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TIME SERIES MODELLING AND FORECASTING OF SARAWAK BLACK PEPPER PRICES[1]

Liew Khim Sen
Department of Economics, Faculty of Economics and Management, Universiti Putra Malaysia, 43400 UPM Serdang.

Mahendran Shitan
Department of Mathematics, Faculty of Science and Environmental Science, Universiti Putra Malaysia, 43400 UPM Serdang.

Huzaimi Hussain*
Department of Business Management, Universiti Teknologi MARA, Samarahan Campus, Kota Samarahan, Sarawak.

Abstract

Pepper is an important agricultural commodity especially for the state of Sarawak. It is important to forecast its price, as this can help the policy makers in coming up with production and marketing plans to improve the Sarawak's economy as well as the farmers' welfare. In this paper, the time series models are used to forecast the Sarawak black pepper price. It is formally shown in this paper that the pepper price series does not follow a random walk process. Through a battery of diagnostic tests, this paper further shows that Autoregressive Moving Average (ARMA) time series models fit the price series well. The ARMA (1, 0) model seems to be the best fitting model for predicting the pepper price based on the data used in this study.

1.0 INTRODUCTION

Pepper (Piper nigrum L.), which has been used as a spice since the 4th Century B.C. was first brought into Malacca in the year 1583 by the Portuguese (Abd. Rahman Azmi, 1993). Pepper crop cultivation gained its popularity in Johore and Singapore during the early 19th century and was widely planted in Sarawak since the mid-19th century. Today, 95% (10,100 hectares) of the crop is grown in Sarawak and only 5% is grown in other parts of Malaysia. Due to this, in the world market the pepper produced in Malaysia is commonly known as Sarawak pepper.

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* Corresponding author.

Until 1980, Malaysia was traditionally the largest pepper producing country in the world. After that, Malaysia lost it leading position to India and Indonesia (Abd. Rahman Azmil, 1993) and in 2000[1] Malaysia ranked the world fourth largest producer of pepper after Vietnam, Indonesia and Brazil (Pepper Marketing Board Homepage, 2003). Pepper's contribution to the local socio-economy is substantial. It is reported (Pepper Marketing Bulletin, January to March, 1999) that some 45,000 farming families and more than 115,000 workers are involved in the pepper industry[1]. The crop generates about a third of Sarawak's agricultural export earnings.

It is clear that pepper is an important agricultural commodity and hence it would be important to forecast its price, as this could help the policy makers in coming up with production and marketing plans, to improve the Sarawak's economy as well as the farmers' welfare. In light of this, this study attempts to forecast the pepper price using the time series models. We note here that a few studies in Malaysia have demonstrated the usefulness of time series modelling and forecasting in the agriculture sector (Fatimah and Gaffar, 1986a and 1986b; Mad Nasir 1992 and Lalang et al., 1997). For instance, Fatimah and Gaffar (1986) confirmed the suitability of Box-Jenkins univariate ARIMA models in agricultural prices forecasting.

It has also been shown (Fatimah and Gaffar, 1986) that ARIMA models are highly efficient in short term forecasting. Mad Nasir (1992) has noted that ARIMA models have the advantage of relatively low research costs when compared with econometric models, as well as efficiency in short term forecasting. Lalang et al. (1997) has also shown that ARIMA model is the most suitable technique for modelling palm oil prices. As for pepper prices there is no record of studies using time series models and in view of this it is important to conduct a study of pepper prices using time series models.

In section 2 of this paper, we briefly discuss ARMA time series modelling. In section 3, we present the methodology and results of fitting suitable time series models to Sarawak black pepper price and finally in section 4 our conclusions appear.

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[1] See also Merican (1985), Bong and Saad (1986), Dimbab et al. (1989) and Fang (1994) for more information issues related to pepper in Malaysia.

2.0 ARMA TIME SERIES MODELLING

A sequence of uncorrected random variables each with mean 0 and variance σ^2 is called a white noise process and is denoted by $Z \sim N(0, \sigma^2)$.

