Application of Markov Chain Model in the Stock Market Trend Analysis of Nepal

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Abstract: This paper attempts to apply a Markov chain model to forecast the behavior of Nepal Stock Exchange (NEPSE) index. The Nepal Stock Exchange is a sole trading organization of shares in Nepal. The prediction of stock market behavior is very important for investors who are seekers for capital appreciation. The application of Markov chain model for forecasting the future states is based on the strong feature of randomness of NEPSE index. This study aims to explore the long run behavior of NEPSE index, the expected number of visits to a particular state and to determine the expected first return time of various states. For the study, the NEPSE index of 2741 trading days from August 15, 2007 to June 18, 2017 was taken as a secondary data from the NEPSE office. The NEPSE index shows three different states- increase (U), remains same (S) and decrease (D). The initial state vector and transition probability matrix, which are used to predict the behavior of index has been obtained from the close inspection of numbers of transitions from one state to another. The higher order transition probability matrices were obtained by using Microsoft excel. The study explore that regardless of the present status of NEPSE index, in the long run the index will increase with probability 0.3855, remains in the same state with probability 0.1707 and decrease with probability 0.4436. It is also observed that the index will remain in increasing state after three days when it starts to move from the increasing state.

Keywords: Markov chain, NEPSE index, Steady state probability, Stock market, Transition probability

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1. Introduction

The stock market has a significant contribution in the swiftly growing world economy. The fluctuation in stock market can have a profound influence on individuals and the entire economy as well. In the context of collecting money and capital formation, stock market is one of the best alternative for various business houses and companies for further expansion or settling up a new business venture. Generally stocks are the shares of company or organization. The stock exchange is a legal framework where an individual or group of individual can buy and sell such shares in a systematic way. In other words stock exchange is the meeting place of both buyers and sellers of stock. The stock market refers to the wider domain of trading activities of stocks.

The development of stock market has crucial role in the economic growth of Nepal. The stock market in Nepal is in budding condition. The history of stock market shows that Biratnagar Jute Mills Ltd 1936 followed by Nepal Bank Ltd in 1937 were the beginners to float their shares in the Nepalese stock market. Later, with the span of time, various legal provisions and regulatory measures were introduced in order to improve the corporate governance of the stock market by the government. In 1993, after the establishment of Nepal Stock Exchange (NEPSE), the Nepalese stock market got momentum and opened easy access for significantly greater number of investors in the market. The basic objective of NEPSE is to uplift the marketability and liquidity of corporate securities by providing trading floor through market intermediaries and facilitating & regulating trading activities (7).

The sole objective of investors to purchase stock is motivated by the desire for capital appreciation. Generally the companies making more profit offer greater return to the investors than those companies making less profit or no profit. The price of the share of the companies depends on the performance of the companies. There are various possible reason that affect the overall trend of stock market like; worldwide trend of business, natural calamities, politico-economic situation, poor-corporate governance, varying policy of governing organization etc. (3). In this regard, the return on investment made by individuals, corporate bodies or organizations in the stock market depends on the choice or decision of selecting appropriate companies to purchase stocks. More precisely, the decision on selecting the most beneficial options in the stock market is extremely depends on how well informed you are in the stock analysis. That is why it is most essential to come up with statistical models and their analysis. These models help to predict the share price movement of stocks. A competent stock market is considered to have such integral characteristics in which the price of shares should randomly fluctuate. The random fluctuation of price of shares causes the uniform distribution of market information. This inherent stochastic behavior of stock market makes the prediction of possible states of the market more complicated. However, there are various statistical methods to study such phenomena like; Moving average, Regression analysis, Markov chain model, Hidden Markov processes, Weighted Markov chain etc. to forecast the stock market using past information (1).

2. Literature review

In order to analyze and predict the stock market behavior, the Markov chain model has been used by many researchers in different time. The following references signify the applicability of Markov chain model in this context.

Choji, Eduno and Kassem (2013) applied Markov chain model 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. They used six years data from 2005 to 2010. By obtaining the transition probability matrix (tpm), power of the transition matrix and probability vector, they obtained the long run prediction of the share price of these banks whether appreciate, depreciate or remain unchanged regardless of current share price of the banks. They also estimate the probability of transition between the states by taking the performance of two banks together.

