non-linear programming, NLP), and mixed-integer (mixed-integer programming, MIP). Linear models are suitable for a wide range of tasks, but in some situations they turn out to be too limited. In such cases, it is necessary to take into account nonlinear dependencies in mathematical models. In nonlinear programming, the objective function and/or constraints may be nonlinear, which requires the use of other more complicated methods.

Programming models are unique for each company and they depend on specific characteristics of the company. The model provides a set of variables that align with the strategic purpose of the company incorporated into objective function. The programming model is created for one specific case, whereas scenario based analysis includes various cases. Scenario analysis is performed to assess the impact of possible future events on the operation of the system, taking into account several alternative outcomes, i.e. scenarios. This method helps to identify different development paths and their consequences. Scenario analysis involves predicting the expected value of an efficiency indicator in a given time period, taking into account the occurrence of various situations and changes in system parameters under conditions of uncertainty. This approach allows managers to evaluate the behavior of the system in response to unforeseen events and can be used to study changes in the system in a theoretically optimistic (best-case) or pessimistic (worst-case) scenario. The likelihood of a scenario and its potential impact should be considered together to develop a strategic plan based on the results obtained. The main purpose of the analysis is to study the most extreme results (with high probability or serious consequences) in order to determine an investment strategy (Balaman, 2019). This method is especially important in analyzing risks such as demand fluctuations, supply disruptions, and geopolitical events. Unlike programming models that depend on fixed inputs, scenario-based analysis evaluates the influence of various conditions, making it crucial for strategic decision-making in fast-changing environments.

Supply chain management includes countless complex processes full of risks. Therefore, programming models and scenario based analysis are often applied to optimize operations and reduce risks. For example, the integer linear programming model demonstrated by Bektaş and Laporte (2011) minimizes the total costs, including emission costs, operating costs, and driver costs. The main goal of the model was to build routes for a group of vehicles to meet the demand of all customers when the provided conditions are met. Caramia and Stecca (2024) proposed a more complicated model that uses a financial budget to reduce emissions and optimize the planning of operations in the supply chain.

The authors (Caramia and Stecca, 2024) considered a three-level supply chain that includes input logistics and intermediate operations and presented a bilevel programming approach. The research results indicate the effectiveness of an approach for green supply chain management, emphasizing strategic planning through the integration of sustainability objectives. The authors (Caramia and Stecca, 2024) demonstrate that programming models can transform complex problems, such as minimization of $CO2$ emissions and strategic planning, into solvable mathematical frameworks. On the other hand, Balaman (2019) shows that scenario-based analysis can be applied in the management and design of biomass-based production chains. This technique allowed managers to assess the impact of possible changes in biofuel prices (growth, decline, or stability) on the chain's performance.

Ghomi-Avili et al. (2018) proposed a new approach for designing an optimal closed supply chain by combining a non-linear bi-level model and sensitivity analysis. This approach also takes into account accidental failures, since disruptions in the operation of production facilities can significantly affect the efficiency of the entire supply chain. The authors (Ghomi-Avili et al., 2018) had two objectives. Firstly, to maximize overall profits and minimize supply chain costs by optimally selecting the location of facilities and distributing orders at different levels of the chain. Secondly, to take into account the environmental aspect, aiming to minimize CO_2 emissions arising during the production process. Combining sensitivity analysis with the programming model allowed managers to formulate data-driven decisions. For instance, authors pointed out that “taking into account the risks of disruptions and competition not only increases the resilience of the supply chain to market challenges, but also helps strengthen the company's strategic position among competitors” (Ghomi-Avili et al., 2018).

3. Methodology

3.1 Hypothesis

The main hypothesis of this research is that the combination of decision evaluation tools with statistical forecasting and planning tools can improve supply chain performance in SMEs due to better inventory prioritization, accurate demand forecasts and reduced costs. The traditional supply chain patterns based on reactionary models fail to respond effectively to market changes that occur in demand along with logistics inefficiencies and unclear market conditions. To test the hypothesis, ABC-XYZ classification tool will be used to categorize the products of the partner company based on their inventory value and demand and to identify the products of high priority. Next, forecasting tools such as Holt-Winters, ARIMA and ARIMAX will be applied to products in different categories to determine the most accurate tool for each category. The resulting forecasts will later be used by scenario analysis to construct possible future events, analyze how risks can be mitigated and costs can be reduced in those events. In the end, a set of recommendations from this combined framework will be given to the company and its effectiveness will be evaluated by company representatives.

3.2 Scope

This project focuses on improving inventory forecasting methods within a construction and energy-related product company, specifically targeting its internal inventory management practices rather than broader supplier operations. The aim is to evaluate and refine demand prediction approaches by analyzing real market data, identifying high-demand product categories, and applying advanced forecasting models.

The research does not cover the full supply chain, but instead concentrates on the company's internal processes of stock classification, forecasting, and inventory decision-making. By leveraging genuine sales and inventory data, the project highlights which product groups are most critical for maintaining operational efficiency - particularly those with high turnover or strategic value.

To support these goals, the study applies multiple forecasting techniques, including statistical models like ARIMA, Holt-Winters, and Moving Averages, as well as machine learning-based approaches such as ARIMAX. These models are evaluated for their effectiveness in addressing demand variability and seasonal trends.

The research also includes a cost-benefit assessment related to inventory holding and stock-out risks. It supports the company in reviewing how forecasting accuracy and stock classification can reduce excess inventory while minimizing operational disruptions.

Ultimately, the study aims to guide data-driven inventory decisions by focusing on internal high-impact areas, improving demand planning precision, and helping the company strike a balance between stock availability and cost efficiency.

3.3 Hypothesis testing and evaluation

For the scope of this project, traditional ABC-XYZ, three forecasting methods, and scenario analysis are going to be implemented. Currently, the company which provided data uses Smartzapas system which makes forecasting automatically. So, three different forecasting models (Holt-Winters, ARIMA and ARIMAX) are going to be implemented based on the data provided, forecasts are going to be compared with the actual data and with the forecasts made by Smartzapas system.

First of all, historical data is going to be used and monthly forecasts using three models are going to be identified. Then, these forecasts will be compared with the actual demand. Afterwards, different error metrics are going to be calculated in order to identify which model gives the most accurate results. Error metrics that will be used are Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

After the best forecasting tool is chosen for each category of product, three demand scenarios are modelled. Then, the optimal monthly order quantity is identified for each scenario and potential cost savings are calculated.

3.4 Data extraction and preparation

The company provided us with data for a two-year period for 10 products. In Figure 3.4.1 a segment from the original dataset provided by the company can be seen. After receiving the data, data was prepared for further analysis. It is an important step since clean data is essential for accurate analysis and forecasting. The structured data preparation method ensures the correct performance of supply chain analytics along with forecasting models. Raw data contains multiple errors, including inconsistencies, missing details, and anomalies, which can distort analytical results and lead to suboptimal decision-making. The purpose of data cleaning and preprocessing interventions is to maintain data integrity and guarantee quality input data for inventory forecasting and optimization. An analysis of the company dataset will help to identify and correct possible errors that may impact forecasted demand levels.

Подразделение		Количеств	Выручка
Артикул	Номенклатура, Характеристика		
Период, месяц			
Stroy Energo Trade			3 933 130 204,68
ротбанд	Штукатурка KNAUF "Ротбанд", 30кг,	64 167,00	174 866 225,47
Октябрь 2024 г.		29 153,000	77 529 397,18
Сентябрь 2024 г.		15 029,000	42 485 134,82
Ноябрь 2024 г.		14 520,000	39 140 222,12
Декабрь 2024 г.		4 021,000	11 309 528,49
Август 2024 г.		842,000	2 478 189,29
Октябрь 2023 г.		292,000	963 400,00
Февраль 2023 г.		103,000	314 150,00
Май 2023 г.		56,000	170 800,00
Сентябрь 2023 г.		43,000	141 900,00
Август 2023 г.		32,000	106 600,00
Апрель 2023 г.		32,000	97 600,00
Декабрь 2023 г.		15,000	44 196,42
Ноябрь 2023 г.		11,000	32 764,29
Январь 2024 г.		9,000	26 517,86
Март 2023 г.		9,000	25 825,00
Арсенал 3мм (уп 2,5кг)	Электроды Арсенал ТМ МР-3 Арс 3мм (уп 2,5кг),	41 798,00	125 210 599,36
Ноябрь 2024 г.		5 827,000	20 088 790,03
Октябрь 2024 г.		4 658,000	16 119 635,02
Август 2024 г.		4 146,000	14 032 350,02
Сентябрь 2024 г.		3 310,000	11 396 960,35
Декабрь 2023 г.		3 254,000	9 782 010,72
Декабрь 2024 г.		2 347,000	8 010 426,41
Май 2024 г.		2 276,000	7 577 786,64
Июль 2024 г.		1 956,000	6 557 983,70
Апрель 2023 г.		3 390,000	5 244 690,00
Июнь 2024 г.		1 533,000	5 064 302,84
[illegible]		[illegible]	[illegible]

Figure 3.4.1. A segment from the dataset.

First of all, the dates for the sales were inconsistent and were located in random order. So, first of all, we standardized all of the dates so that it could be used as an input in Python later. Then chronologically sorted the date column so that sales for products were located in order from January 2023 to January 2025. Also, the names of the products were changed to P01, P02, etc. so that it could be analyzed easily using Python.

After cleaning the data, it was noticed that for some products we had insufficient data. So, it was decided to categorize the products by the availability of data. Three categories of products were identified: red category for products where data was available for less than a year, orange category for products where there was enough data for one full year but data for some months of the second year were missing, green category for products that had sufficient data for two whole years. There was one product in the red category, one product in the orange category and eight products in the green category. So, further analysis was conducted on eight products. Figure 3.4.2 shows a segment from the dataset after this stage was completed. It can be seen that dates are in one format, they are chronologically sorted and the main row is highlighted with a green color to show that all of the sales data is given for this product and it is ready for usage.

P03		98 065.00	173 036 736.43		
	01.01.2023	714,00	1 382 000.00	no	Winter
	01.02.2023	870,00	1 724 030.00	no	Winter
	01.03.2023	3 594.000	6 546 250.00	no	Spring
	01.04.2023	1 638.000	3 062 138.84	yes	Spring
	01.05.2023	8 408.000	15 736 365.38	yes	Spring
	01.06.2023	6 925.000	12 120 111.00	yes	Summer
	01.07.2023	4 460.000	8 197 832.00	yes	Summer
	01.08.2023	6 959.000	12 167 598.64	yes	Summer
	01.09.2023	8 569.000	14 762 100.00	yes	Autumn
	01.10.2023	2 856.000	5 037 200.00	no	Autumn
	01.11.2023	1 409.000	2 275 000.00	no	Autumn
	01.12.2023	713,00	1 171 047.86	no	Winter
	01.01.2024	230,00	384 000.00	no	Winter
	01.02.2024	73,00	124 571.42	no	Winter
	01.03.2024	926,00	1 485 823.24	no	Spring
	01.04.2024	1 533.000	2 533 950.02	no	Spring
	01.05.2024	1 390.000	2 213 381.49	yes	Spring
	01.06.2024	6 036.000	10 093 203.51	yes	Summer

Figure 3.4.2. A segment from the dataset after preparation.

3.5 Decision evaluation tools

Businesses require systematic evaluation tools to make effective supply chain decisions about inventory and forecasting plus resource utilization. Supply chain analytics employs decision evaluation methods which help companies divide inventory according to its worth and market behavior patterns so they can perform multiple factor decision analysis for selecting superior forecasting platforms and supplier networks as well as inventory handling protocols.

The ABC-XYZ analysis system merges ABC inventory ranking that measures product value contribution alongside XYZ inventory classification which analyzes item demand forecasting reliability. Under ABC analysis inventory is split into three main categories: A-class items which generate most revenue from few high-value products while A-class items eclipse B-class items in revenue output but have more SKUs and C-class items yield smallest revenue but comprise 50% of stock-keeping units. The XYZ analysis system assigns products into three categories according to their demand stability where X-class items show predictable stable demand patterns and Y-class items display seasonal or external influences which affect their demand levels and Z-class items demonstrate unpredictable fluctuating demand patterns. The combination of ABC and XYZ analysis systems helps organizations create superior inventory management approaches by linking their stock levels to business financial value and market demand stability. Through ABC and XYZ analysis companies should maintain a large stock of valuable yet stable-demand items like A-X whereas they should minimize C-Z products with low value and unpredictable market demand. The stock classification system guides businesses to achieve improved stock availability combined with reduced carrying costs alongside lower stock-out possibility.

The adoption of ABC-XYZ analysis creates an enhanced methodology for businesses to conduct supply chain optimization. The ABC-XYZ process handles inventory management by considering financial effects and demand changes yet enhances decision quality through its framework of comprehensive assessments. Supply chain decision-making becomes stronger through these approaches which provides more accurate forecasts and lowers total supply chain expenses leading to better operational performance and competitive edge.

