Forecasting of PVB Film Using ARIMA

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Abstract. Automotive industries especially car manufacture is the highest technologies at this time. Its production is increase in several years. One of car component that produced in Indonesia is automotive glass. Automotive glass that we knew is Laminated and Temperlite. The kind of glass that can show car quantity is Laminated Glass because it used only one on the car. One of material that used for Laminated Glass is PVB Films. Forecasting become important to set production capacity. In this study we use ARIMA forecasting method by MINITAB to calculate plan of consumption PVB Films based on data of 12 months consumption result on 2017. The result show that ARIMA 0-1-1 is the best model. The quantity result is higher than other ARIMA Model that are 1-1-0 and 1-1-1.

Key words: Forecasting, ARIMA, Automotive, Car Manufacture

1. Introduction

Since Industrial Revolution at the end of XVIII Centuries, industrial development had been growing rapidly. Manufacturing and automotive industries are also important in many countries, with their respective share of the business in the spare-parts area as like automotive glass [1]. Data that was published from Automotive Federation in the studies of automotive-cluster.org show that Indonesia currently become one of important country in ASEAN after Thailand.

Discuss about automotive glass, two types of automotive glass that currently produced by glass manufacture are Temperlite and Laminating glass. Laminating Glass is used for Windshield Glass only and another kind of glass on car use Temperlite. There for Laminating Glass is can be defined how many cars that is produced. One kind materials to produce Laminating Glass is PVB Film.

With the rapid development of automotive industry, the automobile market is playing more and more important role on the national economic development. The accuracy of market information is the core competitiveness of auto enterprises, the auto sales forecasting can affect the scientific of decision-making of managers, so it is very important to enterprise decision.

Improvements in manufacture for OEM (car manufacture) and spare parts require that forecasts be searched under different points of view. Some studies have been focused on improving or maintaining service levels, while considering inventory metrics as important, since special attention should be given to the rapidly increasing number of actual demand from market and spare-parts for their correct management [1].

Wieczorek (2012) in Felix, et al (2014) mentioned that uncertainty about future can lead to risky event outcomes [2]. Sales and demand forecasting become crucial for planning the production process such as automotive and others complex product [3].

Auto Regressive Integrated Moving Average (ARIMA) model which combines the autoregressive components to a moving average (MA) is also widely researched for application for some forecasting studies. In these linear models, the relationship between the input variables and the forecasted variable...
are derived through statistical analysis [4]. ARIMA models have been very popular in time series modelling for long time as O’Donovan (1983) showed that these models provided better results than other models used [5].

However, more and more forecasting techniques was develop in some studies by researchers. Chan, et al (2014) studied Fuzzy time series forecasting for supply chain disruptions and the value of this studies is suggesting a forecasting system which works best for all the tiers and also for every scenario tested and simultaneously significantly improves on the previous studies available in this area [2]. Ikram, et al (2016) concluded that ARIMA is suitable model for prediction of steel production in that case in Pakistan [6]. Gomes, et al (2016) demonstrate the use of Choquet integral to fuzzy the input data can be efficient to minimize error forecasting, then the result show the strong capability of a neural network using Choquet integral in data with great nonlinear component. Then recommended in the future research to be a comparison between thus model and Box & Jenkins techniques that was known as ARIMA [7]. Zhang, et al (2017) present a singular spectrum analysis (SSA) as a univariate time-series model and vector autoregressive model (VAR) as a multivariate model for electric vehicles sales forecasting [3]. Liu & Li (2015) developed The Comprehensive Forecasting Model (CFM). It was developed base on the combination forecasting ideas. ARIMA, ANN, and ESM were used to predict the time series data of PM25 concentration [8]. Sakhija, et al (2015) provided a variable forecasting methodology, adapting a fuzzy time series combined with evolutionary GA [9]. Wu, et al (2015) developed and applied the ARIMA-NARNN hybrid model and it was be effective method to make better understand the epidemic characteristic of HRFS and could be helpful to the prevention and control JRFS [10].

Base on the previous research ARIMA become the most popular and the basic to develop another forecasting method. Therefor we choose ARIMA to calculate forecasting of PVB Film in the next interval time. We use MINITAB as software to calculate the ARIMA forecasting.

