Journal of Natural Sciences and Mathematics Research
J. Nat. Scien. & Math. Res. Vol. 11 No. 1 (2025) 92-102
ISSN: 2460-4453 (Online); 2614-6487 (Printed)
Available online at http://journal.walisongo.ac.id/index.php/jnsmr

American index exchange movement against IDX stochastic

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ABSTRACT

A giant warehouse full of countless opportunities forms the foundation of this study, which aims to conduct stochastic modeling of the impact of the movement of the American stock index on the IDX (Indonesia Stock Exchange). This research discusses and emphasizes how the movement of the American stock index affects changes in the IDX over a certain period of time using a quantitative approach. The study employs a Hidden Markov Model (HMM) to identify latent market states. It utilizes the Viterbi method to determine the most probable sequence of state transitions based on the observed data. The model was trained using historical movements of the NASDAQ, NYSE, and DOW JONES indices, facilitating the discovery of significant trends in IDX changes. The research results show a trend in the movement of the IDX based on the movement of the American indices NASDAQ, NYSE, and DOW JONES, as follows: Bullish, bearish, bullish, bearish when NASDAQ is observed at 1, 2, 5, 6, and 8; NYSE is observed at 1, 3, 9, 11, and 15; and DOW JONES is observed at 1, 3, 4, 7, 9, 10, 11, 12, 13, 15, and 16. Bearish, bullish, bearish, bullish when NASDAQ is observed at 3, 9, 11, and 15; NYSE is observed at 2, 5, 6, and 8; and DOW JONES is observed at 2, 5, 6, 8, and 14. Bearish, bullish, bearish, bearish when NASDAQ is observed at 4, 12, and 16. Bullish, bearish, bullish, bullish when the NYSE is observed at 4 and 12. Bullish, bearish, bearish, bullish when NASDAQ is observed at seven and when NYSE is observed at 10. Bearish, bullish, bullish, bearish when NASDAQ is observed at 10. Bearish, bearish, bullish, bearish when NASDAQ is observed at 13 and 14. Bullish, bullish, bearish, and bullish when the NYSE is observed at 13, 14, and 16. The analysis indicates that IDX trends generally fluctuate in line with major U.S. indices (NASDAQ, NYSE, DOW JONES). Notably, specific observations 4, 12, 13, 14, 16 reveal a stronger correlation: a bearish NASDAQ movement tends to align with a bearish IDX stochastic, whereas a bearish NYSE movement is more likely to trigger a bullish response in the IDX.

Keywords:
IDX; Index; Markov; Model

Introduction

The stock market possesses a vast repository replete with innumerable prospects. Within the confines of this warehouse, a multitude of forces converge to ascertain prices collectively. These forces operate ceaselessly, with the possibility for one force to exert a significant influence, yet none can be foreseen with absolute certainty. The primary objective for investors is to refine their focus inside this domain by discerning and eliminating the most obscure factors, subsequently directing their attention towards the least ambiguous aspects (Karim et al., 2023).

Stock prices on global exchanges are not fixed; they fluctuate based on the forces of supply and demand (Dahlia Pinem et al., 2023). These fluctuations make the stock exchange attractive to investors (Al-naffouri, n.d.). Currently, an increasing number of people are leveraging these advancements to invest in securities listed on the Indonesia Stock Exchange (IDX). This assignment serves as a practical application of probability theory (Hagstrom, 2014), exploring the multifaceted nature of the global stock market and the specific opportunities presented by the IDX (Setiawan, 2020).

The stock price index is a value used to measure company performance by comparing changes in stock prices over time, so that we can know the decline or increase in stock prices each time (Karim et al., 2023). Changes in the Indonesia Stock Exchange (IDX) are caused by changes in market prices every day and the addition of shares that come from new companies listing on the stock exchange or corporate actions such as rights issues, warrants, splits, dividends, and others (Kalang, 2019).

