FINANCIAL FORECASTING WITH NEURAL NETWORKS

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ABSTRACT

Financial forecasting has become highly complicated by the increasingly interconnected and interdependent nature of financial markets of the world. This complexity requires that we use analytical tools that can detect interrelationships among a large number of diverse market variables. The ability of artificial neural networks (ANN) to detect correlations among hundreds of variables makes it a popular forecasting tool.

We present a rather comprehensive survey of the application of ANNs in various areas of finance and economics. Then we present the steps of using neural networks for forecasting volatility of the S&P 500 Index futures prices. The approach outlined can be used for forecasting market variables in general. We compare out-of-sample volatility forecasts from neural networks with implied volatility from S&P 500 Index futures options using the Barone-Adesi and Whaley (BAW) model for pricing American options on futures. Forecasts from neural networks generally outperform implied volatility forecasts. Volatility forecasts from neural networks are not found to be significantly different from realized volatility. Implied volatility forecasts are found to be significantly different from realized volatility in two of three cases.

Keywords: Neural networks, Volatility forecasting, Historical volatility, Implied volatility, Realized volatility.

INTRODUCTION

Financial forecasting has become highly complicated by the increasingly interconnected nature of financial market variables.. This calls for use of analytical tools that can detect interrelationships among a large number of diverse market variables. The ability of artificial neural networks (ANN) to detect correlations among hundreds of variables makes it a popular forecasting tool.

Since the 1980s ANNs they have assumed importance in scientific and technical use. They have been applied in fields ranging from automated automobile inspection to sensor signal processing (see Exhibit 1). More recently they have been applied to economics and finance to resolve issues like predicting the economy, picking stocks, constructing portfolios, spotting insider dealing, analysis of corporate financial health, assessing bond risk, recognizing financial distress, detecting credit card fraud, improving real estate appraisal, and identifying good credit or insurance candidates, exchange rate prediction, commodity trading.

Academic research works involving the technology have been devoted predominantly to two areas: financial distress prediction and prediction of stock price/stock index. Exhibit 2 lists some of the areas in which the efficacy of using neural networks could be further researched. For example, the technology can be applied to corporate finance (financial simulation, prediction, evaluation, etc.), IPO pricing, identifying arbitrage opportunities, security risk profiling, locating tax evaders, etc. Evaluation of uses in these areas is yet to be seen.

This paper shows the use of ANN for out-of-sample volatility forecasts of S&P 500 Index futures prices and compares the volatility forecasts with implied volatility and realized volatility. The approach outlined can be used for forecasting market variables in general.

PERFORMANCE OF NEURAL NETWORKS IN FINANCIAL APPLICATIONS

Academic studies on the performance of ANNs show promise for the technology in many fields of economics and finance. Many of the studies on early warning failure prediction studies compared the predictive powers of ANN and conventional statistical models like multiple discriminant analysis and logistic regression. A number of studies found neural networks to be superior to these models (e.g., Coats and Fant, 1993; Lenard, Alam and Madey, 1995; Fletcher and Goss, 1993; Salchenberger, Cinar and Lash, 1992). Yet other studies found both approaches yield balanced degree of accuracy (Altman, Marco and Varetto, 1994; Boritz, Kennedy, de Mirande e Albuquerque, 1995; Yang, Platt and Platt, 1999). Boritz and Kennedy (1995) show that the performance of ANNs is sensitive to the choice of variables selected and that the networks cannot be relied upon to evaluate and focus on the most important variables. Zurada, Foster, Ward, and Barker (1998) find neural networks are not superior to logistic regression models for traditional dichotomous response variables, but are superior for more complex financial distress response variables. Perez (2006) analyzes thirty studies in which the authors use neural networks to solve companies' classification problems (healthy and failing firms).

ANNs have been employed with success to make stock market predictions and stock selection (e.g., White, 1988, Yoon and Swales, 1991; Kryzanowski, Galler and Wright, 1993; Rhee, 1994, Gencay, 1998; Qi, 1999; Qi and Maddala, 1999; Ao, 2003; Armano, Marchesi and Murru, 2005; Yu, Wang, and Lai, 2005c), and prediction of stock index futures (Kim, 2004). The networks have been used to determine optimal buy and sell timing for an equity index (Kimoto, Asakawa, Yoda, and Takeoka, 1990; Leigh, Paz and Purvis, 2002; Leigh, Purvis, and Ragusa, 2002; Chen, Lueng and Daouk, 2003) and recognize a specific price pattern, such as the Japanese "candlestick" triangle (Kamijo and Tanigawa, 1990). Ko and Lin (2008) introduce a resource allocation neural network model to optimize investment weight of a portfolio.

