IOSR Journal of Mathematics (IOSR-JM)
e-ISSN: 2278-5728, p-ISSN: 2319-765X. Volume 18, Issue 4 Ser. I (Jul. – Aug. 2022), PP 40-48
www.iosrjournals.org

Stock Market Trend Analysisand Prediction using Markov Chain Approach in the Context of Indian Stock Market

Tirupathi Rao Padi[1],Gulbadin Farooq Dar[1*], Sarode Rekha[1]
[1]*Ramanujan School of Mathematical Science, Department of Statistics, Pondicherry University, Puducherry-605014, India.*

Abstract
Every emerging country's economy relies heavily on stock market trade and India is one among the world's most active electronic stock market dealers. The stochastic modelling is extremely successfully employed in predicting the stock market behaviour, and it has become a high field of research because of its tremendous importance for every profitable industry and stockholders to take out his confident decisions.This study deals with developing and analysing stochastic models using the Markov Chains approach to forecast the stock price in the stock market. Real-time data of the daily closing share price is obtained from the historical price of NSE (National Stock Exchange) for Nifty banks to conduct a detailed and exploratory data analysis. Daily closing price differences are divided into two categories: increase and decrease. If the closing price on day t+1 is higher than the closing price on day t, the state is thought to be increasing, and vice versa. The numerical analysis is based on Nifty Bank data for the previous three years. The findings of these studies will help both short and long-term investors to make more informed portfolio management decisions.

***Keywords**: Markov Processes,Transition Probability matrix, Steady-state probabilities, Stock Market Assessment, Finance Growth Studies.*
***AMS Subject Classifications:** 60J25, 60J28*

Date of Submission: 02-07-2022 Date of Acceptance: 14-07-2022

I. Introduction

In the developing economy, the stock market plays an essential role in the structure of different business sectors in the form of corporations, as well as in the raising of funds and capital formation for such firms. Shares are being used by companies to sell them to individuals or groups of persons in order to meet capital needs. The stock/share market is a market situation that allows anyone to invest and interact in both domestic and international economies. A rising stock market is a solid indication of the country's economic success.The legal and authorized platform on which such equities are exchanged is known as the stock exchange. The two major stock exchanges in India where most of stock takes place are Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). Both BSE and NSE are among the top five stock exchanges in the world's developing economies in terms of market capitalization. The desire to make more profit motivates an investor or a group of individuals to buy and sell shares. In general, companies that perform good offer a better return to investors as compared to other companies that make less profit or sometimes no profit. Therefore, in the stock market, the price of a company's shares rises or falls in response to the company's performance. As a result, it is contingent on having prior knowledge of the company's performance before making any investment.

Prediction of the stock price behaviour has become a high and interesting research area because of its critical necessity for every profitable company, as well as for investors and shareholders in making a confident selection for a solid investment in the stock market.To analyze and forecast the movement of stocks, a variety of statistical projection methodologies have been used. Artificial neural networks (ANN) Neewi et al. (2013), Data mining and Regression Abdulsalam et al. (2011), autoregressive integrated moving average (ARIMA) Adebiyi et al. (2014)and the "head and shoulders" methods are among the prediction methods used. Many of the above forecast models, however, require the stationary time series data. In practice, financial time series data are frequently non-stationary, necessitating the use of nonstationary time series models.

Again, because the stock market is volatile with a random walk feature or nonlinear trend, models that capture volatility are likely to inform accurate forecasting, as stock price data do not fit the conventional statistical time series requirements of constant variance. Renjith et al. (2021) attempted to predict the impact of FII (Foreign

[*]Corresponding author: Gulbadin Farooq Dar
Email ID: gulbadinstst.pu@gmail.com

Institutional Investment) inflows on equities returns in the Indian capital market. In order to model and anticipate market volatility patterns, researchers conducted theoretical and empirical experiments such as Ibiwoye and Adeleke (2008),Hamadu and Ibiwoye (2010),Hamadu (2014a),Hamadu (2014b)andFama (1965).Dar, Q et. al in 2020 used A time series regression approach in [27] for the visualization and forecasting of South Korean international trade using the time series data regarding the amounts of exports and imports. In this study have analyzed the impact of imports and exports on the country's GDP.

This study aimed to forecast and analyse the stock market trend of Nifty bank shares trading in the Indian stock exchange using a Markov chain model (MC model). The study's precise goals are to forecast Nifty Bank's share prices in the long run, to obtain the average number of visits to a certain state, and determine the expected initial return time for distinct states.

