Forecasting of Stock Prices Using Brownian Motion – Monte Carlo Simulation

Rene D. Estember, Michael John R. Maraña
School of Industrial Engineering and Engineering Management
Mapua Institute of Technology
Manila City, Philippines
rdestember@mapua.edu.ph/mjrmarana@live.com

Abstract — This research examined the potential of the Geometric Brownian Motion (GBM) method as an accurate and effective forecasting method compared to the Artificial Neural Network (ANN) method. The number of days the volatility and drift are moved were also determined and this was used to perform the forecast of stock prices of holding companies registered with the Philippine Stock Exchange and also compared to the ANN method. The results showed that the average perentage error of the GBM method was 6.21% or an accuracy of 93.79% while the ANN method generated an average percentage error of 8.83% for the three-year period or an accuracy of 91.17%. This manifests that using the GBM method in forecasting stock prices of these sample holding companies yielded a better accuracy than that of using the ANN method. Hence, it also indicates that the GBM method is more effective than the ANN method in forecasting stock prices of these sample holding companies. This further boosts the potential of the GBM method as a good forecasting method in determining future stock prices of holding companies. In addition to this, the GBM method provides potential investors to determine which investment activities to pursue.

Keywords— accuracy and effectiveness of forecast, artificial neural network, geometric Brownian motion, holding companies, Monte Carlo simulation.

I. INTRODUCTION

Stock is considered as equity, shares, or securities of a company. It gives its holder a claim in the part of a company's assets and earnings. In the Philippines, investors buy stocks from stock brokers accredited by the Philippine Stocks Exchange, Inc. (PSE) who expect great financial return. There are two common ways on how an investor or stockholder can earn money from stocks. One way is by receiving dividends from profit generated by the company. The more shares an investor holds the more the dividends the investor will receive. Another way is by selling the purchased stock when its value increased.

Investors can perhaps be referred to as the lifeblood of the stock market, supporting the success of its counterparts – capital raising activities for listed firms, and the trading of shares for trading participants. The PSE, through its Stock Market Investor Profile (SMIP) report, only began tracking the number of investor accounts and the profile of these investors in 2008. The results every year have shown that, while investors have been growing, the overall investor base of 525,850 investor accounts has not reached a level that would indicate a widespread participation in the local market. This total barely accounts for half a percent of the estimated 100 million - Filipino population, and may indicate that stock market investment continues to be limited to those which have a high level of disposable income and educational background to understand how the market works.

But while the five-year compound annual growth rate (CAGR) of investor accounts has only been at 4 percent, a new class of investors has been emerging due to rapid technological advancements. Online investors, which have recorded an astounding CAGR of 42 percent in the past five years, already account for 14.9 percent of the total investor accounts base – a 10 percent jump from only 4.3 percent in 2008 [1].

The stock market is a platform for investors to own some shares of a company. Investors will become a part of the company members and share in both profits and losses of that company [2]. This is the opportunity for the investors to generate extra income apart from their daily jobs. However, if investors lack enough information and knowledge, it may cause some certain loss of their investment. If stock price could be predicted more accurately, the society's resource can be allocated to a right place that avoids wasting national resource so stock market will expand healthy and people will invest more confidently to avoid blind investment behaviors [3].

Stock market forecasters focus on developing a successful approach for forecasting/predicting index values or stock prices ultimately aiming at earn high profit using well-defined trading strategies. The vital idea to successful stock market prediction is achieving best results and also minimizing the inaccurate forecast of the stock price [4]. According to [5], prediction of stock prices has long been an intriguing topic and is extensively studied by researchers from different fields. Machine learning, a well-established algorithm in a wide range of applications, has been extensively studied for its potentials in prediction of financial markets.

Reference [6] discussed the Artificial Neural Networks (ANN) to predict stock market indices. ANNs have been successfully applied for prediction in the fields related to medicine, engineering and physics. The method has been suggested for modeling include financial and economic forecasting, security price movement, business default and bankruptcy prediction, mortgage risk assessment, predicting investor's behavior, and others to mention [7]. Other methods were also used to forecast stock prices such as decision tree [3], ARIMA [8], and Geometric Brownian motion [2], [9], and [10].

