Time Series Modelling and Forecasting of Sarawak Black Pepper Price

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Abstract

Pepper is an important agriculture commodity especially for the state of Sarawak. It is important to forecast its price, as this could help the policy makers in coming up with production and marketing plan to improve the Sarawak's economy as well as the farmers' welfare. In this paper, we take up time series modelling and forecasting of the Sarawak black pepper price. Our empirical results show that Autoregressive Moving Average (ARMA) time series models fit the price series well and they have correctly predicted the future trend of the price series within the sample period of study. Amongst a group of 25 fitted models, ARMA (1, 0) model is selected based on post-sample forecast criteria.

Keywords: Time series, pepper (*Piper nigrum L.*), Autoregressive Moving Average model, forecasting, forecast accuracy.

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1. Introduction

Pepper (*Piper nigrum L.*), which has been used as spice since 4th B. C. was first brought into Malacca in the year 1583 by the Portugese (I. Abd. Rahman Azmil, 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.

In Malaysia, pepper is available as black pepper or white pepper. The difference between these two forms of pepper is in the way it is processed. Black pepper is prepared by drying mature berries of *Piper nigrum* under the sun for about 3 to 10 days, while white pepper is produced by rotting the ripe or nearly ripe berries in running water in order to remove the pulp and pericap before drying process begins (Zahara Merican, 1985). Up to 80% of the crop is processed into black pepper while the remaining 20% is turned into white pepper. However, the quality of white pepper is higher than that of black pepper and hence white pepper fetches a higher price.

Until 1980, Malaysia was traditionally the largest pepper producing country in the world. After that Malaysia lost it leading position to India and Indonesia (I. Abd. Rahman Azmil, 1993) and is currently ranked the third largest producer of pepper (Pepper Maketing Board Homepage, 1998). Pepper's contribution to the local socio-economy is substantial. Around 45,000 farming families and more than 115,000 workers are involved in pepper industry. The crop generates about a third of Sarawak's agriculture export earnings (Pepper Marketing Bulletin, January to March, 1999).

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. However, in Malaysia, time series modelling and forecasting in the agriculture sector is relatively limited. Fatimah and Roslan (1986) confirmed the suitability of Box-Jenkins (1976) univariate ARIMA models in agricultural prices forecasting. It has also been shown (Fatimah and Gaffar, 1987) 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.

2. 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 $Z_t \sim WN(0, \sigma^2)$.

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

$$X_t - \phi_1 X_{t-1} - \phi_2 X_{t-2} - \ldots - \phi_p X_{t-p} = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \ldots + \theta_q Z_{t-q} \quad (1)$$

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

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 modelling 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 modelling is clearly explained in Chapter 5 of Brockwell and Davis (1996).

3. Methodology and Results

In this section, we present the methodology and results of fitting suitable time series models to Sarawak black pepper price obtained from the Pepper Marketing Board, Malaysia. The data consisted of 331 observations from January 1972 to July 1999 and 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 a computer software known as "*Interactive Time Series Modelling – PEST module*"(due to Brockwell, Davis and Mandario, 1996).

A time series plot of Sarawak black pepper price appears in Figure 1. It is clear that there exists a generally increasing non-linear trend. Hence the original series is not stationary in the sense as defined in Section 2. A plot of the sample autocorrelation functions, ACF and the sample partial autocorrelation functions, PACF of the series is shown in Figure 2. The graph of ACF of the series displays a slow decrease in the size of ACF values, which is a typical pattern for a non-stationary series.

