Multi-criteria Index clustering method with Mean-Variance Optimization in PSE amidst Covid-19 Pandemic

Maricar M. Navarro
Industrial Engineering Department
Technological Institute of the Philippines
Cubao Quezon City
mnavarro.ie@tip.edu.ph

Bryan B. Navarro
Electrical Engineering Department
Technological Institute of the Philippines
Cubao Quezon City
bryanbnavaro@tip.edu.ph

Abstract

This work intends to combine technical analysis and the K-means clustering algorithm in portfolio selection. To choose the appropriate number of clusters, this study suggested the Elbow Method and Multi-Criteria Index Model from the most reputable Index, including Silhouette, Calinski-Harabasz, and Davies-Bouldin. We formed the clusters using the annual average risk data for the years 2019 and 2020, and we evaluated the stocks based on the technical analysis used by investors, such as Moving Average Convergence/Divergence (MACD) and Hybrid MACD with Arnaud Legoux Moving Average (ALMA). In the empirical experiment, we used the mean-variance portfolio optimization model to solve the risk minimization issue on a subset of the companies' shares in order to choose the most effective portfolio. The Philippine Stock Market lists 234 and 239 businesses for 2019 and 2020, respectively. All simulations were carried out using the MATLAB environment platform. The COVID-19 condition is significantly riskier than the pre-COVID-19 condition, according to the results. The MACD approach dominates the MACD-ALMA strategy in terms of the number of assets with a positive annual rate of return.

Keywords
K-means, Technical Analysis, Multi-criteria Index Model, Stock Market, COVID-19

1. Introduction
Online trading is one of the options available to institutional and ordinary investors in the Philippines in the current era of swift technology advancement. Although they are not all the same and there are certain differences between institutional investors and non-institutional, or retail, investors, these sorts of investors can still profit from the internet trading platform. The term "institutional investor" refers to an organization or individual that transacts large amounts of assets in order to qualify for preferential dealing and lower costs. Institutional investors do not invest their own money; rather, they invest other people's money on their behalf. On the other side, a retail investor is an individual or amateur investor who purchases and trades stocks through brokerage houses. They frequently make investments for themselves in brokerage or retirement accounts. During COVID-19, there was a noticeable increase in the number of retail investors using online stock trading platforms in the Philippines. ranging from a novice investor who needs help creating an investing strategy to an experienced investor who can use an internet trading platform to carry out a strategy.

On the other side, a retail investor is an individual or amateur investor who purchases and trades stocks through brokerage houses. They frequently make investments for themselves in brokerage or retirement accounts. During COVID-19, there was a noticeable increase in the number of retail investors using online stock trading platforms in the Philippines. ranging from a novice investor who needs help creating an investing strategy to an experienced investor who can use an internet trading platform to carry out a strategy.It can be challenging to evaluate the risk and returns of various companies, but the clustering technique makes it practically conceivable to group more than 230 stocks on the Philippine stock market. The investor or trader can focus on each group rather than trying to make judgments based on individual equities by using cluster analysis to aggregate returns and risk. Although previous research has concentrated on choosing a portfolio based on fundamental analysis, technical analysis should also be taken into account when employing machine learning to choose a portfolio. Clustering is an unsupervised data mining technique for classifying objects according to their similarities. It is applied to the analysis of various datasets. One of the unsupervised clustering methods that is most frequently used is K-means. Although it might be challenging to estimate the value of the k parameter, which denotes the number of clusters, the cluster validity index is one of the most popular ways to do so. In order to discover appropriate cluster numbers depending on the properties of datasets, numerous internal and external validity indices are applied (Ozge et al. 2021). In the stock market, Cluster analysis helps to distinguish stocks with different characteristics. Unsupervised learning models include the K-means clustering algorithm. Unsupervised models are used to learn from unlabeled or uncategorized data (Tan et al. 2019). It searches for commonalities in the data set and responds to the presence or absence of such commonalities in each data point. Prior Studies include K-means on selecting stocks index, particularly in Asia. In the study of (Gubu et al. 2021) they consider the data preprocessing using trimmed k-means clustering for robust mean-variance portfolio selection.

The PSE, which was established in 1992, was the subject of this investigation. Using the PSE, portfolio selection is affected by a range of factors, both directly and indirectly, just like any other decision-making problem. In this regard, it has proven challenging for researchers, managers, investors, and practitioners to look into, identify, rank, and employ criteria to assess, choose, and optimize portfolios. As a result, this study created a strategy for portfolio selection and optimization in particular. It attempts to use technical analysis and the K-means clustering algorithm. To choose the appropriate number of clusters, this study suggested the Elbow Method and Multi-Criteria IndexModel (Navarro et al. 2022) from the most reputable indices, including Silhouette, Calinski-Harabasz, and Davies-Bouldin. To build the clusters and evaluate the stocks that correlate to investors' technical methods like Moving Average Convergence/Divergence (MACD) and Hybrid MACD with Arnaud Legoux Moving Average, we use the yearly average risk data for the years 2019 and 2020. (ALMA). In the empirical experiment, we used the mean-variance portfolio optimization model to solve the risk minimization issue on a subset of the companies' shares in order to choose the most effective portfolio. The Philippine Stock Market lists 234 and 239 businesses for 2019 and 2020, respectively. All simulations were carried out using the MATLAB environment platform.

2. Methods

There were five sections to this paper. Phase 1 used data collection from (Market watch 2022) Phase 2 involved stock clustering on the Philippine Stock Market based on average yearly risk.. Phase 3 was built on an investing strategy utilizing Moving Average Convergence/Divergence (MACD) and Arnaud Legoux Moving Average as a hybrid technical indicator (ALMA). The stock average yearly risks and returns are assessed in Phase 4 using a clustered MACD or MACD-ALMA approach. Finally, Phase 5 used the mean-variance portfolio optimization methodology to identify the most effective portfolio.

Phase 1: Data Gathering

The information used in this study matched the two-year historical price of the Philippine Stock Market both before and after COVID-19. For 2019 (prior to COVID-19) and 2020 (during COVID-20), it consists of the Bank and Financial sector, Commercial and Industrial, Conglomerates, Consumer, Index, Insurance, mining and oil, Properties, Services, and Telecoms sectors, with a total of 234 and 239 companies in the Philippines, respectively.

