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Original Research

Polynomial Regression Model for Predicting PVC Ceiling Sales Based on Historical Data: A Case Study at CV. Kilaw Maju Bersama

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ABSTRACT

The growth of the building materials industry, particularly PVC ceilings, requires accurate sales forecasting to support production stability, distribution efficiency, and inventory management. CV. Kilaw Maju Bersama, a PVC ceiling distributor, faces weekly sales fluctuations based on 104 weekly observations from January 2023 to December 2024. This study develops a Polynomial Regression model to forecast PVC ceiling sales using average selling price, number of retail stores, and promotional activities as independent variables. A quantitative approach was applied through data collection, data cleaning, exploratory data analysis (EDA), chronological time-series train-test splitting without shuffling, Z-score standardization, polynomial degree selection using TimeSeriesSplit, and model evaluation using MAPE, RMSE, and R^2. The results show that the degree-1 Polynomial Regression model achieved a training MAPE of 3.12%, RMSE of 129.741, and R^2 of 0.643, while the testing set achieved a MAPE of 4.57%, RMSE of 187.311, and R^2 of 0.380. These results indicate low prediction error and satisfactory generalization to unseen data. The model therefore provides a practical decision-support tool for weekly sales forecasting, inventory planning, and data-driven business decision-making in the building materials industry.

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1 INTRODUCTION

The building materials industry in Indonesia continues to develop alongside demand from construction, renovation, and property activities. PVC ceiling panels are widely used because they are lightweight, moisture-resistant, resistant to termites, and relatively cost-effective [1]. For distributors, however, fluctuations in weekly demand create operational challenges because sales forecasts are needed to support inventory planning, distribution, promotional decisions, and the allocation of resources [2]. Retail forecasting literature emphasizes that forecast accuracy is closely related to operational continuity, inventory efficiency, and the management of supply and promotional activities [3].

CV. Kilaw Maju Bersama is a distributor of PVC ceiling panels that records weekly sales activity. Historical observations from January 2023 to December 2024 show variation in weekly sales volume, making it difficult to determine future demand using simple judgment alone [4]. This study considers average selling price, number of retail stores, and promotional activities as explanatory variables for weekly PVC ceiling sales [5]. This choice has a theoretical basis: price is systematically related to quantity demanded through demand theory and price elasticity, while promotion is intended to influence customer behavior and may generate temporary changes in demand [6].

A preliminary analysis of the historical data indicates that the relationships among average price, number of retail stores, promotional activities, and total sales volume (measured in meters) are not entirely linear [7]. Data visualization and scatter plot analysis reveal a curvilinear relationship, suggesting that conventional linear regression may not adequately capture the underlying data patterns [8]. In contrast, Polynomial Regression offers greater flexibility in modeling non-linear relationships, making it a promising approach for improving forecasting accuracy. The marketing-mix perspective also identifies price, place/distribution, and promotion as important components of marketing activity. Here, the number of retail stores is treated as an operational measure of store coverage or distribution reach [9]. Sales forecasting can be approached through classical time-series models, regression-based models, and machine-learning methods. Classical methods such as Autoregressive Integrated Moving Average (ARIMA) model temporal dependence in historical observations, whereas exponential smoothing emphasizes level, trend, and, when relevant, seasonal components. These methods remain useful benchmarks because they primarily exploit the historical behavior of the target series. A study of cement sales directly compared ARIMA and exponential smoothing and found that their relative accuracy differed across product series. Retail forecasting research likewise indicates that causal information, including promotions, can increase forecasting complexity and that the choice of method should reflect the forecasting context and available information.

Machine-learning research has expanded the range of sales forecasting methods, including tree-based algorithms, neural networks, and other nonlinear models [10]. However, more complex methods generally require sufficient data, careful validation, and appropriate feature engineering. Polynomial Regression provides a more interpretable alternative because it extends linear regression by adding polynomial terms while retaining a regression framework. Recent studies have applied Polynomial Regression to market sales and demand forecasting, including applications involving pricing and promotional information [11]. In the present study, preliminary exploratory analysis indicates that the relationships among average price, retail-store coverage, promotional activities, and sales volume are not necessarily strictly linear. Therefore, Polynomial Regression is considered appropriate for testing whether nonlinear terms can improve the representation of the observed sales relationships [12].

The research gap is defined specifically in terms of method, product context, explanatory variables, and data structure [13]. Existing literature has examined retail forecasting using classical time-series, causal, regression, and machine-learning approaches, while Polynomial Regression has been applied to sales and demand problems in other product and market contexts [14]. Nevertheless, the literature reviewed for this study provides limited evidence on weekly PVC ceiling sales forecasting using a combination of average selling price, number of retail stores, and promotional activities within a Polynomial Regression framework [15]. This study addresses that gap by developing and evaluating a Polynomial Regression model for CV. Kilaw Maju Bersama using 104 weekly observations, chronological train-test splitting, Z-score standardization, TimeSeriesSplit-based polynomial degree selection, and MAPE, RMSE, and R^2 [16]. The objective is to identify an appropriate polynomial degree and assess whether the resulting model can provide useful weekly sales forecasts for inventory, distribution, and business planning [17, 18].

2 RESEARCH METHODS

2.1 Research Stages

This study followed a systematic research framework covering the entire process from problem identification to model evaluation. The research began by identifying the need to predict PVC ceiling sales based on key influencing factors. Historical sales data were then collected, and the independent variables average selling price, number of retail stores, and ongoing promotional activities were determined [19]. Each stage of the research supports the subsequent process. Problem identification defined the research objectives, the literature review established the theoretical foundation, and data collection provided the historical dataset for analysis [20]. Data cleaning and Exploratory Data Analysis (EDA) were performed to ensure data quality and readiness before model development. This structured approach improves data reliability and provides a solid foundation for developing and evaluating the prediction model. The overall research workflow is illustrated in Figure 1.

