Abstract — Price movements of stock market are not totally random. In fact, what drives the financial market and what pattern financial time series follows have long been the interest that attracts economists, mathematicians and most recently computer scientists [17]. This paper gives an idea about the trend analysis of stock market behaviour using Hidden Markov Model (HMM). The trend once followed over a particular period will sure repeat in future. The one day difference in close value of stocks for a certain period is found and its corresponding steady state probability distribution values are determined. The pattern of the stock market behaviour is then decided based on these probability values for a particular time. The goal is to figure out the hidden state sequence given the observation sequence so that the trend can be analyzed using the steady state probability distribution(\(\pi\)) values. Six optimal hidden state sequences are generated and compared. The one day difference in close value when considered is found to give the best optimum state sequence.

Keywords—Hidden Markov Model; Stock market trend; Transition Probability Matrix; Emission Probability Matrix; Steady State Probability distribution

I. INTRODUCTION

“A growing economy consists of prices falling, not rising”, says Kel Kelly[9]. Stock prices change every day as a result of market forces. There is a change in share price because of supply and demand. According to the supply and demand, the stock price either moves up or undergoes a fall. Stock markets normally reflect the business cycle of the economy: when the economy grows, the stock market typically reflects this economic growth in an upward trend in prices. In contrast, when the economy slows, stock prices tend to be more mixed. Markets may take time to form bottoms or make tops, sometimes of two years or more. This makes it difficult to determine when the market hits a top or a bottom[3]. The Stock Market patterns are non-linear in nature, hence it is difficult to forecast future trends of the market behaviour.

In this paper, a method has been developed to forecast the future trends of the stock market. The Latent or hidden states, which determine the behaviour of the stock value, are usually invisible to the investor. These hidden states are derived from the emitted symbols. The emission probability depends on the current state of the HMM. Probability and Hidden Markov Model give a way of dealing with uncertainty. Many intelligent tasks are sequence finding tasks, with a limited availability of information. This naturally involves hidden states or strategies for dealing with uncertainty.

II. LITERATURE SURVEY

In Recent years, a variety of forecasting methods have been proposed and implemented for the stock market analysis. A brief study on the literature survey is presented. Markov Process is a stochastic process where the probability at one time is only conditioned on a finite history, being in a certain state at a certain time. Markov chain is “Given the present, the future is independent of the past”. HMM is a form of probabilistic finite state system where the actual states are not directly observable. They can only be estimated using observable symbols associated with the hidden states. At each time point, the HMM emits a symbol and changes a state with certain probability. HMM analyze and predict time series or time depending phenomena. There is not a one to one correspondence between the states and the observation symbols. Many states are mapped to one symbol and vice-versa.

Hidden Markov Model was first invented in speech recognition [12,13], but is widely applied to forecast stock market data. Other statistical tools are also available to make forecasts on past time series data. Box–Jenkins[2] used Time series analysis for forecasting and control. White[5,18,19] used Neural Networks for stock market forecasting of IBM daily stock returns. Following this, various studies reported on the effectiveness of alternative learning algorithms and prediction methods using ANN. To forecast the daily close and morning open price, Henry [6] used ARIMA model. But all these conventional methods had problems when non linearity exists in time series. Chiang et al.[4] have used ANN to forecast the end-of-year net asset value of mutual funds. Kim and Han [10] found that the complex dimensionality and buried
noise of the stock market data makes it difficult to re-
estimate the ANN parameters. Romahi and Shen [14] also
found that ANN occasionally suffers from over fitting
problem. They developed an evolving rule based expert
system and obtained a method which is used to forecast
financial market behaviour. There were also hybridization
models effectively used to forecast financial behaviour.
The drawback was requirement of expert knowledge. To
overcome all these problems Hassan and Nath [15] used
HMM for a better optimization. Hassan et al. [16]
proposed a fusion model of HMM, ANN and GA for stock
Market forecasting. In continuation of this, Hassan [7]
combined HMM and fuzzy logic rules to improve the
prediction accuracy on non-stationary stock data sets. Jyoti
Badge[8] used technical indicators as an input variable
instead of stock prices for analysis. Aditya Gupta and
Bhuwan Dhingra[1] considered  the fractional change  in
Stock value and the intra-day high and low values of the
stock to train the continuous HMM. In the earlier studies,
much research work had been carried out using various
techniques and algorithms for training the model for
forecasting or predicting the next day close value of the
stock market, for which randomly generated Transition
Probability Matrix (TPM), Emission Probability Matrix
(EPM) and prior probability matrix have been considered.

