Online Portfolio Selection of LQ45 Stocks Index with the Adaptive Online Moving Average Method

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Abstract: An online portfolio is a collection or composition of a fund in financial assets with specific returns held online. Online portfolio selection can increase the chances of getting the right stocks. One way to choose an online portfolio is using the Adaptive Online Moving Average (AOLMA) method. This method predicts stock returns using adaptive decay variables from moving averages so that the predictive rate increases even more. In this paper, portfolio selection using the Adaptive Online Moving Average (AOLMA) method is carried out on the LQ45 stock index dataset from April 2012 to April 2022. The portfolio performance is then compared to the Equal Weight Portfolio (EWP). This portfolio is superior to the equal-weight portfolio in terms of mean return.

1 INTRODUCTION

An online portfolio is a collection of funds distributed as financial assets with a specific return. In this study, the portfolio comprises companies from the LQ45 index. Portfolio selection was studied for the first time in 1952 by Markowitz. He developed a fundamental idea of mean-variance to calculate the percentage of asset allocation (Markowitz, 1952). An online portfolio is different from a traditional portfolio. The online portfolio does not consider the return distribution of historical data to manage the portfolio return and risk. One method currently used in an online portfolio is the Adaptive Online Moving Average algorithm or AOLMA. AOLMA was developed based on technical analysis to predict future stock price movements as seen from historical data, including opening, highest, lowest prices, and most importantly, the closing price and the trading volume (Brown and Jennings, 1989). AOLMA focuses primarily on accurate forecasting of future prices to help investors create optimal investment strategies. In this paper, a portfolio from LQ45 index stocks is constructed by maximizing the portfolio's return value. Online selection of portfolios has been carried out using various methods. However, these various methods use quite a lot of historical data and a reasonably long time to predict a stock closing price or stock return in a period in an online portfolio. AOLMA is here to overcome this by only needing data on a stock's latest period's closing price to get predictions of closing prices and returns for future periods. AOLMA can periodically improve the effectiveness of predictions by updating the decay factor every period. Stocks are selected based on stock return predictions from the Adaptive Online Moving Average Algorithm. In addition, the portfolio will be compared to the Equal Weight portfolio by calculating the mean return, standard deviation, and Sharpe ratio.

2 LITERATURE REVIEW

Many studies on online portfolio selection have been conducted in line with the development of computational intelligence techniques that prioritize efficient and practical processes for managing stock as online assets. The selection of this online portfolio does not pay attention to the distribution function to predict future returns. The selection of online portfolios is made by considering the selection of artificial intelligence techniques as a predictor of asset returns and optimal investment strategies. There are many types of portfolio selection, such as benchmarks, following the winner strategy, following the loser strategy, a combination of winner and loser strategies, as well as meta-learning strategies. One version of the benchmark-type portfolio is the market method, which buys and holds or sells the same stocks as an index (Li and Hoi, 2014). The market method is implemented by distributing available capital evenly

