CHAPTER 4

PORTFOLIO DESIGN USING MEAN-VARIANCE OPTIMIZATION AND HIERARCHICAL RISK PARITY APPROACH

Introduction

The design of optimized portfolios has remained a research topic of broad and intense interest among researchers of quantitative and statistical finance for a long time. An optimum portfolio allocates the weights to a set of capital assets in a way that optimizes the return and risk of those assets. Markowitz in his seminal work proposed the *mean-variance optimization* approach which is based on the mean and covariance matrix of returns (Markowitz, 1952). The *mean-variance portfolio* (MVP) design works on an algorithm, known as the *critical line algorithm* (CLA). The CLA algorithm, despite the elegance of its theoretical framework, has some major limitations. One of the major problems is the adverse effects of the estimation errors in its expected returns and covariance matrix on the performance of the portfolio. Since it is extremely challenging to accurately estimate the expected returns of an asset from its historical prices, it is a popular practice to use either a minimum variance portfolio or an optimized risk portfolio with the maximum Sharpe ratio as better proxies for the expected returns. However, due to the inherent complexity, several factors have been used to explain the expected returns.

The *hierarchical risk parity* (HRP) algorithm attempts to address three major shortcomings of quadratic optimization methods which are particularly relevant to the CLA used in the MVP approach to portfolio design (de Prado, 2016). These problems are instability, concentration, and underperformance. Unlike the CLA, the HRP algorithm does not require the covariance matrix of return values to be invertible. Hence, the HRP portfolios can deliver good results even if the covariance matrices are ill-degenerated or singular, which is an impossibility for a quadratic optimizer like CLA. Interestingly, even though MVP's objective is to minimize the variance, HRP is proven to have a lower probability of yielding lower out-of-sample variance than MVP. Given the fact that future returns cannot be forecasted with sufficient accuracy, many researchers have proposed risk-based asset allocation using the covariance matrix of the returns (Jurezenko, 2015). However, this approach brings in another problem of instability that arises because the quadratic programming methods require the inversion of a covariance matrix whose all eigenvalues must be positive. HRP is a new portfolio design method that addresses the pitfalls of the quadratic optimization-based MVP approach using techniques of graph theory and machine learning (de Prado, 2016). This method exploits the features of the covariance matrix without the requirement of its invertibility.

This chapter presents an algorithmic approach for building efficient portfolios by selecting stocks from fourteen sectors listed on the National Stock Exchange (NSE) of India. Based on the report of the NSE published on December 31, 2020, the top ten stocks with the highest free-float market capitalization from thirteen sectors and the 50 stocks included in the NIFTY 50 are first identified (NSE Website). Portfolios are built using the MVP and the HRP algorithms using the historical prices of the stocks from January 1, 2016, to December 31, 2020. The portfolios are backtested on the training data of the stock prices from January 1, 2016, to December 31, 2020, and on the test data from January 1, 2021, to December 31, 2021. The portfolios are evaluated based on their cumulative returns and Sharpe ratios over the training and test periods.

The main contribution of the current work is threefold. First, it presents two different methods of designing robust portfolios, the MVP and the HRP methods. These portfolio design approaches are applied to fourteen sectors of stocks of the NSE including the NIFTY 50 stocks. The results may serve as a guide to investors in the stock market. Second, a backtesting method is proposed for evaluating the performances of the algorithms based on the cumulative daily returns yielded by the portfolios. Since the backtesting is done both on the training and the test data of the stock prices, it can identify the better performing method on both training and test samples. Hence, a robust framework for evaluating different portfolios is demonstrated. Third, the returns of the portfolios on the sectors on the test data highlight the current profitability of investment and the volatilities of the sectors studied in this work. This information can be useful for investors.

The chapter is organized as follows. The section titled *Related Work* presents some of the existing portfolio design approaches proposed in the literature. Next, the section titled *Methodology* presents the research approach followed in the current work. The section titled *Results* presents an extensive set of results and a detailed analysis of the observations. Finally, the chapter is concluded in the section titled *Conclusion*.

Related Work

Portfolio design and optimization is a challenging problem for which numerous solutions and approaches have been proposed by researchers. Portfolio design and optimization is a challenging problem that has attracted considerable attention from researchers. Numerous approaches have been proposed to solve this complex problem involving robust stock price prediction and the formation of the optimized combination of stocks to maximize the return on investment. *Machine learning models* have been extensively used by researchers in predicting future stock prices (Carta et al., 2021; Chatterjee et al., 2021; Mehtab & Sen, 2021; Mehtab & Sen, 2020a; Mehtab & Sen, 2019; Mehtab et al., 2021; Sarmento & Horta, 2020; Sen, J., 2018a; Sen & Datta Chaudhuri, 2017a). The prediction accuracies of the models are found to have been improved by the use of *deep learning architectures and algorithms* (Chatterjee et al., 2021; Chen et al, 2018; Chong et al., 2017; Mehtab & Sen, 2022b; Mehtab & Sen, 2021; Mehtab & Sen, 2020a; Mehtab & Sen, 2020b; Mehtab & Sen, 2019; Mehtab et al., 2021; Mehtab, et al., 2020; Sen, 2018a; Sen & Mehtab, 2021a; Sen & Mehtab, 2021b; Sen et al., 2021a; Sen et al., 2021b; Sen et al., 2021i; Sen et al., 2020; Sen & Mehtab, 2022b; Thormann et al., 2021). Several approaches to *text mining* have been effectively applied on social media and the web to improve prediction accuracies even further (Li & Pan, 2022; Mehtab & Sen, 2019; Thormann et al., 2021; Zhang et al., 2021). Among the other alternative approaches for stock price prediction, *time series decomposition-based statistical and econometric approaches* are also quite popular (Chatterjee et al., 2021; Cheng et al., 2018; Sen, 2022a; Sen, 2018b; Sen, 2017; Sen & Datta Chaudhuri, 2018; Sen & Datta Chaudhuri, 2017b; Sen & Datta Chaudhuri, 2016a; Sen & Datta Chaudhuri, 2016b; Sen & Datta Chaudhuri, 2016c; Sen & Datta Chaudhuri, 2016d; Sen & Datta Chaudhuri, 2015). For estimating future volatility and risk of stock portfolios the use of several variants of GARCH has been proposed in some works (Sen et al., 2021d). Over the last few years, *reinforcement learning* has been used in robust and accurate prediction of stock prices and portfolio design (Brim, 2020; Fengqian & Chao, 2020; Kim et al., 2022; Kim & Kim, 2019; Lei et al., 2020; Lu et al., 2021; Park & Lee, 2021).

The classical *mean-variance optimization* approach is the most well-known method for portfolio optimization (Sen & Mehtab, 2022a; Sen et al., 2021e; Sen et al., 2021g; Sen et al., 2021h). Several alternatives to the mean-variance approach to portfolio optimization have also been proposed by some researchers. Notable among these methods are *multiobjective optimization* (Wang et al, 2022; Zheng & Zheng, 2022), *eigen portfolios* using *principal component analysis* (Sen & Dutta, 2022b; Sen & Mehtab, 2022), *risk parity-based methods* (Sen & Dutta, 2022a; Sen & Dutta, 2022c; Sen & Dutta, 2021; Sen et al., 2021c; Sen et al., 2021f), and *swarm intelligence-based approaches* (Corazza et al., 2021; Thakkar & Chaudhuri, 2021). The use of *genetic algorithms* (Kaucic et al., 2019), *fuzzy sets* (Karimi et al., 2022), *prospect theory* (Li et al., 2021), and *quantum evolutionary algorithms* (Chou et al., 2021) are also proposed in the literature.

As an alternative to portfolios with multiple stocks, *pair-trading portfolios* involving two stocks have been also proposed by researchers in the literature (Flori & Regoli, 2021; Gupta & Chatterjee, 2020; Ramos-Requena et al., 2021, Sen, 2022b).

The current work presents two approaches to portfolio design, the MVP and the HRP method to introduce robustness while maximizing the portfolio returns for fourteen sectors of stocks listed on the NSE of India. Based on the past prices of the stocks from January 1, 2016, to December 2020, portfolios are designed for each sector using the MVP and the HRP methods. The backtesting of the portfolios is carried out on the in-sample data (i.e., the training data) of stock prices from January 1, 2016, to December 31, 2020, and on the out-of-sample data (i.e., the test data) from January 1, 2021, to December 31, 2021. The portfolios are finally evaluated on their cumulative returns and Sharpe Ratios on both training and the test data. The cumulative returns yielded by the portfolios reveal the current profitability of the sectors. Since there are no such studies done so far in this direction, the results of this work are expected to be useful to financial analysts and investors interested in the Indian stock market.

Methodology

This section discusses the methodology followed and the steps involved in designing the MVP and HRP portfolios. The methodology involves in following seven steps.

(i) *Choice of the sectors for analysis:* Twelve important sectors are first selected from those listed in the NSE so that they exhibit diversity in the Indian stock market. The chosen twelve sectors are: (i) *auto*, (ii) *banking*, (iii) *consumer durable*, (iv) *fast moving consumer goods* (FMCG), (v) *information technology* (IT), (vi) *pharma*, (vii) *realty*, (viii) *metal*, (ix) *oil & gas*, (x) *media*, (xi) *private banks*, and (xii) *PSU banks*. The monthly reports of the NSE identify the ten stocks with the maximum free-float capitalization from each sector. In this work, the report published on

December 31, 2020, is used for identifying the ten stocks from each of the thirteen sectors and the NIFTY 50 stocks (NSE Website).

(ii) ***Data Extraction from the web:*** From the Yahoo Finance website, the historical daily prices of the stocks are extracted from January 1, 2016, to December 31, 2021, using the *DataReader* function of the *pandas_datareader* module of Python. The portfolios are built on the records from January 1, 2016, to December 31, 2020. The portfolios are tested on the records from January 1, 2021, to December 31, 2021. The *close* values of the stocks are used in designing the portfolios.

(iii) ***Derivation of the return and volatility of portfolios:*** This step involves the computation of the daily return values for the stocks in the fourteen sectors (including the NIFTY 50 stocks). The daily return values reflect the percentage change in the *close* values for successive days. For computing the daily returns, the *pct_change* function of Python is used. Using the daily returns, the daily volatility values are obtained by computing the square root of the variance of the daily return values. Assuming that there are 250 operational days in a calendar year, the annual volatility values for the stocks are derived by multiplying the daily volatilities by a square root of 250. Next, the covariance matrix of the daily returns of the stocks for a sector is computed. Based on the covariance matrix of the returns of the stocks, the portfolio annual return and annual risk for a sector are computed. If a portfolio involves n stocks and if w_i represents the weight assigned to the stock i which has an annual return of R_i, then the annual return (R) of the portfolio is given by (1).

$$R = \sum_{i=1}^{n} w_i * R_i \tag{1}$$

The variance (V) of a portfolio is given by (2).

$$V = \sum_{i=1}^{n} w_i s_i^2 + 2 * \sum_{i,j} w_i * w_j * cov(i,j) \tag{2}$$

In (2) s_i represents the annual standard deviation of the stock i, and $cov\ (i,j)$ is the covariance between the returns of stocks i and j. The square root of V, i.e., the standard deviation of the annual return indicates the annual risk associated with the portfolio.

(iv) ***Designing the MVP portfolios:*** At this step, the *minimum-variance* portfolio for each sector is designed first. The portfolio with the minimum risk is referred to as the minimum-variance portfolio. The *efficient frontier* for a given sector represents the contour of many portfolios in which the returns and the risks are plotted along the *y*-axis and the *x*-axis, respectively. The points on an efficient frontier represent portfolios that yield the highest return for a specified risk level. As the risk is depicted on the horizontal axis, the left-most point on the efficient frontier is the minimum risk portfolio. However, due to its very low return, the minimum risk portfolios are rarely adopted in practice, and a trade-off between the risk and return is done based on a parameter known as the *Sharpe ratio* (SR). SR of a portfolio is the ratio of the difference between its return and that of the risk-free one, to its standard deviation. Essentially, SR optimizes the return and the risk by yielding a substantially higher return with a very marginal increase in the risk. The MVP portfolio design approach is based on maximizing the Sharpe ratio, and as mentioned earlier, the algorithm used in designing this portfolio is referred to as CLA. The MVP portfolios for all the fourteen sectors including NIFTY 50 are built.

(v) ***Designing the HRP portfolios:*** At this step, the HRP portfolios are designed for each sector. The HRP portfolio design involves three phases: (a) *tree clustering*, (b) *quasi-diagonal*ization, and (c) *recursive bisection*. These steps are described in the following.

Tree Clustering: The tree clustering used in the HRP algorithm is an agglomerative clustering algorithm. To design the agglomerative clustering algorithm, a hierarchy class is first created in Python. The hierarchy class contains a dendrogram method that received the value returned by a method called linkage defined in the same class. The linkage method received the dataset after pre-processing and transformation and computes the minimum distances between stocks based on their return values. There are several options for computing the distance. However, the *ward distance* is a good choice since it minimizes the variances in the distance between two clusters in the presence of high volatility in the stock return values. In this work, the ward distance has been used as a method to compute the distance between two clusters. The linkage method performs the clustering and returns a list of the clusters formed. The computation of linkages is followed by the visualization of the clusters through a dendrogram. In the dendrogram, the leaves represent the individual stocks, while the root depicts the cluster containing all the stocks. The distance between each cluster formed is represented along the y-axis, longer arms indicate less correlated clusters.