II. Literature Review

The existing prediction methods are based on linear time series data, however in practice the patterns of the stock market are not linear, it contains some non-linearity. When evaluating market circumstances and the transition law among various states, the MC model can be used as a method to deal with time series problems that are unaffected by whether the dataset is linear or not. Andrei Andreevich Markov (1856–1922), a Russian mathematician, was the first to introduce the Markov chain. The MC model has been utilized by several scholars at various times to examine and forecast share price movement.For forecasting the stock market movement in China, Zhang and Zhang (2009) used a MC model. The MC has memory less property, and this model is better appropriate to assess and predict the closing stock price under the market mechanism. They obtained relatively decent results using the MC model alsorecommended that MC modelcan be employed to other industries such as bond markets etc. The reason that the MC model provides more accurate results than the classic trend forecasting method, according to Vasanthi et al. (2011), is that the MC model considers the change in the daily stock prices to determine the states of the MC such the bull and bear states. On demonstrating the behaviour of the top two banks, the Guarantee Trust Bank of Nigeria and First Bank of Nigeria, Choji et al. (2013) used the MC model to predict the probable states.Simeyo et al. (2015) used the MC model to predict and anticipate the Safaricom stock trading trend in Nairobi, Kenya's Securities Exchange. They calculated the initial probability vector(IPV) and transition probability matrix (TPM), which they utilized to accurately forecastthe movement of states. They also observed the share prices in long-term tendency by the steady state probabilities. Raheem and Ezepue in (2016) provide an alternate approach for assessing and forecasting the daily prices as well as the market return of a first-generation bank on the Nigerian Stock Exchange.For the prediction of the change in the opening share price of the Nifty50, Singh et al. (2017) applied a Markov model and obtained the predicted results in terms of the parameters of MC model and in same year for the prediction of stock movement of HTC (Taiwan) stock, Huang et al. (2017) used regular and absorbing Markov chains.Bhusal in (2017) alsoapplied the MC Model in order to predict and evaluate the trend movement of Nepal Stock Exchange Index (NEPSE).Aparna and Kakaty (2017) used the MC model to estimate the upcoming market prices of potatoes and in that regard, they collected the historical data price of potatoes for the period from June, 2014 to April 2017, contains of 478 days and forecasted the future price for the next15 days. The interpretation of TPM and IPV were used to make short-term forecasting. The findings in the analyses were indistinguishable from the actual situation.In 2018, Tharshan and Arivalzahan used the MC model for the stock market volume behaviour analysis and to predict the stock market behaviour and the model is tested through its assumptions.Tuyen (2018) provides a novel higher-order MC model based on distinct levels of change in the series. Transition probabilities are estimated by making the use of fuzzy sets whereas the accuracy is matched with ARIMA and ANN time series algorithms. Ashik et al. (2019) used a variety of statistical approaches to predict the Indian share market's daily price and M. Manoharan and V.M. Chacko (2020) suggested a transition probability function-based measure for determining and comparing the degree of linkage in time between two processes and further they explored the time association of a Markov process. The TPM approach was utilized by Ashik et al. (2021) to get the Reliance Communication Ltd (RCOM) weekly stock transaction price projection. According to the findings, the state of small decrease (SD) trends is more likely to be in future weeks since it has a higher likelihood possibility.In 2022, Dar et. al used an HMM in [18] for stock price analysis and prediction by observing the effect of Sensex on the share price of HDFC bank in terms of the parameters of the model. After observing the parameters of the model, they stated that the change in Sensex closing prices have positive influence on the share price of HDFC bank.

Since the brief literature review discussed above demonstrates that the MC model has been observed to be a very effective and accurate statistical prediction technique for forecasting stock price patterns therefore, we used the MC model on Nifty Bank share prices in the context of the Indian stock market to assess its behaviour and forecast share prices trend in the near and in long term, which is important for investors.

III. Materials and Methods

A stochastic or random process is defined as a process that changes with the change of time in an unexpected way. Through the definition of the joint distribution function, stochastic processes can be categorised into several classes on the basis of its index parameter, its state space and on its dependence relations among the stochastic variables. A Markov process is a particularcategory of random process where only the current value of a variable is used to forecast the future and the variables in the previous history are irrelevant that is given current, the future and past are independent. In most cases, share prices are observed to follow a Markov process according to Hull (2018).A prominent Russian mathematician Andrei Andreevich Markov (1856-1992) initially introduced the Markov chain. The MC model's most fundamental property is that the occurrence of any future event depends only on the current state. The state-space space of a Markov process is the set of all possible values it takes. A Markov process whose state space is discrete is known as a Markov chain by J. Medhi (2009).

