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HYBRID DECOMPOSITION AND ENSEMBLE FRAMEWORK FOR STOCK PRICE FORECASTING: A COMPARATIVE STUDY

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In this study, a hybrid decomposition and ensemble framework incorporating Ensemble empirical mode decomposition (EEMD) and selected modeling methodologies are proposed for stock price forecasting. Under the framework, the original stock price series was first decomposed into several subseries including a number of intrinsic mode functions (IMFs) and a residue using EEMD technique. Then, extracted subseries was modeled to generate forecasts respectively. Finally, the forecasts of all extracted subseries were aggregated to produce an ensemble forecasts for the original stock price series. An extensive experiment was conducted to compare the feasibility and validity of the proposed hybrid framework employing different modeling methodologies, such as support vector machines (SVMs) (in the formulation of support vector regression (SVR), feed forward neural networks (FNN), and autoregressive integrated moving average (ARIMA). The real daily closing price series of Thirty Dow Jones industrial stocks from New York Stock Exchange (NYSE) was used for experimental evaluation. The results demonstrate that significant improvement can be achieved with the proposed hybrid decomposition and ensemble framework across all the three modeling methodologies, particularly, hybrid EEMD-based FNN modeling framework achieved the most significant improvement but hybrid EEMD-based SVMs modeling framework performed best in terms of root mean squared error (RMSE), mean absolute percentage error (MAPE), and directional symmetry (DS).

Keywords: Stock price forecasting; ensemble empirical mode decomposition; support vector regression; ensemble modeling.

1. Introduction

Forecasting stock price is one of the fascinating issues of stock market research. Accurately forecasting stock price, which forms the basis for the decision making of financial investment, is probably the biggest challenge for capital investment industry. Stock market prices prediction is regarded as a challenging task of the

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financial time series prediction process since the financial time series are noisy and nonstationary [Yaser and Atiya (1996)]. The noisy characteristic implies that there is no complete information that can be obtained from the past behavior of financial markets to fully capture the dependency between future and past prices. The nonstationary characteristic means that the distribution of financial time series is changing over time.

In the past decades, academic researchers and practitioners have made many contributions on stock price forecasting. Most of the quantitative forecasting models abounded in the literature can mainly be classified into two categories, namely econometric modeling and time series modeling. In the econometric modeling, pioneering works can be found in the papers by Tsaih and Hsu [1998], Kim and Lee [2004], Thawornwong and Enke [2004], and Mieko and Seiji [2007]. Most econometric models aimed to reveal the relationship between stock price and selected macroeconomic variables such as interest rates (IR), consumer price index (CPI), government consumption (GC), and industrial production (IP). Due to the complexity of econometric modeling in variables selection and testing, time series approach is a promising alternative in stock price forecast though they are handicapped by their inability to indentify the causes of stock price volatility with clear interpretation. Over the past years, the most popular and widely used methods in practice are autoregressive integrated moving average (ARIMA) [Box and Jenkins (1976)], ARCH [Engle (1982)]/GARCH [Bollerslev (1986)] family models, etc. Mok [1993] used the ARIMA model to forecast the daily close and morning open price in Hong Kong stock market. Akgiray [1989] showed that out-of-sample forecasts of return variances of stock indices based on a GARCH model are superior predictors of the actual ex-post variances in comparison to the forecasts that are generated using standard rolling regression methods. However, these traditional time series methods always do not work in practice. The main reason is that the underlying assumption of these traditional time series methods is linearity and they cannot capture the nonlinear patterns hidden and recognize the irregularity well.

Recent research efforts on modeling time series with complex nonlinearity, dynamic variation, and high irregularity provided two promising directions. One is to establish emerging artificial intelligence models such as artificial neural networks (ANN), support vector machines (SVMs), and genetic programming (GP). Unlike the traditional statistical models, neural networks are data-driven, nonparametric weak models, and they let "the data speak for themselves" [Bao *et al.* (2005)]. The other is to use hybrid learning framework to integrate different AI approaches to forecast complex nonlinear time series with great fluctuation and irregularity. For example, Hsu *et al.* [2008] developed a two-stage architecture by integrating a self-organizing map (SOM) and support vector regression (SVR) for stock price prediction. Pai and Lin [2005] proposed a hybrid methodology that exploits the unique strength of the ARIMA model and the SVR model in forecasting stock prices problem. The basic idea of the hybrid methods is to overcome the drawbacks of individual models and to generate a synergetic effect in forecasting. Motivated by hybrid methodologies, Yu *et al.* [2008] presented a decomposition-and-ensemble ANN learning paradigm in crude oil price. The most attracting point of their work is to decompose the time series into several sub-series first by empirical mode decomposition (EMD) technique, then model them respectively by an independent three-layer feed-forward network (FNN) model and ensemble the forecasts using an adaptive linear neural network (ALNN) finally. Further empirical evidence on the advantages of using EMD technique in forecasting task has been given by Chen and Jeffrey [2009] and Mallikarijuna and Kanth [2010].

This study extended the hybrid decomposition and ensemble framework into stock price forecasting by conducting an extensive and comparative experiment with different modeling scenarios. For the decomposition technique selection, ensemble empirical mode decomposition (EEMD) technique, a substantial improved version of EMD [Huang *et al.* (1998)] was selected for the sake of increasing the robustness of EMD and alleviating some of the common problems of EMD such as mode mixing [Wu and Huang (2009); Niazy *et al.* (2009)]. For the modeling methodologies, SVR, FNN, and ARIMA were chosen. The goals of the experiment have two folds. One is to examine how significant improvement can be achieved by using the hybrid decomposition and ensemble framework. The other is to compare the performance across different modeling methodologies within or not within the proposed hybrid framework. The real daily closing prices of the Thirty Dow Jones industrial stocks are used for performance evaluation.

The rest of the paper is organized as follows: Section 2 gives a brief introduction to EEMD, SVMs, FNN, and ARIMA. The proposed decomposition and ensemble framework are presented in Section 3 by raising EEMD-based SVMs modeling framework as an example. Section 4 illustrates the data source and the experimental design on accuracy measure, implementation, and parameters selection in details. In Section 5, the experimental results are discussed. Finally, conclusions are drawn in Section 6.

2. Methodologies

2.1. *Ensemble empirical mode decomposition*

EEMD as proposed by Wu and Huang [2009] is a substantial improvement over the original EMD method developed by Huang *et al.* [1998], because it avoids the problem of mode mixing. The underlying idea of EEMD is based on the understanding that the use of noise can be helpful in data analysis. Adding noise to data helps to detect the weak signals with hidden modes and to delineate the underlying processes.

Intrinsic-mode functions (IMF) and the sifting process are the two key parts of the original EMD method as well as of EEMD. The term "intrinsic-mode function" is used because it represents the oscillation mode embedded in the data. An IMF is a function that satisfies two conditions: (i) in the whole data series, the number of extrema (the sum of local maxima and local minima) and the number of zero crossings must either be equal or differ at most by one and (ii) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima are zero.

With this definition, IMFs can be extracted from the data series $X(t)$ according to the following sifting process:

(1) Identify all the local extrema, including local maxima and local minima;
(2) Connect the local maxima by a cubic spline to define the upper envelope, $X_{\text{up}}(t)$, and the local minima by a second cubic spline to define the lower envelope, $X_{\text{low}}(t)$;
(3) Compute the point-by-point local envelope mean $m(t)$ from the upper and lower envelopes as $m(t) = (X_{\text{up}}(t) + X_{\text{low}}(t))/2$;
(4) Obtain the component h by taking the difference between the data and the local envelope mean, $h = X(t) - m(t)$;
(5) Treat h as a data series and repeat Steps 1–4 as many times as is required until the envelopes are symmetric with respect to zero mean under certain criteria;
(6) The final h is designated as an IMF component c;
(7) Obtain the residue r as $r = X(t) - c$;
(8) Then, treat r as a new data series and repeat Steps 1–7 until the final residue becomes a monotonic function from which no more IMFs can be extracted.

Generally, the process from Steps 1 to 6 is called the IMF extraction process, and the process from Steps 1 to 8 is called the whole sifting process. After finishing the whole sifting process, the data series $X(t)$ can be decomposed into IMFs and a residue, i.e.,

$$x(t) = \sum_{i=1}^{n} c_j + r_n, \tag{1}$$

where n is the number of IMFs, $c_j (j = 1, 2, \ldots, n)$ are the IMFs, and r_n is the residue, which represents the overall trend of the data series $X(t)$.

The sifting process described above is the core of the original EMD method. In implementation, some algorithm issues arise, such as the stopping criteria for IMF extraction and for the whole sifting process; a recent detailed discussion of these issues can be found in references [Huang *et al.* (2003); Shen *et al.* (2005)]. In this study, the number of sifting passes for IMF extraction is fixed at 10, and the whole sifting process stops after $\log_2 N$ IMFs have been extracted, where N is the length of the data series.

The principal concept of the EEMD approach is as follows: the added white noise presents a uniform reference frame in the time-frequency and time-scale domains for the signals of comparable scales to collate into one IMF and then cancel themselves out by ensemble averaging after serving their purpose. Thus, the problem of mode mixing in the original EMD method can be limited significantly.

For a given data series $x(t)$, the EEMD procedure can be described as follows:

(1) Generate series with added white noise, $x_i(t) = x(t) + w_i(t)$;
(2) Decompose the $x_i(t)$ by the sifting process described above and obtain the IMF components, $\sum_{j=1}^{n} c_{ij} + r_{in}$;
(3) Repeat Steps 1 and 2 m times with a different white noise series each time; then, obtain a set of IMF components, $\sum_{i=1}^{m}(\sum_{j=1}^{n} c_{ij} + r_{in})$, where m is the ensemble number; and
(4) Obtain the (ensemble) means of the corresponding IMFs of the decompositions as the final result, i.e., the jth ensemble IMF, $\overline{c_j} = \frac{1}{m}\sum_{i=1}^{m} c_{ij}$, and the ensemble residue, $\overline{r_n} = \frac{1}{m}\sum_{i=1}^{m} r_{\text{in}}$.

2.2. *Support vector machines*

The SVMs are a new and powerful approach for data classification and regression that employs the structural risk minimization (SRM) principle. For a detailed introduction to this subject, please refer to Dibike and Velickov [2001] and Smola and Scholkopf [2004].

Given a set of training data points $G = \{(x_i, y_i)\}_i^n$, where $x_i \in X, y_i \in R$, x_i is the input vector, y_i is the desired value, and n is the total number of the data patterns. The aim is to find a function that can evaluate all these data well. SVR is one of the methods to perform the above regression task.

In general, SVR approximate the function using the following:

$$f(x) = (w \cdot \phi(x)) + b, \tag{2}$$

where $(\cdot)$ denotes the inner product and $\phi(x)$ is the high dimensional feature space that is nonlinearly mapped from the input space x. The coefficients w and b are estimated by minimizing:

$$R_{\text{reg}}(f) = C\frac{1}{n}\sum_{i=1}^{n}\Gamma(f(x_i), y_i) + \frac{1}{2}\|w\|^2, \tag{3}$$

$$\Gamma(f(x), y) = \begin{cases} |f(x) - y| - \varepsilon, & \text{if } |f(x) - y| \geq \varepsilon \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

In the regularized risk function given, the first term $C\frac{1}{n}\sum_{i=1}^{n}\Gamma(f(x_i), y_i)$ is the empirical risk. They are measured by the ε-insensitive loss function (Fig. 1) given by Eq. (4). This loss function provides the advantage of enabling one to use sparse data points to represent the decision function given by Eq. (2). The second term $1/2\|w\|^2$, is the regularization term to be used as a measure of flatness or complexity of the function. Hence, C is referred to as the regularized constant and it determines the trade-off between the empirical risk and the regularization term. Increasing the value of C will result in the relative importance of the empirical risk with respect to the regularization term to grow. ε is called the tube size and it is equivalent to the approximation accuracy placed on the training data points. Both C and ε are user-prescribed parameters.