Quasi-Diagonalization: In this step, the rows, and the columns of the covariance matrix of the return values of the stocks are reorganized in such a way that the largest values lie along the diagonal. Without requiring a change in the basis of the covariance matrix, the quasi-diagonalization yields a very important property of the matrix – the assets (i.e., stocks) with similar return values are placed closer, while disparate assets are put at a far distance. The working principles of the algorithm are as follows. Since each row of the linkage matrix merges two branches into one, the clusters (C_{N-1}, 1) and (C_{N-2}, 2) are replaced with their constituents recursively, until there are no more clusters to merge. This recursive merging of clusters preserves the original order of the clusters (Baily & de Prado, 2012). The output of the algorithm is a sorted list of the original stocks.

Recursive Bisection: The quasi-diagonalization step transforms the covariance matrix into a quasi-diagonal form. It is proven mathematically that the allocation of weights to the assets in an inverse ratio to their variance is an optimal allocation for a quasi-diagonal matrix (Baily & de Prado, 2012). This allocation may be done in two different ways. In the bottom-up approach, the variance of a contiguous subset of stocks is computed as the variance of an inverse-variance allocation of the composite cluster. In the alternative top-down approach, the allocation among two adjacent subsets of stocks is done in inverse proportion to their aggregated variances. In the current implementation, the top-down approach is followed. A python function computeIVP computes the inverse-variance portfolio based on the computed variances of two clusters as its given input. The variance of a cluster is computed using another Python function called clusterVar. The output of the clusterVar function is used as the input to another Python function called recBisect which computes the final weights allocated to the individual stocks based on the recursive bisection algorithm.

(vi) ***Computation of the portfolio cumulative returns:*** In the final step, based on the weights allocated by the MVP and the HRP portfolios, the cumulative return values for the training and the test samples are computed. The weighted sum of the daily return values of the stocks in a given portfolio is used to compute the portfolio returns. The cumulative returns of the two portfolios for the sectors are then computed.

Experimental Results

This section presents the detailed results and analysis of the portfolios. The sectors selected for the study are (i) *auto*, (ii) *banking*, (iii) *consumer durables*, (iv) FMCG, (v) IT, (vi) *pharma*, (vii) *realty*, (viii) *metal*, (ix) *oil & gas*, (x) *media*, (xi) *private banks*, (xii) *PSU banks*, (xiii) *financial services*, and (xiv) NIFTY50. The portfolios are implemented using Python 3.9.7 and its associated libraries of *numpy*, *pandas*, *matplotlib*, *statsmodels*, and *seaborn*. The models are trained and validated on the GPU environment of Google Colab (Google Colab).

Auto sector: As per the report published by the NSE on December 31, 2021, the top ten stocks of the *auto* sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: Maruti Suzuki India (MSZ): 19.53%, Mahindra & Mahindra (MHM): 16.81%, Tata Motors (TAM): 14.94%, Bajaj Auto (BAJ): 9.25%, Eicher Motors (ECM): 6.98%, Hero MotoCorp (HMC): 6.20%, Tube Investments of India (TII): 3.50%, Ashok Leyland (ASL): 3.48%, Bharat Forge (BFG): 3.42%, and Balkrishna Industries (BAL): 3.31% (NSE Website). The stock of TII was first found to be listed in NSE on November 2, 2017. Hence, the portfolios for the *auto* sector are designed on November 3, 2017.

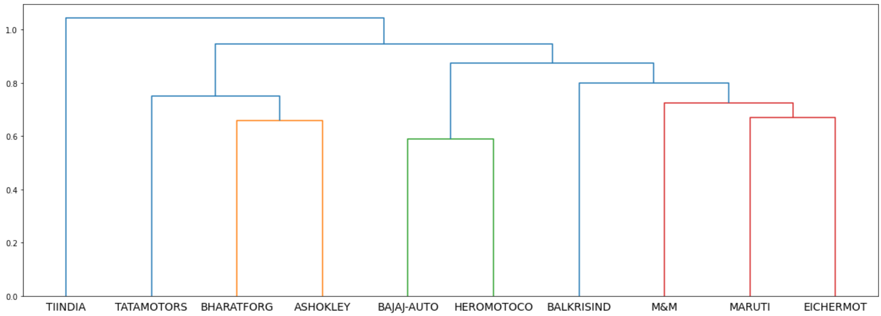

Figure 4-1. The dendrogram of the agglomerative clustering of the *auto* sector stocks (Period: November 3, 2017 – December 31, 2020).

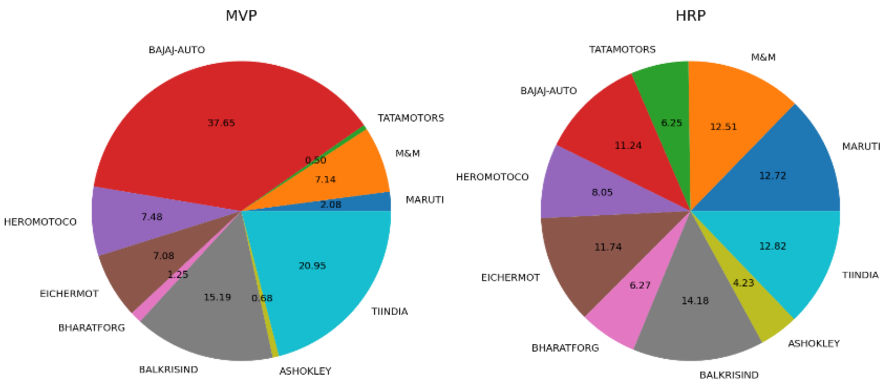

Figure 4-2. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the stocks of the *auto* sector (Period: November 3, 2017 – December 31, 2020).

TABLE 4-1. THE PORTFOLIO COMPOSITIONS OF THE AUTO SECTOR STOCKS (PERIOD: NOVEMBER 3, 2017 - DECEMBER 31, 2020)

Stock	MVP Portfolio	HRP Portfolio
MSZ	0.0208	0.1272
MHM	0.0714	0.1251
TAM	0.0050	0.0625
BAJ	0.3765	0.0625
ECM	0.0708	0.1124
HMC	0.0748	0.0805
TII	0.2095	0.1282
ASL	0.0068	0.0423
BFG	0.0125	0.0627
BAL	0.1519	0.1418

The dendrogram of the clustering of the stocks of the *auto* sector is shown in Figure 4-1. The *y*-axis of the dendrogram depicts the *ward linkage* values, where a longer length of the arms signifies a higher distance and hence a cluster with less compactness. For example, the cluster containing the Bajaj Auto and Hero MotoCorp stocks is the most compact one, while the one containing Maruti and Eicher Motors is the least homogeneous. Figure 4-2 depicts the weight allocation done by the MVP and the HRP portfolios to the *auto* sector stocks. Table 4-1 shows the weight allocations for the two portfolios in tabular format.

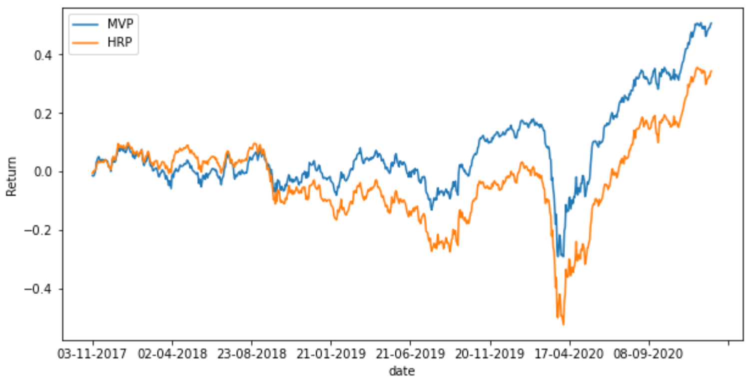

Figure 4-3. The cumulative returns yielded by the MVP and the HRP portfolios of the *auto* sector stocks on the training data from January 1, 2017, to December 31, 2020.

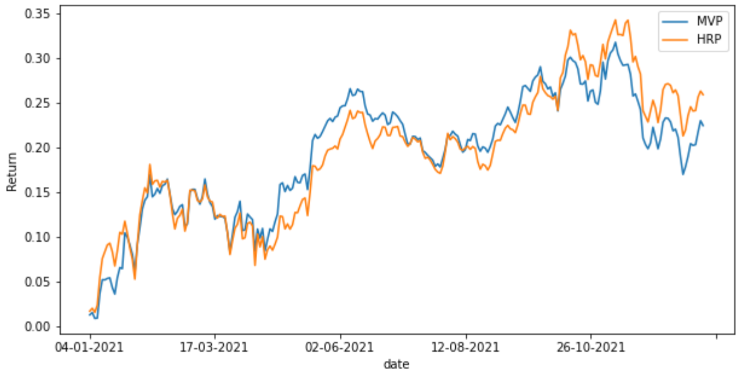

Figure 4-4. The cumulative returns yielded by the MVP and the HRP portfolios of the *auto* sector stocks on the test data from January 1, 2021, to December 31, 2021.

The cumulative returns yielded by the portfolios over the training and the test periods are depicted in Figure 4-3 and Figure 4-4, respectively. Table 4-2 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the *auto* sector stocks over the training and the test periods. It is observed that while the MVP portfolio yielded a higher return over the training period, for the test period, the return yielded by the HRP portfolio is higher.

TABLE 4-2. THE PERFORMANCE RESULTS OF THE AUTO SECTOR PORTFOLIOS

Period	**MVP Portfolio**		**HRP Portfolio**	
	Cumulative Return	**Max Sharpe Ratio**	**Cumulative Return**	**Max Sharpe Ratio**
Training	16.38%	0.6957	11.09%	0.4350
Test	23.00%	1.2045	26.54%	1.3079

Banking sector: As per the report published by the NSE on December 31, 2020, the top ten stocks of the *banking* sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows:: (i) HDFC Bank (HDF): 27.80%, (ii) ICICI Bank (ICI): 22.62%, (iii) Kotak Mahindra Bank (KTB): 11.61%, (iv) Axis Bank (AXS): 11.52%, (v) State Bank of India (STB): 11.45%, (vi) IndusInd Bank (IIB): 5.91%, (vii) AU Small Finance Bank (ASF): 2.33%, (viii)

Bandhan Bank (BNB): 1.75%, (ix) Federal Bank (FDB): 1.70%, and (x) IDFC First Bank (IFB): 1.54% (NSE Website).

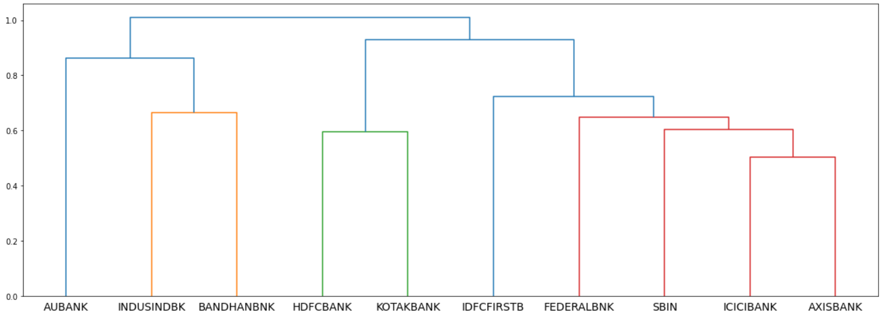

Figure 4-5. The dendrogram of the agglomerative clustering of the *banking* sector stocks (Period: March 28, 2018 – December 31, 2020).

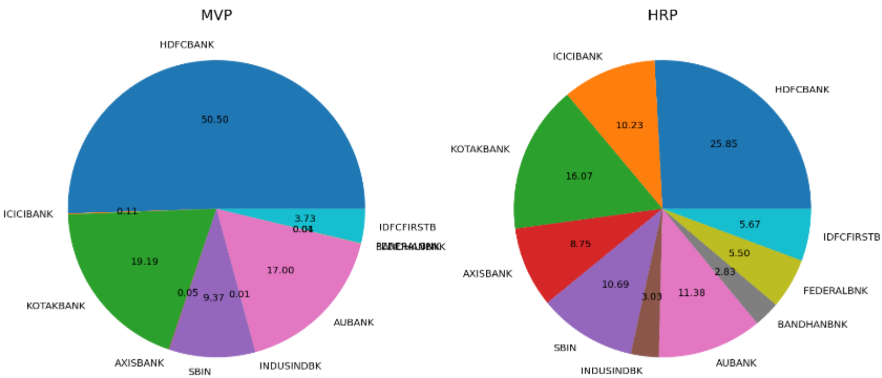

Figure 4-6. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the stocks of the *banking* sector (Period: January 1, 2017 – December 31, 2020).

The dendrogram of the clustering of the stocks of the *banking* sector is shown in Figure 4-5. Since the stock of Bandhan Bank was first listed on March 27, 2018, the portfolios were formed on March 28, 2018. Figure 4-6 depicts the weight allocation done by the MVP and the HRP portfolios to the *banking* sector stocks. Table 4-3 shows the weight allocations for the two portfolios in tabular format. It is observed that both portfolios allocated the highest weights to the stock HDF.