As discussed by [2], a Geometric Brownian Motion (GBM) model is a continuous-time stochastic process in which the logarithm of the randomly varying quantity follows a Brownian motion also known as Wiener process [10]. GBM is important in the modeling financial process mathematically. It is the derivative of continuous model from discrete model that can be used to predict the movement of the stock prices in the short term period. Furthermore, the pattern of the stock market's prices is unpredictable and follows the random walk where random walk model in the GBM is outperforming other methods [11].

Thus, in this study, GBM is used as the method to forecast the future closing prices of selected holding companies registered under the Philippines Stock Exchange. The Brownian motion equation involves a constant volatility and drift, however, volatility and drift are not constant in real world scenarios. Furthermore, this study attempts to improve the Brownian motion process by simulating number of days the volatility and drift is moved. The optimal number of days the variables are moved is then used to compare the GBM and ANN methods in terms of their accuracy and effectiveness.

This research paper is organized into four more sections as follows: Section 2 discusses the methodology, Section 3 presents the results, and Section 4 discusses the conclusion.

II. METHODOLOGY

A. Data Gathering Procedure

The stock prices (open, high, low, and close) of the holding company members of the Philippine Stock Exchange are used to gather the data. Six holding companies are chosen from among the fourteen holding companies registered from the Philippine Stock Exchange. Two companies (MPI and DMC) come from the top two holding companies according to their number of shares, two (JGS and AEV) samples are taken from the middle rank, and two (AC and GTCAP) from the lowest rank of holding companies. The annual volatility and the annual drift or rates of return are computed using the twelve months historical data from the sample companies.

The GBM and ANN methods are used to forecast stock prices of these selected holding companies using the Monte Carlo simulation in the EXCEL software to determine their accuracy and effectiveness.

For the GBM method, the procedures are the following:

1) The data are tested for normality using the computer software, Stat Fit.

2) The daily drift, daily volatility, and the average drift are determined using the formula shown below:

$$\text{Daily Rate of Return} = \frac{\text{Annual Rate of Return}}{\text{No. of trading days in a year}} \tag{1}$$

$$\text{Daily Volatility} = \frac{\text{Annual Volatility}}{\sqrt{\text{No.of trading days in a year}}} \tag{2}$$

$$\text{Average Drift} = \text{Daily Rate of Return} - 0.5 \text{ x Daily Volatility}^2 \tag{3}$$

3) The value of the random number generated from probability distribution, ε, is determined using the EXCEL function of NORM.S.INV(RAND()). This function gives a random number from the normal distribution table.

4) Once all variables are known, the future stock value is determined using the Geometric Brownian motion formula as shown below:

$$S(t) = S(o)e^{\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma\varepsilon(t)} \tag{4}$$

Where:

S(t) = future stock value

S(0) = initial stock value

μ = daily drift

σ = daily volatility

ε = value from probability distribution

5) The simulation process starts using the Microsoft EXCEL.

On the other hand, the procedures for the ANN method are the following:

1) The Microsoft Excel Add In, "NeuroXL Predictor" is used to perform an artificial neural network forecast. Neuro XL Predictor is a neural network-forecasting tool that quickly and accurately solves forecasting and estimation problems in Microsoft Excel. It is designed from the ground-up to aid experts in solving real-world forecasting problems. The Neuro XL Predictor interface is easy-to use and intuitive, does not require any prior knowledge of neural networks, and is integrated seamlessly with Microsoft Excel.

2) The open, high, low, and close price of sample are used as inputs because the more numerical data are used for training the neural network, the more accurate and reliable prediction can be. .

B. Volatility and Drift Determination

The Brownian motion equation involves a constant volatility and drift, however, volatility and drift are not constant in real world scenarios. In this regard, before the simulation process is undertaken for both methods, the optimal volatility and drift (rate of return of stocks) is determined to improve the Brownian motion process by simulating number of days the volatility and drift is moved. The optimal number of days the variables are moved is then used in the forecast to compare the GBM and ANN methods in terms of their accuracy and effectiveness.

