International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

An Optimal Portfolio Construction for Asset Management with Back-Test Using PSO Algorithm and PyPortfolioOpt in Indian Stock Market

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Submitted: 17/07/2023 **Revised**: 09/09/2023 **Accepted**: 24/09/2023

Abstract: The paper studies the concept of Portfolio optimization and back-testing in the context of BSE and NSE for a group of selected stocks in FMCG sector. Optimizing a portfolio refers to the process where assets are allocated such that the allocation results in maximum returns with minimum variance. This is also the fundamental theory proposed by Harry Markowitz. An optimal allocation which is mathematically valid can be constructed by a combination of different stocks with varying expected returns and volatilities. A comparative analysis is made in the study with Particle Swarm optimization algorithm used for constructing the optimal Portfolio from the selected sector of stocks firstly and next the same stocks are optimized using PyPortfolioOpt package. Suitable Back-testing is applied and the results evaluated. In Back-testing a predictive model or a strategy is applied to historical data which helps to assess its accuracy. We can consider the back-tested results of the trading system as reliable parameters for future performance based on probability. A comparison of the portfolio optimization using PSO and the package PyPortfolioOpt is done in this paper.

Keywords*: Artificial Intelligence, Particle Swarm Optimization, Sharpe Ratio, Portfolio Optimization, Back-testing, Simple Moving Average Crossover*

1. Introduction

A stock portfolio constructed by balancing the risks and volatilities is vital to creating wealth for shareholders and companies. Among all the markets, the equities tend to give higher returns. This fact holds true in the case of the Indian equity market. To capitalize on this fact, the need arises to secure high returns with minimum risk. This also makes sure the worthiness of the financial portfolio will be more in the future.

When the decision is taken on determining the risk bearing capacity, the next task is to determine asset allocation. The fact remains that different classes of assets are imperfectly correlated which can lead to higher returns while maintaining minimum portfolio volatility. The asset allocation has often helped to build wealth during bear markets.

In the study a comparative analysis is done by adopting two methods. The former uses Particle Swarm optimization as a standard algorithm to reach the optimal asset allocation among a given set of stocks. The latter makes use of the modules available in a python package for portfolio optimization called the PyPortfolioOpt.

PSO mimics the animal behavior like a shoal of fish searching for prey or a flock of birds thereby simulating the swarm behavior. In this manner, iterations are carried out until the problem at hand is optimized. In PSO, each particle is represented as (x, y) position. The PSO then searches for the best solution by moving each particle with a certain velocity. There are two factors governing the particle velocity: the best of the local position and the best of the global position. For each iteration, these are calculated and once the swarm of particles converges to the best solution, the iteration stops.

Each particle represents a potential capital allocation among the portfolio assets, in the case of Portfolio Optimization. To determine the relative fitness of the different combinations of portfolio the Sharpe ratio is chosen. It is a measure which balances risk and expected return. In the second case, the functions from the PyPortfolioOpt package are applied to the same set of stocks chosen for PSO. Once again, the Sharpe Ratio is chosen as the metric to study the portfolio allocation of the assets chosen. Other parameters chosen are the Max Drawdown (MMD), Skewness and kurtosis. A portfolio or allocated assets may peak or fall down during the period observed. The sharp loss from the peak of a portfolio to the valley is called Max Drawdown. It represents the amount of risk involved during the specified time period. Skewness indicates how the returns distribution are shaped. The peakiness of the distribution of returns is measured by kurtosis.

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1.1Back-testing

Building an equity portfolio is one of the best ways to create wealth. However, the Model predicting the future prices of equities have to undergo back-testing for its future viability. Back-testing is the method employed to see how a trading strategy / model would fare retrospectively with historical data. If the back-testing proves to be good for the past data, it could be employed going forward. Therefore, Back-testing allows a model that is simulated on historical data and helps to analyze risk and profitability of using the model in real world.

There are many readymade software's available to conduct Back-testing on equities. However, the paper goes forward to use a methodology, Simple Moving Average (SMA) Crossover system for carrying out back-testing on the selected stocks.

Simple Moving Average (SMA) Crossover system is one of the widely used methods. In this method the lengths of two moving averages are compared to see and back-test to decide which lengths of moving averages performs better on the past data. The figure1 illustrates the process of back testing.

