Available online at https://journal.rescollacomm.com/index.php/ijqrm/index

International Journal of Quantitative Research and Modeling

e-ISSN 2721-477X
p-ISSN 2722-5046

Vol. 6, No. 2, pp. 264-274, 2025

Investment Portfolio Optimization Using the Mean-Variance Model Based on Holt-Winters Stock Price Forecasting of Food Sector in Indonesia

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Abstract

The importance of the food sector to Indonesia's economy makes it one of the most attractive sectors to consider in an investment portfolio. An optimal portfolio is the best choice for investors among various efficient portfolios, aiming to maximize returns while minimizing risk. Moreover, since investment is inherently associated with fluctuating stock prices, accurate forecasting is necessary to anticipate future stock movements. This study aims to accurately predict stock prices and construct an optimal portfolio consisting of five food sector stocks listed on the Indonesia Stock Exchange, namely DMND, ICBP, HOKI, INDF, and ULTJ. Stock price predictions are generated using the Holt-Winter method, which can identify seasonal patterns and trends from historical data. The predicted stock prices are then used to calculate returns, which serve as the basis for portfolio optimization using the Mean-Variance model. The results show that the Holt-Winter method successfully produces accurate stock price forecasts, with Mean Absolute Percentage Error (MAPE) values for all stocks below 10%. These forecasts are used to calculate returns in the portfolio optimization process. The optimal portfolio composition is determined with the following weight proportions: HOKI (4%), ICBP (18%), ULTJ (21%), DMND (26%), and INDF (30%). This portfolio yields an expected return of 0.0441% and a portfolio variance of 0.0063%, reflecting a balanced trade-off between potential return and risk.

Keywords: optimal portfolio, food sector, risk, return, Mean-Variance model, Holt-Winter method, stock prediction

1. Introduction

The capital market is a vital component of the financial system, serving as an economic indicator that reflects the performance of companies and economic sectors as a whole (Ananda et al., 2024). It benefits not only companies in need of capital but also offers investment opportunities to the public. According to Pranata (2023), investment is a strategy to manage funds by placing them in assets expected to yield future returns. Stock market investment is a popular instrument due to its potential for high returns compared to alternatives like deposits or bonds. However, it carries significant risk, as stock prices may fluctuate sharply due to both internal company factors and external conditions like global economic shifts.

In Indonesia's capital market, economic sectors have varying characteristics and risks. The food sector stands out as relatively stable with long-term prospects, as it produces essential goods for daily consumption like food and beverages. This makes the sector more resilient even in uncertain economic conditions (Osman et al., 2022). However, it is not entirely risk-free. Factors like raw material prices, currency fluctuations, and food-related government policies may impact company performance. Hence, accurate stock price forecasting is crucial for investors in this sector.

The Holt-Winter method, developed from simple exponential smoothing, is effective for short-term forecasting of time series data such as sales or demand. It considers three components—level, trend, and seasonality—giving more weight to recent data and producing low-error forecasts (Agustina et al., 2021). Previous studies have demonstrated its effectiveness. Ayunda et al. (2022) applied it to forecast commuter train passengers in Jabodetabek, showing high accuracy. Marpaung et al. (2023) compared Holt-Winter to Extreme Learning Machine for forecasting cargo volumes at Soekarno-Hatta Airport, with Holt-Winter yielding lower forecast errors.

Agustina et al. (2021) combined Holt-Winter stock predictions with portfolio optimization using Model Predictive Control (MPC), showing that predicted returns could guide investors effectively toward near-target capital growth. This supports Holt-Winter's reliability in forecasting stock prices for investment decisions.

Investment decisions inherently involve risk—the possibility of deviation between expected and actual returns. One key way to reduce risk is through portfolio diversification, where funds are spread across various assets (Chandra & Hapsari, 2014). This principle underlies Modern Portfolio Theory by Harry Markowitz (1952), which introduced the Mean-Variance Model to optimize portfolios by selecting asset combinations that offer maximum return for a given level of risk. It improves upon random diversification by utilizing all available information to construct optimal portfolios (Tandelilin, 2010).

