applied sciences

Article

Time Series Methods and Business Intelligent Tools for Budget Planning—Case Study

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Abstract: Corporate budget planning involves forecasting expenses and revenues to support strategic goals, resource allocation, and supply chain coordination. Regular updates to forecasts and collaboration across organizational levels ensure adaptability to changing business conditions. Long-term sales forecasts form the foundation for budgeting, guiding resource allocation and enhancing financial efficiency. The budgeting process in organizations is complex and requires data from various operational areas, which is collected over a representative period. Key inputs include quantitative sales data, direct costs indirect costs, and historical revenues and profitability, which are often sourced from ERP systems. While ERP systems typically provide tools for basic budgeting, they lack advanced capabilities for forecasting and simulation. We proposed a solution, which includes dynamic demand forecasting based on time series methods such as Build-in method in Power BI (which is ETS—exponential smoothing), linear regression, XGBoost, ARIMA and flexible product groupings, which are simulations for cost changes. The case study concerns a manufacturing company in the mass customization industry. The solution is designed to be intuitive and easily implemented in the business.

Keywords: data-driven decision making; predictive methods application; AI-related management; machine learning; ERP and BI systems

Academic Editors: Carlos J. Costa and Manuela Aparicio

Received: 30 November 2024
Revised: 27 December 2024
Accepted: 28 December 2024
Published: 31 December 2024

Citation: Grobler-Dębska, K.; Mularczyk, R.; Gawęda, B.; Kucharska, E. Time Series Methods and Business Intelligent Tools for Budget Planning—Case Study. *Appl. Sci.* **2025**, *15*, 287. https://doi.org/10.3390/app15010287

1. Introduction

Creating budgets for the upcoming year is a crucial element of a company's strategic planning. A budget is a structured plan, typically financial, but not exclusively, that is designed for a specific timeframe, often a year. It may include projected sales volumes and revenue, resource allocations, costs and expenses, environmental considerations such as greenhouse gas emissions, as well as other factors such as assets, liabilities and cash flows. It enables companies to better manage their resources, plan the supply chain, prepare for future investments, and achieve financial goals [1].

Corporate budget planning involves forecasting future expenses and revenues, which is essential for strategic financial planning, supply chain planning, resource management, and achieving organizational goals. The appropriately constructed budgets help companies forecast the financial resources needed to achieve the goals (e.g., increase in sales, purchase of new machinery, adequate staffing) and identify potential financial obstacles (e.g., fluctuations in exchange rates, unforeseen expenses for emergency equipment repairs, increases in raw material costs) in advance. By effectively planning budgets, companies can achieve tighter control over expenditures, revenues, and potential investments, ultimately leading to cost efficiency and increased profitability by identifying areas that require close monitoring. Budgeting is crucial to effective business management [2]. Effective budgeting involves regularly updating cost and revenue forecasts and adapting them to changes in business conditions. It is a dynamic process that requires the participation of management and employees at every level of the company. Budgeting requires long-term sales forecasts that serve as the foundation for demand planning in the supply chain. Based on these forecasts, a company determines the quantity of raw materials, products, or services needed, which in turn influences the allocation of funds in the budget.

For organizations dealing with complex decision-making environments, budgeting methods can provide sophisticated tools to enhance objectivity and manage uncertainties. By understanding and selecting the appropriate budgeting method, organizations can optimize their financial and volume planning and improve overall effectiveness [3]. Therefore, in the rapidly changing market environment, where companies must respond quickly to new challenges and opportunities, accurate forecasting and a flexible approach to budgeting are crucial. Unfortunately, traditional methods often prove insufficient in the face of increasing data complexity and the need to integrate various scenarios and data. There is a lack of tools that intuitively support this process.

The contribution of the paper is a solution to support appropriate budget planning in the company using an ERP system that combines time series data prediction methods with a BI system. A solution allows the use of advanced forecasting methods, with the possibility of hierarchical forecasting at different levels of aggregation of the company's data, along with the possibility of simulating changes in exchange rates or including the possibility of simulating the growth defined by the management. An important aspect of our solution is its ease of implementation in the industry, which is facilitated by the utilization of Business Intelligence (BI) systems. These systems are increasingly adopted by companies primarily due to their user-friendly interfaces, which enable seamless use by employees.

The paper is organized as follows. In Section 2, we present a review of the literature on quantitative and value strategic planning methods for budget. Section 3 includes an analysis of the budgeting process and its support with the ERP system tools. In Section 4, we describe the case study and solution to support budgeting with predictive methods and Business Intelligence tools. The last Section 5 contains conclusions and future work.

2. Methods of Quantitative and Value Strategic Planning of Budget

Budgeting methods are essential tools that organizations use to manage their finances efficiently and align their resources with strategic goals. The choice of a budgeting method can significantly impact how resources are allocated, costs are controlled, and performance is evaluated. This section provides a literature overview of various budgeting methods, each with its unique approach and advantages, ranging from traditional methods to more dynamic and performance-focused techniques.

The following types of budgeting methods can be distinguished:

- Incremental-Based Budgeting (IBB) is a traditional budgeting method where the previous period's budget serves as the base. Adjustments are then made for the new period based on expected increases or decreases in costs. This approach assumes that future expenses will be similar to past ones with only incremental changes [4,5].
- Performance-Based Budgeting (PBB) allocates funds based on the achievement of specific, measurable performance goals and outcomes. This method links the funding of programs to their results, aiming to improve efficiency and effectiveness in resource allocation [5,6].
- Activity-Based Budgeting (ABB) is a budgeting method that focuses on identifying and analyzing activities that incur costs within an organization. The budgets are then

developed based on the costs associated with these activities. This approach aims to create efficiencies by scrutinizing every activity that leads to costs [5,7].

- Zero-Based Budgeting (ZBB) is a budgeting method where every expense must be justified for each new period, starting from a "zero base". Unlike traditional budgeting, which adjusts previous budgets, ZBB requires a fresh evaluation of all expenses, ensuring that only essential and efficient costs are included [5,8].
- Priority-Based Budgeting (PYBB) allocates funds based on the priorities and goals of an organization. This method identifies the most important goals and directs resources to areas that align with these priorities, ensuring that spending is focused on achieving key outcomes [5].

The above-mentioned forecasting methods only use descriptive analysis techniques, indicating which indicators or underlying data should be taken into account in budgeting. They do not provide analytical tools for evaluating indicators or priorities but rely on internal expert judgement.

