Dynamic Portfolio Rebalancing using Genetic Algorithm and Reinforcement Learning

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SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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DYNAMIC PORTFOLIO REBALANCING USING GENETIC ALGORITHM AND REINFORCEMENT LEARNING

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Abstract

Dynamic rebalancing is combined with the concept of Strategic and Tactical Asset Allocation to explore its feasibility and effectiveness. The performance of dynamically rebalanced portfolios are benchmarked with the performance their underlying assets to validate its effectiveness. Two methods were proposed to implement the dynamic rebalancing for a portfolio: by using the Genetic Algorithm (GA) and a novel risk algorithm, and by using Reinforcement Learning (RL).

The risk algorithm introduces an equation that takes into account all 3 aspects of market trends, risks and returns and has demonstrated the ability of to dynamically adjust portfolio compositions. Experiments were done on the portfolios of Goldman Sachs, Global Indexes and Individual stocks which demonstrated that the algorithm can work well in the global and local market environments and for both market indexes and individual stocks. It was found that the algorithm even performs well for portfolio construction, although further tests are needed to verify its results. The effect of the amount of base rates (part of the Strategic Asset Allocation) allowed in each portfolio were also explored and analysed. In conclusion, the algorithm generally is able to outperform all except the highest performing stock/ index in each experiment in spite of commission fees, in terms of returns, while generally carrying less risk.

The RL agent has also demonstrated the ability to dynamically adjust portfolio compositions according to the market trends, risks and returns of each stock/ index in the Global indexes. With exploration into different policies of gradual and immediate changes in portfolio composition, and the inclusion of a better stock prediction model to reduce the time lag introduced by technical indicators, the performance of the RL algorithm could be able to match the performance of the GA and risk algorithm as an online algorithm.

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Chapter 1

Introduction

1.1 Background

With the global stock trading value increasing from US$1.7T in 1984 to US$68T in 2018 [1], it is evident that stock trading has become a driving force in the financial world. However, to capitalise on the growth in stock trading, it is essential for an investor to be able to handle market risks. Handling Market Risks is one of the objectives of Modern Portfolio Theory, where a portfolio aims to maximise returns while minimising risk through diversification [2]. However, individual investors usually lack the ability to have a truly diversified portfolio as [3], it is found that a diversified portfolio must contain at least 30-40 different stocks to be effective.

Therefore, Portfolio Management (PM) is often aggregated by and delegated to portfolio managers in Asset Management Firms (AMFs). In 2019, the total asset value managed by the top 3 AMFs alone surpassed €10T [4]. However, AMF management fees are expensive at up to 2% annually [5] and yet, more than 90% of active fund managers in AMFs still do not outperform the Standard&Poor's 500 (S&P500) Index according to the SPIVA (S&P Indices Versus Active) Scorecard in 2018 [6]. Thus, it is valuable to understand the asset management strategies utilised by active fund managers in AMFs to improve PM.

In finance, there is much interest in studying the market and behavioural risk involved in optimising portfolios such as in [7], [8] and [9]. In market risk management, two important strategies used are the ***Strategic Asset Allocation(SAA) and Tactical Asset Allocation(TAA)*** [10]. AMFs usually employ a mix of SAA and TAA, where they consist of a fixed percentage amount and a variable percentage amount in a portfolio respectively such as in JPMorgan (JPM) [11] and Goldman Sachs (GS) [12]. Both the TAA and SAA rely heavily on market conditions. Alternatively, in behavioural risk management, research focuses on how the *risk adversity* of portfolio managers can affect the returns of a portfolio [13]. The risk adversity of an individual ranges from being *risk-adverse* to *risk-seeking* [14].

Conversely, in Computer Science(CS), there is much interest in maximising portfolios returns using ***machine learning*** such as in [15], [16] and [17]. Two important techniques often used are the Genetic algorithm(GA) and Reinforcement Learning(RL). GA is commonly used to either optimise initial portfolio creation or to periodically rebalance portfolio composition, while RL is used to ***time the market***. Generally, both techniques aim to maximise portfolio returns.

Therefore, it is beneficial to explore the application of machine learning techniques commonly used in CS, with the portfolio construction strategies of the TAA and SAA used in finance. While attempts to consider both market conditions and returns have been made such as in [18], there seems to be a lack of research regarding the use of machine learning techniques to optimise portfolios with regard to all 3 components of market conditions, risk and returns. As such this report focuses on maximising portfolio returns using machine learning techniques, with consideration of market and behavioural risks through portfolio rebalancing. However, in PM, the TAA is usually done by using a periodic approach, with the rebalancing of TAA done from a fixed period varying from monthly to quarterly. As such it is hypothesised that if rebalancing can be done more dynamically, better results can be obtained.

Therefore, this project aims to improve PM by introducing dynamic rebalancing of portfolios through two methods: 1) a novel risk portfolio algorithm optimised using GA 2) and an RL agent to dynamically rebalance portfolios. This is done while accounting for market conditions, risk and returns in the global financial market. Insights from this project will help portfolio managers systematically improve the performance of portfolios by dynamically taking into consideration of market conditions, risks and returns.

1.2 Objective

This project aims to improve portfolio management by introducing dynamic portfolio rebalancing which accounts for market conditions, risks and returns. This is done by using two methods: 1) a risk algorithm optimised with Genetic Algorithm (GA) 2) and Reinforcement Learning (RL). The objectives of the project are listed below:

- To develop 2 dynamic rebalancing strategies that incorporates the 1) risk level of a stock, 2) the market trend of a stock and 3) the potential of swing of a stock.
- To develop and verify the effectiveness of a novel risk algorithm that is optimised by Genetic Algorithm for dynamic rebalancing.
- To develop and verify the effectiveness of a Reinforcement Learning agent for dynamic rebalancing.

1.3 Project Organisation

This report is organised as follows:

- Chapter 2 provides the literature review, which is focused on the background of finance and machine learning.
- Chapter 3 describes implementation of a risk algorithm and Genetic Algorithm used in the project to dynamically rebalance portfolios. This chapter will focus on the implementation of the developed algorithm and analysis of the results obtained.
- Chapter 4 describes implementation of a Reinforcement Learning agent used in the project to dynamically rebalance portfolios. This chapter will focus on the implementation of the developed algorithm and analysis of the results obtained.
- Chapter 5 will conclude and summarise the project.

Chapter 2

Literature Review

2.1 Literature Review in Finance

2.1.1 Market Trends

Periodically, different market trends can appear in the market, characterised by distinct periods of general share price appreciation or depreciation. Market trends can affect how investors invest in different stocks [19], which in term further affects the share prices. Typically, an Exponential Moving Average (EMA) graph is used to instead of the original price-return graph to visualise market trends, as the EMA graph smooths out noise as can be seen in 2.1.

Market trends can be characterised into three distinct groups:

- Bullish - A bullish period is associated with a period of rising share values. During a bullish market trend, the return rates are usually higher and is associated with less risk.
- Bearish - Conversely, a bearish period is associated with a period of falling share values. During a bearish trend, the return rates are usually lower (if not negative) and is associated with more risk.
- Stagnant - A stagnant period is a period of very low to no growth in share values. During a stagnant trend, return rates are usually close to zero and has moderate risk.

Figure 2.1: Exponential Moving Average Smoothing in DJI

Due to the differences in the nature of the market trends in terms of return rates and risk, it is imperative to be able to determine the market trends in a period to maximise returns and minimise risk.

Techniques to Determine Market Trends

Typically, technical analysis is commonly used to predict market trends and/or prices, such as in [20], [21] and [22]. Technical analysis attempts to locate points of inflexion, where a trend changes from one to the next (bearish to bullish for example), and profit from the change in values. Some common techniques used are:

- **Moving Average Convergence/ Divergence (MACD)** - In MACD, a Signal line (26 period EMA) and a MACD line (12 period EMA) is used to visualise the relationship of trends and momentum.

$$\mathrm{MACD} = \mathrm{EMA}[12] - \mathrm{EMA}[26] \tag{2.1}$$

Crossovers (intersections) are monitored to obtain insights of the price trends. During a buy crossover, where the MACD line intersects upwards with the Signal line, it indicates that the period will be undergoing a bullish period. Conversely, during a sell crossover, where the MACD line intersects downwards with the Signal line, it indicates that the period will be undergoing a bearish period. An advantage of the MACD is that both the momentum and trend can be determined in a single indicator.

- **Relative Strength Index (RSI)** - RSI indicates the rate of change of price shifts [22]. It indicates a possible reversal in trend.

$$\mathrm{RSI} = 100 - (100/(1+\mathrm{RS})) \tag{2.2}$$

where *RS* is the average of high periods divided by the average of low periods

$$RS = \frac{\text{Average Gain}}{\text{Average Loss}} \tag{2.3}$$

- **Stochastic Oscillator** - There consist of 2 Oscillators, the %K Oscillator and the %D Oscillator. Trend reversal signals happen when the %D Oscillator is above 80 (indicating it is overbought) or below 20 (indicating it is under bought).

$$\text{Stochastic \%K} = \frac{C_t - LL_{t-n}}{HH_{t-n} - LL_{t-n}} \times 100 \tag{2.4}$$

$$\text{Stochastic \%D} = \frac{\sum_{i=0}^{n-1} K_{t-1}\%}{n} \tag{2.5}$$

[20]

2.1.2 Risk

In finance, risk is an important measure as it directly corresponds to returns. This is because investors require an appropriate level of return matching the level of risk to take part in an investment activity. For example, an investor would require an investment that is of high risk to have high returns. Two factors of risk are being considered in this project: market risk and investor risk.

Market Risk

Market risks are composed of the systemic and unsystematic risks. Systemic risks are defined as the risk of systemic events, which can damage the ability of markets or financial institutions to effectively provide efficient investment returns, happening and systemic risks can happen on a scale from the industrial level to national level [23]. Therefore, different markets/industries are exposed to different risks depending on the market region or the industry.

Unsystematic risks are the risks within each organisation such as decisions made by management. Unsystematic risks can be minimised and will be discussed further in 2.1.3.

Investor Risk

In this project, the investor risk refers to erratic or irrational investment decisions made by investors. This is influenced by factors such as the *myopic loss aversion* in [24] where people were not willing to wager for a larger gain in view of a smaller loss with the same probability, emotional processes damaging performance in gambling tasks in [25] and the greater influence of immediate punishment over delayed gain in [26].

One popular theory often discussed in conjunction with risk is the Utility Theory (UT). It was first proposed in [27] and its extension, the Expected Utility Theory (EUT), is used extensively in reinforcement learning applications such as in [28], [29] and [30]. Traditionally the EUT for human behaviour is regarded as a linear function, but alternative forms such as in [31], where a concave utility function which occurs due to the relative wealth of an individual is suggested. Generally the equation of the EUT is as follows:

$$\mathbb{E}[u(x)] = \int_{-\infty}^{+\infty} u(x) f(x)\, dx \tag{2.6}$$

Where E is the EUT, $u(x)$ is the utility of x and $f(x)$ is the probability density function of x

Another popular theory to describe risk-aversion is the Prospect Theory (PT). PT can be summarised as the behaviour of being risk-seeking when making losses, while being risk-averse when making gains [32]. Investors reflect this behaviour by showing more acceptance in identifying gain than in loss as shown in [32]. The PT function described by [14] is shown in 2.2, and its equation is shown in 2.7.

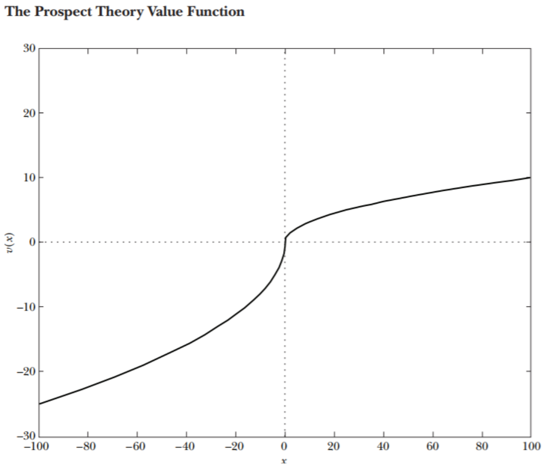


Figure 2.2: Prospect Theory Function [14]

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-x)^{\beta} & \text{if } x < 0 \end{cases} \tag{2.7}$$

[14] Where α and β controls the risk sensitivity and λ represents the value of loss aversion.

2.1.3 Portfolio Theory

The main issue that portfolio theory tackles is to minimise the risks as described in 2.1.2, while maximising returns through diversification. Diversification in portfolio theory is the practice of having multiple different shares with different risks associated grouped as a single portfolio. Diversification is thus, important due to the idea that systematic risk is a vital component to consider in the construction of a optimal portfolio [33].

While occasionally, there exists disproportionate risk to return ratios in various shares as mentioned in [34], we have decided to focus on the general risk to return ratio of the market/index in the project due to the choice of Exchange Traded Funds (ETFs) for portfolio construction.

2.1.4 Optimal portfolio construction

Ideally, there should exist minimal risk in a portfolio for the maximum returns. As such, the definition of optimising a portfolio is defined as being able to minimise risk and maximise returns in a specific portfolio in this report. Three measures that are often used in the construction of portfolios are explored in this report:

Mean-Variance

The Mean-Variance Theory was first proposed in [2], where remains popular and utilised in articles such as [35] and [36]. The theory the importance of variance in a portfolio and its equation (for a two security portfolio) is given in 2.8.

$$\sigma_P^2 = \sum_j x_j^2 \sigma_j^2 + \sum_j \sum_{k \neq j} x_j x_k \rho_{jk} \sigma_j \sigma_k \tag{2.8}$$

[37] Where σ_P^2 is the variance of the returns of a portfolio, x_j is the proportion of security j normalised to 1, x_k is the proportion of security k normalised to 1 and ρ_{jk} is the correlation of j and k.

Value-at-Risk (VaR)

The VaR is a measure of the potential of value loss. It is usually measured in terms of the probability of potential value loss in a given timeframe.

In this report, the historical VaR will be used, where calculations will be based on percentiles. Further details will be given in section 3.2.1.

However, the limitations of the VaR is that it often assumes a normal distribution for the data, which may not be true. As such, the CVaR is commonly used instead.

Conditional-Value-at-Risk (CVaR)

The CVaR or the Expected Shortfall (ES) is an improvement over VaR as it does not assume that the data is of a normal distribution. As such, it is also used to measure the expected risky value and is further elaborated in section 3.2.1.