ANNs have been found to generate improved risk ratings of bonds (Dutta and Shekhar, 1988; Moody and Utans, 1991; Surkan and Singleton, 1991; Kim, Weistroffer and Redmond, 1993; Maher and Sen, 1997) and useful in mortgage risk assessment (Collins, Ghosh and Scofield, 1988; Reilly, Collins, Scofield and Ghosh, 1991; Grudnitski, Quang, and Shilling, 1995).

Vishwakarma, (1994) and Qi (2001) have found ANNs to be useful in predicting business cycle turning points. It has been used for predicting U.S. recessions via leading indicators (Qi, 2001). Three studies by Swanson and White (1995, 1997a,b) find that nonlinear neural networks are useful in economic time series forecasting of interest rates, unemployment, GNP, etc.

In prediction of corporate takeover targets, Sen and Gibbs (1994) found several ANN models map the data very well, but did not predict merger targets significantly better than logistic regression.

Furthermore, the technology has been found useful in other diverse applications like commodity trading (Kaastra and Boyd, 1995); exchange rate forecasting (Zhang, 1994; Kuan and Liu, 1995; Gencay, 1999; Huang, Lai, Nakamori and Wang, 2004; Lai, Yu and Wang, 2004; Yu, Wang and Lai, 2005a,b); real estate valuation (Worzala, Lenk and Silva, 1995); option pricing

(Hutchinson, Lo and Poggio, 1995; Garcia and Gencay, 2000); detection of management fraud (Fanning, Cogger and Srivastava, 1995); earnings forecasting (Charitou and Charalambous, 1996; Kim, 1996), and inflation forecasting (Moshiri and Cameron, 2000).

In theory, ANNs are suitable for nonlinear problems. Zhang (2001) found that neural networks are quite effective in linear time-series modeling and forecasting. This implies that the technology can compete with linear models for linear problems.

ANNs have also been used in volatility forecasting. Ormoneit and Neuneier (1996) predict volatility of the German stock market. Donaldson and Kamstra (1997) have used ANN-GARCH model to capture volatility effects in stock returns. González Miranda, and Burgess (1997) have used ANN to predict intraday volatilities for the Spanish stock market. Schittenkopf, Dorffner and Dockner (1998) predict the volatility of the Austrian stock market and find ANNs outperform ARCH models. Schittenkopf, Dorffner and Dockner (2000) use daily DAX data and find that volatility predictions from ANN are superior to GARCH models. Meissner and Kawano (2001) use a combined GARCH-ANN approach to capture the volatility smile of options on high-tech stocks.

The reference section includes a more comprehensive listing of articles on application of ANNs in finance and economics. Bahrammirzaee (2010) makes comparative review of three famous artificial intelligence techniques: artificial neural networks, expert systems, and hybrid intelligence systems in three domains: credit evaluation, portfolio management and financial prediction and planning. For each technique, recent researches are discussed in comparative aspect. Results show that artificial intelligent methods are superior to that of traditional statistical methods in dealing with financial problems, especially involving nonlinear patterns.

In sum, ANNs have been found useful in many different types of applications in economics and finance. They have outperformed linear models in various cases. However, ANNs have not consistently outperformed in all studies. As White (1989b) and Kuan and White (1994) report, they have been particularly effective in capturing complex relationships in which linear models fail to perform well.

This paper shows in simple steps how ANN can be used to forecast the volatility of S&P 500 Index future prices. The same approach can be used to forecast various market variables. When the technology is better understood, it will spur research in the many other potential applications. Practitioners in greater numbers can reap the benefits of present and potential uses of the technology.

We compare volatility forecasts from ANN with implied volatility obtained from Barone-Adesi and Whaley (1987) American futures options pricing model. The two types of volatility forecasts are for similar horizons and time periods. We then evaluate the accuracy of the two types of forecasts by comparing with volatility realized over horizons similar to volatility forecasts.

Volatility forecasts from ANN are out of sample in the sense that the forecast data was not seen by the ANN during model selection and training. We find that volatility forecasts from ANN are not found to be significantly different from realized volatility and also generally outperform implied volatility.

The next section briefly explains ANN. We then show how a back propagation network can be used for forecasting the volatility of S&P 500 Index futures prices using data on a number of market variables. This is followed by analysis of results and conclusion.

WHAT IS ANN?

ANN is a computational technique that seeks to mimic the structure and operations of the three- dimensional lattice of network among brain cells (or neurons, and hence the term "neural") in processing data and information for solving various types of problems. Problem solving approaches in which the networks have been used include classification, filtering, pattern association, optimization, conceptualization and prediction. (This paper draws on prediction use of ANN.) The technology is modeled after the architecture of the human brain which uses many simple processing elements operating in parallel to obtain high computation rates. The ANN is similarly composed of many simple processing elements or neurons operating in parallel whose function are determined by network structure, connection strengths, and the processing performed at computing elements or nodes.