An ARMA (p, q) time series model is defined as a sequence of observations (Y_t) that satisfy the following difference equation (Brockwell and Davis, 1996),

$$Y_t - \phi_1 Y_{t-1} - \phi_2 Y_{t-2} - \ldots - \phi_p Y_{t-p} = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \ldots + \theta_q Z_{t-q} \qquad (1)$$

where $\phi_1, \ldots, \phi_p$ and $\theta_1, \ldots, \theta_q$ are numerically specified values of parameters and $Z_t \sim N(0, \sigma^2)$.

The process as defined in (1) is a weakly stationary process. A weakly stationary process is a process with constant mean and covariance (Brockwell and Davis, 1996).

The process of time series modeling involves transformation of data in order to achieve stationarity, followed by identification of appropriate models, estimation of parameters, validation of the model and finally forecasting. A complete description of these processes and steps of time series modeling is clearly explained in Brockwell and Davis (1996, pp. 135 – 175).

3.0 METHODOLOGY AND RESULTS

In this section, we present the methodology and results of fitting suitable time series models to Sarawak black pepper prices obtained from the Pepper Marketing Board, Malaysia. The series, consisting of 331 monthly data from January 1972 to July 1999, was divided into two portions for the purpose of this study. The first 318 observations were used for model fitting purpose, while the rest were kept for post-sample forecast accuracy checking.

The process of model fitting for the Sarawak black pepper price, was done by using computer software known as "Interactive Time Series Modeling – PEST module" (developed by Brockwell, Davis and Mandarino, 1996).

The time series plot of Sarawak black pepper price is shown in Figure 1. Figure 1 indicates that there exists a generally increasing non-linear trend. The plots of the sample autocorrelation functions (ACF) and the sample partial autocorrelation functions (PACF) for this series are shown in Figure 2. Figure 2 confirms that there exists a typical pattern of non-stationarity in the pepper price.

In order to achieve stationarity, the trend component should be detrended from the original series, which could be achieved by using either method of differencing or classical decomposition (Brockwell and Davis, 1996, p. 186). In this article, the original series was differenced at lag 1 (thus resulting the first differenced series) in order to achieve stationary pattern. The first differenced series may be represented by

$$X_t = Y_t - Y_{t-1} \quad (2)$$

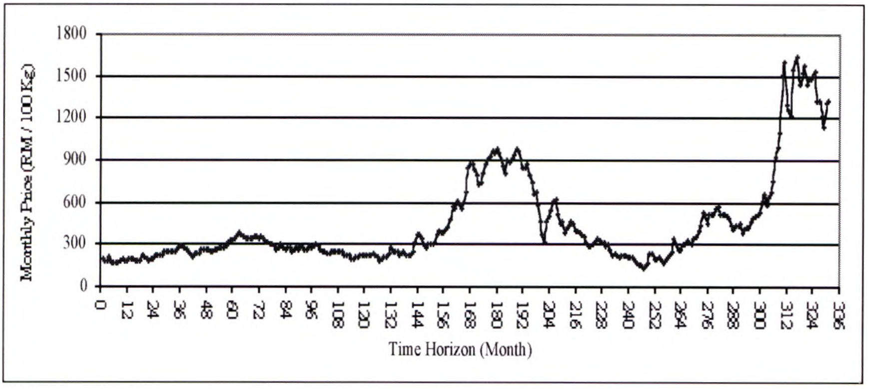
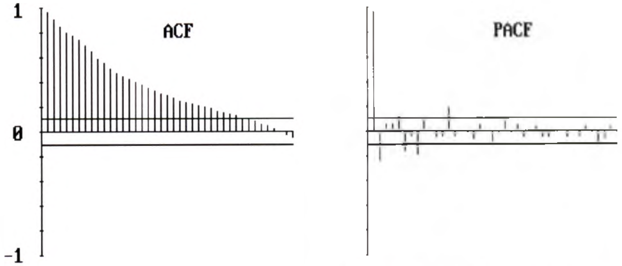


Figure 1: Monthly Sarawak black pepper price in Kuching (Jan. 1972 to Jul. 1999)



ACF:	.960	.903	.850	.806	.775	.740	.699	.643	.590	.549
	.511	.476	.449	.424	.400	.378	.352	.329	.310	.290
	.270	.251	.234	.221	.209	.195	.182	.166	.152	.138
	.124	.109	.093	.077	.062	.048	.027	.002	-.023	-.045
PACF:	.960	-.236	.064	.058	.131	-.155	-.030	-.192	.107	.029
	-.045	-.040	.186	-.035	.006	-.014	-.060	.051	.007	-.089
	-.023	.077	-.010	.042	-.045	.001	.040	-.046	-.046	.003
	-.005	-.043	.004	-.032	.032	-.007	-.120	-.055	.038	-.019

Figure 2: Sample ACF and PACF of the Sarawak black pepper price series.