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

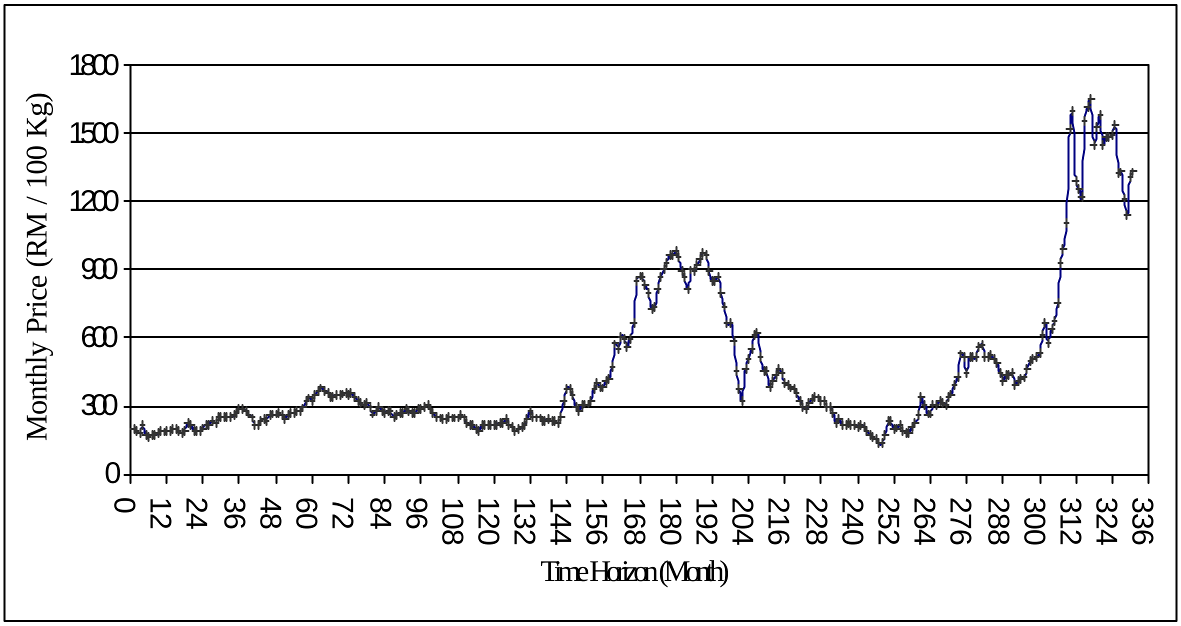
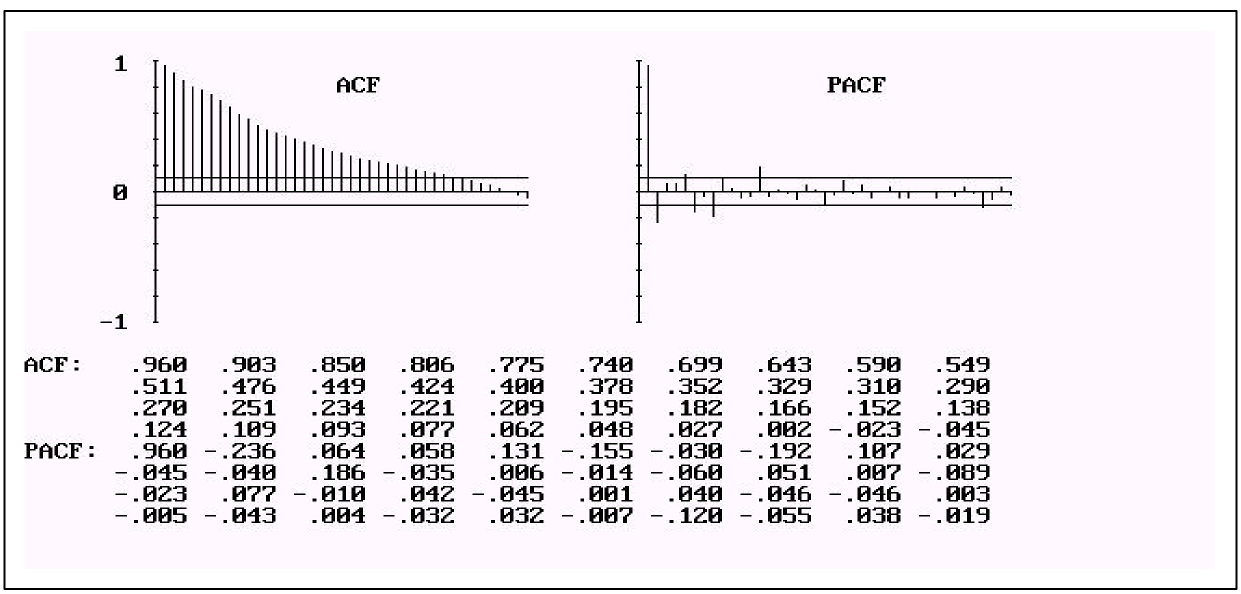
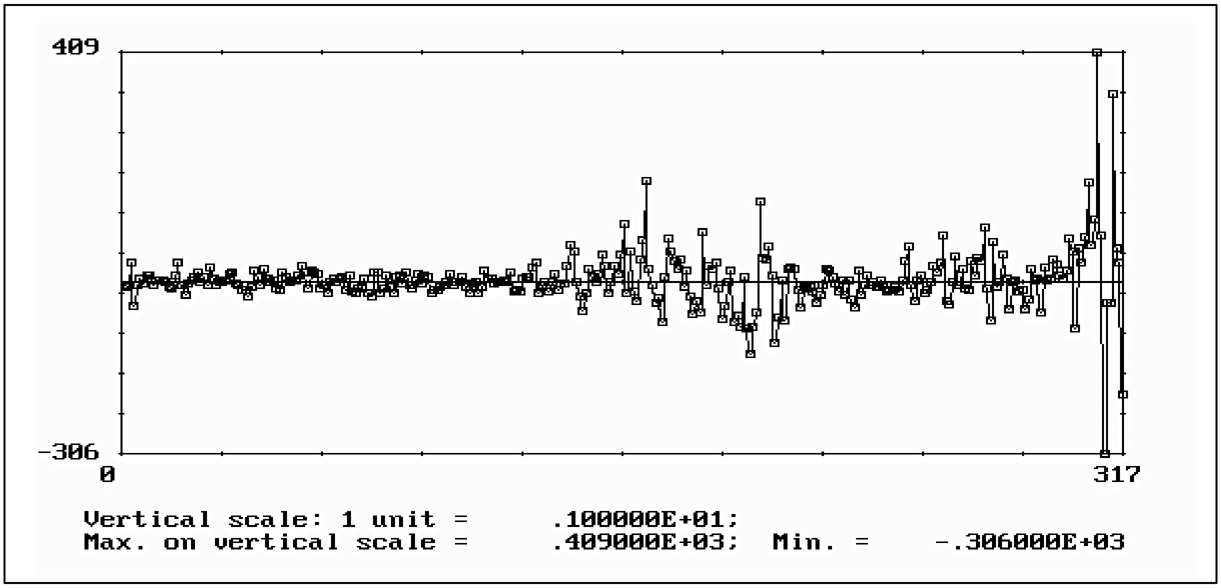


