CHAOS IN COMMODITY MARKETS: A NEURAL NETWORK APPROACH

By

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ABSTRACT

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Chaos theory suggests that seemingly random variables may come from nonlinear deterministic functions. In such cases linear moels cannot capture the underlying regularities of the chaotic time series. This study develops an alternative neural network approach to the commonly used BDS test of chaos to study the non-linear dynamics of the commodity market. This paper uses neural networks, a type of computer artificial intelligence which has recently shown strong potential for identifying and forecasting economic time series. This paper will examine the performance of neural networks with that of time series methods for predicting conmmodity prices.

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1. Introduction

Price forecasting is an integral part of commodity trading and price analysis. Quantitative accuracy with small errors, along with turning point forecasting power, are both important in evaluating forecasting models. Numerous studies have found that univariate time series, such as Box-Jenkins ARIMA models are as accurate as more expensive linear regression or vector autoregressive models [2, 10, 12]. The success of linear models, however, is conditional upon the underlying data generating process being linear and not being random. The traditional view in financial economics is that market prices are random and that past prices cannot be used as a guide for the price behaviour in the future. Chaos theory, however, suggest that a seemingly random process may have been in fact generated by a deterministic function that is not random. In such a case, ARIMA methods are no longer a useful tool for estimation and forecasting.

However, recent developments in the study of artificial neural networks show that feedforward neural networks are non-linear mapping structures that can approximate any arbitrary function [9, 15, 18]. Therefore, such a nonlinear model may be superior to ARIMA models for time series forecasting.

The objective of this study is to examine whether the neural network can outperform a traditional ARIMA model for forecasting commodity prices. Specifically, we use a neural network to forecast US cattle prices and compare the results with the ARIMA model as a benchmark. The remainder of the paper is organized as follows. In section 2, chaos theory is briefly discussed. In section 3, the traditional univariate time series approach to forecasting is described. In section 4, neural network architecture that is designed for this study is discussed.

Section 5 discusses evaluation methods for comparing the two forecasting approaches. Data and forecast procedure are discussed in section 6. Section 7 shows results obtained from ARIMA and artificial neural network simulations. In Section 8, overall evaluation and comparison of two techniques are discussed, and finally, section 9 provides the concluding remarks.

2. Chaos Theory and Forecasting

Chaos theory suggests that a time series which seems to be random may be generated by a deterministic function. An obvious example of such processes are random numbers generated by computers [5]. In such cases, it is quite possible that even simple dynamic structure involving only a few irreducible degrees of freedom can lead to complex dynamic trajectories [11]. As a result, statistical tests such as spectral analysis or autocovariance analysis will fail to differentiate between deterministic chaos and stochastic processes. Another difficulty with chaotic series is that linear models such as time series or regressions cannot capture regularities in such a series.

A logistic map function is a standard example by which the behaviour of chaotic processes can be explained. Consider the following data generating process

$$x_t = Ax_{t-1}(1 - x_{t-1}) \tag{2.1}$$

where x_{t-1} takes values between 0 and 1 and A is between 0 and 4. For positive values of A less than 3.5699, x_t generated by (1) is stable and well behaved. But, for values of A from the interval [3.5699, 4] the system becomes a low dimensional chaotic system. As a result, it produces a rich variety of behaviour which do not repeat themselves in small sample sizes. A more complex function which exhibits higher dimension chaotic behaviour is Mackey-Glass equation given by:

$$x(t) = \frac{ax(t - c)}{1 + x(t - c)^{10}} - bx(t) \tag{2.2}$$

where a = 0.2, b = 0.1, and c = 100.

If the data is not generated by a high dimension process, it should have short-term predictability, but not with the use of linear forecasting models [17]. However, in addition to the small sample size problem which is usually the case with most economic data, measuring the initial state x_0, even small errors in estimating the parameters of the model exponentially propagates into the future and makes the forecasting impossible. Occasional success of linear models in short run forecasting associated with the long run failure indicates that these models have not captured the true nature of data generating process [3].