We note here that if the first difference series (X_t) is purely white noise, then Equation (2) would reduced to

$$Y_t = Y_{t-1} \qquad (3)$$

which implies that the original series follows a white noise process[2].

To be consistent with the requirement of ARMA (p, q) modelling procedure, the mean was also subtracted from the series so that it could be modelled as a zero mean stationary process (Figure 3).

[2] We thank an anonymous referee for pointing this out.

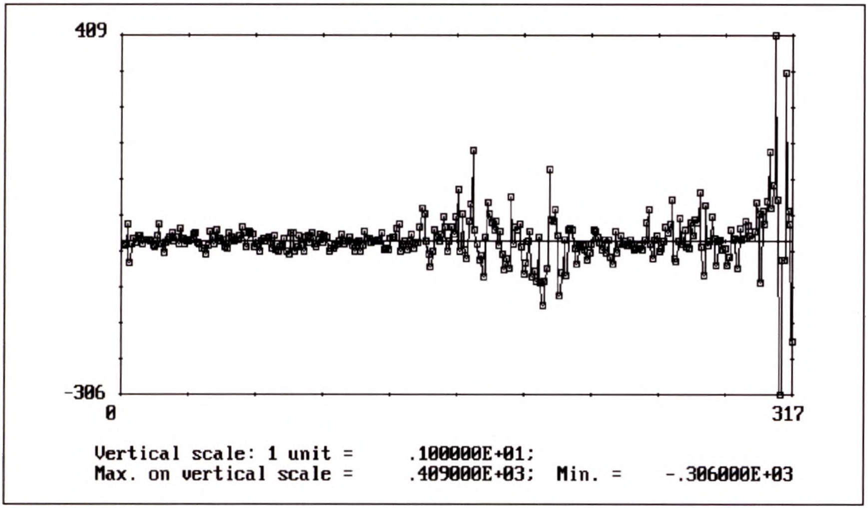
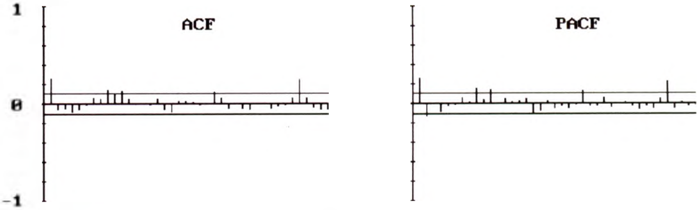


Figure 3: Graph of Sarawak black pepper price after a lag 1 differencing.

The ACF and PACF of the first difference series are shown in Figure 4. It is obvious, from the sample ACF of the differenced series that most of the spikes had decayed to a level not significantly different from 03[3]. Moreover, the dominant spike at lag 1 of the PACF is not so outstanding as before. Hence, this first difference series (X_t) appears to be stationary[4]. We note here that there is a possibility that X is indeed a white noise as the ACF and PACF values are all close to zero for most lags. However, a formal checking of the Q statistics for the first 12, 24 and 36 lags are thus conducted to see whether all lags are significantly zero. The computed Q statistics are, in that order, 42.175, 53.886 and 66.287 respectively, implying that we have enough evidence to reject the null of white noise at 1% significance level. The implication of this finding is that the price level does not follow random walk behavior and this study therefore modelled it as a stationary ARMA model.

[3] Spikes exceeding the 95% confidence intervals (horizon lines) considered significantly different from zero, where the 95% confidence intervals are computed on the basis of $\pm 1.96/\sqrt{n}$, where n is the sample size. For n=331 as in our case here, the 95% confidence intervals are thus ± 0.108 (Brockwell and Davis, 1996, p. 143).

[4] A formal statistical test of stationarity, namely the augmented Dickey-Fuller (ADF) Unit Root Test (see Dickey and Fuller, 1979 and Mackinnon, 1991 for details) was conducted and the results verified that the pepper price is non-stationary in its level but is stationary after the first differencing (Appendix A).