2.1.Markov ChainModel

Markov chain is a series of random variables having discrete state spaceand following the memory less property (short term memory). The probability of a particle reaching to state j starting from state i is P_{ij}. MC can be defined as a series of transitions going from one state to another, with the associated probabilities such that theprobability of reaching the future state is based solely on its current state and not on its past history.

The MC model can mathematicallybe defined as the sequence $\{X_t, t \geq 0\}$ such that $P[X_{t+1} = j \mid X_t = i, X_{t-1} = i_{t-1}, \ldots, X_1 = i_1, X_0 = i_0] = P[X_{t+1} = j \mid X_t = i]$. That is, the system's state at time t+1 is solely determined by the system's state at time t. This is called memoryless or Markov property.The basic difference between the MC model and other statistical methods of prediction, such as regression models and time series analysis, is that the MC does notneed anyjoint laws betweenfactors from complex predictors, instead, it only needs the initial state probabilities to estimate the transition probabilities for various possible states at different times in the future. Therefore, after knowing the IPV and TPM, it is simple to forecast the potential state value for some particular period of time using the help of the MC model. The MC model has widely been used to forecast stock indexes for both a group of stocks and a single stock. If the state space of an MC cannot be partitioned into two or more disjoint closed sets, it is said to be irreducible MC.

2.2. Description of theStates of Markov Chain

In this paper, it is assumed that the stock price variations represent Markov's dependence and time-homogeneity, and we specify a two-state Markov process, i.e., price increase (I) and price decrease (D). These two states are obtained on the basis of the difference between the next day and the previous day closing share price. Symbolically, we write theIncreasing and the Decreasing state as follows.

a) When $(C_t - C_{t-1}) \geq 0$, the process is in an increasing state (I).

b) When $(C_t - C_{t-1}) < 0$, the process is in decreasing state (D).

Where, C_t *is*the current and C_{t-1} is the previous closing price.

2.3.Initial Probability Vector

The state space of the Markov chain is E(*D*,*I*). Therefore, theIPVis the Probabilities of the states I and D. These initial probabilities are denoted as $P(X_1 = i) = \pi_i, \forall\, i = 1, 2$ Such that $\sum_{i=1}^{2} \pi_i = 1$ that is the sum of all these probabilities must be 1. Hence the IPV is represented as $\pi = \begin{bmatrix} \pi_1 & \pi_2 \end{bmatrix}$,Where π_1 and π_2 are the probabilities of Decreasing and Increasing closing share price.

2.4.Transition probability and transition probability matrix

Since the share price movement has been separated into two states (D, I), the TPM will also include these two states. The TPM gives a detailed description of how an MC behaves. The probability of going from one state to another is represented by each element in the TPM.

As discussed in section 2.1, a random process is called a MC if, it follows the following property $P[X_{t+1} = j \mid X_t = i, X_{t-1} = i_{t-1}, \ldots, X_1 = i_1, X_0 = i_0] = P[X_{t+1} = j \mid X_t = i]$ .The probabilities $P[X_{t+1} = j \mid X_t = i]$ are called transition probabilities and are denoted by a_{ij} Such that $\sum_{j=1}^{2} a_{ij} = 1, \forall i, j = 1, 2$. In the matrix form,the two state TPM is expressed as

$$A = \begin{array}{c|cc} & I & D \\ \hline I & a_{11} & a_{12} \\ D & a_{21} & a_{22} \end{array} \quad\text{i.e.}\quad A=\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

The elements of TPM are represented through the diagram known as transition diagram or the Schematic Diagram

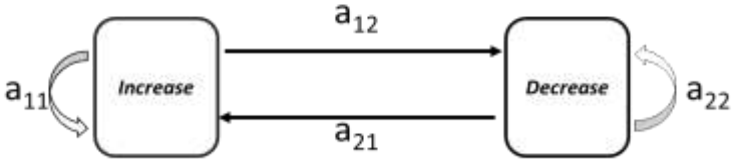

FIGURE 1: STATE TRANSITION DIAGRAM

Where,a_{11}=P (I/I)= Probability of price will increase tomorrowif it is in increasing state today.
a_{12}=P (D/I) = Probability of price will decrease tomorrow if it is in increasing state today.
a_{21}=P (I/D) = Probability of price will increase tomorrow if it is in decreasing state today.
a_{22}=P (D/D) = Probability of price will decrease tomorrow if it is in decreasing state today.