Phase 2: K-means Algorithm

The Philippine Stock Market was clustered using the K-means algorithm. The average annual risk served as the input data for the evaluation of clusters. In this investigation, a maximum of 20 potential clusters were examined. To identify the ideal cluster, the proposed elbow and multi-criteria techniques were both used. This work provides the most well-known indexes, such as Silhouette Score, Calinski-Harabasz Score, and Davies-Bouldin Score, for the suggested Multi-criteria Index Model. Each data set's cluster centroid and cluster labels were also determined using the K-means approach. The cluster profile or characteristics were also looked into and examined. The modified procedure of K-means from Navarro et al. (2022) was used in this method.

Phase 3: Technical Analysis

Technical analysis indicators are linear functions that compute repeating values from previous trading data such volume, open interest, open, high, low, and closing prices. Utilizing price actions and technical analysis helped short-term investments. In this study, we proposed a technical indicator, such as the Moving Average Convergence/Divergence Method (MACD) and Arnaud Legoux Moving Average, for an investment approach to find lucrative companies (ALMA). The technical investing method employed in this study used the MACD (12,26,9), MACD (4,22,3), MACD-ALMA (12,26,9), and MACD-ALMA (4,22,3).

Method using MACD Is one of the most used momentum indicators in technical analysis, MACD, or moving average convergence/divergence, was developed by Gerald Appel towards the end of 1970. MACD stands for moving average convergence/divergence and is one of the most widely utilized momentum indicators in technical analysis (Gerald Appel,1970) It is typically employed by both long-term and short-term investors. The MACD line is calculated as the difference between the exponential moving averages of days 12 and 26, (Sanel Halilbegovic 2016). With n1, n2, and n3 combinations, MACD is frequently utilized, however alternative values might be used instead depending on the objectives. Typically, this is displayed as MACD (n1, n2, n3). In the instance of 12,26,9, it was displayed as a MACD (12,26,9). Below are MACD trading rules used in this paper:

Buy Signal: $Histogram_t = MACD_t - Signal_t > 0$ (1)

Sell Signal: $Histogram_t = MACD_t - Signal_t < 0$ (2)

Also, the annual return is calculated as,

$$R_A = \sum_{i=1}^{M} P_{Sell} - \sum_{j=1}^{N} P_{Buy} \tag{3}$$

And the annual rate of retun,

$$R_i = \frac{R_A}{R_{BS}} \times 100\% \tag{4}$$

Annual Return is R_A. Annual Rate of Return, or R_i, RBS = Closing Index Value, which represents the initial transaction (Buy or Sell), M is the number of sell signals. *N* is the quantity of a purchase signal. The closing index values on the days when buying and selling transactions are to be completed are P_{Buy} and P_{Sell}, respectively.

A positive (negative) value of R_A denotes a gain (loss), and this is true for both long and short trades. The single-line crossover is used in this study as a MACD indicator. In the analysis, MACD (12,26,9) and MACD (4,22,3) both employed.

Figure 1 displays the same sample stock along with the matching MACD (12,26,9) and MACD buying and selling index values (4,22,3). The letters "B" and "S" stand for the respective buying and selling points.

In this study, ALMA is included in the MACD trading guidelines. The investor would purchase equities if the MACD and signal both showed bullish crossovers in a buying condition. If MACD is in an uptrend and the closing or opening price is greater than ALMA, this indicates a buying position. On the other hand, the Sell position will argue that the first selling point should be sold right away if both the opening and closing prices were below ALMA. To select only those companies that meet the investing strategy parameters of MACD and ALMA, this two-indicator hybrid was used in a clustered group setting. The trading guidelines for MACD-ALMA employed in this study are listed below:

Buy Signal: $Histogram_t = MACD_t - Signal_t > 0$ and $ALMA_t < P_{(O,C)t}$ (5)

Sell Signal: First $ALMA_{t+m} > P_{(O,C)t}$ after Buy_t (6)

Where $P_{(O,C)t}$ are the opening and closing points, and (t+m) is the point after Buy_t. The MACD calculation includes the signal line, histogram, yearly return, and annual rate of return. We also looked at MACD-ALMA (12,26,9) and MACD-ALMA (4,22,3). Figure 1 displays the same sample stock together with the accompanying MACD-ALMA (12,26,9) and MACD-ALMA buying and selling index values (4,22,3).

Phase: 4: Stock Rate of Return by Cluster Evaluation (Portfolio Selection)

The next step is to choose the maximum number of companies per cluster to include in the portfolio after calculating the rate of return (R_i) using the trading rules previously covered. This essay outlined some guidelines for choosing a portfolio:
1. Delete businesses with a negative return rate (R_i)
2.Companies having a window below the MACD or ALMA window should be removed.
3. 10 firms maximum per cluster
4.Choose organizations with the lowest risk for each cluster.

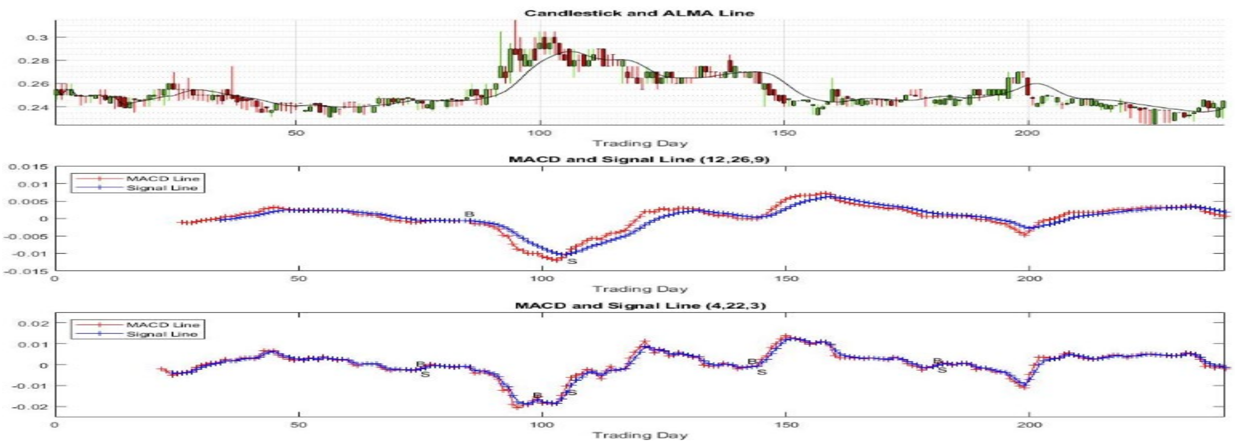

Figure 1. MACD-ALMA (12,26,9) and MACD-ALMA (4,22,3) trading guidelines.

