Adaptive spline autoregression threshold method in forecasting Mitsubishi car sales volume at PT Srikandi Diamond Motors

D. Susanti, E. Hartini and A. Permana
Department of Mathematic, Padjadjaran University Sumedang 45363, Indonesia
E-mails: dwi.susanti@unpad.ac.id, euis_hartini@yahoo.co.id, permanaarif009@gmail.com

Abstract. Sale and purchase of the growing competition between companies in Indonesian, make every company should have a proper planning in order to win the competition with other companies. One of the things that can be done to design the plan is to make car sales forecast for the next few periods, it’s required that the amount of inventory of cars that will be sold in proportion to the number of cars needed. While to get the correct forecasting, on of the methods that can be used is the method of Adaptive Spline Threshold Autoregression (ASTAR). Therefore, this time the discussion will focus on the use of Adaptive Spline Threshold Autoregression (ASTAR) method in forecasting the volume of car sales in PT.Srikandi Diamond Motors using time series data. In the discussion of this research, forecasting using the method of forecasting value Adaptive Spline Threshold Autoregression (ASTAR) produce approximately correct.

1. Introduction
This research method used is the method of Adaptive Threshold Autoregression Spline. Adaptive Threshold Autoregression Spline method (ASTAR) can be used in various types of data so that its application be varied. Thesis research on the development of Stevens, J.G. (1991) and the simulation data using the volume of sales of Mitsubishi cars at PT Srikandi Diamond Motors, with variable used is the number of car sales. The data obtained were tested using normality test for measuring the data obtained so that it can be used in parametric statistics (inferential statistics).

2. Model Identification
Identification of the model is the data that will be tested is stationary or not. There are two ways that can be used in stationary test, graphs plot the data (time plot) and the unit root test commonly referred to Augmented Dickey Fuller test (ADF). In the graph plots the data, the way we need to do is look at the visible time series data is stationary or not. While using a stationary test unit root test. If data is stationary, then the time series model that can be used, namely the AR(p), MA(q), ARMA(p,q). Meanwhile, if the data is not stationary, it must go through the process different advance until the data becomes stationary. Next, use the Order Identification Time Series model by analysing the data plot of the autocorrelation function (ACF) and partial autocorrelation function (PACF). As for the use, for the AR using the partial autocorrelation function (PACF) while for the MA process using the autocorrelation function (ACF). Then do the Time Series Model Parameter Estimation order to obtain...
3. Parameter Estimation Model ASTAR

In estimating model parameters Adaptive Threshold Autoregression Spline (ASTAR), by calculating the autocorrelation parameter values and a constant value of the time series model. Parameter autocorrelation is a characteristic that states the correlation coefficient of a population. The general shape parameter \( p \) order autocorrelation to have the following equation:

\[
\theta_l = \frac{n(\sum (Y_{t-1}Y_t)) - \sum (Y_{t-1})\sum (Y_t)}{n(\sum (Y_{t-1})^2) - (\sum Y_{t-1})^2},
\]

(1)

4. Method Spline Adaptive Threshold Autoregression (ASTAR)

Adaptive Threshold Autoregression Spline method (ASTAR) is a nonlinear time series modeling threshold with the predictor is a lag value \( Y_{t-d} \) as in the time series [3]. The method can form a model with a limit cycles when the data time series model shows the periodic behavior. Adaptive Threshold Autoregression Spline method (ASTAR) is the development of methods Autoregressive (AR). In the journal, entitled A New Approach to Adaptive Spline Threshold Autoregression Toprak and Taylan suggested a continuity between the methods of autoregressive (AR) and Spline Adaptive Threshold Autoregression (ASTAR). The general form of the equation with the order \( p \) AR method is as follows:

\[
AR(p) = Y_t = c + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \ldots + \theta_p Y_{t-p} + \epsilon_t.
\]

(2)

The general form of the equation with the order \( p \) ASTAR method is as follows:

\[
ASTAR(p) = Y_t = c + \theta_1(\lambda_1 Y_{t-1}) + \theta_2(\lambda_2 Y_{t-2}) + \ldots + \theta_p(\lambda_p Y_{t-p}) + \epsilon_t
\]

\[Y_t = c + \sum_{i=1}^{p} \theta_i(\lambda_i Y_{t-i}) + \epsilon_t\]

(3)

5. Result and Discussion

The data used is the volume of car sales and inventory PT Srikandi Diamond Motors in June 2013 until May 2015 (Table 1).

