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LQ45 Stock Portfolio Optimization by considering Return Predictions using the Holt Winter Method

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Abstract

A portfolio represents a selection of assets owned by individuals or groups with the goal of generating profit. Stocks are among the various forms of investments available. Investors typically consider two key factors: expected returns and associated risks. Portfolio optimization endeavors to maximize returns while minimizing risks. With the progression of time, portfolio optimization strategies increasingly incorporate return predictions using machine learning techniques. In this study, the Holt-Winter method is employed to forecast stock prices and returns, known for its accuracy in estimating seasonal time series data. Previous research primarily utilized the Mean-Variance method for portfolio optimization, but the outcomes were deemed unsatisfactory. Therefore, this study adopts a novel approach by integrating the Mean-Variance model with forecasting. Performance testing of the optimal portfolio emphasizes sensitivity, aiming for substantial average returns, minimal standard deviation, and a high Sharpe ratio. Comparative analysis with the LQ45 index portfolio reveals that the sensitivity-driven portfolio exhibits superior performance, yielding higher values in terms of average returns, standard deviation, and Sharpe ratio.

Keywords: Portfolio Optimization, Stocks, Return, LQ45, Holt-Winter, Mean-Variance.

Abstrak

Portofolio mewakili pilihan aset yang dimiliki oleh individu atau kelompok dengan tujuan menghasilkan keuntungan. Saham adalah salah satu dari berbagai bentuk investasi yang tersedia. Investor biasanya mempertimbangkan dua faktor utama: imbal hasil yang diharapkan dan risiko terkait. Optimalisasi portofolio berusaha untuk memaksimalkan keuntungan sambil meminimalkan risiko. Seiring perkembangan waktu, strategi optimasi portofolio semakin banyak menggabungkan prediksi return menggunakan teknik machine learning. Dalam penelitian ini, metode Holt-Winter digunakan untuk meramalkan harga dan return saham, yang dikenal dengan keakuratannya dalam memperkirakan data deret waktu musiman. Penelitian sebelumnya terutama menggunakan metode Mean-Variance untuk optimasi portofolio, tetapi hasilnya dianggap tidak memuaskan. Oleh karena itu, penelitian ini mengadopsi pendekatan baru dengan mengintegrasikan model Mean-Variance dengan peramalan. Pengujian kinerja portofolio optimal menekankan pada sensitivitas, yang bertujuan untuk menghasilkan rata-rata return yang besar, standar deviasi yang minimal, dan rasio Sharpe yang tinggi. Analisis komparatif dengan portofolio indeks LQ45 menunjukkan bahwa portofolio berbasis sensitivitas menunjukkan kinerja yang lebih baik, menghasilkan nilai yang lebih tinggi dalam hal rata-rata return, standar deviasi, dan rasio Sharpe.

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Kata Kunci: Optimasi Portofolio, Saham, Return, LQ45, Holt-Winter, Mean-Variance

I. INTRODUCTION

A. *Background*

The investment that many investors are interested in is shares because the frequency of share trading is higher compared to the frequency of other investments in the capital market. Shares are securities that are part of company ownership. Investors in investing, apart from taking into account the return value, also need to consider the level of risk as a basis for forming investment decisions. The greater the difference, the greater the investment risk [1]. Investors in the stock market usually determine the future return from their investment shares and find out the optimal weight of each share to build a portfolio [2].

Portfolio optimization is the distribution of wealth among many assets, where the two parameters expected return and risk are very important. Portfolio optimization is expected to generate profits from investments, by obtaining large returns but with smaller risks. To minimize risk by diversifying or spreading investments by forming a portfolio into several shares. In research conducted for the first time by Markowitz (1959), the spread of investment can be done in several ways, namely by using the Mean Variance model approach [3].

The Mean-Variance approach proposed by Markowitz is one of the best models for solving portfolio optimization problems [4]. In the Mean Variance approach, investment risk is measured through the expected value and return variance from historical data. Mean-Variance only provides basic ideas for selecting an optimal portfolio. This Mean-Variance model aims to make a trade-off that maximizes returns and minimizes risk [5]. However, this Mean-Variance model has many limitations in practical applications, such as limiting assumptions and computational complexity of large-scale assets [6]. Over time, advancements allow for the creation of portfolio optimization techniques that incorporate return predictions through machine learning methodologies, such as Holt-Winter, yielding favorable outcomes.

Holt-Winter is used to overcome trend patterns and seasonal patterns from time series data, so that this method can be used to predict non-stationary data in general [7].

