ISSN 1022-4734

JUJSS
Vol. 34, 2017, pp. 49-58

The Choice of Support Vector Machines for Forecasting Selected Shareson Dhaka Stock Exchange (DSE)

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Abstract

Recently support vector machines are a focus research field in the scientific research. In this paper, we use the method of support vector machines for forecasting a stock market of Bangladesh and compare this method with usual parametric time series method. These are a nonparametric type technique which can be used to forecast stock market prices. In real life, most of the models are nonlinear. The Linear model is comparatively simpler than nonlinear one to estimate, test, as well as forecast. But non-linear or generalized linear models are more appropriate in real life situation. Parametric methods are the best choice if it follows all the underlying assumptions of the assumed models. If assumptions are violated then without checking it is better to use the nonparametric method. This paper establishes a model of stock market prediction based on support vector machines, collects the daily closing price of some selected Company of DSE such as AB Bank Limited, Apex Food Company Limited, and R.A.K Ceramics (Bangladesh) Limited, Padma Oil Company Limited, Reneta Company Limited and use these data to train the model and checks the predictive power of the model. Only analyzed results of Reneta Company Limited are presented in this paper because same results have been produced for others remaining companies. The obtained results show that all the companies closing stock prices are non-stationary. Also the number of support vectors and mean square error is decreasing pattern with the increase of kernel parameter. It is also found that original data and predicted data are very much identical. So SVMs predict the actual data very well. The result shows that in all the cases SVM model has some predictive power it can be used to forecast financial time series. We compare the SVM method to usual parametric methods such as MA, Exponential Smoothing, Holt Winters and it is found that Support Vector machines are more appropriate to forecast.

***JEL classification*:** C38, C39, C53, N25.

***Key words**: Time series Forecasting, Financial Market, Support Vector Machines, Usual Parametric Methods, Support vector regressions.*

1 Introduction

Bangladesh is a developing country with huge population. In a developing country, it has the strong economical condition. But a developing country economical condition depends on many issues, such as financial market, stock market, political issue, formulation of government etc. We work with stock market data. Stock market prediction is regarded as a challenging task of financial time-series. There have been many studies for forecasting time-series data. Recently, a support vector machine (SVM), a novel neural network algorithm, developed by Vapnik and his colleagues(1995) is a focus research field in the world. The support vector machine

(SVM) is a training algorithm for learning classification and regression rules from data (Burges, C.J.C., 1998).

Non-linear models are usually transformed to linear model to avail a benefit of the linear model by different transformation techniques (Alpha C. Chiang, Kevin Wainwright, 2005). But sometimes it is difficult to apply the different types of transformation techniques. To overcome this difficulty we can use the nonparametric procedure. The recently developed nonparametric procedure is Support Vector Machine (SVM), which is an extension of Generalized Linear Model. It is a novel technique in time series forecasting. In the cases of time series prediction, we expect that the Support Vector Machine will provide better solutions.

2. Problem and motivation

In Bangladesh, most of the financial time series data are forecasted by parametric method but parametric methods follow some assumptions if assumptions are violated then non-parametric methods are used to forecast the stock prices in Bangladesh. Recently, the Support Vector Machine (SVM) method, which was first suggested by Vapnik (1995), has recently been used in a range of applications such as in data mining, classification, regression and time series forecasting (Cao and Tay, 2001; Flake and Lawrence, 2002; Zhao et al., 2006). Parametric methods are the best choice if it follows all the underlying assumptions of the assumed models. If most of the assumptions are violated then without checking it is better to use nonparametric and robust methods or some other data mining techniques. Support Vector Machine is one of them (David L. Olson, Dursun Delen, 2008).

3. Objectives of the study

Any work has some defined objectives. This study has also some objectives. The main objectives of the study are given below:

To develop support vector model for the different cost (c) and different kernel parameter (γ) of radial basis function, determine the application of Support Vector Model in solving various time series forecasting problems, calculate the result of Support Vector Machine. In our technique we will use test (01 Jan 2013 to 30 April 2013) and training data set (02 January 2011 to 30 December 2012) closing prices index for our selected companies for developing and testing the validity of the model, and calculate model performance criteria (mean square error, normalized mean square error, root mean square error) to measure forecasting accuracy, and to compare Support Vector Machines with usual parametric time series methods such as Moving Average, Exponential Smoothing, Holt Winters, ARIMA, ARMA etc.

