J. Basic. Appl. Sci. Res., 2(11)11537-11541, 2012
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ISSN 2090-4304
Journal of Basic and Applied Scientific Research
www.textroad.com

Prediction of Agricultural Commodity Price Using Artificial Neural Networks: Case of Chicken Price in Fars province, Iran

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ABSTRACT

Given the importance of predicting agricultural commodity price, in this study price of chicken was predicted and different methods include Autoregressive Conditional Heteroskedasticity (ARCH) model, Autoregressive Moving Average (ARMA) model and Artificial Neural Networks (ANNs) was used. The monthly data of chicken price in the Fars province as one of the most important region of chicken production of Iran were collected from agricultural ministry for the period of March 1997 to November 2010. The data set, were divided in two series, First series was used as training data and another series was used for testing the ability of prediction models. Therefore, data from December 1997 to November 2008 was used as the training data and other was used to test the accuracy of forecasting. Results showed that, Feed Forward artificial neural network with three layers and six neurons in the hidden layer minimize the error of prediction and this network is more efficient than other networks and other methods in prediction of chicken price.

KEYWORDS: Chicken Price, Time series Methods, Artificial Neural Networks.

1. INTRODUCTION

Agriculture is one of the activities that are always exposed at risk. Therefore, in most cases farmers are uncertain about their future production and income. The risk associated with agricultural activities may be due to fluctuation in prices, production, and government policies. But in developing countries, fluctuation in agricultural commodity price is the main reason of risks in these countries. Therefore, many studies have been compared different methods of agricultural commodity price prediction.

The Box–Jenkins methodology and ARIMA models have been one of the most widely used statistical technique in time series prediction and many researchers have been used this models in agricultural commodity prices forecasting [1, 17, 12, 18].

Now a day, new forecasting methods such as ANNs have been used in prediction. In these methods, the complex relationships between variables can be learned through artificial intelligence. ANNs have applications in many different fields, and one of the major application areas is prediction [14, 19]. ANNs are based on mimicking the human brain and they can learn from experience and generalize based on previous knowledge. ANNs are being used more frequently in the analysis of time series data and many studies have been used ANNs in prediction economic variables and agricultural commodity prices [9, 10]. Also, numerous comparative studies have been conducted between regression models and ANNs [21, 16, 15].

Therefore, in this study the prediction accuracy of various methods including simple averages, moving average, autoregressive conditional variance model, autoregressive moving average and artificial neural network are compared. The monthly data of chicken price in the Fars province foe the period of March 1997 to November 2010 was used.

METHODS

Quantitative predictive methods generally can be divided into two categories of regression and non-regression methods. Non-regression methods include the simple average method, moving average methods and exponential smoothing methods. Regression methods are classified into two groups of causal and non-causal methods. Among causal regressive methods we can refer to autoregressive conditional heteroskedasticity (ARCH) models and

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generalized auto regressive conditional heteroskedasticity (GARCH). Non-causal regression techniques also include the harmonic method and ARIMA and ARMA processes.

However, these models include theoretical guesses and hypotheses about the underlying laws that govern the system from which the data are generated [6]. In contrast, artificial neural networks (ANNs) make few priori assumptions about the models and seem to be suited for predicting agricultural commodity prices [9, 10]. Also, numerous comparative studies have been conducted between ARIMA and ANNs [21]. Therefore, in this study ARIMA model, ARCH model and ANN performance are compared for predicting chicken price in Fars province, Iran.

ARIMA: Traditionally, the Box–Jenkins approach has been used to modeling and forecasting a stochastic process in a great many fields [7]. The Box–Jenkins involving an iterative four-stage process, identification, parameters estimation, diagnostic checking and forecasting [3]. In the first step, by using graphs, statistics, ACFs and PACFs, stationary and tentatively identify patterns and model components is achieved. In the second step, the coefficients are estimated through software application of least squares and maximum likelihood methods. In the third step, by using graphs, statistics, ACFs and PACFs of residuals the model validity is verified and the best model is selected. In the last step, by using graphs, simple statistics and confidence intervals, the validity of the forecast and track model performance to detect out of control situation is determined. In ARIMA terms, a time series is a linear function of past actual values and random shocks. A non-seasonal ARIMA (p, d, q) process for variable x can be shown as follow:

$$y_t = f(t) + \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + ... + \theta_q \varepsilon_{t-q} \qquad (1)$$

Where

$$y_t = \Delta^d x_t = (1-L)^d x_t \qquad (2)$$

In the most economic variables, d = 0 and, therefore f(t) = α + δ= 1 or d=1, thus f(t) =μ. In a ARIMA (p, d, q) process, p, d, and q represent the number of their self regressive terms, the degree of differences, and the number of moving average terms, respectively. If d = 0, the ARIMA process will change into ARMA.