2.5.The n-step Transition matrix and the Stationary distribution

The n-step TPM is used to calculate the likelihood of states at any stagen such that n>1. These are called the higher-order transition probability $P_{ij}(n)$. The behaviour of share prices n days later is depicted in the n-step TPM. These repeated transition steps are obtained to evaluate if the TPM converge to the identical columns over repeated iterationswhich is called stationary probability matrix of the MC. According to this property of the MC, the probabilities of transitioning from the state i to state j settles down to a certain constant value regardless of how the system is initially set or how the stochastic process develops over time.Thus,symbolically we write the stationary property of Markov chain is

$$\lim_{n\to\infty} P_{ij}(n) = \pi_j$$

Such quantities are also referred to as steady-state probabilities. The steady state probabilities are applied in order to forecast the behaviour of states of the MC in the long run.

IV. Numerical data analysis and Modelling

For investors, the stock price index is a key indicator for analyzing and forecasting the stock market. It reflects a portfolio management of securities trading on a certain market and measures the variation in that market. In order to examine the reliability of the MC model's forecasting in the context of the Indian stock market, we applied the discrete-time MC model to the closing prices of a Nifty Bank in this study. The daily data of Nifty Bank closing prices were taken from *www.Yahoofinance.com* for the period from August 01, 2018, to Oct, 29, 2021. It was the secondary data that consist of 794 trading days of Nifty Bank during the period. The trend movement of the daily data of Nifty Bank closing prices are presented in figure 2.

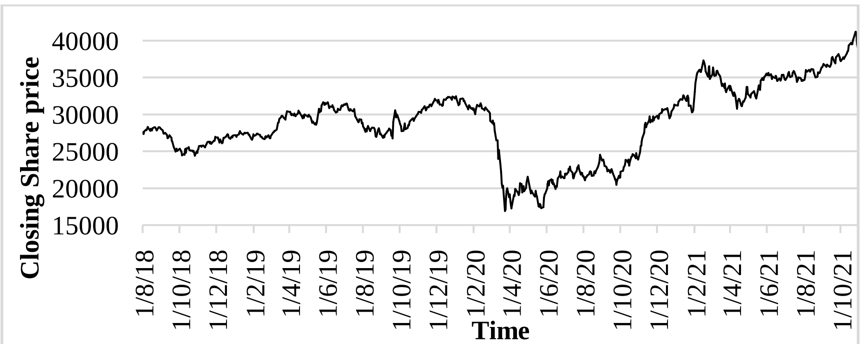

FIGURE 2: STOCK MARKET TREND FOR NIFTY BANK

The analysis starts with finding the change in the daily closing price for all 794 days using the formulae defined in section 2.2. These differencesareconverted into states such I and D using IF functions in MS excel. Figure 3 shows the volatility of change in the share prices of Nifty bank from Aug. 01, 2018, to Oct.29, 2021.

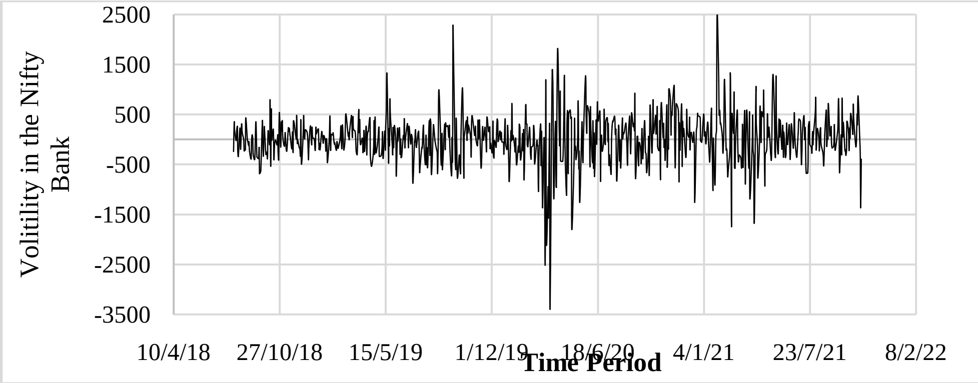

FIGURE 3: VOLITILITY IN THE SHARE PRICES OF NIFTY BANK

All the mathematical analysis is done in MS excel and R software. The column of transition states in MS excelis obtained using the command (=A_1&" "&A_2) or using (CONCAT) function to construct TPM for the model where A_1 and A_2 is previous and next cell. The function MMULT is used in Ms excel or(>A%*%A) in R software is used for the multiplication of TPM to get the higher order TPM reaching the stationary probability matrix.

