

Optimization of Stock Portfolios Using Goal Programming Based on the Kalman-Filter Method

Fauziyah¹, Evita Purnaningrum^{2*}

¹Department of Accounting, Universitas PGRI Adi Buana Surabaya, Surabaya, Indonesia

²Department of Management, Universitas PGRI Adi Buana Surabaya, Surabaya, Indonesia

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Abstrak. Pengembangan investasi saham jangka panjang dilakukan dengan cara optimasi portofolio. Pemilihan saham untuk portofolio bukan saja berdasarkan harga saham yang bernilai tinggi tetapi juga memperhatikan fluktuasinya. Estimasi fluktuasi harga saham di masa yang akan datang secara tidak langsung memberikan dampak bagi pembentukan portofolio yang akan datang. Penelitian ini telah mengimplementasikan metode Kalman filter untuk memperoleh hasil estimasi terbaik dari berbagai harga saham dengan tingkat akurasi yang tinggi. Hasil tersebut selanjutnya digunakan untuk membentuk portofolio saham dengan basis Goal Programming. Penelitian ini telah membandingkan hasil optimasi dengan nilai riil harga saham. Hasil yang didapat, Goal Programming berbasis Kalman filter lebih efektif untuk memprediksi portofolio masa depan dibandingkan dengan metode Goal Programming dengan selisih return sebesar Rp 178.039.848. Hal ini menunjukkan bahwa optimasi dengan Pemrograman Tujuan berbasis Kalman Filter dapat digunakan sebagai alat untuk menentukan portofolio saham yang akan datang.

Abstract. Long-term stock investment development is carried out by means of portfolio optimization. Selection of stocks for portfolios is based not only on high-value stock prices but also on their fluctuations. Estimation of future stock price fluctuations has an indirect impact on future portfolio formation. This research has implemented the Kalman filter method to obtain the best estimation results from various stock prices with high accuracy. The results are then used to form a stock portfolio based on Goal Programming. This study has compared the optimization results with the real value of stock prices. The results obtained, Kalman filter-based Goal Programming is more effective for predicting future portfolios compared to the Goal Programming method with a return difference of Rp. 178,039,848. This suggests that optimization with the Kalman Filter-based Objective Programming can be used as a tool to determine future stock portfolios.

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CONTACT:

Evita Purnaningrum,  purnaningrum@unipasby.ac.id  Department of Management, Universitas PGRI Adi Buana Surabaya, Surabaya, Jawa Timur 60234, Indonesia

1. Introduction

Optimization of the stock portfolio is needed to maximize returns and reduce risk in investing. A collection of various stock prices is used to form a portfolio, in other words, the movement of stock values affects optimization. However, future portfolio formation strategies need to be planned and measured for effectiveness and efficiency to minimize the risk level in the future. Because stock prices fluctuate, stochastic techniques are needed to estimate the stock price. Stock forecasting is very important in the decision-making process, especially in the financial sector. Forecasting can be used to monitor future stock price movements. Therefore, Forecasting will provide a better basis for planning and decision making.

In addition, mathematical models have been applied to solve challenging problems in certain fields. The application of mathematical models needs to be supported by effective and efficient computations. The combination of mathematical and statistical theories with modern economic theory describes the solution to problems that exist in the field of economics. There have been many problem topics raised in capital market research with discussions in various scientific fields such as statistical journals, applied mathematics economics, estimation, banking, etc. Several studies that take the topic of the stock market are ranking of cement companies on the Tehran stock exchange [1], Value-at-Risk prediction on Karachi stocks using the Bayesian method [2], examining exchange rate responses to changes in stock prices in OECD countries [3], comparing the performance of OLS bias correction estimator with NASDAQ prediction [4], combining the Vector Auto-Regressive method and Wavelet transform (MODWT) to determine the effect of global stock market spillover on African stocks [5], analyzing the condition of the Russian stock market after the 1998 crisis [6], developing methodology to predict daily stocks by combining the three prediction models tested in Istanbul [7], evaluating two models to estimate the Value at Risk of the return of SROCOI shares in Iran [8], Optimization of portfolios using a polynomial objective programming model [9], the impact of a pandemic for stock prices [10] and estimation stock prices in Indonesia after the pandemic [11].

