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# The Hybrid Approach for Forecasting Stock Prices Based on Support Vector Regression and Genetic Algorithms

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***Abstract*—The accurate forecasting of stock prices is crucial to investors. However, the stock price forecasting can be considered a challenging task since the stock price series have the properties of high volatility, complexity, dynamics and turbulence. In recent years, the artificial intelligent techniques are often used to forecast the stock prices based on technical indicators. However, they only applied a single technique or used all technical indicators as predictors. However, the noisy technical indicators will decrease the forecasting performance of the forecasting model. Therefore, this study proposes a hybrid approach based on the support vector regression (SVR) and genetic algorithms (GAs) to forecast the stock prices. Notably, the SVR is used to construct the forecasting model and the GAs are applied to screen out the technical indicators which are critical to the stock prices. The efficiency and effectiveness of the proposed approach are demonstrated through experiments which aim at forecasting the closing stock prices in the first, the second and the third trading day in the future in the TAIEX (Taiwan stock exchange capitalization weighted stock index) in Taiwan. The experimental results show that the proposed hybrid approach can obtain the better results than the single SVR approach and the execution time of exploring the SVR models by GAs is short enough. Hence, the proposed hybrid approach can be considered a feasible, effective and efficient method for forecasting stock prices in the real investment.**

***Index Terms*—stock price forecasting, support vector regression, genetic algorithms, feature selection, technical indicators**

## I. Introduction

THE correct forecasting of stock prices is a critical issue to investors. However, the stock price series are high volatility, complexity, dynamics and turbulence thus the stock price forecasting has been considered a challenging task in the field of finance, and has received considerable attention from both researchers and practicers in recent years. In the past, many methodologies for forecasting stock prices had been attempted. Specially, the artificial intelligent/evolutionary methods have been important approaches for resolving the stock price forecasting problems in recent researches. For example, Kim, Min and Han [1], Lee [2], Hsu, Hsieh, Chih and Hsu [3], Pan [4], Yeh, Huang and Lee [5], Zuo and Kita[6], Hsu [7], Xiong, Bao and Hu [8] and Wu et al. [9]. From the previous studies, we can conclude that the artificial intelligent tolls, e.g. neural networks (NNs), genetic algorithms (GAs), support vector regression (SVR) and fuzzy systems etc. were broadly used in the stock price forecasting and yielded adequate results. In addition, several technical indicators were used in constructing the forecasting models. However, we cannot determine which technical indicator is really critical to the stock prices. The uses of the unnecessary (unimportant) technical indicators will become noises which are unfavorable in building the forecasting model and even lower the forecasting accuracy. Therefore, this study proposes a hybrid approach based on the support vector regression (SVR) and genetic algorithms (GAs) to forecast the stock prices. Notably, the SVR is first used to build the forecasting model based on all of the technical indicators. The GAs are then applied to determine the most important (critical) technical indicators to the stock prices based on the full model, i.e. the feature selection. Finally, the SVR is utilized again to construct the simplified model according to the selected technical indicators to forecast the stock prices. The feasibility and effectiveness of the proposed approach is evaluated by a case study aiming to forecast the closing stock price in the first, the second and the third trading day in the future in the TAIEX (Taiwan Stock Exchange Capitalization Weighted Stock Index) stock market.

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## II. Research methodologies

### A. Support Vector Regression

The support vector machine (SVM) is originally developed by Vapnik and his co-workers [10–14]. The SVM is a supervised learning algorithm for constructing a hyperplane in a high dimensional feature space used for classification. The SVM can also be applied to approximate the functions or to the regression, call support vector regression (SVR) [14–15]. Suppose there is a training data $\{X_k, d_k\}_{k=1}^{Q}$ whose input variable $X_k \in \mathbb{R}^n$ is an n-dimensional vector and the output variable $d_k \in \mathbb{R}$ is a real value. We want to construct an appropriate model to describe the functional dependence of $d$ on $X$. The SVR uses a map $\Phi$ to transform a non-linear regression problem into a linear regression problem in a high dimensional feature space. Hence, the approximation function has the form

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$$f(X,W)=\sum_{i}^{m} w_i\phi_i(X)+w_0 = W^T\Phi(X)+w_0 \quad (1)$$

where $w_i$ is the weight; W is the weight vector; $\phi_i(X)$ is the feature; $\Phi(X)$ is the feature vector; $w_0$ is the bias. Furthermore, Vapnik [16] designed a general error function, called the ε-insensitive loss function, to evaluate the prediction error, as follows

$$L_\varepsilon(d,f(X,W))=\begin{cases}0 & \text{if } |d-f(X,W)|\le\varepsilon \\ |d-f(X,W)|-\varepsilon & \text{otherwise}\end{cases} \quad (2)$$