TABLE 4-3. THE PORTFOLIO COMPOSITIONS OF THE BANKING SECTOR STOCKS (PERIOD: MARCH 28, 2018 - DECEMBER 31, 2020)

Stock	MVP Portfolio	HRP Portfolio
HDF	0.5050	0.2585
ICI	0.0011	0.1023
KTB	0.1919	0.1607
AXS	0.0005	0.0875
STB	0.0937	0.1069
IIB	0.0006	0.0303
ASF	0.1700	0.1138
BNB	0.0002	0.0283
FDB	0.0004	0.0550
IFB	0.0373	0.0567

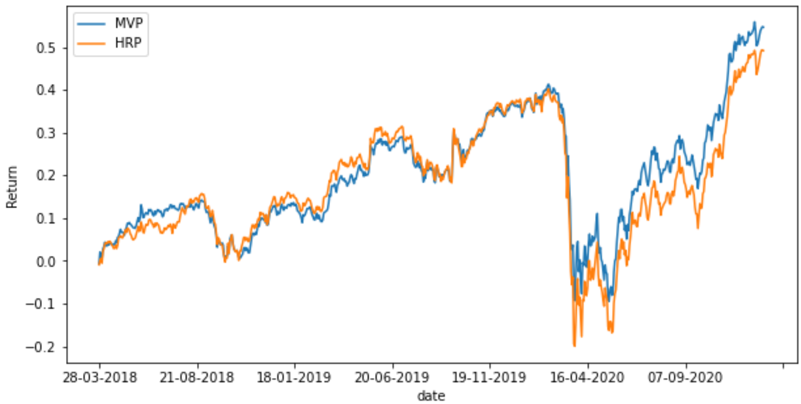

Figure 4-7. The cumulative returns yielded by the MVP and the HRP portfolios of the *banking* sector stocks on the training data from March 28 1, 2018, to December 31, 2020.

The cumulative returns yielded by the portfolios over the training and the test periods are depicted in Figure 4-7 and Figure 4-8, respectively. Table 4-4 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the *banking* sector stocks over the training and the test periods. It is observed that while the MVP portfolio yielded a higher return over the training period, for the test period, the return yielded by the HRP portfolio is higher.

Figure 4-8. The cumulative returns yielded by the MVP and the HRP portfolios of the *banking* sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-4. THE PERFORMANCE RESULTS OF THE BANKING SECTOR PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	Max Sharpe Ratio	Cumulative Return	Max Sharpe Ratio
Training	20.22%	0.7681	18.19%	0.6355
Test	12.23%	0.5291	16.33%	0.7122

Consumer Durable sector: As NSE's report published on December 31, 2020, the top ten stocks of the *consumer durables* sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: (i) Titan Company (TTC): 34.16%, (ii) Havells India (HAV): 12.79%, (iii) Voltas (VOL): 10.32%, (iv) Crompton Greaves Consumer Electrical (CRG): 9.44%, (v) Dixon Technologies (DXT): 7.41%, (vi) Bata India (BAT): 4.13%, (vii) Kajaria Ceramics (KJC): 3.90%, (viii) Rajesh Exports (RJE): 3.66%, (ix) Relaxo Footwears (RLF): 3.46%, and (x) Blue Star (BLU): 2.17% (NSE Website).

The dendrogram of the clustering of the stocks of the *consumer durables* sector is shown in Figure 4-9. Since the stock of Dixon Technologies was first listed on September 18, 2017, the portfolios were formed on September 19, 2017. Figure 4-10 depicts the weight allocation of the MVP and the HRP portfolios to the *consumer durables* sector stocks. Table 4-5 shows the weight allocations for the two portfolios in tabular format. It is observed that both portfolios allocated the highest weights to the stock RJE.

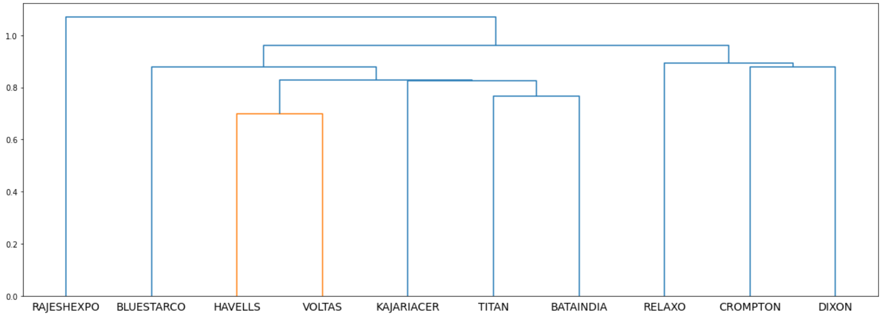

Figure 4-9. The dendrogram of the agglomerative clustering of the *consumer durables* sector stocks (Period: September 19, 2017 – December 31, 2020).

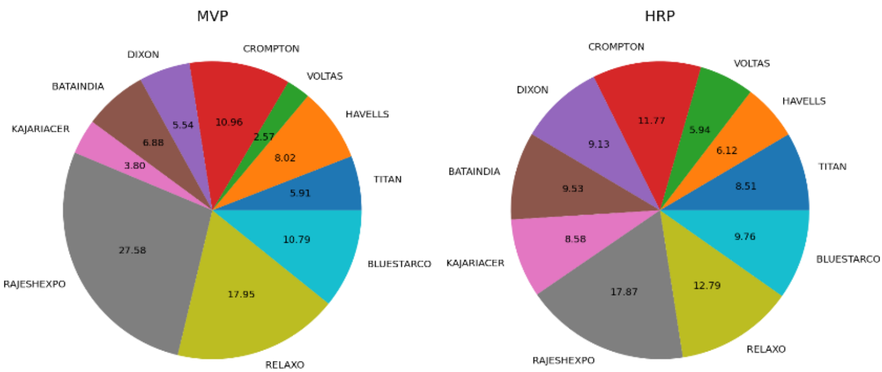

Figure 4-10. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the stocks of the *consumer durables* sector (Period: September 19, 2017 – December 31, 2020).

TABLE 4-5. THE PORTFOLIO COMPOSITIONS OF THE CONSUMER DURABLES SECTOR STOCKS (PERIOD: SEPTEMBER 19, 2017 - DECEMBER 31, 2020)

Stock	MVP Portfolio	HRP Portfolio
TTC	0.0591	0.0851
HAV	0.0802	0.0612
VOL	0.0257	0.0594
CRG	0.1096	0.1177
DXT	0.0554	0.0913
BAT	0.0687	0.0953
KJC	0.0380	0.0858
RJE	0.2758	0.1787
RLF	0.1795	0.1279
BLU	0.1079	0.0976

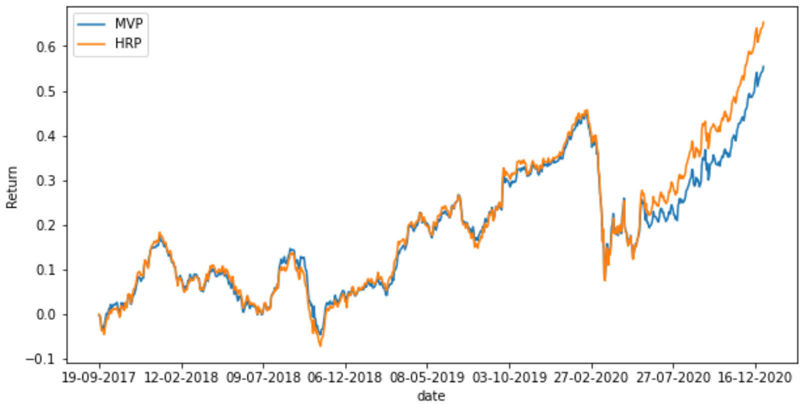

Figure 4-11. The cumulative returns yielded by the MVP and the HRP portfolios of the *consumer durables* sector stocks on the training data from September 19, 2017, to December 31, 2020.

The cumulative returns yielded by the portfolios over the training and the test periods are depicted in Figure 4-11 and Figure 4-12, respectively. Table 4-6 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the *consumer durables* sector stocks over the training and the test periods. It is observed that the HRP portfolio yielded higher returns over both training and test periods.

Figure 4-12. The cumulative returns yielded by the MVP and the HRP portfolios of the *consumer durables* sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-6. THE PERFORMANCE RESULTS OF THE CONSUMER DURABLES SECTOR PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	Max Sharpe Ratio	Cumulative Return	Max Sharpe Ratio
Training	17.21%	0.9723	20.29%	1.1121
Test	43.45%	2.7758	44.43%	2.8388

FMCG sector: Based on the NSE's report published on December 31, 2020, the top ten stocks of the FMCG sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: (i) Hindustan Unilever (HIU): 27.62%, (ii) ITC (ITC): 25.01%, (iii) Nestle India (NSI): 9.22%, (iv) Tata Consumer Products (TCP): 5.85%, (v) Britannia Industries (BRI): 5.59%, (vi) Godrej Consumer Products (GCP): 4.81%, (vii) Dabur India (DBI): 4.45%, (viii) United Spirits (MCD): 3.52%, (ix) Marico (MAR): 3.48%, and (x) Colgate Palmolive India (CPL): 2.59%) (NSE Website).

The dendrogram of the clustering of the stocks of the FMCG sector is shown in Figure 4-13. The portfolios were designed on January 1, 2016. Figure 4-14 depicts the weight allocation done by the MVP and the HRP portfolios to the FMCG sector stocks. Table 4-7 shows the weight allocations for the two portfolios in tabular format. It is observed that both portfolios allocated the highest weights to the stock CPL.

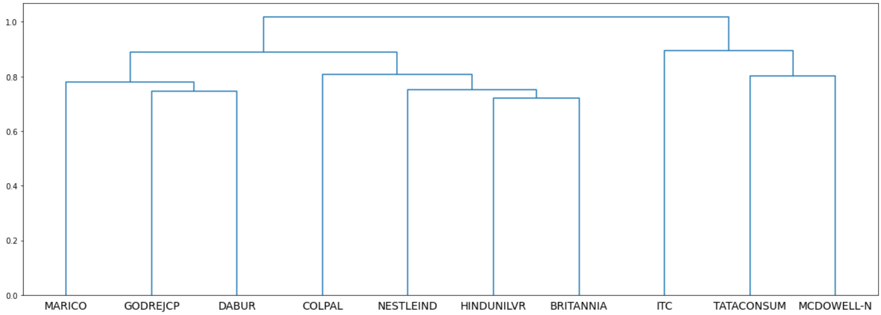

Figure 4-13. The dendrogram of the agglomerative clustering of the FMCG sector stocks (Period: January 1, 2017 – December 31, 2020).

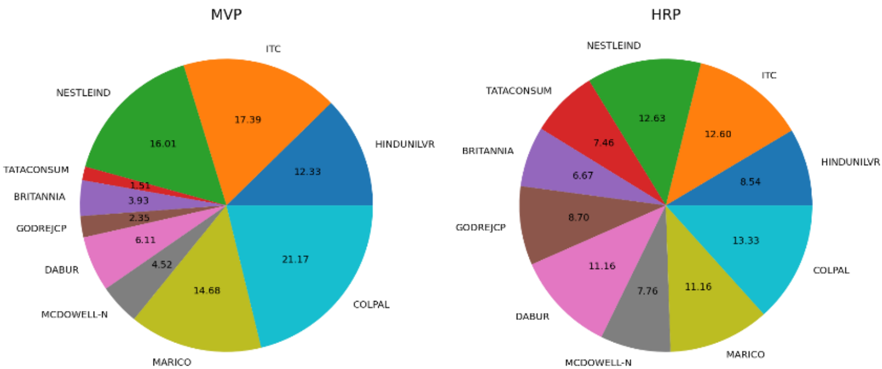

Figure 4-14. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the stocks of the FMCG sector (Period: January 1, 2021 – December 31, 2021).

The cumulative returns yielded by the portfolios of the FMCG sector over the training and the test periods are depicted in Figure 4-15 and Figure 4-16, respectively. Table 4-8 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the FMCG sector stocks over the training and the test periods. It is observed that the HRP portfolio yielded higher returns over both training and test periods.

TABLE 4-7. THE PORTFOLIO COMPOSITIONS OF THE FMCG SECTOR STOCKS (PERIOD: JANUARY 1, 2017 - DECEMBER 31, 2020)

Stock	MVP Portfolio	HRP Portfolio
HIU	0.1233	0.0854
ITC	0.1739	0.1260
NSI	0.1601	0.1263
TCP	0.0151	0.0746
BRI	0.0393	0.0667
GCP	0.0235	0.0870
DBI	0.0611	0.1116
MCD	0.0562	0.0776
MAR	0.1468	0.1116
CPL	0.2117	0.1333

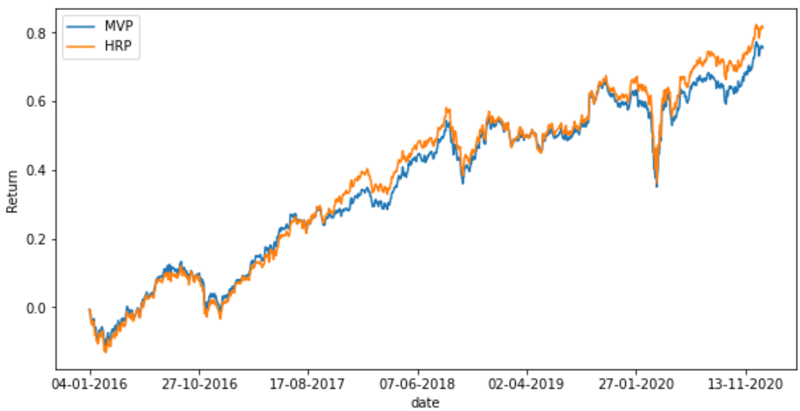

Figure 4-15. The cumulative returns yielded by the MVP and the HRP portfolios of the *FMCG* sector stocks on the training data from January 1, 2016, to December 31, 2020.