2.1.5 Portfolio Rebalancing

Portfolio Rebalancing is defined as the act of changing the percentage composition of a portfolio through transactions of its underlying assets in this report. Portfolio Re-balancing is done to address the constantly changing performance of a portfolio's underlying assets, so as to maintain an optimal portfolio.

Some common strategies used include buy-and-hold, periodic rebalancing, threshold rebalancing, range rebalancing, sharpe ratio rebalancing, average drawdown rebalancing and volitility rebalancing [38] [39].

Generally, strategies can be classified under fixed or dynamic portfolio rebalancing.

- **Fixed Portfolio Rebalancing**. In fixed portfolio rebalancing, rebalancing is done periodically, such as monthly, quarterly or annually.
- **Dynamic Portfolio Rebalancing**. In a dynamic portfolio, rebalancing is done independent of time.

2.2 Literature Review in Machine Learning

Machine learning has been used extensively in many fields such as engineering, finance and biology [40]. An overview of some common machine learning algorithms are given in 2.3

2.2.1 Overview of Machine Learning Techniques in Finance

In this report, we will be focusing on the machine learning applications utilised in stock prediction, trading and portfolio construction. Some of the techniques used in recent endeavours are reviewed and summarised in 2.1.

Title	Strategy	Details
A novel forecasting method based on multi-order fuzzy time series and technical analysis [41]	Genetic Algorithm	Proposed a model with directional accuracy rate with exponential smoothing and multi-order and multivariate fuzzy time series

Portfolio strategy optimizing model for risk management utilizing evolutionary computation [17]	Genetic Algorithm	Applied GA to build portfolio and trade
An improved genetic-based forecasting model for high-speed trading [42]	Genetic Algorithm	Presents a genetic algorithm based method for HFT
A stock market risk forecasting model through integration of switching regime, ANFIS and GARCH techniques [43]	Markov switching fuzzy inference neural network GARCH (MS-FNN-GARCH)	improved forecasting by using combined macroeconomic variables with fuzzy intelligent system in MS-FNN-GARCH
A Dynamic Fuzzy Money Management Approach for Controlling the Intraday Risk-Adjusted Performance of AI Trading Algorithms [44]	Fuzzy logic, Neural Network	Used a fuzzy and neural network approach to dynamically obtain risk-adjusted returns
Online evolving fuzzy rule-based prediction model for high frequency trading financial data stream [45]	Fuzzy rule learning	Created a online evolving fuzzy rule-based prediction model and applied the model for HFT data
Decision-making for financial trading: A fusion approach of machine learning and portfolio selection [46]	Support Vector Machine (SVM), Mean-Variance(MV) Portfolio Selection	Used SVM and MV to create an optimal portfolio
Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques [21]	Random Forest, Artificial Neural Network, Support Vector Machine, Naive Bayes Classifier	Compares 4 machine learning techniques for their performances

A bat-neural network multi-agent system (BN-NMAS) for stock price prediction: Case study of DAX stock price [47]	Bat Neural Network Multi Agent System Architecture	Proposed a four layer BNNMAS architecture for dealing with the distributed nature of stock prediction problem
Trading financial indices with reinforcement learning agents [29]	Reinforcement Learning	Utilized Reinforcement Learning agents for trading financial indices in a retirement portfolio
A Multi-objective Deep Reinforcement Learning Approach for Stock Index Future's Intraday Trading [48]	Deep reinforcement learning	Devised and tested a Multi Objective Deep Reinforcement Learning algorithm
Improving financial trading decisions using deep q-learning: Predicting the number of shares, action strategies, and transfer learning [49]	Deep Q-learning, transfer learning	Used transfer learning with Q-learning and a Deep Neural Network regressor to determine number of stocks to trade.
Algorithmic trading behavior identification using reward learning method [50]	Gaussian Process Inverse Reinforcement Learning	Inverse Reinforcement Learning is used to capture the key characteristics of HFT strategies
Combining technical trading rules using particle swarm optimization [51]	Performance-based reward strategy (PRS)	A new performance-based reward strategy (PRS) is proposed as a stock trading strategy, and a time variant particle swarm optimisation (TVPSO) is adopted to optimise the PRS parameters

Table 2.1: Machine learning strategies for stocks

2.2.2 Genetic Algorithm

Genetic Algorithm is modeled after evolution, where the fittest survives and produces offsprings which can survive better in the same circumstances. In Genetic algorithm,

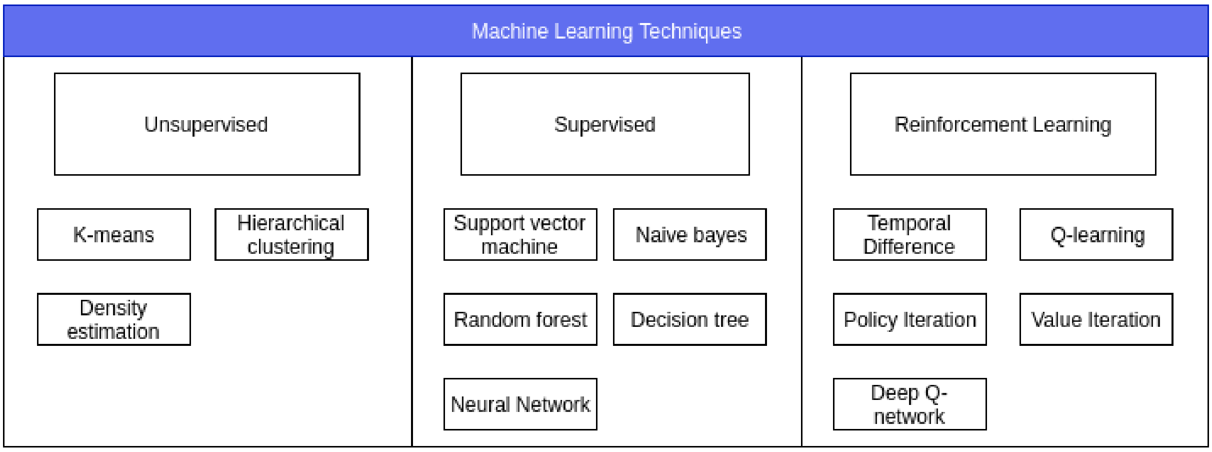


Figure 2.3: Machine learning algorithms

there consists of mainly 3 stages, namely the: 1) fitness calculation, 2) crossover 3) and the mutation. Fitness is modeled by the survivability in evolution, while crossover assumes that the fittest of a population can mate, and mutation is modeled after the random mutations that happen in DNA during crossovers.

Generally, there are 4 types of crossovers as defined in [52]:

1. Single-point crossover
2. Two-point crossover
3. Uniform crossover
4. Flat crossover

2.2.3 Reinforcement Learning

Reinforcement learning is a popular machine learning algorithm used in research such as in [29], [48], [49], [50], [51].

Reinforcement learning agents base the decisions on Q values that is calculated by the equation given in 2.9.

$$Q_\pi(s,a) \equiv E[R_1 + \gamma R_2 + \cdots + |S_0 = s, A_0 = a, \pi] \tag{2.9}$$

where $\gamma \in [0,1]$ is the discount factor, π is the policy, a is the value of action in state s. Maximisation of $Q_\pi(s,a)$ will yield the optimal value of policy π

Q-learning

The Q-learning algorithm is a policy-free algorithm that uses the equation given in 2.10 to update its Q-values and in 2.11 to derive the optimal actions for a given state. Q-values are often stored in a table.

$$\theta_{t+1} = \theta_t + \alpha(Y_t^Q - Q(S_t, A_t; \theta_t)) \bigtriangledown_{\theta_t} Q(S_t, A_t; \theta_t) \tag{2.10}$$

$$Y_t^Q \equiv R_{t+1} + \gamma \max_{\alpha} Q(S_{t+1}, a; \theta_t) \tag{2.11}$$

Deep Q Networks (DQN)

In the case of a DQN, the Q-values of states may be too numerous, and thus a Deep Learning Network is used instead to predict the Q-values of an action in a given state, as given in 2.12.

$$Y_t^{DQN} \equiv R_{t+1} + \gamma \max_{\alpha} Q(S_{t+1}, a; \theta_t^-) \tag{2.12}$$

Chapter 3

Dynamic GA rebalancing

To implement dynamic rebalancing, this chapter introduces a novel risk algorithm to be used along with a Genetic Algorithm.

3.1 Trend Classification

Firstly, to provide an indication as to when a portfolio rebalancing action should be done, trend reversals in the market conditions must be identified. As such, technical indicators could be used to fulfil the role of trend reversal identification. Therefore, a preliminary analysis of the effectiveness of technical indicators as determinants of trend reversals are first conducted using the stocks of APPLE (AAPL), GOOGLE (GOOGL), FACEBOOK (FB), Hewlet Packard (HPQ), CITIBANK (C) and AIG (AIG). The technical indicators being tested are the MACD, RSI, Stochastic Oscillator and CCI.

A simple test is set up to determine the effectiveness of technical indicators in predicting trend reversals, by comparing the length of holding period, average length of holding period and the average return per holding period of each stock (calculated by the percentage difference in price of the start and end of the period), from the time of each company's inception.

A sample of the data created for AAPL is shown in table 3.1, where it is found that the MACD seems to give the best indication of trend reversals, with a reasonable number of holding period and returns per holding period. As such, the MACD will be used as the indicator to detect trend reversals due to the results of this simple test.

	Number of holding periods (days)	Average holding period (days)	Average return per period (%)
MACD	176	20.4	4.45
RSI	26	6.5	-4.75
Stochastic Oscillator	344	3.7	1.35
CCI	8	1.75	0.98

Table 3.1: Effectiveness of Technical Indicators for APPLE (AAPL)

3.2 Algorithm for dynamic rebalancing

A novel risk algorithm that incorporates market trends, risks and returns will be presented in this section.

3.2.1 Risk algorithm

The risk algorithm consists of 3 components, namely the:

1. Market Condition
2. Market Risk
3. Market Swing Potential

The risk algorithm introduces an equation that takes into account all 3 aspects of market trends, risks and returns, and its mathematical representation is presented in the following subsection:

Market Condition

The market condition/ trend at time t of a market is the general direction of movement of prices at time t. They can be either be bullish, an upwards trend, or bearish, a downwards trend or rarely, stagnant. As such, as the trend reversals provided by the

MACD indicator in the form of crossovers can indicate a upwards or downwards trend, it can be utilised to predict trend directions in the near future. The first aspect of market condition/ trend is given in the following equation:

$$f_{\mathrm{MC}}(X) = Z(\mathrm{MACD}(X) - \mathrm{SIGNAL}(X)) + c_1 \tag{3.1}$$

Where f_{MC} is the function for Market Condition, Z is the z-normalisation as defined in equation 3.2, and c_1 is a constant to be optimised by GA.

$$Z = \frac{X - \mu}{\sigma} \tag{3.2}$$

Market risk

One of the effective indicators used in finance for market risk is the Conditional Value at Risk (CVaR). The CVaR indicates probability of an amount of assets at risk during a period of time. Thus, the lower the value of the CVaR, the less risk is associated with a portfolio/ stock. As such, it is incorporated into the second aspect of market risk as the following equation:

$$f_{\mathrm{MR}}(x) = |CVaR\%(x) + c_2| \tag{3.3}$$

Where f_{MR} is the function for Market Risk, *CVaR%* is the Percentage Conditional Value at Risk, where CVaR is defined in equation 3.4, c_2 is a constant to be optimised by GA.

$$\mathrm{CVaR} = \frac{1}{1-c} \int_{-1}^{\mathrm{VaR}} x p(x) dx \tag{3.4}$$

Where *VaR* the Value at Risk defined in equation 3.5.

$$\mathrm{VaR} = \left\lceil \frac{95}{100} \times \Delta S_{p,t} \right\rceil \tag{3.5}$$

Where $\Delta S_{p,t}$ is the percentage change in value per period t and VaR is simply the 95^{th} percentile of $\Delta S_{p,t}$.

Market swing potential

The market swing potential primarily concerns the potential of a market to experience an upswing or downswing, with the magnitude of the swing representing the magnitude of the upswing or downswing, and the direction of the swing indicated by the sign of the function of market swing potential. As such the mean of the EMA of prices can be used to represent the market swing potential. The third aspect of market swing potential is presented in the following equation:

$$f_{\text{SP}}(x) = \mu(\text{EMA}(x)) \tag{3.6}$$

Where f_{SP} is the function for Swing Potential, μ is the mean as defined in equation 3.7.

$$\mu = \frac{\sum_{i=1}^{N} X_i}{N} \tag{3.7}$$

3.2.2 Equation of Risk Algorithm

As such, by combining all 3 of the individual equations of market risk, market trend and market swing potential with additional normalisation, we get the following equation:

$$\sum_{s \in S} \text{m\_tanh}(f_{\text{MR}_x}(s_{p,t}) \times f_{\text{MC}_y}(s_{p,t})) \times f_{\text{SP}_z}(s_{p,t}) + \text{BR}_s = 1 \tag{3.8}$$

Where S is the set of all stocks used, s is an individual stock in the set of S stocks such that $s \in S$, t is the time, p is the price of s at time t, x is the CVaR period of f_{MR}, y is the MACD period of f_{MC}, and z is the EMA period of f_{SP}. m_tanh is defined in equation 3.9, and BR is defined in equation 3.10.

Define m_tanh: $\mathbb{R} \mapsto [0,1)$ as

$$\text{m\_tanh}(x) = \begin{cases} \tanh(x), & \text{if } x \geq 0 \\ \tanh(x) + 1, & \text{if } x < 0 \end{cases} \tag{3.9}$$

The equation of m_tanh is given

$$(\mathrm{BR}_1+\alpha)\times s_1+(\mathrm{BR}_2+\beta)\times s_2+(\mathrm{BR}_1+\gamma)\times s_3=1 \tag{3.10}$$

where α, β and γ are the TAA percentages for s_1, s_2 and s_3 obtained by each component in the summation of equation 3.8 respectively.

In the main equation at 3.8, x, y, z, c_1 (in equation 3.1) and c_2 (in equation 3.3) are all constants to be optimised according to each market using GA. Additionally, the shape of the modified tanh function in 3.9 is shown in Figure 3.9. A modified tanh function as defined is used due so as normalise the values of the output of $f_{\mathrm{MR}_x}(s_{p,t})\times f_{\mathrm{MC}_y}(s_{p,t})$ to the desired characteristics of the equation. However, note that this modified tanh function may not be the optimal function to model such a behaviour and further tests can be done which is out of the scope of this report.