The learning process of the ANN can be likened to the way a child learns to recognize patterns, shapes and sounds, and discerns among them. For example, the child has to be exposed to a number of examples of a particular type of tree for her to be able to recognize that type of tree latter on. In addition, the child has to be exposed to different types of trees for her to be able to differentiate among trees.

The human brain has the uncanny ability to recognize and comprehend various patterns. ANN is extremely primitive in this aspect. The network's strength, however, is in its ability to detect subtle patterns in a large number of variables at a time without being overwhelmed by detail. It can also carry out multiple operations simultaneously. The ability of ANN to detect correlations in hundreds of variables is particularly suitable in analyzing relationships among a large number of market variables. The networks learn from experience and can cope with patterns that are difficult to reduce to precise rules such as "fuzzy" patterns. They can also be retrained and thus can adapt to changing market behavior.

ANN holds particular promise for econometric applications. Multilayer feedforward networks with appropriate parameters are capable of approximating a large number of diverse functions arbitrarily well (see White, 1989a). ANN can learn important features of the data even when a data set is noisy or has irrelevant inputs. The promise of ANNs lies in their ability to learn patterns in a complex signal.

A popular and useful forecasting tool is time series models. However, time series models pose a challenge in terms of identification of the model (autoregressive versus moving average, or a combination of the two) that will fit a particular time series of data, and the order specification that will be appropriate is the difficult first step in using time series models. As Davies (1995) points out, ANN does not depend on assumptions regarding the data but adapt to the data.

It is convenient to think of ANNs as being arranged in layers with neurons in each layer that are connected to each other. The type of problem to be solved has a great deal to do with network architecture. For each problem solving approach more than one architecture may be used. Each architecture goes with numerous variations depending on parameters selected. Network parameters vary in factors as the following:

- The number of layers in the network through which input variables are processed and the number of neurons or nodes per layer;
- Nature of connections between neurons in each layer and the strength (weight) of each connection;

- Transfer function, through which the network seeks to relate the input data with the output data.

LIMITATIONS OF ANN

The steps or process which involves the lattice of connection weights cannot at present be translated into an algorithm that would be intelligible outside ANNs. Another major shortcoming is the generic tendency to "overfit" the data which can "actuate memorization" of idiosyncratic patterns in the training data that will not be of help in out-of-sample data. Solutions suggested to prevent overfitting involve (a) using "fuzzy logic" which instructs the network not to be emphatic when its conclusion is tentative, (b) using "genetic algorithm" -- a mechanism similar to how evolution works by mutation and natural selection (see Ridley, 1993), and (c) not using too many data columns.

Users need some experience in terms of selection of input variables and specifying appropriate network architecture since ANN lacks formal theory in model building. Approaches suggested in this regard include using in-sample model selection criteria like Akaike's information criteria (AIC) and Bayesian information criteria (BIC). However, Qi and Zhang (2001) find that the commonly used in-sample model selection criteria are not able to identify the best ANN model for out-of-sample prediction which means model specification via trial and error will continue. However, some networks, as the one we use, provide coefficients to reflect the relative contribution of input variables to the prediction of desired output. Also, use of correlation coefficients between input variables and the output variable(s) is also helpful in identifying which input variables are to be included.

DESIGN OF THE STUDY

To predict the volatility of the S&P 500 Index futures prices we initially use daily closing settlement prices of sixteen futures contracts and three spot indexes. We also use one-day lagged S&P 500 Index futures prices. We use the futures contracts which have the nearest maturity. The maturity months are March, June, September and December of each year. The twenty variables are listed in Exhibit 3. Seven of the sixteen futures contracts are on commodities, three on Treasury obligations, and six on foreign currencies. The three spot indexes are DJIA, NYSE Composite Index and S&P 500 Index. We use ten years of daily data on them -- from February 1, 1984 to January 31, 1994 – a total of 2,531 observations per variable. This allows us to train our network with a large enough data set.

Since we forecast volatility, we calculate from the raw data series 20-day rolling series of historical (HV). The HV on a given day is calculated as standard deviation of the daily percentage price changes of the previous twenty days. The daily percentage price changes are calculated from natural log relatives of the price or index series. The percentage change for day 2 based on prices P_1 and P_2 (for days 1 and 2 respectively) will be given as $Ln(P_2/ P_1)$. Of approximately 2,500 HVs, we use about five hundred observations to train the network, and the rest for forecasting.

