

Application of Markov Process for Prediction of Stock Market Performance

Lakshmi G, Jyothi Manoj

Abstract: Prediction of stock market performance is a challenging problem. There are numerous methods which are tried by various researchers in this regard. The memoryless property of Markov process seems to be more relevant when stock market prices are analysed for futuristic prediction. It is a stochastic process where the future probabilities are determined by the immediate present and not past values. This is suitable for the random nature of stock market fluctuations. The present study adopts this property to compare the performance of five prominent stocks in Oil and Gas Sector in India. The analysis is carried out based on past three years data of 5 prominent stocks in Oil and gas sector. The findings suggest that Bharat Petroleum, Reliance and Hindustan Petroleum are having high probability of increase in its value while Indian Oil corporation (IOC) and Oil India exhibits a higher chance of being stable with no significant increase or decrease.

Key words: Markov Chain, Memoryless property, Steady State probability, State transition probability, Stock performance

I. INTRODUCTION

One of the six core industries in India which contributes significantly to the growth of Indian economy is Oil and Gas sector. The Natural Gas and Petroleum sector, which is inclusive of refining, transportation, and marketing of these products, contributes about 15% to India's GDP [1]. The Indian stock market prices are highly volatile. They are largely affected by a host of macroeconomic factors like oil prices, exchange value of dollar, political scenario and worsening government finances. The impact of these events in Oil and Gas sector is even more and so is the returns on investment in this sector is comparatively high. Hence it is worth to do a comparison of the prominent stocks in this sector. In the present study Markov chain modelling is adopted for the comparison since the performance of the stock market is assumed to depend on immediate past or short history. In the present study closing price of five major stock holders in the Oil and Gas sector is analysed to find which among them has better futuristic features. The findings of this analysis using a simple but powerful tool will aid investors to find the prospects of the five stocks based on past performance.

II. REVIEW OF LITERATURE

Optimal prediction for the stock indices and returns continues to be a challenge due to the randomness in the values.

Revised Manuscript Received on February 22, 2020.

Lakshmi G, Student, Department of Mathematics, Amrita School of Arts and Science, Amrita Viswa Vidyapeetham, Amritapuri, Kollam, India, 690525

Jyothi Manoj, Associate Professor, Department of Statistics, Kristu Jayanti College (Autonomous), Bengaluru, India 560077

Most of the studies adopt time series modelling for estimation. But analysis using Markov process is comparatively less. Yudong and Lenan(2009) suggests a non-linear, non-parametric, convoluted and essentially dynamic nature for stock prices. Zhang and Zhang (2009) investigated the assignment of foreseeing stock prices by the method of Markov model. They established a Markov chain stochastic model for forecasting the stock market trends in the Chinese stock market. Their study divulged that the Markov process lack after-effect property and Markov model has far-flung implementation in the prediction of stock market prices. Norris (1998) researched the conduct of discrete-time Markov chain and discovered that the Markov process is memory-less. In some cases, it is conceivable to break the Markov chain into smaller pieces, each of which is moderately straightforward and which together give a comprehension of the entirety. This is accomplished by spotting the communicating classes of the chain. Kumar(2016) et al analyses the causal relationship between stock process and trading volume of 50 companies from NSE of Indian stock market to reveal that a huge majority of 46 companies have unidirectional or bidirectional causal relationships between these two variables. Typical analysis of time series models on financial data is usually carried out by Autoregressive models and heteroskedasticity models. Unnikrishnan J and Suresh K K (2016) presents the ARIMA modelling of the financial series on gold price to forecast future price. The study incorporates intervention analysis within ARIMA (1, 1, 1) model. A study carried out in Jyothi and Suresh (2014) adopts the non-linear model of conditional heteroskedasticity GARCH to model volatility of S&P 500 stock price index. A time series analysis carried out in Pranesh (2017) examines the determinants of Volatility Index in Indian stock market and finds using Granger causality that Business Confidence Index is the only factor that causes variations in volatility. Purchasing Managers Index and Foreign Investors Index and Domestic Institutional Investors index seem to have insignificant influence in this aspect. Tuyen (2018) presents a novel Markov model of higher order constructed on various levels of changes in the series. The transition probabilities are calculated based on fuzzy sets and the accuracy is compared with other time series models like ARIMA and ANN. Park et al (2009) suggests the application of Hidden Markov Model to capture the dynamic nature of financial time series of stock prices. Big data analysis is also getting popularity in stock market analysis.

