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TRANSFER FUNCTION MODEL USED TO PREDICT WHITE EGG PRICES, 2000 – 2017

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ABSTRACT

Egg is one of the most accessible and widely available protein sources in the market. The objective of this study was to develop a time series model to predict monthly nominal average white egg prices paid to the producer (AWEPP) in Mexico using transfer function models (TFM) and to evaluate their relation with nominal average rural sorghum prices (NARSP). The parameters and the predictions were estimated with the maximum likelihood method and were statistically appropriate and significant. The best TFM that represented the behavior of AWEPP was that of two autoregressive coefficients, three of moving average, two degrees of denominator *r*, one degree of numerator *s*, and one coefficient *b*. It was found that the NARSP has an influence on the AWEPP one month later, decreasing the original variance of the AWEPP from 0.01036 to 0.009771 with the transfer model. The TFM generates better predictions of the AWEPP than the SARIMA model, because it takes into account the temporal evolution of the NARSP obtaining estimates that are closer to reality, useful for planning and for decision-making in the poultry sector in the short and medium term.

Keywords: box Jenkins, egg, prediction, poultry production, SARIMA, sorghum.

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INTRODUCTION

The Mexican poultry industry is the most dynamic livestock activity in the country and one of the strategic food sectors in Mexico. In 2018, the total percentage participation of poultry farming in the Gross Domestic Product (GDP) was 0.89%. In the livestock GDP it participated with 36.6% (UNA, 2018). The average *per capita* consumption of egg in the year 2018 was 23 kg, while production was lower than consumption (2,806,000 t), so 0.92% of the total was imported in order to cover the demand (UNA, 2018); and between 1994 and 2018 it increased at a mean annual rate of 2.7%.

The main egg producing states in Mexico are Jalisco, Puebla and Sonora, and together they contributed 75% of the national production in 2018 (UNA, 2018). The costs of feed, packaging and labor are three of the most important inputs in egg production, representing 62.4%, 6.5% and 5.0% respectively. In the year 2018, 16.2 million tons of balanced feed were consumed, from which 63% was fodder grain such as (*Zea mays* L) and sorghum (*Sorghum vulgare*), equivalent to 10.2 million tons, while egg production generated 213,000 direct jobs and 1,064,000 indirect jobs in the same year (UNA, 2018). García *et al.* (2003) carried out studies to predict the AWEPP through moving averages, where they obtained the trend, seasonal, cyclic and random index, of the series of real white egg prices paid to the producer and conducted predictions through the multiplicative method. Ortega (2014) used data from 1976 to 2013 and through multiple regression models estimated the national poultry production until the year 2024, as well as corn (*Zea mays* L) and soy (*Glycine max*) prices. Cruz *et al.* (2016) used a series from 1960 to 2012 and, with least squares estimations in two stages, obtained elasticity coefficients for egg and could carry out estimations with the results regarding the price paid to the producer, in the short term.

Luis *et al.* (2019) used a univariate temporal series of monthly white egg prices paid to the producer from 2000 to 2016, and through the Box Jenkins methodology showed that the series behaves as a seasonal SARIMA model (*Seasonal Autoregressive Integrated Moving Average*) of coefficients $(0,1,1)X(1,0,1)_{s=12}$ and with the model results they could conduct estimations regarding the price paid to the producer, until December 2019. However, in their study they only contemplated the prices of the variable of white egg average prices paid to the producer (AWEPP) and did not evaluate the impact exerted by sorghum (*Sorghum vulgare*) on the egg price.

In this study, the Box-Jenkins methodology was used through Transfer Function Models (TFM). These models are useful in situations where it is assumed that relationships are not momentary or static, that is, they consider the temporal dimension of observations and allow to measure how the effects between variables are transmitted, which is why they are considered as an instrument to evaluate dynamic responses (Box & Jenkins, 1976).

Mexico imports more than 16 million tons of grains and seeds from the United States, placing it as a high dependent on US production and sale, which brings about for costs of raw materials to increase, and producers gradually transfer the cost of the diet to the final consumer. Therefore, the objective of this study is to develop and evaluate the relationship and impact of the NARSP as independent variable that has an influence in predicting the AWEPP in the short and medium term, through a bivariate transfer function model in time series. In the hypothesis it is established that the prices of fodder grains (corn and sorghum) have an immediate impact on the present and future prices of the AWEPP.

MATERIALS AND METHODS

Transfer function models (TFM) are an extension of the classic regression model (CRM). However, the CRM presents two important limitations: first, it assumes that the relation is momentary and static, and second, that the part unexplained by the independent variable (or variables) is white noise. Meanwhile, the TFM allow for the noise model to have a different structure.

The CRM are static, while the TFM are dynamic (Ramírez, 1993), which is to say that they combine the concepts of multiple regression with those of univariate time series models. The TFM resolve these two limitations, since they consider the temporal dimension of the observations and allow for the noise to follow an ARMA model (p,q).

The TFM connect two or more temporal series elaborating causal prediction models. This considers the form of relating a temporal series, called *output* (Y_t), in function of one or other temporal series, which are called *input* X_t. It is also considered *a priori* that there is unidirectional causality from the inputs to the output, rejecting the possibility of feedback.

