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Trend Estimation of Stock Market: An Intelligent Decision System

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***Abstract* - Stock market is a marketplace that facilitates buying and selling of company stocks. Finding a right time to buy/sell stock considering market movement is a tricky task to decide. Therefore, predicting the trend of stock buying/selling price is of great interest to stock traders and investors to find the right time to buy/sell stocks. This paper, aims to develop an intelligent system using Trend Estimation with Linear Regression (TELR) for predicting and visualizing the predictions. This system can guide a trader/investor however, with or without expertise in the stock market to achieve profitable investments. We have used the Stock data from Stock Exchange Bangladesh which covers 300+ companies including 29 Banks to train and test our system. We have fitted the trend with maximum likelihood estimation method to train our system with the stock data until December 2017 and then test it with the stock value of January 2018. A comparative result of the trend value derived from the intelligent system with real stock value has been presented to show the effectiveness of the Intelligent Decision System.**

***Keywords* – Stock Market Prediction, Forecasting, Decision System, Artificial Intelligence, Trend Estimation.**

I. INTRODUCTION

THE stock market denotes to the exchange marketplace where the issuing and trading of equities or stocks are held. There, investors choose one or more company to buy its stock and sell it when its value rises, thus they earn money effortlessly.

In general the value of a stock is determined by its entry on the stock market and the volume of its transactions [1]. The more a share is transacted, the more it is valuable, and conversely, if a share is put into transaction in a low volume, it is not so important for some traders and by default its value decreases [2]. This anticipation of the market can generate profits or losses, depending on the power to predict future values. Therefore the problem becomes: for stock market history of a particular company to determine the particular moment of buying or selling the stock for generating profit.

The investors in the stock market use their heuristic technique to predict the stock trends for ensuring risk free profit generation. But, the potential risk in this trading is the innate nature of stock prices [3] This impulsive and vigorous nature of stock price sometimes refers investors in enormous loss for wrong or immature prediction in buying/selling stocks. This motivates the researchers in the domain field to develop an intelligent decision system forecasting stock price.

Therefore, it can be assumed that forecasting the value of a stock is based on publicly available data that has some predictive relationships to the future stock returns [4]. Exploring various stock exchange websites for stock value; date-wise opening value, closing value, highest value, lowest value, average value etc. are mostly common. However, stock trend forecasting is still one of the most challenging tasks to accomplish in finance market because of its volatile nature.

Stock prices are not randomly generated values rather they can be treated as a discrete time series model which is based on a set of well-defined numerical data items collected at successive points at regular intervals of time [5]. Though plotting these stock values in a time series and predicting real-time series values is a complicated task because of its 'random hike' nature. However, a lot of economic factors like demand–supply, earnings, investors' sentiments, expected growth couldn't be quantized into a single theory or a model that predicts flawlessly.

Since, it is essential to identify a model in order to analyse trends of stock prices with adequate information for decision making, it recommends that transforming the time series using ARIMA is a better algorithmic approach than forecasting directly, as it gives more authentic results. Autoregressive Integrated Moving Average (ARIMA) model converts a non-stationary data to a stationary data before working on it [5]. It is one of the most popular models to predict linear time series data.

The remainder of this paper is organized as follows. Section II highlights related literature. Section III puts forward an intelligent decision system forecasting stock trends in detail. Section IV describes the experimental results thus obtained followed by the concluding remarks and future work Section V.

II. RELATED WORK

In stock market, investors are particularly concerned about stock price fluctuation of the company while buy/sell stock, which is one of the core issues of modern financial research in this arena. Yan et al. pointed out that, the price instability in short-term asset reduces the willingness of buy/sell stock and investors switch to other investment area [6]. However, the economic and financial theory indicates that the instability of an investment project reduce the investors persistence in that market due to their risk averse nature [7]. Also, the stock market crash on 1987 in USA commenced researchers to pay attention for reducing stock price fluctuation.

The state of the art financial market hypothesis articulates that the current market price rely on available information. This implies that past and current information is immediately incorporated into stock prices, thus price changes are merely due to new information and independent of existing information [8]. However, stock price follow a random pattern and the next day price is quiet unpredictable.

