PREDICTION OF STOCK PRICE USING A HYBRID TECHNICAL ANALYSIS METHOD

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ABSTRACT**:** *The enhancing of financial time series prediction is one of the most challenging tasks that analysts and decision-makers come across. However, in order to achieve more accurate and reliable forecasting techniques, numerous efforts have been made. The main objective of this study is to improve the prediction accuracy of the of stock price index movement by using a new hybrid model based on the weighted moving average and the exponential moving average techniques involving all available values in the time series data set. To evaluate the proposed method, several experiments conducted on three benchmark datasets, namely, the opening of Dow Jones Industrial Average Index (DJIAI), the daily closing of S&P500 index (S&P500), and the monthly closing price of the Shenzhen Integrated Index (SZII), the experimental results indicate that the predictive capability and accuracy of our proposed method is significantly high compared to some of the well-known forecasting techniques the Autoregressive Integrated Moving Average (ARIMA), Multilayer perceptron (MLP), Hybrid model based on genetic algorithm (GAHM), Simple Average Hybrid Model (SAHM), Least squares-based Proposed Hybrid Model (LPHM), Simple Moving Average (SMA) and Simple Weighted Moving Average(WMA). And therefore, our proposed method can be used in different applications for stock prices forecasting.*

KEYWORD — Financial time series forecasting; Stock markets; forecasting methods; technical analysis**.**

1. INTRODUCTION

The prediction of stock market as well as other traded financial instruments has always been a challenging task, due to the instable and complex nature of such markets, data amount, high degree of ambiguity, noise and it is always affected by many factors [1, 2]. The Prediction of stock market represents the action that is taken in order to allow interested parties, such as investors, to have a predictable picture of the direction and fluctuation of the instrument price in the future. The precise prediction of future stock's price would pave the road for investors to make a profitable decision or avoid losses.

The motivation behind this research is to develop a new technique (based on existing ones) that can be considered a better tool to predict stock prices. This effort of developing a new technique, will firstly, take into consideration the importance of new financial data that would significantly indicate what the stock price might be for tomorrow, comparing to older data. Thus, our tool is developed to be more sensitive and responsive to new information and gives them more weight in its equation.

Secondly, our research arose because of the ambiguity, and subjectivity surrounded choosing the best time range that a predictor can consider to make a meaningful estimation. As there is no optimal specific range of time, and no consensus among analysts on what is the best number of days, months, or years from a time series, which the forecaster can pick to have a reasonable and accurate prediction. This might affect the accuracy of forecasting results and give different results (for example see Tables 1 and 2) of mean signed deviation (MSD), mean absolute deviation (MAD), mean absolute percent error (MAPE), mean percentage error (MPE), mean square error (MSE) and tracking signal (TS).

Table 1. The performance of the simple moving average (sma) using the daily close prices of visa inc. in dow jones industrial average

Period	MSD	MAD	MAPE	MPE	MSE	TS
10	-0.579	1.365	0.014	-0.005	3.226	-0.42
50	-2.372	3.084	0.031	-0.023	13.73	-0.77
100	-4.523	5.004	0.050	-0.043	34.28	-0.90
500	-12.19	12.55	0.116	-0.112	263.8	-0.97

As can be seen from Tables 1 and 2, the SMA and WMA achieved different results depending on the range of time (10, 50, 100,500 days) used, and this may lead to inaccurate stock's price prediction, and unreasonable investment decision. The accuracy of results using 50 days for example; is less than that of 10 days. Thus, the stock's price prediction and its accuracy depend on the relevance of time scale chosen, which is strongly reliant on the personal experience. Therefore, our proposed method will consider all possible and available data points that can be found in a time series dataset.

Table 2. The performance of the weighted moving average (WMA) using the daily close prices of Visa Inc. I n Dow Jones Industrial Average

Period	MSD	MAD	MAPE	MPE	MSE	TS
10	-1.65	2.37	0.03	-0.02	99.58	-0.70
50	-9.09	9.61	0.12	-0.11	585.87	-0.95
100	-18.37	18.76	0.23	-0.22	1249.26	-0.98
500	-95.43	95.43	0.99	-0.99	9434.70	-1.00

The goal of this paper is to propose and examine the validity of a simple forecasting model based on the weighted moving average (WMA) and exponential moving average techniques (EMA). This technique takes into account the whole time series, as we are convinced that we need a technical analysis method that considers all data, not a method that only takes k past data points. In addition, this new technique will give higher weights to the most recent stock's price, as it is more useful and meaningful than older price. That is because the deeper we go in a time series the more we allow for other factors to affect the stock prices, and since the prediction is based on the patterns found in a time series dataset, the most recent values account more for the near future value. Notably, the literature approves that there is no specific method or model that can 100% accurately analyze and predict complex patterns in data, not to forget as well that stock markets are influenced by numerous economic and noneconomic factors [2].