In a linear system of a single *input* and a single *output*, the series Y_t and the series X_t are related through a linear filter in the following form:

$$Y_t = v_0 X_t + v_1 X_{t-1} + v_2 X_{t-2} + \ldots + N_t$$
$$Y_t = \left(v_0 + v_1 B + v_2 B^2 + \ldots\right) X_t + N_t \quad (1)$$
$$Y_t = v\left(B\right) X_t + \ldots N_t$$

where X_t, X_{t-1}, X_{t-2}, $\ldots X_{t-n}$ are the present and past values of the input series, $v(B)=v_0+v_1B+v_2B^2+\ldots v_nB^n$ is the transfer function of the Chiogna (2007) filter; $N(t)$ is the noise of the system which is independent from the series input X_t. The coefficients of $v(B)$ are known as the response function to the system impulse and represent the impact on Y_t of a change of unit in X_t. For the system suggested in equation (1) to be stable, it must fulfill for a finite variation to produce a variation that is also finite in the output. That is, the following should be fulfilled:

$$\sum_{j=0}^{\infty} v_i = g \quad (2)$$

where g is the finite *profit* of the model. The value of g represents the total change in Y_t, motivated by a unitary change in X_t, maintained in time.
The purposes of transfer function modeling are: to identify and to estimate the transfer function $v(B)$ and the noise model $N(t)$, on the basis of the information provided by the *input* and *output* series.
In practice, it cannot be expected for the variations in output Y_t to exactly follow the pattern determined by the transfer function model, since there are disturbances of different types that are represented by the noise N_t which are not captured by the series X_t.
Thus, the transfer function model with noise included is:

$$Y_t = v\left(B\right) X_t + N_t \quad (3)$$

The model (3) is understood as the distributed lag model and it is inestimable, since an infinite number of parameters appear in it. The problem can be alleviated by expressing the transfer function, as a parsimonious representation of the response weight to the impulse $v(B)$, which is given by the relationship between two finite (rational) polynomials, obtaining:

$$Y_t = \frac{\omega\left(B\right) B^b}{\delta\left(B\right)} X_t + N_t \quad (4)$$

where $\omega(\mathrm{B})=\omega_0-\omega_1B-\ldots-\omega_sB^s$, is a polynomial of degree s and represents the magnitude of the effect that an input has on the output (for example, abrupt or gradual impact), while

$\delta(B)$=1-$\delta_1 B$-...-$\delta_r B^r$ is a polynomial of degree *r*, indicating the type of durations of the impact transferred from the input to the output (for example, temporal or permanent); thus, *b* is a lag parameter, which represents the time that passes before the impulse in the *input* variable produces an effect on the *output* variable.

On the other hand, the error term does not necessarily have to be white noise. It can be assumed, in general, that N_t continues to be an ARIMA process (*p*, *d*, *q*) although it continues to be independent from the variable of *input* X_t that is:

$$N_t = \frac{\theta(B)}{\phi(B)(1-B)^d} a_t \tag{5}$$

with $\theta(B)$=(1-$\theta_1 B$-$\theta_2 B^2$-...-$\theta_q B^q$) and $\phi(B)$=(1-$\phi_1 B$-$\phi_2 B^2$-...-$\phi p B^p$), so that all the roots from both polynomials fall within a unity circle, with (1-B)^d being the operator of consecutive differences, used to induce seasonality and a_t is white noise.

Once the stationarity was achieved in both variables, the process N_t ought to be *ARIMA*(*p*, *d*, *q*), with which the transfer function model can be written as:

$$PPHBP_t = \mu + \frac{C\omega(B)}{\delta(B)} B^b PPSRG_t + \frac{\theta(B)}{\phi(B)} a_t \tag{6}$$

where $\omega(B)$, $\delta(B)$: Are polynomials in the operator of lag *B*; *b*: Is the number of periods that happen before the sorghum price (*NARSP*) affects the egg price (*AWEPP*); a_t: disturbances (term of disturbances that do not behave as white noise); *C*: constant of scale for the direct effect of the sorghum price (*NARSP*) on the average price of white egg paid to the producer (*AWEPP*); $\phi(B)\eta_t$=$\theta(B)a_t$: ARMA specification for a_t; a_t=*iidN*(0, σ^2) White noise, which is assumed to be a random variable independently distributed identically, sampled from a distribution with mean equal to zero and constant variance.

To understand the behavior of the AWEPP, a monthly series of time reported by the Mexican Poultry Producers Association (*Unión Nacional de Avicultores*, UNA) was used, from January 2000 to December 2017 \$MXN kg^{-1} (UNA, 2018). For the time series of the monthly sorghum average price (NARSP), the prices provided by the National System of Information and Integration of Markets (*Sistema Nacional de Información e Integración de Mercados*, SNIIM) of the Ministry of Economy expressed in \$MXN kg^{-1} were used for the same period (SNIIM, 2018).

To perform the analysis, Brocwell (2004) starts from the premise that the models of this type can only be obtained and validated when they correspond to series associated significantly. The methodology proposed by Box and Jenkins (1976) was used to adequately calculate the term *v* for the construction of transfer function models. It consists of the following stages: a) Identifying ARIMA models for Y_t and X_1, b) Preparation of the input and output series, c) Prewhitening of the input (X_t) and output (Y_t) series to obtain α_t

and β_t, d) Calculating the crossed correlation function between (α_t, β_t), e) Identifying the transfer function, f) Estimating the transfer function, g) Validating and forecasting. The elaborated models were validated through statistical tests of the model residuals and their independence. The PROC ARIMA procedure of the Statistical Analysis System (SAS) software version 9.4 (SAS, 2014) was used for the analysis.

