[1] V. Parimyndhan *
[2] K. Senthamarai Kannan

Markov Chain Model for NIFTY50 Index

Journal of Electrical Systems

Abstract: - For the last two decades, financial market forecasting has been one of the sensational topics in research, but the market prediction is not easy because of its uncertainty. Though the trend is uncertain by its nature, some researcher is attempted to trace the movement with more accuracy. This study focuses on creating and analyzing a stochastic model that employs the Markov Chains method to anticipate stock prices on the stock exchange. By supposing that prices fluctuate have the feature of Markov dependence with their transition probabilities, study, four states are determined to construct the Markov model in this study. The daily fluctuations in the NIFTY 50 Index, which includes the top 50 firms of Indian stocks are tracked and analyzed. The TPM and IPV, the anticipated number of transitions, and the expected number of return times are established.

Keywords: Expected first reaching time, Markov chain, NIFTY50, Steady state probability, Stock Performance, Stock price. TPM.

1. Introduction

The stock market is a significant part of the global economy. It is considered that a country's strong economy is reflected in its rising stock market. Stock prediction is difficult due to randomness. A long-term stock investment pays off, but a short-term investment is risky due to fluctuating stock prices. Because of the fluctuations in the stock price, it is necessary to develop a method for forecasting stock prices that can help market participants complete the process of buying and selling shares. The reason behind the utilized NIFTY50 index is the primary benchmark of the NSE (National Stock Exchange), This has an index of the top 50 publicly listed firms in terms of free-float market capitalization. It is intended to represent the health of all market conditions of the listed universe of Indian firms and, by extension, the whole economy[11]. The NSE is one of the top stock exchanges in India. The NSE is a fully automated trading system in India. [3]. Traders place their orders through online brokers who offer stock trading services on these platforms, the platforms where the majority of stock trading occurs. Based on the behavior and trend of stock prices, the statistical models provide insight into whether investing is a good idea or not. The Markov Chain (MC) is one method that can be used to forecast stock prices.

One of the benefits of this forecasting approach is its adaptability, which requires only the capacity to calculate the likelihood at any given time [6]. During the 1930s and 1940s, the general theory of Markov chains was created. In an MC, the possible values are discrete-valued, which means that their state spaces are finite or measurable. Many practical problems can be modeled using MC. MC has been extensively utilized and employed in a variety of fields, including law, healthcare, data mining, income distribution, finance, marketing, software dependability, manufacturing, migration meteorology, and so on. The study of their evolution is useful when it is not possible to accurately forecast the state of a system [1].

An MC is an ideal model to analyze the future condition of the share market using simple matrix calculations. In this way, it was possible to not only predict whether the stock price would rise in the future but also how long it would rise [10]. This study attempts to construct a discrete-time MC model to analyze the movement of stock prices.

2. Literature Survey

Armstrong et.al., (1969) attempted to understand the nature of stock price movements, and stochastic models such as Markov Chains were applied to the stock market. Accurate out-of-sample forecasting is one of the key benefits of Markov analysis. Predictions from simpler models are frequently more accurate than those from more advanced systems. The econometrics field uses this finding [2].

Between the period of 1969 to 2002, there is a lot of researchers who developed the Markov model for the financial market like the HMM, the Markov decision process, Markov random field. Hierarchical Markov models, Tolerant Markov model, etc., Bhattacharya and Kaushik. (2002) proposed the MC model has been utilized by various

[1,2] Department of Statistics, Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India

researchers over the years to examine and forecast stock market activity. There was a study that discussed a two-state MC Model for discretized return and convergence of the MC to its steady state [4].

Dai et.al., (2014) discuss the empirical study findings and demonstrate that this novel forecast approach, which combines an enhanced back-propagation NN (Neural Network) with an MC, can accurately forecast stock indices, which might be a helpful benchmark for stock market investing [7]. Furthermore, Bhusal (2017) investigated the long-run performance of the Nepal Stock index and determined the anticipated number of visits for every state as well as the anticipated time at the first return of various states through daily trading data [5]. Khaing et.al., (2020) developed the MC model that extracts share trends from trend-related data in one and forecasts trend variations from news using transition probability matrices and starting state vectors [12].