The ABC-XYZ analysis proceeded with actual company's data through Microsoft Excel platform. The analysis became the vital element to interpret inventory patterns at the organization and build supply chain decision frameworks. The organization maintained twelve active products for sales which produced dissimilar impacts on both revenue and sales figures. All product names were changed to P01 through P12 for analytical purposes. For example, some metal products were named as P03 and e.t.c.

The definition of inventory classification becomes essential because it directly affects how the company handles its inventory management operations. Company performs a standardized inventory management process that starts with market demand evaluation through client inquiries together with seasonal trend analysis before selling its products. In example of how the products are stored in a warehouse, here is the visual breakdown of the decision making process.

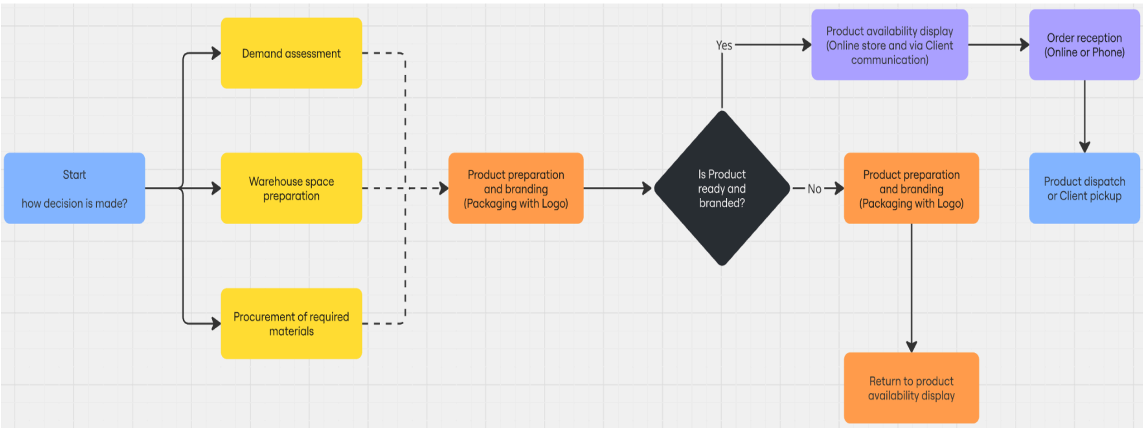

Figure 3.5.1. Operational workflow of inventory decision making process and order fulfillment.

After completing an assessment the warehouse team uses the established plans to arrange the storage area based on projected stock requirements. Stroidenergotrade procures materials from suppliers while simultaneously preparing products for sale by adding brand logo and packing materials to each item. The company displays its finished products through both online sales channels and makes direct client communications about product availability. The final stages of the process involve order fulfillment, either through client pickups or arranged deliveries.

The description of this operational workflow exists because inventory prioritization demands direct attention to it. Warehouse capacity limitations together with demands for efficient operations underline the business need to determine which products should receive priority attention for storage and restocking. The owner of the company identified repetitive warehouse occupation inefficiencies as ongoing business issues during our conversations. A structured classification system was missing from the organization yet multiple key revenue products were known. This lack of inventory organization caused low-priority items to fill valuable warehouse space thus reducing operational responsiveness during peak times. The ABC-XYZ approach provided operational value by optimizing warehouse capacity when it would be applied to inventory control systems to ensure both effective warehouse usage and prompt shipment readiness of priority products.

The supplied dataset arrived in Excel format containing performance records that extended across a duration from January 2023 up to December 2024. The main indicators for ABC-XYZ analysis were product revenue contribution and units sold numbers. The analysis excluded products P01 and P02 because multiple months contained missing data which threatened the validity of the findings. The study adopted a uniform time frame for its evaluation in order to maintain analysis reliability.

Table 3.5.1. Pivot table visualization for ABC.

<table>
<tr><th>Product ID</th><th>Total quantity</th><th>Total revenue (kzt)</th><th>%</th><th>% distribution</th><th>ABC</th></tr>
<tr><td>P03</td><td>98,065</td><td>173,036,736.43</td><td>29.88%</td><td rowspan="5">74.37%</td><td>A</td></tr>
<tr><td>P04</td><td>111,952</td><td>72,277,657.26</td><td>12.48%</td><td>A</td></tr>
<tr><td>P07</td><td>28,214</td><td>64,479,086.49</td><td>11.14%</td><td>A</td></tr>
<tr><td>P06</td><td>29,817</td><td>62,976,310.11</td><td>10.88%</td><td>A</td></tr>
<tr><td>P08</td><td>69,901</td><td>57,870,320.47</td><td>9.99%</td><td>A</td></tr>
<tr><td>P10</td><td>49,966</td><td>56,126,160.41</td><td>9.69%</td><td rowspan="2">19.03%</td><td>B</td></tr>
<tr><td>P05</td><td>25,476</td><td>54,085,266.08</td><td>9.34%</td><td>B</td></tr>
<tr><td>P09</td><td>86,402</td><td>38,165,944.11</td><td>6.59%</td><td>6.59%</td><td>C</td></tr>
</table>

Table 3.5.2. Pivot table visualization for XYZ.

<table>
<tr><th>Product ID</th><th>Total quantity</th><th>Average quantity per product</th><th>STDEV</th><th>CV</th><th>XYZ</th></tr>
<tr><td>P03</td><td>98,065</td><td>4,086.04</td><td>4,061.43</td><td>99.40%</td><td>Z</td></tr>
<tr><td>P04</td><td>111,952</td><td>4,664.67</td><td>3,352.34</td><td>71.87%</td><td rowspan="2">Y</td></tr>
<tr><td>P07</td><td>28,214</td><td>1,410.70</td><td>1,159.57</td><td>82.20%</td></tr>
<tr><td>P06</td><td>29,817</td><td>1,490.85</td><td>931.40</td><td>62.47%</td><td>X</td></tr>
<tr><td>P08</td><td>69,901</td><td>2,912.54</td><td>215.70</td><td>73.88%</td><td>Y</td></tr>
<tr><td>P10</td><td>49,966</td><td>2,081.92</td><td>1,910.38</td><td>91.76%</td><td rowspan="2">Z</td></tr>
<tr><td>P05</td><td>25,476</td><td>1,061.50</td><td>1,183.63</td><td>11.,51%</td></tr>
<tr><td>P09</td><td>86,402</td><td>3,600.08</td><td>2,302.13</td><td>63.95%</td><td>X</td></tr>
</table>

Excel allowed the creation of a pivot table that ordered products according to their total revenue with a descending arrangement (Figure 3.6.2 shows this). The products received their group classification as A, B or C using the cumulative revenue share according to classical ABC principles. The analysis divided products into categories known as A-class for maximum revenue producers and B-class for moderate revenue producers together with C-class for minimal revenue producers. The revenue-based system allowed the company to identify its most crucial products for strategic decision-making (Abolghasemi et al., 2020).

$$CV\ (coefficient\ of\ variation) = \frac{STDEV}{Average\ quantity\ per\ Product} * 100\% \qquad (3.6.3)$$

A process of XYZ classification followed an assessment of sales quantity stability. The team evaluated product quantity sales through calculation of average values and standard deviation measure (STDEV) analysis (Equation 3.6.2). The coefficient of variation (CV) for each product required calculation through the standard deviation divided by the average monthly sales followed by multiplication by 100%. The classification divided products based on CV values where below 70% meant X (stable demand), 70-100% designated Y (moderate variability) and Z (unstable demand) applied to above 100%. The system utilized two categories which allowed researchers to examine inventory characteristics from financial significance combined with physical demand stability.

Table 3.5.3. ABC-XYZ matrix.

	X (stable demand)	**Y** (moderate demand)	**Z** (unpredictable demand)
A (high revenue generation)	P06	P04 P07 P08	P03
B (moderate revenue generation)			P10 P05
C (low revenue generation)	P09		

The ABC-XYZ matrix contains a framework to evaluate products by their revenue generation rate and sales variability level (Figure 3.6.3) through integrated assessment. The two-dimensional approach helps organizations structure their inventory fmanagement process through its ability to select different strategic approaches for different products categories. Products that fall under the A-X category demand continuous stocking strategies because they combine high financial value with stable market demand patterns. Strategic products belonging to both A-Y and B-X classifications need flexible restocking plans due to moderate demand fluctuations. Items positioned in A-Z or B-Z categories should be managed through dynamic methods including constant forecasting revisions and elevated buffer stocks and scenario prediction methods to address their volatile demand behavior. Products classified as C-X or C-Y often have limited revenue significance yet predictable customer demand which makes minimum inventory holding beneficial for maximizing warehouse effectiveness. The interpretive method supports modern supply chain analytic standards by enabling inventory classification to increase operational performance and create market stability and supply risk resilience (Suryaputri, Gabriel, & Nurcahyo, 2022). Managers can find detailed ABC-XYZ framework implementations with product categorizations in Chapter 4 of this paper.

3.6 Forecasting tools

After the completion of the ABC-XYZ analysis, in the scope of the research three forecasting methods were considered: Holt-Winters model, ARIMA, and ARIMAX. Each of the models and their implementation will be discussed in the following subsections.

3.6.1 Holt-Winters

Holt-Winters Exponential Smoothing is a time series forecasting method that extends simple exponential smoothing by adding components for trend and seasonality. This method is particularly useful for data with clear seasonal patterns and long-term trends.

- Level smoothing: Captures the baseline value of the series at each time step.
- Trend smoothing: Accounts for long-term increase or decrease in the data.
- Seasonal smoothing: Adjusts for repeating seasonal variations over a fixed period.

As the first step of the forecasting process, data was cleaned. The process of preparing the dataset was described in Section 3.4. As a result of the Data Preparation step, eight products were selected. Afterwards, the code for this stage was written using Python. The main line of code for the Holt-Winters model can be found in the figure below.

```
model = ExponentialSmoothing(
    dataset_product['Units sold'],
    trend='add',
    seasonal='add'
).fit()
```

Figure 3.6.1. Holt-Winters model in Python.

The Holt-Winters method includes three key parameters:

α (alpha): Controls the weight given to recent observations in level smoothing.

β (beta): Determines the impact of trend smoothing.

γ (gamma): Adjusts for seasonality.

These parameters were found automatically by the model in order to minimize errors. Trend and seasonality were considered in the Holt-Winters model and were added to the model. Afterwards, the performance of the model was evaluated using error metrics such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

```python
mae = mean_absolute_error(dataset_product['Units sold'], fitted)
mape = mean_absolute_percentage_error(dataset_product['Units sold'], fitted) * 100

print(f"Error Metrics for {product}:")
print(f"MAE: {mae:.2f}")
print(f"MAPE: {mape:.2f}%")
```

Figure 3.6.2. Calculating MAE and MAPE in Python.

3.6.2 ARIMA

Another model that was trained on the same dataset is ARIMA. It is a statistical model that is used to forecast future values based on historical values. ARIMA stands for Autoregressive Integrated Moving Average. It works in a way that trends are removed from the data in order to make it more stable, and the average of past errors is identified in order to improve the prediction. To be more precise:

- Autoregressive means that a certain number of past values are used to make a forecast for the future. For this purpose, parameter **p** is chosen. If p is equal to 5, it means that data for the last 5 months is used.
- Integrated means that trends are eliminated via differencing. In this step, parameter **d** is used. If d is equal to 2, it means that differencing was applied twice.
- Moving average means that past forecast errors are also used in order to make predictions more accurate. Parameter used for this step is **q**, if q equals to 3, it means that the last 3 past errors were used.

As it was mentioned previously, data was prepared and two products were eliminated, sothe model was applied to eight products from the green category. Code for the model was written using Python. Firstly, we tried to tune p, d, q parameters by ourselves, however, after trying manual tuning, it was decided to use auto tuning since the auto arima function gives the best parameters with minimized errors. Auto arima model tunes the model by itself by identifying best p, d, and q parameters that minimize errors and increase accuracy.

```python
auto_model = auto_arima(
    dataset_product['Units sold'],
    stepwise=True,
    suppress_warnings=True,
    error_action='ignore',
    trace=False
    )
```

Figure 3.6.3. ARIMA model in Python.

Afterwards, the performance of the model was evaluated using error metrics such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). They were calculated using the same functions as for the Holt-Winters model.

3.6.3 ARIMAX

The implementation of the ARIMAX (AutoRegressive Integrated Moving Average with Exogenous Variables) model begins with the collection of historical data and relevant external factors that might have influenced demand, such as weather conditions, promotional campaigns, or holidays. Data was already prepared previously, the same eight products were used for the ARIMAX model. In addition, one column regarding the promotions was added to the dataset. Company provided us with data where they mentioned how much money was spent on marketing each month. This data was then added to the dataset in the “Promotions” column and marked as “yes” and “no” depending on the spendings.

Initially, seasons in the dataset were given as “Winter”, “Summer”, “Fall”, and “Spring.” In order to make it simpler, mapping was used. So each season was given a number from 1 to 4. Also, Promotion in the dataset was marked as “yes” and “no”, which were replaced in the code with “1” and “0”, respectively.

```
dataset['Promotion'] = dataset['Promotion'].map({'yes': 1, 'no': 0})
season_mapping = {season: i for i, season in enumerate(df['Seasonality'].dropna().unique())}
dataset['Seasonality'] = dataset['Seasonality'].map(season_mapping)
```

Figure 3.6.4. Mapping values of promotion and seasonality.