This research focused on portfolio optimization on the JII stock index (Jakarta Islamic Index). Portfolio optimization was the process by which the optimal portfolio (distribution of assets) was selected according to some objective measure, with the caveat that the associated risks must also be minimized [12]. Portfolio optimization was concerned with maximizing the expected return from a series of investments and minimizing the associated risks, such as stock market volatility [13]. Instead, one must consider how assets affect the risk and return of the entire portfolio. Based on this portfolio optimization theory, it was possible to formulate a multi-objective problem that simultaneously maximizes returns and minimizes risk [14]. Although various mathematical models have been developed to optimize portfolios such as [15]–[18], there have been studies that use the development of goal programming, one of which is [19]–[23].

In this paper, we have applied the Kalman filter method based on GBM (General Brownian Motion) to predict future stock values [24], the estimation results have been applied as the basis for forming a stock portfolio using the goal programming method [25]. In other words, this research has presented the development of a new model of the goal programming method, namely the combination of the Kalman filter and goal programming.

As an additional note, this portfolio has been designed based on sharia principles, namely stocks that are included in the JII (Jakarta Islamic Index), so that investors can get the maximum portfolio without worrying about being mixed with usury and providing solutions for estimating optimal future ownership portfolios. The remainder of this paper is organized as follows: Section 2 discusses the formulation of methods for obtaining optimal portfolio objectives. Section 3 reports the results of the proposed model. Finally, the conclusions are summarized in Section 4.

2. Methods

This research uses mathematical methods to predict sharia future stock portfolio values. The value of the portfolio is compared with portfolio values that have been optimized by the goal programming method. Figure 1 shows the flow of research design:



Figure 1. Research Design

The data used in this research is the closing price of monthly JII stocks from January 2012-May 2017. The data consists of 30 stocks that are included in JII stocks in the period of December 2016-May 2017. There are three new shares included in the JII calculation, namely Adhi Karya (ADHI), Aneka Tambang (ANTM) and Hanson International (MYRX).

Table 1. Sharia Stocks in Jakarta Islamic Index period of December 2016-May 2017 [26]

No.	The Shares Name	Code	No.	The Shares Name	Code
1	Astra Agro Lestari Tbk.	AALI	16	Mitra Keluarga Karyasehat Tbk.	MIKA
2	Adhi Karya (Persero) Tbk.	ADHI	17	Hanson International Tbk.	MYRX
3	Adaro Energy Tbk.	ADRO	18	Perusahaan Gas Negara (Persero) Tbk	PGAS
4	AKR Corporindo Tbk.	Akra	19	Tambang Batubara Bukit Asam (Persero) Tbk	PTBA
5	Aneka Tambang (Persero) Tbk.	ANTM	20	PP (Persero) Tbk	PTPP
6	Astra International Tbk.	ASII	21	Pakuwon Jati Tbk	PWON
7	Bumi Serpong Damai Tbk.	BSDE	22	Siloam International Hospitals Tbk.	SILO
8	Indofood CBP Sukses Makmur Tbk.	ICBP	23	Semen Indonesia (Persero) Tbk	SMGR
9	Vale Indonesia Tbk.	INCO	24	Summarecon Agung, Tbk	SMRA
10	Indofood Sukses Makmur Tbk.	INDF	25	Sawit Sumbermas Sarana Tbk.	SSMS
11	Indocement Tunggul Prakarsa Tbk.	INTP	26	Telekomunikasi Indonesia (Persero) Tbk	TLKM
12	Kalbe Farma Tbk.	KLBF	27	Traktor Bersatu Tbk	UNTR
13	Lippo Karawaci Tbk.	LPKR	28	Unilever Indonesia Tbk	UNVR
14	Matahari Department Store Tbk.	LPPF	29	Wijaya Karya (Persero) Tbk	WIKA
15	PP London Sumatra Indonesia Tbk.	LSIP	30	Waskita Karya (Persero) Tbk.	WSKT

The stock opening price is used as the next stock price prediction using mathematical models, namely geometric Brownian motion [27] and the Kalman filter method. This method has been developed for estimation, one of which is in the research of Evita et al. [28]. If X_t is a stochastic process that meet the following stochastic differential equations [29]:

$$dX_t = \mu X_t dt + \sigma X_t dW_t \quad (1)$$

The equation is called Geometric Brownian Motion (GBM), with μ , σ is constant, and dW_t is an increment from Wiener Process or increment from Brownian Motion. The GBM equation can be applied to the stock price movement model into the following equation:

$$dS_t = \mu S_t dt + \sigma S_t dW_t \quad (2)$$

μ is the direction of the stock price which is usually observed for a long time. σ^2 is the volatility of the S_t stock price, the Kalman filter algorithm for stock predictions using Table 2.