4. Methodology

We can use different methods which are given below

- Radial basis function neural network(RBFNN),
- Forecasting technique,
- Support Vector Machine(SVM) with two forms
  1. Dual form of SVM, and
  2. Primal form of SVM.

5. Prediction Theory of Support Vector Machine

Suppose the training nonlinear time series sample is $\{(x_1, y_1), (x_2 y_2), \Lambda, (x_k, y_k)\}$ $(x_i \in R^n, y_i \in R, i = 1,2, \Lambda k,$ is the number of training sample data). The basic idea of Support Vector Machine for time series prediction is a nonlinear mapping ϕ that transfer time series to the high dimension feature space F, and then construct the optimized linear regression function in the high feature space, and the expression of the linear regression function as follows:

$$f(x) = w\phi(x) + b. \tag{1}$$

In the aforesaid expression, w and $\phi(x)$ are both m-dimension vector, and b is the offset value. Support Vector Machine adopts the structural risk minimization principle to determine the values of w and b. Namely

$$\min R_{str} = \frac{1}{2}\|w\|^2 + CR_{emp}. \tag{2}$$

In the expression (2), $\|w\|^2$ is the complexity of control and c is the weight which is used to control the punishment degree that exceeds the error sample.

$R_{emp} = \frac{1}{k}\sum_{i=1}^{k} L_t[x_i, y_i - f(x_i)]$ is the error control function, which is usually measured by the ε insensitive loss function, and the insensitive loss function is defined as follows:

$$L_e = \begin{cases} |y - f(x)| - \varepsilon & |y - f(x)| \geq \varepsilon \\ 0 & |y - f(x)| < \varepsilon. \end{cases}$$

According to the structural risk minimization principle considering thecomplexity of the regression model obtained from the training set, regression based on the Support Vector Machine essentially is a solution of an optimized question, and the optimized question is in the following.

$$\min \quad \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{k}\left(\xi_i + \zeta_i^*\right).$$

In the question ζ_i and ζ_i^* are slack variables and the question is described as the originaquestion of the support vector machine. For the value of dimension w is huge, in order to conveniently solve the question, introduces the Lagrange multiplier α_i and α_i^* according to the duality theorem, and establish a Lagrange function, then the optimized question is converted to the dual space, and acquires the dual question of the original question, the formula is shown as the (2) expression.

$$\min \quad \frac{1}{2}\sum_{i,j=1}^{k}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)k(x_i, x_j) + \varepsilon\sum_{i=1}^{k}(\alpha_i^* + \alpha_i) - \sum_{i=1}^{k} y_i(\alpha_i^* - \alpha_i)$$

$$s.t. \begin{cases} \sum(\alpha_i^* - \alpha_i) = 0 \\ 0 \leq \alpha_i^*, \alpha_i \leq c(I = 1,2 \wedge k). \end{cases}$$

In the expression $k(x_i, x_j) = [\phi(x_i) \bullet \phi(x_j)]$ is the kernel function, and the most commonly used optimized kernel function is the Gauss function and the concrete formula $k(x_i, x_j) = \exp(-\frac{\left\|x_i - x_j\right\|^2}{\sigma^2})$. Supposed the solution to the dual question of the original question is, consequently the regression function is expressed as follows.

$$f(x) = \sum_{i=1}^{k} (\overline{\alpha_{i1}} - \overline{\alpha_i}) k(x_i, x) + b.$$

5.1 Kernel Function

For Support Vector Machine the following four basic kernels are used:

- Linear: $K(x_i, x_j) = x_i^T x_j.,$
- Polynomial: $(\gamma x_i^T x_j + r)^d, \gamma > 0$
- Radial basis function (RBF): $\mathrm{Exp}\left(-\gamma\left\|x_i - x_i\right\|^2\right), \gamma > 0$ and
- Sigmoid: $K(x_i, x_j) =$ $\tanh(\gamma x_i^T x_j + \gamma)$.where, γ, r, and d are kernel parameters. (Dunham, M.H, 2003)

6. Results and Discussions

The use of SVMs of one of the selected companies' stock prices forecasting's are studied in this paper. Here we use Support Vector Model to forecast and measure the forecasting accuracy by MSE, RMSE, NRMSE, etc and Compare this method by usual parametric techniques. The obtained result shows that SVM model has some predictive power; it can be used to forecast financial time series**.**