Zhang and Zhang (2009) implemented a Markov chain model for forecasting the stock market trend in China. This study explore that the Markov chain has no after-effect and this model is more appropriate to analyze and predict the stock market index and closing stock price is more effective under the market mechanism. By applying the Markov chain model in the stock market, the researcher achieved relatively good result. They recommended that this model could be used in other fields like future market and bond market. They also suggested that the result obtain from Markov chain model for prediction should be combine with other factors having significant influence in stock market variations and the method should be used as a basis for decision making.

Otieno, Otumba and Nyabwanga (2015) introduced Markov chain model to forecast stock market trend of Safaricom share in Nairobi Securities Exchange in Kenya. They used Markov chain model based on probability transition matrix and initial state vector to predict the Safaricom share prices using the data collected over April 1, 2008 to April 30, 2012. In this study the Markov chain prediction has been applied for a specific purpose to forecast the probability and this forecasted value indicate the probability of certain state of stock or shares prices in future rather than be in absolute state. This study also reveals that the memory less property and random walk capability of Markov chain model facilitates to best fit the data and to predict the trend. By using the Markov chain model they observed good results to predict the probability of each states of the shares of Safaricom.

Mettle, Quaye and Laryea (2014) used Markov chain model with finite states to analyze the share price changes for five different randomly selected equities on the Ghana Stock Exchange. This study concluded that the application of Markov chain model as a stochastic analysis method in equity price studies improves the portfolio decisions. They have suggested that Markov chain model can be apply as a tool for improving the stock trading decisions. Application of this method in stock analysis improves both the investor knowledge and chances of higher returns.

2.1. Objectives of the study

This study aims to predict and analyze the market behavior of NEPSE index by using Markov chain model with the help of past information. The specific objectives of the study are;

a) To study the long run behavior of NEPSE index
b) To determine the expected number of visits to a particular states and
c) To find out the expected first return time of various states.

3. Materials and methods

Stochastic processes can be distinguished in different types depending upon the state space, index parameter and the dependence relations among the random variables through the specification of the joint distribution function. Among such processes Markov chain is a special type of random process. Markov chain was introduced by Andrei Andreevich Markov (1856 – 1922). One of the important property of Markov chain model is that the occurrence of any event in the future depends only in the present state. The set of values taken by the Markov process is known as state space. A Markov process having discrete state space is termed as Markov chain (4). The fundamental difference between the Markov chain model and other statistical methods of projection like; regression model, time series analysis is that the Markov model does not require any mutual laws among the factors from complex predictor, it only requires the characteristic of evolution on the history of event (i.e. initial probability) to estimate the transition probability for different possible states at various time to come. By using Markov chain model it is easier to predict the possibility of state value in a certain period of time after knowing the initial probability distribution and transition probability matrix (tpm). Markov chain model has been extensively applied in predicting stock index for a group of stock as well as for a single stock (8).

3.1. Definition of Markov chain

The sequence $\{X_n, n \geq 0\}$ is said to be a Markov chain if for all state values $i_0, i_1, i_2, \ldots\ldots, i_n \in I$, then

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

Where, $i_0, i_1, i_2, \ldots\ldots, i_n$ are the states in the state space I. This type of probability is called Markov chain probability. This indicate that regardless of its history prior to time n, the probability that it will make a transition to another state j depends only on state i. Here it should be noted that whether the particle was in that state for only a short period or a long period of time does not matter.

3.2. Transition probability and transition probability matrix

The transition probability as defined by the Markov chain is called transition or jump probability from state i to state j. Then,

$$P\{X_{n+1} = j / X_n = i\} = p_{ij}$$

This is also termed as one-step transition probability. If the transition probabilities defined above are independent of time (n), then such assumption is called homogenous or stationary Markov chain. Thus,

$$P\{X_{n+1} = j / X_n = i\} = P\{X_1 = j / X_0 = i\} = p_{ij}$$

The transition probabilities $p_{ij's}$can be written or arranged in a matrix form as,

$$P = [p_{ij}], \quad i, j \in I$$

Here, the matrix *P* is called transition probability matrix (tpm) or stochastic matrix. The matrix *P* insists non-negative elements with row sum unity. Hence

$$0 \leq p_{ij} \leq 1 \text{ and } \sum_{j=1}^{n} p_{ij} = 1 , \sqrt{} i \in I$$

The probability

$$p_{ij}(k) = P\{X_{n+k} = j / X_n = i\}, \sqrt{} k > 0, n \geq 0, \quad i, j \in I$$

is the k-step transition probability from state *i* to state *j* in *k* steps.