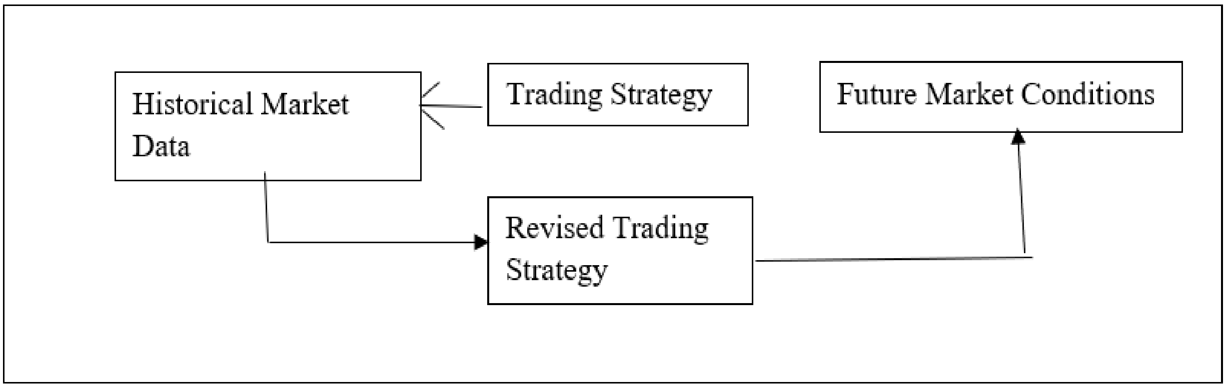

Fig. 1 A trading strategy development model

Back testing is performed on the historical data. And we gauge its performance based on certain parameters. Some of the back-testing statistics include: Net profit or loss, Volatility measures**,** Averages**,** Exposure- Percentage of capital invested (or exposed to the market), Ratios**,** Annualized return and Risk-adjusted return.

2. Literature Review

In Paper (Jamous et al., 2015) , PSO technique is studied in the domain of Portfolio selection for predicting stocks with minimum risk and maximum profit. The application of various modifications of the PSO in stock market has been studied extensively. Paper (Samigulina & Massimkanova, 2020) presents a modified PSO named (CPSOIW) algorithm for forecasting complex objects. The application of parallel computing of subswarms achieves more efficiency. Paper (Zhang et al., 2018) discusses a modification of Swarm Optimization named SPSORC algorithm which is efficient in terms of search time and computing accuracy. Paper (Zhu et al., 2011) uses PSO technique in the area of optimization of financial portfolio. The algorithm is found to be useful in constructing optimal risky portfolios. In paper (Abd-El-Wahed et al., 2011) the particle swarm optimization algorithm is integrated with genetic algorithms to solve nonlinear problems. The study on data taken from literature showed superior results for the hybrid model. Paper (De et al., 2013) applies an intelligent hybrid system to forecast the concentration of pollutants in the atmosphere, which is a time series forecasting problem. The methodology achieves a fair prediction. The improvement of prediction accuracy in a time series forecasting problem is studied in paper (Xiao et al., 2017). A hybrid model is used for the study. The model consists of a Feedforward network with multiple layers based on an improvised form of PSO. In paper (Seidy, 2016) a modification of particle swarm optimization (PSOCoM) is applied. The model was applied on stock market to make prediction and displays superior prediction accuracy. Paper (Bin Shalan & Ykhlef, 2015) studies the problem of Portfolio Optimization and proposes a new hybrid evolutionary algorithm which is using clonal selection. Paper (Ertenlice & Kalayci, 2018) discusses how different variations of PSO deals with Portfolio Optimization. Paper (Hu et al., 2015) provides a systematic literature review of methodologies in Evolutionary Computation that could be applied in stock prediction and Trading. Artificial Bee Colony algorithm is applied for optimizing portfolio in Paper (Kumar & Mishra 2017). Paper (Macedo et al., 2017) studies the usage of evolutionary algorithms with multi-objectives in the context of optimization of portfolios. Paper (Saborido et al., 2016) uses a model, abbreviated MDRS model to optimize portfolio of stocks. Paper (Meghwani & Thakur,