G. Parambalath et al (2019) adopts the conventional Bollinger Bands set at two standard deviations based on a band of moving average over 20 minute-by-minute price values of the Nifty 50, a portfolio of blue chip companies in the stock index of National Stock Exchange (NSE) of India is used for analysing overall market sentiment to identify stocks that generates maximum profit. When there are advanced method attempting to bring more accurate predictions, the present study is an attempt to find the efficiency of the simple Markov method to compare the performance of 5 different stock market prices

III. METHODOLOGY

Markov model is named after Andrei A Markov, the individual who originally distributed his outcome about the model of Markov. Markovian model is a stochastic model based on the Markovian property, which states that the future is independent of the past, given the present state. Markov forms are the characteristic stochastic analogues of the deterministic procedures depicted by differential and distinction conditions. They structure one of the most significant classes of arbitrary procedures.

The initial step of Markov chain is to construct a Markov forecasting model that foresee the condition of an item in a specific time frame later by the temperance of likelihood vector of the underlying state and state transition probability matrix. Markov model is significant in statistics as it has Markovian properties ,the powerless interest on authentic information and anticipating strategy with numerous preferences. The Markov chain is memory-less,which does not hold information about the past states.This implies that the probability of the next transition depends only on the present state.

Consider a random process $\{X_n\}, n = 0,1,2, \dots$ with discrete state space S and is said to be a Markov chain if it satisfies the following:

$$P(X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \dots, X_1 = i, X_0 = i_0) = P(X_{n+1} = j | X_n = i) \quad (1)$$

for any $i, j, i_1, i_2, \dots, i_{n-1} \in S$

The state of the process may vary in each time-step. The likelihood that the process changes from i^{th} state in the n^{th} trial to state j in the $(n + 1)^{th}$ trial is referred to as transition probability and it is denoted as P_{ij} . Therefore,

$$P_{ij} = P(X_{n+1} = j | X_n = i) \text{ forevery } i, j \in S \text{ and } n \geq 0, 1 \leq i, j \leq n \quad (2)$$

with the state transition coefficients having the properties: $P_{ij} \geq 0$ &

$$\sum_{j=1}^n P_{ij} = 1 \quad (3)$$

The above stochastic process could be called a detectable Markov model, since the yield of the process is the arrangement of states at every moment of time, where each state corresponds to a physical event. The transition probabilities for each pair of states structure a square matrix of size n . The dynamics of the discrete-time Markov chain with state space S is given by this exhibit. All the possible states of Markov chain are utilized as rows and columns and

the row whole is constantly one. This gives the transition probability matrix, $P = [P_{ij}]_{m \times n}$.

The Markov chain's initial distribution at time 0 is given by, $p^{(0)} = P[X_0 = i]$ and $p^{(n)} = P[X_n = i], i \in S$ is the row vectors of probabilities at the time n . The transition probability matrix together with the initial probability distribution completely specifies a Markov chain $\{X_n\}$.

$$p^{(n)} = p^{(n-1)}P = p^{(n-2)}P * P = p^{(n-2)}P^2. \quad (6)$$

$$\text{In general, } p^{(n)} = p^{(0)}P^n \quad (7)$$

as indicated by this recursive equation, the gauge dependent is obtained on the understanding of dynamic framework

$$\text{The components of } p \text{ are elements of unique solution of } \pi = \pi P \quad (8)$$

$$\text{And } \sum \pi = 1 \quad (9)$$

By the Chapman-Kolmogorov theorem, (Ross, Sheldon M. 2014). if P is the transition probability matrix of homogeneous Markov chain, then the n -step transition probability matrix $P^{(n)}$ is same as P^n ,

$$i. e, P^n = P^{(n)} \quad (10)$$

The normal transition process of Markov chain just relies upon the framework underlying state and the transfer matrix, where the framework's underlying state is a line matrix presented by the likelihood vector $M^{(0)} = [M^{(0)}_{ij}]_{1 \times n}$ (11)

In essence, the basic Markov chain might be of any order and the yields from its states might be multivariate random process having some continuous joint probability distribution.