Kostadinova et.al., (2021) used the MC model to forecast price trends for three distinct stocks, and the findings are based on the probability transition matrix and starting state vector [13]. Han et.al., (2021) proposed Elman NN and the MC were integrated to create a forecasting model, which was used to anticipate the interval of stock price, and good results were produced by forecasting the top stocks in the 6 sectors [9]. Dar et.al., (2022) applied the MC model to anticipate stock prices and analyze stock market activity. The Markov chain models have successfully predicted market patterns in stock market data using a variety of statistical methodologies [8].

3. Material and Methods

3.1.1 Material:

We considered NIFTY50 Index data from September 1st, 2020 to August 31st, 2022 in this analysis. The daily data is gathered after the trading day and comprises around 495 observations. This dataset contains statistics on the open, close, high, and low prices. The closing price of the stock is used in this study. There is a bullish trend. Though some fluctuations occur, the overall trend appears to be Positive.

3.1.2 Daily Returns

The close value of the NIFTY50 index return at time n is established by,

$$R = \frac{Today\ close\ value - Yesterday\ close\ value}{Yesterday\ close\ value}$$

If there is a difference of more than 0 between the closing prices of today and yesterday, then it is described as a bull (indicating highs) and if this difference is less than 0, then it is described as a bear (indicating lows). If two consecutive days forming a high is considered Higher Highs, if two consecutive days forming a low is considered Lower Low, if two consecutive days forming a high and low is considered Higher Low, if two consecutive days forming a low and high is considered Lower. Assuming that R follows a stationary first-order Markov chain and future movement of R is determined only by its current state. The stock value can be seen as a system toggling between highs and lows. Stock traders use highs and lows as reference points. They are important points in daily charts. Their close link to the trend definition is the reason for this. Higher highs and Higher lows characterize an upward trend. Lower Highs and Lower Lows define a downward trend. In this analysis, we use 4 states to mark this behavior.

3.2 Methods:

3.2.1 Markov chain (MC)

An MC is a Markov process with discrete state space. A specific kind of stochastic/random process called a Markov process depends on the instantaneous preceding state of the future event rather than on the past. For predicting both group stock indexes as well as individual stock indexes, the Markov chain model is extensively used. Stochastic models based on the Markovian property state that future events are independent of the past. Once the transition probability matrix (TPM) and the initial probability distribution are known, it is simpler to make use of the MC model to estimate the possibility of a state value in a specific period. For all states i_0, i_1, i_2, ..., $i_n \in I$, the sequence $\{X_n, n \geq 0\}$ is a Markov chain if,

$$P\{ X_{n+1} = j/ X_0 = i_0, X_1 = i_1, \ldots, X_n = i\} = P\{X_{n+1} = j/ X_n = i\}$$

Here, I represent the state space. Probabilities of this type are called Markov chain probabilities. Therefore, no matter what state i is before time n, the probability of it changing to a different state j purely depends on state i. There are three types of Markov Chain,

A Regular Markov Chain is one in which all the elements of matrix A^k are strictly positive if there is a natural k. An Ergodic MC can be defined as a Markov chain where any state can reach any other state that is, K exists so that $ak_{ij}>0$ for all i, j $\in$ N. Since every MC is ergodic, they all are. An irreducible MC is one in which the state space cannot be divided into two or more discontinuous closed sets. That is, it contains only one class. This paper has a state space of E (HH, HL, LH, LL), so here have a four-state Markov chain and a four-by-four TPM. The definition and notations of the four states are presented in the next section.