ACF:	.253	-.060	-.051	-.083	-.055	-.012	.059	.047	.143	.109
	.126	.047	.005	.003	-.009	.044	-.064	-.077	.025	.028
	.013	-.007	.003	.115	.054	-.046	.004	-.044	-.062	-.002
	-.003	-.050	-.023	-.015	.062	.245	.058	-.040	-.064	-.058
PACF:	.253	-.133	.000	-.083	-.018	-.008	.059	.007	.148	.039
	.138	.006	.049	.016	.018	.046	-.103	-.065	.022	-.046
	-.020	-.052	-.009	.132	-.020	-.018	.058	-.035	-.001	.009
	-.023	-.058	-.026	-.045	.044	.229	-.047	.017	-.018	-.009

Figure 4: Sample ACF and PACF of Sarawak black pepper price after a lag 1 differencing.

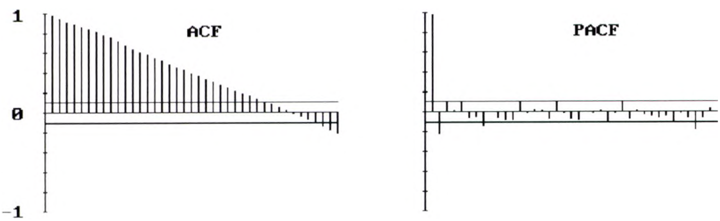
Next, we identified tentative models for this transformed series by inspecting the ACF and PACF. The ACF revealed that autocorrelation coefficients are significant at 95% confident level at lag 1, 9, 11, 24 and 36[5]. The ACF values at other lags are all not significantly different from 0. This suggested that fitting moving average models of 24, 11, 9 and 1 should be attempted. On the other hand, autoregressive models of order 1, 2, 9, 11 and 24 should also be taken into consideration as the PACF values at lag 1, 2, 9, 11 and 24 are significantly different from 0 at 95% confident level[6]. ARMA (p, q) models where p and q could be of order 1 or 2 were also considered in this study.

[5] The ACF values for lag 1, 9, 11, 24 and 36 are 0.253, 0.143, 0.126, 0.115 and 0.245 respectively, which are all exceeding the 95% confidence intervals of $\pm$ 0.108 as described in Footnote 1.

[6] The PACF values for lag 1, 2, 9, 11, 24 and 36 are, in that order, 0.253, - 0.133, 0.148, 0.138, 0.132 and 0.229 (Figure 4), which are all exceeding the 95% confidence intervals of $\pm$ 0.108 as described in Footnote 1.

Besides fitting ARMA (p, q) models, we also attempted to fit models by taking seasonality into account, as there exists of a seasonal trend in the Sarawak black pepper price (Sulau, 1981). In addition, the sample ACF of the original series displays a very slowly damped periodicity. According to Brockwell and Davis (1996), this indicates the presence of seasonal periods. Furthermore, a close inspection of the graph of the sample ACF in Figure 4 revealed that autocorrelation coefficients were significant at 95% confident level at lag 1, 9, 11, 24 and 36. Since 24 and 36 are multiples of 12, it is reasonable to suspect that there is a seasonality of order 12. The presence of seasonality is reinforced, by the fact that PACF values at lag 24 and 36 are also significant at 95% confident level.

Following the classical decomposition method in "PEST", a seasonal trend with a period of 12, and a quadratic trend from the series were eliminated. The ACF and PACF of the transformed series are presented in Figure 5. Since the ACF values decay slowly, the model is likely to come from AR family (Ahmad, 2000); see also Janacek and Swift (1993, p. 145). AR models of order 1 and 2 were among those being considered, as the PACF values at lag 1 and 2 are significant at 95% confident level.