The growing threat of health and economic crises has led foreign investors to withdraw their funds, replaced by local investors as the main driving force for domestic stock exchange transactions. This shift in investor dynamics highlights the resilience and adaptability of domestic markets in the face of global challenges (Resti Aulia Safitri et al., 2023). Regulation also plays an important role in stock market behavior. Changes in financial regulations, both national and international, have a significant impact on market behavior. For public companies, compliance is of paramount importance, affecting business and investor confidence (Adielyani, 2023). In the Indonesian stock market, the stock market index consists of two indices, one sectoral and one non-sectoral (Kalang, 2019).

Macroeconomic events, political factors, and international developments constantly affect the stock market and cause fluctuations in share prices, which is a major source of concern for investors (Ayyildiz & Iskenderoglu, 2023). Moreover, financial globalization, characterized by its intricate aspects, serves as an external determinant impacting the stability of economic and financial systems (Raihan et al., 2023). Undoubtedly, this process has brought about a profound transformation in the global environment, impacting not only the economic sector but also various other sectors. In theory, financial globalisation and the unrestricted flow of funds around the world are expected to bring significant economic benefits to both investing and receiving countries (Asongu & Nnanna, 2020). Productivity and employment growth are expected to accelerate worldwide, lifting less developed countries out of poverty and maintaining (or further improving) living standards in developed countries. Low-income households in particular are expected to benefit, reducing global and inter-country inequalities (Idode & Sanusi, 2019). As a result, the phenomenon of financial globalisation will have ramifications for the growing interconnectedness between a nation's domestic capital market and the global capital market (Salim JF, Jamal A, 2017). In the realm of financial globalization, currency exchange rates and cross-border capital flows are integral components that intertwine with the dynamics of domestic and global markets. Understanding these interconnections provides investors with a more comprehensive view of the potential risks and rewards associated with global investments (Wang et al., 2023).

The Hidden Markov Model (HMM) is often regarded as a highly appropriate model for forecasting fluctuations in stock indices. However, the flexibility of HMM is limited as transitions and outliers are constant throughout the time interval, and in practice, HMM must rely on written data (Li et al., 2021). A hidden Markov model (HMM) is a statistical model named after Russian mathematician Andrei Markov (Pietrzykowski & Sałabun, 2014). However, the flexibility of HMM is limited as transitions and outliers are constant throughout the time interval, and in practice, HMM must rely on written data (Pratiwi & Utomo, 2017). While the probability of transitioning between states in an event is established, such as the movement of the American stock market index against the IHSG, the specific sequence of states over time remains undetermined and is dependent on the probability values generated by the model, which may not be optimal (Al-adawiyah, 2021). Hence, it is imperative to employ a procedural or algorithmic approach that facilitates the identification of the most favorable sequence of states, leveraging the hidden Markov model probabilities. This is achieved through the utilization of the Viterbi algorithm. The Viterbi algorithm is a dynamic programming algorithm used to find the most probable sequence of hidden states, called Viterbi paths (Al-Naffouri, n.d.).

Previous research has been conducted to examine the effects of international indices, such as the DOW JONES index (Herlianto & Hafizh, 2020). This study conducted an analysis and examination of the impact exerted by the Dow Jones Index, Nikkei 225, Shanghai Stock Exchange, and the Singapore Straits Times Index on the Indonesia Stock Exchange over the period spanning from 2015 to 2019. In a separate investigation conducted (Mamonto et al., 2016), the Hidden Markov Model was employed to forecast the probability of price escalation for PT. Bank BNI Tbk, PT. Bank BRI Tbk, PT. Bank BTN Tbk, and PT. Bank Mandiri Tbk. Observation of changes in macroeconomic indicators is believed to assist investors in making investment decisions in the capital market. Understanding these indicators becomes crucial as they play a significant role in shaping the market environment and influencing investment (Santosa & Roselli, 2023).