3.2.2 Initial Probability Vector (IPV)

In the current MC model, the state space of E = {HH, HL, LH, LL}, so the initial probability vector contains four elements π_1, π_2, π_3, π_4. IPV represents the probabilities of the states HH, HL, LH, and LL. The initial probability vector is, $P(X_0=i)=\pi_i$, ∀, i=1,2,3,4 $such\ that, \sum_{i=1}^{4} \pi_i = 1$. The IPV is represented as Π_0 in the form, $\Pi_0 = [\pi_1, \pi_2, \pi_3, \pi_4]$. where π_1 denotes the probability of HH, π_2 is the probability of HL, π_3 is the probability of LH, and π_4 is the probability of LL in the NIFTY50 index price.

3.2.3 Transition Probability Matrix (TPM)

The sum of the row $\sum_{j=1}^{4} a_{ij}=1$, ∀ i,j=1,2,3,4. One-step Transition Probabilities are denoted by a_{ij}. A matrix of transition probabilities a_{ij} is called a TPM. A Markov Chain is possible states are represented by rows and columns, so the TPM must always be a square matrix, with the sum of each row being one. In our four-state Markov Chain, the TPM will be written as,

$$A = \begin{array}{c} \\ HH \\ HL \\ LH \\ LL \end{array} \begin{array}{c} \begin{array}{cccc} HH & HL & LH & LL \end{array} \\ \begin{bmatrix} P(HH|HH) & P(HL|HH) & P(LH|HH) & P(LL|HH) \\ P(HH|HL) & P(HL|HL) & P(LH|HL) & P(LL|HL) \\ P(HH|LH) & P(HL|LH) & P(LH|LH) & P(LL|LH) \\ P(HH|LL) & P(HL|LL) & P(LH|LL) & P(LL|LL) \end{bmatrix} \end{array}$$

Based on what has been observed today, P(HH|HH) represents the probability that there will be Higher Highs for the next four days. Therefore, the four-state TPM (HH, HL, LH, LL) represents,

$$A = \text{Current } X_n \begin{array}{c} \\ HH \\ HL \\ LH \\ LL \end{array} \begin{array}{c} \text{Future } X_{n+1} \\ \begin{array}{cccc} HH & HL & LH & LL \end{array} \\ \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \end{array}$$

There are 16 potential transitions between the four states (HH, HL, LH, and LL). If we are at "HH," here could transition to HL, LH, LL, or stay at "HH." If there at "LL," here could transition to LH, HH, HL, or stay at "LL," and so on. Where, a_{11} = HH|HH is a probability of two consecutive days form Higher High to Higher High, a_{21} = HH|LH is a probability of two consecutive days form Higher High to Lower Higher Low, and so on.

Assuming k steps, the probability of transitioning from state i to state j,

$a_{ij} = P(X_{n+k}= j/ X_n = i) \geq 0$ ∀ k>0, i,j=1,2,3 and n≥0 (2)

3.2.4 Schematic Diagram

State Transition Diagrams or Schematic Diagrams are diagrammatic representations of Markov chains, which are quite similar to the TPM but diagrammatic. $\lambda = (A,\pi)$ is the one-way directed graph of the Markov chain where each vertex represents the model current state.

3.2.5 State Probabilities for Predicting the States in Future

An MC model process is entirely determined by the initial state probability and TPM. This IPV is often referred to as the system initial state probabilities defined as,

$\pi_0= P(X_0 = i) = P(0) = [P_0 (0), P_1 (0),\ldots, P_n (0)]$, such that $0 \leq P_i (0) \leq 1$ and $\sum_{j=1}^{3} P_i(0) = 1$ for every state. Similarly, at time n,

$\pi_n = P(X_n = i) = P(n) = [P_0 (n), P_1 (n),\ldots, P_n (n)]$, such that $0 \leq P_i (n) \leq 1$ and $\sum_{j=1}^{3} P_i(n) = 1$ for every state. IPV and TPM are required to fully understand the chain.

Therefore,

$\pi_1 = \pi_0 A$, $\pi_2 = \pi_1 A = \pi_0 A*A = \pi_0 A_2$, etc. $\pi_{n+1} = \pi_n A = \pi_0 A_{n-1} *A = \pi_0 A_{n+1}$ ∀ n ≥ 1

Using the above formula, there could understand the result of multiplying the IPV by the $(n+1)^{th}$ power of the one-step TPM is the state probability vector after $(n+1)^{th}$ steps. State probabilities play an important role in predicting long-term behavior.