Two external factors in the code were considered. They are promotions applied by the company and seasonality. The optimal values for p (autoregressive order), d (differencing order), and q (moving average order) were determined automatically using the auto_arima function from the pmdarima library on Python. Model was then evaluated using different error metrics such as MAE and MAPE as with previous models.

```
main = dataset_product['Units sold']
external_factors = dataset_product[['Promotion', 'Seasonality']]

model = auto_arima(
    main,
    exogenous=external_factors,
    trace=True,
    error_action='ignore',
    suppress_warnings=True,
    stepwise=True
)
```

Figure 3.6.5. ARIMAX model in Python.

3.7 Planning tools

This project uses linear programming models (LP) and scenario analysis to optimize supply chain management for SMEs. The main goals are to minimize inventory costs, balance inventory, and ensure the sustainability of supply chains under conditions of uncertainty.

3.7.1 Linear programming models

Linear programming allows us to determine the optimal amount of inventory and orders, minimizing total costs. The general formulation of the model is presented as follows:

Example of objective function:

$$\text{Minimize: } Z = \sum(H*I + S*N + St*StL) \quad (3.7.1)$$

Here:

H - holding costs (kzt/item),

I - inventory level,

S - ordering costs (kzt/order),

N - number of order placed in a month,

St - stockout costs (kzt/item),

StL - stockout level.

Example of the constraint: Maximum level of inventory

$$I(max) > I(t) \quad (3.7.2)$$

$$I(t) = I(t\text{-}1) + Q(t) - D(t) \quad (3.7.3)$$

Here:

I(max) - maximum level of inventory,

I(t) - inventory level at time t,

I(t-1) - inventory level at time t-1,

Q(t) - order quantity at time t,

D(t) - demand level at t.

Similarly, minimum level of inventory also can be included as a constraint.

$$I(min) < I(t) \quad (3.7.4)$$

The linear programming model is solved using Python.

3.7.2 Scenario analysis

Scenario analysis is used to model various possible situations faced by small and medium-sized businesses (SMEs) and assess their impact on costs in the supply chain. In conditions of limited data, this method allows managers to take into account the uncertainties associated with changes in demand and costs, and identify strategies that minimize potential risks. The scenario analysis procedure includes the following steps:

- Identification of key uncertainty factors: changes in demand, fluctuations in storage costs, shortages and orders.

- Formation of alternative scenarios: optimistic (high demand), basic (average demand), pessimistic (low demand).
- Cost estimation for each scenario based on demand forecasts and cost estimates.
- Compare the results between scenarios to identify solutions that minimize total costs.

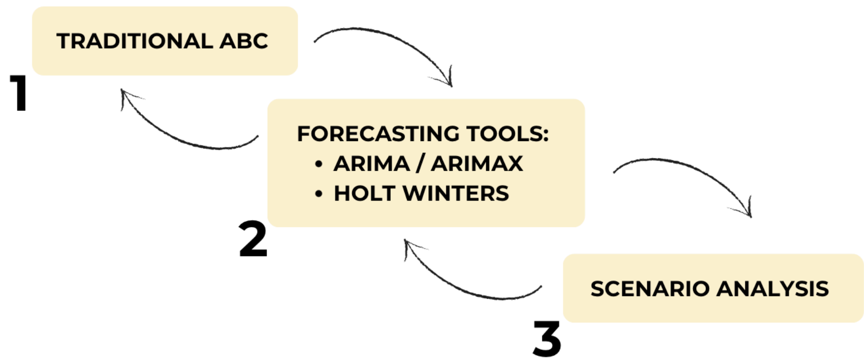

Figure 3.7.1. Flow of analysis tools applied.

As shown in the Fig.3.7.1 the scenario analysis is conducted after Traditional ABC-XYZ and forecasting methods. It allows us to incorporate all the available information and conduct thorough analysis. As the main categories are identified at the beginning of analysis and demand is forecasted for all products using the most accurate tool for the category, scenario analysis uses the forecasted demand as the input data. Cost of goods for each product provided by the company and inventory costs estimates were also used as input data, as shown in Fig.3.7.2.

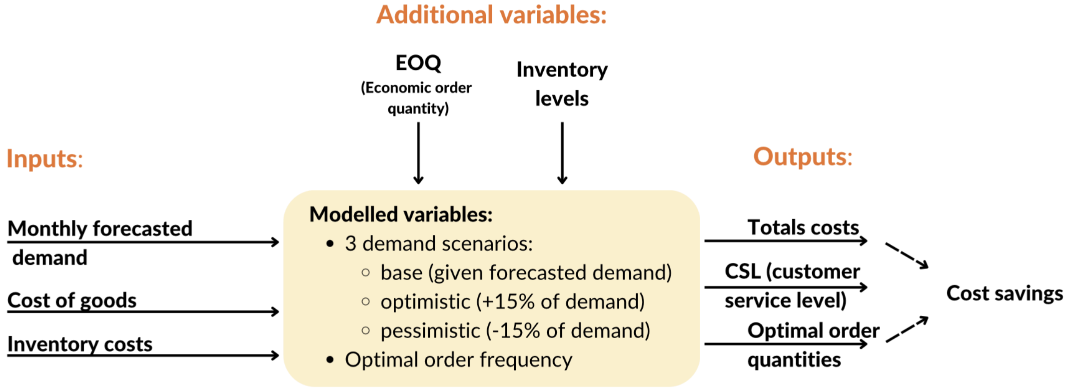

Figure 3.7.2. Scenario analysis flow.

Since actual inventory data is not available, cost calculations are performed using projected sales and estimated cost coefficients based on industry research. The following costs estimates were used in the project:

- Holding costs:
  - the cost of storing unsold inventory (warehousing, insurance, depreciation, opportunity costs)
  - 20% of total annual value (Tuovila, 2024)

- Ordering costs:
  - the fixed cost of each order, regardless of its quantity (administrative, transportation, handling costs)
  - depends on the cost of goods
- Stockout costs:
  - the cost of unmet demand due to insufficient inventory (lost sales, expedited shipping, customer dissatisfaction.)
  - 500% of holding costs (Kırmızı et al., 2024)

Furthermore, additional variables, such as EOQ and inventory levels were calculated using the predefined formula. The formula of EOQ is shown below in Eq.3.7.5 and inventory levels formula was shown above in Eq.3.7.3.

$$EOQ = \sqrt{\frac{2*D*S}{H}} \tag{3.7.5}$$

Here:

D - annual demand,

S - ordering costs (kzt/order),

H - holding costs (kzt/item).

Microsoft Excel and Python were used to build scenario models and calculate totals. Programming models were incorporated into the scenario analysis to calculate the optimal order quantity for each month. Programming models were necessary, as in classical inventory management models, EOQ is used as a tool to determine the optimal order volume, minimizing the cost of storing and placing orders with constant demand. However, in conditions of variable or seasonal demand, as in this project, a fixed EOQ value may lose relevance and reduce planning flexibility. Therefore, in the scope of this project, EOQ was not used as a static strategy, but plays the role of an approximate calculated value, on the basis of which an adaptive ordering strategy was formed. To increase the flexibility of the model, an approach was implemented in which EOQ is calculated for each product based on aggregated parameters (average annual demand, holding and ordering costs). Then, based on it, the optimal order volume for each month was modeled in Python, taking into account the actual forecast of demand, the initial inventory level, and the target strategy for minimizing total costs. The Python model was used due to several reasons:

- selects the most profitable option by iterating through EOQ multipliers (0, 1×, 2×, 3×, etc.) or arbitrary order volumes
- takes into account monthly changes in demand and initial inventory levels
- calculates holding, ordering, and stockout costs for each period;
- additionally, takes into account the customer service level.

Thus, EOQ serves only as a reference point, and actual order decisions are made on a dynamic basis, which allows the system to remain adaptable and cost—effective even when demand conditions change.

To assess not only the economic, but also the operational advantages of the model, the CSL (customer service level) metric was included in the calculation. This indicator demonstrates how effectively the inventory management system copes with meeting demand without causing a shortage. CSL is calculated using the following formula:

$$CSL = 1 - \frac{StL(t)}{D(t)} \tag{3.7.6}$$

Here:

CSL - customer service level,

StL(t) - stockout levels at time t,

D(t) - demand level at time t.

Therefore, stockout level is the amount of units of unmet demand at a certain month. In this case, CSL = 1 means that all of the demand in a month is satisfied and there are no stockouts. The CSL indicator was not directly involved in the optimization process, but was used as an evaluation indicator of the model's compliance with business requirements from the collaboration with our team. In real-world conditions, the company strives for a high level of service (for example, CSL ≥ 95%) to ensure customer loyalty and stable sales. The Python model that was described before also calculated the CSL for each month and scenario, which makes it possible to verify that the model meets customer service expectations desired by the company. Thus, the inclusion of CSL in the analysis highlights that the proposed model not only minimizes costs, but also maintains a high level of customer service, ensuring a balance between efficiency and quality.

4. Results and discussion

4.1 Decision evaluation tools results

After ABC-XYZ analysis has been done to categorize their product range into three categories according to their revenue stream importance and customer demand stability. Mapping products into the ABC-XYZ matrix enables the company to divide them into distinct categories for dynamic stocking approaches and risk management as well as inventory neglect. The methodical classification system drives operational excellence which enables the firm to respond effectively to market changes and warehouse capacity limitations and customer service requirements. The evaluation showed that products classified under the A-X segment give the company two major benefits. The demand profiles for such products show stability together with high financial criticality. The managers should sustain frequent replenishment of A-X products with tight safety stock margins while decreasing inventory expenses while preserving stockout protection. Boosted sales revenue and reduced inventory capital are achieved through proper management of A-X product levels. The organization should establish A-X items as their fundamental products for which procurement and warehouse management structures should revolve.

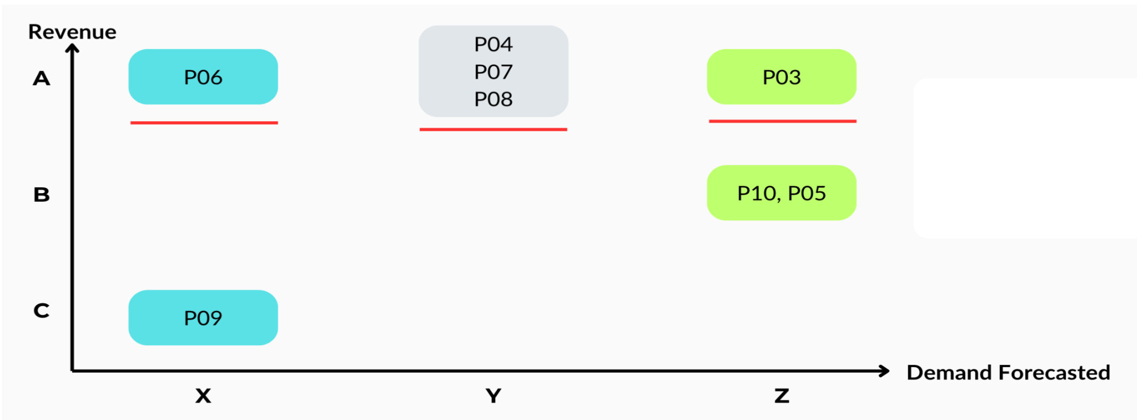

Figure 4.1.1. Product Positioning on Revenue vs Demand Forecasted Matrix.

By using the ABC-XYZ classification framework the product portfolio received organized investigation through financial contribution assessment and demand predictability analysis. As it can be seen above how products match strategic dimensions as it immediately supports supply chain and inventory management decisions.

The products included in P06 appear in the upper left quadrant since they generate substantial revenue (62,976,310 kzt) while exhibiting predictable demand patterns. The operational benefits of this strategic placement indicate that these products establish fundamental financial stability for the organization. This combination of dependable demand patterns and lucrative returns makes it possible to execute continuous stock replenishment while maintaining low inventory risk since it enables effective service level optimization at reasonable cost levels. The financial performance receives notable contributions from these revenue-generating products (P04, P07, P08) which amount to 72,277,657, 64,479,086 and 57,870,320 kzt respectively because they exhibit moderate demand variability. The A-Y zone reveals that managers need to implement rolling demand forecasts and seasonal adjustment models for maintaining cost-effective inventory policies.

As the most successful product in P03, the manufacturer collects 173,036,736 kzt in individual revenue making up 29.88% of total turnover while operating under extreme demand instability. The analysis demonstrates the intricate nature of managing products with critical financial value in uncertain market conditions so executives should adopt strategic inventory approaches which unite strategic stock buffers with sophisticated prediction methods. P10 (56,126,160 kzt) and P05 (54,085,266 kzt) generate moderate revenue from unstable sales patterns that earn B-Z classification thus putting their operational performance at risk. The product P09 (38,165,944 kzt) belongs to the C-X category with its low revenue and stable demand which makes reorder point models or automated replenishment systems suitable choices for stocking strategy.

Table 4.1.1. Product Prioritization Table Based on ABC-XYZ.

