Final Report

Portfolio Risk Assessment Theory with Particle Swarm Optimizer

Baibhav Pathy

June 2023

Contents

1 Abstract

This paper outlines how Modern Portfolio Theory can be implemented using notable financial engineering techniques. The generated algorithm discussed within this paper combines a dynamic implementation of Modern Portfolio Theory with a robust metaheuristic solver to find the globally minimum risk portfolio, given the desired set of stocks and sample date range. Specifically, the metaheuristic called "Particle Swarm Optimization" intends to overcome issues with local optima in non-linear modeling. The model delivers the optimal weights to invest in a certain set of stocks, defined by the user of the tool. Additionally, the model displays key summary statistics like the risk and expected return of the portfolio.

2 Introduction

Specifically, the project uses Python to pull monthly data for the `N` number of stocks defined by the user, as well as the Treasury Bill rate (as a proxy for the risk-free rate). The decision variables will be the weights to invest in each stock that minimizes the risk of a portfolio. Since the objective is to minimize the risk of the portfolio, this method must account for within-stock variances as well cross-stock covariances. The objective function becomes non-linear in parameters. To solve this non-linear objective, the tool will use metaheuristic techniques to search for the optimal portfolio. The algorithm uses the particle swarm metaheuristic.

3 Modeling

3.1 Model Formulation

3.1.1 Overview of Model Formulation

Overall, this developed computer programming application in Python accomplishes a direct application of financial engineering by implementing Modern Portfolio Theory, while also improving the modeling by leveraging the metaheuristic technique, Particle Swarm Optimization. The modeling within this tool primarily relies on the use of Modern Portfolio Theory, which Markowitz introduced in 1952, to minimize the risk of a multi-stock portfolio while meeting an investor's desired return. To minimize the risk, or standard deviation of a portfolio, the model must use a non-linear optimizer to solve for the optimal allocation of weights in each stock; the tool makes use of a popular metaheuristic technique called Particle Swarm Optimization (PSO), which famously overcomes issues with local minima.

3.1.2 Minimizing Risk of Portfolio using Modern Portfolio Theory

The tool pulls stock data from Yahoo Finance, then implements Modern Portfolio Theory to that data. Shortly, this method gives a "statistical" way to "diversify" investments in a multiple stock portfolio and not "put all their eggs in one basket" (Benninga 306).

3.1.2.1 Importing Stocks using `yfinance` Package

Using the popular package called `yfinance`, the tool takes a list parameter named `StockList` with publicly traded stock tickers to evaluate when considering inclusion within the portfolio. Yahoo Finance supplies detailed-historical data surrounding money market assets. Although `yfinance` allows real-time data for each minute, the tool uses monthly stock data with the adjusted close price of each stock. Commonly, financiers use the adjusted close price for historical data.

This paper will refer to a parameter named `Periods`, which are the monthly periods of a given stock in a sample date range. Please note that the user of the program defines the date range to include within the sample.

Lastly, the tool imports the previous, or most recent, adjusted close price for the 3-month Treasury Bill (ticker `^IRX` as a proxy for the risk-free rate), which is used when calculating the Sharpe ratio. See later sections for the uses and definitions. Note that the risk-free rate proxy will be referred to as the `riskFreeRate` in later calculations.

3.1.2.2 Returns of Each Stock

After importing the adjusted close price of each stock, the tool calculates the percentage return of each month, for all stocks in the `StockList` parameter, as well as months in all `Periods`. Note that this calculation finds the percentage rate of return from the prior period to the current period `t`. See the calculation of the return of the stock below.

$$Returns_{stock,t} = \ln\left(\frac{AdjClose_{stock,t}}{AdjClose_{stock,t-1}}\right),$$
$$\forall\ stock \in StockList,\ \forall\ t \in Periods$$