3.2.6 Stationary Distribution or Long run behavior

The property of the Markov chain says that, when the number of transition steps is large enough, the probability of transitioning from one state i to another state j reaches a constant value, regardless of the initial state. Therefore, $\lim_{n\to\infty} P_{ij}(n) = \pi_j$

These quantities are known as steady-state probability. If $\pi_j = \lim_{n\to\infty} P_{ij}(n)$ exists and is independent of the initial state. Therefore,

$P_j(n) = \sum_k P_k(n-1)P_{kj}$ turn into $\pi_j = \sum_k \pi_k P_{kj}$ where, $n\to\infty$ for j=0,1,2,….

Similarly,

$$\pi = \pi * P$$

A stationary distribution $\{\pi_i, i \epsilon I\}$ is invariant for all chains if,

$\pi_i = \sum_{i \epsilon I} \pi_i P_{ij}$ $\forall \pi_i \geq 0$ and $\sum_i \pi_i = 1$

The long-run behavior of MC is determined by this property.

3.2.7 Estimation of the anticipated number of visits and Return

In the anticipated Number of Visits, $\mu_{ij}(n) = E(N_{ij}(n))$ provides the estimated number of visits that the chain will make to state j after leaving state i. Where N_{ij} (n) refers to the number of visits to state j in n steps after state i.

That is,

$N_{ij}(n) = \sum_{k=1}^{n} Y_{ij}(k)$ with $Y_{ij}(0) = \partial_{ij}$, the Kronecker delta.

$$Y_{ij}(k) = \begin{cases} 1, if\ X_k = j / X_0 = i \\ 0, Otherwise \end{cases}$$

Then,

$$\mu_{ij}(n) = E\left[\sum_{k=1}^{n} Y_{ij}(k)\right]$$

$= \sum_{k=1}^{n} E(Y_{ij}(k))$

$= \sum_{k=1}^{n} P[Y_{ij}(k) = 1]$

Therefore,

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

In addition, after a long run, the number of visits from state i to state j is;

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

In the Expected Return duration, it is possible to determine the estimated return duration to state j by considering the reciprocal of the limiting probability $P_{ij}(n)$ for a finite irreducible Markov chain.

4. Results And Discussion

4.1. Construction of the Initial probability vector (IPV)

One of the four different transition states at the end of two consecutive trading days is shown in the close observation of the NIFTY50 index. In such cases, the NIFTY50 index could move in one of the four directions: HH, HL, LH, and LL. The states indicate Higher Highs (HH), Lower Lows (LL), Lower Highs (LH),or Higher Lows (HL). If two consecutive days close positively, it represents higher highs; if two consecutive days close negatively, it represents lower lows; two consecutive days close positively and negatively represent higher lows; and two consecutive days close negatively and positively represent lower highs. For TPM determination, these four distinct movements are regarded as four distinct states in the MC. The transition probability provides information about the MC transition behavior. The TPM elements indicate the likelihood of the transition of one state into another. In other words, the transition probability is the likelihood of a typical state arising from one of the existing states.

Table 1: Frequency of states

States	HH	HL	LH	LL	Total
Frequency	82	53	51	61	247

4.2. The Initial state vector determination

In this case, the initial state vector is represented as $\boldsymbol{\pi_0} = [\pi_1, \pi_2, \pi_3, \pi_4]$ then π_1, π_2, π_3 and π_4 gives the probability of HH, HL, LH, and LL in the share price as π_1 = 82/247 = 0.33, π_2 = 53/247 = 0.21, π_3 = 51/247 = 0.21 and π_4 = 61/247 = 0.25. Therefore, the Initial Probability Vector for the NIFTY50 index price is