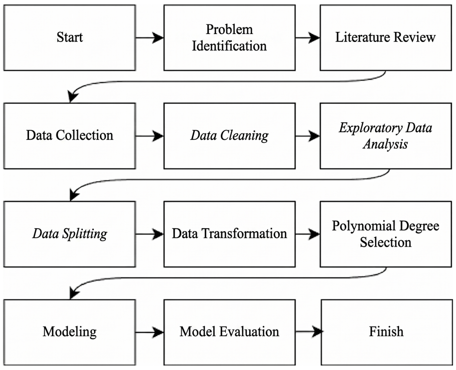


Figure 1. Research Stages

2.2 Problem Identification

This study addresses the challenge of predicting PVC ceiling sales at CV. Kilaw Maju Bersama using historical weekly sales data from January 2023 to December 2024. Sales fluctuations create uncertainty in inventory planning, distribution, and promotional strategies, making accurate sales forecasting essential for effective business decision-making.

To address this issue, the study applies Polynomial Regression to model the relationship between historical sales and the influencing variables. Model performance is evaluated using MAPE, RMSE, and R^2, while time series cross-validation is employed to determine the optimal polynomial degree and ensure reliable evaluation without information leakage. This approach aims to develop a robust and accurate sales prediction model for supporting business planning.

2.3 Literature Review

The literature review focuses on four related areas: sales forecasting and its operational role, classical time-series forecasting, regression and machine-learning approaches, and the theoretical basis for the explanatory variables. Retail forecasting research shows that forecasts support operational decisions such as inventory and supply-chain planning, while promotional information and other explanatory variables can increase the complexity of demand prediction. Classical methods such as ARIMA and exponential smoothing remain important because they explicitly model temporal patterns. Evidence from cement sales forecasting shows that ARIMA and exponential smoothing can produce different levels of accuracy depending on the series, reinforcing the need to select a method according to the characteristics of the data. Machine-learning reviews further show the growing use of linear models, tree-based models, and deep-learning methods in sales prediction, while also highlighting the importance of data volume, validation, and problem context.

Regression-based approaches are useful when sales are modeled in relation to observable business variables. Polynomial Regression extends linear regression by allowing nonlinear or curvilinear relationships through polynomial terms. Recent studies have applied Polynomial Regression in sales and demand settings, including market sales prediction and applications involving price and promotional information. The theoretical rationale for the variables in this study is also important. Demand theory establishes a systematic relationship between price and quantity demanded through price elasticity, while marketing-mix theory identifies price, place/distribution, and promotion as factors that can influence market response. Research on sales promotion further explains that promotional actions are intended to induce changes in customer behavior and can generate short-term demand responses. Therefore, average selling price, number of retail stores, and promotional activities are treated as observable business variables with a conceptual connection to weekly sales variation. The specific research gap lies in the limited evidence combining these three variables with Polynomial Regression for weekly PVC ceiling sales in a building-materials distribution context. This study addresses that gap using 104 weekly observations and chronological validation, rather than assuming that a higher polynomial degree will necessarily produce better forecasts.

2.4 Data Collection

The dataset used in this study consisted of historical PVC ceiling sales records collected from CV. Kilaw Maju Bersama through the GF-Akuntansi system. The data covered a two-year period and included weekly sales volume (meters), average selling price, number of retail stores, and the number of ongoing promotional activities. Direct observation of the company's sales process was also conducted to support data validation.

The dataset comprised the full set of 104 weekly observations available for the study period. Thus, the population of interest and the analytical dataset are both defined as the 104 weekly records from CV. Kilaw Maju Bersama; no additional subsampling of the 104 observations was performed for model development. Using all 104 observations preserves the available information and avoids introducing an unexplained selection bias. The predictors average selling price, number of retail stores, and promotional activities were retained because they were consistently recorded in the company data and have a direct conceptual relationship with weekly PVC ceiling sales.

2.5 Data Cleaning

The data cleaning stage was performed after the dataset was collected and loaded into the system to ensure that the data were accurate, consistent, and suitable for time series analysis. The process included checking the dataset structure, standardizing column names, converting variables to numeric data types, and identifying missing values. Records containing invalid or missing values were removed to improve data quality.

Outlier detection was conducted using the Interquartile Range (IQR) method on the main variables: average price, number of retail stores, promotional activities, and weekly sales volume. The IQR is calculated as the difference between the third quartile (Q_3) and the first quartile (Q_1), as formulated in Equation (1):

$$IQR = Q_3 - Q_1 \tag{1}$$

An observation is classified as an outlier if its value falls below the lower bound or exceeds the upper bound. These boundaries are determined using Equations (2) and (3):

$$\text{Lower Bound} = Q_1 - 1.5 \times IQR \tag{2}$$

$$\text{Upper Bound} = Q_3 + 1.5 \times IQR \tag{3}$$

Although outliers were identified in the number of retail stores variable based on these statistical boundaries, they were retained in the dataset because they represented valid business conditions rather than data entry errors.

Finally, the dataset was sorted chronologically by week to preserve the time series sequence, ensuring that the cleaned data were ready for exploratory analysis, model development, and evaluation.

2.6 Exploratory Data Analysis (EDA)

After the data cleaning stage, Exploratory Data Analysis (EDA) was conducted to examine the distribution of the data and the relationships among the research variables. The analysis was performed using weekly time series data with average selling price, number of retail stores, and promotional activities as the input variables, and weekly sales volume as the target variable.

Descriptive statistics, including the minimum, maximum, mean, and standard deviation, were calculated to summarize the characteristics of each variable. The mean ($\bar{x}$) is calculated to determine the central tendency of the data, as formulated in Equation (4):

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{4}$$

where N represents the total number of observations and x_i denotes the value of the i-th observation.