Researching the influence of American indices (NASDAQ, NYSE, and DOW JONES) on the IDX using a Hidden Markov Model (HMM) and the Viterbi algorithm is urgent due to the profound interconnectedness of global markets and the need for precise forecasting tools. These indices frequently influence the global market state, affecting the IDX through changes in investor behavior and capital flows. Hidden Markov Models facilitate the detection of hidden market conditions and stochastic transitions, whereas the Viterbi algorithm provides precise forecasts of market trends. This method supports investors and regulators in solving volatility while facilitating risk management and strategic decision-making. Moreover, utilizing sophisticated quantitative techniques improves comprehension of cross-market interactions and provides a competitive advantage in financial modeling, delivering essential insights for stabilizing and maximizing market results.

Methods

This research study is classified as quantitative research, a scientific inquiry method that uses quantitative or numerical data to test hypotheses and acquire objectively measurable outcomes. The data utilized in this study can be classified as secondary data, referring to information that is acquired indirectly or through intermediaries and documented by individuals other than the researchers themselves. The secondary data included in this study consist of the Indonesian Stock Exchange (IDX) and the American stock market indexes, namely NASDAQ, NYSE, and DOW JONES (Robiyanto et al., 2019). These data were obtained from Yahoo Finance, covering the time span from May 23, 2022, to May 19, 2023. The data utilized in this study include discrete data points that depict the magnitudes of upward and downward movements in the IDX, as well as the American stock market indexes, NASDAQ, NYSE, and DOW JONES. The probabilistic model used to analyze stochastic processes organizes the data into a discrete sample space. In this particular study, the sample space for the IHSG is represented as $Q = \{bullish, bearish\}$, while the American stock market indexes (NASDAQ, NYSE, and DOW JONES) are marked as $O = \{rise, fall\}$. The research employed the Hidden Markov Model as the data analysis technique to ascertain the relationship between the movement of American stock market indexes and the IDX. The Viterbi Algorithm was utilized to discover the optimal states.

The Hidden Markov Model (HMM) is a statistical instrument intended to model time-related systems with hidden states affecting observable results. It involves a set of hidden states, observable events, and probabilities that determine transitions between states and the generation of observations. In financial markets, HMM can simulate underlying market conditions (e.g., bullish or bearish patterns) using visible data, such as stock index fluctuations. The model encapsulates the stochastic characteristics of markets, wherein each seen event (e.g., NASDAQ, NYSE, Dow Jones fluctuations) is probabilistically associated with a hidden state. By estimating the transition probabilities among hidden states and the emission probabilities of observations, researchers can deduce the fundamental market dynamics and examine the impact of global indexes on local markets such as the IDX.

The Viterbi algorithm is a dynamic programming technique employed alongside Hidden Markov Models (HMM) to determine the most probable sequence of hidden states based on a set of observations. It operates by sequentially computing probabilities: initially, the probability of the starting states yielding the first observation; subsequently, the probability of transitioning between states while generating successive observations. Upon completing every phase of analysis, the algorithm backtracks to rebuild the sequence of hidden states that optimizes the overall probability. The Viterbi algorithm in financial research deciphers concealed market trends from stock index data, providing insights into market dynamics and facilitating forecasts of future movements. By integrating HMM with the Viterbi algorithm, researchers may reveal concealed patterns and correlations in time-series data, establishing a robust framework for the analysis of intricate financial systems.

Results and Discussions

Exploratory Data

It is imperative to commence with the first stage of performing descriptive analysis and exploring the gathered data. Subsequently, the closing values of the indices will be presented. The return refers to the absolute value of the change in level at time 't' relative to the rate at time 't-1'. The return values are derived from the natural logarithm of the ratio between the current value y_t and the previous value y_{t-1}.