RESULTS AND DISCUSSION

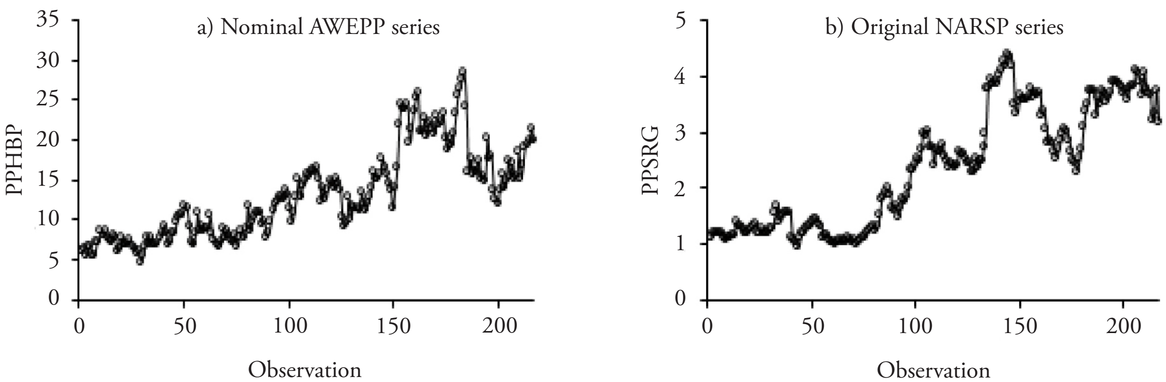
Identifying the ARIMA models for Y_t (AWEPP) and for X_1 (NARSP)

The data of the NARSP series (input series) and AWEPP (output series) fluctuate with time, and follow a similar behavior. The highest peaks of the temporal series of AWEPP correspond to the months of August 2012 to May 2014 (observations 152 to 173), and they are explained by the outbreak of bird flu that attacked flocks in Mexico. The peaks from November 2014 to April 2015 (observations 179 to 184) are explained by the volatility and devaluation of the Mexican peso against the US dollar, which directly affect the egg industry. Approximately 65% of the production costs are dollarized, and this brings with it for costs of raw materials to increase and for producers to gradually transfer the cost of the feed to the final consumer (Figure 1a).

The data from the NARSP series show a rising trend, and peaks are seen in observations 135 to 146, corresponding to the months of March 2011 to February 2012. This is due to the price volatility of basic grains in the agriculture and livestock sector at the global level (CEDRSSA, 2014). Caused primarily by the adverse climate conditions faced by producing countries, such as droughts, frosts and floods (Figure 1b).

Stage 1: Preparation of the input and output series

The *AWEPP* and *NARSP* series are transformed into natural logarithms for variance to be constant (Cox and Box, 1964). Trend is observed in both series, although through the first difference (∇), that is (1-*B*)$LPPSRG_t$ and (1-*B*)$LPPHBP_t$, the series were transformed into



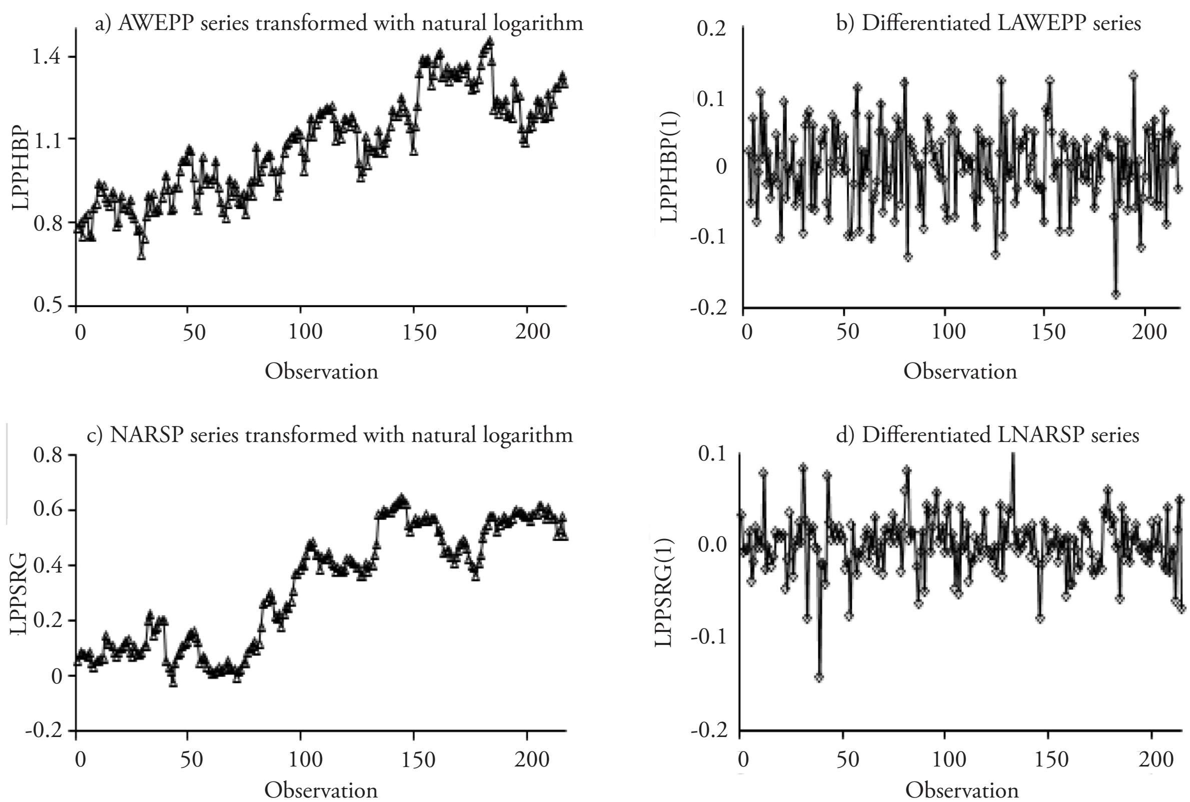
Source: prepared by authors with data from UNA (2018).

