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Forecasting Hog Prices with a Neural Network

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Abstract: *Neural network models were compared to traditional forecasting methods in forecasting the quarterly and monthly farm price of hogs. A quarterly neural network model forecasted poorly in comparison to a quarterly econometric model. A monthly neural network model outperformed a monthly ARIMA model with respect to the mean square error criterion and performed similarly to the ARIMA model with respect to turning point accuracy. The more positive results of the monthly neural network model in comparison to the quarterly neural network model may be due to nonlinearities in the monthly data which are not in the quarterly data.*

Key Words and Phrases: *Forecasting, Hog prices, Neural networks, ARIMA, Econometric.*

Econometric and autoregressive-integrated-moving average (ARIMA) models are commonly used to generate forecasts of commodity prices. Both econometric and ARIMA models have been developed and compared for the purpose of forecasting the monthly and quarterly farm price of hogs, e.g., Brandt and Bessler (1981, 1983); Harris and Leuthold; and Leuthold, Garcia, Adam and Park. Generally, these models are linear. If there are nonlinearities in the process being modeled, then a method which can account for these nonlinearities should produce superior forecasts. Neural networks are reported to be such a method. Neural networks are capable of approximating almost any nonlinear function (Kuan and White).

The purpose of this paper is to determine how well a neural network can predict quarterly and monthly hog prices relative to traditional methods. The first part of this paper briefly explains neural networks and some of their applications. Part two presents econometric and neural network forecasting models for the quarterly price of hogs and ARIMA and neural network forecasting models for the monthly price of hogs.¹ Part three presents the evaluation procedures to evaluate the forecasting ability of the models. In particular, part three explains the Henriksson-Merton (HM) test for informational value in directional forecasts. Part four presents the forecasting performance of the neural network, ARIMA and econometric models. The last part summarizes the research findings and discusses the results.

Neural Networks

The popularity of neural networks has extended into almost every area of science. Neural networks have been used to translate printed English into speech (Sejnowski and Rosenberg) and to decode deterministic chaos (Lapedes and Farber). Neural networks have been compared with time series forecasting techniques such as the Box-Jenkins approach (Tang, Almieda and Fishwick; Hill et al.). Kang provides a good comparison using the M-111 competition data. In agricultural-economics-related areas, neural networks have been applied to corn yield prediction (Uhrig, Engel and Baker), price prediction (Claussen and Uhrig; Kohzadi et al.), and production function estimation (Joerding, Li and Young). Forecasts of monthly live cattle and wheat prices from neural networks and ARIMA models were compared in a study by Kohzadi et al. who claimed that the neural network forecasts were considerably more accurate than those of the traditional ARIMA models. Generally the studies concerning time series data have concluded that neural networks are at least as effective as Box-Jenkins time series models, and sometimes better, in providing forecasts.

The development of neural networks was inspired by the way information is processed by a collection of brain cells or neurons. Therefore, the development of neural networks has its roots in neuroscience; however, it would be inaccurate to say that neural networks simulate the behavior of the human brain.

The process by which biological neurons process information is complex. The communication between biological neurons is both electrical and chemical and each of these communication processes is complex. As will become clear, the neurons or processing elements in a neural network are simple nonlinear functions and the "communication" between the neurons is linear. Therefore, a neural network is neither a realistic description of a small group of neurons nor of the human brain which contains about 1.5×10^{10} neurons with each neuron receiving signals from 10 to 10^4 other neurons (Ripley). If a neural network is not a model of the brain, what is it?

In general, a neural network can be viewed as estimating a mapping $f: X \rightarrow Y$ where X is the space of inputs or independent variables and Y is the space of outputs or dependent variables. The ability of a neural network to estimate the mapping function f is called the universal approximation property or nonlinear approximation property. In other words, the functional form of the model need not be made explicit, as is done in a traditional nonlinear regression. Neural networks have a flexible nonlinear functional form, thus a neural network approximates a function which relates the independent to the dependent variables. There are several types of neural networks which possess the universal approximation property, the most popular being feedforward neural networks. This research is limited to the feedforward neural network. The following section explains the specifics of the feedforward neural network. It will become clear in the following discussion that a neural network may be interpreted as a nonlinear regression function (Kuan and Liu). Economists are

likely to find neural networks easier to understand if they view them in the framework of a nonlinear regression.