3.1.2.3 Expected Returns of Each Stock

The program takes the arithmetic mean over for all periods to understand what the expected rate of return of each stock is. Note that a known limitation of Modern Portfolio Theory is that the use of expected returns does not consider the future, which diminishes the potential for predictive analytics; fitting the model to historical data will help find optimality in hindsight, but may not work well for forward-looking analysis (Benninga, 305). For example, imagine if an investor used stock data from the COVID-19 pandemic shutdown months to optimize the portfolio. Using this data assumes that the stocks in the sample perform similarly outside of the COVID-19 pandemic. This assumption could have bias; however, if the investor chose to investigate the bounds of potential loss, a season like the shutdown months could provide a platform for natural experiments. Additionally, the investor may ground themselves in the Modern Portfolio Theory method if they forecast that future months may perform similarly to the sample period. See the calculation below for the expected return of each stock, where `numPeriods` represents the number of months in the sample.

$$ExpectedReturns_{stock} = \frac{1}{numPeriods} \sum_{t \in Periods} Returns_{stock,t}, \quad \forall\ stock \in StockList$$

3.1.2.4 Excess Return of Each Stock

The tool calculates the excess return of each stock for all periods to discover how the return of a given period outperforms or underperforms the expected return of the stock. Simply, the excess return is the percentage return of a stock in excess of the stock's expected, or mean, return. See calculation below.

$$ExcessReturns_{stock,t} = Returns_{stock,t} - ExpectedReturns_{stock,t}, \quad \forall\ stock \in StockList,\ \forall\ t \in Periods$$

3.1.2.5 Accounting for Covariances Among Stocks

To evaluate the risk, or portfolio sample standard deviation, we must account for covariances among stocks. Conceptually, when accounting for covariances among stocks, the investor can diversify "away" risk when stock prices "move", or co-vary, together, which that notion could enhance the overall risk of the portfolio. Note that `N` represents the number of stocks in the parameter `StockList`. See below for the calculation (using matrix notation) of the variance-covariance matrix (Benninga, 206).

$$VarCov = \frac{ExcessReturns^T.ExcessReturns}{N-1}$$

3.1.3 Solving for Optimal Portfolio using Particle Swarm Optimization (PSO)

Once the tool prepares the data needed for optimization using Modern Portfolio Theory, the metaheuristic technique (PSO) solves for the minimum risk portfolio.

3.1.3.1 Need Non-Linear Optimizer due to Covariance Matrix

From an overview perspective, the goal of the optimization problem is to minimize the overall risk of the portfolio. In order to search for the optimal combination of stocks to invest in that reaches the minimum risk, the algorithm will search for the set of `Weights` to invest into each stock in the portfolio. See the definition of `risk` below. Note that `12` is explicitly written to represent the number of months within a calendar year.

$$risk = \sqrt{12} \times \sqrt{Weights.VarCov.Weights^T}$$

While we must minimize the risk, two key constraints must be met. Namely, the `Weights` of the stocks must total 1, or 100%. Additionally, another important constraint is to only consider `Weights` that yield the minimum desired expected return of the portfolio set by the user.

Minimize: $risk$
Subject to:
$\sum_{stock \in StockList} Weights_{stock} = 1$
$\sum_{stock \in StockList} (Weights_{stock} \times ExpectedReturns_{stock}) \geq minDesiredReturn$

In addition to minimizing the risk, the tool can also minimize the Sharpe ratio if the user prefers. The Sharpe ratio measures the risk-adjusted returns of the portfolio, in excess of the risk free rate. Note that through experimentation, this method does not consider the importance of diversification, which typically causes the optimal allocation of stock weights to converge to a single stock. Since the Sharpe ratio does offer important measures of risk-adjusted performance, the statistic is always reported when the optimal portfolio is found. **For all later examples, please assume the objective is to minimize the risk of the portfolio unless otherwise stated.** Below contains the formula for the Sharpe ratio.

$$sharpeRatio = \frac{expectedReturn - riskFreeRate}{risk}$$

3.1.3.2 Conceptual Overview of PSO Algorithm

Particle swarm optimization (PSO) is a metaheuristic optimization technique poised to overcome issues of discovering sub-optimal solutions, commonly called local optima. Conceptually, PSO mimics swarms of individual organisms, such as fish, moving towards an unknown overall objective. The individual particles, previously noted as "organisms," use their cognitive ability, as well as a social ability to search and move towards the objective. Social refers to the other particles within the swarm of particles. When the algorithm begins, the swarm initializes stochastically, or randomly. Thereafter, the particles will independently move as a swarm towards the best solution.