We get a total of ninety forecasts over three different horizons. Thirty of the forecasts are over 55 trading days following the forecast dates (55-day forecasts), and we have equal numbers of 35-day and 15 day forecasts (all days refer to trading days and not calendar days). The 55-day forecast is on January 2, 1986. Twenty trading days after this, on January 30, 1986, we get the first 35-day forecast. Another twenty trading days after this, on February 28, 1986, we get the first 15-day forecast. The second 55-day forecast is on April 3, 1986 – about sixty-five trading days after the first 55-day forecast. The two forecasts are over non-overlapping horizons. In this way, every 55-day forecast is non-overlapping with previous or subsequent forecasts. The same is the case with all the 35-day and 15-day forecasts. This ensures that forecast errors will be uncorrelated with previous or subsequent forecasts.

The forecast dates and horizons correspond to implied volatility (IV) forecasts we obtain using the Barone-Adesi and Whaley (1987) American futures options pricing model.

IMPLIED VOLATILITY FROM BARONE-ADESI AND WHALEY (BAW) MODEL

Since volatility forecasts extracted from options pricing model (implied volatility) have been found to be unbiased estimates of future expected volatility, and are highly regarded, we compare volatility obtained from ANN (NV) with implied volatility (IV). Since we find volatility of futures prices using ANN, we use the BAW model for pricing American options on futures which has does not have analytic solution. We create an algorithm for extracting ISDs from the model. We execute the algorithm on a connection machine to extract the implied volatilities from the BAW model. (Connection machines are parallel processors that have speed beyond the reach of PCs.) The implied volatilities are obtained from call options on S&P 500 Index futures contracts. We use just-out-of-the-money options on dates and horizons for which we obtained volatility forecasts using ANN. Just-out-of-the-money options are ones for which futures price minus exercise price is nearest to 1 but negative.

We compare forecasts from ANN and from BAW model with volatility realized over each of the three forecast horizons (55-day, 35-day, and 15-day). We modify the BAW model to get ISDs based on trading days since the realized volatilities are obtained on the basis of trading days as opposed to calendar days.

REALIZED VOLATILITY

The 55-day realized standard deviation (RV) is calculated from daily log relatives of the present value of S&P 500 Index futures settlement prices from 55 days before maturity until the day of maturity. For the 35-day and 15-day forecast horizons, the daily returns are based on daily log relatives of the present value of the index futures settlement prices respectively from 35 and 15 days before maturity until the day of maturity. RSD on day t is calculated as follows:

$$\mathrm{RV}_t = [\sum_{j=t}^{t+n} (\mathrm{R}_j - \bar{\mathrm{R}})^2 / n]^{1/2} \quad \text{.....(1)}$$

where:

$R_j = \ln [F_j / F_{(j-1)}]$

$\bar{R} = R_j / n$

F_j = Present value of futures price on date j

n = 55, 35, 15 respectively for RVs over the three horizons.

The 55-day NV and IV forecasts are compared with 55-day realized volatilities (RVs). Similarly, we separately evaluate the accuracy of the 35-day and the 15-day NV and IV forecasts by comparing with corresponding RVs.

FORECAST ACCURACY

Forecast accuracy is measured by mean of absolute errors (MAE) and root mean of squared errors (RMSE) of volatility forecasts (NV and IV) compared to realized volatility (RV) for the three forecast horizons, as follows:

$$MAE = 1/30 * \sum_{i=1}^{30} [Abs(Y_{it} - \hat{Y}_{it})] \qquad (2)$$

$$RMSE = [1/30 * \sum_{i=1}^{30} (Y_{it} - \hat{Y}_{it})^2]^{1/2} \qquad (3)$$

where:

$\hat{Y}_{it}$ = forecasted standard deviation
t = forecast horizon (15, 35, 55 trading days)
Y_{it} = realized standard deviation.

We also separately test for the differences in the means of each type of forecast with respect to the means of realized volatility for each of the three forecast horizons using standard test statistics.

VOLATILITY FORECASTS USING ANNS

To obtain volatility forecasts from ANN, typical steps would involve the following:
(a) Select input variables
(b) Preprocess input data
(c) Specify a network
(d) Train the network and get forecasts

(a) Selecting input variables

We need to identify the variables that contribute the most to forecasting the target variable. Too many or too few variables can be counterproductive. Our perspective on the markets will affect the choice of input data. Mendelsohn (1993) proposes a synergistic market analysis -- combining technical analysis and fundamental analysis approaches with intermarket analysis -- implemented using an ANN to predict, for example, the next day's high and low for the Treasury bond market. Technical price data on Treasury bonds would be fed into the network, allowing it to learn the general price patterns and characteristics of the target market. In addition, fundamental data that affect the market can also be input into the network. Few examples are federal funds rate, Gross Domestic Product, money supply, inflation rate and consumer price index. Mendelsohn argues that using fundamental data as well as technical data can improve the overall performance of the network. He further claims that incorporating intermarket input data on related markets enables the network to utilize this information to find intermarket relationships and patterns that affect the target market. A few examples of intermarket data are US dollar index, S&P 500 Index and currency exchange rates.