Therefore, we can express the penalty (loss) by

$$d_i - W^T\Phi(X)-w_0-\varepsilon \le \xi_i, i=1,...,Q \quad (3)$$

$$W^T\Phi(X)+w_0-d_i-\varepsilon \le \xi_i^{'}, i=1,...,Q \quad (4)$$

$$\xi_i \ge 0, i=1,...,Q \quad (5)$$

$$\xi_i^{'} \ge 0, i=1,...,Q \quad (6)$$

where $\xi_i$ and $\xi_i^{'}$ are non-negative slack variables which are used to measure the errors above and below the predicted function, respectively, for each data point. Therefore, the empirical risk minimization problem can be defined as [16, 17]

$$\frac{1}{2}\|W\|^2+C\left(\sum_{i=1}^{Q}\xi_i+\sum_{i=1}^{Q}\xi_i^{'}\right) \quad (7)$$

subject to the constraints in (3)–(6), where $C$ is a user specified parameter for the trade-off between complexity and losses. To solve the optimization in (7), the Lagrangian in primal variables are constructed as follows

$$L_P(W,w_0,\Xi,\Xi',\Lambda,\Lambda',\Gamma,\Gamma') = \frac{1}{2}W^TW+C\left(\sum_{i=1}^{Q}\xi_i+\sum_{i=1}^{Q}\xi_i^{'}\right)-\sum_{i=1}^{Q}\lambda_i\left(W^T\Phi(X_i)+w_0-d_i+\varepsilon+\xi_i\right)- \sum_{i=1}^{Q}\lambda_i^{'}\left(d_i-W^T\Phi(X_i)-w_0+\varepsilon+\xi_i^{'}\right)-\sum_{i=1}^{Q}(\gamma_i\xi_i+\gamma_i^{'}\xi_i^{'}) \quad (8)$$

where $\Xi=(\xi_1,...,\xi_Q)^T$ and $\Xi^{'}=(\xi_1^{'},...,\xi_Q^{'})^T$ are slack variable vectors; $\Lambda=(\lambda_1,...,\lambda_Q)^T$, $\Lambda^{'}=(\lambda_1^{'},...,\lambda_Q^{'})^T$, $\Gamma=(\gamma_1,...,\gamma_Q)^T$ and $\Gamma^{'}=(\gamma_1^{'},...,\gamma_Q^{'})^T$ are the Lagrangian multiplier vectors for (3)–(6), respectively. The partial derivatives of $L_P$ with respective to the primal variables have to vanish at the saddle point for optimality. Therefore,

$$\frac{\partial L_P(W,w_0,\Xi,\Xi',\Lambda,\Lambda',\Gamma,\Gamma')}{\partial W}=0\Rightarrow W=\sum_{i=1}^{Q}(\lambda_i-\lambda_i^{'})\Phi(X_i) \quad (9)$$

$$\frac{\partial L_P(W,w_0,\Xi,\Xi',\Lambda,\Lambda',\Gamma,\Gamma')}{\partial w_0}=0\Rightarrow \sum_{i=1}^{Q}(\lambda_i-\lambda_i^{'})=0 \quad (10)$$

$$\frac{\partial L_P(W,w_0,\Xi,\Xi',\Lambda,\Lambda',\Gamma,\Gamma')}{\partial \xi_i}=0\Rightarrow \gamma_i=C-\lambda_i \quad (11)$$

$$\frac{\partial L_P(W,w_0,\Xi,\Xi',\Lambda,\Lambda',\Gamma,\Gamma')}{\partial \xi_i^{'}}=0\Rightarrow \gamma_i^{'}=C-\lambda_i^{'} \quad (12)$$

Substitute (9), (11) and (12) into (8), the simplified dual form $L_D$ then can be obtained, as follows

