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Milam Aiken
The University of Mississippi

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ABSTRACT

Forecasting the Gross Domestic Product (GDP) of the United States is one of many estimates to predict the economic health of the country. Current forecasting techniques use consensus estimates of experts, econometric models, or other statistical methods. Relatively little research has been devoted to how artificial neural networks may improve these forecasts, however. This paper describes how a neural network using leading economic indicator data predicted annual GDP percentage changes one year into the future more accurately than competing techniques over a ten-year period.

INTRODUCTION

Gross Domestic Product (GDP) is that part of Gross National Product (GNP) attributed to labor and property located in the United States. Economists seek to predict future changes in GDP, GNP, and other measures to recommend policy changes designed to preclude recessionary or inflationary periods. However, these forecasts often are inaccurate or untimely.

One technique which may increase the accuracy of economic forecasts is artificial neural network modeling. Neural networks have been applied to many financial applications that require prediction such as bankruptcies (Stocks, Singleton, & Aiken, 1995) and T-Bill rates (Aiken, 1995), and some research has shown how neural networks may be applied to macroeconomic forecasts (e.g., Aiken, 1996; Aiken, Krosp, Govindarajulu, Vanjani, & Sexton, 1995). This paper shows how a neural network may be used to forecast GDP in the United States more accurately than existing techniques.

FORECASTING THE ECONOMY

Several methods have been used to forecast the national economy. Generally, these may be classified as those based upon leading economic indicator (LEI) data prepared by the Department of Commerce, consensus forecasts of economic experts, or other techniques. Two based upon the LEI are summarized below:

1. **Neftci** (Nazmi, 1993). The Neftci probability technique provides an example of poor forecasts using leading economic indicators. Using this technique, the average lead time of forecasts is ten months using a 90% rule or six months using a 95% criterion. The time span between the signal and actual turning point varies from a lead of 13 months at 90% probability to a lag of four months. Further, the technique as absolutely accurate (correct signal at the correct time) for only one of the 16 turning points for which a signal was given.
2. **Three-Month Rule-of-Thumb** (Steckler, 1991). Another, perhaps more common approach, relies on the rule-of-thumb of three consecutive months of decline or advance in the LEI composite. Using this approach, eight cyclical peaks between 1948 and 1981 were predicted with a lead time varying between nine months and zero months, but the eight cyclical troughs were not predicted, on average, until after the turning point.

Consensus forecasts of economic experts are used, also. For example, Blue Chip Economic Indicators, Inc. (BCEI) polls 50 economic forecasters each month to provide predictions for 15 macroeconomic variables. Finally, the simplest or "naive" approach simply estimates that the next period's growth rate will be the same as the current period's growth rate.

NEURAL NETWORKS

Artificial neural networks are based upon the biological principles underlying the human brain. Much like the human brain, they learn new associations, new patterns, and new functional dependencies inductively by observing the data supplied to them (Haykin, 1994).

Neural networks provide several advantages over alternate statistical modeling and prediction techniques. Neural networks are not programmed, like some software packages, but rather are "trained" by exposing the network to individual examples of the data to be used for predictions or classifications. The process is repeated until the neural network recognizes underlying patterns between inputs (independent variables) and outputs (dependent variables).

In addition, the neural network does not require any assumptions for the underlying data to be forecasted. For example, multi-linear regression requires that the data meet certain conditions of homoscedasticity (variance) and independence of variables and assumes that the underlying relationship of the data is linear rather than non-linear. Other forecasting techniques require other assumptions for the data. Therefore, using a neural network, no tests need to be conducted for these assumptions as other statistical techniques require.

A neural network is developed in a three-stage process (Klimasauskas, 1993). First, decisions must be made about what the input variables will be, how many layers and nodes in each layer the network will have, the transfer function, and other training (or learning) parameters. Next, the network is trained using a subset of the data until the average error between the forecast and the actual values is reduced to a minimum (typically, as close to zero as possible). Finally, the trained neural network is used to forecast with the remainder of the data to test whether or not the decisions made in the first stage were appropriate. For example, if the forecasts are poor, new variables may need to be added, the numbers of layers and nodes in the network may need to be changed, or a different learning algorithm may need to be used. The development of a neural network may take several iterations until a sufficiently accurate network model is generated.

