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Evaluation of ARIMA model performance in projecting future sales: case study on electronic products

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Abstract

The sales performance of electronic products is significantly affected by a variety of internal and external factors, necessitating precise forecasting models to aid strategic decision-making. This research investigates the effectiveness of ARIMA models in predicting future sales, focusing on a case study involving electronic products. The study utilizes monthly sales data obtained from company records and industry databases. The methodology includes assessing data stationarity through the Augmented Dickey-Fuller (ADF) test, applying differencing when required, and determining ARIMA parameters using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analyses. The findings reveal that ARIMA models effectively capture seasonal variations and trend patterns. Their performance is assessed using metrics such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). This study highlights the need to incorporate external factors into prediction models to enhance accuracy and recommends exploring alternative approaches that can better adapt to dynamic market conditions.

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1. Introduction

In the highly competitive and dynamic electronics industry, accurate sales projections play a critical role in supporting strategic decision-making[1]. Companies in this sector are faced with the challenge of balancing fluctuating market demand, rapid technological change, and the need to efficiently manage supply chains and inventories.[2][3] Inappropriate sales projections can lead to excess inventory or product shortages, which in turn can negatively impact a company's profitability and competitiveness[4]. Therefore, the development of reliable predictive models has become a necessity for companies that want to stay ahead in the ever-changing business landscape. One approach that is widely used in sales forecasting is time series data analysis. Autoregressive Integrated Moving Average (ARIMA) models have become one of the most popular methods and have proven effective in capturing seasonal patterns as well as long-term trends in various industry sectors.[5][6] ARIMA has the advantage of being able to model non-stationary time series, which is often characteristic of electronic product sales data.[7] However, there are still concerns regarding the predictive accuracy of this model when faced with the complexity of sales data influenced by external factors such as promotions, technological changes, and unpredictable consumer behavior.[8] Therefore, it is important to further evaluate the performance of ARIMA models in the context of the electronics industry to determine whether these models can provide reliable results for future sales projections.

Although the Autoregressive Integrated Moving Average (ARIMA) model has been widely recognized as one of the reliable methods in time series forecasting, its application to electronic product sales data presents its own challenges.[9][10] The electronics industry tends to experience high variability triggered by external factors such as promotion cycles, new technology releases, changing consumer preferences, as well as global economic fluctuations. Electronic product sales patterns are often influenced not only by seasonal or long-term trends, but also by unexpected events that are difficult to predict using conventional time series models. [9][11]This raises concerns regarding the ability of ARIMA to effectively capture the complex dynamics of these highly variable sales patterns. In addition, while ARIMA can be optimized to handle non-stationary data, the model requires a careful adjustment process to ensure optimal results. This process includes selecting the right parameters, controlling for seasonal effects, and handling anomalies that may appear in the sales data. [12]The lack of empirical evaluation of ARIMA's performance in handling the complexity of the electronics market has led to the need for further research. This study aims to fill this gap by thoroughly evaluating the performance of ARIMA in projecting electronic product sales and assessing whether this model is reliable in an increasingly dynamic context.[7]

Various previous studies have highlighted the successful use of ARIMA models in predicting time series patterns in various industry sectors, such as retail, finance, and manufacturing. [13]These studies show that ARIMA can provide accurate predictive results for data that exhibit seasonal patterns and long-term trends. However, studies that are more specific to the electronics sector are limited, especially those that focus on the challenges of sales projections in the context of high variability caused by promotional cycles, new product releases, and rapid technological changes. For example, research by Smith et al. (2020) showed that ARIMA has limitations in projecting sales data influenced by external factors, such as large promotions or unexpected events, which often occur in the electronics market. Another study by Zhang et al. (2021) also noted that ARIMA requires further customization to handle non-stationary data often found in sales of products with short life cycles, such as consumer electronics products.[14] Based on these studies, this research aims to evaluate in more depth the performance of ARIMA models in projecting electronic product sales by taking into account various influencing variables, such as seasonal factors, promotions, and dynamic consumer behavior. [15]Suggestions for improvement from previous research include the integration of ARIMA models with hybrid methods or machine learning techniques to improve prediction accuracy, especially in handling highly volatile data.[16] This research also seeks to fill the gap by providing a more specific empirical analysis of the application of ARIMA in the electronics industry, which is expected to provide deeper and more practical insights for decision-makers in the industry.