Priority	Product ID	ABC	XYZ	Reason
1	P03	A	Z	High revenue (29.88%) generation, despite unstable demand (Z category). It is in first place due to the reason that this product generates a lot of revenue
2	P06		X	Very stable (X category) and high value (A category) — ideal product.
3	P04		Y	Moderately stable (Y category) and high value (A category).
	P07		Y	Moderately stable (Y category) and high value (A category).
	P08		Y	Moderately stable (Y category) and high value (A category).
4	P10	B	Z	Lower value and unstable demand (BZ). Company should monitor this product carefully or optimize.
	P05		Z	Lower value and unstable demand (BZ).Company should monitor this product or optimize.
5	P09	C	X	Stable but low revenue value (CX).

A product prioritization table in Figure 4.1.2 analysis helps to better understand strategic business needs through its product ranking approach. The ABC-XYZ classifications are distributed across a structured priority framework in the table to determine the main operational focus for each product. The critical inventory items for Nuovo Retail are P03 and P06 since they fall in the high-priority category either through financial significance or financial stability combined with high profits. The products within the middle priority group (P04, P07, P08) retain their high value position even though flexible management becomes necessary because of average demand fluctuations. Products within P10, P05 and P09 groups should be handled with caution because they demonstrate either poor financial performance or operational instability.

The structured allocation process generates various advantages for management. Active stock management becomes clear for products through this approach allowing managers to categorize them within appropriate inventory practices. The warehousing layout should embrace strategic area placement because managers must position essential A-X and A-Y products within quick-access zones in addition to locating C-category items in secondary storage spaces. The procurement procedure enhances its performance by establishing special contracts with decisive suppliers for essential A-category items and implementing versatile or on-demand purchasing systems for subordinate products. Decision-makers can use forecasting models alongside dynamic stock review policies for volatility management to plan proactively because they determine which products unite financial value with erratic demand patterns.

The research findings confirm academic literature that ABC-XYZ segmentation functions as a vital mechanism for implementing strategic inventory control systems. The application of ABC-XYZ frameworks by manufacturing companies led to a documented 18% decrease in holding costs according to Randall, Gibson, Defee, and Williams (2011) without affecting service quality levels. Retail businesses implementing ABC-XYZ segmentation method improved their warehouse space use by 12% along with faster order processing according to Spieske, Gebhardt, Kopyto, and Birkel (2022). Medical institutions that used ABC-XYZ methods during emergencies achieved more than 20% better procurement effectiveness through which they maintained essential product availability with minimal surplus buildup according to Ramanathan (2006).

Through ABC-XYZ analysis managers receive strategic insights that help them develop from reactive managers to proactive supply chain governors. Organizations achieve better results from inventory management by splitting their portfolios into specific financial and demand-based segments which helps them refine supplier connections while creating different warehouse zones for placement and optimizing flow sequences and setting realistic performance goals. The corporate strategy protects A-X and A-Y products by ensuring suppliers maintain lead time guarantees but B-Z and C-X products work optimally with opportunistic or flexible sourcing approaches. The combined strategy both decreases working capital needs and protects company revenue flows.

The ABC-XYZ analysis system creates an environment for implementing sophisticated supply chain technological solutions. Warehouse management systems (WMS) with automated optimization functions can choose pick-path improvements by following ABC-XYZ rankings so predictive analytics improves replenishment precision for A-Z type products. The integrated systems applied from ABC-XYZ analysis enable users to leverage the analysis results in multiple ways for wider digital supply chain improvement. The ABC-XYZ product classification method restructures inventory management into a value-creation process that helps businesses establish better market resilience, financial outcomes and operational flexibility in changing complex markets.

4.2 Forecasting tools results

For forecasting, three models were implemented. First model is Holt-Winters. After the Data preparation and extraction, two products were eliminated due to insufficient data. So, forecasting was conducted on eight remaining products because it is important for forecasting to have at least two full years of data. For comparing the efficiency of different methods, two error metrics were used - MAE and MAPE. Also, the results of the forecasting were analyzed using the results of the ABC-XYZ in order to identify if there are any patterns.

4.2.1 Holt-Winters

In the following graphs, actual and forecasted values can be seen. Black line represents actual historical values, blue line represents values forecasted using historical data and red line shows forecasts for the nearest six months. It can be seen that for products P03, P04, P05, P09 and P10, Holt-Winters model was able to catch fluctuations and peaks. However, results for P06, P07 and P08 are less accurate.
As a result of ABC analysis, it was identified that P03 is the most important product for the company since it accounts for almost 30% of the profit of the company. So, using Holt-Winters for this product in particular can be not efficient since even if the model is able to catch peaks, there are deviations from the actual values.

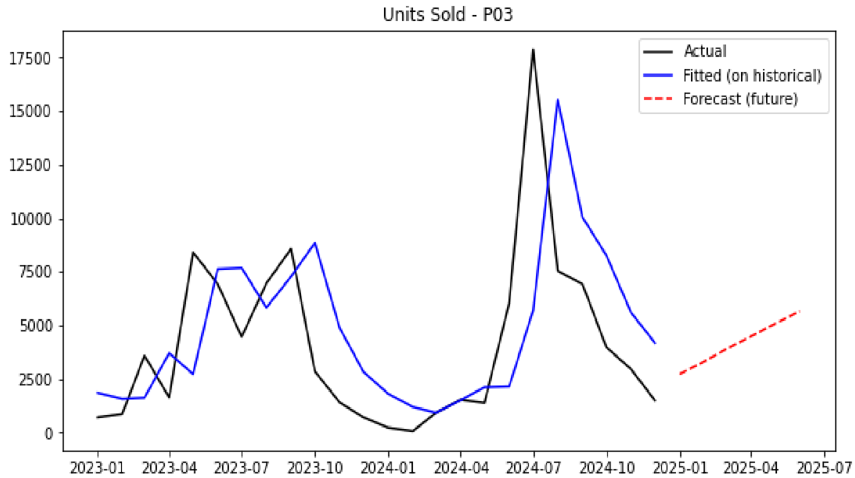

Figure 4.2.1 Forecast for P03 using Holt-Winters.

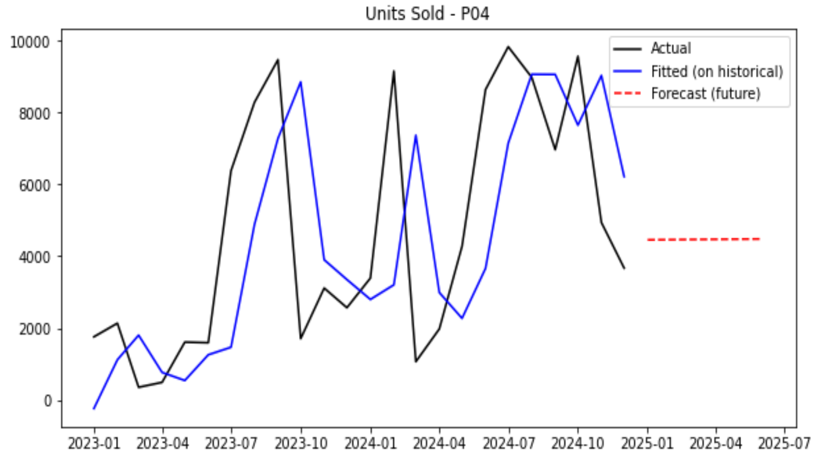

Figure 4.2.2 Forecast for P04 using Holt-Winters.

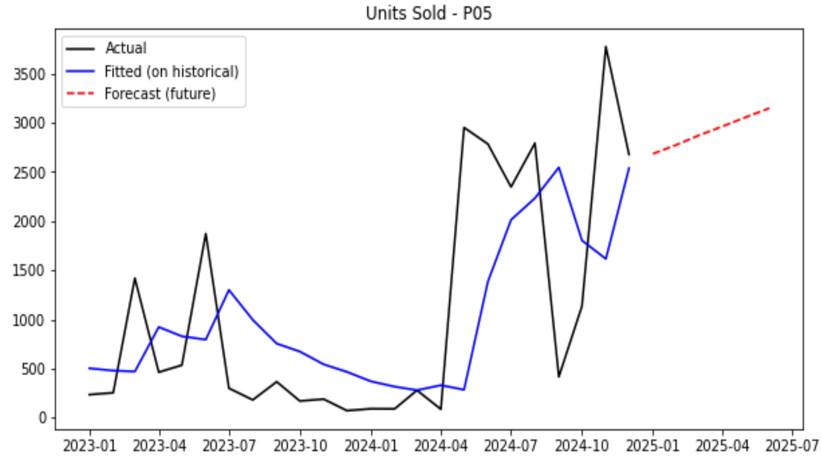

Figure 4.2.3 Forecast for P05 using Holt-Winters.

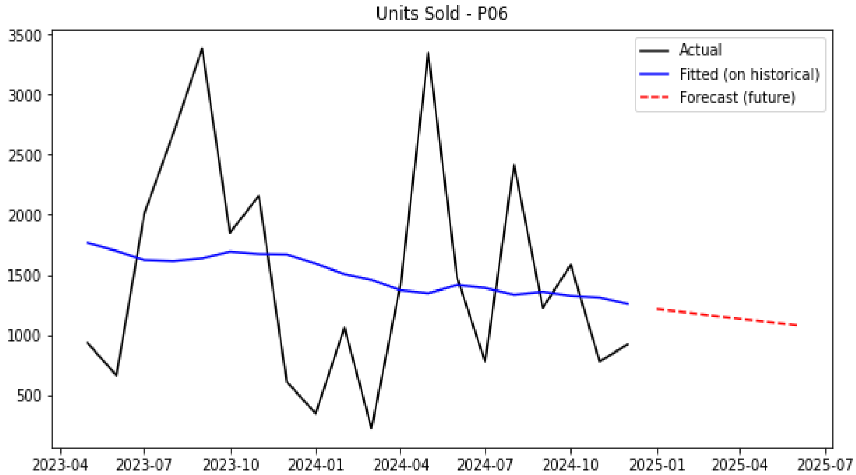

Figure 4.2.4 Forecast for P06 using Holt-Winters.

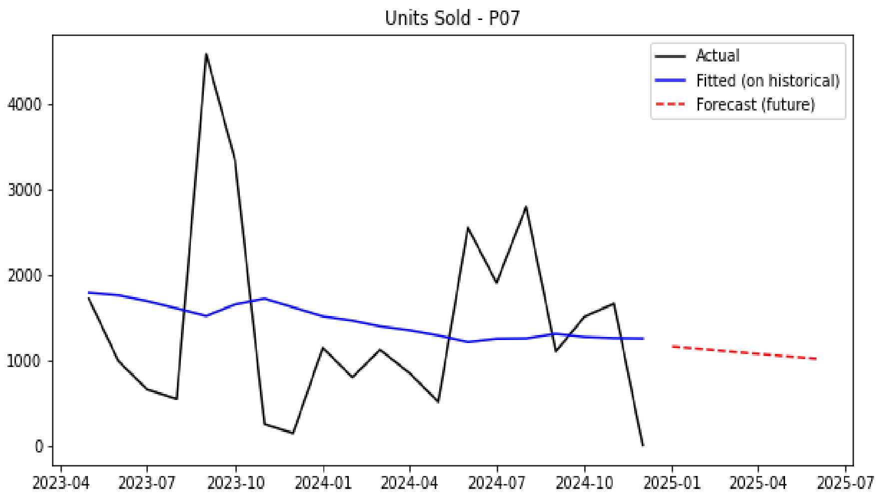

Figure 4.2.5 Forecast for P07 using Holt-Winters.

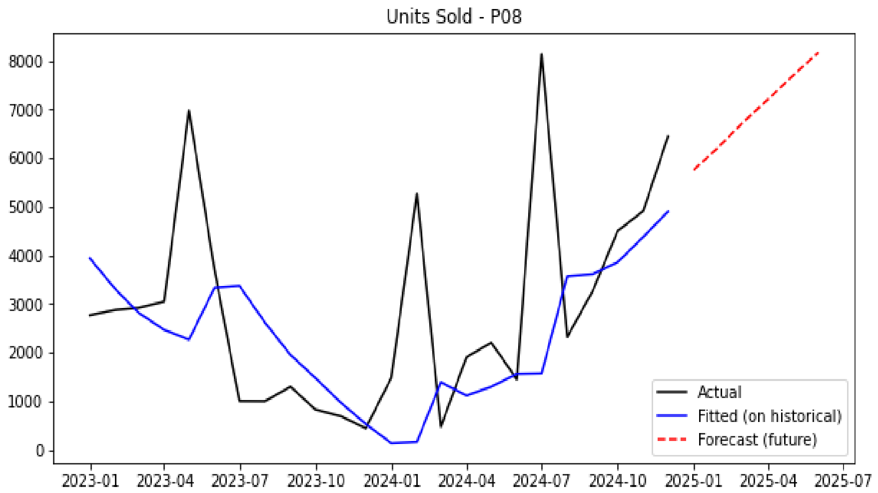

Figure 4.2.6 Forecast for P08 using Holt-Winters.