C. Mean Absolute Percent Error

In order to predict the accuracy of the forecast of the two models based on a two-year historical data of the sample holding companies, the mean absolute percent error (MAPE) is used to measure the size of the error in percentage. This is also used to determine the optimal number of days the volatility and drift is moved. The formula is as follows:

$$\text{MAPE} = \left(\frac{1}{n}\sum\frac{|\text{Actual}-\text{Forecast}|}{|\text{Actual}|}\right) \text{X}100\% \qquad (5)$$

D. Statistical Test

The t- test is used to determine significance between two means. The formula is shown below:

$$t_0 = \frac{y-\mu_0}{s/\sqrt{n}} \qquad (6)$$

III. RESULTS

There are fourteen (14) holding companies registered in the Philippine Stock Exchange of which six of them were considered in this study. Two of these sample holding companies (MPI and DMC) come from the top two holding companies according to their number of shares, two (JGS and AEV) samples are taken from the middle rank, and two (AC and GTCAP) from the lowest rank of holding companies as shown in in Table 1.

TABLE I. SAMPLE HOLDING COMPANIES REGISTERED IN THE PHILIPPINE STOCK EXCHANGE

Security Name	Ticker Symbol
Ayala Corporation	AC
Aboitiz Equity Ventures Inc.	AEV
DMCI Holdings, Inc.	DMC
GT Capital Holdings, Inc.	GTCAP
JG Summit Holdings, Inc.	JGS
Metro Pacific Investments Corporation	MPI

Source: Philippine Stock Exchange

In this research, an experiment was conducted of moving the constant volatility and drift of the Brownian motion model to a periodic period of 5, 10, 15, 20, and 25-day basis based on the actual data of these sample holding companies. Table 2 shows the statistics of the experiment.

TABLE II. GEOMETRIC BROWNIAN MOTION IMPROVEMENT STATISTICS

Number of Days Volatility and Drift Moved	Average Percentage Error	Standard Deviation of the Error
Normal (Constant Volatility and Drift)	10.70	0.05935
5-Day Moving Variables	10.51	0.44532
10 -Day Moving Variables	8.37	0.05173
15-Day Moving Variables	9.48	0.05435
20-Day Moving Variables	11.50	0.06965
25-Day Moving Variables	15.78	0.07328

As presented in Table 2, the number of days volatility and drift are moved to either 5, 10, 15, 20, or 25-day period was computed. The results showed that a 10-day volatility and drift showed a lower average percentage error of 8.3% using the mean absolute percentage error (MAPE). Furthermore, the standard deviation of the error of 0.051728 was the lowest at 10-day volatility and drift are moved. This means that the lower the standard deviation, the better is the accuracy. Thus, the 10-day moving volatility and drift was used to forecast the stock prices using the Geometric Brownian motion (GBM) and compared to the Artificial Neural Network (ANN) method.

Based on this, a computed sample forecast of stock prices of AEV, one of the sample holding companies, is presented in Table 3. A one-week actual data were used to forecast the stock prices and compare the performance of the GBM and ANN. Using the MAPE, the average percentage error of GBM was 1.58% while the ANN's average percentage error was 4.89%. It indicated that the GBM's accuracy in terms of forecasting short-term period was much bettet than that of the ANN method. Furthemore, the range of error of the GBM showed a minimal fluctuation ranging from 0.09% to 3.82%. However, the ANN method's error ranges from 1.05% to 9.54% which indicate a higher range of error. This was evidenced by a lower standard deviation of the error (%) of GBM method compared to ANN method which is 12.22 and 34.53, respectively.

As a result of this computation, GBM method showed a better accuracy and effectiveness compared to ANN method on a short-term period.