In addition to the methods mentioned above, decision-making processes in the budgeting framework can be supported by advanced techniques of advanced decision making, including the following:

- Multiple criteria decision making (MCDM) is a critical approach (rather one particular method) in strategic planning, enabling organizations to evaluate and prioritize multiple competing criteria [9]. By quantifying subjective judgments, MCDM reduces bias and enhances the objectivity of the decision-making process. Some methods considered as part of MCDM are: simple additive weighting (SAW), technique for order preference by similarity to ideal solution (TOPSIS) [10], or analytic hierarchy process (AHP) [11].
- The Quantitative Strategic Planning Matrix (QSPM) method is designed to objectively evaluate and prioritize strategic alternatives based on input provided by the user [12]. It offers a quantitative approach, enhancing objectivity and rigor in strategic planning. QSPM requires identifying key factors influencing considered decisions; then, weights are assigned to factors and attractiveness scores to decisions. Based on those inputs, Total Attractiveness Scores are calculated, allowing us to compare those options. This method is widely used [13,14].
- Fuzzy methods introduced by Zedah are a collection of methods based on fuzzy logic [15]. As its name suggests, those methods excel in situations where membership criteria are not precisely defined and are used to enhance the robustness and reliability of strategic planning by providing a structured way to deal with the inherent uncertainties in strategic decision making. These methods are particularly useful when dealing with complex and ambiguous strategic issues.

The above-described methods require specialized mathematical knowledge and advanced modeling for the specific business case. They are used for qualitative analysis and the evaluation of alternative scenarios when, for example, organizations need to allocate scarce resources between competing business objectives or determine business priorities, or when data are incomplete.

All of the above-described methods can be supplemented with time-series-based forecasting results by providing financial and operational projections for future periods. They can support decision-making processes by providing information on trends and seasonality in the analyzed data.

2.1. Forecasting Methods

Forecasting methods are useful for budgeting, as they enable forecasting future values. Traditional econometric methods, such as exponential smoothing, ARIMA, and regression models, have long dominated time series analysis, providing tools to interpret trends and seasonality. Additionaly, advances in technology and machine learning have opened new opportunities, introducing more sophisticated models capable of processing complex patterns of data. In recent years, models based on Transformer architectures have received particular attention, such as NBEATS [16], N-HiTS [17], TFT [18] and PatchTST [19], which are characterized by their ability to efficiently process and forecast time series data. These models are distinguished by their high performance on benchmark sets.

However, there is still a gap in business where forecasting tools are not used due to a lack of employee skills [20]. Therefore, in the first stage of our research, closely related to business needs, we start with the following classical methods: exponential smoothing, linear regression, ARIMA, and XGBoost. Below is a brief description of the exponential smoothing, linear regression, XGBoost and ARIMA methods with examples of use.

2.1.1. Exponential Smoothing

The Holt–Winters method, which is often referred to as exponential smoothing for time series with a trend and seasonality, is a widely used and simple forecasting technique. Its main objective is to predict future values based on historical data, considering two main model variations: additive and multiplicative [21].

This method is based on the iterative analysis of two basic components of a time series: the trend and the seasonality of the series.

- Trend refers to long-term changes in the level of a time series. In the Holt–Winters model, the evolution of the trend is modeled by means of progressive smoothing, which is the estimation of the changes in the level over time. In the case of a linear trend, the additive approach is used. The multiplicative model is used when the trend shows an exponential rise or fall.
- Seasonality refers to cyclical patterns that occur in the data at regular intervals, such as monthly or quarterly. The Holt–Winters model takes this into account by using exponential smoothing for seasonal periods. When seasonal fluctuations are constant over time, an additive model is used. When the amplitude of the seasonal fluctuations changes proportionally to the level of the time series, a multiplicative model is preferred.

In paper [22], the authors analyzed the prediction of electricity consumption in office buildings using different forecasting methods such as the Holt–Winters model, ARIMA/SARIMA and neural networks. The purpose of this study was to compare the effectiveness of classical statistical methods with modern approaches based on artificial intelligence. The results show that relatively simple methods, such as exponential smoothing or ARIMA/SARIMA, significantly outperform more advanced neural network-based methods. This finding suggests that when analyzing data of a specific nature, simple statistical models may be more effective and practical than complex AI. The obtained results can be used to determine the expected costs of electricity consumption in the budget of enterprises with a large number of office properties of different types.

The paper [23] presents the development of an innovative hybrid model that is dedicated to the very short-term forecasting of the electricity consumption of Chinese households. The model integrates the HW technique, which is used to analyze the linear part, with the ELM net, which is used to analyze the nonlinear part. The input data were preprocessed using a moving average filter, and the prediction was performed in two stages: the linear components were analyzed using HW, while the nonlinear components were analyzed using ELM. The results of the investigation showed that the hybrid HW and ELM model outperforms other methods in terms of both accuracy and efficiency, especially for limited training datasets, and confirms its potential as an effective tool to predict electricity consumption. Thus, it can be useful in estimating household budgets that take into account the necessity of electricity consumption of household appliances.

Paper [24] uses data from 2012 to 2022 to predict rainfall in the Abiansemal area, where agriculture is highly dependent on weather. The analysis included a comparison between additive and multiplicative models. The results showed the higher efficiency of the multiplicative model in the context of rainfall forecasting. However, both model configurations had high error values. This indicates a limited prediction accuracy, especially under variable weather conditions. Despite these limitations, the authors consider the multiplicative model to be a more adequate tool for the prediction of future rainfall trends while at the same time suggesting the need for further improvement of the methodology.

The article [25] uses Holt–Winters exponential smoothing to forecast the demand for an antibiotic used to treat COVID-19. It considers the impact of the pandemic on the increase in demand in March 2020 and analyzes consumption of the drug from 2017 to 2020. The results show that before the pandemic, the model accurately reproduced actual consumption, while the significant deviations in the forecasts from February 2020 onward were due to unexpected changes in consumer behavior linked to the pandemic. This suggests that the model can be used to forecast demand in dynamic and unforeseeable contexts.

2.1.2. Linear Regression

Linear regression is a statistical technique used to model the relationship between a dependent (explanatory) variable and one or more independent (explanatory) variables [26]. The key assumption is that the relationship between the variables is linear, meaning that changing one causes the other to change proportionally. The values of the independent variables are used to predict the values of the dependent variable when forecasting using this model. This method is widely used in economics, social sciences, and data analysis. It is simple, and the results are easy to interpret.

The linear regression model defines the straight line equation:

$$y = \beta_0 + \beta_1 x + \epsilon$$

where

β_0—the intercept;

β_1—the regression coefficient;

ϵ—represents the random error.

The paper [27] compares three forecasting methods—linear regression, exponential smoothing, and weighted moving average—on the basis of the lowest values of the forecast errors. The results show that linear regression is the most accurate. Analysis of the tracking signal and moving range values confirmed that the method results were within acceptable control limits, indicating its accuracy and reliability. The linear regression method is therefore considered to be suitable for making predictions and providing a basis for making decisions in the future.

The paper [28] presents one-dimensional models for short-term electricity demand forecasting using linear regression and daily cycle patterns in time series. These patterns simplify the problem by eliminating trend, seasonality, and mean and variance nonstationarity, allowing local modeling of relationships between variables. Techniques that reduce the number of predictors and facilitate data visualization include stepwise regression, lasso, principal components, and PLS. The high accuracy of the proposed approaches is confirmed by comparison with other methods such as ARIMA, neural networks, and exponential smoothing.

