

Forecasting Petroleum Fuel Price in Malaysia by ARIMA Model



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Abstract Over the years the retail price of petroleum fuel in Malaysia, Ron95, Ron97 and Diesel have been controlled by the governments using the Automatic Price Mechanism (APM) which made the price of fuel in Malaysia relatively stable up until 2004. Beyond the year 2004, the price of petroleum fuel has been volatile even with the APM still being implemented. Even after changing the Policy to Managed float system in 2016 fuel prices have still not been stable. Reasons that have been attributed to the volatilities are the international crude oil price and foreign exchange volatilities and reduction of subsidies to improve government fiscal space. Predicting fuel Prices has become difficult. In this paper we apply the Time Series method Autoregressive Integrated Moving Average (ARIMA) to model and forecast fuel price.

Keywords ARIMA · Equation · Forecasting · Fuel · Price · Malaysia · Managed float system (MFS) · Ron97

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1 Introduction

Efficient Transport systems depends on cheap fuel prices. One aspect of obtaining cheap fuel is the planning of the fuel price. The fuel price is announced weekly by The government's body Ministry of Domestic Trade and Consumer Affairs in conjunction with the Ministry of Finance based on the Managed Floating System (MFS) Policy [1–5]. Transport owners, pump station managers and other stakeholders of petroleum fuel would want to forecast the fuel price to ensure there is an optimized fuel budget. Based on the MFS policy, the fuel price can be modelled by the formular (1) [2, 6].

$$P = A + B + C + D + E + F \quad (1)$$

Here, (A) is the Refined fuel price, Mean of Platts Singapore (MOPS), published by Platts [7]. (B) is Alpha, the difference between the MOPS and actual purchasing price from the refinery's companies, (C) is Tax/Subsidy [8], (D) is Operational cost at bulk storage for transportation and advertisement, (E) is Bulk distribution company's margin and (F) is Fuel station margins. Using the formula (1) is quiet and difficult and expensive as the MOPS value s is not accessible to all. (A) MOPS is a subscription-based Time series. Medium to small scale and entities are unwilling to subscribe to it, because of the expense liability, and technicalities associated with its Assessment Methodology. To solve this problem, ARIMA modelling is explored. The historical weekly data on fuel price is modelled. This paper focuses on modelling Ron97 a variant of petrol that that has the oxidation number 97. The MFS policy allows Ron97 price to float at the international market price without subsidies. The pricing Policy of 97 has remained consistent. It is a premium product as compared to Ron 95 and Diesel sold on the Malaysian Market. The sometimes subsidized [9–11].

2 Data

Data source for the study is the weekly price of Ron97 announced by the Ministry of trade and Consumerism, Malaysia [3, 4, 12] starting from 7 April 2017 to 6 March 2020, Fig. 1. Validation of the forecasting model is done using Fuel price from 13 march 2020 to 7 August 2020. There are some weeks in the time series where the Policy MFS was suspended for the APM Policy or the period of review of fuel price was changed to one month [1, 13]. Where there is such problem linear interpolation is applied to fill Missing weekly fuel price [14, 15]. The weekly day for announcing Fuel Price, has changed in the timeline of the time series. The dates are aligned to a common day point by taking a weekly average of the historical price of Ron97. Saturday is assigned as the common date point. The compiled data can be found on [16].