Neural networks are often illustrated graphically as in Figure 1. Each circle in Figure 1 is called a neuron. These neurons are arranged in layers: an input layer, an output layer, and one or more hidden layers. In Figure 1 there are two input neurons in the input layer, two hidden neurons in one hidden layer, and two output neurons in the output layer. The input layer contains the input neurons which correspond to the independent variables of a regression. Similarly, the output layer contains the output neurons which correspond to the dependent variables in a regression. Note that similar to a vector autoregression model, there can be more than one output.

To illustrate a neural network mathematically, suppose we have n inputs in the input layer, p hidden neurons in one hidden layer, and q neurons in the output layer. Then at time t , or for observation t , each of the n neurons in the input layer contains the value of one of our n independent variables at time t . The i th neuron in the input layer is connected with the j th neuron in the hidden layer via a parameter γ_{ij} . The value of each hidden neuron j at time t , h_{jt} , is a nonlinear function ψ of a weighted average of the values in the input layer plus a parameter γ_{0j} which is analogous to an intercept in a regression:

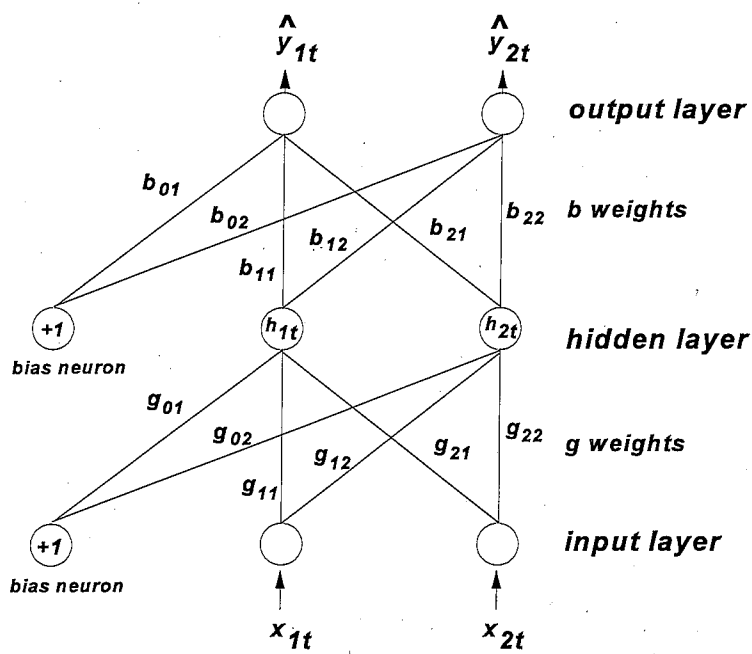
$$h_{jt} = \psi_j \left(\gamma_{0j} + \sum_{i=1}^n \gamma_{ij} x_{it} \right) \quad j = 1, \dots, p, \tag{1}$$

where p is the number of hidden neurons and ψ_j is a nonlinear function which maps from \mathbb{R} to \mathbb{R} . The function ψ_j is often called a transfer function. The nonlinear transfer functions in the hidden layer(s) are responsible for the nonlinear approximation capabilities of a neural network. The bias neuron shown in Figure 1 is equivalent to an input variable whose value is always one.

The functional form of the nonlinear transfer functions ψ_j in (1) can be chosen quite freely; however, the functions are generally monotonically increasing. The two most common functions are the sigmoid and the hyperbolic tangent given by $f(x) = 1 / (1 + \exp(-x))$ and $f(x) = (\exp(x) - \exp(-x)) / (\exp(x) + \exp(-x))$ respectively. The sigmoid function scales the output from each neuron to be between 0 and 1 and the hyperbolic tangent function scales the output from each neuron to be between -1 and 1. Note that the transfer functions in the hidden layer(s) are indexed by j signifying that each hidden neuron can have a different transfer function. However, it is common to choose all the transfer functions to have the same functional form.

