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Journal of Economic Policy and Research, Vol. 8, No. 2

Performance Evaluation of Neural Networks and Garch Models for Forecasting Volatility and Option Strike Prices in a Bull Call Spread Strategy

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Investing in options has many advantages : they provide increased cost efficiency; they have the potential to deliver higher percentage returns due to increased leverage; and they offer a number of hedging and strategic alternatives. It is, therefore, worthwhile to investigate the option trading strategies that offer high payoffs. This paper provides a performance evaluation of models used in the pricing of options for a bull spread options strategy. The strategy is highly profitable when the price of the underlying primitive reaches the second out-of-the-money strike price before the expiration date of the options, but no further. The challenge lies in choosing the optimal out-of-the-money option strike price. The option exercise price, past primitive price jumps, and primitive volatility shifts are the important factors that are to be analyzed. Since the understanding of the primitive volatility is important, this thesis investigates the forecasting ability of Feed Forward Neural Networks (FNN) using back propagation learning and Recurrent Neural Networks (RNN) models, using implied volatility forecasts obtained from a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The performance of the three models is studied and compared using the data from the S&P 500, DJIA, NYSE, and NASDAQ indexes. The resultsshown by the volatility forecasts indicate that RNN is a better forecasting tool. These results are further used to evaluate the performance of RNN and GARCH models in forecasting the sell option strike price in a bull call spread strategy. The trading profitability of these models is tested using SPY, DIA and SIRI options over a 1 month, 3month and 6 month trading horizon.

Keywords : Options, Bull Call Spread, GARCH, Artificial Neural Networks, Volatility.

Introduction

The tremendous increase in the awareness and activities of derivative securities in recent years has led to the popularity of option markets as one of the

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most sought financial instruments. Derivative securities are those securities whose prices are derived from the price of the underlying security. These assets are also called as contingent claims, because their payoffs are contingent on the price of other securities. Because the value of the derivatives depends on the value of other securities, they are powerful tools for hedging and speculation. To explore the markets well and improve on the investments, it is necessary to study derivative tools and their implications.

Volatility is one of the most important variables in the pricing of derivative securities. To price an option, we need to know the volatility of the underlying asset from now until the option expires. The use of neural networks as non-linear forecasters in the financial area is a relatively established area, however, the development of financial applications using neural network can still be a complex process. Extensive data pre-processing and experimentation with network parameters during the model development is a time consuming process that requires both art and skill. Experiments have been tested using market data throughout the global financial world. In addition, different input variables and neural network architectures have been applied. Neural networks have been studied in many financial areas such as stock trading (Wilson, 1994), currency option trading (Quah et al, 1995), foreign exchange rate forecasting (White and Racine, 2001), initial public offering pricing (Jain and Nag, 1995), and prediction of corporation bankruptcy (Fletcher and Goss, 1993).

Artificial neural networks (ANNs) are one of the technologies that are recognized in the financial markets. They provide interesting techniques that can theoretically approximate non-linear continuous functions on a compact domain to any designed degree of accuracy (Cybenko, 1989). The novelty of ANNs lies in their ability to model nonlinear processes without a prior assumption about nature of generating process (Hagen et al., 1996). It is useful in security investments and other financial areas where much is assumed and little is known about the nature of the process determining asset prices (Burrell and Folarin 1997).

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are applied to a very wide range of time series, but applications in finance have been particularly successful (Engle, 2001). They have been applied to risk management, option pricing, volatility forecasting, and other fields. But GARCH models are usually applied to return series and hence we use it for forecasting returns from different option trading strategies and also for volatility forecasting. Poon and Granger

(2003) survey 39 studies comparing the out-of-sample forecasting ability of GARCH and historical volatility. Twenty-two find that historical volatility which includes weighted standard deviation measures forecasts better and seventeen that GARCH forecasts better. In GARCH models there are more than just two parameters to estimate, and the likelihood functions are more complex (Engle, 1982 and Bollersev, 1986).

In the last decade, nonparametric approach using neural networks have been studied for option pricing and volatility estimation, including studies by Hutchinson (et.al, 1994) and Hanke (1999). Chen and Lee (1997) and Chidambaram, et. Al (1998) applied genetic algorithms for option forecasting and pricing. Salchenberger (1994) and Karaali et. al (1997) and Malliaris (1994) applied neural networks for volatility prediction benchmarked with conventional techniques in time series, digital signal processing, historical volatility, and implied volatility. Schittenkopf and Dorffner (2001) developed a risk-neutral density extraction method for option prices based on mixed density networks.