The BR in the equation refers to the base rates, modeled after the SAA and TAA strategies in equation 3.10, where the algorithm controls the Tactical allocation while the base rates control the Strategic allocation of portfolio composition. Therefore, the equation shows that the BRs and portfolio allocation by the algorithm must add up to 1 as they must add up to 100% of the portfolio.

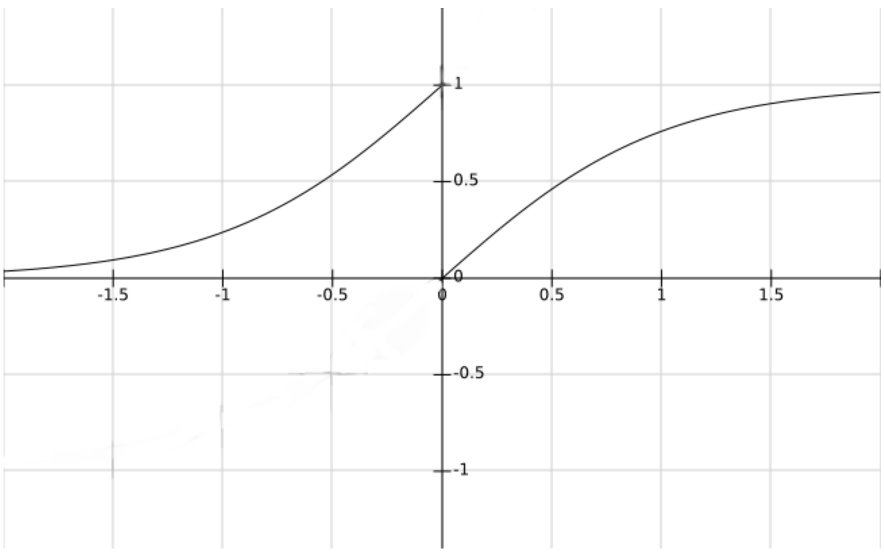


Figure 3.1: Shape of the m_tanh curve

3.3 Genetic Algorithm

For the genetic algorithm, a two-point crossover is used as demonstrated in Figure 3.2, where the child is produced from the two-point crossover of the genetic algorithm. Also, a population size of 8 is used, with 16 parameters to be optimised. The parameters are the sets of x, y, z, c_1 and c_2 as discussed in the previous section for each market, for a total of 15, plus a constant for the threshold of action for portfolio adjustment. This threshold is introduced so that minute changes in portfolio composition will be ignored, as such actions bring little value to the final net asset value (NAV) of the algorithm.

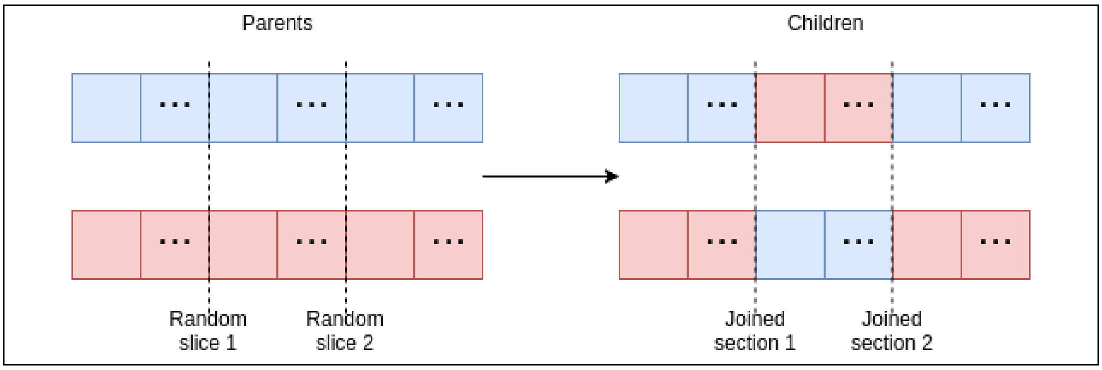


Figure 3.2: Genetic Algorithm two point crossover

The fitness of a child is determined by the product of the resultant NAV and the weighted CVaR of the markets created by the portfolio with parameters given in the child in equation 3.8. To elaborate further, in each generation, an initial NAV amount of \$300000 is given to the portfolio, where each market initially bears \$100000 each in equal portfolio composition. The algorithm is then run on each trend reversal to determine the optimal amount of allocation in each trend reversal with the algorithm parameters provided by the child. At the end of the period tested, the NAV obtained is then multiplied with the weighted CVaR of all the markets involved, to produce a fitness score. The largest 4 fitness scores of the children is then selected as the parents for the next generation. This is shown in algorithm 1

The mutation of children is then set to a rate of 0.5, where a selected child has a 0.5 chance to have its parameters changed by a random amount of -5 to 5 for the indicator periods and -1 to 1 for all the other parameters.

The best child obtained after 200 generations is then used as the optimised parameters for the algorithm at each market. The pseudo algorithm is shown in algorithm 2.

Algorithm 1 Fitness calculation of children for Genetic Algorithm

```
Get data for high, medium and low risk markets
Get trend reversal dates for all markets
for child in set of children do
    Set initial portfolio NAV to 300000
    for date in set of dates in data do
        Get fitness value
        if date in set of trend reversal dates then
            Calculate portfolio allocation using risk algorithm
            Calculate new NAV
            Deduct trade commission fees
            Update NAV
        end if
    end for
    Update final NAV with latest prices
    Calculate weighted CVaR values for markets
    Calculate fitness by the product of the weighted CVaR values
and final NAV
    Store fitness value
end for
Return fitness values
```

Algorithm 2 Genetic Algorithm for dynamic portfolio allocation

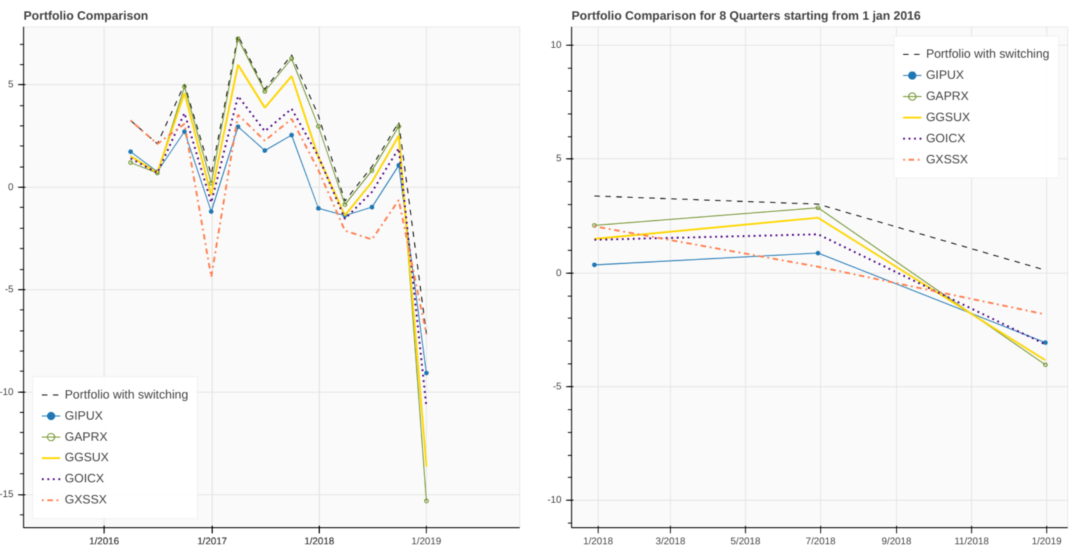
```
Generate new population
for gen == 0 to 200 do
    for child in population do
        Get fitness value
    end for
    Get children with the highest fitness values
    Use a two-point crossover for selected children
    if Random mutation number > 0.5 then
        Mutate children's parameters
    end if
    Update population
end for
Obtain fitness of children with best fitness
Return parameters obtained
```

3.4 Experiment 1 - Goldman Sachs Portfolios

In this experiment, we intend to apply the algorithm developed on some existing portfolios managed by ASMs. This is because the performance of the existing portfolios can be used as a benchmark to our algorithm's performance. As such, we have looked into ASMs such as GIC, GS and JPM due to the availability of their data to the public. Recent performances of some funds (not exhaustive) in GIC, GS and JPM in the Institutional class category can be seen in appendix table A.1.

GS's fund of funds portfolios are chosen for this experiment due to the availability of data and the consistency of data, such as the consistent operation dates across portfolios. Additionally, GS's portfolios uses a hybrid SAA and TAA strategy for portfolios, where each portfolio's TAA can change up to 40%, adjusted quarterly [11].

3.4.1 Fund switching and rebalancing



(a) GS quarterly returns comparison (b) GS 8 quarterly returns comparison

Figure 3.3: GS portfolio returns comparison

A preliminary analysis was first carried out on GS's portfolios. We first investigated the optimal switches that can be made depending on market trend based on all GS portfolio funds from the institutional class. Figure 3.3 shows the results, where the maximum returns possible achievable by optimal switching is represented by 'Portfolio with switching'. Figure 3.3a suggests that switching funds quarterly at the right period can have a better return than the subscription to a single fund due to the difference in performance of funds through each period. Figure 3.3b shows the 8 quarterly returns of quarterly switching (such as in figure 3.3a) from 2016-2019. This shows that 8 quarterly portfolio returns can be improved by at least 4% in the period of 2016-2019 just by having the optimal switching of funds quarterly. Thus, this indicates that returns can be improved if optimal switches in GS portfolio funds can be done depending on the market trend during each period.

As such, we want to simulate the fund switching behaviour shown in Figure 3.3 without hindsight and dynamically, by incorporating the algorithm as discussed in section 3.2 to rebalance funds. Additionally, we want the rebalancing behaviour to occur each time a market trend reversal is detected instead of quarterly to increase the frequency of rebalancing. Trend reversals are identified using MACD crossovers as introduced in section 2.1.1. However, we do not want to have a full switch from funds to funds similar to in our preliminary analysis by having a base portfolio allocation rate for each fund. This base allocations will help hedge against the risks from mistakes that can happen during each portfolio rebalancing. As such, the rebalancing strategy will be similar to the hybrid SAA and TAA strategy, in which base composition rates are given to each fund to prevent rebalancing from completely switching to a single fund.

3.4.2 Experimental setup

Symbol	Start Period	End Period	1yr return	5 yr return	10 yr return
GGSIX	01/01/2018	31/12/2018	-10.65%	3.64%	8.32%
GOIIX	01/01/2018	31/12/2018	-8.63%	3.00%	7.23%
GIPIX	01/01/2018	31/12/2018	-6.53%	2.40%	5.73%

Table 3.2: GS performance statistics

We have chosen 3 specific GS portfolios to be experimented on, namely the Growth Strategy Portfolio (GGSIX), Growth and Income Strategy Portfolio (GOIIX) and the Balanced Strategy Portfolio (GIPIX). With consideration of their individual asset compositions (see appendix A.2) and performance, we rank GGSIX, GOIIX and GIPIX as the high risk, medium risk and low risk portfolios respectively. Table 3.2 gives an overall picture of performance for these 3 portfolios.

The trading period of 2016-2018 was chosen for the experiment due to the presence of prominent bullish and bearish trends in the portfolios. Prices data for all funds was fetched by using alpha vantage's service [53].

Initial Base Composition Rates (BCRs) and asset values for the portfolios were set to 0.2 and $\$100,000$ respectively for each portfolio. As such, the total BCR and NAV for the portfolios are 0.6 and $\$300,000$ respectively.

(insert algo)

3.4.3 Experiment results and analysis

Fund	mr_periods	mc_periods	sp_periods	c1	c2	thres
GGSIX	8	9	6	0.97	-3.41	
GOIIX	6	5	12	-1.67	-0.18	0.081
GIPIX	12	9	6	-1.07	-0.72	

Table 3.3: Genetic Algorithm Parameters for Goldman Sachs Funds

The parameters obtained from the genetic algorithm from algorithm 3.4.2 are shown in table 3.3. As seen from the results shown in Figure 3.4, the net asset value (NAV) increased from an initial value of $\$300,000$ to around $\$310,000$, which underperformed both the returns of GOIIX and GGSIX which netted around $\$320,000$ and $\$330,000$ respectively. This failure to rebalance appropriately at different market trends and conditions is due to the similarity of all 3 funds as shown in Figure 3.4, which shows that funds are very correlated. After running a Pearson Correlation [54] on the prices of all 3 funds, results were obtained in Table 3.4. In the table, it shows the correlation between the prices of all 3 funds were over 0.9 which indicates very high correlation. As such, it can be hypothesised that the reason that the algorithm in 2 could not outperform the both the GOIIX and GGSIX as it is unable to find sufficiently different trends to switch to, to take advantage of trend reversals. Moreover, the introduction of a BCR causes a 0.2 allocation to be always stuck with the lowest performing fund, GIPIX which reduces the overall asset value. Therefore, in summary, due to the almost identical trends present in all 3 funds, the algorithm is unable to make use of trend reversals to dynamically rebalance the portfolio. This similarity in trend is due to the nature of GS portfolios which are mostly based in the US, causing the portfolios to be more correlated to each other. Thus, further testing must be done to ensure that the algorithm can perform in markets that are less correlated to each other.