2018) proposes to optimize the task of portfolio allocation taking into consideration risk, return and transaction costs. The risk measures are studied with respect to variance, Value-At-Risk and Conditional Value-At-Risk by applying evolutionary algorithms with multi-objectives in the proposed work. Paper (Mishra et al., 2016) deals with optimization problem in portfolios by application of a novel PSO called SR-MOPSO. Paper (Qu et al., 2017) uses Evolutionary computation methods for optimizing a large-scale portfolio. The model tends to be superior to other algorithms in the comparative analysis. Paper (Perrin & Roncalli, 2019) studies large scale optimization problems and how it could benefit portfolio allocation. In Paper (Lv et al., 2019), different ML algorithms are evaluated on stocks to observe how the day-to-day trading of stocks perform with and without transaction costs. DNN models had superior performance compared to the traditional machine learning algorithms while considering transaction cost. Paper (Martin, 2021) illustrates and develops PyPortfolioOpt, a novel python package that implements financial portfolio optimization techniques. Paper (Bailey & de Prado, 2013) implements the Critical line Algorithm as an open-source implementation in Python. In Paper (Ta et al., 2020), LSTM network, is modelled to forecast stock prices based on past values. Paper (Ban et al., 2018) applies regularization and cross-validation in machine learning models, for portfolio optimization. Paper (Milhomem & Dantas, 2020) proposes a comprehensive review of the various algorithms for optimizing portfolio. Paper (Kulshrestha Nitin & Srivastava Vinay K., 2020), reviews the optimization of stocks selected from Nifty fifty. The duration of the stock was from Jan 2013 to Jan 2020. Paper (Fafuła & Drelczuk, 2015) compared Ichimoku trend with buy & hold benchmark on Warsaw stock Exchange. Paper (Harvey R Campbell & Liu Yan, 2014)deals with the new tools to evaluate trading strategies.

3. Implementation of PSO and Data used

The two important constraints to be considered for optimizing portfolios using PSO (Particle Swarm Optimization) are 1) The total value of the assets should be 100% 2) Negative allocations are not allowed.

A pseudo code of PSO Algorithm is given below:

```
Initialize for each particle p
For dimension d
    P= Random value
   V=Random value
End For
Initialize count<-1
```

```
Do
  For each p
     get Fitness
    If fitness > p_good
       current fitness = p_good
    End If
  End for
 Let p with max_fit =g_best
  For each p,
    For each d
       compute velocity
       Update particle position
     End For
  End for
count<- count+1
while (max iterations/min error)
```

5 stocks from BSE Sensex from the Consumer goods sector were chosen for study. They are Asian Paints, Britannia, Hindustan Unilever, ITC, Titan. With these stocks listed from 03-01-2000 to 31-12-2020, the entire data for the period is taken and analyzed. In the previous study, the historic prices of the data are fed into LSTM and stock prices predicted for the above companies for multiple time periods. Once the prediction is done, we can make an informed decision on which stock is trending up and which one is trending down.

The last step is the construction of the optimal portfolio for the given set of stocks. The PSO algorithm is used for this purpose.

To begin with, we decide on the factor to be chosen for optimization goal. Sharpe Ratio is one of the widely used indicator for measuring returns of a stock against its risk. In this case, maximizing returns will be the fitness function. However, for the stock market there occur lot of spikes and busts. A portfolio has to be resilient to spikes in volatility. This is achieved by spreading out equal risk contribution among assets/stocks in the portfolio.

The optimization goal is given as maximizing Sharpe ratio while preserving equal risk contribution. The equation is given below in eq (1)

$$\text{Sharpe} * \propto + 1/\text{volatility dispersion} * (1 - \propto) + 1 \quad (1)$$

Where volatility dispersion stands for inequality in risk contribution compared to average.

Volatility Dispersion $= \sum(stock\ risk\ contribution_i - average\ risk)$ (2)

Volatility dispersion is equal to the sum of absolute deviations of individual standard deviation components from mean deviation. In other words, the less the deviation the more individual risks are aligned with mean, and vice versa. The alpha coefficient ranges from 0 to 1. At alpha=1 the expression results in Sharpe ratio +1.

Each particle is a randomly generated portfolio consisting of vector of size n (number of stocks), each position ranges from 0 to 1 (negative weights (shorting) are not allowed). When you add up all the weights it should be equal to 1.

An analysis of the results for 2017 for the selected stocks is given in figure-2 below. Data is smoothed using Savitzky-Golay filter.