The study of chaotic time series began in natural science, physics and chemistry, and further attracted economists for studying economic variables [35]. Empirical applications of non-linear dynamics are mainly concentrated in macro economic analysis or capital markets [1, 29]. However, recently, there have been a few studies trying to address non-linear dynamics in the commodity markets [3, 7, 37, 38]. Results of these studies are mixed, as Blank [3] and Chavas and Holt [7] found deterministic chaos in soybean futures market and dairy industry, while Yang and Brorsen [36] concluded that changes in cash prices of seven commodities they studied do not follow a low dimension deterministic chaos process. Yang and Brorsen [37] also found no strong support for or against deterministic chaos in the futures markets for most of the above commodities.

As far as forecasting is concerned, the most difficult part is the modelling of chaotic time series. As discussed above, small measurement errors or simplifying assumptions in non-linear modelling may amplify further into the forecasting horizon and, as a result, produce unsatisfactory forecasts. Artificial neural networks provide an alternative for modelling chaotic time series. Since they are data-driven approaches, as opposed to model-driven approaches, therefore, they do not suffer from model misspecification per se [6]. Hence, Lapedes and Farber [22], and white [34], were able to well approximate the logistic map and high dimensional Mackey-Glass chaos with the neural network.

3. ARIMA Time Series Model

Dorfman and McIntosh [10] suggest that "structural econometrics may not be superior to time series techniques even when the structural modellers are given the elusive true model." Therefore, a common approach to forecasting is the Box-Jenkins ARIMA time series approach which is used here for comparison with the neural networks. It has attracted researchers because it is a parsimonious approach which can represent both stationary and non-stationary stochastic processes [13]. The objective here is to build an Autoregressive Integrated Moving average model (ARIMA) which adequately represents the data generating process. This basic Box-Jenkins model has the following form:

$$y_t = \alpha_o + \Sigma\alpha_i y_{t-i} + \Sigma\beta_j e_{t-j} \quad i=1...p \text{ and } j=0,1,...q \qquad (3.1)$$

where y_t is a stationary stochastic process with non-zero mean , α_o is constant term, and e_t is a white noise disturbance term. The second and third terms in the right hand side of equation 3.1 are autoregressive and moving average parts of the model. Equation 3.1 is denoted by ARIMA(p,d,q) in which p is the number of dependent variable lagged in the right hand side, "d" is the number of differencing performed on y_t before estimating the above model, and q is the number lagged error term in the right hand side of Eq. 3.1.

Box-Jenkins method involves the following four-step iterative cycle:

(i) model identification,

(ii) model estimation,

(iii) diagnostic checking, and

(iv) forecasting with the final model

Forecasting with the estimated model is based on the assumption that the estimated model will hold in the horizon for which the forecasts are made. The AR part of the model indicates that the future values of y_t are weighted averages of the current and past realizations. Similarly, the MA part of the model shows how current and past random shocks will affect the future values of y_t.

4. The Artificial Neural Network Approach

Artificial neural networks are computational structures modelled on the gross structure of the brain. As far application to economics is concerned, they have been primarily used to address financial economics problems. Typical applications in finance have included mortgage risk assessment, economic prediction, risk rating of exchange-traded fixed-income investments, portfolio selection/diversification, simulation of market behaviour, index construction, and identification of explanatory economic factors. For example, the US government in 1989 "embarked on a five-year, multi-million dollar program for neural network research, but financial services organizations have been the principal sponsors of research in neural network applications" [33].

There are a number of studies in which, along with conventional methods, neural networks are used to address financial economic problems [19, 21, 26, 30, 31, 32, 33]. For instance, Surkan and Singleton [31] found that the neural network model outperforms the "multivariate discriminate analysis" (MDA) for bond rating. In their study, the neural network model provided 88% correct classification compared with, at most, 56.6% by the MDA method. Odom and Sharda [26] set up both MDA and neural network models for predicting bankruptcy for various companies listed in the Wall Street Journal. They also found that neural networks were over 20% more accurate that the MDA. Trippi and DeSieno [33] compared a neural network based trading strategy in S&P 500 Index futures with passive buy and hold strategy. They found that the neural network model strongly outperformed buy and hold strategy by as high as 228%, even after inclusion of brokerage charges.

