Stock Market Timing Decisions Using Neuro Rough Set Forecasting Model

Shipra Banik*[1], A.F.M. Khodadad Khan[2]

School of Engineering and Computer Science, Independent University, Bangladesh Dhaka, Bangladesh
*[1]shiprabanik@yahoo.com.au; [2]khoda@secs.iub.edu.bd

Abstract

Modeling share market is a very difficult work for practitioners because of very chaotic and volatile characters of facts. Conversely, it is done by many experimental studies and a number of applied researchers have proficiently applied machine learning procedures to project stock market. It is all the times true shareholders in general get loss because of uncertain investment purposes and unsighted assets. This paper proposes a hybrid neuro rough set model to find optimal buy and sell of a share on Chittagong stock market. Our experimental results exhibit that the recommended hybrid model has higher precision than other considered forecasting models selected for this study. We believe that findings of this paper will be useful for stock investors to make a decision about optimal buy and/or sell time on this stock market.

Keywords

Stock Market; Forecasting; Fuzzy Set; Rough Set; Neural Network; Hybrid Modeling; Confusion Matrix

Introduction

Awareness about the share market price values is very important for stock investors, buyers and/or sellers, policy makers, applied practitioners and many others who are concerned to recognize different features of a stock market to improve their investments performances. Hence, modeling the behavior of stock index values has drawn substantial interest in literatures [e.g. Abraham et al. (2003), Boyacioglu and Avci (2010), Banik et al. (2012a, 2014), Shamsuddin et al. (2009) and many others]. Forecasting stock market index values usually believed to be a very difficult task even for professional players also, because stock market data observed in practice are chaotic and non-linear (see Abraham et al. (2003), Banik et al. (2012b), Dutta et al. (2006), Jang (1993)]. Predictions of stock market movements are affected by many factors including political events, economic conditions and investors' expectations. However, stock market specialists are continuously researching and devising procedures that could assist them in predicting an accurate stock market outcome[Shamsuddin et al. (2009), Banik et al. (2012b), Tsai and Wang (2009), Lingras (1996), Shamsuddin et al. (2009)]. Usually, in a stock market, systems employed to formulate investment choices fall into two categories: (i) fundamental analysis (ii) technical analysis. Fundamental analysis is a complete method that includes reliable information of a company's financial report, economic conditions and competitive strength. This technique believes that present price depends on its fundamental value, expected return on investment and new information about a corporation. On the other hand, technical analysis believes that real record of trading and cost in a stock. In predicting market development, about 90% of stock traders use this method in their investment study. This is mainly psychological analysis of market contributors and typically concerned with market indicators. The main theory of these indicators is that once a trend is in motion, it will persist in that track. Relative strength index, moving average, moving average convergence/divergence, price rate of change have been commonly used technical indicators are used to study the trend of a market track via diagram presentations. To make huge earnings from the share market, most excellent forecasting methods are used by several analyzers (for example, see Abraham et al. (2003), Banik et al. (2012b), Banik et al. (2014), Maryam et al. (2013)]. Currently, analyzers relies multiple techniques to get information about the future markets [Abraham et al. (2003), Banik et al. (2012a, 2012b), Shamsuddin et al. (2009), Dutta et al. (2006), Kamruzzaman and Sarker (2003), Kihoro et al. (2000)].

This paper studied stock prediction for the use of investors and proposes a hybrid neuro rough set model to find optimal buy and sell time of a share on Chittagong stock exchange (CSE). Conventional predicting methods (regression methods, Box and Jenkins approach etc.) often fail to predict future values when the behavior of time series is chaotic and non-linear [Banik et al. (2012a, 2012b), Jang (1993), Kihoro et al. (2000)]. New methods known as artificial intelligence methods (e.g. neural network (NN), genetic algorithm (GA), rough set (RS), adaptive network based fuzzy inference system (ANFIS) and others) have emerged that increase the accuracy of non-linear time series predictions. If the system is non-linear, these methods have potential to provide a viable solution through its versatile approach to self-organization. It has been found that these techniques yield better results compared to the statistical approaches when the time series is chaotic [e.g. see Abraham et al. (2003), Banik et al.(2012a), Dutta et al. (2006), Jang (19933), Kamruzzaman and Sarker (2003), Kihoro et al. (2000)]. The problem studied in this paper is about the stock prediction for investors' usage. To study it, two popular intelligent methods known as ANFIS and RS models has been chosen to find optimal buy and sell time of a share on CSE. Although the NN and GA methods have been found to perform better compared to the conventional statistical methods, the drawback of NN and GA techniques is their prediction capabilities deteriorate over a short period of time especially when the time series data are very much chaotic. ANFIS and RS have been proposed by many authors [Shamsuddin et al. (2009), Tsai and Wang (2009), Smolinski el al. (2004), Tay and Shen (2002), Yao and Herbert (2009)] to overcome this drawback and develop a reliable prediction of time series data. Thus, to create a hybrid neuro rough set model we have chosen ANFIS model of superior ability of knowledge discovery and RS model for powerful rules extraction abilities. We wish to extract knowledge in form of rules from the daily Chittagong stock movements that would guide investors, buyers, sellers whether to buy, sell or hold a share. The most important technical indicators are used to create a hybrid neuro rough set model.