2.1.3. XGBoost

XGBoost (Extreme Gradient Boosting) is an advanced machine learning algorithm based on the gradient boosting framework, which is optimized for both speed and performance [29]. It builds an ensemble of decision trees in a sequential manner to minimize errors in predictions. The algorithm introduces regularization techniques to reduce overfitting and handles missing values effectively, making it particularly suitable for large and complex datasets.

The study [30] evaluates the performance of XGBoost in predicting real estate prices. The research shows that XGBoost outperforms traditional models such as linear regression and decision trees in terms of prediction accuracy. Its ability to capture complex nonlinear relationships between features and target variables is highlighted as a key advantage.

In [31], the authors applied modified XGBoost to forecast stock market trends. The study employs a novel multi-objective optimization approach to fine-tune model parameters, integrating factors like volatility and return rates. This framework leverages XGBoost's ability to handle large datasets efficiently, aiming for a robust, risk-adjusted investment strategy. Through backtesting, the proposed model demonstrated performance in predicting stock trends compared to traditional methods, highlighting its potential in financial decision-making scenarios.

The paper [32] explores the use of XGBoost to predict solar energy output. The model's high predictive accuracy and low computational cost make it a preferred choice for real-time forecasting applications. The study emphasizes the flexibility of the algorithm in integrating additional meteorological features, further improving the forecast precision.

2.1.4. ARIMA

ARIMA (Autoregressive Integrated Moving Average) is a time series analysis technique for forecasting future values on the basis of historical data.

This method is effective when the time series tend to trend or vary seasonally. ARIMA has three main components:

- Autoregression (AR): models the relationship between current and past series values, where the value is determined as a linear combination of past observations and random errors.
- Differentiation (I): transforms the time series into a stationary form by calculating the differences between successive values, thus eliminating the trend and the seasonality.
- Moving Average (MA): models the relationship between the current value and errors in previous times, removing the influence of these errors on the predictions.

ARIMA models are defined by three parameters: p (lag number in AR models), d (differentials) and q (lag number in MA models). The appropriate values for these parameters are selected by analyzing graphs [33].

The article [34] examines the use of ARIMA models to forecast the spread of the COVID-19 pandemic. The study shows how ARIMA models, despite their limitations in dealing with complex and dynamic scenarios, can be effective in forecasting the short-term evolution of the pandemic, which is of crucial importance for public health strategies. Although the results show high prediction accuracy in the short run, prediction errors are found to increase with the length of the prediction horizon. The article highlights challenges related to COVID-19 data quality in Brazil but shows the potential of ARIMA models for short-term forecasting, suggesting the need for further research to improve long-term forecasting.

The article [35] analyzes the application of the ARIMA model in forecasting Gross Domestic Product (GDP). A detailed review of the literature is carried out, which shows that two models—ARIMA (2, 2, 2) and ARIMA (3, 1, 1)—are commonly used in the study of treasury bills. In addition, the use of ARCH and GARCH models in GDP analysis is proposed. The expenditure approach is recommended as a method of measuring GDP.

The article [36] examines the frequency of fires in China. Their regularity allows the SARIMA model to be used to predict when fires start to burn. The results presented in the article demonstrate the effectiveness of the method used.

In summary, the above examples of the application of forecasting methods show their usefulness in various spheres of life and the economy. The results of these methods can be extremely useful in creating budgets, whether for individual households, businesses, or other large organizations.

3. Analysis of the Budgeting Process and Its Support with ERP Systems Tools

The process of defining an organization's budget, usually for the following year, is a multi-stage process that includes analyzing data from various areas of the company, planning expenses and revenues, and approving the budget. This process is commonly divided into several steps:

1. Defining the company's goals and strategies, such as revenue growth, profitability, debt reduction, etc.
2. Analyzing past financial performance to understand which areas performed well and where issues arose. This includes a detailed review of operational and material costs as well as a revenue analysis.
3. Revenue forecasting: Estimating revenue based on market expectations, trends, and customer order forecasts.
4. Cost forecasting: Estimating costs, including operational costs, production costs, wages, marketing expenses, and other expenditures.
5. Developing a preliminary budget based on departmental budgets: Each department (e.g., marketing, production, sales) prepares its own budget aligned with the company's overall objectives.
6. Data aggregation: Compiling budgets from individual departments to create a comprehensive company budget.
7. Risk and opportunity assessment: Identifying potential financial risks and opportunities that could impact the budget.
8. Goal alignment verification: Ensuring that the preliminary budget aligns with the company's strategic goals and is realistic.
9. Negotiations and revisions: If needed, the budget may be adjusted following negotiations among various departments.
10. Budget approval: The preliminary budget is presented to the company's management for approval. Once accepted by the board, it becomes the official financial plan for the upcoming period.
11. Budget monitoring and control: Continuous monitoring of financial performance compared to the budget, such as through monthly or quarterly reports, allows for the identification and analysis of budget deviations and enables corrective actions when necessary.

Thus, the budgeting process in organizations is a complex process that takes into account many different aspects. An essential element for the implementation of the budget is data on various areas of activity and sourced in an appropriate manner and a representative period of time. The budget process requires gathering data across the organization, most often recorded in an ERP system, followed by cross-sectional analysis and forecasts, including the following:

- Quantitative sales data;

- Direct costs such as materials, storage, logistics, manufacturing;
- Indirect costs like administrative, general management, energy, heating, and water;
- Historical revenues and profitability.

3.1. Supporting Budgeting by ERP Systems

The ERP system (Enterprise Resource Planning) allows easy access to consistent and up-to-date information by combining data from several company departments into a single database. Centralizing data enables more accurate forecasting and analysis, and this is crucial for effective budgeting. ERP systems reduce errors and save time by streamlining a number of standard financial and accounting operations. This automation facilitates efficient data processing for budgeting, including liquidity management, expense tracking, and report preparation. With the help of ERP, companies can effectively monitor and control expenses. These tools help discover possible areas of cost reduction and analyze the impact of different scenarios on fixed and variable costs. They also facilitate a detailed tracking of operating and production costs. This makes ERP systems extremely necessary for effective corporate budget planning.