To predict the next days high and low for the Treasury bond market one can select any number of variables. But the larger the number of variables, the longer will be the training period required and greater the possibility that the data will overfit the model determined by the network. As an upper limit to the number of input variables, Kean (1993) suggests around ten percent of the number of data observations. Thus, if there are three hundred days of observations to train a network, Kean recommends thirty variables.

In selecting input variables, apart from the knowledge of what affects the target variable, the use of statistical tools to find correlation between the target and the other variables are important. It can be a lengthy process of trial and error. Multiple regression analysis, principal component analysis and stepwise regression analysis can help to identify statistically significant variables that can be used as input variables.

We initially included twenty explanatory variables mentioned earlier and shown in Exhibit 3. The exhibit shows the correlations of the daily price changes of eighteen of the twenty variables with the daily price changes of S&P 500 Index futures contracts. (The correlation of the S&P 500 Index futures prices with its lag or with S&P 500 Index is not calculated since it will be very high.) From the twenty variables, we select eleven explanatory variables as indicated in the last column of Exhibit 3. We select a variable if it meets one of the two conditions:

- correlation with futures prices is greater than 5% and less than -5%; or,
- high relative contribution to forecasting (relative contribution coefficient greater than 0.07 is the criteria used; this coefficient is provided by the network we use).

This excludes Treasury notes, Swiss frank, German mark and British pound, and leaves us with sixteen explanatory variables. Under the apprehension that this number may "overfit" the data, we dropped five more variables: silver and gold for their low correlation (-0.10 and -0.07) with S&P 500 Index futures prices and low relative contribution coefficients (0.10 and 0.07); Canadian dollar (relative contribution coefficient of 0.33) because of its very low correlation (0.005) with S&P 500 Index futures prices; Eurodollar in spite of its modest correlation with S&P 500 Index futures prices (0.15) and modest relative contribution coefficient (0.23); DJIA (relative contribution coefficient of 0.078 and correlation of 0.94) under the assumption that its effect will be captured by the included variable -- S&P 500 Index. We understand that there is potential for obtaining better forecasts from the networks by using a different set (and number) of input variables than we used.

(b) Preprocessing the input data

Data fed into an ANN has to be in the proper form (that is, transformed) to enable the network to process and generate sound forecasts. The common ways of preprocessing data are transformation, normalization and data smooothing. Transformation involves taking differences between inputs or ratios of inputs through which few input variables are coalesced to form a single input category. Reducing the inputs may help the network learn better. It is not necessary to transform data before feeding into a network.

Data smoothing techniques like simple and exponential moving averages and polynomial regression filter out noise in the data. Data smoothing serves two purposes. First, the network has been given useful information at a reasonable level of detail. Second, the noise entering the data is reduced.

Some commercial networks possess built-in preprocessing capabilities like scaling and randomly rearranging data to remove serial dependence. But these networks cannot transform or smooth data. If data transformation or smoothing is needed, that has to be done before feeding the data into the system.

Preprocessing involves two aspects: arranging the data in the form that the network can read, and scaling the data so that the maximum and minimum of each variable falls in a range of 1 and –1 (or 0 and 1 depending on the type of transfer function specified), and the other values are scaled accordingly.

(c) Specifying a network

Since a feedforward backpropagation network is typically used for forecasting, we use a network of this form. Feedforward refers to network architecture, whereas back-propagation is a training method. And since a backprop network should have at least three-layers, we specify a three-layered network. Appropriate specification of number of layers is an art. It needs experimentation. The countless combinations of layers and neurons that we can make and the time it takes to train a network after each specification is an arduous exercise. A single or two-layer network would be rather inadequate in capturing the complex interrelationships between market variables. The number of layers specified -- three -- is such that it is not too few and not too many. We could also use four layers. But that would increase the training time. The resulting improvement in forecast accuracy may not be worth the extra time.

We specified eleven neurons in the first layer, equal to the number of input variables. We specified two times that many neurons in the second layer. The number of neurons in the second layer typically should be from half the number of input neurons to twice that number. There is scope for trial and error experimentation in this aspect, as in other aspects of the use of ANN.

In the network specification stage a number of default parameters or values that influence the behavior of the training process can be adjusted. These deal with the learning, forgetting and error tolerance rates of the network, the overlearning threshold, the maximum number of runs, stop value for terminating training and randomizing weights with some specified dispersion. In the absence of objective guidelines, we set most of these parameters to default values of the network we used.

(d) Training the network and forecasting

An ANN learns from past experience and so has to be trained with a sufficient number of training cases. When trained with too few training cases, the network will map an inadequate model for the output. Much of the art of using ANNs comes into play in the training phase. Among the decisions involved at this stage which will also determine the time taken to train the network are:

- the number of layers and neurons per layer; these can be varied depending on the performance of the network during the training phase;
- type of transfer function; the standard sigmoid is the most commonly used for forecasting market variables;
- number of iterations on each day's data set;
- the learning rate: extent of correction applied to the connection weights at each step of training.