IV. RESULTS

A total of closing price changes of 36 trading months of 5 major oil and gas companies from 1/01/2017 to 1/12/2019 is used for the analysis. The closing prices are segregated into three states: up, down and zero-plus by a difference of 10 points and are investigated using Markov chain. The construction of state process and determining the state probability matrix is the initial process. The state probability refers to the possibility size of emergence of a variety of states. The state vector of each state is computed by obtaining the number of ups, downs and zero-plus in the 36 sample points.

Table I: State vector of 5 stock indices

	IOC	BPCL	Hindustan Petroleum	Reliance	Oil India
Up	0.194	0.444	0.333	0.555	0.167
Zero-plus	0.5	0.111	0.222	0.083	0.555
Down	0.306	0.444	0.444	0.361	0.278

Second stage of computation involves finding the closed state transition probability matrix using the state vectors. The total number of ups, downs and zero-plus from each state is figured out and the corresponding probability is computed in this stage. The state transition probability matrix of the five companies are tabulated in Table II:



Table II: State transition probability of 5 stock indices

		up	zero-plus	Down
IOC	up	0	0.57	0.43
	zero-plus	0.24	0.47	0.29
	down	0.18	0.55	0.27
BPCL	up	0.25	0.06	0.69
	zero-plus	0.5	0	0.5
	down	0.6	0.2	0.2
Hindustan Petroleum	up	0.25	0.17	0.58
	zero-plus	0.5	0.125	0.375
	down	0.27	0.33	0.4
Reliance	up	0.5	0.1	0.4
	zero-plus	0.67	0	0.33
	down	0.67	0.08	0.25
Oil India	up	0.17	0.5	0.33
	zero-plus	0.16	0.63	0.21
	down	0.2	0.4	0.4

tan Petroleum			0.22 [0.44]	0.23 [0.46]
Reliance	[0 0 1]	[0.67 0.08 0.25]	[0.56 0.087 0.36]	[0.58 0.085 0.34]
Oil India	[0 1 0]	[0.16 0.63 0.21]	[0.17 0.56 0.26]	[0.17 0.55 0.28]

The calculations provided in the state probability vector gives the trend of each of the stocks. For all the 5 stocks, it is observed that the state probability tends to the value that is independent of the initial state and more or less stabilised. From the table, we can observe the closing price pattern of BPCL, Hindustan Petroleum, and Reliance are promising as there is high probability of closing price of each day is to increase from the previous closing price. The financial exchange of BPCL is up about the possibility of around 50 percent, zero plus around 10 percent, and down around 40 percent, while that of Reliance is up around 60 percent, zero-plus around 10 percent and down around 30 percent. This demonstrates that BPCL and Reliance are ought to be idealistic for the not so distant future, when compared to the others. Oil India has 63 percent probability of zero-plus while for IOC, it is 47 percent and for HP, it is 33%. Among all HP shows the highest probability of 40 percent to fall down the previous closing price.

V. CONCLUSION

The research is an attempt to compare the performances of five popular stocks using Markov modelling. Markov Chain has no eventual outcome, hence utilizing this strategy to examine and anticipate the stock exchange value is increasingly successful under the market mechanism. However, this being a likelihood estimating method, the anticipated outcomes is basically communicated as likelihood of a specific state of stock costs in the future, rather than be in a flat out state. The finding of the analysis based on 3 year monthly closing price provides insight to the future possibilities of these five stocks. The findings suggest that Reliance has the highest futuristic probability followed by BPCL. While Oil India and IOC has higher probability to remain stable without much fluctuation, HP indicated the highest probability of a fall from the existing state. This finding can be considered while decisions are made on port-folio by an investor. The methodology adopted is simple and reliable as it depends only on the immediate past behaviour of the stock prices.