Figure 2: Sample ACF and PACF of the Sarawak black pepper price series.



To achieve stationarity, the trend component should be extracted from the original series. This could be achieved by using either method of differencing or classical decomposition. We differenced the original series at lag 1 in order to achieve a more or less constant level. The mean was also subtracted from the series so that it could be modelled as a zero mean stationary process (Figure 3).

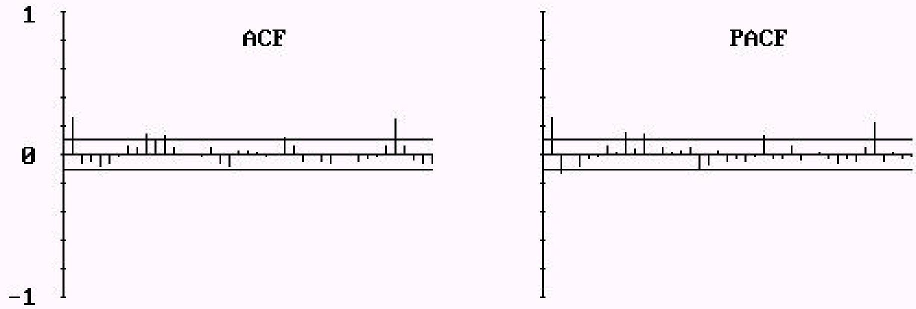
Figure 3: Graph of Sarawak black pepper price after a lag 1 differencing.