A NEURAL NETWORK MODEL FOR GDP

A neural network was developed to predict annual GDP percentage changes using *NeuroForcaster/GA 3.1,* a product of NewWave Intelligent Business Systems (*NeuroForecaster User's Guide,* 1993), following the process described above.

Data were obtained from Media Logic Incorporated's *Business Cycle Indicators* (BCI) software which contains monthly and quarterly observations for approximately 250 macroeconomic time series over a period of about 50 years. The specific input variables for the neural net model were selected from the component series of the Leading Economic Indicators index plus two additional composite indices (see the *Appendix* for a detailed description of these variables). Visual inspection of the series' graphs also tended to confirm their selection for the model. For example, Figure 1 (a sample screen from the BCI software) shows that two time series (series #990: the Center for International Business Cycle Research (CIBCR) long-leading composite index and series #991: CIBCR short-leading composite index) tend to lead changes in GDP. (The darker vertical lines in this figure indicate the beginning and ending dates for recessionary periods.)

Correlation analyses were conducted on the input variables to further study their value to the model. For example, Figure 2 shows that input variable #2 (Series #5: average weekly initial claims for unemployment insurance) had a moderately strong leading positive correlation of about .5 for four to five years before the current period. (In the chart, lead times are indicated toward the right and lag times are indicated toward the left.) Series #5 had an even higher positive correlation for six to 13 years prior, but only four years of data were included in the forecasting model. Series 8, 19, 20, 106, 990, and 991 had strong correlations; series 1, 5, and 83 had moderate correlations; and series 29, 32, 92, and 99 had weak correlations.

Annual data observations were obtained by averaging the GDP's quarterly data and the 13 independent variables' monthly data for the years 1959 to 1986 and were loaded into *Neuroforecaster.* All of *NeuroForecaster's* default training parameters (e.g., learn rate, momentum, output processing, normalization, etc.) were used with the exception that "serial presentation" was chosen instead of "random presentation" (the problem is a time series) and the network was configured to include data from the past four years (in accordance with the correlation analysis described above). In addition, the network used the genetic algorithm which is often more accurate (but slower than backpropagation techniques also offered as choices (Hawley, Johnson, and Raina, 1990).

The data were separated into training (or in-sample) and testing (or out-of-sample) sets. Because the first estimated year provided by Kacpyr (1996) was 1977, all of the data for the years 1959 to 1976 were included in the first training set. The training set was subsequently increased for estimating later years. Training was continued for approximately 60,000 iterations until the in-sample error was reduced to approximately 1% (the stopping point is subjective).