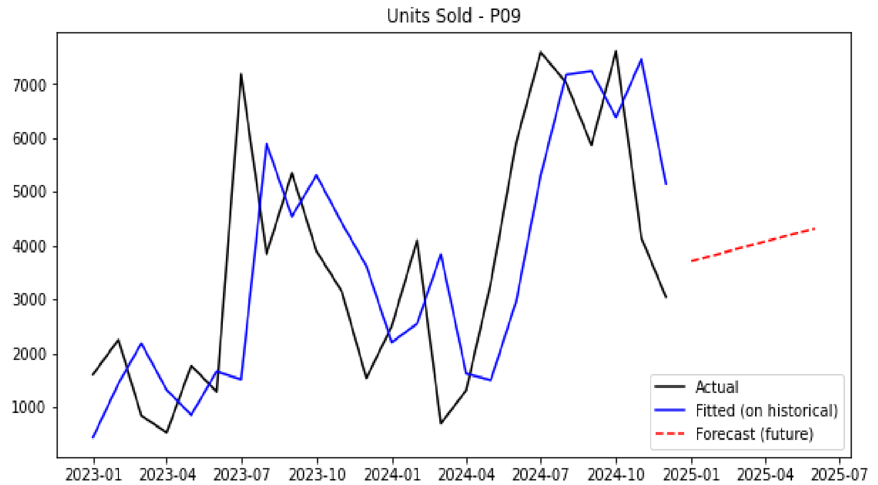

Figure 4.2.7 Forecast for P09 using Holt-Winters.

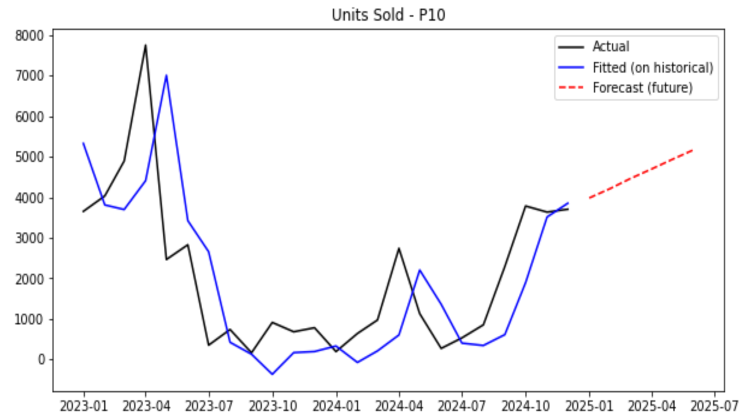

Figure 4.2.8 Forecast for P10 using Holt-Winters.

4.2.2 ARIMA

For ARIMA, forecasting was conducted on the same products. In the figures below, graphs for eight products can be seen and number of units sold is forecasted. Black line represents actual values, blue line represents values fitted on historical data and red line represents forecast for the nearest six months. It can be observed that Arima catches peaks for most of the products and follows the trends. However, there are quite big deviations from actual values. It can be seen that ARIMA demonstrates the best results for products P04 and P05 because it catches the peaks and deviations from the actual values are not very big in comparison with other models. From the results of the ABC-XYZ analysis, P04 belongs to category Y, it is a product with a moderate variability in demand while P05 belongs to category Z and it is a product with unpredictable demand.

Also, ARIMA shows quite good results on products P06 and P09 and both of these products belong to category X - products with stable demand. So, ARIMA works well on products that have more or less stable demand because it does not take into account any external factors and seasonality and that is why it may not be very suitable for products from category Z and for our main product P03 since it belongs to this category.

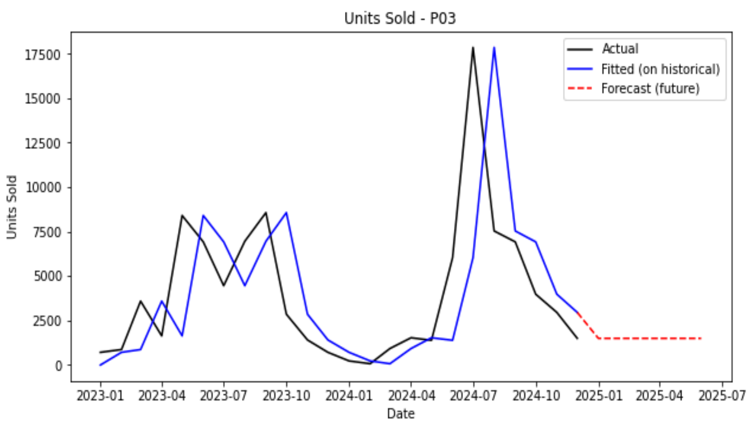

Figure 4.2.9 Forecast for P03 using ARIMA.

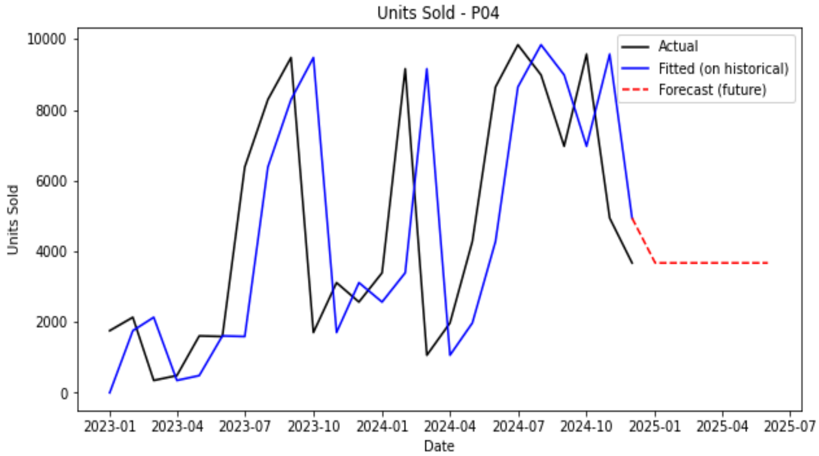

Figure 4.2.10 Forecast for P04 using ARIMA.

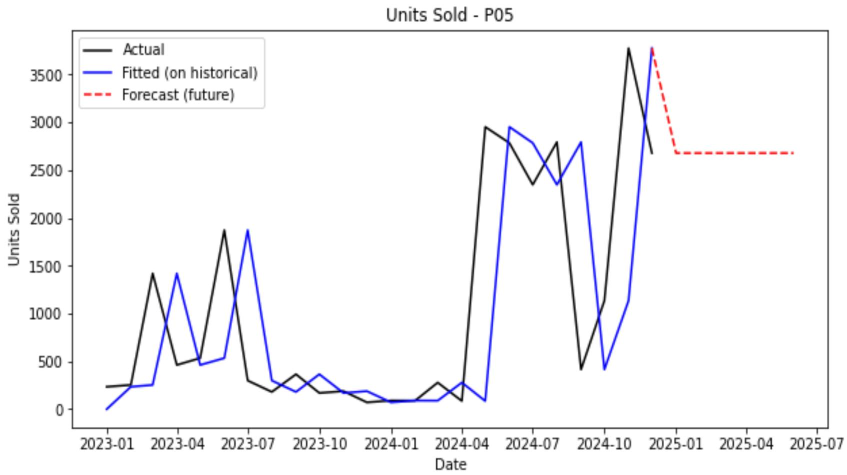

Figure 4.2.11 Forecast for P05 using ARIMA.

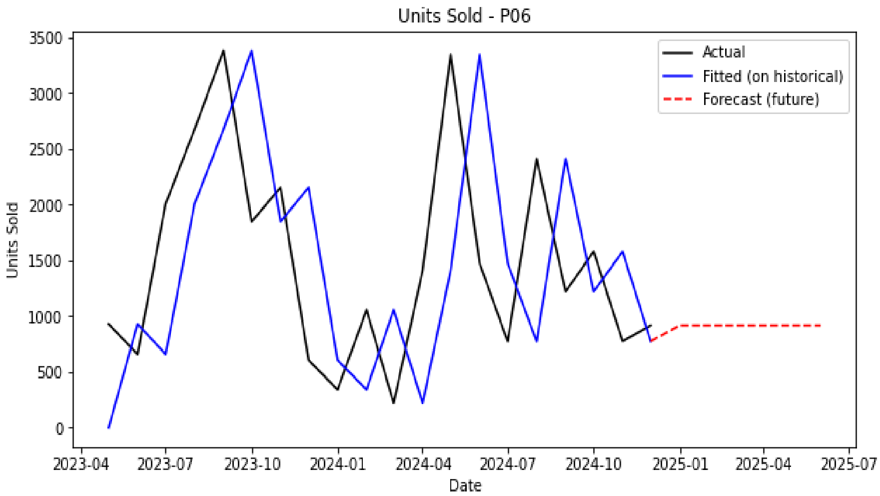

Figure 4.2.12 Forecast for P06 using ARIMA.

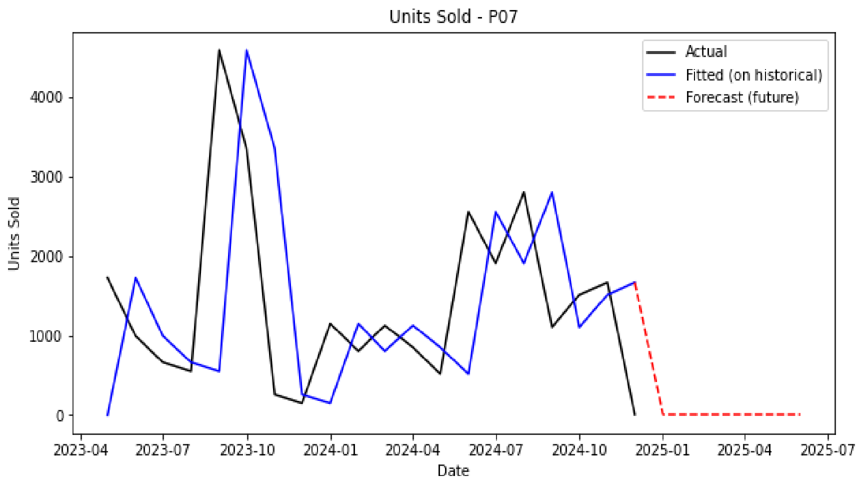

Figure 4.2.13 Forecast for P07 using ARIMA.

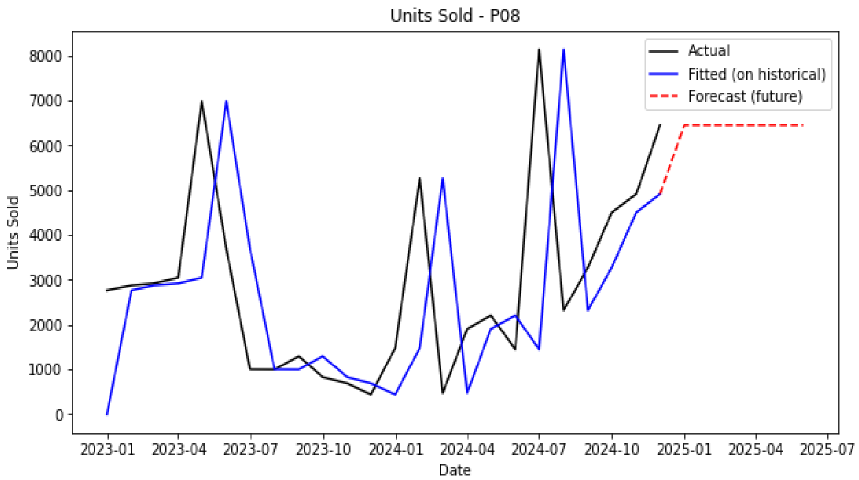

Figure 4.2.14 Forecast for P08 using ARIMA.

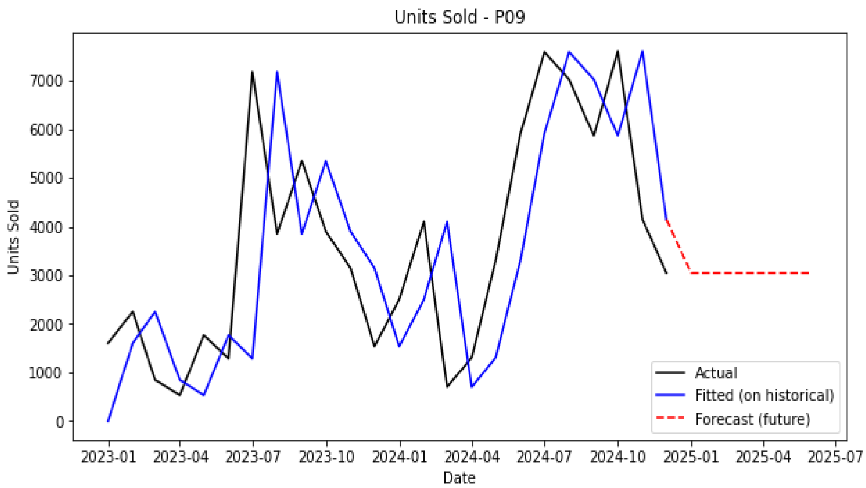

Figure 4.2.15 Forecast for P09 using ARIMA.