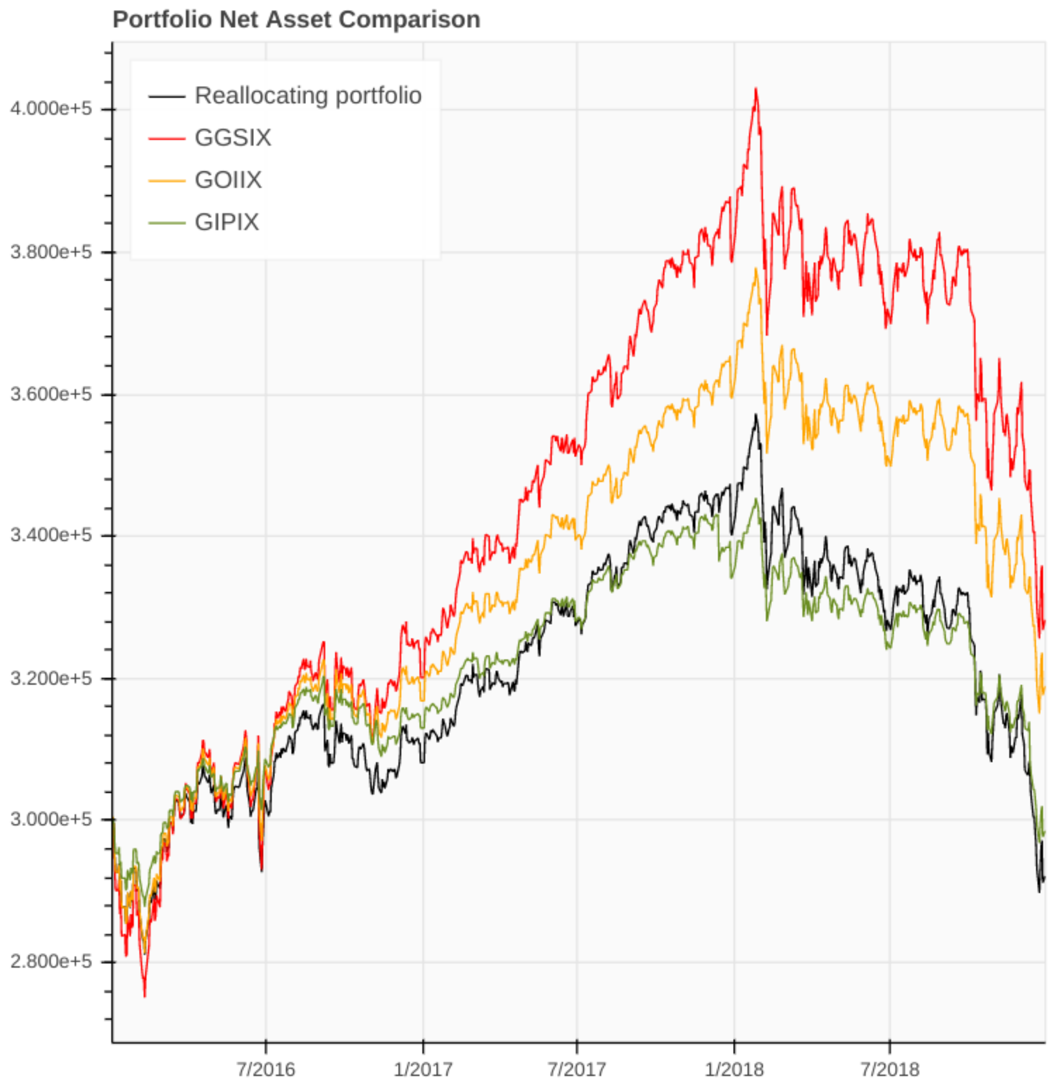


Figure 3.4: GS portfolio rebalancing comparisons

	GGSIX	GOIIX	GIPIX
GGSIX	1.0	0.998	0.918
GOIIX	0.998	1.0	0.940
GIPIX	0.918	0.940	1.0

Table 3.4: Correlation Matrix for GS prices

3.5 Experiment 2 - Global Indexes

After the experiment results in 3.4, we want to investigate if algorithm 2 works well in a global environment, which has more variations to volatility and risk. Also, we want to determine if decreased correlation of the prices will lead to better NAVs obtained using the algorithm.

3.5.1 Experimental setup

3.5.2 Experiment results and analysis

(a) Index NAV from 2014-2018 (b) Composition of each index for 2014-2018

Figure 3.5: Index portfolio NAV comparison

The results for the parameters of the algorithm tuned by Genetic Algorithm are given in Table 3.5. Figure 3.5 shows the results obtained from the experiment. In this experiment, due to the more frequent bullish trends of BVSP, more frequent portfolio rebalances by the algorithm were made to it than the other two indexes (Figure 3.5b).

In the experiment, the portfolio outperformed both the TWII and IXIC in terms of the NAV at the end of 2018. As for BVSP, the algorithm performed a little worse, but was still comparable in performance at a difference of only around 4%, while a reduction in risk is achieved in the price fluctuations of the dynamically rebalanced portfolio as seen in the decreased magnitude of the price fluctuations and the overall CVaR value. A further analysis of the behaviour of the algorithm is shown in Figure 3.6.

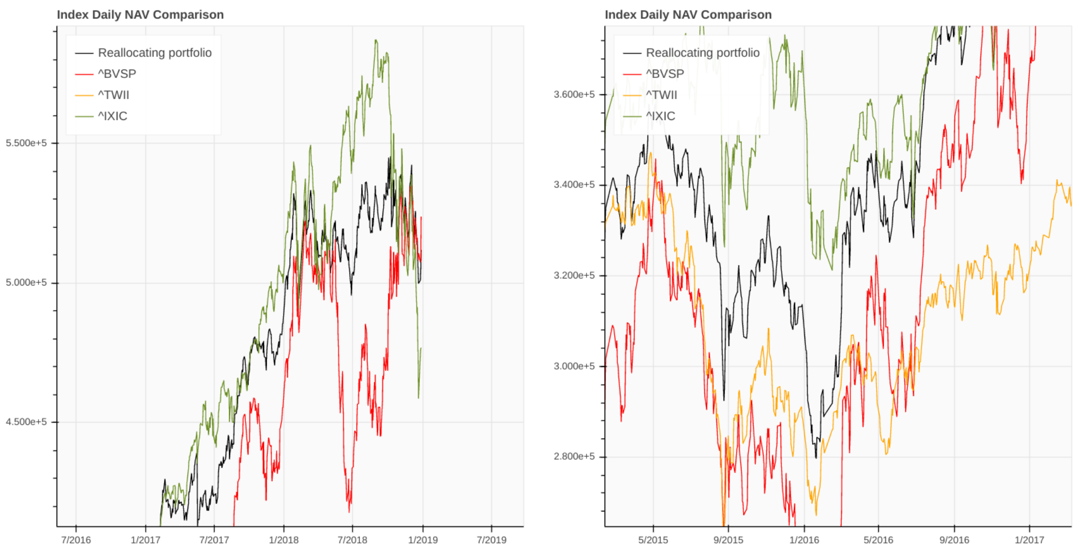
Index	mr_periods	mc_periods	sp_periods	c1	c2	thres
^BVSP	8	11	15	1.36	-1.71	0.0724
^TWII	14	11	10	2.72	2.51	
^IXIC	11	2	2	-4.32	-4.06	

Table 3.5: Genetic Algorithm Parameters for Indexes

In Figure 3.6, 3.6a shows that during periods of bearish trends of the risky market, BVSP, the mid 2018, the algorithm shifted more composition towards both TWII and

IXIC as shown in the mid 2018 period of Figure 3.5b. This shows that the algorithm can detect the downward trend of BVSP and rebalance the portfolio to consist of more TWII and IXIC. Additionally, the algorithm also identified the bullish trend of ÎXIC, and tried to exploit the trend by increasing the composition of IXIC in the portfolio. The quarterly returns of 2018 can also be found in Table 3.6.

Also, during the bearish period in Figure 3.6b from the end of 2015 to mid 2016, the algorithm increased the composition of IXIC, which is the index with low risk. This is due to the uncertainty in the market risk of all 3 indexes, and as such, the algorithm rebalanced the portfolio to more composition in IXIC, and TWII (to a lesser extent). This shows that the algorithm will adopt a bearish stance during periods of uncertainty, where it will prefer less risky investments. Additionally, this is in line with the assumption of the high, medium and low risk levels of the BVSP, TWII and IXIC respectively.



(a) Bullish rebalancing (b) Bearish rebalancing

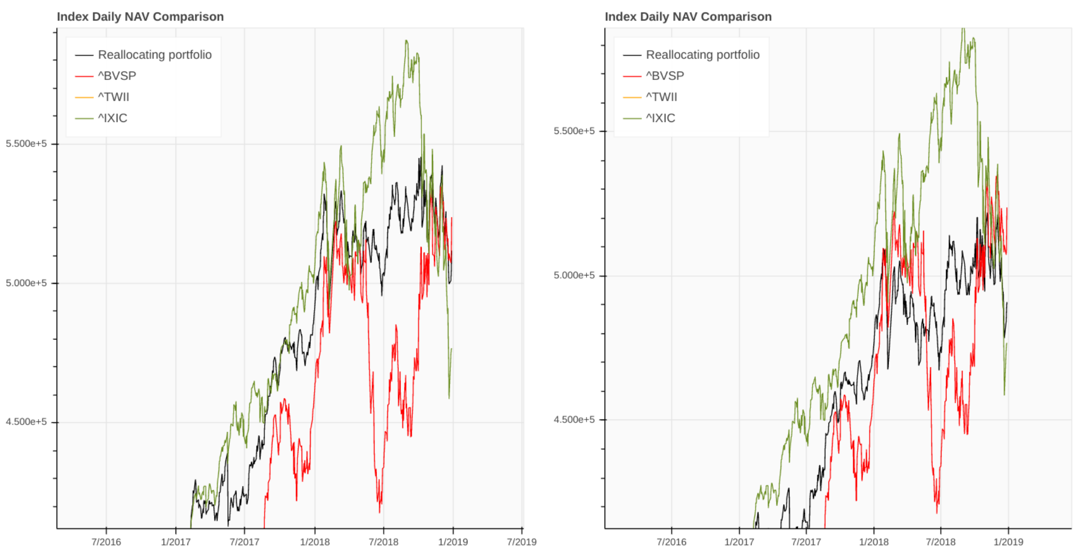
Figure 3.6: Index portfolio rebalancing

Therefore, as the algorithm can dynamically rebalance the portfolio composition of the Indexes, it outperformed the various individual indexes while also simultaneously being able to hedge for risks through base rates, despite commission fees. As compared to 3.4, the algorithm worked better due to the presence of indexes with different cycles and risks, as compared to GS portfolios. As such, the algorithm is able to differentiate market trends and rebalance dynamically the portfolio compositions with consideration to market risks. This helped the algorithm perform better and achieve higher returns.

3.6 Base rates

As the experiment is set to a base rate of 60%, further tests are conducted to investigate the effect of base rates and the algorithm. This is to validate the strategy of the combination of having base rates and tactical rebalancing rates. As such, the experiment is repeated with the same conditions, with the exception of having 0 base rates. Therefore, in this experiment, the algorithm will be able to have more control of the portfolio adjustments, from a 40% tactical rate to 100% due to the reduction in base rate.

As such, the results for the experiment is shown in Figure 3.7, in 3.7b. It can be noted that the final NAV performance of the algorithm without base rates decreased by around 5%. Upon further inspection of the results, it can be hypothesised that the decreases in performance usually occurs during the periods where there are sudden sharp dips or improvements in the indexes such as in mid 2018 as shown in Figures 3.7a and 3.7b. As such, the difference in performance may be attributed to the time lag that technical indicators introduce. As such, short periods of drastic price changes may reduce the performance of the algorithm. However, it there still lacks evidence in such a hypothesis and further testing is required.



(a) Index NAV with base rates (b) Index NAV without base rates

Figure 3.7: Index portfolio rebalancing base rates comparison

	2018Q1	2018Q2	2018Q3	2018Q4
ˆBVSP	9.60	-14.06	8.93	11.78
ˆTWII	1.26	-0.47	2.12	-11.98

^IXIC	0.81	9.32	6.33	-18.08
Algo (base rate)	4.47	-1.16	5.84	-3.67
Algo (no base rate)	2.93	-2.00	5.98	-2.38

Table 3.6: Quarterly returns for indexes

3.7 Experiment 3 (Individual stocks)

While experiment 2 shows that the algorithm can work in a global context by using global indexes, the effectiveness of the algorithm regarding individual stocks in a market must be verified as well. Thus, in this experiment, 3 stocks from each index used in experiment 2 are taken to be rebalanced, and then benchmarked against their respective indexes to determine if the algorithm can indeed work on individual stocks.

3.7.1 Experimental setup

In this experiment, a similar setup is used like in experiment 2: $300000 as the initial NAV, with an even initial split of 100000 for each index, BCRs of 0.2 for each index and a 0.125% commission rate. There will consist of 3 different stocks for each of the 3 different market indexes used in experiment 2.

3.7.2 BVSP

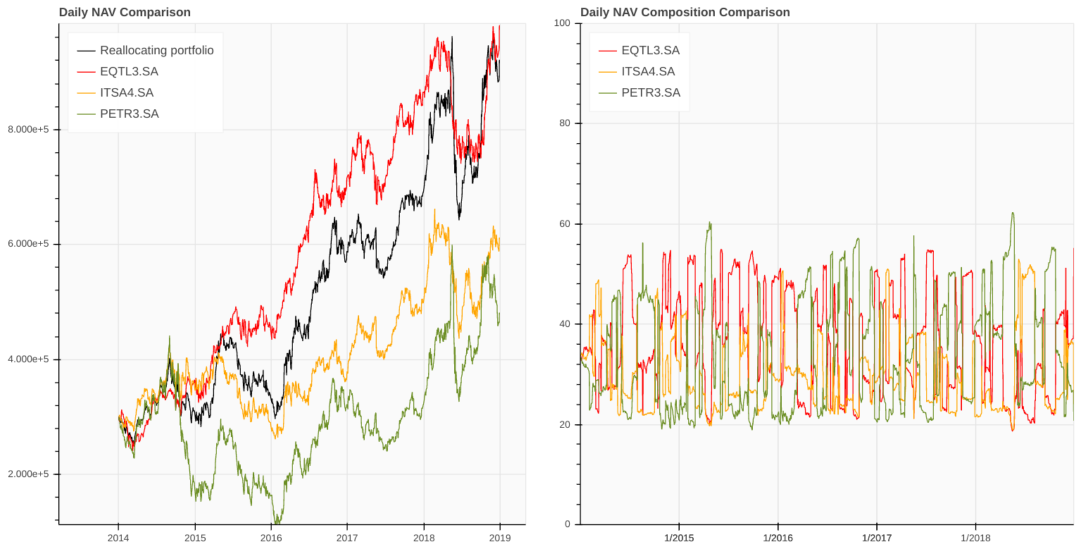
For the high risk market BVSP, 3 of the stocks selected are the Equatorial Energia S.A. (EQTL3.SA), Itausa - Investimentos Itau S.A. (ITSA4.SA) and the Petroleo Brasileiro S.A. - Petrobras (PETR3.SA). The optimal parameters after being tuned by the Genetic Algorithm is given in Table 3.7.

<table>
<tr><th>Stocks</th><th>mr_periods</th><th>mc_periods</th><th>sp_periods</th><th>c1</th><th>c2</th><th>thres</th></tr>
<tr><td>EQTL3.SA</td><td>3</td><td>11</td><td>8</td><td>0.06</td><td>-1.39</td><td rowspan="3">0.155</td></tr>
<tr><td>ITSA4.SA</td><td>3</td><td>5</td><td>4</td><td>0.56</td><td>2.82</td></tr>
<tr><td>PETR3.SA</td><td>13</td><td>9</td><td>18</td><td>1.96</td><td>0.95</td></tr>
</table>

Table 3.7: Genetic Algorithm Parameters for ^BVSP stocks

3.7.3 Results

The results after running the algorithm is given in Figure 3.8, where 3.8a shows the overall results for NAV and 3.8b shows the changes in composition in that period.