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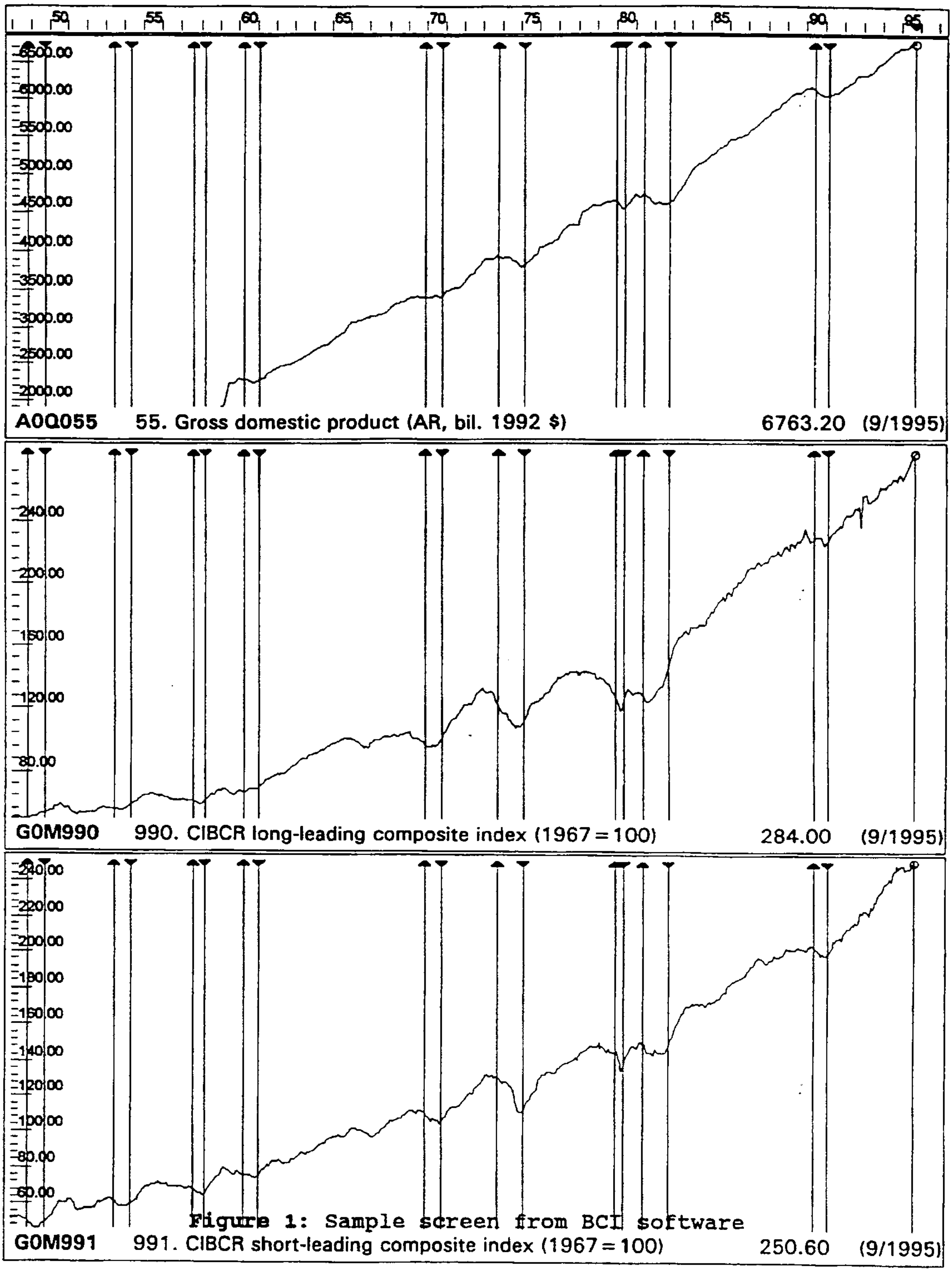