6.1 Research Data

We know the stock market pattern is changeable. In this section, we conduct experiments to illustrate the usefulness of SVM for financial prediction. In this study, we considered the daily closing price index of Dhaka stock index from different company such as AB Bank Limited, Apex Food Company Limited, R.A.K Ceramics(Bangladesh) Limited, Padma Oil Company Limited, and Reneta Company Limited 02-01-2011 to 30-12-2012. In our experiments, the kernel parameter γ, ε and c are selected based on the validation set. In order to choice the best SVM model MSE, RMSE, NRMSE and the number of support vectors with respect to the three free parameters are investigated. Only the results of kernel parameter γ are illustrated, the same can be applied to the other two parameters. Among these data points, the training data points cover the period from 02 January 2011 up to end of 30 December 2012, while the data points starting from 01 Jan 2013 up to 30 April 2013 are used as the test data. The dynamic system is modeled as $\hat{I}_t = f(I_{t-4}, I_{t-3}, I_{t-2}, I_{t-1})$, where I_t is the real stock price at time t, and $\hat{I}_t$ is the predictive value at time t. Therefore, the first training data set is a total of 238 days of DSE index.

6.2 Analysis of the Reneta Company limited by the Support Vector Machines.

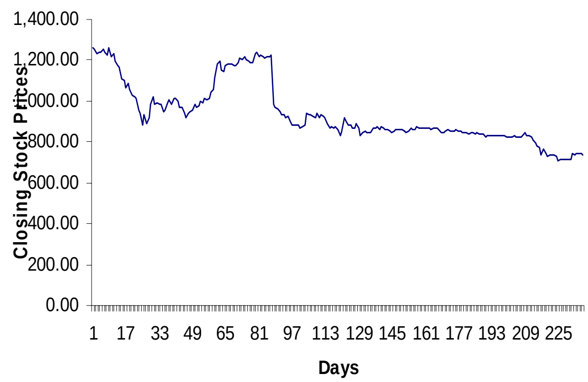

Figure 1 Closing Stock Price of Reneta Company Limited for 238 days

From the Figure 1 it can be illustrated that the closing stock price is decreased with the increase of time. Therefore the resulting data is non-stationary. We use this closing price to predict the next day index.

The Figure 2 gives the NSV using different kernel parameters $\gamma((0.1, 10000))$ respectively in which c and ε are fixed at 100 and .01. The figure shows that the NSV is decreased as γ increases. This indicates that too small value of γ (.1, 100) or too large value of γ (100, 10000) can cause the SVM indicates that most of the data points are converged to the support vector in the under fitting cases. In the end by summing up the analysis above and after several testing we found $\gamma = 100$, $c = 100$, $\varepsilon = .001$ as the best choice our experiment and then use these to train the model again, then to predict the test data set. The final results are MSE = 221.23 and number of support vectors are 54 which assistsin producing the final model after cross validation approach.

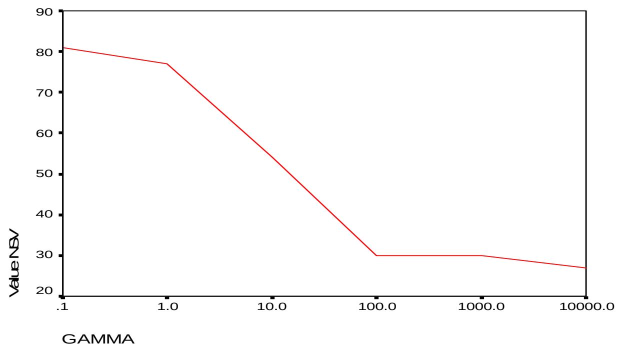

Figure 2: The Number of Support Vectors (NSV) for using different kernel parameter (γ)

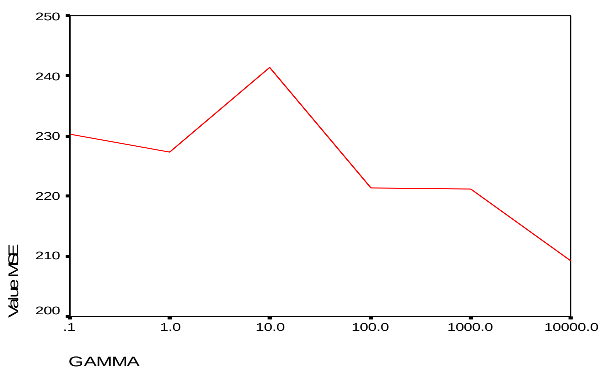

Figure 3: The Mean Square Error for using Different Kernel Parameter (γ)

The Figure 3 shows the MSE for using different kernel parameters $\gamma((0.1, 10000))$ respectively in which c and ε are fixed at 100 and .01. The figure shows that when γ (1, 10), the MSE increase as γ increase, while $\gamma \in (100, 10000)$ it decreases as γ increase. This indicates that too small value of γ (1,100) or too large value of γ (1000, 10000) can cause the SVM indicates that most of the data points are converged to the support vector in the under fitting cases.