Each hidden neuron h_{jt} is connected to each of the q output neurons \hat{y}_{kt} in the output layer via a parameter β_{jk} , where j is the hidden neuron and k is the output neuron. The output of the k th output neurons at time t is given by the following:

Figure 1.
Feedforward Neural Network with One Hidden Layer, Four Input Variables and Two Output Variables



$$\hat{y}_{kt} = F_k \left(\beta_{0k} + \sum_{j=1}^p \beta_{jk} h_{jt} \right), \quad k = 1, \dots, q, \tag{2}$$

where \hat{y}_{kt} is the predicted value of y_{kt} . The transfer functions F_k in (2) can be chosen to be a nonlinear transfer function or the identity function, $F(a) = a$. It is only necessary for the hidden layer transfer functions to be nonlinear for the nonlinear approximation capabilities of the network to hold. If a neural network has more than one hidden layer, the output from the hidden neurons in (1) would be processed by the next hidden layer. The output from each hidden layer is processed by the next succeeding hidden layer. The output from the last hidden layer would be processed as in (2). Putting (1) and (2) together and assuming a linear transfer function in the output layer and one output neuron we get:

$$\hat{y}_t = G(\mathbf{X}_t, \theta) = \beta_{0k} + \sum_{j=1}^p \beta_{jk} \psi_j(\gamma_{0j} + \sum_{i=1}^n \gamma_{ij} x_{it}), \quad (3)$$

where \mathbf{X}_t is an n -vector containing the independent variables and θ is a set containing all parameters β and γ . The parameters β and γ are often called weights in the neural network literature.

From the proceeding discussion, we can see that there are two types of neurons in a neural network, those that "hold" values and those that are nonlinear processors. The inputs neurons "hold" the values of the inputs (independent variables) for a specific observation of the data and the hidden neurons are processing elements. If the output layer transfer function is linear than the output neurons "hold" the values of the outputs (dependent variables), otherwise they are also nonlinear processors.

From (3) it is easy to see that a neural network is a regression equation with a highly nonlinear functional form. Therefore, some of the concepts and tools with which economists would be familiar can be applied with neural networks. An example would be the various nonlinear estimation techniques, such as the various quasi-Newton methods, that could be used to estimate the parameter set θ . The neural network literature refers to estimation of the parameter set θ as learning. The traditional learning algorithm to estimate the parameter set θ is known as backpropagation. The feedforward type of neural network given in (1), (2) and (3) is sometimes called the backpropagation network. It is important to separate the specific functional form of the neural network from its learning algorithm. Feedforward networks are not intimately tied with the backpropagation learning algorithm. Other algorithms more familiar to economists can be used.

Until recently, and perhaps even still, backpropagation was sometimes viewed with mystique. As Kuan and White write:

For a period, artificial neural network models coupled with the method of backpropagation came to be viewed as magic, with considerable accompanying hype and extravagant claims (p. 18).

Backpropagation is a quasi-gradient descent method whereby the parameters are updated after presentation of each observation. Adjusting or updating the parameters after each observation is sometimes called recursive least squares. Those familiar with nonlinear optimization know that gradient descent has poor convergence properties. This can be seen empirically in the neural network literature in which thousands or tens of thousands of iterations are required. In addition, various methods have been used to stop the iterations before convergence is achieved. Thus, reported results may not be replicable.

For most implementations that economists would be interested in, traditional nonlinear least squares is probably the preferred estimation method. In traditional

nonlinear least squares the SSE is minimized.² SSE is defined as:

$$\text{SSE} = \sum_t (\hat{y} - y)^2 \quad (4)$$

Thus, to find the parameter set θ we solve:

$$\min_{\theta} \text{SSE} = \min_{\theta} \sum_t (G(X_t, \theta) - y)^2 \quad (5)$$

where $G(X_t, \theta)$ is from (3). Solving (5) can be done using optimization methods such as Levenberg-Marquardt, various Newton methods, and conjugate gradient methods (see Hagan and Menhaj; Johansson, Dowla and Goodman; Barnard; Battiti; Kinsella). In this research we use a quasi-Newton algorithm. Finding a solution to (5) is complicated by numerous local minimums because of the complicated functional form and the large number of parameters of neural networks. Some research has been done with global optimization algorithms in the context of neural networks, e.g., Baba et al; Chin; Brunelli; Styblinski and Tang. For simplicity, a method involving many restarts from random starting values is used here.

