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STOCK PRICE PREDICTION USING A MARKOV CHAIN MODEL: A STUDY FOR TCS SHARE VALUES

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Abstract

In every developing country, stock market plays a very important role for the economic growth. The volatility and randomness in the stock price behavior make a risky investment for the investors. The investors need the information about the stock market behavior in order to get maximum profit on their investments. In this regard, to defend the features of randomness and disorder of stock market volatility in India, this paper applies a Markov chain model for the analysis of the stock market movement and forecasting its share prices. The Markov chain models have widely applied statistical techniques in predicting

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the market trends in stock market data. The main purpose of this paper is to apply the Markov chain to model and forecast the trend of Tata Consultancy Services Limited (TCS Ltd.) shares prices in the Indian stock market. The study is conducted through a longitudinal and empirical case study design. The secondary data of the daily closing share prices of TCS Ltd. is retrieved from (www.yahoofinance.com) over a period from 1st January 2020 to 31 January 2022. The Markov chain model parameters are the transition probability matrix (TPM) and initial state probability vector (IPV) based on the historical daily data. In order to meet the objectives of this study, the movements in the long run behavior of the stock price, expected number of visits to some particular state and the expected return time to different states are obtained.

1. Introduction

A stock market is a trading place which permits anyone to participate not only in national but also in an international economy through their investments. The growth in the stock market is directly proportional to the growth of a nation. It has been observed that a stock market that is on the rising state gives a good indication for the economic strength of the country. The stock markets are made up of exchanges in which different financial tools such as an equity shares, bonds etc. are being traded. In India, we also have a meeting place for buyers as well as for sellers to meet each other for stock trading, we call it as the *stock exchange of India*. Stock exchange is a legal platform where an individual or a group of individuals can buy or sell such shares in a legal and in a systematic way. The Indian stock market generally trades on two major stock exchanges, the primary is the BSE (Bombay Stock Exchange) and the secondary is the NSE (National Stock Exchange) of India. Both BSE and NSE are listed in the world's top five stock exchanges of developing countries in terms of their market capitalization. Since the stock market plays a vital role for the economic growth, the change and volatility in the stock market have a profound effect not only on individuals but also on the entire economy. Abu-Mustafa and Atiya in [1] stated that the stock prices in stock market are highly volatile, disordered, with randomness and non-linear. This is why, it is difficult for the investors to predict the future trends of stock prices.

Prediction of this stock market trend is presently a high and interesting research area because of its influential importance for every profitable industry, investor and shareholder in taking a wise decision for a good investment option in the stock market. In this context, not only the investors, but also many researchers in different fields such as economics, finance and statistics have proposed different statistical prediction models in order to predict the stock price movements in their studies which make this as an extensively explored subject in literature [2]. In India, the development of stock market has crucial role in its economic growth. Thus, the stock market analysis and prediction are very significant for investors and stock holders. Those who are dealing with the share market are curious to know the future behavior of the market. Share prices in the stock market are usually assumed to follow a Markov process stated in 2018 by Hull in [3]. The Markov chain (MC) model plays a vital role in the modern statistics for the prediction of the future trend behavior because as it has a Markov property (short term memory or memory less property). Dar et al. in 2020 used a time series regression approach in [4] 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, they have analyzed the impact of imports and exports on the country's GDP. The statistical prediction models such as linear regression models, time series models, ARIMA, SARIMA, ARCH, etc are different from the Markov chain model because these models are based on linear time series trend but Markov chain model is applicable for both linear and nonlinear time series data. In any process, the internal state can be predicted by using Markov model on calculating the TPM, and therefore, it is broadly applicable in the predication of the share market movement.

