Forecasting the Prices of TAIEX Options by Using Genetic Programming and Support Vector Regression

Chih-Ming Hsu, Ying-Chi Fu, Yu-Chun Liu, and Chun-Yi Peng

***Abstract*—The Black-Scholes (B-S) model is the traditional tool for giving a theoretical estimate of the price of European-style options. However, the basic assumptions on the assets and market made in the B-S model are ideal. Furthermore, a lot of factors which might affect the prices of options have not been considered in the B-S model. In this study, the genetic programming (GP) and support vector regression (SVR) are applied to forecast the prices of stock options by using the six basic factors in the B-S model and the other factors, such as the opening and closing prices, highest and lowest prices, trading volume, open interest etc., as the predictors. The performance of GP and SVR forecasting models are also compared to the B-S pricing model. The feasibility and effectiveness of the proposed approach are demonstrated by forecasting the closing prices of Taiwan Stock Exchange Capitalization Weighted Stock Index Options (TAIEX Options) from April 1, 2010 to March 29, 2013.**

***Index Terms*—options, genetic programming, support vector regression, Black-Scholes model**

I. Introduction

THE financial investment is very popular as the economies developed rapidly. The options which provide the characteristic of making an infinite profit while taking a finite risk have become one of the major investing instruments. Investors can make more accurate investment decisions thus making higher returns on investment as well as avoiding risks, if the prices of options can be forecasted accurately. Therefore, the forecasting of options price has become a hot issue in the field of financial researches, and has received considerable attention from both researchers and practitioners.

The forecasting of options price is considered a challenging task since the prices are highly volatile, complex and dynamic. The Black-Scholes (B-S) model [1] is the traditional and important option pricing model for providing a theoretical estimate for the price of European-style options. However, the basic six assumptions on the assets and market made while using the B-S option pricing formula are too ideal. In addition, the B-S model has not considered a lot of factors which might affect the prices of options, such as the opening and closing prices, highest and lowest prices, trading volume, open interest etc. Therefore, some approaches for tackling the problems of options price forecasting have been proposed by using the six basic factors in the B-S model and the other factors as the predictors, and/or by applying methodologies from various fields, e.g. data mining, neural networks and computational intelligence techniques [2]–[15].

This study applies the genetic programming (GP) and support vector regression (SVR) to forecast the prices of stock options based on the predictors consisting of the six basic factors in the B-S model and the other factors, including the opening and closing prices, highest and lowest prices, trading volume, and open interest. In addition, the forecasting performance of GP and SVR models are compared to the B-S options pricing model. The Taiwan Stock Exchange Capitalization Weighted Stock Index Options (TAIEX Options) are used to verify the feasibility and effectiveness of the proposed approach by forecasting the closing prices in the next trading day from April 1, 2010 to March 29, 2013.

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II. Methodologies

A. Black-Scholes Model

The Black-Scholes (B-S) model [1] is one of the most important concepts in modern financial theory. It is considered the standard model for valuing options and is still widely used today. The six basic assumptions underlying the B-S model of calculating options pricing include (1) no dividends, (2) European return calculations, (3) efficient markets, (4) no commissions, (5) constant interest rates and (6) lognormally distributed returns. The values of call and put options for a non-dividend-paying underlying stock are calculated, respectively, by

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

and

$$P = N(-d_2)Ke^{-rt} - N(-d_1)S \tag{2}$$

where $N(\cdot)$ is the cumulative standard normal distribution; S is the current price of the underlying stock; K is the option striking price; r is the risk-free interest rate; t is the time to maturity. In addition, the parameters d_1 and d_2 are determined, respectively, by

$$d_1 = \frac{\ln(S/K) + (r + \sigma^2/2)t}{\sigma\sqrt{t}} \tag{3}$$

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and

$$d_2 = d_1 - \sigma\sqrt{t} \tag{4}$$

where σ is the volatility of returns of the underlying stock.