First to identify the time series model with stationary identification data to determine the sales data of Mitsubishi cars in Diamond Motors PT Srikandi whether stationary or not, with a Unit Root Tests using the Augmented Dickey-Fuller (ADF) with the help of software E-Views 7 of SPSS results are in Table 2.

From Table 2, it is known that the statistical value of \( t = -3.081740 < 0.1347 -3.632896 \) and probability value > 0.05. Data is not stationary, subsequent differentiation process is carried out first (first difference), the result is Table 3.
Table 1. Sales Volume Data and Car Inventory

| Year | Period | Month | Sale | Stock |
|------|--------|-------|------|-------|
| 2013 | 1      | June  | 162  | 300   |
|      | 2      | July  | 186  | 300   |
|      | 3      | August| 144  | 300   |
|      | 4      | September | 151 | 300   |
|      | 5      | October| 141 | 300   |
|      | 6      | November| 154 | 300   |
|      | 7      | December| 160 | 250   |
| 2014 | 8      | January| 168 | 250   |
|      | 9      | February| 142 | 250   |
|      | 10     | March  | 160  | 250   |
|      | 11     | April  | 169  | 250   |
|      | 12     | May    | 151  | 250   |
|      | 13     | June   | 140  | 250   |
|      | 14     | July   | 84   | 250   |
|      | 15     | August | 99   | 250   |
|      | 16     | September| 124 | 250   |
|      | 17     | October| 75   | 175   |
|      | 18     | November| 109 | 175   |
|      | 19     | December| 110 | 175   |
| 2015 | 20     | January| 116  | 175   |
|      | 21     | February| 95  | 175   |
|      | 22     | March  | 112  | 175   |
|      | 23     | April  | 131  | 175   |
|      | 24     | May    | 103  | 175   |

Table 2. Results of Augmented Dickey-Fuller (ADF test)

Null Hypothesis: PENJUALAN has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| t-Statistic | Prob.* |
|-------------|--------|
| Augmented Dickey-Fuller test statistic | -3.081740 | 0.1347 |
| Test critical values: | |
| 1% level | -4.440739 |
| 5% level | -3.632896 |
| 10% level | -3.254671 |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PENJUALAN)
Method: Least Squares
Date: 06/04/16   Time: 05:09
Sample (adjusted): 2013M07 2015M04
Included observations: 22 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| SALE(-1) | -0.732093   | 0.237558   | -3.081740   | 0.0061 |
Table 3. Results First Difference

| Null Hypothesis: D(PENJUALAN) has a unit root |
|------------------------------------------------|
| Exogenous: Constant, Linear Trend             |
| Lag Length: 0 (Automatic - based on SIC, maxlag=4) |

| Augmented Dickey-Fuller test statistic | -6.628693 | 0.0001 |
| Test critical values:                  |           |        |
| 1% level                               | -4.467895 |
| 5% level                               | -3.644963 |
| 10% level                              | -3.261452 |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PENJUALAN,2)
Method: Least Squares
Date: 06/04/16   Time: 05:15
Sample (adjusted): 2013M08 2015M04
Included observations: 21 after adjustments

| Variable            | Coefficient | Std. Error | t-Statistic | Prob. |
|---------------------|-------------|------------|-------------|-------|
| D(SALE(-1))         | -1.392185   | 0.210024   | -6.628693   | 0.0000 |
| C                   | -12.75254   | 11.38217   | -1.120396   | 0.2773 |
| @TREND(2013M06)     | 0.766643    | 0.845363   | 0.906881    | 0.3765 |

| R-squared           | 0.712181    | Mean dependent var | 0.0095 |
| Adjusted R-squared  | 0.680201    | S.D. dependent var  | 24.79566 |
| S.E. of regression  | 23.45316    | Akaike info criterion | 9.072852 |
| Sum squared resid   | 9900.916    | Schwarz criterion   | 9.221631 |
| Log likelihood      | -96.80137   | Hannan-Quinn criter. | 9.10790 |
| F-statistic         | 4.851597    | Durbin-Watson stat  | 1.840305 |
| Prob(F-statistic)   | 0.019853    |                         |         |

From Table 3, it is known that the statistical value $t = -6.628693 > -3.644963$ 0.0001 and a probability value of <0.05. The results show that the data is stationary on the differentiation of the first stage (1st
difference). Once the data is stationary, it will further analyse the data plot of the autocorrelation function (ACF) and partial autocorrelation function (PACF) as shown in Table 4 below.

