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A Prediction of the Iran's Chicken Price by the ANN and Time Series Methods

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Abstract: The objective of this paper is to forecast the price of chicken in Iran within a time path (one months, six months and twelve months), which includes an estimation period from March-1991 to January-2005 and a forecasting period from February-2005 to January-2006. Three methods were applied in this study to compare the trends of fitted data that are the artificial neural network (ANN), ARIMA and ARDL. The results confirm the more precession of the ANN than that of the ARIMA and ARDL methods and can thus be applicable for the optimal policymaking in the price forecasting and the market alignments through the risk prediction.

Key words: Chicken price prediction · Artificial neural networks · Time series methods

INTRODUCTION

Despite the short age of the poultry industry, it has now a pertinent role in providing required protein of people. The industry has started its activity in Iran since three decades ago. There is now a serious competition between meat and chicken industries in terms of production and consumption. This reveals the fact that a precise prediction of price in the poultry sector can result in optimizing resource allocation, efficiency enhancement and an increase in income of the poultry industry. These developments should lead to a decrease in instability and risk of the poultry market [1-5].

The objective of this paper is to forecast the price of chicken in Iran within a time path (one months, six months and twelve months), which includes an estimation period from March-1991 to January-2005 and a forecasting period from February-2005 to January-2006. Accordingly, two approaches were applied, in which the first one includes the artificial neural network (ANN) and the second one involves both ARIMA and ARDL methods, to compare the trends of fitted data [5-8].

In fact, a difference between neural networks ANNs and regression models is that, in the latter case, certain assumptions regarding the distribution of error terms must hold. Moreover, in regression models, whether linear or non linear, a functional form is assumed. But in the neural networks, these assumptions are not required.

However, a disadvantage of neural networks in comparison with regression models is their lack of explanation. Regression analysis can identify the contribution of each individual input in determining the output and also can give some measures of confidence about the estimated coefficients. On the other hand, currently there is no theoretical or practical way of accurately interpreting the weights in neural networks. For example, weights cannot be interpreted as a regression coefficient not used to compute causal impacts or elasticities. Therefore, neural networks are generally better suited for forecasting or prediction rather than for a policy analysis. Section 2 presents materials and methods explaining ARIMA, ARDL and ANNs. Section 3 provides empirical results and discusses findings. Finally, Section 4 concludes [8-13].

MATERIALS AND METHODS

Artificial Neural Network (ANN) Model: The major advantage of neural networks is their flexible nonlinear modeling capability. With ANNs, there is no need to specify a particular model form. Rather, the model is adaptively formed based on the features presented from the data. This data-driven approach is suitable for many empirical data sets where no theoretical guidance is available to suggest an appropriate data generating process [5]. An ANN is typically composed of three layers of neurons (nodes): the lowest layer which is an input layer where external information is received, the highest layer which is an output layer where the problem solution is obtained and hidden layers in which input and output layers are separated by one or more intermediate layers. There is no theoretical basis to determine the appropriate number of hidden units or layers in a network. The most common way in determining the number of hidden nodes is via experiments or by trial-and-error [13].

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In this paper, the following three-layer feed-back network was used:

$$F = F\left[\beta_0 + \sum_{j=1}^{J} \beta_j G\left[\sum_{k=1}^{K} \gamma_{kj} X_J\right]\right] \quad (1)$$

where F is the output function of the output layer unit, β_0 is the bias unit (equal to 1), G is the output function of the hidden layer units j, γ_{KJ} denotes the weight for the connection linking input k to the hidden unit j, β_j is the weight of outputs from the hidden layers in the output layer unit and X is the input vector.

The activation function determines the relationship between inputs and outputs of a node and a network. In general, the activation function introduces a degree of nonlinearity that is valuable for most ANN applications. A network may have different activation functions for different nodes in the same or different layers. Y*et al*most all the networks use the same activation functions particularly for the nodes in the same layer [13]. Some common types used in ANNs are Sigmoid (Sig) and Hyperbolic Tangent (Than) functions.

Neural net workers usually divide their sample into two separate data sets. The *training set* is used by the algorithm to estimate the network weights, while the *test set* is used to evaluate the forecasting accuracy of the network. Since the test set is not used during the estimation of the network weights, the forecasts made from the test set amount to an *ex-post* out-of-sample forecast. The neural networks aims at minimizing the forecasting error in the training set using a criterion such as the mean squared error (MSE).