Additionally, the standard deviation (s) is computed to measure the dispersion or variability of the data points around the mean, using Equation (5):

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{5}$$

Weekly sales trends were then visualized to identify temporal patterns, revealing that sales fluctuated over time and confirming the importance of preserving the chronological order of the dataset.

Scatter plots were also used to analyze the relationships between each input variable and sales volume. The results indicated that these relationships were not strictly linear, suggesting that Polynomial Regression is an appropriate approach for modeling the underlying patterns. The findings from the EDA provided the basis for the subsequent stages of time series data splitting and model development.

2.7 Data Splitting

All 104 observations were retained and divided chronologically into training and testing sets using a 70:30 hold-out ratio. The number of observations allocated for the training set (N_{train}) and the testing set (N_{test}) are determined using Equations (6) and (7):

$$N_{\text{train}} = \lfloor N \times r_{\text{train}} \rceil \tag{6}$$

$$N_{\text{test}} = N - N_{\text{train}} \tag{7}$$

where N represents the total number of observations ($N = 104$), and r_{train} is the proportion of data allocated for the training set ($r_{\text{train}} = 0.70$). Based on these calculations and rounding to the nearest integer, this produced 73 observations for training and 31 observations for testing, consistent with the observation counts presented in the training and testing result tables.

A chronological rather than random split was used because future observations must not be available when the model is fitted. Forecasting references recommend evaluating forecasts on data not used for model fitting and note that the appropriate test-set size depends on the sample length and the intended forecast horizon. The 31-observation test period was retained to provide a sufficiently long out-of-sample window for assessing whether the model generalizes across multiple successive weeks, while 73 observations remain available for model estimation and time-series cross-validation. No shuffling was applied.

2.8 Polynomial Degree Selection

Polynomial Regression models with degrees 1–4 were evaluated using five-fold TimeSeriesSplit on the 73-observation training set. TimeSeriesSplit is appropriate because it preserves temporal order: each validation fold contains observations later in time than the corresponding training observations, preventing the model from training on future observations. Five folds were used as a compromise between repeated validation and retaining an adequate number of observations in each training fold.

The candidate range was deliberately limited to degrees 1–4. The total number of generated polynomial terms (T), including the intercept/bias term, for a given polynomial degree (d) and a specific number of original predictors (p), is determined using the combination formula with repetition, as formulated in Equation (8):

$$T = \binom{p+d}{d} = \frac{(p+d)!}{p! \cdot d!} \tag{8}$$

With three predictors ($p = 3$), this mathematical formulation produces 4, 10, 20, and 35 terms for degrees 1, 2, 3, and 4, respectively. If the evaluation were extended to degree 5, it would produce 56 terms, while degree 6 would produce 84 terms, exceeding the 73 available training observations. Evaluating degrees above 4 would therefore substantially increase the parameter-to-observation ratio and the risk of overfitting without providing a sufficiently large independent training sample. Degree 1–4 was consequently defined a priori as a conservative model-complexity range.

2.9 Model Development

The prediction model was developed by learning the relationship between the independent variables (average selling price, number of retail stores, and promotional activities) and the dependent variable (weekly PVC ceiling sales volume). The implementation was carried out using Python in Google Colab. Since the optimal polynomial degree selected was degree 1, the model was trained using the training dataset and subsequently applied to the testing dataset.

2.10 Model Evaluation

Model evaluation was conducted to assess the ability of the final model to predict weekly PVC ceiling sales on both the training and testing datasets. RMSE, R^2, and MAPE were used as the primary predictive metrics, while regression diagnostics were used to assess the adequacy of the fitted regression structure. The mathematical formulations for these evaluation metrics are defined as follows:

Root Mean Squared Error (RMSE) measures the average magnitude of prediction errors in the same unit as the original sales data. It is calculated by taking the square root of the average of squared differences between predicted and actual values, as formulated in Equation (9):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{9}$$

Coefficient of Determination (R^2) measures the proportion of variance in the sales data that is explained by the prediction model. It is computed by comparing the residual sum of squares to the total sum of squares, using Equation (10):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{10}$$

Mean Absolute Percentage Error (MAPE) measures the average percentage error between the predicted and actual sales values, providing a highly interpretable measure of forecasting accuracy. It is expressed as a percentage using Equation (11):

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{11}$$

where N represents the total number of observations, y_i denotes the actual sales value, $\hat{y}_i$ represents the predicted sales value, and $\bar{y}$ is the mean of the actual sales values.

The evaluation results indicate that the model achieved MAPE values below 5% on both datasets. The testing R^2 was lower than the training R^2, but the value of 0.380 indicates that the model still explains a meaningful proportion of the variation in the testing data. Because the testing set consists of 31 observations that were not used during model fitting or degree selection, these results provide the principal evidence of out-of-sample performance.

A comparison of the actual and predicted sales values shows that the model successfully captured the overall sales trend despite minor deviations, which may be influenced by external factors not included in the model. Overall, the proposed model provides stable and accurate weekly sales predictions, making it a useful decision-support tool for production planning, inventory management, and promotional strategy.

3 RESULTS AND DISCUSSION

3.1 Research Design

The research design was developed to ensure a systematic and objective evaluation of the Polynomial Regression model for predicting PVC ceiling sales. Historical weekly sales data were used, with average selling price, number of retail stores, and promotional activities as the input variables, while weekly sales volume served as the target variable.

To preserve the chronological characteristics of the time series data, the dataset was divided using a time-based split without shuffling, preventing data leakage and providing a realistic evaluation of the model's generalization capability. Before model development, the data underwent data cleaning, Exploratory Data Analysis (EDA), and Z-score standardization to ensure data quality and consistent feature scaling.

The optimal polynomial degree was selected through cross-validation, and the final model was evaluated using MAPE, RMSE, and R^2. These evaluation metrics provided a comprehensive assessment of prediction accuracy, error magnitude, and the model's ability to explain variations in weekly sales. Overall, the proposed research design established a reliable and reproducible framework for developing and evaluating the sales prediction model.