Recently, various scholars have applied Markov chain model at different times, to analyze and predict the stock price movement in the stock market. Initially, the concept of Markov chain was introduced by a Russian mathematician after his name Markov (1856-1922). Enough literature is found in the context of stock market forecasting by applying the MC model. Zhang and Zhang in the year 2009 implemented a Markov model in [5] for the prediction of stock market trend in China. They explored that the Markov chain has a memory less property and it is more applicable to predict the closing share price trend in the stock market. Vasanthi et al. 2011, explained in [6] that the reason MC model produces comparatively accurate results as compared with the traditional prediction methods is that in Markov chain model, we take the daily difference in the share prices to find the states of bullish and the bearish stock market. In 2013, Choji et al. applied Markov chain model in [7] in order to predict the possible states by illustrating the performance of the top two banks viz. Guarantee Trust bank of Nigeria and First bank of Nigeria. Later in 2014, Mettle et al. modelled Ghana Stock Exchange (GSE) as Markov chains [8] and he observed the randomness and unusual volatilities of the share prices in the share market and the stock prices are having Markovian property. In 2015, Otieno et al. used Markov chain in [9] in order to predict the stock prices of Safaricom in the context of Nairobi Securities Exchange, of Kenya (SEK). The IPV along with TPM are obtained to forecast the states of stock price. Applying the results of the stationary matrix, they also made an attempt to find the long run movement of the share price. In 2005, Hassan and Nath used HMM in [10] in order to predict the share price for the interrelated market. In the year 2011, Doubleday and Esunge introduced a Markov chain model in [11] to determine the portfolio management of stocks by using a discrete time MC model on Dow Jones Industrial Average (DJIA). Huang et al. in 2017 developed a MC model in [12] to analyze the stock price deviation of a Taiwanese company HTC using an absorbing Markov chain. In 2022, Dar et al. used an HMM in [13] 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. In 2017, Bhusal applied Markov chain model in

[14] to forecast and analyze the Nepal stock exchange index (NEPSE). Ky and Tuyen in 2018 presented a Markov chain model in [15] of higher order established on different levels of changes in the process. Transition probabilities based on fuzzy sets are calculated and the results are compared with other time series models such as ARIMA and ANN to find its accuracy. In 2018, Petković et al. applied a Markov chain model in [16] for the analysis of returns on the Belgrade stock exchange (BSE). Same approaches are used to other stock exchanges, such as in 2020, Lakshmi and Manoj have applied Markov chain analysis in [17] for the analysis and forecast the Indian stock market and Yavuz in 2019 [18] for the Turkish stock market (TSM). Padi et al. [19] used two state Markov chains approach for the prediction of the stock price in the stock market. They used the real time historical daily data of Nifty bank in order to forecast its future behavior in the probability measures.

As per the above brief reported research, Markov chain model has been observed as an efficient and an accurate method to predict the share price movement in the stock market. This study aims to analyze and forecast the market behavior of Tata Consultancy Service Limited (TCS Ltd.) by using the MC model with the help of historical data of the share prices. The basic objective of the present study considers the long run behavior of TCS share prices using steady state probabilities and stationary transition matrix. Also, an attempt is made to determine the expected number of visits to a certain state and the expected first reaching time.

2. Methodology

Stochastic processes are classified into different types based upon the time parameter, the state space and the dependence relations of the random variables and in such processes, Markov process is a particular type of random process. MC model follows an important property that is the probability of the future state wholly depends upon its current state and not on its past history. The set of possible values that each random variable in the process takes is known as the state space. A Markov process that has a discrete state space is known as Markov chain. By using Markov chain, it is now easy to forecast the probability of a state in the future after obtaining its parameters such as the IPV and TPM. Markov chain model has been widely used in forecasting stock index for a group of stocks and for a single stock.