B. Genetic Programming

Genetic programming (GP), inspired by biological evolution, is an evolutionary algorithm-based methodology that can automatically create computer programs to perform a user-defined task by genetically breeding a population of computer programs based on the principles of Darwinian natural selection and biologically inspired operations. The solution technique of GP is closely relates to genetic algorithms (GAs). However, the evolving individuals in GP are themselves computer programs, instead of fixed-length strings consisting of numbers, alphabetic letters, or symbols. The computer programs in GP are traditionally represented in memory as tree structures composed of terminal and function sets. The terminal set defines the terminal elements available for the branches of computer programs, such as independent variables, zero-argument functions, random constants, etc. On the other hand, the function set is a set of primitive functions available to each branch of computer programs, e.g. addition, square root, multiplication, sine, etc. Like other evolutionary algorithms, a fitness function is defined and used to explicitly or implicitly measure the fitness (adaptability) of individuals in the population. It specifies a desired goal in the search for GP. In addition, users must specify parameters including population size, maximum size of programs, crossover rate, mutation rate, etc., and set the termination criterion. The steps of GP are briefly described, as follows [16]–[18]:

Step 1: Generate an initial population appropriate to a problem subject to a pre-specified maximum size.

Step 2: Evaluate computer programs based on a pre-defined fitness function.

Step 3: Select a pool of programs from the population using a probability based on the fitness.

Step 4: Apply reproduction, crossover, mutation, and architecture-altering operations to the selected programs to produce the offspring.

Step 5: Replace the current population with the population of offspring based on a certain strategy to create the next generation.

Step 6: Designate the outcome as the final results when the termination criterion is satisfied. Otherwise, execute Steps 2 to 5 iteratively.

C. Support Vector Regression

Support vector regression (SVR) [19] is the application of the support vector machine (SVM) [20] to cases of function approximation or regression. SVR intends to construct a mathematical model to describe the functional dependence of d on X given a training data $\{X_k, d_k\}_{k=1}^{Q}$, where the input variable $X_k \in R^n$ is an n-dimensional vector and the output variable $d_k \in R$ is a real value. In order to resolve a non-linear regression problem, SVR utilizes a map Φ to transform the original problem into a linear regression problem in a high dimensional feature space, and approximates a function of the form

$$f(X,W) = \sum_{i}^{m} w_i \phi_i(X) + w_0 = W^T \Phi(X) + w_0 \tag{5}$$

where w_i is the weight; W is the weight vector; $\phi_i(X)$ is the feature; $\Phi(X)$ is the feature vector; and w_0 is the bias. Vapnik [21] introduced the ε-insensitive loss function to evaluate the prediction error by

$$L_\varepsilon(d, f(X,W)) = \begin{cases} 0 & \text{if } |d - f(X,W)| \le \varepsilon. \\ |d - f(X,W)| - \varepsilon & \text{otherwise} \end{cases} \tag{6}$$

Therefore, the loss is expressed by

$$d_i - W^T\Phi(X) - w_0 - \varepsilon \le \xi_i, i = 1,...,Q. \tag{7}$$

$$W^T\Phi(X) + w_0 - d_i - \varepsilon \le \xi_i^{'}, i = 1,...,Q. \tag{8}$$

$$\xi_i \ge 0, i = 1,...,Q. \tag{9}$$

$$\xi_i^{'} \ge 0, i = 1,...,Q. \tag{10}$$

where ξ_i and $\xi_i^{'}$ are non-negative slack variables used to measure the errors above and below the predicted function, respectively, for each data point. The empirical risk minimization problem can then be defined as [21]–[22]

$$\frac{1}{2}\|W\|^2 + C\left(\sum_{i=1}^{Q}\xi_i + \sum_{i=1}^{Q}\xi_i^{'}\right). \tag{11}$$

subject to the constraints in (7)–(10), where C is a user specified parameter for the trade-off between complexity and losses. The simplified dual form can be obtained, by constructing the Lagrangian in primal variables and making the partial derivatives with respect to the primal variables vanish at the saddle point for optimality, as follows

$$\text{Maximize} \quad \begin{aligned} L_D(\Lambda,\Lambda') = &\sum_{i=1}^{Q} d_i(\lambda_i - \lambda_i^{'}) - \varepsilon\sum_{i=1}^{Q}(\lambda_i + \lambda_i^{'}) \\ &-\frac{1}{2}\sum_{i=1}^{Q}\sum_{j=1}^{Q}(\lambda_i - \lambda_i^{'})(\lambda_j - \lambda_j^{'})K(X_i, X_j) \end{aligned} \tag{12}$$