Phase 5: Mean-Variance Model

According to the mean-variance model, investors favor the security with the higher return while taking into account specific hazards or the one with the lower risk based on a specified projected return. By assessing the level of risk that investors are willing to accept in exchange for benefits, it is accomplished (Kizys et.al 2021). This article employs a reduced risk based on a certain expected return criterion because clustering was based on average annual risk in the past. A minimization issue is used to frame the model:

$$\min\left(\sigma_P{}^2\right)=\sum_{i=1}^{n}\sigma_i{}^2 w_i{}^2+2\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} w_i w_j \sigma_{ij}\rho_{ij} \tag{7}$$

Subject to:

$$R_P=\sum_{i=1}^{n} w_i R_i \tag{8}$$

$$\sum_{i=1}^{n} w_i = 1 \tag{9}$$

Where σ_{p2} = represents the portfolio P's variance, w_i = stands for the asset's weight., σ_i = represents the asset's standard deviation., σ_{ij} = represents the covariance of asset i and asset j, ρ_I= indicates the relationship between the assets i and j and R_P = Expected portfolio return.

4. Results and Discussion

The information used included 234 and 239 businesses in the Philippines for the years 2019 (before to COVID-19) and 2020 (during COVID-20), respectively. Every simulation for the suggested strategy, including K-means clustering, technical analysis, and portfolio optimization, was carried out in the MATLAB platform.

Results of K-means Clustering

The average annual risk was used as the clustering attribute in the K-means technique for the 2019 and 2020 data. The most effective clusters for the supplied data were found using the Elbow Method and the Multi-criteria Index Model. The amount of danger per cluster would be based on the cluster centroids. According to the simulation, the optimal cluster for the 2019 data (234 firms) using the Elbow Method and Multi-criteria Index Model, respectively, was 5 clusters and 18 clusters. The best cluster for 2020 data (239 firms) was 6 clusters and 17 clusters, respectively. The Elbow Method's compiled findings for the 2019 and 2020 data are shown in Table 1, respectively.

Table 1. Elbow Method for 2019 data and 2020 data.

2019 Data				2020 Data		
Cluster Group	Centroid (Risk Level)	Count	Percent of Total	Centroid (Risk Level)	Count	Percent of Total
1	3.9015	45	19.23%	3.1248	68	28.45%
2	2.4912	84	35.90%	7.6709	19	7.95%
3	6.1234	20	8.55%	5.8248	30	12.55%
4	1.5564	77	32.91%	4.1802	66	27.62%
5	9.8569	8	3.42%	10.4966	9	3.77%
6				2.1784	47	19.67%

Table 2. Multi-criteria Index Model for 2019 and 2020 data.

2019 Data				2020 Data		
Cluster Group	Centroid (Risk Level)	Count	Percent of Total	Centroid (Risk Level)	Count	Percent of Total
1	1.4940	10	4.27%	4.4848	13	5.44%
2	0.9068	12	5.13%	3.9387	16	6.69%
3	3.2408	13	5.56%	4.8888	12	5.02%
4	5.8761	13	5.56%	5.5715	15	6.28%
5	1.3306	9	3.85%	3.4973	10	4.18%
6	2.3898	10	4.27%	2.9126	20	8.37%
7	2.7323	14	5.98%	7.7643	17	7.11%
8	3.7196	23	9.83%	1.4144	5	2.09%
9	2.9510	11	4.70%	6.3974	14	5.86%
10	2.0632	14	5.98%	3.3087	14	5.86%
11	1.8936	21	8.97%	10.4966	9	3.77%
12	7.1864	5	2.14%	2.5976	22	9.21%
13	1.6002	8	3.42%	3.7223	15	6.28%
14	2.5464	10	4.27%	4.1795	15	6.28%
15	1.6974	15	6.41%	3.1510	14	5.86%
16	4.6125	16	6.84%	2.2192	21	8.79%
17	2.2067	22	9.40%	1.8757	7	2.93%
18	9.8569	8	3.42%			

The Multi-criteria Index Model's results are given in Table 3 for data from 2019 and 2020, respectively. The simulation's findings demonstrate that the 2020 data (during COVID-20) is significantly riskier than the 2019 data (pre-COVID-19). The risk level for 2019 data and 2020 data, respectively, ranges from 1.5564 to 9.8569 and from 2.1784 to 10.4966 based on Tables 2 and 3 utilizing the Elbow Method. Using the Multi-criteria Index Model, Tables 4 and 5 show that the risk level for the 2019 data and 2020 data, respectively, varies from 0.9068 to 9.8569 and from 1.4144 to 10.4966.

Findings from Technical Analysis

The annual rate of return (Ri), which is strongly reliant on the trading rules, was calculated using the MACD (12,26,9), MACD (4,22,3), MACD-ALMA (12,26,9), and MACD-ALMA (4,22,3). The annual rate of return (Ri) may have a positive or negative value that denotes a gain or loss, or it may have a "zero" value that denotes that there is no buying or selling point or that the stock window is below the necessary MACD window. Table 4 display the findings summary for the data from 2019 and 2020, respectively. The symbols "E1" and "MC3" stand for the Elbow Method's cluster 1 and the Multi-Criteria Index Model's cluster 3, respectively.According to Table 4, the MACD method outperforms the MACD-ALMA strategy in terms of the percentage of firms with positive Ri relative to the total number of companies for the 2019 data (pre-COVID-19). In comparison to MACD-ALMA (12,26,9) and MACD-ALMA (4,22,3), which have respective values of 4.27% (10/234) and 7.69% (18/234), it has MACD (12,26,9) and MACD (4,22,3) values of 73.50% (172/234) and 61.97% (145/234). The MACD method has a significant impact on performance during the COVID-19 condition (2020 data; see Table 5) and significantly lowers the percentage to 35.98% (86/239) and 34.31% (82/239) for MACD (12,26,9) and MACD (4,22,3), respectively.

Table 3. Technical analysis summary of 2019 and 2020 data.

