Appropriate marketing information system tools for citrus plantation in Lattakia, Syria: a revisitation

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***Abstract* — A seasonal autoregressive integrated moving average (SARIMA) model proposed and fitted to observed lemon Autochton monthly prices has been included among marketing information system tools for citrus production in the Lattakia Region of Syria. The order of the model is (2, 1, 0)x(1, 0, 1)$_{12}$ chosen on the basis of minimum mean square error (MSE) and mean absolute error (MAE) among the set of SARIMA models of orders (2, 1, 0)x(1, 0, 1)$_{12}$, (2, 1, 1)x(1, 0, 1)$_{12}$, (2, 1, 0)x(2, 0, 1)$_{12}$ and (2, 1, 0)x(2, 1, 1)$_{12}$ using the MINITAB software. In this work a re-analysis of the data using Eviews 7 confirms that the chosen model is still the best on minimum Akaike Information Criterion (AIC) grounds, each of the rest of the models being non-stationary. Moreover based on the observed autocorrelation structure the SARIMA(0, 1, 1)x(1, 0, 1)$_{12}$ model is even better than the chosen model on all counts. Hence it is hereby proposed as the most adequate model to adopt for the purpose of the price prediction.**

Keywords—Marketing Information System; Lattakia; Syria; citrus fruits; decision making; SARIMA model; Eviews 7; minitab.

I. INTRODUCTION

In their bid to contribute to the question of finding appropriate Agricultural Management Information tools for Citrus plantation in Lattakia region of Syria, Sulaiman *et al.* [1] proposed that the best model to explain the variation in monthly prices of lemon Autochton is a Seasonal Autoregressive Integrated Moving Average (SARIMA) model of order (2, 1, 0)x(1, 0, 1)$_{12}$. This model was chosen on the basis of the minimum mean square error (MSE) and the minimum mean absolute error (MAE) criteria from a set of four SARIMA models of orders (2, 1, 0)x(1, 0, 1)$_{12}$, (2, 1, 1)x(1, 0, 1)$_{12}$, (2, 1, 0)x(2, 0, 1)$_{12}$ and (2, 1, 0)x(2, 1, 1)$_{12}$. They used the Minitab software.

In this work this research problem is revisited in order to proffer a better solution to it. The approach adopted herein is comparing the proposed models using the minimum Akaike Information Criterion (AIC) criterion. Moreover the analysis is done using the Eviews 7 package. By a further inspection of the empirical results, a better SARIMA model is proposed.

II. LITERATURE REVIEW

Sarima models were proposed to model seasonal time series. Prices have been known to show some seasonality. Prices of many commodities have been modeled by SARIMA techniques. For instance, Jaehnert *et al.* [2] modeled the regulating state determination by a SARIMA model. Ashiru and Lu [3] fitted a SARIMA model to Construction Cost Index (CCI) and used it to make systematic forecasts. Suleman and Sarpong [4] modeled Ghanaian price inflation rates by a SARIMA(2, 1, 3)x(2, 1, 1)$_{12}$ model. Mohammadinia *et al.* [5] “deploy the 24-hour SARIMA model to forecast the price of energy package in the wholesale market”. The Consumer Price Indices of Bangladesh have been modeled as a SARIMA(1, 1, 1)x(1, 0, 1)$_{12}$ (See [6]). SARIMA modeling of Chinese stock price and trading volume has been used to predict them [7]. Monthly Nigerian Import Commodity Price Indices have been modeled as a SARIMA(0, 1, 1)x(1, 1, 1)$_{12}$ [8]. This is to mention a few.

Sulaiman *et al.* [1] opine that agricultural product price modeling could assist farmers make decisions and this could lead to improved sales of the products. Agricultural products whose prices have been modeled by SARIMA techniques are rice ([9], [10]), potato [11], rubber [12], tomato [13], fish [14] and cucumber [15], to mention only a few.

The relative merits of the SARIMA approach to other approaches of modeling have been highlighted. For instance, Sulaiman *et al.* [1] claim that SARIMA models not only provide high hypothesis testing power but could enable producers have better marketing positions. Pargami *et al.* [10] have observed that the SARIMA approach outperforms other seasonal models. Etuk [16] has also observed the supremacy of this approach over the more traditional autoregressive integrated moving average (ARIMA) model.