Finally, using the Lagrange function and exploiting the optimality constraints, we obtain the following quadratic programming (QP) problem:

$$\begin{aligned}\arg\min_{a,a^*} \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(a_i - a_i^*)(a_j - a_j^*)(\phi(x_i)\cdot\phi(x_j)) \\ +\sum_{i=1}^{n}(\varepsilon - y_i)a_i + \sum_{i=1}^{n}(\varepsilon + y_i)a_i^*\end{aligned} \tag{5}$$

Subject to

$$\sum_{i}^{n}(a_i - a_i^*) = 0, a_i, a_i^* \in [0, C], \tag{6}$$

where a_i and a_i^* are corresponding Lagrange multipliers used to push and pull $f(x_i)$ toward the outcome of y_i respectively.

Solving the above QP problem of Eq. (5) with constraints of Eq. (6), we determine the Lagrange multipliers a and a^* and obtain $w = \sum_{i=1}^{n}(a_i - a_i^*)\phi(x_i)$. Therefore, the estimation function in Eq. (2) becomes:

$$f(x) = \sum_{i=1}^{n}(a_i - a_i^*)(\phi(x)\cdot\phi(x_i)) + b. \tag{7}$$

So far, we have not considered the computation of b. In fact, this can be solved by exploiting the Karush-Kuhn-Tucker (KKT) conditions. These conditions state that at the optimal solution, the product between the Lagrange multipliers and the constraints has to equal to zero. In this case, it means that

$$\begin{aligned} a_i(\varepsilon + \zeta_i - y_i + (w\cdot\phi(x_i)) + b) = 0 \\ a_i^*(\varepsilon + \zeta_i^* + y_i - (w\cdot\phi(x_i)) - b) = 0 \end{aligned} \tag{8}$$

and

$$\begin{aligned} (C - a_i)\zeta_i = 0 \\ (C - a_i^*)\zeta_i^* = 0, \end{aligned}$$

where ζ_i and ζ_i^* are slack variables used to measure the error of up and down side. Here, $\zeta_i > 0$ corresponds to a point for which $y_i > (w\cdot\phi(x_i)) + b + \varepsilon$, and $\zeta_i^* > 0$ corresponds to a point for which $y_i < (w\cdot\phi(x_i)) + b + \varepsilon$.

Since $a_i \cdot a_i^* = 0$ and $\zeta_i^{(*)} = 0$ for $a_i^{(*)} \in (0, C)$, b can be computed as follows:

$$b = \begin{cases} y_i - (w\cdot\phi(x_i)) - \varepsilon, & \text{for } a_i \in (0, C) \\ y_i - (w\cdot\phi(x_i)) + \varepsilon, & \text{for } a_i^* \in (0, C) \end{cases}. \tag{9}$$

Using the trick of kernel function, Eq. (7) can be written as:

$$f(x) = \sum_{i=1}^{n}(a_i - a_i^*)K(x,x_i) + b,$$

$K(x, x_i) = (\phi(x) \cdot \phi(x_i))$ is defined as the kernel function. The value of the kernel is equal to the inner product of two vectors X_i and X_j in the feature space $\phi(x_i)$ and $\phi(x_j)$, that is, $K(x_i, x_j) = (\phi(x_i) \cdot \phi(x_j))$. The elegance of using the kernel function is that one can deal with the feature spaces of arbitrary dimensionality without having to compute the map $\phi(x)$ explicitly. Any function satisfying Mercer's condition [Vapnik (1995)] can be used as the kernel function. In this study, we select a common kernel function, e.g., radical basis function (RBF) function, $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0$, as the kernel function.

2.3. *Feed-forward neural network*

In this study, we employ a particular structure of ANN, multi-layer FNNs [Hornik *et al.* (1989); White (1990)] on the basis of error back-propagation algorithm, which is the most popular and widely used network paradigm in time series forecasting. Generally, FNN consists of a large number of simple processing units, called neurons, which are organized in layers. A numerical value, known as weight, is associated with the connection of two neurons, which can be used for storing various types of information, especially the knowledge or experience. The FNN system has three layers, which are input layer, hidden layer, and output layer; the upper layer nodes connect to the lower layer nodes, but the nodes of the same layer cannot connect. The input layer consists of all the input factors, then knowledge or information from the input layer is processed in the hidden layer, and the output vector that follows is computed in the output layer. Generally, hidden and output layers have a mathematical function (generally nonliner and called as an activation function). A sigmoid function as an activation function is a widely used nonliner activation function whose output lies between 0 and 1.

2.4. *ARIMA*

ARIMA proposed by Box and Jenkins [1976] is a popular univariate time series model. In an ARIMA model, the future value of a variable is supposed to be a linear function of several past observation and random errors. That is, the underlying process that generates the time series has the form

$$y_t = \theta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}, \tag{10}$$

where y_t and ε_t are the actual value and random error at time t, respectively; $\phi_i (i = 1, 2, \ldots, p)$ and $\theta_j (j = 1, 2, \ldots, q)$ are coefficients. p and q are integers and often referred to as autoregressive and moving average polynomials, respectively. Random ε_t are assumed to be independently and identically distributed with a mean of zero and a constant variance of σ^2. Basically, this method has three phases: model identification, parameters estimation, and diagnostic checking.

3. Proposed Hybrid Decomposition and Ensemble Framework

In this section, details on the proposed hybrid decomposition and ensemble framework are presented. For the purpose of illustration, the EEMD-based SVMs modeling framework is raised as an example.

The general process of the proposed framework is as follows. The original stock price series were first decomposed into a finite and often a small number of IMFs and a residue with EEMD technique. After the components (IMFS and a residue) were adaptively extracted via EEMD, each component was modeled by an independent model to forecast the component series respectively. Finally, the forecasts of all components were aggregated using another independent SVMs model, which model the relationship among the IMFs and the residue, to produce an ensemble forecasts for the original stock price series. Figure 1 illustrates the framework of the proposed approach using the example of EEMD-based SVMs modeling framework.

Suppose that $X(t)$ $(t = 1, 2, \ldots, n)$ is a time series for training. Building upon the previous techniques and methods, an EEMD-based SVMs ensemble learning

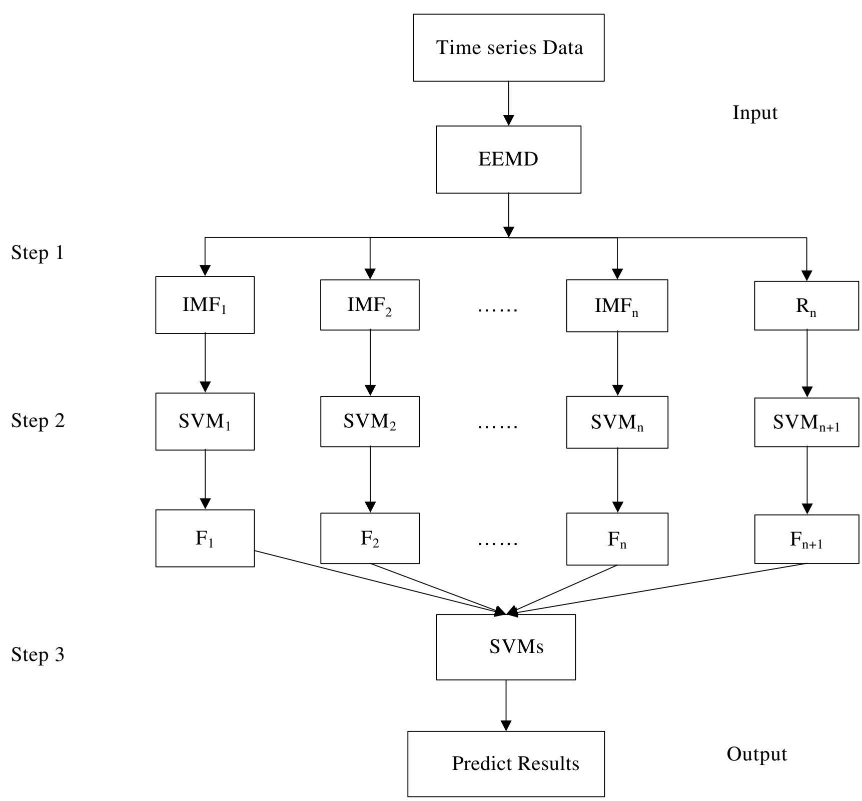


Fig. 1. The framework of the proposed EEMD-based SVMs.

process is formulated as the following procedures:

(1) The original time series $X(t)$ is decomposed into m IMFs components, $c_j(t), j = 1, 2, \ldots, m$ and the a residual component $r_m(t)$ using EEMD technique;
(2) Employ SVMs to model each IMF components and the residual component using a rolling origin and roll window training strategy to get the model specifications of each components respectively;
(3) For the purpose of seeking the ensemble function, an SVMs model is established to model the relationship between the actual values and the forecast values of all extracted components in the same time points. For instance, F_{ij} $(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$ denotes the forecast of jth IMF component at ith time, and $F_{i(m+1)}(i = 1, 2, \ldots, n)$ denotes the forecast of the residue at ith time, the ensemble SVMs is to model the relationship between X_i and $(F_{i1}, F_{i2}, \ldots, F_{im}, F_{i(m+1)})$.

In this study, we name it as EEMD (decomposition)-SVMs (forecasting)-SVMs (ensemble), EEMD-SVMs-SVMs for abbreviation. Similarly, we developed the EEMD-FNN-FNN framework. However, for the ARIMA, we use the followed procedure instead of the third procedure above:

(3′) Sum up the forecasts of each component and take it as the ensemble forecast,

$$F(t) = \sum_{j=1}^{m+1} F_{tj}(j = 1, 2, \ldots, m, m+1), \quad t = 1, 2, \ldots, n.$$

Therefore, we name it as EEMD-ARIMA-SUM in the following sections.

4. Experiment Settings

4.1. *The datasets and preprocessing*

Thirty Dow Jones industrial stocks were used in this study to examine the forecasting performance of the proposed hybrid framework. The daily closing prices of the stocks were collected from Web site of yahoo finance (http://finance.yahoo.com/). The main reason of selecting these Dow Jones industrial stocks is that these companies are most famous in each field and represent the development trend of the stock market. Hence, Dow Jones industrial stocks are a popular choice among researchers for illustrating prediction methods in financial time series.

In our experiment, the daily closing prices of the Thirty Dow Jones industrial stocks are used as the data sets. For each of the company, the sampling data period ranges from January 3, 2007 to September 5, 2008, including 423 daily observations. Then, we divided the original data into two groups: the training data sets for training the models and tuning the parameters and the testing data sets to evaluate the models. The daily closing prices of the first 318 observations were used for training and the last 105 observations were used for testing. Note that this study only considers one step ahead forecasting, because one step ahead forecasting can prevent problems associated with cumulative errors from the previous period for out of sample forecasting [Huang and Wu (2006)].

In this study, we adopt liner transformation to adjust the original data set scaled into the range of [0, 1] as shown in Eq. (11). The two main advantages of scaling are to avoid inputs in greater numeric ranges from dominating those in smaller numeric ranges and to prevent numerical difficulties during the calculation [Yu *et al.* (2008)].

$$y_{k,t} = \frac{x_{k,t} - \min(x_k)}{\max(x_k) - \min(x_k)}, \tag{11}$$

where $x_{k,t}$ is original value, $y_{k,t}$ is the scaled value, $\max(x_k)$ is the maximum value of dataset k, and $\min(x_k)$ is the minimum value of dataset k.

The descriptive statistics of the daily closing prices are shown in Table 1. It can be seen a big difference by examining the minimum and maximum of the listed stocks such as AIG, BA, C, and IBM, while smaller differences in PFE, INTC, and DIS. In addition, the sixth column shows that most varieties in AIG, BA, C, and IBM. Figure 2 depicts all the 30 stocks' mean and standard deviation, showing

Table 1. Descriptive statistic of the daily data series.

