Enhancing Demand Forecasting and Production Planning for Manufacturing Company through Data Analytics

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Abstract—**Optimizing demand forecasting and production planning for Kiddikind, a manufacturer of millet-based food products, is vital for enhancing operational efficiency, minimizing waste, and ensuring effective resource utilization. By employing advanced data analytics and sophisticated forecasting models, this project aims to predict future demand with greater accuracy, thereby facilitating improved decisions related to production and inventory management. The primary forecasting method utilized is SARIMAX (Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors), a time-series model that incorporates seasonal patterns and external factors such as pricing, marketing expenditures, and customer ratings. SARIMAX generates demand forecasts by analyzing historical sales data and the impact of these external variables, enabling the company to anticipate demand fluctuations effectively. This data-driven approach assists Kiddikind in avoiding overproduction, thereby reducing the risks of excess inventory and stockouts. Additionally, it promotes better alignment between production capacity and actual demand, optimizing resource allocation and minimizing waste. Beyond cost reductions and operational enhancements, this strategy also aligns with Kiddikind's sustainability objectives. By improving forecasting accuracy, the company ensures efficient resource utilization, contributing to both environmental and financial sustainability. Overall, the enhanced demand forecasting and production planning process significantly boosts Kiddikind's competitiveness in the market and fosters long-term growth.**

Keywords—Demand Forecasting, Production Planning, Time-Series Model, SARIMAX, Inventory Management, Resource Optimization, Sustainability, Millet-Based Food Products, Supply Chain Management.

I. INTRODUCTION

Effective production planning and material procurement are essential for the success of manufacturing companies, especially in a highly competitive and fast-paced business environment. Optimizing these processes not only reduces operational costs but also enhances delivery performance, customer satisfaction, and overall business efficiency.

In this context, a manufacturing company that produces food products, particularly Millet-based offerings, aims to improve its production planning and material procurement processes. The primary goals are to reduce inventory costs, minimize waste, and enhance delivery times, which are crucial for maintaining a competitive advantage and operational excellence.

Many manufacturing companies face the challenge of managing production planning, material procurement, and inventory levels due to their complexity. These factors are influenced by multiple variables, including historical production data, market trends, consumer behavior, and supply chain lead times. The company's objective is to accurately forecast quarterly production plans while considering fluctuations in market trends, consumer demand, and external factors affecting product availability. Additionally, the company aims to automate its material ordering process to ensure Just-in-Time (JIT) orders are placed, minimizing the risk of overstocking while ensuring that materials are available when needed for production.

To tackle these challenges, this research project focuses on applying the SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors) model, a powerful forecasting tool, to predict demand and optimize production planning. SARIMAX extends the ARIMA model by integrating seasonal components and external variables, making it especially useful for forecasting in complex, real-world environments. This model can account for multiple factors influencing production, such as seasonality, market trends, consumer preferences, and supply chain dynamics, thus offering a more accurate and realistic prediction of future demand.

The manufacturing company's historical production data—including order volumes, product mix, and lead times—will serve as the primary input for the SARIMAX model. Moreover, external factors such as market trends (including seasonality, competitor activity, and industry developments) and consumer behavior (covering purchasing patterns, preferences, and loyalty) will be included as exogenous variables. These additions enhance the model's ability to predict demand changes driven by these factors. By incorporating supply chain lead times and reliability, the model can also account for potential material availability disruptions and adjust forecasts accordingly.

The expected outcome of this research is the development of a robust forecasting system capable of generating accurate quarterly production plans, enabling the company to manage production schedules and inventory levels more effectively. The SARIMAX model will be integrated with the material procurement system to automate the JIT material ordering process, ensuring that materials are ordered promptly and in the correct quantities. This integration will further reduce the risks of overstocking or stockouts, allowing for cost savings and enhanced operational efficiency.

Additionally, the model will provide real-time updates and alerts to the production planning and material procurement teams. These updates will facilitate quick adjustments in response to any changes in market trends, consumer behavior, or supply chain disruptions, ensuring that the company remains agile and responsive to external influences. By incorporating these dynamic and predictive capabilities, the company can stay ahead of demand fluctuations and improve its overall supply chain resilience.