Several works has been carried out in literature to predict stock price index data using the ANFIS model or/and the RS model. For example, Boyacioglu and Avci (2010) investigate the predictability of stock market return with ANFIS. They predict the return on stock price index of the Istanbul Stock Exchange (ISE). Their results reveal that the ANFIS model successfully forecasts the monthly return of ISE National 100 Index with an accuracy rate of 98.3%. Thus, ANFIS provides a promising alternative for stock market prediction. Maryam et al. (2013) develop an ANFIS model to predict Tehran stock index values and compared their results with the NN model. They found ANFIS can predict better Tehran stock index values than the NN model. Banik et al. (2012a) propose an ANFIS model to predict Dhaka stock price index. Results obtained by this model are also compared to the NN model and the traditional autoregressive integrated moving average (ARIMA) model to show advantages of the proposed ANFIS model. Findings suggest that the ANFIS model can be used as a better predictor for daily stock values as compared to the NN and the ARIMA models. Shen and Loh (2004) did a detailed case study using the RS model to build a trading system in S&P 500 stock index. Their findings show that a RS model was an effective tool for forecasting S&P 500 stock index values. Jaaman et al. (2009) analyzed and predicted Malaysian stock market movements i.e. when to buy and sell a share by applying the RS methodology. Their results show that the RS model is an applicable and effective tool for stock market analysis. Recently Nair et al. (2010) proposed a decision tree RS hybrid model for predicting the next day's trend in Bombay stock exchange. Performance of the proposed hybrid model is compared that of an NN model. It is observed that the proposed model outperformed than the NN model. Shamsuddin et al (2009) combine NN and RS models to predict the movements of the Kuala Lumpur Composite Index. Results convinced that the hybrid NN and RS approaches can learn knowledge in stock market time series and give profit to investors. They claimed that it can be an alternative tool for investor to predict the stock market outcomes. Banik et al. (2014) proposes a hybrid NN and RS model to find optimal buy and sell of a share on Dhaka stock exchange. Their investigational findings show that the proposed hybrid model has higher precision than the considered single RS model and the NN model. Tsai and Wang (2009) propose a hybrid NN and decision tree model to forecast Taiwan stock price forecasting model. Their experimental result shows that the hybrid NN and decision tree based model prediction accuracy is higher than the single NN and the decision tree based model.

Recently, a comparative study has been conducted by Banik et al. (2012b) to predict Chittagong stock index values using soft computing models and time series model. They have used well-known models: the GA model and the ANFIS model as soft computing forecasting models. Very widely used forecasting models in applied time series econometrics, namely, the generalized autoregressive conditional heteroscedastic model is considered as time series model. Their findings have revealed that the use of soft computing model is more successful than the considered time series model to predict Chittagong stock index values. According to our knowledge, this is the study available in literature about soft computing model for Chittagong stock market. We observe that no empirical research for this market is available to predict buy, sell or hold a share under the hybrid neuro rough set model. This paper takes this issue and thus, it is expected that the findings of the study will be of interest to academics, investors, policy makers and others who want to make wise policies about Chittagong stock market. The paper is planned as follows: Section 2 explains suggested forecasting models. Explanation about technical indicators is provided in section 3. Experimentation is included in section 4. Finally some concluding remarks and future works are given in section 5.