2.1. Markov chain

Any random process that follows Markov property is called a *Markov process*. A Markov property can be stated as, the state at time $t+1$ of the process wholly depends on its immediate past state that is on the state at time *t*." Mathematically, if $\{X_t,\ t \geq 0\}$ is a sequence of events, then

$$P[X_{t+1} = j | X_t = i,\ X_{t-1} = i-1, \ldots, X_1 = 1,\ X_0 = 0]$$
$$= P[X_{t+1} = j \mid X_t = i] = a_{ij} \geq 0,$$

where $\sum_{j=1}^{n} a_{ij} = 1.$ Such type of the random process is termed as a discrete time MC according to Medhi in [20], where $X_0, X_1, X_2, \ldots, X_t, X_{t+1}$ are the states of the Markov chain in the state space *S* and the probability a_{ij} is called *transition* or *MC probability*.

2.2. Descriptions of proposed stochastic model

We have considered five different states of Markov chain in this paper. The five states of the MC are defined below:

Hg: When $(x_n - x_{n-1}) > +10,$ the process is in the state of High gain.

Lg: When $+1 < (x_n - x_{n-1}) < +10,$ the process is in the state of Low gain.

Nc: When $-1 < (x_n - x_{n-1}) < +1,$ the process is in the state of No change.

Ll: When $-10 < (x_n - x_{n-1}) < -1,$ the process is in the state of Low loss.

Hl: When $(x_n - x_{n-1}) < -10,$ the process is in the state of High loss, where x_n is current and x_{n-1} is the previous closing share prices of TCS limited. The Markov chain model is denoted by $\lambda = (S, A, \pi^{(0)}),$ where S is the set of states' $S = \{\text{Hg, Lg, Nc, L1, H1}\},$ A and $\pi^{(0)}$ are the TPM and IPV which are called the *parameters of the model*.

2.3. Parameters of Markov chain model

The state space defined above in Section 2.2 of the present MC model is $S = (\text{Hg, Lg, Nc, Ll, Hl}).$ Therefore, the IPV consists of five elements $\pi_1, \pi_2, \pi_3, \pi_4, \pi_5.$ The elements of IPV are the probabilities of the states Hg, Lg, Nc, Ll and Hl, i.e., $P(X_0 = i) = \pi_i,$ where $i = 1, 2, 3, 4, 5$ such that $\sum_{i=1}^{5} \pi_i = 1.$ Therefore, the IPV is $\pi^{(0)} = [\pi_1, \pi_2, \pi_3, \pi_4, \pi_5].$

Markov chain defines the TPM as transition or jump probability of a particle moving from one state to next states. TPM depicts an exact explanation of the behavior of a MC. The entries of TPM are denoted by a_{ij} which represent the probability measures of reaching to state *j* from state *i*. Mathematically, we write the transition probability a_{ij} as $a_{ij} = P(X_{n+1} = j / X_n = i) \geq 0$ for all $i,$ $j = 1, 2, 3, 4, 5$ and $n \geq 0$ such that $\sum_{j=1}^{5} a_{ij} = 1$, called the *one step transition probability*. The one step transition probabilities are represented in matrix form called as the *transition probability matrix* (*TPM*) written as $A = [a_{ij}]_{n \times n}.$

Similarly, the probability $a_{ij}{}^{(k)} = P(X_{n+k} = j / X_n = i) \geq 0,$ $\forall i,$ $j =$ $1, 2, 3, 4, 5,$ $k > 0$ and $n \geq 0$ is the transition probability from state *i* to state *j* in *k* steps.

Markov chain is explained through the diagrammatic representation called the *state transition diagram* or *schematic diagram*, that is quite same as the TPM along with IPV but diagrammatically. If the transition probability $a_{ij} > 0$, then there is a directed edge from vertex i to vertex j on the diagram. The transition diagram of our five state MC model $\lambda = (S, A, \pi^{(0)})$ is presented in Figure 1.