The transition matrix *P* has the following property.

$$P(n) = P^{n-1} {}_* P = P^n$$

3.3. State probability matrix

The average transition process of Markov chain depends on the system's initial state and the transition probability matrix. The system initial state is a line matrix called initial probability vector defined as; $P(X_0 = i) = P(0) = [p_0(0) \ \ p_1(0) \ \ \ldots\ldots\ldots \ p_n(0)], \ 0 \leq p_i(0) \leq 1$ and $\sum_{i=0}^{n} p_i\,(0) = 1$ for all states.

Similarly, the probability vector at time n may be defined as

$P(X_n = i) = P(n) = [p_0(n) \ \ p_1(n) \ \ \ldots\ldots\ldots\ldots \ p_n(n)], \ 0 \leq p_i(n) \leq 1$ and $\sum_{i=0}^{n} p_i\,(n) = 1$ for all states.

By knowing the initial state of system and transition matrix after nth step,

$$P(k+1) = P(k)_* P$$

Which gives; $P(1) = P(0)_* P$

$$P(2) = P(1) * P = P(0) * P^2$$

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$$P(k) = P(k-1) * P = P(k-2) * P^2 = \ldots\ldots\ldots\ldots = P(0) * P^k$$

Hence, $P(k+1) = P(0) * P^{k+1}$, for $k \geq 0$

This indicate that the transition probability matrix after $(k+1)$ step is the product of initial probability vector and $(k+1)^{th}$ power of the one-step transition probability matrix.

3.4. Irreducible Markov chain

A Markov chain is said to be irreducible if it is not possible to partition the state space into two or more disjoint closed set. That means it consists only a single class.

3.5. Absolute probability

The state probability distribution $\{P_j(n),\ j \epsilon I\}$shows the probability of finding the particle at state j at the n^{th} trial. If $P_i(0)$ be the probability of finding such particle at state i at initial trial then,

$$P(X_n = j) = P_j(n) = \sum_i P(X_n = j, X_0 = i) = \sum_i P\left({X_n = j}/{X_0 = i}\right) P(X_0 = i)$$

$$= \sum_i P_i(0).P_{ij}(n) \quad , n > 0$$

Here, $\{P_i(0),\ i \epsilon I\}$ is the initial probability distribution.

3.6. Stationary distribution of a Markov chain

This property of Markov chain states that regardless of the initial state of the system how does the stochastic process evolves, when the number of transition steps is sufficiently large, then the transition probability from state i to state j becomes settle down to some constant value. Thus,

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

Such quantities are referred as steady state probabilities.

If the limits $\pi_j = \lim_{n \to \infty} P_j(n) = \lim_{n \to \infty} P_{ij}(n)$ exists and does not depend on the initial state, then

$P_j(n) = \sum_k P_k(n-1) P_{kj}$ becomes $\pi_j = \sum_k \pi_k P_{kj}$, as $n \to \infty$ for $j = 0, 1, 2, \ldots\ldots\ldots$

This is equivalent to $\pi = \pi * P$

The probability distribution $\{\pi_i\ ,\ i \epsilon I\}$ is called stationary or invariant for the given chain if

$\pi_i = \sum_{i \in I} \pi_i P_{ij}$ such that $\pi_i \geq 0$ and $\sum_i \pi_i = 1$

This property of Markov chain helps to determine the long –run behavior of the chain.

3.7. Expected number of visits

The expected number of visits made by the chain to state j starting from state i is given by

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

Where, $N_{ij}(n)$ denote the number of visits to state *j* starting from state *i* in n-steps.

Where,

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

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

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

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

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

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

Also the expected number of visits to state j from state i after long - run is;

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

3.8. Expected return time

For a finite irreducible Markov chain the expected return time to state *j, j ϵ I* can be obtain by taking the reciprocal of limiting probability $p_{ij}(n)$.

3.9. Data source

The stock price index is very important indicator for investors in order to analyze and forecast the stock market. It measures the changes in a financial market and represents a portfolio of securities trading on a particular market.

In this study the data regarding the NEPSE index were taken from the NEPSE office. It was the secondary data which consist the trading day's closing price change of NEPSE index from August 15, 2007 to June 18, 2017. It includes 2741 trading day's NEPSE index during the period.