The main objective of this study is to evaluate the performance of the Autoregressive Integrated Moving Average (ARIMA) model in projecting future sales of electronic products amid dynamic market fluctuations. [17]Specifically, this study aims to assess the ability of ARIMA in capturing seasonal patterns, long-term trends, as well as responses to external factors such as promotions and new product releases that often occur in the electronics industry.[18] In addition, this study also aims to identify the extent to which the prediction accuracy generated by the ARIMA model can assist in strategic decision-making related to inventory management, production planning, and marketing strategies. Through a case study on electronic products, this research is expected to provide deeper insights into the effectiveness of ARIMA as a sales projection tool and open up opportunities for the development of more complex and adaptive predictive models in the future.[19]

Although ARIMA models have been widely used in research related to time series forecasting, studies on their application in electronic product sales projections are still limited. [5][20]Most of the previous studies focused on the retail and manufacturing sectors in general, without paying special attention to the electronics industry which has unique market characteristics, such as short product life cycles, rapid technological innovation, and high volatility due to external factors such as promotions and new product releases. Research by Brown et al. (2019) and Kim et al. (2020), for example, show that ARIMA works effectively in modeling seasonal product sales data, but does not provide an in-depth analysis of external factors that may affect the accuracy of predictions, especially in the highly dynamic electronics market. In addition, most existing studies do not integrate prediction models with complex variables that often arise in electronic product sales, such as sudden promotions or demand spikes following the launch of new technologies.[4][21] This gap suggests a need for more specific research on the performance of ARIMA in the context of electronics sales projections, where complex seasonal patterns and the influence of external variables require a more adaptive analysis approach. [22]This research seeks to fill this gap by evaluating the performance of ARIMA in modeling electronic product sales, and identifying potential adjustments or combinations with other predictive methods to improve the accuracy and relevance of the model in fast-changing market conditions.[23]

This research presents a novel contribution to the sales forecasting literature by placing focus on evaluating the performance of ARIMA models in projecting sales of electronic products, a sector characterized by high levels of volatility and market dynamics. In contrast to previous studies that have focused more on the retail and manufacturing industries in general, this study specifically investigates how ARIMA can handle complex seasonal patterns and the influence of external factors, such as promotion cycles, new product releases, as well as rapid changes in consumer preferences, which often occur in the electronics market.[24] The novelty of this research also lies in the attempt to integrate empirical analysis with a more adaptive approach, which involves recommending the development of hybrid models or the integration of other predictive methods to improve forecasting accuracy in a constantly changing market environment. [4][3] The justification for this research lies in the increasingly urgent need to improve the accuracy of sales projections in the electronics industry, where strategic decisions regarding inventory, production, and marketing rely heavily on reliable forecasting results.[25] In this context, this research not only provides empirical insights into the performance of ARIMA, but also opens up opportunities for the development of more sophisticated and relevant predictive approaches for the electronics sector that have the potential to improve the operational efficiency and competitiveness of firms. As such, this research makes a significant contribution in both academic and practical terms in the field of sales prediction analysis.

2. Research Methodolgy

Research Design

This research uses a quantitative approach with experimental methods and time series analysis. The *Autoregressive Integrated Moving Average* (ARIMA) model is chosen as the main model to evaluate its performance in projecting electronic product sales. This study focuses on sales data from one of the major electronic product manufacturers for the past five years (2019-2023). This data was chosen because it contains seasonal variations, high fluctuations in demand, as well as the intervention of large promotions and new product releases.

Data Source and Data Collection

The data used in this study consists of monthly sales data of electronic products collected secondarily from company sales reports and industry databases. The data also includes additional information such as promotion cycles, new product launches, and relevant external market conditions. To ensure the validity of the data, collection was done through official company access with a verification process from the company's internal team. Any data that does not meet the accuracy requirements will be excluded from the analysis.

ARIMA Modeling

The ARIMA modeling process begins with an examination of the stationarity characteristics of the data using the Augmented Dickey-Fuller (ADF) test. If the data is not stationary, differentiation will be applied to make it stationary. Then, ARIMA parameters are selected based on the *Autocorrelation Function* (ACF) and *Partial Autocorrelation Function* (PACF) results. After that, the best ARIMA model is selected based on the *Akaike Information Criterion* (AIC) and *Bayesian Information Criterion* (BIC) values. This ARIMA model will be applied to electronic product sales time series data to predict future sales trends.

The process of modeling and formulating an ARIMA model to project sales begins with systematic steps to ensure the accuracy and fit of the model to the data. The following is a detailed description of the process:

1. Stationarity Check with Augmented Dickey-Fuller (ADF) Test

$$\Delta y_t = \alpha + \beta t + \emptyset y_{t-1} + \sum_{i-1}^{p} \gamma_i \Delta y_{t-i} + \in_t \tag{1}$$

Where : Δy_t =the first difference of the time variable yt, $\alpha =$ a constant, $\beta t =$ the time trend (if any), $\emptyset$ =the coefficient of $yt-1$,$\gamma_i =$ the coefficient of the previous lag difference, $\in_t$=the error term.

The null hypothesis of the ADF test is that there are unit roots (data is not stationary), and the alternative hypothesis is that the data is stationary.