subject to

$$\sum_{i=1}^{Q}(\lambda_i - \lambda_i^{'}) = 0 \tag{13}$$

$$0 \le \lambda_i \le C, i = 1,...,Q \tag{14}$$

$$0 \le \lambda_i^{'} \le C, i = 1,...,Q \tag{15}$$

where $K(X_i, X_j) \equiv \Phi(X_i)\cdot\Phi(X_j)$ is called the kernel function. With the Lagrangian optimization done, the optimal weight vectors can be obtained as follows

$$\hat{W} = \sum_{i=1}^{Q}(\hat{\lambda}_i - \hat{\lambda}_i)\Phi(X_i) = \sum_{k=1}^{n_s}(\hat{\lambda}_k - \hat{\lambda}_k)\Phi(X_k) \tag{16}$$

Where n_s is the number of support vectors, and the index k only runs over support vectors. Finally, the optimal bias can be obtained by exploiting the Karush–Kuhn–Tucker (KKT) conditions [23]–[24], as follows

$$\hat{w}_0 = \frac{1}{n_{us}}\sum_{i=1}^{n_{us}}\left(d_i - \sum_{k=1}^{n_s}\beta_k K(X_k, X_i) - \varepsilon\,\text{sign}(\beta_i)\right) \tag{17}$$

where n_{us} is the number of unbounded support vectors with Lagrangian multipliers satisfying $0 < \lambda_i < C$ and $\beta_i = \hat{\lambda}_i - \hat{\lambda}$.

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III. Procedure of Forecasting Options Prices

In this study, the genetic programming (GP) and support vector regression (SVR) are utilized to resolve problems inherent in forecasting options prices, where the six basic factors in the B-S model and the other factors which might affect the prices of stock options are considered the predictors. The proposed forecasting procedure is illustrated in Fig. 1 and is briefly described as follows:

Step 1: Collect the six basic factors in the B-S model and trading data of stock call options, including the price of underlying stock, striking price, risk-free interest rate, cash dividend yield, time to maturity, volatility of the underlying stock, opening price, closing price, highest price, lowest price, trade volume and open interest, in each trading day. Notably, the data are collected for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options.

Step 2: Normalize the collected data into a range between 0 and 1 to avoid variables with larger numeric ranges from dominating those with smaller numeric ranges.

Step 3: Construct GP and SVR forecasting models of options prices.

Step 3-1: The normalized data are arranged into the form $(x_1, x_2, ..., x_n, y)$, and are then partitioned into training and test data based on a pre-specified proportion, e.g. 4:1, where x_1 to x_n are predictors and y is the closing price of stock option in the next trading day.

Step 3-2: Apply GP and SVR to construct several forecasting models.

(1) Construct five GP models, called $GP_{BS\text{-}In\text{-}2}$, $GP_{BS\text{-}In\text{-}1}$, $GP_{BS\text{-}At}$, $GP_{BS\text{-}Out\text{-}1}$ and $GP_{BS\text{-}Out\text{-}2}$, to forecast the prices for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options, respectively, where the predictors x_1 to x_n are the six basic factors in the B-S model. Similarly, five SVR models, called $SVR_{BS\text{-}In\text{-}2}$, $SVR_{BS\text{-}In\text{-}1}$, $SVR_{BS\text{-}At}$, $SVR_{BS\text{-}Out\text{-}1}$ and $SVR_{BS\text{-}Out\text{-}2}$, are built to forecast the prices for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options, respectively.

(2) Construct a GP model, called $GP_{BS\text{-}All}$, to forecast the prices for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options where the predictors x_1 to x_n are the six basic factors in the B-S model. Similarly, an SVR models, called $SVR_{BS\text{-}All}$, is built to forecast the prices for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options.