4. Results and discussion

4.1. Derivation of three state transition probability matrix

The close observation of NEPSE index over the study period shows that it involves one of the three different states of transition at the end of each trading day. The possible movements of NEPSE index in such states are either increasing or decreasing or remains same. For the purpose of development of transition probability matrix these three different movements are considered as three different states in the Markov chain. The transition probability provides the information regarding the transition behavior of Markov chain. The elements of transition probability matrix indicate the probability of transitions from a particular state to another state. In other word, the transition probability refers to the probability of occurrence of a typical state from one of the existing states. This transition probability helps to make an idea about the likelihood of occurrence of future state and accordingly one can make the decisions.

The NEPSE index of 2741 trading day's shows that it was up 1075 days, remains same 477 days and down 1190 days. The NEPSE index recorded in the last trading day was in decreasing state and there is no further information about the transition state of NEPSE index in the next day. Due to this reason the total numbers of decreasing states are taken as 1189.

Table 1: The transition matrix of NEPSE index

	Increase in NEPSE index (U)	NEPSE index remains same (S)	Decrease in NEPSE index (D)
Increase in NEPSE index (U)	521	231	323
NEPSE index remains same (S)	184	29	264
Decrease in NEPSE index (D)	356	208	625

The transition probability matrix of NEPSE index using the above information can be constructed as;

$$P_{\text{NEPSE Index}} = \begin{bmatrix} 0.4847 & 0.2148 & 0.3005 \\ 0.3857 & 0.0608 & 0.5535 \\ 0.2994 & 0.1749 & 0.5257 \end{bmatrix}$$

The transition diagraph for the explicit presentation of transition probability of NEPSE index is shown below.

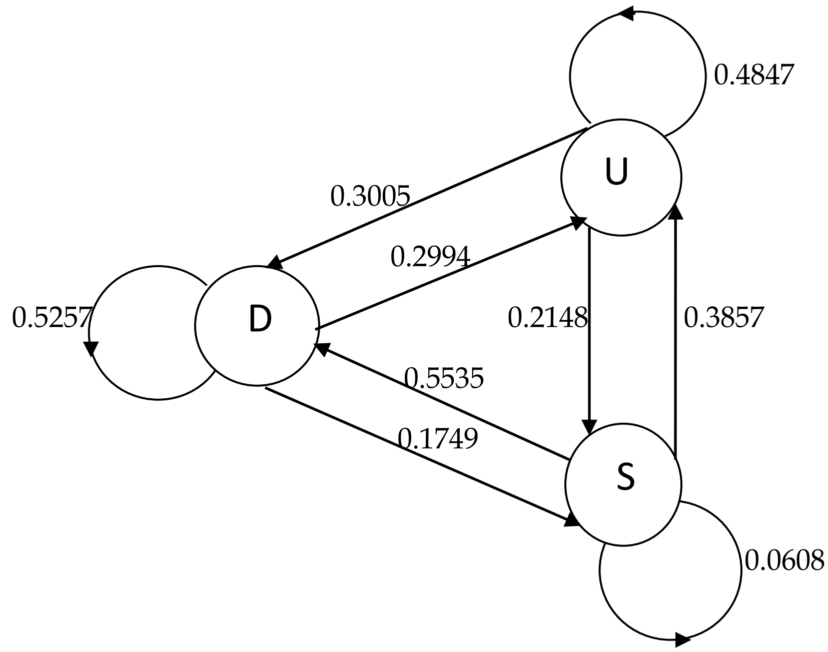

Figure 1: Transition diagraph of NEPSE index

4.2. Determination of initial state vector

The NEPSE index during the study period shows three different states increase (U), remains same (S) and decrease D). The probability of occurrence of these three different states can be obtained from the initial state vector. The initial state vector is denoted by η(0) and given by

$$\eta(0) = (\eta_1, \eta_2, \eta_3)$$

Where, η_1, η_2 and η_3 provide the probability that NEPSE index increase, remains same and decrease respectively. Then,