Figure 4-16. The cumulative returns yielded by the MVP and the HRP portfolios of the FMCG sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-8. THE PERFORMANCE RESULTS OF THE FMCG SECTOR PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	Max Sharpe Ratio	Cumulative Return	Max Sharpe Ratio
Training	15.45%	0.9438	16.63%	0.9870
Test	9.22%	0.7258	13.81%	1.0788

Information Technology (IT) sector: As per the report published by the NSE on December 31, 2020, the top ten stocks of the IT sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: (i) Infosys (INF): 27.52%, (ii) Tata Consultancy Services (TCS): 25.09%, (iii) HCL Technologies (HCL): 9.28%, (iv) Wipro (WIP): 9.16, (v) Tech Mahindra (TCM): 8.95%, (vi) Larsen & Toubro Infotech (LTI): 5.34%, (vii) MindTree (MNT): 4.91%, (viii) MphasiS (MPS): 4.48%, (ix) Coforge (CFG): 2.81, and (x) L&T Technology Services (LTS): 2.46% (NSE Website).

The dendrogram of the clustering of the stocks of the IT sector is shown in Figure 4-17. The portfolios were designed on September 26, 2016, since the prices of all the ten stocks in the IT sector were available from September 25, 2016, onwards. Figure 4-18 depicts the weight allocation done by the MVP and the HRP portfolios to the IT sector stocks. Table 4-9 shows the weight allocations for the two portfolios in tabular format. It is observed that both portfolios allocated the highest weights to the stock TCS.

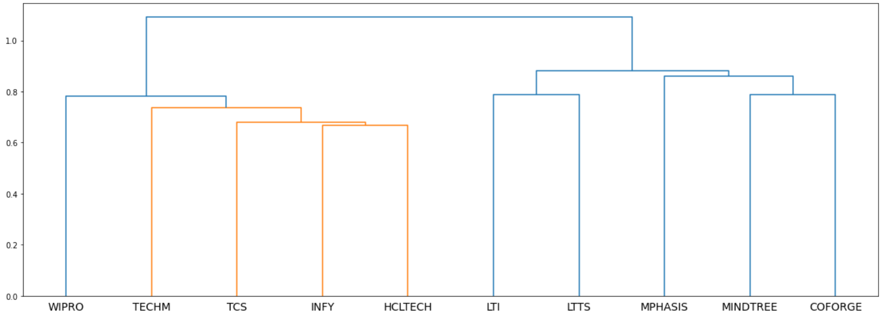

Figure 4-17. The dendrogram of the agglomerative clustering of the IT sector stocks (Period: September 26, 2016 – December 31, 2020).

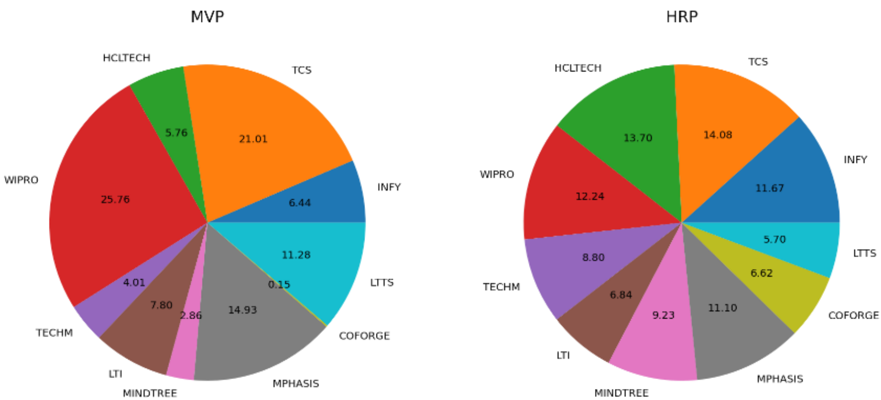

Figure 4-18. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the stocks of the IT sector (Period: September 26, 2016 – December 31, 2020).

TABLE 4-9. THE PORTFOLIO COMPOSITIONS OF THE IT SECTOR STOCKS **(**PERIOD: SEPTEMBER 26, 2016 - DECEMBER 31, 2020)

Stock	MVP Portfolio	HRP Portfolio
INF	0.0879	0.1219
TCS	0.2289	0.1449
HCL	0.0501	0.1362
WIP	0.2361	0.1159
TCM	0.0432	0.0877
LTI	0.0654	0.0660
MNT	0.0245	0.0933
MPS	0.1568	0.1120
CFG	0.0013	0.0674
LTS	0.1058	0.0548

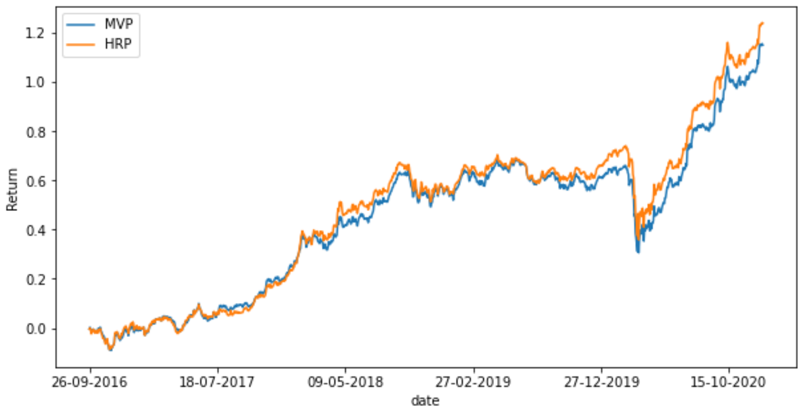

Figure 4-19. The cumulative returns yielded by the MVP and the HRP portfolios of the IT sector stocks on the training data from September 26, 2016, to December 31, 2020.

The cumulative returns yielded by the portfolios of the IT sector over the training and the test periods are depicted in Figure 4-19 and Figure 4-20, respectively. Table 4-10 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the IT sector stocks over the training and the test periods. It is observed that the HRP portfolio yielded higher returns over both training and test periods for the IT sector stocks.

Figure 4-20. The cumulative returns yielded by the MVP and the HRP portfolios of the IT sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-10. THE PERFORMANCE RESULTS OF THE IT SECTOR PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	**Max Sharpe Ratio**	**Cumulative Return**	**Max Sharpe Ratio**
Training	27.51%	1.4063	29.65%	1.4367
Test	63.49%	2.8750	64.58%	2.8819

Pharma sector: As per the report published by the NSE on December 31, 2020, the top ten stocks of the *pharma* sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: (i) Sun Pharmaceuticals Industries (SPH): 19.52%, (ii) Dr. Reddy's Labs (DRD): 12.74%, (iii) Divi's Laboratories (DIV): 12.74%), (iv) Cipla (CPL): 10.42%, (v) Lupin (LPN): 4.89%, (vi) Laurus Labs (LRU): 4.51%, (vii) Aurobindo Pharma (AUP): 4.41%, (viii) Gland Pharma (GLP): 4.21%, (ix) Biocon (BIO): 3.65%, and (x) Alkem Labs (ALB): 3.61% (NSE Website). The stock of Gland Pharma could not be included in the analysis as the first available record of this stock was on November 20, 2020. Due to the unavailability of a sufficient number of records for the stock Gland Pharma, the remaining nine stocks are included in the analysis.

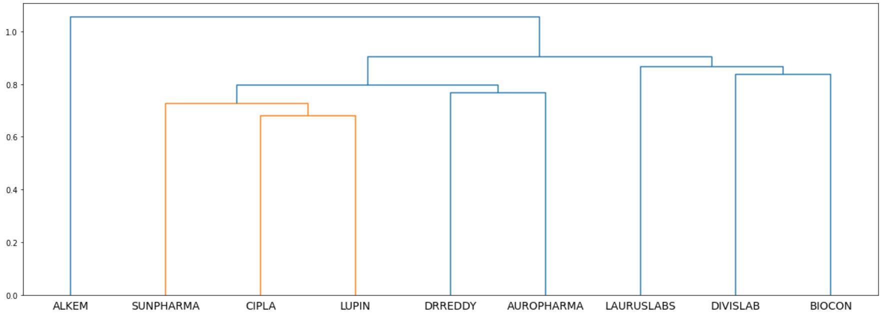

Figure 4-21. The dendrogram of the agglomerative clustering of the *pharma* sector stocks (Period: December 20, 2016 – December 31, 2020).

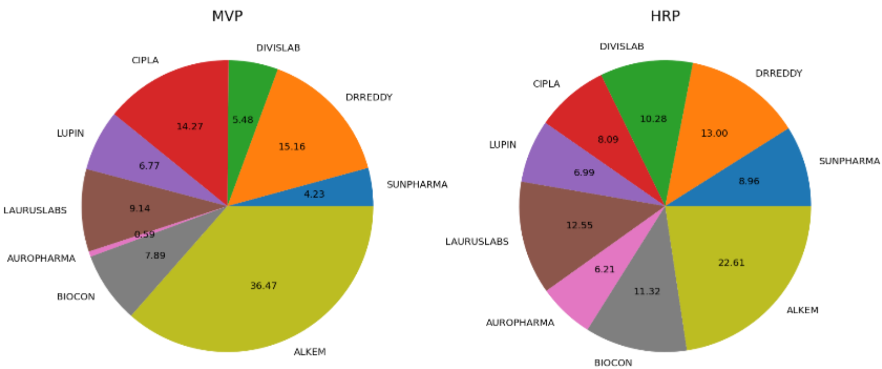

Figure 4-22. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the stocks of the *pharma* sector (Period: December 20, 2016 – December 31, 2020).

The dendrogram of the clustering of the stocks of the *pharma* sector is shown in Figure 4-21. The portfolios were designed on December 20, 2016, since the prices of all the nine stocks of the *pharma* sector were available from December 19, 2016, onwards. Figure 4-22 depicts the weight allocation done by the MVP and the HRP portfolios to the *pharma* sector stocks. Table 4-11 shows the weight allocations for the two portfolios in tabular format. It is observed that both portfolios allocated the highest weights to the stock ALB.

TABLE 4-11. THE PORTFOLIO COMPOSITIONS OF THE PHARMA SECTOR STOCKS (PERIOD: DECEMBER 20, 2016 - DECEMBER 31, 2020)

Stock	MVP Portfolio	HRP Portfolio
SPH	0.0423	0.0896
DRD	0.1515	0.1300
DIV	0.0548	0.1028
CPL	0.1427	0.0809
LPN	0.0677	0.0700
LRU	0.0914	0.1255
AUP	0.0059	0.0621
BIO	0.0789	0.1132
ALB	0.3647	0.2261

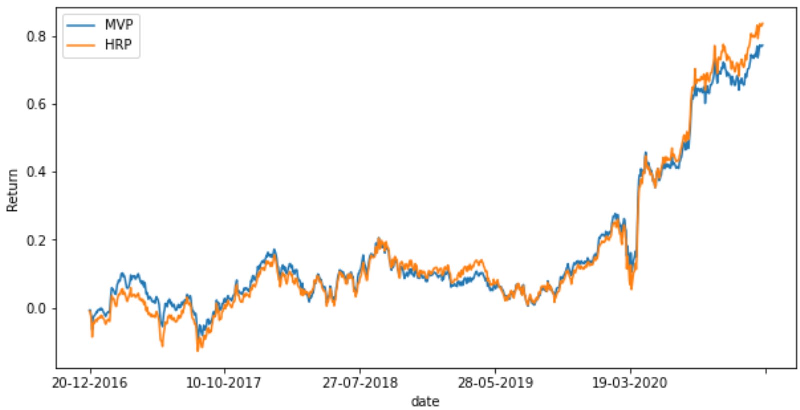

Figure 4-23. The cumulative returns yielded by the MVP and the HRP portfolios of the *pharma* sector stocks on the training data from December 20, 2016, to December 31, 2020.

The cumulative returns yielded by the portfolios of the *pharma* sector over the training and the test periods are depicted in Figure 4-23 and Figure 4-24, respectively. Table 4-12 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the *pharma* sector stocks over the training and the test periods. It is observed that while the HRP portfolio for the training period yielded a higher return, for the test period, the MVP portfolio's return was higher.

Figure 4-24. The cumulative returns yielded by the MVP and the HRP portfolios of the *pharma* sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-12. THE PERFORMANCE RESULTS OF THE PHARMA SECTOR PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	Max Sharpe Ratio	Cumulative Return	Max Sharpe Ratio
Training	19.51%	1.0256	21.13%	1.0552
Test	16.26%	0.9288	14.88%	0.8483

Realty sector: As per the report published by the NSE on December 31, 2020, the top ten stocks of the *realty* sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: (i) DLF (DLF): 24.12%, (ii) Godrej Properties (GRP): 21.82%, (iii) Macrotech Developers (MDV): 10.67%, (iv) Oberoi Realty (OBR): 10.01%, (v) Phoenix Mills (PHM): 9.15%, (vi) Prestige Estate Projects (PRP): 6.65%, (vii) Brigade Enterprises (BRE): 6.31%, (viii) Indiabulls Real Estate (IBR): 5.67%, (ix) Sobha (SBH): 3.22%, and (x) Sunteck Realty (SUR): 2.37% (NSE Website). The stock Macrotech Developers (MDV) could not be considered for inclusion in the analysis due to the unavailability of a sufficient number of records. The date on which the first record of the stock was available was April 19, 2021.