TABLE III. SAMPLE ACTUAL AND FORECAST STOCK PRICES OF AEV USING GBM AND ANN METHODS

Date	Actual Stock Price (PhP)	Forecast Stock Price (PhP)		Percentage Error	
		GBM Method	ANN Method	GBM Method	ANN Method
Oct 29, 2013	601.50	604.3172	607.8357	0.47	1.05
Oct 30, 2013	601.50	608.2000	620.6611	1.11	3.19
Oct 31, 2013	603.00	579.9872	624.7586	3.82	3.61
Nov 4, 2013	599.5	590.6060	623.0708	1.48	3.93
Nov 5, 2013	597.00	585.9534	622.3937	1.85	4.25
Nov 6, 2013	589.50	590.0566	628.5628	0.09	6.63
Nov 7, 2013	578.00	591.5019	633.1355	2.34	9.54
Nov 8, 2013	592.50	601.3716	633.7067	1.50	6.95
Average Percentage Error				**1.58**	**4.89**
Standard Deviation of the Percentage Error				**12.22**	**34.53**

On the other hand, Table 4 shows the standard deviation of the percentage error based on the actual data of the sample holding commpanies in forecasting their stock prices using the GBM method and ANN method.

TABLE IV. STANDARD DEVIATION OF THE PERCENTAGE ERROR OF SAMPLE HOLDING COMPANIES USING GBM AND ANN METHODS

Company	Standard Deviation of the Percentage Error	
	GBM Method	ANN Method
1. MPI	0.34	0.12
2. DMC	3.19	3.07
3. JGS	5.83	7.89
4. AEV	3.74	3.44
5. AC	0.83	1.72
6. GTCAP	7.89	5.26
Average Standard Deviation	**3.64**	**3.58**
p - value (2 – tail)	**0.9363**	

For long run forecasting, GBM method also showed comparable standard deviation of error (JGS and AC), although at a little higher value, compared to the ANN method in forecasting some stock prices (MPI, DMC, AEV, and GTCAP) of selected holding companies as shown in Table 4. The average standard deviation of the error of GBM was 3.6 which was a little bit higher compared to the standard deviation of error of the ANN method. However, the results showed no significant difference as indicated by the p-value of 0.9363 when these values are subjected to a t-test.

This means that the ability of the GBM to forecast long term stock prices of the six sample holding companies is comparable with the ANN method. Hence, GBM has a potential to forecast stock prices comparable to the ANN method.

Furthermore, the forecast on the stock prices of the actual data of the sample holding compannies was calculated using the GBM and ANN methods for the three-year period and the average percentage error per year was computed as shown in Table 5. The average perentage error of the GBM method was 6.21% or an accuracy of 93.79% while the ANN method generated an average percentage error of 8.83% for the three-year period or an accuracy of 91.17%. This manifests that using the GBM method in forecasting stock prices of these sample holding companies yielded a better accuracy than that of using the ANN method. Hence, it also indicates that the GBM method is more effective than the ANN method in forecasting stock prices of these sample holding companies. This further boosts the potential of the GBM method as a good forecasting method in determining future stock prices of holding companies

The three-year forecast average percentage error between GBM and ANN methods indicates that there is a significant difference between them as shown by the p-value of 0.00204 using the t-test. This signifies that the GBM method showed a better accuracy and effectiveness compared to the ANN method in foreasting the stock prices of the sample holding companies..

TABLE V. AVERAGE THREE-YEAR FORECAST AVERAGE PERCENTAGE ERROR OF GBM AND ANN METHODS

Forecast Year	Average Percentage Error	
	GBM Method	ANN Method
1st Year	6.42	7.97
2nd Year	7.54	9.23
3rd Year	6.21	9.29
Average	**6.72**	**8.83**
p - value (2-tail)	**0.0204**	

Considering the performance of the forecast of the stock prices of the six sample holding companies for the two-year period, the GBM method showed significant difference from the ANN method on majority of the holding companies as shown in Table 6.

TABLE VI. STATISTICAL TEST ON THE FORECAST OF STOCK PRICES OF SAMPLE HOLDING COMPANIES USING GBM AND ANN METHODS

Company	**Year 1**		**Year 2**	
	p-value (2-tail)	**Interpretation**	**p-value (2-tail)**	**Interpretation**
AC	0.5384	Not Significant	5.93E-52	Significant
AEV	2.89E-09	Significant	5.52E-07	Significant
DMC	6.82E-69	Significant	1.52E-11	Significant
JGS	2.16E-09	Significant	0.01169	Significant
MPI	0.16176	Not Significant	0.02608	Significant
GTCAP	3.34E-58	Significant	0.00054	Significant

.