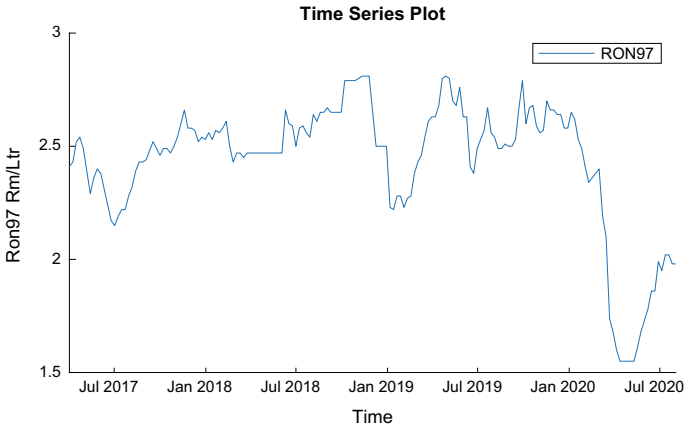


Fig. 1 Time series of Ron97 price in Rm/Ltr

3 Methodology

ARIMA or the Box–Jenkins methodology of order ARIMA (p, d, q) model is a time series forecasting method for non-stationary data series. The future value of a variable y_t , is assumed to be a linear function of several past observations (Ron97 price) and random errors, ε_t as represented by Eq. (2). ARIMA modelling is segmented into three-part process; model identification, parameter estimation and diagnostic checking. Here, p represents the autoregressive order, q , represents the moving average and d is the differencing order of the Time series, fuel price [17, 18].

$$\phi(1 + L)^p(1 + L)^d y_t = c + \theta(1 + L)^q \varepsilon_t \tag{2}$$

MATLAB Econometric Modeler [19] is used to do the model. We implement the models in MATLAB to forecast. Validation and forecast performance are assessed by comparing the Ron97 price with an 18-week horizon forecast Results.

4 Results

Ron97 fuel price has been modelled in a three-step procedure; ARIMA modelling.

4.1 ARIMA Modelling

Model Identification

The first step in identifying the ARIMA model is to check for stationarity of the time series, Ron97. It is not stationary as the fuel price does not fluctuate uniformly around a mean with a constant variance as shown in Fig. 1. The Time series is differenced to achieve stationarity time series. Figure 2a–c are the Sample autocorrelation (SAC) of Ron97 Sample partial autocorrelation (SPAC) of Ron97 of the first difference. They are stationary. The identified order for the SAC and SPAC is 14 and 14 respectively as the relevant leading spiking Lags in the correlograms are found at the 14th Lags respectively, and the rest the rest of the correlations die down. ARIMA (14, 1, 14) is the Identified model.

The Autoregressive order obtained from the SPAC, and Moving Average order obtained from the SAC are too high for the first differencing. Generally lower orders are preferred. The second differencing correlograms, Fig. 2d–f are assessed to determine its order. The SPAC has an order of 0 as the correlation Lags do not die done. The SAC has spikes at Lag 1 and relatively die down after it. Hence ARIMA (0, 2, 1) is identified at the second differencing.

Model Estimation

The Models identified are estimated using the Econometric Modeler or Econometric Tool box in MATLAB. Ron97 has a *t* distribution and from the estimation process it is observed that the models are more parsimonious when the constant, term, *c* is zero