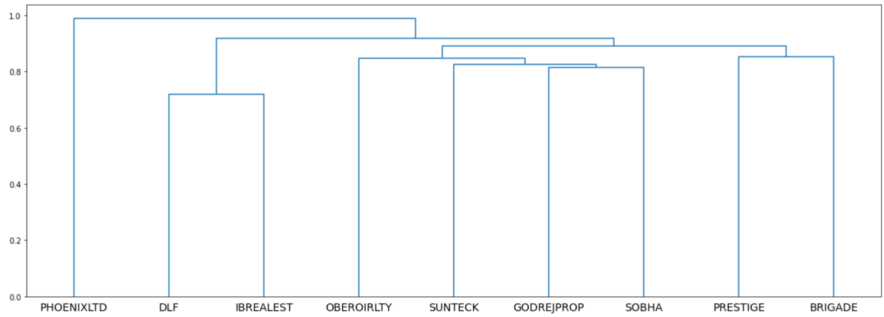

Figure 4-25. The dendrogram of the agglomerative clustering of the *realty* sector stocks (Period: January 1, 2016 – December 31, 2020).

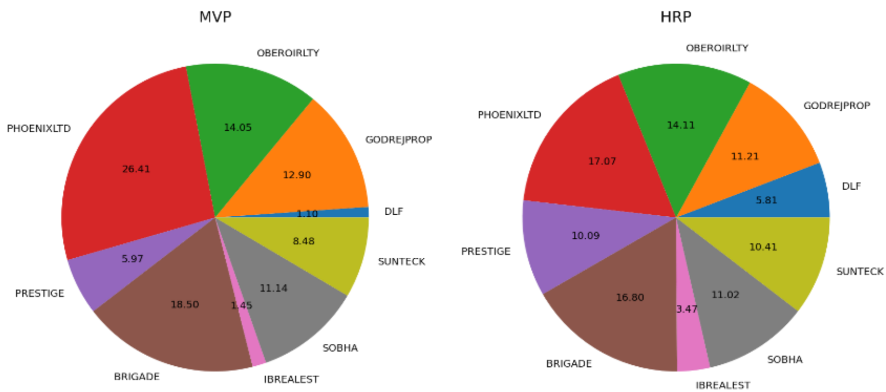

Figure 4-26. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the stocks of the *realty* sector (Period: January 1, 2016 – December 31, 2020).

The dendrogram of the clustering of the stocks of the *realty* sector is shown in Figure 4-25. The portfolios were designed on January 1, 2016, since the prices of all the nine stocks of the *realty* sector (excluding the stock MDV) were available from January 1, 2016, onwards. Figure 4-26 depicts the weight allocation done by the MVP and the HRP portfolios to the *realty* sector stocks. Table 4-13 shows the weight allocations for the two portfolios in tabular format. It is observed that both portfolios allocated the highest weights to the stock PHM.

TABLE 4-13. THE PORTFOLIO COMPOSITIONS OF THE REALTY SECTOR STOCKS (PERIOD: JANUARY 1, 2016 - DECEMBER 31, 2020)

Stock	MVP Portfolio	HRP Portfolio
DLF	0.0110	0.0581
GRP	0.1290	0.1121
OBR	0.1405	0.1411
PHM	0.2641	0.1707
PRP	0.0597	0.1009
BRE	0.1850	0.1680
IBR	0.0145	0.0347
SBH	0.1114	0.1102
SUR	0.0848	0.1041

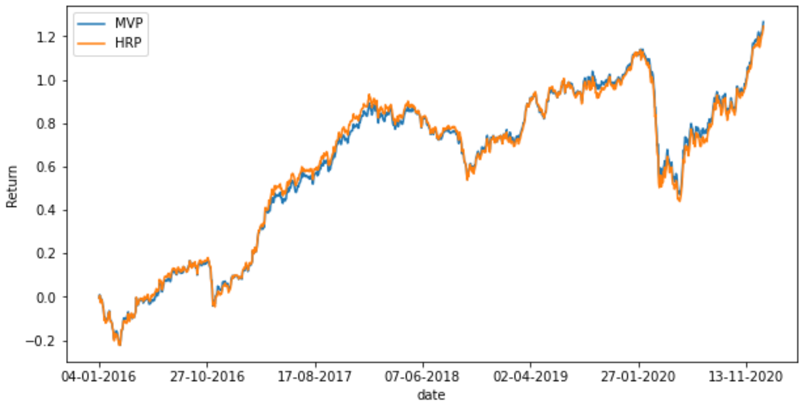

Figure 4-27. The cumulative returns yielded by the MVP and the HRP portfolios of the *realty* sector stocks on the training data from January 1, 2016, to December 31, 2020.

The cumulative returns yielded by the portfolios of the *realty* sector over the training and the test periods are depicted in Figure 4-27 and Figure 4-28, respectively. Table 4-14 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the *realty* sector stocks over the training and the test periods. It is observed that while the MVP portfolio for the training period yielded a marginally higher return, for the test period, a considerably higher return is yielded by the HRP portfolio.

Figure 4-28. The cumulative returns yielded by the MVP and the HRP portfolios of the *realty* sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-14. THE PERFORMANCE RESULTS OF THE REALTY SECTOR PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	Max Sharpe Ratio	Cumulative Return	Max Sharpe Ratio
Training	25.88%	1.0386	25.45%	0.9994
Test	54.66%	1.7609	57.92%	1.8376

Metal sector: As per the report published by the NSE on December 31, 2020, the top ten stocks of the *metal* sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: (i) Tata Steel (TAS): 20.45%, (ii) Hindalco Industries (HND): 16.09%, (iii) JSW Steel (JSS): 15.06%, (iv) Adani Enterprises (ADE): 10.89%, (v) Vedanta (VED): 10.28%, (vi) Coal India (COI): 7.09%, (vii) Steel Authority of India (SAI): 3.59%, (viii) Jindal Steel & Power (JSP): 3.57%, (ix) NMDC (NMD): 3.53%, and (x) APL Apollo Tubes (AAT): 3.24% (NSE Website).

The dendrogram of the clustering of the stocks of the *metal* sector is shown in Figure 4-25. The portfolios were designed on January 1, 2016, since the prices of all the ten stocks of the *metal* sector were available from January 1, 2016, onwards. Figure 4-30 depicts the weight allocation done by the MVP and the HRP portfolios to the *metal* sector stocks. Table 4-15 shows the weight allocations for the two portfolios in tabular format. It is observed that both portfolios allocated the highest weights to the stock COI.

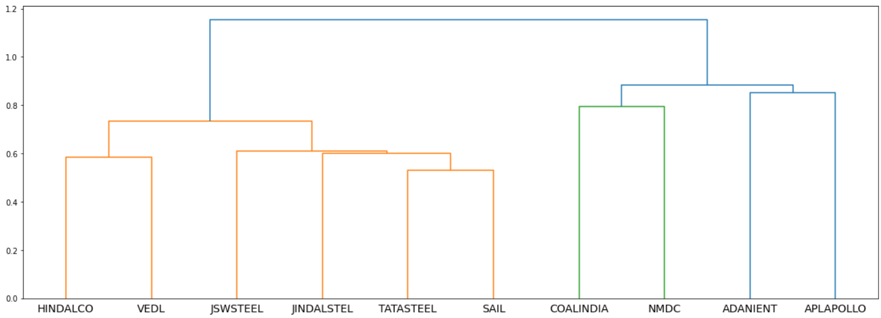

Figure 4-29. The dendrogram of the agglomerative clustering of the *metal* sector stocks (Period: January 1, 2016 – December 31, 2020).

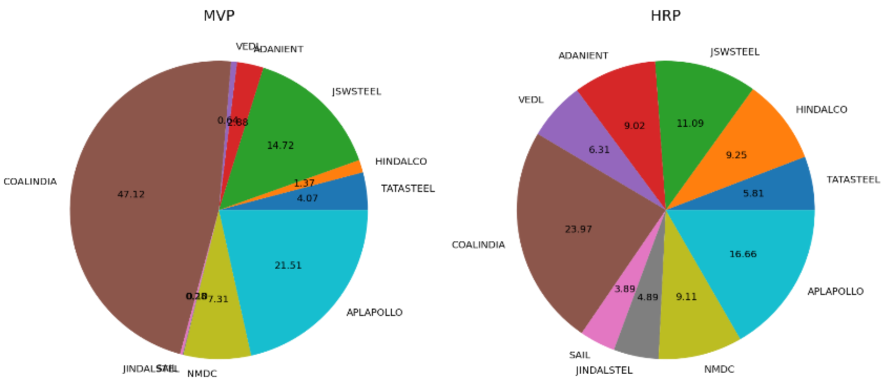

Figure 4-30. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the stocks of the *metal* sector (Period: January 1, 2016 – December 31, 2020).

The cumulative returns yielded by the portfolios of the *metal* sector over the training and the test periods are depicted in Figure 4-31 and Figure 4-32, respectively. Table 4-16 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the *metal* sector stocks over the training and the test periods. It is observed that the HRP portfolio yielded higher returns for both training and test periods.

TABLE 4-15. THE PORTFOLIO COMPOSITIONS OF THE METAL SECTOR STOCKS (PERIOD: JANUARY 1, 2016 - DECEMBER 31, 2020)

Stock	MVP Portfolio	HRP Portfolio
TAS	0.0407	0.0581
HND	0.0137	0.0925
JSS	0.1472	0.1109
ADE	0.0288	0.0902
VED	0.0064	0.0631
COI	0.4712	0.2397
SAI	0.0028	0.0389
JSP	0.0010	0.0489
NMD	0.0731	0.0911
AAT	0.2151	0.1666

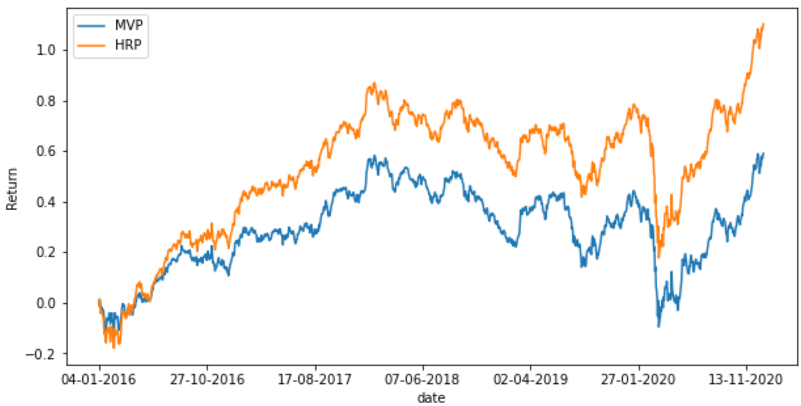

Figure 4-31. The cumulative returns yielded by the MVP and the HRP portfolios of the *metal* sector stocks on the training data from January 1, 2016, to December 31, 2020.

Figure 4-32. The cumulative returns yielded by the MVP and the HRP portfolios of the *metal* sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-16. THE PERFORMANCE RESULTS OF THE METAL SECTOR PORTFOLIOS

Period	**MVP Portfolio**		**HRP Portfolio**	
	Cumulative Return	**Max Sharpe Ratio**	**Cumulative Return**	**Max Sharpe Ratio**
Training	12.09%	0.4959	22.52%	0.8355
Test	45.73%	1.7479	61.00%	2.2166

Oil & Gas sector: The NSE's report published on December 31, 2020, the top ten stocks of the *oil & gas* sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: (i) Reliance Industries (REL): 32.76%, (ii) Oil & Natural Gas Corporation (OGC): 12.59%, (iii) Adani Total Gas (ADG): 11.47%, (iv) Bharat Petroleum Corporation (BPC): 8.92%, (v) Indian Oil Corporation (INC): 6.87%, (vi) GAIL (GAL): 5.70%, (vii) Hindustan Petroleum Corporation (HPC): 4.52%, (viii) Indraprastha Gas (IGS): 3.99%, (ix) Petronet LNG (PLG): 3.93%, and (x) Gujarat Gas (GJG): 2.65% (NSE Website).

The dendrogram of the clustering of the stocks of the *oil & gas* sector is shown in Figure 4-33. The portfolios were designed on November 6, 2018, since the prices of all the ten stocks of the *oil & gas* sector were available from November 5, 2018, onwards. Figure 4-34 depicts the weight allocation done by the MVP and the HRP portfolios to the *oil & gas* sector stocks.