Maximize
$$L_D(\Lambda,\Lambda')=\sum_{i=1}^{Q}d_i(\lambda_i-\lambda_i^{'})-\varepsilon\sum_{i=1}^{Q}(\lambda_i+\lambda_i^{'})- \frac{1}{2}\sum_{i=1}^{Q}\sum_{j=1}^{Q}(\lambda_i-\lambda_i^{'})(\lambda_j-\lambda_j^{'})K(X_i,X_j) \quad (13)$$

$$\sum_{i=1}^{Q}(\lambda_i-\lambda_i^{'})=0 \quad (14)$$

$$0\le\lambda_i\le C, i=1,...,Q \quad (15)$$

$$0\le\lambda_i^{'}\le C, i=1,...,Q \quad (16)$$

where $K(X_i,X_j)\equiv\Phi(X_i)\cdot\Phi(X_j)$ is called the kernel function. Furthermore, the data points for which $\lambda_i$ or $\lambda_i^{'}$ is not zero are called the support vectors. The optimal weight vectors can then be obtained with the Lagrangian optimization done as follows

$$\hat{W}=\sum_{i=1}^{Q}(\hat{\lambda}_i-\hat{\lambda}_i^{'})\Phi(X_i)=\sum_{k=1}^{n_s}(\hat{\lambda}_k-\hat{\lambda}_k^{'})\Phi(X_k) \quad (17)$$

where $n_s$ is the number of support vectors, and the index $k$ only runs over support vectors. In addition, the optimal bias can be obtained, by exploiting the Karush–Kuhn–Tucker (KKT) conditions [18, 19] as follows

$$\hat{w}_0=\frac{1}{n_{us}}\sum_{i=1}^{n_{us}}\left(d_i-\sum_{k=1}^{n_s}\beta_kK(X_k,X_i)-\varepsilon\,\mathrm{sign}(\beta_i)\right) \quad (18)$$

where $n_{us}$ is the number of unbounded support vectors with Lagrangian multipliers which satisfy $0<\lambda_i<C$, and $\beta_i=\hat{\lambda}_i-\hat{\lambda}_i^{'}$. Thus, we can obtained the approximated regression model as follows

$$f(X,\hat{\lambda}_i,\hat{\lambda}_i^{'})=\sum_{i}^{Q}(\hat{\lambda}_i-\hat{\lambda}_i^{'})K(X_i,X)+\hat{w}_0\,. \quad (19)$$

*B. Genetic Algorithms*

Genetic algorithms (GAs) are robust adaptive optimization techniques which can perform an efficient probabilistic search in a high dimensional space[20] based on the natural and biological evolution. For applying GAs to a specific problem, two issues including (1) encoding a potential solution, and (2) identifying the fitness function (objective function) must be defined in advance. The encoding a potential solution is a genetic representation of a solution which is a vector composed of several components (genes), called a chromosome. The initial population of chromosomes is usually generated according to some principles or randomly selected. The qualities of potential solutions are then evaluated through the fitness function (objective function). In addition, the optimization is achieved through the selection and matching (crossover). Besides the matching, small mutations can also occur in the new offspring. The bad solutions are then replaced with new ones based on some fixed strategies and the chromosomes evolve through successive iterations, called generations. The solution procedure continues until the stopping criteria are satisfied. Let *P(g)* and *C(g)* represent the parents and offspring in the current generation g, respectively. The general procedure of GAs can be described as follows [21]:

**Procedure Genetic Algorithms**

**begin**

```
g←0;
    initialize P(g);
    evaluate P(g);
    while (not termination condition) do
        recombine P(g) to yield C(g);
        evaluate C(g);
        select P(g+1) from P(g) and C(g);
        g←g+1;
    end
end
```

## III. Proposed hybrid Forecasting approach

In this study, a hybrid approach that applies the support vector regression (SVR) and genetic algorithms (GAs) was proposed to forecast the stock prices. The proposed procedure comprises three stages. At the first stage, the collected data are used to calculate the technical indicators. The technical indicators along with closing stock price in the first or the second or the third trading day in the future for each trading day are divided into two groups: (1) training data and (2) test data, according to the odd or even number of the trading datum. The SVR is then utilized to construct a full forecasting model, call $SVR_{full}$, for the first or the second or the third trading day in the future or the third trading day in the future based on the training and test data. Notably, the optimization of parameters $C$, $\gamma$ and $\varepsilon$ in the SVR are done with the grid-search approach [22]. Furthermore, the 10-fold cross validation is applied to determine the best SVR model by minimizing the MSE. In the second stage, the genetic algorithms (GAs) screen out the technical indicators which are critical to the stock prices by exploring the well-constructed $SVR_{full}$ model and the fitness function in GAs is the total MSE regarding the training and test data. Finally, the SVR technique is applied again to construct the simplified model, called $SVR_{simp}$, to be the final forecasting model based on the selected technical indicators chosen from the second stage and the data for constructing the SVR simplified model include the training and test data divided in the first stage. The forecasting performance is evaluated by the MSE, MAPE and R-square. The proposed approach is conceptually illustrated in Fig. 1.