For this reason, the author is interested in researching the performance and advancing portfolio optimization models by considering return predictions using the Holt-Winter method. Apart from that, this research uses LQ45 shares which consist of 42 shares. This research focuses on data from 2013 to 2020, for predictions using the last year.

B. *Topics and Limitations*

In this research, the topics analyzed are how to apply return predictions using the Holt-Winter method, and how to form a portfolio that considers return predictions using the Holt-Winter method. The problem limits in this research are 42 LQ45 shares obtained from finance.yahoo.com, the data used is weekly stock closing prices (close) data over a period of 7 years (2013-2020).

C. *Objective*

The aim of this research is to apply the Holt-Winter method to predict stock returns, and obtain a portfolio that considers return predictions using Holt-Winter and measures portfolio performance compared to the LQ45 index.

D. Writing Organization

The next chapter, namely chapter 2, explains the literature studies that support the research. Chapter 3 explains the design of the system built in this research. Chapter 4 contains results and analysis of results. Chapter 5 provides conclusions about the entire research process carried out and suggestions for further research.

II. RELATED STUDIES

A. *Share*

Shares are one of the securities traded on the capital market. Shares are also one of the most popular products on the financial market and are used as an alternative investment because they are more profitable than other investments such as mutual funds and bonds. However, shares have quite high risks. The higher the investment risk, the higher the return. On the other hand, low-risk investments have lower returns [8].

B. Return

Return is the level of profit enjoyed by an investor and can also be interpreted as the result of an investment. To find the return value, use the following equation.

$$R_i = \frac{P_i - P_{(i-1)}}{P_{(i-1)}} \quad (1)$$

WhereRi namely the return at time i, Pi namely the share price for period i, and P(i-1) namely the share price for period i − i.

C. Excepted Returns

Excepted Return is a weighted average of several past/historical returns. Excepted Return can be calculated with the following equation [9]:

$$\mathrm{E}(R_i) = \frac{\sum_{i=1}^{n} R_{ij}}{n} \quad (2)$$

With E(Ri) is the expected stock return, Rij The return from securities in the j and n months is the number of individual returns.

D. Stock Portfolio

A stock portfolio is a combination of financial assets in the form of shares. In carrying out portfolio calculations, investors hope to get appropriate portfolio returns with a fairly high level of accuracy. The aim of forming a stock portfolio is to get the maximum possible results to increase wealth with the smallest risk [10].

E. Portfolio Returns

Portfolio return is a linear combination of several assets forming a portfolio. So the portfolio can be written as follows:

$$R_p = W_1 R_1 + W_2 R_2 + \ldots + W_n R_n = \sum_{i=1}^{n} W_i R_i \quad (3)$$

Where:

Rp =*portfolio returns*

Wi =*the weight of the funds formed on share i, where = 1 and ≥* $0\sum_{i=1}^{i} W_i W_i$

Ri = share return I

n = many shares in the portfolio

F. Sharpe Ratio

To avoid portfolio risk, a larger Sharpe Ratio is chosen. The formula used is the following equation:

$$Sr = \frac{\overline{r_i}}{\sigma_i} \tag{4}$$

Where:

ri = Average portfolio return

oi = *STD portfolio returns*

G. Holt-Winter

Holt - Winter was first developed by Professor Charlest C. The function of Holt is to predict production trends, after that Professor Peter R refined the model by adding seasonality, namely Winter, so that this model can handle time series that generally experience emerging trend patterns and seasonal patterns. simultaneously in time series data. Holt-winter itself has 3 elements, namely real, trend and seasonal data with three weightings in predicting, namely (alpha), (beta), and (gamma). The initial stage in using the Holt-Winter method is to determine the initial value, the following is the equation for determining the initial value [11]:

i. Smoothing Levels

$$L_c = \frac{1}{C}(Y_1 + Y_2 + \dots + Y_c) \tag{5}$$

ii. Smoothing Trends

$$T_c = \frac{1}{K}\left(\frac{Y_{c+1} - Y_1}{C} + \frac{Y_{c+2} - Y_1}{C} + \dots + \frac{Y_{c+k} - Y_k}{C}\right) \tag{6}$$

a) Holt-Winter Addictive

To plot real/original data showing constant (relatively stable) seasonal fluctuations, it is carried out using an additive model.