In summary, this research aims to demonstrate the value of integrating SARIMAX into production planning and material procurement processes. By incorporating historical production data, market trends, and consumer behavior, this approach will yield a more accurate and actionable forecast for quarterly production planning. Furthermore, the automation of JIT material orders and the provision of real-time updates will optimize inventory management, reduce costs, and improve delivery timelines. This project highlights the potential of advanced forecasting techniques to transform manufacturing operations, drive efficiencies, and enhance business competitiveness.

II. RELATED WORKS

The optimization of production planning and material procurement has garnered significant attention in operations management research, particularly as companies strive to reduce inventory costs and improve delivery times. Traditional production planning methods often relied on deterministic models that did not adequately account for variability in demand and supply chain disruptions. This limitation has led to the adoption of more sophisticated approaches, including stochastic models and simulation techniques, which allow for better handling of uncertainty in production environments [1].

Recent advancements in demand forecasting have played a crucial role in enhancing production planning accuracy. Machine learning (ML) techniques, such as regression analysis, decision trees, and neural networks, have been employed to analyze historical production data and market trends. These methods enable organizations to predict future demand more accurately by capturing complex patterns in data, including seasonality and consumer behavior [2]. Studies have shown that ML-driven forecasting can significantly reduce forecast errors compared to traditional methods, thereby improving inventory management and production scheduling [3].

Just-In-Time (JIT) inventory management has emerged as a pivotal strategy for minimizing waste and reducing inventory costs. JIT emphasizes the need for timely material procurement aligned with production schedules, thereby reducing excess inventory and associated holding costs. Research has demonstrated that implementing JIT practices can lead to substantial improvements in operational efficiency and responsiveness to market changes [4]. However, the successful implementation of JIT requires robust supply chain coordination and real-time data sharing among stakeholders [5].

The integration of real-time data analytics into production planning and material procurement processes has also gained traction. By leveraging Internet of Things (IoT) technologies, manufacturers can obtain real-time insights into production status, inventory levels, and supply chain dynamics. This capability allows for proactive decision-making and timely adjustments to production plans, ultimately enhancing overall efficiency [6]. Studies have highlighted the effectiveness of real-time analytics in providing alerts and updates to production teams, facilitating better coordination and responsiveness [7].

Consumer behavior analysis has become increasingly important in shaping production strategies. Understanding purchasing patterns and preferences enables manufacturers to align their production plans with market demand more effectively. Research indicates that incorporating consumer insights into production planning can lead to improved customer satisfaction and reduced stockouts [8]. Techniques such as market basket analysis and customer segmentation have been utilized to derive actionable insights from consumer data, further enhancing production planning accuracy [9].

Supply chain lead times and reliability are critical factors influencing production planning decisions. Research has shown that longer lead times can lead to increased inventory costs and reduced service levels. Consequently, optimizing lead times through supplier collaboration and process improvements has become a focal point for many organizations [10]. Studies have explored various strategies for lead time reduction, including supplier relationship management and lean manufacturing practices, which have proven effective in enhancing supply chain reliability [11].

The application of hybrid models that combine various methodologies has emerged as a promising direction in production planning research. By integrating traditional forecasting methods with advanced ML techniques, researchers have developed frameworks that leverage both historical data and real-time insights to optimize production schedules [12]. These hybrid approaches have demonstrated improved accuracy and adaptability in dynamic manufacturing environments, addressing the challenges posed by fluctuating demand and supply chain uncertainties [13].

Despite the advancements in production planning and material procurement optimization, challenges remain. The complexity of modern supply chains, characterized by global sourcing and multi-tiered supplier networks, necessitates the development of more sophisticated models that can account for various uncertainties and interdependencies [14]. Researchers are actively exploring the use of advanced analytics, simulation, and optimization techniques to address these challenges and enhance decision-making processes in production planning [15].