4.1 Feedforward network with conjugate gradient algorithms

Feedforward networks are a class of neural network which performs supervised learning. Prediction with the neural network involves the following two steps: training and forecasting. For training, the sample data are broken down into training set, which consists of major part of the data (e.g. 75%-90%), and testing set. At the training stage, both inputs and desired output are presented to the network. Through learning algorithms, the network produces its own output and tries to minimize the discrepancies between its own output and the target output. If the series to be predicted is not random, a well trained network should be able to forecast the remainder of sample data, the testing set. Otherwise, the architecture and/or parameters of the network are changed to improve performance on the testing set. A satisfactorily tested network then can be used for forecasting.

Training a network can be described as moving down an error surface which takes place by weight adjustments during the learning phase. The standard backpropagation network, proposed by the PDP group [24] and others, employs the steepest descent algorithm for adjusting the weights. The magnitude of adjustments depends on the learning rate and momentum factors selected by the researchers. Selecting a high learning rate may cause the network to jump from one side of the error surface to the other side and never reach the minimum point. On the other hand, a low learning rate slows down the training and may cause the network to be trapped in local minima. The conjugate gradient method used in this study is an improvement over steepest descent method in the sense that it explores the minimization of the network error in all possible directions and guarantees the network convergence. Moreover, it does not require to set the learning rate and momentum factors.

The conjugate gradient method (CG) constructs a set of n directions which are all conjugate to each other along the minimization direction u such that minimization subdirections u_i's are not interfering. The Fletcher-Reeves version of CG method is as follows [20]: consider the function $f(x)$ to be minimized can be approximated by the Taylor series

$$f(x) = (1/2)\, x' A x - b' x + c \qquad (4.1.1)$$

where ' denotes transpose and $b \equiv -\nabla f|_p$ and A is matrix of the second partial derivatives of $f(x)$ over all patterns. A change in x results in the change in the gradient of $f(x)$ as

$$\delta(\nabla f(x)) = A\,(\delta x) \qquad (4.1.2)$$

When $f(x)$ is to be minimized along direction u_i, the perpendicularities of the gradients ensure that moving along u_{i+1} does not impair minimization along u_i. In such case u_i and u_{i+1} are said to be conjugate. This is true when the following equation holds:

$$u_t = u_t'(g_{t+1} - g_{t+2}) = u_t'\delta(\nabla f(x)) = u_t'Au_{t+1} \tag{4.1.3}$$

Starting the minimization at any point results in new points until all possibilities are exhausted and the minimization is completed.

5. Forecast Evaluation Methods

Three criteria will be used to make comparison between the forecasting ability of the ARIMA time series model and the neural network model. The first is mean squared error, MSE, which measures the overall performance of a model. The formula for MSE is

$$MSE = \frac{1}{T}\Sigma(P_t - A_t)^2 \tag{5.1}$$

Where P_t is the predicted value for time t, A_t is the actual value at time t, and T is the number of predictions.

The second criterion is the absolute mean error, AME. It is a measure of average error for each point forecast made by the two methods. AME is given by

$$AME = (1/T)\Sigma|P_t - A_t| \tag{5.2}$$

While MSE and AME are good measures of deviation of predicted values from the actual values, they do not say much about the power of models in predicting the turning points. For many traders and analysts the market direction and turning points are as important as the value forecast itself. "In these markets, money can be made simply by knowing the direction in which the series will move" [25]. A correct turning point forecast requires:

$$\text{sign}(P_t - A_{t-1}) = \text{sign}(A_t - A_{t-1})$$

Ability of a model to forecast the turning points can be measured by a third method developed by Cumby and Modest [8] which is a version of Merton's test [23]. Merton's test is as follows: define a forecast variable F_t and an actual direction variable A_t such that

$$A_t = 1 \text{ if } \Delta A_t > 0 \text{ and } A_t = 0 \text{ if } \Delta A_t \leq 0 \qquad (5.3)$$

$$F_t = 1 \text{ if } \Delta P_t > 0 \text{ and } F_t = 0 \text{ if } \Delta P_t \leq 0 \qquad (5.4)$$

where ΔA_t is the amount of change in actual variable between time t-1 and t and ΔP_t is the amount of change in the forecasting variable for the same period.