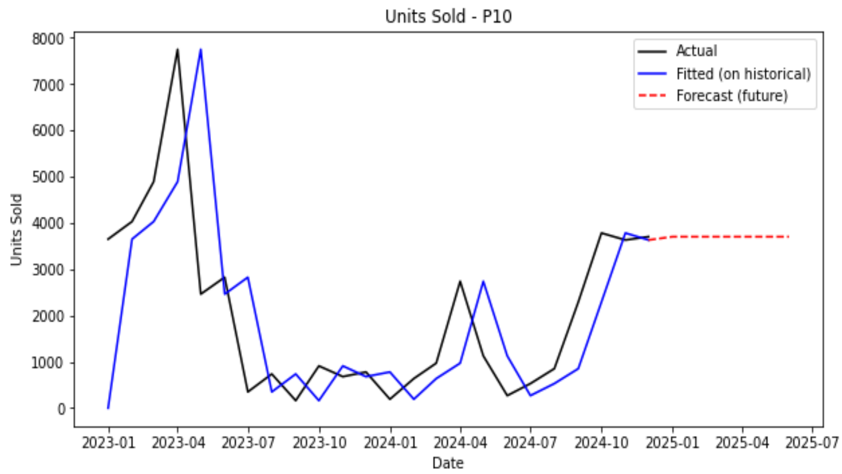

Figure 4.2.16 Forecast for P10 using ARIMA.

4.2.3 ARIMAX

For the ARIMAX model two external factors were considered - Promotion and Seasonality. Below, the results for the ARIMAX model can be found. Black line shows actual values, the blue line shows values fitted on historical data and the red line shows forecasts for the future. In the graph for P03, it can be seen that overall deviations for fitted values are lower than in the previous models. However, this model does not always catch peaks and fluctuations.

ARIMAX showed the best performance for product P03 and as it was mentioned previously, it belongs to category A and is the most important product for the company in terms of profit. In terms of demand variability, it belongs to category Z and has very unstable demand which can be also seen in Figure 4.2.17 since there are a lot of fluctuations on the graph with random peaks. Even though it was not able to catch a peak, the fitted values are located close to the actual values and the deviation is not high. Also, it was proved in terms of error metrics that ARIMAX had the best performance in comparison with the other two models. Error metrics for each product can be found on Table 4.2.1.

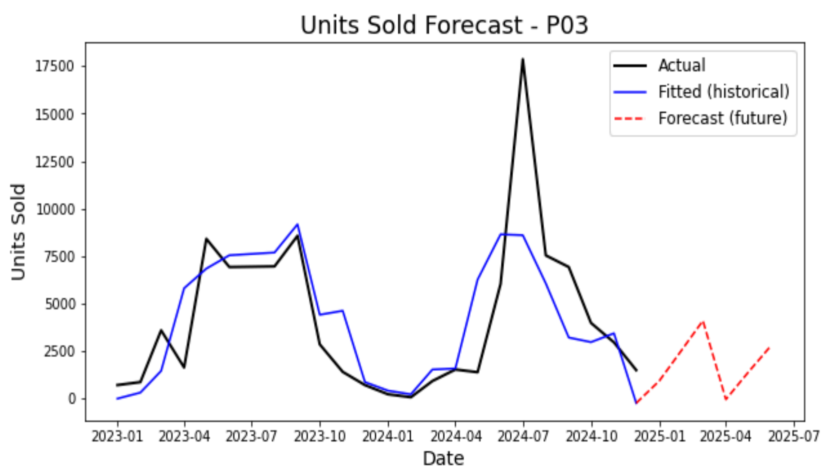

Figure 4.2.17 Forecast for P03 using ARIMAX.

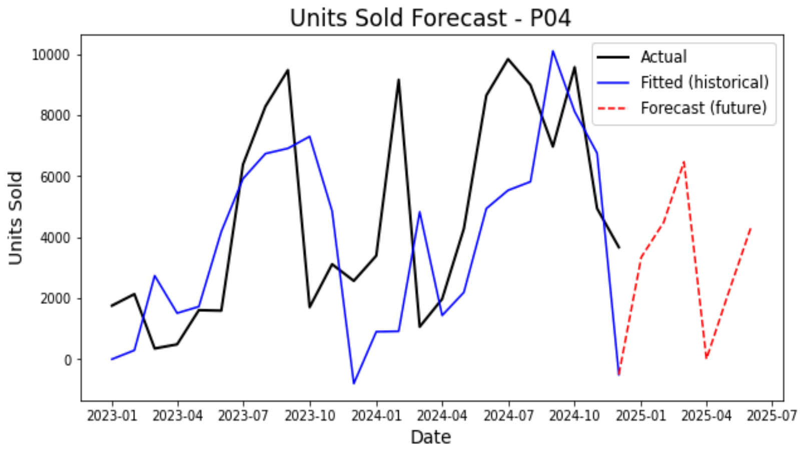

Figure 4.2.18 Forecast for P04 using ARIMAX.

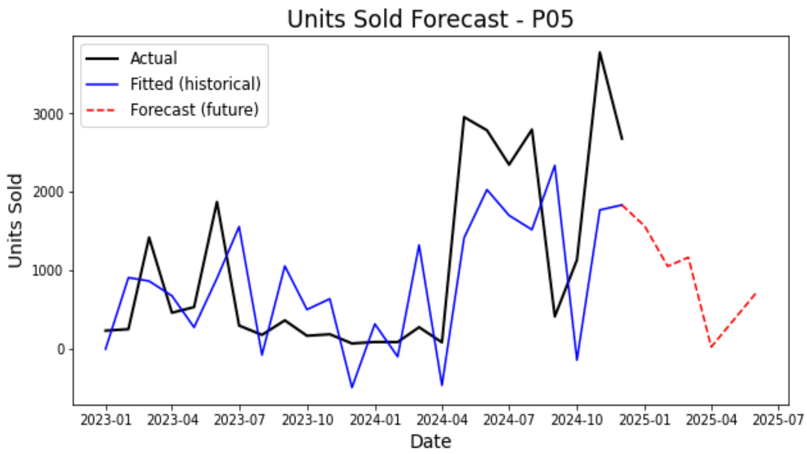

Figure 4.2.19 Forecast for P05 using ARIMAX.

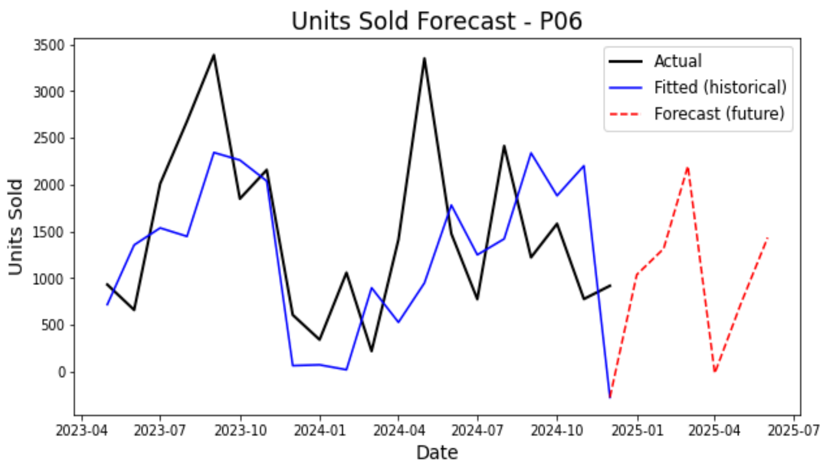

Figure 4.2.20 Forecast for P06 using ARIMAX.

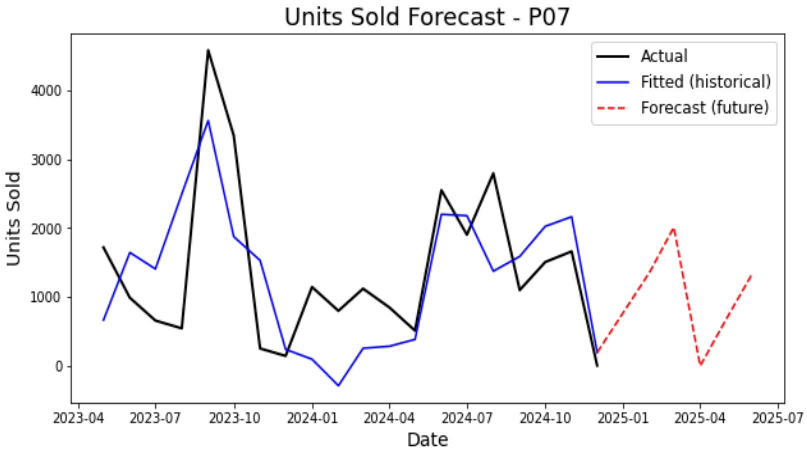

Figure 4.2.21 Forecast for P07 using ARIMAX.

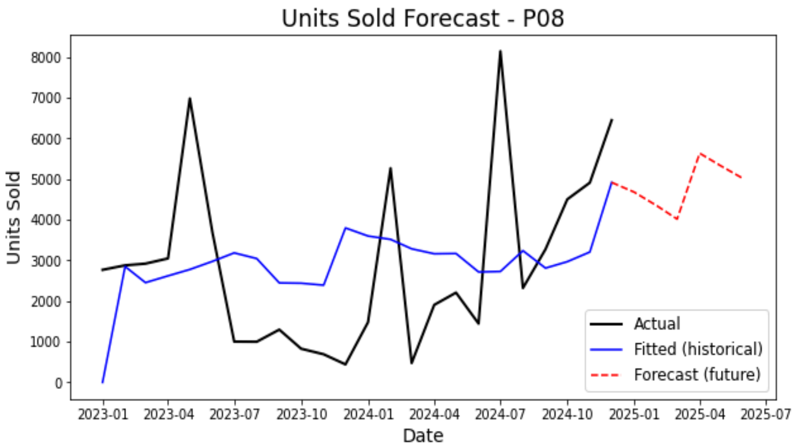

Figure 4.2.22 Forecast for P08 using ARIMAX.

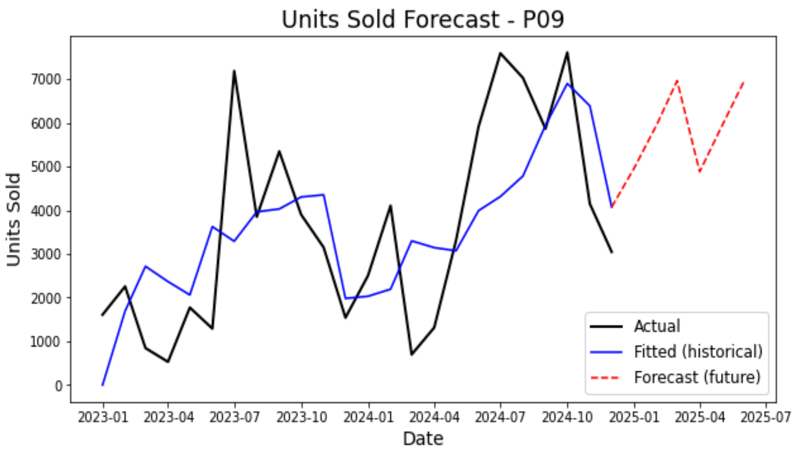

Figure 4.2.23 Forecast for P09 using ARIMAX.

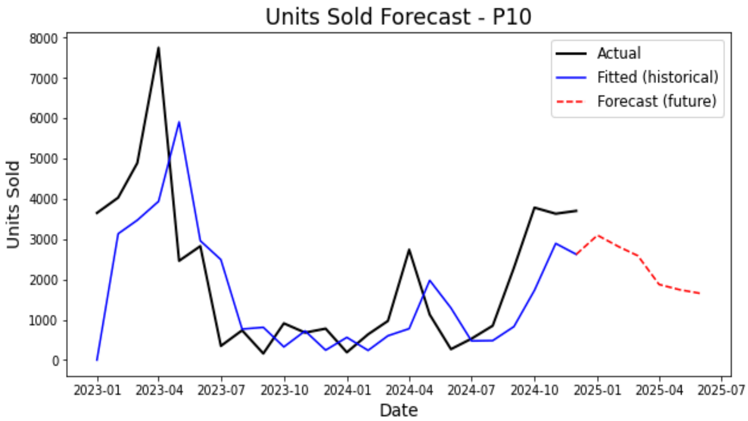

Figure 4.2.24 Forecast for P10 using ARIMAX.

4.2.4 Comparison of models

For comparing the models, two error metrics were used - MAE and MAPE. Based on the results, ARIMAX performed better than the other models at three products: P03, P06 and P07. It can be noticed that these are one of the products that show the highest fluctuations. So, it can be implied that ARIMAX performs better at forecasting when data is fluctuating more since it considers external factors such as seasonality or promotions that can cause these fluctuations. Holt-Winters worked better at forecasting units sold for products P08, P09 and P10. These are the products that fluctuate less in comparison with other products. Some peaks in units sold can be observed but overall the number of units sold are fluctuating less. ARIMA performed the best for P04 and P05. It can be seen that fluctuations for these two products are more frequent and periodic. So, ARIMA may work better for products that show periodic fluctuations.

