Forward Forecast of Stock Price Using Sliding-Window Metaheuristic-Optimized Machine-Learning Regression

Jui-Sheng Chou and Thi-Kha Nguyen

***Abstract*—Time series forecasting has been widely used to determine the future prices of stock, and the analysis and modeling of finance time series importantly guide investors' decisions and trades. In addition, in a dynamic environment such as the stock market, the nonlinearity of the time series is pronounced, immediately affecting the efficacy of stock price forecasts. Thus, this paper proposes an intelligent time series prediction system that uses sliding-window metaheuristic optimization for the purpose of predicting the stock prices of Taiwan construction companies one step ahead. It may be of great interest to home brokers who do not possess sufficient knowledge to invest in such companies. The system has a graphical user interface and functions as a stand-alone application. The developed hybrid system exhibited outstanding prediction performance and it improves overall profit for investment performance. The proposed model is a promising predictive technique for highly nonlinear time series, whose patterns are difficult to capture by traditional models.**

***Index Terms*—Construction company, data mining, machine learning (ML), prediction system, sliding window, stock price forecasting, swarm intelligence and metaheuristic optimization, time series.**

I. Introduction

FINANCIAL markets are highly volatile and generate huge amounts of data daily. Investment is a commitment of money or other resources to obtain benefits in the future. Stock is one type of securities. It is the most popular financial market instrument and its value changes quickly [1]. It can be defined as a sign of capital participation by a person or an enterprise in a company or a limited liability company.

Manuscript received June 30, 2017; revised September 9, 2017, November 14, 2017, and December 8, 2017; accepted January 5, 2018. Date of publication January 18, 2018; date of current version July 2, 2018. This work was supported in part by the Ministry of Science and Technology, Taiwan, under Grant 103-2221-E-011-144-MY3 and in part by the Ministry of Education—Aim for Top University Project. Paper no. TII-17-1416. *(Corresponding author: Jui-Sheng Chou.)*

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Digital Object Identifier 10.1109/TII.2018.2794389

The stock market provides opportunities for brokers and companies to make investments on neutral ground [2]. Stock prices are predicted to determine the future value of companies' stock or other financial instruments that are marketed on financial exchanges [3]. However, the stock market is characterized by nonlinearities, discontinuities, and high-frequency multipolynomial components because it interacts with many factors such as political events, general economic conditions, and traders' expectations [4]. Therefore, drawing inferences from historical patterns and making precise predictions of stock values are challenging.

Investors can buy stocks in the construction firms that design infrastructure projects, hire contractors, and handle the requisite paperwork, and decision-makers at construction firms can buy stocks in other companies. When the direction of the market is successfully predicted, investors are better guided and monetary rewards may be greater. The challenge in today's environment, where bad news can always be heard, is to forecast proactively, rather than reactively. Therefore, construction corporations are trying to predict stock prices despite sudden drops in the market.

Time series forecasting is designed to solve various problems, mainly in the financial area [5]. It is noteworthy that investors typically use tools that can facilitate decision making to minimize investment risks. This objective is obvious when one wants to analyze financial markets and, for this reason, it is necessary to ensure good accuracy of forecasting tasks.

According to Saini *et al.* [6], forecasting based on a time series enables the provision of information and knowledge to support a subsequent decision. Thus, the analysis of time series focuses on identifying dependence relationships among historical data. The two broad categories of forecasting models are linear and nonlinear. For many decades, traditional statistical forecasting models in financial engineering were linear. Some well-known statistical models can be used in time series forecasting [6]. Conventional modeling techniques, such as the Box–Jenkins autoregressive integrated moving average, have been shown not to be sufficient for stock market price forecasting [7].

Machine learning (ML) is coming into its own as a powerful technique in a wide range of critical applications. Among ML algorithms, support vector machines (SVMs) have many advanced features that are responsible for their favorable generalization capacity and rapid computation [6]. They are also not very sensitive to assumptions about error terms and they can tolerate noise and chaotic components. Notably, SVMs are increasingly used in materials science [8], the design of engineering systems [9], and financial risk prediction [10].

Vapnik [11] developed support vector regression (SVR), a variant of the SVM, which is typically used to solve nonlinear regression problems by constructing an input–output mapping function. The least squares support vector regression (LSSVR) algorithm is a further development of SVR by Suykens [12] and involves equality instead of inequality constraints, and uses a least squares objective function. The LSSVR approach considerably reduces computational complexity and increases efficiency compared to standard SVR.

Recently, Lu *et al.*, used independent component analysis to remove noise from forecasting variables. The filtered forecasting variables, which contain less noise information, then serve as the input variables of the SVR forecasting model [13]. Hao *et al.*, examined the feasibility of methods in stock composite index forecasting and improved the accuracy of parameter selection by SVR. They concluded that SVR exhibits high prediction performance [14].

Some studies have demonstrated the superiority of LSSVR over standard SVR in estimating product cost [15] and energy utilization [16]. LSSVR solves linear equations instead of a quadratic programming problem. It is preferred for large-scale regression problems that demand fast computation [12]. Since time series data can be formulated by regression analysis, LSSVR can be very efficiently applied to the issue of interest. However, the efficacy of LSSVR strongly depends on its tuning hyperparameters, which are the regularization parameter and the kernel function. Inappropriately setting these parameters may lead to significantly poor performance of the model [17]. Therefore, the evaluation of such hyperparameters is a real-world optimization problem.

The hyperparameters used to be set in advance based on the experience of practitioners, by trial-and-error, or using a grid search algorithm [18]. Optimizing the values of regularization and kernel function parameters for the LSSVR-based models is an important and time-consuming step. Therefore, a means of automatically finding the hyperparameters of LSSVR algorithm, while ensuring its generalization performance, is sought.