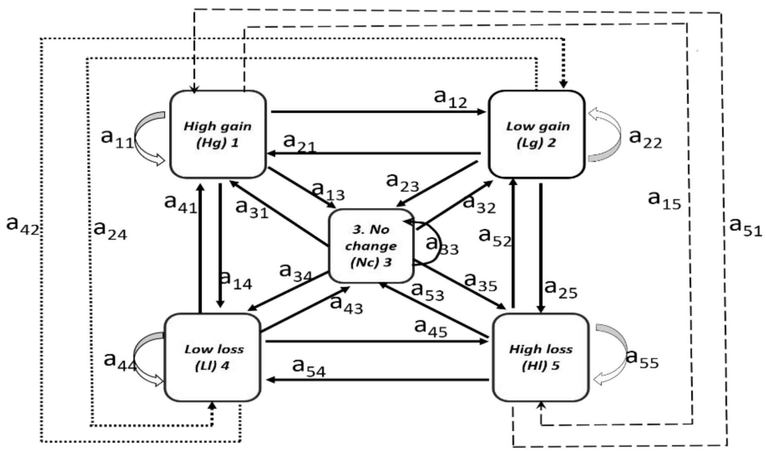

Figure 1. Schematic diagram of the Markov chain model.

In state transition diagram, the probability of an edge sequence is obtained by the product of the probabilities of its edges.

2.4. State probability distributions

The average transition process of MC is based upon the initial state of the system and the TPM. This IPV is required with TPM to understand the chain fully. We have $\pi^{(1)} = \pi^{(0)}A$, $\pi^{(2)} = \pi^{(0)}A^2$, and in general, $\pi^{(n+1)} = \pi^{(n)}A^n = \pi^{(0)}A^{n+1}$, for $n \geq 1$.

From the above state probabilities, we can interpret that the state probability vector at $(n+1)$ is the product of IPV and $(n+1)^{\text{th}}$ power of the one-step TPM. State probabilities form the basis of observing the long run movement in the behavior of the MC. Let $\overline{\pi}$ be the stable probability distribution. Then $\overline{\pi} = \overline{\pi}A$, that is the input and the output steady vectors will be the same at the time of steady state probabilities or stationary probability distributions.

2.5. Stationary or stable probability distribution of Markov chain

The stationary property of Markov chain states that irrespective of its initial state, how does the stochastic process evolve, if transition steps increase, then the transition probability of reaching to state *j* from state *i* will converge to some constant value. Thus,

$$\lim_{n \to \infty} A_{ij}(n) = \lim_{n \to \infty} A^n = \pi_j.$$

Such quantities are termed as steady state probabilities. This stationary property of MC is also used to analyze movement and predict the long run behavior of the system. The *n*-step TPM represents the behavior of the chain after *n* steps.

2.6. Expected number of visits and expected return time

Expected numbers of visits of reaching to a particular state *j* starting from some state *i* in *n* different time steps is computed to know the expected time the moving particle remains in certain state. The formula for calculating the number of visits on an average to a state *j* from state *i* is $\mu_{ij}(n) = E[N_{ij}(n)]$ or in terms of transition probabilities

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

where $N_{ij}(n)$ denotes the number of visits starting from i^{th} state and reaching to state j^{th} in *n*-steps. The expected number of visits to state *j* in matrix form is given by $\mu_{jj} = \sum_{k=1}^{n-1} A^k$.

Also, the expected return time to state *j* from the same state *j* in a finite irreducible Markov chain is obtained by taking the reciprocal of limiting probabilities $p_{ij}(n)$, that is, $\mu_{jj} = 1/\pi_j$, $j = 1, 2, 3, 4, 5$.

3. Empirical Data Modeling and Analysis

In this study, the data regarding the closing share prices of Tata Consultancy Service Limited (TCS Ltd.) were extracted from www.yahoofinance.com. It is the secondary data which consists of the daily trading day's closing price change of TCS Ltd. from 1st January 2020 to 31 January 2022. It consists of 518 trading days daily data of TCS during the period. Stock market trend of TCS from 1st January 2020 to 31 January 2022 is displayed in Figure 2.

Figure 2. Stock market trend of TCS Ltd.

We carried over all mathematical and statistical computations using Microsoft Excel and R software.