Table 4.2.1 Comparison of the forecasting models.

Product	Model	Error metrics	Product	Model	Error metrics
P03	Holt-Winters	MAE: 2904.97 MAPE: 179.05%	P07	Holt-Winters	MAE: 941.67 MAPE: 912.87%
	ARIMA	MAE: 2637.58 MAPE: 82.80%		ARIMA	MAE: 1056.10 MAPE: 1146.71%
	ARIMAX	**MAE: 1833.56** **MAPE: 81.14%**		**ARIMAX**	**MAE: 784.71** **MAPE: 209.66%**
P04	Holt-Winters	MAE: 2486.85 MAPE: 100.00%	P08	**Holt-Winters**	**MAE: 1377.67** **MAPE: 58.72%**
	ARIMA	**MAE: 2401.79** **MAPE: 106.87%**		ARIMA	MAE: 1785.79 MAPE: 99.70%

	ARIMAX	MAE: 2662.12 MAPE: 114.33%		ARIMAX	MAE: 1765.69 MAPE: 129.12%
	Holt-Winters	MAE: 731.16 MAPE: 170.06%		**Holt-Winters**	**MAE: 1632.74** **MAPE: 70.98%**
P05	**ARIMA**	**MAE: 714.96** **MAPE: 109.11%**	P09	ARIMA	MAE: 1713.12 MAPE: 72.15%
	ARIMAX	MAE: 779.81 MAPE: 200.90%		ARIMAX	MAE:1433.95 MAPE: 76.54%
	Holt-Winters	MAE: 738.52 MAPE: 92.80%		**Holt-Winters**	**MAE: 1125.27** **MAPE: 99.69%**
P06	ARIMA	MAE: 948.80 MAPE: 89.97%	P10	ARIMA	MAE: 1136.04 MAPE: 115.27%
	ARIMAX	**MAE: 790.07** **MAPE: 75.54%**		ARIMAX	MAE: 1169.69 MAPE: 105.91%

Based on ABC-XYZ analysis, it was identified that P03 is the product that is the most valuable for the company. If we compare the performance of the models on this product, it can be seen that ARIMAX is the model that works the best since its MAE and MAPE is lower than Holt-Winters and ARIMA. For example, MAE for ARIMAX is 81.14% while for ARIMA it is equal to 82.8% and for Holt-Winters it is equal to 179.05% which is twice worse than MAPE metric for ARIMAX. From the table it can also be seen that ARIMAX performed the best on products P06 and P07. All three products (P03, P06 and P07) belong to category A. If product P03 accounted for 29.88% of the profit of the company, P06 and P07 accounted for 10.88% and 11.14% of the company's profit, respectively (Table 3.6.2). So, more than 50% of the company's profit is coming from these three products. So, if it is important for the company to accurately predict the demand for the products that bring the most profit, ARIMAX might be the best choice.

4.3 Planning tools results

Scenario analysis was conducted after Traditional ABC-XYZ and forecasting methods, taking into account the monthly forecasted demand for each product. A Python model has been created that minimizes costs for each month by varying the order volume and including initial inventory levels, as well as cost estimates. As a result, holding, ordering, and stockout costs, totals costs were calculated. To include the varying demand into the analysis, three scenarios were formed:

- base — forecast demand;
- optimistic — demand increased by 15%;
- pessimistic — demand has been reduced by 15%.

The goal was to assess the resilience of the order strategy to changes in demand. Finally, the following results were obtained:

- optimized order volumes for each month
- minimal total costs
- reduced possibilities of stockout
- improved customer service level.

The following table Table 4.3.1 shows the example of results obtained for the base scenario for product P003.

Table 4.3.1. Results for base scenario for product P003.

Date	Demand	Order quantity	Final inventory level	Holding costs (kzt)	Ordering costs (kzt)	Stockou t costs (kzt)	CSL	Total costs (kzt)
01.2025	926.45	0.00	711.86	31,101.79	0.00	0.00	1	31,101.79
02.2025	2,587.25	2,584.31	708.92	18,802.34	30,000	0.00	1	48,802.34
03.2025	4,102.15	3,445.74	52.51	10,076.64	40,000	0.00	1	50,076.64
04.2025	0.00	0.00	52.51	1,389.91	0.00	0.00	1	1,389.90

Similarly, the calculations were performed for all products and all scenarios. The following tables below show the results for all products and for all scenarios in the year 2025.

Table 4.3.2. Result for all scenarios for product P003.

Scenario	Year	Total demand	Average order quantity	Total costs (kzt)	Cost savings (kzt)
Base	2025	11,784.55	1,722.87	195,056.73	
Optimistic (+15%)	2025	13,552.23	2,309.47	232,228.67	1,624,236.70
Pessimistic (-15%)	2025	10,016.86	1,720.78	210,825.01	2,316,055.13

Table 4.3.3. Result for all scenarios for product P004.

Scenario	Year	Total demand	Average order quantity	Total costs (kzt)	Cost savings (kzt)
Base	2025	20,738.38	3,477.50	152,921.52	
Optimistic (+15%)	2025	23,849.14	3,729.20	127,955.79	647,996.62
Pessimistic (-15%)	2025	17,627.62	2,671.75	148,842.40	870,938.54

Table 4.3.4. Result for all scenarios for product P005.

Scenario	Year	Total demand	Average order quantity	Total costs (kzt)	Cost savings (kzt)
Base	2025	16,074.00	2,627.30	245,691.35	
Optimistic (+15%)	2025	18,485.10	3,169.65	277,873.16	3,588,725.78
Pessimistic (-15%)	2025	13,662.90	2,270.86	200,920.44	779,428.55

Table 4.3.5. Result for all scenarios for product P006.

Scenario	Year	Total demand	Average order quantity	Total costs (kzt)	Cost savings (kzt)
Base	2025	6,706.44	1,010.25	127,341.55	
Optimistic (+15%)	2025	7,712.40	1,203.75	165,916.50	3,088,384.63
Pessimistic (-15%)	2025	5,700.47	827.92	160,185.30	642,297.46

Table 4.3.6. Result for all scenarios for product P007.

Scenario	Year	Total demand	Average order quantity	Total costs (kzt)	Cost savings (kzt)
Base	2025	6,173.63	1,074.45	168,298.56	
Optimistic (+15%)	2025	7,099.68	1,267.44	151,959.62	2,732,199.25
Pessimistic (-15%)	2025	5,247.59	891.53	129,100.11	699,510.39

Table 4.3.7. Result for all scenarios for product P008.

Scenario	Year	Total demand	Average order quantity	Total costs (kzt)	Cost savings (kzt)
Base	2025	28,976.64	4,927.70	205,022.84	
Optimistic (+15%)	2025	33,323.14	5,284.37	197,285.46	4,010,468.89
Pessimistic (-15%)	2025	24,630.14	4,259.17	199,792.47	868,698.24

Table 4.3.8. Result for all scenarios for product P009.

Scenario	Year	Total demand	Average order quantity	Total costs (kzt)	Cost savings (kzt)
Base	2025	24,094.53	3,927.56	103,165.20	
Optimistic (+15%)	2025	27,708.71	4,776.48	111,116.86	2,575,963.31
Pessimistic (-15%)	2025	20,480.35	3,342.49	86,647.73	546,201.21

Table 4.3.9. Result for all scenarios for product P010.

Scenario	Year	Total demand	Average order quantity	Total costs (kzt)	Cost savings (kzt)
Base	2025	22,218.00	3,750.38	184,095.08	

Optimistic (+15%)	2025	25,550.70	4,273.20	195,950.95	3,700,380.43
Pessimistic (-15%)	2025	18,885.30	3,241.58	183,173.17	784,178.50

In the case of base scenario, the model showed results with minimal total costs and order quantities that satisfy all of the demand. The average order is at a balanced level (approximately a multiple of EOQ).

In an optimistic scenario, an increase in demand of 15% led to an increase in the volume of orders. Therefore, total costs increased due to increased frequency of orders and possible risks of stockout, thus increasing the ordering and potential stockout costs, respectively. The model helped to adapt to growth, avoiding excessive losses, which translates into significant savings compared to unsuitable fixed strategies. Despite the increase in total costs, the model allowed achieving significant cost savings. For example, the greatest cost savings was observed in P008, where the value is equal to 4,010,468.89 tenge. This confirms the effectiveness of the adaptive approach when demand increases and the risk of shortage is particularly high.

In a pessimistic scenario, the decrease in demand led to reductions of the volume of orders. Therefore, the total costs were lower than in the base scenario. Similar to the optimistic case, the model provided substantial cost savings. For example, the greatest cost savings was — 2,316,055.13 tenge in P003, which demonstrates the ability of the model to adapt to lower demand, avoiding excess inventory and storage costs. However, the savings potential was lower than in the optimistic case, as the total volume of operations was lower. However, with an excessive order, holding costs could arise, which is important to monitor in real situations.

Finally, conducting the scenario analysis led to the following observations:

- The flexibility of the order strategy (depending on demand) helped to minimize overall inventory costs.
- The scenario analysis enabled us to assess risks and uncertainties.
- The data highlighted the importance of regularly reviewing purchase parameters, especially when demand is seasonal or unstable.

4.4 Discussion

From Table 4.4, it is clear that the Smartzapas, Holt-Winters, ARIMA, and ARIMAX models have different strengths and weaknesses. Each model handles trends, seasonality, external factors, forecast accuracy, automation, and scalability in its own way.

Smartzapas is based on fixed rules and does not detect trends or use external data, which makes it less flexible when demand changes. As shown in Table 4.4, Holt-Winters can automatically catch trends and seasonality, while ARIMA and ARIMAX need some manual settings for seasonality. When looking at external factors, Table 1 shows that Smartzapas and Holt-Winters do not use them at all, but ARIMAX can add extra data like prices or promotions. This helps ARIMAX make more accurate forecasts when outside events impact demand.

Forecast accuracy is also different. According to Table 4.4, Smartzapas is less reliable if demand changes a lot, Holt-Winters is good for steady seasonal patterns, ARIMA is better for regular time trends, and ARIMAX gives the best results when external factors matter. In terms of automation, Smartzapas needs a lot of manual updates, which makes it harder to scale. Holt-Winters is fully automatic once it is set up. ARIMA and ARIMAX need some extra work, especially if external data is involved.

Overall, from Table 4.4, we can conclude that Smartzapas is fine for simple and stable demand, Holt-Winters is better for products with clear seasons, ARIMA is good for regular patterns, and ARIMAX is the best option when external factors affect demand. The choice of model really depends on how complex and changeable the environment is.

Table 4.4.1. Comparison of Smartzapas and forecasting models.

Aspect	Smartzapas	Holt-Winters	ARIMA	ARIMAX
Model Type	Rule-based	Statistical + seasonal	Time series + (with)	Time series + outside factors
Trend Detection	Not included	Automatic	Yes	Yes
Seasonality	Manual setup only	Adjusts seasons automatically	You have to add seasonality yourself	You have to add seasonality yourself
External Variables	Doesn’t use external data	Doesn’t support	Doesn’t support	Can use extra info (like prices or promotions)
Forecast Accuracy	Not great if demand changes a lot	Works well with seasonal data	Good for regular time patterns	Best when many things affect demand
Automation	Requires manual rule tuning	Fully automatic once set up	Some parts are automatic	Needs careful setup for external inputs
Scalability	Needs customization per product	Easily applied to multiple products	Scalable but parameter-sensitive	Needs a lot of data and context

5. Conclusion and future work

Validation and verification

The value that the framework brings to the company comes from the validation part where the relevance of the methods proposed by the project to the company's challenges can be proven, and from the verification part, where the correctness of implementation of the methods and tools can be checked. That is why several meetings were arranged with the representative of the company to make sure that the proposed solution addressed their problems. The framework and the tools that it consists of were presented to the company, where it was discussed how each tool might help them. The presented framework consisted of 3 types of methods that assist the most in supply chain management: decision evaluation tools, forecasting tools, and planning tools. Decision evaluation tools consisted of ABC-XYZ classification analysis and the AHP method. As a result, it was decided to focus only on ABC-XYZ analysis due to the extensive and subjective implementation of AHP while the company needed a more automated classification of their products. Forecasting methods, which are Holt-Winters, ARIMA, and ARIMAX, were presented, and it was decided to fit the tools to the sales dataset to find out the most accurate one for the company's needs. Last but not least, the company was introduced to possible planning tools, which were programming models and scenario-based analysis. The programming models were then incorporated into scenario analysis to keep the framework simple and yet flexible. The company preferred this analysis method due to the absence of complex mathematical formulations, making it easier to evaluate risks.

At the end, the company was presented with the results of the models, and it was confirmed that decision evaluation and planning tools aligned with the company's objectives. However, the forecasting results were inconsistent due to the instability of the company's demand as well as broader market instability caused by various factors such as the emergence of new competitors, more competitive pricing strategies from other market players, or simply a decline in customer purchasing behavior due to external reasons. It was suggested to use different forecasting models for different demand scenarios: ARIMAX for products with unstable demand with high fluctuations, ARIMA for products with periodic fluctuations and Holt-Winters for products with stable performance.