Table 1. Kalman filter algorithm

Algorithm: Kalman filter implementation
Initial Value $\mu, \sigma, \Delta t, Q, R$
Set $k = 1$
System Model: $S_t = (1 + \mu\Delta t + \sigma(W_t - W_{t-1}))S_{t-1} + w_k$
Observation: $z_t = H_k S_k + v_k$
Predictive:
State Estimation $\hat{S}_{(k k-1)} = (1 + \mu\Delta t + \sigma(W_t - W_{t-1}))S_{t-1 t-1}$
Covariance Error
$\hat{P}_{(k k-1)} = (1 + \mu\Delta t + \sigma(W_t - W_{t-1}))P_{t-1 t-1}(1 + \mu\Delta t + \sigma(W_t - W_{t-1})) + Q_k$
Update:
Pre-fit Residual $\hat{y}_k = z_k - H_k \hat{S}_{(k k-1)}$
Covariance $Cov_k = R_k + H_k \hat{P}_{(k k-1)} H_k^T$
Kalman Gain $K_k = \hat{P}_{(k k-1)} H_k^T Cov_k^{-1}$
Update state Estimate $\hat{S}_{(k k)} = \hat{S}_{(k k-1)} + K_k \hat{y}_k$
Covariance Estimate $P_{k k} = (I - K_k H_k) P_{k k-1}$
Measurement Post-fit Residual $\hat{y}_{k k} = z_k - H_k \hat{S}_{(k k)}$
Set $k = k + 1$ and repeat the prediction step

Then the estimation results from Kalman filter are used for portfolio optimization using goal programming with the following objectives and constraints [25]:

Table 2. Constraints and Objective function

Constraint function and Objective function	Goal Programming Model
Maximizing All Funds for Investment	
Formation of portfolios using 100% funds (Assumed investment funds are 100.000.000)	$100 \sum_{i=1}^{30} y_i P_i + d_1^- + d_1^+ = 100.000.000$
Maximizing Portfolio Returns	
Expectations of Investors can get more than the minimum return value on the capital market	$100 \sum_{i=1}^{30} E(R_i) y_i P_i + d_2^- - d_2^+ = 100.000.000 R_n$
Minimizing Risk	
The portfolio risk is as minimal as possible so the portfolio beta is assumed $0 \leq \beta_i \leq 1$.	$100 \sum_{i=1}^{30} \beta_i y_i P_i + d_3^- - d_3^+ = 0$ and
	$100 \sum_{i=1}^{30} \beta_i y_i P_i + d_4^- - d_4^+ = 100.000.000$
Limited allocation of stocks	
Assumed that the limit of each stock is a maximum of 15% of the funds	$100 y_i P_i + d_{4+i}^- - d_{4+i}^+ = 15\% \times 100.000.000,$ where $i = 1, 2, \dots, 30$

The simulation in goal programming is that one has an investment fund of 100.000.000 rupiahs used to form a portfolio with constraints following table 3. The maximum funds owned are 100.000.000, and we assume a maximum value of each stock of 15% of the total funds.

The calculation of the Expected return (profits expected by investors in the future) uses the equation [30]

$$E(R) = \frac{\sum_{i=1}^n R_i}{n-1} \quad (3)$$

$E(R)$ is expected return, n is number of periods of stock calculation, and R_i is realized return at the i -time which is calculated from comparing the difference between n and $n - 1$ stock prices compared to the $n - 1$ stock price. While beta stocks are calculated based on comparing the number of realized returns and the expected return on stock prices with market prices (stock index). Stock calculation is calculated using the equation:

$$\beta = \frac{\sum_{i=1}^n (R_i - E(R))(R_{mn} - E(R_m))}{\sum_{i=1}^n (R_{mn} - E(R_m))^2} \quad (4)$$

β is a stock beta, R_{mn} is a market return at the n -time. R_m is a market return. The stock market in this study is JII. The estimated Kalman filter data is used as input for the expected return and beta stock calculations.