Optimization is one of the cornerstones of science and engineering. Recently, the field of nature-inspired optimization algorithms has grown incredibly fast. The algorithms are usually general purpose and population based. They are normally referred to as evolutionary algorithms because many of them are motivated by biological evolution. In a broad sense, evolutionary algorithms cover those that iteratively vary a group of solutions based on some nature-inspired operations.

Many evolutionary algorithms, such as artificial bee colony and cuckoo search (CS) algorithms, have been adopted to tune the hyperparameters of SVR [19], [20]. For instance, Wang *et al.*, proposed hybrid intelligent forecasting models that were based on CS, the singular spectrum analysis, time series, and ML methods to conduct short-term power load prediction [20]. Hsieh *et al.*, demonstrated that the particle swarm optimization (PSO)-based SVR model was superior to traditional SVR in forecasting the daily Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) [19].

The firefly algorithm (FA) [21], which is a nature-inspired metaheuristic method, has recently performed extremely well in solving various optimization problems such as stock price forecasting [18] and electricity price prediction [22]. The standard FA was developed by modeling the behavior of tropical fireflies. Notably, the smart FA-based LSSVR has been demonstrated to be very effective in solving complex problems in civil engineering [23], [24].

FA and its variants are used to solve many optimization and engineering problems. Gandomi *et al.* in [25] used FA to solve mixed continuous/discrete structural optimization problems in the design of welded beams, pressure vessels, helical compression springs, reinforced concrete beams, stepped cantilever beams, and car-side impact design. The optimization results indicated that FA is more efficient than other metaheuristic algorithms, such as PSO, genetic algorithm, simulated annealing and differential evolution.

Recent research suggests that hybrid forecasting models can be usefully applied to the stock market's fluctuations, yielding satisfactory forecasting precision [4]. The authors used a hybrid model to capture the linear and nonlinear characteristics of a stock price time series and confirmed that hybrid forecasting models are powerful tools for practitioners in management science. A review of the literature has indicated that enhancing the effectiveness of LSSVR based on a nature-inspired metaheuristic optimization algorithm, such as the FA [24], [26] is an unsolved problem in the field of stock price prediction.

Although artificial intelligence techniques and metaheuristic optimization algorithms are powerful, practitioners must be able to perform the extensive manual operations. Users, such as traders in the financial market, are very interested in conveniently obtaining results that support their decisions. The computational cost of such advanced algorithms is high owing to their complexity. Therefore, creating an intelligent user system, which combines a knowledge base, a computing engine, and a graphical user interface, is a subject of great interest for many investors and financial analysts.

For example, Lee designed the iJADE Stock Advisor—an intelligent agent-based stock prediction system [27]. He integrated his proposed hybrid radial basis-function recurrent network (HRBFN) with the iJADE framework. Experimental results demonstrated that the HRBFN model can be successfully integrated with mobile-agent technology to provide a truly intelligent, mobile and interactive stock advisory solution.

Considering the above mentioned facts, this work develops an intelligent time series prediction system using sliding-window metaheuristic optimization. It involves the hybrid model of a metaheuristic FA and LSSVR (MetaFA-LSSVR) to forecast the prices of construction corporate stocks. The MetaFA is chosen as the optimizing algorithm to enhance the efficiency of, and reduce the computational burden on the machine learner, LSSVR.

The remainder of this paper is organized as follows. Section II presents the research methodology. Section III describes in detail the system applications. The final section provides concluding remarks and an outline for future work.

II. Methodology

A. Phase Space Reconstruction

In a sliding-window analysis, the time series are typically expanded into three- or higher-dimensional space to exploit the information that is implicit in them. Selecting a suitable pairing of embedding dimension m (*lag*) and time delay τ is very important for phase space reconstruction [28]. The precision of m and τ is directly related to the accuracy of the constant of the described characteristics of the strange attractors in phase space reconstruction. The choices of delay time and embedding dimension are important, because favorable choices can reduce both the amount of data required and the effect of noise.

In this study, the optimum values of the embedding parameters are determined by performing a sensitivity analysis. Consider a time series $\vec{x} = \{x_1, x_2, \ldots, x_N\}$. The time-delay vectors can be reconstructed as follows, where X is the input matrix and Y is the corresponding output matrix. The output of the analysis is fed back to the input and future values are predicted from previous values in the time series

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} \xrightarrow{m} X$$

$$= \begin{bmatrix} x_1 & x_2 & \cdots & x_{m-1} & x_m \\ x_2 & x_3 & \cdots & x_m & x_{m+1} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{N-m-\tau+1} & x_{N-m-\tau+2} & \cdots & x_{N-\tau-1} & x_{N-\tau} \end{bmatrix},$$

$$Y = \begin{bmatrix} x_{m+\tau} \\ x_{m+1+\tau} \\ \vdots \\ x_N \end{bmatrix}. \qquad (1)$$

As suggested in [29], the learning dataset used in this study was collected within a sliding window. Fig. 1 depicts the sliding window and phase space construction. Since the forecast is one step ahead (hence, the term "one-step ahead forecasting"), the forecast horizon is 1. In the first validation, the working window includes p historical observations $(x_1, x_2, \ldots, x_p)$, which are used to forecast the next value x_{p+1}. In the second validation, the oldest value x_1 is removed from the window and the latest value x_{p+1} is added, keeping the length of the sliding window constant at p. The next forecast value will be x_{p+2}. The window continues to slide until the end of the dataset is reached. If the number of observations is N, then the total number of validations is (N–p).