For the additive model equation, namely:

i. Exponential Smoothing:

$$L_c = \alpha(X_t - S_{t-S}) + (1 - \alpha)(L_{t-1} + T_{t-1}) \tag{7}$$

ii. Trend Pattern Smoothing:

$$T_c = \beta(L_t - L_{t-1}) + (1 - \beta)(T_{t-1}) \tag{8}$$

iii. Seasonal Smoothing:

$$S_t = \gamma(X_t - L_t) + (1 - \gamma)(S_{t-S}) \tag{9}$$

iv. Forecasting for the next period:

$$X_{t+p} = L_t + pT_t + S_{t-S+p} \tag{10}$$

With :

St =*seasonal smoothing value in period t*

y =*smoothing constant for seasonal patterns 0 < y < 1*

s =*seasonal period*

b) Holt-Winter Multiplicative

A multiplicative model is carried out if the original data plot contains varying seasonal fluctuations. For the equations used by the multiplicative model, namely:

For the additive model equation, namely:

iii. Exponential Smoothing:

$$L_c = \alpha\left(\frac{X_t}{S_{t-S}}\right) + (1 - \alpha)(L_{t-1} + T_{t-1}) \tag{11}$$

iv. Trend Pattern Smoothing:

$$T_c = \beta(L_t - L_{t-1}) + (1 - \beta)(T_{t-1}) \tag{12}$$

v. Seasonal Smoothing:

$$S_t = \gamma\left(\frac{X_t}{L_t}\right) + (1 - \gamma)(S_{t-S}) \tag{13}$$

vi. Forecasting for the next period:

$$X_{t+p} = (L_t + pT_t) + S_{t-S+p} \tag{14}$$

H. Portfolio Optimization Model that considers Return predictions

Markowitz (1959) explains a solution to resolve the trade-off between maximizing the expected value of return and minimizing risk. In the paper "Portfolio optimization with return prediction using deep learning and machine learning" namely combining the results of return prediction in advancing the Mean - Variance model to build a Mean - Variance with Forecasting (MVF) model.

For Mean - Variance with Forecasting (MVF) it has 3 objective functions, namely objective 1 minimizing the risk value, objective 2 maximizing the predicted value of return and objective 3 maximizing the value of the difference between predicted returns and actual returns (epsilon). The value of the 3 objects is searched for the x value using the Sequential Least Squares Programming (SLSQP) solver. After that, the x value of each objectivity is obtained. Judging from the results obtained, one of the x values of these 3 objectives will be dominant/too large, so portfolio optimization is carried out by considering return predictions with weighting/gamma. The following is the model equation for Mean – Variance with Forecasting [6]:

$$min\, \gamma_1 \sum_{i,j=1}^{n} x_i x_j \sigma_{ij} - \gamma_2 \sum_{i=1}^{n} x_i \hat{r}_i - \gamma_3 \sum_{i=1}^{n} x_i \bar{\varepsilon}_i \quad (15)$$

Who fulfills:

$$\sum_{i=1}^{n} x_i = 1$$
$$0 \leq xi \leq 1 \; i = 1,2,\ldots,n \quad (16)$$

Where:

xi =*the proportion of asset i in the portfolio*

xj =*proportion of assets j in the portfolio*

n =*number of assets in the portfolio*

oij =*covariance of assets i and j*

ri =*return prediction*

Ei =*average prediction of asset i, over the sample period*

Y1 =*objectivity 1 (risk)*

Y2 =*objectivity 2 (prediction return)*

Y3 =*objectivity 3 (epsilon)*

III. BUILT SYSTEM

A. Data

The data used in this research is the LQ45 Stock Index. Data source obtained from finance.yahoo.com. In this research, weekly stock index data was used from the LQ45 index from January 2013 to January 2020.

B. System planning

The overall design of a system that is built is in the form of a flowchart, which is a system design workflow to help the system work from start to finish.