Forcasting Models

The RS model and the ANFIS model have been employed in share market prediction [Abraham et al. (2003), Shamsuddin et al. (2009), Tsai and Wang (2009), Lingras (1996), Smolinski et al. (2004), Tsay and Shen (2002), Yao and Herbert (2009)]. Many RS models have been developed for several areas including applications: Forecasting [Smolinski et al. (2004)], feature selection [Zhang and Yao (2004)], financial and investment areas [Banik et al. (2012a, 2012b 2014), Kihoro et al. (2000), Yao and Herbert (2009)], analysis of share market data [Abraham et al. (2003), Boyacioglu and Avci (2010), Banik et al. (2012a, 2012b, 2014), Shamsuddin et al. (2009), Maryam (2013) and others. Like RS, the ANFIS model has been used to forecast stock market for past few years [Abraham et al. (2003), Boyacioglu and Avci (2010), Banik et al. (2012a, 2012b, 2014), Shamsuddin et al. (2009) and others] and is still being investigation many researches with the goal of achieving higher and perfect prediction. Based on successful results in applied literature given by RS and ANFIS in stock market prediction, we have chosen the following models to optimal buy and sell time of a share on CSE. These are models based on

1) ANFIS model
2) RS model
3) hybrid model of ANFIS and RS (ANFIS_RS)

Anfis Model

It is a combination of two intelligence systems (proposed by Jang (1993)), namely ANN system and fuzzy inference system (FIS) in such a way that the ANN learning algorithm is used to determine the parameters of the FIS. The process of FIS involves:

1) Membership functions (mfs)
2) Fuzzy logic operators and
3) If-then-rules

A typical ANFIS architecture is given in the FIG. 1 and a detailed coverage can be found in Jang (1993). FIG. 1 shows that the structure of ANFIS has 5 layers (1 input layer, 3 hidden layers that represent mfs and fuzzy rules and 1 output layer) and it uses the Sugeno-fuzzy inference model to be the learning algorithm.

ANFIS uses a two pass of learning algorithm to reduce the error:

1) Forward pass and
2) Backward pass

The hidden layer is computed by the gradient descend method of the feedback structure and the final output is estimated by the least square estimation method. ANFIS is available in the Fuzzy Logic Toolbox of MATLAB.

Rs Model

It is introduced by Pawlak (1982) and is developed based on mathematical tool to deal with uncertainty in classification of objects in a set. In RS, data is organized in a table called decision table, containing attributes as columns and data elements as rows. The class label is called as decision attribute. The rest of attributes are condition attributes. For rows, RST employs notion of indiscernible class, while for columns it employs notion of indiscernible attribute to identify significant attributes.

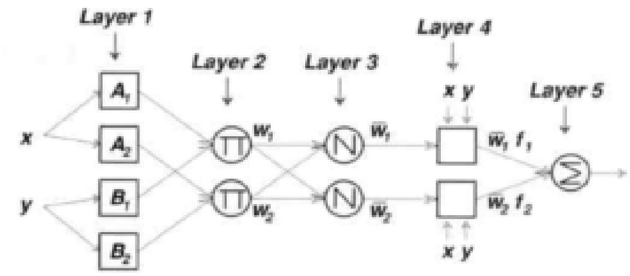

FIG. 1 AN ANFIS ARCHITECTURE WITH A 2-INPUT, 2-RULES FIRST-ORDER SUGENO MODEL

RST defines three regions based on equivalent classes induces by attribute values:

1) Lower approximation
2) Upper approximation and
3) Boundary

The lower approximation concerns of all objects which definitely belong to the set. The upper approximation consist all objects which probably belong to the set. The boundary is the difference between upper approximation and lower approximation.

Analysis of data by RS can be divided into five steps:

1) Construct information table
2) Identify indiscernibility relations
3) Finding reducts
4) Generation rules and
5) Finally classification

An information table is in form of rows and columns represent original data. The set of indiscernibility relations based on information table are derived using objects with set of features. The upper and lower approximations are used to deal with inconsistent objects that probably belong to the set. The main concern of RST is to find the smallest subset (known as reducts, computed by discernibility matrix) of features without losing any information. From reducts, production rules to classify objects are generated by logical statements of type IF-THEN condition. The decision rules are measured by support, length, coverage and accuracy. The rule support is number of records that fully exhibit the property described by IF-THEN condition. The length is defined as number of conditional elements of IF part. The coverage is defined as proportion of records that are identified by IF or THEN parts. The accuracy measures reliability of rule in THEN parts.