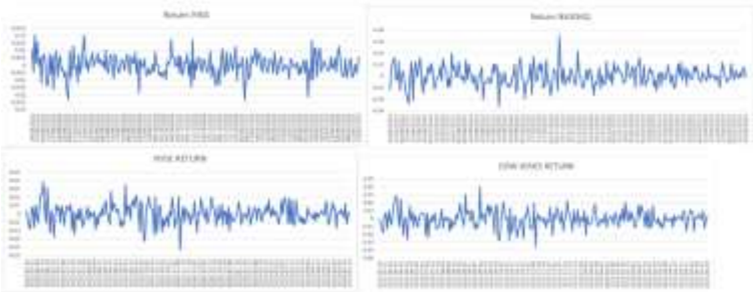

Figure 1. Daily plot return of IDX, NASDAQ, NYSE, and DOW JONES

As depicted in Figure 1, there is an observable propensity for the IHSG to exhibit cumulative level changes over the specified time period, a phenomenon frequently observed in economic and financial variables. The closing return fluctuations observed in the Indonesian Stock Exchange Composite Index (IHSG) exhibit a tendency to fluctuate between a range of -2% to 2%. The NASDAQ has a maximum return value of 7% and a minimum value of -5%. Typically, the return values of NASDAQ exhibit fluctuations within a band spanning from -4% to 4%. The New York Stock Exchange (NYSE) exhibits a maximum return value of 4% and a minimum return value of -4%. Typically, the fluctuation of return values in the NYSE adheres to a band spanning from -2% to 2%. The maximum return value observed for the DOW JONES index is 4%, while the minimum return value approaches -4%. In general, the fluctuations in the return values of the DOW JONES index fall between a range of -2% to 2%.

Hidden Markov Model Parameters

Prior to conducting the modeling process, it is vital to ascertain various parameters of the Hidden Markov Model. These parameters encompass the hidden state, observable state, transition probabilities, emission probabilities, and probability distributions.

The latent variable in this research is the trend movement of the Indonesian Stock Exchange (IDX), denoted as $Q = \{bullish, bearish\}$. The observed state, conversely, refers to the alteration in the values of the American stock market indexes. The model selects four sets of observed states, denoted as $O = \{o_1, o_2, o_3, o_4\}$, for examination. Given that the American stock market indices are subject to only two requirements for changes in their values, it is possible to generate all potential sequences of observed states using the following approach: The set O consists of 16 elements, denoted as $o_1, o_2, o_3, \ldots, o_{16}$. Each element o_i, where i ranges from 1 to 16, represents a sequence of four events. Specifically, o_1 corresponds to a sequence of four "rise" events, o_2 represents a sequence of three "rise" events followed by one "fall" event, and so on, until o_{16} represents a sequence of four "fall" events.

$$o_1 = \{rise, rise, rise, rise\}$$
$$o_2 = \{rise, rise, rise, fall\}$$
$$o_3 = \{rise, rise, fall, rise\}$$
$$o_4 = \{rise, rise, fall, fall\}$$
$$o_5 = \{rise, fall, rise, rise\}$$
$$o_6 = \{rise, fall, rise, fall\}$$
$$o_7 = \{rise, fall, fall, rise\}$$
$$o_8 = \{rise, fall, fall, fall\}$$
$$o_9 = \{fall, rise, rise, rise\}$$
$$o_{10} = \{fall, rise, rise, fall\}$$
$$o_{11} = \{fall, rise, fall, rise\}$$
$$o_{12} = \{fall, rise, fall, fall\}$$
$$o_{13} = \{fall, fall, rise, rise\}$$
$$o_{14} = \{fall, fall, rise, fall\}$$
$$o_{15} = \{fall, fall, fall, rise\}$$
$$o_{16} = \{fall, fall, fall, fall\}$$

The transition probabilities in this study are derived from the transitions of latent states in the trend dynamics of the IDX. Based on the available data, the observed transitions can be delineated as Table 1.

Table 1. IDX trend movement transitions

q_i	q_j		
	Bullish	**bearish**	**total**
bullish	52	64	116
bearish	64	55	119
total	116	119	235

Table 1 illustrates the transitions in IDX trend movements, showing 52 instances where a bullish trend continued on the following day, 64 instances where a bullish trend shifted to bearish, 64 instances where a bearish trend shifted to bullish, and 55 instances where a bearish trend persisted.