**Table 4. Plot ACF and PACF**

| Correlogram of PENJUALAN |
|--------------------------|
| Date: 06/15/16  Time: 10:30 |
| Sample: 2013M07 2015M04 |
| Included observations: 23 |
| Autocorrelation | Partial Correlation | AC | PAC | Q-Stat | Prob |
|-----------------|---------------------|----|-----|--------|------|
| ![Graph showing autocorrelation and partial autocorrelation plots.](image)

In Table 4, plots of ACF disconnected (cuts off) ranging from lag to 1, so there is an indication to model data using the model MA (1), and plot PACF disconnected (cuts off) ranging from lag to 1, can also model the model data AR (1). Possible models are good enough to model Mitsubishi car sales data is an AR (1) or MA (1). In the next phase of parameter estimates are calculated for both models. The equation used in the estimation of the parameters are as follows:

Model AR(1): \( r_t = c + \phi r_{t-1} + \epsilon_t \)

Model MA(1): \( r_t = \mu + \theta \epsilon_{t-1} + \epsilon_t \)

The result of estimation of the model parameters AR (1) and MA (1) are:

**Table 5. Parameter Estimation models AR (1)**

| Dependent Variable: SALE |
|--------------------------|
| Method: Least Squares |
| Date: 06/15/16  Time: 20:39 |
| Sample (adjusted): 2013M07 2015M04 |
| Included observations: 22 after adjustments |
| Convergence achieved after 3 iterations |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 130.2205    | 13.83645   | 9.411414    | 0.0000 |
| AR(1)    | 0.644284    | 0.164777   | 3.910046    | 0.0009 |
| R-squared | 0.433242    | Mean dependent var | 132.7727 |
| Adjusted R-squared | 0.404905  | S.D. dependent var | 29.66147 |
| S.E. of regression | 22.88358   | Akaike info criterion | 9.185050 |
| Sum squared resid | 10471.33   | Schwarz criterion | 9.284235 |
| Log likelihood | -99.03555 | Hannan-Quinn criter. | 9.208415 |
In the table 5, it can be seen that the probability (t-statistic) of parameter c and φ respectively are 0.0000 and 0.009 is smaller than α = 0.05 so H_0 t-test for the AR model (1) is rejected. Then for the F-test, it can be seen that the value of probability (F-statistic) = 0.000868 < α, so H0 F-test was rejected for the AR model (1). Thus, it can be said that all the independent variables in the model AR (1) significantly to the model. The next table shows the results of the estimation model MA (1) as follows:

**Table. 6 Parameter Estimation models MA (1)**

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 134.0130    | 7.967499   | 16.81996    | 0.0000|
| MA(1)    | 0.522741    | 0.185667   | 2.815483    | 0.0104|

R-squared    0.302369  Mean dependent var 134.0435
Adjusted R-squared  0.269149  S.D. dependent var 29.61338
S.E. of regression 25.31644  Akaike info criterion 9.387326
Sum squared resid 13459.36  Schwarz criterion 9.482465
Log likelihood -105.9128  Hannan-Quinn crit. 9.408558
F-statistic 9.101883  Durbin-Watson stat 1.638561
Prob(F-statistic) 0.006563

In Table 6, it can be seen that the probability (t-statistic) of parameter c and φ respectively are 0.0000 and 0.0104 is smaller than α = 0.05 so H0 t-test for models MA (1) was rejected. Then for the F-test, it can be seen that the value of probability (F-statistic) = 0.006563 < α, so H0 F-test was rejected for models MA (1). Thus, it can be said that all the independent variables in the model MA (1) significantly to the model. To determine the best models of both models can use comparative value of Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). Based on the Tables 5 and 6, obtained Table 7 as follows:

**Table 7. Comparison of AIC and SIC**

| Time Series Model | AIC    | SIC    |
|-------------------|--------|--------|
| AR(1)             | 9.185050 | 9.284235 |
| MA(1)             | 9.383726 | 9.482465 |