3.1.3.3 Application of PSO to Modern Portfolio Theory

From the general example above, Particle swarm optimization can easily be applied to the optimal portfolio problem. Like most optimization techniques, the objective, or evaluation function, will use decision variables to calculate where the objective stands at any given point in the algorithm. Concerning Modern Portfolio Theory, each movement of particles evaluates the risk of a set of portfolio `Weights` and then continues to find the minimum risk portfolio based on other possible solutions. Until the algorithm meets the stopping criteria, which is both a total number of iterations and meeting all required constraints, the swarm of possible portfolios will keep searching for the minimum risk portfolio.

3.1.3.3.1 Initialize Random Feasible Solution

The model starts with a random set of portfolios, which each contains randomly generated `Weights` for each stock in the `StockList`. Please note that all initial solutions meet both required restraints for the optimization problem. All solutions are associated with a certain risk value, based on the risk equation above.

3.1.3.3.2 Stochastically Change Weights of Portfolio in Each Swarm

The key to PSO is that each particle within a swarm will move based on its own personal best and the swarm's global, or local, best solutions. For brevity and to remain within the scope of this research topic, assume that each portfolio will use information about its past best `Weights` and the swarm's past best `Weights` to look for the optimal solution. The user can place more or less weight on the "social" or "cognitive" components but are equally distributed by default. Within this model, below is the movement update equation for reference:

$$V_i^{t+1} = \underbrace{V_i^t}_{\text{Inertia}} + \underbrace{\varphi_1 \cdot r_1 \left(P_i - X_i^t\right)}_{\text{Cognitive Component}} + \underbrace{\varphi_2 \cdot r_2 \left(P_g - X_i^t\right)}_{\text{Social Component}}$$

where $r_1, r_2 \sim U(0,1)$, or are random constants that are distributed uniformly from `0` to `1`; these random constants encourage random movements. φ_1, φ_2 are acceleration constants, which can cause larger or smaller changes in the stock `Weights` from one iteration to another. V_i^{t+1} represents the updated velocity vector, indicating how the algorithm will change the `Weights` of the portfolio. V_i^t is the current velocity that previously was generated on the last iteration. X_i^t resembles the current `Weights` before any changes have been made. P_i is the *particle*, or portfolio's individually best `Weights` over all past iterations; they are the "best" with respect to its evaluated risk. P_g is the *swarm's* best `Weights` over all past iterations; note that P_l is substituted in the algorithm later to represent the "local" best neighborhood structure using a "ring" topology. *Local* best only shares particle bests among a few other particles, whereas the *global* shares among all particles. See future sections for more elaboration.

Each movement from one potential solution to the next is calculated by $X_i^{t+1} = X_i^t + V_i^{t+1}$. The outcome generates a new set of `Weights` for all simulated portfolios. Note that the algorithm performs some redistribution of weight to ensure feasible solutions.

3.1.3.3.3 Evaluate and Document Risk of Each Change in Weights

As noted above, each time the model searches for a better solution than it has seen in the past, it evaluates the risk of the `Weights` of the portfolio, then documents it so that other portfolios can make decisions on how to change their `Weights`.