If coverage is 1 for a rule, then this rule is known as complete it means that any objects belonging to class while deterministic rules are rules with accuracy equal to 1. The rules are correct with both coverage and accuracy equal to 1. For a detailed report of RS, see Pawlak (1982).

Technical Indicators

The following most widely used indicators were used in this study:

1) Price rate of change (PROC)
2) Relative strength index (RSI)
3) Moving average over a 5-days period (MA5)
4) Moving average over a 12-days period (MA12) and
5) Moving average convergence/divergence (MACD)

A brief description about above indicators is described as follows:

Proc

PROC is a price momentum indicator and is calculated by: (TI-IN)/IN, where TI is the today's index and IN is the index n periods ago. If the stock's price is higher (lower) today than n periods ago, PROC will be a positive (negative) number. As the security's price increases (decreases), its PROC will rise (fall). Faster prices rise (or fall), faster PROC will rise (or fall). Thus, PROC values indicate an overall picture of trend strength generation.

Rsi

One of the most popular technical indicators is the RSI, developed by Wilder (1978). It is an oscillator that measures current price strength in relation to previous prices. It is calculated by RSI = 100-(100(1+R)), 0<RSI<100, where R=AG/AL, AG is average price gain over some periods and AL is average price drop over some periods. RSI is used to generate buy and sell signals. It also show overbought and oversold conditions that confirm price movement and warn of potential price reversals through divergences. If we choose (e.g.) two references lines at 40 and 80 and if we observe RSI dips below 40 line, a buy signal is generated. Likewise, if RSI exceeds 80 line, a sell signal is generated.

Ma5

By MA, a trader is able to understand the strength of the long-term trend of the prices. MA5 is the 5-days moving average and is calculated by last 5 indexes are added together and then divided by 5.

Ma12

MA12 is the 12-days moving average and is formulated by last 12 indexes are added together and then divided by 12.

Macd

It is an oscillator function to spot overbought and oversold conditions. MACD is calculated by subtracting values of a 26-periods exponential MA from a 12-periods exponential MA. As its name implies, MACD is all about convergence and divergence of two MAs. Convergence occurs when MAs move towards each other. Divergence occurs when MAs move away from each other. The shorter MA (12-days) is faster and responsible for most MACD movements. The longer MA (26-days) is slower and less reactive to price changes in underlying stock.

The above technical indicators are used as dependent attributes in our analysis. The decision attribute is the trend of stock market and can be used to make decisions.

Data, Experimentation and Result

FIG. 2 TIME PLOTS OF CSESPI

To evaluate and certify prediction capability of selected models, daily stock movement of all stocks (CSESPI) traded in CSE and spanning over a period of 10 years (01 Jan 2004- 02 February 2014) were captured (Data source: http://www.cse.com.bd)). FIG. 2 shows stock's movements with respect to time. We can detect that there has an increasing trend of the prices up to October 2010. Then there is a (seems to be) collapse in market observed after that. Certainly, there have some reasons those could be economic, political and/or psychological. Details, see http://www.cse.com.bd.

Statistical properties of CSESPI are examined first before applying it to selected models and tabulated in Table 1. We have reported selected attributes (PROC, RSI, MA5, MA12, and MACD) used in the creation of RS decision table and inputs to the ANFIS model in Table 2. These attributes are calculated from the CSESPI general index. The decision attribute D in this table indicates the future direction of data set and is made using the following rule:

Where index (0) is today's index and index (i) is the i^{th} index in future. The above equation specifies a range -1 to +1 for D. A value of -1 show next day's price is lower than that of current date, 0 show no change and +1 show next day's price is higher than of current date. From raw data, we executed data preparation tasks that resulted in a new information table with conditional attributes A = (PROC, RSI, MA5, MA12, and MACD) and a decision attribute D.

In the next section, we will create RS model, ANFIS model and a hybrid model ANFIS_RS based on selected technical indicators.