Dewi and Candradewi (2020) applied the Markowitz model to IDX80 stocks and achieved an optimal portfolio with an expected return of 1.806% and portfolio risk of 0.705%. Similarly, Basuki et al. (2017) found that including a risk-free asset in the Mean-Variance model provided better returns than portfolios without it.

This study applies the Mean-Variance model to construct an optimal portfolio based on stock price predictions using the Holt-Winter method in Indonesia's food sector. Unlike prior studies, this research uses Holt-Winter to forecast stock prices, which are then used to calculate returns for portfolio optimization. The aim is to provide practical insights for investors managing portfolios in this strategic sector.

2. Literature Review

2.1. Time Series Forecasting

Time series data refers to a sequence of observations or data points arranged chronologically with consistent time intervals. This type of data is commonly used to analyze trends and seasonal variations in observations that occur over time. The process of time series data analysis involves examining historical data to identify trends, which are then used by the model to generate forecasts for a specific period. This is possible because time series data typically exhibits autocorrelation, meaning that future values are dependent on past values (Nurcahyo & Susanti, 2023).

Forecasting is generally carried out to reduce uncertainty regarding future events or to estimate the magnitude of a variable at a future point in time based on past data (Dewi, 2018). To address such uncertainty, forecasting methods are employed. These methods represent a quantitative approach to predicting future occurrences based on relevant historical data. In this context, time series forecasting involves sequential observation of a variable over a specific period (Ginatra et al., 2019).

2.2. Capital Market

The capital market is an essential component of the financial system, facilitating the trading of long-term financial assets such as stocks and bonds. It serves as a platform for companies to raise capital through public offerings and for investors to trade securities, thereby supporting economic growth and development. The capital market includes activities related to public offerings, securities trading, and institutions involved in these processes (Morenties et al., 2023).

According to the Capital Market book published by the Financial Services Authority (OJK), the capital market plays an important role in a country's economy due to its dual functions. First, from an economic perspective, the capital market provides a platform that connects two key interests: investors with excess funds and issuers in need of funding. Second, from a financial perspective, it offers fund owners the opportunity to earn returns, depending on the characteristics of the investments they choose.

2.3. Investment

Investment refers to an asset or item acquired with the expectation that it will generate income or appreciate in value over time. From an economic standpoint, investment involves the allocation of resources into assets expected to yield returns in the future (Akbari et al., 2019). Investment choices encompass various types, such as stocks, mutual funds, deposits, gold, real estate, and others. Each of these instruments has different levels of risk and return, requiring investors to align their choices with their individual preferences. Investment inherently involves balancing risks and expected returns, where safer instruments such as deposits are favored for their stability, while equities are appealing for their potential higher returns, albeit with greater risks (Sisili et al., 2018). Therefore, a proper analysis is essential before making any investment decisions.

In general, there are two types of assets used as investment vehicles. Real assets refer to tangible investments such as gold, real estate, and artwork. Meanwhile, financial assets involve investments in the financial sector, including deposits, stocks, bonds, and mutual funds (Adnyana, 2020).

2.4. Stock

According to idx.co.id, stocks are among the most popular financial market instruments. Companies often choose to issue stocks as a means of raising capital. For investors, stocks are a preferred investment option due to their potential for high returns. Stock represents ownership in a company or a limited liability corporation, held by individuals or business entities. By investing in stocks, shareholders are entitled to a portion of the company's income, have claims on its assets, and are eligible to participate in the General Meeting of Shareholders (GMS). Thus, stock serves as proof of ownership in a company, clearly outlining the rights and responsibilities of each shareholder (Munandar et al., 2021).

Stock return refers to the profit an investor earns from owning shares, either through dividends or capital gains. It is influenced by several factors, such as company performance, economic conditions, and market sentiment. Return can be calculated historically based on past stock prices, which can be used to forecast future performance. The return of stock *i* at time *t* can be calculated as follows:

$$R_{i,t} = \frac{P_{i,t} - P_{i(t-1)}}{P_{i(t-1)}}, \tag{1}$$

where $P_{i,t}$ and $P_{i(t-1)}$ represent the closing prices of stock *i* at time *t* and *t-1*, respectively. Over a series of periods, the expected return can be obtained by averaging these historical returns:

$$E(R_{i,t}) = \frac{\sum_{t=1}^{m} R_{i,t}}{m}, \tag{2}$$

where m is the number of observed periods.