2019 Data					**2020 Data**				
Method/ Cluster	**MACD (12,26,9) N(x,y,z)**	**MACD (4,22,3) N(x,y,z)**	**MACD-ALMA (12,26,9) N(x,y,z)**	**MACD-ALMA (4,22,3) N(x,y,z)**	**Method/ Cluster**	**MACD (12,26,9) N(x,y,z)**	**MACD (4,22,3) N(x,y,z)**	**MACD-ALMA (12,26,9) N(x,y,z)**	**MACD-ALMA (4,22,3) N(x,y,z)**
E1	45(32,13,0)	45(32,13,0)	45(0,15,30)	45(2,19,24)	E1	68(19,49,0)	(12,56,0)	8(3,30,35)	68(13,32,23)
E2	84(56,26,2)	84(44,39,1)	84(4,45,35)	84(4,58,22)	E2	19(10,9,0)	19(10,9,0)	19(0,7,12)	19(4,5,10)
E3	20(15,3,2)	20(12,7,1)	20(0,7,13)	20(1,9,10)	E3	30(14,16,0)	30(13,17,0)	30(3,13,14)	30(8,14,8)
E4	77(62,15,0)	77(50,26,1)	77(6,22,49)	77(11,30,36)	E4	66(23,42,1)	66(26,40,0)	66(7,26,33)	66(15,33,18)
E5	8(7,0,1)	8(7,0,1)	8(0,2,6)	8(0,1,7)	E5	9(5,1,3)	9(4,5,0)	9(0,1,8)	9(0,1,8)
Total	**234(172,57,5)**	**234(145,85,4)**	**234(10,91,133)**	**234(18,117,99)**	E6	47(15,30,2)	47(17,30,0)	47(3,18,26)	47(10,16,21)
MC1	10(6,4,0)	10(9,1,0)	10(0,5,5)	10(3,3,4)	**Total**	**239(86,147,6)**	**239(82,157,0)**	**239(16,95,128)**	**239(50,101,88)**
MC2	12(9,3,0)	12(9,3,0)	12(1,3,8)	12(2,5,5)	MC1	13(5,8,0)	13(9,4,0)	13(1,6,6)	13(4,4,5)
MC3	13(11,1,1)	13(10,3,0)	13(0,6,7)	13(0,9,4)	MC2	16(5,11,0)	16(4,12,0)	16(0,5,11)	16(3,7,6)
MC4	13(11,2,0)	13(8,5,0)	13(0,5,8)	13(0,7,6)	MC3	12(4,7,1)	12(4,8,0)	12(1,5,6)	12(3,5,4)
MC5	9(7,2,0)	9(3,6,0)	9(0,2,7)	9(2,2,5)	MC4	15(7,8,0)	15(7,8,0)	15(3,7,5)	15(5,9,1)
MC6	10(6,4,0)	10(5,5,0)	10(1,5,4)	10(1,5,4)	MC5	10(4,6,0)	10(0,10,0)	10(0,4,6)	10(1,6,3)
MC7	14(9,5,0)	14(7,7,0)	14(0,6,8)	14(0,7,7)	MC6	20(3,17,0)	20(5,15,0)	20(2,9,9)	20(6,8,6)
MC8	23(15,8,0)	23(18,5,0)	23(0,8,15)	23(0,9,14)	MC7	17(8,9,0)	17(8,9,0)	17(0,7,10)	17(4,4,9)
MC9	11(7,4,0)	11(5,6,0)	11(2,6,3)	11(2,7,2)	MC8	5(1,4,0)	5(2,3,0)	5(1,2,2)	5(3,1,1)
MC10	14(12,2,0)	14(7,7,0)	14(1,6,7)	14(1,11,2)	MC9	14(8,6,0)	14(6,8,0)	14(0,5,9)	14(2,5,7)
MC11	21(18,3,0)	21(13,7,1)	21(3,4,14)	21(3,8,10)	MC10	14(6,8,0)	14(2,12,0)	14(1,11,2)	14(3,9,2)
MC12	5(2,1,2)	5(2,2,1)	5(0,1,4)	5(1,1,3)	MC11	9(5,1,3)	9(4,5,0)	9(0,1,8)	9(0,1,8)
MC13	8(6,2,0)	8(6,2,0)	8(1,2,5)	8(0,4,4)	MC12	22(3,18,1)	22(7,15,0)	22(0,6,16)	22(3,8,11)
MC14	10(6,3,1)	10(7,2,1)	10(0,6,4)	10(0,7,3)	MC13	15(5,10,0)	15(7,8,0)	15(2,5,8)	15(3,9,3)
MC15	15(14,1,0)	15(8,7,0)	15(0,5,10)	15(1,6,8)	MC14	15(6,9,0)	15(4,11,0)	15(3,7,5)	15(3,10,2)
MC16	16(11,5,0)	16(10,6,0)	16(0,5,11)	16(2,6,8)	MC15	14(5,9,0)	14(3,11,0)	14(0,4,10)	14(3,4,7)
MC17	22(15,7,0)	22(11,11,0)	22(1,14,7)	22(0,19,3)	MC16	21(7,13,1)	21(6,15,0)	21(1,7,13)	21(2,8,11)
MC18	8(7,0,1)	8(7,0,1)	8(0,2,6)	8(0,1,7)	MC17	7(4,3,0)	7(4,3,0)	7(1,4,2)	7(2,3,2)
Total	**234(172,57,5)**	**234(145,85,4)**	**234(10,91,133)**	**234(18,117,99)**	**Total**	**239(86,147,6)**	**239(82,157,0)**	**239(16,95,128)**	**239(50,101,88)**

* N = total number of companies,
x = number of companies with positive *Ri*,
y = number of companies with negative *Ri*

z = number of companies with "zero" *Ri*
x = number of companies with positive *Ri,*
y = number of companies with negative *Ri*
z = number of companies with "zero" *Ri*

In spite of the COVID-19 scenario, which makes the market down and in a high-risk situation, the MACD-ALMA strategy unexpectedly increased to 6.69% (16/239) and 20.92% (50/239) for MACD-ALMA (12,26,9) and MACD-ALMA (4,22,3), respectively. According to the findings, regardless of the number of businesses with positive Ri, the MACD strategy performs well under pre-COVID-19 conditions and MACD-ALMA performs well under COVID-19 conditions. The outcome additionally demonstrates how much superior MACD (12,26,9) is than MACD (4,22,3). The MACD-ALMA (4,22,3) approach, however, performs better than the MACD-ALMA strategy in the MACD-ALMA scenario (12,26,9).

Portfolio Choice

The portfolio for each cluster was established using the findings from Tables 6 and 7. The selection is restricted to assets having a good R_i. Per cluster, the least risky assets will be chosen. A portfolio may have a maximum of 10 companies (2 >*N* >10), where *N* is the total number of assets. The quantity of assets or businesses in a portfolio is shown in Table 5 by cluster. "*N/A*" stands for "*N* of less than two companies."