In this paper, the trend analysis of the stock market
is found using Hidden Markov Model by considering the
two day difference in close value for a particular period.
For a given observation sequence, the hidden sequence of
states and their corresponding probability values are found.
The probability values of $\pi$ gives the trend percentage of
the stock prices. Decision makers make decisions in case
of uncertainty. The proposed approach gives a platform for
decision makers to make decisions on the basis of the
trend of probability values obtained from the steady
state probability distribution.

III. RESEARCH SET UP

A. Basics of HMM

HMM is a stochastic model where the system is assumed
to be a Markov Process with hidden states. HMM gives
better accuracy than other models. Using the given input
values, the parameters of the HMM ($\lambda$) denoted by A, B
and $\pi$ are found out.

![Trellis Diagram](image-url)
The main problems of HMM are: Evaluation, Decoding, and Learning.

**Evaluation problem**

Given the HMM \( \lambda = \{A, B, \pi\} \) and the observation sequence \( O = o_1 \ o_2 \ldots \ o_M \), the probability that model \( \lambda \) has generated sequence \( O \) is calculated.

Often this problem is solved by the Forward Backward Algorithm (Rabiner, 1989) (Rabiner, 1993).

**Decoding problem**

Given the HMM \( \lambda = \{A, B, \pi\} \) and the observation sequence \( O = o_1 \ o_2 \ldots \ o_M \), calculate the most likely sequence of hidden states that produced this observation sequence \( O \).

Usually this problem is handled by Viterbi Algorithm (Rabiner, 1989) (Rabiner, 1993).

**Learning problem**

Given some training observation sequences \( O=o_1 \ o_2 \ldots \ o_M \) and general structure of HMM (numbers of hidden and visible states), determine HMM parameters \( \lambda = \{A, B, \pi\} \) that best fit training data.

The most common solution for this problem is Baum-Welch algorithm (Rabiner,1989) (Rabiner,1993) which is considered as the traditional method for training HMM.

In this paper, IBM daily close value data for a month period is considered.

Two observing symbols “ I ” and “ D ” have been used:

“I indicates Increasing”, “ D indicates Decreasing ”.

If Today’s close value – Yesterday’s close value > 0, then observing symbol is I

If Today’s close value – Yesterday’s close value < 0 then observing symbol is D

There are six hidden states assumed and are denoted by the symbol

\[ S1, S2, S3, S4, S5, S6 \]

where

- \( S1 \) indicates “very low”;
- \( S2 \) indicates “low”;
- \( S3 \) indicates “moderate low”;
- \( S4 \) indicates “moderate high”;
- \( S5 \) indicates “high”;
- \( S6 \) indicates “very high”.

The States are not directly observable. The situations of the stock market are considered hidden. Given a sequence of observation we can find the hidden state sequence that produced those observations.

**B. Database**

The complete set of data for the proposed study has been taken from yahoofinance.com. The Table 1 given below shows the daily close value of the stock market:

| S.NO | CV   | D.in.1 day CV | O.S.1 | D.in.2 days CV | O.S.2 | D.in.3 days CV | O.S.3 | D.in.4 days CV | O.S.4 | D.in.5 days CV | O.S.5 | D.in.6 days CV | O.S.6 |
|------|------|---------------|-------|---------------|-------|---------------|-------|---------------|-------|---------------|-------|---------------|-------|
| 1    | 77.91|               |       |               |       |               |       |               |       |               |       |               |       |
| 2    | 77.39| 0.52          | D     |               |       |               |       |               |       |               |       |               |       |
| 3    | 76.5 | 0.89          | D     | -1.41         | D     |               |       |               |       |               |       |               |       |
| 4    | 75.86| 0.64          | D     | -1.53         | 0.05  | D             |       |               |       |               |       |               |       |
| 5    | 72.45| 1.59          | I     | 0.95          | I     | 0.06          | I     | 0.46          | D     |               |       |               |       |
| 6    | 79.33| 1.88          | I     | 3.47          | 2.83  | I             | 1.94  | 1.42          |       |               |       |               |       |
| 7    | 79.51| 0.18          | I     | 2.08          | 3.65  | I             | 3.01  | 2.12          | I     | 1.6           | I     |               |       |
| 8    | 79.15| 0.96          | D     | 0.18          | 1.7   | I             | 3.29  | 2.93          | I     | 1.78          | I     |               |       |
| 9    | 79.05| 0.8           | I     | 0.44          | I     | 0.62          | I     | 2.5           | D     | 6.09          | I     | 3.45          | I     |
| 10   | 78.56| 1.39          | D     | -0.59         | 0.95  | D             | 0.77  | 1.11          | I     | 2.7           | I     |               |       |
| 11   | 79.07| 0.51          | I     | 0.88          | 0.08  | D             | 0.44  | 0.68          | D     | 1.62          | I     |               |       |
| 12   | 77.4 | 1.63          | D     | 1.16          | 2.55  | D             | 1.75  | 2.11          | D     | 1.91          | D     |               |       |
| 13   | 77.28| 1.32          | D     | 1.79          | 1.28  | D             | 2.67  | 1.87          | D     | 2.23          | D     |               |       |
| 14   | 77.95| 0.67          | I     | 0.55          | 1.12  | D             | 0.61  | D             | -2    | D             | -1.2  |               |       |
| 15   | 77.33| 0.52          | D     | 0.95          | 0.07  | D             | 0.74  | D             | -1.21 | D             | -2.51 |               |       |
| 16   | 76.7 | 0.63          | D     | 1.25          | 0.58  | D             | 0.7   | D             | 2.37  | D             | -1.66 | D             |       |
| 17   | 77.73| 1.03          | I     | 0.64          | 0.22  | D             | 0.45  | 0.93          | I     | 1.38          | I     |               |       |
| 18   | 77.37| 0.66          | D     | 0.87          | 0.26  | D             | 0.88  | D             | 0.21  | D             | -0.33 | D             |       |
| 19   | 77.3 | 0.83          | I     | 0.17          | 1.2   | I             | 0.57  | 1.05          | D     | 0.64          | I     |               |       |
| 20   | 75.7 | 2.2           | D     | 3.17          | 2.01  | D             | 3.01  | 1.63          | D     | 2.25          | D     |               |       |

C.V – Close value; O.S – Observing symbol

D.in.1 day CV - difference in 1 day close value;
D.in.2 days CV - difference in 2 days close value;
D.in.3 days CV - difference in 3 days close value;
D.in.4 days CV - difference in 4 days close value;
D.in.5 days CV - difference in 5 days close value;
D.in.6 days CV - difference in 6 days close value
IV. CALCULATION

The various probability values of TPM, EPM and $\pi$ for difference in one day, two days, three days, four days, five days, six days close value close value are calculated as given below.

A. Probability values of TPM, EPM and $\pi$ for difference in one day close value:

| S1  | S2  | S3  | S4  | S5  | S6  |
|-----|-----|-----|-----|-----|-----|
| 0   | 0   | 1   | 0   | 0   | 0   |
| S2  | 0   | 0   | 0.5 | 0.5 | 0   |
| S3  | 0.143 | 0.143 | 0.5714 | 0.143 |
| S4  | 0.5 | 0   | 0   | 0   | 0   |
| S5  | 0.25 | 0.25 | 0.5 | 0   | 0   |
| S6  | 0   | 0   | 0   | 0.5 | 0.5 |

Fig 2. TPM

| I   | D   |
|-----|-----|
| S1  | 0   |
| S2  | 0.5 |
| S3  | 0.71|
| S4  | 0   |
| S5  | 0   |
| S6  | 1   |

Fig 3. EPM

Steady state probability distribution

$\pi = [0.06 \ 0.11 \ 0.39 \ 0.11 \ 0.22 \ 0.11]$}

B. Probability values of TPM, EPM and $\pi$ for difference in two days close value:

| S1  | S2  | S3  | S4  | S5  | S6  |
|-----|-----|-----|-----|-----|-----|
| 0   | 0   | 0.5 | 0.5 | 0   | 0   |
| S2  | 0.33 | 0.33 | 0.33 | 0   | 0   |
| S3  | 0.33 | 0.17 | 0.5 | 0   | 0   |
| S4  | 0   | 0   | 0   | 0   | 0   |
| S5  | 0   | 1   | 0   | 0   | 0   |
| S6  | 0   | 0   | 0   | 1   | 0   |