Alongside returns, investors must consider the risk involved in stock investment, which reflects the uncertainty of receiving the expected returns. Risk can be systematic, stemming from macroeconomic factors, or unsystematic, related to specific companies. Generally, a higher expected return comes with higher associated risk. One way to measure this risk is by calculating the variance, which shows how much returns deviate from the expected value:

$$\sigma_i^2 = \sum_{t=1}^{m} \frac{(R_{i,t} - E(R_{i,t}))^2}{m-1}, \tag{3}$$

In addition, the relationship or co-movement between two stock returns can be measured through covariance:

$$\sigma_{i,j} = \sum_{t=1}^{m} \frac{\left((R_{it} - E(R_{it})) \cdot (R_{jt} - E(R_{jt}))\right)}{m}, \tag{4}$$

These risk measures are essential for analyzing portfolio performance and forming an optimal combination of assets.

2.5. Portfolio

A portfolio is a collection or combination of assets owned by an investor, commonly formed through diversification, which involves spreading investments across various companies or instruments. The main purpose of portfolio formation is to reduce the level of investment risk. By allocating capital into multiple alternatives, investors aim to avoid concentrating their funds in a single asset, which could lead to significant losses if that asset underperforms. Diversification allows investors to manage the uncertainty of market movements by balancing the potential losses of one investment with the potential gains of another (Halim, 2023).

According to Vimelia et al. (2024), Let $\boldsymbol{\mu}$ be the vector of expected returns. $\mathbf{w}$ be the vector of portfolio weights, and $\mathbf{e}$ be a unit vector, respectively defined as:

$$\boldsymbol{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{bmatrix}. \tag{5}$$

$$\mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}. \tag{6}$$

$$\mathbf{e} = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}. \tag{7}$$

The portfolio return R_p, assuming the weights sum to $1 (\sum_{i=1}^{N} w_i = 1)$, is given by:

$$R_p = \sum_{i=1}^{N} \sum_{t=1}^{M} w_i \, r_{i,t} = \mathbf{w}^{\mathbf{T}} \mathbf{r}, \tag{8}$$

After that, the expected portfolio return μ_p can be written as:

$$\mu_p = E[r_p] = \sum_{i=1}^{N} w_i E[r_{i,t}] = \mathbf{w}^{\mathbf{T}} \boldsymbol{\mu} = \boldsymbol{\mu}^T \mathbf{w}, \tag{9}$$

Let $\boldsymbol{\Sigma}$ be the covariance matrix between the stock returns and written as:

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1^2 & \sigma_{1,2} & \cdots & \sigma_{1,2} \\ \sigma_{1,2} & \sigma_1^2 & \cdots & \sigma_{1,2} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{1,2} & \sigma_{1,2} & \cdots & \sigma_1^2 \end{bmatrix}. \tag{10}$$

Then, the portfolio variance, which measures portfolio risk, is calculated as:

$$Var(r_p) = \sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{ij} = \mathbf{w}^{\mathbf{T}} \boldsymbol{\Sigma} \mathbf{w}. \tag{11}$$

3. Materials and Methods

3.1. Materials

The object of this research is the daily closing stock prices of companies in the food sector listed on the Indonesia Stock Exchange. The data was accessed through the website https://id.investing.com/ on January 17, 2025,The dataset spans from October 2022 to October 2024, a period chosen to capture historical price patterns, seasonal trends, and significant market changes. This extended timeframe is expected to provide a representative and relevant analysis of the food sector stock performance in Indonesia. The list of companies used in this research is as follows:

Table 1. List of Food Sector Stocks

Stock Code	Company Name
DMND	PT Diamond Food Indonesia Tbk.
ICBP	PT Indofood CBP Sukses Makmur Tbk.
HOKI	PT Buyung Poetra Sembada Tbk.
INDF	PT Indofood Sukses Makmur Tbk
ULTJ	PT Ultrajaya Milk Industry & Trading Company Tbk.