Many modern ERP systems offer tools to support budgeting. In particular, the largest ERP systems include the following functionalities related to forecasting, planning, and creating budgets for organizations [37–40]:

1. SAP ERP (including SAP S/4HANA)
    - SAP BPC (Business Planning and Consolidation) module—a budgeting, forecasting and consolidation tool. Enables scenario simulation, forecasting, reporting, and deviation analysis.
    - SAP Analytics Cloud—enables planning, analysis and forecasting using financial and operational data.
    - SAP Integrated Business Planning (IBP)—an extension of SAP S/4HANA, which is particularly useful for demand planning and budgeting based on demand forecasts and production costs.
2. Oracle ERP Cloud
    - Oracle Planning and Budgeting Cloud Service (PBCS)—part of Oracle EPM (Enterprise Performance Management), offers support for budgeting, forecasting and scenario analysis. It includes tools for cost analysis and revenue forecasting.
    - Oracle Financials Cloud—a financial management module with budget monitoring capabilities integrating data from different business units.
    - Oracle Analytics Cloud—supports advanced budget analytics and forecasting
3. Microsoft Dynamics 365 Finance—includes built-in planning and budgeting tools to forecast and manage financial budgets. Integration with Power BI and Azure AI enables predictive analytics to support revenue and cost forecasting processes.
4. Infor Cloud Suite (including Infor LN, Infor M3)
    - Infor d/EPM (Dynamic Enterprise Performance Management)—a tool that offers support for planning, budgeting and financial consolidation. It also supports reporting.
    - BI tools and analytics—thanks to integration with Infor Birst analytical tools, the system enables budget forecasting and analysis.
5. IFS Cloud
    - IFS Planning and Budgeting—IFS offers planning and budgeting tools within its ERP system, allowing for the creation of budgets, financial forecasts and profitability analysis. It also enables integration with manufacturing and operations modules to help better estimate costs.

- IFS Analytics—an analytics module that supports budget reporting and deviation analysis, which allows for detailed performance monitoring.

6. Epicor ERP
    - Epicor Financial Management—includes features for financial budgeting and forecasting.
    - Epicor BI and Data Analytics—supports forecasting and budget analysis based on historical and current data, allowing the creation of reports and cost analysis.
7. Unit4 ERP
    - Unit4 Financial Planning and Analysis—a comprehensive tool for planning, forecasting, and budgeting with flexible financial modeling capabilities. It allows variance analysis from the budget and creating alternative financial scenarios.
    - Business World Module—supports comprehensive operational budget management, enabling budget scenario simulations and integration with HR data and employment-related costs.
8. Sage Intact—Sage Budgeting and Planning—a tool for budget management and forecasting. It is easily integrated with other Sage modules, enabling accurate financial planning and performance analysis.

3.2. Challenges and Constraints in Budgeting in ERP Systems

The budgeting modules in ERP systems, despite their advanced features, often have certain limitations and drawbacks that can reduce their effectiveness [20,40]. There are some common challenges and constraints in this area:

- Limited Flexibility and Customization—Many ERP systems offer budgeting modules with a fixed set of features that may not meet the specific requirements of a company. For example, the budgeting process in a service-based company can differ significantly from that in a manufacturing firm. High standardization in ERP can make it challenging or costly to adapt to the unique financial models of a company. Customization and report tailoring often require the involvement of developers.
- Limitations in Advanced Analytics and Forecasting—Many ERP systems focus more on historical budget data than on advanced forecasting models. These modules do not always support modern predictive techniques, such as machine learning-based analysis. More advanced tools, such as scenario analysis or dynamic financial modeling, are often limited or require additional modules and tools, e.g., analytical solutions outside the ERP system.
- Scalability and Performance—ERP systems may encounter performance issues when processing large volumes of budgetary and analytical data, especially when used on older hardware or without proper configuration.
- Scaling for Larger Organizations: Larger companies with more complex structures often face challenges in creating consolidated budgets, particularly when aggregating data from multiple divisions or regions. Complexity of Use and Training Needs
- Complex Interface: The budgeting modules in ERP are often extensive and have complex interfaces that require user training. Understanding and efficiently using budgeting functions takes time, and user errors can lead to inaccurate budgeting.
- High Entry Barrier: Non-technical users may struggle with complex budgeting and reporting functions. Companies often need to invest in training or hire dedicated ERP specialists.
- Limited Reporting and Visualization Capabilities: Visualization features in ERP systems are often limited compared to dedicated BI tools such as Power BI or Tableau, which restrict the ability to create clear and interactive reports for management.

- High Implementation and Maintenance Costs: Most budgeting modules, especially those with complex configurations, come with high costs for licensing, technical support, and periodic updates.
- Issues with Integration with External Data.

Although most of the necessary data for budgeting data can be accessed in an ERP system and large ERP systems include functions to support budgeting, there are generally no tools available for advanced budget forecasting and simulation, such as the following:

- Advanced demand forecasting;
- Forecasting with dynamic product groupings;
- Budget simulation in response to changes in costs, e.g., energy, materials, or currency rates;
- Long-term material planning, with the ability to account for incomplete planning BOMs.

4. Supporting Budgeting with Predictive Methods and Business Intelligence Tools

The limitations of ERP systems outlined in the previous section mean that other tools and methods are needed for budgeting. Thus, as part of the solution, it is proposed to leverage the advantages of Business Intelligence (BI) systems, such as the following:

- Integration with Python, allowing the application of relevant libraries for advanced predictive modeling and data analysis.
- Comprehensive visualization capabilities, enabling clear representation of key metrics, trends, and analysis results in real time.
- New options for defining persistent editable fields in dashboards, which, when combined with integration into the ERP system, facilitate the creation of interactive "what-if" scenarios. This approach allows users to make dynamic adjustments and assess their impact on key business metrics.
- An intuitive user interface, enabling ease of use even for individuals without advanced technical expertise.

"What-if" scenarios play a critical role in the company's budgeting process, enabling the simulation of various business development scenarios and assessment of risks and opportunities. Furthermore, BI systems support decision-making processes by automating reporting and providing access to up-to-date data, thereby enhancing the efficiency of strategic actions.

4.1. Business Intelligence Systems

Business Intelligence systems, also known as programs or applications, are employed by enterprises and organizations to effectively manage various types of data, including data pertaining to warehouses, customers, employees, and products. These systems play a crucial role in processing, altering, and modeling data to ensure that each type meets the company's standards. Additionally, businesses often use multiple programs or systems to gather data, making it necessary to use these systems to consolidate data from diverse sources. As a result, these systems are used to visualize and report on the current status of the company. The systems are equipped with basic chart capabilities including line charts, bar charts, and tables. However, with modern capabilities, we have the option to connect with a community that builds its own chart database. This enables us to utilize charts shared by other members of the user community. Users can share their own charts and select from charts shared by others, which can enhance efficiency and interest during visualization creation. Furthermore, utilizing programming languages like Python or R allows for the use of visualization libraries (matplotlib, seaborn, ggplot, plotly) to generate dynamic charts, providing extensive opportunities for data analysis. By using programming languages, we can improve our data analysis capabilities, which includes predicting future data and evaluating our company's performance while recognizing important trends. We analyze how different variables are related and how these correlations affect each other. Examining past data allows us to identify areas of improvement within the company and recognize the factors contributing to our success. These systems enable us to integrate data from various sources into one central location seamlessly.