Our study applies performance measures to evaluate various neural network models for financial volatility forecasting. The forecasted value determines how well the system fits the model. The Mean Squared Error (MSE) will be used as the measurement method used to compare the performance of the neural network models. Based on these results, the neural network and GARCH models are further evaluated for their forecasting ability of option strike prices in a bull call spread strategy. The strategy is highly profitable when the price of the underlying primitive reaches the second out-of-the-money strike price before the expiration date of the options, but no further. The challenge here lies in choosing the optimal out-of-the-money option strike price.

The organization of this paper is as follows. Section-2 comprises a brief description of volatility which includes historical volatility and implied volatility. Section 3 describes the basic concepts of options, option trading strategies and in particular, the bull call spread strategy. Description of Neural networks and GARCH models is dealt with in Section-4 and Section-5. The experimental results consisting of volatility and option strike price forecasts is in Section-6. Then we conclude with a section on results and suggestions for further research.

Volatility

Volatility Forecasting

Volatility has become a topic of enormous importance to all those involved in the financial markets. For those who deal with derivative securities, understanding volatility, forecasting it accurately, and managing the exposure of their investment portfolios to its effects is crucial. Stock price, strike price, time to option expiration can be obtained from the market, but volatility must be forecasted. Although the realized volatility over recent periods can easily be computed from historical data, an option's theoretical value today depends on the volatility that will be experienced in the future, over the options entire remaining lifetime. Hence volatility forecasting is vital for derivatives trading.

Historical Volatility

Historical volatility reflects the past price movements of the underlying asset, also referred to as the asset's actual or realized volatility. Historical volatility is an Exponentially Weighted Average (EWA) of the past squared returns. The historical measure is similar to the basic volatility measure and is well suited for the purpose of trading options on financial indexes. A measurement of Historical Volatility (HV) estimates volatility using the historical stock price data, which is normally observed at fixed intervals of time, such as daily, weekly, or monthly. Historical volatility is calculated as the standard deviation of a stock's return over a fixed period of time. Stock return is defined as the natural logarithm of the closing prices between each interval of time.

The return and historical volatility are calculated as shown in Equations 1 and 2.

$$X_i = \ln\left(\frac{P_i}{P_{i-1}}\right) \text{............}(1)$$

$$HV = \sqrt{\frac{1}{n-1}\sum\left(X_i - \overline{X}\right)^2} \text{ ...}(2)$$

X_i : Return at the i^{th} interval

P_i : Stock close price at the end of i^{th} interval

n+1 : Number of observations or number of observed days.

A basic rule for determining the appropriate number of observations is to set n equal to the number of days for which the volatility is to be applied (Hull, 2003). Normally, more observations can lead to increased accuracy, however, volatility changes over time and data from deep in the past may not be relevant for predicting the future. When historical volatility is high, the stock has previously been displaying increased movement in price. When it is low, the volatility implies quiet trading, or low movement in price. Benchmarking allows comparing the volatility of a stock with the general market, or the stocks within a specific sector. In the same way, benchmarking the volatility of a stock with its own historical volatility allows one to estimate the increased or decreased movement of volatility. Historical Volatility measure is frequently compared with implied volatility to determine if options prices are over-valued or undervalued. Historical volatility is also used in all types of risk valuations. Stocks with a high historical volatility usually require a higher risk tolerance.

Implied Volatility

Implied Volatility of a stock or an index is computed using an option pricing model such as the Black-Scholes or Binomial. In contrast to historical volatility, which is a measure of price changes in the past, Implied Volatility reflects expectations regarding the stock or market's future volatility. Implied volatility yields a theoretical value for the option equal to the current market price. It is derived by adding all known variables and market option price into the formula, and then calculating the volatility. This calculated volatility is called implied volatility.

It can also help to gauge whether options are cheap or expensive. Rising implied volatility causes option prices to rise or become more expensive; falling implied volatility results in lower option premiums. Therefore, with everything else being equal, when implied volatility on an option is high, it is better to sell that option; if the implied volatility is low, the option more suitable for buying. Implied volatility increases when the market is bearish and decreases when the market is bullish. This is due to the common belief that bearish markets are more risky than bullish markets. To determine whether the implied volatility is high or low, it is important to compare the current value of volatility to the past levels. Option contracts have values of implied volatility which change over time and therefore lack reliability.