HH HL LH LL

$\boldsymbol{\pi_0} = [0.33\ 0.21\ 0.21\ 0.25]$

The probability of the initial state acquiring a Higher High in 247 days is 0.33, the probability of the initial state acquiring a Higher Low in 247 days is 0.21 The probability of an initial state acquiring a Lower High in 247 days is 0.21 The probability of the initial state of acquiring a Lower Low in 247 days is 0.25

4.3. The Transition matrix of the NIFTY50 index

According to the data, for the next two consecutive days, the closing share price of NIFTY50 has a Higher High, Lower High, Higher Low, and Lower Low. Since the TPM is determined utilizing four states, the state space of the MC is E = {HH, HL, LH, LL}. The states are defined in section 3.2.8. The transition frequencies of the closing price are tabulated below.

Table 2: Transition Frequency table

	HH	HL	LH	LL	Total
HH	34	18	11	20	83
HL	12	6	15	19	52
LH	19	15	8	9	51
LL	17	14	17	13	61

The above information can be used to create a TPM. Table 2 shows that the NIFTY50 index traded for 495 days in the period from 01.09.2021 to 31.08.2022. The TPM is constructed by dividing class frequencies by total class frequencies. Thus a_{11} = 34/83=0.41, a_{21}=12/52=0.23, and so on. The TPM here get is as follows.

$$A = \begin{array}{c} \\ HH \\ HL \\ LH \\ LL \end{array} \begin{array}{c} \begin{array}{cccc} HH & HL & LH & LL \end{array} \\ \begin{bmatrix} 0.41 & 0.22 & 0.13 & 0.24 \\ 0.23 & 0.12 & 0.29 & 0.36 \\ 0.37 & 0.29 & 0.16 & 0.18 \\ 0.28 & 0.23 & 0.28 & 0.21 \end{bmatrix} \end{array}$$

The IPV and TPM are best explained using a diagram known as the state transition diagram or Schematic diagram. Figure 1 depicts a schematic diagram of the current study for the real-time data set using the Markov Chain model.

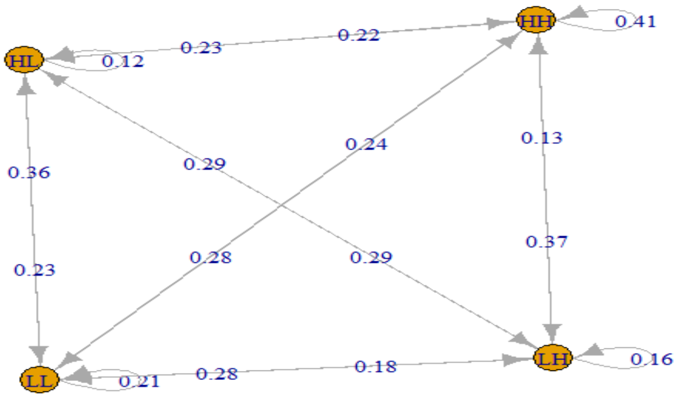

Figure 1: Schematic diagram of Markov chain.

Observing the previous two pairs of the day price interval yields the initial state vector $\boldsymbol{\pi_0}$. The data show that the starting state for future prediction is

$\boldsymbol{\pi_0} = [0.33\ 0.21\ 0.21\ 0.25]$

Let this be the starting point for predicting future stock prices.

4.4. Stationary Distribution or Long run behavior of the NIFTY50 index

Forecasting the long-term action of the NIFTY50 index is critically essential to investors. The identification of the market is likely future condition serves as a guide for investing decisions. The bullish market encourages investors to make large investments to maximize their return. The n^{th} step TPM can be utilized to predict the index price long-run behavior. The index behavior could be identified from the TPM P(n). As the number of steps increases, the TPM P(n) converges to the limiting transition matrix. This limiting TPM predicts the future steady-state probability of the NIFTY50 index in various states such as HH, HL, LH, and LL.