In Table 7, note that the value in the AIC and SIC AR model (1) is smaller than the model MA (1), so the model AR (1) it is better to use in the data model Mitsubishi car sales in PT Srikandi Diamond.
Motors. After identification of the time series model, do the model parameter estimation Adaptive Threshold Autoregression Spline (ASTAR). Parameter estimation is performed to find the value of $\theta_i$ and $c$ as autocorrelation parameters and constants, the results obtained in table 8 below:

\[
\begin{align*}
\theta_i &= \frac{n(\sum(Y_t - \bar{Y})^2) - (\sum(Y_t)^2)}{n(\sum(Y_{t-1})^2) - (\sum(Y_{t-1})^2)^2} = \frac{(23^2(417862) - (3083^2))(3083^2)}{23^2(432549) - (3083^2)} = \frac{9610826 - 9322992}{9948627 - 9504889} = 0.6486575 \approx 0.65 \\
c &= \bar{Y} + \theta_i \bar{Y}_{t-1} = \frac{3024}{23} + 0.65 \left(\frac{3083}{23}\right) = 44.52994785 \approx 44.53
\end{align*}
\]

Thus, the value of sales data parameter is almost equal to a constant value of 0.65 and sales data is almost equal to 44.53, with the construction of the probability of normal table values obtained broad areas as follows:

\[
\begin{align*}
\text{Table 9. Wide Area } (\lambda) \\
\hline
\text{No} & \text{Lower Bound} & Z & \text{Square Area } (\lambda) \\
\hline
1 & 74.5 & -0.60 & 0.2743 \\
2 & 93.5 & -0.40 & 0.3446 \\
3 & 112.5 & -0.21 & 0.4168 \\
4 & 131.5 & -0.01 & 0.4960 \\
5 & 150.5 & 0.19 & 0.5753 \\
6 & 169.5 & 0.39 & 0.6517 \\
\hline
\end{align*}
\]

According to the table 9, the value of the area with a lower limit of 74.5, 93.5, 112.5, 131.5, 150.5, 169.5 respectively are 0.2743, 0.3446, 0.4168, 0.4960, 0.5753, and 0.6517. Preliminary analysis of data were normally distributed and stationary, and has obtained parameter values and constants, we then determined Spline models Adaptive Threshold Autoregression (ASTAR), using the formula:

\[
Y_t = c + \theta_1(Y_{t-1}) + \theta_2(Y_{t-2}) + \cdots + \theta_p(Y_{t-p}) + \epsilon_t = 44.53 + 0.65(\lambda_1 Y_{t-1}) + 0.65(\lambda_2 Y_{t-2}) + 0.65(\lambda_3 Y_{t-3}) + \epsilon_t.
\]
Equation (4) will be used in forecasting the volume of sales of Mitsubishi cars PT Srikandi Diamond Motors with independent variable volume sales of 2 or 3 periods before time \( t \). The results of the forecast volume of car sales in the period to 25, 26, and 27 are as follows:

The forecast for the period to 25 (June 2015) using two independent variables the previous period, the sales volume for the period 23 (April 2015), and the period to 24 (May 2015).

\[
Y_{25} = 44.53 + 0.65(\lambda_1 Y_{24}) + 0.65(\lambda_2 Y_{23}) = 44.53 + 0.65(\lambda_1(103)) + 0.65(\lambda_2(131)) \\
= 44.53 + 0.65(0.3446(103)) + 0.65(0.4168(131)) = 103.09 \approx 104
\]

The forecast for the period to 26 (July 2015) using two independent variables the previous period, the volume of sales in the period to 24 (May 2015), and the period of the 25th (June 2015).

\[
Y_{26} = 44.53 + 0.65(\lambda_1 Y_{25}) + 0.65(\lambda_2 Y_{24}) \\
= 44.53 + 0.65(\lambda_1(103)) + 0.65(\lambda_2(103)) \\
= 44.53 + 0.65(0.3446(103)) + 0.65(0.3446(103)) = 90.67194 \approx 91
\]

The forecast for the period to 27 (August 2015) using two independent variables the previous period, the volume of sales in the period to 25 (June 2015), and the period to 26 (July 2015).

\[
Y_{27} = 44.53 + 0.65(\lambda_1 Y_{26}) + 0.65(\lambda_2 Y_{25}) \\
= 44.53 + 0.65(\lambda_1(91)) + 0.65(\lambda_2(103)) \\
= 44.53 + 0.65(0.2743(91)) + 0.65(0.3446(103)) = 93.692375 \approx 94
\]