This showed that the GBM method is significantly different from the ANN method, meaning, the forecast of the GBM method of forecasting stock prices has the potential of almost nearing to the actual data. It was evident that the GBM method showed a small average percentage error compared to ANN method.

After analyzing GBM method as a potential method to forecast stock prices, the actual data of the sample holding companies were used to forecast the market prices of stock for the succeeding six-month period. This covered the period of October 2014 to Apri 2015 as shown in Table 7.

After analyzing GBM method as a potential method to forecast stock prices, the actual data of the sample holding companies were used to forecast the market prices of stock for the succeeding six-month period. This covered the period of October 2014 to Apri 2015 as shown in Table 7.

Four sample holding companies have standard deviation of the forecast stock prices below 10 while two sample holding companies have a standard deviation of more than 10.

TABLE VII. FORECAST OF STOCK PRICES OF THE SAMPLE HOLDING COMPANIES USING GBM METHOD

Date	**MPI**	**DMC**	**JGS**	**AEV**	**AC**	**GTCAP**
October 2014	4.574	16.010	58.286	56.954	692.218	1018.964
November 2014	4.482	12.189	56.812	62.008	711.486	1062.860
December 2014	4.539	9.597	54.488	66.725	724.518	1098.356
January 2015	4.350	7.630	57.415	68.197	778.954	1105.013
February 2015	4.582	4.723	60.745	66.569	799.549	1108.346
March 2015	4.924	6.065	66.912	62.472	873.824	1068.749
April 2015	5.339	9.289	70.893	59.305	969.654	1032.668
Average Stock Price	**4.686**	**8.531**	**61.034**	**63.938**	**802.688**	**1077.201**
Standard Deviation	**0.343**	**3.194**	**5.831**	**3.742**	**89.420**	**40.518**

Fig. 1 shows the stock price forecast graph of holding companies using the GBM method.