Forecasting Models

Forecasting models for the quarterly and monthly price of hogs are developed. The following sections describe development of econometric and neural network models for forecasting quarterly hog prices and ARIMA and neural network models for forecasting monthly hog prices.

Quarterly Econometric Model. The econometric model is a single-equation, reduced-form model with lagged supply and demand variables. Supply of hogs in quarter t is represented as a function of the pig crop in quarter $t-1$ and $t-2$. Beef is assumed to be a substitute for pork; therefore, cattle placed on feed during quarter $t-2$ is included to represent cattle slaughter in quarter t . Chicken is not included as a substitute because of the insignificant relationship with pork demand (Moschini and Meilke). Following Brandt and Bessler (1983) the hog-corn price ratio for quarter $t-1$ is included as an explanatory variable. Per-capita disposable income should be positively related to price.

The proposed econometric model is

$$PH_t = f(PC_{t-1}, PC_{t-2}, CPOF_{t-2}, H/C_{t-1}, \log(I_{t-1}/N_{t-1})) \quad (6)$$

where PH is the quarterly price of barrows and gilts in dollars per hundredweight; PC is the ten-state quarterly pig crop, 1,000 head; CPOF is the thirteen-state cattle placed on feed during the quarter, 1,000 head; H/C is the hog-corn price ratio; and $\log(I/N)$ is the log of per capita disposable income. The quarterly hog price is a quarterly average of the monthly prices used in the monthly model discussed in the next section. The pig crop, cattle placed on feed, and hog-corn ratio data were collected from the U.S. Department of Agriculture *Hogs and Pigs* (U.S. Department of Agriculture, 1974-1996d), *Cattle on Feed* (U.S. Department of Agriculture, 1974-1996c), and *Agricultural Prices* (U.S. Department of Agriculture, 1974-1996a), respectively. Per capita disposable income was collected from the *Survey of Current Business* (U.S. Department of Commerce). The specific time periods to be used for estimation and forecasting are given in Table 1.

The econometric model was originally estimated using ordinary least squares. This estimation produced a Durbin-Watson statistic of 1.012 over the first time period of estimation given in Table 1. This suggests positive autocorrelation at the 1 percent significance level. It was determined that a first-order autoregressive process was appropriate for this model. For the first time period of estimation the estimated model with t-value given in parentheses is given below:

$$\begin{aligned} PH_t = & -290.920 - 0.0005566 PC_{t-1} - 0.0009910 PC_{t-2} - 0.0019692 CPOF_{t-2} \\ & (-1.821) \quad (-1.283) \quad (-3.426) \quad (-2.197) \\ & + 0.60910 H/C_{t-1} + 43.2210 I/N_{t-1} + \varepsilon_t \\ & (2.439) \quad (2.188) \end{aligned} \quad (7)$$

$$\varepsilon_t = .53782 \varepsilon_{t-1} + u_t$$

$$(4.465)$$

$$\text{adjusted } R^2 = .5785$$

where u_t is an identically, independently distributed error term. All coefficients except for the constant and coefficient on PC_{t-1} are significant at the 5 percent level. All coefficients are of the expected sign. The estimation was done using Shazam, software version 7.0.

Table 1.

Time Periods Pertaining to Estimation and Forecasting for Econometric and Neural Network Forecasting Models for Quarterly Hog Prices

| Period Number | Estimation Interval Year.Quarter | Forecasting Interval Year.Quarter |
|---------------|-------------------------------------|--------------------------------------|
| 1 | 1973.4-1985.4 | 1986.1-1987.4 |
| 2 | 1975.4-1987.4 | 1988.1-1989.4 |
| 3 | 1977.4-1989.4 | 1990.1-1991.4 |
| 4 | 1979.4-1991.4 | 1992.1-1993.4 |
| 5 | 1981.4-1993.4 | 1994.1-1995.2 |

Monthly ARIMA Model. The Box-Jenkins methodology (Box and Jenkins) was used to build an ARIMA model to forecast the monthly price of hogs. The price of hogs was the monthly price of barrows and gilts as reported by USDA's *Livestock and Poultry Situation and Outlook* (U.S. Department of Agriculture, 1974-1993) subsequently renamed *Livestock, Dairy and Poultry Situation and Outlook* (U.S. Department of Agriculture, 1994-1996).³ The specific time periods to be used for estimation and forecasting are given in Table 2.