3.1.3.3.4 Keeping Track of Best Solutions in Swarm: Global and Local Best

Another approach to PSO is to use differing neighborhood structures than the global best method. Alternatively, a local best approach disables the particles to know the best solutions of every other particle's best; the particles only are aware of some of the other particles' best solutions. This model uses the local best "ring" structure, in which each particle only can see four other particles' past best solutions; note that there is no significance to choosing four other than limiting exposure. With the application of Modern Portfolio Theory, the local best "ring" structure performs better on some tests mentioned in later sections performing experimentation.

3.1.3.3.5 When the Algorithm Stops: Overcoming Local Minima

When the algorithm should stop is a critical component to finding the global best solution. As mentioned previously, the non-linear objective function can lead to local minima or incorrect optimal solutions. By adjusting the stopping criteria (when the algorithm assumes it has found the best possible solutions), the output could vary greatly. For this algorithm, the user can adjust the number of iterations to test if increasing search iterations will give a better solution. Note that no matter the number of iterations performed, the algorithm will not stop until it has satisfied both constraints.

3.2 Model Solution

This section shows executions of the algorithm using real stock data. The paper compares performance among executions with various parameters chosen.

3.2.1 Base Solution and Results

The "base" solution used the fifty highest market valued stocks in the S&P 500 (as of 6/22/2022) with a sample date range of the past 9.4 years. Upon each iteration (total of 3,000), the model simulates thirty feasible portfolios. The minimum desired return to be met is 7.5%. The model minimizes the risk using a local best neighborhood structure with a ring topology

See below for the output of the solution for all stocks to invest in. Note the model only shows stocks with `Weights` at or over 0.1%. See that the solution arrives at a portfolio with 19 stocks that evaluate to an annualized risk of 10.0%. The expected return is 15.0% and has a Sharpe ratio of 1.44.

```
Key Summary Statistics -----------------
Global Best Annualized Risk:    10.0%
Annualized Expected Return:     15.0%
Sharpe Ratio:                   1.44
Expected Return over 9.4 Years: 373.9%

Global best weights in each stock (Only includes stocks to invest in):
```

Ticker	Opt. Weight
V	0.3%
NVDA	0.7%
PG	0.3%
MA	3.4%
PFE	3.7%
KO	0.4%
ABBV	11.6%

Ticker	Opt. Weight
PEP	12.2%
VZ	0.5%
COST	0.6%
AVGO	11.5%
MCD	0.1%
CSCO	9.7%
DIS	1.0%
TMUS	13.5%
UPS	5.0%
INTC	6.6%
WFC	9.0%
RTX	9.5%

Note that the b elow graph shows the historical performance of the optimal portfolio over the near-ten-year sample period; the optimal portfolio assumes reb alancing of the ab ove`Weights` in each period over the sample. From the ab ove statistics, you can glean that the optimal portfolio realizes an expected Return of `373.9%` over the 9.4 Years.

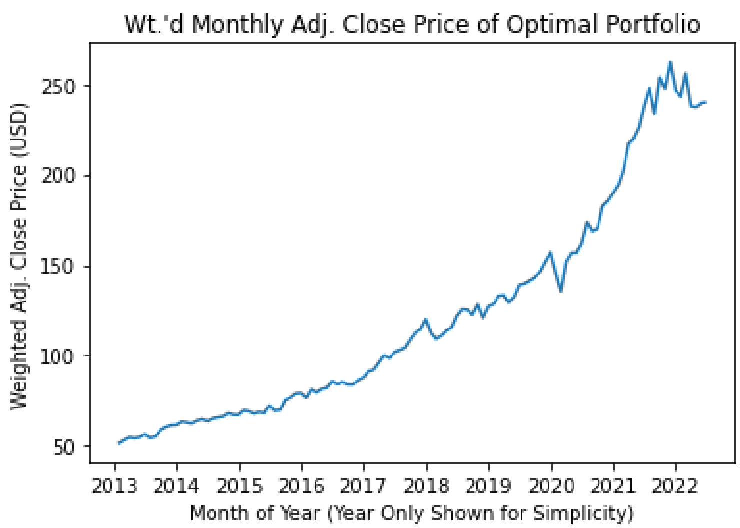

Figure 1: Base Model Historical Performance over Sample

3.2.2 Testing Algorithm with Various Parameters

The goal of running the model with various parameters is to see how those changes affect the ob jective outcome. Please note that each change does not accumulate. Each change is in isolation and a comparison of the "b ase" solution seen previously. This approach is for a more direct comparison of performance.