RMSE (Root Mean Square Error) is calculated using the following formula

$$RMSE = \sqrt{\frac{(error)^2}{n}} \quad (5)$$

3. Results and Discussion

Data on monthly closing prices of sharia stocks from January 2012 to May 2017 are used as data for estimation using the Kalman filter method. The Kalman filter method estimates 30 stock prices in JII. Investors can utilize this because it only requires one mathematical model, unlike other time series methods where each stock index requires one model. This is evidenced by calculating the value of RMSE (Root Mean Square Error) from the estimated Kalman filter results of 30 sharia stocks showing a relatively small value. The RMSE (equation (5)) result diagram of each stock can be seen in figure 2.

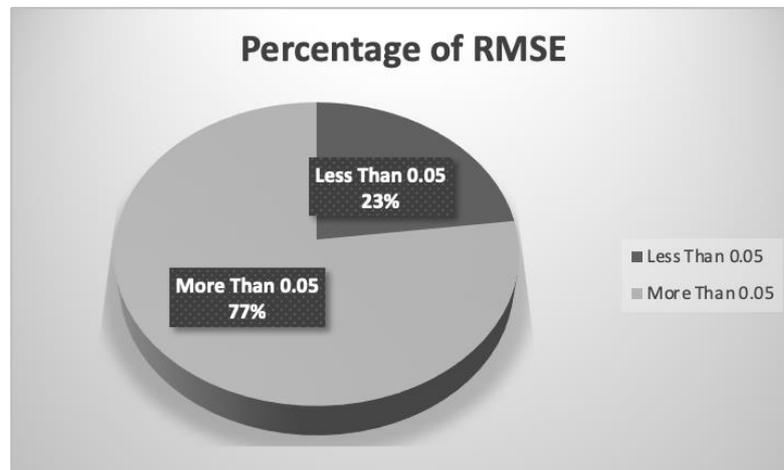


Figure 2. Percentage of RMSE for thirty Islamic stocks

The RMSE results showed approaches to 0 or very small, that's means the model has good performance if used as a stock price prediction model. The average RMSE of stocks at JII is 0,0552 or equal to 5,52%, this is smaller than the estimation results from the research conducted by previous researchers. In other words, the geometric Brownian mathematical model with the Kalman filter approach can predict the value of stock prices on stock indexes at one time. This is beneficial for investors, especially sharia stocks as an effective way to estimate stock prices. Figure 2 shows that 77% of stocks have RMSE value of less than 0,05, while only 23% of the RMSE value is more than 0,05. Investors could choose to invest in sharia stocks on stocks that have RMSE of less than 0,05. After

getting the estimated stock price, the researchers conducted an analysis of the portfolio to make it easier for investors to calculate their portfolio and determine the amount of wealth that was purchased to obtain the optimal value.

Based on Table 4, there is a comparison of the estimated value and the actual value of each sharia stock in the JII index in May 2017. From these results, it can be seen that the most striking comparison is in the stock price with a high value. This means if Investors want to do investment planning, invest in share which has a low stock price. This reduces the risk of returning returns.

Table 3 Comparing Closing Price and Estimation

NO	CODE	CLOSE	ESTIMATE	NO	CODE	CLOSE	ESTIMATE
1	AALI	14.300	14.300,04223	16	MIKA	2.040	2.039,99991
2	ADHI	2.350	2.349,99992	17	MYRX	123	122,99949
3	ADRO	1.520	1.520,01781	18	PGAS	2.400	2.400,00175
4	AKRA	6.625	6.625,00702	19	PTBA	2.180	2.179,99638
5	ANTM	775	774,99974	20	PTPP	3.130	3.129,99270
6	ASII	8.750	8.749,99258	21	PWON	610	610,00256
7	BSDE	1.810	1.809,99637	22	SILO	10.733,90039	10.733,86004
8	ICBP	8.700	8.700,01750	23	SMGR	9.450	9.449,97729
9	INCO	1.905	1.905,02877	24	SMRA	1.320	1.319,98700
10	INDF	8.750	8.749,99258	25	SSMS	1.790	1.790,00114
11	INTP	18.500	18.500,00140	26	TLKM	4.350	4.349,99664
12	KLBF	1.540	1.539,99767	27	UNTR	27.775	27.775,00572
13	LPKR	680	679,99912	28	UNVR	46.175	46.174,93269
14	LPPF	15.100	15.099,86690	29	WIKA	2.290	2.289,99618
15	LSIP	1.525	1.524,99990	30	WSKT	2.380	2.379,98815

The gap estimate data and real data can be seen in figure 3. A positive error indicates that the estimation result was smaller than the actual price. A negative error value indicates the estimation result has a value higher than the actual value. Investors will get a lower return if they choose a stock that has a negative error. Otherwise, a positive error means that the stock price is higher than the estimated stock. Investors will get a higher return.