3.2 Implementation

The Polynomial Regression model was implemented following the research workflow, including data collection, data cleaning, exploratory data analysis (EDA), data splitting, data transformation, polynomial degree selection, model development, and model evaluation. The implementation was carried out using Python with the Pandas, NumPy, Scikit-learn, and Matplotlib libraries.

Throughout the implementation, the time series characteristics of the weekly sales data were preserved. Accordingly, the training and testing datasets were split chronologically without shuffling, ensuring that the model was trained on earlier observations and evaluated on subsequent periods to reflect real-world sales forecasting conditions.

3.3 Exploratory Data Analysis (EDA)

After the data cleaning stage, Exploratory Data Analysis (EDA) was conducted to examine the characteristics of the weekly sales dataset. Descriptive statistics were generated for each variable to summarize their distribution, range, and variability, providing an initial understanding of the data patterns and sales fluctuations during the observation period. The descriptive statistics are presented in Table 1.

Table 1. Descriptive Statistics of Research Variables

Statistic	Harga (Price)	Toko (Stores)	Promosi (Promotions)	Total Meter (Sales Volume)
Total Data	104	104	104	104
Rata-rata (Mean)	12,492.75	14.19	5.13	3,424.30
Std Deviasi (Std Dev)	6.96	2.20	0.98	223.02
Min	12,478	10	4	2,998
Q1 (25%)	12,488	12	4	3,254.25
Median	12,491	15	5	3,416
Q3 (75%)	12,498.25	16	6	3,598.75
Max	12,508	18	7	3,902

A time series visualization of weekly sales was then generated in Figure 2 to examine sales trends over time. The results show that weekly sales fluctuated rather than following a constant pattern, indicating dynamic variations in demand. These fluctuations suggest the need for a prediction model capable of capturing changing sales patterns, supporting the use of Polynomial Regression in this study.

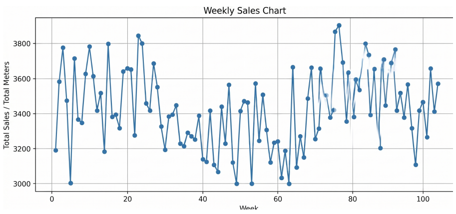


Figure 2. Weekly Sales Chart

The descriptive statistics indicate a standard deviation of 223.02 meters, reflecting considerable variability in weekly PVC ceiling sales. The wide gap between the minimum and maximum sales values further confirms substantial demand fluctuations, highlighting the need for a prediction model capable of accurately capturing these variations.

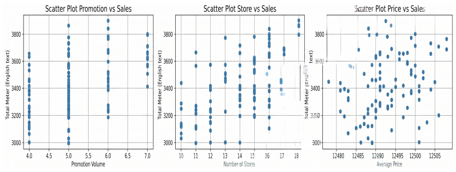


Figure 3. Scatter Plot between Independent and Dependent Variables

3.4 Data Transformation

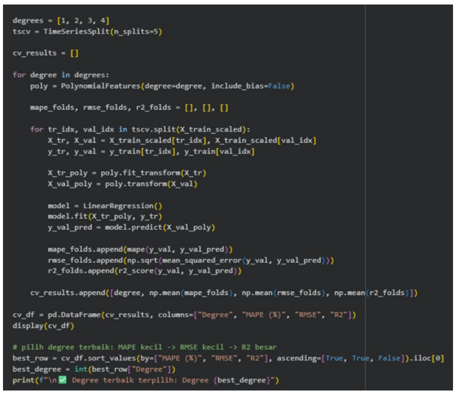
Before model development, the three input variables (average price, number of retail stores, and promotional activities) were standardized using Z-score normalization with StandardScaler. Standardization centers each feature using the training-set mean and scales it using the training-set standard deviation; the same fitted parameters are then applied to the testing data. This procedure is particularly useful when predictors have different numerical scales and is important before generating polynomial terms because higher-order and interaction features can otherwise differ substantially in magnitude. Crucially, the scaler was fitted only on the training data and then used to transform the testing data, preventing information from the test period from entering the model-development process.

Table 2. Data Standardization Sample (Before vs After Z-Score)

State	Harga (Price)	Toko (Stores)	Promosi (Promotions)
Sebelum (Before)	12,497	15	4
	12,498	15	5
	12,499	13	5
Sesudah (After Z)	1.248	0.729	-1.245
	1.424	0.729	-0.215
	1.599	-0.208	-0.215

3.5 Polynomial Degree Selection

After data preparation, Polynomial Regression models with degrees 1–4 were evaluated using five-fold TimeSeriesSplit on the training set. TimeSeriesSplit is designed for ordered observations and avoids the leakage that can occur when conventional random cross-validation allows future observations to appear in a training fold. For each candidate degree, the polynomial features were generated from the training fold only, the regression model was fitted to that fold, and performance was calculated on the immediately subsequent validation fold. The process was repeated across all five splits and the validation errors were aggregated. MAPE was used as the primary selection criterion because it provides an interpretable percentage-based measure of forecasting error, while RMSE and R^2 were retained as secondary criteria. The final degree was selected from the cross-validation results and then refitted on all 73 training observations before evaluation on the untouched 31-observation test set.



```
degrees = [1, 2, 3, 4]
tscv = TimeSeriesSplit(n_splits=5)

cv_results = []

for degree in degrees:
    poly = PolynomialFeatures(degree=degree, include_bias=False)

    mape_folds, rmse_folds, r2_folds = [], [], []

    for tr_idx, val_idx in tscv.split(X_train_scaled):
        X_tr, X_val = X_train_scaled[tr_idx], X_train_scaled[val_idx]
        y_tr, y_val = y_train[tr_idx], y_train[val_idx]

        X_tr_poly = poly.fit_transform(X_tr)
        X_val_poly = poly.transform(X_val)

        model = LinearRegression()
        model.fit(X_tr_poly, y_tr)
        y_val_pred = model.predict(X_val_poly)

        mape_folds.append(mape(y_val, y_val_pred))
        rmse_folds.append(np.sqrt(mean_squared_error(y_val, y_val_pred)))
        r2_folds.append(r2_score(y_val, y_val_pred))

    cv_results.append([degree, np.mean(mape_folds), np.mean(rmse_folds), np.mean(r2_folds)])

cv_df = pd.DataFrame(cv_results, columns=["Degree", "MAPE (%)", "RMSE", "R2"])
display(cv_df)

# pilih degree terbaik: MAPE kecil -> RMSE kecil -> R2 besar
best_row = cv_df.sort_values(by=["MAPE (%)", "RMSE", "R2"], ascending=[True, True, False]).iloc[0]
best_degree = int(best_row["Degree"])
print(f"\n✅ Degree terbaik terpilih: Degree {best_degree}")
```