The probability matrix for the forecasted direction of changes in the actual value conditional upon the direction of changes in the forecasting variable F_t is

$$P_1 = \text{Prob}[F_t = 0 | A_t = 0] \qquad (5.5)$$

$$1 - P_1 = \text{Prob}[F_t = 1 | A_t = 0] \qquad (5.6)$$

$$P_2 = \text{Prob}[F_t = 1 | A_t = 1] \qquad (5.7)$$

$$1 - P_2 = \text{Prob}[F_t = 0 | A_t = 1] \qquad (5.8)$$

In other words, (5.5) and (5.7) are the probability that the forecasted direction have actually occurred and (5.6) and (5.8) are probabilities of wrong forecasts.

By assuming that the magnitude of changes in F_t and A_t are independent, Merton [23] showed that a necessary and sufficient condition of market timing ability is that

$P_1(t) + P_2(t) > 1$

i.e. the forecaster on average has to be right in more than half of the time the forecasts are made. So the null hypothesis to be tested is

$$H_0 : \quad P_1 + P_2 - 1 \leq 0$$

vs

$$H_1 : \quad P_1 + P_2 - 1 > 0$$

Cumby and Modest [8] showed that the above hypothesis can be tested through the regression equation:

$$X_t = \alpha_0 + \alpha_1 A_t + \varepsilon_t \tag{5.9}$$

where

X_t is the change in actual price from previous period at time t

A_t is the realized price direction variable defined in (5.3)

ε_t is the error term,

$\alpha_1 = P_1 + P_2 - 1$,

and an α_1 significantly different from zero is needed to prove the forecasting ability.

6. Data and Forecast Procedure

Monthly commodity prices ($/100 lb.) of US beef cattle (900-1100 lb) traded in Omaha are used to test the prediction power of the two approaches. Data are obtained from the CRB Commodity Year Book, various issues, and covers period 1973-1987. Monthly data from 1973 through 1986 are used to estimate the time series model. The estimated coefficients are then used to forecast cattle prices *out of sample* and twelve steps ahead without updating. The forecasted values are then compared with the actual prices for 1987. The same monthly data, 1973-1986, are also used for training and testing the neural network and to predict monthly cattle prices out of sample in 1987.

7. Results

7.1 ARIMA time series results

7.1.1 Identification and estimation results

Results of the identification step suggest that an ARIMA(3,1,0) can best represent the price behaviour for the period of study. The Maximum Likelihood Estimate of the model produced:

$$y_t = 0.09644 + 0.25228 y_{t-1} - 0.27087 y_{t-2} - 0.18760 y_{t-3} \qquad (7.1)$$

$$(0.59) \qquad (3.49) \qquad (-3.61) \qquad (-2.48)$$

T statistics in parentheses show that all coefficients are significant other than the constant term. However, since the mean is not subtracted from differenced data, therefore, the constant term is kept in the model for the forecasting step.

7.1.2 Diagnostic checking

Plots of autocorrelation of estimated residuals were inside the two standard error bands (figure 1). This is indicates a white noise error term in the estimated model and proper modelling procedure in that all information has been extracted from the error terms. Ljung-Box test statistics reported in Table 1 show that all estimated probabilities are greater than 1%. Therefore, equation 7.1 can be considered as an acceptable representation of data generating process for the ARIMA model.