ARIMA Method: The ARIMA method was presented by Box and Jenkins for linear time series modeling. Generally this method has 4 stages including identification, estimation, diagnostic checking and forecasting.

The *ARIMA (p, d, q)* model for the series of variable y is as follows:

$$y_t = f(t) + \phi_1 y_{t-1} + ... + \phi_p y_{t-p} + e_t + \theta_1 e_{t-1} + ... + \theta e_{t-q} \quad (2)$$

Where p, d and d are the orders of autoregressive, integration and moving average terms, respectively. The main purpose of the BJ method is to forecast the trend of economic variables over time. Also the major point in predicting refers to the stationary time series variables. Thus, the advantage of ARIMA with respect to the other methods is to use stationary time series variables in the prediction processes [9].

Auto-Regressive Distributed Lag (ARDL) Model: ARDL is an appropriate method suggested to analyze the long-term and short-term relations between variables [8]. This method estimates long-run and short-run variable relations simultaneously, while removes problems of missed variables and autocorrelation in structural models [11]. An augmented ARDL model is shown as follows:

$$\alpha(L,P)y_t = \alpha_0 + \sum_{i=1}^{k} \beta_i (L, q_i) x_{it} + u_t,\ i = 1,2,....k \quad (3)$$

Where; α_0, y_t and L denote intercept, dependent variable and lag operator, respectively (that is, $L^j y_t = y_{t-j}$).

Accordingly relevant method is used to test the existence of the long-run relationship between considered variables. The test is done by the co-integration technique is focusing on the following hypotheses:

$$H_0: \sum_{i=1}^{m} \beta_i - 1 \geq 0$$

$$H_1: \sum_{i=1}^{m} \beta_i - 1 < 0$$

There hypotheses are tested by the following t statistic developed by Banerjee *et al.* [1]:

$$t = \frac{\sum_{i=1}^{m} \hat{\beta}_i - 1}{\sum_{i=1}^{m} S_{\hat{\beta}_i}} \quad (4)$$

Where $\hat{\beta}_i$ and $S_{\hat{\beta}_i}$ are the coefficients and their standard errors of the lagged dependent variables, respectively.

Hence, the ARDL equation chicken price is introduced as follows as:

$$LP^{CH}{}_t = \alpha_0 + \sum_{j=1}^{p} \alpha_i LP^{CH}{}_{t-j} + \sum_{j=0}^{q_1} \beta_{1j} LP^{FE}{}_{t-j} + \sum_{j=0}^{q_2} \beta_{2j} LP^{C}{}_{t-j} +$$

$$\sum_{j=0}^{q_3}\beta_{3j}LP^{M}_{t-j}+\sum_{j=0}^{q_4}\beta_{4j}LY_{t-j}+\sum_{j=0}^{q_5}\beta_{5j}LQ_{t-j}+\gamma_1 DUM1+\gamma_2 DUM2 \quad (5)$$

where LP_t^{CH} is the log of chicken price, LP_t^{FE} is the log of poultry food input price, LP_t^{C} is the log of one-day-old chicken input price, LP_t^{M} is the log of livestock meat, LY_t is the value added of the agricultural sector, LQ_t^{CH} is the log of chicken products, $DUM1$ and $DUM2$ are dummy variables indicating the effect of temperature on the chicken price and government policies to be applicable in the market, respectively.

Model selection criterions: The criterions include the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The following general formulas for them are used:

- Mean Square Error (MSE): $MSE=\frac{1}{T}\sum(P-A)^2$
- Root Mean Square Error (RMSE): $RMSE=\sqrt{\frac{1}{T}\sum(P-A)^2}$
- Mean Absolute Error (MAE): $MAE=\frac{1}{T}\sum|P-A|$
- Mean Absolute Percentage Error (MAPE): $MAPE=\frac{1}{T}\sum\left|\frac{P-A}{A}\right|$

A and P are the actual and fitted values of a dependent variable, respectively, while T is the number of observations.

Data Resources: Data on the above variables are derived from Iran's State Livestock Affairs Logistics. The data report a period over the March-1991 to January-2006. The data over March-1991 to January-2005 are used for estimation and the remaining are use to evaluate ex-Post prediction. All empirical results have been obtained by the MATLAB and Microfit packages.