Therefore, various Machine Learning algorithms are applied to forecast the trend of stock price. Some of them are: AR models (Autoregressive) [7], ARIMA (autoregressive integrated moving average) [5], ANN (Artificial Neural Networks) [8, 9, 10], GA (Genetic Algorithm) [11], SVM (Support Vector Machines) [12], SVR (Support Vector Regression) [13]. Due to the non-linear nature of the stock market values, some methods have yet to give promising answers, others have not reacted as well on the stock market exchange.

Sabaithip et al. have proposed a decision support system using different multi-class classification techniques through neural networks [14]. The multi-binary classification experiments using one-against-one (OAO) and one-against-all (OAA) are conducted on the historical stock data of Thailand stock exchange and further compared with traditional Neural Network systems.

Reviewing stock market performance through business analytic Chang used the Heston model and it's associated API to forecast stock index movement with high accuracy [15]. On the other hand, Sharang et al. took DBN to extract the features of hidden layer and then input these features into three different classifiers to predict the up and down of US Treasury note futures in five days. The accuracy of these three models is 5–10% higher than the random predictor [16].

Empirical studies carried out that stock price are not purely random; rather in a shot-time series it follows a pattern. Thus the stock market should be in a certain range of predictable using Neural Network [17]. However, some researchers reject the random hike behaviour of stock prices [18, 19]. Later, ANN, k-Nearest Neighbour and Decision Tree are individually assembled individually achieving 34.64% error rate that is very low according to state-of-art approaches [8].

Besides the efficient market hypothesis, there are two schools of thought regarding stock market predictions: Technical analysis and Fundamental analysis. Fundamental analysis examines a company's financial conditions, operations, and/or macroeconomic indicators to derive the intrinsic value of its common stock. Fundamental analysts will buy/sell if the intrinsic value is greater/less than the market price; however, the proponents of the efficient market hypothesis argue that the intrinsic value of a stock is always equal to its current price. Technical analysis, on the other hand, is a study of the market itself [8].

Zhu et al. used 14 technical analysis indicators such as the opening, higher, lower, closing price etc. as input, and through the Deep Belief Networks (DBN) applied the learning of the historical data. From that stock price forecast much better prediction was examined [20]. Similarly, Jadhav et al. used open, high, low, close, adjclose indicators as input and applied Regression, Moving Average, Forecasting and Neural Network separately and achieved 37%, 41%, 38% and 47% efficiency respectively [21].

Kuremoto et al. fitted a variety of time series data using a three-layer restricted Boltzmann machines (RBMs) [21] and also proposed optimized Deep Belief Networks - Multi Layer Perceptron (DBN-MLP) through Particle Swarm Optimization (PSO) to predict the chaotic time series [22]. Likewise, Takeuchi et al. used past 12 months earnings, that is t-13 to t-2 months along with previous 20 days as input and then classify US stocks using multiple RBM models and achieved 53% of accuracy [23].

Finally, it can be assumed that, Stock price is reflected by price and volume as well as moves in trends; however the random nature is also repeated [8]. Consequently, it can be conclude that price (open, high, low, and close) and trading volume time series are enough for prediction tasks. However, market-driving forces (i.e., human psychologies) hardly change, the projection of the stock price are periodic that can help for certain prediction.

III. PROPOSED METHOD

The overall framework of the proposed model of Trend Estimation with Linear Regression (TELR) is illustrated as Figure 1 and two major phases are provided. To detail the proposed model Trend estimation of Stock Market: An Intelligent Decision System, each process of the proposed model is described as follows.

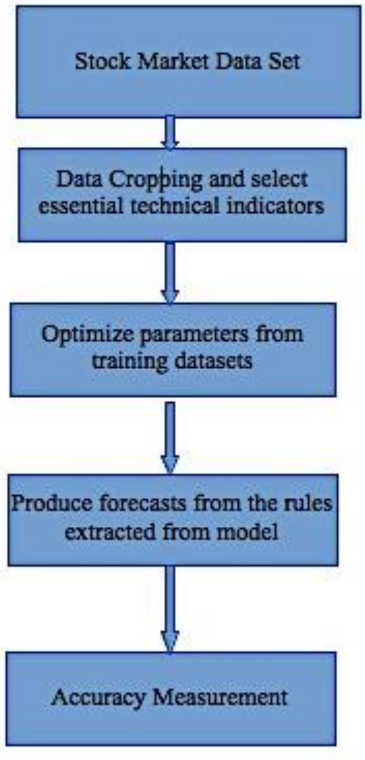

Figure 1: The framework of proposed model

Simulate observations from the extrapolated generative model. It returns dataframe with trend, seasonality, and $\hat{y}$, each like 't'. Under sample model we get 'trend' from sample predictive trend function where we pass dataframe and iteration (sampling iteration to use parameters) as an arguments it return array of simulated trend over time.