3.2. Methods

This study employs a quantitative approach based on secondary numerical data to draw conclusions. The data used consists of daily closing stock prices from the food sector in Indonesia, which are forecasted using the Holt-Winter method and subsequently used to construct an optimal portfolio using the Mean-Variance model. Data processing is carried out using Microsoft Excel and Google Colaboratory with Python programming language.

3.2.1. Holt-Winter Methods

Forecasting is often essential in decision-making processes, particularly for decisions with long-term consequences. One of the forecasting methods offered for time series analysis is the Holt-Winter method, a combination of Holt's method further developed by Winter. This method applies triple exponential smoothing and is suitable for non-stationary data that exhibit both trend and seasonal patterns (Utami and Atmojo, 2017).

The Holt-Winter method is based on three smoothing components: level, trend, and seasonal factors. It applies three smoothing constants in the prediction process: α (alpha), β (beta), and γ (gamma). According to Hendikawati (2015), to determine the optimal parameter values that yield the best forecasting results, trial and error is performed. The best model is obtained by selecting parameter values between 0 and 1 that minimize the prediction error. This involves iteration beginning from values such as 0.1 to 0.9.

According to Ayunda et al. (2022), the Holt-Winter method requires initial values for the smoothing process. To estimate the initial seasonal indices, complete data for one seasonal cycle is required. Thus, initial values for all attributes are initialized in period p.

The Holt-Winter method consists of three main components—level, trend, and seasonality—which are updated using exponential smoothing formulas. These components enable the model to capture trends and seasonal fluctuations in time series data. Before applying smoothing, initial values for each component must be estimated from the first full seasonal cycle:

- Initial Level

$$L_p = \frac{1}{p}\left(x_1 + x_2 + \cdots + x_p\right), \tag{12}$$

- Initial Trend

$$T_p = \frac{1}{p}\left(\frac{x_{p+1} - x_1}{p} + \frac{x_{p+2} - x_2}{p} + \cdots + \frac{x_{p+p} - x_p}{p}\right), \tag{13}$$

- Initial Seasonal

$$S_p = \frac{x_p}{L_p}, \tag{14}$$

For each time step t, the components are updated using the following formulas:

- Level (L_t) represents the baseline value or smoothed estimate at time t, adjusted by alpha (α):

$$L_t = \alpha\left(\frac{x_t}{(S_{t-1})}\right) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{15}$$

- Trend (T_t) indicates the rate of increase or decrease in the data, smoothed with beta (β):

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}, \tag{16}$$

- **S**easonality (S_t) captures repeating patterns over fixed intervals, smoothed using gamma (γ):

$$S_t = \gamma\left(\frac{x_t}{L_t}\right) + (1-\gamma)S_{t-p}, \tag{17}$$

Once all smoothing values have been determined, forecasting for k future periods can be done using the following formula:

$$F_{t+k} = (L_t + nT_t)S_{t-p+k} \tag{18}$$

After obtaining several Holt-Winter forecasting models, their error levels are measured. This study uses Mean Absolute Percentage Error (MAPE) to evaluate model accuracy. According to Hutasuhut et al. (2014), MAPE measures the average of absolute percentage errors between actual and forecasted data. MAPE values are expressed as a percentage and the formula is:

$$MAPE = \frac{\sum\left|\frac{x_t - F_{t+k}}{x_t}\right|}{n} \times 100\%, \tag{19}$$

3.2.2. Mean-Variance Model

The Mean-Variance Model is a portfolio optimization model developed by Harry Markowitz in 1952. This model aims to help investors select an optimal asset portfolio by considering the trade-off between the expected return (mean) and risk (variance). Using this model, investors can maximize the expected return for a given level of risk or minimize the risk for a given level of return.

