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Empirical of the Taiwan stock index option price forecasting model – applied artificial neural network

Chin-Tsai Lin* and Hsin-Yi Yeh

Graduate School of Management, Ming Chung University, Taipei 11103, Taiwan, R.O.C.

This work presents a novel neural network model for forecasting option prices using past volatilities and other options market factors. Out of different approaches to estimating volatility in the option pricing model, this study uses backpropagation neural network to forecast prices for Taiwanese stock index options. The ability to develop accurate forecasts of grey prediction volatility enables practitioners to establish an appropriate hedging strategy at in-the-money option.

I. Introduction

Recently, there has been significantly increased awareness of and trading in derivative securities. Among these derivative securities, options are now traded on numerous exchanges and also by banks and other financial institutions worldwide. By protecting practitioners from stock market randomness, options can help them reduce financial risk. Forecasting option prices thus is very important for practitioners.

Basically, the probability of a stock price rising or falling increases with volatility, simultaneously increasing the value of call and put options. Methods of accurately measuring and forecasting volatility thus are critical for option pricing models. Volatility is a measure of price movement frequently used to assess risk and signal large moves in underlying markets. The predictability of market volatility is important for options practitioners in predicting closing prices and setting expectations regarding market returns. Some studies have specified the volatility of underlying asset as a deterministic function of time and underlying asset price (such as, Rubinstein, 1994; Coleman *et al.*, 2001). Meanwhile, other studies have examined stochastic volatility models (such as, Hull and White, 1987; Heston, 1993; Bates, 1996; Watanabe, 1999; Kim and Kim, 2004) and GARCH models (such as, Duan, 1995; Chu and Freund, 1996; Sabbatini and Linton, 1998; Williams *et al.*, 1998; Chung and Hung, 2000; Duan and Zhang, 2001; Szakmary *et al.*, 2003; Chan *et al.*, 2004; McMillan and Speight, 2004; Kalotychou and Staikouras, 2006).

Predicting market volatility is important for options practitioners in forecasting closing prices and determining expected market returns. However, price forecasting traditionally requires large quantities of data and assumptions, creating difficulties for efficient research and practical implementation. Currently, these problems can be resolved via the grey prediction approach. Because the grey prediction approach requires as few as four inputs to forecast price and can solve the problem of nonlinear forecasting without making any assumptions and thus achieve a good forecasting result. The grey prediction approach differs from traditional forecasting approaches that require extensive data. Therefore, this study proposes a grey prediction approach for estimating volatility in addition to traditional methods.

*Corresponding author. E-mail: ctlin@mail.ypu.edu.tw

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This study proposes an alterative data-driven method for option pricing, a neural network model, in which the data can provide direct evidence supporting the estimation of the underlying generation process. The neural network model is widely used as a promising alternative approach to time series forecasting (Zhang and Berardi, 2001). Studies on pricing derivative securities using the neural network model have attracted researchers and practitioners, Hutchinson *et al*. (1994), Malliaris and Salchenberger (1996), Qi (1999), Yao *et al*. (2000), Amilon (2003), Santín *et al*. (2004), Binner *et al*. (2005) and Lin and Yeh (2005) applied the neural network model and obtained better results than achieved using the traditional stochastic model.

In short, this study employs the forecasting property of the GM (1, 1) model to estimate underlying asset volatility and uses different estimation approaches: historical volatility, implied volatility and GARCH model, all of which provide an input into the backpropagation neural network model for comparing option pricing performance given different volatilities. The contribution of this study is attempting to integrate the grey prediction approach with the neural network model, and to investigate stock market behaviour in developing financial markets.

The remainder of this study is organized as follows: Section II presents a general discussion of neural network as a prediction model and demonstrates the computations involved in the historical volatility, implied volatility, GARCH approach, and Grey prediction approaches. Section III describes the data set and presents the empirical results, while the final section presents conclusions.

II. Methodology

Approach of neural network

A neural network is an interconnected group of artificial neurons that uses a mathematical model for information processing based on a connection computational approach. Such a network comprises a network of simple processing elements (neurons) which can exhibit complex global behaviour, determined by the connections between the processing elements and element parameters. In a neural network model, simple nodes (or 'neurons') are linked into a network of nodes. A neural network model comprises numerous highly interconnected processing elements (neurons) working together to solve specific problems. The practical advantages of neural networks derive from algorithms designed to alter the weights of the network connections to produce a desired signal flow.