Options

Fundamentals of Options

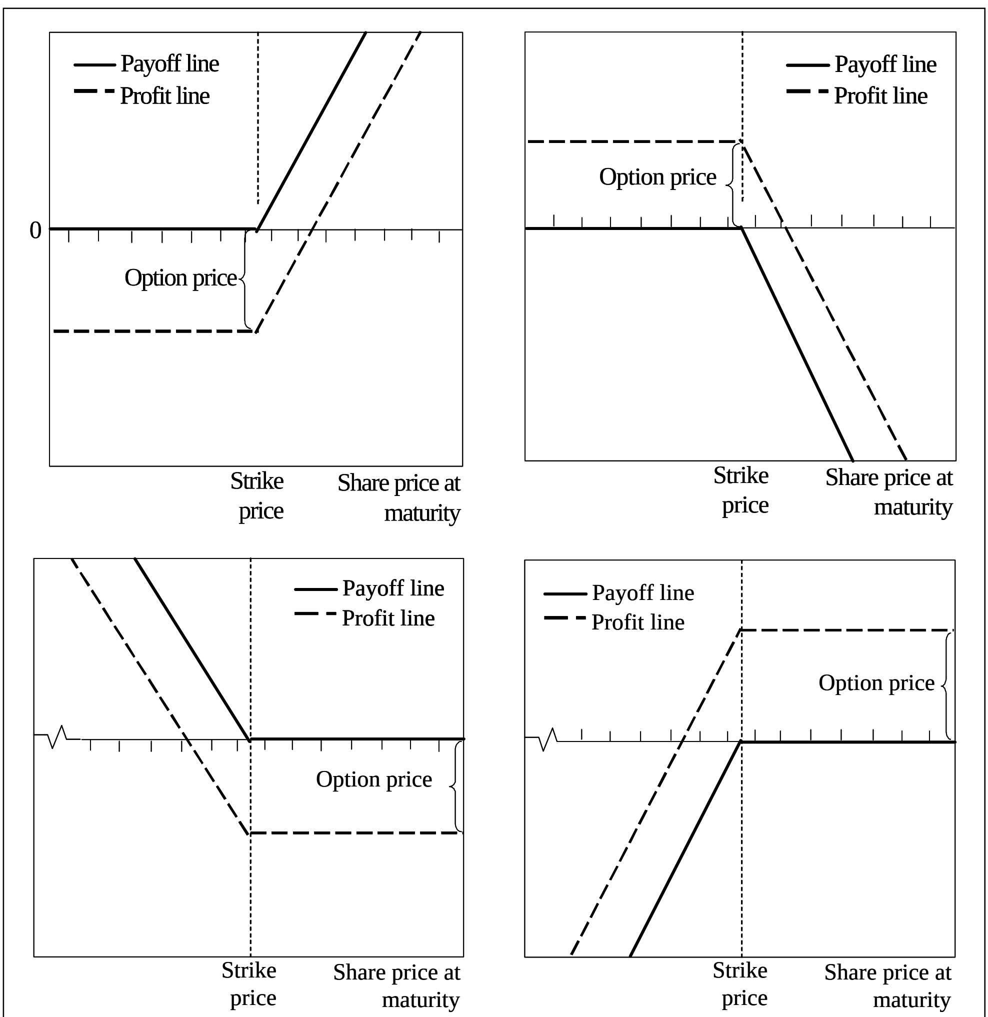
An option gives the holder of the option the right to do something, but the holder does not have to exercise the right. In order to acquire this right, the purchase of an option requires an up-front payment, often called option price or premium. There are basically two types of options, call options and put options. A call option gives the holder of the option the right to buy an asset by a certain date for a certain price. A put option gives the holder the right to sell an asset by a certain date for a certain price. The date specified in the contract is known as the exercise date or the maturity date. The price specified in the contract is known as exercise price or strike price. Most traded options expire on the third Friday of the expiration month. Buyers and sellers of exchange-traded options do not usually interact directly – the futures and options exchange acts as intermediary. The seller guarantees the exchange that he can fulfill his obligation if the buyer chooses to execute.

The option style determines when the buyer may exercise the option. It will affect the valuation. Generally, the contract will either be American Option which allows exercise up to the expiration date - or European Option where exercise is only allowed on the expiration date - or Bermudan Option where exercise is allowed on several, specific dates up to the expiration date. European contracts are easier to value. Due to the American option having the advantage of an early exercise day, they are always at least as valuable as the European option. Payoffs would be different when American options are used. This is because of the early exercise possibility and levels of risk exposure. In U.S markets, most exchange traded options are American, with each contract being an agreement to buy or sell 100 shares of the underlying security. In the market, the price quoted is per share and hence the trader needs to pay 100 times the quoted price to control 100 shares.

Options can be in-the-money, at-the-money or out-of-the-money. The in-the-money option has a positive intrinsic value; options in at-the-money or out-of-the-money have an intrinsic value of zero. An in-the-money option for a call is one where the strike price is less than the current market price of the underlying security. An in-the-money option for a put option is one where the option strike price is greater than current market price of the underlying security. Additional to the intrinsic value an option has a time value, which decreases the closer the option is to its expiration date. The option premium is equal to the intrinsic value plus the time value.