In Basuki et al. (2016), referring to Panjer et al. (1998), Ruppert (2004), and Ryck et al. (2007), selecting an efficient portfolio can be achieved by maximizing the objective function as shown in equation (10):

$$\text{maximize } \{2\tau\mu_p - \sigma_p^2\},$$

$$\text{subject to the constraint: } \sum_{i=1}^{n} w_i = 1. \tag{20}$$

Equation (2.23) can be rewritten in vector notation as:

$$\max\{2\tau\boldsymbol{\mu}^T\mathbf{w} - \mathbf{w}^T\boldsymbol{\Sigma}\mathbf{w}\}, \tag{21}$$

$$s.t\ \mathbf{e}^T\mathbf{w} = 1,$$

The weight vector of the portfolio can be calculated using the following formula:

$$\mathbf{w} = \frac{1}{\mathbf{e}^T\boldsymbol{\Sigma}^{-1}\mathbf{e}}\boldsymbol{\Sigma}^{-1}\mathbf{e} + \tau\left(\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} - \frac{\mathbf{e}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}}{\mathbf{e}^T\boldsymbol{\Sigma}^{-1}\mathbf{e}}\boldsymbol{\Sigma}^{-1}\mathbf{e}\right); \tau \geq 0 \tag{22}$$

Once the efficient portfolios are obtained, the ratio between the expected return and variance of each portfolio is calculated to support decision-making using equation (23):

$$\text{Ratio} = \frac{\mu_p}{\sigma_p^2} \tag{23}$$

4. Results and Discussion

4.1. Stationarity Test

The stationarity test was conducted using two methods: the Augmented Dickey-Fuller (ADF) test and the Box-Cox transformation. The ADF test was used to determine whether the time series data is stationary in mean, with a significance level of 5%, while the Box-Cox transformation was applied to assess stationarity in variance. The stationarity test was carried out using Google Colaboratory with Python programming language, and the results are presented in Table 2.

Table 2. Stationarity Test Results of Stock Price Data

Stock Code	ADF Test				Box-Cox Transformation	
	$t_{statistic}$	$t_{0,05,480}$	*p-value*	Stationary in Mean	Rounded Value	Stationary in Variance
DMND	-2.0051	-2.8677	0.2843	No	1.7145	No
WAPO	-1.5607	-2.8677	0.5032	No	-1.7325	No
HOKI	-1.6698	-2.8677	0.4466	No	0.2016	No
INDF	-1.8445	-2.8677	0.3585	No	-2.2265	No
ULTJ	-1.8263	-2.8677	0.3674	No	1.8671	No

Table 2 shows that all stock price data from the five analyzed companies are not stationary, either in mean or variance. This is indicated by the ADF test results, where all t-statistics are greater than the critical value at the 5% significance level, and p-values are above 0.05, implying insufficient evidence to reject the null hypothesis that the data contains a unit root. Furthermore, the Box-Cox transformation did not stabilize the variance, as all companies remained non-stationary after the transformation. Therefore, the five stock data sets do not meet the assumption of stationarity, making forecasting approaches such as Holt-Winter, which are suitable for non-stationary data, relevant for use.

4.2. Stock Price Forecasting Using the Holt-Winter Method

4.2.1. Initial Smoothing Value Determination

The first step in the Holt-Winter method is to determine the initial smoothing values for level (L_p), trend (T_p), and seasonal components (S_p). These values are calculated based on actual data from the initial seasonal period and serve as the basis for subsequent smoothing calculations.

In this study, the seasonal period assumed for the Holt-Winter method is a monthly seasonal cycle with p = 30. This assumption is based on the characteristics of stock price data recorded on a daily basis, where one seasonal cycle is considered to cover approximately 30 trading days, or one month. This approach aims to capture monthly recurring seasonal patterns in stock price movements. The following is an example calculation for DMND stock data:

$$\boldsymbol{L_{30}} = \frac{\mathbf{1}}{\mathbf{30}}(\boldsymbol{x_1} + \boldsymbol{x_2} + \cdots + \boldsymbol{x_{30}}),$$

$$L_{30} = \frac{(810 + 815 + 815 + \cdots + 815)}{30},$$

$$L_{30} = \frac{24655}{30} = 821.8333.$$

Next, the initial smoothing trend value can be calculated using equation (3.2). Below is an example calculation for DMND stock data:

$$T_{30} = \frac{1}{30}\left(\frac{x_{13} - x_1}{30} + \frac{x_{14} - x_2}{30} + \cdots + \frac{x_{60} - x_{30}}{30}\right),$$

$$T_{30} = \frac{1}{30}\left(\frac{825 - 810}{30} + \frac{825 - 815}{30} + \cdots + \frac{825 - 815}{30}\right),$$

$$T_{30} = \frac{1}{30}(1.25 + 0.833 + \cdots + 0.833) = -0.5166.$$

Then, the initial smoothing for the seasonal pattern can be calculated using equation (3.3). The following is an example for DMND stock data:

$$S_1 = \frac{810}{821.8333} = 0.9856,$$

$$S_2 = \frac{815}{821.8333} = 0.9916,$$

$$S_3 = \frac{815}{821.8333} = 0.9916,$$

$$\vdots$$

$$S_{30} = \frac{815}{821.8333} = 0.9916.$$

4.2.2. Determination of Smoothing Parameter Estimates

After obtaining the initial values, the next step is to determine the optimal values for the smoothing parameters: alpha (α), beta (β), and gamma (γ). These three parameters are estimated with the objective of minimizing the forecast error using the Root Mean Squared Error (RMSE) approach.

The coefficients α, β, and γ range between 0 and 1 and are obtained through a combination method. The range for each value is limited to one decimal place. The Holt-Winter forecasting calculation is performed iteratively by combining all possible values of the three parameters. Each parameter value is tested from 0.1 to 0.9, resulting in the calculation of corresponding RMSE values. The parameter combination with the lowest RMSE is selected because it indicates the lowest prediction error, and is therefore considered to provide the most accurate forecast result among all combinations.

From the calculation of all combinations of α, β, and γ, a total of 729 model combinations were obtained. Through processing using Google Colaboratory with Python programming language, the optimal values of α, β, and γ for each stock were obtained and are presented in Table 3.

Table 3. Values of Alpha (α), Beta (β), and Gamma (γ) Parameters

Stock Code	Alpha (α)	Beta (β),	Gamma (γ).
DMND	0.90	0.10	0.30
ICBP	0.90	0.10	0.10
HOKI	0.90	0.10	0.30
INDF	0.70	0.10	0.10
ULTJ	0.70	0.10	0.10

4.2.3. Smoothing Component Calculation and Stock Price Forecasting

With the obtained parameters, the smoothing process is applied to the entire historical data set to obtain the smoothing level, trend, and seasonal components at each time point. The following is an example of the calculation for DMND stock data on November 28, 2022, which corresponds to the 31st observation out of 480:

Level Smoothing Calculation:

$$L_{31} = \alpha\left(\frac{x_{31}}{S_1}\right) + (1-\alpha)(L_{30} + T_{30})$$
$$L_{31} = 0.9\left(\frac{815}{0.9856}\right) + (1-0.9)(821.8333 + (-0.5166))$$
$$L_{31} = (0.9)(826.9064) + (0.1)(821.3167) = 826.3474$$

Trend Smoothing Calculation:

$$T_{31} = \beta(L_{31} - L_{31-1}) + (1-\beta)T_{31-1}$$
$$T_{31} = \beta(L_{31} - L_{30}) + (1-\beta)T_{30}$$
$$T_{31} = 0.1(826.3474 - 821.8333) + (1-0.1)(-0.5166)$$
$$T_{31} = 0.1(4.5141) + (0.9)(-0.5166) = -0.0135$$

Seasonal Smoothing Calculation:

After obtaining the smoothing components, the stock price forecasts for the next 30 periods are generated based on the 480 historical data points. The forecasts are made using a combination of the smoothing level, trend, and seasonal components as defined in the Holt-Winters method. Below is an example of the forecast for the next day (the 481st day) for DMND stock:

$$F_{480+1} = (L_{480} + 1T_{480})S_{480-30+1}$$
$$F_{481} = (L_{480} + 1T_{480})451$$
$$F_{481} = \big(801.5384 + 1(0.7852)\big)0.9951$$
$$\mathrm{F}_{481} = 795.6524$$

The final step is to evaluate the forecasting accuracy using the Mean Absolute Percentage Error (MAPE). MAPE shows the relative prediction error compared to the actual data, and a smaller MAPE value indicates higher forecasting accuracy. MAPE calculations, performed using Google Colaboratory, are presented in Table 4.