Stock	N	Min	Max	Mean	Std	Skewness	Kurtosis
AA	423	28.30	47.35	36.04	3.44	0.299	0.082
AIG	423	18.78	72.65	55.45	15.88	−0.818	−0.607
AXP	423	35.37	65.55	52.59	8.45	−0.420	−1.219
BA	423	61.11	107.23	86.79	11.34	−0.551	−0.510
BAC	423	18.52	54.05	43.60	8.45	−0.791	−0.367
C	423	14.56	55.25	37.38	14.04	−0.093	−1.691
CAT	423	58.17	86.98	73.25	6.27	−0.139	−0.676
CVX	423	66.43	103.09	85.43	8.29	−0.266	−0.477
DD	423	40.92	53.35	47.97	2.82	−0.29	−0.685
DIS	423	28.12	36.55	33.24	1.76	−0.526	−0.461
GE	423	26.26	42.12	35.39	3.87	−0.594	−0.452
GM	423	9.38	42.64	26.72	8.28	−0.605	−0.640
HD	423	21.46	41.76	32.34	5.78	0.096	−1.464
HPQ	423	38.67	53.41	45.92	3.37	0.034	−0.682
IBM	423	90.90	130.00	110.96	10.22	0.042	−1.044
INTC	423	18.61	27.98	22.84	2.22	0.251	−0.881
JMP	423	31.02	53.20	45.19	4.58	−0.478	−0.271
JNJ	423	59.77	71.73	64.89	2.68	0.370	−0.339
KO	423	45.89	65.56	55.13	4.80	0.045	−1.049
MCD	423	42.91	65.95	53.73	5.63	−0.228	−0.968
MMM	423	67.69	95.85	80.74	6.53	0.215	−0.750
MRK	423	31.33	60.77	46.72	7.35	−0.410	−0.877
MSFT	423	25.15	37.06	29.74	2.43	0.964	0.718
PFE	423	17.17	27.68	23.25	2.88	−0.467	−0.945
PG	423	60.49	74.67	66.41	3.56	0.571	−0.750
T	423	30.17	42.83	37.88	2.99	−0.837	0.019
UTX	423	59.70	82.07	70.55	4.67	0.049	−0.640
VZ	423	33.60	46.07	39.41	3.41	0.195	−1.288
WMT	423	42.27	60.76	50.08	4.86	0.660	−0.787
XOM	423	69.86	95.05	84.41	6.35	−0.460	−0.667

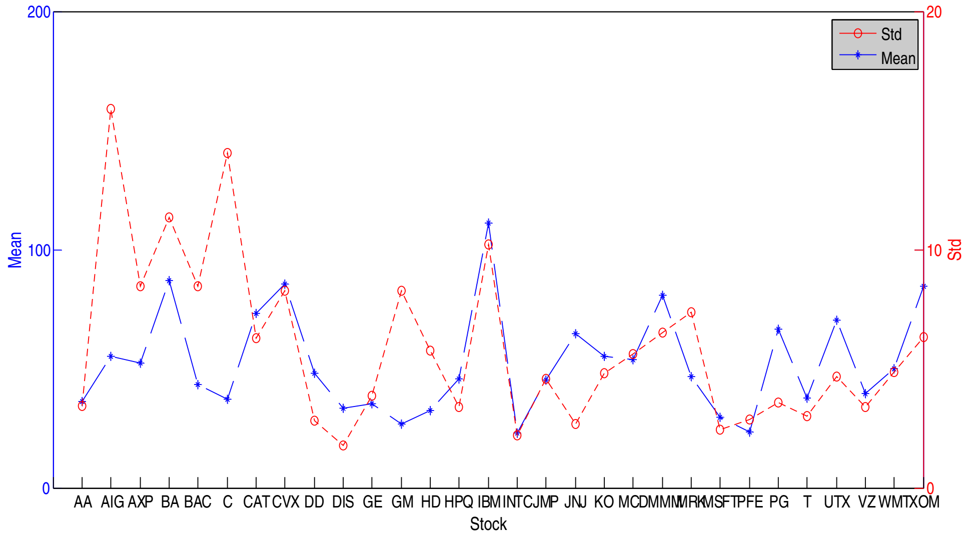


Fig. 2. Daily closing price characteristics: mean price and standard deviation.

a highly fluctuation. The kurtosis and skewness of the daily closing prices series indicate the high differences against the normal distribution. Generally speaking, the selected price series illustrate a high fluctuation pattern with irregularity.

4.2. *Accuracy measures*

To evaluate the forecasting performance, the root mean squared error (RMSE), mean absolute percentage error (MAPE), and directional symmetry (DS) are used as the accuracy measures. RMSE and MAPE are the absolute and relative error measures of the actual and predicted values, respectively. The smaller the values of RMSE and MAPE, the closer are the predicted time series values to the actual values. DS provides an indication of the correctness of the predicted direction and the large value suggests a better predictor. The definitions of them are shown as follows:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(x_i - \hat{x}_i)^2}{n}}, \tag{12}$$

$$\mathrm{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \frac{|x_i - \hat{x}_i|}{x_t}, \tag{13}$$

$$DS = \frac{100}{n} \sum_{i=1}^{n} d_i, d_i = \begin{cases} 1, & (x_i - x_{i-1})(\hat{x}_i - \hat{x}_{i-1}) \geq 0 \\ 0, & \text{otherwise} \end{cases}, \tag{14}$$

where n is the number of forecasting periods, x_i is the actual stock price at period i, and $\hat{x}_i$ is the forecasting stock price at period i.

4.3. *Wilcoxon's signed-rank test*

In this study, a nonparametric Wilcoxon's signed-rank test [Diebold and Mariano (1995)] is performed to determine if there is significant difference between the two approaches based on the prediction error of the testing data sets. This test performs a two sample rank test for the difference between two population medians. Since the population distributions of the performance measures are unknown, a nonparametric test is suggested for the performance comparison of the two models [Conover (1980)].

4.4. *EEMD implementation*

In this study, EEMD is implemented using the program provided by Wu and Huang [2009] (http://rcada.ncu.edu.tw/). The ensemble number is set to 100; the standard deviation of the added white noise is set to 0.3 by the rule of thumb.

4.5. *SVMs implementation*

In this study, we employ LibSVM (version 2.86) [Chang and Lin (2001)] for SVMs modeling. The RBF is selected as the kernel function in single SVMs and EEMD-based SVMs model when modeling the IMFs data due to the prior works [Smola (1998)]. The linear kernel function is selected to model the relationship among the IMFs and the residue due to its simplicity and better performances after extensive experimental trials on different kernel functions. To save the space, the trial results are not listed.

To determine the hyper-parameters, namely C, ε, γ (in the case of RBF as the kernel function), straightforward Grid Search (GS) is employed with exponentially growing grids of (C, ε, γ) parameters. The reasons are as follows. First, the main purpose of this study is to examine the performance of the proposed hybrid framework against the single use of selected modeling methodologies, which only requires on the same methods for parameters selection and make them comparable. Second, the performance of finding optimal parameters by GS is more stable than some heuristics methods such as genetic algorithms and simulation annealing, and stable parameters selection performance facilitate this kind of comparative study. Note that 10-fold cross validation is used in training phase to evaluate the modeling performance.

4.6. *FNN implementation*

The FNN models used in this experiment are implemented using the MATLAB (Version R2006b) ANN toolbox. The architecture of the FNN model is as follows: the number of input nodes is set at five; the number of hidden nodes varies from 8 to 20 and the optimum number of hidden nodes that minimizes the error rate on the validation set is determined; the number of output nodes is set at one. For the stopping criteria, the number of learning epochs is chosen as 10,000, as there is no prior knowledge of this value before the experiment. In the training phase, gradient descent with momentum algorithms is applied to update weight and bias values. The learning rate is chosen as 0.9 and the momentum constant is chosen as 0.1. The activation function of the hidden layer is sigmoid and the output node uses the linear transfer function. Each experiment is repeated 10 times and the average values are represented.

4.7. *ARIMA implementation*

In this study, we employ the forecast package in R (version 1.13) (Hyndman, 2008) for ARIMA modeling. The specifications are selected based on the ACF and PACF and evaluated according to Akaike's information criterion (AIC).

5. Results and Discussions

The testing forecasting performances of all the examined models (EEMD-SVMs-SVMs, EEMD-FNN-FNN, EEMD-ARIMA-SUM, individual SVMs, FNN, and ARIMA) in terms of RMSE, MAPE, and DS for the daily data are shown in Fig. 3. Furthermore, Fig. 4 depicts the mean and standard deviation of in sample and out of sample forecasting performances in terms of RMSE, MAPE, and DS for the daily data sets in the form of error bar. Additionally, the overall rank of six methodologies' average performances at three metrics for daily closing prices is shown in Table 2.

As mentioned in the introduction, the goals of the experiment-based study have two folds. One is to examine how significant improvement can be achieved by using the hybrid decomposition and ensemble framework. The other is to compare the performances across different modeling methodologies within the proposed hybrid framework or not. The following paragraphs discuss these two folds based on the results achieved.

Focusing on the first goal, this is to say, by comparing the forecasting performances between hybrid EEMD-based models and individual models, two conclusions can be drawn from Fig. 4. First, EEMD-based models show better forecasting performances than the corresponding individual models in terms of three metrics across all the daily data series. Second, the gaps between in-sample and out-of-sample errors in terms of three indicators by hybrid models are smaller. Thus, this shows that hybrid EEMD-based models exhibit more stable and consistent performance in stock market dynamic exploration.

Note that the most significant improvement is witnessed while comparing the EEMD-FNN-FNN and individual FNN. Table 2 shows that the average RMSE, MAPE, and DS of EEMD-FNN-FNN on daily closing prices are 0.870, 1.413, and 0.69 respectively, while these of individual FNN are 2.385, 5.191, and 0.53 respectively. These results indicate that EEMD can facilitate the modeling for forecasting by decomposing the original complex data series into several simple time series.

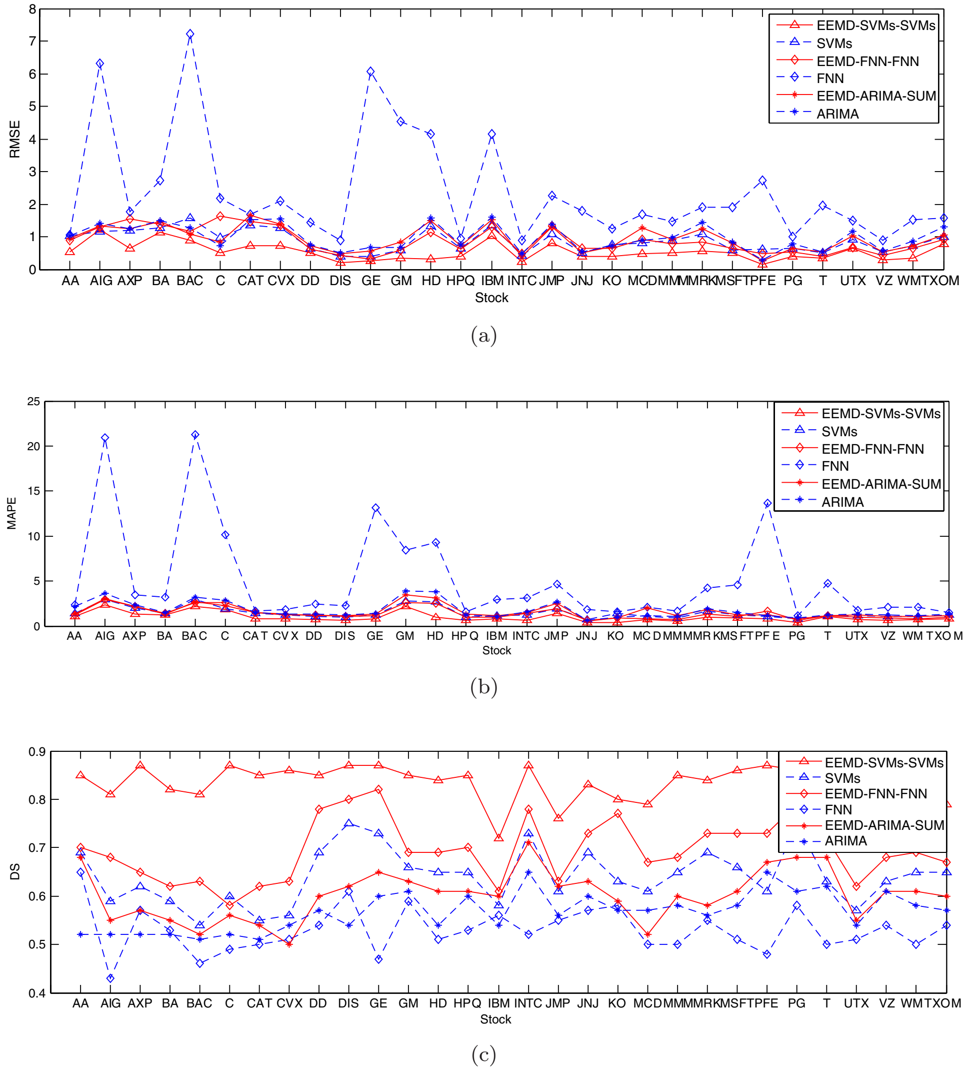


Fig. 3. Forecasting performance at different metrics for daily closing prices (testing dataset): (a) RMSE, (b) MAPE, and (c) DS.