III. MATERIALS AND METHODS

A. Data

The data for this work are the 48 Lemon Autochton monthly prices from 2010 to 2013 published and analyzed by Sulaiman *et al.* [1].

B. Sarima Models

A stationary time series $\{X_t\}$ is said to follow an *autoregressive moving average of order p and q if*

$$X_t - \alpha_1 X_{t-1} - \alpha_2 X_{t-2} - \ldots - \alpha_p X_{t-p} = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \ldots + \beta_q \varepsilon_{t-q} \quad (1)$$

where $\{\varepsilon_t\}$ is a white noise process and the α's and the β's are constants such that model (1) is stationary as well as invertible. Suppose that model (1) can be written as

$$A(L)X_t = B(L)X_t \quad (2)$$

where A(L) is the autoregressive (AR) operator defined by $A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \ldots - \alpha_p L^p$ and B(L) is the moving average (MA) operator defined by $B(L) = 1 + \beta_1 L + \beta_2 L^2 + \ldots + \beta_q L^q$ where L is the backshift operator defined by $L^k X_t = X_{t-k}$. Model (1) or (2) is denoted by ARMA(p, q).

If a time series $\{X_t\}$ is nonstationary, Box and Jenkins [17] proposed that differencing a sufficient number of times could make the series to be stationary. Let this number of times be d. Suppose that the d^{th} difference of $\{X_t\}$ is denoted by $\{\nabla^d X_t\}$. Then the differencing operator ∇ is defined by $\nabla = 1 - L$. Suppose $\{\nabla^d X_t\}$ follows an ARMA(p, q). $\{X_t\}$ is said to follow an *autoregressive integrated moving average model of order p, d and q* denoted by ARIMA(p, d, q).

If in addition $\{X_t\}$ is seasonal of period s and it is differenced seasonally for at least D times for stationarity, Box and Jenkins [17] proposed that the series could be modeled by

$$A(L)\Phi(L^s)\nabla^d \nabla^D_s X_t = B(L)\Theta(L^s)\varepsilon_t \quad (3)$$

where $\Phi(L)$ and $\Theta(L)$ are the seasonal AR and MA operators. Suppose that Φ and Θ are polynomials in L of degrees P and Q respectively such that their coefficients would make (3) both stationary and invertible. Model (3) is called a *multiplicative seasonal autoregressive moving average model of order p, d, q, P, D, Q and s* denoted by SARIMA(p, d, q)x(P, D, Q)$_s$.

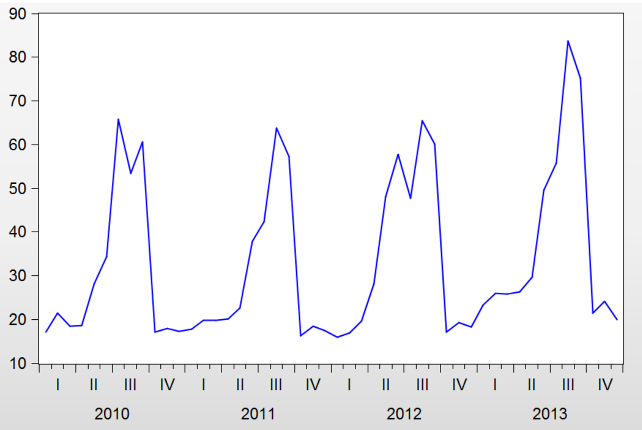


FIGURE 1: LAMP

C. Sarima Fitting

Sarima fitting starts with the determination of the orders p,d,q,P,D, Q and s. The seasonal period s might naturally emerge from knowledge of the seasonal nature of the series or from an inspection of the data to confirm a hypothesized seasonal nature. Another diagnostic aid is the correlogram; a significant spike at a lag suggests that the lag is the seasonal period. The AR orders p and P are estimated by the non-seasonal and the seasonal cut-off lags of the partial autocorrelation function (PACF) respectively. Similarly the MA orders q and Q are estimated by the non-seasonal and the seasonal cut-off lags of the autocorrelation function (ACF) respectively. The difference orders d and D are often chosen so that at most they add up to 2 to avoid undue model complexity. Augmented Dickey Fuller (ADF) Test shall be used for stationarity tests before and after series differencing.