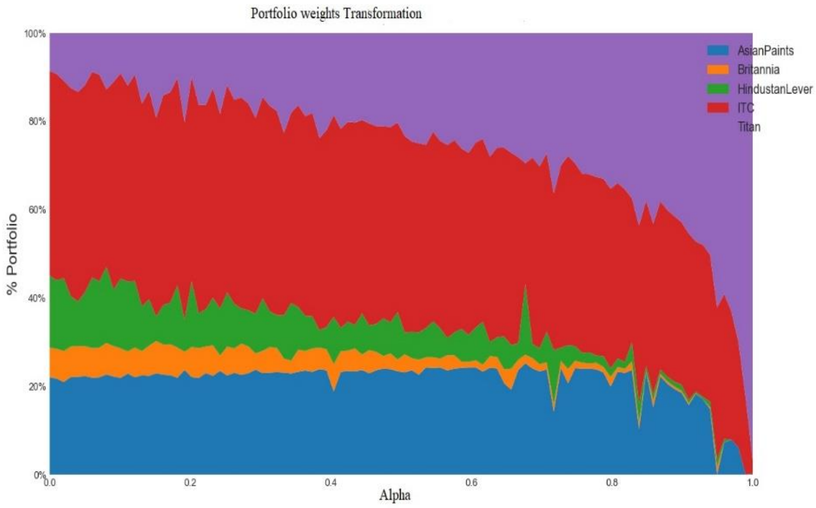

Fig 2. Raw portfolios' evolution:

Portfolio theory is applied so that the stocks are spread out and diversified. Due to this diversification, it is possible to build a portfolio with less risk factor. The study has utilized 5 stocks from the Consumer goods sector to demonstrate this. The entire portion of the wealth of the investor is assigned by allowing only long positions (Positive) and the sum of these positions should add up to 100%.

The stocks are then subject to Sharpe ratio analysis and volatility dispersion on the progress of best values is illustrated in Figure 3.

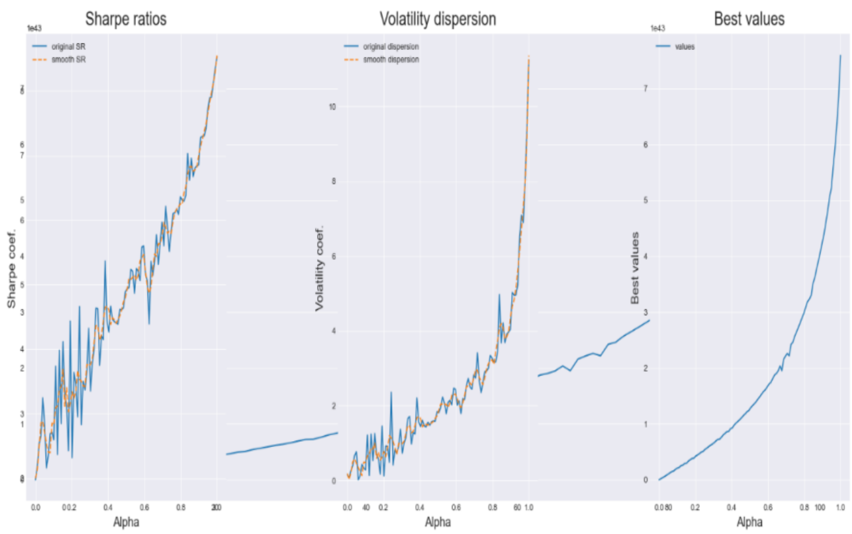

Fig 3. Statistics for the evolution of Sharpe ratio, volatility dispersion on the progress of best values.

It is viewed, that the Sharpe ratio rises quickly to the plateau of around 4 while volatility dispersion almost linearly rises along with all alpha values. It is beneficial for an investor to sacrifice the Sharpe ratio a little bit for greater risk-parity at alpha around 0.4.

The composition of portfolio at alpha = 0.4 is depicted in Figure 4.

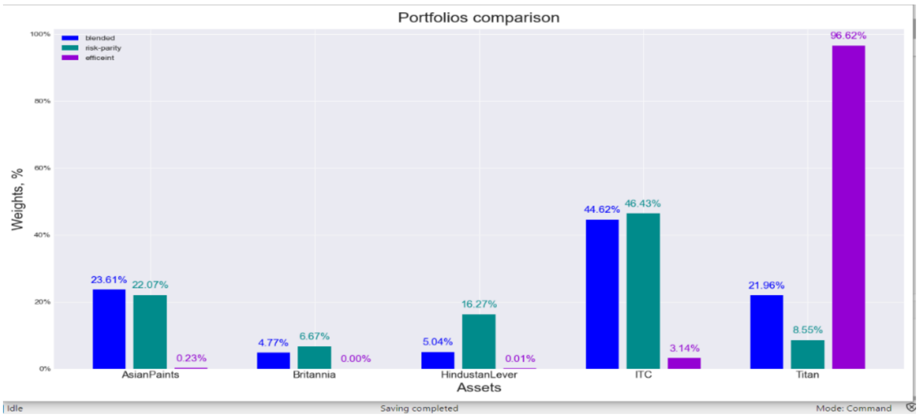

Fig 4. A comparison of the assets with their weights in portfolio

Interesting point, is how quickly the weights of different ETFs evaporates. Britannia drastically decreases to 0, while Asian Paints, ITC and Hindustan Lever increases smoothly. Another point, is that portfolio fluctuations become bumpier as the move towards alpha=1. This is the result of the Sharpe ratio optimization because it is more sensitive to initial conditions.