It is obvious, from the sample ACF of the differenced series (Figure 4), that most of the spikes had decayed to a level not significantly different from 0. Moreover, the dominant spike at lag 1 of the PACF is not so outstanding as before. Hence, this series appears to be stationary and we therefore modelled it as a stationary ARMA model.

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. 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, auto regressive 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. ARMA (p, q) models where p and q could be of order 1 or 2 were also considered in this study.

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

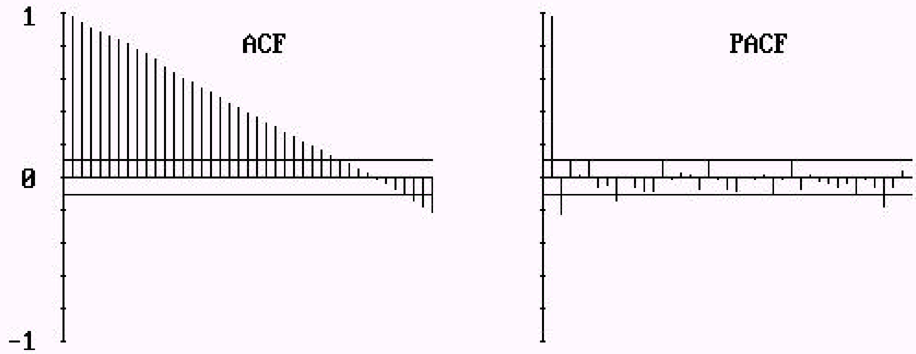


ACF:	.253	-.060	-.051	-.083	-.055	-.012	.059	.047	.143	.109
	.126	.047	.005	.003	-.009	.044	-.064	-.077	.025	.028
	.013	-.007	.003	.115	.054	-.046	.004	-.044	-.062	-.002
	-.003	-.050	-.023	-.015	.062	.245	.058	-.040	-.064	-.058
PACF:	.253	-.133	.000	-.083	-.018	-.008	.059	.007	.148	.039
	.138	.006	.049	.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

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 period. 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, the model is likely to come from AR family. 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.

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.



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

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 (2)] appear 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 (1978) Portmanteau Statistics, Mcleod-Li (1983) Portmanteau Statistics, Turning Point Test, Difference-Sign Test, and Rank Test.

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
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) $X_t = Z_t + 0.2949Z_{t-1} + 0.0574Z_{t-7} + 0.1399Z_{t-9} + 0.1686Z_{t-11} + 0.1880Z_{t-24}$ where $\{Z_t\} \sim WN(0, 0.00626)$	- 694.754
7	ARMA (0, 24) $X_t = Z_t + 0.2944Z_{t-1} + 0.0573Z_{t-7} + 0.1397Z_{t-9} + 0.1683Z_{t-11} + 0.1876Z_{t-24}$ where $\{Z_t\} \sim WN(0, 0.00626)$	- 694.754
8	ARMA (0, 11) $X_t = Z_t + 0.2864Z_{t-1} + 0.0886Z_{t-7} + 0.1529Z_{t-9} - 0.1343Z_{t-11}$ where $\{Z_t\} \sim WN(0, 0.00642)$	- 689.867
9	ARMA (0, 9) $X_t = Z_t + 0.3214Z_{t-1} + 0.0623Z_{t-7} + 0.1620Z_{t-9}$ where $\{Z_t\} \sim WN(0, 0.00642)$	- 687.228
10	ARMA (0, 7) $X_t = Z_t + 0.3285Z_{t-1} + 0.0838Z_{t-7}$ where $\{Z_t\} \sim WN(0, 0.00665)$	- 683.321
11	ARMA (0, 1) $X_t = Z_t + 0.3109Z_{t-1}$ where $\{Z_t\} \sim WN(0, 0.00670)$	- 682.946
12	ARMA (1, 1) $X_t = -0.2300X_{t-1} + Z_t + 0.2864Z_{t-1}$ where $\{Z_t\} \sim WN(0, 0.00668)$	- 680.028
13	ARMA (2, 1) $X_t = 0.4942X_{t-1} - 0.1841X_{t-2} + Z_t + 0.2864Z_{t-1}$ 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