An ARIMA(p,q) model has the following basic form:

$$p_t = \mu + \sum_{i=1}^p \phi_i p_{t-i} + \sum_{i=1}^q \alpha_i e_{t-i} + e_t, \quad (8)$$

where e_t is white noise. The basic ARIMA model specifies that the process being modeled must be stationary or time invariant. To ensure stationarity of the monthly hog price time series, first differences are taken. Taking first differences creates a new time series

$$z_t = p_t - p_{t-1}, \quad (9)$$

where p_t is the monthly price of hogs. The stationarity of a time series can be statistically tested by checking for a unit root. Two such tests are the Dickey-Fuller

Table 2.

Time Periods Pertaining to Estimation and Forecasting for ARIMA and Neural Network Forecasting Models for Monthly Hog Prices

| Period Number | Estimation Interval | Forecasting Interval |
|---------------|---------------------|----------------------|
| | Year.Month | Year.Month |
| 1 | 1973.7-1990.6 | 1990.7-1991.6 |
| 2 | 1974.7-1991.6 | 1991.7-1992.6 |
| 3 | 1975.7-1992.6 | 1992.7-1993.6 |
| 4 | 1976.7-1993.6 | 1993.7-1994.6 |
| 5 | 1977.7-1994.6 | 1994.7-1995.6 |

(Dickey and Fuller) and the Phillips-Perron unit root tests (Phillips; Perron). In all estimation periods in Table 2, both tests rejected the presence of a unit root in the first-differenced data.

Using the Box-Jenkins methodology an ARIMA model with no mean and autoregressive terms at lags 1, 2 and 11 and moving-average terms at lags 1, 2 and 12 was specified. Estimation results for the first estimation period in Table 2 are presented below with *t* statistics in parentheses:

$$z_t = 1.0411z_{t-1} - 0.5253z_{t-2} + .3140z_{t-11} - 0.9398e_{t-1} + 0.3325e_{t-2} - 0.3490e_{t-12} \quad (10)$$

(14.950) (-8.209) (8.057) (-11.200) (3.823) (-9.999)

where Δz_t is the first difference of the monthly price of hogs given in (2). The estimation was done using Shazam software version 7.0. Using the Box-Jenkins methodology, the specification of the monthly ARIMA model in (10) is subject to individual interpretation. An advantage of a neural network over an ARIMA model is that all lags that may be significant can be inputs to a neural network and given enough data, the neural network will determine which ones are significant.

Neural Network Models. The inputs (independent variables) and outputs (dependent variables) of the quarterly neural network model are the same as the independent and dependent variables of the quarterly econometric model. The output of the monthly neural network model is the first difference in the monthly price of

hogs as given in (9). The inputs are 12 lags of the output variable. The choice of 12 lags for the inputs was chosen a priori on an ad hoc basis. Theoretically, 24 or 36 lags could be used, then given enough observations of data, a neural network should be able to estimate a model which uses only those lags which are significant. However, as in most economic processes, the observations available to model the process are limited. In addition, more inputs to a neural network increase computational time. Thus, 12 lags were felt to be parsimonious yet sufficient to model the time series. The time periods of estimation and forecasting for the quarterly and monthly neural network models correspond to those of the respective quarterly econometric and monthly ARIMA models.

Once the inputs to a neural network are chosen, several critical parameters remain to be chosen for the neural network models, the number of hidden layers and number of hidden neurons. One hidden layer is all that is required for a neural network to be a "universal approximator" (Kuan and White). Thus both the quarterly and monthly neural network models were chosen to have one hidden layer. Choosing the number of hidden neurons is not as easy.