Thus, the results obtained forecasting sales volume car with two independent variables previous period, i.e. the period to 25 104 cars, a period of 26 to as many as 91 cars, and a period of 27 to as many as 94 cars:

The forecast for the period to 25 (June 2015) by using three independent variables previous period, the sales volume for the period 22 (March), the period to 23 (April 2015), and the period to 24 (May 2015):

\[
Y_{25} = 44.53 + 0.65(\lambda_1 Y_{24}) + 0.65(\lambda_2 Y_{23}) + 0.65(\lambda_3 Y_{22}) \\
= 44.53 + 0.65(\lambda_1(103)) + 0.65(\lambda_2(131)) + 0.65(\lambda_3(112)) \\
= 44.53 + 0.65(0.3446(103)) + 0.65(0.4168(131)) + 0.65(0.3446(112)) \\
= 128.17837 \approx 129
\]

Forecast period to 26 (June 2015) by using three independent variables previous period, the sales volume for the period 23 (April 2015), the period to 24 (May 2015), and the period of the 25th (June 2015):

\[
Y_{26} = 44.53 + 0.65(\lambda_1 Y_{25}) + 0.65(\lambda_2 Y_{24}) + 0.65(\lambda_3 Y_{23}) \\
= 44.53 + 0.65(\lambda_1(128)) + 0.65(\lambda_2(103)) + 0.65(\lambda_3(131)) \\
= 44.53 + 0.65(0.4168(128)) + 0.65(0.3446(103)) + 0.65(0.4168(131)) \\
= 137.76925 \approx 138
\]

Forecast period to 27 (June 2015) by using three independent variables previous period, the volume of sales to 24 (May 2015), the period of the 25th (June 2015), and the period to 26 (July 2015).

\[
Y_{27} = 44.53 + 0.65(\lambda_1 Y_{26}) + 0.65(\lambda_2 Y_{25}) + 0.65(\lambda_3 Y_{24}) \\
= 44.53 + 0.65(\lambda_1(138)) + 0.65(\lambda_2(128)) + 0.65(\lambda_3(103)) \\
= 44.53 + 0.65(0.4960(138)) + 0.65(0.41681(128)) + 0.65(0.3446(103)) \\
= 132.38177 \approx 133
\]

Thus, the results obtained forecasting sales volume by 3 independent variables previous period, the period to 25 as many as 129 cars, a period of 26 to 138 cars, and a period of 27 to as many as 133 cars.
5.1. Mean Y Variables 2 and 3 Period Prior t

Y_t value calculation results. Y_t average value can be determined that is a suspected closest to the actual value, the value of the average for the month of June, July and August 2015 as follows:

1. Mean value for period 25 (June 2015).
\[ \bar{y}_{25} = \frac{Y_{25(2)}+Y_{25(3)}}{2} = \frac{104+129}{2} = \frac{233}{2} = 116.5 \approx 117 \]

2. Mean value for period ke 26 (July 2015).
\[ \bar{y}_{26} = \frac{Y_{26(2)}+Y_{26(3)}}{2} = \frac{91+138}{2} = \frac{229}{2} = 114.5 \approx 115 \]

3. Mean value for period ke 27 (August 2015).
\[ \bar{y}_{27} = \frac{Y_{27(2)}+Y_{27(3)}}{2} = \frac{94+133}{2} = \frac{227}{2} = 113.5 \approx 114 \]

Thus, the value of the average volume of car sales, i.e. the period to 25 as many as 117 cars, a period of 26 to 115 cars, and a period of 27 to as many as 114 units.

5.2. Comparison of Forecasting and Actual Value

Comparison of forecasting (\(Y_{t(2)}\), \(Y_{t(3)}\)) and the actual value (\(Y_t\)) as follows:

| No | Period     | \(Y_{t(2)}\) | \(Y_{t(3)}\) | \(\bar{y}_t\) | \(Y_t\) |
|----|------------|---------------|---------------|---------------|---------|
| 1  | 25 (June)  | 104           | 129           | 117           | 107     |
| 2  | 26 (July)  | 91            | 138           | 115           | 126     |
| 3  | 27 (August)| 94            | 133           | 114           | 114     |

From Table 10, it appears that the average value has a value close to the true value. Where the value of the forecast for the period to 25 (June 2015), 26 (July 2015), and 27 (August 2015) have flats (\(Y_t\)) 117, 115, 114, while the actual value in the period to 25 (June 2015), 26 (July 2015), and 27 (August 2015) respectively 107, 126, 114.