ACF:	.975	.941	.909	.881	.860	.838	.813	.781	.747	.713
	.676	.637	.603	.571	.541	.513	.481	.451	.423	.394
	.363	.331	.300	.272	.243	.214	.188	.161	.135	.110
	.082	.053	.022	-.008	-.039	-.069	-.106	-.144	-.181	-.213
PACF:	.975	-.218	.099	.016	.109	-.063	-.049	-.136	.003	-.061
	-.084	-.086	.098	-.015	.026	.008	-.076	.099	-.010	-.068
	-.078	-.005	-.015	.012	-.097	-.014	.089	-.071	.015	-.024
	-.039	-.057	-.031	-.094	-.016	-.053	-.174	-.058	.039	-.001

Figure 5: Sample ACF and PACF of Sarawak black pepper price after a classical decomposition with seasonal period and a quadratic trend being taken away.

Note: ADF unit root test results of –2.292 and –3.747 (both significant at 5% level) for the regression that includes an intercept term and intercept with trend terms suggest that this deseasonalized and detrended series are stationary.

Next, the coefficients of each of the above tentative models were estimated using the "*PEST*" module. Results of the estimated models and the corresponding AICC values [see Equation (4)] are summarised in Tables 1 and 2.

Various methods were employed to check the suitability of each model. These include checking the distribution as well as ACF and PACF of the model's residuals, Ljung-Box Portmanteau Statistics, Mcleod-Li Portmanteau Statistics, Turning Point Test, Difference-Sign Test, and Rank Test.

We used the well-known minimum biased-corrected information criterion of Akaike, AICC (Hurvich and Tsai, 1989) to choose the best model. Out of a class of appropriate models, the best-fitted model is the one with the smallest AICC statistic. AICC statistic is given by

$$\text{AICC} = -2\ln \text{Likelihood}\,(\hat{\phi}, \hat{\theta}, \hat{\sigma}^2) + [2n(p+q+1)]/(n-p-q-2). \quad (4)$$

where $\hat{\phi}$ = a class of autoregressive parameters;

$\hat{\theta}$ = a class of moving average parameters;

$\hat{\sigma}^2$ = variance of white noise;

n = number of observations;

p = order of the autoregressive component;

and q = order of the moving average component.

Table 1: Estimated models for the first difference series.

No.	ESTIMATED MODEL	AICC
1	ARMA (26, 0) $X_t = 0.2479X_{t-1} - 0.1603X_{t-2} + 0.1019X_{t-7} + 0.1741X_{t-9} + 0.1420X_{t-11} - 0.1252X_{t-17} + 0.1574X_{t-24} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00612)$	-697.641
2	ARMA (11, 0) $X_t = 0.2688X_{t-1} - 0.1604X_{t-2} + 0.1574X_{t-8} + 0.1402X_{t-10} + 0.6906X_{t-11} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00612)$	-690.620
3	ARMA (9, 0) $X_t = 0.2814X_{t-1} + 0.1417X_{t-7} + 0.1497X_{t-9} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00654)$	-687.228
4	ARMA (2, 0) $X_t = 0.2882X_{t-1} - 0.1343X_{t-2} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00612)$	-681.710

No.	ESTIMATED MODEL	AICC
5	ARMA (1, 0) $X_t = 0.2544X_{t-1} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00612)$	-678.018
6	ARMA (0, 26) $X_t = Z_t + 0.2949 Z_{t-1} + 0.0574 Z_{t-7} + 0.1399 Z_{t-9} + 0.1686 Z_{t-11} + 0.1880 Z_{t-24}$ where $\{Z_t\} \sim WN(0, 0.00626)$	-694.754
7	ARMA (0, 24) $X_t = Z_t + 0.2944 Z_{t-1} + 0.0573 Z_{t-7} + 0.1397 Z_{t-9} + 0.1683 Z_{t-11} + 0.1876 Z_{t-24}$ where $\{Z_t\} \sim WN(0, 0.00626)$	-694.754
8	ARMA (0, 11) $X_t = Z_t + 0.2864 Z_{t-1} + 0.0886 Z_{t-7} + 0.1529 Z_{t-9} - 0.1343 Z_{t-11}$ where $\{Z_t\} \sim WN(0, 0.00642)$	-689.867
9	ARMA (0, 9) $X_t = Z_t + 0.3214 Z_{t-1} + 0.0623 Z_{t-7} + 0.1620 Z_{t-9}$ where $\{Z_t\} \sim WN(0, 0.00642)$	-687.228
10	ARMA (0, 7) $X_t = Z_t + 0.3285 Z_{t-1} + 0.0838 Z_{t-7}$ where $\{Z_t\} \sim WN(0, 0.00665)$	-683.321
11	ARMA (0, 1) $X_t = Z_t + 0.3109 Z_{t-1}$ where $\{Z_t\} \sim WN(0, 0.00670)$	-682.946
12	ARMA (1, 1) $X_t = -0.2300X_{t-1} + Z_t + 0.2864 Z_{t-1}$ where $\{Z_t\} \sim WN(0, 0.00668)$	-680.028
13	ARMA (2, 1) $X_t = 0.4942X_{t-1} - 0.1841X_{t-2} + Z_t + 0.2864 Z_{t-1}$ where $\{Z_t\} \sim WN(0, 0.00642)$	-679.736
14	ARMA (2, 1) $X_t = 0.2892X_{t-1} - 0.1343X_{t-2} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00642)$	-681.710