The study leads to the conclusion that the application of PSO to the portfolio problem helps to pick the right mix of assets in the portfolio. A lot of attention should be paid to the construction of the optimization goal because the different magnitude of variables can greatly affect the balance.

Use of PyPortfolioOpt for Portfolio Optimization

PyPortfolioOpt is a library available in Python language to implement optimization methods for designing an optimal portfolio. The package focuses on mean-variance optimization (MVO). One of the flavours of MVO is by applying the standard Efficient Frontier.

4. Implementation and Datasets

5 stocks from BSE Sensex from the Consumer goods sector were chosen for study. They are Asian Paint, Britannia, Hindustan Unilever, ITC, Titan. With these stocks listed from 03-01-2000 to 31-12-2020, the entire data for the period is taken and analyzed. In the first part, the historic prices of the data are fed into LSTM and stock prices predicted for the above companies for multiple time periods. Once the prediction is done, we can make an informed decision on which stock is trending up and which one is trending down.

The figure 5 illustrates the closing prices of the above selected stocks.

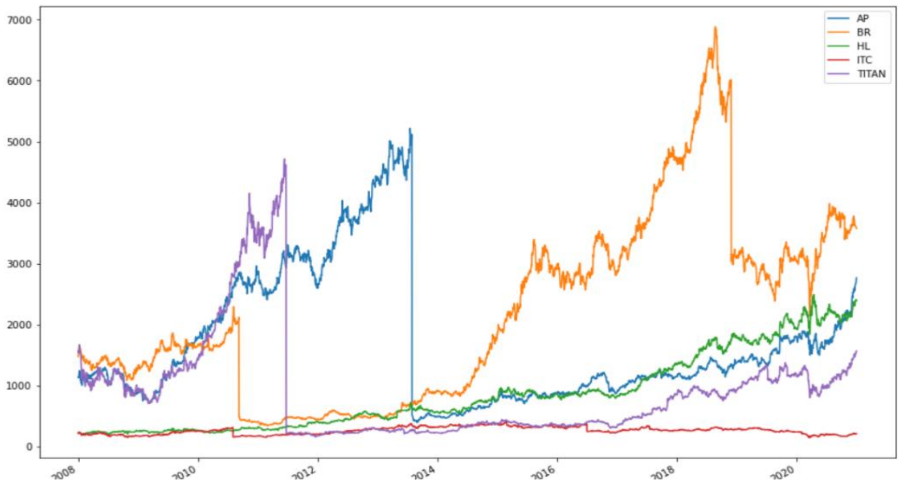

Fig 5: Close prices of selected Stocks

The package offers functions to calculate expected returns, percentage returns, Sharpe ratio calculation, Efficient frontier and other parameters required to perform the portfolio optimization.

To apply MVO (Mean-variance optimization) it is required to have a picture of the expected returns. It is estimated by extrapolating historical data. In the paper the Mean Historical return is calculated. Other implementations in the package include: return function, exponentially weighted mean historical return and CAPM estimate of returns.

The figure 6 is an illustration of the calculated historical returns with a bar chart

```
AP        0.090457
BR        0.097347
HL        0.114080
ITC      -0.062689
TITAN     0.159151
dtype: float64
```