3.1.Initial Probability Vector

Initial state probability vector consists the probability of all the states of Markov Chain. We denote this vector by π and it is be definedas $\pi = [\pi_1, \pi_2]$ Where π_1 *and* π_2 are the initial probabilities that the stock prices would increase anddecreaserespectively. The frequency table for both the states I and D is given by

TABLE 1: FREQUENCY OF STATES

Initial Frequency table			
States	I	D	Total
Probability	419	374	793

Therefore,therequired Initial Probability Vector (IPV) is obtained as fallows

$$\begin{array}{cc} I & D \end{array}$$
$$\pi = [0.528373 \qquad 0.471627]$$

I.e.,P(I)=0.528 and P(D)=0.471

4.3.Transition Probability Matrix

A thorough observation of the closing price of Nifty Bank across the research period reveals that they pass through two distinct states of transition. The values of the Nifty Bank could increase or decrease at the end of each trading day. As a result, these two separate movements are considered two different states in the MC for the sake of building a TPM. In the table 2, we show the frequency transition table from one state to another state of the Nifty bank.

TABLE 2: FREQUENCY TABLE OF TRANSITION STATES

	I	D	Total
I	234	185	419
D	185	188	373

Transition Frequency table shows the number of times the specific state makes the transition to another state. From the given table, we can see that the share prices increase when it was in the increasing state is 234 times. The process makes 188 times transition from decreasing state to decreasing state. In the same way the process goes 185 times from increasing state to decreasing state and 185 times from decreasing state to increasing state.The frequency diagram of the transition matrix is presented in figure 5.

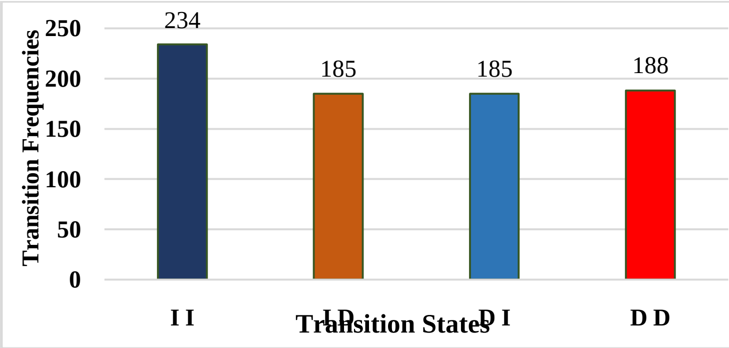

FIGURE 5: FREQUENCY DIAGRAM OF TRANSITION STATES

Therefore, from the above transition frequency table, we have derived the TPM as in matrix A.

$$A = \begin{array}{c} \\ I \\ D \end{array} \begin{array}{c} \begin{array}{cc} I & D \end{array} \\ \begin{bmatrix} 0.5584726 & 0.441527 \\ 0.4959786 & 0.504021 \end{bmatrix} \end{array}$$

We can observe from the above matrix A that no any element is zero, that is both statesof the state space E(I,D)are in communication with one and other which reveals that our MC is an irreducible MC. These transition probabilities are explained in the following schematic diagram.

FIGURE 6: SCHEMATIC DIAGRAM OF MARKOV CHAIN

Where, a_{11}=P(I/I)=0.5584726, a_{12}=P(I/D)=0.441527,a_{21}=P(D/I)=0.4959786 and a_{22}=P(D/D)=0.504021

4.4.Long term behavior of closing share price

The forecasting of long run behavior of NSE (Nifty Bank) is very meaningful for investors. The long run behavior of NSE is observed by determining the higher order TPM of Nifty Bank.The TPMobtained in above section 4.3 is

$$A = \begin{array}{c} \\ I \\ D \end{array} \begin{array}{c} \begin{array}{cc} I & D \end{array} \\ \begin{bmatrix} 0.5584726 & 0.441527 \\ 0.4959786 & 0.504021 \end{bmatrix} \end{array}$$

Since the closing prices of Nifty Bank form an Ergodic MC and this condition will be helpful for the prediction of long-term behaviour of theshare prices since there exists a unique stationary distribution for an Ergodic MC. The chain will converge to its stationary distribution regardless of its initial state distribution as $n \to \infty$. That is,

$$\lim_{n\to\infty} P_{ij}(n) = \pi_j$$

In the matrix form, we can write the stationary distribution as

$$\lim_{n\to\infty} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^n = \begin{bmatrix} \pi_1 & \pi_2 \\ \pi_1 & \pi_2 \end{bmatrix}$$

Where A is the TPM and $\pi_j, j = 1, 2$ the stationary probabilities. Therefore, the stationary matrix for the real time data set is obtained as

$$A^7 = \begin{bmatrix} 0.529039 & 0.4709579 \\ 0.529039 & 0.4709579 \end{bmatrix} = A^8 = A^9 = ... = A^n$$

This stationary matrix A^7 represents that after the 7th trading days since 794 trading days, the TPMwill converge to the state of equilibrium or the stable state and then the TPM remains same for the onwards consecutive trading days. This steady state TPM of NSE(Nifty Bank) reveals the following information.