An option contract comprises of two positions: long and short. The trader who buys the option has taken a long position while the one who sells or writes the option has taken the short position. The buyer pays a premium or option price to enter the position while the seller receives cash premium upfront, with potential liabilities afterward. The writer needs to make a security deposit or post a margin to guarantee the capability to respect their obligations to sell or buy the underlying asset. The writer should pay any loss that result from the position going against them. The profit and loss for writer and buyer are reverse of each other minus the transaction casts. For example, in a long call the trader who believes that a stock's price will increase may buy the right to purchase the stock (a call option). He would have no obligation to buy the stock, only the right to do so until the expiry date. If the stock price increases over the exercise price by more than the premium paid, he will profit. If the stock price decreases, he will let the call contract expire worthless, and only lose the amount of the premium. On the other hand, in short call (Naked short call), the trader who believes that a stock's price will decrease can short sell the stock or instead sell a call. The trader selling a call has an obligation to sell the stock to the call buyer at the buyer's option. If the stock price decreases, the short call position will make a profit

Figure-1 : Long Call, Short Call, Long Put, Short Put



in the amount of the premium. If the stock price increases over the exercise price by more than the amount of the premium, the short will lose money. Unless a trader already owns the shares which he may be required to provide, the potential loss is unlimited. However, such a trader who sells a call option for those shares he already owns has sold a covered call.

The option profit is calculated without including the cost of option. The profit considers the cost to enter the long position and the premium received from the short position. If we consider an option with an initial cost C, strike price K, and the final price S of the underlying security at the maturity, the profit and the payoff from the long call position are max{S-K-C, -C} and max{S-K, 0}, respectively. The profit and payoff of the short position are min{C-K-S, C} and min {K-S, 0}, respectively. The concept is the same for put options.

Option Strategies

Combining the four basic kinds of option trades (Long call, Short call, Long put, Short put) and the other stock trades allows a variety of options strategies. Simple strategies usually combine only a few trades, while more complicated strategies can combine several. Strategies could involve a single stock and option (Protective put, Covered call, Synthetic put, Synthetic call), Spreads (Bull, Bear, Box, Butterfly, Calendar, Diagonal), Combinations (Straddle and Strangle) and various other payoffs. Many of the strategies can be developed by looking at the Put-Call parity theorem.

$$C + Ke^{-rT} = p + S_0 \text{ ....} \quad (3)$$

Where C is the call option price, K is the strike price, r is the risk-free rate, T is the time to maturity, p is the put option price and S_0 is the initial stock price.

The above equation can be rearranged to consider various long and short position.

Spread Options Strategies are a combination of two or more options of the same type (two or more calls or two or more put options). Some are purchased and some written.

- Money spread : Each option has different exercises prices
- Time spread : Each option has different expiration times
- Bullish, bearish, and neutral bias spread are also possible.
- Vertical (Money) : purchase one option and sell a similar option with a different strike price

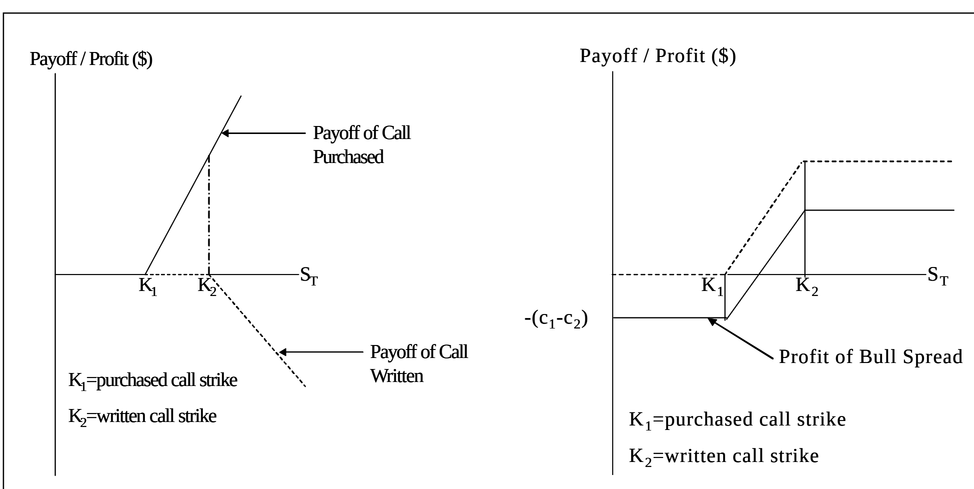
- Horizontal (Time) : purchase one option and sell a similar option with a different maturity date
- Diagonal : purchase one option and sell a similar option with a different strike price and maturity date

Financial engineering which mostly occurs at the institutional level enables the creation of investment portfolios with payoffs that depend in a variety of ways on the values of other securities. Various levels of exposure to the price of the underlying security are attained. It also helps to develop numerous option trading strategies.