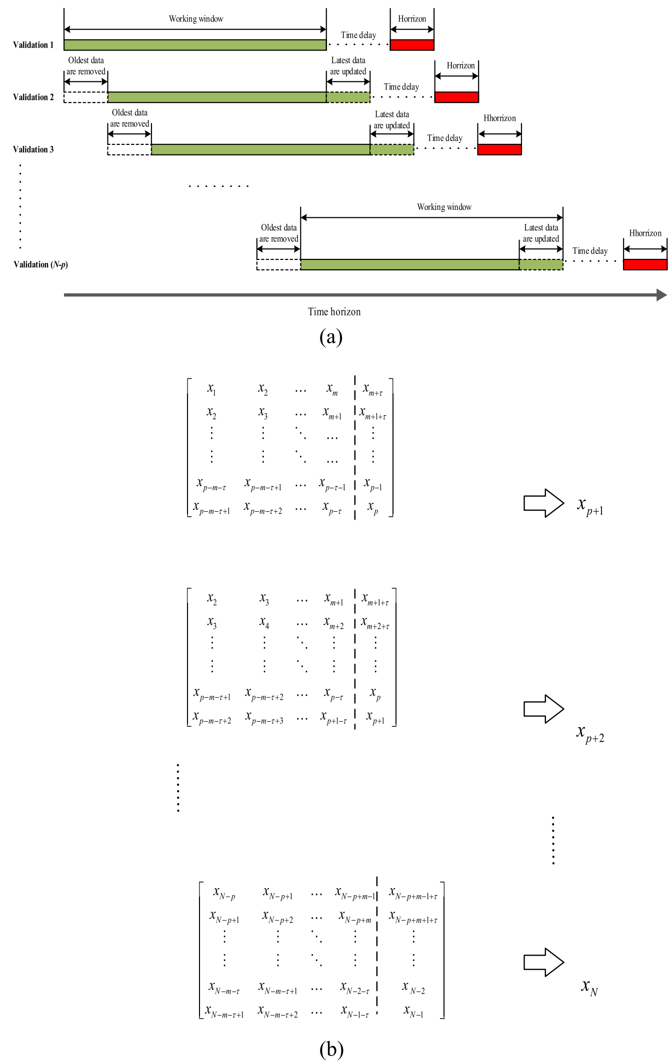

Fig. 1. Sliding-window and phase space reconstruction for time series analysis. (a) Sliding-window representation. (b) Phase space reconstruction.

B. Metaheuristic Optimization in Machine Regression Learner

1) Regression Model: The LSSVR approach proposed by Suykens *et al.* [30] is a well-developed ML technique with many advanced features that support a high generalization capacity and fast computation. The LSSVR training process entails the use of a least squares cost function to obtain a linear set of equations in a dual space to minimize the computational cost. Accordingly, iterative methods, such as the conjugate gradient method are typically used to derive a solution by efficiently solving a set of linear equations. To reduce the computational burden of the LSSVR for function estimation, the regression model in this study uses a quadratic loss function [29].

In a function estimation of the LSSVR, the optimization problem is formulated as

$$\min_{\omega,b,e} J(\omega, e) = \frac{1}{2}\|\omega\|^2 + \frac{1}{2}C\sum_{k=1}^{N} e_k^2. \tag{2}$$

Since the problem is a typical optimization of a differentiable function under constraints, it can be solved using Lagrange multipliers. Equation (3) is the resulting LSSVR model for function prediction

$$f(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b \tag{3}$$

where α_k and b are Lagrange multipliers and the bias term, respectively, and $K(x, x_k)$ is the kernel function. In this study, a radial basis function kernel (RBF) is used. For a detailed technical explanation of this approach applied in this study, the interested readers can refer to the work of Chou *et al.* [24].

Notably, the prediction accuracy of the LSSVR is highly dependent on the determination of its hyperparameters. Therefore, as a part of this study, the enhanced FA algorithm was developed to optimize LSSVR hyperparameters, i.e., the regularization parameter (C) and the sigma of the RBF kernel (σ).

2) Tuning Hyperparameters by Swarm and Metaheuristic Optimization Algorithm: The FA, developed by Yang [21], is among the most successful swarm intelligence methods. This algorithm was inspired by the flashing patterns and behavior of tropical fireflies. For a maximization problem, the brightness is simply set to be proportional to the value of the objective function. Since the attractiveness of a firefly is proportional to the intensity of its light that is visible to adjacent fireflies, the attractiveness β of a firefly satisfies

$$\beta = \beta_0 e^{-\gamma r^2} \tag{4}$$

where β is the attractiveness of the firefly, β_0 is the attractiveness of the firefly at $r = 0$, r is the distance between the firefly of interest and any other, e is a constant coefficient, and γ is the absorption coefficient. The detailed FA procedure has been summarized in [8].

Although the FA is highly efficient in many applications, it often becomes trapped in a local optimum [31]. Moreover, setting tuning parameters that improve the convergence of the FA is another challenge. The FA control parameters should be optimized to balance exploitation and exploration. Therefore, the MetaFA incorporates three metaheuristic components, namely chaotic map, the adaptive inertia weight, and Lévy flight, in the conventional FA to enhance its search and optimization capabilities [32]. Fig. 2 describes the pseudocodes for the MetaFA optimized LSSVR model.