2. Differencing

Differencing is done to transform the data into stationary. The formula for first differencing is:

$$y'_t = y_t - y_{t-1} \tag{2}$$

Where : y'_t =the differencing value of time *t*, y_t =the data value at time *t*, y_{t-1} =the data value at time *t*.

If the data remains non-stationary after first differencing, we can apply second differencing

$$y_t^n = y'_t - y'_{t-1} \tag{3}$$

3. Parameter Selection of ARIMA (p, d, q)

$$y_t = \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-} + \cdots + \theta_q \epsilon_{q-1} + \epsilon_t \tag{4}$$

Where : y_t =the value at time *t*, $\emptyset_i$ =autoregressive (AR) parameters, θ_i =the moving average (MA) parameter, ϵ_t =the error term (white noise)

4. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)

The AIC and BIC criteria are used to select the best model based on model fit and complexity

$$AIC = 2k - 2\log(L)$$
$$BIC = \log(n)k - 2\log(L) \tag{5}$$

Where *k*= the number of parameters in the model, *L*= the maximum likelihood value of the model, *n* = the number of observations.

Model Performance Evaluation

The performance of the ARIMA model is evaluated using several prediction accuracy metrics, including *Mean Absolute Percentage Error* (MAPE), *Root Mean Square Error* (RMSE), and *Mean Absolute Error* (MAE). These metrics were chosen to measure how well the ARIMA model can project sales based on historical data. For validation, the model was tested using the *out-of-sample forecasting* technique, where the training and testing data were separated with an 80:20 scheme. In addition, the ARIMA prediction results are compared with other predictive models such as *Exponential Smoothing* and *Seasonal Decomposition of Time Series* (STL) to determine the superiority of the model.

Handling External Factors

In an effort to understand the influence of external variables, this study also examined the impact of large-scale promotions and new product launches on ARIMA prediction accuracy. In this case, the sales data was separated into two groups, i.e. before and after the promotion or new product launch period. Comparative analysis is conducted to measure whether the presence of external interventions significantly affects the accuracy of the prediction model. If necessary, a combination or hybrid method between ARIMA and machine learning techniques, such as *Random Forest* or *XGBoost*, will be proposed to improve prediction accuracy under more complex conditions.

Analysis and Interpretation

The sales projection results from the ARIMA model are analyzed in depth to understand the patterns generated as well as the factors that affect the prediction accuracy. This research also includes sensitivity analysis to changes in model parameters, such as changes in differentiation, as well as sensitivity to changes in input data related to seasonal cycles and long-term trends. The findings from this analysis will be interpreted to provide insights for business decision-makers in managing inventory, production strategies, and marketing activities.

3. Results and Discussion

Application of the ARIMA formula formulation with clear steps using data tables and final results. We will go through the stages from checking stationarity to modeling with ARIMA.

Table 1. Electronic Product Monthly Sales Data

Month	Sales (Unit)
Jan 2022	200
Feb 2022	210
Mar 2022	250
Apr 2022	270
Mei 2022	300
Jun 2022	320
Jul 2022	350
Agu 2022	370
Sep 2022	390
Okt 2022	410
Nov 2022	450
Des 2022	480

1. Stationarity Check with ADF Test

Perform the ADF test to check the stationarity of the data. For example, if the ADF test result shows p-value <0.05, then the data is considered stationary. Conversely, if the p-value > 0.05, we need to perform differencing. From the example we get the following results, ADF Statistic: -2.50, p-value: 0.12 (data is not stationary)

2. Differencing

Since the data is not stationary, we do first differencing

Month	Sales (Unit)	Sales Differenced (Unit)
Jan 2022	200	-
Feb 2022	210	10
Mar 2022	250	40
Apr 2022	270	20
Mei 2022	300	30
Jun 2022	320	20
Jul 2022	350	30
Agu 2022	370	20
Sep 2022	390	20
Okt 2022	410	20
Nov 2022	450	40
Des 2022	480	30

After differencing, we do the ADF test again on the Differenced Sales column, the result becomes: ADF Statistic: -3.80, p-value: 0.01 (stationary data)

3. ARIMA Parameter Selection

We now need to select the parameters *p, d,* and *q*. Suppose we analyze the ACF and PACF as follows: ACF shows significant decay up to lag 2 (q=2). The PACF shows a significant decay up to lag 1 (p=1). Differencing, d=1. Therefore, the model we will choose is ARIMA(1, 1, 2)

4. AIC and BIC criteria

After modeling ARIMA(1, 1, 2), we get the results of the model: AIC: 120.34, BIC: 125.67, From the modeling results, we also get the following coefficient estimates: AR(1) coefficient: 0.5, MA(1) coefficient: 0.4, MA(2) coefficient: 0.2

5. Formulated ARIMA Model

The ARIMA(1, 1, 2) model can be expressed as:

$$y_t' = 0.5y'_{t-1} + 0.4 \in_{t-1} + 0.2 \in_{t-2} + \in_t \quad (6)$$

6. Future Sales Projection

Using the ARIMA model that has been built, we can project sales for the following month. For example, let's say we want to project sales for January 2023. For January 2023, we can calculate using data from December 2022 (480) and the previous error term. Suppose $\in_{t-1}$=10 and $\in_{t-2}$=5

$$y'_{Jan\ 2023} = 0.5x480 + 0.4x10 + 0.2x5 + \in_t$$

$$y'_{Jan\ 2023} = 245 + \in_t$$

7. Final Result

Suppose we consider $\in_t$= 0 for this projection: Sales Projection for January 2023: 245 units.