Following order determination the model parameters are estimated. The involvement of items of a white noise process in the model (3) makes the adoption of non-linear optimization techniques necessary for the estimation of the parameters. In this write-up the statistical and econometric package Eviews 7 is used for all the analytical work. It is based on the least squares approach.

IV. Results And Discussion

The time plot of the series called herein LAMP in Figure 1 shows evidence of seasonality. An examination of the 48-point data confirms the seasonality hypothesis: the four yearly minimums are in January and October, October, January and December whereas the four yearly maximums occur in July, August, August and August respectively. This means that the minimums lie in the first and fourth quarters of the year and the maximums lie in the second and third quarters of the year. ADF test adjudges LAMP as stationary. The correlogram of LAMP in figure 2 has a sinusoidal nature with period 12 months which is a further confirmation of the 12-monthly seasonality hypothesis. However it invalidates the stationarity assumption. A non-seasonal differencing of the series yields the series DLAMP which has a generally horizontal secular trend (See Figure 3) and a correlogram which has a significant positive spike at lag 12 in the ACF as well as in the PACF, an indication of a 12-monthly seasonality and the presence of a seasonal AR component of order one. Moreover the autocorrelations at lags 11 and 13 are comparable (See Figure 4). ADF test adjudges DLAMP as stationary.

Sulaiman *et al.* [1] compared four SARIMA models with orders: $(2,1,0)x(1,0,1)_{12}$, $(2,1,1)x(1,0,1)_{12}$, $(2,1,0)x(2,0,1)_{12}$ and $(2,1,0)x(2,1,1)_{12}$. Using the software minitab, they chose the first model as the best on the basis of minimum mean square error (MSE) and mean absolute error (MAE). In this work, it is only the first model that is stationary as well as invertible. As estimated in Table 1, it is given by

$$X_t - 0.3899X_{t-1} + 0.4339X_{t-2} - 0.7747X_{t-12} + 0.3461X_{t-13} - 0.4316X_{t-14} = \varepsilon_t + 0.9173\varepsilon_{t-12} \quad (4)$$

Figures 5 and 6 present the correlogram and the histogram of its residuals respectively. The correlogram shows that the residuals are not correlated and the histogram shows that they are normally distributed. Hence the model is adequate.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.612	0.612	19.098	0.000
		2	0.217	-0.251	21.552	0.000
		3	-0.132	-0.247	22.485	0.000
		4	-0.361	-0.188	29.600	0.000
		5	-0.417	-0.093	39.299	0.000
		6	-0.414	-0.209	49.105	0.000
		7	-0.343	-0.170	55.990	0.000
		8	-0.252	-0.201	59.801	0.000
		9	-0.024	0.065	59.836	0.000
		10	0.135	-0.120	60.984	0.000
		11	0.413	0.322	72.073	0.000
		12	0.629	0.322	98.414	0.000
		13	0.421	-0.280	110.59	0.000
		14	0.171	0.059	112.65	0.000
		15	-0.067	0.186	112.98	0.000
		16	-0.255	-0.067	117.85	0.000
		17	-0.345	-0.053	127.06	0.000
		18	-0.342	0.038	136.41	0.000
		19	-0.288	0.032	143.27	0.000
		20	-0.164	-0.012	145.56	0.000