$$A = \begin{bmatrix} 0.41 & 0.22 & 0.13 & 0.24 \\ 0.23 & 0.12 & 029 & 0.36 \\ 0.37 & 0.29 & 016 & 0.18 \\ 0.28 & 0.23 & 028 & 0.21 \end{bmatrix}$$

By calculating the Higher-order TPM for the NIFTY50 index, long-run behavior can be observed.

$$A^2=\begin{bmatrix}0.334 & 0.2095 & 0.2051 & 0.2514\\ 0.33 & 0.2319 & 0.2119 & 0.2262\\ 0.328 & 0.204 & 0.2082 & 0.2598\\ 0.3301 & 0.2187 & 0.2067 & 0.2445\end{bmatrix} A^3=\begin{bmatrix}0.3314 & 0.2159 & 0.2074 & 0.2453\\ 0.3304 & 0.2139 & 0.2074 & 0.2483\\ 0.3312 & 0.2168 & 0.2079 & 0.2442\\ 0.3306 & 0.2150 & 0.2079 & 0.2465\end{bmatrix}$$

$$A^4=\begin{bmatrix}0.3310 & 0.2154 & 0.2076 & 0.2461\\ 0.3309 & 0.2156 & 0.2077 & 0.2458\\ 0.3309 & 0.2153 & 0.2075 & 0.2462\\ 0.3309 & 0.2155 & 0.2076 & 0.2459\end{bmatrix} A^5=\begin{bmatrix}0.3309 & 0.2154 & 0.2076 & 0.2460\\ 0.3309 & 0.2154 & 0.2076 & 0.2460\\ 0.3309 & 0.2154 & 02076 & 0.2460\\ 0.3309 & 0.2154 & 02076 & 0.2460\end{bmatrix}$$

In the 5th step, the stationary matrix is obtained.

4.5. Computation of state probabilities for predicting Stock price;

State probabilities can be calculated using the MC model by multiplying TPM and IPV. The state probabilities are calculated mathematically as

$\pi_1 = \pi_0 A$, $\pi_2 = \pi_1 A = \pi_0 A * A = \pi_0 A^2$ and so on until $\pi_{n+1} = \pi_n A = \pi_0 A^{n-1} * A = \pi_0 A^{n+1}$

The state probabilities for the NIFTY50 closing price will be

$$\pi_1 = \pi_0 A = [0.33\ 0.21\ 0.21\ 0.25]\begin{bmatrix}0.41 & 0.22 & 0.13 & 0.24\\ 0.23 & 0.12 & 029 & 0.36\\ 0.37 & 0.29 & 016 & 0.18\\ 0.28 & 0.23 & 028 & 0.21\end{bmatrix}$$

$\pi_1 = [0.3313\ 0.2162\ 0.2074\ 0.2451]$

The State probabilities π_1 are an upward trend the previous two days will follow the same trend with the highest probability during the first day. On the 496th & 497th day, the end state is Higher Highs, with the highest possibility of 33 percent from their previous day closing price.

At the end of the 496th & 497th day, the probability of ending in the state 'Higher Highs' is 0.3313

At the end of the 496th & 497th day, the probability of ending in the state of Higher Lows' is 0.2162

At the end of the 496th & 497th day, the probability of ending in the state 'Lower Highs' is 0.2074

At the end of the 496th & 497th day, the probability of ending in the state 'Lower Lows' is 0.2451

Similarly, the state probabilities for the second day can be computed using the same equation.

$$\pi_2 = \pi_1 A^2 = [0.3313\ 0.2162\ 0.2074\ 0.2451]\begin{bmatrix}0.41 & 0.22 & 0.13 & 0.24\\ 0.23 & 0.12 & 029 & 0.36\\ 0.37 & 0.29 & 016 & 0.18\\ 0.28 & 0.23 & 028 & 0.21\end{bmatrix}$$

$\pi_2 = [0.3309\ 0.2153\ 0.2075\ 0.2461]$

From π_2 it should be noted that,

At the end of the 497th & 498th day, the probability of ending in the state 'Higher Highs' is 0.3309

At the end of the 497th & 498th day, the probability of ending in the state of Higher Lows' is 0.2153

At the end of the 497th & 498th day, the probability of ending in the state 'Lower Highs' is 0.2075

At the end of the 497th & 498th day, the probability of ending in the state 'Lower Lows' is 0.2461

Similarly, the probability for the rest of the days is found in vectors π_3 and π_4 , respectively.