We use piecewise linear regression as a nested function for trending. It takes some arguments like t, deltas, k, m, changepoint time. Here deltas, k, and m we get from iteration parameter. Then prepend the times and deltas from the history.

Finally we use sample model and store some variables like ‘beta’ get from iteration parameters, ‘seasonal’ get from matrix multiplication on seasonal matrix and beta also multiply by ‘y_scale’, ‘sigma’ from iteration parameter and noise.we get noise using sigma multiply by ‘y_scale’. For ‘$\hat{y}$’ we sum ‘trend’, ‘seasonal’, ‘noise’ and finally get the results.

Time series prediction approach uses two main data transformational processes. These are:

- After making dataset we pull out the stock closing data which is our target value or target label
- Apply the algorithm to forecast the target variables and predict the following time step in the series

We use a decomposable time series model [24] with three main model components: trend, seasonality, and holidays. They are combined in the following equation:

$$y(t) = g(t) + s(t) + h(t) + \delta(t)$$

Here *g(t)* is the trend function which models non-periodic changes in the value of the time series, *s(t)* represents periodic changes (e.g., weekly and yearly seasonality), and *h(t)* represents the effects of holidays which occur on potentially irregular schedules over one or more days. The error term *δ(t)* represents any idiosyncratic changes which are not accommodated by the model.

We used piecewise liner model for trend. The trend model is:

$$g(t) = \left(k + \frac{a(t)}{\delta}\right)t + (m + \frac{a(t)}{\gamma})$$

Here, *k* is the growth rate, *δ* has the rate adjustments, *m* is the offset parameter, and γ_j is set to $-s_j\delta_j$ to make the function continuous. The changepoints s_j could be automatically selected given a set of candidates. We specify a large number of changepoints and use the prior $\delta_j \sim Laplace(0, \tau)$. The parameter τ directly controls the flexibility of the model in altering its rate.

The proposed time series forecasting has two main part:

- Train
- Prediction

A. Train:

After initialized model we checked some validation (eg: inputs, column name) and add seasonality then fitted train data in fit model. When the seasonality and holiday features for each observation are combined into a matrix *X* and the changepoint indicators *a(t)* in a matrix *A*, the entire model can be expressed in a few lines of Stan code [25].

For model fitting we use Stan’s L-BFGS to find a maximum a posteriori estimate but also can do full posterior inference to include model parameter uncertainty in the forecast uncertainty.

Linear Likelihood:

$$y \sim normal\big((k + A \times \delta) \times t + (m + A \times \gamma) + X \times \beta, \sigma\big)$$

Parameter Initialization:

$$k \sim normal\ (0, 5)$$
$$m \sim normal\ (0, 5)$$
$$\varepsilon \sim normal\ (0, 0.5)$$
$$\beta \sim normal\ (0, \sigma)$$
$$\delta \sim doubleExponential\ (0, \tau)$$

In this process, initially we prepared dataframe for fitting using ‘setup dataframe’ method, if any error happened show the error results otherwise store it on history, which is our train data set. ‘Setup dataframe’ has 3 arguments: self, dataframe and initialize scales.

initialize_scale: Set model scaling factors using df

Then check seasonalities using fourier order, Parse seasonality arguments, make all seasonality features and then finally make Data Frame with seasonality features using Fourier series [26]. Set changepoints to the dates of changepoints then get changepoint matrix A for history dataframe.