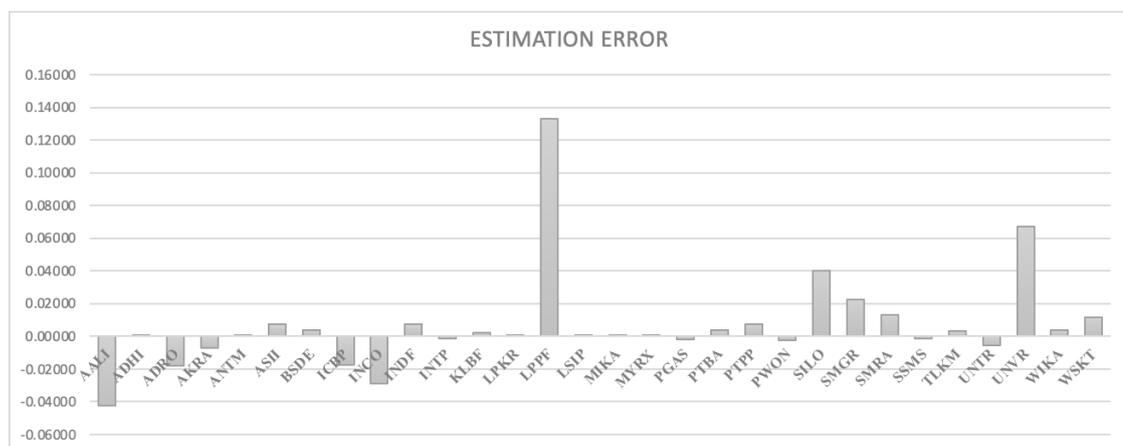


Figure 3. Gap values from original data and their estimates

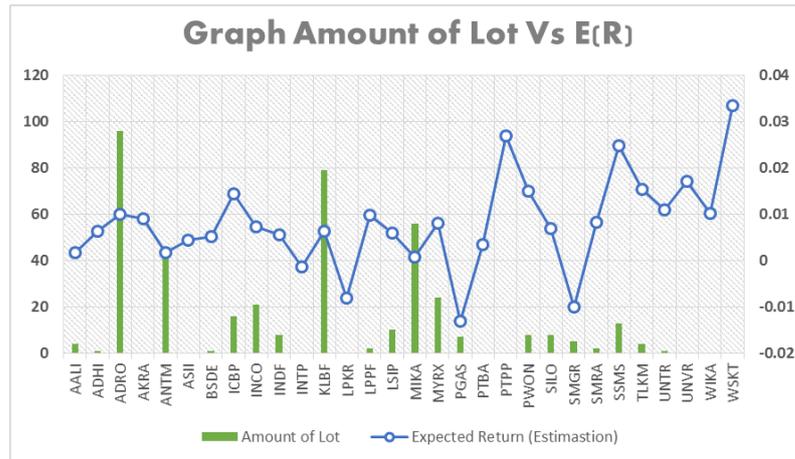


Figure 5 Amount of Lot Vs Expected Return

The highest number of lots is 96 lots, namely the stocks with ADRO code with Expected Return of 0,0099 or 0,99%. $E(R)$ is 0.2% higher than the overall expected return. That is, if we invest 96 slots on ADRO stocks, we expect a stock return of 0,99%. If the current period of ADRO stocks is IDR 1.520,02, that means 96 lots (1 lot = 100 stocks) that we invest in ADRO in the next month will get a profit of IDR 145.512,23. However, there are two stocks in the portfolio, although the expected return is negative, namely stocks with the code PGAS with $E(R)$ of -1,32% and SMGR code of -1%. This is still a reasonable stage because the value is better than the lowest return from the capital market, equal to -8.7%.

If the sum of many optimization results compared with beta stocks, the average number of lines of a lot that is obtained is a stock that has a beta value of the stock at the top of 0,50. Two stocks with the most lots are ADRO and KLBF which have beta values of 0,88 and 1,12. The beta stock is used as a reference for comparing the sensitivity of stock prices with the market index in this case, JII. If ADRO has a stock beta of 0,88, then if JII increases by 2%, ADRO experiences an increase in stock price of 1,76%.