a) Logistic chaotic map for enhancing initial population: The FA uses a typical approach to generating an initial solution at random. The two major disadvantages of this approach are its slow convergence and its tendency to become trapped in local optima because of reduced population diversity. To improve initial diversity of solutions and the quality of the initial population, a logistic chaotic map is used to generate a highly diverse population of fireflies in the initial stage.

```
Perform objective function f(x), x = (x_1,...,x_d)^T
Set search space and number of generations
Generate initial population of fireflies x_i (i = 1,2,...,n) using logistic chaotic map
Determine light intensity I_i at x_i by f(x_i)
Define light absorption coefficient γ
Generate initial population, k = 0
-----------------------------------------------------------------
1. While (t ≤ MaxGeneration) do
   (1) Update the generation number, k = k + 1
   (2) Tune randomization parameter α by adaptive inertia weight
   (α = α_0 0.9^t)
   (3) Tune attractiveness parameter β by using Gauss/mouse chaotic map
      for i = 1: No. fireflies
         for j = 1: No. fireflies
            if (I_j > I_i)
               Move firefly i toward j in d-dimension by Lévy flight;
            end if
            Vary attractiveness with distance r via exp[-γ*r]
            Evaluate new solutions and update light intensity
         end for j
      end for i
      Rank the fireflies and find the current best
   end while
-----------------------------------------------------------------
2. MetaFA-LSSVR function validation
   Set kernel (rbf) and loss-function (least-square) parameters
   Train model with hyperparameters (C,σ)
   Evaluate trained LSSVR model
   Evaluate fitness function f(m), and go to step 1
-----------------------------------------------------------------
3. Has the stopping criterion been met?
   If the criterion has been met,
      Go to step 4
   else
      go to step 1
   End
-----------------------------------------------------------------
4. Optimized LSSVR model
-----------------------------------------------------------------
5. Postprocess results and visualization
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Fig. 2. Pseudocode for the MetaFA-LSSVR model.

b) Gauss/mouse chaotic map for tuning attractiveness: The Gauss/mouse map provides the best means of tuning the attractiveness parameter (β) of the FA. For a detailed technical explanation of this approach applied in this study, the interested readers can refer to the work of He *et al.* [33].

c) Adaptive inertia weight for adjusting randomization: Reducing randomness as the iterations proceed improves the convergent efficiency of a swarm-based algorithm. In the initial stages of the search process, a large inertia weight can boost global exploration performance (searching of a new area). In each of the final stages, reducing the inertia weight enhances local exploration (fine tuning of the current search area). Inertia weight is an essential element in the convergence of the optimal known solutions to the globally optimal value; inertia weight also improves the execution time of the simulation.

d) Lévy flight for controlling movement: Random walk theory plays a critical role in modern swarm intelligence and evolutionary optimization algorithms [34]. Lévy flights are a random walk in which the step length is a Lévy distribution. The step lengths have no characteristic scale as the second moment or even the first moment may diverge, and the distribution exhibits self-affine properties. Lévy flights are used to generate random numbers in two steps: random selection of a direction and generation of steps that obey the selected Lévy distribution. In this work, directions were generated with uniform distributions. The Mantegna algorithm is used to generate steps from a symmetric Lévy stable distribution.

C. Intelligent Time Series Prediction System Using Sliding-Window Metaheuristic Optimization

The development tools that are used herein are MATLAB GUIDE, MATLAB complier, and MATLAB complier runtime, all of which are based on MATLAB software and developed in a Windows 10 environment on a machine with an Intel Core i5 and 4 GB of RAM.

The proposed forecasting framework has two main stages. In the first stage, the values of the time series parameters, *lag* and the size of the sliding window, are determined. Learning data in the sliding window are incorporated into input and output matrices. In the second stage, the MetaFA-LSSVR model is used to perform one-step ahead forecasting. Each validation involves one-step ahead forecasting, so the number of test data equals the number of validations. The window continues to move ahead and validations are conducted. The process is repeated until all validations have been performed.