Table 4. Number of assets/companies with a positive return in a portfolio per cluster

2019 Data					2020 Data				
Method/Cluster	**MACD (12,26,9)**	**MACD (4,22,3)**	**MACD-ALMA (12,26,9)**	**MACD-ALMA (4,22,3)**	**Method/Cluster**	**MACD (12,26,9)**	**MACD (4,22,3)**	**MACD-ALMA (12,26,9)**	**MACD-ALMA (4,22,3)**
E1	10	10	N/A	2	E1	10	10	3	10
E2	10	10	4	4	E2	10	10	N/A	4
E3	10	10	N/A	N/A	E3	10	10	3	8
E4	10	10	6	10	E4	10	10	7	10
E5	7	7	N/A	N/A	E5	5	4	N/A	N/A
MC1	6	9	N/A	3	E6	10	10	3	10
MC2	9	9	N/A	2	MC1	5	9	N/A	4
MC3	10	10	N/A	N/A	MC2	5	4	N/A	3
MC4	10	8	N/A	N/A	MC3	4	4	N/A	3
MC5	7	3	N/A	2	MC4	7	7	3	5
MC6	6	5	N/A	N/A	MC5	4	N/A	N/A	N/A
MC7	9	7	N/A	N/A	MC6	3	5	2	6
MC8	10	10	N/A	N/A	MC7	8	8	N/A	4
MC9	7	5	2	2	MC8	N/A	2	N/A	3
MC10	10	7	N/A	N/A	MC9	8	6	N/A	2
MC11	10	10	3	3	MC10	6	2	N/A	3
MC12	2	2	N/A	N/A	MC11	5	4	N/A	N/A
MC13	6	6	N/A	N/A	MC12	3	7	N/A	3
MC14	6	7	N/A	N/A	MC13	5	7	2	3
MC15	10	8	N/A	N/A	MC14	6	4	3	3
MC16	10	10	N/A	2	MC15	5	3	N/A	3
MC17	10	10	N/A	N/A	MC16	7	6	N/A	2
MC18	7	7	N/A	N/A	MC17	4	4	N/A	2

Given a predetermined expected return (R_P) for each portfolio, the mean-variance portfolio optimization model seeks to minimize the risk (σ_{p2}). Following that, the optimization model will recommend a weight for each company/asset in that portfolio. Additionally, this study sets the correlation parameter to zero because it considers that businesses are autonomous from one another. The investor determines R_P subjectively, hence this study compares R_P that produced varying minimum risk levels (σ_{p2}). The highest and minimum values in a portfolio per cluster serve as the upper and lower bounds of the R_P employed in this study. The global minimum risk of R_P will be determined by the minimum risk (σ_{p2}) between those R_P ranges. R_P at global minimum risk is shown in Table 5 for data from 2019 and 2020, respectively. Tables 6 and 7 displayed the weights per portfolio as a consequence.

Table 5. Portfolio optimization for 2019 and 2020 data.

2019 Data					2020 Data				
Return (R_P) in % at Global Minimum Risk					Return (R_P) in % at Global Minimum Risk				
Method/ Cluster	**MACD (12,26,9)**	**MACD (4,22,3)**	**MACD-ALMA (12,26,9)**	**MACD-ALMA (4,22,3)**	**Method/ Cluster**	**MACD (12,26,9)**	**MACD (4,22,3)**	**MACD-ALMA (12,26,9)**	**MACD-ALMA (4,22,3)**
E1	61.68	64.69	–	15.31	**E1**	52.83	29.79	21.72	55.10
E2	81.40	60.38	7.35	3.82	**E2**	103.83	88.58	–	37.29
E3	101.99	133.54	–	–	**E3**	75.70	91.46	28.85	86.16
E4	34.45	46.41	2.40	10.38	**E4**	59.29	46.48	33.36	56.62
E5	49.90	102.61	–	–	**E5**	68.53	68.31	–	–
MC1	25.12	59.57	–	5.98	**E6**	56.60	84.47	10.09	20.55
MC2	35.57	46.41	–	3.00	**MC1**	50.82	55.21	–	49.54
MC3	50.30	78.74	–	–	**MC2**	47.17	56.72	–	28.83
MC4	82.04	109.00	5.20	–	**MC3**	40.32	41.92	–	33.23
MC5	25.56	88.95	–	27.56	**MC4**	92.06	104.10	28.85	88.57
MC6	80.67	41.15	5.08	–	**MC5**	22.64	–	–	–
MC7	76.46	58.05	–	–	**MC6**	91.85	45.81	21.31	57.53
MC8	95.12	59.26	–	–	**MC7**	107.43	99.43	–	37.29
MC9	66.70	35.96	–	9.18	**MC8**	–	101.36	–	8.18
MC10	90.11	55.92	–	–	**MC9**	69.56	60.92	–	129.90
MC11	69.50	64.80	–	10.08	**MC10**	56.58	18.38	–	30.18
MC12	23.84	45.22	–	–	**MC11**	68.53	68.31	–	–
MC13	63.71	75.41	–	–	**MC12**	27.02	35.74	–	3.29
MC14	80.86	85.78	–	–	**MC13**	68.98	49.49	20.19	42.58
MC15	64.21	74.81	–	–	**MC14**	99.25	78.55	34.32	111.86
MC16	59.80	102.55	–	15.31	**MC15**	21.91	17.19	–	61.22
MC17	39.74	56.45	–	–	**MC16**	56.34	31.90	–	38.65
MC18	49.90	102.61	–	–	**MC17**	62.88	102.61	–	50.35

Table 6. Portfolio optimization weights for 2019 data.

Cluster	Strategy	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}
E1	MACD (12,26,9)	0.1082	0.1068	0.1059	0.1026	0.1004	0.0991	0.1009	0.0980	0.0901	0.0881
	MACD (4,22,3)	0.1105	0.1101	0.1071	0.1059	0.1034	0.1004	0.0916	0.0908	0.0906	0.0897
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.5400	0.4600	–	–	–	–	–	–	–	–
E2	MACD (12,26,9)	0.1038	0.1026	0.1004	0.0999	0.1001	0.0994	0.1002	0.0985	0.0980	0.0971
	MACD (4,22,3)	0.1070	0.1067	0.1054	0.1010	0.1003	0.0952	0.0963	0.0984	0.0952	0.0943
	MACD-ALMA (12,26,9)	0.3321	0.2971	0.1892	0.1816	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.3561	0.2855	0.1842	0.1742	–	–	–	–	–	–
E3	MACD (12,26,9)	0.1210	0.1181	0.1091	0.1043	0.1036	0.1004	0.0923	0.0852	0.0841	0.0819
	MACD (4,22,3)	0.1208	0.1181	0.1084	0.1036	0.1035	0.1001	0.0952	0.0848	0.0835	0.0819
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
E4	MACD (12,26,9)	0.3730	0.1027	0.0933	0.0867	0.0830	0.0651	0.0561	0.0529	0.0481	0.0391
	MACD (4,22,3)	0.1486	0.1398	0.1266	0.1246	0.0944	0.0816	0.0801	0.0745	0.0726	0.0572
	MACD-ALMA (12,26,9)	0.3625	0.1661	0.1242	0.1243	0.1198	0.1030				
	MACD-ALMA (4,22,3)	0.1824	0.1659	0.1234	0.1005	0.0890	0.0843	0.0824	0.0614	0.0561	0.0547
E5	MACD (12,26,9)	0.1731	0.1685	0.1629	0.1532	0.1441	0.1435	0.0547	–	–	–
	MACD (4,22,3)	0.1737	0.1682	0.1629	0.1532	0.1444	0.1431	0.0544	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–

