

Prediction of Low Cost Housing Demand in Malaysia Using ARIMA Model

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Abstract. Among the key challenges in construction industry sector faces are matching supply of and demand for affordable housing. It is very crucial to predict low-cost housing demand to match the demand and supply so that the government can plan the allocation of low cost housing based on the demand. In Johor, housing provision is very crucial due to urbanization. The supply of houses seems to be swamping the demand for luxury condos and houses especially in Johor Bharu. Thus the aim of this study is to predict low-cost housing demand in Johor, Malaysia using ARIMA model. Time series data on low-cost housing demand have been converted to Ln before develop the model. The actual data and forecasted data will be compared and validate using Mean Absolute Percentage Error (MAPE). After that, the results using ARIMA method will be compared with ANN method. The results show that MAPE analysis for ARIMA is 15.39% while ANN is 18.27%. It can be conclude that ARIMA model can forecast low cost housing demand in Johor quite good.

1 Introduction

One of Malaysia's longstanding development objectives is the provision of affordable housing for Malaysian, with a focus on lower-income groups [1]. Low cost housing can be defined as a development projects sold at the price set by the government that is between RM25, 000 to RM42, 000 [2]. Low cost housing built is intended to provide housing that is affordable for low earners in rural and suburban areas. The target groups for this project are households with monthly income of between RM500 to RM750 [3].

To provide adequate housing and affordable for Malaysians, especially for those with low incomes has become the main agenda through Malaysia plans prior to now [4]. However, there is mismatched data between the supply and demand for low-cost housing in Malaysia [5]. In some places, the supplies of low cost housing are exceeding compare to demand and lead to wastage of construction and of course has an impact on the cost and economic aspects. While in other areas the demand is exceeding supply provided, which supplies low-cost houses are insufficient, especially in urban areas [6]. Therefore, an alternative approaches need to be done to resolve these issues.

There are many series of forecasting methods can be used to predict the housing demand such as Artificial Neural Network (ANN), Autoregressive Integrated Moving Average (ARIMA), Power

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Model and Multiple Log linear Regression [7]. In this study ARIMA model known as the Box-Jenkins time series is used because it has good accuracy for the short term forecasting.

2 Scope and Limitation of Study

This study will focuses on forecasting low cost housing demand in Johor, Malaysia only. Previous time series data from [6] will be used to forecast low-cost housing demand in Johor using ARIMA model.

3 Methodology

The time series data were changed to Ln then analyzed using ARIMA software adopted from SPSS 20.0. Results were validated using MAPE where actual and forecasted data were compared to determine the accuracy of the model. Finally, the MAPE value will be compared to establish the performance of model.

4 Results and Discussion

Table 1 shows the monthly time series data on low cost housing demand in Johor from January 2000 to January 2007.

Table 1. Time series data on low cost housing demand.

Month Year	Jan	Feb	Mac	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec	Total
2000	90	272	360	325	360	405	497	488	334	474	472	530	4607
2001	419	485	572	661	1005	544	544	434	318	550	555	356	6443
2002	614	343	546	416	566	529	445	544	398	415	482	209	5507
2003	404	477	424	312	299	414	365	498	280	269	211	264	4217
2004	262	299	283	230	235	303	533	233	215	227	246	303	3369
2005	243	182	230	205	232	180	188	166	209	196	121	210	2362
2006	170	140	223	174	190	199	275	308	259	134	197	197	2466
2007	157												157
Total	2359	2198	2638	2323	2887	2574	2847	2671	2013	2265	2284	2069	29128

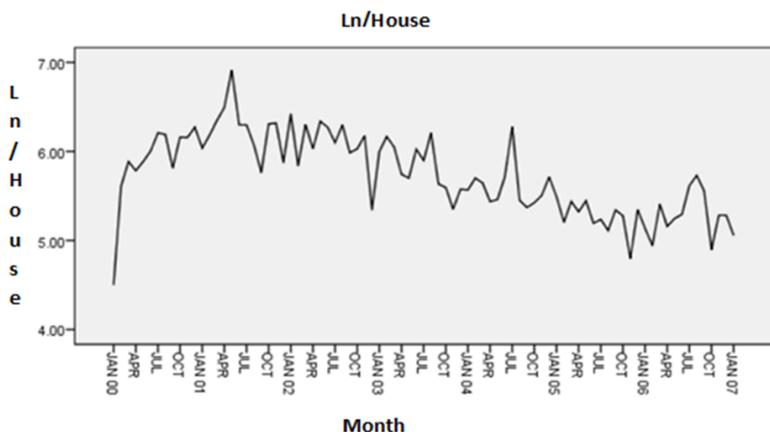


Figure 1. Housing demand (Ln).