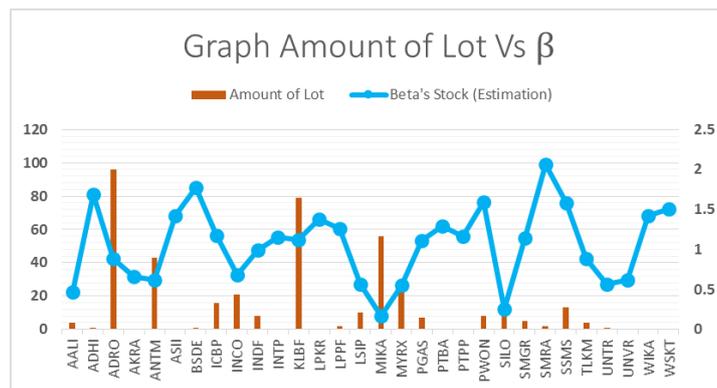


Figure 6 Amount of Lot Vs Beta's Stocks

The results of portfolio optimization and how many rupiahs must be invested in JII's sharia stocks are presented in table 5. The investment limit for each stock is IDR 15.000.000,00 per stock. The highest investment in ADRO stocks is IDR 14.592.170,93, with the highest number of lots, 96 lots. While the lowest value of investment, which is on BSDE stocks, only buys 1 lot from this stock, with the expected return is 0,52.

Table 4. Portfolio Results of Implementation of the Kalman Filter-Based on Goal Programming Methods

No	Code	Amount of Lot	Total	No	Code	Amount of Lot	Total
1	AALI	4	Rp 5.720.016.89	12	MIKA	56	Rp 11.423.999.51
2	ADHI	1	Rp 234.999.99	13	MYRX	24	Rp 295.198.77
3	ADRO	96	Rp 14.592.170.93	14	PGAS	7	Rp 1.680.001.22
4	ANTM	43	Rp 3.332.498.89	15	PWON	8	Rp 488.002.04
5	BSDE	1	Rp 180.999.64	16	SILO	8	Rp 8.587.088.03
6	ICBP	16	Rp 13.920.028,00	17	SMGR	5	Rp 4.724.988.65
7	INCO	21	Rp 4.000.560,42	18	SMRA	2	Rp 263.997.40
8	INDF	8	Rp 6.999.994.06	19	SSMS	13	Rp 2.327.001.49
9	KLBF	79	Rp 12.165.981.58	20	TLKM	4	Rp 1.739.998.66
10	LPPF	2	Rp 3.019.973.38	21	UNTR	1	Rp 2.777.500.57
11	LSIP	10	Rp 1.524.999.89	Total			Rp 100.000.000,00

The amount of investment in the estimate is calculated using the estimated value of the share price and properly spend an investment fund of 100.000.000 IDR. Furthermore, by using the number of lots from the estimation we calculate the return of shares in the month after June 2017 to obtain a return of 100.883.039,8 IDR, this shows that we get a return of 883.039,8 IDR in the following month. Whereas if we use Goal Programming only get a return of 100.705.000. This proves that the Kalman filter-based Goal programming has a good performance for predicting and deciding on future portfolios and can be used as a monthly plan for one year with a return difference of 178.039.848 IDR. Portfolio results obtained from this research are better if compared with the research that has been done previously with the use of optimization without estimation [25]. To further this research could be developed with other models such as machine learning [31] and other data usage such as google trends [10], [32], [33].

4. Conclusions

Based on the analysis carried out by the researcher, the mathematical goal programming method based on the Kalman filter can be used as a method of future portfolio planning. This method is easy to apply to reduce anxiety for investors, especially investors who want to invest in JII stocks. If we compare it with the value of goal programming without estimation, this method distributes investment funds to only a few shares whose value is close to the maximum value of funds for each share of 15.000.000. Meanwhile, if we use goal programming based on the Kalman filter, this method divides the stock funds into some company. This means we get less risk if one of the shares goes down in price. Hanson International Tbk, which is a new stock in the December 2016 period, in both methods was chosen to be included in the portfolio. Goal Programming provided the largest funding at Hanson International Tbk (MYRX) of 1.220 lots. This is quite risky considering MYRX is a new stock on the JII index. Besides the above, this research still needs to be improved in portfolio estimation and selection accuracy. The RMSE obtained still has seven stocks that have RMSE above 5%. This situation can be increased by doing an iteration at the time of estimation. For further research, it can add simulations to investment funds of 100 million but depends on users who want to invest. This method can be developed and formed by an application to make it easier for users to form future portfolios.

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