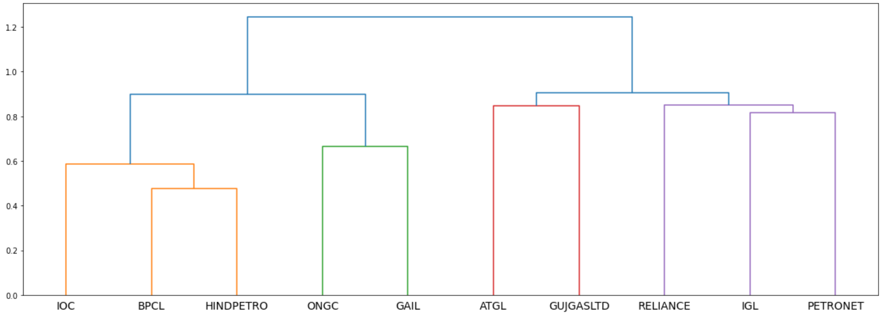

Figure 4-33. The dendrogram of the agglomerative clustering of the *oil & gas* sector stocks (Period: November 6, 2018 – December 31, 2020).

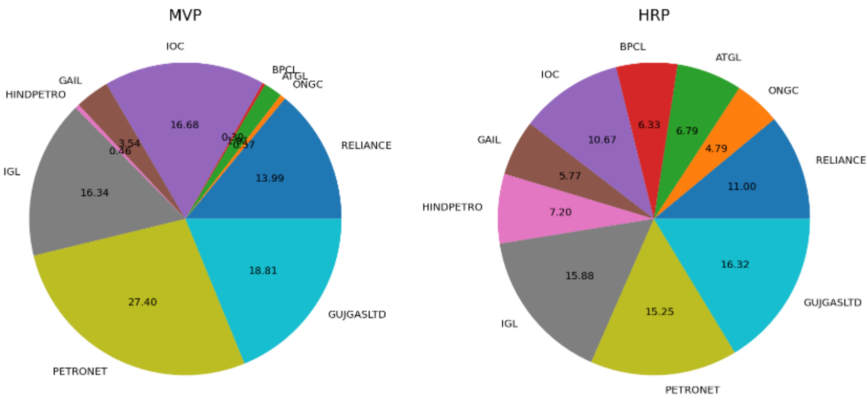

Figure 4-34. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the stocks of the *oil & gas* sector (Period: November 6, 2018 – December 31, 2020).

Table 4-15 shows the weight allocations for the two portfolios in tabular format. It is observed that while the MVP portfolio allocated the highest weight to the stock PLG, the stock GJG received the highest allocation of weight from the HRP portfolio.

TABLE 4-17. THE PORTFOLIO COMPOSITIONS OF THE OIL & GAS SECTOR STOCKS (PERIOD: NOVEMBER 6, 2018 - DECEMBER 31, 2020)

Stock	MVP Portfolio	HRP Portfolio
REL	0.1399	0.1100
OGC	0.0057	0.0479
ADG	0.0191	0.0679
BPC	0.0030	0.0633
INC	0.1668	0.1067
GAL	0.0354	0.0579
HPC	0.0046	0.0720
IGS	0.1635	0.1588
PLG	0.2740	0.1525
GJG	0.1881	0.1632

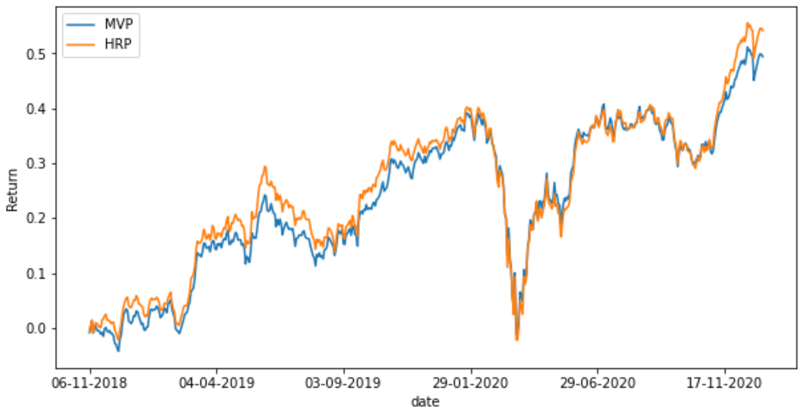

Figure 4-35. The cumulative returns yielded by the MVP and the HRP portfolios of the *oil & gas* sector stocks on the training data from November 6, 2018, to December 31, 2020.

The cumulative returns yielded by the portfolios of the *oil & gas* sector over the training and the test periods are depicted in Figure 4-35 and Figure 4-36, respectively. Table 4-18 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the *oil & gas* sector stocks over the training and the test periods. It is observed that the HRP portfolio yielded higher returns for both training and test periods.

Figure 4-36. The cumulative returns yielded by the MVP and the HRP portfolios of the *oil & gas* sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-18. THE PERFORMANCE RESULTS OF THE OIL & GAS SECTOR PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	Max Sharpe Ratio	Cumulative Return	Max Sharpe Ratio
Training	23.45%	1.0204	25.70%	1.0562
Test	18.37%	1.0003	29.56%	1.5511

Media sector: As per the report published by the NSE on December 31, 2020, the top ten stocks of the *media* sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: (i) Zee Entertainment Enterprises (ZEE): 32.97%, (ii) PVR (PVR): 14.03%, (iii) Sun TV Network (SUV): 11.96%, (iv) Saregama India (SRI): 10.07%, (v) TV18 Broadcast (TBR): 7.47%, (vi) Inox Leisure (INL): 5.77%, (vii) Dish TV India (DTI): 5.69%, (viii) Network18 Media & Investments (NMI): 5.52%, Nazara Tech (NAZ): 4.17%, and Hathway Cable & Datacom (HCD): 2.35% (NSE Website). The stock of NAZ could not be included in the analysis as the number of records for this stock was inadequate. The stock was listed on the NSE on March 30, 2021.

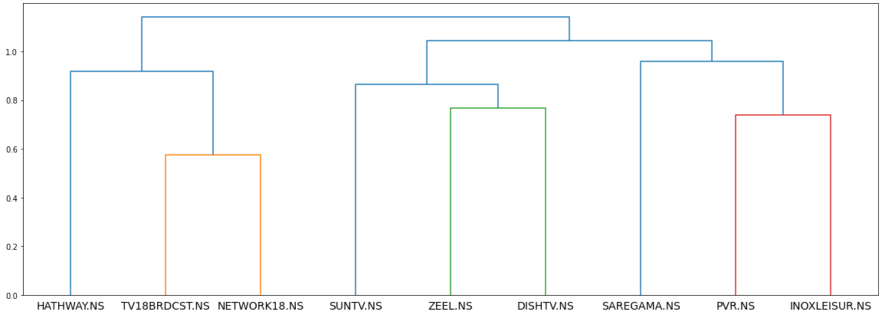

Figure 4-37. The dendrogram of the agglomerative clustering of the *media* sector stocks (Period: January 1, 2016 – December 31, 2020).

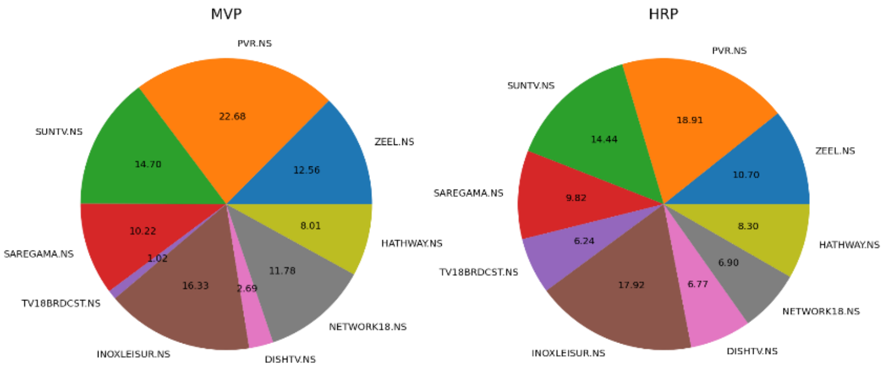

Figure 4-38. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the sectors of the *media* sector (Period: January 1, 2016 – December 31, 2020).

The dendrogram of the clustering of the stocks of the *media* sector is shown in Figure 4-37. The portfolios were designed on January 1, 2016, since the prices of all the ten stocks in the *media* sector were available from January 1, 2016, onwards. Figure 4-38 depicts the weight allocation done by the MVP and the HRP portfolios to the *media* sector stocks. Table 4-19 shows the weight allocations for the two portfolios in tabular format. It is observed that the stock PVR received the highest allocation of weights from both MVP and HRP portfolios.

TABLE 4-19. THE PORTFOLIO COMPOSITIONS OF THE MEDIA SECTOR STOCKS (PERIOD: JANUARY 1, 2016 - DECEMBER 31, 2020)

Stock	MVP Portfolio	HRP Portfolio
ZEE	0.1256	0.1070
PVR	0.2268	0.1891
SUV	0.1470	0.1444
SRI	0.1022	0.0982
TBR	0.0102	0.0624
INL	0.1633	0.1792
DTI	0.0269	0.0677
NMI	0.1178	0.0690
HCD	0.0801	0.0830

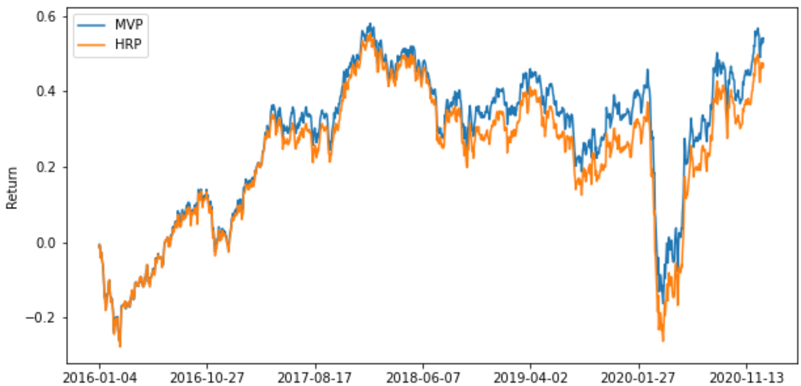

Figure 4-39. The cumulative returns yielded by the MVP and the HRP portfolios of the *media* sector stocks on the training data from January 1, 2016, to December 31, 2020.

The cumulative returns yielded by the portfolios of the *media* sector over the training and the test periods are depicted in Figure 4-39 and Figure 4-40, respectively. Table 4-20 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the *media* sector stocks over the training and the test periods. It is observed that the MVP portfolio yielded higher returns for both training and test periods.

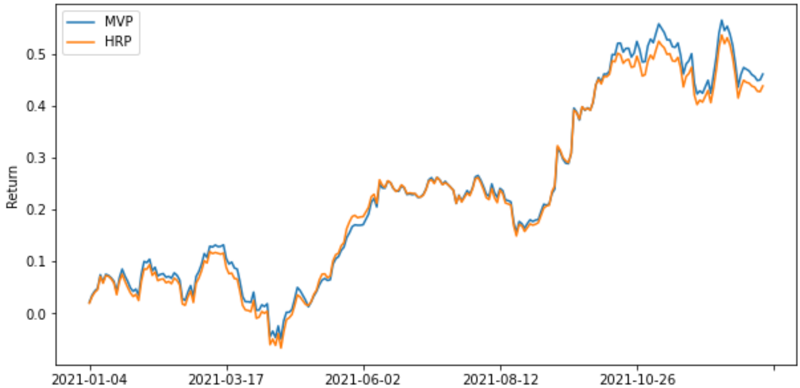

Figure 4-40. The cumulative returns yielded by the MVP and the HRP portfolios of the *media* sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-20. THE PERFORMANCE RESULTS OF THE MEDIA SECTOR PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	Max Sharpe Ratio	Cumulative Return	Max Sharpe Ratio
Training	11.04%	0.4199	9.66%	0.3635
Test	47.04%	1.6473	44.70%	1.6072

Private Banks sector: As per NSE's report published on December 31, 2020, the top ten stocks of the *private banks* sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: HDFC Bank (HDB): 25.17%, ICICI Bank (ICB): 24.32%, Kotak Mahindra Bank (KMB): 12.48%, Axis Bank (AXS): 12.39%, IndusInd Bank (ISB): 12.10%, Bandhan Bank (BNB): 3.58%, Federal Bank (FEB): 3.47%, IDFC First Bank (IDB): 3.15%, City Union Bank (CTB): 2.92%, RBL Bank (RBB): 1.33% (NSE Website). The stock of BNB was listed on the NSE for the first time on March 27, 2018. Hence, the portfolios were designed on March 28, 2018.

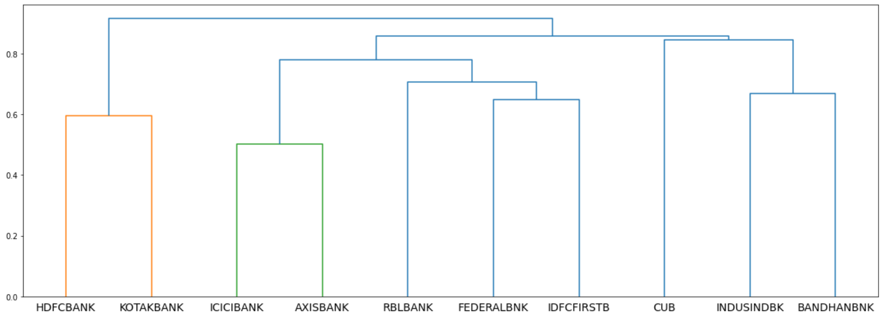

Figure 4-41. The dendrogram of the agglomerative clustering of the *private banks* sector stocks (Period: March 28, 2018 – December 31, 2020).