Figure 1 are time series housing demand in Ln. Data were change to Ln to get idea for p, d, q value for a non seasonal ARIMA model ARIMA (p, d, q), where p is the number of autoregressive terms, d is the number of nonseasonal differences needed for stationarity, and q is the number of lagged forecast errors in the prediction equation. p and d were determined using coefficient Auto Correlation (AC) and Partial Auto Correlation (PAC) where AR(p) and MA(q) are the components for the time series.

Figure 2 views the ACF and PACF of housing demand using ARIMA (0,0,0). It can be seen that there are a few extrusions and improvements were done to create stationary data. From the p,d,q value, significant calculations for each parameters were done to determine the best model. In this study, three model were used; ARIMA (1,0,1); ARIMA (1,0,0) and ARIMA (2,0,0). ARIMA model produced the lowest value Akaike Information Criterion (AIC) and Schwarz Criterion (SC) is the best model.

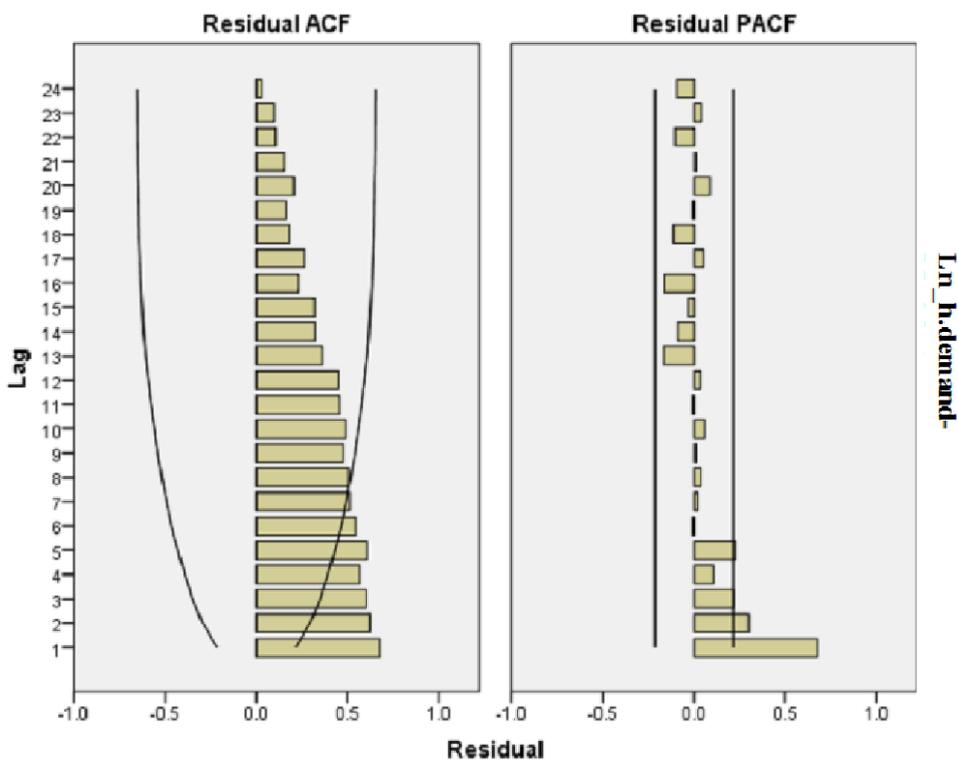


Figure 2. ACF and PACF of housing demand using ARIMA (0,0,0).

Table 2 views the AIC and SC value for each ARIMA model. It can be seen that model ARIMA (1,0,1) is the best compare to ARIMA (1,0,0) and ARIMA (2,0,0).

Table 2. Value for AIC and SC for each model.

Model	AIC	SC
ARIMA (1,0,1)	0.0178	0.2288
ARIMA (1,0,0)	0.0370	0.2499
ARIMA (2,0,0)	0.0656	0.2239

Figure 3 plots the improve ACF and PACF using ARIMA (1,0,1) and Table 3 shows the analysis value from model ARIMA (1,0,1).