Using the state transition probability, stock price on the 36th month, and the subsequent data, we have, $\Psi(0)$, as the initial state vector. The state probability vector of closing price on the 37th month is calculated as

$$P(j)=(j-1) * P ; \quad j = 0,1,2,\dots$$

Forecasting: The state likelihood of subsequent closing months are predicted and provided in the table III

Table III: Prediction of the next 3 months performance of indices of the 5 stocks

	Initial vector	37 th month	38 th month	37 th month
	$\Psi(0)$	$\Psi(1) = \Psi(0) * P$	$\Psi(2) = \Psi(1) * P$	$\Psi(1) = \Psi(0) * P$
IOC	[0 1 0]	[0.24 0.47 0.29]	[0.17 0.52 0.32]	[0.18 0.52 0.32]
BPCL	[0 0 1]	[0.6 0.2 0.2]	[0.37 0.076 0.55]	[0.5 0.13 0.4]
Hindus	[0 0 1]	[0.27 0.33 0.4]	[0.34]	[0.31]

REFERENCES:

- www.investinindia.com/industry/oil-and-gas/oil-and-gas-industry
- Zhang Yudong and Wu Lenan, Stock market prediction of S&P 500 via combination of improved BCO approach and BP neural network: Expert systems with applications, 36, 8849-8854, 2009
- Deju Zhang and Xiaomin Zhang Study on forecasting the stock market trend based on stochastic analysis method; International Journal of Business and Management. Vol 4, No.6 June 2009

4. J.R.Norris, *Markov chains*, Cambridge University Press, *Cambridge Series in Statistical and Probabilistic Mathematics* ISBN: 978-0521633963, 1998
5. A. P. Kumar, V. Suresh, Dr. P. Balasubramanian, and Vijay Krishna Menon, "Measuring stock price and trading volume causality among Nifty 50 stocks: The Toda Yamamoto Method", in International Conference on Advances in Computing, Communications and Informatics, ICACCI, Jaipur, Rajasthan, 2016
6. J Unnikrishnan & KK Suresh, *Modelling the Impact of Government Policies on Import on Domestic Price of Indian Gold Using ARIMA Intervention Method*; Volume 2016 |Article ID 6382926 | 6 pages | <https://doi.org/10.1155/2016/6382926>, 2016
7. Jyothi U. Suresh KK, Estimating Stock Market Volatility Using Non-linear Models; IOSR Journal of Business and Management, e-ISSN: 2278-487X, p-ISSN: 2319-7668. Volume 16, Issue 2. Ver. I, Feb., PP 62-65, 2014
8. K. Kiran Pranesh, P. Balasubramanian, Deepti Mohan The Determinants of India's Implied Volatility Index", International Conference on Data Management, Analytics and Innovation (ICDMAI) 2017
9. Luc Tuyen, A Higher order Markov model for time series forecasting, International Journal of Applied Mathematics and Statistics 57(3):1-18, 2018
10. Sang-Ho Park, Ju-Hong Lee, Jae-Won Song Tae-Su Park, Forecasting Change Directions for Financial Time Series Using Hidden Markov Model; International Conference on Rough Sets and Knowledge Technology, RSKT 2009: Rough Sets and Knowledge Technology pp 184-191. Lecture Notes in Computer Science book series (LNCS), volume 5589, 2009
11. Gokul Parambalath, E. Mahesh, P. Balasubramanian, P. N. Kumar "Big Data Analytics: A Trading Strategy of NSE Stocks Using Bollinger Bands Analysis", Data Management, Analytics and Innovation, vol. 839. Springer Singapore, Singapore, pp. 143-154, 2019
12. Ross, Sheldon M, "Chapter 4.2: Chapman–Kolmogorov Equations". Introduction to Probability Models (11th ed.). p. 187. ISBN 978-0-12-407948-9, 2014

AUTHORS PROFILE



Lakshmi G, Student, Department of Mathematics, Amrita School of Arts and Science, Amrita iswa Vidyapeetham, Amritapuri, Ollam, India, 690525



Dr. Jyothi Manoj, Associate Professor, Department of Statistics, Kristu Jayanti College (Autonomous), Bengaluru