Figure 1. Graphs of the study series: (a) Original AWEPP series in \$MXN kg^{-1}, 2000 – 2017, (b) NARSP series in \$MXN kg^{-1}, 2000 – 2017.

stationary in mean and variance. Therefore, $d = 1$ is considered for both series (Figure 2). Stemming from the visual inspection, the simple (ACF) and partial (PACF) autocorrelation functions of the stationary AWEPP variable and through the maximum likelihood estimation, using the PROC ARIMA process (SAS, 2014), the best model was identified which fulfills the significance of parameters, white noise, and is considered moderate. For a model to be considered moderate, it must include the parameters which have absolute t statistics higher than 2 and *p-values* <0.05 (Box *et al.*, 1994). Therefore, the SARIMA model (0,1,1) X $(1,0,1)_{s=12}$ is better and moderate, since it adjusts to old data without using any unnecessary parameter. This was used to carry out the prewhitening of the *output* variable to later calculate the transfer function (Table 1).

Stage 2: Prewhitening of the *input* series

After an analysis during the preparation stage of the series, it was found that the NARSP input series is generated by an ARMA event that fulfills the usual conditions of stationarity



Source: prepared by authors with data from UNA (2018).

Figure 2. Graphs from the study series: (a) AWEPP series transformed to natural logarithms (LAWEPP), (b) Differentiated LAWEPP series in the non-seasonal part, transformed with natural logarithms and without trend, (c) NARSP series transformed to natural logarithms (LNARSP), (d) Differentiated LNARSP in the non-seasonal part, transformed with natural logarithms and without trend.

Table 1. Estimation of the SARIMA model for the time series LAWEPP(1) by maximum likelihood.

Parameter	Estimation	Standard error	Value t	Approx Pr > |t|	Lag	SBC[þ]	AIC[¤]	δ_ε^2
MA1,1	0.16739	0.06661	2.56	0.0104	2			
MA2,1	0.94368	0.09220	9.13	<.0001	12	-339.93	-350.04	0.01036
AR1,1	0.99710	0.01275	107.19	<.0001	12			

[þ] SBC: Schwarz Bayesian criterion, [¤] AIC: Akaike information criterion, δ_s^2: Variance of the error.
Source: prepared by the authors with output results of the transformations LAWEPP(1), PROC ARIMA SAS (2014).

and invertibility and a_t is a white noise process:

$$(1-\phi_5 B^5-\phi_8 B^8)PPSRG=a_t$$

With the following estimators for ϕ_5=-0.14669 and ϕ_8=-0.19027. Thus, in order to convert the NARSP series to "white noise", the a_t is cleared

$$(1+0.14669B^5+0.19027B^8)PPSRG=a_t$$

The model residual a_t could be obtained by passing series NARSP(1) through a filter defined for the model's parameters; then to obtain the values of a_t, the equation was rewritten in its form of differences

$$a_t = PPSRG + 0.14669PPSRG_{t-5} + 0.19027PPSRG_{t-8} \tag{7}$$

Stage 3: Prewhitening of the *output* series

The same transformation of prewhitening was applied to the output *AWEPP* series using the *SARIMA* model (0,1,1) X $(1,0,1)_{s=12}$. Obtaining from this model the residual series β_t, recalling that the *LAWEPP* series (1) is the stationary *AWEPP* series after the transformation, then it can be said that *AWEPP* follows a seasonal *ARMA* process (0,1) *X*(1,1):

$$(1-\phi_{12}B^{12})LPPHBP=(1-\theta_1 B^2)(1-\Theta_{12}B^{12})\beta t$$

$$(1\text{-}099710B^{12})LPPHBP=(1-0.16739B^2)(1-0.94368B^{12})\beta_t$$

$$\beta_t = \frac{\left(1-0.99710B^{12}\right)LPPHBP}{\left(1-0.16739B^2\right)\left(1-0.94368B^{12}\right)} \tag{8}$$

Stage 4: Calculation of the crossed correlation function (CCF) between a_t and β_t