FIGURE 2: CORRELOGRAM OF LAMP

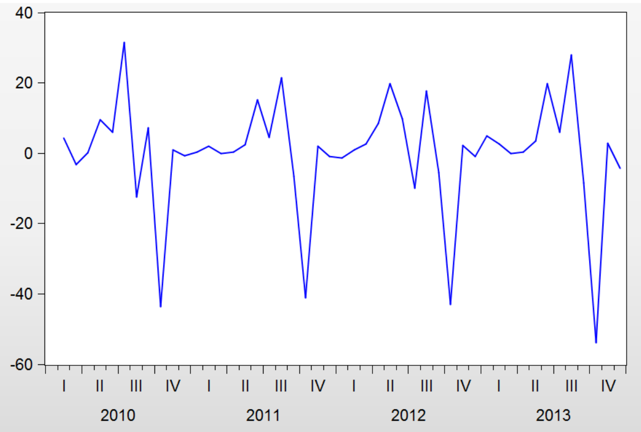


FIGURE 3: DLAMP

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.018	0.018	0.0167	0.897
		2	-0.068	-0.068	0.2499	0.883
		3	-0.104	-0.102	0.8185	0.845
		4	-0.210	-0.214	3.1788	0.528
		5	-0.099	-0.119	3.7169	0.591
		6	-0.058	-0.113	3.9052	0.690
		7	-0.062	-0.144	4.1292	0.765
		8	-0.177	-0.307	5.9727	0.650
		9	0.037	-0.121	6.0534	0.735
		10	-0.158	-0.400	7.6140	0.666
		11	0.081	-0.251	8.0330	0.710
		12	0.558	0.344	28.485	0.005
		13	0.062	-0.045	28.742	0.007
		14	-0.019	-0.114	28.768	0.011
		15	-0.023	0.064	28.804	0.017
		16	-0.121	0.046	29.890	0.019
		17	-0.124	-0.050	31.062	0.020
		18	-0.051	-0.054	31.272	0.027
		19	-0.077	0.005	31.754	0.033
		20	-0.115	-0.046	32.877	0.035

FIGURE 4: CORRELOGRAM OF DLAMP

TABLE 1: ESTIMATION OF MODEL 4

Dependent Variable: DLAMP
Method: Least Squares
Date: 11/03/14 Time: 17:02
Sample (adjusted): 2011M04 2013M12
Included observations: 33 after adjustments
Convergence achieved after 11 iterations
MA Backcast: 2010M04 2011M03

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.389927	0.174274	2.237436	0.0337
AR(2)	-0.433888	0.172180	-2.519968	0.0180
AR(12)	0.774725	0.149749	5.173491	0.0000
AR(13)	-0.346096	0.195617	-1.769251	0.0881
AR(14)	0.431605	0.194830	2.215283	0.0354
MA(12)	0.917274	0.025793	35.56244	0.0000

R-squared	0.846122	Mean dependent var	0.006061
Adjusted R-squared	0.817626	S.D. dependent var	17.28975
S.E. of regression	7.383628	Akaike info criterion	6.999373
Sum squared resid	1471.985	Schwarz criterion	7.271465
Log likelihood	-109.4897	Hannan-Quinn criter.	7.090924
Durbin-Watson stat	2.265320		

Inverted AR Roots	.98	.85+.49i	.85-.49i	.49+.83i
	.49-.83i	.22+.71i	.22-.71i	-.02+.97i
	-.02-.97i	-.50+.85i	-.50-.85i	-.86-.49i
	-.86+.49i	-.99		
Inverted MA Roots	.96-.26i	.96+.26i	.70+.70i	.70-.70i
	.26-.96i	.26+.96i	-.26-.96i	-.26+.96i
	-.70-.70i	-.70-.70i	-.96+.26i	-.96-.26i

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.158	-0.158	0.9046	
		2	-0.024	-0.050	0.9260	
		3	-0.126	-0.142	1.5341	
		4	-0.235	-0.295	3.7311	
		5	0.068	-0.052	3.9245	
		6	-0.125	-0.200	4.5879	
		7	0.199	0.059	6.3430	0.012
		8	-0.033	-0.087	6.3927	0.041
		9	-0.009	-0.059	6.3963	0.094
		10	-0.168	-0.269	7.8082	0.099
		11	0.009	-0.042	7.8128	0.167
		12	-0.071	-0.244	8.0863	0.232
		13	0.113	-0.002	8.8233	0.266
		14	0.045	-0.179	8.9457	0.347
		15	0.143	0.136	10.263	0.330
		16	0.069	-0.026	10.586	0.391

FIG 5: CORRELOGRAM OF MODEL 4 RESIDUALS

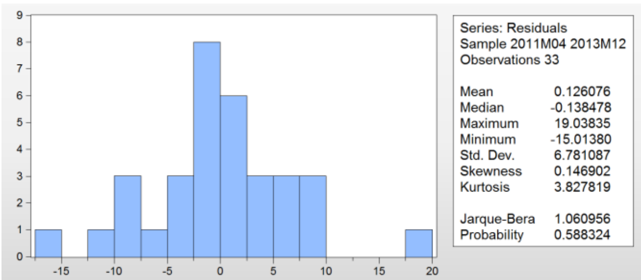


FIGURE 6: HISTOGRAM OF MODEL 4 RESIDUALS

The ACF and PACF of Figure 4 suggest a SARIMA$(0,1,1)x(1,0,1)_{12}$ model for LAMP. Its estimation as summarized in Table 2 is given by

$$X_t - 0.8129X_{t-12} = \varepsilon_t + 0.4237\varepsilon_{t-1} + 0.8786\varepsilon_{t-12} + 0.3232\varepsilon_{t-13} \quad (5)$$

where in models (4) and (5) X represents DLAMP.