Bull Spread Strategy

Bull spread—Long a call with a low exercise price and short a call with a higher exercise price, or long a put with a low exercise price and short a put with a higher exercise price. Bull spread is a vertical, money spread. Investor here is hoping the stock increases. Using call options, the option purchased has a lower strike price than the option sold (same expiration date). It involves an initial cost since the near-term call option purchased is more expensive than the call option sold. The bull spread strategy limits the investors upside and downside risk(less cost). It could either be an aggressive strategy with both the calls initially out-of-money (cheaper, less payoff) or a conservative strategy wherein both calls are initially in-the-money (expensive, likely payoff). When put options are used, it creates positive upfront cash flow, with a payoff that is either zero or negative. In our paper, we focus on the Bull call spread strategy.

Figure-2 : Bull Call Spread Strategy



The payoff and profit of a bull call :

When S_T K_1 are 0 and $-(c_1 - c_2)$,

For $K_1 < S_T$ K_2 are $S_T - K_1$ and $S_T - K_1 - (c_1 - c_2)$,

And for $S_T > K_2$ are $K_2 - K_1$ and $K_2 - K_1 - (c_1 - c_2)$.

From the above, it can be observed that the strategy makes maximum profit when the written call strike price is reached. Hence our paper concentrates on forecasting the option strike price of the written call in the bull call spread strategy.

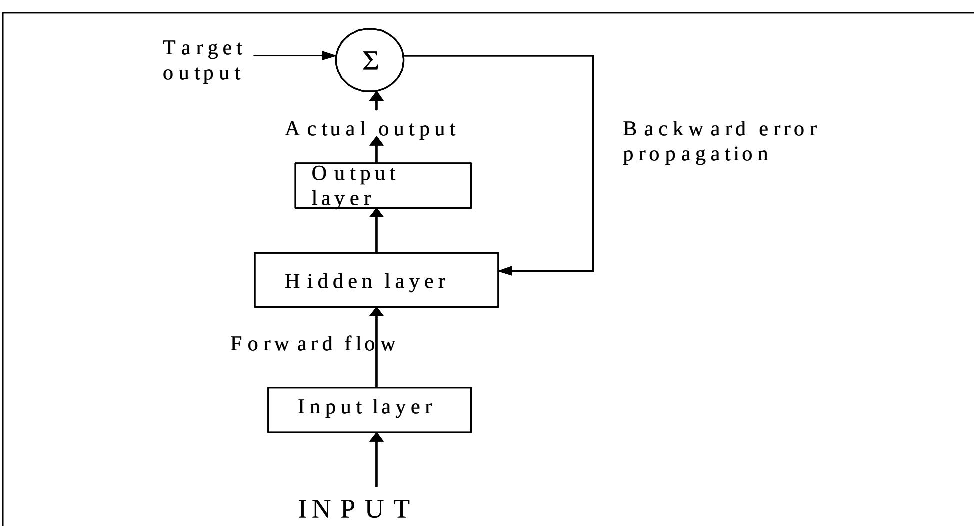
Neural Network Architectures

Feed Forward Network with Backpropagation Learning

A neural network is a collection of interconnected simple processing elements. Ever connection of neural network has a weight attached to it. The backpropagation network is the most well known and widely used amongst the neural network systems available. The backpropagation network is a multilayer feed forward network with a different transfer function in the artificial neuron and a more powerful learning tool.

The typical backpropagation network has an input layer, some hidden layers and an output layer. The error between the predicted output value and the actual value is backpropagated through the network for the updating of the weights, which have initial values. This is a supervised learning procedure that attempts to minimize the error between the desired and predicted outputs.

Figure -3 : The Backpropagation Network



The output value for a unit j is given by :

$$O_j = G\left(\sum_{i=1}^{m} w_{ij}x_i - \theta_j\right) \text{...... (4)}$$

Where is the output value of the th unit in previous layer,

x_i is the weight on the connection from the th unit,

θ_j is the threshold, m is number of units in the previous layer.