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across all assets in the index in each period. Another version of the benchmark-type portfolios is the Constant Rebalanced Portfolio (CRP) which allocates capital to the assets with the same risk level in all periods (Tan et al., 1991). Exponential Gradient (EG) is a portfolio selection version of the winning strategy type with an exponential gradient value adjustment that is used to allocate investments using historical return data and strategies from stocks in the portfolio (Helmbold et al., 1998). The next version for portfolio selection for the winning strategy type is the Online Newton Step (ONS) through the application of the cumulative log return calculation equation with the Hessian matrix variable and the gradient matrix (Agarwal et al., 2006). The adaptive method is another version of the portfolio selection of winning strategy types. This version can determine multiple selections of stocks for portfolios such as optimal constant log portfolio and rebalancing, adaptive Markowitz portfolio selection method, and index-based portfolio selection method (Gaivoronski and Stella, 2003). Portfolio selection following the loser strategy has several versions. The first version is the Anticorrelation method, this method uses the mean return and cross-correlation matrix of various risky stocks in dividing the proportion of portfolio stocks based on stocks that perform well and stocks that perform poorly (Thrun et al., 2004). The next version is passive aggressive mean reversion (PAMR) from the application of the loss equation depending on the mean return portfolio (Li et al., 2012). The Confidence Weighted Mean Reversion (CWMR) method is another version for selecting portfolio types following a loser strategy, this version is based on a vector design on a portfolio with a Gaussian distribution process and the process of adjusting the distribution constantly depends on the nature of the average reversion (Li et al., 2013). The latest version in the portfolio of types following a losing strategy is Robust Median Reversion (RMR), this version predicts the strength of the median L1 value and can be used for symptom revision in a simple linear time frame so that it is easy to use (Huang et al., 2016). The selection of stocks in a pattern-matching portfolio combines the following winner and following loser strategies and consists of two processes. The first process is to determine a sample with the aim of selecting an existing historical price model through a benchmark that is almost aligned with the current price pattern. The second process is to build a better portfolio enhancement model with reference to the selected pricing model. The method used in selecting this type of portfolio is selecting a sample based on a non-parametric kernel to find a consistent price model by considering the different Euclidean model distances, then constructing a log-optimal portfolio based on capital growth theory (Györfi et al., 2006). This method has the latest version by selecting samples based on nonparametric nearest neighbors and proposes a method of embedding the model from the log of the best nonparametric nearest neighbors (Györfi et al., 2008). These two methods were further developed with the existence of a nonparametric sample selection method based on correlation using various model correlation coefficients and proposed a Correlation-driven Nonparametric (CORN) learning algorithm (Li et al., 2011). The metalearning strategy is a type of portfolio selection using various strategies combined to get a suitable portfolio. One strategy is the strategy of using the Aggregating algorithm which can solve the problem of selecting online portfolios, and generalizing the worst case of the Universal Portfolio (UP) algorithm [4]. There are also those who directly implement meta-learning algorithm methods such as Online Newton Update (ONU) and Online Gradient Update (OGU) with satisfactory success rates in selecting stocks for online portfolios (Das and Banerjee, 2011). There is also another strategy implemented in this portfolio using the Follow the Leading History (FLH) algorithm which is implemented in such a way that the basic data set is adjusted periodically and continuously with each base expert making calculations for future prices. with the start being the time period varies in historical data (Hazan and Seshadhri, 2009).

2.1 Portfolio Selection with Online Moving Average Revision

The Online Moving Average Revision or abbreviated OLMAR is the first online portfolio selection algorithm to use a moving average variable that assumes that stocks performing poorly in the present will perform better in the future and vice versa. The OLMAR is exploited from the Moving Average Reversion approach which considers the expected return and stock risk. There are two moving averages used in the OLMAR, namely Simple Moving Average or abbreviated SMA algorithm and the Exponential Moving Average or abbreviated EMA algorithm (Li et al., 2015). The SMA algorithm uses the arithmetic average of truncated historical prices (Johnston et al., 1999). Whereas, the EMA algorithm takes more historical stock prices and then assigns an exponential weight to each stock price.

2.2 Portfolio Selection with Adaptive Online Net Profit Maximization

Portfolio selection using the Adaptive Online Net Profit Maximization or abbreviated AOLNPM algorithm is a development of the Online Moving Average Revision (OLMAR) method. This is because OLMAR has several drawbacks such as the house limit for the rate of return that must be set, the selection of strategies that are found only take the appropriate strategy without looking at other strategies that may have higher returns, and OLMAR returns also do not impose special conditions and there are no transaction costs calculated in making portfolio strategy changes. The purpose of adding NPM is to add value to the transaction cost variable and then transform the non-linear model into a linear programming problem that is commensurate with changes in the variable in the portfolio. Even though AOL NPM is an updated model, there are still limitations such as the risky assets taken are determined only by historical asset data even though asset volume must also be considered and assets with small risks are not considered in selecting online portfolios. This is evidenced by the application of AOLNPM to the MSCI, NYSE-O, NYSE-N, and TSE index stocks. The cumulative return results are satisfactory (Guo et al., 2021).