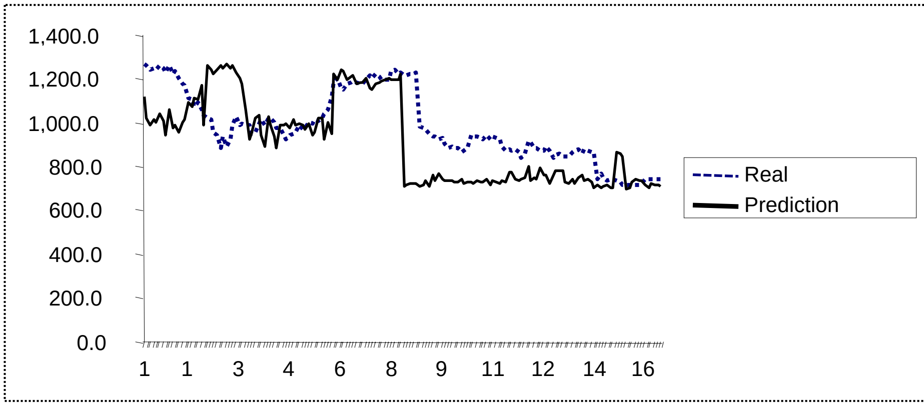

Figure 4: Original Data and Predicted data of Reneta Company Limited

From the Figure 4 it is evident that the original data and predicted data are very much identical. Therefore, support vector machine predicts the original data very well.

Table 1: Different Value of Performance Criteria for using $c = 100$, $\varepsilon = .01$ and Different Kernel Parameter ($\gamma \in (0.1, 10000)$) for Reneta Company Limited.

γ	MSE	RMSE	NRMSE	Number of support vector
.1	230.29	15.175	.02741	81
1	227.31	15.076	.02723	77
10	241.32	15.534	.02806	54
100	221.28	14.875	.02687	30
1000	221.21	14.873	.02686	30
10000	209.28	14.466	.02613	28

The result of Table 1 shows that the Mean Square Error, Number of Support Vector, Normalized Root Mean Square Error is increased first as $\gamma \in (.1, 10)$ and then decreases when kernel parameter $\gamma \in (10, 10000)$. So most of the data points are converged to the support vectors in the under- fitting cases. So the support vector model fits actual data well. Therefore the predicted curve fits the actual curve very well.

Table 2: Measuring Forecasting Accuracy of Support Vector Machines with Different Classical Methods for Reneta Company Limited.

Methods	Measuring forecasting accuracy			
	MAPE	MAD	RMSE	NRMSE
MA	1.421	13.656	19.711	0.0356
Single Exponential Smoothing	1.415	13.596	18.117	0.0327
Double Exponential Smoothing	1.438	13.728	19.432	0.0381
Support Vector Machines	1.358	11.236	14.876	0.0268

We observe from the Table 2 that, Support Vector Machines return the lowest forecasting errors among the models. So, we can say that in terms of minimum error Support Vector Machines has performed well for forecasting purpose for this series.

7. Conclusions

The use of Support Vector Machines (SVM) in financial forecasting is studied in this paper. This work establishes a model of stock market prediction based on support vector machines. The performance of SVM was compared with MA, Single Exponential, and Double Exponential Smoothing. The obtained result shows that for the studied companies in this work SVM model has some predictive power; it can be used to forecast financial time series. We have seen that the predicted value curve is identical to the actual value curve. Therefore SVM predicts actual value very well. It is also found that in all the cases Support Vector Machines are more appropriate to forecast. The support vector machine is a robust technique for function approximation. The study has conducted that SVMs provide a promising alternative to time series forecasting. They offer the following advantages, SVMs forecast better, as SVMs provide a smaller MSE. This is because SVMs adopt the structural Risk Minimization principal eventually leading to better generalization than conventional techniques.

Sometimes the stock market price changes due to some fact such that Record date, Earning per Share, Bonus, Net Asset Value and some other facts whose prior information is known. If all the information is provided in the usual procedure of SVMs, then estimation on forecasting performance will increase.

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