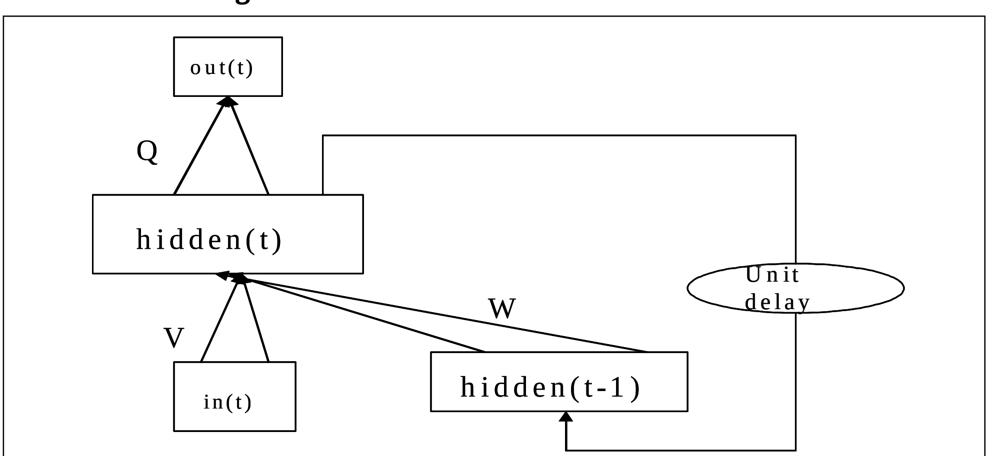
The function G ( ) is a sigmoid hyperbolic tangent function and is the commonly used activation function for time series prediction in backpropagation networks.

Recurrent Neural Networks

Recurrent Neural Networks

Recurrent Neural networks are more complicated because they have feedback paths from their outputs back to their inputs. After applying a input, the output is calculated and then fed back to modify the input. The output is then recalculated and the process repeats itself. An Elman recurrent network is characterized by delayed feedback connections from each of the hidden nodes to all the hidden nodes. The Elman network has a combination of tansig neurons in its hidden (recurrent) layer, and purelin neurons in its output layer. This combination is special because two-layer networks with these transfer functions can approximate any function with a finite number of discontinuities with arbitrary accuracy. The only requirement is that the hidden layer must have enough neurons. More hidden neurons are needed as the function being fit increases in complexity. The first layer in an Elman network has a recurrent connection.

Figure-4 : Elman Recurrent Neural Network



Garch Model

The Autoregressive Conditional Heteroskedastic model was introduced by Engle (1982) and the Generalized Autoregressive Conditional Heteroskedasticity model was developed by Bollersev (1986), which allows for flexible rag structure, and is frequently used to model the serial dependence of volatility. Heteroskedasticity means time-varying variance (volatility) or non-constant variance, conditional implies a dependence on observations of the immediate past, and autoregressive describes a feedback mechanism that incorporates past observations into the present. GARCH is a time series technique that allows the user to model the serial dependence of volatility. GARCH modeling takes into account fat tail behavior and volatility clustering, two important characteristics of financial time series. GARCH provides an accurate forecast of variances and co-variances of asset returns through its ability to model time-varying conditional variances and hence is extensively applied for portfolio management, risk management, option pricing, etc.

Garch (P, Q) Model

A random sequence or stochastic process exhibits a degree of correlation from one observation to the next. This correlation structure can be used to predict future values of the process based on the past history of observations and to exploit the correlation structure. According to the decomposition theorem, it could be said that the time series is a sum of the forecast and the error, or uncertainty associated with the forecasts. The simple GARCH (p, q) model can be expressed as follows:

$$y_t = x_t \beta + u_t \text{ ....(5)}$$

Where is the financial return, is linearly deterministic, and is the linearly regular covariance stationary stochastic process (residual) which can be modeled as

$$u_t = \sqrt{\sigma^{2t} . v_t} \text{ ....(6)}$$

Where v_t, the endogenous variable, is with zero mean and unit variance, and where σ^2 is expressed as a sum of past variances and past innovations(the diffe-rence between predicted value and actual value at time t-q) with their coefficients respectively.

The GARCH (1, 1) is the most popular model in the empirical literature. For example, it has been used by Akgiray (1989), Randolph (1991) for forecasting monthly volatility. Specifically, given daily stock index return data, the GARCH (1, 1) model can be described as follows :

$$\sigma^{2t} = k + \delta_1 \sigma^{2t-1} + \partial_1 u^{2t-1} \text{ ....(7)}$$

In a standard GARCH model, is normally distributed. Alternative models can be specified by assuming different distributions for, for example the t-distribution, Cauchy distribution, etc.