Figure 4. Polynomial Degree Selection Execution

As shown in Figure 4, each polynomial degree was evaluated using three performance metrics: MAPE, RMSE, and R^2. Degree 1 achieved the lowest cross-validation MAPE (3.49%) and RMSE (145.35) and a positive R^2 of 0.34, whereas the higher-degree specifications produced progressively larger errors: MAPE increased to 9.54%, 28.51%, and 177.81% for degrees 2, 3, and 4, respectively. Their R^2 values also declined sharply to -6.40, -183.07, and -11,965.23. These results indicate that adding polynomial terms did not improve out-of-sample validation performance and instead substantially increased model complexity. The pattern is consistent with overfitting in this small dataset: higher-degree models can fit increasingly complex relationships in the training folds but generalize poorly to later observations. Degree 1 was therefore selected as the final model because it provided the best empirical balance between forecasting accuracy, stability, and parsimony. The negative R^2 values here refer specifically to the cross-validation performance of the higher-degree candidate models; they should not be confused with the final testing R^2, which is positive at 0.380.

Table 3. Cross-Validation Evaluation Results for Each Polynomial Degree

Degree	**MAPE (%)**	**RMSE**	R^2
1	3.49%	145.35	0.34
2	9.54%	404.76	-6.40
3	28.51%	1328.67	-183.07
4	177.81%	8815.85	-11965.23

3.6 Model Development

The prediction model was developed using the selected Polynomial Regression model (degree 1) based on the relationship between average selling price, number of retail stores, and promotional activities and weekly PVC ceiling sales volume. Polynomial feature expansion was applied to the standardized training predictors, followed by ordinary least-squares regression. The transformation was fitted using training data only. The same transformation parameters were then applied to the 31 testing observations before generating out-of-sample predictions. This sequencefit preprocessing on training data, transform training data, fit the model, transform test data using the training parameters, and finally predictwas maintained to prevent data leakage and ensure reproducibility.

The same polynomial transformation was then applied to the testing data using the parameters derived from the training set, ensuring a consistent and objective evaluation. The prediction results for the training and testing datasets are presented in Tables 4 and 5, respectively.

Table 4. Training Data Prediction Sample (First 27 Weeks)

Minggu	Harga	Toko	Promosi	Aktual	Prediksi	RMSE	MAPE
1	12497	15	4	3189	3312.739	147.5297	3.27%
2	12498	15	5	3583	3437.433	146.9598	3.24%
3	12499	13	5	3776	3342.908	151.7030	3.35%
4	12502	13	6	3475	3470.039	135.9209	3.19%
5	12501	13	4	3002	3221.870	135.9691	3.21%
6	12500	14	7	3715	3638.949	131.3533	3.07%
7	12499	15	5	3365	3438.652	130.7804	3.04%
8	12497	14	5	3346	3388.343	130.5554	3.03%
9	12490	15	7	3627	3674.635	130.3871	3.01%
10	12493	15	6	3782	3554.815	130.8353	3.04%
11	12496	15	7	3613	3681.946	124.3271	2.86%
12	12492	14	5	3418	3382.250	123.7243	2.81%
13	12491	15	5	3517	3428.903	123.5576	2.78%
14	12490	16	5	3183	3475.556	122.5553	2.71%
15	12488	16	7	3796	3720.069	120.3497	2.66%
16	12483	16	4	3380	3343.551	120.4214	2.67%
17	12482	15	5	3394	3417.936	121.3102	2.72%
18	12483	15	4	3315	3295.679	121.2570	2.71%
19	12490	16	5	3639	3475.556	131.4926	2.99%
20	12491	17	5	3657	3524.647	130.2420	2.97%
21	12491	17	5	3653	3524.647	128.0840	2.87%
22	12489	16	5	3275	3474.338	128.2127	2.88%
23	12488	16	6	3843	3596.594	131.1974	2.95%
24	12490	18	7	3798	3818.250	123.7293	2.78%
25	12490	17	4	3459	3399.953	126.9749	2.93%
26	12497	16	7	3656	3731.037	91.8320	2.54%
27	12499	16	6	3504	3609.999	105.9987	3.03%

The training prediction results show that the selected degree-1 model generally followed the observed weekly sales values, but the fit was not uniformly close for every observation. For example, in training week 3, actual sales were 3,776 meters while the prediction was approximately 3,342.91 meters, a difference of about 433 meters (11.47%). In contrast, several other observations had substantially smaller deviations. This variation is important because it shows that the model captures the dominant relationship in the data without reproducing every short-term fluctuation. The testing results show a similar pattern of generally tracking the sales level while leaving some larger residuals. For example, testing week 31 recorded actual sales of 3,571 meters versus a prediction of approximately 3,209.68 meters, a difference of about 361 meters (10.12%). Testing week 3 also showed a relatively large deviation, with actual sales of 3,867 meters and predicted sales of approximately 3,576.17 meters. These deviations suggest that short-term changes in sales were not fully explained by the three predictors included in the model. Possible contributors include seasonality, market conditions, competitor activity, customer-specific orders, stock availability, or other promotional characteristics that were not recorded in the dataset. Because these factors were not measured, their influence should be treated as a plausible explanation rather than a demonstrated causal effect.