Fig 4. TPM

| I   | D   |
|-----|-----|
| S1  | 0.6 |
| S2  | 0.33 |
| S3  | 0.5 |
| S4  | 1   |
| S5  | 0   |
| S6  | 0   |

Fig 5. EPM

Steady state probability distribution

$\pi = [0.29 \ 0.18 \ 0.35 \ 0.06 \ 0.06 \ 0.06]$
### Table III. Transition table with probability values for difference in two days close values

| TRANSITION OF STATES WITH OBSERVING SYMBOLS | S1 | S2 | S3 | S4 | S5 | S6 |
|---------------------------------------------|----|----|----|----|----|----|
| I/D                                         | 0  | 0  | 0  | 0  | 0  | 0  |
| S1                                          | 0  | 0.4| 0  | 0  | 0  | 0  |
| S2                                          | 0  | 0.33| 0 | 0.33| 0  | 0  |
| S3                                          | 0  | 0.33| 0 | 0.167| 0.5 | 0  |
| S4                                          | 0  | 0  | 0  | 0  | 0  | 0  |
| S5                                          | 0  | 0  | 0  | 0  | 0  | 0  |
| S6                                          | 0  | 0  | 0  | 0  | 0  | 0  |

C. Probability values of TPM, EPM and $\pi$ for difference in three days close value:

\[
\begin{bmatrix}
S1 & S2 & S3 & S4 & S5 & S6 \\
I/D & 0 & 0.5 & 0.5 & 0 & 0 & 0 \\
S1 & 0 & 0.5 & 0.5 & 0 & 0 & 0 \\
S2 & 0 & 0.25 & 0.75 & 0 & 0 & 0 \\
S3 & 0 & 0.2 & 0.2 & 0.2 & 0 & 0.2 \\
S4 & 0 & 0.5 & 0 & 0.5 & 0 & 0 & 0 \\
S5 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 \\
S6 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 \\
\end{bmatrix}
\]

**Fig 6. TPM**

\[
\begin{bmatrix}
S1 & S2 & S3 & S4 & S5 & S6 \\
I/D & 0.5 & 0.5 & 0 & 1 & 0 & 0 \\
S1 & 0.5 & 0.5 & 0 & 1 & 0 & 0 \\
S2 & 0 & 1 & 0 & 0 & 0 & 0 \\
S3 & 0.4 & 0.6 & 0 & 0 & 0 & 0 \\
S4 & 0 & 0 & 0 & 0 & 0 & 0 \\
S5 & 1 & 0 & 0 & 0 & 0 & 0 \\
S6 & 1 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}
\]

**Fig 7. EPM**

Steady state probability distribution $\nu = [0.13, 0.23, 0.31, 0.15, 0.00, 0.13]$

### Table IV. Transition table with probability values for difference in three days close values

| TRANSITION OF STATES WITH OBSERVING SYMBOLS | S1 | S2 | S3 | S4 | S5 | S6 |
|---------------------------------------------|----|----|----|----|----|----|
| I/D                                         | 0  | 0  | 0  | 0  | 0  | 0  |
| S1                                          | 0  | 0  | 0  | 0  | 0  | 0  |
| S2                                          | 0  | 0  | 0  | 0.25| 0.75| 0  |
| S3                                          | 0  | 0.2| 0.2| 0.2 | 0.2 | 0  |
| S4                                          | 0  | 0.5| 0  | 0  | 0  | 0  |
| S5                                          | 0  | 0  | 0  | 0  | 0  | 0  |
| S6                                          | 0  | 0  | 0  | 0  | 0  | 0  |

D. Probability values of TPM, EPM and $\pi$ for difference in four days close value:

\[
\begin{bmatrix}
S1 & S2 & S3 & S4 & S5 & S6 \\
I/D & 0.33 & 0.33 & 0.33 & 0 & 0 & 0 \\
S1 & 0.33 & 0.33 & 0.33 & 0 & 0 & 0 \\
S2 & 0 & 0 & 0 & 0.33 & 0.67 & 0 \\
S3 & 0 & 0 & 0 & 0 & 0.33 & 0 \\
S4 & 0 & 1 & 0 & 0 & 0 & 0 \\
S5 & 0 & 0 & 0 & 0 & 0 & 0 \\
S6 & 0 & 0.33 & 0 & 0 & 0 & 0.67 \\
\end{bmatrix}
\]

**Fig 8. TPM**

\[
\begin{bmatrix}
S1 & S2 & S3 & S4 & S5 & S6 \\
I/D & 0.67 & 0.33 & 0 & 1 & 0 & 0 \\
S1 & 0 & 1 & 0 & 0 & 1 & 0 \\
S2 & 0.67 & 0.33 & 0 & 0 & 0 & 0 \\
S3 & 0.33 & 0.67 & 0 & 0 & 0 & 0 \\
S4 & 0 & 1 & 0 & 0 & 0 & 0 \\
S5 & 0 & 0 & 0 & 0 & 0 & 0 \\
S6 & 0.67 & 0.33 & 0 & 0 & 0 & 0 \\
\end{bmatrix}
\]