$$\eta_1 = 1075/2742 = 0.3920$$

$$\eta_2 = 477/2742 = 0.1739$$

$$\eta_3 = 1190/2742 = 0.4339$$

Hence the initial state vector for NEPSE index is

$$\eta(0) = (0.3920,\ 0.1739,\ 0.4339)$$

4.3. Computation of state probabilities for forecasting the NEPSE index

The Markov chain model suggests that, the state probability for various periods can be obtained by multiplying transition probability matrix and initial state vector i.e. $\eta_{(i+1)} = \eta_{(i)} * P$. Where, $\eta_{(i)}$ is the state vector for i^{th} state and P is the transition probability matrix. The state probability for the NEPSE index at the end of 2743th day will be

$$\eta_{(1)} = \eta_{(0)} * P_{\text{NEPSE index}} = (0.3920,\ 0.1739,\ 0.4339)\begin{bmatrix}0.4847 & 0.2148 & 0.3005\\0.3857 & 0.0608 & 0.5535\\0.2994 & 0.1749 & 0.5257\end{bmatrix}$$

$$= (0.3869,\ 0.1710,\ 0.4421)$$

The above result shows that there is maximum possibility that the NEPSE index will be decrease with probability 0.4421 at the end of 2743th day. The index will be in the state increase with probability 0.3869 and it will remain in the same state with probability 0.1710. In the similar manner, the state probability of NEPSE index at the end of 2744th day will be

$$\eta_{(2)} = \eta_{(1)} * P_{\text{NEPSE index}} = (0.3859,\ 0.1708,\ 0.4433)$$

The above probability shows that the NEPSE index will be increase with probability 0.3859, the index will remain in the same state with probability 0.1708 and the index will decrease with probability 0.4433 at the end of 2744th trading day.

4.4. Decision making under long run behavior of NEPSE index

The forecasting of long run behavior of NEPSE index is very meaningful for investors. The identification of probable future state of the market is the guideline to make decision for investment. The optimistic market attracts the investors to invest much in order to appreciate their investment. The long run behavior of stock index can be determined by using n^{th} step transition probability matrix. The behavior of stock index n^{th} step later can be identify from n^{th} step transition probability matrix P(n). The transition probability matrix P(n) converges to limiting transition matrix with the increase in number of steps. This limiting transition probability matrix provides the steady state probability of stock index in different states like increase, remains same and decrease in the future. The long run behavior of NEPSE index is observed by determining the higher order transition probability matrix of NEPSE index by using Microsoft Excel as given below:

$$P(2)_{\text{NEPSE index}} = \begin{bmatrix}0.4077 & 0.1697 & 0.4225\\0.3761 & 0.1833 & 0.4405\\0.3699 & 0.1668 & 0.4631\end{bmatrix}$$

$$P(4)_{\text{NEPSE index}} = \begin{bmatrix}0.3864 & 0.1708 & 0.4427\\0.3853 & 0.1709 & 0.4437\\0.3849 & 0.1706 & 0.4443\end{bmatrix}$$

$$P(5)_{\text{NEPSE index}} = \begin{bmatrix}0.3857 & 0.1708 & 0.4434\\0.3855 & 0.1707 & 0.4436\\0.3854 & 0.1707 & 0.4437\end{bmatrix}$$

$$P(6)_{\text{NEPSE index}} = \begin{bmatrix} 0.3856 & 0.1708 & 0.4435 \\ 0.3855 & 0.1707 & 0.4436 \\ 0.3855 & 0.1707 & 0.4436 \end{bmatrix}$$

$$P(7)_{\text{NEPSE index}} = \begin{bmatrix} 0.3855 & 0.1707 & 0.4436 \\ 0.3855 & 0.1707 & 0.4436 \\ 0.3855 & 0.1707 & 0.4436 \end{bmatrix} = P(8) = P(9) = P(10) = \ldots\ldots\ldots \text{ and so on.}$$

The higher order transition probability matrix of NEPSE index computed above shows that after the 6th trading days since 2742 trading days, the transition probability matrix tends to the steady state or the state of equilibrium. After then the transition probability matrix remains unchanged for the onward consecutive trading days. This steady state transition probability matrix of NEPSE index reveals the following information.

The probability that the NEPSE index decrease in near future irrespective of its initial states increase, remains same or decrease is 0.4436.

There is 0.3855 chances that the NEPSE index will increase in near future irrespective of its initial states increase, remains same or decrease.

The chance of NEPSE index remaining in the same state in near future irrespective of its initial states increase, remains same or decrease is 0.1707.