2. RELATED LITERATURE

The Efficient Market Hypothesis (EMH) [3] and the random walk theory [4] [5], were used as primary models that a large number of methods of predicting stock's market are build on. However, studies based on these models revealed that stock's price prediction cannot be predicted precisely. This argument is defeated by some empirical research, which stated that although financial market is a complicated, noisy, disordered, nonlinear and vigorous system, but it can be predicted with an accurateness exceeds 50% such as [6] [7] [8] and it does not follow random walk process [9].

Different methods are being used in order to predict the stock's trend. Generally, those prediction methods fall into three main categories the fundamental analysis, technical analysis, and technological/machine learning methods.

The technical analysis is an approach employed to forecast the direction and movement of future stocks price [10] and other traded securities, using solely the company's historical stock prices and trading volumes [11]. In technical analysis, we look at the price data patterns that gesture continuances or setbacks in stock market trend. Technical analysis encompasses numerous techniques such as the simple moving average (SMA), exponential moving average (EMA), weighted moving average (WMA), Candlestick Agent, and others. In financial field, most of traditional techniques of stock price prediction use statistical methods, which were generated from historical prices data [12]. On the other hand, the fundamental analysis approach considers the company's intrinsic values based on the analysis of the company's financial statements and economic indicators to predict future stock prices. The Machine Learning Method involves the use of different tools and approaches in predicting stock market, such as artificial neural networks (ANNs) and Genetic Algorithms (GA). Many papers investigated the usefulness of deploying Machine Learning Method, in addition to many other papers that tried to develop and find new machine learning techniques, such as [13], [14] and [15].

Nevertheless, experts expose the usefulness and applicability of technical analysis. This is most seen in financial websites and newspapers that use technical analysis in processing their financial and statistical data. Additionally, research on the profitability of technical analysis has increased during the past years. [16] conducted a review of those studies that investigated likely profits generated by technical analysis. They find that technical analysis steadily make profitable returns in variant markets, such as the stock and foreign exchange markets.

Zulkarnain [17] in his research tried to determine whether the SMA technical analyses is a useful tools to forecast the top gainers stock prices in the Indonesia Stock Exchange (IDX) during up and down trend pattern. The result stated that the variance between the predicted and actual prices is not significant.

"How rewarding is technical analysis?", this paper, which is conducted by [18] focuses on the role of technical analysis in specifying the timing of stock market entry and exit. The results indicate that the used indicators can be used to generate significantly positive return. It is found that member firms of Singapore Stock Exchange (SES) depend comprehensively on technical analysis, and this led them to enjoy significant profits.

Therefore, technical analysis seems like an ideal approach to select some features of its techniques, and try to propose a new model based on, in order to enhance the investor's prediction capability.

3. THE PROPOSED METHOD

Our proposed method is a hybrid of both of WMA and EMA, but different in the weight and in the time period used, here there is no specific period to use since the method uses all available data starting from the current value back to day 1, and it gives higher weight to the current and nearest values, this is similar to WMA but going back to day 0, however, to stress the importance of recent values we propose to assign a weight which is twice the weight of the previous value, thus the method becomes similar to EMA in terms of weighting system, in this paper the weight is empirically assigned to a specific initial weight, which is equal to 2, where this weight decreases with each previous price/value by half (Exponential decay). In other words, the current price/value is given weight equal to 2 then the day/time before is given weight 2/2, and the day before will be given 1/2 and so on. We call this method exponential decay weighted moving average (EDWMA).

If the length of the time series is very long, it is possible that the decaying weight approaches to zero; this is due to the precision of the floating point in current computers. To work around this problem, we use the minimum weight reached to be assigned to all remaining points in the time series. EDWMA is calculated as follows

$$\mathrm{EDWMA} = \frac{w_1 v_t + w_2 v_{t-1} + w_3 v_{t-2} + \cdots + w_n v_{t-n+1}}{w_1 + w_2 + w_3 + \cdots + w_n} \quad (1)$$

where $w_1 = 2, w_2 = \frac{w_1}{2}, w_3 = \frac{w_2}{2}, \ldots, w_n = \frac{w_{n-1}}{2}$,

Figure 1 shows the exponential decay of the weights used by EDWMA.