**Fig 9. EPM**
Steady state probability distribution

\[ \pi = [0.04 \ 0.04 \ 0.04 \ 0.13 \ 0.07 \ 0.04] \]

**Table V. Transition table with probability values for difference in four days close values**

| Transition of States with Observing Symbols | S1 | S2 | S3 | S4 | S5 | S6 |
|---------------------------------------------|----|----|----|----|----|----|
| S1 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |
| S2 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |
| S3 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |
| S4 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |
| S5 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |
| S6 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |

**E. Probability values of TPM, EPM and \( \pi \) for difference in five days close value:**

\[ \begin{bmatrix}
  S1 & S2 & S3 & S4 & S5 & S6 \\
  0.5 & 0.25 & 0.25 & 0.25 & 0.25 & 0.25 \\
  1 & 0 & 0 & 0 & 0 & 0 \\
  0.33 & 0.67 & 0.67 & 0.67 & 0.67 & 0.67 \\
  0 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\
  0 & 0 & 0 & 0 & 0 & 0 \\
  0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix} \]

**Fig 10. TPM**

\[ \begin{bmatrix}
  I & D \\
  S1 & 0.25 0.75 \\
  S2 & 0 1 \\
  S3 & 0 1 \\
  S4 & 0.5 0.5 \\
  S5 & 1 0 \\
  S6 & 1 0
\end{bmatrix} \]

**Fig 11. EPM**

Steady state probability distribution

\[ \pi = [0.29 \ 0.14 \ 0.21 \ 0.14 \ 0.14 \ 0.07] \]

**Table VI. Transition table with probability values for difference in five days close values**

| Transition of States with Observing Symbols | S1 | S2 | S3 | S4 | S5 | S6 |
|---------------------------------------------|----|----|----|----|----|----|
| S1 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |
| S2 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |
| S3 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |
| S4 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |
| S5 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |
| S6 0.33 0.33 0.33 0.33 0.33 0.33           |    |    |    |    |    |

**F. Probability values of TPM, EPM and \( \pi \) for difference in six days close value:**

\[ \begin{bmatrix}
  S1 & S2 & S3 & S4 & S5 & S6 \\
  0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\
  0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\
  0 & 0 & 0 & 0 & 0 & 0 \\
  0 & 0 & 0 & 0 & 0 & 0 \\
  0.33 & 0.33 & 0.33 & 0.33 & 0.33 & 0.33 \\
  0 & 0 & 0 & 0 & 0 & 0 
\end{bmatrix} \]

**Fig 12. TPM**

\[ \begin{bmatrix}
  I & D \\
  S1 & 0 1 \\
  S2 & 0 1 \\
  S3 & 0 1 \\
  S4 & 0 1 \\
  S5 & 0.67 0.33 \\
  S6 & 1 0
\end{bmatrix} \]

**Fig 13. EPM**

Steady state probability distribution

\[ \pi = [0.31 \ 0.15 \ 0.06 \ 0.06 \ 0.25 \ 0.13] \]
Table VII. Transition table with probability values for difference in six days close values

| TRANSITION OF STATES WITH OBSERVING SYMBOLS | S1 | S2 | S3 | S4 | S5 | S6 |
|---------------------------------------------|----|----|----|----|----|----|
| I                                           | 0  | 0.5| 0  | 0  | 0  | 0  |
| D                                           | 0  | 0  | 0  | 0  | 0  | 0  |
| S1                                          | 0  | 0  | 0  | 0  | 0  | 0  |
| S2                                          | 0  | 0  | 0  | 0  | 0  | 0  |
| S3                                          | 0  | 0  | 0  | 0  | 0  | 0  |
| S4                                          | 0  | 1  | 0  | 0  | 0  | 0  |
| S5                                          | 0  | 0  | 0  | 0  | 0  | 0  |
| S6                                          | 0  | 0  | 0  | 0  | 0  | 0  |

The MATLAB function “Hmmgenerate” is used to generate a random sequence of emission symbols and states. The length of both sequence and states to be generated is denoted by L.