The selection of Power BI to our solution was based on a Gartner report that evaluates BI platforms according to key criteria such as ease of use, analytical functionality, and integration with other systems. Ranked as a leader in the field, Power BI meets the requirements to create interactive reports and data visualization. It is a scalable and innovative tool. The most important elements included in the system are the following:

- Connectivity to various data sources, which allows for easily integrating data from many sources (MS Excel, databases, cloud services, ERP systems) into one central report.
- Wide integration with all tools and programs provided by Microsoft. This allows for the easy sharing of reports and helps with collaboration (via MS Teams services). It also allows for creating interesting and quick reports (Power Point).
- Possibility to model data and use advanced analytical techniques using a specially dedicated DAX language and scripts in Python and R. This allows for creating predictive and ML models.
- Modern, interactive visualizations that are built-in, but also co-created by the Microsoft community. Additionally, the use of Python and its libraries provides a larger visualization base.

4.2. Advanced Forecasting Methods in Power BI Support Organization's Budgeting—Case Study

The case study concerns a manufacturing company, in the mass customization industry, selling its products to various retail chains, to different markets, and from several branches. Planning the budget for the next year on the basis of last year's budget and management's planned growth does not work due to the high volatility of demand for individual finished products and the significant impact of changes in currency exchange rates. Budget planning determines the sales target related to the appropriate determination of the volume of contacts with key customers for the next year.

As part of the considered case study, historical data from the company were collected in the following areas: sales, lost sales, sales prices, production costs of sales parts, sales markets, product structures, and the location of the company managing sales orders. The data were extracted from the company's ERP system and include the six most important product groups. These groups include 175 finished products, representing approximately 10% of the company's total sales parts. The product groups were defined such that sales parts that contain the same key semi-finished product were grouped together. The data cover the period following the COVID-19 pandemic, which significantly altered the sales market, specifically from July 2021 to July 2024. Thus, the time series spans 36 monthly periods. This quantitative sales history data allow for the decomposition of the series into trend and seasonality components. The collected selling prices enable time series analysis not only in terms of quantities but also in value.

In the proposed solution, the budget is constructed based on forecasts for sales groups, which can be analyzed and subjected to "what-if" scenarios across multiple dimensions, such as customer, sales market, company branch, or the entire organization. The flow of data and information between the ERP system and the proposed solution is presented in Figure 1.

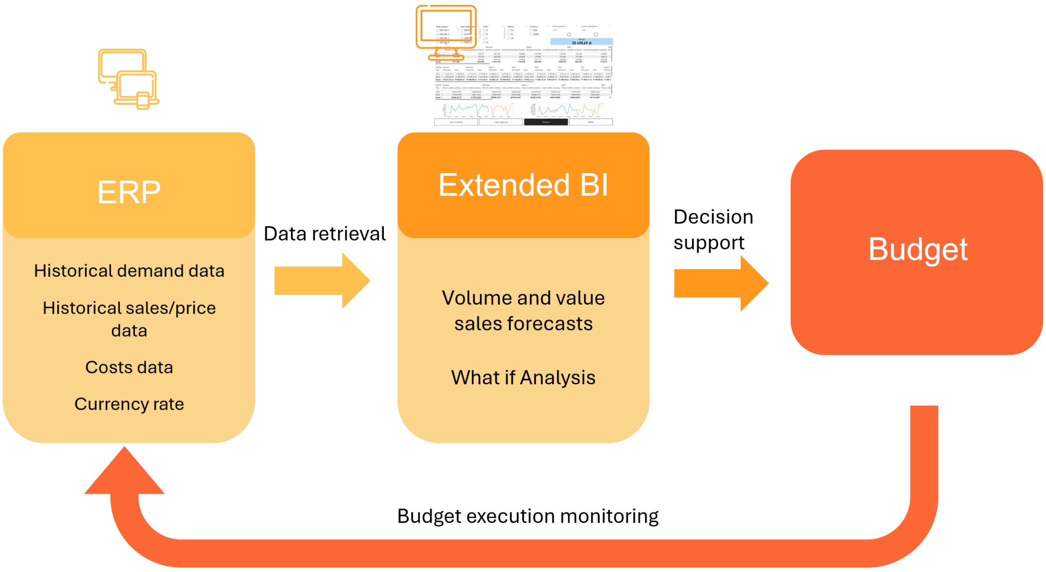

Figure 1. The figure shows the flow of data and information in the proposed solution. Quantitative and value forecasts and what-if analyses are carried out based on data from the ERP system. Data on historical sales, lost sales, selling price in different periods, manufacturing costs, changes in currency exchange rates, distribution and sales system are the basis for forecasts and what-if analysis. Based on these results, a budget can be calculated. Verification of budget execution will be based on transactions executed in the ERP system.

In budgeting, it is essential to not only forecast the quantity and value of sales based on time series analysis but also enable scenario analysis considering factors such as an increase in sales volume driven by management-defined goals, projected price increases, or currency exchange rate changes.

In addition, the actual production costs of the sold items are analyzed, integrating three key areas: material production, sales costs, and financial forecasts in different currencies. Introducing a dynamic recalculation of sales costs in selected currencies serves as a valuable tool in an international context. This allows for drill-down analysis. In the proposed solution, this is achieved through a currency slicer that allows users to simulate the impact of fluctuating exchange rates on financial results.

The forecasting functionality supports strategic decision making. For budgeting purposes, long-term forecasts are required, which are often subject to significant errors. In this case, it is more advantageous to forecast aggregated data for product groups. Furthermore, integration with Python has been implemented, enabling the use of advanced forecasting methods, such as the Built-in method in Power BI (which is ETS—exponential smoothing), linear regression, XGBoost, and ARIMA.

The proposed dashboards consist of the following components:

- Filtering and grouping parameters such as finished products, grouping of products by key semi-finished components, customer segmentation by markets, and company branches;
- Field for determining the assumed increase in sales, field for completing the exchange rate;
- Tables showing historical demand by quantity, value and costs;
- Calculated margin;
- Forecast chart sales volume and sales value.

The solution is presented in the figures, where the budget effect using different forecasting methods is shown: the Build-in method in Power BI (which is ETS—exponential smoothing) in Figure 2, linear regression in Figure 3, XGBoost in Figure 4, and ARIMA in Figure 5. The last figure collectively shows the analysis of all methods, which is Figure 6.