Table 4. MAPE Calculation Result

Stock Code	MAPE
DMND	2.27%
ICBP	5.56%
HOKI	4.40%
INDF	6.22%
ULTJ	4.21%

Based on the 30-day-ahead forecasts of the five food sector stocks using the Holt-Winters method, all MAPE values are below 10%: 2.27% for DMND, 5.56% for ICBP, 4.40% for HOKI, 6.22% for INDF, and 4.21% for ULTJ.

These low MAPE values indicate that the Holt-Winters method provides high forecasting accuracy. A MAPE value below 10% is categorized as very good in forecasting model performance evaluation. Thus, the Holt-Winters approach applied in this study can be considered effective and appropriate for short-term stock price forecasting.

4.3. Determination of the Optimal Portfolio

After obtaining the 30-period-ahead forecast results for each stock, the actual data is combined with the forecasted data, and then the stock return values are calculated. A manual example of daily stock return calculation is presented below using daily closing prices of DMND stock:

$$R_{12} = \frac{815 - 810}{815} = 0.00617.$$

The next step is to construct the **μ** vector, **e** vector, and **Σ** matrix for portfolio optimization. The **μ** vector contains the expected daily return for each of the five stocks, The **e** vector is a unit vector with all entries equal to 1, ensuring that the total portfolio weight equals one, The **Σ** matrix represents the covariances between stock returns. Diagonal values show each stock's variance, while off-diagonal values represent covariances between stocks:

$$\boldsymbol{\mu} = \begin{bmatrix} 0.00007266 \\ 0.00031726 \\ 0.00045851 \\ 0.00065749 \\ 0.00072928 \end{bmatrix}.$$

$$\mathbf{e} = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}.$$

$$\boldsymbol{\Sigma} = \begin{bmatrix} 0.00013102 & 0.00001417 & 0.00000630 & 0.00000485 & -0.000006069 \\ 0.00001417 & 0.00111603 & 0.00001503 & 0.00000385 & -0.000014450 \\ 0.00000630 & 0.00001503 & 0.00014789 & 0.00001479 & 0.000077441 \\ 0.00000485 & 0.00000385 & 0.00001479 & 0.00030506 & 0.000044469 \\ -0.00000606 & -0.00001445 & 0.00007744 & 0.00004446 & 0.000296440 \end{bmatrix}.$$

Following the construction of the vectors and covariance matrix, the next step is to determine the optimal portfolio by calculating the capital allocation weights for each stock. Initially, the weights are computed using a risk aversion value of τ = 0. However, this calculation still results in some negative weights, indicating short selling. A portfolio is considered optimal when all weights are positive and their sum equals one, meaning the capital is fully and proportionally allocated without any short positions. To achieve this, a new risk aversion value, denoted as τ_B, is determined by gradually increasing the previous risk aversion value τ_L with a small increment Δτ until the allocation conditions are satisfied.

Once the optimal τ is found, the expected return, return variance, and portfolio ratio are calculated to assess the performance of the portfolio. The results of these calculations, including the final weights, expected return, variance, and performance ratio, are presented in Table 5.