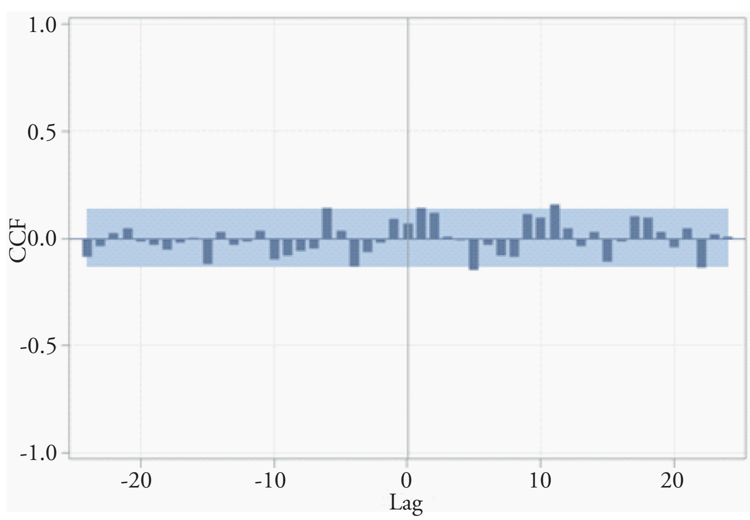
The crossed-correlation function (CCF) is a very useful measure of the force and the direction of the relationship between two random variables, that is, it represents the direction of causality (Granger, 1969). Stationary series must be used in this case, since crossed covariances can only be interpreted when they are done on stationary series.

It is assumed that the NARSP variable influences the AWEPP variable, but not the opposite; that is, there is unidirectional causality of NARSP to AWEPP, but there is no feedback. In the TFM methodology, there is only interest in understanding the linear relationship between variables, so that only the positive part (positive lags) of the CCF are taken into account. Thus, the crossed correlations were calculated using equations (7) and (8), with k = ±1, ..., ±25.

It is observed that in the CCF there is feedback between a_t and β_t, that is, there can be a feedback effect of the NARSP on the AWEPP from the lag k_1. However, it should be noted that after lag 5, the other crossed correlations are essentially zeros, in addition to there being a sinusoidal behavior pattern of these crossed correlations (Figure 3).

Stage 5: Identification of the transfer function

The orders r and s of the polynomials of the denominator and the numerator, respectively, were identified, as well as the initial lag b of the transfer function model. The orders r and s of the polynomials $\delta(B)$ and $\omega(B)$ could be determined by the form of the crossed correlation function between α and β from the lag b suggested by Hillmer & Tiao (1979). In the CCF a peak was observed in b=1, which means that it takes a month for the NARSP variable to affect the AWEPP variable. Regarding the operator of the order r, it is observed that the CCF from the sample is extinguished from a sinusoidal wave mode, buffered from lag 1, which is why it is reasonable to fix r=2, and therefore the value s is obtained since the decaying pattern begins in v_{b+s+1}. For this case, the decaying pattern begins in v_1, then v_{b+s+1}=v_1, therefore s=0 and the values of b, r and s remain in the following form (b,r,s) = (1,2,0).



Source: prepared by authors with output results from PROC ARIMA, SAS (2014).

Figure 3. Crossed correlation between prewhitened NARSP (*input*) and AWEPP (*output*) series.

The tentative model of the transfer function identified is the following:

$$PPHBP_t = \frac{\omega_0}{\left(1-\delta_1 B-\delta_2 B^2\right)} B^1 PPSRG_t + \left(\text{noise model}\right)$$

Stage 6: Estimation of the transfer function

The CCF calculated reveals a possible structure, highlighting that the operator of the numerator and denominator can have complex roots to produce the effect. The model with the lowest SBC and AIC level for these sets of data was the model (1,2,0).

For the interpretation and significance of the estimators, Box *et al.* (1994) suggest that the parameters whose absolute *t* statistic is higher than 2 and *p-values* <0.05 should be included. Therefore, the transfer model (1,2,0) is considered to be moderate, since it adjusts to old data without using any unnecessary parameter (Table 2).

Therefore, since the model has been identified and its parameters have been estimated, the final transfer model remains in the following form:

$$PPHBP_t = \frac{0.18756}{\left(1-0.69095B+0.5717B^3\right)} LPPSRG_t + \frac{\left(1-0.16074B^2\right)\left(1-0.93248B^{12}\right)}{\left(1-0.99614B^{12}\right)} a_t$$