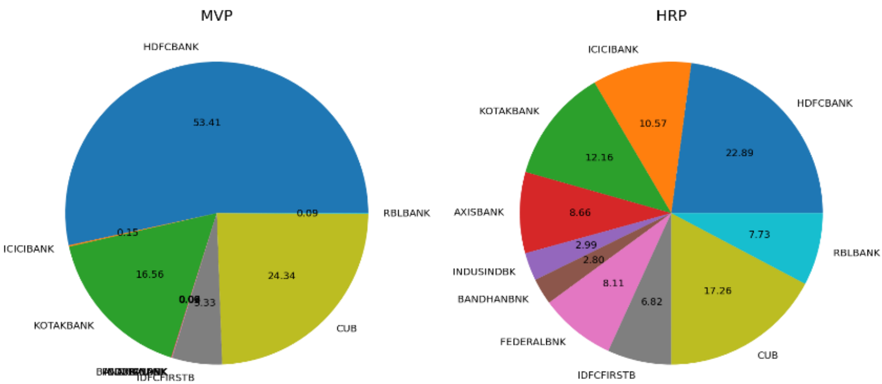

Figure 4-42. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the *private banks* sector (Period: March 28, 2018 – December 31, 2020).

The dendrogram of the clustering of the stocks of the *private banks* sector is shown in Figure 4-41. The portfolios were designed on March 28, 2018. Figure 4-42 depicts the weight allocation done by the MVP and the HRP portfolios to the *private banks* sector stocks. Table 4-21 shows the weight allocations for the two portfolios in tabular format. It is observed that the stock HDB received the highest allocation of weights from both MVP and HRP portfolios.

TABLE 4-21. THE PORTFOLIO COMPOSITIONS OF THE PRIVATE BANKS SECTOR STOCKS (PERIOD: MARCH 28, 2018 - DECEMBER 31, 2020)

Stock	**MVP Portfolio**	**HRP Portfolio**
HDB	0.5341	0.2289
ICB	0.0015	0.1057
KMB	0.1656	0.1216
AXS	0.0006	0.0866
ISB	0.0000	0.0299
BNB	0.0002	0.0280
FEB	0.0004	0.0811
IDB	0.0533	0.0682
CTB	0.2434	0.1726
RBB	0.0009	0.0774

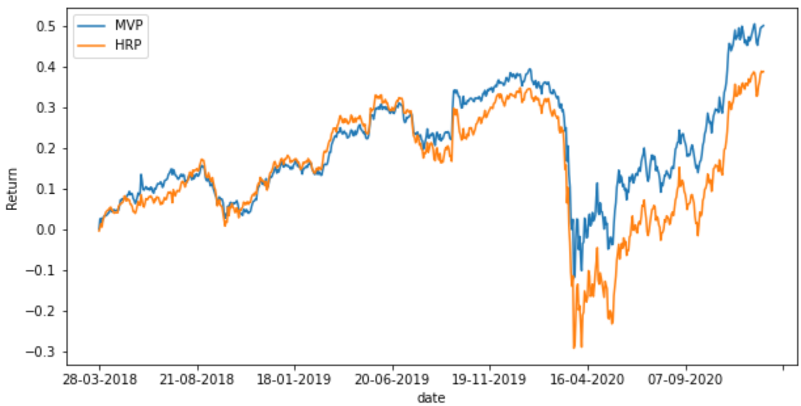

Figure 4-43. The cumulative returns yielded by the MVP and the HRP portfolios of the *private banks* sector stocks on the training data from March 28, 2018, to December 31, 2020.

The cumulative returns yielded by the portfolios of the *private banks* sector over the training and the test periods are depicted in Figure 4-43 and Figure 4-44, respectively. Table 4-22 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the *private banks* sector stocks over the training and the test periods. It is observed that while the MVP portfolio yielded a higher return for the training period, for the test period, the HRP portfolio yielded a higher return.

Figure 4-44. The cumulative returns yielded by the MVP and the HRP portfolios of the *private banks* sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-22. THE PERFORMANCE RESULTS OF THE PRIVATE BANKS SECTOR PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	Max Sharpe Ratio	Cumulative Return	Max Sharpe Ratio
Training	18.57%	0.7080	14.38%	0.4883
Test	-2.97%	-0.1448	0.68%	0.0303

PSU Banks sector: As per the report published by the NSE on December 31, 2020, the top ten stocks of the *PSU banks* sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: (i) State Bank of India (STB): 31.06%, (ii) Bank of Baroda (BOB): 16.59%, (iii) Canara Bank (CAN): 14.59%, (iv) Punjab National Bank (PUN): 14.15%, (v) Union Bank of India (UNB): 6.43%, (vi) Bank of India (BIN): 5.11%, (vii) Indian Bank (IBA): 4.44%, (viii) Indian Overseas Bank (IVB): 1.96%, (ix) Central Bank of India (CNB): 1.65%, and (x) Bank of Maharashtra (BAM): 1.48% (NSE Website).

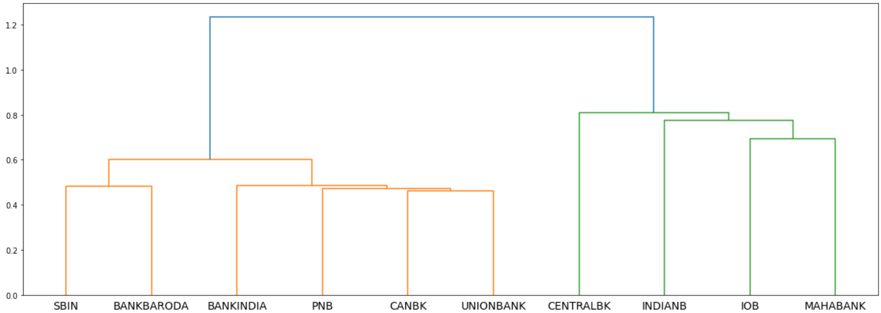

Figure 4-45. The dendrogram of the agglomerative clustering of the *PSU banks* sector stocks (Period: January 1, 2016 – December 31, 2020).

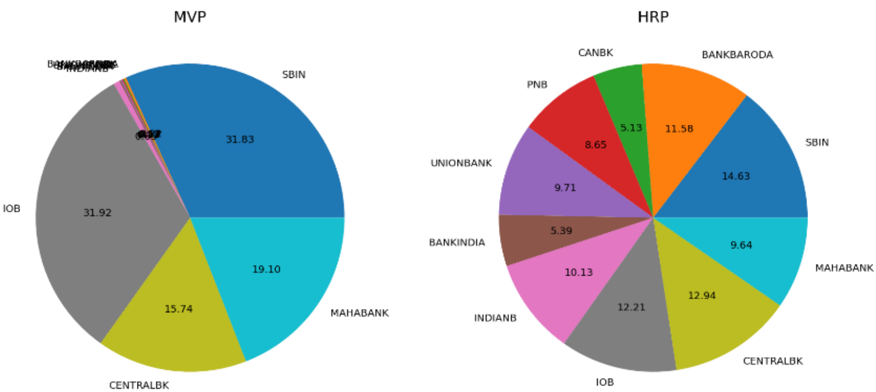

Figure 4-46. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the sectors of the *PSU banks* sector (Period: January 1, 2016 – December 31, 2020).

The dendrogram of the clustering of the stocks of the *PSU banks* sector is shown in Figure 4-45. The portfolios were designed on January 1, 2016, since the prices of the ten stocks of the *PSU banks* sector were available from January 1, 2016. Figure 4-46 depicts the weight allocation done by the MVP and the HRP portfolios to the *PSU banks* sector stocks. Table 4-23 shows the weight allocations for the two portfolios in tabular format. It is observed that while the stock IVB received the highest allocation of weight from the MVP portfolio, the HRP portfolio assigned the highest weight to the stock STB.

TABLE 4-23. THE PORTFOLIO COMPOSITIONS OF THE PSU BANKS SECTOR (PERIOD: JANUARY 1, 2016 - DECEMBER 31, 2020)

Stock	MVP Portfolio	HRP Portfolio
STB	0.3183	0.1463
BOB	0.0022	0.1158
CAN	0.0012	0.0513
PUN	0.0013	0.0865
UNB	0.0013	0.0971
BIN	0.0017	0.0539
IBA	0.0065	0.1013
IVB	0.3192	0.1221
CNB	0.1574	0.1294
BAM	0.1910	0.0964

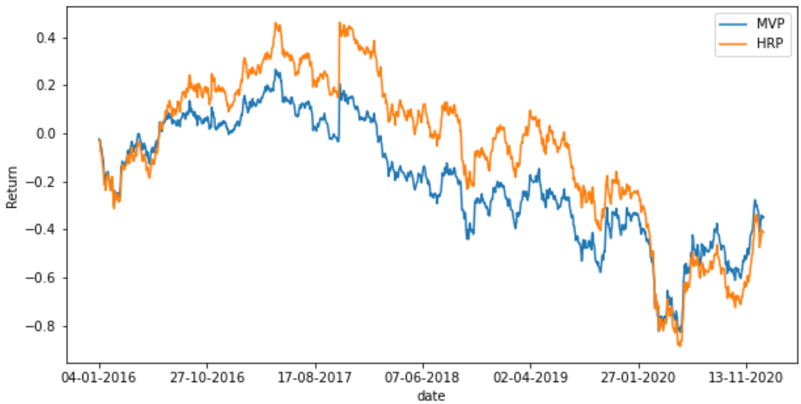

Figure 4-47. The cumulative returns yielded by the MVP and the HRP portfolios of the *PSU banks* sector stocks on the training data from January 1, 2016, to December 31, 2020.

The cumulative returns yielded by the portfolios of the *PSU banks* sector over the training and the test periods are depicted in Figure 4-47 and Figure 4-48, respectively. Table 4-24 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the *PSU banks* sector stocks over the training and the test periods. It is observed that the MVP portfolio yielded higher returns for both training and test periods.

Figure 4-48. The cumulative returns yielded by the MVP and the HRP portfolios of the *PSU banks* sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-24. THE PERFORMANCE RESULTS OF THE PSU BANKS SECTOR PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	Max Sharpe Ratio	Cumulative Return	Max Sharpe Ratio
Training	-7.12%	-0.2361	-8.43%	-0.2471
Test	66.11%	1.4305	50.78%	1.2610

Financial Services sector: As per the report published by the NSE on December 31, 2020, the top ten stocks of the *financial services* sector in terms of their free-float market capitalization and their contributions (in percent) to the overall sectoral index are as follows: HDFC Bank (HDB): 24.41%, Housing Development Finance Corporation (HDF): 16.67%, ICICI Bank (ICB): 16.31, Kotak Mahindra Bank (KMB): 9.35%, Axis Bank (AXS): 7.19%, State Bank of India (STB): 6.01%, Bajaj Finance (BJF): 5.97%, Bajaj Finserv (BFS): 2.73%, HDFC Life Insurance Company (HLI): 2.12%, SBI Life Insurance Company (SLI): 1.66% (NSE Website).

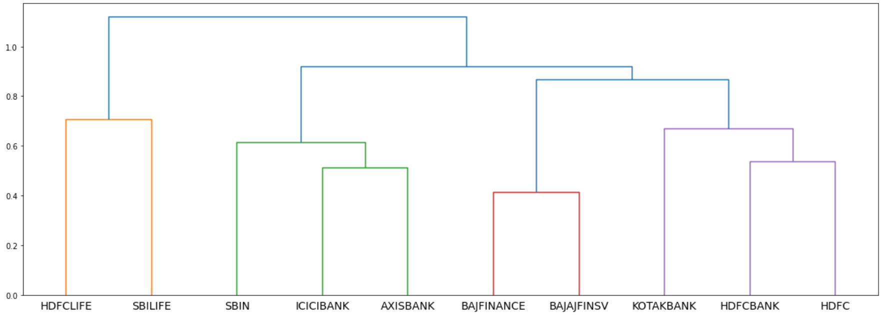

Figure 4-49. The dendrogram of the agglomerative clustering of the *financial services* sector stocks (Period: November 20, 2017 – December 31, 2020).

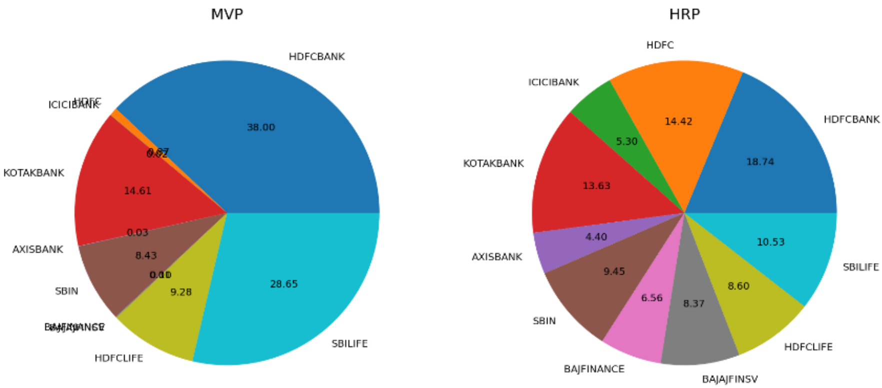

Figure 4-50. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the sectors of the *financial services* sector (Period: November 20, 2017 – December 31, 2020).