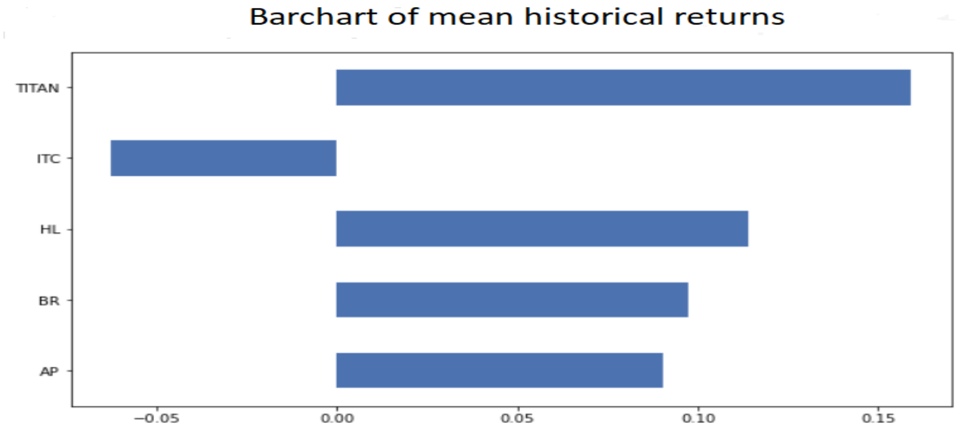

Fig 6: Mean Historical Returns of selected Stocks

Thus, we have the expected returns and it also requires a risk model in the Portfolio theory. This is to achieve to identify the risk associated with the asset. The covariance matrix is used very often to evaluate asset volatilities and their co-dependence. This is to ensure that the risk can be diversified with the help of uncorrelated assets. The figure 7 depicts this.

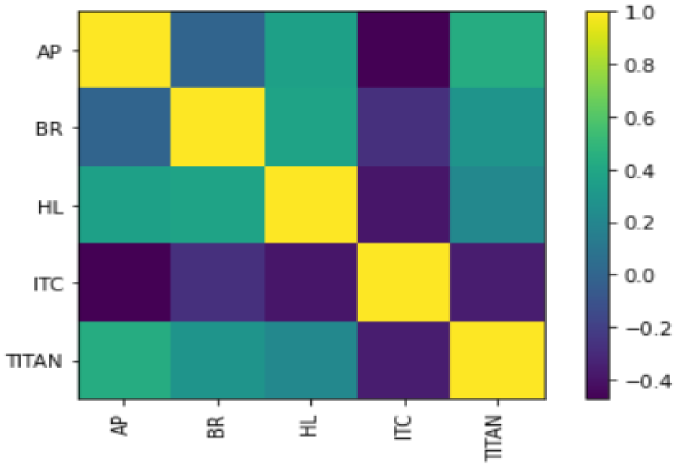

Fig 7. covariance matrix of selected Stocks

The Figure 8 gives a picture of the Optimal weights with the expected performance of the portfolio.

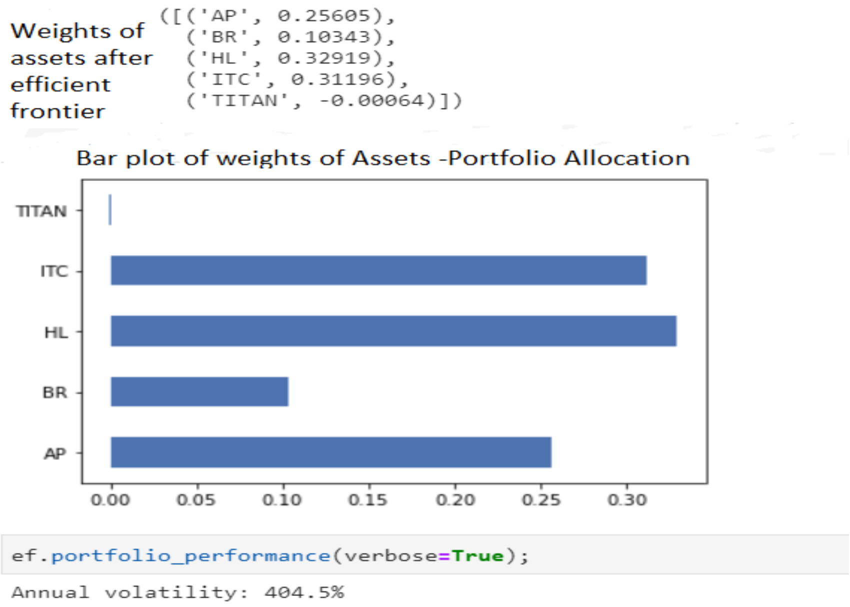

Fig 8. Portfolio allocation of selected Stocks

A different portfolio may be obtained if we change the value of the target return. – Efficient Frontier refers to the set of all these optimal portfolios.

4.1 Mean-Variance Optimization and General Efficient Frontier

In finance there are various convex optimization problems. The portfolio optimization is one among them.

PyPortfolioOpt aims to do all the above, and to generate a portfolio that minimizes the volatility. The module cvxpy, in python is used for convex optimization upon which PyPortfolioOpt's efficient frontier functionality lies.