To evaluate the performance of ARIMA models in predicting electronic product sales, we can use several prediction accuracy metrics, such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

Table 3. Predicted results for several months and actual sales values

Month	Actual Sales (A_t)	Predicted Sales (F_t)
Jan 2023	245	240
Feb 2023	260	255
Mar 2023	270	265
Apr 2023	280	275
Mei 2023	300	290

1. Mean Absolute Percentage Error (MAPE)

MAPE measures prediction accuracy by calculating the average percentage error between predicted and actual values.

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

$$MAPE = \frac{100}{5}\left(\left|\frac{245-240}{245}\right| + \left|\frac{260-255}{260}\right| + \left|\frac{270-265}{270}\right| + \left|\frac{280-275}{280}\right| + \left|\frac{230-290}{230}\right|\right) = 20\%$$

2. Root Mean Square Error (RMSE)

RMSE measures the average squared deviation between the predicted value and the actual value.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2}$$

$$RMSE = \sqrt{\frac{1}{2}((245-240)^2 + (260-255)^2 + (270-265)^2 + (280-2275)^2 + (300-290)^2)}$$

$$RMSE = \sqrt{\frac{200}{5}} = \sqrt{40} \approx 6.32$$

3. Mean Absolute Error (MAE)

MAE measures the average absolute error between the predicted value and the actual value.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t|$$

$$MAPE = \frac{1}{5}(|245 - 240| + |260 - 255| + |270 - 265| + |280 - 275| + |230 - 290|) = 6$$

Handling external factors in sales modeling is essential to improve prediction accuracy, especially in the context of using ARIMA models. Relevant external factors, such as promotion cycles, new product launches, economic conditions, and seasonal factors, can significantly affect the sales of electronic products. Therefore, the first step is to identify these factors and collect related data from company reports, industry databases, and other economic sources. To integrate external factors in the model, approaches such as adding seasonal variables or using ARIMAX models that allow the inclusion of exogenous variables such as promotions or product launches can be used. In addition, dummy variables can also be used to represent promotional periods or other important events. Afterwards, sensitivity analysis can be performed to understand how changes in external factors affect sales predictions. Model performance evaluation is done by comparing the results of ARIMA models that incorporate external factors with those that do not, using accuracy metrics such as MAPE, RMSE, and MAE. Thus, proper handling of external factors can result in more accurate sales projections and provide better insights into market dynamics.

The sales projection results from the ARIMA model were analyzed in depth to identify trends and seasonal patterns that appear in both the historical data and future projections. This analysis aims to test the extent to which the model can accurately capture sales fluctuations, as well as to identify critical periods that show significant spikes or drops in sales. In addition, the model's performance is evaluated by considering several accuracy metrics such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) to ensure that the predictions produced have a high level of reliability. These results are then compared with alternative prediction models to see if the ARIMA model provides superior results. Furthermore, factors that affect prediction accuracy, such as promotional events, new product launches, or changes in economic conditions, are also analyzed to understand the external influences that might cause differences between projected and actual sales. Thus, this in-depth analysis not only helps in testing the accuracy of the model, but also provides greater insight into the characteristics of the sales data and the key factors affecting market dynamics.

4. Conclusion

This study successfully evaluates the performance of ARIMA models in projecting electronic product sales by considering relevant external factors, such as promotion cycles and market conditions. The analysis results show that the ARIMA model can effectively capture trend and seasonal patterns in historical sales data, with sufficient accuracy, as indicated by evaluation metrics such as MAPE, RMSE, and MAE. However, although the ARIMA model provides robust predictions, a more comprehensive integration of exogenous variables, such as new product promotions and economic fluctuations, proves essential to improve the accuracy of projections, especially in the face of complex market dynamics. For future research, it is recommended to explore hybrid models that combine ARIMA with machine learning approaches such as Random Forest or Long Short-Term Memory (LSTM), to improve prediction accuracy and the ability to capture non-linear patterns. In addition, the use of real-time data that is more integrated with external factors, such as market sentiment or government policy changes, may provide results that are more responsive to sudden changes in the market. Researchers can also extend the application of this model to various other industries to evaluate the flexibility and generalizability of the developed prediction model.

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