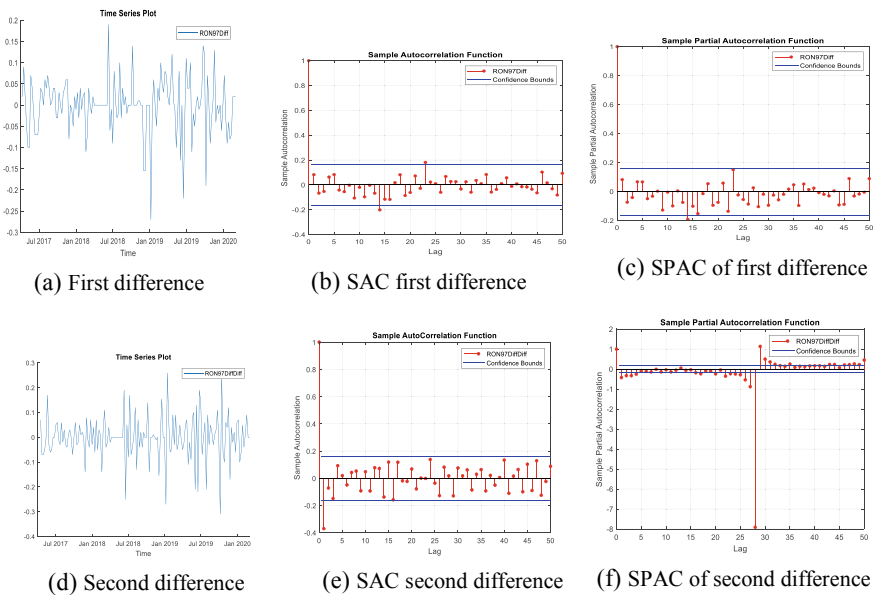


Fig. 2 Correlograms of Ron97

(0). These conditions are specified in the software during the estimating process. The best model is the one with the least Akaike Information Criteria (AIC) or Bayesian Information Criteria (BIC). Tables 1, 2 and 3 are summary of estimates of the model parameters. Comparing the AIC and BIC respectively, it is established that ARIMA (14, 1, 14) is the most parsimonious and the best fit model. Equation (3) is the ARIMA (14, 1, 14). Model.

$$(1 - \phi_{14}L^{14})(1 - L)y_t = (1 + \theta_{14}L^{14})\varepsilon_{14} \tag{3}$$

Equation (3) is expanded to give Eq. (4)

$$y_t = y_{(t-1)} + \phi_{(14)}y_{(t-14)} - \phi_{(14)}y_{(t-15)} + \theta_{14}\varepsilon_{(t-14)} + \varepsilon_t \tag{4}$$

If the parameters are substituted in Eq. (4), with the parameter estimates in Table 1. Estimation Results for ARIMA (14, 1, 14) , the tentative forecasting model is achieved as Eq. (5)

$$y_t = y_{t-1} - 0.7084y_{t-14} + 0.7084y_{t-15} + 0.6308\varepsilon_{t-14} + \varepsilon_t \tag{5}$$

Table 1 Estimation results for ARIMA (14, 1, 14)

Parameter	Value	Standard error	t statistic	P-value
Constant	0	0		
AR{14}	-0.7084	0.0620	-11.4199	3.3269e-30
MA{14}	0.6308	0.0817	7.7248	1.1201e-14
DoF	2.2366	0.7204	3.1049	0.0019
Variance	0.0114	0.0291	0.3901	0.6965

Table 2 Estimation results for ARIMA (0, 1, 2)

Parameter	Value	Standard error	t statistic	P-value
Constant	0	0		
MA{1}	-0.9834	0.0108	-91.0724	0
DoF	2.2273	0.7612	2.9261	0.0034
Variance	0.0134	0.0382	0.3518	0.7250

Table 3 Goodness of fit, of models

Model	AIC	BIC
ARIMA(14, 1, 14)	-439.1807	-427.4717
ARIMA(0, 2, 1)	-420.5204	-411.4686

Table 4 Ljung-box Q-test

	Null rejected	P-value	Test statistic	Critical value	Lags	DOF	Significance level
1	True	0.0191	13.5066	11.0705	15	5	0.05
2	True	0.0012	20.1843	11.0705	20	5	0.05
3	True	3.2044e-05	28.2830	11.0705	25	5	0.05
4	True	8.5631e-06	31.1974	11.0705	30	5	0.05
5	True	2.2489e-06	34.1245	11.0705	35	5	0.05
6	True	5.8798e-07	37.0400	11.0705	40	5	0.05
7	True	4.1995e-07	37.7686	11.0705	45	5	0.05
8	True	7.1972e-09	46.4961	11.0705	50	5	0.05
9	True	3.173e-09	48.2400	11.0705	55	5	0.05
10	True	1.9315e-10	54.1725	11.0705	60	5	0.05

Model Diagnostic Checking

The model is assessed for its adequacy in forecasting the fuel price, Ron97. The model residual is assessed, using the Ljung-Box Q-test and residual correlation plot. The Ljung-Box Q-test is a quantitative way to test for autocorrelation at multiple lags jointly. In performing the Ljung-Box test, we specify the degree of freedom to 5 as there are only five independent variables in the model. The number of possible lags is increased by 5 lags from the 15th lag onward till the 150th lag, Table 4. The p -value of the Ljung test remains less than 5% for the Null Hypothesis: "The first m autocorrelations of the residuals of ARIMA_ROM97 are jointly 0". This implies there are no autocorrelations in the ARIMA residual. The Residual correlation plot Fig. 3 shows only one feeble spike at the 23rd lag which is not that significant. Hence the Model is adequate for the forecasting of Ron97 price in the neighbourhood of the period considered.