2. Literature Review
The Autoregressive Integrated Moving Average Model is an important time series prediction method. It was presented by Box and Jenkins in 1970s [8]. ARIMA model is a traditional method to study the time series data [10]. The basic ideas of the ARIMA model areas follows. In the ARIMA model, the time series data of the prediction object are regarded as a stochastic sequence, and this sequence is fitted with some mathematical models. Once this model is identified, the future values would be predicted by the time series of past and present values [8]. The ARIMA model can be divided into three types: (1) The autoregressive model (AR model), where p is the number of self-regression items; (2) The moving average model (MA model), where q is the number of moving average items; (3) The autoregressive integrated moving average model, that is ARIMA (p, d, q), where d is the difference of frequency of time series data that become the stationary difference, and d is generally less than 2 in the practical application [8]. The three values p, d and q denote the orders of each of these parts, respectively [2]. In ARIMA (p,d,q), the p denotes the number of autoregressive terms; the d the number of non-seasonal differences; and q, the number of lagged forecast errors in the prediction equation [11].

MINITAB is a computer program designed to perform statistical processing. Minitab combines ease of use like Microsoft Excel with its ability to perform complex statistical analysis. MINITAB is a powerful statistical software that provides a wide range of basic and advanced capabilities for statistical analysis. MINITAB’s broad, powerful capabilities and unmatched ease of use make it the ideal teaching tool. As a result more than 4000 colleges, universities and high schools worldwide rely on MINITAB. Developed over 30 years ago, by professors for professor, MINITAB has become the standard for statistic education. And because MINITAB is the leading package used in industry for quality and process improvement, student who learn MINITAB in class will have the advantage of knowing how to use a real-world business tool [12].
3. Methodologies
In order to meet the objective of the study, we have applied different Auto Regressive Integrated Moving Average (ARIMA) models. ARIMA processes are a class of stochastic processes used to analyse time series. The application of the ARIMA methodology for the study of time series analysis. It constantly out performed complex structural models in short-term prediction [6]. The modelling processes of ARIMA model are as follows.
1. Sample pre-treatment. The establishment of the ARIMA model requests that the time series data should be stationary stochastic process. Thus the data should be tested for stationary
2. Pattern recognition. After the differential transform for the non-stationary time series, the key step is to determine the order of the ARIMA model. There are four methods to determine the order: (i) Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) method; (ii) Final Prediction Error (FPE) method; (iii) Aikake Information Criterion (AIC) method; (iv) Aikake Information Corrected Criterion (AICC) method. The ACF and PACF method were used to master the direction of the general model to determine the order in this study.
3. Model testing. After the order determination and parameter estimation, the applicability of the model established should be tested. If the model error is white noise, the obtained model is qualified. Otherwise, the order re-determination and parameter re-estimation are needed.
4. Prediction. The time series data are forecasted in this step. The processes of model identification, parameter estimation, and model diagnosis are often improved gradually. The initial choices need to be constantly adjusted according to concrete problems [8].

The ARIMA model can find out the characteristics and trends of the variables from the time series data, and forecast the future values effectively. The ARIMA model is a prediction method with a good statistical theory, and has the advantages of high accuracy, and strong adaptive ability [8].

4. Result and Discussion
Data was taken from the actual PVB Films consumption result on 2017 with kind of PVB Film is Standard Clear as below on Table 1.

| Month | PVB Film STD Clear |
|-------|---------------------|
| Jan-17 | 101,883             |
| Feb-17 | 122,225             |
| Mar-17 | 130,635             |
| Apr-17 | 116,158             |
| May-17 | 131,895             |
| Jun-17 | 89,070              |
| Jul-17 | 120,160             |
| Aug-17 | 119,028             |
| Sep-17 | 114,390             |
| Oct-17 | 123,730             |
| Nov-17 | 119,735             |
| Dec-17 | 95,218              |
| TOTAL (m²) | 1,384,127       |
1. First step is sample pre-treatment by plotting data like Figure 1 and check the stationery data. If the Lambda rounded value is not equal to 1, we have to transform until it equals to 1. The data can be said stationary if the lambda value is 1.