3.2.2.1 *(Test 1)*: More Iterations and Less Simulated Portfolios Performs Worse

This test model increases the total numb er of iterations from 3,000 to 10,000 while decreasing the numb er of simulated portfolios (for each iteration) from 30 to 10. All other parameters are unchanged from the "b ase" model. See that the numb er of stocks to invest in and the expected return has increased, b ut the overall risk increased. See the output of the model b elow.

```
Key Summary Statistics ------------------
Global Best Annualized Risk:    12.0%
Annualized Expected Return:     18.1%
Sharpe Ratio:                   1.45
Expected Return over 9.4 Years: 477.7%

Global best weights in each stock (Only includes stocks to invest in):
```

Ticker	Opt. Weight
AAPL	4.3%
MSFT	1.4%
GOOG	5.3%
AMZN	0.5%
TSLA	0.4%
META	0.4%
V	2.9%
NVDA	1.7%
XOM	1.0%
WMT	2.4%
LLY	1.1%
PFE	0.4%
CVX	10.9%
BAC	3.8%
PEP	6.2%
VZ	1.7%
TMO	2.7%
COST	1.4%
ABT	4.9%
DHR	0.6%

Ticker	Opt. Weight
MCD	5.9%
ADBE	1.6%
CSCO	3.1%
CMCSA	0.6%
CRM	1.3%
TMUS	1.5%
NKE	4.9%
BMY	5.7%
UPS	0.6%
INTC	4.9%
NEE	3.4%
T	7.6%
TXN	1.5%
RTX	1.2%
QCOM	2.3%

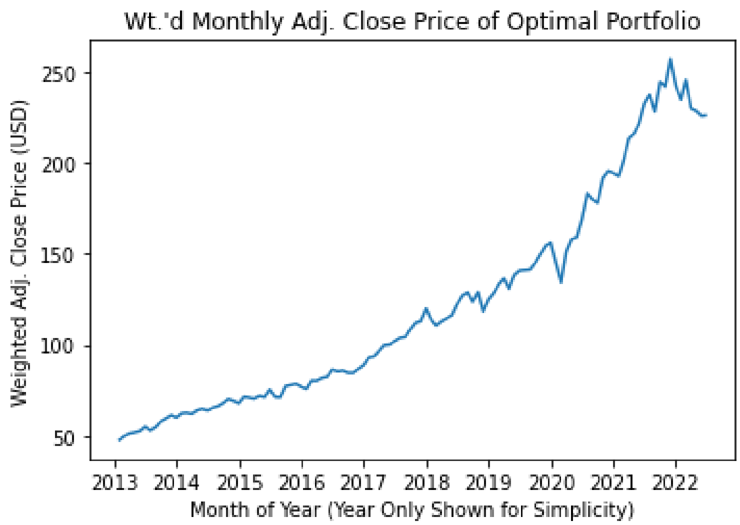

Figure 2: Test 1: Historical Performance over Sample

3.2.2.2 *(Test 2)*: Maximizing Sharpe Ratio Tends to Invest in only 1 Stock

After trials of maximizing the Sharpe ratio, the metaheuristic converges to investing in only one stock. This outcome leads to the recommendation of not using the Sharpe ratio as the objective. This portion of the model has potential for future development. All other parameters are unchanged from the "base" model. See the output of the model below.

```
Key Summary Statistics -----------------
Global Best Annualized Risk:    68.4%
Annualized Expected Return:     68.4%
Sharpe Ratio:                   0.99
Expected Return over 9.4 Years: 13544.6%

Global best weights in each stock (Only includes stocks to invest in):
```