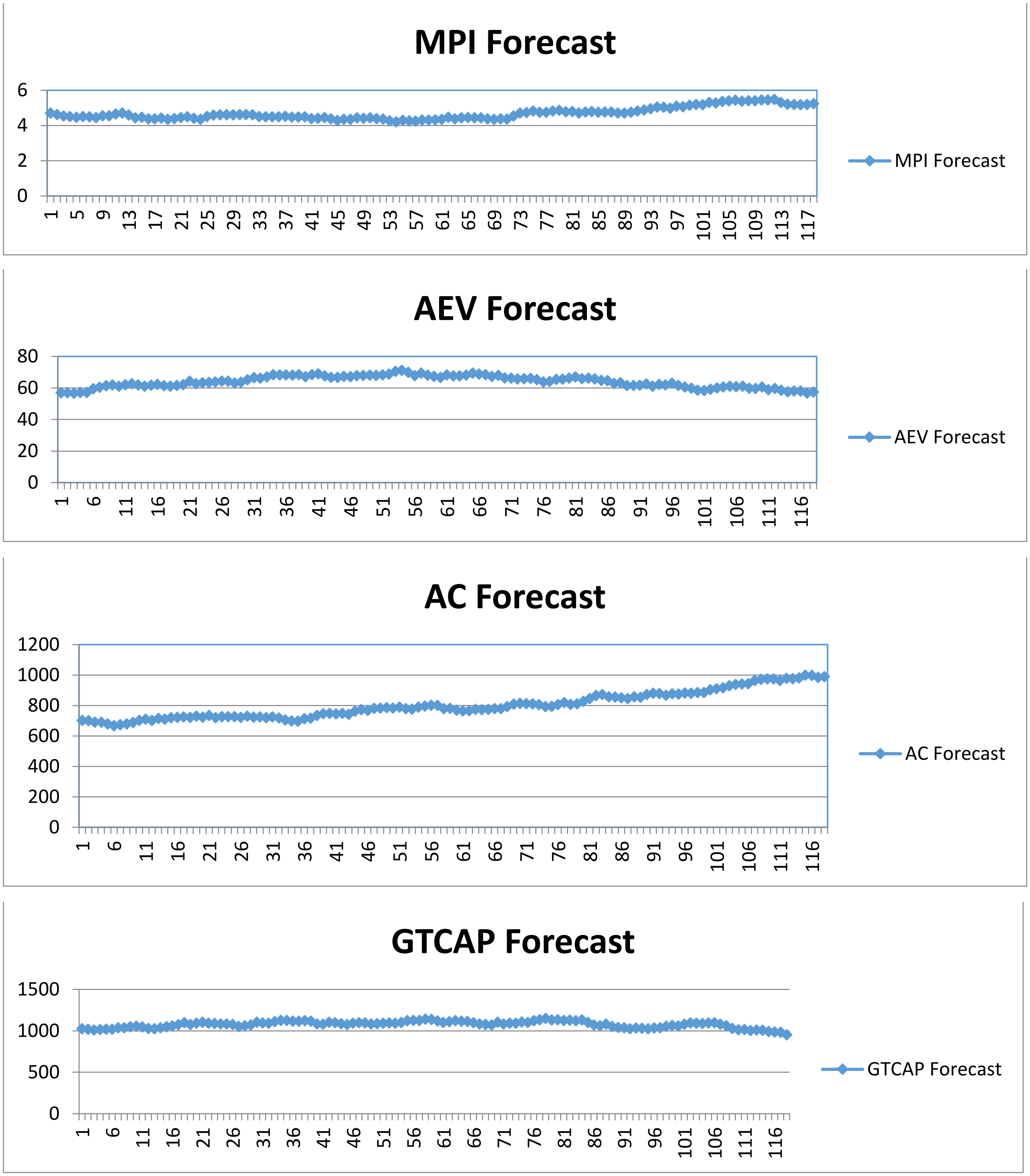
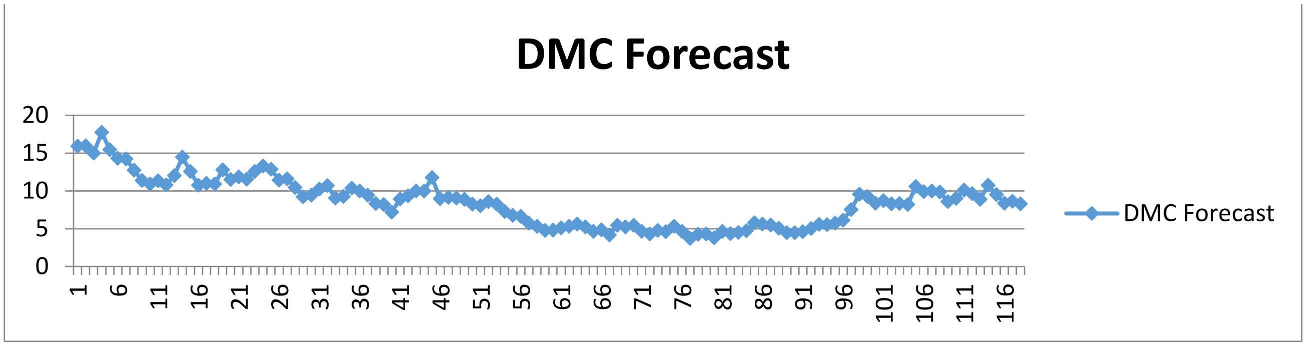


Fig. 1. Examples of stock price forecast graphs of MPI, AEV, AC and GTCAP Holding Companies

Fig. 2 shows othe stock price forecast graphs for DMC and JGS holding companies.