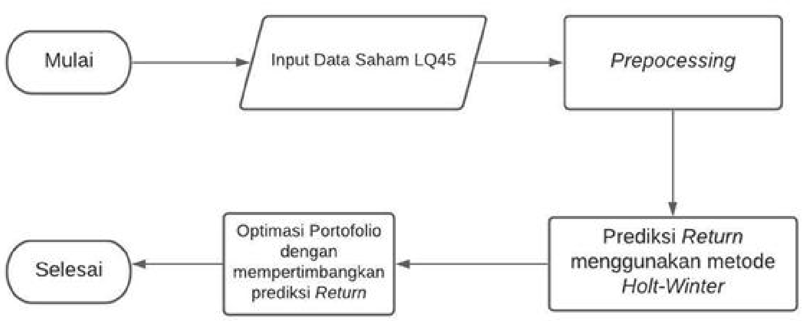

Fig. 1. Flowchart/Flow Diagram

a) Data Input

The first step in this process is to input weekly stock price index data/weekly LQ45 index for the period January 2013-January 2020.

b) Data Preprocessing

The data preprocessing stage is a process for preparing raw data before the data is subjected to other processes. In this preprocessing step, data cleaning is carried out, namely eliminating incorrect data values and correcting inconsistent data. And normalization, normalization here is scaling to be described as a normal distribution.

c) Return Prediction using Holt-Winter

In the stage of predicting returns using Holt-Winter, this is done using additive and seasonal trends or seasonal multiplicative.

- Determine the initial value of the smoothing level, the initial value of the trend, and the initial value of the seasonal pattern (additive and multiplicative).
- After determining the initial value, the next process is determining the estimated parameters of alpha(), beta() and gamma().αβγ
- Then forecasting using Holt-Winter Additive can be done using equation (8) and for predicting returns using Holt-Winter Multiplicative using equation (12).

d) Portfolio optimization by considering return predictions.

In this final stage, portfolio optimization is carried out by considering the LQ45 return using the Mean-Variance with Forecasting (MVF) method. As in equations 16 and 17. To find the x value, the x value is obtained using the Sequential Least Squares Programming (SLSQP) solver.

IV. EVALUATION

A. Testing Scenarios

a) The data held is a time span of 7 years (January 2013 - January 2020), 6 years (January 2013-December 2018) as train data and 1 year for test data (January 2019 - January 2020).

b) Predict stock prices so that you can get the portfolio return value per week from (January 2019 to January 2020) using the Holt-Winter method.

c) Find the x value or portfolio weight using the Mean-Variance with Forecasting method

d) Analyzing sensitivity by varying the weight value of each objectivity in the Mean-Variance with Forecasting equation, namely risk objectivity, return objectivity and epsilon objectivity, based on the highest average return value, the smallest standard deviation and the portfolio value. value).

e) Comparing the results of portfolio value analysis, the LQ45 index, the largest average return, the smallest standard deviation and the largest Sharpe ratio for each gamma.

B. *Test result*

a) Predicting LQ45 stock prices with Holt-Winter.

(a) ICBP.JK shares

(b) BBTN.JK shares

(c) TLKM.JK shares

Fig. 2. The blue graph is training data from January 2013 - December 2018. And the red graph is the testing data used for testing data is data from January 2019-January 2020. The green graph is the result of stock price predictions using the method Holt–Winter.

b) Results of the average return, standard deviation value and Sharpe ratio of each gamma.

TABLE I
AVERAGE RETURN, STD & SHARPE RATIO FOR EACH GAMMA

Y=(, ,) y1y2y3	**Average Return**	**Std**	**Sharpe Ratio**
Y1 = (, ,)1 11	0.005518	0.053381	0.10337
Y2 = (1 , 0.104338, 1)	0.005518	0.053381	0.10337
Y3 = (1 , 0.010886, 1)	0.005518	0.053381	0.10337
Y4 = (1 , 1 , 0.195275)	0.00463	0.030546	0.151586
Y5 = (1 , 1 , 0.038132)	**0.006297**	**0.023254**	**0.151586**
Y6 = (1 , 0.104338 , 0.195275)	0.00463	0.030546	0.151586

Y7 = (1 , 0.104338 , 0.038132)	0.006297	0.023254	0.151586
Y8 = (1 , 0.010886, 0.195275)	0.00463	0.030546	0.151586
Y9 = (1 , 0.010886, 0.038132)	0.006297	0.023254	0.270796

From the MVF results, the 3 objectivities have their own values and one of these objects can have the greatest value. And after optimization, the portfolio value with objectivity 1 (risk objectivity) was 0.005354, objectivity 2 (return objectivity) was 0.05131 and objectivity 3 (epsilon objectivity) was 0.0274. It can be seen that the dominant of the 3 objects is the second objectivity, namely return. With this, an investment strategy is carried out, namely weighting using gamma as in the table above. The aim of carrying out this investment strategy is to weight it using gamma, namely so that the portfolio value is comparable, namely by scaling it.