4.2 Model Forecast Performance and Validations

The forecast for ARIMA(14, 1, 14) performed better than ARIMA(0, 1, 2) as shown in the circled area in the plot. It is the second best in the graph compared to observed data. NARNET, Nonlinear autoregressive neural network model was even better (Fig. 4).

5 Conclusion

The main objective of this paper is to assess the ability to forecast Ron97 fuel price using ARIMA models. It is possible to forecast accurately fuel price using

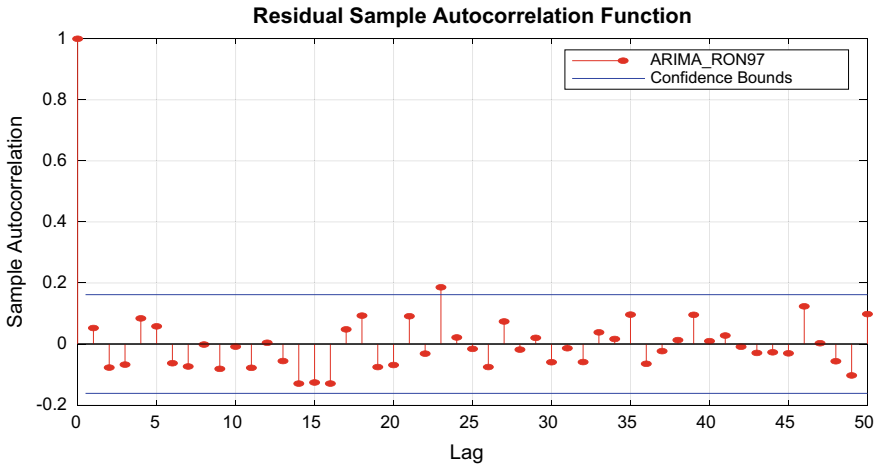


Fig. 3 Residual SAC of ARIMA_Ron97

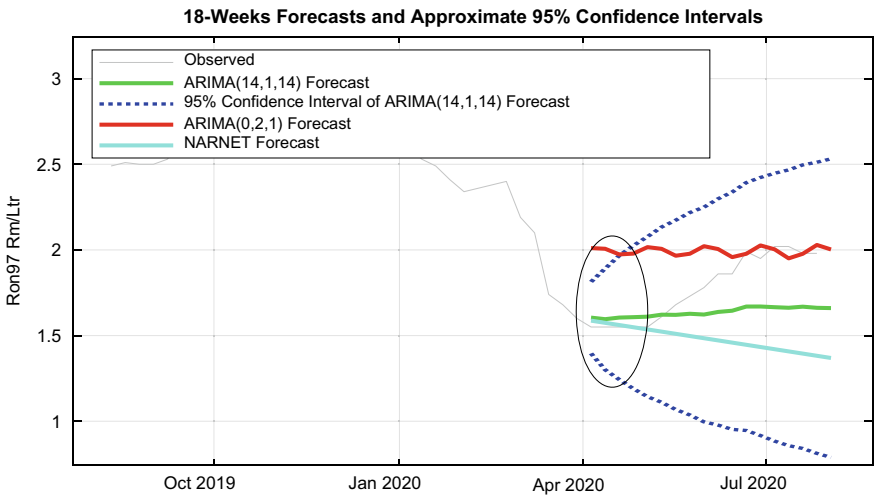


Fig. 4 Forecast performance of the ARIMA models

the ARIMA models but limited to a shorter period, month. Improvement can thought be made to the model to increase the length of forecast periods.