The efficient frontier calculated for the stocks selected is illustrated in Figure 9 below.

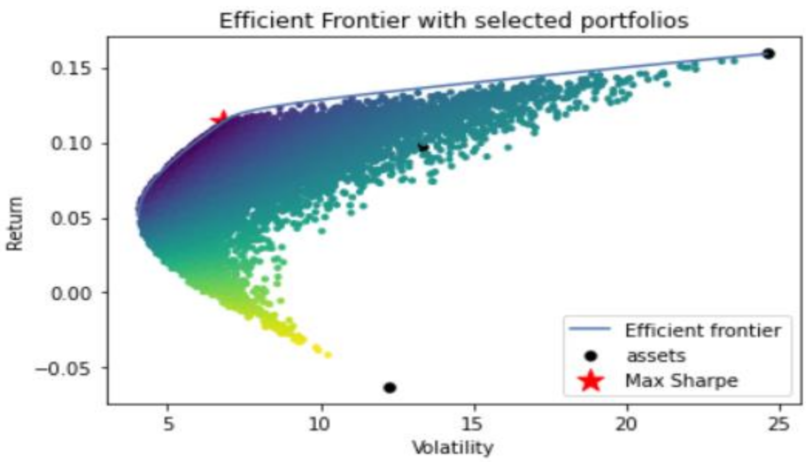

Fig 9. Efficient Frontier of selected Stocks

The figure above represents a class of diversified portfolios which is depicted by each dot. The darker blue shades refer to good portfolios which are measured by their Sharpe Ratios. The efficient frontier is highlighted by the blue line. The best portfolios which have maximum Sharpe ratios are represented by triangular markers.

In other words, Sharpe ratio is an indication of the volatility. The Sharpe ratio is the portfolio's return in excess of the risk-free rate, per unit risk.

SR=RP−Rf / σ (3)

The concept of Sharpe Ratio is extremely important in MVO theory. It is an indication of the value of returns adjusted for some risk. Therefore, it is sensible to find the portfolio that results in a maximum value of the Sharpe Ratio.

5. Implementation and Data Sets for Back testing

Next to reinstate our LSTM prediction results done in our previous paper, a back testing strategy is applied on the stocks selected for study.

In the proposed study, the following two parameters are considered for evaluating the performance of our back testing strategy. One is called the Maximum Drawdown, and the other is the Sharpe Ratio. The former measures risk which indicates the fall in the asset value from a peak value. This denotes the amount of loss that we would face if we choose a particular trading strategy. The other parameter is the Sharpe ratio which helps to measure the risk adjusted return. For example, we may have different strategies that result in equal returns. However, the strategy with a lesser risk factor would be considered better. This is exactly what the Sharpe ratio calculates and it is called the risk-adjusted return.
Going long or short in markets is referred to as a trading strategy. The two variations in this are the momentum strategy (trend trade) and the reversion strategy(also called ranging). A stock is bullish or bearish which can be checked with suitable technical indicators. If we employ ranging mostly check the RSI for confirmation signals. If it is trending check moving averages to confirm a re-entre or a break in the trend.

When you follow trend trading or momentum strategy, the stocks exhibit trends which may move up or down. These characteristics or trends may be used in momentum strategies such as the crossover of moving averages, and crossover of the dual moving averages.

The movement of asset values from one side to the other of a moving average is known as the Moving average crossover. This is considered a critical point to decide to buy or sell.

Similar terms, when a short-term average cross a long-term average it represents a dual moving average crossover.

A signal cycle is established like Buy-Sell, Short - Cover. Next, the historical data was split into two- the first set, the training set and the second called the testing set. The strategy is applied and the model looks at the data and understands the relationship by looking at the training set and then is expected to continue on the test set, so, it will predict on the test set. There is also an optional Validation set which is used as a first evaluation check and optimization for the parameters. This set can tune and tweak the model before presenting it to the test set. The Training Set and Validation Set work on data from in sample Period. The Test set is data from Out-of-Sample Period. The only out-of-sample period is the one we haven't seen yet (i.e., the future).

5.1 Results of Simple Moving Average crossover

The optimized carry trade portfolio was back-tested from 2019 to 2020. The lookback periods of 40 and 100 days were created for Simple Moving averages. When the 40 SMA crosses over the 100-day SMA, a long position is generated. Otherwise, we exit. The stock prices go up in future when a long position is generated. This leads to buy signal; When you go short it is denoting a sell signal. The figure 10 indicates the Buy and Sell signals.