For more details, can be seen in Figure 4 below:

**Figure 4. Comparison Graph Forecasting Value and Actual Value**

Based on Figure 4, the actual value is between two values forecast by the order and the value forecast by the order 3. It shows Spline method Adaptive Threshold Autoregression (ASTAR) suitable to be applied in forecasting the volume of sales of Mitsubishi cars PT Srikiand Diamond Motors with single-element data. The value of error ratio predictive value and the actual value in the period of June, July and August 2015 as follows:
Value of error for the period to 25 (June 2015):

\[ E_{25} = \left| \frac{Y_{25} - Y_{\text{forecast}}}{Y_{\text{actual}}} \right| \times 100\% = \frac{107 - 117}{107} \times 100\% = 0.0935 \times 100\% = 9.35\% \]

Value of error for the period to 26 (July 2015):

\[ E_{26} = \left| \frac{Y_{26} - Y_{\text{forecast}}}{Y_{\text{actual}}} \right| \times 100\% = \frac{126 - 115}{126} \times 100\% = 0.0873 \times 100\% = 8.73\% \]

Value of error for the period to 27 (August 2015):

\[ E_{27} = \left| \frac{Y_{27} - Y_{\text{forecast}}}{Y_{\text{actual}}} \right| \times 100\% = \frac{114 - 114}{114} \times 100\% = 0 \times 100\% = 0\% \]

Thus, the error value comparison of forecast and actual value in the period to 25, 26 and 27 respectively is 9.35%, 8.73%, and 0%.

For more details can be seen in Figure 5 as follows:

**Figure 5. Compare to Error Value**

In figure 5 shows the value uniformity errors that occur from 3 to forecast period. The error value occurred in the period 25 and the value of the smallest error occurred in the period of 27. The results forecast approaching its true value, and includes a maximum estimated value of sales and minimal sales so as to facilitate in determining the amount of supply of cars needed in some future period and can be used for all types of data both data trend, seasonal, or cyclical.

6. Conclusion

Based on the results of data processing and discussion can be concluded that:

Based on our forecasting method Spline Adaptive Threshold Autoregression (ASTAR) for Mitsubishi car sales volume PT Srikandi Diamond Motors in the period to 25, 26, and 27, respectively 115, 114, and 113 cars with a maximum of alleged number 128, 138, and 132 cars and the alleged minimal amount of 103, 91, and 94, and the forecast can only be applied to data that is stationary. Great forecasting error ratio value and the actual value for the volume of car sales Mitsubishi Diamond Motors PT Srikandi period to 25, 26 and 27 respectively at 7.48% 9.52% and 0.88%.

References

[1] Arsyil, H.S. 2013. *Proses Differencing pada Analisis Runtun Waktu.* [Online]. In https://statistikawanku.wordpress.com/2013/03/29/proses-differencing-pada-analisis-runtun-waktu/ [25 September 2015].

[2] Hogg, M. dan Craig. 2007. *Introduction to Mathematical Statistics.* India: Dorling Dharma Patria.
[3] Lewis, P. W. dan Stevens, J. C. 1991. Nonlinear Modelling of Times Series Using Multivariate Adaptive Regression Splines.

[4] PQ Bandung. 2013-2015. Laporan Penjualan. Bandung: PT Srikandi Diamond Motors.

[5] Putra, W. 2013. Analisis Statistika. [Online]. In http://analisis-statistika.blogspot.co.id/2013/03/mengenal-distribusi-normal-dan-cara.html [8 December 2015].

[6] Stevens, J.G. (1991). An Investigation of Multivariate Adaptive Regression Splines for Modeling and Analysis of Univariate and Semi-Multivariate Time series Systems. Ph.D. Thesis, Naval Postgraduate School, California, USA.

[7] Subagyo, P. 1986. Forecasting Konsep Dan Aplikasi. Yogyakarta: Penerbit BPFE Yogyakarta.

[8] Supranto, J. 1981. Metode Peramalan Kuantitatif Untuk Perencanaan. Jakarta: Penerbit Gramedia.

[9] Secil Toprak dan Pakize Taylan, Journal of the American Statistical Association, 2012 : A New Approach to Adaptive Spline Threshold Autoregression