Stage 7: Validation and prediction

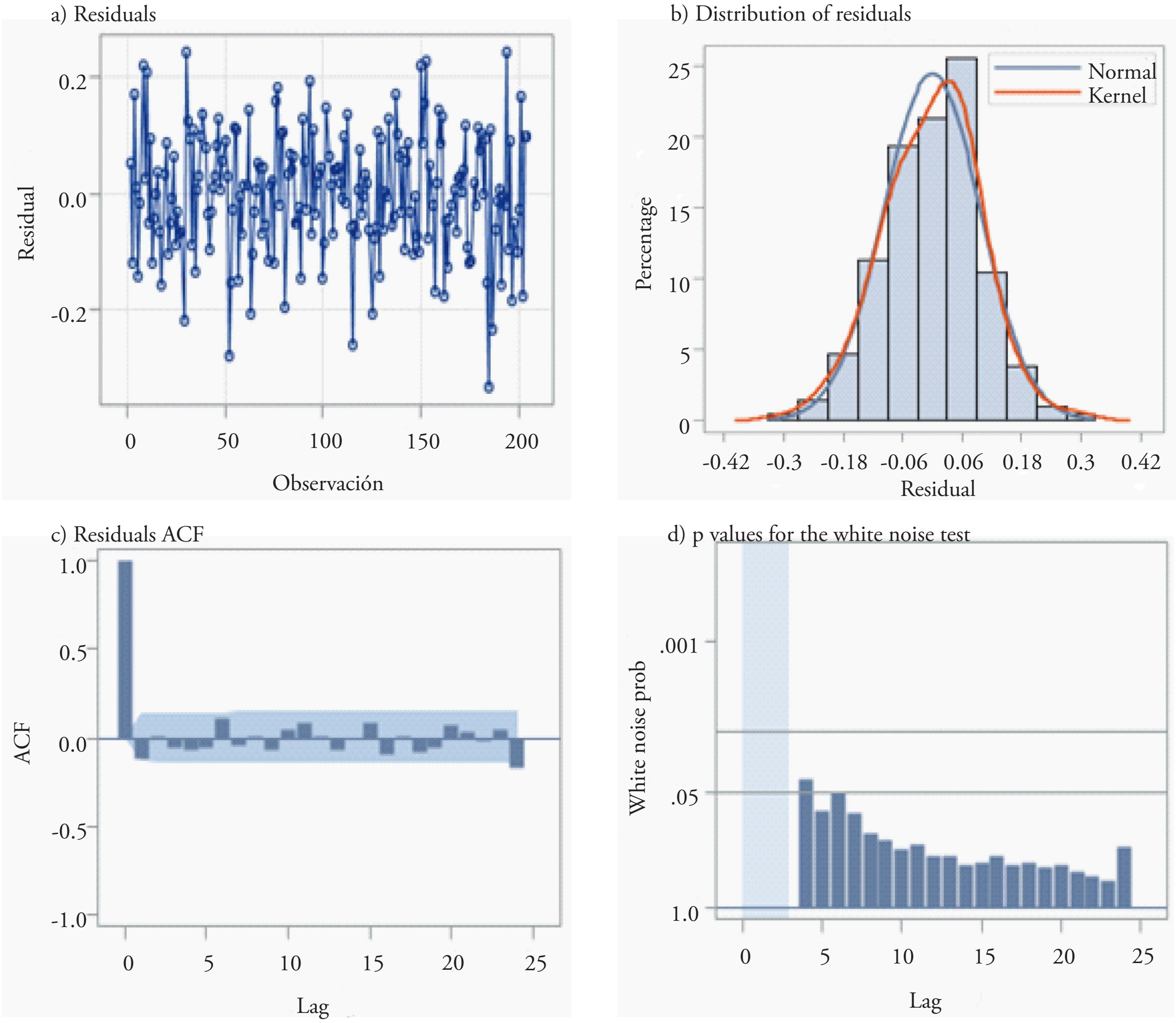
After estimating the model parameters, it was validated through the residual analysis (Yafee, 1999). The standardized residuals, their histograms, the respective ACF graph, and the values of *p* for the white noise tests are presented in Figure 4.

Figure 4(a) shows that the standardized residuals estimated from this model ought to behave as an independent sequence and identically distributed with a mean of zero and constant variance. The histogram from Figure 4(b) shows that the standardized residuals for the model approach a normal distribution as suggested by Jarque and Bera (1987). The ACF of the residuals in Figure 4(c) shows that the autocorrelations are inside the

Table 2. Estimation of the transfer model for the time series LAWEPP(1) by maximum likelihood.

Parameter	Estimation	Standard error	Value t	Approx. Pr > |t|	Lag	Variable	Desp.	SBC[b]	AIC[¤]	δ_ε^2
MA1,1	0.16074	0.06757	2.38	0.0174	2	LPPHBP	0	-332.84	-352.95	0.00977
MA2,1	0.93248	0.10891	8.56	<.0001	12	LPPHBP	0			
AR1,1	0.99614	0.01131	88.06	<.0001	12	LPPHBP	0			
NUM1	0.18756	0.05739	3.27	0.0011	0	LPPPSG	1			
DEN1,1	0.69095	0.04899	14.11	<.0001	1	LPPPSG	1			
DEN1,2	-0.57169	0.05694	-10.04	<.0001	3	LPPPSG	1			

[b]SBC: Schwarz Bayesian criterion, [¤]AIC: Akaike information criterion.
Source: prepared by authors with output results from PROC ARIMA, SAS (2014).