Particularly, there are two modules, Evaluation and Forecast, provided in the interface system. The Evaluation module examines the performance of the sliding-window MetaFA-LSSVR and LSSVR models. For evaluation, the user can choose from several options, which are use the opened data file, use the test file, hold-out, and sliding-window validation. The Forecast module performs one- or multi-day ahead forecasting. The system returns a performance evaluation or predicted values, as required. The system also provides a feature that allows the user to save the model after it is run, enabling the user to reuse it for another purpose.

Fig. 3 displays the architecture of the proposed intelligent time series prediction system with sliding-window metaheuristic optimization. The user of the system involves the following simple steps - parameter setting, normalization, optimization, and purpose with MetaFA-LSSVR model. The results are shown in the interface. The user can also read the analysis report or save results to an electronic file for further analysis.

Equation (5) is the fitness function of the MetaFA-LSSVR

$$f(m) = \text{objective\_function}_{\text{Validation-data}} \tag{5}$$

in which the objective function can be designated as the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), the nonlinear regression multiple correlation coefficient or the mean square error (MSE). However, if the dataset contains actual zero values, then the MAPE cannot be used as an objective function.

D. Performance Evaluation Methods

The performance metrics that were used to assess the predictive accuracy of the proposed system included the RMSE, the MAE, the MAPE, the MSE, the correlation coefficient (*R*), the nonlinear regression multiple correlation coefficient (R^2),

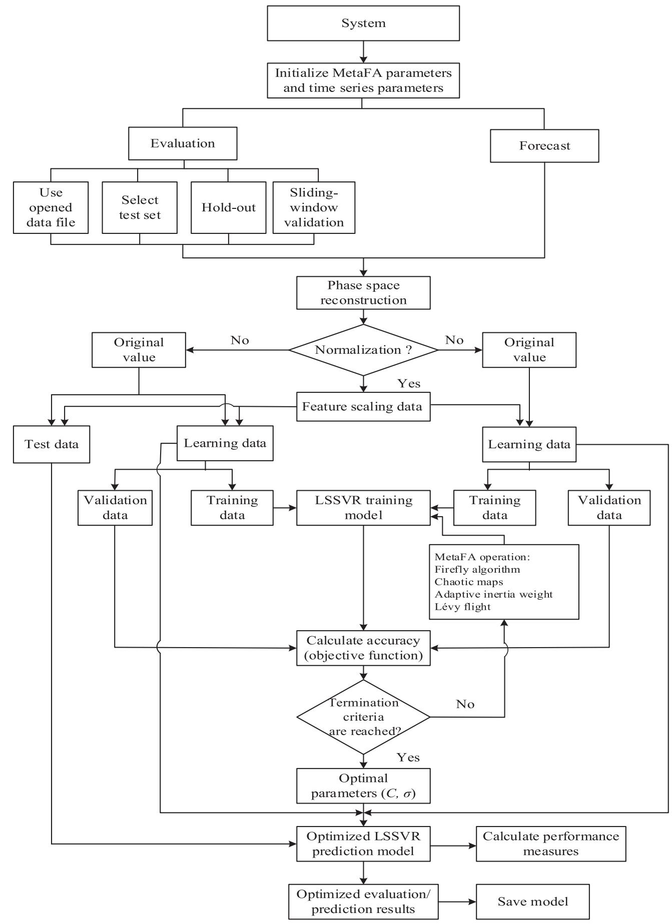

Fig. 3. System flowchart.

and the synthesis index (SI). These indexes are used to measure whether the predicted values are close to the actual values. Table I summarizes the formulas for these indexes, where y is the actual value, y' is the predicted value, $\bar{y}_i$ is the average across data samples, n is the number of data samples, m is the number of performance measures, and P_i is the ith performance measure. The SI ranges from 0 to 1 and an SI value of close to 0 indicates a highly accurate predictive model.

III. System Applications

A. Data Collection

Historical daily prices were taken from Yahoo! Finance, a publicly accessible website, as they were by Xiong *et al.* [18] . Six years (October 5, 2011 to May 31, 2017) of daily data on five stocks—Yuanta/P-shares Taiwan Top 50 ETF (0050.TW), Highwealth Construction Corp. (2542.TW), Huang Hsiang Construction Corporation (2545.TW), Ruentex Engineering & Construction Co., Ltd. (2597.TW), and Chong Hong Construction Co., Ltd. (5534.TW)—were downloaded from Yahoo! Finance. The data were closing stock prices. The 0050.TW stock dataset includes top 50 stocks by market capitalization in Taiwan. 2542.TW, 2545.TW, 2597.TW, and 5534.TW stocks provide an important indicator of the overall performance of the con-

TABLE I
MATHEMATICAL FORMULAS FOR PERFORMANCE MEASURES

Measure	Formula
RMSE	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y'-y)^2}$
MAE	$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert y-y'\rvert$
MAPE	$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\lvert\frac{y-y'}{y}\rvert$
MSE	$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y-y')^2$
The correlation coefficient (R)	$R = \frac{n\sum y.y' - (\sum y)(\sum y')}{\sqrt{n(\sum y^2)-(\sum y)^2}\sqrt{n(\sum y'^2)-(\sum y')^2}}$
Nonlinear regression multiple correlation coefficient (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{i+1}-y'_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y}_i)^2}$
SI	$\mathrm{SI} = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{P_i - P_{\min,i}}{P_{\max,i}-P_{\min,i}}\right)$

TABLE II
DESCRIPTION OF ANALYZED STOCKS AND DATASETS

Dataset	Total no. of data points	Duration
0050.TW	1357	Oct 5, 2011 to May 31, 2017
2542.TW	1457	Oct 5, 2011 to May 31, 2017
2545.TW	1457	Oct 5, 2011 to May 31, 2017
2597.TW	1457	Oct 5, 2011 to May 31, 2017
5534.TW	1457	Oct 5, 2011 to May 31, 2017

struction market in Taiwan. Table II presents the list of stocks and the number of data instances for each stock.

B. Input Setup

The performance of the proposed model in short-term prediction over the next 1, 10, and 15 days and in long-term prediction over the next 30, 60, 90, 180, and 360 days is evaluated using five stock datasets. Its performance is compared with those of previously reported models. Then, its performance is further tested using other popular stock datasets that are available in literature. Even though this investigation focuses mostly on short-term price prediction, long-term price predictions were carried out. Part of the default system settings were provided in [8]. The number of learning/training data was equal to the size of the sliding-window. The size of the sliding window was set to 840. Based on several trials and experiments, the optimal *lag* was 2.