MC1	MACD (12,26,9)	0.1825	0.1689	0.1674	0.1619	0.1604	0.1590				
	MACD (4,22,3)	0.1193	0.1166	0.1163	0.1149	0.1094	0.1071	0.1064	0.1054	0.1044	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.3534	0.3295	0.3171	–	–	–	–	–	–	–
MC2	MACD (12,26,9)	0.3867	0.1064	0.0978	0.0909	0.0871	0.0675	0.0582	0.0556	0.0499	–
	MACD (4,22,3)	0.1598	0.1462	0.1362	0.1301	0.1013	0.0874	0.0830	0.0796	0.0763	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.5200	0.4800	–	–	–	–	–	–	–	–
MC3	MACD (12,26,9)	0.1066	0.1050	0.1044	0.1023	0.1010	0.1000	0.0970	0.0949	0.0936	0.0952
	MACD (4,22,3)	0.1059	0.1020	0.1066	0.1017	0.1015	0.1009	0.1003	0.0950	0.0952	0.0909
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC4	MACD (12,26,9)	0.1185	0.1137	0.1134	0.1098	0.1005	0.0928	0.0915	0.0904	0.0854	0.0839
	MACD (4,22,3)	0.1425	0.1358	0.1363	0.1316	0.1248	0.1117	0.1096	0.1076	–	–
	MACD-ALMA (12,26,9)	0.5100	0.4900	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC5	MACD (12,26,9)	0.1659	0.1485	0.1413	0.1411	0.1382	0.1370	0.1279	–	–	–
	MACD (4,22,3)	0.3692	0.3198	0.3110	–	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.5600	0.4400	–	–	–	–	–	–	–	–
MC6	MACD (12,26,9)	0.1787	0.1670	0.1677	0.1657	0.1615	0.1594	0.0000	0.0000	0.0000	0.0000
	MACD (4,22,3)	0.2088	0.2110	0.1986	0.1941	0.1875	0.0000	0.0000	0.0000	0.0000	0.0000
	MACD-ALMA (12,26,9)	0.3383	0.3357	0.3260	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC7	MACD (12,26,9)	0.1176	0.1174	0.1155	0.1149	0.1117	0.1069	0.1061	0.1061	0.1038	–
	MACD (4,22,3)	0.1503	0.1481	0.1456	0.1455	0.1391	0.1366	0.1348	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC8	MACD (12,26,9)	0.1041	0.1017	0.1045	0.1010	0.1012	0.1016	0.1002	0.0980	0.0925	0.0951
	MACD (4,22,3)	0.1015	0.1037	0.1024	0.1012	0.1007	0.0994	0.0979	0.0961	0.0977	0.0995
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC9	MACD (12,26,9)	0.1523	0.1488	0.1474	0.1425	0.1415	0.1343	0.1331	–	–	–
	MACD (4,22,3)	0.2097	0.2020	0.2004	0.1966	0.1913	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.5100	0.4900	–	–	–	–	–	–	–	–
MC10	MACD (12,26,9)	0.1061	0.1057	0.1017	0.1035	0.1002	0.0986	0.0956	0.0971	0.0945	0.0969
	MACD (4,22,3)	0.1485	0.1484	0.1461	0.1425	0.1404	0.1397	0.1344	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC11	MACD (12,26,9)	0.1048	0.1044	0.1028	0.1028	0.1003	0.0986	0.0990	0.0967	0.0959	0.0945
	MACD (4,22,3)	0.1055	0.1060	0.1030	0.1050	0.1008	0.0968	0.0971	0.0966	0.0960	0.0933
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.3509	0.3338	0.3153	–	–	–	–	–	–	–
MC12	MACD (12,26,9)	0.5100	0.4900	–	–	–	–	–	–	–	–
	MACD (4,22,3)	0.5100	0.4900	–	–	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC13	MACD (12,26,9)	0.1725	0.1707	0.1706	0.1678	0.1613	0.1571	–	–	–	–
	MACD (4,22,3)	0.1732	0.1729	0.1692	0.1656	0.1603	0.1587	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC14	MACD (12,26,9)	0.1695	0.1723	0.1710	0.1688	0.1647	0.1537	–	–	–	–
	MACD (4,22,3)	0.1476	0.1469	0.1423	0.1418	0.1434	0.1377	0.1403	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC15	MACD (12,26,9)	0.1034	0.1023	0.1018	0.1014	0.1008	0.1000	0.0989	0.0979	0.0969	0.0966
	MACD (4,22,3)	0.1309	0.1263	0.1255	0.1278	0.1264	0.1206	0.1227	0.1198		
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC16	MACD (12,26,9)	0.1183	0.1137	0.1132	0.1072	0.1057	0.0959	0.0909	0.0874	0.0853	0.0825
	MACD (4,22,3)	0.1246	0.1230	0.1147	0.1012	0.0951	0.0930	0.0937	0.0896	0.0848	0.0804
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.5400	0.4600	–	–	–	–	–	–	–	–
MC17	MACD (12,26,9)	0.1013	0.1037	0.0999	0.1029	0.0998	0.0985	0.0977	0.1009	0.0987	0.0967
	MACD (4,22,3)	0.1033	0.1042	0.1058	0.1025	0.1018	0.1002	0.0981	0.0966	0.0958	0.0917
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC18	MACD (12,26,9)	0.1731	0.1685	0.1629	0.1532	0.1441	0.1435	0.0547	–	–	–
	MACD (4,22,3)	0.1737	0.1682	0.1629	0.1532	0.1444	0.1431	0.0544	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–

Table 7. Portfolio optimization weights for 2020 data.