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) $X_t = 1.2648X_{t-1} - 0.4209X_{t-2} + 0.1387X_{t-3} + Z$ 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) $X_t = 0.9790X_{t-1} + Z_t + 3.0214Z_{t-1}$ where $\{Z_t\} \sim WN(0, 0.00681)$	-707.289
6	ARMA (2, 2) $X_t = 1.4710X_{t-1} - 0.4878X_{t-2} + Z_t + 0.2258Z_{t-2}$ where $\{Z_t\} \sim WN(0, 0.00626)$	-694.164
7	ARMA (0, 24) $X_t = Z_t + 1.0575Z_{t-1} + 1.0567Z_{t-2} + 0.9523Z_{t-3} + 0.7705Z_{t-4} + 0.8030Z_{t-5}$ $+ 0.7780Z_{t-6} + 0.9331Z_{t-7} + 0.9642Z_{t-8} + 0.8875Z_{t-9} + 0.7792Z_{t-10}$ $+ 0.8356Z_{t-11} + 0.6404Z_{t-12} + 0.7271Z_{t-13} + 0.5007Z_{t-14} + 0.5459Z_{t-15}$ $+ 0.6316Z_{t-16} + 0.4892Z_{t-17} + 0.5793Z_{t-18} + 0.5244Z_{t-19} + 0.4737Z_{t-20}$ $+ 0.5858Z_{t-21} + 0.4793Z_{t-22} + 0.4998Z_{t-23} + 0.3606Z_{t-24}$ 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.

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

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

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

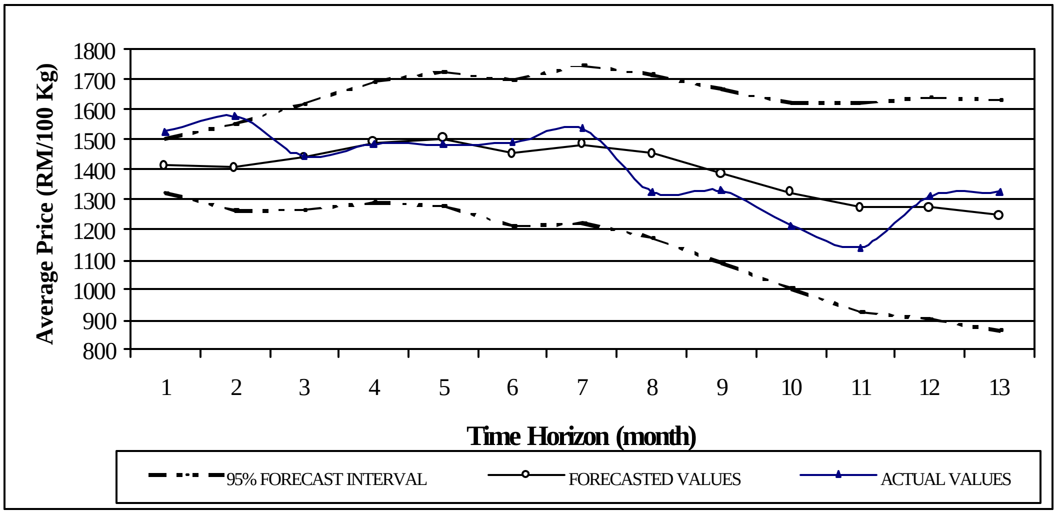
According to the minimum AICC criterion, ARMA (12, 0) model (no. 8, Table 2) for the seasonally adjusted series had been chosen to be the most appropriate. The equation of this model is given by

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

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

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 is useful in modelling time series, the performance of the model has still to be evaluated by post sample forecast accuracy criterion. 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 $= \dfrac{\sum_{t=1}^{n} \left| x_t - \hat{x}_t \right|}{n}$ (4)

Root mean square error, RMSE $= \sqrt{\dfrac{\sum_{t=1}^{n} (x_t - \hat{x}_t)^2}{n}}$ (5)

Mean absolute percentage error, MAPE $= \dfrac{\sum_{t=1}^{n} \left| \dfrac{x_t - \hat{x}_t}{x_t} \right|}{n} \times 100\ \%$ (6)

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 criterion 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 criterion 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.