C. Analysis of Experimental Results

1) Results of the Proposed Hybrid Prediction System: Eight scenarios were compared (i.e., 1, 10, 15, 30, 60, 90, 180, and 360 days ahead of time). Table III presents results for the 0050.TW stock. Fig. 4 displays the predicted closing prices of the 0050.TW stock dataset for the specified days ahead. This figure indicates that values that were predicted one day ahead by the system were closer to the actual values than the others. Tables IV–VII present similar results for 2542.TW, 2545.TW, 2597.TW, and 5534.TW stocks.

The above results clearly reveal that the error increases with the number of days in advance for which the prediction is made. This may be obvious for any prediction system. Overall, the proposed system yielded better predictions for the 0050.TW stock dataset than the other stock datasets. For instance, one-day ahead prediction using the 0050.TW stock dataset yielded favorable overall performance measures. However, the RMSE, MAE, MAPE, and MSE values of the 360 day-ahead prediction were smaller than those of the 90 day-ahead prediction and the 180 day-ahead prediction (with an RMSE of 4.763, an MAE of 4.086, an MAPE of 5.936 %, and an MSE of 22.690), motivating future research for long-term investment.

For the 2597.TW stock dataset, the one day-ahead forecast of the stock price was the best with an RMSE of 1.548, an MAE of 0.617, an MAPE of 1.372%, an R of 0.990, an R^2 of 0.973 and an MSE of 2.396. Table VI also reveals that RMSE, MAE, MAPE, and MSE values of the 360 day-ahead prediction were smaller than those of the 180 day-ahead prediction (with an RMSE of 16.333, an MAE of 8.608, an MAPE of 19.948%, and an MSE of 266.769). Similar results were obtained using the other construction company stock datasets.

2) Further Tests of the Hybrid Prediction System: To verify the robustness of the intelligent time series prediction system, several experiments are performed with more stocks. The daily closing prices of three popular stocks from October 5, 2011 to May 31, 2017 were obtained from Yahoo! Finance. Table VIII presents the details of the datasets. One-day-ahead predictions were made using the additional stock datasets and were obtained by the proposed system. Table IX further compares the performances with the existing techniques in the literature.

For example, Table IX shows RMSE, MAE, MAPE, and MSE values of the National Association of Securities Dealers Automated Quotation System (NASDAQ) stock of 0.712, 0.536, 0.901%, and 0.507, respectively. Notably, the one-day-ahead predictions of the 0050.TW stock dataset that were made using the proposed model were much better than those based on the BIST 100 and NASDAQ stocks. For the 2597.TW stock, the RMSE, MAE, MAPE, and MSE values were 1.548, 0.617, 1.372%, and 2.396, respectively. The one-day-ahead prediction of the price of the 2597.TW stock was better than that of the price of the stock of any of the other construction companies in MAPE. The best prediction performance was achieved for the S&P 500 stock price.

Table IX also reviews the key literature that is relevant to the present work and provides details about the choices of datasets and performance measures in those papers. Table IX lists the average values of the performance measures that were obtained in previous works [4], [22], [35]–[39], in which different datasets and learning algorithms were used to predict the closing prices of stock one day ahead. Clearly, the one-day-ahead predictions

TABLE III
PREDICTION PERFORMANCE OF THE PROPOSED MODEL FOR 0050.TW STOCK

Scenario	Forward day	Average performance measure in test data						SI	Rank
		RMSE	MAE	MAPE (%)	R	R^2	MSE		
1	**1**	**0.644**	**0.474**	**0.713**	**0.992**	**0.969**	**0.414**	**0.000**	**1**
2	10	1.863	1.515	2.302	0.930	0.848	3.472	0.239	2
3	15	2.368	1.909	2.906	0.885	0.765	5.609	0.341	3
4	30	3.135	2.557	3.884	0.789	0.401	9.829	0.513	4
5	60	4.416	3.777	5.628	0.536	0.220	19.498	0.850	5
6	90	4.757	4.145	6.131	0.458	0.100	22.624	0.948	7
7	180	4.940	4.062	5.974	0.353	0.032	24.400	0.987	8
8	360	4.763	4.086	5.936	0.605	0.092	22.690	0.878	6

Note: bold values denote the best performance measures among the others.

TABLE IV
PREDICTION PERFORMANCE OF THE PROPOSED MODEL FOR 2542.TW STOCK

Scenario	Forward day	Average performance measure in test data						SI	Rank
		RMSE	MAE	MAPE (%)	R	R^2	MSE		
1	**1**	**2.308**	**0.863**	**1.745**	**0.982**	**0.957**	**5.239**	**0.000**	**1**
2	10	4.729	4.177	5.446	0.942	0.877	17.445	0.070	2
3	15	5.041	3.347	6.809	0.915	0.823	25.414	0.100	3
4	30	8.572	5.420	10.874	0.766	0.508	73.483	0.209	4
5	60	11.066	9.043	18.703	0.583	0.185	122.453	0.337	5