Ticker	Opt. Weight
PM	100.0%

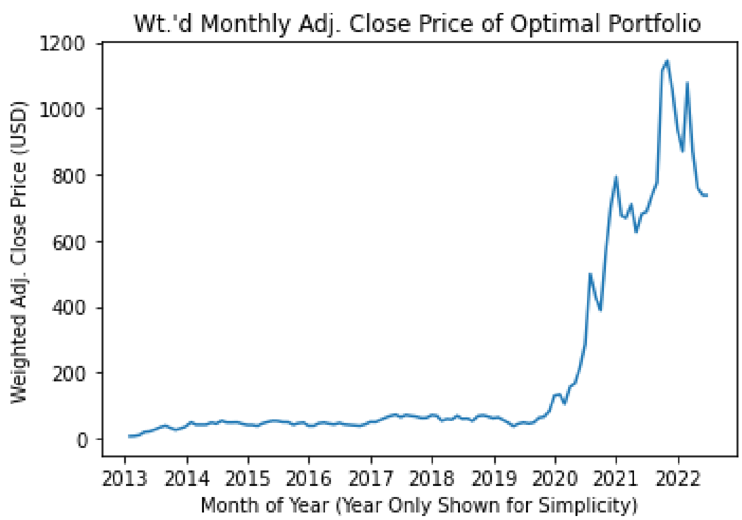

Figure 3: Test 2: Historical Performance over Sample

3.2.2.3 *(Test 3)*: Global Best Neighborhood Operator Performs Worse than Local Best

This test uses the global best neighborhood structure rather than the local best "ring" neighborhood structure. For each portfolio, having an understanding of every other portfolio leads to a sub-optimal result relative to the local best method. See that the risk increased with a similar Sharpe ratio. All other parameters are unchanged from the "base" model. See the output of the model below.

```
Key Summary Statistics -----------------
Global Best Annualized Risk:    12.7%
Annualized Expected Return:     19.0%
Sharpe Ratio:                   1.45
Expected Return over 9.4 Years: 513.2%

Global best weights in each stock (Only includes stocks to invest in):
```

Ticker	Opt. Weight
AAPL	3.3%
GOOG	2.2%
GOOGL	1.1%
AMZN	1.5%
TSLA	0.9%
JNJ	0.5%
UNH	2.1%
META	0.2%
V	3.8%
NVDA	0.7%
XOM	1.4%
PG	3.7%
WMT	3.2%
JPM	1.9%
MA	3.9%
LLY	3.9%
HD	2.7%
PFE	4.1%
CVX	0.3%
BAC	1.6%
KO	3.8%
ABBV	2.8%
MRK	0.2%
PEP	4.3%
VZ	1.0%
TMO	3.4%

Ticker	Opt. Weight
COST	0.9%
AVGO	3.4%
ABT	2.3%
DHR	0.8%
ORCL	1.7%
MCD	0.7%
ADBE	1.7%
CSCO	0.4%
CMCSA	3.6%
CRM	2.8%
DIS	3.5%
TMUS	1.1%
NKE	0.2%
BMY	3.6%
PM	3.1%
INTC	3.0%
NEE	1.0%
T	1.8%
WFC	0.1%
TXN	2.5%
RTX	3.0%