Exhibit 5 depicts operation of fully-connected feedworward back-propagation network. To forecast, the network has to be trained using historical data. Data inputs have to be in numbers -- prices, volume, ratios, etc.

A single input category is fed into a single neuron in the input layer. Thus, there are as many neurons in the input layer as there are input categories. Each neuron multiplies the input data by some initial weight and passes on the value to every neuron in the hidden layer. Thus, each hidden layer neuron receives input from every input layer neuron in a fully-connected network.

Each neuron in the hidden layer sums the values it receives and runs the summed value through a transfer function contained in it. The transfer function determines a weight with which the summed value is multiplied and then passed on to the single neuron in the output layer.

The neuron in the output layer receives values from all the neurons in the hidden layer. It sums the values, runs the result through its transfer function and multiplies the value by some weight to produce an output. The network compares this output with the desired output and determines the difference between the two. This forms the error signal after the first run.

The error signal is fed back through the output layer and the hidden layer(s) to the first layer. As the error signal goes backward, each hidden neuron modifies its weight in proportion to the error times the input signal which reduces the error in the direction of most rapid reduction in error. The transfer function specified for each hidden neuron provides the rule for adjusting the weights based on the magnitude of the error in the output neuron. As the process of feedforward and back propagation of values continues for the specified number of times after the first set of data intake, the error between the output generated and the output desired is gradually minimized. In this way, the network trains itself to generate output closer and closer to desired output. Then the network is fed with the second set of training data and the same process continues. The process continues until all the training data is exhausted. This process of trial and error enables the network to recognize patterns, relationships and correlations between the input variables and the output category. The errors will not be reduced to zero specially with real financial data. When the network can hardly minimize errors as more input data is fed, it reaches a steady state and the trained network can then be used for testing or forecasting.

We train the network using eleven explanatory variables mentioned earlier. We use 500 days of data for training purpose. Each set of observations is run 500 times through the network. After each run, the network compares the forecasted volatility of futures prices with the desired volatility. It calculates and feeds the error backward. The neurons reset their weights each time the errors are fed back.

The volatility we desire on a particular day for the 55-day forecast horizon is the volatility realized in the subsequent 55 days. The volatility we desire on a particular day for the 35-day forecast horizon is the volatility realized in the subsequent 35 days. For the 15-day horizon, the desired volatility on a particular day is the 15-day volatility realization.

After each volatility forecast, we change the training observations. In each case, we use 500 20-day rolling HSD observations for training. These observations are for the 500 trading days prior to a forecast date. After the training phase, the network made out of sample forecasts. In other words, at every stage, the forecast data is unseen by the network. In all we get thirty forecasts for each of horizons: 55, 35 and 15 trading days -- a total of ninety forecasts.

ANALYSIS OF RESULTS

Exhibit 6 shows performance of volatility forecasts from ANN (NVs) and implied volatilities (IVs) compared to realized volatilities (RVs) for the three forecast horizons of this study: 55, 35 and 15 days to the maturity of nearest futures and corresponding options contracts. For each forecast class we have thirty forecasts. The table shows the means of RV, NV and IV. T-tests for differences in means of RVs versus NVs show no significant differences in the means in the case of all three forecast classes. T-tests for differences in means of RVs versus IVs show significant difference in the means of 15-day and 35-day forecasts (p-value = 0.02 and 0.01 respectively in one-tailed test), and no significant difference in the case of 55-day forecasts (p-value =0.34 in one-tailed test). That means, whereas IVs have provided good forecast over the 55-day horizon, neural forecasts have been good in the case of all three horizons.

Exhibit 6 also shows the mean absolute errors and root mean squared errors of the two types of forecasts. On both measures, and for all three forecast classes, neural forecasts outperform ISDs.

It clearly implies that for the data in our sample, volatility forecasts from ANNs yielded superior results compared to implied volatilities.

CONCLUSION

The use of ANNs in economics and finance is a promising field of research specially given the ready availability of large mass of data sets and the ability of ANNs to detect relationships between a large number of variables. However, the realization of the potentials of ANNs in forecasting the market involves more of an art than science. There are many ways and combinations in which a network can be specified and many types of data can be simultaneously used. Much of that is yet unexplored. The principles that can guide us in effectively utilizing the networks in financial applications remain a fertile area of research.