(a) BVSP NAV from 2014-2018 (b) Composition of each stock for 2014-2018

Figure 3.8: BVSP stocks NAV comparison

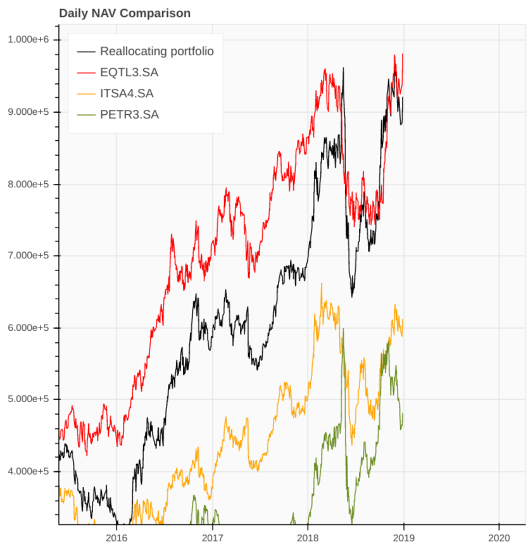
Table 3.8 shows the results of the final 4 quarters of 2018, and compares the performances of each quarter obtained from the results. Note that only returns from 2018 is used, so that short term trends can be observed instead of long term trends (which may contain more noise such as the changes in trend patterns, which can appear as pseudo-trends). From the results, it can be seen that Q1 and Q4 are generally bullish periods, while Q2 is a bearish period for all 3 stocks.

	2018Q1	2018Q2	2018Q3	2018Q4
EQTL3.SA	8.79	-20.44	-1.77	30.82
ITSA4.SA	25.02	-26.34	8.83	20.92
PETR3.SA	34.79	-14.59	23.11	5.045
Algo (base rate)	21.66	-20.02	12.57	20.32
Algo (no base rate)	23.20	-22.74	13.01	18.79

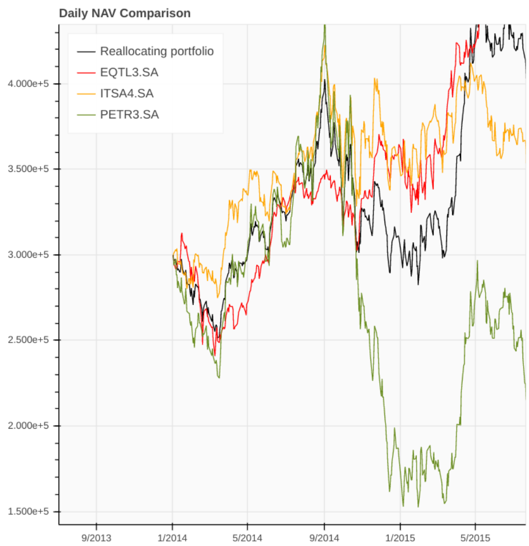
Table 3.8: Quarterly returns for ^BVSP

In this experiment with BVSP stocks, the algorithm performed well, with only a difference in around 3% with the riskiest stock, the EQTL3.SA. Upon further inspection, behaviours of rebalancing can be explained similar to experiment 2. In Figure 3.9a, a bullish switch from EQTL3.SA to PETR3.SA can be seen in the same period of Figure 3.8b. This is because of the more bullish trends of PETR3.SA during that period as compared to EQTL3.SA which caused the algorithm to prefer a higher composition of PETR3.SA at that point in time. This shows that the algorithm is able to differentiate different degrees of bullishness for BVSP stocks.

Additionally, in 3.9b, it can be seen that while in late 2014, the algorithm prefered to hold more PETR3.SA stocks, when PETR3.SA's performance dipped during october 2014, the algorithm was able to detect and rebalance to a higher composition of EQTL3.SA as can be seen in 3.8b. This proves that the algorithm is able to detect a rapid dip in performance and rebalance accordingly. As such, it can be concluded that the algorithm can work well in this environment of the 3 BVSP stocks.



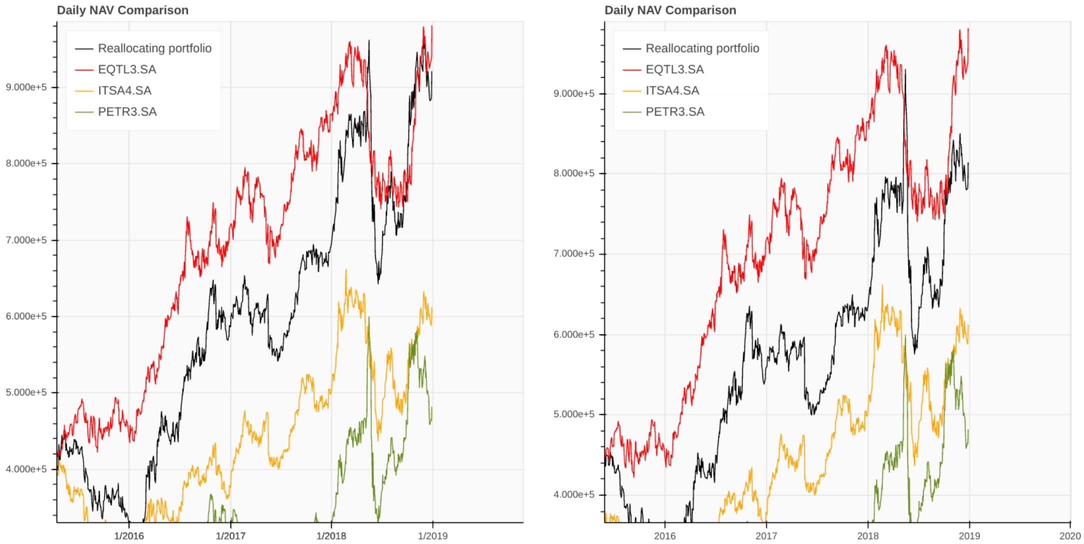
(a) Bullish switch at mid 2018



(b) Bearish switch at late 2014

Figure 3.9: BVSP portfolio rebalancing behaviour

Additionally, we investigate the effects of having no base rates on the algorithm for this case, similar to in experiment 2. As seen in Figure 3.10, in this case, a similar conclusion that with no base rate, the algorithm performs worse than with base rate.



(a) BVSP stocks with base rate (b) Bvsp stocks without base rate

Figure 3.10: BVSP portfolio base rate comparison

3.7.4 TWII

In the TWII index, the 3 stocks selected were the 1326.TW - Formosa Chemicals & Fibre Corporation, 2882.TW - Cathay Financial Holding Co., Ltd. and the 3008.TW - LARGAN Precision Co.,Ltd, which represents the high, medium and low risk stocks respectively. For this selection, all the stocks are selected from different industries, the chemical, engineering and financial industries so as to decrease the correlation of the stock prices.

The results of the parameter tuning by the GA is given in 3.9.

Stocks	mr_periods	mc_periods	sp_periods	c1	c2	thres
1326.TW	3	4	2	0.30	2.77	
2882.TW	9	14	2	1.10	-1.37	0.174
3008.TW	4	3	16	1.84	-2.34	

Table 3.9: Genetic Algorithm Parameters for ^TWII stocks

3.7.5 Results

Table 3.10 shows the results of returns obtained in the 4 quarters of 2018. From the returns, it can be seen that Q4 is generally bearish and 3008.TW is extremely volatile in terms of returns ranging from 40.97% at the highest point to -21.74% at the lowest point in 2018.

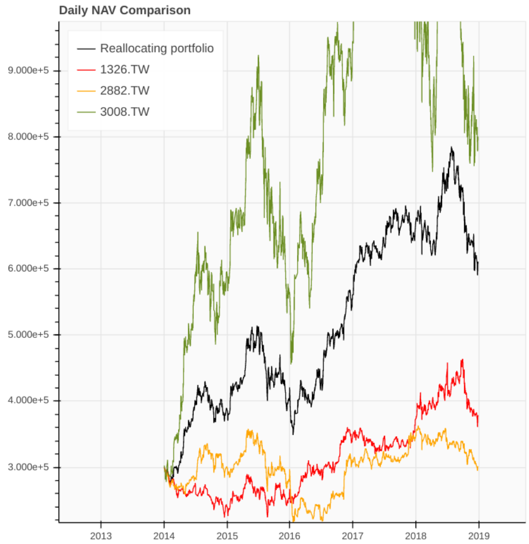
	2018Q1	2018Q2	2018Q3	2018Q4
1326.TW	4.83	13.02	3.64	-18.29
2882.TW	-4.24	2.47	-1.31	-11.15
3008.TW	-21.74	40.97	-20.29	-14.04
Algo (base rate)	-6.87	18.50	-3.85	-15.54
Algo (no base rate)	-5.25	20.02	-0.55	-19.29

Table 3.10: Quarterly returns for ˆTWII

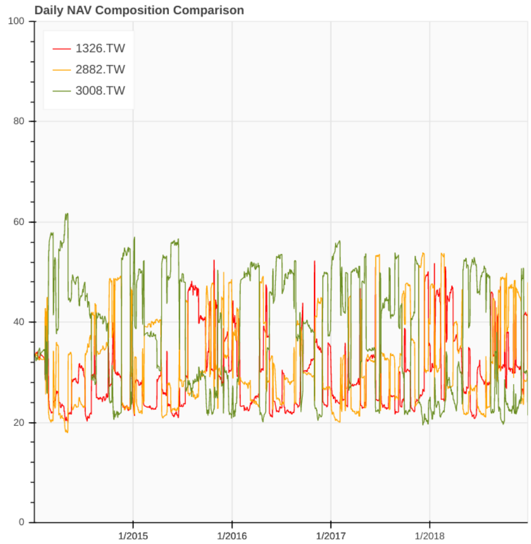
Figure 3.11 shows the results obtained from utilising the parameters in table 3.9 to run the algorithm. In this experiment, the portfolio being rebalanced by the algorithm outperformed both the 2882.TW and 1326.TW. However, it underperformed when compared to 3008.TW by a large amount of around 20%. However, as can be seen in Figure 3.11a, there is a very high volitility of 3008.TW. As such, the difference in returns of 3008.TW and the algorithm can be largely attributed to the volatility, as the algorithm would prefer lower volatility due to the use of CVaR in the algorithm's calculations.

Despite the volatility in 3008.TW, it can be seen in periods such as between end 2016 and start 2017 that the algorithm still could take advantage of the bullish trends of 3008.TW as seen in the change in composition to a largely 3008.TW during the same period in 3.11b.

Similar to previous experiments, the results with and without base rates introduced are shown in 3.12. Surprisingly in this case, different from the previous experiments, the algorithm performed better without base rates than with base rates. This is due to the difference in performance of the 3 stocks, with 3008.TW vastly outperforming 2882.TW and 1326.TW, for which the algorithm without base rates made use of by being able to have higher compositions of 3008.TW rather than being limited to only a 40% tactical asset rate.

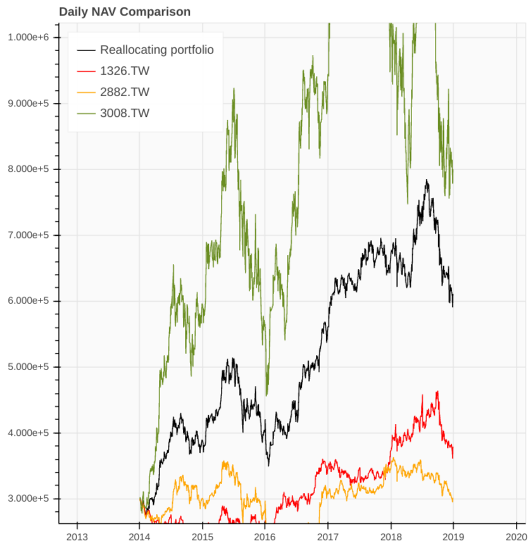


(a) TWII NAV from 2014-2018

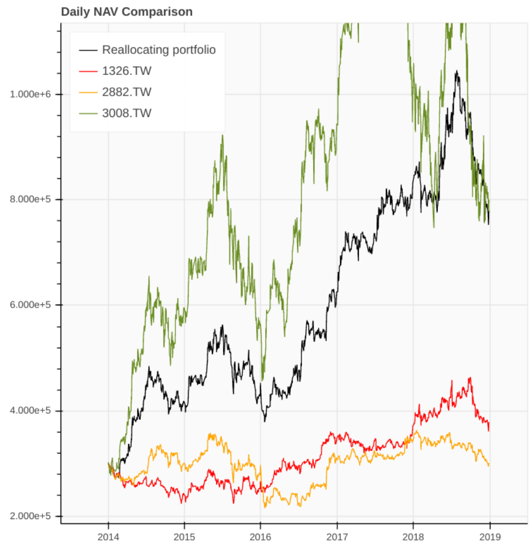


(b) Composition of each stock for 2014-2018

Figure 3.11: TWII stocks NAV comparison



(a) TWII with base rates



(b) TWII without base rates

Figure 3.12: TWII base rates comparison

3.7.6 IXIC

In this experiment, the 3 stocks chosen from IXIC are the TSLA - Tesla, Inc., IBKC - IBERIABANK Corporation, FEYE - FireEye, Inc., being the high, medium and low risk assets respectively. The industries for the stocks are also varied with TSLA being in the manufacturing industry, IBKC in finance and FEYE in cybersecurity.

Similarly, GA is used to optimise the variables in the algorithm, and is given in Table

3.11.

Stocks	mr_periods	mc_periods	sp_periods	c1	c2	thres
TSLA	2	4	7	0.28	-0.21	
IBKC	5	2	5	0.17	1.29	0.158
FEYE	11	2	5	-0.45	2.00	

Table 3.11: Genetic Algorithm Parameters for ˆIXIC stocks

3.7.7 Results

Table 3.12 shows the quarterly returns for IXIC stocks in 2018. As seen in the table, it can be noted that TSLA and FEYE is anti-cyclical to each other at least in 2018 as their returns are inversely related to each other (such as in 2018Q1 where TSLA has a -16.79% return while FEYE has a positive 16.19% return).