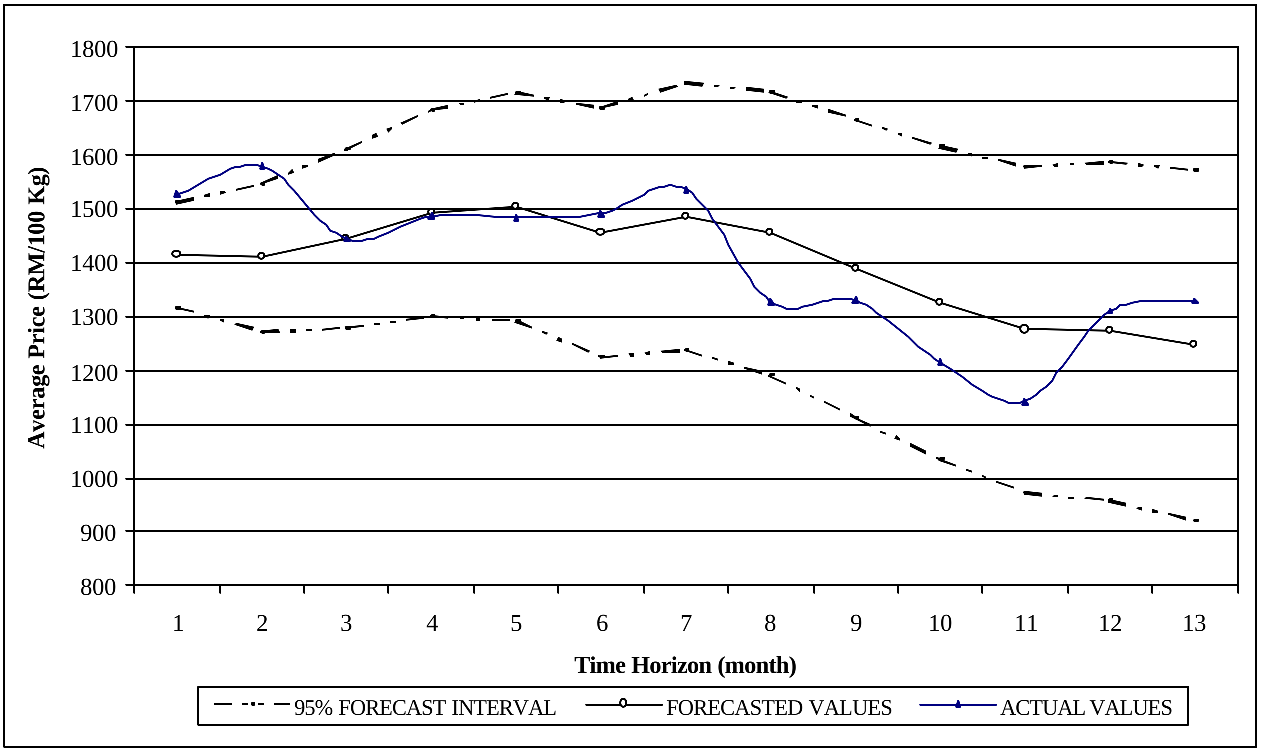
According to the post sample accuracy criteria, ARMA (1, 0) model of the seasonally adjusted series (no. 11, Table 2) performs the best. It has the smallest MAE (72.842), RMSE (89.371) and MAPE (5.358) values simultaneously. Its equation is

$$X_t = 0.9866X_{t-1} + Z_t \qquad (7)$$

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

Forecast produced using ARMA (1, 0) model is shown in Figure 7. Similar to the interpretation as 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. Conclusions

This paper takes up the modelling and forecasting of Sarawak black pepper price using the Autoregressive Moving Average (ARMA) time series models. Our empirical results suggest 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, ARMA (1, 0) model emerged as the best model. This result agrees with Lalang et al. (1997) that best model selected based on AICC criterion does not have to be the best, in term of post sample accuracy.

Finally, the recommended model for Sarawak black pepper price is 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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