In our forecasting, we used eleven input variables. Could the results have improved with a different number of variables? Could the results have improved with a different number of neurons in the hidden layer, or with two rather than one hidden layer? Guidelines available at present are rather sketchy at best. A great deal of trial and error experimentation is called for. Programming skills are not essential with many commercial software tools for neural networks that are available. A useful site listing many such softwares with links to description on them is: www.emsl.pnl.gov:2080/proj/neuron/neural/systems/software.html.

EXHIBIT 1
APPLICATIONS OF NEURAL NETWORKS

Among the areas in which neural networks have been used are:

- sensor signal processing and data fusion;
- filtering out noise in electronic communications systems;
- pattern classification, image processing, and machine vision; for example, in designing an airport security system;
- automated inspection to diagnose malfunctions in automobiles;
- robotics and sensor-motor control;
- speech recognition and synthesis, and natural language; for example, converting written into spoken English;
- knowledge processing;
- database retrieval;
- computer-based handwriting and character recognition;
- medical diagnosis, healthcare, and biomedical applications, such as hybrid scheme for diagnosing skin diseases;
- manufacturing and process control;

- defense applications;
- assessing credit/insurance risk;
- financial forecasting applications;
- stock picking/portfolio management/automated trading.

EXHIBIT 2
POTENTIAL RESEARCH AREAS IN FINANCE USING NEURAL NETWORKS*

A. CORPORATE FINANCE

1. Financial simulation

- Simulate the behavior of firm's credit customers as economic conditions change: to plan for:
    - Planning for bad-debt expenses and accounts receivable cyclicity
    - Evaluating credit terms and limits
- Cash management
- Capital budgeting
- Exchange rate risk management
- Prediction of credit costs and availability
- Sales prospect selection
- Analyze corporate financial health

2. Prediction

- Train network to mimic the behavior of investors in response to changes in economic conditions or company policies (dividend policy, capital structure, accounting standards, etc.)
- Predicting changes in market trends
- Forecast personnel requirement

3. Evaluation

- Value an acquisition target based on financials.
- Identify desirable acquisition targets based on qualitative criteria or learn personal preferences of human expert.

B. FINANCIAL INSTITUTIONS

- Pricing IPOs
- Simulation of market behavior

C. INVESTING

1. Arbitrage pricing/identifying arbitrage opportunities
2. Technical analysi
3. Fundamental analysis
4. Security risk profiling
5. Index construction

D. OTHERS

- Locating tax evaders
- Property tax analysis
- Mining of financial and economic data bases
- Identification of explanatory economic factors

EXHIBIT 3

Correlation between S&P 500 Index futures daily settlement price changes and the daily price changes of 16 futures contracts and 2 spot indexes using data from February 1984 to January 1994. Also shown are the relative contributions of 20 variables in forecasting volatility of S&P 500 Index futures prices; last column shows contribution of 11 selected variables in forecasting index futures price volatility. The relative contribution coefficients are taken after training the network with 15-day forecast file. The training was with 500 days of data on the 11 variables.

	Contract	Correlation coefficient	Relative contribution coefficient	
			All 20 variables	11 select variables
1	Swiss frank	-0.0572	0.0439	***
2	Japanese yen	-0.0293	0.3293	0.6539
3	NYSE#	0.9000	0.1243	0.1455
4	Treasury bonds	0.3164	0.0736	0.6335
5	Treasury notes	0.2779	0.0676	***
6	Treasury bills	0.0595	0.3239	0.4947
7	Silver	-0.1026	0.1026	***
8	Platinum	-0.0465	0.2686	0.3944
9	Palladium	-0.0488	0.7043	0.8373
10	Heating oil	-0.0682	0.3735	0.1655
11	Copper	0.0590	0.4742	0.6173
12	Gold	-0.1220	0.0675	***
13	Euro-dollar	0.1466	0.2311	***
14	German mark	-0.0393	0.0663	***
15	DJIA#	0.9384	0.0776	***
16	Crude oil	-0.0742	0.4462	0.1513
17	Canadian dollar	0.0054	0.3316	***
18	British pound	-0.0368	0.0684	***
19	S&P 500 Index#	NC	0.0655	0.2042
20	S&P 500 Futures-L	NC	0.1102	0.1617

Notes:

1. #: Represents spot indexes.
2. Relative contribution measures extent of contribution of rolling historical standard

deviation (HV) series of 17 futures contracts and 3 spot indexes in forecasting the realized volatility of S&P 500 Index futures prices using data from 1984-1989. Higher the relative contribution coefficient, higher the contribution of a particular variable in forecasting. Exhibit 4 explains the concept.

3. ***: Represents variables not included in network training and forecasting.
4. L: Rolling HVs computed from log relatives of 1-day lagged index futures prices.
5. NC: Not calculated.

EXHIBIT 5

A fully connected, three-layered network. All three neurons in the input layer are connected to all three neurons in the hidden layer. All hidden layer neurons are connected to the neuron(s) in the output layer. Neurons in a given layer do not interconnect.

