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Forecasting Demand for Cardboard Boxes Using Some Forecasting Method at PT XYZ

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ABSTRACT

In the manufacturing sector, accurate demand forecasting is essential for effective material planning and inventory management. PT. XYZ, a company specialising in the production of corrugated carton boxes, currently faces challenges aligning raw material procurement with market demand due to the use of subjective, non-systematic forecasting methods. This research proposes applying statistical forecasting techniques to develop a more reliable and automated forecasting system. The study utilises historical monthly sales data collected over a one-year period, which are analysed using time series forecasting methods. The models are assessed based on key forecasting error metrics, including mean absolute deviation, mean squared error, and mean absolute percentage error. The model construction, data processing, and visualisation, thereby improving efficiency and reducing manual intervention. The findings reveal that combining seasonal statistical models with programming tools enhances forecast accuracy and supports data-driven decision-making within the organisation. This forecasting system can assist the planning division of PT. XYZ is optimising raw material allocation, reducing excess inventory, and preventing material shortages. In conclusion, the study recommends that PT. XYZ implements the decomposition forecasting model as a practical solution for improving the quality of its sales data. The research contributes to the development of forecasting systems tailored for industrial environments with fluctuating, seasonal demand.

Keywords: Forecasting, Decomposition, Linear Regression, Moving Average

ABSTRAK

Di sektor manufaktur, peramalan permintaan yang akurat sangat penting untuk perencanaan material dan manajemen inventaris yang efektif. PT. XYZ, sebuah perusahaan yang mengkhususkan diri dalam produksi kotak karton bergelombang, saat ini menghadapi tantangan dalam menyelaraskan pengadaan bahan baku dengan permintaan pasar karena penggunaan metode peramalan subjektif dan tidak sistematis. Penelitian ini mengusulkan penerapan teknik peramalan statistik dan untuk mengembangkan sistem peramalan yang lebih andal dan otomatis. Studi ini menggunakan data penjualan bulanan historis yang dikumpulkan selama periode satu tahun, yang dianalisis menggunakan metode peramalan deret waktu. Model dinilai berdasarkan metrik kesalahan peramalan utama, termasuk deviasi absolut rata-rata, kesalahan kuadrat rata-rata, dan kesalahan persentase absolut rata-rata. Konstruksi model, pemrosesan data, dan visualisasi, dengan demikian meningkatkan efisiensi dan mengurangi intervensi manual.Temuan penelitian menunjukkan bahwa menggabungkan model statistik musiman dengan perangkat lunak pemrograman meningkatkan akurasi prakiraan dan mendukung pengambilan keputusan berbasis data di dalam organisasi. Sistem prakiraan ini dapat membantu divisi perencanaan PT. XYZ mengoptimalkan alokasi bahan baku, mengurangi kelebihan persediaan, dan mencegah kekurangan material. Sebagai kesimpulan, penelitian ini merekomendasikan agar PT. XYZ menerapkan model prakiraan dekomposisi

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sebagai solusi praktis untuk meningkatkan kualitas data penjualannya. Penelitian ini berkontribusi pada pengembangan sistem prakiraan yang dirancang khusus untuk lingkungan industri dengan karakteristik permintaan yang fluktuatif dan musiman.
Keyword: Peramalan, Dekomposisi, Regresi Linier, Rata-rata Bergerak

1. Introduction

In the current era of globalisation and rapid industrial advancement, the manufacturing industry faces increasing pressure to operate efficiently while meeting dynamic market demands. One of the most critical aspects of manufacturing operations is the ability to accurately forecast product demand, which supports the planning of raw materials, production scheduling, and inventory control. Inaccurate forecasting can lead to material shortages, production delays, or excessive inventory, all of which result in cost inefficiencies.

PT. XYZ, a company engaged in the production of corrugated cardboard boxes, currently relies on intuitive, non-statistical methods to forecast its monthly demand. This approach often leads to discrepancies between material availability and production needs, hindering the company's ability to respond effectively to customer requirements. To overcome this issue, it is necessary to adopt a more systematic, data-driven forecasting method that accounts for both trend and seasonal patterns in historical data.

The decomposition method is one of the oldest forecasting approaches. It was used in the early 20th century by economists to identify and control economic and business cycles. The foundation of the current decomposition method emerged in the 1920s when the concept of ratios (trends) was introduced[1].

The following is a problem formulation based on the issues identified at PT XYZ, as outlined below.