The number of hidden neurons determines to what degree the data can be "fit" by the neural network. If there are too many hidden neurons, the neural network will overfit the data and will produce poor forecasts. On the other hand, there need to be enough hidden neurons to sufficiently model the process at hand. Methods to pick the number of hidden neurons are, to a large extent, an open research question. For simplicity, the Schwartz Bayesian Criterion (SBC) is used in this research to pick the number of hidden neurons.

The SBC is a reasonably effective method of picking the number of hidden neurons and is computationally cheap (Sarle). Other methods are available, but they generally involve pretesting a network on a cross-validation subset of the data. These methods are appropriate in situations in which data is more plentiful. For the quarterly and monthly neural network models and for each of the estimation periods given in Table 1 and Table 2, a neural network is trained to convergence (to be explained in more detail below). For each of the estimation periods, the neural network configuration (number of hidden neurons) which minimizes the SBC is chosen to produce forecasts over the appropriate forecast interval.

The transfer functions were chosen to be the identity function for the output layer and the hyperbolic tangent for the hidden layer. There are theoretical reasons why the hyperbolic tangent transfer function in the hidden layer may help convergence of the learning algorithm (Kalman and Kwasny; Refenes et al.). Both the inputs and outputs of the neural networks are normalized or scaled between -1 and 1. Values of the hyperbolic tangent transfer function range between -1 and 1. Thus scaling the inputs and outputs can help limit numerical problems which can occur in the training of the neural networks.

Estimation of the parameters of the networks, i.e. θ in (3), was done using a Fortran program. The Fortran program was compiled using Microsoft Fortran Powerstation, version 4.0, and a quasi-Newton optimization algorithm in the IMSL math libraries to solve (5).⁴ As discussed in the neural networks section, the solution to (5) is complicated by that fact that there are many local minimums. To increase the probability of finding a global minimum, or a value close to the global minimum, the estimation or training procedure is performed 500 different times using 500 different randomly chosen starting values. For the 500 restarts, only the parameter set θ associated with the lowest SSE after convergence is retained. The SBC criterion is then computed from this network to choose the number of hidden neurons. One advantage of using many random restarts is that the results reported in this research are more likely to be replicable than past research which typically only considered one set of random starting values.

Evaluation Procedure

The forecasting accuracy of the ARIMA, econometric and neural network models are compared using mean squared error, turning point accuracy and the Henriksson-Merton test (HM test) for information value in the turning point forecasts.

Mean square error (MSE) is defined as

$$MSE = [\sum_t (P_t - A_t)^2 / n] \quad (11)$$

where n is the number of forecasts and P and A are predicted and actual values respectively. Small gains in forecasting accuracy can be of considerable economic benefit. Models have been proposed in which gains are proportional to the square of forecast errors (Hayami and Peterson; Freebairn). Such models offer support for using a criterion such as MSE for ranking forecasts.

A correct turning point forecast is defined as:

$$\text{sign}(P_t - A_{t-1}) = \text{sign}(A_t - A_{t-1}) \quad (12)$$

where P and A are as defined for (11). Percentage turning point accuracy (%TPA) is then defined as the percentage of forecasts in which (12) is satisfied. Correct turning point forecasts can provide valuable information to decision makers. However, it would be useful to have a statistical test of the ability of a set of forecasts to predict the future direction of a price series. Henriksson and Merton developed a

nonparametric statistic to evaluate a model's ability to predict direction.

The Henriksson-Merton test (HM test) is used to test the null hypothesis of no information in the forecasts. The HM test provides confidence and significance levels for rejection of the null hypothesis. As given in McIntosh and Dorfman, the confidence level, C , is given by:

$$C = 1 - \sum_{x=n_1}^{\min(N_1, n)} \binom{N_1}{n} \binom{N_2}{n-x} / \binom{N}{n} \quad (13)$$

where:

- N_1 = the number of observations with downward movement,
- N_2 = the number of observations with non downward movement,
- $N = N_1 + N_2$
- n_1 = the number of correct forecasts of downward movement,
- n_2 = the number of incorrect forecasts of downward movement,
- $n = n_1 + n_2$ = the number of forecasts of downward movement.

Equation (13) is based on the hypergeometric distribution. The significance level for rejection of the null hypothesis is given by $1-C$, where C is from (13).