Recently, Pesaran & Pesaran [13]suggested a new method that used in this study. In the first step, the stationary of data was tested to select the ARIAMA or ARMA model. In the second step the order of AR (p) and MA (q) were selected. To select the order of P and q, set them equal to the maximum value that is selected by researcher and depend on the data. Then, different model over the same period were estimate and the value of Akaike Information Criterion (AIC) and Schwarz Baysian criterion (SBC) these models are saved. Then comparing the vales of AIC and\or SBC the model specification with the highest value is selected.

GARCH: In econometric models, homoskedasticity is always regarded as one of the most important econometric assumptions. On the other hand, heteroskedasticity can pose problems in ordinary least squares analysis, especially in cross sectional models. But to get rid of this restrictive assumption, a method called ARCH introduced by Engle [5] as a convenient way of modelling time-dependent conditional variance. This model was generalized by Bollerslev [2] as the GARCH model (Generalized Autoregressive Conditional Heterocesdasticity). A GARCH(q,p) model is defined as a discrete time stochastic process ε_t of the form:

$$\varepsilon_t = w_t \sqrt{h_t} \qquad (3)$$

where $w_t \sim i.i.d.\, N(0,1)$, $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + ... \beta_p h_{t-p}$, and $q > 0$, $p \geq 0$, $\alpha_0 > 0$, $\alpha_i \geq 0$ (i = 1,…,q) and $\beta_i \geq 0$ (i = 1,…,p). When p =0 the GARCH reduced to an ARCH(q) model. Of course, the above model can be used if the ARCH effect in the model is guaranteed. The test of ARCH effect is done automatically by using Microfit Software, without need of complex calculations.

Artificial Neural Networks: The recent development of ANNs provides a new alternative, particularly in situations where variables have a nonlinear relationship and they can not deal with complex realities. The basic elements of an artificial neural network are denoted as neurons. Two or more of the neurons can be combined in a layer, and a particular network can contain one or more layers. Neurons are connected to each other through a connection strength called weight [9]. This structure is similar to its biological counterpart, where a single neuron is the basic unit and is the part of a complex neural network. The most widely applied ANN is the multi-layers feedforward perceptron (MLP) network [20]. This kind of neural network consists of three layers—the input layer, hidden layer(s), and output layer. These layers are connected to each other and the output of each previous layer becomes the input to the next layer

Under normal conditions, the first layer is the input layer and the last one is the output layer. Inputs are weighed and sent to processing neurons in the next layers. Popular ANNs contain one input layer and one output layer that act like independent and dependent variables in a regression model. The number of neurons in the input and output layers relate to the number of parameters taken from the problem and equal to independent and dependent variables.

The hidden layers play a very important role in the successful application of ANNs. It is the hidden neurons in the hidden layer that allow ANNs to capture the pattern in the data and allow the network to generate numerous relationships between the inputs and outputs. One hidden layer may be enough for most forecasting problems. The hidden layer might contain one or more neurons, but networks in which the number of hidden neurons is equal to the number of input neurons were reported to yield better forecasting results in several studies [20].
The single hidden layer feedforward network can show as follows [8]:

$$y = G(a_0 + \sum_{j=1}^{n} a_j F(b_{0j} + \sum_{i=1}^{m} b_{ji} x_i)) \qquad (4)$$

Where y is the output layer with one neuron and x_i is the i th input. Any hidden layer unit receives the weighted sum of all inputs and a bias term (b_{0j}) and produce an output signal through the hidden transfer function (F). Where b_{ij} is the weight of its connection from the i th input unit to the j th hidden layer unit. Similarly, the output unit receives the weighted sum of the output signal of the hidden layer with a bias term (a_0), and produce a signal through the output transfer function (G). Where a_j is the weight of the connection from the j th hidden layer. Where n and m represent the number of neuron in hidden and input layers.

The performance of ANNs depends on various factors, such as number of hidden layers, number of hidden neurons, and initial weight. In this study, networks with one to ten neurons in hidden layer were examined. To determine the best initial weight, each ANN was trained 30 times using the MATLAB package [4].