2.3 Portfolio Selection with Adaptive Online Moving Average

Adaptive Online Moving Average (AOLMA) is an algorithm that focuses on predicting stock movements to determine optimal investment strategies. AOLMA uses historical data analysis that comes from financial markets such as historical stock prices and stock trading volume. The AOLMA uses technical analysis to determine whether or not the trend will continue in a stock. Instruments that can be used to carry out trend analysis are trend lines, candlestick formations, and other systematic visualizations. The AOLMA relies on design to factor decay over a given period. The AOLMA method is based on regression techniques, namely techniques obtained from analyzing two different and separate variables to obtain an equation to estimate returns effectively and accurately. Adaptive Online Moving Average (AOLMA) works by adjusting the stock decay factor gradually from the moving average according to stock performance (Li and Hoi, 2012). The advantages provided by the AOLMA method include predictions that are made faster and in real time, the data needed is only the latest stock close price data, and the effectiveness of the prediction is further improved by updating the decay factor value by adding and subtracting Y values.

2.4 Equal Weight Portfolio

qual weight portfolio is the simplest and easiest to implement portfolio selection approach. An equal-weight portfolio is based on giving each company the same weight. This portfolio can be relied upon to maximize stock returns in the portfolio and is very easy to allocate to many stocks. Equal weight portfolio can be formulated as follows (Brandel,).

$$w_i = \frac{1}{N'} \;\; i = 1, 2, ...N, \tag{1}$$

where w_i is the weight i^{th} stock in the portfolio, and N is the number of stocks contained in the portfolio.

3 METHODOLOGY

The design of all processes of a system that is in this article is built-in visualization with the format in the form of a flow chart (flowchart) containing a workflow explanation of the system design built for the basic work of the system from the beginning to the end of the process as shown in Figure 1.

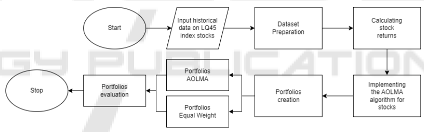

Figure 1: Methodology.

The initial step in creating this system was to input all weekly stock price index data with the LQ45 index in the period April 2012 - April 2022 by taking the dataset from the Yahoo Finance website. The sample dataset used is shown in Table 1.

Table 1: Dataset Sample.

Date	Close BBCA	Close TLKM	Close ASII	Close PTBA	Close INTP
30/04/2012	1610	1670	7270	3650	18850
07/05/2012	1600	1640	6885	3250	18150
14/05/2012	1510	1580	6840	3290	17300
21/05/2012	1450	1450	6585	3240	17200
28/05/2012	1420	1520	6335	3000	17250

The next stage is the data preprocessing stage. Data preprocessing is carried out to prepare raw data on LQ45 stocks that have been previously obtained to be processed into data that is ready to be used in the system created. This data preprocessing step focuses on data cleaning, namely eliminating or modifying incorrect or empty data values (missing values), and correcting inconsistent data. Furthermore, the data normalization process is carried out, data normalization is the process of comparing data so that it can be described as data with normal distribution.

3.1 Adaptive Online Moving Average (AOLMA) Algorithm

The process of forming a portfolio by applying the AOLMA algorithm is as follows:

1. Determine the first decay factor α_1 with $0 \leq \alpha_1 \leq$ 1and the updating value of the next decay factor γ with $\gamma \leq 0.001$. The decay factor will be a vector in the portfolio $(\alpha = (\alpha_1, \alpha_2, ..., \alpha_m))$ in a period (t) of an asset (i) (i = 1, 2, . . . , m).
2. Calculating stock predictions for period t with the Simple Moving Average for the first 10 weeks.
3. Calculating stock predictions in period t + 1:
$$P^1_{(t+1)} = a_{(t+1)}.P_{(t)} + (1 - a_{(t+1)}).P'_{(t)} \quad (2)$$
Where P_{t+1} is prediction close period $t+1, a_{t+1}$ is period decay factor t+1, $P_{(t)}$ is close period t, and $P'_{(t)}$ is prediction close period t(from SMA prediction calculations).
4. Calculating the expected stock return in the t+1 period:
$$r'_{(r+1)} = a_{(t+1)}.1 + (1 - a_{(t+1)})P_{(t)}.\frac{r'_t}{r_t} \quad (3)$$
Where $r'_{(r+1)}$ is expected stock return period t+1, $a_{(t+1)}$ is period decay factor t+1, r'_t is expected stock return period t, and r_t is period stock return t.
5. Calculating the expected return of stock i in period t:
$$r'_{(ti)} = a_{(ti)} + (1 - a_{(ti)}).\frac{r'_{(t-1)i}}{r_{(t-1)i}} \quad (4)$$
the following formula is generated:
$$r'_{(ti)} - r'_{(ti)} = r_{(ti)} - \frac{r'_{(t-1)i}}{r_{(t-1)i}} - (1 - \frac{r'_{(t-1)i}}{r_{(t-1)i}}.a_{(ti)}) \quad (5)$$
Where $r'_{(ti)}$ is expected stock return i period t, $r_{(ti)}$ is stock return i period t, $a_{(ti)}$ is stock decay factor i period t, $r'_{(t-1)i}$ is expected stock return i period t-1, and $r_{(t-1)i}$ is stock return i period t-1.
6. Determine the conditions that occur in the portfolio:

1st condition : $r_{(ti)} > r'_{(ti)}$ and $r_{(t-1)i} > r'_{(t-1)i}$
2nd condition : $r_{(ti)} > r'_{(ti)}$ and $r_{(t-1)i} \leq r'_{(t-1)i}$
3rd condition : $r_{(ti)} \leq r'_{(ti)}$ and $r_{(t-1)i} > r'_{(t-1)i}$
4rd condition : $r_{(ti)} \leq r'_{(ti)}$ and $r_{(t-1)i} \leq r'_{(t-1)i}$

If the first condition or 4th condition is found, the decay factor coefficient is updated:
$$a_{(ti)} = -(1 - \frac{r'_{(t-1)i}}{r_{(t-1)i}} < 0 and a_{(t+1)i} = a_{(ti)} + \gamma \quad (6)$$
If the 2nd condition or 3rd condition is found, the decay factor coefficient is updated:
$$a_{(ti)} = -(1 - \frac{r'_{(t-1)i}}{r_{(t-1)i}} \geq 0 and a_{(t+1)i} = a_{(ti)} + \gamma \quad (7)$$
Increasing and decreasing the value of the decay factor can increase the accuracy as well as adaptive updates in getting close stock price predictions and stock return predictions from the AOLMA method.

7. Calculating the effectiveness of the Adaptive Online Moving Average (AOLMA) return prediction. This is done by calculating the relative prediction error of the stock at time j using the formula.
$$Er_{(j)} = \frac{\left|r'_{ji} - r_{ji}\right|}{r_{ji}}.100\% \quad (8)$$
and the average relative error of predictions:
$$Er = \frac{1}{n}\sum_{j=1}^{n}\frac{\left|r'_{ji} - r_{ji}\right|}{r_{ji}}.100\% \quad (9)$$
Where Er(j) is a relative error of time stock prediction j, Er is the average relative error, n is many stocks in the portfolio, r'_{ji} is the expected Return of stock i time j, and r_{ji} is stock return i time j.

4 EVALUATION

4.1 Metric

In investigating the accuracy of the prediction results, evaluation metrics are used, namely, the root means square error is abbreviated as RMSE and the mean absolute error is abbreviated as MAE (Chen et al., 2021).
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y'_i)^2} \quad (10)$$

$$MAE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|y_i - y_i')|} \tag{11}$$

Where y_i' is the predicted stock return and y_i is the actual stock return, and n is the total number of samples.

4.2 Sharpe Ratio

The Sharpe Ratio is a way of measuring the performance of a portfolio. The way to evaluate portfolio performance with the Sharpe ratio is to look at the value of the portfolio's expected return and portfolio risk. If the Sharpe values the smaller the ratio, the less good portfolio performance will result and vice versa. The portfolio Sharpe ratio can be formulated as follows (Iorio et al., 2018).

$$MAE = \frac{R_{exp}}{\sigma_p} \tag{12}$$

Where S_p is the Sharpe ratio, R_{exp} is the Expected return portfolio, and σ_p is portfolio risk.