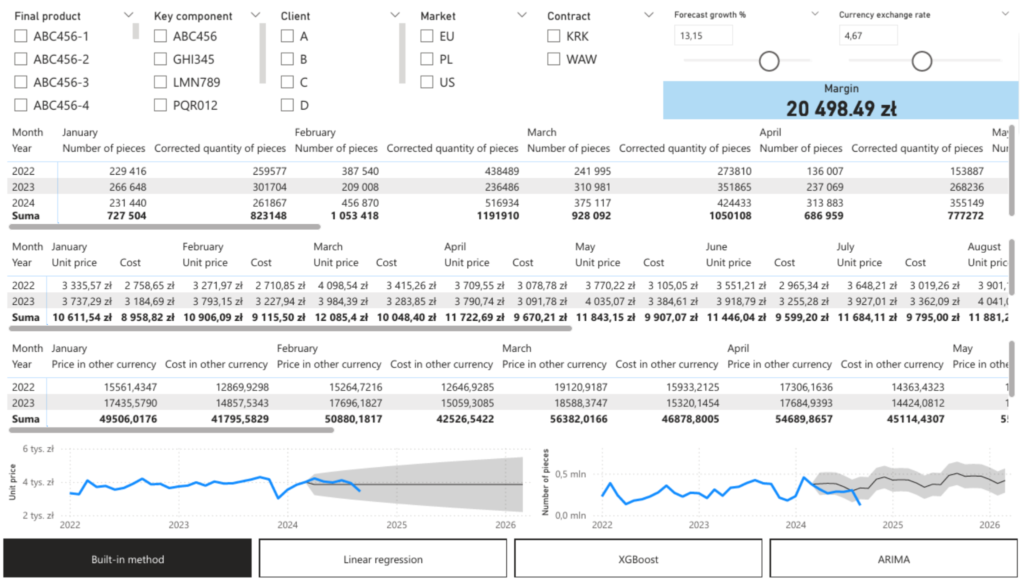

Figure 2. The figure illustrates a summary of price, cost, and product stock data, enhanced by system and adjusted price and quantity forecasts. A key element of the visualization is the interactive fragments, allowing the filtering and selection of data of interest. In addition, historical price and volume trends are presented in the form of graphs and a forecast for the next 18 months, which is based on the exponential smoothing method implemented in the Power BI system. This approach supports more efficient business decision making.

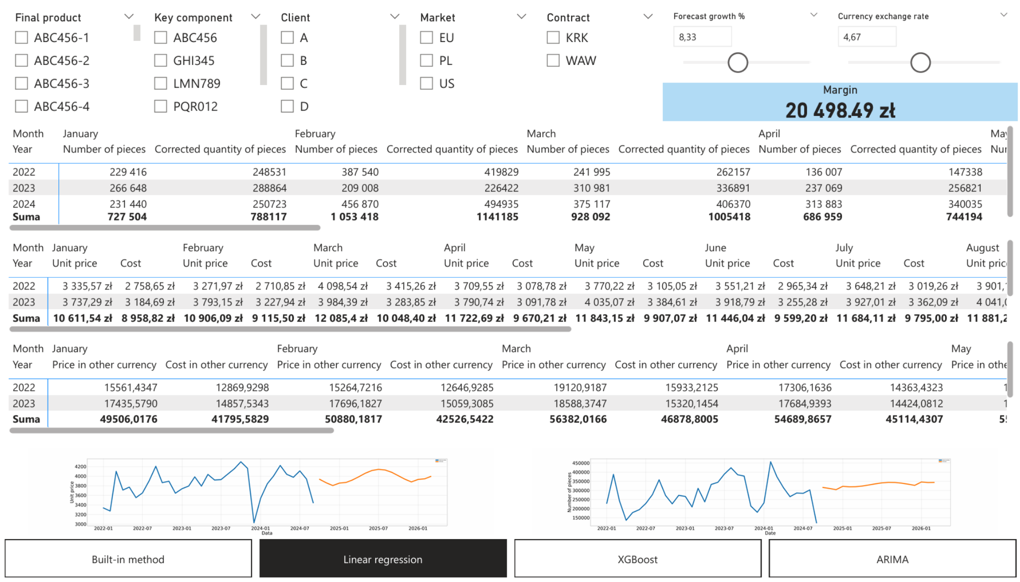

Figure 3. Thefigure shows a summary of data on prices, costs, and quantities of products in stock, which is supplemented by system forecasts and adjusted for these parameters. An important element of the visualization is the fragmenters, which allow for the selective filtering of data of interest. In addition, historical price and quantity trends are presented, together with a forecast for the next 18 months, based on the linear regression method. A visualization created in Python was used, allowing the construction of a predictive model and the visualization of historical and forecast data to support data-driven decision making. The linear regression method averages the results for both prices and product quantities, which does not give good forecasting results.

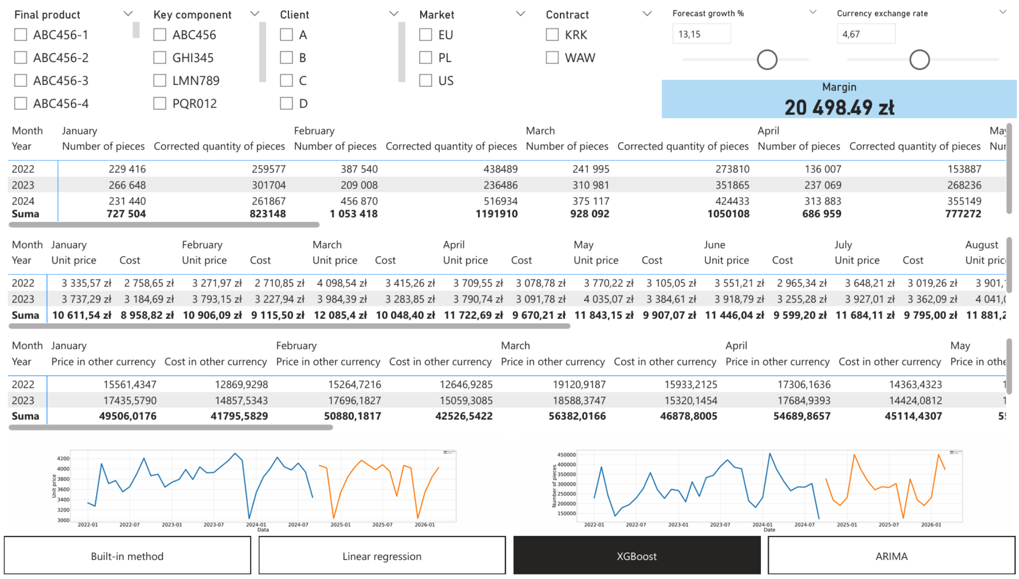

Figure 4. The figure shows a summary of data on prices, costs, and quantities of products in stock, which are supplemented by system forecasts and adjusted for these parameters. An important element of the visualization is the fragmenters, which allow for the selective filtering of data of interest. In addition, historical price and quantity trends are presented, together with a forecast for the next 18 months, based on the XGBoost method. A visualization created in Python was used, allowing the construction of a predictive model and the visualization of historical and forecast data to support data-driven decision making. The method produces better prediction results than the linear regression method. The selection of parameters for the model was carried out using the random search method, which was one of the key stages in the modeling process. This procedure was performed for one selected scenario, and the parameter values obtained as a result were considered representative and potentially effective for the remaining scenarios as well. The adopted assumption is based on the assumption that the characteristics of the data in the studied scenario are similar to those occurring in other cases, which allows for a generalization of the results of the parameter optimization process.