6	90	11.993	9.424	19.655	0.424	0.048	143.821	0.433	7
7	180	11.686	9.503	20.583	0.541	0.105	136.555	0.410	6
8	360	122.047	16.919	34.821	0.011	–96.350	14 895.569	1.000	8

Note: bold values denote the best performance measures among the others.

TABLE V
PREDICTION PERFORMANCE OF THE PROPOSED MODEL FOR 2545.TW STOCK

Scenario	Forward day	Average performance measure in test data						SI	Rank
		RMSE	MAE	MAPE (%)	R	R^2	MSE		
1	**1**	**1.372**	**0.558**	**1.701**	**0.984**	**0.959**	**1.883**	**0.000**	**1**
2	10	2.707	1.756	5.345	0.866	7.329	0.866	0.123	2
3	15	3.212	2.166	6.631	0.810	10.314	0.810	0.169	3
4	30	4.541	3.256	9.821	0.639	20.625	0.639	0.301	4
5	60	5.740	4.624	13.865	0.423	32.943	0.423	0.449	5
6	90	6.972	5.773	17.740	0.569	0.150	48.612	0.616	6
7	180	10.963	9.017	28.170	0.351	–1.074	120.191	1.000	8
8	360	8.434	7.130	20.460	0.637	–0.236	71.139	0.693	7

Note: bold values denote the best performance measures among the others.

TABLE VI
PREDICTION PERFORMANCE OF THE PROPOSED MODEL FOR 2597.TW STOCK

Scenario	Forward day	Average performance measure in test data						SI	Rank
		RMSE	MAE	MAPE (%)	R	R^2	MSE		
1	**1**	**1.548**	**0.617**	**1.372**	**0.990**	**0.973**	**2.396**	**0.000**	**1**
2	10	3.075	1.792	3.963	0.962	0.916	9.459	0.082	2
3	15	5.169	2.823	6.319	0.902	0.770	26.717	0.178	3
4	30	5.569	3.668	8.367	0.882	0.735	31.011	0.229	4
5	60	8.396	5.684	13.754	0.764	0.410	70.494	0.406	5
6	90	9.870	7.050	17.262	0.718	0.190	97.417	0.507	6
7	180	19.444	11.600	28.536	0.295	–2.110	378.059	1.000	8
8	360	16.333	8.608	19.948	0.443	–1.198	266.769	0.756	7

Note: bold values denote the best performance measures among the others.

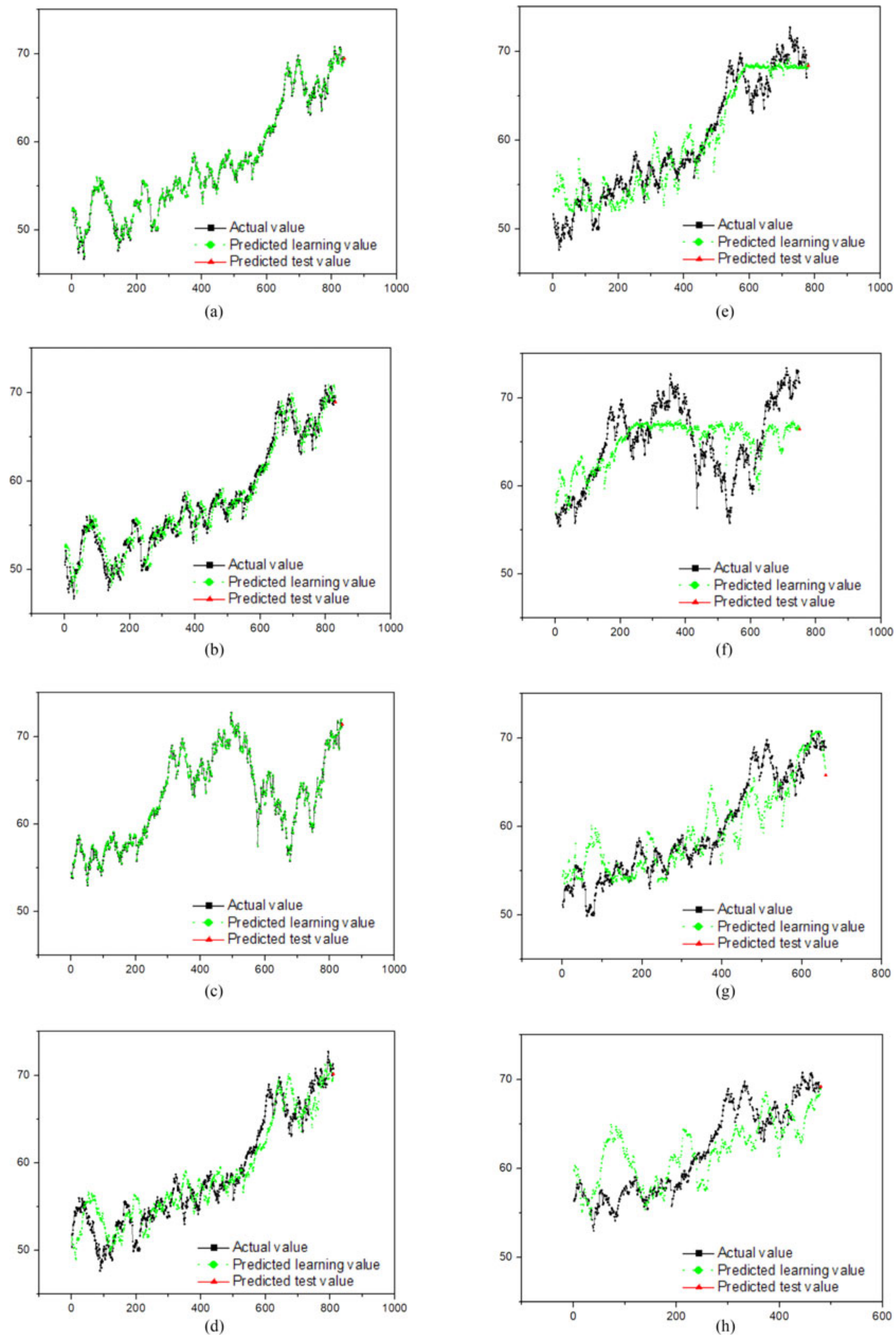

Fig. 4. Actual and predicted values of the last validation (for 0050.TW stock). (a) Actual and predicted values of 1-day-ahead validation. (b) Actual and predicted values of 10-day-ahead validation. (c) Actual and predicted values of 15-day-ahead validation. (d) Actual and predicted values of 30-day-ahead validation. (e) Actual and predicted values of 60–day-ahead validation. (f) Actual and predicted values of 90-day-ahead validation. (g) Actual and predicted values of 180-day-ahead validation. (h) Actual and predicted values of 360-day-ahead validation.

TABLE VII
PREDICTION PERFORMANCE OF THE PROPOSED MODEL FOR 5534.TW STOCK

Scenario	Forward day	Average performance measure in test data						SI	Rank
		RMSE	MAE	MAPE (%)	R	R^2	MSE		
1	**1**	**1.728**	**0.823**	**1.494**	**0.985**	**0.956**	**2.986**	**0.000**	**1**
2	10	3.760	2.709	4.855	0.930	0.842	14.135	0.101	2
3	15	7.701	5.591	10.188	0.851	0.379	59.309	0.266	4
4	30	6.298	4.786	8.722	0.821	0.571	39.671	0.231	3
5	60	9.698	7.840	14.325	0.608	0.003	94.049	0.434	5
6	90	13.301	10.643	19.774	0.442	–0.857	176.920	0.621	6
7	180	20.026	16.997	31.787	0.137	–3.194	401.023	1.000	8
8	360	13.888	10.903	21.392	0.379	–1.030	192.878	0.665	7

Note: Bold values denote the best performance measures among the others.

TABLE VIII
THREE STOCK DATASETS

Dataset	Total no. of data points	Duration
Borsa Istanbul 100 (BIST 100)	1395	Oct 5, 2011 to May 31, 2017
NASDAQ	1421	Oct 5, 2011 to May 31, 2017
Standard's & Poor's 500 (S&P 500)	1421	Oct 5, 2011 to May 31, 2017

TABLE IX
ONE-DAY-AHEAD PREDICTION PERFORMANCE COMPARISON BETWEEN THE PROPOSED METHOD AND EXISTING METHODS

Method	Dataset	Performance measures			
		RMSE	MAE	MAPE (%)	MSE
Intelligent time series prediction system	2542.TW	2.308	0.863	1.745	5.239
	2545.TW	1.372	0.558	1.701	1.883
	2597.TW	1.548	0.617	1.372	2.396
	5534.TW	1.728	0.823	1.494	2.986
	0050.TW	0.644	0.474	0.713	0.414
	BIST 100	1.056	0.782	0.981	1.115
	NASDAQ	0.712	0.536	0.901	0.507
	S&P 500	0.182	0.127	0.613	0.033
Göçken *et al.* [4] and Hadavandi *et al.* [35]	BIST 100	2.413	2.833	3.688	12.651
Bhattacharya *et al.* [38] and Shen *et al.* [39]	NASDAQ	0.042	–	0.160	5.721
Rout *et al.* [22], Anish *et al.* [36], and Dash *et al.* [37]	S&P 500	0.037	–	9.436	0.003

TABLE X
COMPARISON IN HIT-RATE

Dataset	Frequency of correct prediction	Hit rate
2542.TW	160 out of 299	53.511%
2545.TW	143 out of 299	47.826%
2597.TW	162 out of 299	54.180%
5534.TW	136 out of 299	45.484%
0050.TW	146 out of 299	48.829%
BIST 100	139 out of 299	46.488%
NASDAQ	143 out of 299	47.826%
S&P 500	136 out of 299	45.484%

of the values in the eight stocks achieved superior MAPEs compared with previously reported models.

In this study, "hit-rate" is also used as a performance measure for predicting whether stocks will go up or down in a given timeframe. The hit rate indicates how often a model gives a correct prediction in terms of the direction of price [40]. Table X shows a hit-rate comparison of the proposed model using the eight stock datasets. The one-day-ahead prediction of the price direction for the 2542.TW and 2597.TW stocks was better than the others using the proposed system as can be seen easily.