![Figure 1. Plotting data Standard Clear PVB Film](image1.png)

2. Pattern recognition. After the differential transform for the non-stationary time series, the key step is to determine the order of the ARIMA model. In here we use ACF & PACF.

![Figure 2. Box Cox Plot Trans-1](image2.png)

![Figure 3. ACF](image3.png)
From the ACF and PACF result on Figure 3 and Figure 4 above we got the result both of them do not found lag that is out of the range. It is mean that the data was stationary, then we can continue to the next step that is model testing

3. In the ARIMA model testing in here we have three model that are (1-1-0, 0-1-1, 1-1-1), with the result as like Table 2.

**Estimation Model 1-1-0**

| Variable | Coefficient | Std Error | t-Statistic | Probability |
|----------|-------------|-----------|-------------|-------------|
| AR (1)   | -0.6357     | 0.2714    | -2.34       | 0.041       |

Residuals: SS = 2973149156
MS = 297314916

**Estimation Model 0-1-1**

| Variable | Coefficient | Std Error | t-Statistic | Probability |
|----------|-------------|-----------|-------------|-------------|
| MA (1)   | 0.9572      | 0.3151    | 3.04        | 0.013       |

Residuals: SS = 1846078511
MS = 184607851

**Estimation Model 1-1-1**

| Variable | Coefficient | Std Error | t-Statistic | Probability |
|----------|-------------|-----------|-------------|-------------|
| AR (1)   | -0.0828     | 0.3326    | -0.25       | 0.809       |
| MA (1)   | 1.3685      | 0.0835    | 16.40       | 0.000       |

Residuals: SS = 1089642498
MS = 121071389

After estimation model was generated, then forecasting can be proceed and the result can be shown in the Table 5.
Table 5. Forecasting Model Result

| Month  | PVB Film Standard Clear Consumption | ARIMA 1-1-0 | ARIMA 0-1-1 | ARIMA 1-1-1 |
|--------|------------------------------------|-------------|-------------|-------------|
| 17-Jan | 101,883                            | 110,805     | 117,191     | 114,770     |
| 17-Feb | 122,225                            | 100,895     | 117,191     | 113,151     |
| 17-Mar | 130,635                            | 107,195     | 117,191     | 113,285     |
| 17-Apr | 116,158                            | 103,190     | 117,191     | 113,274     |
| 17-May | 131,895                            | 105,736     | 117,191     | 113,275     |
| 17-Jun | 89,070                             | 104,118     | 117,191     | 113,275     |
| 17-Jul | 120,160                            | 105,147     | 117,191     | 113,275     |
| 17-Aug | 119,028                            | 104,492     | 117,191     | 113,275     |
| 17-Sep | 114,390                            | 104,908     | 117,191     | 113,275     |
| 17-Oct | 123,730                            | 104,644     | 117,191     | 113,275     |
| 17-Nov | 119,735                            | 104,812     | 117,191     | 113,275     |
| 17-Dec | 95,218                             | 104,705     | 117,191     | 113,275     |
| TOTAL (m2) | 1,384,127                      | 1,260,648   | 1,406,286   | 1,360,676   |

From the result forecast calculation is gotten the model 1-1-0 forecast result is 1,260,648, model 0-1-1 forecast result is 1,406,286 and model 1-1-1 is 1,360,676

5. Conclusion
The paper present extensive process of building ARIMA model for PVB Film with the kind of PVB Film is Standard Clear. The experimental results obtained with best ARIMA model demonstrated the potential of ARIMA model to predict PVB Film consumption on next 12 months. It is conclude that our model 0-1-1 is the best model to forecast of PVB Film consumption. The forecasted value of 2018 is 1,406,286 m2 is higher 1.6% than 2017 consumption result. It is mean that production quantity also predict will be increase. Likewise, we can predict more values by using the forecasting technique. So we can use different planning and policies to increase the production, maximize production capacity and arrange its inventory management. For future studies should be analysed and should be taken consideration the forecasting method and if possible shall be compare with another forecasting methods whether will be gotten another result to be compared.

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