Figure 1: Sample screen from BCI software

Figure 2. Weekly Unemployment Claims Correlation with GDP

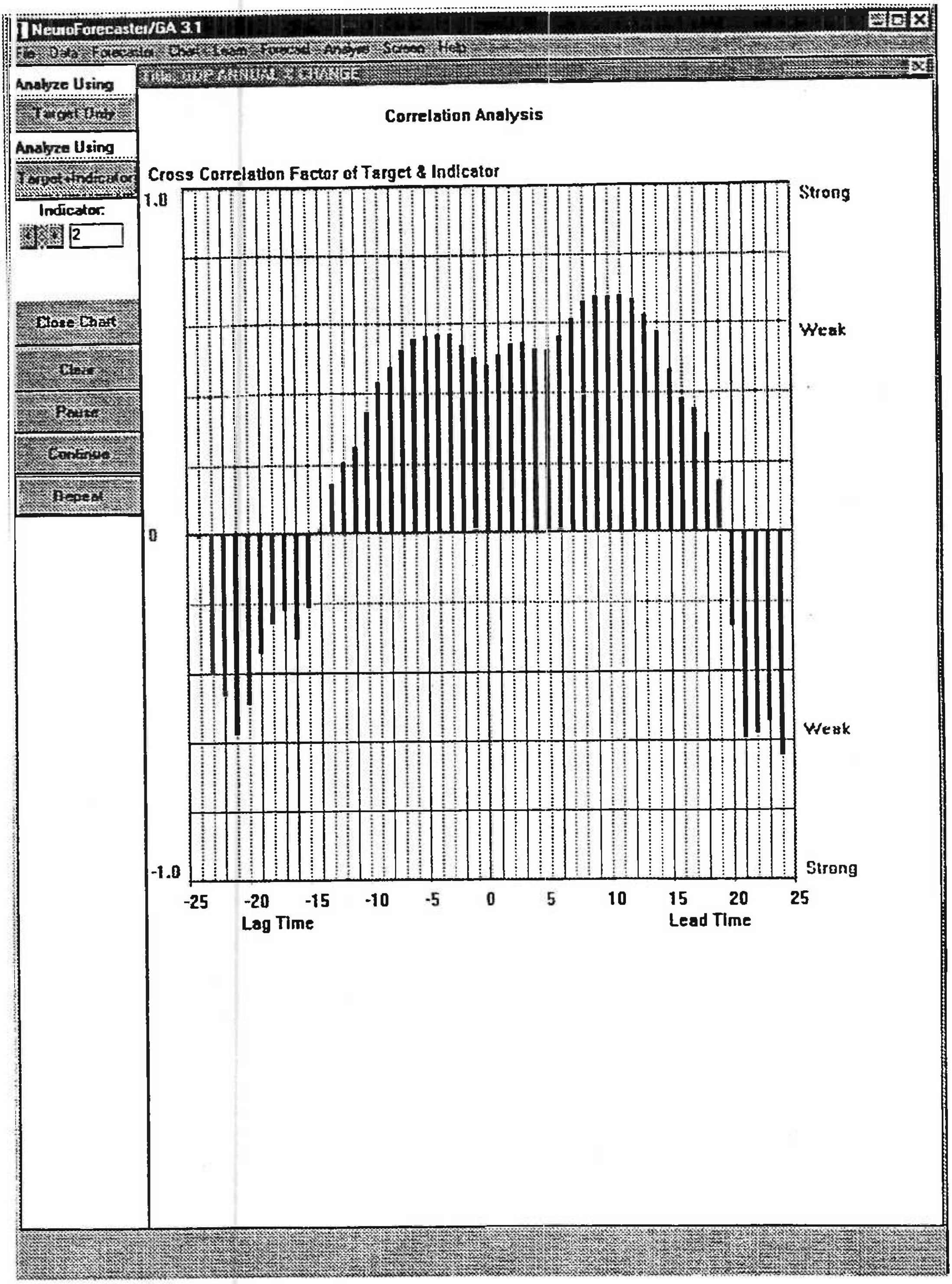


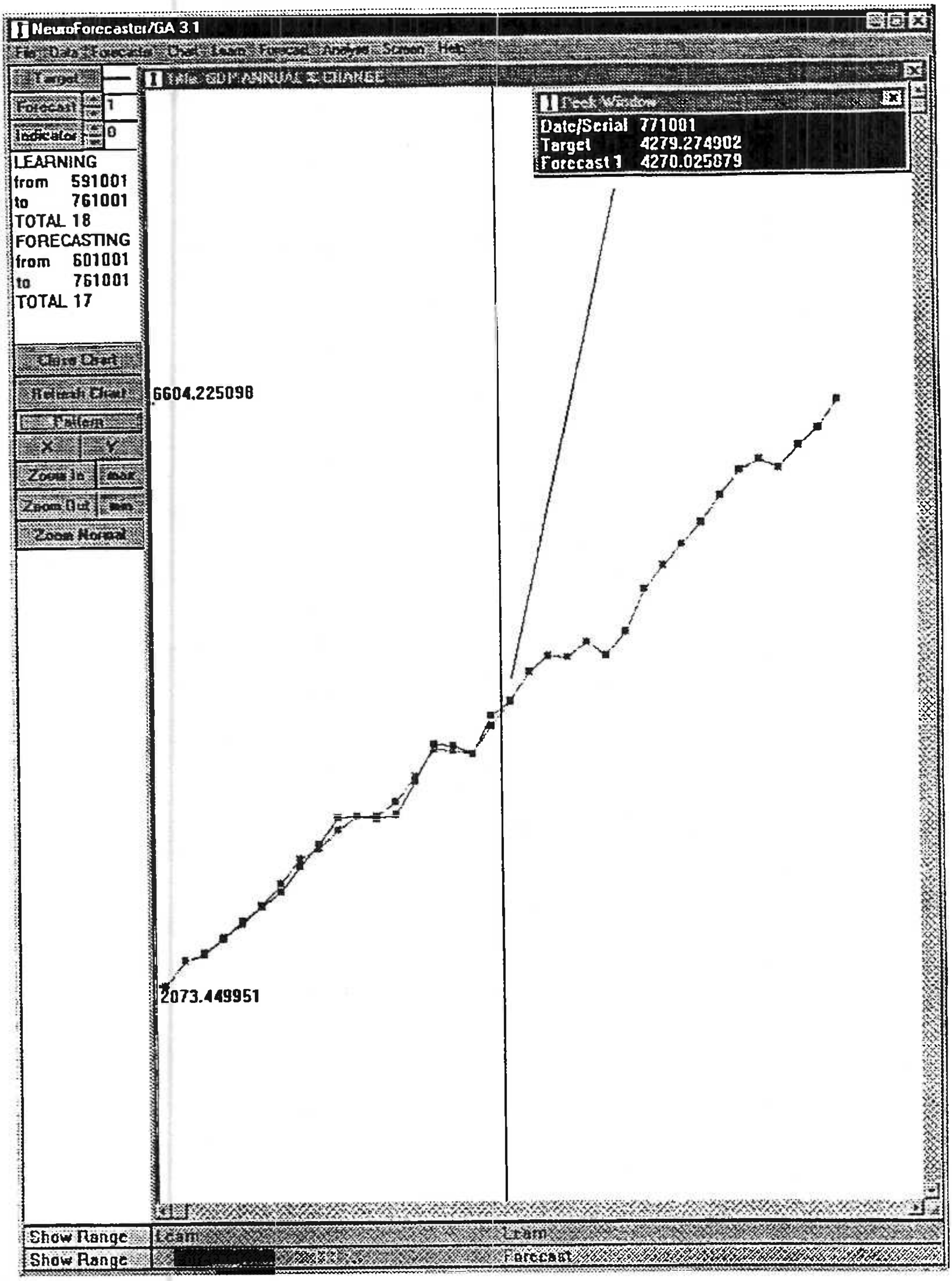
Figure 3 shows the first test of the neural network for the year 1977. The in-sample observations in this figure are to the left of the vertical line and the out-of-sample observations are to the right. The neural network's estimate for that year's average GDP was $4270 billion while the actual value was $4279 billion, an error of about 0.2%. The actual GDP percentage change from 1976 to 1977 was 4.85%, while the neural network estimated a change of 3.84%, an absolute error of about 1% in the growth rate.

Table 1 shows the absolute errors and mean absolute errors for the neural network, the BCEI consensus, and the naive estimates. The neural network was the most accurate on average, but was not the most accurate every year. However, the consensus estimate for 1982 was for continued growth instead of the recession which actually occurred. The naive forecast missed the recession of 1982 and the recession of 1980. The neural network did not miss either recession.