A weak improvement can be observed by comparing the EEMD-ARIMA-SUM and individual ARIMA, while EEMD-SVMs-SVMs achieve a moderate improvement compared with individual SVMs.

As for the comparisons across different modeling methodologies within the proposed hybrid framework or not, the experimental results reveal some important hints for common forecasting practice.

The experimental results indicate that the proposed EEMD-SVMs-SVMs framework outperform the other five methodologies in all cases across all the three

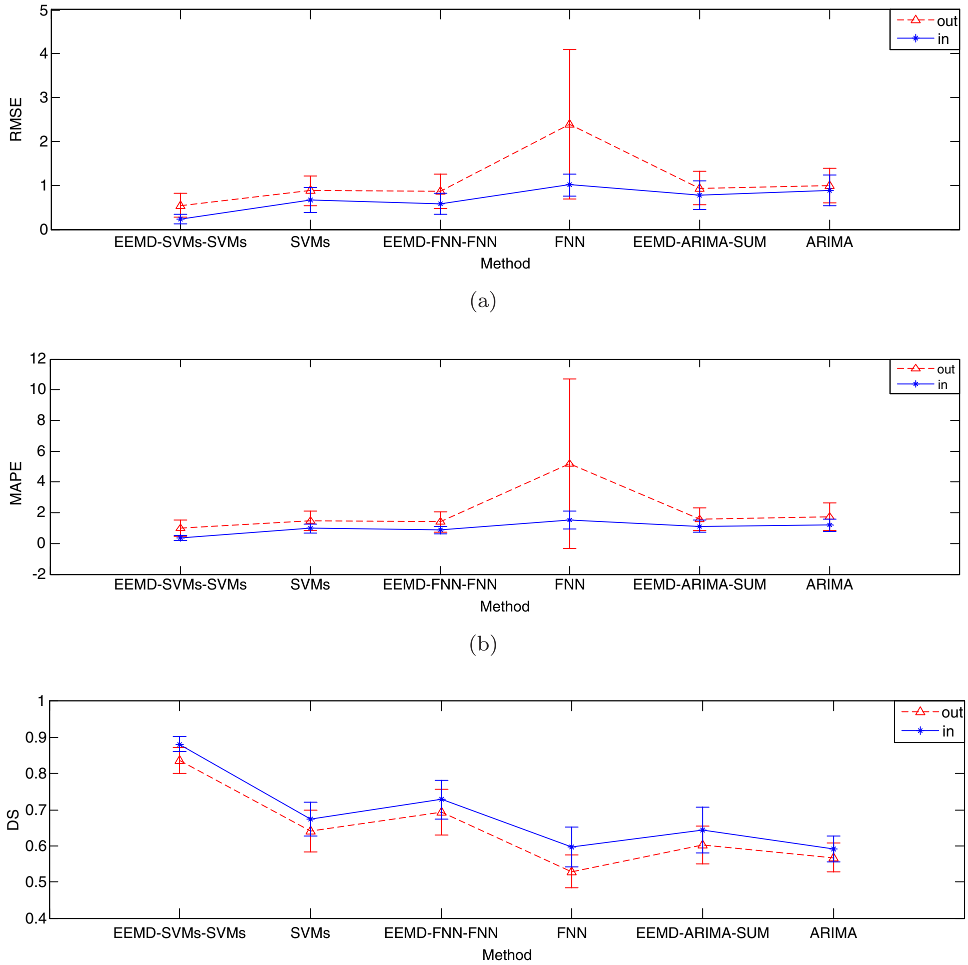


Fig. 4. Forecasting errors at different metrics for daily closing price: mean and standard deviation: (a) RMSE, (b) MAPE, and (c) DS.

Table 2. The rank of six methodologies' average performances for daily closing prices in terms of three metrics (testing dataset).

Methodology	Accuracy criteria			Rank
	RMSE	MAPE	DS	
EEMD-SVMs-SVMs	0.5418	0.9909	0.8357	1
SVMs	0.8758	1.4712	0.6403	3
EEMD-FNN-FNN	0.8701	1.4126	0.694	2
FNN	2.3851	5.1907	0.5293	6
EEMD-ARIMA-SUM	0.938	1.6016	0.6017	4
ARIMA	0.9851	1.743	0.567	5

Table 3. Wilcoxon's signed-rank test between EEMD-based SVMs and other methodologies on daily closing prices (testing dataset).

Accuracy criteria	EEMD-SVMs-SVMs vs. SVMs	EEMD-SVMs-SVMs vs. EEMD-FNN-FNN	EEMD-SVMs-SVMs vs. FNN	EEMD-SVMs-SVMs vs. EEMD-ARIMA-SUM	EEMD-SVMs-SVMs vs. ARIMA
RMSE	1.9185e−006*	1.7344e−006*	1.7344e−006*	1.7344e−006*	1.7344e−006*
MAPE	1.7344e−006*	1.7344e−006*	1.7344e−006*	1.7344e−006*	1.7344e−006*
DS	1.6987e−006*	1.7094e−006*	1.7051e−006*	1.7127e−006*	1.7181e−006*

*Achieving 1% significance levels respectively (2-tailed).

metrics, followed by EEMD-FNN-FNN, individual SVMs, EEMD-ARIMA-SUM, individual ARIMA, and individual FNN. The ranking details can be found in Table 2. The Wilcoxon's signed-rank tests for EEMD-SVMs-SVMs against any other methodologies are shown in Table 3, which statistically supports the promising performance of EEMD-SVMs-SVMs framework with $\alpha = 0.01$ significance level. Furthermore, the individual SVMs outperform than other individual methodologies, indicating it as a promising alternative for individual modeling tasks.

It can be seen from Fig. 3 that the performance of FNN is not stable in overall data sets. The result shows that small RMSE appear in some stocks, such as DIS, INTC, and VZ, while the large RMSE appear in AIG, BAC, GE, and IBM; small MAPE appear in CVX, JNJ, and MMM, while the large MAPE appear in AIG, BAC, GM, and PFE. Moreover, the performance of individual FNN model is worst in all six learning approaches, as shown in Table 2. This may be due to the intrinsic drawbacks of ANNs, although FNN is noise tolerant, having the ability to learn complex systems with incomplete and corrupted data. However, FNN suffers from difficulties with generalization because of over fitting. However, the performance can be improved significantly by employing the proposed hybrid decomposition and ensemble framework.

ARIMA achieves a poor performance either within the hybrid framework or not. The possible reasons could be that stock market is a high volatility market and the stock prices often show nonlinear and nonstationary patterns. ARIMA is not only linear model, but also based on stationary before the integration.

6. Conclusions

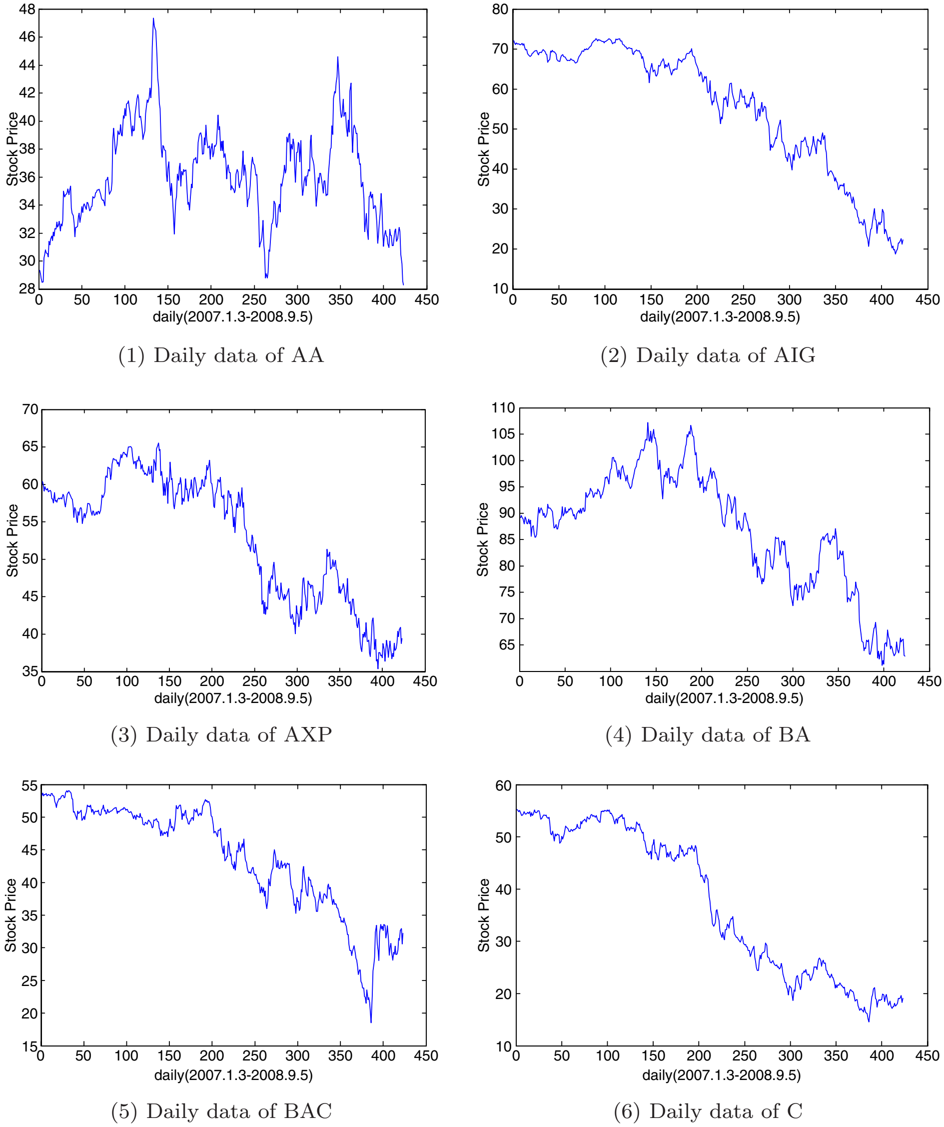
Due to the complex and dynamic pattern with nonlinearity and nonstationarity, stock price forecasting still remains one of the most challenging tasks in the field of financial time series modeling and forecasting. This studies steps on the way to establish hybrid learning framework for time series modeling and forecasting and contributes to examine the EEMD-based hybrid modeling framework through extensive experiments.

Generally speaking, in terms of the experiments presented in this study, we can draw the following conclusions: (1) The experimental results show that

EEMD-based frameworks achieve better as well as more stable forecasting performances than the corresponding individual models in terms of RMSE, MAPE, and DS across all the daily data series. (2) The proposed EEMD-SVMs-SVMs framework outperforms the other five methodologies in all cases across all the three metrics and individual SVMs achieve best performance than other individual models. This indicates that SVMs is the promising alternative for modeling methodology selection. (3) More attention and efforts should be paid to the unstable performance and over fitting issue while employing FNN in practice, but using the proposed hybrid framework can significantly improve the performance of FNN. (4) Due to the characteristics of linearity, ARIMA achieves poor performance both within and not within the proposed hybrid framework.