$\pi_3 = \pi_0 A^3 = [0.3309\ 0.2153\ 0.2076\ 0.246]$

$\pi_4 = \pi_0 A^4 = [0.3309\ 0.2154\ 0.2076\ 0.246]$

$\pi_5 = \pi_0 A^5 = [0.3309\ 0.2154\ 0.2076\ 0.246]$and so on

From the above state probabilities, it is observed $\pi_4 = \pi_5 = \ldots = \pi_n$

4.6. Estimation of the anticipated number of visits:

The purpose of the study is to calculate the total number of visits to a specific state from other states. To determine how long a moving particle will spend in one state it may be estimated how many visits the particle will make from other states over a specified period. The matrix illustrates how often the NIFTY50 Index visits a particular state during the pair of five trading days.

$$\mu_{jj}(5) = \begin{bmatrix}1.65 & 1.05 & 0.65 & 1.2\\ 1.15 & 0.6 & 1.45 & 1.8\\ 1.85 & 1.45 & 0.8 & 0.9\\ 1.4 & 1.15 & 1.4 & 1.05\end{bmatrix}$$

According to the matrix $\mu_{jj}(5)$ produced previously, if the NIFTY50 closing price begins in the HH state, the average number of visit the chain for NIFTY50 make to the HH state out of five consecutive trading day is 1.65, 1.05 for the HL state, 0.65 for the LH state, and 1.2 for the LL state. Similarly, if the NIFTY50 index begins in the state of LL, how many visits the chain is anticipated to make to the state HH is 1.4, 1.15 for the HL state, 1.4 for the LH state, and 1.05 for the LL state

4.7. Estimation of the anticipated return time:

It is important to know the anticipated time of the NIFTY50 index. The anticipated return duration to a state is predicted by the steady-state TPM. The anticipated return time to the same state for a finite irreducible MC is the reciprocal of the steady-state probability.

The anticipated return time of Higher Highs is

$\mu_{HH} = {}^{1}/_{0.33} = 3.03$

NIFTY50 pricing visits the state of HH on average every 3 trading pair days, based on the anticipated initial return time from the state of HH to the state of HH.

The anticipated return time of Higher Lows is

$\mu_{HL} = {}^{1}/_{0.21} = 4.76$

NIFTY50 pricing visits the state of HL on average every 5 trading pair days, based on the anticipated initial return time from the state of HL to the state of HL.

The anticipated return time of Lower Highs is

$\mu_{LH} = {}^{1}/_{0.21} = 4.76$

NIFTY50 pricing visits the state of LH on average every 5 trading pair days, based on the anticipated initial return time from the state of LH to the state of LH.

The anticipated return time of Lower Lows is

$\mu_{LL} = {}^{1}/_{0.25} = 4$

NIFTY50 pricing visits the state of LL on average every 4 trading pair days, based on the anticipated initial return time from the state of LL to the state of LL.

5. Summary and Conclusion

Stock market performance is assumed to be entirely stochastic in the Markov chain method to analyze the market performance. In this study, NIFTY50 index secondary data was gathered from Yahoo Finance, which covered 495 trading days between September 1, 2021, and August 31, 2022. Finally, our model analyses the movement of the NIFTY50 index prices using a Markov chain. The technique may be preferable since the Markov model calculates daily changes in index values and categorizes them into four categories. The transition probability matrix is also utilized to compute transitions from one state to the other. The supplied script might be in one of four states at any one time. The stock price was either higher or lower according to the HH LL, HL, and LH. The evaluation of IPV and TPM demonstrates the volatility of the NIFTY50 by showing that the likelihood of the states HL and LH is less likely.