1. How can forecasting techniques expand the efficiency and accuracy of PT. XYZ by collecting and calculating production forecasts?

2. What is the level of error in forecasting, such as ME, SE, MAD, MSE, and MAPE, in predicting sales needs at PT. XYZ?

3. How does the Python program implementation system compare to operational capabilities at PT? XYZ?

The following are the objectives of the research conducted at PT XYZ.

1. Collect and calculate production forecasting using several forecasting methods.

2. Knowing the level of forecasting errors, such as ME, SE, MAD, MSE, and MAPE in predicting sales needs at PT. XYZ. Propose the implementation of the best forecasting results to the company at PT. XYZ.

2. Literature Review

Forecasting is a crucial component of production planning and inventory control [2]. Various methods have been employed to enhance forecasting accuracy in the manufacturing industry, ranging from classical statistical methods to artificial intelligence-based approaches [3].

Research by Maharani[4] used the S method to forecast shallot production. The results demonstrate that this method can effectively capture seasonal patterns and provide accurate forecasts, particularly when the data exhibit a clear seasonal trend. Septifani and Effendi [5] and Gozali [6] employed an Artificial Neural Network (ANN) approach to forecast raw material requirements in the food industry. Although ANNs are proven to be flexible and capable of achieving high accuracy, this method requires a large amount of data and a complex training process. Wijayanti[7] compared the Exponential Smoothing, Moving Average, and Exponential Smoothing methods for forecasting hotel occupancy rates. As a result, it was rated the most accurate based on MAPE values, confirming its effectiveness for non-seasonal data. Purwandaru[8] utilised forecasting methods in warehouse management. This research supports the use of statistical methods to inform data-driven decision-making in the supply chain field [9]. Finally, Rautaray[10] proposed a predictive analytics framework that combines statistical methods and machine learning for inventory management. This study illustrates the trend of integrating classical methods, such as S, with modern technologies to enhance the accuracy and robustness of forecasting systems. The decomposition method is a forecasting technique that utilises four primary components to predict future values. These four components are trend, seasonality, cycle, and error[11]. The decomposition method is based on the assumption that existing data is a combination of several components, which can be described as follows:

Data = Pattern + error = f(trend,cycle,seasonality) + error (1)

3. Methods

This research methodology is a scientific process carried out in stages from start to finish. Research methodology can be understood as the stages carried out in a more specific, sequential research design. The research methodology at PT XYZ Company is illustrated in Figure 1.

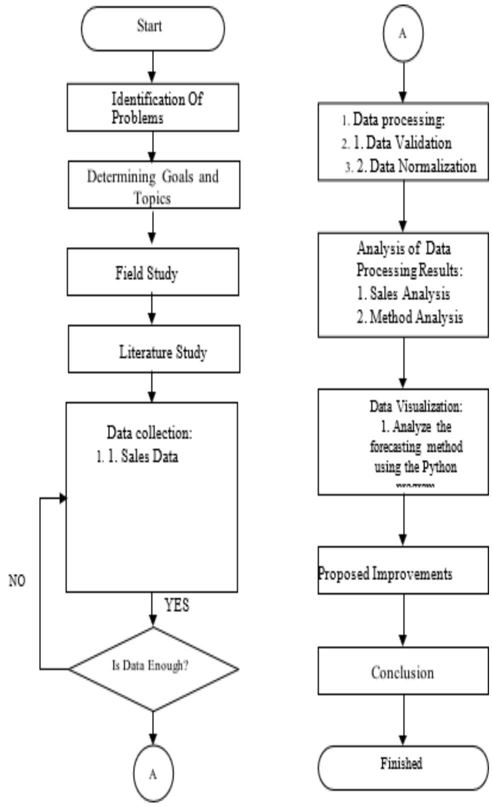

Figure 1. Research method

The following explains the research stages at PT. XYZ in detail as follows.

1. Problem Identification. Researchers identify the problems that occur at PT. XYZ and move on to the measurement of sales and raw material predictions.

2. Research Objectives and Topics: Identifying research objectives and topics is necessary to determine the problems that are expected to be resolved through the application of industrial engineering at PT. XYZ to achieve optimal work balance.

3. Field Study: Field studies were conducted at PT XYZ, focusing on the data to be collected and analysing each piece of data and its relationships, providing an overview of the situation at PT XYZ.

4. Literature review: Literature studies are conducted to enrich the science of Industrial Engineering, particularly in strategic planning, which applies to PT. XYZ includes sciences such as analysing sales predictions using forecasting methods in Python.