3.1. Volatility in the stock market trend

The volatility refers to the change and fluctuations in the share price in stock market. This volatility is risky but can bring a maximum profit if the trader is skilled and stocks may fall down within very short time. Therefore, high volatility can also result in a severe loss. The historic randomness and volatility in the share prices are obtained using a series of past market prices. Figure 3 shows the historic volatility of the TCS share prices from 1st January 2020 to 31 January 2022.

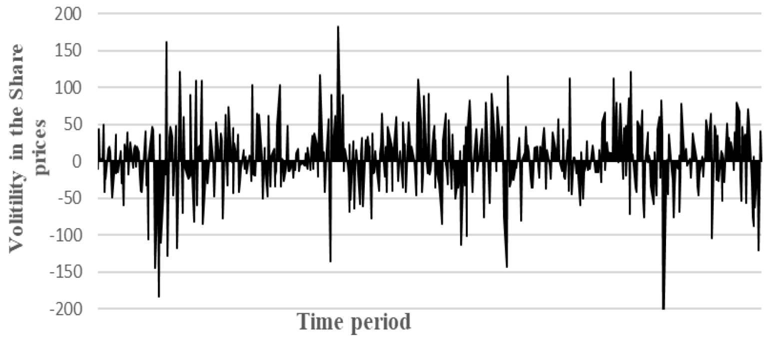

Figure 3. Volatility in stock prices of TCS Ltd.

3.2. Initial probability vector

From the data of closing share price of TCS, it is observed that the next day price is either in the state of Hg, Lg, Nc, Ll or Hl defined in Subsection 2.2. These states are obtained in MS Excel using ‘IF’ function. The following table represents the frequencies of the states Hg, Lg, Nc, Ll and Hl.

States	Hg	Lg	Nc	Ll	Hl	Total
Frequency	217	57	15	47	181	517

Hence, the required initial probability vector (IPV) is obtained as follows:

$$\begin{array}{ccccc} \text{Hg} & \text{Lg} & \text{Nc} & \text{Ll} & \text{Hl} \\ \end{array}$$
$$\pi = [0.419729 \quad 0.110251 \quad 0.029014 \quad 0.090909 \quad 0.350097]$$

i.e., P(Hg) = 0.419729, P(Lg) = 0.110251, P(Nc) = 0.029014, P(Ll) = 0.090909 and P(Hl) = 0.350097.

3.3. Transition probability matrix

Note that the state space of our MC model is $S = \{\text{Hg, Lg, Nc, Ll, Hl}\}$. Therefore, to determine the TPM, the frequencies of transitions from one state to another such (Hg Hg, Hg Lg, Hg Nc, Hg Ll, Hg Hl); (Lg Hg, Lg Lg, Lg Nc, Lg Ll, Lg Hl); (Nc Hg, Nc Lg, Nc Nc, Nc Ll, Nc Hl); (Ll Hg, Ll Lg, Ll Nc, Ll Ll, Ll Hl) and (Hl Hg, Hl Lg, Hl Nc, Hl Ll, Hl Hl) are obtained in MS Excel using COUNTIF function. The transition frequencies are presented in the following Table 1. For example, the state Hg moves to state Hg 88 times and state Hl reaches state Hl 59 times.

Table 1. Transition frequency table

	Hg	Lg	Nc	Ll	Hl	Total
Hg	88	26	9	20	73	216
Lg	25	7	2	3	20	57
Nc	8	2	0	1	4	15
Ll	14	3	1	4	25	47
Hl	82	19	3	18	59	181

Therefore, using Table 1, the required TPM is obtained in the matrix A.