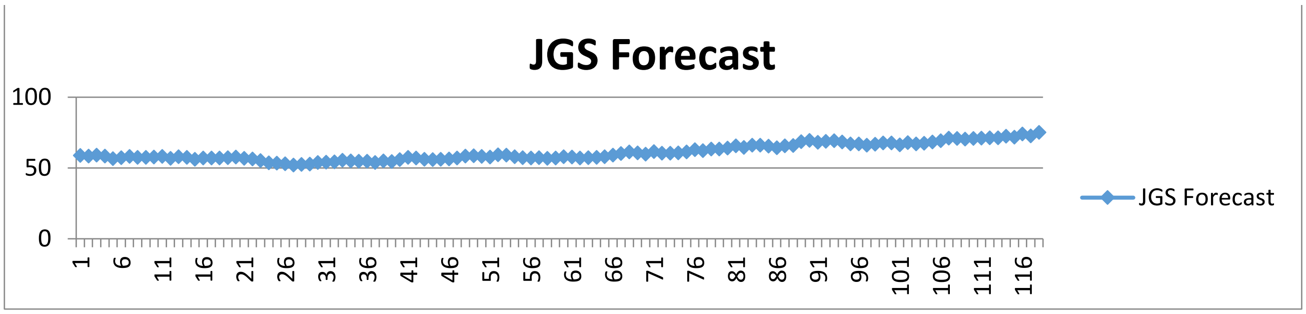


Fig. 2. Examples of stock price forecast graphs of DMC and JGS Holding Companies

From the forecast of the stock prices of the sample holding companies, some financial forecast summary of the six holding companies was determined to assist prospective investors in deciding which holding companies to invest in. These financial indicators were presented in Table 8.

Based on Table 8 and Fig. 1 and Fig. 2, the companies in the holding firms index that can yield a significant potential capital gain for investors in a six month period are AC that yielded a return on investment of 33.23%, average daily rate of return of 0.03%, and volatility of 1.14% and JGS which yielded an average of 30.59% return on investment, 0.02% rate of return, and 1.52% volatility rate for six months.

On the other hand, MPI has also potential opportunities for investors. It has a 22.95% return on investment, 0.0008% average rate of return, and 1.38% volatility rate for six months. In addition, AEV also manifested a good potential of 20.47% return on investment, 0.03% average rate of return, and 1.46% volatility rate for six months. Moreover, GTCAP has a maximum return on investment of 17.203%, 0.0007% average rate of return and 1.27% volatility rate. On the other hand, DMC has a downward trend in its line graph which can be said as a not so good choice to invest since it has a -79.23% return on investment, -0.00005% average daily rate of return, and 10.60% volatility rate.

TABLE VIII. FINANCIAL FORECAST SUMMARY USING GBM METHOD

Category	MPI	DMC	JGS	AEV	AC	GTCAP
Max Return on Investment (%)	22.95	-79.23	30.59	20.47	33.23	17.20
Ave. Daily Rate of Return (%)	0.0008	-0.00005	0.02	0.03	0.03	0.0007
Volatility	1.38	10.60	1.52	1.46	1.14	1.27

IV. CONCLUSION

The following are the generalizations derived from the results of the study.

1) Based on the actual stock prices of the sample holding companies, the optimal number of days the volatility and drift are moved was 10 days since this has the smallest average percentage error and the lowest standard deviation. This was used to improve the Geometric Brownian Motion method in forecasting the stock prices of these holding companies. Furthermore, the volatility and drift of 10 days were also used to forecast the stock prices using the ANN method.

2) GBM method showed a good potential for forecasting stock prices at a short-term period since it showed a smaller average percentage error compared to the ANN method. This indicates that the GBM's accuracy in terms of forecasting short-term period was much better than that of the ANN method. Furthermore, the GBM method showed a lower standard deviation indicating the accuracy and effectiveness as a forecasting technique.

3) Analyzing the stock prices of the individual holding company for long-run forecasting, the GBM method showed comparable standard deviation of error, although at a little higher value, compared to the ANN method. However, the results showed no significant difference as indicated by the p-value of 0.9363 when these values are subjected to a t-test. This also signifies that the ability of the GBM method to forecast long-term stock prices of the six holding companies is comparable with the ANN method.

4) The forecast on the stock prices of the sample holding compannies using the GBM and ANN methods for the three-year period showed that the average perentage error of the GBM method was 6.21% or an accuracy of 93.79% while the ANN method generated an average percentage error of 8.83% for the three-year period or an accuracy of 91.17%. This manifests that using the GBM method in forecasting stock prices of these sample holding companies yielded a better accuracy than that of using the ANN method. This can be construed that the GBM method is more effective than the ANN method in forecasting stock prices of these sample holding companies. This further boosts the potential of the GBM method as a good forecasting method in determining future stock prices of holding companies as evidenced by having significant difference between the two forecasting methods. Thus, this signifies that the GBM method showed a better accuracy and effectiveness compared to the ANN method in foreasting the stock prices of the sample holding companies.