Table 1. Actual GDP with Neural Network, Consensus, and Naive GDP Estimate Errors (Adapted from Kacapyr, 1996, p. 143)

Year	Actual GDP % Change	NN Error	BCEI Consensus Error	Naive Error
1997	4.7	0.23	0.2	0.2
1978	5.3	-0.19	-1.0	-0.6
1979	2.5	1.56	0.2	2.8
1980	-0.2	0.01	0.0	2.7
1981	1.9	0.33	-1.0	-2.1
1982	-2.5	0.01	4.7	4.4
1983	3.6	1.71	-0.4	-6.1
1984	6.4	2.46	-1.3	-2.8
1985	2.7	0.69	0.8	3.7
1986	2.5	0.34	0.6	0.2
Mean Absolute Error		0.753	1.0	2.6

Figure 3. Neural Network Estimate for 1977 GDP



CONCLUSION

Neural networks are powerful tools for forecasting many macroeconomic variables including inflation, industrial production, and GDP. In this paper, a neural network developed using *NeuroForecaster* and macroeconomic data from *Business Cycle Indicators* software outperformed expert consensus and naive estimates of annual GDP percentage growth over a period from 1977 to 1986. Further research will investigate additional variables and time periods.

REFERENCES

Aiken, M. (1995). Forecasting T-bill rates with a neural network. *Technical Analysis of Stocks and Commodities, 13*(5), 85-89.

Aiken, M. (1996). A neural network to predict civilian unemployment rates. *Journal of International Information Management, 5*(1), 35-45.

Aiken, M., Krosp, J., Govindarajulu, C., Vanjani, M., & Sexton, R. (1995). A neural network for predicting total industrial production. *Journal of End User Computing, 7*(2), 19-23.

The Economist Guide to Global Economic Indicators. (1994). New York: The Economist Books.

Hawley, D., Johnson, J., & Raina, D. (1990, November). Artificial neural systems: A new tool for financial decision making. *Financial Analysts Journal,* 63-72.

Haykin, S. (1994). *Neural networks: A comprehensive foundation.* New York: MacMillan.

Kacpyr, E. (1996). *Economic forecasting: The state of the art.* New York: Sharpe.

Klimasauskas, C. (1993). Applying neural networks. In *Neural Networks in Finance and Investing* (R. Trippi and E. Turban, Eds.), pp. 47-63. Chicago: Probus.

Nazmi, N. (1993). Forecasting cyclical turning points with an index of leading indicators: A probabilistic approach. *Journal of Forecasting, 12*(3-4), 215-226.

NeuroForecaster User's Guide. (1993). Singapore: New Wave Intelligent Business Systems.

Plocek, J. (1991). *Economic Indicators.* New York: New York Institute of Finance.

Stekler, O. (1991). Turning point predictions, errors, and forecasting procedures. In *Leading Economic Indicators* (K. Lahiri and G. Moore, Eds.), Ch 10, pp. 169-181. New York: Cambridge University Press.

Stocks, M., Singleton, T., & Aiken, M. (1995). Forecasting bankruptcies using a neural network. *International Business Schools Computing Quarterly, 7*(1), 32-35.

APPENDIX

Variables Included in the Neural Network Model

Series Number	Series Description
	Dependent Variable
55	Gross Domestic Product (Annual rate, billions 1987 $) Quarterly data
	Independent Variables (Monthly Data)
	Component Series of the Leading Economic Indicators (LEI) Index
1	Average Weekly Hours in manufacturing.
5	Average weekly initial claims, unemployment insurance (thousands)
8	Manufacturers' new orders, consumer goods & materials (billions 1982 $)
19	Index of stock prices, 500 common stocks
20	Contracts and orders for plant and equipment (billions 1982 $)
29	Building permits for new private housing units (1967 = 100)
32	Vendor performance, slower deliveries diffusion index (%)
83	Consumer expectations, NSA, (1966 = 100)
92	Smoothed changes in manufacturers' unfilled orders (billions 1982 $)
99	Smoothed changes in sensitive materials prices (%)
106	Money supply M2 (billions 1982 $)
	Two Alternative Composite Indices
990	CIBCR long-leading composite index (1967 = 100)
991	CIBCR short-leading composite index (1967 = 100)