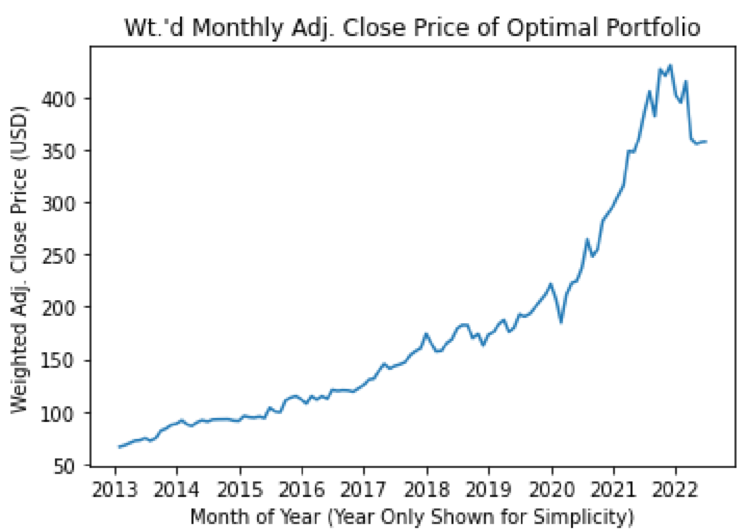

Figure 4: Test 3: Historical Performance over Sample

3.2.2.4 *(Test 4)*: More Iterations and More Simulated Portfolios Performs Marginally Better

In this test, the model increases the numb er of iterations from 3,000 to 10,000, while the numb er of portfolios simulated for each iteration increases from 30 to 100. Overall, this change improved, or decreased, the risk. The risk decreased from 10.0% to 9.5%, while the Sharpe ratio increased from 1.44 to 1.45. See the output of the model b elow.

```
Key Summary Statistics -----------------
Global Best Annualized Risk:    9.5%
Annualized Expected Return:     14.4%
Sharpe Ratio:                   1.45
Expected Return over 9.4 Years: 355.4%

Global best weights in each stock (Only includes stocks to invest in):
```

Ticker	Opt. Weight
UNH	4.8%
NVDA	2.4%
MA	0.6%
PFE	3.6%
BAC	0.6%
ABBV	10.9%
PEP	8.8%
TMO	5.5%
AVGO	8.9%
ORCL	9.8%
CSCO	17.4%
TMUS	6.5%
BMY	6.6%
WFC	7.3%
RTX	6.1%

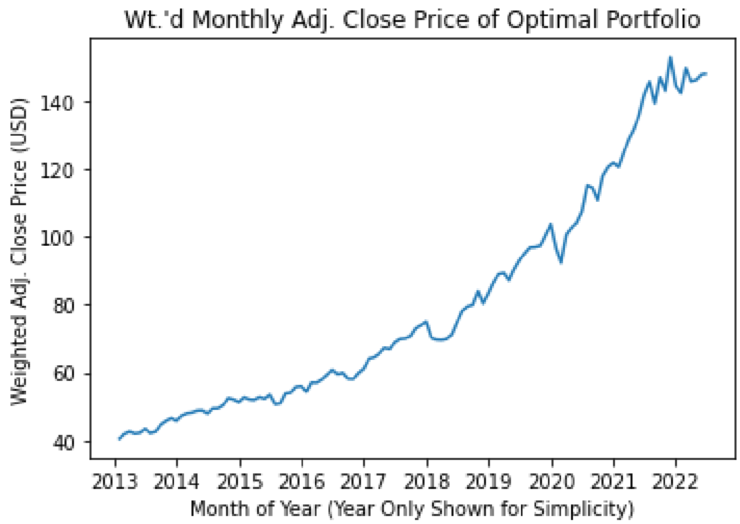

Figure 5: Test 4: Historical Performance over Sample

3.2.2.5 *(Test 5)*: More Iterations and Even More Simulated Portfolios Performs Marginally Better

In this test, the model increases the numb er of iterations from 3,000 to 10,000, while the numb er of portfolios simulated for each iteration increases from 30 to 200. Overall, this change improved, or decreased, the risk. The risk decreased from 10.0% to 9.5%, while the Sharpe ratio marginally increased from 1.44 to 1.46. Note that the change did not improve the ob jective value relative to `Test 4`. See the output of the model b elow.

```
Key Summary Statistics -----------------
Global Best Annualized Risk:    9.5%
Annualized Expected Return:     14.5%
Sharpe Ratio:                   1.46
Expected Return over 9.4 Years: 357.8%

Global best weights in each stock (Only includes stocks to invest in):
```