RESULTS AND DISCUSSION

Table 1 shows that the results for the chicken price obtained by *ARIMA*(3,1,3), in which the orders of the model (*p*, *d* and *q*) have been optimized by AIC and SBC and unit root tests offered by Pesaran and Pesaran [8]. All coefficients estimated are significant at the one percent significant level.

Table 1: Results for the chicken price, based on ARIMA (3,1,3)

Variable	Coefficient	Standard Error	T-Ratio	Probability
C	0.023	0.0068	3.36	0.001
$dLP^{CH}(-1)$	0.20	0.076	2.68	0.008
$dLP^{CH}(-2)$	-0.25	0.066	-3.79	000
$dLP^{CH}(-3)$	-0.67	0.092	-7.27	000
R^2= 0.47		D-W=1.84	U=E+0.55*E(-3) (5.07)	

Source: Research findings

Table 2: Estimated results for the chicken price, based on ARDL (1,0,1,1,0,0)

Variable	Coefficient	Standard Error	T-Ratio	Prob
LP_{t-1}^{CH}	0.58	0.05	10.88	000
LP_t^{FE}	0.18	0.03	5.24	000
LP_t^{C}	0.15	0.01	9.83	000
LP_{t-1}^{C}	0.06	0.01	3.39	000
LP_t^{M}	0.76	0.16	4.6	000
LP_{t-1}^{M}	-0.61	0.17	-3.58	000
LY_t	0.06	0.04	1.38	0.17
LQ_t^{CH}	-0.05	0.03	-1.42	0.15
C	0.17	0.53	0.32	0.75
DUM1	0.03	0.009	3.52	0.001
DUM2	-0.04	0.02	-2.05	0.04

Source: Research findings

The results estimated by the ARDL for the chicken price in the considered period are shown in Table 2, in which the numbers of lags have been optimized by the Shwarz-Bayesian Criterion (SBC). The coefficient of the final regression, based on *ARDL*(1,0,1,1,0,0), has been statistically significant and has mostly expected signs. Thus, all results reported in these tables seem to be useful for the use of chicken price forecasting, accompanied by the ANN approaches.

In the next step, the methods of Artificial Neural Networks (ANNs) were used as well as econometric models (ARIMA and ARDL) to predict ex-post values of the chicken price variable. In the economic literature, a selection of neurons of the primary layer should be on the basis of an economic theory in order to get better results [12]. Hence, the following equation is defined on the basis of ANN methods in order to compare the predicted results with those obtained by the ARDL models.

Table 3: The Ex-post predicted results for the chicken price using ANNs and time series models

Time Horizon	Method	No. of Neurons in Input Layer	No. of Neurons in Hidden Layer	Transfer Function in Hidden Layer	Evaluation Criteria MSE	RMSE	MAE	MAPE
1 Month ahead	BPAR	1	2	Sig	0.000002	0.0017	0.0017	0.00017
	BPST	8	5	Than	0.00051	0.022	0.022	0.0023
	ElmanAR	1	2	Than	0.000004	0.002	0.002	0.00020
	ElmanST	8	7	Than	0.00025	0.015	0.015	0.0016
	ARIMA	-	-	-	0.0034	0.058	0.058	0.0060
	ARDL	-	-	-	0.00041	0.020	0.020	0.0021
6 Month ahead	BPAR	1	2	Sig	0.0001	0.010	0.009	0.0010
	BPST	8	4	Sig	0.0020	0.045	0.035	0.0036
	ElmanAR	1	2	Than	0.0036	0.060	0.044	0.0045
	ElmanST	8	3	Sig	0.0013	0.036	0.029	0.003
	ARIMA	-	-	-	0.0021	0.046	0.038	0.0040
	ARDL	-	-	-	0.00045	0.021	0.016	0.0017
12 Month ahead	BPAR	1	2	Sig	0.0003	0.018	0.017	0.0017
	BPST	8	4	Sig	0.0020	0.044	0.035	0.0036
	ElmanAR	1	2	Than	0.0028	0.053	0.038	0.0039
	ElmanST	8	3	Sig	0.0016	0.040	0.034	0.0035
	ARIMA	-	-	-	0.0061	0.078	0.063	0.0064
	ARDL	-	-	-	0.0036	0.060	0.043	0.0044