(3) Construct five GP models, called $GP_{BS\text{-}OF\text{-}In\text{-}2}$, $GP_{BS\text{-}OF\text{-}In\text{-}1}$, $GP_{BS\text{-}OF\text{-}At}$, $GP_{BS\text{-}OF\text{-}Out\text{-}1}$ and $GP_{BS\text{-}OF\text{-}Out\text{-}2}$, to forecast the prices for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options, respectively, where the predictors x_1 to x_n are the six basic factors in the B-S model and the other factors including the opening price, closing price, highest price, lowest price, trade volume and open interest. Similarly, five SVR models, called $SVR_{BS\text{-}OF\text{-}In\text{-}2}$, $SVR_{BS\text{-}OF\text{-}In\text{-}1}$, $SVR_{BS\text{-}OF\text{-}At}$, $SVR_{BS\text{-}OF\text{-}Out\text{-}1}$ and $SVR_{BS\text{-}OF\text{-}Out\text{-}2}$, are built to forecast the prices for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options, respectively.

(4) Construct a GP model, called $GP_{BS\text{-}OF\text{-}All}$, to forecast the prices for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options where the predictors x_1 to x_n are the six basic factors in the B-S model and the other factors including the opening price, closing price, highest price, lowest price, trade volume and open interest. Similarly, an SVR models, called $SVR_{BS\text{-}OF\text{-}All}$, is built to forecast the prices for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options.

Step 4: Apply the B-S model to evaluate the prices for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options.

Step 5: Evaluate the forecasting performances of GP and SVR models constructed in Step 3, and the B-S model used in Step 4 through the mean absolute percentage error (MAPE) and mean squared error (MSE).

IV. Case Study

In this section, a case study on forecasting the closing prices of TAIEX Options of the spot month is presented to demonstrate the feasibility and effectiveness of the proposed forecasting procedure. The details of the case study and the procedure are described below.

A. Data Collection

The six basic factors in the B-S model and trading data of stock call options, including the price of underlying stock, striking price, risk-free interest rate, cash dividend yield, time to maturity, volatility of the underlying stock, opening price, closing price, highest price, lowest price, trade volume and open interest, for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options in each trading day from April 1, 2010 to March 29, 2013 are first collected from the CMoney database (http://www.cmoney.tw). In order to reflect the latest market status, the forecasting models of options prices are re-designed per three months and are used for forecasting in the succeeding three months. In addition, the six basic factors in the B-S model and trading data of stock options required for constructing forecasting models are collected from the last twelve months, which end on the day of re-designing the forecasting models. Table 1 summarizes the periods of collecting the data for constructing forecasting models, and the corresponding forecasting horizons.

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TABLE I
PERIODS OF COLLECTING DATA AND FORECASTING HORIZONS

Case No.	Periods of collecting the data for constructing forecasting models	Forecasting horizons
1	2010/04/01~2011/03/31	2011/04/01~2011/06/30
2	2010/07/01~2011/06/30	2011/07/01~2011/09/31
3	2010/10/01~2011/09/31	2011/10/01~2011/12/31
4	2011/01/01~2011/12/31	2012/01/01~2012/03/31
5	2011/04/01~2012/03/31	2012/04/01~2012/06/30
6	2011/07/01~2012/06/30	2012/07/01~2012/09/31
7	2011/10/01~2012/09/31	2012/10/01~2012/12/31
8	2012/01/01~2012/12/31	2013/01/01~2013/03/31

B. Data Normalization

The collected data are normalized into a range between 0 and 1.