This study also has some limitations. One is about the optimization of parameters for SVMs modeling. Heuristic methods can be chosen for the future experimental study. The another unsolved issue is concerned with the end effect of EMD. Generally, the time series forecasting method presumes the past data pattern could be projected into the future. Thus, the end effects of EMD could get any applications in trouble in the case of dealing with the decomposed sub-series alone. In our case, however, the modeling framework is established in the way of decompose-ensemble. This is, a sub-modeling task to ensemble the respective forecasts of decomposed sub-series is conducted to guarantee an accurate forecast for the original series. We believe that the ensemble will reduce the defectiveness of end effect to some extent. We do think that the further research on the end effect in the case of time series forecasting (like in our study) is of interest and we wish future studies could contribute to deal with the end effect of EMD.

Appendix



(1) Daily data of AA

(2) Daily data of AIG

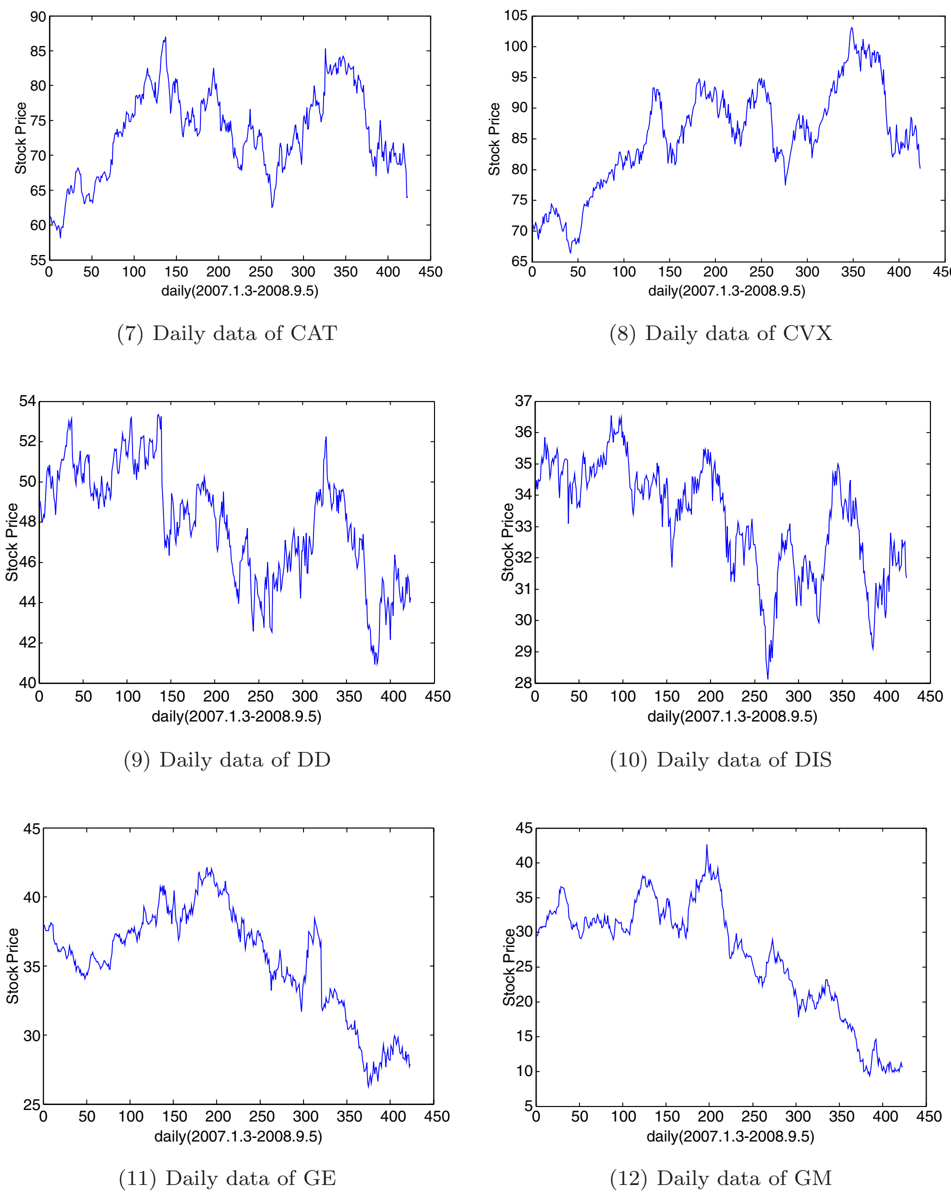
(3) Daily data of AXP

(4) Daily data of BA

(5) Daily data of BAC

(6) Daily data of C

Fig. A.1. The daily closing prices of the thirty dow jones industrial stocks.



(7) Daily data of CAT

(8) Daily data of CVX

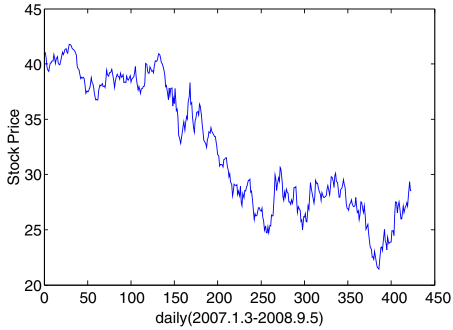
(9) Daily data of DD

(10) Daily data of DIS

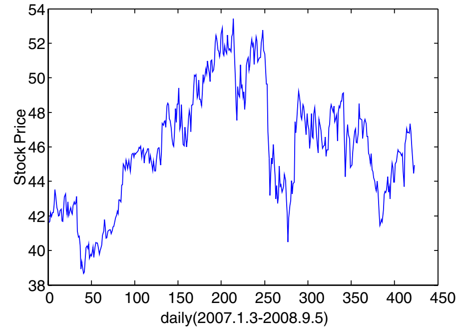
(11) Daily data of GE

(12) Daily data of GM

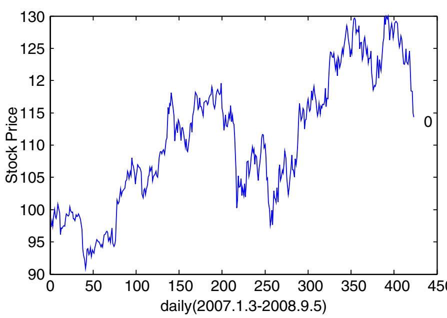
Fig. A.1. (*Continued*)



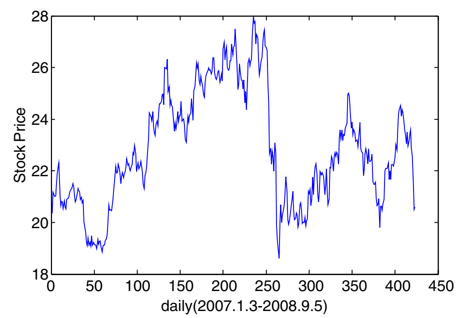
(13) Daily data of HP



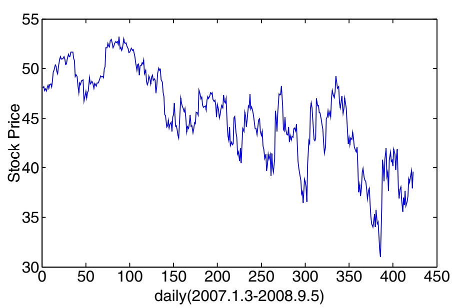
(14) Daily data of HPQ



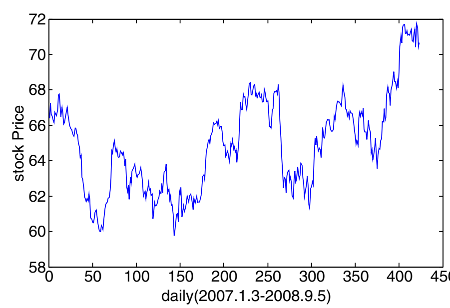
(15) Daily data of IBM



(16) Daily data of INTC

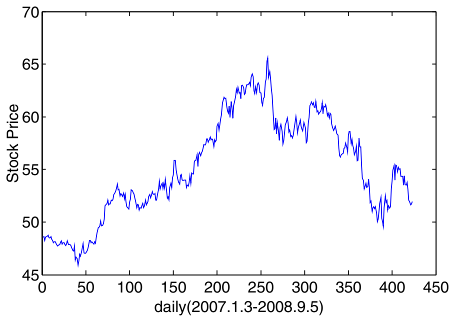


(17) Daily data of JMP

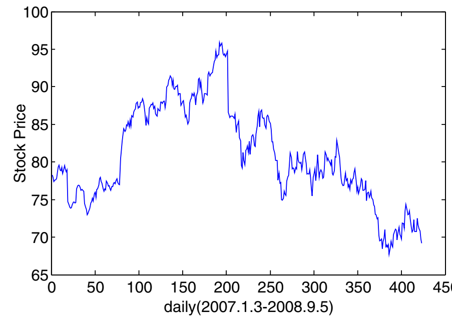


(18) Daily data of JNJ

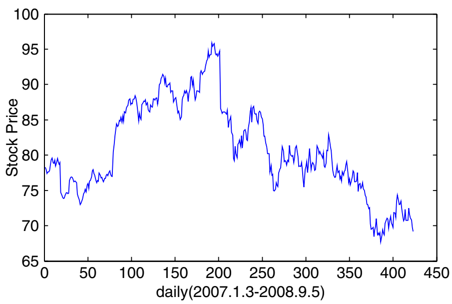
Fig. A.1. (*Continued*)



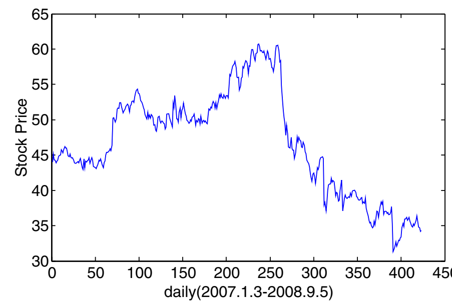
(19) Daily data of KO



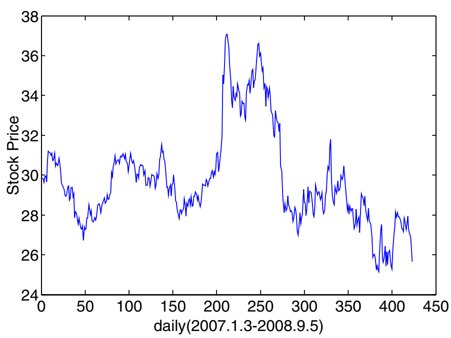
(20) Daily data of MCD



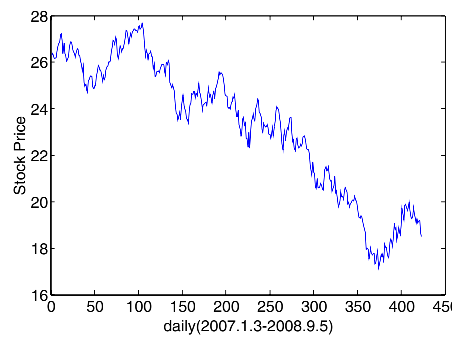
(21) Daily data of MMM



(22) Daily data of MRK

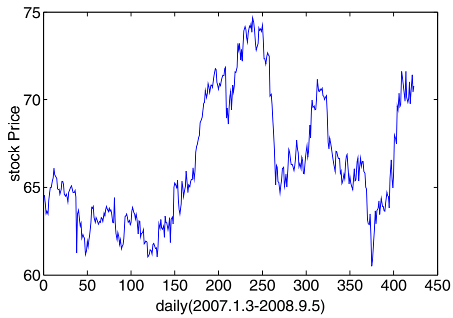


(23) Daily data of MSFT

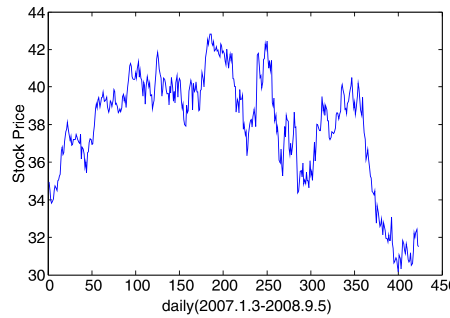


(24) Daily data of PFE

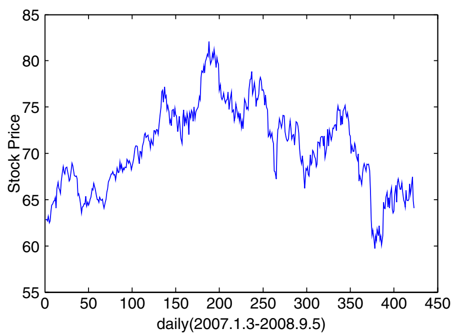
Fig. A.1. (*Continued*)