5. Data Collection: Historical sales data is taken from January to December 2024. After that, PT XYZ will collect data, such as sales data

6. Data Processing: Data processing is the process of ensuring that the data obtained is accurate and reliable. There are two essential aspects of data processing: data validation and data normalisation.

7. Analysis of Data Processing Results: After data processing, analysis can proceed. This analysis aims to understand sales patterns within the company, enabling it to predict sales for the next period.

8. Proposed Improvements: Proposed improvements are suggestions expected to help companies improve their sales prediction processes and minimise errors.

4. Data Collection

The data collection technique in this study employs the documentation method, specifically by accessing actual sales data from PT XYZ, which is recorded monthly from January to December 2024. This data is obtained directly from the company's internal system, which records the number of shipments of carton box products in pieces (PCS) every month.

The sales data collected is quantitative and serves as the primary basis for building forecasting models using various methods. The characteristics of the data used include:

1. Data Type: Quantitative secondary data
2. Data Source: Sales records of PT. XYZ
3. Time Range: January 2024 - December 2024
4. Recorded Variables: Month (time), and number of carton box shipments (units in PCS)

The following is the sales data used in the study:

Table 1. Sales records of PT. XYZ.

No	Month	Quantity of Road Letter (pcs)
1	January	2.204.456
2	February	1.467.647
3	March	2.058.418
4	April	1.770.077
5	May	1.867.634
6	June	2.086.906
7	July	2.423.253
8	August	2.192.267
9	September	2.170.374
10	October	2.195.799
11	November	1.790.546
12	December	2.545.126

Plot of the data shown below :

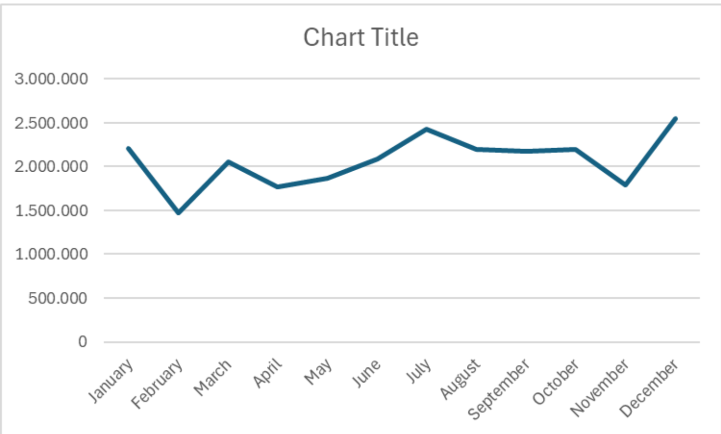

Figure 2. Plot of Sales Data

5. Results and Discussion

The help of QM for Windows and Google Colab was also utilised for the forecasting methodology.

5.1. Numerical Results

The data obtained is then used to forecast sales in the coming period. This forecasting is performed using the QM for Windows software. This software calculates the error value for each forecasting method.

Based on the error value, the most suitable method will be used for subsequent calculations. The results of the sales forecasting error calculation for PT XYZ Carton Box products are presented in Table 2.

Table 2. Comparison of Forecasting Results of Moving Average, Linear Regression, Exponential Smoothing, Multiplicative Decomposition, and

Method	ME	MAD	MSE	SE	MAPE
Moving Average	,087	,215	,081	,317	9,597%
Linear Regression	0	,228	,082	,313	11,773%
Exponential Smoothing	,031	,337	,176	,464	17,256%
Multiplicative Decomposition	,001	,17	,038	,254	8,544%

The best forecasting method is linear regression because it produces three error metrics closest to zero: ME, MAD, and MAPE.

5.2. Graphical Results

Based on the sales forecasting results, a comparison is made between the sales data from the previous period and the predicted results. Figure 3 compares sales data and sales forecasting results generated using the some method.