Hence, the calculation of transition probabilities can be achieved by employing the equation as seen in [6, eq. (8.1)]:

$$p_{ij} = Pr(X_{n+1} = j | X_n = i) \tag{1}$$

The outcome of this process yields a probability matrix denoted as A.

$$A = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} 0{,}448 & 0{,}552 \\ 0{,}538 & 0{,}462 \end{bmatrix} \tag{2}$$

By examining the temporal fluctuations of the American stock market index in conjunction with the movements of the IDX trend, one may derive the emission matrix for observation B. The emissions pertaining to the American stock index and IDX are presented as Table 1.

Table 2. American stock index emission

q_i	v_j (NASDAQ)		v_j (NYSE)		v_j (DOW JONES)	
	rise	**fall**	**rise**	**fall**	**rise**	**fall**
bullish	62	55	56	61	57	60
bearish	51	68	66	53	59	60

Table 2 presents 62 instances where a rise in NASDAQ corresponded with a bullish trend in the IDX, 55 instances where a decline resulted in a bullish trend, 51 instances where a rise led to a bearish trend, and 68 instances where a decline corresponded with a bearish trend. A similar pattern is observed for the NYSE and DOW JONES indices.

In a similar manner to equation (1), the emission probability matrix for the American Index and IDX is obtained.

$$B_1 = \begin{bmatrix} b_1(v_1) & b_1(v_2) \\ b_2(v_1) & b_2(v_2) \end{bmatrix} = \begin{bmatrix} 0{,}523 & 0{,}470 \\ 0{,}428 & 0{,}571 \end{bmatrix} \quad (3)$$

$$B_1 = \begin{bmatrix} b_1(v_1) & b_1(v_2) \\ b_2(v_1) & b_2(v_2) \end{bmatrix} = \begin{bmatrix} 0{,}479 & 0{,}521 \\ 0{,}555 & 0{,}445 \end{bmatrix} \quad (4)$$

$$B_1 = \begin{bmatrix} b_1(v_1) & b_1(v_2) \\ b_2(v_1) & b_2(v_2) \end{bmatrix} = \begin{bmatrix} 0{,}487 & 0{,}513 \\ 0{,}496 & 0{,}504 \end{bmatrix} \quad (5)$$

The observation of the complete starting state distribution can be achieved by examining the frequency of hidden states in each movement of the IDX trend. Moreover, the probability of the initial distribution can be computed utilizing the subsequent equation:

$$\pi_i = P(X_0 = q_i) \quad (6)$$

Holds true for all values of i ranging from 1 to N, where N is a positive integer. Additionally, the values of π_i must satisfy the condition $0 < \pi_i \leq 1$ (Farid, 2015). As a consequence, the outcome is the establishment of the initial probability distribution matrix.

$$\pi = [0{,}494 \quad 0{,}506] \quad (7)$$

The problem can be represented by illustrating the predetermined probability of hidden state transitions and emissions.

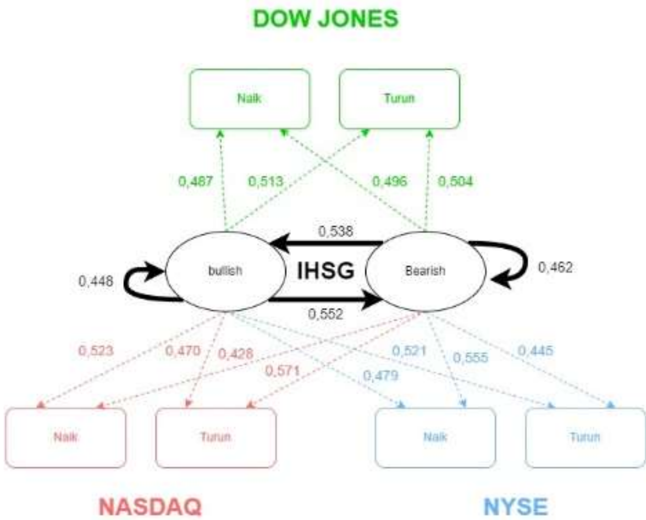

Figure 2. Problem transition illustration

Figure 2 illustrates the probability values for trend movement transitions and emissions. For example, the probability of the IDX transitioning from a bullish to a bearish trend is 0.552, while the emission probability of the IDX turning bearish when the NYSE is rising is 0.555.