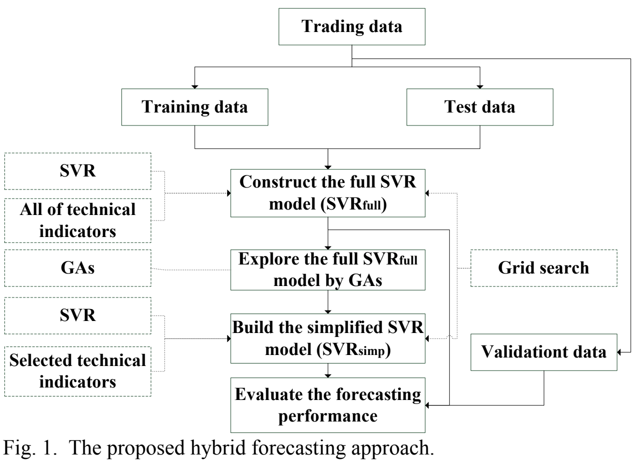


Fig. 1. The proposed hybrid forecasting approach.

## IV. Case study

### A. Collect trading data and calculate technical indicators

In this study, the daily trading data including the open piece, highest price, lowest price and closing price of the TAIEX, are collected during 1/1/2009 to 12/13/2014 form the CMoney database (www.cmoney.com.tw). The technical indicators are then calculated based on these trading data. Sixteen technical indicators are involved in this study according to previous study in [23–29].

### B. Build the full SVR forecasting models

The data where the input variables (predictors) are the technical indicators calculated previously and the output variable (response) is the closing stock price in the next trading day in the TAIEX from 1/1/2009 to 12/31/2011 are divided into two groups including the (1) training data and (2) test data according to the odd or even number of the trading datum. The SVR technique is then utilized to construct the full forecasting model, call $SVR_{full\_1}$. Similarly, the full forecasting models where the output variables (responses) are the closing stock prices in the next 2 trading days and next 3 trading days, i.e. the second trading day and the third trading day in the future, respectively, can then be built, call $SVR_{full\_2}$ and $SVR_{full\_3}$, respectively. The information about the obtained SVR full forecasting models are summarized in Table 1. From Table 1, we can conclude that the MSEs are small and the R-squares are good enough (all R-squares are larger than 0.98). Therefore, we are confident that we can use these SVR full forecasting models for further exploring the critical technical indicators by GAs.

TABLE I
The Information about the Obtained SVR Full Forecasting Models.

| Types of forecasting | 1 day's forecasting | 2 days' forecasting | 3 days' forecasting |
|---|---|---|---|
| Total number of the training data | 374 | 374 | 374 |
| Total number of the test data | 374 | 374 | 373 |
| Training MSE | 0.000400008 | 0.000668459 | 0.000990816 |
| Test MSE | 0.000332013 | 0.000712591 | 0.000914454 |
| Training $R^2$ | 0.99132 | 0.984839 | 0.997627 |
| Test $R^2$ | 0.99247 | 0.983897 | 0.979025 |
| Model's name | $SVR_{full\_1}$ | $SVR_{full\_2}$ | $SVR_{full\_3}$ |

### C. Explore the full SVR models

The full SVR forecasting models listed in Table 1 are further explored by GAs. The crossover and mutation rates are set as 0.5 and 0.1, respectively, and the population size is set as 40 according to our past experience. Furthermore, the maximum searching cycles (generations) are set as 400 and the GAs stop searching the better solution until the fitness function does not improve during the last 20 generations. The fitness function in this study is evaluated by:

$$fitness = \frac{MSE_{GAs}}{MSE_{Total}}. \tag{20}$$

where $MSE_{GAs}$ is the total of training and test MSEs of the SVR when forecasting the stock prices based on the selected technical indicators chosen by GAs and $MSE_{Total}$ is the MSE regarding the training and test data by using the full SVR forecasting model built in the previous section to forecast the stock prices. In addition, the GAs are implemented for five times for each full forecasting models. The acquired results are shown in Table 2. Notably, the boldface represented the best results selected for each full SVR model by maximizing the fitness and the model's name indicates the simplified SVR forecasting model built according to the selected technical indicators. From Table 2, we can conclude that the GAs can effectively select the technical indicators which are critical to the closing stock prices. Therefore, the values of fitness are all very high and they can exceed one in the most cases. In some cases, the values of fitness in the selected results of GAs are smaller than one, but are very close to one. In other words, the GAs can sift the important technical indicators which are significant to the closing stock prices in the future from the all technical indicators without significantly reducing the forecasting performance. In addition, the CPU time is less than 6 minutes thus the GAs method can be considered efficient. Based on these observations, we can conclude that the GAs really can determine the important technical indicators to the closing stock prices, thus constructing the simpler and more accurate forecasting models by removing the useless (unimportant) noisy technical indicators effectively and efficiently.