The main advantage of neural networks is their ability to provide an arbitrary function approximation mechanism which 'learns' from observed data. That is, their advantage lies in their ability to learn how to perform tasks based on data given for training or initial experience. A trained neural network can be conceived as an 'expert' in the category of information it has been given to analyse. The ability of such networks to learn by example makes them extremely flexible and powerful.

In one word, neural network is an information processing technology that models mathematical relationships between inputs and outputs. Neural network can model nonlinear patterns and learn from historical data. The architecture of the human brain is such that a set of processing elements are interconnected and organized in layers (Malliaris and Salchenberger, 1996). The neural network model is an emerging and challenging computational technology and thus provides a new avenue for examining the dynamics of various financial applications.

Procedure

This study employs a backpropagation neural network, the most widely used network in business applications. A three-layer backpropagation neural network is shown in Fig. 1. The backpropagation process learns the weights for connections between nodes based on data training, yielding a minimized least-mean-square error measure of the actual, desired and estimated values of the neural network output. The connection weights are assigned initial values. Furthermore, the error between the predicted output value and the actual value is backpropagated through the network for weight updating. The supervised learning procedure then attempts to

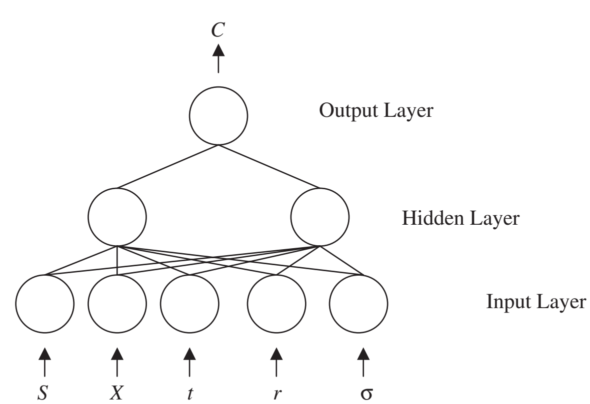

Fig. 1. A one hidden layer neural network

minimize the error between the desired and forecast outputs. Theoretically, neural network can simulate any kind of data pattern given sufficient training. A neural network requires training before being applied for forecasting. During training, neural network learns from experiences based on the proposed hypotheses. Furthermore, this study employs one hidden layer for each neural network model, and the sigmoid function provides the activation function.

Calculating volatilities

The seminal work by Black and Scholes (1973) on option pricing assumed that stock prices follow a standard lognormal diffusion:

$$\mathrm{d}S_t/S_t = \mu \mathrm{d}_t + \sigma \mathrm{d}W_t$$

where S_t denotes the current stock price, μ represents the constant drift, σ is the constant volatility, and W_t denotes a standard Brownian motion. The standard Black–Scholes option pricing formula for calculating the equilibrium price is

$$C = S_t N(d_1) - Xe^{-rt} N(d_2) \tag{1}$$

where $d_1 = [\ln(S_t e^{-rt}/X) + (r + \sigma^2/2)t]/(\sigma\sqrt{T})$; $d_2 = d_1 - \sigma\sqrt{t}$. C is the call price; S denotes the current underlying asset price; X is the exercise price; t denotes the time to maturity (in years); σ represents the volatility of the underlying asset; r is the short-term risk free interest rate and $N(d_i)$ is the cumulative probability function for d_i, $i = 1, 2$. Equation 2 presents the Black–Scholes model (BS) in simple form.

$$\text{Option price} = \text{BS }(S, X, t, \sigma, r) \tag{2}$$

All variables besides volatility can easily be obtainable from the market. σ is the only unknown factor in the formula, and is frequently assumed to be unchanged when forecasting option prices. An estimate of the asset volatility becomes the focus of attention for both theorists and traders.