Table 5.1. Validation and verification of tools.

Tools	How were they validated and verified
Decision evaluation tools	A two-step validation system was executed for ABC-XYZ analysis reliability through assessments between internal consistency checks and external managerial evaluations. The methodology started by performing an internal verification method which independently computed both revenue share accumulations and demand variability measurements. The mathematical methodology showed that product categories classified as A, B, C and X, Y, Z produced identical results between original data and analysis outputs. The confirmation process established that the ABC-XYZ matrix correctly

	demonstrated all financial and demand variation thresholds established by the method. The internal operations team made a managerial review of the classification outcomes following an exhibition of the results. Internal discussions and feedback sessions established a match between the categorization of products as A-X with historically chosen items and the proper placement of A-Z and B-Z products which caused existing operational challenges. The ABC-XYZ model proved its worth to stock management operations through its successful real-world application. The matrix rankings from the ABC-XYZ analysis matched historical stock-out data alongside fulfillment records which confirmed their operational significance in past records. The combination of computational verification and managerial feedback as validation methods follows supply chain analytics best practices according to Ramanathan (2006) and Spieske et al. (2022). The ABC-XYZ matrix resulting from validation serves well as the vital basis for developing recommendations in subsequent sections.
Forecasting tools	The results of forecasting were validated using in-sample evaluation. MAE and MAPE error metrics were used in order to analyze the performance of the three selected models. The forecasted results on the datasets were compared to the actual demand during that period. Results of different models were then compared using these two error metrics and the best model one for each product was identified.
Planning tools	The results of the model were compared with a base scenario. A scenario assessment (optimistic, base, pessimistic demand) was carried out to check the stability of the model in case of deviation from the forecast. In each scenario, the total costs were calculated for three components: holding, ordering, and stockout. Comparing the total costs between the scenarios allowed us to determine how stable and effective the model is under different market conditions. For each month and scenario, the CSL indicator was calculated, reflecting the proportion of satisfied demand. CSL consistently remained high, which confirms the model's ability to provide a desired level of customer service. Sensitive adjustments were made to key parameters, including initial inventory level, order frequency, and cost structure. This made it possible to ensure that the model maintains adequate performance and stability when the input data changes.

Limitations

For forecasting tools, it is important to consider external factors since from the results of the forecasting analysis it was observed that ARIMA is the model that works the worst. It can be explained by the fact that it does not take into account any external factors that may influence units sold and is based on historical data only. Overall, all of the models show high deviations from actual values and it might be due to the fact that sales of the majority of the products were fluctuating a lot and there could have been other factors that influenced the sales that were not taken into the consideration due to insufficient data. Also, the data was provided for two years only and for P01, P02 some of the data was missing and analysis conducted could have been better if more accurate data was given. For forecasting, it is important to have more data because it can help to improve the performance of any model.

In addition, while the Holt-Winters model was able to capture seasonal patterns effectively, it still struggled to adapt when there were sudden changes or irregular sales trends. Holt-Winters also does not take external variables into account, which limits its forecasting accuracy for products influenced by factors such as promotions or market shifts. For forecasting, it is important to have more data because it can help to improve the performance of any model.

For decision evaluation tools, the inventory management optimization through ABC-XYZ analysis delivers useful insights to decision evaluation tools but companies need to consider its methodological and contextual boundaries which structure evaluation tools commonly encounter. Revenue-based historical records and demand fluctuation patterns formed the foundation of classification methods providing strong analytical capabilities but they presume future market trends will remain similar to the past data. Companies operating in dynamic markets encounter demand variations which historical records do not adequately predict since environmental, economic and seasonal and competitive market changes affect current patterns. Even though the adoption of standardized time frames together with detailed data cleaning practices brought about better reliability in the initial classification scheme.

The establishment of threshold limits for revenue contribution and demand stability categories involves subjective determinations in their setting. The established thresholds for supply chain literature followed common standards but slight modifications might change product classification results. Property evaluators agree that setting flexible boundaries for ABC-XYZ classification constitutes an acceptable part of implementing the model according to previous studies. The model focuses its result interpretations on revenue levels and forecast reliability but fails to include product importance or gross margins or supplier response times to enhance inventory optimization methods. Future model enhancements should incorporate multi-criteria frameworks to develop from the established current framework.

The validity of the classification system stands strong because of both internal performance checks and input from managers although their evaluations rest on their personal judgments. Findings gained strength from the assessment process which relied on the operational knowledge of a group with expertise in the company's supply chain system although this review method could miss sector-specific views applicable across different industries. The combination of quantitative alongside qualitative validation methods conforms to supply chain analytics best practices by producing overall accurate assessment results. Although it admits certain anticipated restrictions, the ABC-XYZ analysis creates a highly beneficial and efficient decision-making instrument. The organized inventory segmentation method provides operational benefits and establishes a strong foundation to advance strategic decisions concerning inventory planning, warehouse operations and procurement functions.

Even though proposed **planning tools** demonstrated the high adaptability and practical value in calculating the optimal order volume, it has some limitations that must be taken into account when interpreting the results and using the model:

- limited accuracy of demand forecasting: the model was based on forecasted demand, the accuracy of which directly affects the calculation of orders. Any deviations in forecasts can lead to excess inventory or stockouts.

- simplified cost assumptions: holding, ordering, and stockout costs were estimated based on industry data. Although these values were confirmed with the company representative, in reality, these values may vary depending on the season, suppliers, price fluctuations, and storage conditions.
- lack of logistical constraints consideration: the model does not include limits on available personnel, or other logistical constraints, which may affect the implementation of the proposed order volumes.
- CSL is calculated, but is not used as a limiter or objective function in optimization. In future versions, the model can be improved to take into account the dynamic control of CSL.
- the model does not take into account turnover and spoilage of goods. It is assumed that goods do not lose their value and do not have a limited shelf life, which is not always applicable, especially for materials that are sensitive to storage periods or conditions.

Conclusion

In this project, several supply chain analytics methods were implemented to improve the company's decision-making processes which are ABC-XYZ methodology from decision evaluation tools, Holt-Winters, ARIMA and ARIMAX from forecasting methods and scenario-based analysis from planning tools.

The ABC-XYZ methodology established a systematic process which businesses can use to organize inventory items by how much they contribute financially and how well their demand can be estimated. The research utilized Microsoft Excel as its primary instrument to handle and analyze the data. The calculated data included product-wide revenue totals and cumulative sales percentages in addition to monthly sales patterns from January 2023 through December 2024 by which sales data was systematically analyzed through pivot tables. Products received X, Y, or Z demand stability designations through the calculation of coefficient of variation (CV) which used standard deviation to mean monthly sales ratios for each product. Products were organized in revenue-descending order to achieve group categorization through predefined revenue thresholds that established A, B and C classifications. Through the planned implementation of pivot tables, revenue analysis and variability calculation the decision evaluation process gained full transparency while maintaining consistent mathematical integrity.

The ABC-XYZ matrix demonstrated significant descriptive results that summarized the product business structure. The product P03 which makes up 29.88% of total revenue is classified as an A-Z product while generating ₸173 million in revenue. This requires monitoring inventory because of the unpredictable nature of its demand. The P06 product earned around ₸63 million bringing financial importance alongside monthly demand stability at 1,491 units. The products within the P04 and P07 groups (both worth ₸72 million and ₸64 million respectively) needed flexible stock auditing through systematic procedures because they were classified as A-Y. The company determined P10 and P09 items respectively as B-Z and C-X categories which exposes opportunities for tailored inventory distribution decisions and lean financial resource allocation.

Operationally the provided methodology offers several clear advantages but this type of quantitative classification system contains several unavoidable limitations. The evaluation used isolated historical revenue patterns as its main input but this practice cannot guarantee proper depiction of future market patterns. The industry standard-based thresholds used for revenue share classification and demand variability had the potential to cause slight changes in classifications when the administrators redefine these thresholds. The ABC-XYZ model excluded specific business performance indicators like profit margins as well as supplier lead times and products' business strategy significance. Results should be interpreted by management teams through business intelligence alongside their quantitative outputs while staying attentive to market changes that could need periodic revalidation of the applied classifications.

While taking into account these factors the ABC-XYZ framework delivers substantial benefits within managerial operations. The organized prioritization process helps managers optimize warehouse real estate distribution and develop procurement strategies for essential items and establish safety measures for unpredictable demand commodities. Companies should optimize their reorder points with safety stock policies for their high-revenue items with stable demand patterns yet need dynamic forecasting and scenario planning for monitoring their volatile financial significant inventory. The ABC-XYZ analysis allows managers to develop actionable decision-making foundations through quantifiable inventory segmentation which leads to service level improvement and reduced carrying costs and inventory loss and better supply chain response. This decision evaluation tool drives organizations to transition from unplanned inventory management toward strategic supply chain leadership which builds both financial strength and organizational stability in modern dynamic business sectors.

After completing the ABC-XYZ analysis, all three forecasting methods were implemented for the company - Holt-Winters, ARIMA, and ARIMAX - to find out the most effective one in forecasting the demand for the given dataset. The results have shown that Holt-Winters performed the best for products with stable demand, trends and seasonality whereas ARIMA forecasted accurately for products with periodic fluctuations. Moreover, the best performance was achieved by ARIMAX, which included exogenous variables like promotions and seasonality to forecast demand for products with highly unpredictable demand. Even though models performed well compared to each other, the overall MAE, MAPE results were not satisfactory for the accurate prediction of demand. Forecasting accuracy across all models was affected by the limited data availability and the overall instability of the market environment.As a result of the ABC analysis it was identified that P03 is the most profitable product for the company and if it is important for the company to choose one model - ARIMAX might be the best choice since it showed the best performance for the products that accounted for more than 50% of the sales.

After receiving demand forecasts based on the selected model (Holt-Winters, ARIMA, ARIMAX), an instrumental model was developed and implemented to determine the optimal order volume for each month. Unlike the classical EOQ approach, which assumes a fixed and uniform order for the entire period, the proposed model is based on a monthly demand forecast and dynamically determines the order volume. EOQ is used solely as a base value, on the basis of which further optimization modeling in Python takes place.

The model takes into account various parameters of each product: forecasted demand, initial and final inventory levels, as well as several costs (holding, ordering and stockout costs). In addition, the CSL was introduced as an indicator of efficiency, which provides an understanding of how well the proposed solutions meet the company's goals of minimizing stockouts and increasing customer satisfaction.

To increase the reliability of the model, a scenario analysis was carried out: base, optimistic and pessimistic scenarios were created. This approach evaluated the behavior of the model in case of deviation from the expected demand. As a result, potential cost savings and optimal inventory levels were identified. For instance, results showed that optimistic and pessimistic scenarios may provide up to 4,010,468.89 and 2,316,055.13 tenge in cost savings, respectively.

Thus, our hypothesis that the combined framework consisting from decision evaluation tool, forecasting tools and planning tool can improve the supply chain performance of the SME was proved. The developed model provides the cohmpany with a flexible and scalable tool that allows it to make informed decisions on replenishment, reduce costs and maintain a high level of customer service. The implementation of this model can significantly increase the transparency and adaptability of supply chain management processes.

Directions for future research

While the current study demonstrates the potential of integrating forecasting, decision evaluation, and planning tools into the supply chain management process for SMEs, several opportunities remain for further investigation.

Firstly, future research could explore the incorporation of more advanced machine learning techniques, such as XGBoost, LightGBM, or deep learning-based time series models (e.g., LSTM networks). These methods may offer superior forecasting accuracy, particularly in environments with highly volatile or non-linear demand patterns. Comparing traditional statistical models with machine learning approaches on larger datasets would provide deeper insights into performance differences and model robustness.

Secondly, although external variables such as seasonality and promotions were considered in the ARIMAX model, a more comprehensive inclusion of diverse exogenous factors (e.g., macroeconomic indicators, competitor activities, weather conditions) could further enhance forecast accuracy. Future studies could systematically assess the impact of various external drivers on demand forecasting performance across different product categories.

Thirdly, the development of dynamic, real-time inventory management frameworks represents a promising avenue. Integrating live sales data, supplier lead times, and logistic constraints into adaptive forecasting and planning models could significantly improve responsiveness and minimize the risk of stockouts or overstocking. Future research could propose architectures for automated, real-time decision support systems tailored to SMEs.

Moreover, expanding the scope beyond a single company and conducting cross-industry comparisons would add significant value. Investigating how supply chain analytics frameworks perform across various sectors, such as retail, manufacturing, or healthcare, would enable the generalization of findings and reveal industry-specific best practices. Finally, further exploration of sustainability aspects within supply chain optimization models is necessary. Future work could integrate environmental and social impact metrics into decision evaluation tools, promoting more responsible and ethical supply chain practices in line with global sustainability goals.

In conclusion, while this study establishes a foundation for integrating supply chain analytics into SME decision-making, the rapid advancement of technologies and the increasing complexity of global supply chains require continuous research. By addressing these future directions, scholars and practitioners alike can contribute to the creation of more resilient, efficient, and sustainable supply chain systems.

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