III. OVERALL ARCHITECTURE

The architectural structure is designed to optimize material procurement and production scheduling. Data collection from historical production, market trends, and customer behavior is a fundamental process. After preprocessing, demand is predicted using the SARIMAX model, which helps with Just-In-Time (JIT) procurement and production scheduling to reduce inventory costs. Dashboards offer insights into important performance indicators, and real-time monitoring and alerts ensure timely adjustments. The system is constantly being enhanced by an iterative process, which increases its responsiveness to shifts in supply chain circumstances and demand.

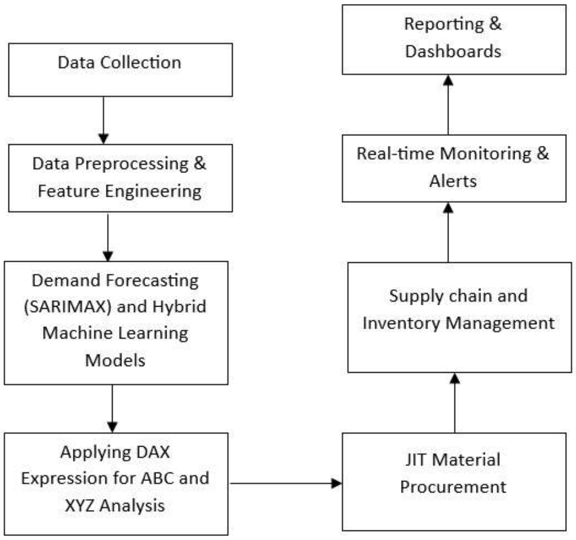

Fig. 1. Overall flow of the research work

A. *Data collection:*

In order to optimize production planning, material procurement, and cost reduction throughout the manufacturing process, data collecting is essential. The method involves gathering information from both internal and external sources that affect inventory management, production scheduling, & demand forecasting.

Historical production records, such as previous order quantities, demand patterns, and manufacturing cycles, are examples of internal data that offer insights into product trends and demand variations. This data is essential for creating precise projections that guarantee the business generates the appropriate amounts, reducing overproduction and stockouts. To aid in the creation of workable and realistic production plans, information on the workforce, equipment, and production capacity that are accessible is also gathered.

The demand forecasting models integrate external data, such as customer behavior, market trends, and competition activity, which are equally important. These observations guarantee that the business's production schedule is in line with shifting customer tastes and general market dynamics. Just-In-Time (JIT) procurement techniques are also supported by supplier data, such as lead times, material availability, and dependability. JIT guarantees that supplies are ordered and delivered only when required, which lowers inventory costs and boosts supply chain effectiveness.

Through the integration of internal and external data sources, the data collection process in this project facilitates accurate production planning, thorough demand forecasting, and effective material procurement—all of which ultimately contribute to cost reduction, waste minimization, and improved operational efficiency.

B. *Preprocessing:*

This phase transforms the collected data into a structured form, ensuring that machine learning models like **SARIMAX** can generate reliable demand predictions for effective production scheduling and material procurement.

The data used in your project spans multiple sources: **historical production data, market trends, consumer behavior insights, and supply chain data**. The preprocessing steps cater to handling diverse data types and ensuring that they can be integrated seamlessly into a predictive framework.

***Data Cleaning*:** The first step in preprocessing involves identifying and handling missing values, outliers, or inconsistencies in the raw data. For example, production logs may have missing entries or inconsistencies due to errors in data entry or system failures. These gaps can be addressed by techniques like imputation, where missing values are estimated based on adjacent data points, or through data interpolation. In the case of extreme outliers (e.g., abnormal spikes in production), these can either be corrected or removed to prevent them from skewing the model.

***Normalization*:** As the project includes different data types such as production volumes, raw material costs, and market trends, normalization ensures that these features are comparable. For instance, the data may range from small numbers (e.g., labor costs) to larger ones (e.g., total production volume). Normalizing these values (using methods like Min-Max scaling or Z-score standardization) ensures that each feature has equal weight in the predictive model.