Table 5. Optimal Portfolio Result

τ	DMND	HOKI	INDF	ULTJ	ICBP	$\mathbf{w}^T\boldsymbol{e}$	μ_p	σ_p^2	ratio
0.01	0.3918	0.0424	0.2941	0.1582	0.1134	1	0.000364	0.000057	6.4022
0.02	0.3707	0.0425	0.2959	0.1670	0.1240	1	0.000376	0.000057	6.5825
0.03	0.3495	0.0425	0.2977	0.1757	0.1345	1	0.000389	0.000058	6.7306
0.04	0.3284	0.0426	0.2995	0.1845	0.1451	1	0.000402	0.000059	6.8455
0.05	0.3072	0.0427	0.3012	0.1933	0.1556	1	0.000415	0.000060	6.9274
0.06	0.2861	0.0427	0.3030	0.2020	0.1662	1	0.000427	0.000061	6.9770
0.07	0.2649	0.0428	0.3048	0.2108	0.1768	1	0.000440	0.000063	6.9958
0.08	0.2438	0.0428	0.3066	0.2195	0.1873	1	0.000453	0.000065	6.9861
0.09	0.2226	0.0429	0.3084	0.2283	0.1979	1	0.000466	0.000067	6.9504
0.10	0.2015	0.0429	0.3101	0.2371	0.2084	1	0.000478	0.000069	6.8914

0.11	0.1803	0.0430	0.3119	0.2458	0.2190	1	0.000491	0.000072	6.8123
0.12	0.1591	0.0430	0.3137	0.2546	0.2296	1	0.000504	0.000075	6.7159
0.13	0.1380	0.0431	0.3155	0.2634	0.2401	1	0.000517	0.000078	6.6052
0.14	0.1168	0.0431	0.3172	0.2721	0.2507	1	0.000529	0.000082	6.4828
0.15	0.0957	0.0432	0.3190	0.2809	0.2612	1	0.000542	0.000085	6.3512
0.16	0.0745	0.0432	0.3208	0.2897	0.2718	1	0.000555	0.000089	6.2128
0.17	0.0534	0.0433	0.3226	0.2984	0.2824	1	0.000568	0.000094	6.0696
0.18	0.0322	0.0433	0.3243	0.3072	0.2929	1	0.000580	0.000098	5.9232
0.19	0.0111	0.0434	0.3261	0.3160	0.3035	1	0.000593	0.000103	5.7752
0.20	-0.010	0.0434	0.3279	0.3247	0.3140	1	0.000606	0.000108	5.6268

Based on Table 4.8, efficient portfolios are obtained within the risk tolerance range of $0 \le \tau \le 0.19$. For τ values greater than 0.19, some capital allocation weights become negative, which disqualifies those portfolios from being considered efficient, even though the total weights still sum to one. The highest portfolio ratio is achieved at $\tau = 0.07$, with a value of 6.9958. Therefore, the portfolio corresponding to $\tau = 0.07$ is selected as the optimal portfolio, as it provides the best balance between expected return and associated risk. The percentage composition of the optimal portfolio allocation for the five stocks is as follows: 4% for HOKI, 18% for ICBP, 21% for ULTJ, 26% for DMND, and 30% for INDF. This optimal portfolio yields an expected return of 0.0441% and a portfolio variance of 0.0063%.

5. Conclussion

Based on the results of this study, the Holt-Winter forecasting method has proven effective in predicting stock prices for five companies in the food sector. All the stocks analyzed showed Mean Absolute Percentage Error (MAPE) values below 10%, which indicates a high level of accuracy in the prediction results. The MAPE values were 2.27% for DMND, 5.56% for ICBP, 4.40% for HOKI, 6.11% for INDF, and 4.21% for ULTJ. This suggests that the Holt-Winter method is highly reliable for short-term stock price forecasting, particularly for stocks with seasonal patterns.

Furthermore, based on the forecasted prices, an optimal investment portfolio was formed using the Mean-Variance model. The resulting portfolio consists of allocation weights of 4% for HOKI, 18% for ICBP, 21% for ULTJ, 26% for DMND, and 30% for INDF. This composition yields an expected return of 0.0441% and a portfolio variance of 0.0063%. These results indicate a balanced and efficient asset allocation that offers a good trade-off between return and risk, especially for investors with a moderate risk tolerance.

To enhance future research, it is recommended to explore other forecasting methods such as ARIMA or machine learning-based approaches to compare their performance with the Holt-Winter method in predicting stock prices. In addition, the portfolio optimization process could be further refined by integrating other models that account for market volatility and investor preferences, so that the resulting portfolio is more robust under different market conditions.

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