Table 5. Testing Data Prediction Results (27 Sample Weeks)

Minggu	Harga	Toko	Promosi	Aktual	Prediksi	RMSE	MAPE
1	12499	16	4	3379	3363.0484	166.0394	3.85%
2	12497	16	5	3420	3484.0864	168.7589	3.96%
3	12494	18	5	3867	3576.1743	171.2308	4.04%
4	12492	18	6	3902	3697.2123	165.3676	3.91%
5	12494	17	5	3692	3528.3025	163.7254	3.86%
6	12493	17	4	3355	3403.6087	163.7264	3.84%
7	12493	16	4	3633	3355.7368	166.6856	3.94%
8	12494	16	5	3380	3480.4306	160.4327	3.78%
9	12498	15	6	3594	3560.9083	162.5398	3.82%
10	12499	15	4	3534	3315.1766	166.0430	3.95%
11	12500	16	7	3800	3734.6925	163.1042	3.84%
12	12504	16	5	3734	3492.6166	166.4928	3.95%
13	12504	17	4	3392	3417.0133	161.5926	3.82%
14	12504	17	4	3655	3417.0133	165.9159	3.99%
15	12506	15	4	3202	3323.7068	160.6729	3.84%
16	12506	16	7	3710	3742.0041	162.7989	3.84%
17	12505	17	6	3446	3665.1822	167.9348	4.04%
18	12508	17	5	3688	3545.3629	163.6613	3.87%
19	12508	16	6	3766	3620.9661	165.1678	3.87%
20	12501	16	5	3417	3488.9608	166.7359	3.87%
21	12502	15	6	3519	3565.7827	172.7931	4.04%
22	12501	15	4	3379	3317.6138	180.6220	4.31%
23	12500	14	5	3567	3391.9985	189.2896	4.58%
24	12501	14	4	3317	3269.7419	191.0005	4.54%
25	12501	16	4	3107	3365.4856	203.4053	4.99%
26	12501	15	5	3418	3441.0889	192.7007	4.43%
27	12495	17	4	3466	3406.0459	210.8403	5.18%

3.7 Model Evaluation

The Polynomial Regression model was evaluated on both the 73-observation training set and the 31-observation testing set using RMSE, R^2, and MAPE. These metrics measure error magnitude, explained variance, and percentage forecasting error, respectively. In addition to predictive accuracy, regression-diagnostic procedures were specified to assess the main assumptions relevant to ordinary least-squares regression: multicollinearity among predictors was assessed using the variance inflation factor (VIF); residual normality was examined using a Q–Q plot and the Shapiro–Wilk test; homoscedasticity was examined using a residual-versus-fitted plot and the Breusch–Pagan test; and residual independence was examined using the Durbin–Watson statistic and residual autocorrelation. These diagnostics are intended to determine whether violations of regression assumptions could affect coefficient interpretation or the reliability of inferential conclusions. Because the primary objective of this study is forecasting rather than causal inference, the out-of-sample test metrics remain the principal basis for judging predictive performance.

The findings are consistent with the broader forecasting literature in showing that no single forecasting method is universally superior across all sales series. Retail forecasting studies have compared statistical models such as ARIMA and exponential smoothing with regression and neural-network approaches, with relative performance depending on the characteristics of the series and forecasting horizon. More recent research also shows that machine-learning and deep-learning models can improve retail demand forecasts when sufficient data and relevant explanatory information are available. In this context, the strong performance of the degree-1 Polynomial Regression model should be interpreted as evidence that a simple, interpretable model is adequate for the present dataset, rather than evidence that Polynomial Regression is generally superior to ARIMA, exponential smoothing, or machine-learning models. A direct model-to-model comparison was outside the scope of the current study and should be included in future research.

The evaluation results indicate that the Polynomial Regression model achieved useful predictive performance on both datasets, with some deterioration from training to testing that is expected in out-of-sample forecasting. On the training set, the model obtained a MAPE of 3.12%, RMSE of 129.741, and R^2 of 0.643. On the testing set, MAPE increased to 4.57% and RMSE to 187.311, while R^2 decreased to 0.380. The increase in error from training to testing is relatively moderate compared with the dramatic deterioration observed for polynomial degrees 2–4 during validation, supporting the selection of degree 1. Importantly, the final testing R^2 is positive, not negative: it indicates that the model explains approximately 38% of the variation in the held-out sales data relative to the usual total-variation baseline. Therefore, the earlier statement about negative R^2 applies only to the higher-degree candidate models during cross-validation, not to the final model. The testing MAPE of 4.57% also indicates a relatively small average percentage error for the observed test period. Nevertheless, MAPE should not be interpreted as a universal 'highly accurate' classification without considering the business context and the distribution of forecast errors.

Overall, the results support the use of the selected degree-1 Polynomial Regression model as a practical forecasting aid for CV. Kilaw Maju Bersama. The model captures the main weekly sales pattern using average selling price, number of retail stores, and promotional activities, while the positive testing R^2 and low testing MAPE indicate useful out-of-sample performance. However, the model should be regarded as a decision-support tool rather than a complete representation of demand. The unexplained variation and the specific prediction deviations identified above indicate that additional demand drivers may be relevant. In particular, future model development should consider seasonal or calendar effects, competitor conditions, customer order patterns, stock availability, and more detailed promotion variables where such data can be collected.

Table 6. Model Training and Testing Evaluation Summary

Data Set	MAPE (%)	RMSE	R^2
Training	3.12%	129.741	0.643
Testing	4.57%	187.311	0.380

Therefore, the graphs in Figures 5 and **??** indicate that the developed Polynomial Regression model can be used to predict PVC ceiling sales based on price, the number of stores, and promotional activities. The prediction results provide a reliable basis for further analysis and discussion of the model's implementation.