Historical volatility and implied volatility. Essentially, two approaches exist for computing or estimating volatility: historical and implied volatility approaches. The historical approach is simpler than the implied volatility approach. The historical approach for estimating volatility is based on historical stock price returns. This study uses the simple weighted moving average approach to determine daily volatility based on the mean historical returns of underlying assets over a 60 day horizon. The annualized SD of historical daily returns then is calculated as the historical volatility. The method to estimate historical volatility is as follows:

$$\begin{aligned} R_t &= \ln(S_t) - \ln(S_{t-1}) \\ \hat{\sigma}_t &= \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}\left(R_t - \bar{R}\right)^2} \\ \hat{\sigma}^H &= \hat{\sigma}_t\sqrt{N} \end{aligned} \tag{3}$$

where R_t denotes the return of the stock at time t, $\bar{R}$ represents the mean of the R_t, S_t is the stock closing price, N is the number of trading days.

However, the historical approach assumes that future volatility will remain constant and that history will repeat itself. Implied volatility thus is a more common approach for estimating volatility since it is future oriented. Implied volatility assumes the option market is effective, and that the call option price can be treated as the actual market price because it reflects the opinions of trading participants regarding future returns. The implied volatility uses the Black–Scholes formula in reverse, and thus can be calculated using the Black–Scholes formula.

The simplified approach to estimate implied volatility is as follows:

$$\hat{\sigma}^I = \frac{1}{n}\sum_{j=1}^{n}\sigma_j \tag{4}$$

where σ_j represents the implied volatility on day j.

GARCH approach. Rather than the historical and implied approach, numerous models are based on the stochastic volatility process characteristic. One widely known model is the ARCH approach, devised by Engle (1982). This model sets an unconditional volatility constant while permitting conditional volatility to change over time. The generalized approach of ARCH models was proposed by Bollerslev (1986), and is as well known as the GARCH model. The GARCH is commonly applied to economic data and particularly stock markets. The GARCH approach is important in economics, and is attracting growing interest in the empirical study of common behaviour of international stock markets.

In GARCH, the volatility is calculated based on observations of historical daily asset prices and the estimation process considers both the conditional and unconditional variance. In the GARCH approach, the conditional variance is specified not only as a linear function of past sample variance, but also includes lagged conditional variances in the equation. Although many GARCH approaches have been designed, GARCH (1, 1) is the most popular use in empirical study among the GARCH approaches.

This study uses the GARCH (1, 1) approach, which is expressed as:

$$\sigma_i^2 = \omega + \alpha \cdot u_{i-1}^2 + \beta \cdot \sigma_{i-1}^2 \tag{5}$$

Grey prediction approach. The grey theory first proposed by Deng (1982) avoids the inherent deficiencies of conventional statistical methods; assumptions regarding the statistical distribution of data are unnecessary and only a limited amount of data is required to estimate the activities of unknown systems. When using historical and implied volatility together with the GARCH approach to calculate price, enormous quantities of data are required to meet with the assumption. However, grey theory can deal with systems characterized by poor information or for which information is lacking. The fields to which grey theory can be applied include systems analysis, data processing, prediction, decision-making and control. Unlike statistical methods, assumptions regarding the statistical distribution of data are unnecessary when applying grey theory. The grey prediction approach has been widely used in many applications.[1] The grey prediction approach, GM (1, 1), is one of the most common in grey theory. When using grey theory, it is not necessary to employ all the data from the original series in constructing the GM (1, 1), and the forecast potency of the series can use just four or more than four observation. The GM (1, 1) approach constructing process used in this study is described below:

Denote the original data sequence by

$$\sigma^{(0)} = \left(\sigma^{(0)}(1), \sigma^{(0)}(2), \sigma^{(0)}(3), \ldots, \sigma^{(0)}(n)\right),$$

where n is the number of days observed.

The accumulated generation operation (AGO) formation of $\sigma^{(0)}$ is defined as:

$$\sigma^{(1)} = \left(\sigma^{(1)}(1), \sigma^{(1)}(2), \sigma^{(1)}(3), \ldots, \sigma^{(1)}(n)\right),$$

where

$$\sigma^{(1)}(1) = \sigma^{(0)}(1), \text{ and } \sigma^{(1)}(k) = \left(\sum_{k=1}^{1} \sigma^{(0)}(k), \sum_{k=1}^{2} \sigma^{(0)}(k), \ldots, \sum_{k=1}^{T} \sigma^{(0)}(k)\right)$$