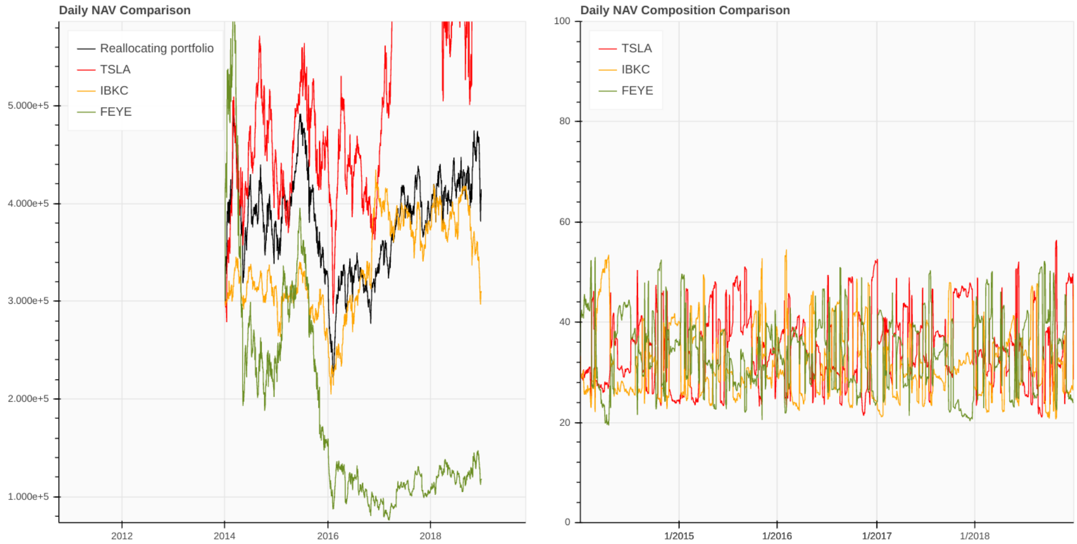
	2018Q1	2018Q2	2018Q3	2018Q4
TSLA	-16.97	35.83	-20.98	7.11
IBKC	0.97	-1.36	6.27	-20.29
FEYE	16.19	-8.33	8.00	-3.91
Algo (base rate)	-0.84	9.55	-0.25	-5.22
Algo (no base rate)	-3.69	18.95	4.10	-10.29

Table 3.12: Quarterly returns for ˆIXIC

With the use of the parameters generated by GA, the results are as given in 3.13. As can be seen from Figure 3.13a, the performance of the stocks given vary greatly, especially in TSLA and FEYE, which caused the algorithm to underperform TSLA by about 20%, similar to in TWII's stock experiment. Yet, it was still able to outperform both the IBKC and FEYE.

Similar to the other stocks, the algorithm exhibits rebalancing behaviours according to the market trends of the underlying stocks. In 3.14, it can be seen during the end of 2014 that the algorithm rebalanced and exploited the bullish trend of TSLA with reference to the composition in Figure 3.13b.

Similarly, experiments without base rate is carried out and shown in Figure 3.15. Similar to TWII stocks, the algorithm performed better without base rates as compared to



(a) IXIC stocks NAV from 2014-2018 (b) IXIC stocks composition from 2014-2018

Figure 3.13: IXIC stocks NAV composition

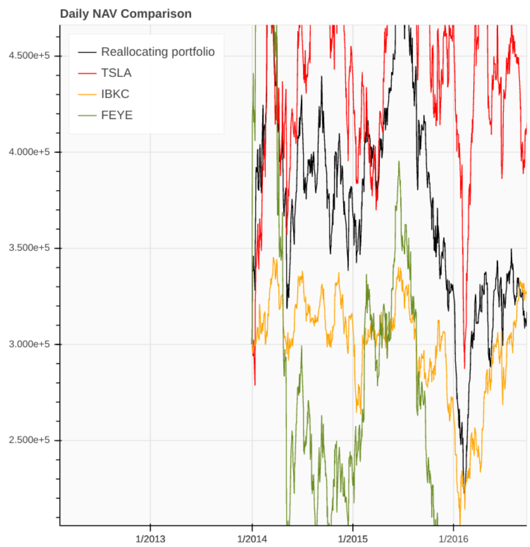
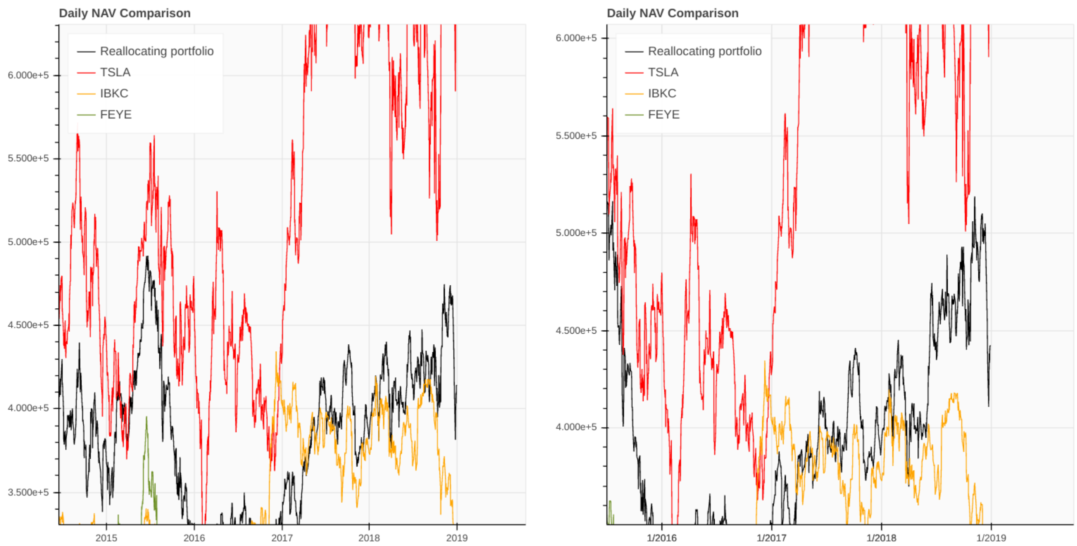


Figure 3.14: BVSP portfolio rebalancing

with base rates. However, in this case, the differences in returns are less prominent at only around 6%. Thus, it can be hypothesised the reduction in base rates could be beneficial to a portfolio with higher differences in performance of individual stocks.



(a) IXIC stocks with base rates (b) IXIC stocks without base rates

Figure 3.15: IXIC stock base rates comparison

3.8 Conclusion and analysis for experiment 3

Therefore, as seen from the results in the stocks of BVSP, TWII, IXIC, the algorithm is able to exhibit risk seeking behaviours during bullish periods by drastically increasing stakes in a high-risk market, and risk-averse behaviours during bearish periods by balancing stakes and reducing stakes in the high risk markets. Also, all algorithms are able to outperform the stocks with medium and low risk in terms of returns, and outperform the high risk stocks in terms of risks due to the decreased magnitude of fluctuations and the reduced CVaR value in each market.

Additionally as seen in the experiment with IXIC and TWII, the reduction of base rates to 0 actually improved the performance of the algorithm while the experiments with BVSP and Indexes in Section 3.5 reduced the performance of the algorithm. The similarity between IXIC and TWII stocks are that they both contain stocks that vary drastically in performance, 3008.TW in TWII and TSLA & FEYE in the case of IXIC. As such, it can be hypothesised that a strategy containing both the base rates and the dynamic rebalancing of the algorithm works well with markets that have similar performances. As for markets with drastically different performances, further testing is needed to find out the derivation of the optimal base rates of each market. However, optimisation is out of the scope of this report and thus is a point of improvement in future research.

3.9 Experiment 4 (Individual stocks combined)

3.9.1 Experimental setup

With the results obtained in Experiment 3, another experiment can be run to compare the performance of the combination of the stocks, with the stock indexes. As such, this experiment is to test if the algorithm can work well on the combinations of stocks (in experiment 3) and can be benchmarked against the original indexes.

The combined stocks are used represent the original indexes, as such the combination of the 3 stocks of each index will be taken to have the same risk levels as the indexes; the 3 combined stocks of each of BVSP, TWII and IXIC will be taken to be as the high, medium and low risk markets.

Additionally, as the prices of each group of 3 stocks are different, they are normalized using the Laspeyres Price Index. The Laspeyres Price Index is given in equation 3.11.

$$\text{Laspeyres Price Index} = \frac{\sum \text{End Price} \times \text{End Quantity}}{\sum \text{Base Price} \times \text{Base Quantity}} \times 100 \tag{3.11}$$

The setup of the experiment is with a base price of 100, with the rest of the experiment similar to that of the others: BCRs of 0.2 for each combined index and a 0.125% commission rate.

For the comparison of the constructed index with the original indexes, a base NAV of $300000 is used for comparison.

3.9.2 Evaluation

The parameters obtained by running GA is given in 3.13.

Index Stocks	mr_periods	mc_periods	sp_periods	c1	c2	thres
^BVSP	4	2	14	1.39	-1.60	0.137
^TWII	6	4	2	0.18	1.34	
^IXIC	3	7	5	2.64	-1.98	

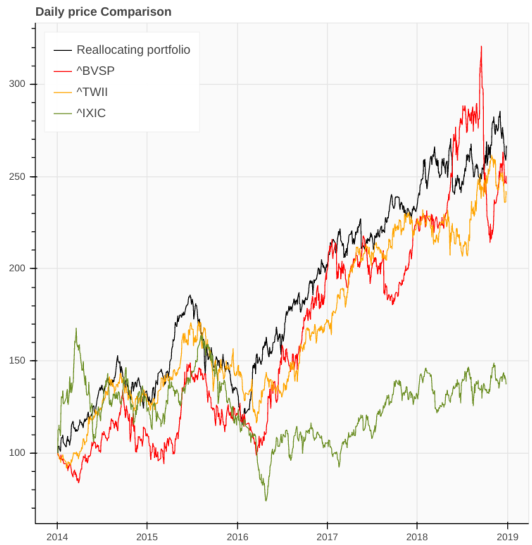
Table 3.13: Genetic Algorithm Parameters for created index from sample

The results obtained for the 4 quarters of 2018 is shown in table 3.14.

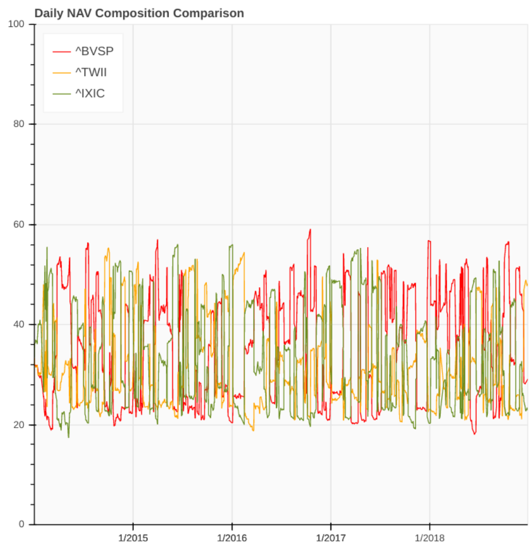
	2018Q1	2018Q2	2018Q3	2018Q4
ˆBVSP	21.66	-20.03	12.57	20.32
ˆTWII	-6.89	18.50	-3.86	-15.54
ˆIXIC	-0.84	9.55	-0.26	-5.20
Algo (base rate)	6.91	-1.63	1.52	4.31
Algo (no base rate)	9.79	-3.95	-1.95	9.76

Table 3.14: Quarterly returns for the constructed indexes

Figure 3.16 shows the results of the dynamic rebalancing. It is interesting to note that the algorithm actually outperformed all 3 of the constructed indexes in this case, despite the extra cost of commission fees incurred.



(a) Constructed Index Price from 2014-2018



(b) Composition of the constructed index for 2014-2018

Figure 3.16: Constructed Index Price comparison

The resultant price index that is obtained from the dynamic rebalancing is then compared with the performance of the original indexes, and the results are given in Figure 3.17. The constructed indexes outperformed the original indexes by up to 35% despite the 2 layers of commission incurred during the index construction phase and the index rebalancing phase.

Thus, it can be seen in this experiment that the algorithm may also be used for the construction of a portfolio of index through individual stocks, as the results obtained

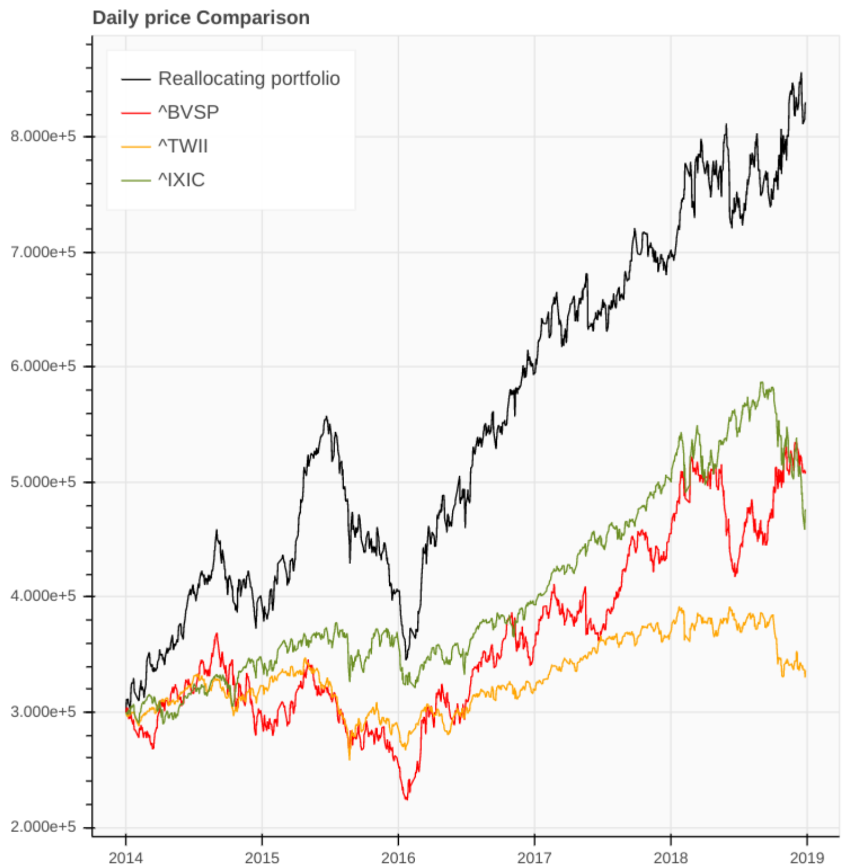


Figure 3.17: Constructed Index comparison

from this experiment far outperformed all of the original indexes. However, it is also important to note that this experiment may not be conclusive as the stocks selected may coincidentally be the top performers of any of the indexes during the period of 2016-2018. As such, more tests will need to be carried out on more varieties of stocks to verify the ability of the algorithm to construct portfolios.