Experimental Results

Forecasting Volatility

Volatility is an important metric in the financial markets. Using neural networks to the forecast volatility of stock market indices and the performance evaluation of different models under dynamic market conditions will be very useful to study option strategies and option valuation. The forecasting ability of FNN using backpropagation learning and the RNN with the Elman network architecture have been investigated using the data from various stock markets. The returns data of the NASDAQ, DJIA, NYSE and S&P 500 markets have been used to obtain the 180-day implied volatility data using GARCH models. A volatility forecast over a multiple period horizon is used. Many uses of volatility forecasts, such as option valuation, require volatility estimates over a much longer horizon than that from t to t+1. Typically the GARCH model is estimated using daily data, so t+1 represents the next day, but for option valuation purposes, what is required is a volatility estimate over the life of the option which may expire months in the future. To generate the required long-horizon volatility forecast, estimated forecast volatilities in subsequent periods out to the expiration date are generated. The forecast horizon lengthens, better volatility forecasts are obtained by decreasing the weights on the most recent observations while increasing the weights on older observations relative to the parameter estimates generated by the GARCH procedure. This 180-day forecast has been compared against the historical volatility using FNN and RNN models.

Data Set

Data Set

The specific data used for this study was the price and volatility data over a period of 8 years for the NASDAQ Composite (COMPQX), Dow Jones Industrial Average (DJIA), New York Stock Exchange (NYSE) and the S&P 500 (SPX) stock indexes. All the four major market indices have been used for our analysis based on their variability.

The period of 8 years from 1996-2004 (2016 days) has been used. The training set has been chosen as a period of 6 years from 1996-2001(1512 days) and testing set is from 2002-2004 (504 days). The input used is the open, high, low and closing prices of the stocks for obtaining volatility as the output. The number of hidden layers and the weights assigned to each layer have been chosen based on the complexity of the input and output data.

MSE Results

The Mean Squared Error (MSE) is the measurement methods used to compare the performance of the neural network models for this research. It is used to evaluate and compare the productive power of the models by finding the error between the predictive output value and the actual value. The equation used for MSE is given in below :

$$MSE = \frac{\sum\left(Y_t - \hat{Y}_t\right)^2}{N} \quad ....(8)$$

Where Y_t is the actual price is the price $\hat{Y}_t$ forecasts produced by the neural network models and N is the number of test data sets. Low MSE usually means high accuracy and better prediction ability, although low MSE is not necessary a sign of high return or profitability in the stock market.

Conclusion

From the analysis, it is concluded that RNN models give a better forecast of the volatility than the historical volatility. But these indications definitely depend on the data, because the models perform differently for different stocks, and sometimes may be market specific. Mean Squared Error (MSE) was also utilized to evaluate the results of the neural network, but the research has shown that low MSE does not always produce better return in a stock market when our model is a combination of a neural network prediction. From the table, it can be concluded that for a given set of data, the RNN gives a better prediction of the volatility measurement compared to the FNN with backpropagation learning.

Forecasting Option Strike Prices

Dataset

The specific data used for this study is the option price and volatility data over a period of 18 months for the Diamonds Trust (AMEX:DIA), Spiders (AMEX:SPY) and Sirius Satellite Radio Inc. (NASDAQ:SIRI) stocks. Exchange traded funds: ETFs are securities certificates that state legal right of ownership over part of a basket of individual stock certificates. Several different

Table-I : Comparing MSE to Evaluate Results of Neural Networks

SYMBOLS	SPX	COMPQX	NYSE	DJIA
FFN	167.24	57.23	264.63	171.08
RNN	151.21	4.24	186.39	157.45

kinds of financial firms are needed for ETFs to come into being, trade at prices that closely match their underlying assets. We have chosen ETFs (DIA and SPY) trading on AMEX and SIRI, which is a small cap stock which offers diversification. The period of 18 months from January 2004-June 2005 has been used. The training set has been chosen as a period of 12 months from January 2004- December 2004 and testing set is from January 2005-June 2005. The input used is the option strike prices, the stock prices and the implied volatility data. Each of these data is tested and trained for 1-month, 3-month and 6-month options.

MSE Results

As used earlier in Section 6.1.2, Mean Squared Error (MSE) is the measurement method used to compare the performance of the neural network and GARCH models for this part of research. From the conclusion in volatility forecasts, Recurrent Neural Networks give a better forecast if the volatility measurements. Based on these results, we will compare the forecasting ability of RNN and GARCH models for option strike prices.