$$A = \begin{array}{c} \\ Hg \\ Lg \\ Nc \\ Ll \\ Hl \end{array} \begin{array}{c} \begin{array}{ccccc} \quad Hg \quad & \quad Lg \quad & \quad Nc \quad & \quad Ll \quad & \quad Hl \quad \end{array} \\ \begin{bmatrix} 0.407407 & 0.12037 & 0.041667 & 0.092593 & 0.337963 \\ 0.438596 & 0.122807 & 0.035088 & 0.052632 & 0.350877 \\ 0.533333 & 0.133333 & 0 & 0.066667 & 0.266667 \\ 0.297872 & 0.06383 & 0.021277 & 0.085106 & 0.531915 \\ 0.453039 & 0.104972 & 0.016575 & 0.099448 & 0.325967 \end{bmatrix} \end{array}.$$

The parameters of MC model, namely, the IPV $\pi^{(0)}$ and the TPM (A) are presented through a diagram known as the schematic diagram or the state transition diagram of the MC model. The schematic diagram of the present study for the real time data is given in Figure 5.

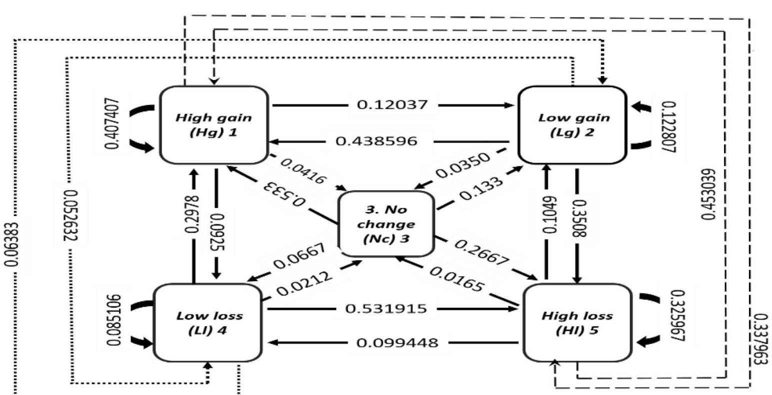

Figure 5. Schematic diagram of the MC model.

3.4. Long run or stationary probability distribution of share prices

The higher-order TPM matrix is used in order to obtain the equilibrium situation for the states of the Markov chain. Since the forecasting of the long run behavior of Tata Consultancy Service Limited (TCS Ltd.) is very meaningful for investors, the stationary matrix is obtained to observe its long run behavior.

Long run behavior of TCS is obtained by determining the higher-order TPMs reaching the stationary probability distribution of TCS by using Microsoft Excel and R software. The stationary probability distribution for our study is given below:

$$A^6 = \begin{array}{c} \\ Hg \\ Lg \\ Nc \\ Ll \\ Hl \end{array} \begin{array}{c} \begin{array}{ccccc} \quad Hg & \quad\quad Lg & \quad\quad Nc & \quad\quad Ll & \quad\quad Hl \end{array} \\ \begin{bmatrix} 0.420747 & 0.110581 & 0.029116 & 0.089153 & 0.350403 \\ 0.420747 & 0.110581 & 0.029116 & 0.089153 & 0.350403 \\ 0.420747 & 0.110581 & 0.029116 & 0.089153 & 0.350403 \\ 0.420747 & 0.110581 & 0.029116 & 0.089153 & 0.350403 \\ 0.420747 & 0.110581 & 0.029116 & 0.089153 & 0.350403 \end{bmatrix} \end{array}$$

$$= A^7 = A^8 = \cdots = A^n.$$

The stationarity condition is reached at the 6^{th} step. This has been done by multiplying the TPM 6 number of times in order to get the matrix with identical columns. The higher-order TPM of TCS computed above in the matrix A^6 represents that after the 6^{th} trading day since 518 trading days, the TPM of our Markov chain reaches to the state of equilibrium and after that the TPM will not change for the onwards consecutive trading days. This steady state TPM of TCS limited reveals the following information.