The forecasting literature provides a number of measures of accuracy [11]. However, in the present study the forecasting performance of the models was evaluated against the three widely used statistical metrics Absolute Percent Error (MAPE), Root of Mean of Squared Error (MSE) and Mean Absolute Error (MAE) criteria. Smaller values of these criteria indicate higher accuracy in prediction [7].

As an example, suppose the forecast sample is t = 1, 2, ... n and it denotes the actual and forecasted value of agricultural electricity consumption in period t as y_t and $\hat{y}_t$, respectively. These criteria are computed as follows:

$$MAPE = (1/n) \cdot \sum_{t=1}^{n} \left| (y_t - \hat{y}_t)/y_t \right| \qquad (5)$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{n}} \qquad (6)$$

$$MAE = \frac{\sum_{t=1}^{n} \left| (y_t - \hat{y}_t) \right|}{n} \qquad (7)$$

In the present study, the prediction accuracy of various methods including simple averages, moving average, autoregressive conditional variance model, autoregressive moving average and artificial neural network are compared. The monthly data of chicken price in the Fars province were collected from agricultural ministry for the period of March 1997 to November 2010 and Eviews, Microfit and MATLAB software packages were used.

RESULTS

Using Eviews 5.0, the stationary of time series of chicken price is tested. The standard Augmented Dickey-Fuller unit root tests and Phillips-Perron test for the chicken price indicated that monthly Price of chicken is clearly a stationary series. Therefore, ARMA process was used to predict the chicken price. In the present study, to determine the autoregressive order (p) and moving average (q), the Pesaran and Pesaran [13] method is used and finally, ARMA (1,0) was chosen for prediction.

The ARCH model can be used if the effect of ARCH in the model is decisive. The results of ARCH effect are presented in Table (1) and models with different degrees of p and q are estimated and, finally, the GARCH (0,4) or ARCH (4) model was selected.

Table (1): Results of testing ARCH effects

Variable	Statistics to be used	
Chicken prices	LM statistic	F statistic
	11.65**	1.43**

Notes: ** denote 5% level of significant.

The LM version of the test yield a statistic of 11.65 which is well above 95 percent critical value and hence reject the hypothesis that there are no ARCH effect. The same conclusion reached by using F version of the test. Therefore, results indicate that there is an ARCH effect in the chicken price. Table (2) is listed forecasting performance and predictive accuracy for the time series models.

Table (2): Results of predicting chicken prices based on time series models

Predicting Method	MSE	MAE	MAPE(%)
ARMA(1,0)	1,883.0	1366.2	4.7
ARCH(4)	5,969.3	4,774.9	38.5

Result show that the MAPE of the ARMA (1,0), however, was 4.7%, which was less than that of the ARCH (4) model, and the ARMA also had the smaller MSE than ARIMA models. Therefore, ARMA can predict chicken price better than ARCH model.

To compare several models, the same data set (training and test sample) was used in ARCH, ARIMA and ANN models. Result show that Feed Forward artificial neural network with back proportion algorithm in which the number of hidden neurons is equal 6 neurons, has the best result. In addition, the numbers of input and output layer neurons were equal to 1 and 1, respectively. Also, Tan-sing and linear Function is used in hidden and output layer, respectively. The result of prediction performance of the ANN model is presented in Table 3.

Table (3): Prediction performance of the ANN models

The number of neurons in the hidden layer	RMSE	MAE	MAPE (%)
1	1817.6	1319.7	4.6
2	1821.1	1313.5	4.5
3	1847.2	1331.9	4.6
4	1840.5	1261.0	4.3
5	1834.9	1308.3	4.5
6	903.6	789.9	2.6
7	1847.9	1308.1	4.5

The MAPE of the ANN, however, was 2.6%, which was less than that of the ARIMA model (4.7%), and the ANN also had the smaller RMSE and MAE than ARIMA models. Therefore, ANN performed better compared to ARIMA models for predicting the monthly chicken price in Fars province of Iran.

Conclusions

The results of the present study indicated the predicted price of chicken by Feed Forward artificial neural network with back proportion algorithm in which the number of hidden neurons is equal 6 neurons, has the best result. In addition, the numbers of input and output layer neurons were equal to 1 and 1, respectively. Therefore, ANN performed better compared to ARIMA and ARCH models for predicting the monthly price of chicken in Iran. Therefore, Agricultural ministry can use this method in future agricultural commodity prediction. In addition, the government can use the results of the studies on predicting prices to take some action and make some plans in advance to balance the market through granting import or export licenses. Also use of neuro-fuzzy models might decrease the error of prediction and improve the results.

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