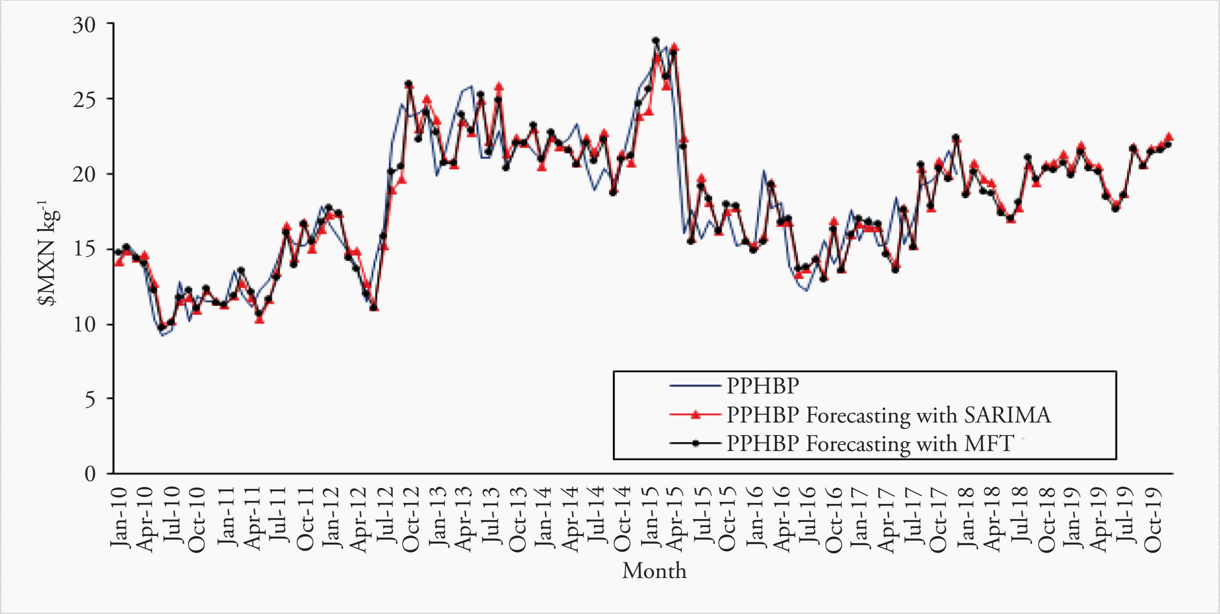


Source: prepared by authors with output results from PROC ARIMA, SAS (2014).

Figure 4. Graphs used to evaluate the adjustment of the SARIMA model $(0,1,1)X(1,0,1)_{s=12}$: (a) Standardized residuals, (b) Histogram of the standardized residuals, (c) ACF of the residuals, and (d) Values p for the white noise tests.

confidence band, that is, they are close to zero. This result means that the residuals did not deviate significantly from a process of zero white noise and are purely random, so there is no dependency information of some data with others through time. Figure 4(d) shows the *p-values* for the white noise test. Given that the *p-value* associated with the chi-squared statistics is high, there is no reason to reject the null hypothesis that the residuals are white noise (*p-value* < 0.05). Therefore, the TFM selected is adjusted to the LAWEPP data.

Finally, the estimated models (SARIMA and TFM) were used to make predictions outside the sample for the 24 months after the last observation (Figure 5).



Source: prepared by authors with output results from PROC ARIMA, SAS (2014).
Figure 5. Nominal and predicted price of the white egg paid to the producer in Mexico.

The models predict values of AWEPP quite near those observed for the months of the years 2000 to 2017, since these are located inside the confidence band estimated at ±95%. The estimated prices follow a seasonal behavior typical of most agriculture and livestock prices and products. In the case of the white egg prices paid to the producer in Mexico, in the years 2018 and 2019, they fluctuated at a TCMA of 0.74%, that is, between $16.97 and $22.47 with the SARIMA model. With the TFM the estimated rate fluctuated 0.58%, that is, between $17.46 and $24.80. For the years projected, the nominal prices will have an upwards trend, within the ranges mentioned before, from this the importance of using these models, since they can be a support for decision-making with scientific rigor (Figure 5).

With the SARIMA and TFM models, the AWEPP were predicted for the months of the year 2017 and these prices were compared with those of the AWEPP series. Good predictions were obtained with a mean absolute percentage error (MAPE) of 8.46% for the first model and 8.13 % for the second. This indicates that the TFM is better to predict the AWEPP. However, Maridakis and Wheelwright (1989) suggest that the prediction should not be based solely on this indicator; the chi-squared test should also be examined to know if the series presents residuals that behave as white noise. The existence of white noise in the residuals was carried out and proved, as the authors indicate. These models predict values of AWEPP very close to those observed, since they are located within the confidence band estimated at ±95% (Table 3).

The effects of the NARSP on the AWEPP indicate that the increase was of 0.21, that is, when the sorghum price (NARSP) increases by one peso; the average price (13.12 $MXN kg^{-1}) of white egg for the producer in Mexico (AWEPP) increases in $0.21 ±0.099 pesos, 30 days after the increase of the first.

Table 3. Observed and estimated nominal egg white prices paid to the producer in Mexico, 2017 ($MXN kg^{-1}), obtained through the SARIMA and TFM model.

Year 2017	Month												MAPE (%)
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
PPHBP	15.54	17.10	15.16	15.38	18.48	15.30	17.01	19.28	19.50	20.16	21.55	20.03	
Forecast with SARIMA	16.69	16.39	16.43	14.88	14.04	17.67	15.19	20.33	17.75	20.82	19.93	22.39	8.46
Forecast with MFT	17.02	16.82	16.61	14.59	13.54	17.58	15.07	20.56	17.89	20.36	19.66	22.41	8.13

Source: prepared by authors with output results from PROC ARIMA, SAS (2014).