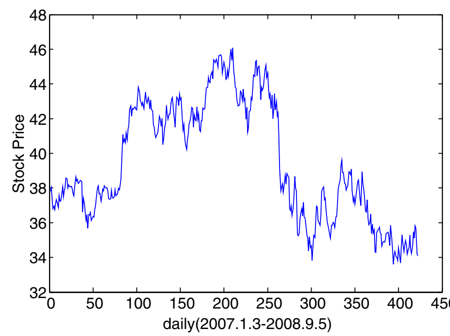
(25) Daily data of PG



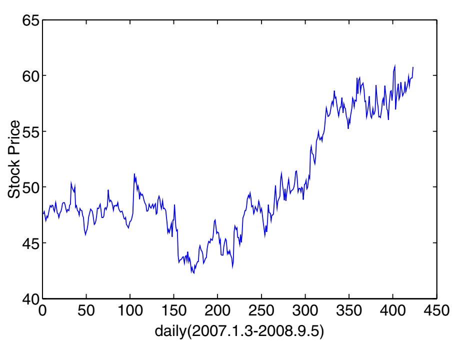
(26) Daily data of T



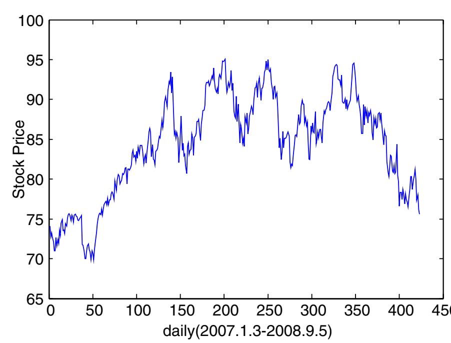
(27) Daily data of UTX



(28) Daily data of VZ



(29) Daily data of WMT



(30) Daily data of XOM

Fig. A.1. (*Continued*)

Table A.2. The optimal parameters selection and kernel function of SVMs for the daily closing prices.

Kernel function	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	Residue	Ensemble	SVR
	RBF	RBF	RBF	RBF	RBF	RBF	RBF	Linear	Linear	RBF
ALCOA INC. (AA)										
Parameters	$C = 32$	$C = 0.5$	$C = 0.25$	$C = 32$	$C = 16$	$C = 16$	$C = 16$	$C = 8$	$C = 16$	$C = 32$
	$\gamma = 10$	$\gamma = 1$	$\gamma = 0.1$	$\gamma = 0.01$	$\gamma = 0.01$	$\gamma = 0.01$	$\gamma = 0.0001$	$\varepsilon = 0.005$	$\varepsilon = 0.001$	$\gamma = 1$
	$\varepsilon = 0.001$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.001$	$\varepsilon = 0.01$	$\varepsilon = 0.01$			$\varepsilon = 0.1$
AMER INTL GROUP INC. (AIG)										
Parameters	$C = 16$	$C = 32$	$C = 8$	$C = 4$	$C = 1$	$C = 64$	$C = 32$	$C = 16$	$C = 32$	$C = 64$
	$\gamma = 1$	$\gamma = 0.5$	$\gamma = 0.1$	$\gamma = 0.01$	$\gamma = 0.1$	$\gamma = 0.1$	$\gamma = 0.001$	$\varepsilon = 0.01$	$\varepsilon = 0.001$	$\gamma = 1$
	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.05$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$			$\varepsilon = 0.01$
AMER EXPRESS INC. (AXP)										
Parameters	$C = 16$	$C = 0.25$	$C = 32$	$C = 4$	$C = 16$	$C = 16$	$C = 32$	$C = 32$	$C = 32$	$C = 64$
	$\gamma = 0.1$	$\gamma = 10$	$\gamma = 0.1$	$\gamma = 0.1$	$\gamma = 0.01$	$\gamma = 0.1$	$\gamma = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.001$	$\gamma = 0.1$
	$\varepsilon = 0.005$	$\varepsilon = 0.01$	$\varepsilon = 0.05$	$\varepsilon = 0.1$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$			$\varepsilon = 0.01$
BOEING CO (BA)										
Parameters	$C = 4$	$C = 32$	$C = 0.25$	$C = 16$	$C = 64$	$C = 0.5$	$C = 16$	$C = 32$	$C = 64$	$C = 4$
	$\gamma = 1$	$\gamma = 0.1$	$\gamma = 0.05$	$\gamma = 0.1$	$\gamma = 0.1$	$\gamma = 0.01$	$\gamma = 0.001$	$\varepsilon = 0.05$	$\varepsilon = 0.01$	$\gamma = 0.1$
	$\varepsilon = 0.1$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$			$\varepsilon = 0.1$
BK OFAMERICA CP (BAC)										
Parameters	$C = 2$	$C = 32$	$C = 16$	$C = 8$	$C = 32$	$C = 0.5$	$C = 64$	$C = 8$	$C = 16$	$C = 64$
	$\gamma = 1$	$\gamma = 0.01$	$\gamma = 10$	$\gamma = 0.01$	$\gamma = 0.01$	$\gamma = 0.1$	$\gamma = 0.001$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\gamma = 0.01$
	$\varepsilon = 0.01$	$\varepsilon = 0.001$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.05$	$\varepsilon = 0.01$	$\varepsilon = 0.01$			$\varepsilon = 0.01$
CITIGROUP INC. (C)										
Parameters	$C = 8$	$C = 32$	$C = 64$	$C = 64$	$C = 16$	$C = 32$	$C = 8$	$C = 4$	$C = 32$	$C = 32$
	$\gamma = 0.1$	$\gamma = 1$	$\gamma = 10$	$\gamma = 0.1$	$\gamma = 0.1$	$\gamma = 0.1$	$\gamma = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\gamma = 0.01$
	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.001$	$\varepsilon = 0.05$	$\varepsilon = 0.05$	$\varepsilon = 0.01$	$\varepsilon = 0.01$			$\varepsilon = 0.05$

Table A.2. (*Continued*)

Kernel function	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	Residue	Ensemble	SVR
	RBF	RBF	RBF	RBF	RBF	RBF	RBF	Linear	Linear	RBF
CATERPILLAR INC. (CAT)										
Parameters	$C = 16$ $\gamma = 1$ $\varepsilon = 0.05$	$C = 64$ $\gamma = 0.1$ $\varepsilon = 0.05$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 8$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 4$ $\gamma = 0.01$ $\varepsilon = 0.001$	$C = 32$ $\gamma = 0.001$ $\varepsilon = 0.01$	$C = 16$ $\varepsilon = 0.01$	$C = 32$ $\varepsilon = 0.001$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.1$
CHEVRON CORP (CVX)										
Parameters	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 0.125$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 64$ $\gamma = 0.1$ $\varepsilon = 0.05$	$C = 8$ $\gamma = 0.01$ $\varepsilon = 0.05$	$C = 16$ $\gamma = 0.001$ $\varepsilon = 0.01$	$C = 32$ $\varepsilon = 0.01$	$C = 8$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.1$
DU POINT EI DE NEM (DD)										
Parameters	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.05$	$C = 4$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 1$ $\varepsilon = 0.01$	$C = 64$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.001$ $\varepsilon = 0.001$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\varepsilon = 0.01$	$C = 8$ $\varepsilon = 0.01$	$C = 2$ $\gamma = 1$ $\varepsilon = 0.001$
WALT DISNEY-DISNEY C (DIS)										
Parameters	$C = 16$ $\gamma = 1$ $\varepsilon = 0.01$	$C = 8$ $\gamma = 0.1$ $\varepsilon = 0.001$	$C = 16$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 64$ $\gamma = 0.1$ $\varepsilon = 0.001$	$C = 0.5$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.001$ $\varepsilon = 0.05$	$C = 32$ $\varepsilon = 0.01$	$C = 64$ $\varepsilon = 0.001$	$C = 64$ $\gamma = 0.1$ $\varepsilon = 0.1$
GEN ELECTRIC CO (GE)										
Parameters	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.05$	$C = 0.25$ $\gamma = 0.1$ $\varepsilon = 0.001$	$C = 32$ $\gamma = 1$ $\varepsilon = 0.01$	$C = 64$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.001$	$C = 64$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 8$ $\varepsilon = 0.01$	$C = 16$ $\varepsilon = 0.001$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$
GEN MOTORS (GM)										
Parameters	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.001$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 64$ $\gamma = 1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.001$	$C = 16$ $\gamma = 0.001$ $\varepsilon = 0.01$	$C = 0.5$ $\gamma = 0.1$ $\varepsilon = 0.05$	$C = 16$ $\varepsilon = 0.001$	$C = 64$ $\varepsilon = 0.01$	$C = 8$ $\gamma = 0.1$ $\varepsilon = 0.1$

Table A.2. (*Continued*)

Kernel function	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	Residue	Ensemble	SVR
	RBF	RBF	RBF	RBF	RBF	RBF	RBF	Linear	Linear	RBF
HOME DEPOT INC. (HD)										
Parameters	$C = 16$ $\gamma = 1$ $\varepsilon = 0.001$	$C = 64$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 8$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 4$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.0001$ $\varepsilon = 0.05$	$C = 0.5$ $\varepsilon = 0.01$	$C = 16$ $\varepsilon = 0.001$	$C = 64$ $\gamma = 0.01$ $\varepsilon = 0.5$
HEWLETT PACKARD CO (HPQ)										
Parameters	$C = 0.5$ $\gamma = 1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.001$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.05$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 64$ $\gamma = 0.1$ $\varepsilon = 0.05$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 64$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 16$ $\varepsilon = 0.001$	$C = 32$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.1$
INTL BUSINESS MACH (IBM)										
Parameters	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 0.25$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 1$ $\varepsilon = 0.01$	$C = 64$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 64$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 8$ $\gamma = 0.01$ $\varepsilon = 0.005$	$C = 32$ $\varepsilon = 0.01$	$C = 4$ $\varepsilon = 0.001$	$C = 8$ $\gamma = 0.1$ $\varepsilon = 0.1$
INTEL CP (INTC)										
Parameters	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.005$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 0.125$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.01$ $\varepsilon = 0.001$	$C = 0.25$ $\gamma = 1$ $\varepsilon = 0.05$	$C = 32$ $\gamma = 0.001$ $\varepsilon = 0.01$	$C = 4$ $\gamma = 0.0001$ $\varepsilon = 0.01$	$C = 64$ $\varepsilon = 0.01$	$C = 4$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.01$
JP MORGAN CHASE CO (JMP)										
Parameters	$C = 64$ $\gamma = 0.01$ $\varepsilon = 0.001$	$C = 32$ $\gamma = 1$ $\varepsilon = 0.05$	$C = 8$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 0.5$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.001$	$C = 64$ $\gamma = 0.001$ $\varepsilon = 0.01$	$C = 32$ $\varepsilon = 0.001$	$C = 0.25$ $\varepsilon = 0.05$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.1$
JOHNSON AND JOHNS DC (JNJ)										
Parameters	$C = 0.5$ $\gamma = 1$ $\varepsilon = 0.05$	$C = 32$ $\gamma = 10$ $\varepsilon = 0.05$	$C = 16$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 2$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.001$	$C = 32$ $\gamma = 0.001$ $\varepsilon = 0.01$	$C = 0.125$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 16$ $\varepsilon = 0.05$	$C = 16$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.1$
COCA COLA CO THE (KO)										
Parameters	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.001$	$C = 32$ $\gamma = 1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 1$ $\varepsilon = 0.001$	$C = 0.25$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.01$ $\varepsilon = 0.005$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.05$	$C = 0.5$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\varepsilon = 0.01$	$C = 32$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$

Table A.2. (*Continued*)