Determining the sequence of hidden states

The first step in finding the sequence of hidden states is the initialization stage. Given a set $O = \{o_1, o_2, o_3, ..., o_{16}\}$ with $o_n = \{s_1, s_2, s_3, s_4\}$ for each $1 \leq n \leq 16$, it is worth noting that there are two potential observations: one where s_1 corresponds to a rise, and another where s_1 corresponds to a fall.

$$\begin{aligned} V_1(j) &= P\{X_1 = j, S_1 = s_1\} \\ &= p_j p(s_1|j) \end{aligned} \tag{8}$$

The equation (8) as seen in [7, eq. (4.35)] allows for the determination of the initial probability process for bullish and bearish outcomes when $t = 1$ and s_1 represents the observation of a rise in the NASDAQ index.

$$\begin{aligned} V_1(1) &= p_1 p(s_1 = rise|1) \\ &= (0{,}494)(0{,}523) = 0{,}258362 \end{aligned} \tag{9}$$

$$\begin{aligned} V_1(2) &= p_2 p(s_1 = rise|2) \\ &= (0{,}506)(0{,}47) = 0{,}23782 \end{aligned} \tag{10}$$

Meanwhile, for s_1 is fall.

$$\begin{aligned} V_1(1) &= p_1 p(s_1 = fall|1) \\ &= (0{,}494)(0{,}428) = 0{,}211432 \end{aligned} \tag{11}$$

$$\begin{aligned} V_1(2) &= p_2 p(s_1 = fall|2) \\ &= (0{,}506)(0{,}571) = 0{,}288926 \end{aligned} \tag{12}$$

The aforementioned computation procedure is likewise conducted for the NYSE and DOW JONES indices.

The subsequent phase involves recursion. Following the initialization and acquisition of initial probability values for the hidden states, these values can be employed to ascertain the maximum sequence of states for the subsequent time t. This iterative procedure is then repeated until time n, utilizing the subsequent equation as seen in [7, eq. (4.37)]:

$$V_k(j) = p(s_k|j) \max P_{i,j} V_{k-1}(i) \tag{13}$$

The probability of bullish and bearish with the observation sequence $o_1 = \{rise, rise, rise, rise\}$ and for $t = 2$ to $t = 4$ based on the movement of NASDAQ.

$$\begin{aligned} V_2(1) &= p(s_2|1) \max\{V_1(1)a_{11}, V_1(2)a_{21}\} \\ &= (0{,}523)(0{,}127947) = 0{,}066916 \end{aligned} \tag{14}$$

$$\begin{aligned} V_2(2) &= p(s_2|2) \max\{V_1(1)a_{12}, V_1(2)a_{22}\} \\ &= (0{,}470)(0{,}142616) = 0{,}067029 \end{aligned} \tag{15}$$

$$\begin{aligned} V_3(1) &= p(s_3|1) \max\{V_2(1)a_{11}, V_2(2)a_{21}\} \\ &= (0{,}523)(0{,}036062) = 0{,}01886 \end{aligned} \tag{16}$$

$$\begin{aligned} V_3(2) &= p(s_3|2)\max\{V_2(1)a_{12}, V_2(2)a_{22}\} \\ &= (0{,}470)(0{,}036938) = 0{,}017361 \end{aligned} \tag{17}$$

$$\begin{aligned} V_4(1) &= p(s_4|1)\max\{V_3(1)a_{11}, V_3(2)a_{21}\} \\ &= (0{,}523)(0{,}00934) = 0{,}004885 \end{aligned} \tag{18}$$

$$\begin{aligned} V_4(2) &= p(s_4|2)\max\{V_3(1)a_{12}, V_3(2)a_{22}\} \\ &= (0{,}470)(0{,}010411) = 0{,}004893 \end{aligned} \tag{19}$$