According to the stationary distribution findings, in any case of the NIFTY50 price for the initial stage, over the long term, here could expect the share price to experience higher highs with a probability of 0.3309, higher highs with a probability of 0.2154, lower lows with a probability of 0.2076, and lower lows with the probability of 0.2460. From the aforementioned findings, There will be deduced that investing in NIFTY50 is a wise decision for investors looking to generate capital gains because the likelihood of a Lower Low in the price of NIFTY50 in the future is lower than the likelihood of a Higher High.

The results indicate that the anticipated return duration to state a Higher High is 3.03 or approximately 3 trading pair days, a Higher Low is 4.76 or approximately 5 trading pair days, a Lower High is 4.76 or approximately 5 trading pair days and Lower Low is 4 trading pair days. As a result, our stochastic analysis research tool delivers precise and compelling information to help investors make better judgments in the Indian stock market.

Reference

[1] Anderson, D. R., Sweeney, D. J., Williams, T. A., Camm, J. D., & Cochran, J. J. (2012). *Quantitative Methods for Business (Book Only)*. Cengage Learning.

[2] Armstrong, J. S., & Farley, J. U. (1969). A note on the use of Markov chains in forecasting store choice. *Management Science*, *16*(4).

[3] Ashik, A. M., & Kannan, K. S. (2019). Time series model for stock price forecasting in India. In *Logistics, Supply Chain and Financial Predictive Analytics* (pp. 221-231). Springer, Singapore.

[4] Bhattacharya, Kaushik. (2002). "A measure of relative efficiency of financial markets from eigenvalue-based mobility indices." Finance India 16.4: 1419.

[5] Bhusal, M.K. (2017). Application of Markov Chain Model in the Stock Market Trend Analysis of Nepal. *International journal of scientific and engineering research, 8*, 1733-1745.

[6] Ashik, A. M., & Kannan, K. S. (2019). Time series model for stock price forecasting in India. In *Logistics, Supply Chain and Financial Predictive Analytics* (pp. 221-231). Springer, Singapore.

[7] Dai, Y., Han, D., & Dai, W. (2014). Modeling and computing of stock index forecasting based on neural network and Markov chain. *The Scientific World Journal*, *2014*.

[8] Dar, G.F., Padi, T.R., & Rekha, S. (2022). Stock Price Prediction Using A Markov Chain Model: A Study For Tcs Share Values. *Advances and Applications in Statistics*, 18(4), (2022): pp. 40-48.

[9] Han, S., & Song, C. (2020, August). Stock Price Forecasting Analysis Based on Elman Neural Network and Markov Chain Correction. In *The International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery* (pp. 261-270). Springer, Cham.

[10] Huang, J., Huang, W., Chu, P., Lee, W., Pai, H., Chuang, C.C., & Wu, Y. (2017). Applying a Markov chain for the stock pricing of a novel forecasting model. *Communications in Statistics - Theory and Methods, 46*, 4388 - 4402.

[11] Kallah-Dagadu, G., Apatu, V., Mettle, F.O., Arku, D., & Debrah, G. (2022). Application of Markov Chain Techniques for Selecting Efficient Financial Stocks for Investment Portfolio Construction. *J. Appl. Math., 2022*, 2863302:1-2863302:9.

[12] Khaing, E.T., Thein, M.M., & Lwin, M.M. (2020). Trend Extraction from High Dimensional Stock News based on Markov Chain. *2020 International Conference on Advanced Information Technologies (ICAIT)*, 218-223.

[13] Kostadinova, V., Georgiev, I., Mihova, V., & Pavlov, V. (2021, February). An application of Markov chains in stock price prediction and risk portfolio optimization. In *AIP Conference Proceedings* (Vol. 2321, No. 1, p. 030018). AIP Publishing LLC.

[14] Mettle, F.O., Quaye, E.N., & Laryea, R.A. (2014). A methodology for stochastic analysis of share prices as Markov chains with finite states. *SpringerPlus, 3*.