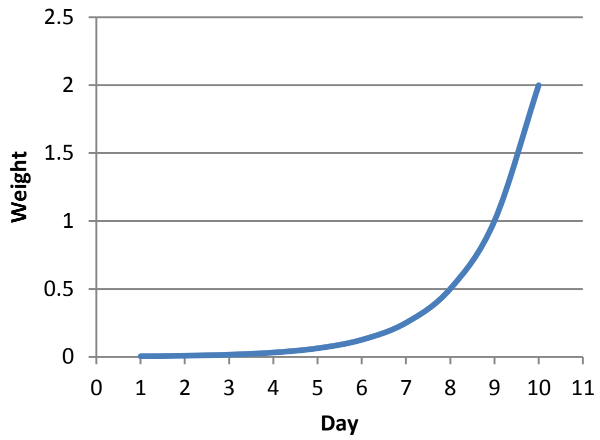

Figure 1 The decreasing curve of weights used by EDWMA to predict the value at day 11

The pseudo code of EDWMA is shown in Algorithm 1.

```
Algorithm1: predicate the value at time t+1.
Input: time series Data of length T.
Output predicted value at time T+1.
----------------------------------------------
Index=0;
SumWeight=0
Array Weights [T]=2
for  t=T-1 down to 1, do
        Weights [t] ← Weights [t+1]/2
        SumWeight← SumWeight+ Weights [t]
        If Weights [t]==0
            Index←t
            Break
If Index not = 0
    WT ←Weights [index+1]
    for  t= Index down to 1, do
        Weights [t] ← WT
        SumWeight← SumWeight+ Weights [t]

Sum=0
for each value V_t in DATA, do
    Sum ← Sum+  Weights [t] * V_t

Sum ← Sum/ SumWeight
Output Sum.
```

4. DATA AND METHODOLOGY

In order to evaluate the proposed method (EDWMA), we divided our experiments into 2 sets. The first set is based on the use of the daily close prices of Dow Jones Industrial Average (DJIA). Dow Jones Industrial Average is a price-weighted index of 30 leading component companies, such as Microsoft, Visa, Boeing, and Walt Disney. The information base of such online systems usually depends on the historical prices of a stock and/or technical indicators generated from a time-series analysis of stock prices [11,19, 20].

The dataset is collected from March 2000 to March 2016 on a daily basis, and totally has 4526 daily data points.

EDWMA was applied on those time series datasets to find the deviations between the actual and predicted values using major error indicators. Those indicators include Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), Mean Signed Deviation (MSD), Mean Error (ME), Mean Absolute Error (MAE), and Tracking Signal (TS). [21, 22]

The second set of the experiments is dedicated to test our proposed method against other major forecasting methods that found in the literature. The researcher used those reported results for comparison, those methods include (Autoregressive Integrated Moving Average (ARIMA), Multilayer perceptrons (MLP), Hybrid model based on genetic algorithm (GAHM), Simple Average Hybrid Model (SAHM), Least squares-based Proposed Hybrid Model (LPHM)) which all referred to a paper researched by [22]. In addition, Simple Moving Average (SMA), Adaptive rate smoothing, Exponential smoothing and Simple Weighted Moving Average (WMA) are used after being programmed by us.

Those prediction methods are used in this investigation whether it is classified under technical or intelligent analysis, as our research is concerned with finding a valid and efficient forecasting method, that can be compared to or compete other forecasting tools. Three benchmark datasets are used, including the opening of Dow Jones Industrial Average Index (DJIAI), which started from January 1992 to October 2016 on a monthly basis. The daily closing of S&P500 index (S&P500), the data set covers the period from 23rd October 1998 to 27th February 2008. The closing price of the Shenzhen Integrated Index (SZII), Shenzhen Integrated Index (SZII) data set covers from January 1993 to December 2010 on a monthly basis.

5. RESULTS AND DISCUSSIONS

As can be seen from Table 3, we notice the significant low deviation/error in the predicted values compared to the actual data. The prediction accuracy is very high as the error or deviation between the actual and forecasting values is very low. For instance, MAD for all components is in the range of 0.14 to 1.17 and the MSE is in the range of 0.04 to 2.78. MAPE for all components is in the range of 0.004547 to 0.010149. The reason behind these significant accuracies is due to two factors, a) all the available values in the time series contribute with different weights to the final the prediction, and b) recent values, which are given the highest weights found to affect significantly the final result. These results approved the capability of the proposed method to take a place in the current business-forecasting missions.