C. Constructions of GP and SVR Forecasting Models

For each case in Table I, the data are randomly partitioned into training and test data groups, based on the proportion of 4:1. The GP algorithm is then applied to the training and test data to establish the $GP_{BS\text{-}In\text{-}2}$, $GP_{BS\text{-}In\text{-}1}$, $GP_{BS\text{-}At}$, $GP_{BS\text{-}Out\text{-}2}$, $GP_{BS\text{-}Out\text{-}2}$ and $GP_{BS\text{-}All}$ models as described in Section III. Here, the Discipulus 4.0 (http://www.rmltech.com) software is employed where the fitness of a program is evaluated through the MSE. The termination criterion is that the generations without improvement have reached 100 and the remaining parameters are set as their default values in the software. The Discipulus 4.0 software is executed 5 times for each of the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options. Table II summarizes the best GP forecasting models selected from the 5 runs for case 1 in Table I. Similarly, $GP_{BS\text{-}OF\text{-}In\text{-}2}$, $GP_{BS\text{-}OF\text{-}In\text{-}1}$, $GP_{BS\text{-}OF\text{-}At}$, $GP_{BS\text{-}OF\text{-}Out\text{-}1}$, $GP_{BS\text{-}OF\text{-}Out\text{-}2}$ and $GP_{BS\text{-}OF\text{-}All}$ models where the predictors are the six basic factors in the B-S model and the other factors including the opening price, closing price, highest price, lowest price, trade volume and open interest, as described in Section III, are constructed and summarized in Table III. Similarly, the SVR forecasting models as described in Section III can also be obtained and shown in Table IV and V. Here, LIBSVM 2.86 [25] with a radial basis function (RBF) kernel is utilized to implement the SVR technique. The optimal settings for parameters C, γ, and ε in SVR are determined by the grid-search approach [25]. In addition, the LIBSVM 2.86 utilizes the 10-fold cross-validation accuracy to calculate the overall MSE thus determining the final optimal model. Hence, the normalized data can be directly fed into the SVR tool to build the model instead of partitioning the data into the training and test data groups in advance.

TABLE II
INFORMATION ABOUT OPTIMAL GP FORECASTING MODELS FOR CASE 1 IN TABLE I (PREDICTORS ARE BASIC FACTORS IN THE B-S MODEL)

Models' names	Training MSE	Test MSE	Training R^2	Test R^2
$GP_{BS\text{-}In\text{-}2}$	0.058993	0.064769	0.51016	0.45809
$GP_{BS\text{-}In\text{-}1}$	0.047715	0.040711	0.58070	0.65402
$GP_{BS\text{-}At}$	0.036713	0.028582	0.72549	0.74292
$GP_{BS\text{-}Out\text{-}1}$	0.025630	0.028385	0.81997	0.75284
$GP_{BS\text{-}Out\text{-}2}$	0.024888	0.019691	0.80763	0.88846
$GP_{BS\text{-}All}$	0.023026	0.022646	0.88823	0.88395

TABLE III
INFORMATION ABOUT OPTIMAL GP FORECASTING MODELS FOR CASE 1 IN TABLE I (PREDICTORS ARE BASIC FACTORS IN THE B-S MODEL AND OTHER FACTORS)

Models' names	Training MSE	Test MSE	Training R^2	Test R^2
$GP_{BS\text{-}OF\text{-}In\text{-}2}$	0.056189	0.074744	0.51887	0.46891
$GP_{BS\text{-}OF\text{-}In\text{-}1}$	0.051648	0.036121	0.55521	0.67848
$GP_{BS\text{-}OF\text{-}At}$	0.032068	0.025314	0.75099	0.81539
$GP_{BS\text{-}OF\text{-}Out\text{-}1}$	0.022321	0.024872	0.81818	0.87259
$GP_{BS\text{-}OF\text{-}Out\text{-}2}$	0.020321	0.016109	0.85130	0.89877
$GP_{BS\text{-}OF\text{-}All}$	0.013583	0.014854	0.93399	0.92134

TABLE IV
INFORMATION ABOUT OPTIMAL SVR FORECASTING MODELS FOR CASE 1 IN TABLE I (PREDICTORS ARE BASIC FACTORS IN THE B-S MODEL)

Models' names	Overall MSE	Overall R^2
$SVR_{BS\text{-}In\text{-}2}$	0.055994	0.535634
$SVR_{BS\text{-}In\text{-}1}$	0.039450	0.650397
$SVR_{BS\text{-}At}$	0.050024	0.609386
$SVR_{BS\text{-}Out\text{-}1}$	0.048294	0.652249
$SVR_{BS\text{-}Out\text{-}2}$	0.038440	0.723557
$SVR_{BS\text{-}All}$	0.018799	0.906678

TABLE V
INFORMATION ABOUT OPTIMAL SVR FORECASTING MODELS FOR CASE 1 IN TABLE I (PREDICTORS ARE BASIC FACTORS IN THE B-S MODEL AND OTHER FACTORS)