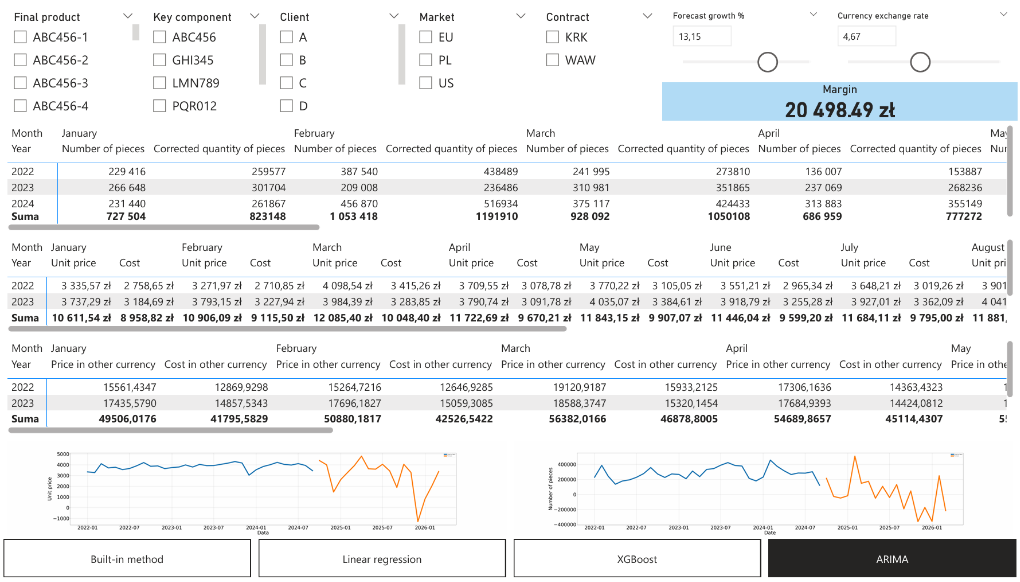

Figure 5. The figure shows a summary of data on prices, costs, and quantities of products in stock, which is supplemented by system forecasts and adjusted for these parameters. An important element of the visualization is the fragmenters, which allow for the selective filtering of data of interest. In addition, historical price and quantity trends are presented, together with a forecast for the next 18 months, based on the ARIMA/SARIMA method. A visualization created in Python was used, allowing the construction

of a predictive model and the visualization of historical and forecast data to support data-driven decision making. This method does not produce good results for our data. However, for specific types of products, it allows a good estimate of the forecast. In the modeling process using ARIMA/SARIMA, data differentiation and the selection of appropriate model parameters were performed based on data from one selected scenario. It was assumed that the parameters and the differentiation scheme determined in this way are effective and adequate for the remaining analyzed cases as well. This type of approach allows for simplifying the modeling process, but it is associated with a certain degree of generalization, which may not fully reflect the specificity of all components in different scenarios. The effect of further stages of work will be the creation of interactive dashboards that allow the user to analyze the differentiation results for any selected component. These dashboards are a tool supporting the user in the process of selecting model parameters. Based on the visualization of the differentiation result data, the user can independently determine the optimal parameter values for the ARIMA/SARIMA model, which increases the flexibility and adaptability of the method in the context of various data.

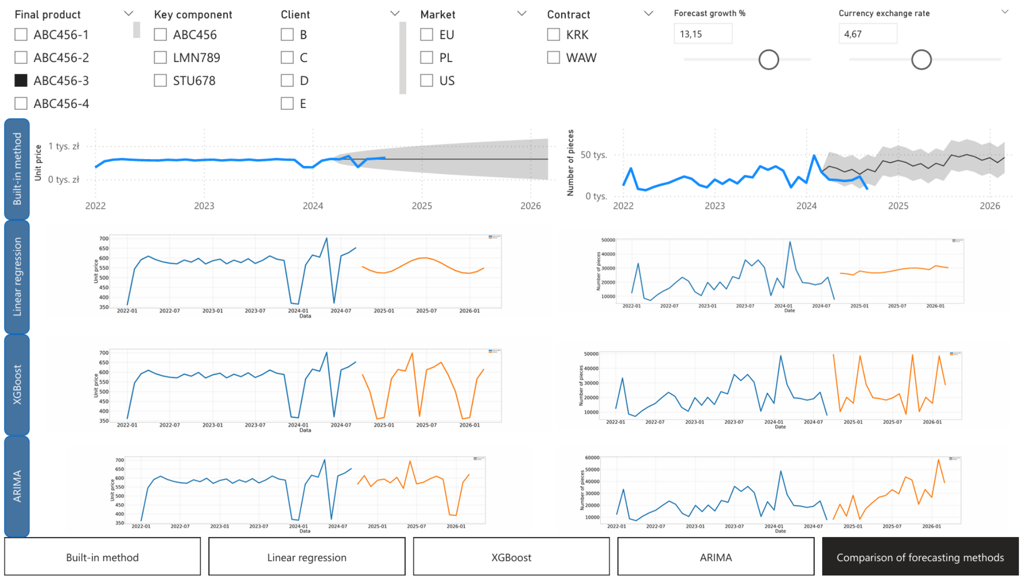

Figure 6. The dashboard, which summarizes the forecasts of the four methods (built-in exponential smoothing, linear regression, XGBoost and ARIMA), allows for analyzing the differences in the results of the forecasting models and assessing their accuracy. Each method is based on different mathematical and statistical assumptions, which leads to differences in the obtained forecasts but also gives a broader view.

As a result, the proposed solution not only functions as a dashboard but also enables dynamic analysis. Dashboard elements allowing for value adjustments, such as currency exchange rates or sales growth, are integrated with tables, enabling continuous adaptation and real-time data updates in response to user actions. The combination of slicers and forecasts within a single tool facilitates multidimensional scenario analysis. Users can simulate how various external factors, such as fluctuating currency exchange rates or increased demand, might influence the company's future operational outcomes.

Thus, the dashboard is not just a tool for historical analysis but also a forecasting and strategic planning system. It is accessible to both data analytics specialists and decision makers thanks to the integration of advanced analytical features and user-friendly operation. Its high responsiveness and calculation accuracy ensure its applicability in business environments requiring swift decision making.

The dashboard is a highly valuable tool in the context of business analytics. It enables the integration of data from various sources, which is essential for a comprehensive view of production and sales processes. It also helps users better understand the analytical results through the visual presentation of the data in the form of tables and charts. The ability to export data to external formats, such as Excel or PDF, further enhances the tool's usability.

The proposed interactive dashboard is an advanced tool for multidimensional data processing and visualization. Its structure is designed for the efficient analysis of historical data and the forecasting of future sales and production trends. It addresses the limitations of transactional systems, which often lack advanced predictive tools and dynamic multidimensional analysis capabilities. It is easy to use and allows for the incorporation of new data that can impact the analysis results.

4.3. Comparison of Forecasting Methods

To compare the chosen methods, we selected three popular error measures based on [41], where Y_i is the observed value at time i, $\hat{Y}_i$ is the predicted value at time i, and n is the number of observations (Table 1).

Table 1. Forecast error values for unit price for client B.