TABLE 1 NUMERICAL SUMMARIES OF CSESPI

Minimum	Maximum	Mean	SD	Skewness	Kurtosis
1566	24921	9.3373e+003	5.7754e+003	0.4261	2.1626

TABLE 2 AFTER POST PROCESSING SAMPLE OF CSESPI

Date	CSESPI	PROC	RSI	MA5	MA12	MACD	D
15-Dec-13	10799.36	-5234	38.8365	1326	1321	-3578	1
17-Dec-13	10788.63	-1578	36.036	1325	1321	-3856	-1
18-Dec-13	10720.02	-7078	27.9545	1321	1322	-4142	-1
19-Dec-13	10737.27	-2877	27.1923	1318	1326	-4333	1
22-Dec-13	10818.36	-2378	27.5373	1315	1329	-4532	1
23-Dec-13	10793.03	-3742	20.8866	1312	1333	-4863	1

Training data	Testing data
Support (LHS) =179	Support (LHS) =189
Coverage (LHS) = 0.1849	Coverage (LHS) = 0.1952
Accuracy (RHS) =0.6201	Accuracy (RHS) =0.6768

Model Building

The ANFIS_RS hybridizes high generality of ANFIS and rules extraction ability of RS. Data are divided into 2 parts: training and testing sets. The training set holds 60% of the collected data and testing set holds remaining data. Confusion matrix is applied to assess performance of observed and predicted classes for selected models. This matrix is a table summarizing the number of truepositive (TP) class, false positive (FP) class, false negative (FN) class and true negative (TN) class. For example, FN means output of prediction model is fall and stock price actually falls and so on.

RS Model

Stock market data prediction process and analysis is demonstrated in the following steps:

1) Create efficient indicators based on data
2) Select training data set and test data set
3) Place into RS model
4) Extract trading rules
5) Apply in real market

The RS analysis of data involved calculation of reducts from data, derivation of rules from reducts, rule evaluation and prediction processes. The rosetta rough set toolkit was employed to carry out reducts and generate decision rules. The reducts were created from our selected data are revealed in Table 3. We used the Johnhon's reducer algorithm and the equal binning decretized method. Table 3 illustrates a partial set of generated rules. These obtained rules are used to make prediction systems. From our considered data, we got a set of 10 reducts. The following is an example of a rule obtained from reducts 3 in Table 3.

IF-THEN Rule:

IF MACD((-4539, 3532.3)), MA5((*,1675.7)),
MA12((1335, 1425.9)) and PROC((-5761, 3188))
THEN Decision class (-1) OR (1)

The rule has 3 conditional attributes corresponding to IF part. The rule has a decision of -1 or 1. From this rule we can see that conditional attributes have a support of 179 objects from a total of 968 objects. Of those 179 objects, 111 objects (62%) have a decision value of -1 or 1. We are looking for rules with relatively high support and high accuracy. Once rules were obtained, testing of each rule guaranteed that knowledge was precise. Each rule fired against testing set to verify support, precision and confidence measures. Comparison between measures obtained by firing rules against training and testing data is needed to make sure that knowledge is a correct illustration of raw data.

The confusion matrix for the RS model is presented in Table 4. On average, RS model provides 71.73% prediction accuracy of falling stock prices, 82.02% prediction accuracy of rising stock prices and overall 87% prediction accuracy. Therefore we can say that this model is 72% helpful to forecast falling stock and 87% helpful to forecast rising stock.

TABLE 3 GENERATED REDUCTS

Reduct #	Reduct
1	{MACD, MA12, RSI}
2	{MA5, MA12}
3	{MACD, MA5, MA12, PROC}
4	{MA5, PROC, RSI}
5	{MA12, MA5, PROC}
6	{MACD, PROC, RSI}
7	{MA12, PROC, RSI}
8	{MACD, MA12, RSI}
9	{MACD, MA5, RSI, PROC}
10	{MACD, MA12, PROC, RSI}

TABLE 4 CONFUSION MATRIXES FOR THE RS MODEL

	Projected		Accuracy(%)
Actual	Fall (-1)	Rise (+1)	
Fall (-1)	302	119	0.7173
Rise (+1)	4	543	0.9927
Accuracy(%)	0.9869	0.8202	0.8729

Anfis Model

An error and trial process is used to design the topology of ANFIS. Firstly, a number of networks are trained and the error gradient was watched. Training algorithm is used to update the mfs parameters of FIS, is a hybrid rule. As a result, a decreased training error throughout the learning process is gained. The performance of the networks is assessed by decreasing or increasing the no. of inputs and the premise rules. Best performance is obtained by a network consists of 4 inputs with 2 mfs (type Gaussian-shaped) with each input. Thus, the previous 4 days index values of A are used as inputs to forecast the CSESPI future values for the fifth trading day. In our experiment, the number of mfs for each input was set to 2 and the type selected was the Gaussian shaped that had given better results in preliminary tests. The confusion matrix is provided in Table 5.