Models' names	Overall MSE	Overall R^2
$SVR_{BS\text{-}OF\text{-}In\text{-}2}$	0.062520	0.530361
$SVR_{BS\text{-}OF\text{-}In\text{-}1}$	0.044611	0.631761
$SVR_{BS\text{-}OF\text{-}At}$	0.027769	0.792306
$SVR_{BS\text{-}OF\text{-}Out\text{-}1}$	0.024913	0.828414
$SVR_{BS\text{-}OF\text{-}Out\text{-}2}$	0.033035	0.765719
$SVR_{BS\text{-}OF\text{-}All}$	0.001031	0.994098

D. Pricing Options by the B-S Model

The B-S model is used to evaluate the prices for the in-the-money at the first and second series, at-the-money, and out-of-the-money at the first and second series call options based on the collected data of the six basic factors.

E. Evaluation of Forecasting Performance

The MAPE and MSE are used to evaluate the forecasting performances of GP, SVR and B-S models. Table VI and VII summarize the three models with the best forecasting performance based on the MAPE and MSE, respectively, for each case in Table I. According to Tables VI and VII, the models constructed by the GP technique have the best forecasting performance, either based on the MAPE or based on the MSE, for all cases. Furthermore, the most accurate forecasting model for each case is constructed by using the six basic factors in the B-S model and the other factors as predictors, except for the forecasting model evaluated by the MAPE in case 3. Therefore, we can conclude that the GP models performance better than the models constructed by using either the SVR technique or the B-S pricing method. In addition, the addition of predictors, including the opening price, closing price, highest price, lowest price, trade volume and open interest, can indeed improve the performance of models for forecasting the prices of stock call options.

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TABLE VI
THE BEST THREE FORECASTING MODELS BASED ON THE MAPE

Case No.	Ranking of forecasting performance		
	1	2	3
1	$GP_{BS\text{-}OF\text{-}All}$	$GP_{BS\text{-}OF\text{-}In\text{-}2}$+ $GP_{BS\text{-}OF\text{-}In\text{-}1}$+ $GP_{BS\text{-}OF\text{-}At}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}1}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}2}$ (#)	$SVR_{BS\text{-}OF\text{-}In\text{-}2}$+ $SVR_{BS\text{-}OF\text{-}In\text{-}1}$+ $SVR_{BS\text{-}OF\text{-}At}$+ $SVR_{BS\text{-}OF\text{-}Out\text{-}1}$+ $SVR_{BS\text{-}OF\text{-}Out\text{-}2}$
2	$GP_{BS\text{-}OF\text{-}All}$	$GP_{BS\text{-}OF\text{-}In\text{-}2}$+ $GP_{BS\text{-}OF\text{-}In\text{-}1}$+ $GP_{BS\text{-}OF\text{-}At}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}1}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}2}$ (#)	$GP_{BS\text{-}All}$
3	$GP_{BS\text{-}In\text{-}2}$+ $GP_{BS\text{-}In\text{-}1}$+ $GP_{BS\text{-}At}$+ $GP_{BS\text{-}Out\text{-}1}$+ $GP_{BS\text{-}Out\text{-}2}$	B-S	$GP_{BS\text{-}All}$
4	$GP_{BS\text{-}OF\text{-}In\text{-}2}$+ $GP_{BS\text{-}OF\text{-}In\text{-}1}$+ $GP_{BS\text{-}OF\text{-}At}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}1}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}2}$ (*)	$GP_{BS\text{-}In\text{-}2}$+ $GP_{BS\text{-}In\text{-}1}$+ $GP_{BS\text{-}At}$+ $GP_{BS\text{-}Out\text{-}1}$+ $GP_{BS\text{-}Out\text{-}2}$	B-S
5	$GP_{BS\text{-}OF\text{-}In\text{-}2}$+ $GP_{BS\text{-}OF\text{-}In\text{-}1}$+ $GP_{BS\text{-}OF\text{-}At}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}1}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}2}$ (*)	$GP_{BS\text{-}OF\text{-}All}$ (#)	$GP_{BS\text{-}In\text{-}2}$+ $GP_{BS\text{-}In\text{-}1}$+ $GP_{BS\text{-}At}$+ $GP_{BS\text{-}Out\text{-}1}$+ $GP_{BS\text{-}Out\text{-}2}$
6	$GP_{BS\text{-}OF\text{-}In\text{-}2}$+ $GP_{BS\text{-}OF\text{-}In\text{-}1}$+ $GP_{BS\text{-}OF\text{-}At}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}1}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}2}$ (*)	$GP_{BS\text{-}OF\text{-}All}$ (#)	$SVR_{BS\text{-}OF\text{-}In\text{-}2}$+ $SVR_{BS\text{-}OF\text{-}In\text{-}1}$+ $SVR_{BS\text{-}OF\text{-}At}$+ $SVR_{BS\text{-}OF\text{-}Out\text{-}1}$+ $SVR_{BS\text{-}OF\text{-}Out\text{-}2}$
7	$GP_{BS\text{-}OF\text{-}In\text{-}2}$+ $GP_{BS\text{-}OF\text{-}In\text{-}1}$+ $GP_{BS\text{-}OF\text{-}At}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}1}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}2}$	$GP_{BS\text{-}OF\text{-}All}$	B-S
8	$GP_{BS\text{-}OF\text{-}In\text{-}2}$+ $GP_{BS\text{-}OF\text{-}In\text{-}1}$+ $GP_{BS\text{-}OF\text{-}At}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}1}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}2}$	$GP_{BS\text{-}OF\text{-}All}$ (#)	$GP_{BS\text{-}In\text{-}2}$+ $GP_{BS\text{-}In\text{-}1}$+ $GP_{BS\text{-}At}$+ $GP_{BS\text{-}Out\text{-}1}$+ $GP_{BS\text{-}Out\text{-}2}$