Results

As discussed in the "Forecasting Models" section of this paper, the Schwartz Bayesian Criterion (SBC) was used to pick the number of hidden neurons for each of the forecasting periods for the quarterly and monthly neural network models. For the quarterly model, the SBC resulted in four hidden neurons for the first forecasting interval in Table 1 and six hidden neurons for the other four forecasting intervals. For the monthly model, two hidden neurons were chosen for period numbers 1, 3, 4 and 5 and three hidden neurons for period 2.

The performance of the quarterly econometric and neural network model is given in Table 3 and Table 4. Over all forecasting periods, the neural network forecasting models' MSE was 92.17 and %TPA .53 compared to the econometric models' MSE of 49.51 and %TPA .68. Thus the quarterly neural network model performed considerably worse than the econometric model. This is also reflected in Table 4 which presents the numbers for the HM test. We cannot reject the null hypothesis of no information value in the directional forecasts of the neural network model. However, in the case of the econometric model, the null was rejected at a significance level less than 3 percent.

Table 3.
Performance of Quarterly Hog Price Forecasts

| Forecast Interval Year.Quarter | Neural Network | | Econometric | |
|-----------------------------------|------------------|-------------------|-------------|------|
| | MSE ^a | %TPA ^b | MSE | %TPA |
| 1986.1-1987.4 | 85.35 | .38 | 106.12 | .50 |
| 1988.1-1989.4 | 31.63 | .63 | 37.39 | .75 |
| 1990.1-1991.4 | 145.99 | .75 | 67.98 | .75 |
| 1992.1-1993.4 | 45.08 | .38 | 13.89 | .63 |
| 1994.1-1995.2 | 173.00 | .50 | 13.09 | .83 |
| 1986.1-1995.2 | 92.17 | .53 | 49.51 | .68 |

^a Mean square error (MSE) for predictions.

^b %TPA is the percentage of correct turning point forecasts.

Table 4.
Test for Value of Information in Quarterly Hog Price Predictions

| Model | %TPA Upturn ^a | %TPA Downturn ^b | %TPA | HM Confidence Level ^c |
|----------------|------------------------------|--------------------------------|------|--|
| Neural Network | .40 | .67 | .53 | .5345 |
| Econometric | .80 | .56 | .68 | .9739 |

^a %TPA|Upturn is the percentage of correct turning point forecasts for those turning points in which there was an upward movement in the price series.

^b %TPA|Downturn is the percentage of correct turning point forecasts for those turning points in which there was a downward movement in the price series.

^c (1-HM Confidence Level) gives the significance level for rejecting the null hypothesis of no information value in the directional forecasts.

The performance of the monthly ARIMA and neural network model is given in Table 5 and Table 6. Over all forecasting periods, the neural network forecasting models' MSE was 11.96 and %TPA .60 compared to the ARIMA models' MSE of 15.62 and %TPA .62. The neural network performed better than the ARIMA model

Table 5.
Performance of Monthly Hog Price Forecasts

| Forecast Interval Year.Month | Neural Network | | ARIMA | |
|---------------------------------|------------------|-------------------|-------|------|
| | MSE ^a | %TPA ^b | MSE | %TPA |
| 1990.7-1991.6 | 14.37 | .58 | 12.26 | .50 |
| 1991.7-1992.6 | 14.08 | .42 | 17.40 | .67 |
| 1992.7-1993.6 | 10.97 | .58 | 17.51 | .67 |
| 1993.7-1994.6 | 10.91 | .58 | 14.76 | .75 |
| 1994.7-1995.6 | 9.44 | .83 | 16.18 | .50 |
| 1990.7-1995.6 | 11.96 | .60 | 15.62 | .62 |

^a Mean square error (MSE) for predictions.

^b %TPA is the percentage of correct turning point forecasts.

Table 6.
Test for Value of Information in Monthly Hog Price Predictions

| Model | %TPA Upturn ^a | %TPA Downturn ^b | %TPA | HM Confidence Level ^c |
|----------------|------------------------------|--------------------------------|------|--|
| Neural Network | .52 | .67 | .60 | .8819 |
| ARIMA | .54 | .71 | .62 | .9237 |

^a %TPA|Upturn is the percentage of correct turning point forecasts for those turning points in which there was an upward movement in the price series.