If the NEPSE index starts in a given state with initial state vector $\eta(0)$ = (0.3920, 0.1739, 0.4339), then the probability of NEPSE index will increase, remains same or decrease at a particular trading day in steady state condition can be determine by multiplying the initial state vector by the higher order transition probability matrix obtained at state of equilibrium. Then,

$$\eta(0) * P(7) = (0.3920 \quad 0.1739 \quad 0.4339) \begin{bmatrix} 0.3855 & 0.1707 & 0.4436 \\ 0.3855 & 0.1707 & 0.4436 \\ 0.3855 & 0.1707 & 0.4436 \end{bmatrix}$$

$$= (0.3856 \quad 0.1708 \quad 0.4436)$$

This result indicates the long run probability of NEPSE index being in increasing, remains same or in decreasing states. The probability that the NEPSE index increasing at the state of equilibrium is 0.3856, decreasing is 0.4436 and the probability that the index remains unchanged is 0.1708.

4.5. Determination of expected numbers of visits

The expected numbers of visits to a particular state from another state in different steps can be computed to know the expected number of time the moving particle stay in certain states. Here, for NEPSE index the number of visits to a particular state in five trading days is shown in the following matrix.

$$\mu_{ij}(5) = \begin{bmatrix} 2.0542 & 0.8980 & 2.0477 \\ 1.9175 & 0.7548 & 2.3275 \\ 1.8221 & 0.8538 & 2.3239 \end{bmatrix}$$

The matrix obtained above to explore the expected number of visits reveals that if the NEPSE index starts from the increasing state, the expected number of visits the chain for NEPSE index makes to the increasing state out of five trading days is 2.0542, to the state remains same is 0.8980 and to the state decrease is 2.0477.

Likewise if the NEPSE index starts from decreasing state, the expected number of visits the chain makes to the state increase is 1.8221, to the state remains same is 0.8538 and to the state decrease is 2.3239.

4.6. Determination of expected return time

It will be meaningful to understand about the expected duration the NEPSE index will stay in the increase, decrease or remains in the same state. The steady state transition probabilities are used to determine the expected return time to a state starting from the same state. For a finite irreducible Markov chain the expected return time to the same state is reciprocal of the steady state probabilities. Here for the NEPSE index the expected return time to the increasing state (U), starting from the same increasing state (U) is μ_U = 1/ 0.3855 = 2.594. This result shows that the chain for NEPSE index should visit the increasing state (U) on average in three days. In the similar fashion, the expected return time to remain in the same state (S), starting from the state remains same (S) is μ_S = 5.858. This means the chain for NEPSE index should visits the state remains same (S) on an average six days. The expected return time to the decreasing state (D), starting from the decreasing state (D) is μ_D = 2.254. This result helps to conclude that the chain should visits the decreasing state (D) on an average two days.

5. Conclusion

The Markov chain model to predict the stock market behavior assume that the performance of stock market is completely affected by the stochastic factors. The movement of stock index to the various states in a particular trading day is independent with the index of initial trading days but depends only on the index of the most recent day. The prediction of behavior of stock market is very complicated because many factors like regional and global economic conditions, socio-political conditions, poor-corporate governance, varying policies of the government, psychological factors of investors etc. have crucial role behind the performance of the market. Due to such complexity it is much better to make investment decisions on the basis of forecast results obtained using Markov chain model as well as giving prime considerations to the factors mentioned above.

In this study the Markov chain model is applied to predict the behavior of NEPSE index. The predicted results are expressed in terms of probability of certain state of NEPSE index in the future. The model does not provide the forecasting results in an absolute state.

The initial state vector and the transition probability matrices are used to estimate the probability of NEPSE index being in different states in the upcoming days. The steady state probabilities are obtained from the n^{th} step transition probability matrices. The result of steady state probability matrix shows that the chance of NEPSE index will increase in the near future is 0.3855. The probability that the index will decrease in near future is 0.4436 and the index will remain in the same state with probability 0.1707. The expected number of visits to a particular state from other states are computed. The result shows that out of five trading days, the expected number of visits the chain for NEPSE index made to the increasing state starting from the increasing state is 2.0542. The expected number of visits to the decreasing state starting from the decreasing state out of five trading days for the chain is 2.3239. The result for expected first return time to a certain state starting from the same state shows that the NEPSE index will be in increasing state after three days when it was initially in increasing state. The chain for NEPSE index will be in decreasing state after two days when it was in decreasing state initially.

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