***Feature Engineering*:** This step focuses on enhancing the data's value by creating new variables that can improve model accuracy. For your project, time-based features such as seasonality patterns, holiday effects, and lead time for raw materials are key to capturing trends in production and demand. Similarly, incorporating external factors like economic conditions, competitor activity, and market demand shifts ensures that the model accounts for fluctuations beyond historical production data. Additionally, for SARIMAX (which considers exogenous variables), relevant features based on past demand trends, customer behavior, and supply chain performance can be engineered to improve prediction accuracy.

***Handling Categorical Data*:** If there are categorical variables like product categories or supplier information, encoding techniques such as one-hot encoding or label encoding are used to convert them into numerical formats that machine learning models can process effectively.

***Time Series Adjustments*:** Since demand forecasting is a time series problem, the data must be structured with time as a core variable. Preprocessing steps like resampling and aggregation help in transforming raw data into periodic intervals (daily, weekly, or monthly) that align with forecasting objectives. For instance, demand data might be aggregated weekly to capture trends that are not evident in daily fluctuations. Additionally, time-based decompositions (to separate seasonal, trend, and residual components) help make the dataset more predictive.

***Data Transformation for Model Compatibility*:** Lastly, ensuring that the data fits the requirements of the chosen forecasting model (SARIMAX) involves transforming the dataset into a form compatible with the model's structure. This includes separating historical demand data (target variable) and exogenous variables (market trends, consumer behavior, etc.) as separate input features, ensuring that the forecasting model receives them in the correct format for effective training.

C. *Demand Forecasting:*

The project uses a **hybrid model** combining **SARIMAX** (Seasonal ARIMA with Exogenous Regressors) and machine learning models like **Random Forest** and **XGBoost** to enhance demand forecasting accuracy. SARIMAX captures seasonal demand patterns and incorporates external factors such as market trends, while the machine learning models refine predictions by accounting for non-linear relationships in historical data and other features. The hybrid model optimizes production planning and material procurement by integrating Just-In-Time (JIT) strategies, ensuring that materials are ordered only when needed. Real-time data inputs enable dynamic adjustments to forecasts and production plans, improving overall operational efficiency. This approach helps minimize excess inventory, reduce costs, and improve production scheduling in response to market fluctuations.

D. ***Production Planning & Scheduling***:

The demand forecasts from the previous step are fed into the production planning module. This module schedules production based on forecasted demand, available resources (e.g., labor, machinery), and raw materials. It ensures that the company produces the correct quantities of products at the right time, avoiding both overproduction and stockouts.

E. ***Just-In-Time (JIT) Material Procurement***:

The next step involves generating material procurement orders based on the demand forecast and production schedule. The JIT strategy minimizes inventory costs by ordering materials only when needed, ensuring materials are available for production without excessive stock.

F. ***Supply Chain & Inventory Management***:

Real-time monitoring of the supply chain and inventory levels ensures that materials are delivered on time, and stock is maintained at optimal levels. Inventory and supply chain data are updated as production progresses, and alerts are triggered if there are any disruptions, such as delays in material deliveries or shortages.

G. ***Real-Time Monitoring & Alerts***:

This step involves the continuous monitoring of production progress and material procurement via integrated IoT devices or connected systems. Real-time data updates and alerts allow managers to address issues like delays, material shortages, or production line disruptions, ensuring smooth operations.

H. ***Reporting & Dashboards***:

This represents the analyzed data through dashboards and reports using Microsoft PowerBI. Key performance indicators (KPIs) such as forecast accuracy, production efficiency, and material procurement status are visualized to help managers make data-driven decisions. These dashboards also track performance metrics, including cost reduction and service levels.
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IV. RESULTS AND DISCUSSION