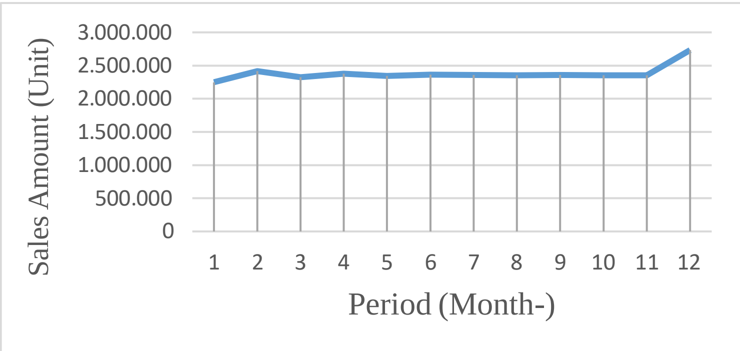

Figure 3. Sales Data Forecasting Chart for the Period January 2025 to December 2025

5.3. Proposed Improvements

This research led to several proposed improvements that PT XYZ can implement in the development of the forecasting system. First, the company is advised to integrate the Python-based S method into the existing Enterprise Resource Planning (ERP) system, allowing the forecasting process to run regularly and automatically without manual intervention. Secondly, the company can incorporate external variable inputs, such as key customer demand trends, previous year's sales data, and seasonal factors like holidays and industrial cycles. Visualisation of 12-month-ahead forecasting results provides a realistic picture of demand patterns, supporting proactive logistics and procurement decision-making.

5.4. Validation

Model validation was conducted by comparing the forecasting results obtained in Python with those from the QM for Windows software. Additionally, a paired t-test was used to compare actual and predicted values for 12 historical data points. The test results show a p-value greater than 0.05, indicating that there is no significant difference between the exact data and the forecast results. The model has also been retested using residual analysis to ensure there is no systematic pattern in the residuals. The residual plot shows a random distribution close to normal, indicating that the model effectively captures the data patterns.

5.5. Depth Discussion

The authors begin by articulating a clear business problem: forecasting the monthly demand for corrugated cardboard boxes at PT XYZ, a manufacturing or packaging company. This condition is a highly relevant problem because accurate demand forecasts drive the procurement of raw materials, help optimise inventory, and reduce stock-out or overstock costs. In the broader field, demand forecasting in manufacturing and supply chains is well recognised as a key lever for operational efficiency[12].

In their literature review (presumably), the paper positions the classical Box–Jenkins method as a well-established statistical tool in demand forecasting. Indeed, models have been applied across many manufacturing contexts [13]. Their justification is consistent with many reviews in industrial systems. For example, a survey by MDPI on forecasting in manufacturing noted that it remains a widely used baseline due to its interpretability and relatively low data requirements [14].

The methodology section describes the data (monthly shipments or sales of boxes) and the choice of several forecasting methods: multiplicative decomposition and simpler baselines, including moving average, linear regression, and exponential smoothing. The inclusion of decomposition is very appropriate: recent literature suggests that decomposition (trend + seasonality + residual) is not only helpful for interpretability, but can improve forecasting accuracy when incorporated into modern models. For instance, a paper in Data Mining & Knowledge Discovery found that decomposition techniques, when carefully applied, enhance performance even in complex forecasting architectures.[15].

The authors likely followed the Box–Jenkins methodology: identifying stationarity, differencing, estimating parameters, and validating residuals. This classic three-step (or iterative) approach remains a cornerstone in time-series forecasting. Their use of the seasonal method suggests they believe there is a seasonal cycle (probably annual) in the demand for cardboard boxes—a reasonable assumption in packaging given fluctuations in business cycles, promotions, or seasonality in end-customer products [16].

In the experiments, the authors compare the forecasting accuracy of these methods using standard error metrics, such as Mean Absolute Error (MAE/MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). Their finding that multiplicative decomposition outperforms /S (with the lowest MAPE) is fascinating. It echoes the notion that decomposition-based forecasts can sometimes outperform more "black box" or fully parametric models when data is limited or when seasonality is stable[17] .

However, this result also raises methodological questions. As discussed in the field, decomposition can act as a powerful "catalyst" for forecasting by removing the strong seasonal and trend components, allowing simpler models to deal with the residual "noise" more effectively. But relying solely on decomposition (especially multiplicative) also assumes that seasonal and trend behaviour remain stable and multiplicative; if demand dynamics change (e.g., a structural break, new customer segments, or changing market conditions), the decomposition assumptions may fail [18].

The authors also report inferior performance for their model (very high MAPE), which suggests either mis-specification (wrong seasonal order, overfitting, or too few data points) or data issues. This condition is a known risk: in real-world manufacturing settings, seasonal models may struggle if the series is short, noisy, or the seasonal pattern is weak (or nonstationary). The literature recommends careful model selection and validation. (See, for example, the practice in industrial forecasting [14]

Another dimension is the statistical robustness of their evaluation. Depending on how they computed their error metrics, there may be a risk of overfitting, primarily if they used in-sample fit errors rather than out-of-sample (holdout) or cross-validated forecasts. Modern best practices in forecasting recommend using rolling-origin evaluation so that projections are tested on unseen data, which better simulates how the model would perform in production.