Cluster	Strategy	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}
E1	MACD (12,26,9)	0.1176	0.1174	0.1095	0.0986	0.0970	0.0966	0.0967	0.0918	0.0885	0.0862
	MACD (4,22,3)	0.1168	0.1168	0.1070	0.1065	0.0988	0.0977	0.0968	0.0889	0.0884	0.0824
	MACD-ALMA (12,26,9)	0.3847	0.3488	0.2665	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.1158	0.1127	0.1121	0.1048	0.1019	0.1000	0.0951	0.0894	0.0877	0.0804
E2	MACD (12,26,9)	0.1206	0.1175	0.1112	0.1046	0.1010	0.0988	0.0948	0.0897	0.0860	0.0757
	MACD (4,22,3)	0.1215	0.1156	0.1091	0.1042	0.1038	0.1000	0.0934	0.0902	0.0874	0.0749
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.2610	0.2568	0.2490	0.2331	–	–	–	–	–	–
E3	MACD (12,26,9)	0.1146	0.1087	0.1070	0.1071	0.1071	0.1018	0.0995	0.0896	0.0837	0.0810
	MACD (4,22,3)	0.1159	0.1140	0.1056	0.1029	0.1016	0.0982	0.0959	0.0940	0.0893	0.0826
	MACD-ALMA (12,26,9)	0.3570	0.3465	0.2965	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.1539	0.1380	0.1369	0.1362	0.1163	0.1163	0.1077	0.0947	–	–
E4	MACD (12,26,9)	0.1121	0.1067	0.1051	0.1054	0.0985	0.0983	0.0953	0.0967	0.0914	0.0906
	MACD (4,22,3)	0.1082	0.1033	0.1028	0.1025	0.1006	0.1003	0.1004	0.0949	0.0960	0.0910
	MACD-ALMA (12,26,9)	0.1749	0.1741	0.1401	0.1401	0.1400	0.1234	0.1075	–	–	–
	MACD-ALMA (4,22,3)	0.1145	0.1141	0.1140	0.1026	0.1006	0.1000	0.0921	0.0909	0.0874	0.0837
E5	MACD (12,26,9)	0.2378	0.2339	0.1999	0.1812	0.1471	–	–	–	–	–
	MACD (4,22,3)	0.2959	0.2684	0.2515	0.1842	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
E6	MACD (12,26,9)	0.2078	0.1168	0.1049	0.0875	0.0868	0.0829	0.0801	0.0800	0.0789	0.0744
	MACD (4,22,3)	0.2001	0.1404	0.1042	0.1006	0.0847	0.0841	0.0763	0.0752	0.0677	0.0666
	MACD-ALMA (12,26,9)	0.5186	0.2929	0.1886	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.1716	0.1517	0.1465	0.1202	0.0901	0.0764	0.0676	0.0626	0.0581	0.0550
MC1	MACD (12,26,9)	0.2106	0.2011	0.2012	0.2025	0.1846	–	–	–	–	–
	MACD (4,22,3)	0.1180	0.1130	0.1144	0.1123	0.1115	0.1108	0.1113	0.1051	0.1035	
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.2622	0.2527	0.2502	0.2349	–	–	–	–	–	–
MC2	MACD (12,26,9)	0.2070	0.2074	0.1998	0.1931	0.1927					
	MACD (4,22,3)	0.2591	0.2531	0.2461	0.2417	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.3424	0.3308	0.3268	–	–	–	–	–	–	–
MC3	MACD (12,26,9)	0.2704	0.2582	0.2485	0.2229	–	–	–	–	–	–
	MACD (4,22,3)	0.2708	0.2660	0.2319	0.2313	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.3512	0.3472	0.3016	–	–	–	–	–	–	–
MC4	MACD (12,26,9)	0.1506	0.1483	0.1486	0.1488	0.1414	0.1382	0.1242	–	–	–
	MACD (4,22,3)	0.1532	0.1492	0.1483	0.1421	0.1398	0.1372	0.1302	–	–	–
	MACD-ALMA (12,26,9)	0.3570	0.3465	0.2965	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.2138	0.2120	0.2110	0.1815	0.1816	–	–	–	–	–
MC5	MACD (12,26,9)	0.2583	0.2531	0.2477	0.2409	–	–	–	–	–	–
	MACD (4,22,3)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC6	MACD (12,26,9)	0.3417	0.3406	0.3178	–	–	–	–	–	–	–
	MACD (4,22,3)	0.2117	0.2106	0.1935	0.1929	0.1912	–	–	–	–	–
	MACD-ALMA (12,26,9)	0.5300	0.4700	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.1789	0.1745	0.1735	0.1624	0.1576	0.1531	–	–	–	–
MC7	MACD (12,26,9)	0.1436	0.1377	0.1323	0.1313	0.1242	0.1159	0.1145	0.1004	–	–
	MACD (4,22,3)	0.1424	0.1361	0.1358	0.1308	0.1229	0.1180	0.1150	0.0991	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.2610	0.2568	0.2490	0.2331	–	–	–	–	–	–
MC8	MACD (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD (4,22,3)	0.5900	0.4100	–	–	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.3689	0.3200	0.3111	–	–	–	–	–	–	–
MC9	MACD (12,26,9)	0.1398	0.1363	0.1310	0.1298	0.1236	0.1194	0.1117	0.1085	–	–
	MACD (4,22,3)	0.1959	0.1755	0.1676	0.1582	0.1553	0.1476	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.5300	0.4700	–	–	–	–	–	–	–	–
MC10	MACD (12,26,9)	0.1747	0.1696	0.1656	0.1641	0.1653	0.1606	–	–	–	–
	MACD (4,22,3)	0.5100	0.4900	–	–	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.3337	0.3343	0.3320	–	–	–	–	–	–	–
MC11	MACD (12,26,9)	0.2378	0.2339	0.1999	0.1812	0.1471	–	–	–	–	–
	MACD (4,22,3)	0.2959	0.2684	0.2515	0.1842	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	–	–	–	–	–	–	–	–	–	–
MC12	MACD (12,26,9)	0.3476	0.3320	0.3205	–	–	–	–	–	–	–
	MACD (4,22,3)	0.1539	0.1446	0.1451	0.1440	0.1445	0.1341	0.1339	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.3588	0.3291	0.3121	–	–	–	–	–	–	–
MC13	MACD (12,26,9)	0.2086	0.2048	0.1991	0.1954	0.1922	–	–	–	–	–