Eventually, the model provides a strong initialization for linear growth by calculating the growth add offset parameters that pass the function through the first and last points in the time series. Initialized linear growth returns some value in a tuple *(k, m)* with the rate (k) and offset (m) of the linear growth function. Linear growth function work likes:

$$i_0, i_1 = minDate, maxDate$$
$$T = t \times i_1 - t \times i_0$$
$$k = \frac{\hat{y} \times i_1 - \hat{y} \times i_0}{T}$$
$$m = (\hat{y} \times i_0) - k \times t \times i_0$$

B. Prediction:

First we store data into dataframe (history) then invoke this data on ‘setup dataframe’ then add a dictionary key ‘trend’ on it, which has predict trend values.

Then, we evaluate the piecewise linear function, *g(t)* with t (date), δ (rate change at each point), *k*, *m* and s_j (change point time). There we have analyzed the intercept changes with γ. Then we get cumulative slope and intercept at each point in respect of date. For this we have constructed a time array *N*, $\forall i = 1 \ldots . t$ that returns an array of ones with the same shape and type as a given array.

Algorithm 1: Piecewise Linear

Input: t, δ, k, m, s_j
Output: Time Series Vector *y(t)*

```
Begin
    γ ← −s_j × δ
    N ← ∀i = 1 … . t
    k′ ← ∅
    m′ ← ∅
    k′ ← k × N(t)
    m′ ← m × N(t)
    for each s, t_s ∈ s_j(t) do
        index ← max(t, t_s)
        k′[index] ← k′ + δ[s]
        m′[index] ← m′ + γ[s]
    end for
    y(t) ← k′ × t + m′
    return y(t)
End
```

Then predicting seasonal components with history data frame and find predict uncertainty, which means intervals. Next, create a new data frame from: *cols = ['ds', 'trend'], intervals* and *seasonal components.* Prediction intervals for $\hat{y}$ and trend return dataframe with uncertainty intervals on predict method, where, *y_train* is the predicting values.

$$y\_train = trend + seasonal$$

Finally, the time series vector, *y(t)* has been calculated which is the predicted value in respect of that date. Thus, the linear trend model gives the forecast of the stock value in time series.

IV. EXPERIMENTAL RESULT AND DISCUSSION

Stock data are collected from the website and the dataset has been collected from popular Bangladeshi Companies, like: Daffodil, City Bank, ACI, Grameenphone, Jamuna Bank, Dutch Bangla Bank Limited (DBBL), Delta Life, Asianpaints, Desco, Eastern Bank Limited (EBL), Uttara Bank, ICIB Bank from December 2011 to December 2017 [27]. The year 2011-2017 had been very challenging year for Bangladesh share market. In this study stock information for that period is taken to analyze the performance of the system at hard times.

Stocks listed in Few Bangladeshi Companies are used to evaluate the system. For experimentation, the stock market datasets are divided into two sets such as: (1) training dataset and (2) testing dataset. The stock data from January 2011 to December 2017 were used for training dataset and the stock data of January 2018 were used for test along with measuring accuracy.

Table 1: Sample Data (EBL Stock Value)

Date	Open	High	Low	Close	Volume
27-12-11	67.7	67.8	66.8	66.9	738600
28-12-11	67.9	68	66.5	66.6	626000
29-12-11	67.9	67.9	65.5	65.8	1080800
01-01-12	67.9	67.9	65.9	66.8	638600
02-01-12	44.4	45.3	43.3	43.8	339800
04-01-12	43.2	44.9	41.5	44	1025600
08-01-12	35.5	35.8	35	35.3	140200
10-01-12	32.6	35.5	32.5	34.1	405000
11-01-12	33.2	33.4	32.9	32.9	66200
15-01-12	63	63.6	61.5	61.6	409600
16-01-12	60	60.8	57	59.7	474400
18-01-12	58	60.9	56.9	57.7	492800
19-01-12	59.5	61.8	58.3	60.9	461400

The stock data has several attributes, the details of those attributes are given below:

Open: The term "open" appears is several usages in the financial markets. However, there are two that hold particular significance, depending on the context in which they are used. The open is the starting period of trading on a securities exchange or organized over-the-counter market. An order to buy or sell securities is considered to be open, or in effect, until it is either cancelled by the customer, until it is executed, or until it expires.

Close: The close is the end of a trading session in the financial markets when the markets close. It can also refer to the process of exiting a trade or the final procedure in a financial transaction in which contract documents are signed and recorded.

High: High refers to a security's intraday high trading price. Today's high is the highest price at which a stock traded during the course of the day. Today's high is typically higher than the closing or opening price. More often than not this is higher than the closing price.