Kernel function	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	Residue	Ensemble	SVR
	RBF	RBF	RBF	RBF	RBF	RBF	RBF	Linear	Linear	RBF
MCDONALDS CP (MCD)										
Parameters	$C = 0.125$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 8$ $\gamma = 1$ $\varepsilon = 0.001$	$C = 4$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.001$ $\varepsilon = 0.001$	$C = 16$ $\varepsilon = 0.01$	$C = 16$ $\varepsilon = 0.005$	$C = 64$ $\gamma = 0.01$ $\varepsilon = 0.5$
3M COMPANY (MMM)										
Parameters	$C = 16$ $\gamma = 10$ $\varepsilon = 0.5$	$C = 2$ $\gamma = 0.1$ $\varepsilon = 0.5$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.001$	$C = 16$ $\gamma = 1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 0.5$ $\gamma = 0.001$ $\varepsilon = 0.01$	$C = 8$ $\varepsilon = 0.01$	$C = 16$ $\varepsilon = 0.001$	$C = 8$ $\gamma = 0.1$ $\varepsilon = 0.01$
MERCK CO INC. (MRK)										
Parameters	$C = 8$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 0.25$ $\gamma = 1$ $\varepsilon = 0.001$	$C = 16$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 1$ $\varepsilon = 0.05$	$C = 64$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.001$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 8$ $\varepsilon = 0.01$	$C = 4$ $\varepsilon = 0.01$	$C = 4$ $\gamma = 0.1$ $\varepsilon = 0.1$
MICROSOFT CP (MSFT)										
Parameters	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 1$ $\varepsilon = 0.01$	$C = 2$ $\gamma = 0.1$ $\varepsilon = 0.001$	$C = 64$ $\gamma = 0.01$ $\varepsilon = 0.001$	$C = 8$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 0.5$ $\gamma = 0.0001$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\varepsilon = 0.001$	$C = 32$ $\varepsilon = 0.01$	$C = 64$ $\gamma = 0.1$ $\varepsilon = 0.1$
PFIZER INC. (PFE)										
Parameters	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.005$	$C = 0.5$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 0.125$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 16$ $\gamma = 0.01$ $\varepsilon = 0.0001$	$C = 16$ $\gamma = 0.01$ $\varepsilon = 0.05$	$C = 4$ $\gamma = 0.0001$ $\varepsilon = 0.01$	$C = 32$ $\varepsilon = 0.01$	$C = 16$ $\varepsilon = 0.001$	$C = 32$ $\gamma = 0.01$ $\varepsilon = 0.01$
PROCTER GAMBLE CO (PG)										
Parameters	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 1$ $\varepsilon = 0.05$	$C = 4$ $\gamma = 0.1$ $\varepsilon = 0.05$	$C = 64$ $\gamma = 0.01$ $\varepsilon = 0.01$	$C = 32$ $\gamma = 0.1$ $\varepsilon = 0.001$	$C = 32$ $\gamma = 0.001$ $\varepsilon = 0.01$	$C = 8$ $\gamma = 0.1$ $\varepsilon = 0.01$	$C = 32$ $\varepsilon = 0.01$	$C = 32$ $\varepsilon = 0.001$	$C = 16$ $\gamma = 0.1$ $\varepsilon = 0.01$

Table A.2. (*Continued*)

Kernel function	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	Residue	Ensemble	SVR
	RBF	RBF	RBF	RBF	RBF	RBF	RBF	Linear	Linear	RBF
AT & T INC. (T)										
Parameters	$C = 8$	$C = 64$	$C = 0.5$	$C = 32$	$C = 32$	$C = 8$	$C = 16$	$C = 4$	$C = 16$	$C = 64$
	$\gamma = 0.1$	$\gamma = 1$	$\gamma = 0.1$	$\gamma = 0.01$	$\gamma = 0.1$	$\gamma = 0.1$	$\gamma = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.001$	$\gamma = 0.1$
	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.05$	$\varepsilon = 0.01$	$\varepsilon = 0.05$	$\varepsilon = 0.001$			$\varepsilon = 0.1$
UNITED TECH (UTX)										
Parameters	$C = 16$	$C = 32$	$C = 32$	$C = 8$	$C = 0.25$	$C = 32$	$C = 32$	$C = 4$	$C = 16$	$C = 32$
	$\gamma = 0.1$	$\gamma = 0.1$	$\gamma = 0.01$	$\gamma = 0.01$	$\gamma = 0.1$	$\gamma = 0.01$	$\gamma = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.0001$	$\gamma = 0.1$
	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.001$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.0001$	$\varepsilon = 0.01$			$\varepsilon = 0.1$
VERIZON COMMUN (VZ)										
Parameters	$C = 4$	$C = 32$	$C = 16$	$C = 16$	$C = 0.125$	$C = 32$	$C = 0.25$	$C = 32$	$C = 0.5$	$C = 8$
	$\gamma = 0.1$	$\gamma = 1$	$\gamma = 0.1$	$\gamma = 0.01$	$\gamma = 0.01$	$\gamma = 0.1$	$\gamma = 0.001$	$\varepsilon = 0.05$	$\varepsilon = 0.001$	$\gamma = 0.1$
	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.001$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.001$			$\varepsilon = 0.1$
WAL MART STORES (WMT)										
Parameters	$C = 16$	$C = 32$	$C = 8$	$C = 32$	$C = 0.5$	$C = 4$	$C = 32$	$C = 0.125$	$C = 32$	$C = 64$
	$\gamma = 0.1$	$\gamma = 0.01$	$\gamma = 0.1$	$\gamma = 0.1$	$\gamma = 0.1$	$\gamma = 0.01$	$\gamma = 0.001$	$\varepsilon = 0.01$	$\varepsilon = 0.05$	$\gamma = 0.1$
	$\varepsilon = 0.01$	$\varepsilon = 0.001$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.05$			$\varepsilon = 0.01$
EXXON MOBIL CP (XOM)										
Parameters	$C = 32$	$C = 32$	$C = 0.5$	$C = 16$	$C = 4$	$C = 8$	$C = 32$	$C = 16$	$C = 8$	$C = 32$
	$\gamma = 0.01$	$\gamma = 0.1$	$\gamma = 0.1$	$\gamma = 0.01$	$\gamma = 0.1$	$\gamma = 0.1$	$\gamma = 0.0001$	$\varepsilon = 0.01$	$\varepsilon = 0.0001$	$\gamma = 0.1$
	$\varepsilon = 0.05$	$\varepsilon = 0.01$	$\varepsilon = 0.001$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$	$\varepsilon = 0.01$			$\varepsilon = 0.01$

Table A.3. The forecasting performances of six methodologies on daily closing prices.

	EEMD-SVMs-SVMs		SVMs		EEMD-FNN-FNN		FNN		EEMD-ARIMA-SUM		ARIMA	
	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out
ALCOA INC. (AA)												
RMSE	0.115	0.546	0.813	1.021	0.543	0.879	0.946	1.059	0.753	0.941	0.852	1.032
MAPE	0.315	1.048	1.036	1.378	0.854	1.247	1.959	2.356	0.926	1.315	1.039	2.203
DS	0.89	0.85	0.65	0.69	0.76	0.70	0.74	0.65	0.75	0.68	0.56	0.52
AMER INTL GROUP INC. (AIG)												
RMSE	0.429	1.214	0.984	1.157	0.883	1.307	1.047	6.318	1.016	1.327	1.131	1.414
MAPE	0.524	2.357	1.152	2.981	1.129	2.943	1.272	20.943	1.157	3.075	1.318	3.609
DS	0.87	0.81	0.64	0.59	0.71	0.68	0.56	0.43	0.63	0.55	0.55	0.52
AMER EXPRESS INC. (AXP)												
RMSE	0.168	0.649	1.052	1.194	0.952	1.543	1.131	1.754	1.013	1.248	1.165	1.26
MAPE	0.425	1.318	1.264	2.046	1.031	2.158	1.529	3.431	1.363	2.181	1.557	2.392
DS	0.91	0.87	0.65	0.62	0.72	0.65	0.61	0.57	0.60	0.57	0.56	0.52
BOEING CO (BA)												
RMSE	0.417	1.149	1.184	1.264	0.751	1.384	1.224	2.734	1.012	1.459	1.279	1.496
MAPE	0.375	1.216	1.297	1.428	0.894	1.415	1.06	3.183	0.892	1.365	1.091	1.529
DS	0.86	0.82	0.65	0.59	0.66	0.62	0.63	0.53	0.73	0.55	0.56	0.52
BK OFAMERICA CP (BAC)												
RMSE	0.215	0.892	1.184	1.574	0.582	1.164	0.871	7.221	0.731	1.069	0.803	1.277
MAPE	0.425	2.197	1.527	2.954	1.247	2.648	1.426	21.254	1.163	2.721	1.239	3.234
DS	0.89	0.81	0.65	0.54	0.65	0.63	0.60	0.46	0.61	0.52	0.54	0.51
CITIGROUP INC. (C)												
RMSE	0.376	0.495	0.754	0.981	0.624	1.629	0.996	2.187	0.752	0.842	0.814	0.721
MAPE	0.946	1.857	1.054	1.961	1.391	2.647	2.049	10.14	1.389	2.278	1.584	2.892
DS	0.88	0.87	0.58	0.60	0.63	0.58	0.61	0.49	0.57	0.56	0.55	0.52

Table A.3. (*Continued*)

	EEMD-SVMs-SVMs		SVMs		EEMD-FNN-FNN		FNN		EEMD-ARIMA-SUM		ARIMA	
	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out
CATERPILLAR INC. (CAT)												
RMSE	0.381	0.716	1.095	1.351	0.902	1.473	1.104	1.684	1.124	1.647	1.152	1.514
MAPE	0.429	0.815	1.246	1.408	0.983	1.472	1.181	1.643	1.012	1.486	1.198	1.456
DS	0.88	0.85	0.63	0.55	0.68	0.62	0.54	0.50	0.53	0.54	0.55	0.51
CHEVRON CORP (CVX)												
RMSE	0.357	0.724	0.948	1.267	1.018	1.354	1.257	2.098	1.051	1.372	1.273	1.555
MAPE	0.395	0.804	1.047	1.204	0.874	1.272	1.191	1.834	1.016	1.296	1.21	1.325
DS	0.87	0.86	0.58	0.56	0.64	0.63	0.55	0.51	0.53	0.50	0.56	0.54
DU POINT EI DE NEM (DD)												
RMSE	0.129	0.517	0.524	0.648	0.584	0.617	0.998	1.44	0.642	0.718	0.7	0.759
MAPE	0.197	0.746	0.894	1.084	1.127	1.246	1.613	2.479	1.041	1.174	1.123	1.291
DS	0.90	0.85	0.71	0.69	0.80	0.78	0.59	0.54	0.65	0.60	0.60	0.57
WALT DISNEY-DISNEY C (DIS)												
RMSE	0.114	0.207	0.214	0.403	0.342	0.427	0.915	0.886	0.362	0.469	0.436	0.51
MAPE	0.169	0.641	0.247	0.974	0.741	1.054	2.262	2.237	0.943	1.152	1.022	1.256
DS	0.91	0.87	0.78	0.75	0.80	0.80	0.69	0.61	0.65	0.62	0.65	0.54
GEN ELECTRIC CO (GE)												
RMSE	0.104	0.264	0.274	0.397	0.197	0.328	0.897	6.08	0.321	0.548	0.489	0.662
MAPE	0.215	0.847	0.591	1.218	0.518	1.197	1.559	13.175	0.867	1.354	0.97	1.42
DS	0.89	0.87	0.75	0.73	0.85	0.82	0.57	0.47	0.69	0.65	0.63	0.60
GEN MOTORS (GM)												
RMSE	0.195	0.347	0.471	0.598	0.386	0.599	1.594	4.521	0.639	0.835	0.807	0.68
MAPE	0.648	2.157	1.046	2.815	1.191	2.614	2.894	8.457	1.897	3.493	2.015	3.882
DS	0.87	0.85	0.65	0.66	0.70	0.69	0.61	0.59	0.68	0.63	0.59	0.61

Table A.3. (*Continued*)