The GM (1, 1) approach can be constructed by establishing a first order differential equation as:

$$\sigma^{(0)}(k) + aZ^{(1)}(k) = b, \quad k = \{1, 2, 3, \ldots, n\} \tag{6}$$

Therefore, the solution of Equation 6 can be obtained by using the least square method. That is,

$$\hat{\sigma}^{(1)}(k+1) = \left(\sigma^{(0)}(1) - \frac{b}{a}\right))^{-ak} + \frac{b}{a} \tag{7}$$

where

$$[a, b]^T = (B^T B)^{-1} B^T X_n$$

and

$$B = \begin{bmatrix} -0.5(\sigma^{(1)}(1) + \sigma^{(1)}(2)) & 1 \\ -0.5(\sigma^{(1)}(2) + \sigma^{(1)}(3)) & 1 \\ \vdots & \vdots \\ -0.5(\sigma^{(1)}(n-1) + \sigma^{(1)}(n) & 1 \end{bmatrix},$$

$$X_n = \left[\sigma^{(0)}(2), \sigma^{(0)}(3), \sigma^{(0)}(4), \ldots, \sigma^{(0)}(n)\right]^T$$

We obtained $\hat{\sigma}^{(1)}$ from Equation 7. Let $\hat{\sigma}^{(0)}$ denote the fitted and predicted series,

$$\hat{\sigma}^{(0)} = \left(\hat{\sigma}^{(0)}(1), \hat{\sigma}^{(0)}(2), \ldots, \hat{\sigma}^{(0)}(n), \ldots\right)$$

where $\hat{\sigma}^{(0)}(1) = \sigma^{(0)}(1)$.

Applying the inverse AGO, then

$$\hat{\sigma}^{(0)}(k) = \left(\sigma^{(0)}(1) - \frac{b}{a}\right) e^{-a(k-1)}, \quad k = 1, 2, 3, \ldots, n \tag{8}$$

where $\hat{\sigma}^{(0)}(1), \hat{\sigma}^{(0)}(2), \ldots, \hat{\sigma}^{(0)}(n)$ are labelled the GM (1, 1) fitted series, while $\hat{\sigma}^{(0)}(n+1), \hat{\sigma}^{(0)}(n+2), \ldots,$ are termed the GM (1, 1) forecast values. The prediction value is calculated based on the last Equation 8.

Valuation performances

Regarding the forecasting performance of the volatility model for forecasting, the literature contains some common approaches, including root of mean square error (RMSE, Gemmill, 1986), mean absolute error (MAE, Gemmill, 1986; Gwilym, 2001) and mean absolute percentage error (MAPE, Makridakis, 1993).

This study first uses RMSE to identify the neural network models with good performance; small RMSE is taken to indicate good forecasting performance.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{j=1}^{n} \left[C_j^{\text{MP}} - C_j(\sigma_i)\right]^2}, \quad i = 1, 2, 3, 4 \tag{9}$$

[1] The grey prediction model for the time series model, include Lin and Yang (2002), Tseng *et al.* (2001), Lin *et al.* (2005) and so on.

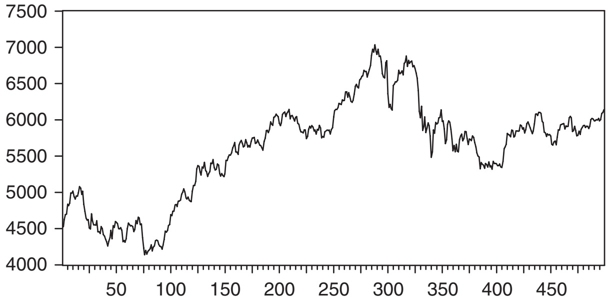

Fig. 2. The stock index in sample period

The values estimated using the different volatility approaches are then used to establish a neural network to compare the forecasting ability using MAE and MAPE. The errors are calculated with the following formula:

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n}\left|C_j^{\mathrm{MP}} - C_j\right| \tag{10}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{C_j^{\mathrm{MP}} - C_j}{C_j^{\mathrm{MP}}}\right| \tag{11}$$

where

C_j^{MP}: the market price of the option for observation *j*, and

C_j: the model value for observation *j* using the volatility estimate resulting from the four volatility (σ^{HV}, σ^{IV}, σ^{GP}, σ^{GARCH}) estimates defined above.

III. Data and Empirical Results

This study, adopts as inputs the primary Black–Scholes model variables that influence the option price, including current underlying asset price, strike price and time-to-maturity and then defines the option price as the output into which the learning network maps the inputs. Given proper training, the network 'becomes' the option pricing formula, which can be used for pricing just like formulas obtained using the parametric pricing method.