On average, ANFIS model offers 73.04% prediction precision of falling stock prices, 81.07% prediction precision of rising stock prices and overall 79.44% prediction exactness. It is notable that although this model performs better than RS model to predict falling stock prices, but it performs poorly for overall prediction. The reason rate of prediction for the class of FN is higher as compare to the RS model.

ANFIS_RS Model

The concept of neural-rough set model was first proposed by Pawan Lingras (1996). The topology of the ANFIS_RS model is described as follows: First ANFIS model is created alone as baseline, then ANFIS and RS models are combined to improve rate of forecasting accuracy. An ANFIS topology is selected by error and trial system. A number of networks are trained and the error gradient was observed. By a hybrid rule training algorithm is used to update the mfs parameters of FIS. A decreased training error throughout the learning process is obtained. The performance of the networks is evaluated by decreasing or increasing the no. of inputs and the premise rules. Best performance is obtained by a network consists of 4 inputs with 2 mfs (type Gaussian-shaped) with each input. Thus, the previous 4 days index values are used as inputs to predict the future index values for the fifth trading day. In our experiment, the number of mfs for each input was set to 2 and the type chosen was gaussian shaped. The total number of ANFIS parameters $|S| = 16 + 80 = 96$. Calculation is as follows: Each mf has 2 parameters, so, for 4 inputs we have $|S1|=2*2*4=16$. On the other hand, 4 inputs create 2^4 rules giving $|S2| =16*(4+1)=80$. Then the rosetta rough set toolkit was used to execute reducts and create decision rules based on ANFIS predicted CSE index. The Johnhon's reducer algorithm and the equal binning decretized method are used to execute reducts and create decision rules. To examine performance of model, confusion matrix is tabulated in Table 6. The hybrid model ANFIS_RS provides the 93.18% forecast correctness of falling stock prices, 94.58% forecast exactness of rising stock prices and overall 96.38% forecast precision.

From Tables 4-6, one can easily recognize that the hybrid ANFIS_RS model has higher average prediction accuracy than the ANFIS model and the RS model. Therefore, based on our findings, the hybrid ANFIS_RS model can be advised to forecast the daily Chittagong stock movements.

TABLE 5 CONFUSION MATRIX FOR THE ANFIS MODEL

	Projected		Accuracy (%)
Actual	**Fall (-1)**	**Rise(+1)**	
Fall (-1)	298	110	0.7304
Rise (+1)	89	471	0.8411
Accuracy (%)	0.7700	0.8107	0.7944

TABLE 6 CONFUSION MATRIX FOR THE ANFIS_RS MODEL

	Projected		
Actual	**Fall (-1)**	**Rise (+1)**	**Accuracy (%)**
Fall (-1)	410	30	0.9318
Rise (+1)	5	523	0.9905
Accuracy (%)	0.9880	0.9458	0.9638

Conclusions

A hybrid machine learning model is proposed in this paper to decide optimal buy and sell time on CSE. The most popular forecasting models ANFIS and RS is combined to improve rate of prediction accuracy. Findings of this proposed hybrid model is compared for the baseline RS model and the ANFIS model. Confusion matrix is used to assess performance of chosen models and classes (fall and rise). Experimental result shows that our proposed hybrid model has 96% accuracy which is higher than the single RS forecasting model and the single ANFIS forecasting model. Other forecasting models, for example, hidden markov forecasting model, genetic algorithm forecasting model and others can be applied for further evaluations. This is left for future works.

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Shipra Banik received her PhD degree in Applied Financial Econometrics from the La Trobe University, Australia in 2000. Currently, she is an Associate Professor at the School of Engineering and Computer Science, Independent University, Bangladesh.

A.F.M. Khodadad Khan obtained his M.S. degree in Mathematics from the University of Arizona, USA in 1975. Currently, he is a Professor at the School of Engineering and Computer Science, Independent University, Bangladesh.