5) Considering the performance of the forecast of the stock prices of the six sample holding companies for the two-year period, the GBM method showed significant difference from the ANN method on majority of the holding companies. This showed that the GBM method is significantly different from the ANN method, meaning, the forecast of the GBM method of forecasting stock prices has the potential of almost nearing to the actual data. It was evident that the GBM method showed a small average percentage error compared to ANN method.

6) The GBM method provides a good forecasting method since four out of six sample holding companies when their actual data were used to forecast their stock prices have standard deviation below 10.

7) The GBM method provides a good decision tool for investors since it can provide an accurate and effective approximation of financial returns to them.

REFERENCES

[1] Regina Georgia R. Crisostomo, Sarah L. Padilla, Mark Frederick V. Visda, " Philippine stock market in perspective," 12th National Convention on Statistics, 2013, unpublished.

[2] Siti Nazifah Zainol Abidin and Maheran Mohd Jaffar, "Forecasting share prices of small size companies in Bursa Malaysia using Geometric Brownian Motion," Applied Mathematics Information Sciences, vol. 8, No. 1, pp. 107-112, January 2014.

[3] C.F. Tsai, and S.P. Wang, "Stock Price Forecasting by Hybrid Machine Learning Techniques," Proceedings of the International Multi Conference of Engineers and Computer Scientists 2009, Vol. I, IMECS 2009, March 18 - 20, 2009, Hong Kong.

[4] G. Preethi, and B. Santhi, "Stock market forecasting techniques: a survey," Journal of Theoretical and Applied Information Technology, Vol. 46, No.1, 15th December 2012.

[5] Shunrong Shen, Haomiao Jiang, and Tongda Zhang, "Stock market forecasting using machine learning algorithms," available at: http://cs229.stanford.edu/proj2012/ShenJiangZhang-StockMarketForecastingusingMachineLearningAlgorithms.pdf

[6] A. Kar, "Stock Prediction using Artificial Neural Networks," avaliable at: http://www.cs.berkeley.edu/~akar/IITK_website/EE671/report_stock.pdf

[7] S. C. Nayak, B. B. Misra and H. S. Behera, "Impact of Data Normalization on Stock Index Forecasting," International Journal of Computer Information Systems and Industrial Management Applications. ISSN 2150-7988 Volume 6 (2014) pp. 257 – 269.

[8] Ayodele Ariyo Adebiyi, Aderemi Oluyinka Adewumi, and Charles Korede Ayo, "Comparison of ARIMA and Artificial Neural Networks Models for Stock Price Prediction," Journal of Applied Mathematics, Volume 2014 (2014), Article ID 614342, 7 pages. http://dx.doi.org/10.1155/2014/614342

[9] G. S. Laddle, and L. Wu, "Development of modified geometric Brownian motion models by using stock price data and basic statistics, Nonlinear Analysis: Theory Methods & Applications," 71, 1203-1208 (2009).

[10] P. Wilmott, "Quantitative Finance," John Wiley & Son, Ltd, Chichester, (2000).

[11] E. Fama, "Random walks in stock market prices," Financial Analysis Journal, **51**, 1-6 (1965).

BIOGRAPHY

Rene D. Estember is a Professor in the School of Industrial Engineering and Engineering Management at the Mapua Institute of Technology in Manila City, Philippines. He earned his B.S. in Management and Industrial Engineering from Mapua Institute of Technology, Master in Business Administration from Ateneo de Manila University, Master of Science in Industrial Engineering from the University of the Philippines, and finishing his Doctorate in Business Administration from the Pamantasan ng Lungsod ng Maynila (PLM), all located in the Philippines. He is presently undertaking consultancy work on quality management systems documentation and also involved as a regular resource speaker of a training company conducting technical trainings. He is a Professional Industrial Engineer. He is a regular participant of the Industrial Engineering and Operations Management (IEOM) research conference and an awardee of the Best Track Paper in Human Factors and Ergonomics during the IEOM 2015 research conference in Dubai, United Arab Emirates. His research interests include human factors and ergonomics, simulation and modeling, risk management, and optimization.

John R. Maraña is a graduate of B.S. in Industrial Engineering at the Mapua Institute of Technology in Manila City, Philippines.