Source: Research findings

Back-Propagation Network model (BPST):

$$LnP_t^{CH} = b + F\left[[b_0 + \sum_{j=1}^{J} b_j G + \left[\sum_{k=1}^{K} a_{kj} \left[\begin{array}{l} LnP_{t-1}^{CH} + LnP_{t-1}^{FE} + LnP_{t-1}^{C} + LnY_t + \\ LnQ_t^{CH} + LnP_t^{M} + DUM1 + DUM2 \end{array} \right] \right] \right] \tag{6}$$

and

Elman Network Model (Elman ST):

$$LnP_t^{CH} = F\left(b_0 + \sum_{j=1}^{J} Z_{tj} b_j \right) \tag{7}$$

Where

$$Z_{tj} = G\left(\sum_{j=1}^{J} \gamma_j \left(\begin{array}{l} LnP_{t-1}^{CH} + LnP_{t-1}^{FE} + LnP_{t-1}^{C} + LnY_t + \\ LnQ_t^{CH} + LnP_t^{M} + DUM1 + DUM2 \end{array} \right) + Z_{t-1}\delta_j \right)$$

In addition, the ability of neural networks is compared with that of the ARIMA approach. The specified equations are defined as follow:

Back-Propagation Network Model (BPAR):

$$LnP_t^{CH} = b + F\left(b_0 + \sum_{j=1}^{J} b_j G\left[\sum_{k=1}^{K} a_{kj} Ln\left[P_{t-i}^{CH} \right] \right] \right) \tag{8}$$

and,

Elman Network Model (ElmanAR):

$$LnP_t^{CH} = F\left(b_0 + \sum_{j=1}^{J} Z_{tj} b_j \right) \tag{9}$$

Where

$$Z_{tj} = G\left(\sum_{j=1}^{J} \gamma_j Ln\left(P_{t-i}^{CH} \right) + Z_{t-1}\delta_j \right).$$

Using the MATLAB software and the algorithms of the ANNs as well as processes of forecasting in the ARIMA and ARDL, the results for forecasting the chicken price in Iran within a time horizon (one month, six months and twelve months ahead) are shown in Table 3.

According to the data in Table 3, such findings related to the BPAR seem to be more precised than those of others. The reason is that the least forecast errors of the chicken price in Iran have been earned by the BPAR. However, ANNs (BPAR and ElmanAR) are not sometimes able to consider determinants that influence the price chicken. This may reduce the degree of the forecast preciseness as a result of possible fluctuations in variables (such as a sudden decrease in the one-day-old chicken input price or in the poultry food input price). The ANNs have used such changes within the different periods considered in this paper.

Table 4: Comparative forecasting performance (ratios to performance of an ANN model) of the chicken price

Model		MSE	RMSE	MAE	MAPE
		Precision Criterion			
ARDL	1 Month ahead	1.64	1.33	1.33	1.31
	6 Month ahead	0.34	0.27	0.55	0.56
	12 Month ahead	2.25	1.50	1.26	1.25
BPST	1 Month ahead	2.04	1.47	1.47	1.45
	6 Month ahead	1.53	1.25	1.22	1.20
	12 Month ahead	1.25	1.10	1.03	1.02
ARIMA	1 Month ahead	170	34.11	34.11	35.29
	6 Month ahead	21.00	4.60	4.22	4.00
	12 Month ahead	20.33	4.33	3.70	3.76
ElmanAR	1 Month ahead	2.00	1.17	1.17	1.17
	6 Month ahead	36.0	6.00	4.88	4.50
	12 Month ahead	9.33	2.94	2.23	2.29

Source: Research findings

In general, to compare the forecasting performances of the methods, Table 4 presents the results of Table 3 in more useful manner, as the ratios of forecasting errors of each model to the forecasting errors of the ANN model was used. That is, results for ARDL and BPST are compared to those for ElmanST, while results for ARIMA and ElmanAR are compared to those for BPAR. Overall, numbers greater than one indicate poorer forecasting performance than the comparable ANN model and vice versa for numbers less than one. Accordingly, the forecast performance of the ARDL method is much better than that of the ARIMA one.

CONCLUSION

The results obtained by this research indicate that the ANN methods predict the ex-post trends of the Iran's chicken price more precisely than that of the econometric methods. The more appropriate forecasting performance can be obtained when ANNs use main factors of the chicken markets that are detected by the economic approaches.

Such findings, thus, give a chance to the market and also policy makers to raise the ability of their forecasting trends and to reduce their possible decision risks. The implication is that the poultry industry should be equipped by the ANNs computer packages and learning the relevant programs.

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