The study data are transaction data of Taiwan stock index options (TXO) traded on the Taiwan Futures Exchange (TAIFEX). This study investigated 15 582 call option price data points from 2 January 2003 to 31 December 2004. Only traded prices were used. Figure 2 shows the fluctuation of the stock index. Notably, the stock index has the circulate tendency but the figure displayed a gradual rise. The time-to-maturity based on the trading and expiration dates was calculated at the start of the study period.

Table 1. Data partition according to moneyness

Subset	Moneyness	Number
In-the-money	S/X > 1.03	3860
At-the-money	0.97 < S/X ϕ 1.03	4185
Out-of-the-money	0.91 < S/X ϕ 0.97	3622
deep-out-of-the-money	S/X ϕ 0.91	3915

Note: *S* is the current underlying asset price; *X* is the strike price.

Table 2. Entries of each data set

Subset	All	Train	Test
In-the-money	3860	2702	1158
At-the-money	4185	2931	1254
Out-of-the-money	3622	2537	1085
Deep-out-of-the-money	3915	2742	1173

While the Black–Scholes model of Equation 2 holds, S, X, T, σ, r can be used as the inputs and the option price can be used as the output for establishing a neural network. However, much of different prices may occur on a single trading day. To narrow the data range for improving training, moneyness is used for data partitioning. The moneyness is defined as the quotient of the stock price and strike price. This approach accelerates neural network training and facilitates the establishment of more stable models. Moneyness is used to reduce the number of inputs required for larger network and to partition the data set to clarify which sets the neural network models best. This study, divides the data into four subsets based on moneyness. The quotient is defined to balance the number of different sets and these are, including in-the-money, at-the-money, out-of-the-money and deep-out-of-the-money. Quotients of stock prices to strike prices of below 0.91, between 0.91 and 0.97, between 0.97 and 1.03 and exceeding 1.03 are used for data partitioning. Table 1 lists all of the sets used.

Table 2 lists the total number of patterns. These patterns are the data sets studied using the neural network models presented here. This study employs 70% of the data from the data set as the training set, the remaining 30% then comprises the testing set (Yao *et al.*, 2000). Given these preparations, this study uses the time to maturity, moneyness, volatility and risk-free rate as inputs and the option price as outputs in the neural network.

Figure 3 illustrates the historical, implied, grey and GARCH volatility for 2 January 2003 to 31 December 2004. Notably, the historical and GARCH estimates are significantly lower than the implied and grey volatility. Since the historical volatility is an average based on the returns during the preceding 60 days, the estimate becomes smoother and thus less sensitive to daily market fluctuations. The implied volatility for any given day generates a value based only on the trading information for that day, and leading to high fluctuations in estimates. Furthermore, the grey prediction is an average based on returns from the five preceding days, and the fluctuation of the estimated values exceeds the historical volatility.

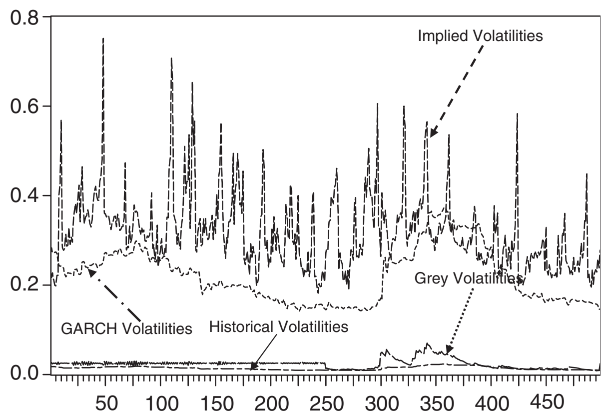

Fig. 3. Graph of historical, implied, grey and GARCH volatilities

Table 3 lists the neural network for the results for the different volatility approaches obtained in RMSE. First, for the in-the-money option, the grey prediction for volatility has lower testing error (0.0229) than the other approaches. Moreover, for the at-the-money, out-of-the-money and deep-out-of-the-money options, the approach with the best performance (namely the smallest error) is the GARCH approach. Additionally, in terms of historical volatility, train error (0.0191) and testing error (0.0230), the in-the-money call option has smaller error than the at-the-money, out-of-the-money and deep-out-of-the-money options. This condition also occurred in implied volatility and grey predictions, which have good performance in forecasting in-the-money option. Meanwhile, in the GARCH approach, the testing error is smallest for the deep-out-of-the-money option (0.0222).