There are 42% chance that there will be high gain (Hg) in the share price of TCS in the near future and in the long run irrespective of its initial states whether Hg, Lg, Nc, Ll or Hl. There is 11% likelihood that the TCS share prices will go to the state of Lg in future independent of its initial states. The probability of Nc in the share price of TCS in near future and in the long run is approximately 0.03 irrespective of its initial states whether it is in Hg, Lg, Nc, Ll or Hl. The probability that the stock value of TCS will go to the state of low loss (Ll) in future is 09%. Finally, the probability that there will be the state of high loss (Hl) in the share price of TCS in the long run irrespective of its initial states whether Hg, Lg, Nc, Ll or Hl is 0.35.

3.5. Computation of state probabilities for forecasting the share price

According to Markov chain model, the state probabilities are obtained by the multiplication of IPV with higher order transition probability matrices as discussed in Subsection 2.4. Mathematically, we write $\pi^{(n+1)} = \pi^{(0)} A^{n+1}$.

Therefore, the state probability distribution for the states of TCS share price shares for 518th day will be:

$$\pi^{(1)} = \pi^{(0)} A = [0.420517 \quad 0.110484 \quad 0.029094 \quad 0.089154 \quad 0.35075].$$

The above state probability distribution reveals that TCS share prices have a likelihood of 0.42 to reach the state of Hg (High gain), 0.11 to Lg (Low gain), 0.029 for Nc (No change), 0.08 to Ll (Low loss) and 0.35 for the Hl (High loss) from their previous closing share price in the future on 518th day.

The second state probability distribution for the states of TCS closing share price shares for 519th day is also obtained by using the formula:

$$\pi^{(2)} = [0.420757 \quad 0.110575 \quad 0.029109 \quad 0.08916 \quad 0.350399].$$

We can interpret from the above probability vector that TCS share prices will go to state of Hg with maximum probability of 42% and a minimum probability of no change as 0.02% on 519th day. In the same way, we have calculated the state probabilities for 520th, 521th and 522th day in Table 2.

Table 2. State probabilities for the future days

$\pi^{(3)}$	0.420745	0.110581	0.029116	0.089154	0.350405
$\pi^{(4)}$	0.420747	0.110581	0.029116	0.089153	0.350403
$\pi^{(5)}$	0.420747	0.110581	0.029116	0.089153	0.350403

We observe that $\pi^{(4)} = \pi^{(5)} = \pi^{(6)} = \cdots$.

3.6. Expected number of visits

The expected frequency of visits the stock prices of TCS make to some specific state starting from another state of the system in different steps is obtained. Expected number of visits to particular state is obtained in order to know the expected time, the moving particle stays in certain states. Here, for TCS the number of visits to a particular state in six trading days using the formula defined in Subsection 2.6 shown in the following matrix:

$$\mu_{jj}(6) = \begin{array}{c} \\ Hg \\ Lg \\ Nc \\ Ll \\ Hl \end{array} \begin{array}{c} \begin{array}{ccccc} \quad Hg \quad & \quad Lg \quad & \quad Nc \quad & \quad Ll \quad & \quad Hl \quad \end{array} \\ \begin{bmatrix} 2.512136 & 0.673503 & 0.186931 & 0.537536 & 2.089894 \\ 2.547349 & 0.678033 & 0.181227 & 0.497878 & 2.095514 \\ 2.633288 & 0.688591 & 0.149089 & 0.511685 & 2.017346 \\ 2.406848 & 0.613731 & 0.163171 & 0.534394 & 2.281855 \\ 2.552973 & 0.65744 & 0.163 & 0.545533 & 2.081053 \end{bmatrix} \end{array}.$$

The first row of matrix $\mu_{jj}(6)$ obtained above explores that, if the share prices of TCS starts from the state of Hg, the expected number of visits the chain for TCS makes again to the state of Hg out of six trading days is 2.5, to Lg is 0.67, to Nc is 0.18, to Ll is 0.53, and to the state of Hl is 2.08. Similarly, the second row depicts that if TCS share price starts from Lg, the number of visits the chain makes a move on an average to the state of Hg, Lg, Nc, Ll and Hl is 2.54, 0.67, 0.18, 0.49 and 2.09, respectively. And finally, the last row of the matrix represents that if TCS share price starts from Hl state, the expected number of visits the chain reaches to the state of Hg, Lg, Nc, Ll and Hl is 2.55, 0.65, 0.16, 0.54 and 2.08, respectively. It has been observed from the above matrix that when TCS's share prices starts from the state of Hg and makes again a visit to the state of Hg has the maximum expectation.