3.10 Algorithm feasibility and extensibility

Therefore, it can be concluded that the algorithm proposed, with optimisation of GA, can be extended to index rebalancing in experiment 2, individual stock rebalancing in experiment 3 and constructed index rebalancing in experiment 4. However, this method will not work on markets/ assets with similar trends and high correlation such as in experiment 1. This is due to the lack of better assets for the algorithm to rebalance to whenever a trend reversal happens.

Also, further experiments will be required to determine the optimal base rate allocation in each experiment as the performance of the algorithm varies according to the market. Variations in performance where the introduction of base rates improves the algorithm results are found in index rebalancing in experiment 2, and BVSP individual stock rebalancing in experiment 3, while cases where the removal of base rates improved algorithm performance are in TWII and IXIC individual stock rebalancing. A trend that emerged from the preliminary analysis of the experiments is that the removal of base rates improve the algorithm when the stocks involved vary drastically in performance, as the algorithm can fully benefit from the bullish trends by being able to rebalance more stakes to the stocks with drastically better performance. Addtionally in the stocks where performances of vary less, it seems that the hedging against wrong trend predictions by the algorithm provided by the base rates was more important. As such, there should be a relationship with the market conditions with regards to base rates. However, this will not be covered in the scope of this report as it is more of an optimisation problem.

3.11 Algorithm limitations

The limitation of the proposed method is that GA is an offline method. As such, rerunning of the GA on the parameters of the algorithm will need to be done for different periods from time to time.

Therefore, in the next section, we will explore the use of reinforcement learning as an online method to explore the method of dynamically re-adjusting portfolio composition to reduce risk and increase returns.

Chapter 4

Dynamic RL rebalancing

In this chapter, an alternative method to dynamically rebalance portfolio is tested. This involves the use of RL to dynamically rebalance the portfolio of the 3 index funds used in experiment 2, the B̂VSP, T̂WII and ÎXIC, representing the high, medium and low risk markets respectively. In this experiment, we aim to find out if RL, an online machine learning technique, can produce performance close to, or as well as the performance obtained from GA in experiment 2.

4.1 Experiment Setup

The time span used in the data of indexes is the period of 2014-2018, similar to experiment 2 so as to be able to have a fair comparison. The experiment is also set up to maximise NAV with \$300000 as the initial NAV, with an even initial split of 100000 for each index, BCRs of 0.1 for each index and a 0.125% commission rate. Tensorflow [55] is used in the following RL experiments and the scikit-learn module [56] is used for feature scaling.

4.2 RL Setup

4.2.1 Environment

The environment of the agent is defined as such:

Observable period

The observable period used by the agent is the market prices of time period of 2014-2018, for which periods of actions are defined by trend reversals. Trend reversals are similarly defined as the MACD crossovers as introduced in section 2.1.1.

State

The state of the environment that is observed by the agent is given in equation 4.1:

$$\text{State} = (EMA_1, MACD_1, EMA_2, MACD_2, \Delta\text{t}) \tag{4.1}$$

Where EMA_1 and EMA_2 are the standardised 6-day EMA of 15 days of the high risk and medium risk index respectively, $MACD_1$ and $MACD_2$ are the normalised 6-day difference in MACD Line and Signal of 15 days of the high risk and medium risk index respectively, and Δt is the difference in number of days from the previous trend reversal.

Action

The action of the reward of the agent is limited to 3 different actions:

1. **Increase high risk index portfolio composition** and reduce the composition of the other 2 indexes.
2. **Increase medium risk index portfolio composition** and reduce the composition of the other 2 indexes.
3. **Increase both the high and medium risk index portfolio composition** and reduce the composition of the low risk index.
4. **Increase low risk index portfolio composition** and reduce the composition of the other 2 indexes.

Details and modifications to this reward structure will be introduced in the experiment later in the section.

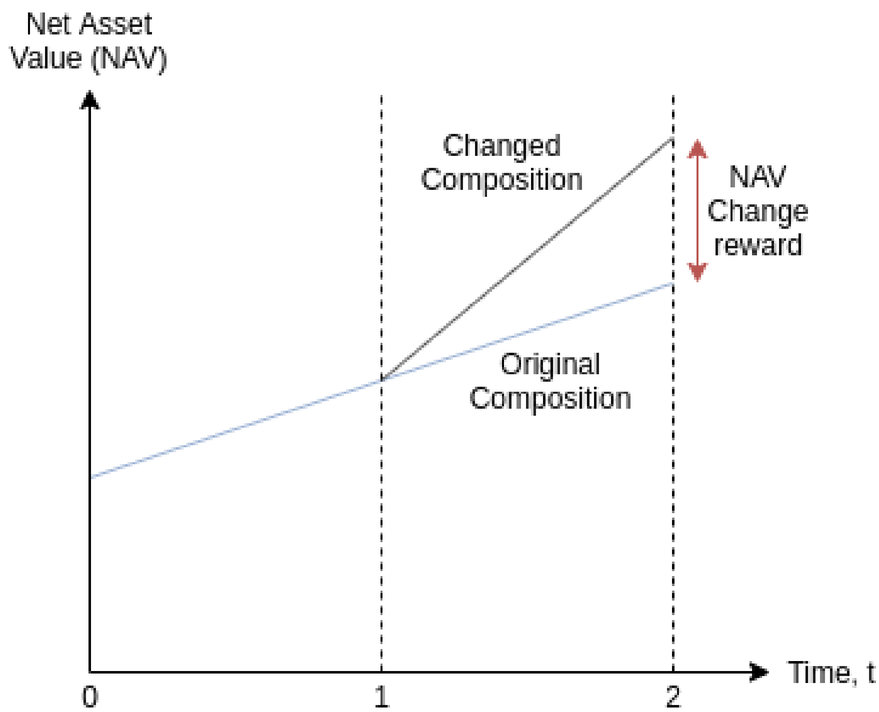


Figure 4.1: Difference in NAV after composition change

Reward

In the environment, rewards are defined per step of the training. Each step refers to each trend reversal detected in the period between 2014-2018. The reward comprises of 2 different components: 1) the change in NAV reward and 2) the current NAV reward. The NAV change reward is calculated by the following equation:

$$\text{NAV change reward} = \frac{\text{Changed NAV} - \text{Passive NAV}}{\text{Passive NAV}} \times \text{Time Scaling Factor} \quad (4.2)$$

Where the Changed NAV is the NAV obtained after a period of 10 days after using the changed portfolio composition by the actions in section 4.2.1, the Passive NAV is the NAV obtained after a period of 10 days after using the original portfolio composition. The main concept is shown in Figure 4.1, where at the difference of the Changed NAV and Passive NAV is visualised at time $t = 2$. Additionally, the Time Scaling Factor's equation is shown as follows:

$$\text{Time Scaling Factor} = 0.5 \times \frac{\text{Number of days past}}{\text{Total number of days}} + 0.5 \quad (4.3)$$

Where the days of the equation refers to the time period in 2014-2018.

The Time Scaling Factor will scaled the rewards from $0.5 - 1.0$ so as to reduce the rewards obtained as the time increases. This is to place more emphasis on initial actions as they impact the final NAV more due to the compounding effect.

The current NAV reward is calculated by simple division of the current NAV over a constant of 10000000 to normalise the reward.

As such, the total reward per step is obtained in the following equation:

$$\text{Total Reward} = \text{NAV change reward} + \text{Current NAV reward} \tag{4.4}$$

Therefore, by referring to the rewards received per step, the RL agent will get an indication of the performance of its immediate action based on the current state of the environment.

4.2.2 RL Agent

For the RL Agent, a Q network is setup to determine the Q values of actions for each state. The Q network is shown in Figure 4.2, where it consists of 1 input layer, 1 hidden layer and 1 output layer, with a hidden layer size of 100 neurons.

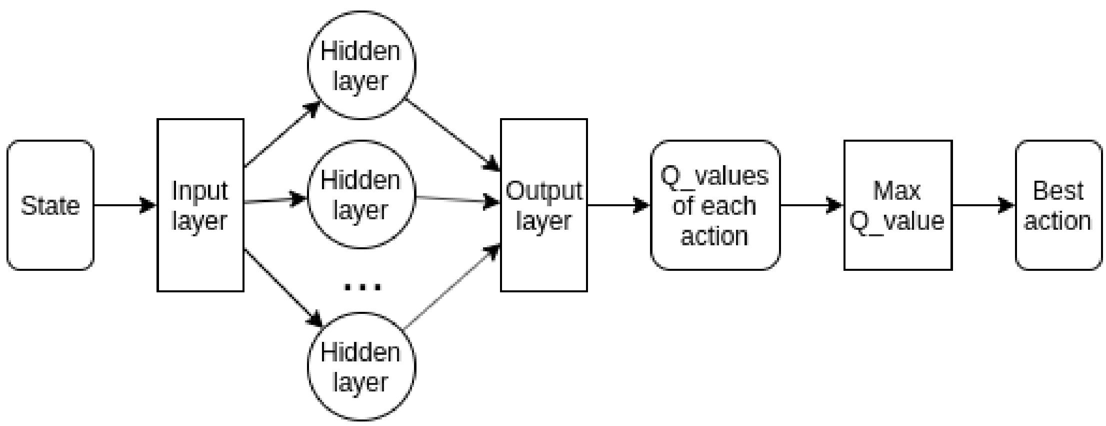


Figure 4.2: Q network

The Q value of an action to be predicted by the Q network is determined by the following Bellman equation [57]:

$$Q(s) = R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s,a) Q(s') \tag{4.5}$$

Where s is the states in the set of S states, s' is next state in the set of S states, a is the action in the set of A actions, $Q(s)$ is the Q value to be determined, $Q(s')$ is the Q value for the next state s', $R(s)$ is the rewards of the current state, γ is the discount of the next Q value set at 0.99 and $P(s'|s,a)$ is the probability of state s' happening given s and a which is set to a value of 1.

4.3 Experiment 5 - Full rebalancing

To first test the algorithm, the action policy of the algorithm is set to switch the targeted market fully from 0.1 to 0.8, while reducing all the other compositions of the other markets to 0.1. As such, upon the detection of a trend reversal, the RL agent will in effect increase the composition of the market with the highest potential to have a better return.

4.3.1 Stock prediction model

The results obtained are shown in Figure 4.3. As seen from the figure, the performance of the RL agent was not ideal, with a $15-20\%$ difference in performance from BVSP and IXIC. Also, during the period of start 2018, the RL agent failed to exploit the bullish trends present in BVSP. However, the RL agent still did manage to adopt a risk averse stance at the start of 2015, which avoided the downturn of BVSP. Yet, the results were not satisfactory, and further inspection into the model is looked into in the next section.

4.3.2 Market Information lag

One of the causes of performance of the reinforcement learning may be due to the information lag in the indicators used to detect trend reversals in the market. Figure 4.4 shows the concept in further detail. In the figure, $C1$ models the EMA window used in the experiment. As it can be seen, the true center of the calculated EMA is actually at $t = 3$ instead of $t = 6$, at the day of action. Therefore, the derived price trend of the

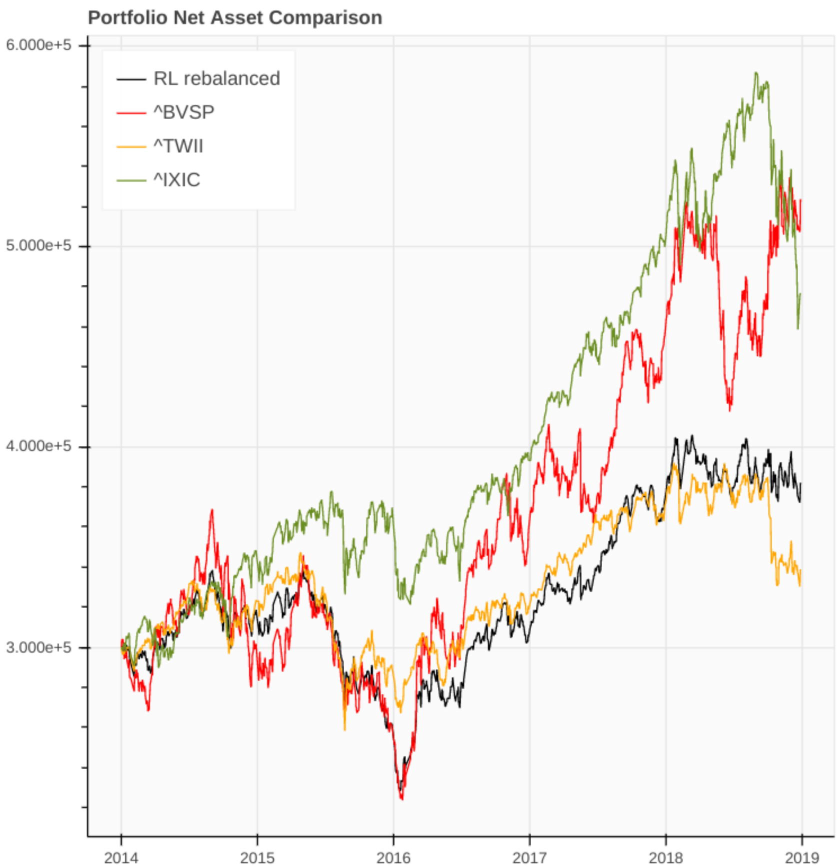


Figure 4.3: Results for RL with full rebalancing

market at $t = 6$ in $C1$ is actually the only the true price trend of the market at $t = 3$, which is a 3 day lag in information, as seen from the figure. As such, for the indicator to give a better and more accurate prediction of the true market trends at $t = 6$, there will be a need to predict the prices for $t = 7$, $t = 8$ and $t = 9$ to calculate the true EMA of stock prices at $t = 6$ as shown in $C4$.