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References

1. Babulal, V.: Government goes back to weekly managed float system to determine fuel prices. In: *New Straits Times*, Kuala Lumpur, 04 Jan 2019
2. Corporate-Malaysia: System, Why govt go for manage-float. In: *The Malaysian Reserve*, p. Business, Kuala Lumpur, 17 Mar 2017
3. The Ministry of Domestic Trade and Consumer Affairs: Fuel prices. In: *The Ministry of Domestic Trade* (2020). <https://www.kpdnhep.gov.my/ms/>
4. M. of F. Malaysia: Retail price of petroleum products. In: *Retail Price of Petroleum Products* (2021). <https://www.mof.gov.my/en/component/tags/tag/price-of-petroleum%0A>
5. Bofinger, P., Wollmershäuser, T.: Managed Floating: Understanding the New International Monetary Order W.E.P. Würzburg, 30, 2001. [Online]. Available: <http://hdl.handle.net/10419/48479>
6. Tan, P.: APM: How fuel prices are calculated in Malaysia. In: *Malaysian Fuel Prices* (2009). <https://paultan.org/2009/02/15/how-fuel-prices-are-calculated-in-malaysia/>
7. P. S & P Global: Methodology and specifications guide Asia Pacific & Middle East refined oil products. In: *Platts*, p. 47 (2017)
8. Chambers, A.G.: *Sales Tax Regulations*, p. 86. Malaysia Sales and Service Tax'Royal, Malaysia (2018)
9. Razak, Y.D.S.M.N.T.H.A.: The 2014 Budget Speech, pp. 1–52. Dewan Rakyat, Putrajaya (2013)
10. Ramasamy, M., Koon, C.P.: Malaysia raises fuel prices as Najib seeks to trim budget gap. In: *Bloomberg Business* (2013). <https://www.bloomberg.com/news/articles/2013-09-02/malaysia-raises-fuel-prices-as-najib-seeks-to-trim-budget-gap>
11. Hakim, R.A., Ismail, R., Razak, N.A.A.: Fuel subsidy reform in Malaysia: an assessment on the direct welfare impact on consumers. *IPBJ* 8(1), 26–36 (2016) [Online]. Available: http://oyagsb.uum.edu.my/images/2018/List_of_Issues/Fuel_Subsidy_Reform_in_Malaysia_An_Assessment_on_the_Direct_Welfare_Impact_on_Consumers.pdf
12. CompareHero.my: Latest Petrol Price for Ron95, Ron97 & Diesel in Malaysia. In: *Money Tips, Transportation* (2020). <https://www.comparehero.my/transportation/articles/latest-petrol-price-ron95-ron97-diesel>
13. NST: PH fulfils pledge to stabilise fuel prices. In: *New Straits Times*, Kuala Lumpur, News, 17 Aug 2018
14. Burden, R.L., Faires, J.D.: *Interpolation and polynomial approximation*. In: Ostedt, G. (ed.) *Numerical Analysis*, 6th edn, pp. 104–165. Brooks/Cole Publishing Company, USA (1997)
15. Moler, C.: *Numerical Computing with MATLAB* (2015)
16. Sarpong-Streeter, R.M.N.Y.: ARIMAX Modelling of Ron97 Price with Crude Oil Price as an Exogenous Variable in Malaysian, Mendeley Data, V1 (2021). <https://doi.org/10.17632/zxjnrpmwd8.1>
17. O'Connell, R.T., Koehler, A.B., Bowerman, B.L., O'Connell, R.T., Koehler, A.B.: *Forecasting, Time Series, and Regression: An Applied Approach*, vol. 4. Thomson Brooks/Cole (2005)
18. Box, G.E.P., Jenkins, G.M., Reinsel, G.C., Ljung, G.M.: *Time Series Analysis: Forecasting and Control*. Wiley (2015)
19. Manjon, J.: *Econometric Modeler*. MathWorks Inc., Massachusetts, United States, 20AD