The above comparisons involve neural network outputs. This study next uses estimated and actual prices to compare the best among the approaches presented here with the four volatility approaches listed in Table 4. The MAE results indicate that for the in-the-money call option grey prediction has smaller error (78.26) than the other approaches. Furthermore, for the at-the-money option the implied

Table 3. Neural network RMSE results for different approaches

Volatility RMSE / Moneyness	Historical volatility		Implied volatility		Grey prediction		GARCH volatility	
	TrE	TeE	TrE	TeE	TrE	TeE	TrE	TeE
In-the-money	0.0191	0.0230	0.0176	0.0251	0.0189	0.0229	0.0181	0.0263
At-the-money	0.0285	0.0352	0.0250	0.0291	0.0284	0.0351	0.0283	0.0290
Out-of-the-money	0.0275	0.0438	0.0211	0.0421	0.0274	0.0440	0.0286	0.0349
Deep-out-of-the-money	0.0353	0.0502	0.0327	0.0334	0.0350	0.0514	0.0372	0.0222

Note: TrE: Training Error, TeE: Testing Error.

Table 4. Different volatility approaches result for MAE and MAPE in the neural network model

Indices Volatility / Moneyness	MAE				MAPE			
	Historical volatility	Implied volatility	Grey prediction	GARCH volatility	Historical volatility	Implied volatility	Grey prediction	GARCH volatility
In-the-money	78.45	89.57	78.26*	94.18	0.2182	0.2625	0.2175*	0.2749
At-the-money	50.49	39.43*	50.30	39.79	2.2038	2.1171	2.1834	1.8147*
Out-of-the-money	39.79	37.80	40.01	28.41*	7.6190	9.7718	7.6349	5.2534*
Deep-out-of-the-money	35.85	21.16	36.83	11.12*	12.4638	7.5921	13.0954	1.3036*

Note: *Is the smallest value.

volatility approach has the smallest error (39.43) among the proposed approaches. Furthermore, for the out-of-the-money and deep-out-of-the-money options the GARCH approach outperforms the other approaches. Consequently, the price estimate based on GARCH volatility more closely reflects the real market price.

The results obtained via MAPE are almost identical to those obtained using the MAE method in addition to the at-the-money option. In the at-the-money option the GARCH approach has the smallest error (1.8147). Additionally, for the in-the-money option this study finds that all the various volatility approaches minimize their error value, while for the deep-out-of-the-money option the volatility approaches have the worst performance. These results mean that the proposed neural network model measures the in-the-money option price reasonably accurately.

IV. Conclusion

This study applies different volatility approaches to forecast Taiwan stock index option prices using neural network models. The empirical results indicate that the GARCH approach achieves better forecasting performance than the historical, implied volatility and grey prediction approaches. The GARCH approach has been shown to have better volatility forecasting ability. However, for the in-the-money option the grey prediction approach has better forecasting ability. This result indicates that the grey method can also be used to forecast prices for derivative securities.

The neural network model possesses several notable advantages over traditional parametric models which enhance its practicality. First, since the model does not rely on restrictive parametric assumptions such as log-normality or sample-path continuity, it is robust to the specification errors that frequently limited the scope when handling nonlinear or nonstandard problems. Second, the neural network model is adaptive and responsive to structural changes in data-generating in methods that are flexible in modelling real-world phenomena for which observations are generally available, but for which the theoretical relationships are not known or testable. Finally, this model is also sufficiently flexible to encompass various derivative securities and fundamental asset price dynamics and thus is relatively simple to implement.

Forecasting economic data is invariably difficult because such data is strongly influenced by economical, political, international and even natural shocks. This study only focused on the Black–Scholes model parameter pricing model. However, in practice, the influences on option price do not merely include the parameters in the Black–Scholes models, and thus future research can experiment with other variables, and can make further performance predictions and comparisons. Additionally, network architectures can be improved. Radial basis networks provide a further avenue of study, owing to having been used for financial forecasting. On the other hand, networks for forecasting medium and long term volatility can be developed using different variables and network architectures.

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