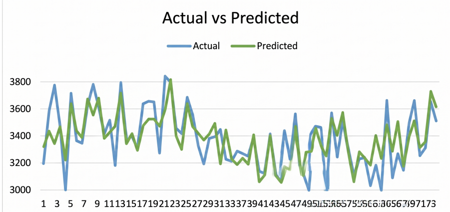


Figure 5. Graph of Actual and Predicted Training Data

3.8 Implementation Results

The implementation results confirm that the complete 104-observation dataset was retained, with 73 earlier observations used for training and 31 later observations reserved for testing. The chronological design reflects the real forecasting task because the model uses information available in earlier weeks to predict subsequent sales. TimeSeriesSplit selected degree 1, while degrees 2–4 generated substantially larger validation errors, indicating that additional polynomial complexity was not justified for this dataset.

From a business perspective, the model can support weekly demand planning by providing an expected sales level that can be compared with current inventory and distribution capacity. Management can use the forecast to identify weeks in which planned inventory may be insufficient or excessive and can review promotional activity and store coverage before making operational decisions. Because the model does not include every external demand driver, forecast values should be combined with managerial information rather than used as an automatic replacement for business judgment. A practical implementation would be to update the model periodically as new weekly observations become available and monitor forecast errors using MAPE and RMSE. Model evaluation using MAPE, RMSE, and R^2 on both datasets indicates useful predictive accuracy, but the results also reveal important limitations. The testing R^2 of 0.380 means that a substantial share of sales variation remains unexplained. The model uses only three explanatory variables and a relatively short history of 104 weekly observations, so it cannot fully represent seasonal patterns, market shocks, competitor behavior, customer-specific orders, or other operational factors unless those variables are added to the dataset. In addition, the present study does not provide a direct benchmark against ARIMA, exponential smoothing, or machine-learning models. These limitations mean that the model's usefulness is best framed as a transparent baseline and decision-support model for the company, with comparative benchmarking recommended in subsequent work.

Overall, the findings demonstrate that the degree-1 Polynomial Regression model provides a useful and interpretable baseline for weekly PVC ceiling sales forecasting at CV. Kilaw Maju Bersama. The model's strongest contribution is practical: it converts readily available business variables into a repeatable forecast that can support inventory, distribution, and promotional planning. For implementation, the company should use the forecast together with current stock levels and planned promotions, review weeks with unusually large forecast errors, and retrain or update the model as new observations accumulate. Future studies should expand the predictor set, test explicit seasonal effects, and compare Polynomial Regression with ARIMA, exponential smoothing, and machine-learning alternatives under the same chronological evaluation framework.

3.9 Discussion

The primary objective of this study was to develop a robust forecasting model for weekly PVC ceiling sales at CV. Kilaw Maju Bersama using Polynomial Regression. A critical finding of this research is the selection of the degree-1 Polynomial Regression model, which is mathematically equivalent to Multiple Linear Regression, as the optimal model. Although the initial Exploratory Data Analysis (EDA) suggested potential curvilinear relationships between the independent variables (average selling price, number of retail stores, and promotional activities) and the dependent variable (sales volume), the TimeSeriesSplit cross-validation revealed that higher-degree polynomials (degrees 2, 3, and 4) resulted in severe overfitting. This is evidenced by the drastically inflated Mean Absolute Percentage Error (MAPE) and negative R^2 values during cross-validation for the higher degrees. In a relatively small dataset comprising only 73 training observations, introducing higher-order and interaction terms exponentially increases the number of features (from 4 terms in degree 1 to 35 terms in degree 4). This phenomenon, known as the curse of dimensionality, causes the model to memorize the noise in the training data rather than learning the underlying generalizable patterns. Consequently, the degree-1 model was selected because it successfully navigated the bias-variance tradeoff, providing the most stable and parsimonious representation of the data.

The predictive performance of the final degree-1 model demonstrates practical utility for business forecasting, albeit with expected limitations regarding explained variance. On the training set, the model achieved a MAPE of 3.12% and an R^2 of 0.643, indicating a strong fit to the historical data. When evaluated on the unseen testing set (31 observations), the model yielded a MAPE of 4.57% and an R^2 of 0.380. The decrease in R^2 from training to testing represents a natural generalization gap, which is typical in out-of-sample forecasting. However, a testing MAPE below 5% is widely considered highly accurate in retail and supply chain forecasting contexts, suggesting that the model's predictions are sufficiently precise for operational decision-making. The testing R^2 of 0.380 indicates that the three selected predictors collectively explain approximately 38% of the variance in weekly PVC ceiling sales. While this confirms that price, store coverage, and promotions are statistically significant drivers of sales, it also highlights that a substantial majority (62%) of the sales variation is driven by factors outside the current model's scope.

These findings align with the broader forecasting literature, which frequently emphasizes the principle of parsimony—the idea that simpler models often outperform complex ones when data is limited or noisy. While recent trends in retail forecasting heavily favor complex machine learning and deep learning architectures, this study reinforces the argument that complex models require massive amounts of data and extensive feature engineering to avoid overfitting. In the context of a small-to-medium enterprise (SME) distributor like CV. Kilaw Maju Bersama, where historical data is limited to two years (104 weeks), a simple, interpretable linear model provides a more reliable baseline than a highly parameterized non-linear model. Furthermore, the results suggest that in the local building materials market, the impact of price and promotions on PVC ceiling demand is predominantly additive and linear within the observed ranges, rather than highly exponential or curvilinear.