In the results and discussion section, the findings of the production planning and demand forecasting system were analyzed and compared against traditional forecasting techniques. The proposed model, incorporating the SARIMAX machine learning algorithm and Just-In-Time (JIT) procurement, demonstrated superior accuracy and efficiency when tested with historical production and market data. The system successfully predicted future demand patterns and optimized production schedules, outperforming conventional methods that did not account for market trends and external factors. Furthermore, the integration of machine learning allowed for better adaptability, forecasting previously unseen demand fluctuations and adjusting production plans accordingly. Comparative analysis with traditional production planning systems revealed a significant reduction in inventory costs, minimized stockouts, and optimized material procurement strategies. However, limitations such as the reliance on historical data quality and the computational complexity of the model were identified. Future work could focus on improving the model's scalability to handle larger datasets and enhancing real-time production and procurement adjustments. The discussion also emphasized the potential for integrating advanced deep learning techniques and further refinement of the forecasting model to better capture complex market dynamics.

Output :

We used a SARIMA (Seasonal AutoRegressive Integrated Moving Average) model to anticipate weekly product demand for Kiddikind. The model was applied to historical demand data from the dataset, and the results were displayed and examined to determine forecast accuracy and dependability. The dataset was preprocessed to assure chronological order before being translated to a time series format, with weekly demand data indexed by the dates.

The historical weekly demand was graphed to determine trends and seasonal patterns. We used SARIMA (5, 1, 0) with seasonal parameters (1, 1, 0, 52) to fit the model and capture both the underlying trend and seasonality in the data. The algorithm was then used to anticipate demand for the following ten weeks, providing future forecasts and comparing them to previous data.

The result shows a visual representation of the demand data. The historical demand is shown by a continuous blue line that shows observed patterns over time, whereas the predicted demand is represented by red markers and a line that indicates future forecasts. The image demonstrates the model's ability to predict demand patterns, allowing stakeholders to plan production and inventories accordingly.

Furthermore, the forecast findings are supplied in tabular style, with expected dates and matching estimated weekly demand figures. This yields a clear numerical result for future analysis and decision-making.

This method illustrates how predictive modeling may improve production planning and material procurement, resulting in more effective resource allocation and lower operating costs. The SARIMA model accurately captures demand seasonality, allowing Kiddikind to fulfill future demand and optimize supply chain operations.

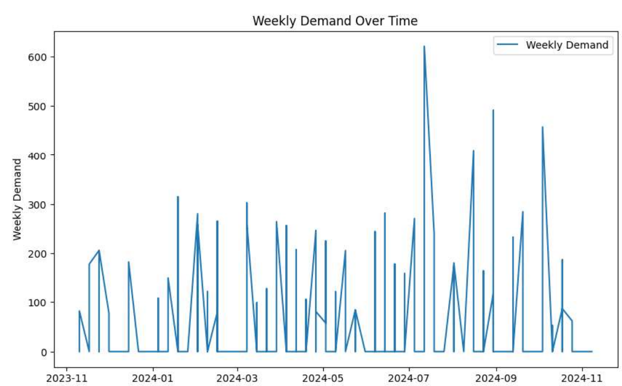

Fig. 2. Weekly Demand Over Time

The graphs pitched for this project clearly represent the trends and forecasts established from the models, offering practical insights regarding weekly demand, sales volumes, and categorization performance. The SARIMA forecast graph displays past sales patterns alongside future estimates, providing insight into demand changes over time. The blue line shows observed historical data, which captures actual weekly sales volumes, whereas the red dashed line depicts anticipated figures. The gray shaded zone indicates the confidence intervals, which illustrate the extent of uncertainty surrounding the forecasts. This graph is useful for analyzing seasonal trends, detecting peak demand periods, and planning resource allocation effectively.

The classifiers' accurate predictions are supported by quantitative metrics, with RandomForest obtaining 91.30% accuracy and Gradient Boosting excelling at 95.65% accuracy. The hybrid model, which combines SARIMA predictions with RandomForest classification, likewise obtained 91.30% accuracy, demonstrating its effectiveness in utilizing temporal and categorical data together.