The asterisk (*) denotes the paired t test for the models with rankings 1 and 2 is significant, and the number sign (#) represents the paired t test for the models with rankings 2 and 3 is significant (α=0.05).

TABLE VII
THE BEST THREE FORECASTING MODELS BASED ON THE MSE

Case No.	Ranking of forecasting performance		
	1	2	3
1	$GP_{BS\text{-}OF\text{-}All}$ (*)	B-S (#)	$SVR_{BS\text{-}OF\text{-}All}$
2	$GP_{BS\text{-}OF\text{-}All}$ (*)	$GP_{BS\text{-}OF\text{-}In\text{-}2}$+ $GP_{BS\text{-}OF\text{-}In\text{-}1}$+ $GP_{BS\text{-}OF\text{-}At}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}1}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}2}$	$GP_{BS\text{-}All}$
3	$GP_{BS\text{-}OF\text{-}All}$ (*)	B-S (#)	$GP_{BS\text{-}All}$
4	$GP_{BS\text{-}OF\text{-}All}$ (*)	B-S (#)	$GP_{BS\text{-}All}$
5	$GP_{BS\text{-}OF\text{-}All}$ (*)	$SVR_{BS\text{-}OF\text{-}All}$ (#)	$GP_{BS\text{-}OF\text{-}In\text{-}2}$+ $GP_{BS\text{-}OF\text{-}In\text{-}1}$+ $GP_{BS\text{-}OF\text{-}At}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}1}$+ $GP_{BS\text{-}OF\text{-}Out\text{-}2}$
6	$GP_{BS\text{-}OF\text{-}All}$ (*)	B-S	$GP_{BS\text{-}All}$
7	$GP_{BS\text{-}OF\text{-}All}$	B-S (#)	$SVR_{BS\text{-}OF\text{-}All}$
8	$GP_{BS\text{-}OF\text{-}All}$ (*)	B-S (#)	$SVR_{BS\text{-}OF\text{-}All}$

The asterisk (*) denotes the paired t test for the models with rankings 1 and 2 is significant, and the number sign (#) represents the paired t test for the models with rankings 2 and 3 is significant (α=0.05).