Note: "ITSM" allows one to first estimate the ARMA (p, q) model and then optimize the estimation by omitting the insignificance lags.

Table 2: Estimated models for the seasonally adjusted series.

No.	ESTIMATED MODEL	AICC
1	ARMA (12, 0) $X_t = 1.2120X_{t-1} + 0.4376X_{t-2} + 0.2482X_{t-3} - 0.1673X_{t-4} + 0.1512X_{t-9} - 0.1599X_{t-10} + 0.1172X_{t-11} - 0.1430X_{t-12} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00579)$	-712.689
2	ARMA (3, 0) $X_t = 1.2648X_{t-1} - 0.4209X_{t-2} + 0.1387X_{t-3} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00613)$	-706.017
3	ARMA (2, 0) $X_t = 1.2316X_{t-1} - 2.4874X_{t-2} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00624)$	-702.019
4	ARMA (1, 0) $X_t = 0.9863X_{t-1} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00666)$	-686.687
5	ARMA (1, 1) $X_t = 0.9790X_{t-1} + Z_t + 3.0214 Z_{t-1}$ where $\{Z_t\} \sim WN(0, 0.00681)$	-707.289
6	ARMA (2, 2) $X_t = 1.4710X_{t-1} - 0.4878X_{t-2} + Z_t + 0.2258 Z_{t-2}$ where $\{Z_t\} \sim WN(0, 0.00626)$	-694.164
7	ARMA (0, 24) $X_t = Z_t + 1.0575Z_{t-1} + 1.0567 Z_{t-2} + 0.9523 Z_{t-3} + 0.7705 Z_{t-4} + 0.8030 Z_{t-5} + 0.7780 Z_{t-6} + 0.9331 Z_{t-7} + 0.9642 Z_{t-8} + 0.8875 Z_{t-9} + 0.7792 Z_{t-10} + 0.8356 Z_{t-11} + 0.6404 Z_{t-12} + 0.7271 Z_{t-13} + 0.5007 Z_{t-14} + 0.5459 Z_{t-15} + 0.6316 Z_{t-16} + 0.4892 Z_{t-17} + 0.5793 Z_{t-18} + 0.5244 Z_{t-19} + 0.4737 Z_{t-20} + 0.5858 Z_{t-21} + 0.4793 Z_{t-22} + 0.4998 Z_{t-23} + 0.3606 Z_{t-24}$ where $\{Z_t\} \sim WN(0, 0.00670)$	-647.389
8	ARMA (12, 0) $X_t = 1.2234X_{t-1} - 0.4129X_{t-2} + 0.1608X_{t-3} + 0.0381X_{t-4} + 0.1425X_{t-9} - 0.1428X_{t-10} + 0.1068X_{t-11} + 0.1447X_{t-12} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00577)$	-714.055
9	ARMA (3, 0) $X_t = 1.2650X_{t-1} - 0.4210X_{t-2} + 0.1382X_{t-3} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00613)$	-705.730
10	ARMA (2, 0) $X_t = 0.1232X_{t-1} - 0.2490X_{t-2} + Z_t$ where $\{Z t\} \sim WN(0, 0.00624)$	-701.791
11	ARMA (1, 0) $X_t = 0.9866X_{t-1} + Z_t$ where $\{Z_t\} \sim WN(0, 0.00670)$	-683.387

Note: Models 1 to 7 contain linear trend. Models 8 to 11 contain quadratic trend.