The meaning of each gamma is as follows:

1. $\overrightarrow{\gamma_1}$ not given any weighting and objective 2 (return) dominates.
2. $\overrightarrow{\gamma_2}$ make objective 1 and objective 2 comparable, and what dominates here is objective 3.
3. $\overrightarrow{\gamma_3}$make the value of objective 2 smaller or ignored and dominated by objective 3.
4. $\overrightarrow{\gamma_4}$ make the value of objective 2 smaller or ignored and dominated by objective 3.
5. $\overrightarrow{\gamma_5}$ make the value of objective 2 smaller or ignored and dominated by objective 3.
6. $\overrightarrow{\gamma_6}$ make the value of objective 2 smaller or ignored and dominated by objective 3.
7. $\overrightarrow{\gamma_7}$ makes objective 1 and objective 2 comparable and for objective 3 it is ignored because it is small.
8. $\overrightarrow{\gamma_8}$ makes objective 1 and objective 2 comparable and for objective 3 it is ignored because it is small.
9. And to$\overrightarrow{\gamma_9}$ make objective 2 and objective 3 smaller and dominated by objective

It can be seen from the table above that$\overrightarrow{\gamma_5}$ And$\overrightarrow{\gamma_7}$ have the same value, after proving it and looking at the number after the comma as a whole, the chosen one is$\overrightarrow{\gamma_5}$ because it has the highest average return, the smallest standard deviation and the largest Sharpe ratio. Then after that we look for the portfolio value.$\overrightarrow{\gamma_5}$

TABLE II
PORTFOLIO RESULTS

	Average Return	**Std**	**Sharpe Ratio**
LQ45	0.000535	0.000535	0.006297
Portfolio Value	0.005518	0.05338	0.10337
Y5	0.006297	0.02325	0.0270796

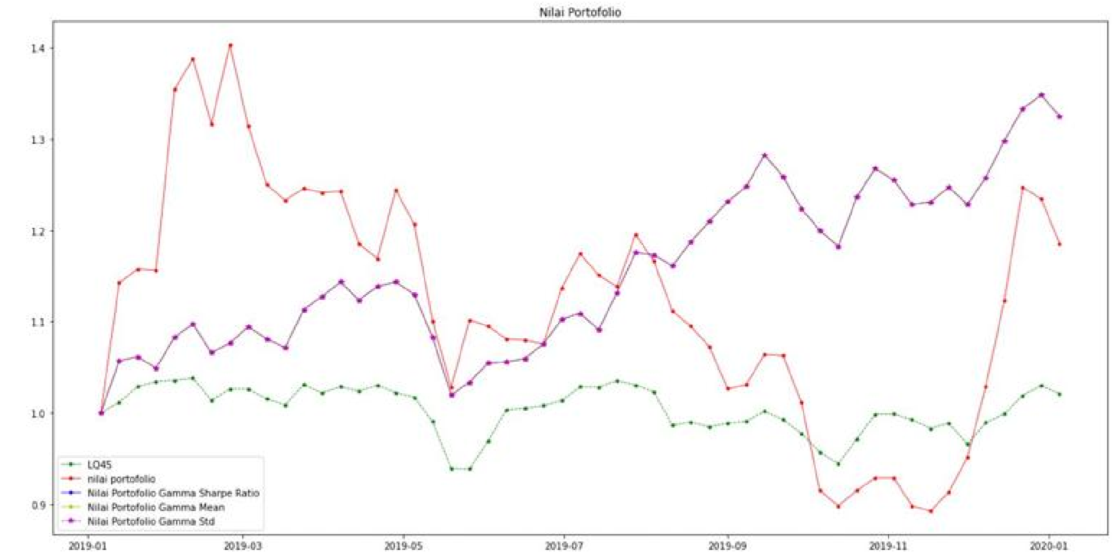

Fig. 3. Portfolio Value Graph, LQ45 Index Portfolio Value & Portfolio Value with Gamma

It can be seen from the table and graph plot above that the portfolio value that uses sensitivity compared to the LQ45 index has a higher value.

V. CONCLUSION

The analysis suggests that achieving optimal portfolio performance entails maximizing sensitivity, characterized by a substantial average return, minimal standard deviation, and a high Sharpe ratio. In contrast to the performance of the LQ45 index portfolio, which is gauged by its highest average return, lowest standard deviation, and highest Sharpe ratio, portfolios emphasizing sensitivity demonstrate superior performance with higher values.

For further research, it is recommended to use other comparisons and this can be done using machine learning time series methods other than the Holt-Winter method.

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