4.3 Testing Scenario

The application of the AOLMA algorithm to the LQ45 stock index is carried out in the following stages:

1. Predict the return of stocks that are on the LQ45 index using AOLMA with an initialization of a decay factor (α) value of 0.5 with γ (modifier of decay factor value) of 0.001. In this paper, a first decay factor (α) value of 0.5 was chosen because it is the middle range in the choice of value and a decay factor value modifier γ of 0.001. The modifier for the decay factor value γ must be smaller than the decay factor value because the decay factor update is carried out every period and the change must not be too significant but can be effective in predicting stock close prices and stock returns from the AOLMA method.
2. Form a portfolio with 2 stocks, 3 stocks, and 5 stocks. Stocks are selected based on the company's industrial activity sector.
3. The selection or determination of stocks taken every week for the portfolio is based on AOLMA's return predictions where the stocks taken must have one of the largest return predictions in the list of stocks in the portfolio every week.
4. Form a portfolio with the same list of stocks as the portfolio obtained from point 3 but the weight used must be the same for each stock in the portfolio (portfolio with the same weight).
5. Comparing the results of portfolio performance in points 3 and 4 with the performance of stocks in the portfolio list using the calculation of the mean return value, standard deviation value, and Sharpe ratio value for each portfolio.
6. Determines the best portfolio to be taken based on its performance from the highest mean return value and the highest Sharpe ratio value of the portfolio in this test.

4.4 Experiment Result

The return prediction results and model evaluation for all stocks that will be formed into several portfolios are shown in Table 2.

Table 2: Evaluation of Return Prediction Results.

Stock	RMSE	MAE
BBCA	0,033205	0,023546
TLKM	0,036214	0,026868
ASII	0,045645	0,032404
PTBA	0,064316	0,047836
INTP	0,051624	0,039506
PTPP	0,075572	0,05426
PGAS	0,065342	0,044468
INDF	0,039979	0,028801

The value of the portfolio using the AOLMA method compared to the portfolio with the same weight was carried out with 2 stocks, 3 stocks, and 5 stocks from different sectors. A comparison of the portfolio with 2 stocks is shown in Figure 3. The first 2 stock portfolios consist of BBCA.JK and TLKM.JK. The second portfolio of 2 stocks with ASII.JK and PTBA.JK. The third portfolio of 2 stocks with INTP.JK and PTPP.JK. The fourth portfolio of 2 stocks with PGAS.JK and INDF.JK.

Based on Table 3, the average return of the portfolio with the method used in this article is better than the equal weight method. The equal weight portfolio has a relatively smaller risk value in terms of the risk obtained from the standard deviation (smaller) and also has better performance than AOLMA in terms of Sharpe ratio (larger). Thus, on testing a portofolio of 2 stocks, the AOLMA portofolio only provides a better mean return than the equal-weight portofolio.

The value of the portfolio using the AOLMA method compared to the portfolio with the same weight carried out with 3 stocks is shown in Figure 5. The first 3 stock portfolios consist of BBCA.JK, TLKM.JK, and ASII.JK. The second portfolio of 3 stocks consists of BBCA.JK, TLKM.JK and PTBA.JK. The third portfolio of 3 stocks consists of BBCA.JK, TLKM.JK and INTP.JK. The fourth port-

Table 3: Comparative Evaluation of Portfolio Value for 2 Stocks.

Portofolio	Evaluation	AOLMA	Equal Weight
BBCA and TLKM	Mean Return	1,00549	1,00323
	Standard Deviation	0,03321	0,02836
	Sharpe Ratio	30,2729	35,3713
ASII and PTBA	Mean Return	1,00198	1,00156
	Standard Deviation	0.05337	0,04074
	Sharpe Ratio	18,7727	24,5833
INTP and PTPP	Mean Return	1,00368	1,00161
	Standard Deviation	0,05916	0,04826
	Sharpe Ratio	16,9639	20,7519
PGAS and INDF	Mean Return	1,00180	1,00055
	Standard Deviation	0,05176	0,04052
	Sharpe Ratio	19,3514	24,6889

folio of 3 stocks consists of BBCA.JK, TLKM.JK and PTPP.JK stock.

Table 4: Comparative Evaluation of Portfolio Value for 3 Stocks.