The dendrogram of the clustering of the stocks of the *financial services* sector is shown in Figure 4-49. The portfolios were designed on November 20, 2017, since the prices of the ten stocks in the *financial services* sector were available from November 19, 2017. Figure 4-50 depicts the weight allocation done by the MVP and the HRP portfolios to the *financial services* sector stocks. Table 4-25 shows the weight allocations for the two portfolios in tabular format. It is observed that the stock HDB received the highest allocation of weight from both MVP and HRP portfolios.

TABLE 4-25. THE PORTFOLIO COMPOSITIONS OF THE FINANCIAL SERVICES SECTOR STOCKS (PERIOD: NOVEMBER 20, 2017 - DECEMBER 31, 2020)

Stock	**MVP Portfolio**	**HRP Portfolio**
HDB	0.3800	0.1874
HDF	0.0087	0.1442
ICB	0.0003	0.0530
KMB	0.1461	0.1363
AXS	0.0003	0.0440
STB	0.0842	0.0945
BJF	0.0001	0.0656
BFS	0.0010	0.0837
HLI	0.0928	0.0860
SLI	0.2865	0.1053

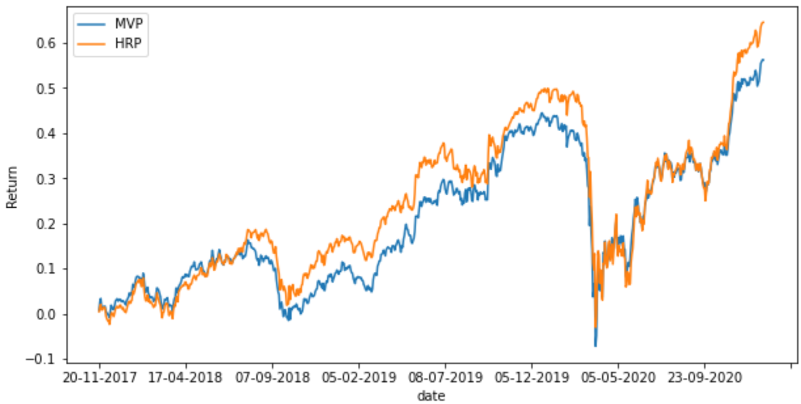

Figure 4-51. The cumulative returns yielded by the MVP and the HRP portfolios of the *financial services* sector stocks on the training data from November 20, 2017, to December 31, 2020.

The cumulative returns yielded by the portfolios of the *financial services* sector over the training and the test periods are depicted in Figure 4-51 and Figure 4-52, respectively. Table 4-26 presents the cumulative returns and the maximum Sharpe ratios of the two portfolios of the *financial services* sector stocks over the training and the test periods. It is observed that the HRP portfolio yielded higher returns for both training and test periods.

Figure 4-52. The cumulative returns yielded by the MVP and the HRP portfolios of the *financial services* sector stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-26. THE PERFORMANCE RESULTS OF THE FINANCIAL SERVICES SECTOR PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	Max Sharpe Ratio	Cumulative Return	Max Sharpe Ratio
Training	18.42%	0.7725	21.15%	0.8103
Test	14.41%	0.8020	18.88%	0.9523

NIFTY 50 stocks: Finally, we consider the NIFTY 50 stocks and construct the MVP and the HRP portfolios for them. These stocks are the market leaders across 13 sectors in the NSE and have a low-risk quotient. As per the NSE's report published on December 31, 2020, the stocks included in the NIFTY 50 group are the following: Asian Paints, Adani Ports, Axis Bank, Bharti Airtel, Bajaj Auto, Bharat Petroleum Corporation, Bajaj Finance, Britannia Industries, Coal India, Cipla, Divi's Laboratory, Eicher Motors, Dr. Reddy's Laboratories, Grasim Industries, HDFC, HCL Technologies, HDFC Life Insurance, Hindalco Industries, HDFC Bank, Hindustan Unilever, Hero MotoCorp, ICICI Bank, Infosys, IndusInd Bank, Indian Oil Corporation, JSW Steel, ITC, Kotak Bank, Mahindra & Mahindra, Larsen & Toubro, Maruti Suzuki, National Thermal Power Corporation, Nestle India, Oil and Natural Gas Corporation, Reliance Industries, Power Grid Corporation, State Bank of India, SBI Life Insurance, Shree Cement, Sun Pharmaceuticals, Tata Motors, Tata Steel,

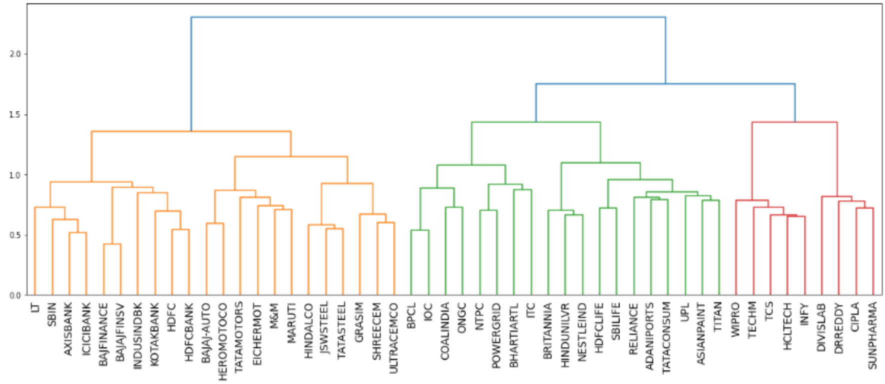

Figure 4-53. The dendrogram of the agglomerative clustering of the *NIFTY 50* stocks (Period: November 20, 2017 – December 31, 2020).

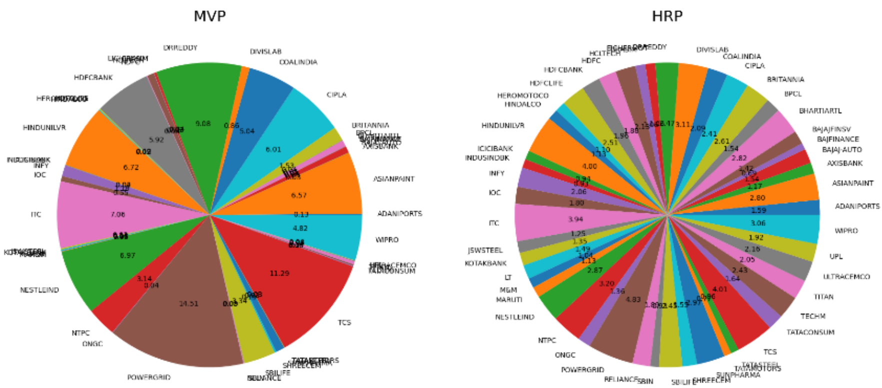

Figure 4-54. The allocation of weights done by the MVP and the HRP algorithms of portfolio optimization for the sectors of the NIFTY 50 stocks (Period: November 20, 2017 – December 31, 2020).

Tata Consultancy Services, Tech Mahindra, Tata Consumer Products, UltraTech Cement, Titan Company, Wipro, and United Phosphorus [5]. The contributions of different sectoral indices in the computation of the NIFTY 50 index are as follows: Financial Services: 37.58, Information Technology: 18.01, Oil and Gas: 11.39, Consumer Goods: 11.05, Auto: 4.58, Metal: 3.75, Pharma: 3.46, Construction: 2.72, Cement and Cement Product: 2.50, Telecom: 2.11, Power: 1.55, Services: 0.74, and Fertilizers and Pesticides: 0.55 (NSE Website). The dendrogram formed after clustering of the NIFTY

50 stocks is presented in Figure 4-53. Figure 4-54 depicts the weights allocated to the stocks by the MVP and the HRP portfolios. Table 4-27 shows the weight allocations for the two portfolios to the NIFTY 50 stocks in tabular format. It is observed that while the stock PGCL received the highest allocation of weight from the MVP portfolio, the HRP portfolio assigned the highest weight to Axis Bank.

TABLE 4-27. THE PORTFOLIO COMPOSITIONS OF THE NIFTY 50 STOCKS (PERIOD: NOVEMBER 20, 2017 - DECEMBER 31, 2020)

Stock	MVP	HRP	Stock	MVP	HRP
Adani Ports	0.0013	0.0159	Indian Oil Corp	0.0055	0.0180
Asian Paints	0.0657	0.0280	ITC	0.0706	0.0394
Axis Bank	0.0003	0.1170	JSW Steel	0.0003	0.0125
Bajaj Auto	0.0069	0.0154	Kotak Bank	0.0014	0.0135
Bajaj Finance	0.0003	0.0069	L & T	0.0012	0.0149
Bajaj Finserv	0.0004	0.0142	M & M	0.0005	0.0104
Bharti Airtel	0.0065	0.0282	Maruti Suzuki	0.0005	0.0113
BPCL	0.0004	0.0154	Nestle India	0.0697	0.0287
Britannia Ind.	0.0153	0.0261	NTPC	0.0313	0.0320
CIPLA	0.0601	0.0241	ONGC	0.0004	0.0136
Coal India	0.0504	0.0209	PGCL	0.1451	0.0483
Divi’s Labs	0.0086	0.0311	Reliance Ind	0.0008	0.0189
Dr. Reddy’s Labs	0.0908	0.0247	SBI	0.0005	0.0093
Eicher Motors	0.0024	0.0106	SBI Life Ins	0.0334	0.0245
Grasim	0.0002	0.0106	Shree Cement	0.0019	0.0155
HCL Tech	0.0075	0.0213	Sun Pharma	0.0093	0.0297
HDFC	0.0008	0.0188	Tata Motors	0.0003	0.0077
HDFC Bank	0.0592	0.0196	Tata Steel	0.0003	0.0086
HDFC Life Ins	0.0012	0.0251	TCS	0.1129	0.0401
Hero MotoCorp	0.0009	0.0110	Tata Cons	0.0008	0.0164
Hindalco Ind	0.0002	0.0113	Tech M	0.0014	0.0243
Hind Unilever	0.0672	0.0400	Titan Co	0.0034	0.0205
ICICI Bank	0.0004	0.0094	Ultra Cement	0.0008	0.0216
IndusInd Bank	0.0002	0.0093	UPL	0.0004	0.0192
Infosys	0.0118	0.0206	Wipro	0.0482	0.0306

The cumulative returns yielded by the portfolios of the NIFTY 50 stocks over the training and the test periods are depicted in Figure 4-55 and Figure 4-56, respectively. Table 4-28 presents the cumulative returns and the maximum Sharpe ratios of the portfolios. It is observed that while the MVP portfolio yielded a higher return for the training period, for the test period, the HRP portfolio produced a higher return.

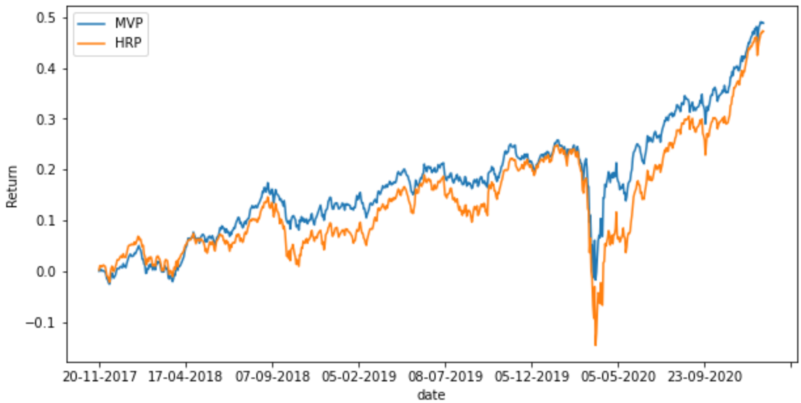

Figure 4-55. The cumulative returns yielded by the MVP and the HRP portfolios of the NIFTY 50 stocks on the training data from November 20, 2017, to December 31, 2020.

Figure 4-56. The cumulative returns yielded by the MVP and the HRP portfolios of the NIFTY 50 stocks on the test data from January 1, 2021, to December 31, 2021.

TABLE 4-28. THE PERFORMANCE RESULTS OF THE NIFTY 50 PORTFOLIOS

Period	MVP Portfolio		HRP Portfolio	
	Cumulative Return	Max Sharpe Ratio	Cumulative Return	Max Sharpe Ratio
Training	16.01%	1.0075	15.47%	0.8277
Test	20.95%	1.6122	27.29%	1.9572

Conclusion

This chapter has presented portfolio design approaches for stocks chosen from fourteen sectors (including NIFTY 50) listed on the NSE of India. Based on the historical prices of the ten stocks with the largest free-float market capitalization from each sector and the 50 stocks in the NIFTY group, MVP and HRP portfolios are designed. The portfolios are backtested on both training and the test data to identify the portfolio with the higher cumulative return and higher Sharpe Ratio for each sector. It is found that while on the training data, the MVP portfolio yielded the higher cumulative returns for seven among the fourteen sectors, the return yielded by the HRP portfolio is found to be higher for eleven sectors on the test data. Since for a portfolio, its performance on the test data is what matters to the investors, the results of the study indicate that the HRP portfolio is a better choice over the MVP for the investors of the Indian stock market. The future work plan includes a similar study on important stocks listed in the other major stock exchanges in the world.

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