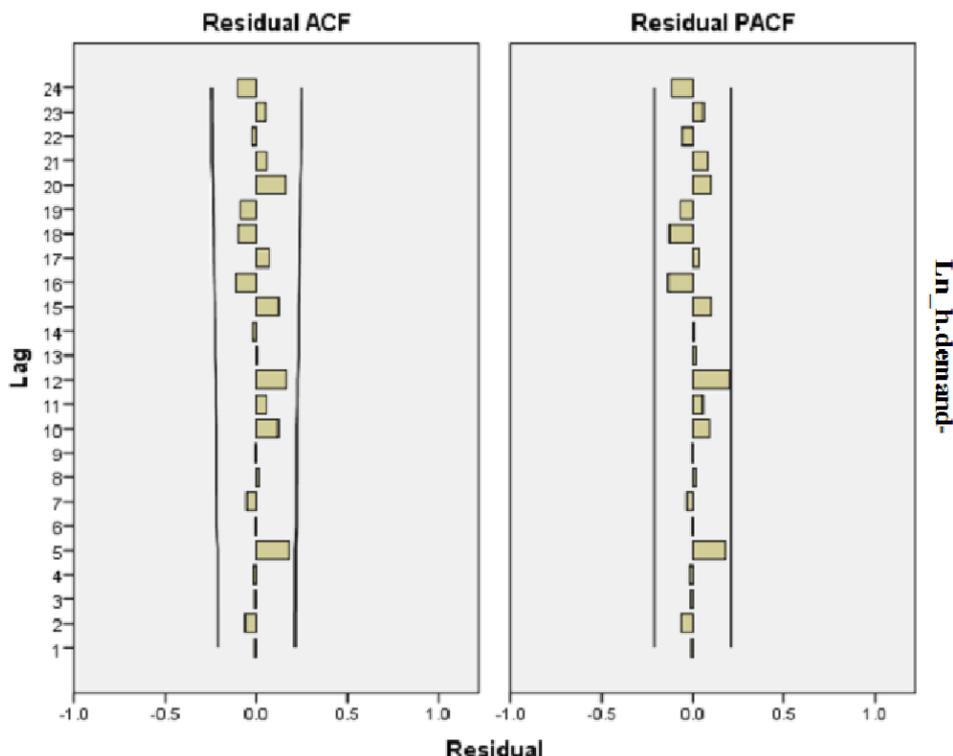


Figure 3. ACF and PACF of housing demand using ARIMA (1,0,1).

Table 3. Analysis value for model ARIMA (1,0,1).

	Intersection	AR(1)	Variable (1)	MA(1)
Coefficients	10.2767	0.6014	-0.0002	-0.4317
Standard Error	1.8472	0.0767	0.0000	0.1283
t-Statistic	5.5634	7.8451	-5.4500	-3.3625
p-Value	0.0000	0.0000		

From Table 3, $|t_{calc}| > t_{table} (= 2.25)$ and p less than α . Therefore, null hypothesis can be rejected and can be concluded that the coefficient is different from zero.

Table 4. Comparison forecasting value between tentative models.

Month	Actual Data	ARIMA (1,0,1)	ARIMA (1,0,0)	ARIMA (2,0,0)
September 2006	5.56	5.54	5.68	5.71
Oktober 2006	4.90	5.54	5.62	5.58
November 2006	5.28	5.31	5.23	5.09
Disember 2006	5.28	5.31	5.23	5.38
Januari 2007	5.06	5.31	5.23	5.39
MAPE	-	3.90	4.42	5.72

Table 4 is the comparison forecasting value between tentative models ARIMA. It shows that ARIMA (1,0,1) have the lowest MAPE with 3.9%.

Therefore, the regression model equation was rewritten:

$$(1 - \phi_1B)(1-B)(1-B12)Y_t = (1 - \theta_1B)(1 - \theta_2B12)at \dots \dots \dots \text{Equation (1)}$$

$$\cdot (1 - \phi_1B)(1-B12-B+B13)Y_t = (1 - \theta_2B12 - \theta_1B + \theta_1\theta_2B13)at$$

$$\cdot (1 - \phi_1B)(1-B12-B+B13)Y_t = (1 - \theta_2B12 - \theta_1B + \theta_1\theta_2B13)at$$

$$\cdot (1-B12-B+B13 - \phi_1B + \phi_1B13 + \phi_1B2 - \phi_1B14) Y_t = (1 - \theta_2B12 - \theta_1B + \theta_1\theta_2B13)at$$