The value of each probability process is contingent upon the preceding process. For instance, if j_n represents the sequence of values for j or the source state along with the path that maximizes $V_n(j)$, then the values of j_n for each t can be described as follows:

$$j_2(1) = bearish, j_2(2) = bullish \tag{20}$$

$$j_3(1) = bearish, j_3(2) = bullish \tag{21}$$

$$j_4(1) = bearish, j_4(2) = bullish \tag{22}$$

The state denoted as $j = \{(bearish, bullish), (bearish, bullish), (bearish, bullish)\}$ represents the routes in which the probability of both bullish and bearish states are maximized, based on the movements of NASDAQ during the time periods $2 \leq t \leq 4$. The recursive procedures are executed iteratively till reaching o_{16}, and are similarly applied to the NYSE and DOW JONES indexes. The ultimate phase in ascertaining the ideal concealed state involves retracing the preceding trajectory that possesses the highest probability value. For instance, if q_t represents the highest state at time t, it is extended to q_{t-1} by following the prior trajectory that maximizes this state with $q_{n-2}(j_{n-1}\,(q_n))$ (Ross, 2014) until $t = 1$. The best sequence of hidden states is obtained by arranging the sequence q. The most advantageous arrangement of concealed states corresponding to the first observation, o_1, in relation to fluctuations in the NASDAQ. The most favorable arrangement of hidden states corresponding to the observation o_1, derived from the fluctuations in the NASDAQ market.

$$\begin{aligned} q_4 &= \max\{V_4(1), V_4(2)\} \\ &= V_4(2) = bearish \end{aligned} \tag{23}$$

$$\begin{aligned} q_3 &= j_4(q_4) \\ &= j_4(2) = bullish \end{aligned} \tag{24}$$

$$\begin{aligned} q_2 &= j_3(q_3) \\ &= j_3(1) = bearish \end{aligned} \tag{25}$$

$$\begin{aligned} q_1 &= j_2(q_2) \\ &= j_2(2) = bullish \end{aligned} \tag{26}$$

The set Q was acquired, consisting of the elements "bullish", "bearish", "bullish", and "bearish". The identical procedure is employed for the NYSE and DOW JONES indexes and executed until o_{16} for every index. The aforementioned previous and all the result processes can be depicted in the following manner:

Table 3. Hidden states result

Q	NASDAQ	NYSE	DOW JONES
1,2,1,2	o_1, o_2, o_5, o_6, o_8	$o_1, o_3, o_9, o_{11}, o_{15}$	$o_1, o_3, o_4, o_7, o_9, o_{10}, o_{11}, o_{12}, o_{13}, o_{15}, o_{16}$
2,1,2,1	o_3, o_9, o_{11}, o_{15}	o_2, o_5, o_6, o_8	$o_2, o_5, o_6, o_8, o_{14}$
2,1,2,2	o_4, o_{12}, o_{16}	-	-
1,2,1,1	-	o_4, o_{12}	-
1,2,2,1	o_7	o_{10}	-
2,1,1,2	o_{10}	o_7	-
2,2,1,2	o_{13}, o_{14}	-	-
1,1,2,1	-	o_{13}, o_{14}, o_{16}	-