According to the minimum AICC criterion, ARMA (12, 0) model (no. 8, Table 2) for the seasonally adjusted series had been chosen to be the most appropriate. The equation of this model is given by

$$X_t = 1.2234X_{t-1} - 0.4129X_{t-2} + 0.1608 X_{t-3} + 0.0381X_{t-4} + 0.1425X_{t-9} - 0.1428X_{t-10} + 0.1068X_{t-11} + 0.1447X_{t-12} + Z_t \quad (5)$$

where $\{Z_t\} \sim N(0, 0.00577)$

A forecast produced using this model is shown in Figure 6. It is clear from this figure that the actual price values are contained in the 95% forecast intervals as indicated by the dotted lines. Moreover, the trend of the fitted values is generally consistent to that of the actual values. These findings suggest that ARMA (12, 0) model can capture the actual black pepper price future movement almost perfectly.

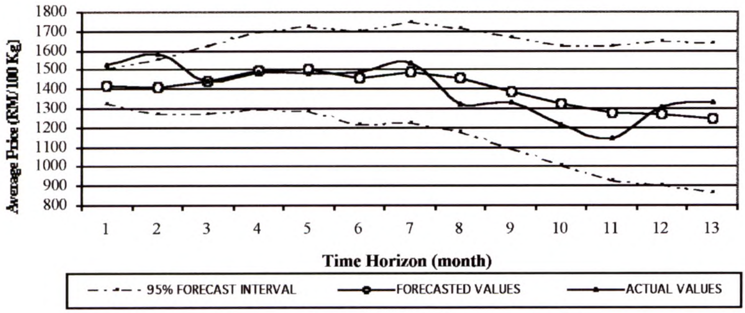


Figure 6: Graph of monthly average Sarawak black pepper price (13 actual and forecasted values from July 1998 to July 1999).

Though the AICC statistics are useful in modeling time series, the performance of the model has still to be evaluated by post sample forecast accuracy criteria. In this paper we use the criteria as summarized in Table 3 to evaluate our models.

Table 3. Forecast accuracy criteria.

Mean absolute error, MAE $= \dfrac{\sum_{t=1}^{n} |x_t - \hat{x}_t|}{n}$ (6)

Root mean square error, RMSE $= \sqrt{\dfrac{\sum_{t=1}^{n} (x_t - \hat{x}_t)^2}{n}}$ (7)

Mean absolute percentage error, MAPE $= \dfrac{\sum_{t=1}^{n} \left|\dfrac{x_t - \hat{x}_t}{x_t}\right|}{n}$ x 100 % (8)

where x_t = actual values, $\hat{x}_t$ = forecast values and n = number of periods.

The smaller the values of MAE, RMSE and MAPE, the better the model is considered to be. In Tables 4 and 5, the MAE, RMSE and MAPE are listed.

Table 4: Accuracy criteria of fitted models for the first-differenced series.

No.	Models	AICC	MAE	RMSE	MAPE (%)
1	ARMA (26, 0)	-697.641	230.452	280.417	17.643
2	ARMA (11, 0)	-690.620	248.718	306.985	19.164
3	ARMA (9, 0)	-687.228	127.014	148.556	9.608
4	ARMA (2, 0)	-681.710	141.575	175.341	10.818
5	ARMA (1, 0)	-678.018	139.175	161.960	10.503
6	ARMA (0, 26)	-694.754	189.135	236.855	14.570
7	ARMA (0, 24)	-694.754	189.081	236.810	14.566
8	ARMA (0, 11)	-689.867	120.184	148.927	9.160
9	ARMA (0, 9)	-687.228	127.014	148.556	9.608
10	ARMA (0, 7)	-683.321	138.848	158.274	10.381
11	ARMA (0, 1)	-682.946	140.780	163.894	10.618
12	ARMA (1, 1)	-680.028	141.311	166.169	10.684
13	ARMA (2, 1)	-679.736	142.568	177.392	10.900
14	ARMA(2, 1)	-681.710	141.586	175.276	10.818

Table 5: The accuracy criteria of fitted models for the seasonally adjusted series.