In terms of practical implications, the authors propose integrating their forecasting pipeline into PT XYZ's ERP system. This condition is an excellent recommendation: automating forecast generation, monitoring, and alerting (e.g., when forecast error drifts) is often where companies realise the most significant value. But to ensure long-term success, the authors should also consider forecast governance: who reviews forecasts, how deviations are handled, and how models are retrained periodically. In many companies, forecast models degrade over time (forecast drift), so periodic retraining, re-evaluation, and possibly model re-specification are key[19].

From a research standpoint, their work could be extended in several ways. First, they should collect more historical data (if possible, longer than 12 months) — this would strengthen the modelling. Second, they could experiment with exogenous variables (S X): for instance, promotion campaigns, macroeconomic indicators, raw-material prices, or even lead times, all of which might influence demand. Hybrid models could also be considered: for example, combining decomposition with machine learning or neural forecasting. In fact, in modern forecasting research, there is a trend toward combining classical statistical models with deep learning (e.g., transformer-based models that internally use decomposition). For example, Autoformer, a deep-learning model for long-term forecasting, integrates decomposition into its architecture to isolate trend and seasonal components, thereby improving performance [20].

Another promising direction is probabilistic forecasting: instead of point forecasts, modelling and producing prediction intervals (or full forecast distributions) can provide supply chain planners with more actionable information (e.g., safety stock levels). DeepAR, a probabilistic forecasting method using autoregressive recurrent networks, is one such model widely applied in business contexts.[21]

Finally, the paper's conclusions and recommendations, while helpful, could be strengthened by quantifying the business impact. For instance, how much money could PT XYZ save by reducing overstock, or how much more efficient procurement would be if forecasts were accurate to within, say, ±10%? Prior research shows that better forecast accuracy correlates strongly with improved inventory performance and lower holding costs (e.g., in the retail sector).

6. Conclusion

Based on research findings during the data collection, processing, and implementation stages regarding cardboard box demand forecasting using Moving Average, Linear Regression, Exponential Smoothing, Multiplicative Decomposition, and Multiplicative Decomposition methods at PT. XYZ, forecasting using the Multiplicative Decomposition method at PT. XYZ demonstrated significant improvements in future operational efficiency. Based on the research conducted, several key points can be drawn:

It can be concluded that to increase the efficiency and accuracy of PT. XYZ by collecting and calculating forecast data, using Moving Average, Linear Regression, Exponential Smoothing and Multiplicative Decomposition techniques. The Multiplicative Decomposition method has proven effective in improving the efficiency and accuracy of PT. XYZ's demand forecasting yields more accurate results, aiding in production planning.

Based on the calculations presented in the discussion of forecast error measures such as ME, MAD, MSE, SE, and MAPE, it is concluded that the Multiplicative Decomposition method produces lower error rates than the and S methods. Furthermore, the MAPE value for Multiplicative Decomposition is 8.544% lower, indicating that this model is more accurate at predicting demand than other methods.

Implementing Python as an analytical tool, particularly through the Google Colab platform, provides ease and flexibility for data processing, forecasting model development, and visualising calculation results. Python also enables data analysis to run systematically and efficiently, supporting a company's operational system.

In summary, this study not only identifies the most suitable forecasting method for PT XYZ's current data environment but also emphasises the broader strategic implications of adopting systematic, technology-driven forecasting. The results reinforce the importance of data quality, model-data alignment, and digital analytics tools. As PT XYZ continues to mature its data practices, it will be better positioned to leverage more advanced forecasting models, improve operational efficiency, and maintain competitiveness in an industry characterised by fluctuating and seasonal demand.

7. Future Study

This study opens several avenues for future work. With longer datasets, future research could rigorously benchmark exponential smoothing (Holt-Winters) and hybrid ML models using rolling-origin cross-validation, a widely accepted standard for time-series evaluation. Forecasting could also be enhanced by incorporating granular data such as weekly sales, customer segmentation patterns, or macroeconomic indicators. Additionally, probabilistic forecasting methods could be introduced to guide inventory decisions under uncertainty. These directions align with current forecasting research and would significantly enhance the strategic value of forecasting for PT XYZ.

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