V. CONCLUSION

In this study, the genetic programming (GP) and support vector regression (SVR) are applied to design the forecasting models for the prices of stock call options where the predictors comprise the six basic factors in the B-S model and the other factors, including the opening price, closing price, highest price, lowest price, trade volume and open interest. The feasibility and effectiveness of the proposed approach are demonstrated via a case study in which the closing prices of Taiwan Stock Exchange Capitalization Weighted Stock Index Options (TAIEX Options) from April 1, 2010 to March 29, 2013 are forecasted. Furthermore, the GP and SVR forecasting models are compared to the traditional B-S pricing model. The experimental results indicate that the GP technique can provide the best models while evaluating the forecasting performance either based on the MAPE or based on the MSE, for all cases. In addition, the forecasting performance of models which only take the six basic factors in the B-S model as the predictors can be significantly improved by considering the other factors, such as the opening price, closing price, highest price, lowest price, trade volume and open interest to be the input variables.

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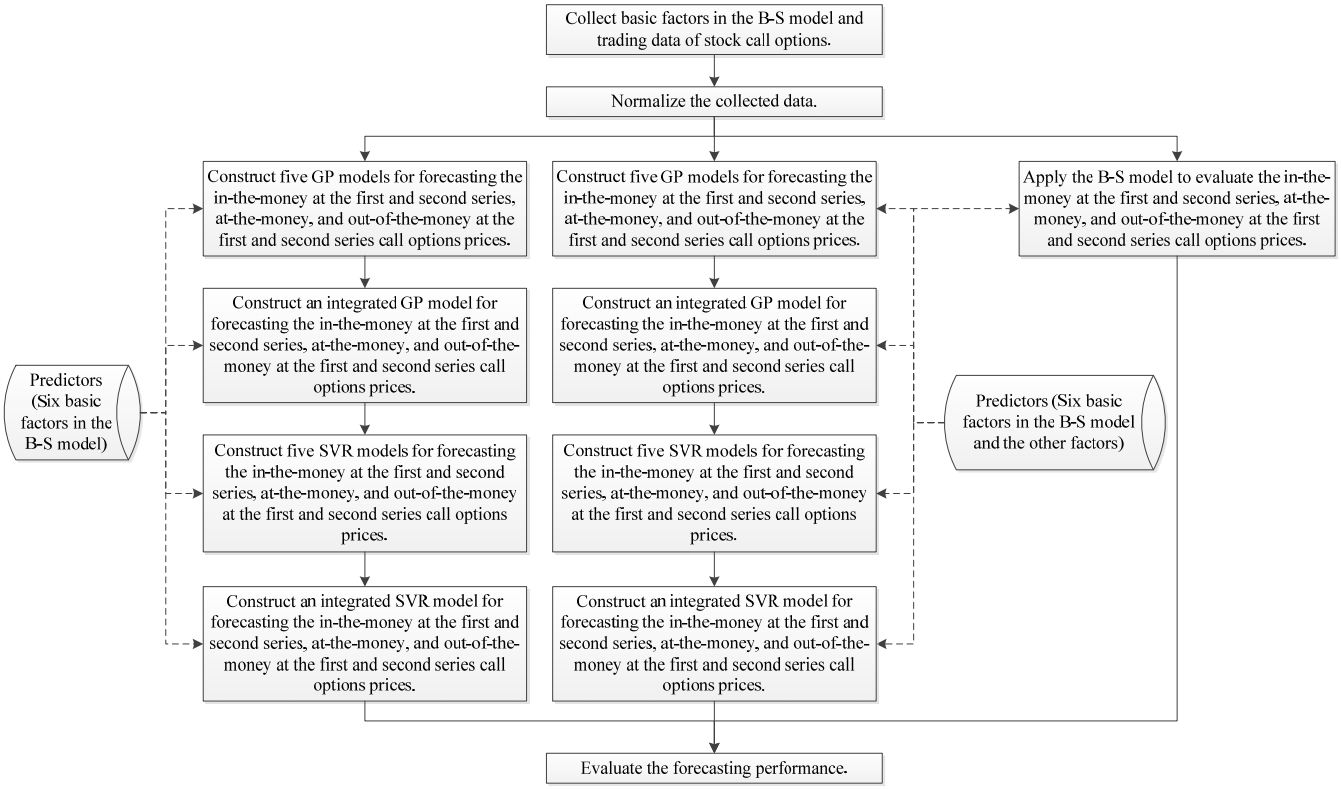

Fig. 1. Procedure of forecasting options prices.

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