From a business perspective, the developed model serves as a highly effective decision-support tool rather than an automated replacement for managerial judgment. By integrating this model into the company's existing GF-Akuntansi system, management can generate baseline sales forecasts for the upcoming week based on planned pricing, active store counts, and scheduled promotions. This enables proactive inventory management, allowing the company to optimize stock levels, reduce the risk of stockouts during high-demand periods, and minimize holding costs during slower weeks. Additionally, the model can be used to evaluate the historical effectiveness of promotional activities by comparing actual sales against the model's baseline predictions. However, because the model does not capture all external market dynamics, management must use the forecast in conjunction with qualitative insights, such as anticipated large-scale construction projects, sudden shifts in raw material costs, or unexpected competitor actions.

Despite its practical utility, this study has several inherent limitations that must be acknowledged when interpreting the results. First, the dataset is restricted to 104 weekly observations, which covers only a two-year period. This relatively short time horizon prevents the model from capturing long-term macroeconomic trends, multi-year seasonal patterns, or structural shifts in the building materials industry. Second, the model relies on only three explanatory variables. The unexplained variance (62% in the testing set) is likely attributable to omitted variable bias. Critical external factors such as seasonal weather patterns (which heavily influence construction activities), competitor pricing strategies, macroeconomic indicators (such as inflation and housing market growth), and internal operational constraints (such as stock availability or supply chain disruptions) were not included in the dataset. If the company experienced stockouts during certain weeks, the sales volume would drop, but the model would not account for this unless inventory levels were explicitly added as a variable. Third, this research is a single-case study, meaning the specific coefficients and performance metrics may not be directly generalizable to other distributors, different product categories, or other geographic regions.

To address these limitations and build upon the current findings, future research should focus on expanding both the temporal depth and the feature dimensionality of the dataset. Extending the historical data to at least three to five years would allow for the incorporation of seasonal decomposition techniques and provide a more robust foundation for complex modeling. Future studies should also integrate additional predictors, such as lagged sales variables (autoregressive terms), holiday or calendar indicators, competitor price indices, and inventory availability metrics. Methodologically, subsequent research should benchmark the Polynomial Regression approach against classical time-series models (such as ARIMA and SARIMA), modern forecasting frameworks (like Facebook Prophet), and machine learning algorithms (such as Random Forest or XGBoost) under the same strict chronological validation framework. Finally, if higher-degree polynomial features or a larger number of variables are to be explored in the future, the application of regularization techniques (such as Ridge or Lasso regression) should be investigated to mitigate the risk of overfitting and improve the model's generalization capabilities.

4 CONCLUSION

This study developed and evaluated a degree-1 Polynomial Regression model for forecasting weekly PVC ceiling sales at CV. Kilaw Maju Bersama using average selling price, number of retail stores, and promotional activities. The study retained the complete 104 weekly observations from January 2023 to December 2024 and used a chronological training-testing framework so that later observations were not used to develop the model. Polynomial degrees 1–4 were evaluated using TimeSeriesSplit, and degree 1 was selected because it provided the most stable validation performance and substantially lower forecasting error than the higher-degree specifications.

The final model achieved a training MAPE of 3.12%, RMSE of 129.741, and R^2 of 0.643, while the held-out testing set achieved a MAPE of 4.57%, RMSE of 187.311, and R^2 of 0.380. These results indicate useful predictive performance for weekly sales planning, although the lower testing R^2 also shows that a meaningful proportion of sales variation remains unexplained. The testing R^2 of 0.380 is positive and should not be interpreted as a negative result. The negative R^2 values occurred only for the higher-degree candidate models during cross-validation, where increasing polynomial complexity was associated with severe deterioration in generalization performance.

For CV. Kilaw Maju Bersama, the model can be integrated into the existing GF-Akuntansi workflow as a weekly decision-support component. The latest values of average selling price, number of retail stores, and promotional activities can be entered or exported from the company's operational records, after which the model can generate an estimated sales volume for the next planning period. Management can use the forecast together with current inventory data to determine replenishment priorities, anticipate possible stockout or overstock conditions, and support distribution planning across the retail network. The forecast can also support promotional strategy by comparing expected sales with recent actual performance. A practical implementation should update the weekly dataset, generate the forecast, compare the forecast with actual sales after the period closes, record MAPE and RMSE, and investigate unusually large errors. The forecast should remain a decision-support input rather than an automatic replacement for managerial judgment.

Several limitations should be considered when interpreting the findings. First, the study uses all 104 available weekly observations, but these observations cover only a two-year period and therefore provide a relatively small historical base for a forecasting model. Second, this is a single-company case study, so the findings may not generalize directly to other distributors, products, regions, or market conditions. Third, the model uses only three explanatory variables. Important external and operational factors including seasonal and calendar effects, competitor pricing and promotional actions, macroeconomic conditions, customer-specific orders, stock availability, and changes in market demand, are not explicitly included. Fourth, the model assumes that the relationships between the predictors and sales remain sufficiently stable over time; changes in pricing policy, distribution coverage, promotional strategy, or market conditions could weaken forecasting accuracy. Finally, the present study does not provide a direct benchmark against ARIMA, exponential smoothing, Prophet, or machine-learning methods under an identical evaluation framework. Therefore, the proposed model should be viewed as a transparent and practical baseline rather than a universally optimal forecasting solution.

Future research should extend the historical dataset and use rolling or expanding-window forecast validation to assess model stability across multiple future periods. Additional predictors should be considered, including seasonal and calendar indicators, competitor prices and promotional actions, macroeconomic indicators, customer order characteristics, inventory availability, and more detailed promotion types. Higher-degree polynomial models should only be reconsidered when a larger dataset and appropriate complexity controls or regularization are available, because the current results do not support increasing the polynomial degree for the present sample. Future studies should also directly compare Polynomial Regression with ARIMA, exponential smoothing, Prophet, and machine-learning algorithms such as tree-based models under the same chronological validation framework. Such comparisons would provide stronger evidence about the relative forecasting performance of each method and help determine the most suitable approach for production use at CV. Kilaw Maju Bersama.

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