3.7. Determination of expected return time

The stationary probability matrix is also helpful for us in order to calculate the expected return time μ_{jj} that is the time the chain visits state j when it left state j. The formula for obtaining the return/reaching time in terms of stationary probability distribution is $\mu_{jj} = 1/\pi_j$, $j = 1, 2, 3, 4, 5,$ where π_j's are the entries in the stationary matrix. This expected first reaching time represents the expected waiting time of TCS share prices in all the states, i.e., Hg, Lg, Nc, Ll and Hl.

3.7.1. Expected return time to the state of high gain (Hg) is

$$\mu_{\text{Hg, Hg}} = 1/0.420747 = 2.37.$$

The expected first reaching time to the state of Hg from the state Hg reveals that the chain for TCS stock prices makes a visit to the state of Hg on average in 2.3 days or approximately 2 days.

3.7.2. The expected return time to the state of no change (Nc) is

$$\mu_{\text{Nc, Nc}} = 1/0.029116 = 34.23.$$

We can observe that TCS share prices will reach to the state of Nc starting from the state of Nc on an average in 34 days. It also represents that the share prices are extremely random and volatile in nature as no stability is found in the stock prices as the maximum return time to the state of no change state depicts.

3.7.3. The expected return time to state of high loss (Hl) is giben by

$$\mu_{\text{Hl, Hl}} = 1/0.350403 = 2.85.$$

The expected return time of high loss (Hl) state represents that the chain of the states for TCS share prices visits to Hl after starting from Hl state takes on an average in 3 days approximately. We can interpret from above that the chain takes relatively minimum time to go to Hg state after starting from the Hg state. Similarly, the expected return time to all the states can be obtained.

4. Results and Conclusions

Markov chain model is an ideal statistical method of prediction to analyze and predict the future behavior of the stock market through IPV, TPM and steady state probability distributions. By applying MC model, it is easy for us to obtain the information not only about whether or not the stock price will increase in the future, but can also forecast how long it will keep on increasing. In this paper, we applied a first order discrete time MC model to the historical stock prices of a Tata Consultancy Service Limited to analyze and estimate the precision of forecasting of the MC model in the context of Indian stock market. Markov Chain model explains the behavior and movement of share price trend in probability measures. The interpretation of IPV and TPM reveals that the probability of the state Nc is very less demonstrating the volatility of the stock market.

The results of stationary probability matrix reveal that regardless of the TCS initial share price, in the long run, we could predict that its share price will have *high gain with probability* 0.420747, *low gain with probability* 0.1105, *no change with probability* 0.0291, *low loss with probability* 0.0891 *and high loss with probability* 0.3504. From the above results, we observe that the probabilities for high loss in share prices of TCS are less than that of high gain in the future and we can conclude that investing in TCS share is a good choice of investment for investors to make capital gain.

The results from Subsection 3.7 depict that if the state of TCS share price is in high gain, then it will reach the state to high gain again after 2 days. The chain will reach to the state of no change after 34 days if it is in the state no change and finally the chain takes 2.85 or 3 days approximately to reach the state of high loss if it is initially in that state.

Although the states such as Hg, Nc and Hl are represented and explained in probability measures yet, these findings have economic significance. These findings will be helpful for the future investors and shareholders to invest wisely for the effective portfolio management. In this paper, we have applied Markov chain model in the stock market, and achieved comparatively good results. This model can also be applied to other fields, such as the futures market, the bond market and such others to analyze the behavior and forecast the future trend movement.

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