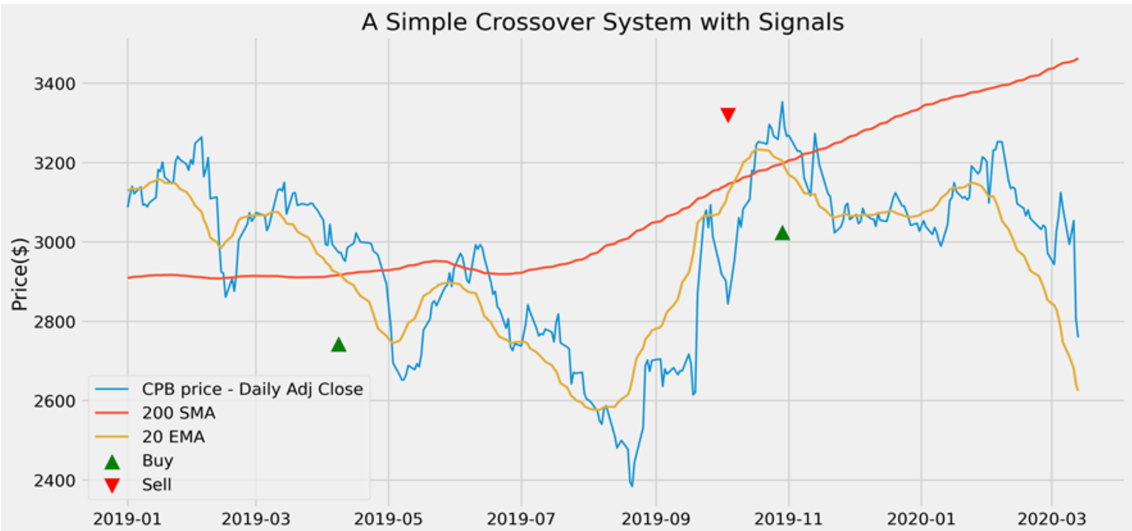

Fig 10. Simple Moving Average crossover for the stock Britannia

Once the trading strategy is ready it is back tested and the performance is calculated.

The results of Drawdown are presented in the figure 11.

Worst drawdown periods	Net drawdown in %	Peak date	Valley date	Recovery date	Duration
0	52.81	2000-01-13	2001-09-17	2004-12-07	1279
1	32.21	2013-07-23	2013-08-28	2014-08-14	278
2	30.41	2006-04-05	2006-06-14	2007-05-29	300
3	29.49	2008-01-07	2009-03-09	2009-06-10	373
4	29.44	2019-10-29	2020-03-23	2020-11-10	271

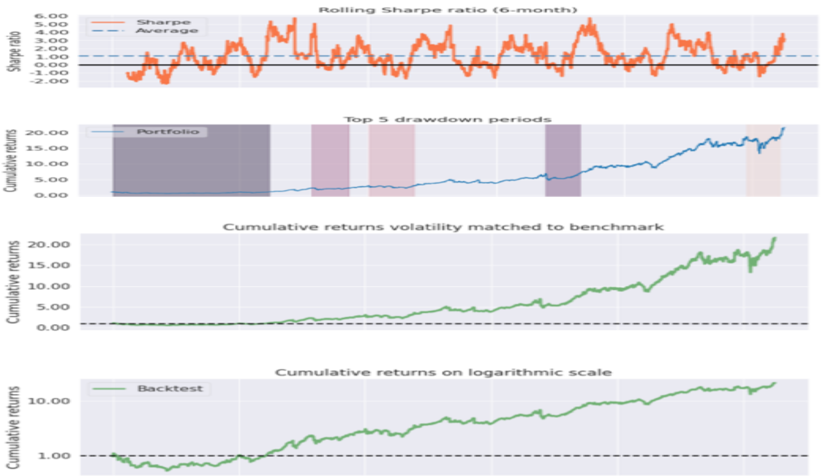

Fig 11. Drawdown performance output

6. Conclusion

The application of Particle swarm optimization to portfolio optimization helps in the improvement of the performance of the assets. From the study it is clear that once the portfolio is optimized it generates better positive returns. The best combination of assets is proved not only by superior returns but also reduced risks. Therefore, particle swarm optimization algorithm proves in the study conducted that it is a good option to solve optimization problems in complex portfolios. Similar results were supported by PyPortfolioOpt Package implementations done in the study. Further, the back testing results help to optimize and improve the strategies to be adopted by traders.

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