Figures 7 and 8 give the correlogram and the histogram of its residuals. Clearly model 5 outdoes model 4 on all counts.

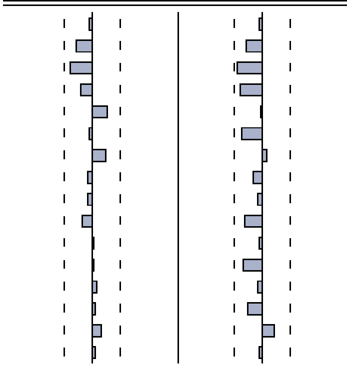
TABLE 2: ESTIMATION OF MODEL 5

Dependent Variable: DLAMP
Method: Least Squares
Date: 11/03/14 Time: 16:00
Sample (adjusted): 2011M02 2013M12
Included observations: 35 after adjustments
Convergence achieved after 11 iterations
MA Backcast: 2010M01 2011M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(12)	0.812859	0.142490	5.704669	0.0000
MA(1)	0.423706	0.165880	2.554283	0.0158
MA(12)	0.878578	0.030097	29.19170	0.0000
MA(13)	0.323236	0.158861	2.034704	0.0505

R-squared	0.836004	Mean dependent var	0.065714
Adjusted R-squared	0.820133	S.D. dependent var	16.77726
S.E. of regression	7.115356	Akaike info criterion	6.869598
Sum squared resid	1569.477	Schwarz criterion	7.047352
Log likelihood	-116.2180	Hannan-Quinn criter.	6.930959
Durbin-Watson stat	2.084144		

Inverted AR Roots	.98	.85+.49i	.85-.49i	.49-.85i
	.49+.85i	.00+.98i	-.00-.98i	-.49-.85i
	-.49+.85i	-.85+.49i	-.85-.49i	-.98
Inverted MA Roots	.95+.26i	.95-.26i	.70-.70i	.70+.70i
	.25-.95i	.25+.95i	-.26-.95i	-.26+.95i
	-.37	-.71+.70i	-.71-.70i	-.96+.25i
	-.96-.25i			



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.045	-0.045	0.0775	
		2	-0.200	-0.202	1.6454	
		3	-0.269	-0.302	4.5779	
		4	-0.152	-0.276	5.5442	
		5	0.176	-0.011	6.8814	0.009
		6	-0.049	-0.253	6.9893	0.030
		7	0.170	0.052	8.3182	0.040
		8	-0.059	-0.107	8.4844	0.075
		9	-0.051	-0.056	8.6157	0.125
		10	-0.126	-0.209	9.4349	0.151
		11	0.012	-0.026	9.4429	0.222
		12	0.016	-0.231	9.4571	0.305
		13	0.060	-0.050	9.6678	0.378
		14	0.029	-0.182	9.7189	0.465
		15	0.114	0.137	10.568	0.480
		16	0.025	-0.045	10.611	0.563

FIG 7: CORRELOGRAM OF MODEL 5 RESIDUALS

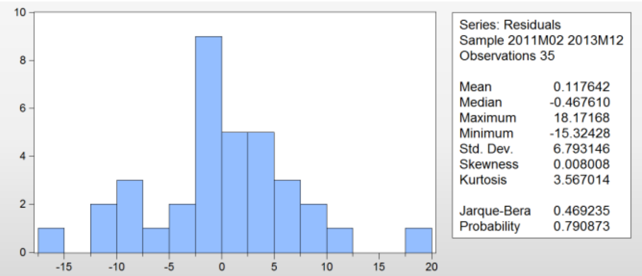


FIG 8: HISTOGRAM OF MODEL 5 RESIDUALS

V. Conclusion

It may be concluded that monthly lemon Autochton prices in the Lattakia region of Syria follow a SARIMA(0,1,1)x$(1,0,1)_{12}$ model. Forecasting of the prices may be done on its basis.

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