Low: Low is a security's intraday low trading price. Today's low is the lowest price at which a stock trades over the course of a trading day.

Volume: Volume is the number of shares or contracts traded in a security or an entire market during a given period of time. For every buyer, there is a seller, and each transaction contributes to the count of total volume. That is, when buyers and sellers agree to make a transaction at a certain price, it is considered one transaction. If only five transactions occur in a day, the volume for the day is five.

We have considered the close value of each date as the Actual value of the stock on that date and train our system in that way for trend estimation. Then use some auxiliary columns for both fitting and predicting. Eventually, use the time series method with piecewise linear regression to forecast the stock value for next 1 month, that is represented on Figure 2.

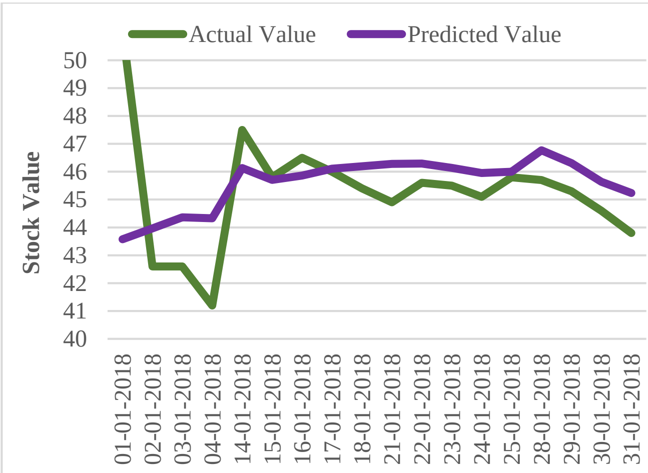

Figure 2: Comparisons of Actual Value and Predicted Value

This graph shows the predicted value is very close in compare to the actual value of the stock on a particular date. This graph results in such accurately because of the low stock price, the actual and predicted value of a company has been displayed on Table 2. For high price of stock, the proposed TELR method doesn't fit well. However, experimenting on Bank Stock Data, we can easily concluded that our proposed system performs much better.

Again, from the graph in Figure 2, it can be determined that, over time the predicted value is deviated from the actual value. From the experiment, we can safely forecast 1 month data, after that, the predicted value get deviated much from actual data because of uncertainty level.

Table 2: Result of Prediction Value (EBL Stock Data)

Date	Actual Value	Predicted Value
01-01-2018	51.1	43.57582
02-01-2018	42.6	43.96696
03-01-2018	42.6	44.36486
04-01-2018	41.2	44.32647
14-01-2018	47.5	46.12922
15-01-2018	45.8	45.70845
16-01-2018	46.5	45.85913
17-01-2018	46	46.10948
18-01-2018	45.4	46.19291
21-01-2018	44.9	46.28212
22-01-2018	45.6	46.29078
23-01-2018	45.5	46.13515
24-01-2018	45.1	45.95402
25-01-2018	45.8	45.99736
28-01-2018	45.7	46.76703
29-01-2018	45.3	46.31134
30-01-2018	44.6	45.63727

However, a model's forecasts are almost never 100% accurate. A forecast may be slightly higher or slightly lower than the actual value, depending on how good the forecasting model is. The difference between a forecast value and its corresponding actual value is the forecast error: Forecast error = $Y_t - F_t$, where Y_t is the actual value and F_t is the forecasted value. The forecast error measures the accuracy of an individual forecast [28].

There are several forecasting performance measures used to evaluate the size of the error. When considering the size of the error different dimensions may be addressed the amount of error, the dispersion of the error or the relative magnitude the error.

Root Mean Square Error (RMSE)

The mean square error (MSE) value measures the amount of dispersion of the errors. From accuracy perspective, the smaller the MSE value the better. The square root of the MSE results in the standard deviation of the errors or standard error (se) and is sometimes called the root mean square error (RMSE) [28]. The MSE is calculated as the average of the sum of the squares of forecast the errors:

$$MSE = \frac{\sum (Y_t - F_t)^2}{n}$$

Where t = time period; n = number of periods forecasted; Y_t = actual value in time period t; F_t = forecast value in time period t.