$$\cdot (1 - B12 - (1 + \phi_1)B + (1 + \phi_1)B13 + \phi_1B2 - \phi_1B14) Y_t = (1 - \theta_1B - \theta_2B12 + \theta_1\theta_2B13)at$$

$$\cdot Y_t - (1 + \phi_1)Y_{t-1} + \phi_1Y_{t-2} - Y_{t-12} + (1 + \phi_1)Y_{t-13} - \phi_1Y_{t-14} = at - \theta_1at-1 - \theta_2at-12 + \theta_1\theta_2at-13$$

$$\cdot Y_t = (1 + \phi_1)Y_{t-1} - \phi_1Y_{t-2} + Y_{t-12} - (1 + \phi_1)Y_{t-13} + \phi_1Y_{t-14} + at - \theta_1at-1 - \theta_2at-12 + \theta_1\theta_2at-13$$

AR(1)	SMA(1)	MA(1)
0.6014	0.9553	-0.431655405

$$Y_t = (1 + 0.6014) Y_{t-1} - 0.6014Y_{t-2} + Y_{t-12} - (1 + 0.6014) Y_{t-13} + 0.6014Y_{t-14} + 0.6014Y_{t-14} + at + 0.431655405at-1 + 0.431655405at-12 + (0.431655405 \times 0.9553)at-13$$

$$Y_t = 1.289 Y_{t-1} - 0.6014Y_{t-2} + Y_{t-12} - 1.2894Y_{t-13} + 0.6014Y_{t-14} + at + 0.431655405at-1 - 0.9553at-12 + 0.8395at-13$$

$$Y_t = Y_{t-12} + [1.2894 Y_{t-1} - 1.2894Y_{t-13} - 0.6014Y_{t-2} + 0.6014Y_{t-14}] + [at + 0.431655405at-1 - 0.9553at-12 + 0.8395at-13] \dots \dots \dots \text{Equation (2)}$$

Therefore, Equation (2) is the ARIMA model to predict low-cost housing demand in Johor.

Table 5. The actual data and forecast data using ARIMA (1,0,1) method.

Time series	Actual	Forecasted	Actual – Forecasted	Percentage Error
June 2006	199	191	8	4.02
July 2006	275	196	79	28.73
August 06	308	124	84	27.27
September 06	259	255	4	1.54
MAPE				15.39

Table 5 shows the actual and forecasted data from June 2000 to September 2006 using ARIMA (1,0,1) model. From the calculations, MAPE value obtained was 15.39%. Predictive ability is very good if the MAPE is less than 10% while MAPE less than 20% is good [8]. The results show that MAPE value for ARIMA less than 20%.

5 Conclusion

Since the MAPE value is less than 20%, it can be conclude that ARIMA model can predict low-cost housing demand in Johor quite good. It is recommend further study should be done to reduce the error of performance since the results generated are able to assist the construction of low-cost housing scheme in terms of the accuracy of necessity based on actual demand. Subsequently there would be a minimal possibility of the procurement of either under-construction or over construction of low cost houses particularly in the state of Johor.

References

[1] The Tenth Malaysia Plan, (2011-2015), Economic Planning Unit, Prime Minister's Department, Putrajaya, (2010).

- [2] Ministry of Housing and Local Government Malaysia, Guidelines for the Implementation of the New Price of Low Cost Housing (Amendment) Act 2002, (2002).
- [3] R. Mahamud and K. Hussein, Studies on potential medium income group in own homes in area Johor Bahru, University Technology Malaysia, Vote Upp, 71, 693, (2002).
- [4] The Ninth Malaysia Plan (2006-2010), Chapter 21 Providing Housing and Urban Services Quality, Prime Minister's Department, Putrajaya, (2006).
- [5] S. Shuid, Low medium cost housing in Malaysia: Issues and challenges, International Islamic University Malaysia, (2004).
- [6] N.Y. Zainun, Computerized Forecasting Model to Forecast Low-Cost Housing Demand in Urban Area in Malaysia using Artificial Neural Networks (ANN), PhD Thesis, Loughborough University, (2012).
- [7] N.Y. Zainun and M.Z. Abd Majid, Evolution on various forecasting models using artificial neural networks (ANN), *Proc. of the 2nd International Conference on Innovation in Architecture, Engineering and Construction*, United Kingdom, (2003).
- [8] S. Harun, Forecasting and Simulation of Net Inflows for Reservoir Operation and Management, PhD Thesis, University Technology Malaysia, Johor, (1999).