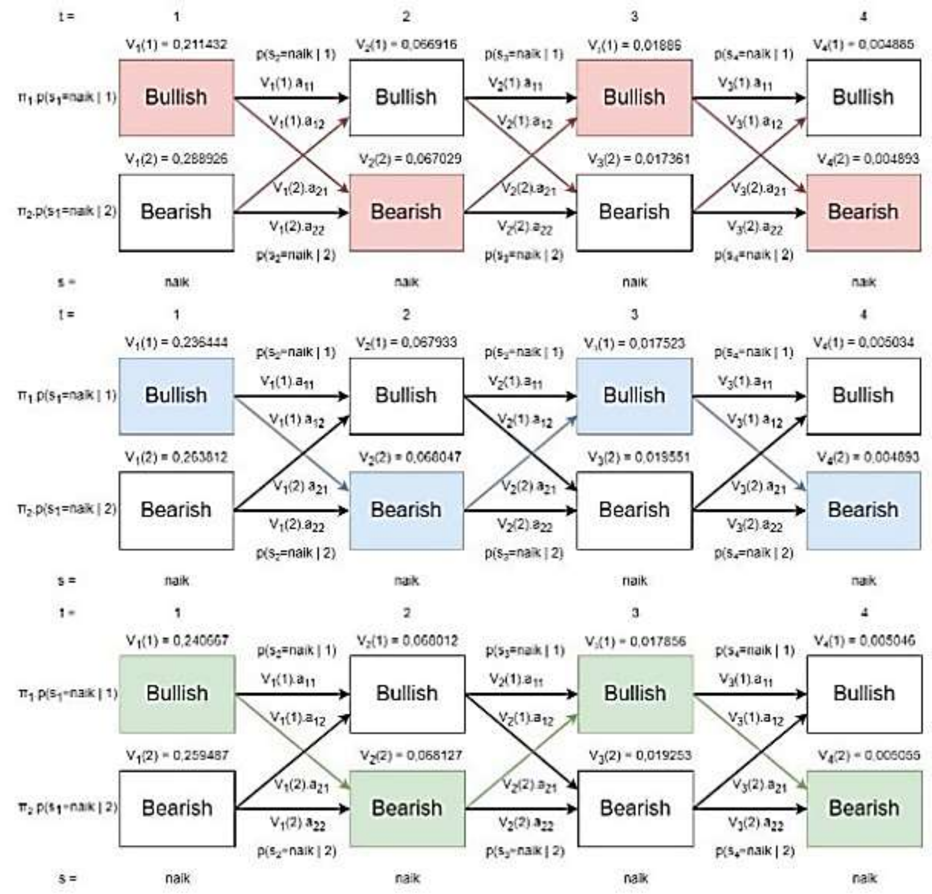

Figure 3. Processes illustration

Table 3 presents the observed movements of the Indonesian Stock Exchange (IDX) in various market conditions, specifically 2 bullish and 2 bearish, while considering the performance of the NASDAQ at specific time points (o_1, o_2, o_5, o_6, o_8), the New York Stock Exchange (NYSE) at specific time points ($o_1, o_3, o_9, o_{11}, o_{15}$), and the Dow Jones Industrial Average (DOW JONES) at specific time points ($o_1, o_3, o_4, o_7, o_9, o_{10}, o_{11}, o_{12}, o_{13}, o_{15}, o_{16}$) and so forth. Figure 3 presents a graphical representation and the calculation flow for Q at observation o_1.

Conclusion

Drawing upon the findings and analyses detailed in the preceding chapter, it is possible to infer a trend in the movement of the IDX based on the movements of the American indices NASDAQ, NYSE, and DOW JONES, generally show a fluctuating pattern. However, some observations specifically ($o_4, o_{12}, o_{13}, o_{14}, o_{16}$) indicate a clearer bullish or bearish trend. These particular observations mostly exhibit a bearish trend. For NASDAQ, these cases tend to result in a more bearish impact on the IDX, whereas for NYSE, they tend to result in a more bullish impact on the IDX. Thus, the conclusion from these findings can be inferred as follows: when the NASDAQ is experiencing a bearish trend, the IDX is also likely to follow a bearish trend; however, when the NYSE is in a bearish trend, the IDX is more likely to experience a bullish trend.

Acknowledgments

This final project would not have been realized without the assistance of various parties. Therefore, the author like to express my sincere gratitude to the following individuals for their invaluable contributions and support throughout the course of this paper. Enggar Prasetyawan, S.Pd, M.Pd. Head of Undergraduate Program in Mathematics and Alfi Maulani, S.Si, M.Si. Lecturer and adviser for this paper. They have been supportive of my career objectives and have actively sought to provide me with protected academic time to pursue those goals.

Conflicts of interest

The authors declare that there are no conflicts of interest.

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