Ticker	Opt. Weight
UNH	4.3%
NVDA	2.5%
MA	0.4%
PFE	3.4%
BAC	2.0%
ABBV	11.0%
PEP	8.1%
TMO	6.0%
AVGO	9.2%

Ticker	Opt. Weight
ORCL	9.1%
CSCO	17.5%
TMUS	6.7%
BMY	6.7%
WFC	6.7%
RTX	6.3%

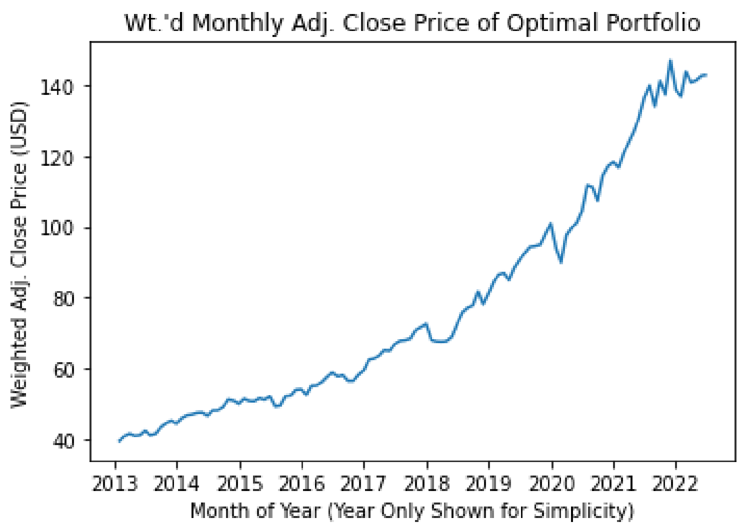

Figure 6: Test 5: Historical Performance over Sample

3.2.3 Summary of Model Solutions

In summary, generally increasing the number of iterations and number of simulated portfolios provides better performance in solving for the optimal portfolio. However, the model's outcome experiences a diminishing effect with increased iterations and simulated portfolios, so increasing these two parameters toward infinity may not realize a substantial benefit. Theoretically, we may hypothesize that the model has found global minima. Local best neighborhood structures work better than global best methods for this application. Additionally, maximizing the Sharpe ratio provided future opportunities for further tuning.

4 Discussion on Modeling Process

4.1 Contribution of Modeling

The major contributions to modeling within this tool and report are

- A direct application of a financial engineering model while solving it using the computer. Accomplished by applying modern portfolio theory (from Markowitz in 1952)
- Developed a new and different financial engineering model for a real problem and presented a solution approach. Accomplished by using a metaheuristic technique.
- Developed or improved a computer program for a financial engineering model. Accomplished by using a metaheuristic technique.

4.2 Difficulties Encountered

Overall, Modern Portfolio Theory contains an arithmetically and conceptually simple implementation; however, understanding how to solve this non-linear problem proved to be more difficult. Particle Swarm Optimization has many parameters to adjust, and some adjustments did not perform well with this type of problem. Without experimentation, it could have been easy to fall into local minima.

4.3 Deviation from Preliminary Objectives

Originally the tool aimed to give the user the option of the following optimizers:

- Particle Swarm Optimization
- Genetic Algorithm
- Simulated Annealing

Since the PSO implementation took an extensive duration to complete, time did not permit the inclusion of the other two algorithms. Including these could have been beneficial to ensure that each of the different algorithms converged to the global minima.

5 Conclusion

Within this algorithm, a dynamic implementation of Modern Portfolio Theory combines itself with a robust metaheuristic solver to find the minimum risk portfolio, given a desired set of stocks. While Modern Portfolio Theory does not offer vast predictive forecasting of stocks, it allows for the evaluation of the historical performance of a possible portfolio to inform investment strategy (Benninga 306). These contributions to financial engineering are significant, as it allows for an investor to perform a quick and effective evaluation of portfolio performance.