3) Comparison of Profit: Statistical performance measurements and direction of stock price do not have much meaning for practical investors. The profit and loss performance of a forecasting model must also be examined to evaluate a forecasting model. The buying and selling behaviors of a typical investor can be simulated. An investor will buy stocks from the market if he/she expects an increase in prices and sell his/her financial assets if he/she expects a decrease in prices. This simple trading logic was simulated using the predictions made using the proposed model. For simplicity, no tax or fees were associated with any transaction.

The profit that was earned on the eight stocks, respectively, during 300 trading days when investments were managed according to the forecasts, was simulated. Table XI compares the results of trading using the proposed hybrid system with those obtained using the BUY and HOLD method. Based on this method, an investor buys stocks with closing price at the beginning of trading period and sells all of them at the end of trading period. The proposed system outperforms with the BIST 100 stock. More profit was made on the 2542.TW stock than on the other construction company stocks. Table XI also reveals that the proposed system with the eight stocks yields greater profits than the traditional BUY and HOLD method.

TABLE XI
COMPARATIVE ANALYSES OF VARIOUS TRADING RESULTS

Stock	Price at the beginning of the investment period (1000 USD)	Price at the end of the investment period (1000 USD)	Profit per share by applying the proposed system (1000 USD)	Profit using BUY and HOLD method (1000 USD)
2542.TW	48.25	48.20	37.40	−0.05
2545.TW	29.35	39.20	32.00	9.85
2597.TW	44.50	37.20	27.35	−7.3
5534.TW	55.7	52.90	35.43	−2.8
0050.TW	60.35	71.75	30.20	11.4
BIST 100	71.34	79.76	39.48	8.42
NASDAQ	50.99	68.44	20.22	17.45
S&P 500	19.14	21.60	26.11	2.46

IV. CONCLUSION AND RECOMMENDATIONS

Decision to buy or sell a stock is very complicated since many factors can affect stock price. This work presents a novel approach, based on a MetaFA-LSSVR, to constructing a stock price forecasting expert system, with the aim of improving forecasting accuracy. The intelligent time series prediction system that uses sliding-window metaheuristic optimization is a graphical user interface that can be run as a stand-alone application. The system makes the prediction of stock market values simpler, involving fewer computations, than that using the other method that was mentioned above.

The original FA is supplemented with three metaheuristic components—chaotic maps, adaptive inertia weight, and Lévy flight—to construct a metaheuristic optimization algorithm (MetaFA). The superior performance of the MetaFA was verified by validating benchmark functions. Thus, the MetaFA was adopted to tune automatically the hyperparameters C and σ of the LSSVR. The optimized LSSVR prediction model was used with the sliding-window approach to evaluate and forecast stock price. Default settings of the system, including prespecified values of parameters, save users time.

To evaluate the proposed approach, it was applied to five datasets for stocks in Taiwan, and three other stock datasets that have been used elsewhere. Statistical measures were obtained when applied to Taiwan construction company stock datasets. In particular, the one day prediction of 2597.TW stock prices was better than that of any construction company stock prices, with an MAPE of 1.372%, an R of 0.990, and an R^2 of 0.973. Toward the end of the study, the financial performance of the proposed system was examined, with encouraging results. Therefore, the proposed system can be used as a decisive tool to forecast stock prices for short-term investing.

This study focuses on the stock market in Taiwan. To generalize the application of the proposed system, future work should use the proposed system to estimate stocks in other emerging or mature markets, such as Vietnam, Indonesia, China, Japan, Hong Kong, Korea, Singapore, Europe, and USA. Secondly, the system could be extended to analyze multivariate time series data and import raw dataset directly. Finally, the development of a web-based application should be considered to improve the user-friendliness and usability of the expert system.

The limitation of the proposed system is its computational speed, especially with respect to sliding-window validation, because of the complexity of solving large mathematical loops in the MATLAB program. The computational cost increases with the number of validations. Another weakness is the need to define many parameters of the system (MetaFA and time series parameters) though the default settings are provided. Moreover, the system does not achieve outstanding results for long-term investment—a finding that will motivate future research.

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