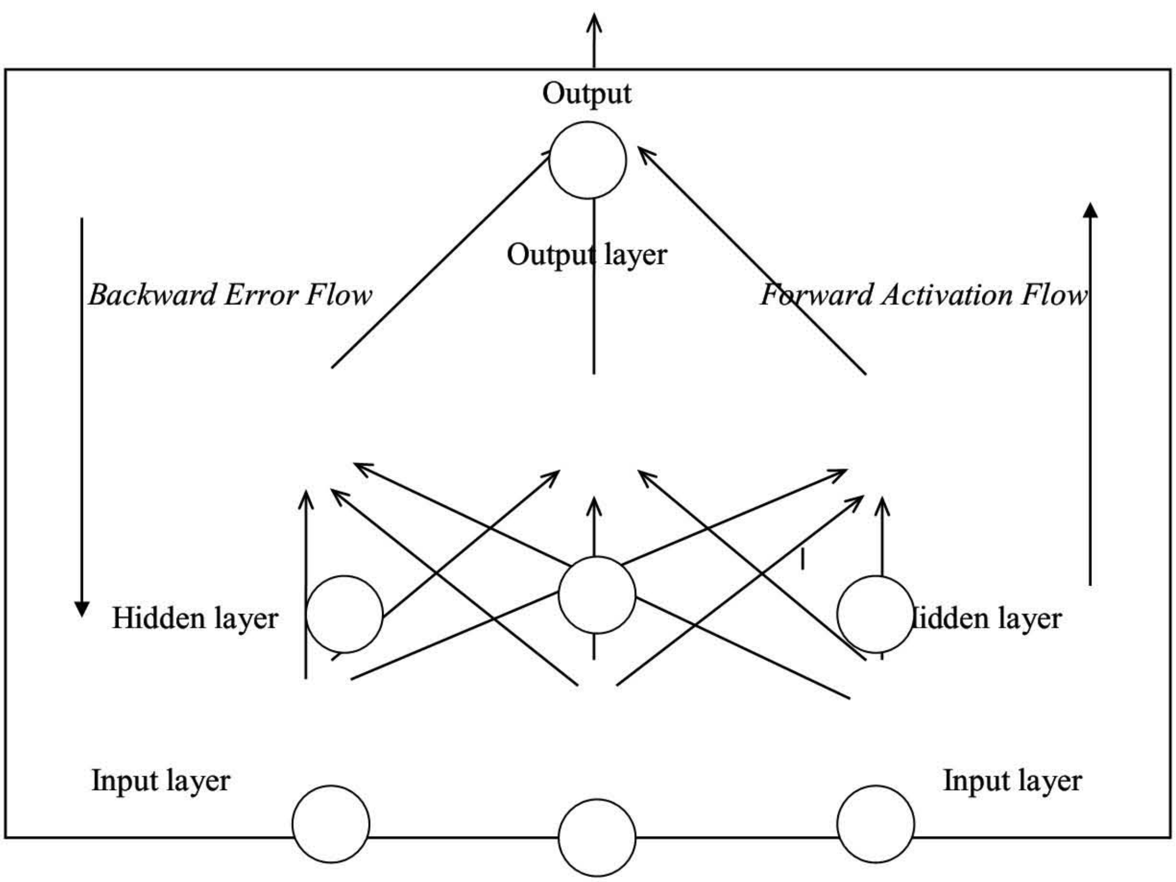

EXHIBIT 6

Means, standard deviations, t-statistics and p-values of tests of differences of means of neural volatility forecasts and implied volatility (IV) forecasts compared to realized volatilities (RVs) for 15-, 35- and 55-day forecast horizons. Neural forecasts are not significantly different from RVs. IVs are not significantly different from RVs only in case of 55-day forecasts. Mean absolute errors (MAE), root mean squared errors (RMSE) of forecasts with respect to RVs show that neural forecasts have lower errors compared to errors of IVs.

Horizon	Type	Mean	Std-Dev	T	p (1-tail)	MAE	RMSE
15-day	RV	0.008642	0.003453				
	NN Volat.	0.008800	0.002696	-0.42	0.34	0.001991	0.003184
	Imp. Volat.	0.010264	0.003098	**-2.06**	**0.02**	0.002681	0.003204
35-day	RV	0.009207	0.003162				
	NN Volat.	0.008767	0.002775	0.44	0.33	0.002186	0.003817
	Imp. Volat.	0.011625	0.004563	**-2.24**	**0.01**	0.003089	0.003979
55-day	RV	0.011340	0.009382				
	NN Volat.	0.011367	0.009275	-0.04	0.48	0.001467	0.002520
	Imp. Volat.	0.010680	0.002653	0.40	0.34	0.003546	0.008811

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