The Coefficient of Variation (CV)

The coefficient of variation (CV) is a measure of dispersion of a probability distribution. It is defined as the ratio of the standard deviation to the mean. The coefficient is a dimensionless number that allows comparison of the variation of populations that have significantly different mean values. It is often reported on a scale of 0 to 100% by multiplying the above calculation by 100, as shown in Equation (9) :

$$CV = \frac{\sigma}{\mu}.100 \text{ ....(9)}$$

Where α is the standard deviation during certain time period and μ is the mean of this period. Since different test samples have significantly different mean

Table-II : Number of Data Records

	Number of data records					
Stock	**1-month**		**3-month**		**6-month**	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**
DIA	1810	905	550	270	324	151
SPY	1515	750	562	258	322	160
SIRI	1620	810	570	285	310	155

Table-III : Comparing the Forecasting Ability of RNN and GARCH Models

Performance Evaluation	Period	Stock Options		
MSE		DIA	SPY	SIRI
	1 MONTH	121.543	306.53	34.213
RNN	3 MONTH	134.428	326.48	33.899
	6 MONTH	256.242	433.608	28.3656
RMSE				
	1 MONTH	0.09	0.0612	0.4151
GARCH	3 MONTH	0.0978	0.0682	0.4575
	6 MONTH	0.1264	0.0755	0.4775

values, CV is a very useful measurement of volatility in this research. Table-IV provides a comparison of CV of our data.

From this Table, it is observed that the volatility of DIA and SIRI is higher than that of SPY. Also 6-months volatility of all the three stocks is higher than that of 1-month and 3-months options. As the purpose of our research is to see the performance of different neural network models over different stock options and variable periods, CV comparison can give some basic idea in which period the neural network models performed better.

Trading Profitability

There are different ways, such as direction accuracy, profitability, etc., to measure the results of trading strategy models. Nonetheless, one of the most straightforward ways is by using a profitability measurement, as it is often an investor's most common criterion for judgment whether a model is acceptable or not. After performing the trading

Table- IV : Comparison of Coefficient of Variation (CV)

SYMBOLS	1-month	3-months	6-months
SPY	9.12	10.57	12.31
DIA	29.31	31.26	33.03
SIRI	26.57	28.43	29.76

simulations, the returns of our stock options with RNN and GARCH models were calculated and compared against a Buy-and-Hold strategy. Buy-and Hold strategy here is applied by using the stock options data for the 1-month, 3-months and 6-months options and using a moving window for these specified periods. This is compared against the results obtained by using RNN and GARCH models for return forecasting.

From the above profitability results, it can be seen that RNN and GARCH models for the bull call spread strategy definitely provide higher returns than the buy-and hold strategy for all the three stock options. Of RNN and GARCH models, it is observed that GARCH models give higher profitability for the same set of data. 1-month stock options give higher profitability than 3-months and 6-months options. This can also be attributed to the fact that more number of 1-month options are traded in the market and hence more training data is available. Also looking at the data used for simulations, fewer numbers of data records have been available for 6-months options, but the numbers of options traded on this stock are relatively low compared to DIA and SPY. During the period 2004-2005, it can be said that the small- cap stock SIRI had higher returns. Also the ETFs were largely traded during this period. Of DIA and SPY, both have given considerably large returns, though SPY performed well over 6-month options. Thus these results conclude that GARCH models give a better prediction of option strike prices for the bull call spread strategy.

Conclusions and Future Work

The research demonstrates the benefits of using neural networks and GARCH models for forecasting option strike prices. We have observed that recurrent neural networks give a better prediction of volatility compared to feedforward neural networks.

Table-V : Trading Profitability

Trading Profitability									
Trading	**1-month**			**3-month**			**6-month**		
Strategy	**DIA**	**SPY**	**SIRI**	**DIA**	**SPY**	**SIRI**	**DIA**	**SPY**	**SIRI**
Buy-and-hold	3.57%	4.52%	7.71%	–5.97%	4.86%	9.03%	–11.32%	–7.53%	–6.95%
RNN	8.76%	11.79%	9.17%	–1.82%	7.32%	5.67%	–12.84%	–8.09%	–8.54%
GARCH	12.65%	15.72%	18.64%	4.73%	18.96%	19.37%	–9.93%	–2.46%	–4.28%

Taking off from these results, we have done a performance evaluation of RNN and GARCH models for forecasting option strike prices. From the results, it can be concluded that that GARCH models give a better prediction of option strike prices for the bull call spread strategy. Thus for the bull call spread strategy, we see higher returns and profitability measurements when GARCH was used for return forecasting.

Further research might consider other forecasting tools such as Monte Carlo simulations, Markov chains etc. to forecast future option prices. Monte Carlo (quasi and pseudo) methods which are exceedingly flexible in dealing with path-dependent payoffs and path-dependent underlying dynamics can be used for obtaining the optimal out of the money option strike price. The performance evaluation of these models could be compared against GARCH models to evaluate their profitability and efficiency. The various trading strategies can also be considered with other statistical techniques to improve profitability from option trading.

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