^b %TPA|Downturn is the percentage of correct turning point forecasts for those turning points in which there was a downward movement in the price series.

^c (1-HM Confidence Level) gives the significance level for rejecting the null hypothesis of no information value in the directional forecasts.

with respect to the MSE criterion, but not with respect to the %TPA criterion. Using the HM test, we fail to reject at the 5 percent significance level the null hypothesis of no information value in the directional forecasts for both the neural network and ARIMA models.

Summary and Conclusions

Econometric and neural network models were constructed to forecast the quarterly farm price of hogs and ARIMA and neural network models were constructed to forecast the monthly farm price of hogs. Thirty-eight out-of-sample forecasts of the quarterly price of hogs were produced from the econometric model given in (7) and a neural network model. The neural network model used the same information to produce forecasts as the econometric model. That is, the independent variables and dependent variables in the econometric model were the same as the inputs and outputs respectively for the neural network. The neural network model performed poorly in comparison to the econometric model.

The cause for this performance may be twofold. First, the true model in this case may be linear. A neural network should be capable of modeling a linear model as successfully as a corresponding linear econometric model. However, given the limited number of observations available for estimation, the neural network may have not converged to a linear model. Second, given the significant autocorrelation in the econometric model, a recurrent neural network (see Kuan and White; Connor, Martin and Atlas) would probably perform superior to the feedforward type of neural network used in this research.

Sixty out-of-sample forecasts of the monthly price of hogs were produced from the ARIMA model given in (10) and a neural network model. In the MSE criterion sense, the neural network model outperformed the ARIMA model. The neural network model performed similarly to the ARIMA model with respect to the %TPA (percentage turning point accuracy) criterion. The ARIMA model which was specified had moving average components. It has been shown that recurrent neural networks have an advantage over feedforward neural networks for time series with a moving average component (Connor, Martin and Atlas). Thus, as in the quarterly model, a recurrent neural network may have performed better in comparison to the feedforward neural network. However, software limitations limited this research to the feedforward type of neural network.

The more positive results of the monthly neural network model in comparison to the quarterly neural network model may be due to nonlinearities in the monthly data which are not in the quarterly data. Indeed, we may not expect a quarterly econometric model to exhibit nonlinearities. The monthly data also provided more observations which could be used to estimate the neural network. Given the difficulty, computationally and otherwise, in constructing a neural network forecasting model, it may be wise to consider a neural network forecasting model only in situations in which one would expect nonlinearities and a large number of observations are available for estimation.

Some success was demonstrated with the monthly neural network hog price forecasting model. Others have obtained positive forecasting results with neural networks on other price series (Kohzadi et al.). Therefore, further research in applying

neural networks to forecasting agricultural price series is warranted. More price series need to be considered as well as other types of neural networks, in particular, recurrent neural networks.

Notes

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1. The choice of a quarterly econometric model and monthly ARIMA model for comparison with corresponding neural network models may not seem consistent. A more logical choice might be quarterly and monthly ARIMA models and/or quarterly and monthly econometric models. The original research was restricted to the quarterly econometric model. Comments from the reviewers led us to consider a monthly model. A monthly econometric model would be difficult to specify and time series models often outperform econometric models. Thus, a monthly ARIMA model was chosen for another comparison between neural networks and traditional forecasting techniques.
2. In practice, $\frac{1}{2}$ the SSE is minimized. This can reduce the number of floating point operations needed to calculate the analytical derivatives of (4). The solution to (5) is identical whether minimizing SSE or $\frac{1}{2}$ SSE.
3. The specific prices used in this research were: July, 1973, through January, 1992, seven markets weighted average price; February, 1992, through February, 1994, six markets weighted average price; and March, 1994, through June, 1995, five markets weighted average price.
4. The specific optimization algorithm was DBCONG in the IMSL libraries. The weights of the neural network were constrained between -30 and 30. The maximum number of iterations was set at 1,500 and the maximum number function and gradient evaluations was set at 3,000. The starting values were initialized using the IMSL function DRNUN and were scaled between .3 and -.3.

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