No.	MODEL	AICC	MAE	RMSE	MAPE (%)
1	ARMA(12, 0)	-712.689	86.420	100.343	6.356
2	ARMA(3, 0)	-706.017	101.178	121.699	7.027
3	ARMA(2, 0)	-702.019	112.598	135.689	7.790
4	ARMA(1, 0)	-686.687	73.880	91.906	5.462
5	ARMA(1, 1)	-707.289	107.352	129.453	7.420
6	ARMA(2, 2)	-694.164	221.617	233.244	15.725
7	ARMA(0, 24)	-647.389	364.753	378.010	15.725
8	ARMA(12, 0)	-714.055	90.160	105.487	6.555
9	ARMA(3, 0)	-705.730	106.874	130.349	7.393
10	ARMA(2, 0)	-701.791	119.949	142.294	8.327
11	ARMA(1, 0)	-683.387	72.842	89.371	5.358

Note: Model 1 to 7 contains linear trend. Model 8 to 11 contains quadratic trend.

According to the post sample accuracy criteria, ARMA (1, 0) model of the seasonally adjusted series (no. 11, Table 2) performs the best. It has the smallest MAE (72.842), RMSE (89.371) and MAPE (5.358) values simultaneously. Its equation is

$$X_t = 0.9866X_{t-1} + Z_t \qquad (9)$$

where $Z_t \sim N(0, 0.0067)$.

Forecast produced using ARMA (1, 0) model is shown in Figure 7. Similar to the interpretation for ARMA (12, 0) model, Figure 7 also indicates that ARMA (1, 0) model can capture the actual black pepper price future movement almost perfectly.

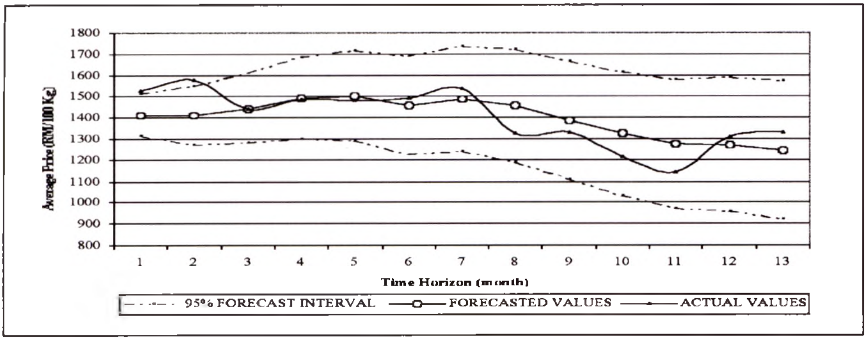


Figure 7: Graph of monthly average Sarawak black pepper price (13 actual and forecasted values from July 1998 to July 1999).

4.0 CONCLUSIONS

This paper takes up the modelling and forecasting of Sarawak black pepper price using the Autoregressive Moving Average (ARMA) time series models. It is formally shown in this paper that the pepper price series does not follow a random walk process. This paper further demonstrates that ARMA models fit the price series well and they are capable of predicting the future trend of the price movement. According to the minimum AICC criterion, ARMA (12, 0) model was considered the best model for the Sarawak black pepper price. However, based on post sample accuracy criterion, the ARMA (1, 0) model emerged as the best model. This result agrees with Lalang et al. (1997) that best model selected based on AICC criteria does not have to be the best, in term of post sample accuracy.

Finally, the recommended model for Sarawak black pepper price is the ARMA (1, 0) model. This model is a parsimonious one and just depends on the most recent observation for forecasting. However continuous monitoring and updating of this model should be regularly taken up.

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APPENDIX A: AUGMENTED DICKEY-FULLER (ADF) UNIT ROOT TEST RESULTS

	Intercept Without Trend		Intercept With Trend	
Variable	Y_t	X_t	Y_t	X_t
ADF	– 0.356	–7.400*	–1.119	–7.454*
		Critical Values		
10%			–2.572 –3.135	
5%	–2.871		–3.425	
1%	–3.453		–3.899	

Notes: Y_t and X_t stand for the level and first difference of pepper price series respectively.

Critical values are given in MacKinnon (1991). Asterisk (*) denotes rejection of the null hypothesis of unit-root at 1% significance level. The results suggest that the pepper price is not stationary but stability has been achieved after the first difference.