An assumption of most forecasting models is that the errors follow a normal distribution with a mean of zero and a certain standard deviation which is estimated by the s_e, or RMSE.

Mean Absolute Percentage Error (MAPE):

A widely used evaluation of forecasting methods which does attempt to consider the effect of the magnitude of the actual values is the mean absolute percentage error (MAPE) [28]. The MAPE is calculated as:

$$MAPE = \frac{\sum \frac{|Y_t - F_t|}{Y_t}}{n}$$

As with MAPE and MSE performance measures, the lower the MAPE, the more accurate the forecast model. A scale to judge the accuracy of model based on the MAPE measure was develop by Lewis [29] where less than 10% is considered as High Accuracy.

Percentage Forecast Error (PFE):

The conventional forecast performance measures have no real-world or business meaning or context that motivates to develop a measure call the percentage forecast error (PFE). The percentage forecast error,

$$PFE = \frac{2 \times s_e}{\hat{Y}_{t+1}} \times 100\%$$

Where s_e is the standard error and $\hat{Y}_{t+1}$ is the forecasted value for the next time period, t+1. The PFE is somewhat similar to the coefficient of variation (CV) in which one measures the relative dispersion around the mean.

The CV is an ideal measurement for comparing the relative variation of two or more data sets, especially when they may be measured in different units. An advantage of the CV is that, regardless of the units of measure, the CV equation cancels the units out and produces a percentage.

With the PFE, there is a similar ratio except that in the numerator of the PFE measure the standard error is multiplied by 2. As a result, the resulting measure is two standard deviates away from the mean in conjunction with the Empirical Rule.

Accordingly, the PFE value allows one to say, with a high level of certainty (actually 95%), that the forecast for the next time period will be within PFE% of the actual value. In other words, one is highly certain that the forecast will be within 20% of the actual value [30].

The Stock Bangladesh Data includes financial statements of different sectors like: Bank, Cement, Ceramics, Corporate, Engineering, Food, Fuel, IT, Insurance, Jute, Pharmaceuticals, Real Estate, Tannery, Textiles, Telecommunication, Travel etc.

We have chosen randomly 10% company's stock history from each sector, measure the accuracy for each company and then calculate the average of those result to find out the accuracy which has been displayed in Table 3.

Table 3: State-of-art Error Rate on Stock Data

Method Name	RMSE	MAPE	PFE
Bank Data			
ARIMA [5]	0.3845	1.85%	0.91%
PROPHET [31]	1.1839	6.91%	0.63%
TELR	1.1534	5.41%	0.46%
Overall Stock Data			
ARIMA [5]	1.5896	2.34%	1.41%
PROPHET [31]	3.3719	6.29%	1.29%
TELR	1.8558	5.42%	1.15%

We have also experienced the ARIMA and PROPHET model along with our proposed TELR on that data and achieved that result with a promising accuracy. The comparison of the state-of-art method has been published on Table 3.

The comparative result on Table 3, concludes that the proposed TELR performs better result than ARIMA and PROPHET model. Also, our another findings is the prediction of the Stock value of Banks, there our proposed method achieved with only 0.46% error rate that is almost close to the actual value.

Therefore, it can be conclude that with a most unstable and challenging stock value of Bangladeshi companies' linear trend estimation performs best compared with state-of-art methods.

V. Conclusion

A major theme of forecasting at scale is that analysts with a variety of backgrounds must make more forecasts than they can do manually. The first component of our forecasting system is the new model that we have developed over many iterations of forecasting a variety of data at Stock Bangladesh.

Work presented in this paper address the Linear Trend Estimation that expresses data as a linear function of time. This proposed model allows analysts to select the components that are relevant to their forecasting problem and easily make adjustments as needed. The second component is a system for measuring and tracking forecast accuracy, and flagging forecasts that should be checked manually to help analysts make incremental improvements.

The stock value forecast will help investors to decide buy/sell stock on the best time as well as can perceive the trend of its change. Again, this research also overcome the challenge of predicting on unstable stock data of Bangladesh in some context.

However, the prediction of high price stock value is still keeps the challenge to the researchers. Again, the trend is estimated based on the stock value only. More research on other indicators of stock market is needed which yields to more accurate result can while forecasting.

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