Method	Equation
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert Y_i - \hat{Y}_i\rvert$
RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}$
MAPE	$\frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{Y_i - \hat{Y}_i}{Y_i}\right\rvert \cdot 100\%$

Tables 2–7 present the results of the forecast error analyses, which are expressed by three measures: mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE). These results were calculated for three different forecasting methods: linear regression, the XGBoost model, and the ARIMA/SARIMA models. The analyses were conducted for forecasts of various elements, including individual products, product groups, and a selected customer. For the built-in forecasting mechanism available in Power BI, it was not possible to determine the error values, because the tool generates forecasts in the form of a chart without providing specific numerical values, which makes it impossible to conduct a precise analysis of the quality of these forecasts.

Table 2. Forecast error values for unit price for client B.

Method	MAE	RMSE	MAPE
Linear Regression	46.74	61.14	9.32%
XGBoost	92.95	135.22	18.95%
ARIMA/SARIMA	74.84	99.95	15.18%

Table 3. Forecast error values for number of pieces for client B.

Method	MAE	RMSE	MAPE
Linear regression	4493.22	6616.46	36.89%
XGBoost	5386.73	7493.90	42.92%
ARIMA/SARIMA	6560.43	8842.41	50.04%

Table 4. Forecast error values for unit price for final product ABC456-1.

Method	MAE	RMSE	MAPE
Linear Regression	0.10	0.11	3.83%
XGBoost	0.11	0.15	4.31%
ARIMA/SARIMA	0.35	0.39	13.75%

Table 5. Forecast error values for number of pieces for final product ABC456-1.

Method	MAE	RMSE	MAPE
Linear Regression	6657.25	8366.31	82.58%
XGBoost	7798.17	9414.95	72.90%
ARIMA/SARIMA	11,581.44	13,712.61	116.22%

Table 6. Forecast error values for unit price for key component ABC456.

Method	MAE	RMSE	MAPE
Linear Regression	6.30	7.51	6.43%
XGBoost	9.11	10.58	9.88%
ARIMA/SARIMA	18.68	21.23	19.77%

Table 7. Forecast error values for number of pieces for key component ABC456.

Method	MAE	RMSE	MAPE
Linear Regression	7010.36	8875.27	71.81%
XGBoost	7697.83	9436.15	62.64%
ARIMA/SARIMA	12,436.63	14,699.62	110.90%

The results indicate that of the methods used, the smallest errors are obtained with the XGBoost and linear regression methods. ARIMA/SARIMA models yield the largest errors due to limitations of scalability to multiple time series, i.e., the inability to select parameters individually for each time series considered. In addition, the data stationary requirement for real sales data is rarely present. Based on these observations, forecasting can be better organized by data category. This can also allow results from different methods to be combined more effectively, leading to the averaging of forecasts to improve their ultimate quality.

5. Conclusions

The paper responds to an important current industry need for decision support in the enterprise budget planning process. A solution has been proposed that integrates advanced forecasting methods with the ability to perform hierarchical data analysis, which can allow the modeling of the financial situation at both the organizational level and the level of individual departments. In addition, the solution proposes the use of a BI system, which companies are increasingly accustomed to using, and designs an easy-to-use dashboard that can be easily used by enterprise employees.

One of the key advantages of the presented tool is its ability to simulate changes in external parameters, such as exchange rates, as well as model various growth scenarios that can be defined by the company's management. This flexibility in forecasting enables companies to respond more quickly and precisely to market changes, which is essential for maintaining competitiveness in today's dynamic economic environment.

Importantly, this solution is characterized by ease of implementation, making it accessible not only to large corporations but also to smaller enterprises. With its intuitive interface and simple implementation, this tool can be adopted by various types of organizations regardless of their size or industry. For forecasting future sales trends, the article demonstrates the use of methods embedded in Power-BI as well as advanced forecasting techniques such as ARIMA, XGBoost, and linear regression. Forecasting results are not fully satisfactory, as it requires the selection of hyperparameters for all combinations of time series. Most statistical and machine learning methods do not work with time series exhibiting nonstationarity, nonlinear relationships between input and output variables or seasonal variation. By downloading data from the ERP system, we only have the assurance of a constant forecasting step and the non-existence of data gaps. Nevertheless, it provides a tool for rapid forecast analysis.

Future work will focus on further developing forecasting methods and the application of modern time series prediction models, such as N-BEATSx, N-HiTS, and TFT, which have achieved impressive results in renowned benchmarks and predictive competitions. A key issue will be the application of these models to analyze real-world data from companies in various industries, allowing for a better adaptation of forecasts to the specific requirements of each organization.

The mass customization industry is characterized by high production complexity, many finished products and therefore frequently changing demand. This paper provides an example on data from one of the most difficult industries to analyze. A solution based on this industry can be applied to many other industries because ERP systems have an established data structure regardless of the industry that uses them. Therefore, the data sources will be established regardless of the industry. Only the analytical difficulties are greater in the design and unit production industries, where the budget is built at a point in time where knowledge of future contacts is uncertain and it is not possible to forecast from time series of historical demand. In addition, the adaptation of forecasting and budgeting tools to the specific needs of different sectors, such as manufacturing, services, and retail is planned. This research area is particularly important as each industry has different financial requirements and variables that must be taken into account during the budgeting process. Future work may focus on creating dedicated models and algorithms that better address the changing financial needs of each sector, enabling more precise forecasting and resource allocation.

The application of these advanced predictive techniques to real-world business scenarios holds significant potential to improve the efficiency of budgeting processes and make more informed financial decisions within companies.

Author Contributions: Conceptualization, K.G.-D. and E.K.; methodology, K.G.-D.; software, R.M. and B.G.; formal analysis, K.G.-D., R.M. and B.G.; investigation, K.G.-D., R.M. and B.G.; data curation, K.G.-D. and B.G.; writing—original draft preparation, K.G.-D., R.M. and B.G.; writing—review and editing, E.K.; visualization, R.M.; supervision, K.G.-D.; project administration, K.G.-D.; funding acquisition, K.G.-D. All authors have read and agreed to the published version of the manuscript.

Funding: Research project partly supported by program "Excellence initiative—research university" for the AGH University of Science and Technology no. 501.696.7996 and by AGH University of Krakow subvention for scientific activity no. 16.16.120.773. The APC was funded by program "Excellence initiative—research university" for the AGH University of Science and Technology no. 501.696.7996 nd by AGH University of Krakow subvention for scientific activity no. 16.16.120.773.

Institutional Review Board Statement: Not applicable

Informed Consent Statement: Not applicable

Data Availability Statement: The datasets presented in this article are not readily available because the data are part of an ongoing study. Requests to access the datasets should be directed to corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ERP	Enterprise Resource Planning
BI	Business Intelligence
ARIMA	Autoregressive Integrated Moving Average
SARIMA	Seasonal Auto-Regressive Integrated Moving Average
HW	Holt–Winters model
XGBoost	Extreme Gradient Boosting

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