There are 53% chances that the Nifty Bank share price will increase after 7^{th} day irrespective of its initialday's state whether increase, or decrease and the probability of decreasing the closing price of Nifty Bank on 7^{th} day onwards is 47% irrespective of its initial state.

4.5.State probabilities for forecasting the share price

The main purposein this paperis to forecast the stock prices movement of Nifty Bank at the end of 794th day and study its long-term behaviours. We first, compute the probabilities of forecasting the stock prices at the end of 794^{th} day for Nifty bank. According to the MC model, the state probabilities are found out by multiplying the IPV with the TPM. Symbolically we write

$\Pi_{n+1} = \Pi_n A = \Pi_0 A^n * A = \Pi_0 A^{n+1}$, where for this study $\Pi_0 = \pi$, the initial probability vector

Therefore, the state probability vector for Nifty Bank closing share price for 795^{th} day will be

$$\Pi_1 = \Pi_0 A = \begin{bmatrix} 0.528373 & 0.471627 \end{bmatrix} \begin{bmatrix} 0.5584726 & 0.441527 \\ 0.4959786 & 0.504021 \end{bmatrix}$$

$$\Pi_1 = \begin{bmatrix} 0.5289987 & 0.4710009 \end{bmatrix}$$

The above state probability reveals that Nifty Bank closing prices have 47% chances to decrease, and 53% likelihood to increase from their previous closing price on 795^{th} day.Now, we compute the state probabilities for the Nifty bank at 796^{th} day Π_2 ,Where:

$$\Pi_2 = \Pi_0 A^2 = \begin{bmatrix} 0.528373 & 0.471627 \end{bmatrix} \begin{bmatrix} 0.5308795 & 0.4691196 \\ 0.5269740 & 0.4730251 \end{bmatrix}$$

$$\Pi_2 = \begin{bmatrix} 0.5290376 & 0.4709615 \end{bmatrix}$$

These results further reveal that on 796^{th} day the probability that the price of Nifty Bank will increases with 53% likelihood and the probability that the price will decrease with probability 47%. These findings provide information that investing in this stock is a good long-term adventure since the possibility of price increase increases with time.

Similarly, we compute the state probabilities for the Nifty bank as on 797^{th} and onwards days presented in $\Pi_3, \Pi_4, \Pi_5, \Pi_6, \Pi_7,$; Where:

$$\Pi_3 = \Pi_0 A^3 = \begin{bmatrix} 0.5290398 & 0.4709589 \end{bmatrix},\ \Pi_4 = \Pi_0 A^4 = \begin{bmatrix} 0.5290397 & 0.4709585 \end{bmatrix}$$

$$\Pi_5 = \Pi_0 A^5 = \begin{bmatrix} 0.5290395 & 0.4709583 \end{bmatrix},\ \Pi_6 = \Pi_0 A^6 = \begin{bmatrix} 0.5290392 & 0.4709581 \end{bmatrix}$$

$$\Pi_7 = \Pi_0 A^7 = \begin{bmatrix} 0.529039 & 0.4709579 \end{bmatrix} = \Pi_8 = \Pi_9 = \ldots$$

The condition for the steady state probability vector is $\Pi A = \Pi$, that is when the input vector and the output vectors reach same. In terms of the transition probabilities, the state probabilities at the time of steady state will be $\overline{\pi_1} = \dfrac{a_{21}}{1 + a_{21} - a_{11}}$ and $\overline{\pi_2} = \dfrac{1 - a_{11}}{1 + a_{21} - a_{11}}$ such that $\overline{\pi_1} + \overline{\pi_2} = 1$. After 7^{th} step, the state probability will be stableand then the state probabilitiesremain same for the onwards consecutive trading days.

4.6.Expected number of visits (ENV)

The average number of visits or ENV to a certain state j from some state i in various steps can be calculated to determine how long the moving particle will spend in each state. The formula for obtaining the expected number of visits in the chain to a specific state j from some state i is denoted by $\mu_{ij}(n)$ and is expressed as

$$\mu_{ij}(n) = E[N_{ij}(n)]$$

Where, $N_{ij}(n)$ is thenumber of times the system is reaching to state j from state i in finite n-steps.

$$\mu_{ij}(n) = \sum_{k=1}^{n} P_{ij}(k) = \sum_{k=1}^{n} A^k$$

Also, after a long run, the ENV to state j from the state i is

$$\mu_{ij}(n) = \lim_{n\to\infty} E[N_{ij}(n)]$$

Here, for Nifty Bank, frequency of visits to a state j in six trading days is shown in the following matrix.