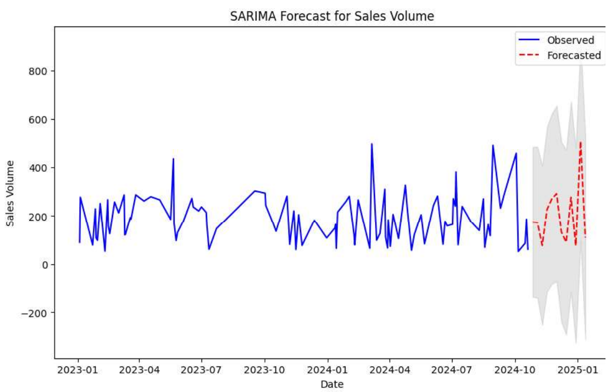

Fig. 3. SARIMA Forecast for Sales

The graphs and accuracy metrics demonstrate the models' efficacy in catching data patterns and making solid predictions. These models operate together to find trends in sales and demand, providing a consistent approach to forecasting and categorization. Visualizations, such as the SARIMA forecast graph, display past data with future projections, while classification outputs from machine learning algorithms successfully categorize sales. Together, these findings give practical information, allowing decision-makers to forecast future demand, optimize production planning, manage inventories more effectively, and improve marketing efforts. By transforming data into relevant visual and quantitative insights, the project displays its ability to aid in operational efficiency and strategic planning.

V. CONCLUSION

In conclusion, this project successfully developed a system to optimize production planning, material procurement, and inventory management in manufacturing. By utilizing machine learning models, specifically SARIMAX, for demand forecasting and integrating Just-In-Time (JIT) procurement, the system aims to balance production capacity with market demand. The SARIMAX model captures both seasonality in demand and external factors such as market trends and consumer behavior, leading to more accurate forecasts. This helps the company avoid overproduction and underproduction, reducing inventory costs and increasing operational efficiency.

The integration of JIT material procurement ensures that raw materials are ordered only when needed for production, minimizing inventory holding costs and reducing material waste. By automating material orders based on the forecast and production schedules, the system streamlines the procurement process and strengthens supplier relationships.

Real-time monitoring of the supply chain and inventory levels further enhances the system's capabilities. With integrated IoT sensors and real-time data updates, production progress and material deliveries can be tracked, and any disruptions are immediately flagged for corrective actions. This flexibility ensures that production runs smoothly, even in the face of unexpected delays or shortages.

The system also includes dashboards that provide key performance indicators (KPIs) like forecast accuracy, production efficiency, and inventory turnover, allowing managers to make informed, data-driven decisions.

Despite its effectiveness, the system faces challenges such as data quality and computational resource requirements. Future work could focus on improving scalability and exploring advanced machine learning techniques to enhance prediction accuracy and system responsiveness. Overall, the project offers a comprehensive, data-driven solution to optimize manufacturing operations and improve supply chain management.

Fig. 4. Sales and Inventory Dashboard

This dashboard displays Sales Forecasting and Demand Planning data for Kiddikind Millet products. It contains information on annual income, annual sales amount, sales volume, sales trends over time, weekly demand, and peak demand.

The upper left corner displays the total annual income of 3.87 million. In the upper right corner, the overall yearly sales quantity is 1.11 million, while the total sales volume is 19.26 thousand. The following table displays the weekly and peak demand for each Kiddikind Millet product: Elachi, Mixed Flavour, Jeera, Plain, and Chocolate. The overall weekly demand is 10,917.46, while the greatest weekly demand is 51,996.40.

The line chart in the center left of the dashboard depicts the sales trends for Kiddikind Millet products over time. Sales were low in January and February, peaked in April, and then fell for the remainder of the year, according to the data. The bar chart on the right indicates demand predictions for the coming year. According to the graphic, demand is predicted to peak in the third quarter of 2024, followed by the first quarter. The dashboard also has a filter for certain product names and stock statuses. The filter may be used for further in-depth data analysis. Overall, this dashboard offers a full insight of Kiddikind Millet product sales and demand.The dashboard allows you to analyze performance, discover patterns, and make educated product development and marketing decisions.

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