	EEMD-SVMs-SVMs		SVMs		EEMD-FNN-FNN		FNN		EEMD-ARIMA-SUM		ARIMA	
	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out
HOME DEPOT INC. (HD)												
RMSE	0.157	0.305	0.718	1.318	0.674	1.145	1.371	4.154	1.154	1.497	0.985	1.574
MAPE	0.447	0.971	1.419	2.674	1.157	2.497	2.856	9.265	2.539	3.156	2.584	3.784
DS	0.89	0.84	0.71	0.65	0.73	0.69	0.68	0.51	0.67	0.61	0.59	0.54
HEWLETT PACKARD CO (HPQ)												
RMSE	0.138	0.392	0.486	0.649	0.514	0.607	0.939	0.944	1.618	0.731	1.756	0.766
MAPE	0.244	0.649	0.972	1.018	0.875	0.974	1.712	1.591	1.061	1.294	1.201	1.221
DS	0.87	0.85	0.66	0.65	0.76	0.70	0.59	0.53	0.58	0.61	0.54	0.60
INTL BUSINESS MACH (IBM)												
RMSE	0.495	1.015	0.846	1.364	0.819	1.294	1.468	4.139	1.231	1.518	1.494	1.613
MAPE	0.346	0.817	0.791	1.157	0.724	0.978	1.043	2.929	0.952	1.131	1.05	1.057
DS	0.81	0.72	0.69	0.58	0.71	0.61	0.51	0.56	0.66	0.60	0.57	0.54
INTEL CP (INTC)												
RMSE	0.107	0.237	0.357	0.426	0.384	0.466	0.914	0.889	0.315	0.384	0.466	0.469
MAPE	0.328	0.681	1.037	1.225	1.183	1.412	3.071	3.127	1.316	1.492	1.465	1.577
DS	0.89	0.87	0.76	0.73	0.78	0.78	0.55	0.52	0.78	0.71	0.67	0.65
JP MORGAN CHASE CO (JMP)												
RMSE	0.267	0.816	0.794	1.081	0.816	1.321	0.966	2.254	0.812	1.291	0.958	1.376
MAPE	0.527	1.438	0.975	1.967	1.064	1.891	1.529	4.637	1.157	2.561	1.478	2.706
DS	0.88	0.76	0.66	0.61	0.67	0.63	0.61	0.55	0.66	0.62	0.63	0.56
JOHNSON AND JOHNS DC (JNJ)												
RMSE	0.127	0.384	0.364	0.507	0.341	0.656	0.638	1.801	0.317	0.519	0.497	0.534
MAPE	0.185	0.406	0.471	0.759	0.411	0.648	0.802	1.823	0.584	0.531	0.59	0.602
DS	0.88	0.83	0.70	0.69	0.79	0.73	0.53	0.57	0.75	0.63	0.61	0.60
COCA COLA CO THE (KO)												
RMSE	0.164	0.388	0.547	0.754	0.414	0.641	0.929	1.257	0.517	0.694	0.557	0.729
MAPE	0.268	0.419	0.818	1.394	0.583	0.894	1.238	1.589	0.692	0.932	0.738	1.011
DS	0.87	0.80	0.66	0.63	0.79	0.77	0.64	0.58	0.67	0.59	0.62	0.57

Table A.3. (*Continued*)

	EEMD-SVMs-SVMs		SVMs		EEMD-FNN-FNN		FNN		EEMD-ARIMA-SUM		ARIMA	
	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out
MCDONALDS CP (MCD)												
RMSE	0.218	0.491	0.711	0.813	0.715	0.918	0.856	1.683	0.861	1.261	0.702	0.895
MAPE	0.376	0.749	0.795	1.081	0.679	0.117	1.248	2.056	1.672	1.982	0.993	1.121
DS	0.86	0.79	0.68	0.61	0.68	0.67	0.59	0.50	0.60	0.52	0.60	0.57
3M COMPANY (MMM)												
RMSE	0.257	0.495	0.768	0.884	0.863	0.775	1.011	1.465	0.852	0.916	1.032	0.976
MAPE	0.307	0.541	0.841	0.918	0.533	0.716	0.837	1.674	0.916	1.153	0.827	1.038
DS	0.89	0.85	0.68	0.65	0.71	0.68	0.52	0.50	0.58	0.60	0.56	0.58
MERCK CO INC. (MRK)												
RMSE	0.384	0.554	0.549	1.085	0.513	0.849	1.472	1.915	0.742	1.253	1.243	1.427
MAPE	0.719	0.984	1.294	1.679	0.984	1.328	1.364	4.248	1.562	1.842	1.621	1.921
DS	0.88	0.84	0.65	0.69	0.76	0.73	0.58	0.55	0.57	0.58	0.58	0.56
MICROSOFT CP (MSFT)												
RMSE	0.248	0.496	0.375	0.589	0.394	0.641	0.847	1.895	0.742	0.796	0.854	0.839
MAPE	0.437	0.887	0.987	1.228	0.748	1.097	1.174	4.542	1.015	1.281	1.180	1.495
DS	0.88	0.86	0.69	0.66	0.76	0.73	0.65	0.51	0.63	0.61	0.62	0.58
PFIZER INC. (PFE)												
RMSE	0.075	0.157	0.344	0.624	0.215	0.491	0.429	2.714	0.215	0.263	0.271	0.288
MAPE	0.284	0.817	0.864	1.064	1.017	1.652	1.383	13.695	0.754	1.272	0.874	1.163
DS	0.92	0.87	0.66	0.61	0.75	0.73	0.68	0.48	0.61	0.67	0.60	0.65
PROCTER GAMBLE CO (PG)												
RMSE	0.187	0.394	0.487	0.645	0.315	0.524	0.798	0.999	0.825	0.652	0.613	0.772
MAPE	0.211	0.387	0.556	0.819	0.515	0.684	0.848	1.182	0.742	0.824	0.651	0.882
DS	0.90	0.86	0.76	0.75	0.80	0.79	0.64	0.58	0.69	0.68	0.64	0.61

Table A.3. (*Continued*)

	EEMD-SVMs-SVMs		SVMs		EEMD-FNN-FNN		FNN		EEMD-ARIMA-SUM		ARIMA	
	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out
AT&T INC. (T)												
RMSE	0.121	0.351	0.448	0.513	0.245	0.398	0.680	1.954	0.431	0.538	0.614	0.528
MAPE	0.261	1.05	1.005	1.198	0.597	1.119	1.370	4.732	1.163	1.124	1.206	1.202
DS	0.90	0.86	0.65	0.63	0.73	0.72	0.61	0.50	0.66	0.68	0.65	0.62
UNITED TECH (UTX)												
RMSE	0.308	0.648	0.846	0.913	0.465	0.677	0.998	1.504	0.845	1.016	0.916	1.159
MAPE	0.323	0.715	1.007	1.154	0.846	0.971	1.101	1.780	0.827	1.254	0.970	1.359
DS	0.85	0.81	0.64	0.57	0.69	0.62	0.53	0.51	0.61	0.55	0.59	0.54
VERIZON COMMUN (VZ)												
RMSE	0.148	0.287	0.364	0.522	0.316	0.431	0.956	0.903	0.414	0.542	0.571	0.570
MAPE	0.305	0.654	0.984	1.058	0.794	0.911	1.915	2.116	1.014	1.062	1.086	1.217
DS	0.88	0.85	0.69	0.63	0.72	0.68	0.57	0.54	0.73	0.61	0.60	0.61
WAL MART STORES (WMT)												
RMSE	0.153	0.346	0.495	0.718	0.432	0.648	0.906	1.525	0.523	0.732	0.630	0.870
MAPE	0.274	0.714	0.815	1.054	0.572	0.849	1.443	2.127	0.832	1.094	0.965	1.157
DS	0.89	0.84	0.66	0.65	0.72	0.69	0.53	0.50	0.63	0.61	0.61	0.58
EXXON MOBIL CP (XOM)												
RMSE	0.218	0.779	1.125	1.013	0.887	0.918	1.178	1.575	1.214	1.062	1.306	1.288
MAPE	0.204	0.846	1.164	1.237	0.758	1.027	1.095	1.476	1.016	1.174	1.174	1.288
DS	0.86	0.79	0.67	0.65	0.68	0.67	0.60	0.54	0.64	0.60	0.58	0.57

Table A.4. The rank of six methodologies' performances for daily closing prices in term of RMSE (testing dataset).

Methodology	Stock														
	AA	AIG	AXP	BA	BAC	C	CAT	CVX	DD	DIS	GE	GM	HD	HPQ	IBM
EEMD-SVMs-SVMs	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SVMs	4	2	3	2	5	5	2	2	3	2	3	2	3	2	3
EEMD-FNN-FNN	2	3	2	3	2	2	3	3	2	3	2	3	2	2	2
FNN	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
EEMD-ARIMA-SUM	3	4	4	4	3	4	5	4	4	4	4	4	4	4	4
ARIMA	5	5	5	5	4	3	4	5	5	5	5	5	5	5	5

(a) Continued

	INTC	JMP	JNJ	KO	MCD	MMM	MRK	MSFT	PFE	PG	T	UTX	VZ	WMT	XOM
EEMD-SVMs-SVMs	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SVMs	3	2	2	4	3	3	3	2	5	3	3	3	3	3	3
EEMD-FNN-FNN	4	4	5	2	2	2	2	3	4	2	2	2	2	2	2
FNN	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
EEMD-ARIMA-SUM	2	3	3	3	5	4	4	4	2	4	4	4	4	4	4
ARIMA	5	5	4	5	4	5	5	5	3	5	5	5	5	5	5

(b) The rank of six methodologies' performances for daily closing prices in term of MAPE (testing dataset)

Methodology	Stock														
	AA	AIG	AXP	BA	BAC	C	CAT	CVX	DD	DIS	GE	GM	HD	HPQ	IBM
EEMD-SVMs-SVMs	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SVMs	4	3	3	4	4	2	3	2	2	2	3	3	3	4	5
EEMD-FNN-FNN	2	2	2	3	2	3	2	3	4	3	2	2	2	3	2
FNN	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
EEMD-ARIMA-SUM	3	4	4	2	3	4	5	4	3	4	4	4	4	5	4
ARIMA	5	5	5	5	5	5	4	5	5	5	5	5	5	4	3

Table A.4. (*Continued*)

	(b) Continued														
	INTC	JMP	JNJ	KO	MCD	MMM	MRK	MSFT	PFE	PG	T	UTX	VZ	WMT	XOM
EEMD-SVMs-SVMs	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SVMs	3	3	5	5	3	3	3	3	2	3	4	3	3	3	3
EEMD-FNN-FNN	2	2	4	2	2	2	2	2	5	2	2	2	2	2	2
FNN	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
EEMD-ARIMA-SUM	4	4	2	3	5	5	4	4	4	4	3	4	4	4	4
ARIMA	5	5	3	4	4	4	5	5	3	5	5	5	5	5	5

(c) The rank of six methodologies' performances for daily closing prices in term of DS (testing dataset)

Methodology	Stock														
	AA	AIG	AXP	BA	BAC	C	CAT	CVX	DD	DIS	GE	GM	HD	HPQ	IBM
EEMD-SVMs-SVMs	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SVMs	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4
EEMD-FNN-FNN	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
FNN	5	6	4	5	6	6	5	5	6	5	6	6	6	6	5
EEMD-ARIMA-SUM	4	4	4	4	4	4	4	6	4	4	4	4	4	4	3
ARIMA	6	5	6	6	5	5	5	4	5	6	5	5	5	5	6

	(c) Continued														
	INTC	JMP	JNJ	KO	MCD	MMM	MRK	MSFT	PFE	PG	T	UTX	VZ	WMT	XOM
EEMD-SVMs-SVMs	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SVMs	3	4	3	3	3	3	3	3	5	3	3	3	3	3	3
EEMD-FNN-FNN	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
FNN	6	6	6	5	6	6	6	6	6	6	6	6	6	6	6
EEMD-ARIMA-SUM	4	3	4	4	5	4	4	4	3	4	4	4	4	4	4
ARIMA	5	5	5	6	4	5	5	5	4	5	5	5	4	5	5

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