TABLE II
THE INFORMATION ABOUT THE EXECUTION RESULTS OF GAS.

| Types of forecasting | 1 day's forecasting | 2 days' forecasting | 3 days' forecasting |
|---|---|---|---|
| Implementation #1 (cycle #, fitness, CPU time (seconds)) | (35,1.01354209, 186.37) | (32,1.00425825, 189.93) | (42,0.99554228, 267.83) |
| Implementation #2 (cycle #, fitness, CPU time (seconds)) | (25,1.01517491, 132.17) | **(31,1.00436390, 173.68)** | **(34,0.99972333, 214.23)** |
| Implementation #3 (cycle #, fitness, CPU time (seconds)) | (32,1.00933667, 169.89) | (40,1.00415327, 221.27) | (31,0.99556640, 193.89) |
| Implementation #4 (cycle #, fitness, CPU time (seconds)) | (22,1.01487199, 118.12) | (23,1.00113771, 133.36) | (35,0.99875523, 218.67) |
| Implementation #5 (cycle #, fitness, CPU time (seconds)) | **(29,1.01584577, 155.42)** | (34,1.00433296, 182.91) | (38,0.99662135, 225.39) |
| The total number of selected technical | 11 | 12 | 14 |

*D. Evaluate the forecasting performance*

The forecasting performance of the full and simplified forecasting SVR models through MSE, MAPE and R-square when they applying to the unknown validation data, i.e. the trading data from 1/1/2012 to 12/31/2014. The results are given in Table 3. Table 3 shows that all of the simplified SVR models are better than the full SVR models constructed by the single SVR technique based on the MSE or MAPE or R-square. Hence, we can conclude that the proposed approach in this study can improve the forecasting performance of SVR models by screening out the critical technical indicators by GAs for all of the cases in forecasting the closing stock prices in the next day, next 2 days and next 3 days. Thus, the proposed method in this study can be considered effectively. Furthermore, we can find that the forecasting performance can improve better by implementing the proposed approach in this study while comparing to the single SVR technique if the forecasting time is farer. In other words, the GAs can improve the forecasting performance more significantly when the forecasting time is farer. This is very helpful to the investors. From the above discussions, we have confidence that the proposed method in his study is an effective and efficient tool and can be used in the real investment situation for investors.

TABLE III
THE EVALUATION OF FORECASTING PERFORMANCE

| Types of forecasting | 1 day's forecasting | 2 days' forecasting | 3 days' forecasting |
|---|---|---|---|
| Full models' names | $SVR_{full\_1}$ | $SVR_{full\_2}$ | $SVR_{full\_3}$ |
| MSE | 0.000188 | 0.001416 | 0.001875 |
| MAPE | 0.006866 | 0.016074 | 0.018626 |
| $R^2$ | 0.988803 | 0.922638 | 0.895563 |
| Simplified models' names | $SVR_{simp\_1}$ | $SVR_{simp\_2}$ | $SVR_{simp\_3}$ |
| MSE | 0.000181 | 0.000587 | 0.001032 |
| MAPE | 0.006763 | 0.010636 | 0.014304 |
| $R^2$ | 0.989007 | 0.968794 | 0.942931 |

## V. CONCLUSIONS

This study proposes the hybrid approach based on the SVR and GAs. The proposed method can screen out the critical technical indicators for forecasting the stock prices thus avoiding the noisy technical indicators and improving the forecasting performance. The proposed procedure is demonstrated by a case study aiming at forecasting the closing stock price of the TAIEX stock markets for the first, the second and the third trading day in the future. The experimental results indicate that the GAs can effectively determine the technical indicators which are critical to the closing stock prices by exploring the full SVR models. In addition, the GAs can sift the important technical indicators which are significant to the closing stock prices in the future from the all technical indicators without significantly reducing the forecasting performance. Furthermore, the CPU time is less than 6 minutes. Hence, the GAs method can be considered efficient. Next, the GAs can improve the forecasting performance more significantly when the forecasting horizon is longer. Therefore, we can conclude that the GAs really can choose the important technical indicators to the closing stock prices, thus constructing the simpler and more accurate forecasting models by removing the useless (unimportant) noisy technical indicators effectively and efficiently.

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