5.1 Comparison with other models

In this section, the predictive capability of the proposed model EDWMA is compared to the predictive capabilities of other methods such as multi-layer perceptron (MLP), (LPHM), autoregressive integrated moving average (ARIMA), genetic algorithm hybrid model (GAHM), simple average hybrid model (SAHM), simple Moving average, adaptive rate smoothing, weighted moving Average and exponential smoothing. However, for the calculation of exponential smoothing, we must select the value of smoothing factor (α). Typically, this selection can be attained by minimizing the MSE or RMSE based on in-sample experiments, "in general, it is best to pick smoothing constants that minimize the error term that a manager is most comfortable with from among MAD, MSE, and MAPE." [23]. To find the best smoothing factor (α), [24] suggested a trial-and-error approach, thus, we conducted several experiments on the daily closing of S&P500 index

(S&P500), changing α from 0.1 to 0.9 (see Figure 2) and we found that 0.9 is the best value of α.

In this section, we compare the predictive capabilities of the proposed model, using the aforementioned time series datasets. Two performance indicators, MAE and MSE, are employed to compare the forecasting performance of the proposed model to other models. Tables 4 show the overall performance of the different methods compared to EDWMA.

For the SZII and S&P 500 and DJIAI datasets, the result reveals that the forecasting error of MAE and MSE obtained by our method are significantly lower than MAE and MSE of other compared models. For example, the MAE of our proposed model is 5.62373 while the MAE of ARIMA, MLP, GAHM, SAHM, LPHM, Exponential smoothing, Simple Moving average, Adaptive rate smoothing and Weighted moving Average methods are 9.3586, 9.2365, 9.1380, 9.2217, 8.9840, 9.869273, 144.0868, 15.3838 and 1225.755 respectively. The MSE of the proposed method of S&P500 index is 56.5929 while the MSE of ARIMA, MLP, GAHM, SAHM, LPHM, Exponential smoothing, Simple Moving average, Adaptive rate smoothing and Weighted moving Average are 173.847, 159.339, 154.792, 164.484, 152.546, 180.9153, 31891.51, 406.8837 and 1535583 respectively, which is an impressive performance of the proposed model.

The results also show that our proposed method, improves the forecasting accuracy over almost all other used models, and has the smallest error comparing to the nine other methods, in both terms of MAE and MSE in all S&P500, SZII and DJIAI indexes. This shows that, our proposed method is a valid technique to predict future stocks price. It can greatly enhance the investment decision and predicting result.

Table 3. The forecasting errors of proposed model using the daily close prices of Dow Jones Industrial Average

NO	Component	MSD	MAD	MAPE	MPE	MSE	TS	RMSE
1	AXP	-0.01333	0.36881	0.008069	0.000021	0.264921	-0.03616	0.5147048
2	AAPL	-0.03838	0.325051	0.010149	-0.00044	0.333923	-0.11807	0.5778607
3	CAT	-0.03035	0.501605	0.008371	-0.00027	0.517089	-0.06051	0.719089
4	CACO	0.005266	0.222368	0.009102	0.000377	0.15351	0.02368	0.3918035
5	CVX	-0.01673	0.482286	0.006337	-0.00012	0.468744	-0.03469	0.6846488
6	KO	-0.00488	0.146164	0.004982	-0.000073	0.042598	-0.03338	0.2063928
7	DWDP	-0.00821	0.301187	0.00865	0.000074	0.166311	-0.02727	0.4078125
8	XOM	-0.00813	0.386064	0.005778	-0.000052	0.302837	-0.02105	0.5503063
9	GE	0.006463	0.196748	0.0072	0.000421	0.091412	0.032849	0.3023442
10	IBM	-0.01116	0.754059	0.006235	0.000042	1.176733	-0.0148	1.0847732
11	INTC	0.002387	0.24955	0.009135	0.000304	0.170462	0.009564	0.4128704
12	JNJ	-0.02143	0.313818	0.004547	-0.00023	0.19911	-0.0683	0.4462174
13	JPM	-0.01368	0.370757	0.008735	0.000112	0.287984	-0.0369	0.5366414
14	MCD	-0.02689	0.323908	0.005741	-0.00024	0.221243	-0.08303	0.4703648
15	MRK	0.000712	0.314713	0.006653	0.000161	0.224053	0.002264	0.4733424
16	MSFT	-0.01011	0.236432	0.007255	0.000030	0.127763	-0.04276	0.3574395
17	MMM	-0.04381	0.494744	0.00557	-0.0003	0.508099	-0.08856	0.7128106
18	NKE	-0.01368	0.142739	0.007051	-0.00047	0.059285	-0.09585	0.2434851
19	PFE	-0.00032	0.175514	0.006177	0.000104	0.066629	-0.00184	0.2581259
20	BA	-0.07038	0.591219	0.007666	-0.00034	0.827762	-0.11905	0.9098143
21	HD	-0.02784	0.382765	0.007589	-0.000073	0.335651	-0.07274	0.579354
22	PG	-0.01125	0.269447	0.004615	-0.00016	0.141509	-0.04176	0.3761768
23	TRV	-0.02603	0.358921	0.00651	-0.00025	0.267654	-0.07253	0.5173529
24	DIS	-0.01533	0.290449	0.007208	-0.000074	0.189283	-0.05276	0.4350667
25	UNH	-0.04845	0.373114	0.007544	-0.0006	0.351698	-0.12986	0.5930413
26	UTX	-0.02382	0.398683	0.006336	-0.00024	0.310797	-0.05974	0.5574917
27	V	-0.04369	0.26543	0.00697	-0.00072	0.154906	-0.1646	0.393581
28	VZ	0.000892	0.236928	0.00614	0.000133	0.11196	0.003764	0.3346042
29	WMT	-0.0088	0.325283	0.005612	-0.000033	0.222604	-0.02704	0.4718093
30	GS	-0.03445	1.167048	0.008819	0.000064	2.778573	-0.02952	1.6669052