$$\mu_{ij}^{(6)} = \begin{array}{c} \\ I \\ D \end{array}\!\!\begin{array}{c} \begin{array}{cc} \quad I & \qquad\qquad D \end{array} \\ \begin{bmatrix} 3.2056331 & 2.7943576 \\ 3.1389732 & 2.8610174 \end{bmatrix} \end{array}$$

The elements of the above matrix can be expressed as if the Nifty Bank starts from the increasing state, the ENV the chain for Nifty Bank makes to the increasing state out of six trading days is 3.20 and to the state decrease is 2.79. Likewise, if the Nifty Bank starts from decreasing state, the ENV the chain makes to the increasing state is 3.138, and to the state decrease is 2.861.

4.7.Determination of expected return time

The steady state probability distribution helps us to compute μ_{jj} (expected return time)that is the time which is taken by theprocess to visit state j when it left state j. The expression of the expected return time (ERT) in terms of steady state probabilities is $\mu_{jj} = 1/\pi_j\, , j = 1, 2$ .As our MC modelis Ergodic that is it has the limiting distribution so we can compute the ERT for the chain. ERTprovides us the information regarding the average time of Nifty Bank closing prices stayed in both the states i.e., I and D. Therefore, using the above formula, we have obtained the average return time for states D and I as

4.7.1. The ERTfor Increasing state is

$$\mu_I = 1/0.529039 = 1.89021$$

The ERT for increasing state indicates that the Nifty Bank price chain visits an increasing state on average 1.89 days or about 2 days approximately.

4.7.2. The ERTfor decreasing state is

$$\mu_D = 1/0.4709579 = 2.12722$$

ThisERTreveals that on an average in 2 days, the chain of closing prices of Nifty Bank visitsto decreasing state.

V. Findings and Conclusion

Stock market price analysis and forecasting is a difficult task since it is heavily affected by different elements such as national and international economic conditions, socio-political considerations, international trade of the economy, investor perception regarding the stock market, government stability etc.In order to apply the MC model, it is considered that the share price of company is only affected by random forces and increase, decrease in the share price in a current day is solely dependent on itsimmediate previous day's price.In this paper, we have applied theMC model to theclosing prices of a Nifty bank to analysis and predictionits future closing share price.The IPV and TPM represents the next day probability of state I and D and transition probabilities from and to the states. It is observed from the TPM that when the current state of Nifty Banks share price is in increasing state, the share price will also be increasing in state in the next day with maximum probability.The result of stationary probability matrix reveals that if the closing price of Nifty Bank is in increasing state, the chance for Nifty Bank share prices will increase with probability53%and decrease with probability47% in the near future and in the long run.This makes investing in this stock not a bad choice for investors as the probability for increasing state increases with time. It is observed from the results of section 4.7, that the average return time to state decrease is 2 days andto state increasedis 2 days approximately. The ERT and average number of visits for share prices reflect how to interpret the Markov prediction model to extract the most important information out of it.Since the forecasted results are represented in probability measures, therefore, MC model is solely a probabilistic prediction method. The present study demonstrates how MC fits the time series data and can forecast the movement because of its randomness capabilities, in which every state in theTPM may be reached directly by every other state, leading to favourable results. The findings are very helpful for the investors to make his effective portfolio and in taking his self-confident decisions.

References

[1]. Neenwi, S., Asagba, P. O., and Kabari, L. G. (2013). Predicting the Nigerian stock market using artificial neural network. EuropeanJournal of Computer Science and Information,1(1), 30-39.

[2]. Abdulsalam, S. O; Adewole, K. S. and Jimoh, R. G. (2011), “Stock Trend Prediction using egression: A Data Mining Approach,” ARPN Journal of Systems and Software, 1(4): 154-157.