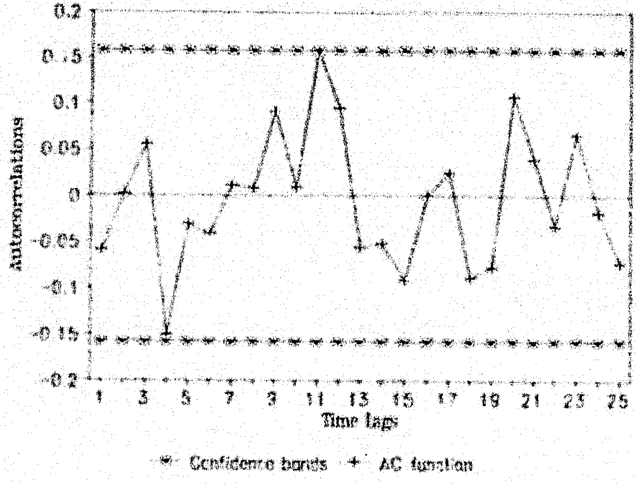

Figure 1. Plot of Residuals Autocorrelation After Differencing

7.1.3 Forecasting results

Results of time series forecasts using equation 7.1 are shown in Table 2. Results show mean squared errors of 36.79 for the ARIMA model. Absolute mean errors indicated that forecasted prices by ARIMA were as much as 5.33 different from the actual prices. Results also show a 8.1% forecasting error.

7.2. *Neural Network Results*

7.2.1 The network's architecture

A multi-layer feedforward neural network with one hidden layer was set up (figure 2). To make the comparison with the time series models, twelve lags of the data series were assumed to be sufficient as inputs to the network to forecast current prices. At the training stage, various numbers of neurons in the hidden layer were examined. The best results were produced by nine neurons in the hidden layer. The output layer had one neuron which was set up to output the current prices. With the above specifications, it took *2666* iterations to train the network

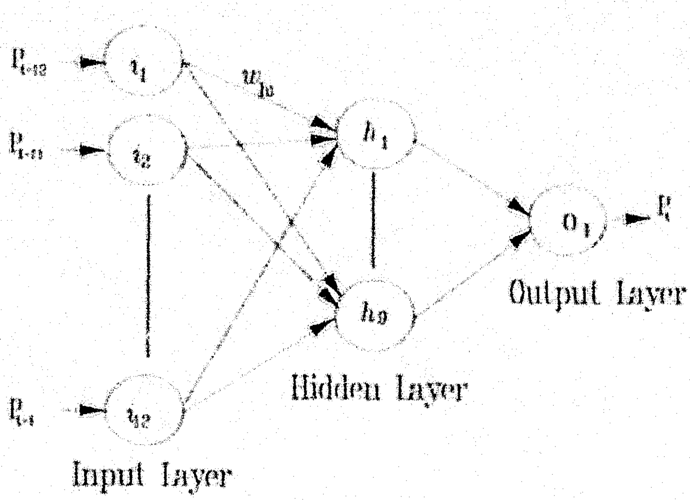

Figure 2. The Proposed Price Forecasting Neural Network Model

7.2.2 Forecasting with the trained network

To do forecasting out of sample, 12 months of 1986 prices were fed into the trained network to forecast the first month of 1987 out of sample. To forecast the second month of 1987, the forecasted price for the first month replaced one of previous inputs, the first one, and a new forecast was obtained without training the network, i.e. at the forecasting stage no training took place and no prices from actual 1987 data, other than the network's own forecasts were fed into the network. This process of forecasting and recursively substituting continued until all 12 months out of sample forecasts of 1987 prices were obtained.

Results of the neural network forecasts are shown in Table 2. Results show that the MSE was 7.99, which is over 450% lower than 36.79 for the ARIMA.

8. Evaluation and Comparison

8.1 Quantitative evaluation

In terms of quantitative forecasts, Table 2 results clearly show that the ARIMA model is outperformed by neural network. The absolute mean error for the ARIMA is 5.33 while this same error measure is much lower at 1.84 for the neural network forecasts. On percentage terms, the last two columns of Table 2 show that neural network errors were three times lower than ARIMA.