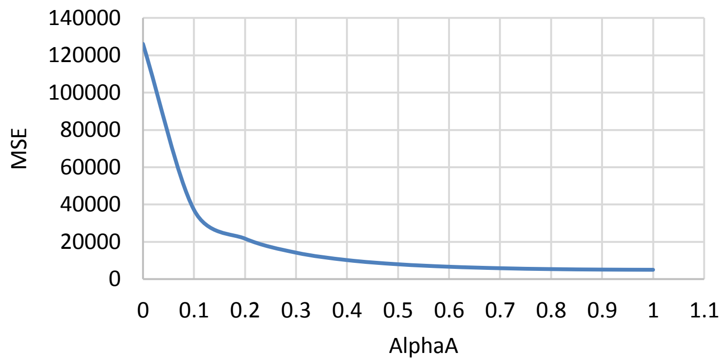

Figure 2. The minimum of MSE occurs at α = 0.9

Table 4. The comparison of EDWMA with other nine methods

Stock indexes	Methods	MAE	MSE
DJIAI	ARIMA	369.84	239,015
	MLP	366.80	221,930
	Hybrid model based on genetic algorithm (GAHM)	350.45	205,431
	Simple Average Hybrid Model (SAHM)	353.26	205,760
	Least squares-based Proposed Hybrid Model (LPHM)	344.99	203,208
	Exponential smoothing	282.6379	152886
	Simple Moving average. 240 monthly data points	2602.54	9681403
	Adaptive rate smoothing	401.8567	358289.4
	Weighted moving Average. 240 monthly data points	8314.89	79076502
	EDWMA	**165.8669**	**52322.51**
S&P500	ARIMA	9.3586	173.847
	MLP	9.2365	159.339
	Hybrid model based on genetic algorithm (GAHM)	9.1380	154.792
	Simple Average Hybrid Model (SAHM)	9.2217	164.484
	Least squares-based Proposed Hybrid Model (LPHM)	8.9840	152.546
	Exponential smoothing	9.869273	180.9153
	Simple Moving average. 2349 daily data points	144.0868	31891.51
	Adaptive rate smoothing	15.3838	406.8837
	Weighted moving Average. 2349 daily data points	1225.755	1535583
	EDWMA	**5.62373**	**56.5929**
SZII	ARIMA	1,166.17	2,221,776
	MLP	1,102.33	1,974,479
	Hybrid model based on genetic algorithm (GAHM)	1,092.06	1,952,713
	Simple Average Hybrid Model (SAHM)	1,123.87	1,997,323
	Least squares-based Proposed Hybrid Model (LPHM)	1,074.87	1,928,479
	Exponential smoothing	282.6379	152886
	Simple Moving average. 216 monthly data points	188.0951	92280.21
	Adaptive rate smoothing. 216 monthly data points	401.8567	358289.4
	Weighted moving Average. 216 monthly data points	572.3942	422793
	EDWMA	**28.57867**	**1997.737**

6. CONCLUSION

Based on two notes, the participation of all values of time series in the forecasting task, and the higher effect of the nearest values; we propose a new forecasting technique to enhance the forecasting performance, particularly for stock prices forecasting.

The experimental results of the predictive capabilities of the proposed model compared to other common forecasting techniques show the significant performance of the proposed method. Empirical results of three well-known benchmark data sets of stock markets indicate that the proposed model is a functional and efficient model, and can be used as an effective forecasting tool for stock prices and might be effective for general time series prediction. However, such generalization needs more experiments, and this will be the main objective of our future works, which will consider examining this method on different time series data from different fields.

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