[3]. Ariyo, A. A., Adewumi, A. O., and Ayo, C. K. (2014, March). Stock price prediction using the ARIMA model. In 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation. IEEE 106-112.
[4]. Renjith, K.S., and Patrick, M. (2021). FII Flows in Indian Capital Market and Volatility, Asian Journal of Economic and Finance 3(3):305-318.
[5]. Ibiwoye, A. and Adeleke, I. A. (2008). Is insurance Nigeria's next capital market 'honey pot'? An investigation using daily stock data. African Journal of Business Management, 2(9), 157–164.
[6]. Hamadu, D. and Ibiwoye, A. (2010). Modelling and forecasting the volatility of the daily returnsof Nigerian insurance stocks, International Business Research, 3(2), 106-116.
[7]. Hamadu, D. (2014a), On modelling and forecasting the market risk volatility of Nigerianbanking stocks, UNILAG Festschrift, University of Lagos, 163-189.
[8]. Hamadu, D. (2014b). On modelling and forecasting the volatility of the Nigerian stock exchangemarket risk, Peer-Reviewed Conference of America Statistical Association, Boston MA.
[9]. Fama, E. F. (1965). The behaviour of Stock Market Prices. Journal of Business, 38, 34-105.
[10]. Zhang, D., and Zhang, X. (2009). Study on forecasting the stock market trend based on stochastic analysis method. International Journal of Business and Management, 4(6), 163-170.
[11]. Vasanthi, S., Subha, M. V., and Nambi, S. T. (2011). An empirical study on stock index trend prediction using Markov chain analysis. Journal of Banking Financial Services and Insurance Research, 1(1), 72-91.
[12]. Choji, D. N., Eduno, S. N., and Kassem, G. T. (2013). Markov chain model application on share price movement in stock market. Computer Engineering and Intelligent Systems, 4(10), 84-95.
[13]. Otieno, S., Otumba, E. O., and Nyabwanga, R. N. (2015). Application of Markov chain to model and forecast stock market trend: A study of Safaricom shares in Nairobi Securities Exchange, Kenya. International Journal of Current Research. 7(4), 14712-14721.
[14]. Raheem, M. A., and Ezepue, P. O. (2016). A three-state Markov model for predicting Movements of asset returns of a Nigerian bank. CBN Journal of Applied Statistics, 7(2), 77-99.
[15]. Singh, W.R., Srivastava, S.K., and J. Ratila (2017): Application of Markov Chain in Predicting Change in Opening Stock Price,International Journal of Mathematics and Its Applications, 5(4-B), 219 – 223.
[16]. Huang, J. C., Huang, W. T., Chu, P. T., Lee, W. Y., Pai, H. P., Chuang, C. C., and Wu, Y. W. (2017). Applying a Markov chain for the stock pricing of a novel forecasting model. Communications in Statistics-theory and Methods, 46(9), 4388-4402.
[17]. Bhusal, M. K. (2017). Application of Markov Chain Model in the Stock Market Trend Analysis of Nepal. International Journal of Scientific & Engineering Research, 8, 1733-1745.
[18]. Aparna, B, and Sarat Ch. Kakaty (2017). Markov Chain Modelling for Prediction on Future Market Price of Potatoes with Special Reference to Nagaon District. IOSR Journal of Business and Management (IOSR-JBM) 12(I9), 25-31.
[19]. Tharshan, R., and Arivalzahan, S. (2018). A Markov model for investigating the stock market volume behaviour. Faculty of Science, Eastern University, Sri Lanka J, Sc EUSL. 9(2), 20-38.
[20]. Ky, D. X., and Tuyen, L. T. (2018). A Higher order Markov model for time series forecasting. International Journal of AppliedMathematics and Statistics, 57(3), 1-18.
[21]. Mohamed Ashik. A, Senthamarai Kannan. K, and Balamurugan. D (2019). Statistical Techniques for Stock Price Prediction in India, Think India Journal, 22(14), 2014 – 2028.
[22]. Manoharan, M., and Chacko, V. M. (2020). On Association in Time of Markov Process with Application to Reliability and Survival Analysis. Statistics and Applications, 19(2), 89–100.
[23]. Mohamed Ashik. A JeromiaMuthuraj. R Velusamy. M (2021). Indian Stock Price Forecast Using Tpm Method, International Journal of Innovative Science and Research Technology, 6 (1), 2456-2165.
[24]. Hull, J. C. (2018). Options, futures, and bother derivatives – Wiener processes and Ito's lemma. New York, Pearson Education.
[25]. Medhi, J. (2009). Stochastic Processes. 3rd Edition, New Age International Publishers, New Delhi, India.
[26]. G. Farooq Dar, T. Rao Padi, S. Rekha and Q. Farooq Dar, Stochastic Modelling for the Analysis and Forecasting of Stock Market Trend using Hidden Markov Model, Asian Journal of Probability and Statistics, 18(1) (2022), 43-56,
[27]. Dar, Q., Dar, G. F., Ma, J. H., &Ahn, Y. H. Visualization, Economic Complexity Index, and Forecasting of South Korea International Trade Profile: A Time Series Approach. Journal of Korea Trade. 2020;24(1):131-145.

Tirupathi Rao Padi, et. al. "Stock Market Trend Analysisand Prediction using Markov Chain Approach in the Context of Indian Stock Market." *IOSR Journal of Mathematics (IOSR-JM)*, 18(4), (2022): pp. 40-48.