Portofolio	Evaluation	AOLMA	Equal Weight
BBCA, TLKM, and ASII	Mean Return	1,00549	1,00253
	Standard Deviation	0,03952	0.02957
	Sharpe Ratio	25,4389	33,8964
BBCA, TLKM, and PTBA	Mean Return	1,00348	1,00282
	Standard Deviation	0,04689	0,03058
	Sharpe Ratio	21,3965	32,7929
BBCA, TLKM, and INTP	Mean Return	1,00452	1,00220
	Standard Deviation	0,04286	0,03079
	Sharpe Ratio	23,4342	32,5485
BBCA, TLKM, and PTPP	Mean Return	1,00429	1,00318
	Standard Deviation	0,05285	0,03451
	Sharpe Ratio	18,9997	29,0654

Based on Table 4, the average return of the portfolio with the method used in this article is better than the equal weight method. The equal weight portfolio has a relatively smaller risk value in terms of the risk from standard deviation (smaller) and also has better performance than AOLMA in terms of Sharpe ratio (larger). In testing the portfolio of 3 stocks, the AOLMA portfolio only provides a better mean return than the equal-weight portfolio.

Table 5: Comparative Evaluation of Portfolio Value for 5 Stocks.

Portofolio	Evaluation	AOLMA	Equal Weight
BBCA, TLKM, ASII, INTP, and INDF	Mean Return	1,00468	1,00176
	Standard Deviation	0,04361	0,02942
	Sharpe Ratio	23,0342	34,0494
BBCA, TLKM, ASII, INTP, and PGAS	Mean Return	1,00347	1,00154
	Standard Deviation	0,05001	0,03227
	Sharpe Ratio	20,0629	31,0356
BBCA, TLKM, ASII, INTP, and PTPP	Mean Return	1,00432	1,00216
	Standard Deviation	0,05483	0,03327
	Sharpe Ratio	18,3153	30,1165
BBCA, TLKM, ASII, INTP, and PTBA	Mean Return	1,00484	1,00195
	Standard Deviation	0,04971	0,03043
	Sharpe Ratio	20,2105	32,9218

The value of the portfolio using the AOLMA method compared to the portfolio with the same weight carried out with 5 stocks. The first 5 stock portfolios are BBCA.JK, TLKM.JK, ASII .JK, INTP.JK , and INDF.JK. The second portfolio of 5 consists of BBCA.JK, TLKM.JK, ASII.JK, INTP.JK and PGAS.JK. The third portfolio of 5 stock consists of BBCA.JK, TLKM.JK, ASII.JK, INTP.JK, and PTPP.JK. The fourth portfolio of 5 stock consists of BBCA.JK, TLKM.JK, ASII.JK, INTP.JK and PTBA.JK.

Based on Table 5, the average return of the portfolio with the method used in this article is better than the equal weight method. Portfolios of equal weight have relatively smaller risk values in terms of standard deviation risk (smaller) and also have better performance than AOLMA in terms of Sharpe ratio (larger). Thus, in testing a portfolio of 3 stocks, the AOLMA portfolio only provides a better average return than a portfolio with equal weight.

A portfolio comparison for 2 stocks, 3 stocks, and 5 stocks as a whole got the results that, the AOLMA portfolio provides better performance in terms of mean return alone. Whereas performance in terms of standard deviation and Sharpe ratio of the equal weight portfolio is better. That matter shows that the AOLMA portfolio can get a bigger profit than the equal portfolio weight, but the big profits are worth the bigger risks too. Besides that, a portfolio consisting of several stocks does not necessarily provide better portfolio performance.

5 CONCLUSIONS

Experimental results for stock selection for a portfolio of 2 stocks, 3 stocks, and 5 stocks with AOLMA and EW show that the portfolio with AOLMA return predictions has better performance than the mean return side compared to equal-weight portfolios, especially with stocks that have history of performance good and uniform. If the stocks selected for selection with AOLMA have performance and movement each week, the value and performance of the AOLMA portfolio are lower than the equal-weight portfolio. The portfolio with the best performance is the one with the most stocks in the experiment is a portfolio of 5 stocks whose performance is seen from the Sharpe ratio. Although the portfolio with AOLMA's return prediction has a high return the risk that is obtained is also higher, that is which makes the shape ratio smaller. This indicates that the increased risk is compensated by a higher increase in returns. In further research, it is suggested to be able to expand the method comparison for the selection of portfolios used in addition to equal weight portfolio and perfect the AOLMA method by changing the parameters used or even combining them with another method.

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