8.2 turning point evaluations

Plots of the two forecasts along with the actual prices are shown in Figure 3. A graph of the actual prices shows that in 1987 there were four turning points in months 1, 5, 8, and 10. Figure 2 shows that only one of the four turning point, month 5, was predicted by ARIMA. On the other hand, the neural network was able to predict almost all of them. However, the neural network made a mistake by predicting one additional turning point between months 6 and 8 which did not materialize.

The formal statistical test of turning points for both models is performed by estimating equation 5.9 above and results, (after adjusting for autocorrelation), are shown in Table 3. The t ratio of slope coefficient, α_1, for the ARIMA model shows that it is not statistically different from zero. This implies that for the period of 1987 the ARIMA model had extremely limited turning point forecasting power. On the other hand, for the neural network predictions, α_1 is highly significant and different from zero. This evidence supports the turning point forecasting power of neural network in addition to accurate price level forecasts.

9. Conclusion

The traditional view in economics is that market prices are random and that past prices cannot be used as a guide for the price behaviour in the future. However, this view is consistent only with linear models and linear tests [5]. In the case of chaotic time series, this conclusion that prices are unpredictable cannot be drawn without applying non-linear tests and models. This study used a nonlinear neural network approach by examining commodity prices using US cattle prices. Results showed that the neural network provided more accurate forecasts than the ARIMA model. This may be because neural networks are nonlinear, and picking up some nonlinearities which the ARIMA model cannot. Finally, the neural network results here conform to the theoretical proofs that a feedforward neural network with only one hidden layer can precisely and satisfactorily approximate any continuous function.

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Table 1. Ljung-Box Test for the ARIMA Residual Autocorrelation.

To Lag	Chi Square	Degrees of Freedom	Probability
6	5.47	3	0.14
12	12.92	9	0.17
18	17.10	15	0.31
24	21.90	21	0.41
30	23.89	27	0.637

A probability value greater that 0.05 indicates that the estimated model is a reasonable representation of the data generating process for the ARIMA model.

Table 2. Results of US Monthly Cattle Price Forecasts by the ARIMA and Neural Network compared, 1987.

Month	Actual	Forecasts		Sq. Errors		Abs. Errors		% Errors	
		ARIMA	NN*	ARIMA	NN	ARIMA	NN	ARIMA	NN
1	58.79	59.7	59.6	0.90	0.66	0.95	0.81	1.6%	1.4%
2	61.02	58.6	59.9	6.05	1.37	2.46	1.17	4.0%	1.9%
3	61.58	58.7	61.4	8.29	0.04	2.88	0.2	4.7%	0.3%
4	66.3	58.8	62	56.25	18.75	7.5	4.33	11.3%	6.5%
5	70.66	59.2	64	131.10	44.89	11.45	6.7	16.2%	9.5%
6	68.83	59.1	63.6	95.65	26.94	9.78	5.19	14.2%	7.5%
7	65.8	59.4	65.6	40.70	0.03	6.38	0.18	9.7%	0.3%
8	64.5	59.5	64.7	24.70	0.03	4.97	0.16	7.7%	0.2%
9	64.81	59.9	65.3	23.72	0.23	4.87	0.48	7.5%	0.7%
10	64.81	60	63.9	22.75	0.85	4.77	0.92	7.4%	1.4%
11	64.2	60.1	63.5	16.56	0.44	4.07	0.66	6.3%	1.0%
12	63.93	60.1	62.6	14.82	1.72	3.85	1.31	6.0%	2.0%
Mean				36.79	7.99	5.33	1.84	8.1%	2.7%

*Neural Network

Table 3. Results of Merton's Test of Turning Point Forecasting Power for the ARIMA and Neural Network.

	$X_t = \alpha_0 + \alpha_1 A_t + \varepsilon_t$		
	α_0	α_1	R^2
ARIMA Model	-0.23	0.85	0.03
(t ratio)	(-0.39)	(0.62)	
Neural Network	-0.84*	2.37*	0.28
(t ratio)	(2.93)	(2.23)	

*Significant at 5 percent levels.