	MACD (4,22,3)	0.1455	0.1444	0.1446	0.1414	0.1446	0.1409	0.1386	–	–	–
	MACD-ALMA (12,26,9)	0.5000	0.5000	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.3379	0.3345	0.3276	–	–	–	–	–	–	–
MC14	MACD (12,26,9)	0.1707	0.1742	0.1675	0.1640	0.1623	0.1612	–	–	–	–
	MACD (4,22,3)	0.2532	0.2530	0.2523	0.2415	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	0.3372	0.3327	0.3301	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.3399	0.3296	0.3305	–	–	–	–	–	–	–
MC15	MACD (12,26,9)	0.2060	0.2034	0.2003	0.1991	0.1911	–	–	–	–	–
	MACD (4,22,3)	0.3406	0.3437	0.3157	–	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.3477	0.3289	0.3234							
MC16	MACD (12,26,9)	0.1583	0.1514	0.1513	0.1492	0.1405	0.1303	0.1191	–	–	–
	MACD (4,22,3)	0.1858	0.1849	0.1650	0.1629	0.1530	0.1483	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.5300	0.4700	–	–	–	–	–	–	–	–
MC17	MACD (12,26,9)	0.2921	0.2627	0.2234	0.2219	–	–	–	–	–	–
	MACD (4,22,3)	0.2784	0.2694	0.2269	0.2253	–	–	–	–	–	–
	MACD-ALMA (12,26,9)	–	–	–	–	–	–	–	–	–	–
	MACD-ALMA (4,22,3)	0.5700	0.4300	–	–	–	–	–	–	–	–

According to Table 6 (2019 data), the R_P at global minimal risk ranges for the MACD (12,26,9), MACD (4,22,3), MACD-ALMA (12,26,9), and MACD-ALMA (4,22,3), respectively, are 23.84%–101.99%, 35.96%–133.54%, 2.40%–7.35%, and 3.00%–27.56%. The ranges are 21.91%-107.43%, 17.19%-104.10%, 10.09%-34.32%, and 3.29%-129.90%, according to Table 7 (2020 data). According to the results of the MACD strategy, the E3 portfolio has the highest R_P (101.99% and 133.54%) for the 2019 data, while MC7 dominates MACD (12,26,9) and MC4 for MACD (4,22,3) for the 2020 data. When using 2020 data, MC9 with MACD-ALMA (4,22,3) outperforms other techniques. This demonstrates how the MACD-ALMA approach was able to manage a high-risk market situation while still producing the highest possible return. In addition, clustering using the Elbow Method outperforms well in pre-COVID-19 settings (2019 data) while the Multi-criteria Index Model performs well in COVID-19 conditions (2020 data)

5. Conclusions and Future Works

A major global health disaster has been caused by the COVID-19 pandemic. Global pandemic COVID-19 has a significant negative impact on the Philippine stock market. In the damaged market, retail investors are still looking for outstanding investments. In this study, the potential portfolio based on annual average risk is determined using the K-means clustering technique. The Elbow Method and the suggested Multi-criteria Index Model were used to estimate the ideal cluster size. The Silhouette Score, the Calinski-Harabasz Score, and the Davie-Bouldin Score were merged in the Multi-criteria Index Model. In all, 234 assets/companies for 2019 (pre-COVID-19 situation) and 239 assets/companies for 2020 (during COVID-19 condition) were utilised. The performance of MACD and the hybrid method (MACD-ALMA) under both typical and COVID-19 settings was compared and examined. The findings indicate that the COVID-19 condition is considerably riskier than the pre-COVID-19 state. The COVID-19 has a significant impact on the Philippine market environment. The MACD approach outperforms the MACD-ALMA strategy in terms of assets with positive annual rates of return. No matter how many assets have a positive annual rate of return, the MACD performs well in the pre-COVID-19 state while the MACD-ALMA performs well in the COVID-19 condition. The outcomes further demonstrate that utilizing the MACD in the pre-COVID-19 condition and MACD-ALMA in the COVID-19 condition, the maximum expected return (R_P) may be attained. The MACD-ALMA exhibits a benefit in high-risk market circumstances and can also offer maximal R_P. In pre-COVID-19 settings, the Elbow Method performs well for clustering, while the Multi-criteria Index Model well suited during-COVID-19 conditions.

Theoretical Contribution

In order to use the proposed Multi-criteria Index Model and the K-means Algorithm to determine the ideal number of clusters, this work contributes theoretically to the body of literature already in existence. In cluster determination, it includes the three well-known model criteria. This Multi-criteria Index model has the highest predicted return, making it ideal for the COVID-19 condition in 2020. The clustering technique will assist the investor in deciding which portfolio to concentrate on in order to achieve the best return. In addition, compared to the traditional MACD (12, 26,9) during-COVID-19 situation (2020), where the market is at high risk, the hybrid MACD-ALMA with a window of (12,26,9) and (4,22,3) (investment strategy) offers a benefit. since the buying/selling transaction points were more than the usual approach (See Figure 1)

Practical Applications

For practitioners, decision-makers, and managers, this paper has ramifications. They can create a cluster trading strategy that enables them to establish a diversified portfolio using technical analysis with the use of K-means and technical analysis. This article outlines a step-by-step process for evaluating, clustering, choosing, and optimizing portfolios while taking risk and return into account. Engineers, managers, institutional investors, and retail investors can all use this method to choose the best stock portfolios and will profit from diversity in this study since it will help to shield an investor's portfolio from systematic risk, which could expose the portfolio to losses.

Limitations and Future Works

In order to verify and validate the effectiveness of the suggested strategy, this research restricts the evaluation in using prior data. Future study may address return estimation using forecasting tools and approaches. Other evolutionary optimization techniques can be used in conjunction with Holt-Winters, neural networks, or other forecasting methodologies.

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Biographies

Maricar M. Navarro is a Professional Industrial Engineer (PIE) awarded by the Philippine Institute of Industrial Engineers (PIIE) and an ASEAN Engineer (AE) awarded by the ASEAN Federation of Engineering Organizations. She is an Assistant Professor IV in the Department of Industrial Engineering and a Professor of the Graduate School Program at the Technological Institute of the Philippines-Quezon City. Engr. Navarro has done research projects that deal on the optimization of production, warehouse operations, and service operations. Her research interests include manufacturing, simulation, optimization, facility layout, and design, She is an active member and Professional Industrial Engineer of the Philippine Institute of Industrial Engineers (PIIE) organization in the Philippines.

Bryan B. Navarro is an Assistant Professor in the Department of Electrical Engineering at the Technological Institute of the Philippines and is currently a Staff Engineer at Manila Electric Company (MERALCO). He earned B.S. in Electrical Engineering from the Technological Institute of the Philippines, Quezon City, Master of Science in Electrical Engineering major in Power Systems from the University of the Philippines, Diliman, Quezon City. He has published journal and conference papers. He is an active member of the Institute of Integrated Electrical Engineers of the Philippines (IIEE).