The HMM matlab toolbox syntax is:

\[
[\text{Sequence, States}] = \text{Hmmgenerate}(L, \text{TPM}, \text{EPM}), \text{ see [11]}
\]

For instance, if the Input is given as,

\[
\text{TPM} = \begin{bmatrix} 0.1 & 0.5 & 0 & 0.5 & 0 & 0 \ 0 & 0.5 & 0.5 & 0 & 0 & 0 \ 0 & 0 & 0.1 & 0 & 0 & 0 \ 0 & 0 & 0 & 0.5 & 0 & 0 \ 0 & 0 & 0 & 0 & 0.5 & 0 \ 0 & 0 & 0 & 0 & 0 & 0 \ \end{bmatrix} \quad \text{EPM} = \begin{bmatrix} 0 & 1 \\ 0.5 & 0.5 \\ 0.71 & 0.29 \\ 0 & 1 \\ 0 & 1 \\ 1 & 0 \end{bmatrix}
\]

\[
[\text{sequence, states}] = \text{Hmmgenerate}(7, \text{TPM}, \text{EPM})
\]

'Sequence Symbols', {'I', 'D'}, 'Statenames', {'very low', 'low', 'moderate low', 'moderate high', 'high', 'very high'}

Then the Output of few randomly generated sequences and states is given below:

Sequence: \( E \rightarrow I \rightarrow D \rightarrow D \rightarrow I \rightarrow I \rightarrow I \rightarrow I \)

states : S3 S2 S3 S6 S6 S6 S6 S6

sequence : \( E \rightarrow D \rightarrow I \rightarrow D \rightarrow D \rightarrow I \rightarrow I \rightarrow I \)

states : S3 S3 S5 S1 S3 S2 S3

where ‘E’ denotes the start symbol.

The fitness function used for finding the fitness value of sequence of states is defined by

\[
\text{Fitness} = \frac{1}{\sum \text{compare}(i, j)}
\]

V. DISCUSSION

Using the Iterative procedure, for each TPM and EPM framed we get an optimum sequence of states generated. The length of the sequence generated is taken as \( L = 7 \), for instance.

The optimum sequence of states obtained from the one day difference TPM and EPM is

1. \( E \rightarrow I \rightarrow D \rightarrow D \rightarrow I \rightarrow D \rightarrow D \)

2. \( E \rightarrow I \rightarrow D \rightarrow D \rightarrow I \rightarrow D \rightarrow D \)

3. \( E \rightarrow D \rightarrow I \rightarrow D \rightarrow I \rightarrow I \rightarrow I \)

4. \( E \rightarrow D \rightarrow I \rightarrow D \rightarrow I \rightarrow D \rightarrow D \)

5. \( E \rightarrow D \rightarrow D \rightarrow D \rightarrow I \rightarrow I \rightarrow D \rightarrow D \)

6. \( E \rightarrow D \rightarrow D \rightarrow D \rightarrow I \rightarrow D \rightarrow D \rightarrow D \)

Using the fitness function we compute the fitness value for each of the optimum sequence of states obtained.
Table VIII. Comparison of Six Optimum State Sequences

| S.No. | Comparison of 6 optimum sequence of states | Calculated value | Fitness = $\sum_{compare(i, j)}$ |
|-------|------------------------------------------|-----------------|---------------------------------|
| 1.    | (1,2) + (1,3) + (1,4) + (1,5) + (1,6)   | 1               | 1                               |
| 2.    | (2,1) + (2,3) + (2,4) + (2,5) + (2,6)   | 1.29            | 0.76                            |
| 3.    | (3,1) + (3,2) + (3,4) + (3,5) + (3,6)   | 1.86            | 0.54                            |
| 4.    | (4,1) + (4,2) + (4,3) + (4,5) + (4,6)   | 1.43            | 0.70                            |
| 5.    | (5,1) + (5,2) + (5,3) + (5,4) + (5,6)   | 2.14            | 0.47                            |
| 6.    | (6,1) + (6,2) + (6,3) + (6,4) + (6,5)   | 2.14            | 0.47                            |

VI. CONCLUSION

In this paper, results are presented using Hidden Markov Model to find the trend of the stock market behavior. The highest is the fitness value, the better is the performance of the particular sequence. One day difference in close value when considered is found to give the best optimum sequence. It is observed that at any point of time over years, if the stock market behaviour pattern is the same then we can observe the same steady state probability values as obtained in one day difference of close value, which clearly determines the behavioural pattern of the stock market.

VII. REFERENCES

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