The AWEPP were predicted with relative accuracy with the TFM, improving the results of the prediction, compared to the estimation of the models of univariate temporal series of SARIMA. However, Chu (1978) suggests that these estimations can possibly not be credible to predict the prices in the medium and long term. It is necessary to point out that the main inconvenience found in this type of models lies in their own foundation, since being based on past facts and learning from their own history to perform predictions, these will be accurate to the extent that the factors which determine the evolution continue to act in the same way and are not noticeably altered.

CONCLUSIONS

The estimation of bivariate temporal series models of TFM type and noise for the average prices of white egg paid to the producer allows achieving a good adjustment in the prediction in the short and medium term, improving the results of the prediction, compared to the estimation of the SARIMA type models of univariate temporal series.

The inclusion of the NARSP variable in the transfer function model improves the prediction of the AWEPP by decreasing the variance from 0.01036 to 0.009771 in comparison to the univariate SARIMA model, which can be improved to the extent that more input variables are included which explain the behavior of the AWEPP.

It was shown that the predictions of the series studied in the short term differ by 8.46% from the data observed through the SARIMA model and 8.13% through TFM, minimizing the random error in both cases. It takes a month for the NARSP variable to affect the AWEPP variable. The estimated AWEPP provide useful information to plan and make decisions in the poultry sector for dish egg production in the short term.

REFERENCES

Box GE, GM Jenkins. 1976. Time Series Analysis: Forecasting and Control. Revised. San Francisco. Ed., Holden-day, 575 p.

Box GE, GM Jenkins, GC Reinsel. 1994. Time Series Analysis: Forecasting and Control. Englewood Cliffs, NJ. 3rd ed. Ed. Prentice Hall.

Brockwell PJ. 2004. Representations of continuous-time ARMA processes. *In:* Journal of Applied Probability. 41: 375-382.

CEDRSSA (Centro de Estudios para el Desarrollo Rural Sustentable y la Soberanía Alimentaria). 2014. Evolución de los precios del maíz, frijol y sorgo. *In:* http://www.cedrssa.gob.mx/?doc=2643.

Chiogna M, C Gaetan, G Masarotto. 2007. Automatic identification of seasonal transfer function models by means of iterative stepwise and genetic algorithms. *In:* J Time Ser Anal, (29)1: 37–50.

Chu KY. 1978. Short-run forecasting of commodity prices: An application of autoregressive moving average models. *In:* IMF Staff Papers. 25(1), pp: 90-111.

Cox DR, GE Box. 1964. An analysis of transformations. *In:* Journal of the Royal Statistical Society. Serie B. 26: 211-252.

Cruz Jiménez S, García Mata R, Mora Flores JS, García Sánchez RC. 2016. El mercado de huevo para plato en México, 1960 – 2012. *In:* Agricultura Sociedad y Desarrollo. 13(3) pp: 385 - 399.

García Mata R, García Salazar JA, García Sánchez RC. 2003. Teoría del Mercado de Productos Agrícolas. Instituto de Socioeconomía, Estadística e Informática, Programa de Postgrado en Economía. Colegio de Postgraduados. Montecillo, Texcoco Edo de México. 382 p.

Granger C, William J. 1969. Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *In:* Econometrica. 37(3):424 – 438.

Hillmer SC. GC Tiao. 1979. Likelihood Function of stationary Multiple Autoregresive Moving Average Models. *In:* Journal of the American Statistical Association 74. pp: 652 – 660.

Jarque CM, Anil KB. 1987. A test for Normality of observations and regression residuals. *In:* International Statistical Review. 55(2):163-172.

Luis Rojas S, García Sánchez RC, García Mata RC, Arana Coronado OA, González Estrada A. 2019. Metodología Box - Jenkins para pronosticar los precios de huevo blanco pagados al productor en México. Agrociencia. 53(6): 347 – 365.

Maridakis SG, Steven CW. 1989. Forecasting Methods for Management. 5th Ed. New York: John Wiley & Sons. 470 p.

Ortega Sánchez de Tagle J. 2014. Plan Rector Visión 2014 – 2024. “Sistema producto huevo para plato”. Imagen Editorial Yire. Cd. de México. 110 p.

Ramírez Guzmán ME. 1993. SAS macro for analyzing step and impulse response functions derived from transfer function models. *In:* http://www.sascommunity.org/wiki/SAS_Global_Forum_Proceedings/SUGI_93. p: 990 – 995.

SAS (Statistical Analysis System) 2014. System for Windows V. 9.4. Sas Institute Inc. Cary, NC. USA.

SNIIM (Sistema Nacional de Información e Integración de Mercados). 2017. Secretaría de Economía. http://www.economia-sniim.gob.mx/nuevo/Home.aspx?opcion=/SNIIM-Pecuarios-Nacionales/SelIng.asp?. Consultado 21 jun, 2017.

UNA (Unión Nacional de Avicultores). 2018. Compendio de Indicadores económicos del sector avícola en México año 2017. 172 p.

Yafee RA, M McGee. 1999. Introduction to time Series Analysis and forecasting. Ed., Academic Press, Inc. Brooklyn, New York. pp: 83 – 89.