4.4 Experiment 6 - Full rebalancing without time lag

As such, to verify the hypothesis of the RL agent having decreased performance due to market information lag, a further experiment is conducted. In this experiment, 2 LSTM models are trained to predict the next 3 stock prices of a market for the high and medium risk market. This prediction is done so as to improve the time lag of the indicators of EMA and MACD in the state of the RL environment in section 4.1 so as to improve the information provided to the RL agent for its actions. A time period of 3 days to be predicted are chosen as it is a reasonable timespan for relatively accurate

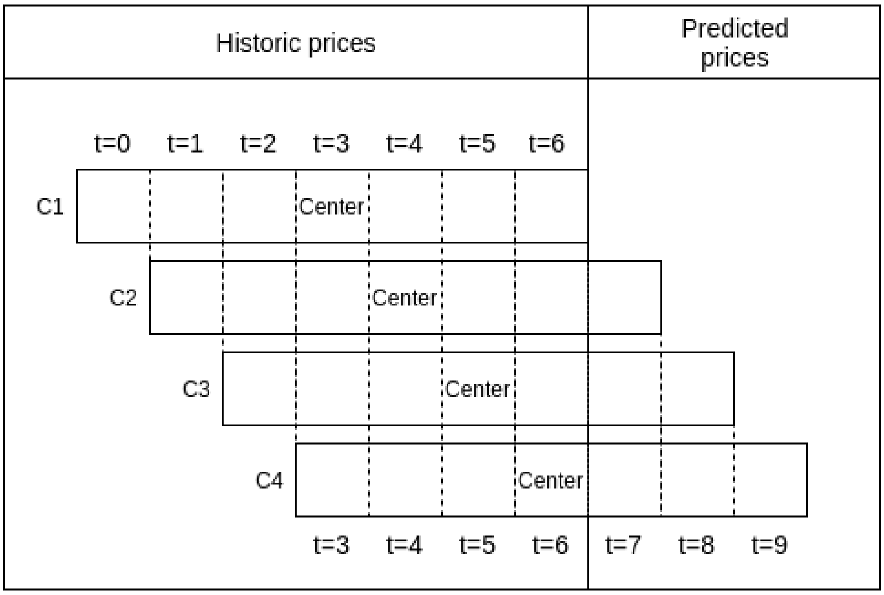


Figure 4.4: Time lag of trend indicators

predictions. The model is described in further details in the following subsection:

4.4.1 Stock prediction model

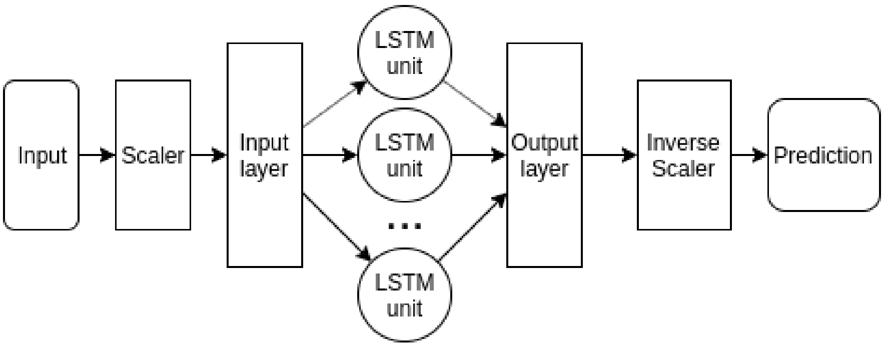


Figure 4.5: LSTM model for stock price prediction

Figure 4.5 shows the LSTM model used to predict stock prices. In this model, 32 LSTM units are used, with a lookback period of 7 days, a learning rate of 0.001 and loss is calculated using the mean squared error approach. All features are normalized before being passed to the input.

Therefore, by using this model setup, models for both the BVSP (high risk) and TWII (medium risk) markets are trained using data from 2014-2018. Using the stock prices predicted for the next 3 days for each market, time lag is eliminated/ reduced, and the derived EMA and MACD is used in the environment state as discussed in section 4.1

instead.

4.5 Experimental results and analysis

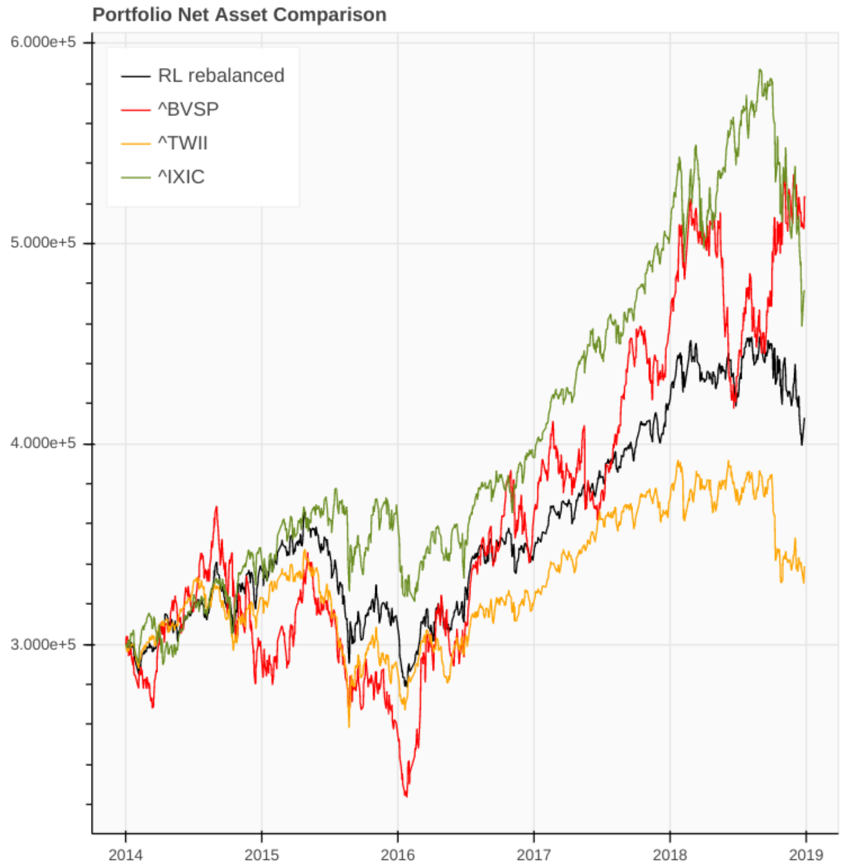


Figure 4.6: Results for RL with full rebalancing, with prediction model

As such, the experiment is rerun with the prediction of the LSTM model in Figure 4.6. As can be seen, the performance of the RL agent improved by about 5%, and the agent is more able to rebalance according to market trends as seen in the period of start 2018 and the period of start 2015. As such, the reduced time lag seems to have improved the results. However, the results obtained were still differs from the results obtained by the GA by about $10+\%$. Therefore, further improvements to the RL model will have to be made in order for it to perform as well, or even better than the GA method proposed.

One aspect of the RL agent to be looked into is the policy of actions. Currently, a full rebalancing method is used where the composition of a portfolio can drastically change from 0.1 to 0.8 for the selected action. However, when such a method is used, the penalty for the RL agent in choosing the wrong action will be maximised in periods of uncertainty due to the high commission fees incurred in a complete change in composition of a single asset. Therefore, it may be better if the agent adopts a gradual change in composition rate instead of a 1 day full switch in composition. This will lower the cost of mistakes and may improve results. However, by using a gradual approach to portfolio rebalancing, the reaction to large short term bullish trends and bearish trends will be slower, causing the algorithm to not be able to rebalance fast enough to either exploit the large bullish trend or protect against the large bearish trends. Therefore, further experiments will be needed to explore if a gradual approach can improve the portfolio performance.

4.6 Experiment 6 - Gradual rebalancing

Thus, while Experiment 5's RL agent uses a full switch from 0.1 to 0.8 for its actions, it is worth exploring if a gradual approach to changing base rates can be done instead. As such, the following actions are revised in section 4.2.1:

4.6.1 Revised RL actions

1. **Increase high risk index portfolio composition** by **0.3** and reduce the composition of the other 2 indexes **per day**, until the other 2 indexes **reaches base rate** or until another **trend reversal**.
2. **Increase medium risk index portfolio composition** by **0.3** and reduce the composition of the other 2 indexes **per day**, until the other 2 indexes **reaches base rate** or until another **trend reversal**.
3. **Increase both the high and medium risk index portfolio composition** by **0.15** and reduce the composition of the low risk index **per day**, until the low risk index **reaches base rate** or until another **trend reversal**.
4. **Increase low risk index portfolio composition** by **0.3** and reduce the composition of the other 2 indexes **per day**, until the other 2 indexes **reaches base rate** or until another **trend reversal**.

In essence, the change in indexes now occur gradually, at 30% per day, instead of an up to 70% change in one day. As such, changes in the portfolio composition less sudden, and continuous trend reversals within short time intervals will have a lesser penalty in commission charges due to a slower composition change. Additionally, mistakes made by the RL agent will be less costly as less commission costs are incurred if the next trend reversal is close by. However, due to the compositional changes, the RL agent may not be able to take full advantage of a bullish swing in prices or a may not be able to reduce stakes fast enough in a bearish price swing.

4.6.2 Experimental results and analysis

As such, two experiments are conducted, with the gradual portfolio composition change with and without the LSTM prediction model.

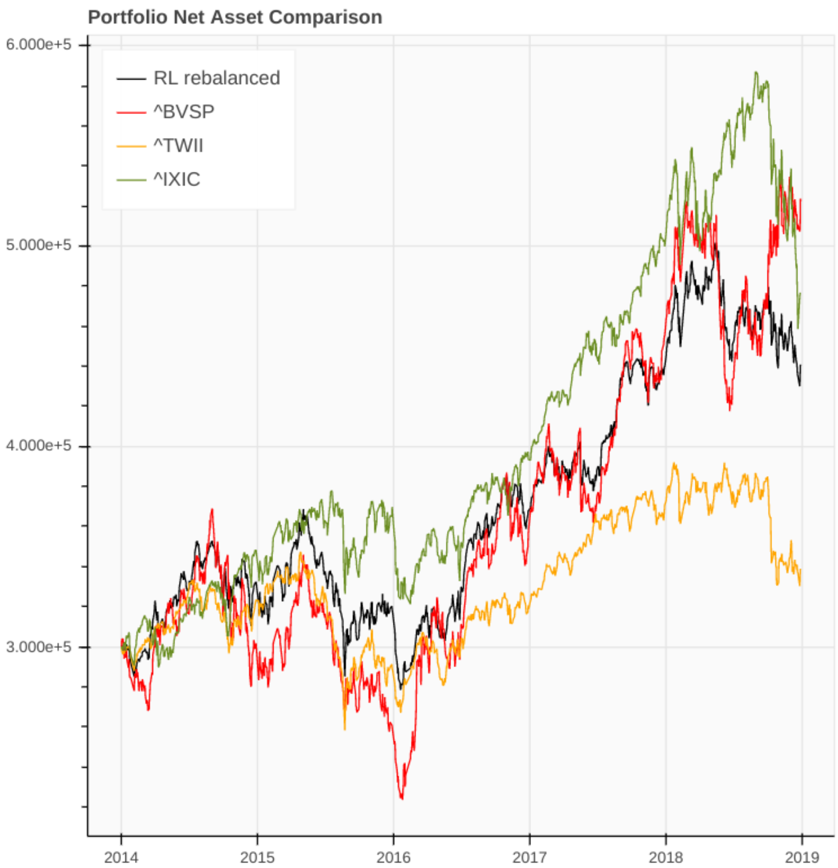


Figure 4.7: Results for RL with gradual rebalancing, without prediction model

Figure 4.7 shows the gradual rebalancing without prediction and it shows a roughly $2-3\%$ improvement over the method with full rebalancing. Thus, gradual rebalancing seems to be able to work better in this experiment, as in addition to the improved performance, periods such as the end of 2014 shows that the RL agent is able to adopt a more risk adverse approach by increasing the portfolio of IXIC which prevented further decreases in NAV. Additionally, at the start of 2018, it adopted a risk seeking stance by increasing the portfolio composition of BVSP, which led to a substantial increase in NAV. However, at the end of 2018, due to the rapid rise in IXIC during the mid 2018, it did not rebalance to BVSP in time to exploit the bullish run BVSP had. Overall, the algorithm had an improved performance and a better risk profile as it's movements were less volatile than the BVSP. Thus, in this experiment, it can be seen that the effect of the reduction in NAV by the commission fees is larger than the effect of the RL agent not being able to exploit bullish and protect against bearish trends. This led to the improvement in performance of the algorithm in this experiment.

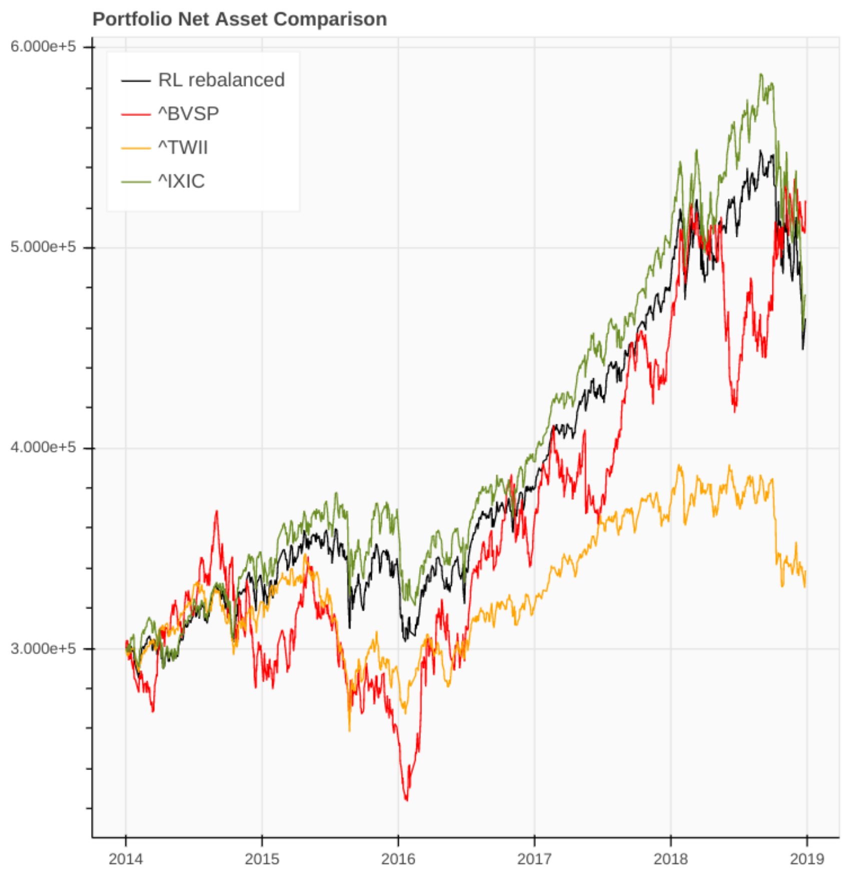


Figure 4.8: Results for RL with gradual rebalancing, with prediction model

In Figure 4.8, the RL agent performed around 1% better than the agent without a LSTM prediction. In this model, there is much preference for the agent to increase the portfolio composition of the IXIC, which led to the similarity in the shape of its NAV curve and the one of IXIC. In this case, this RL agent underperformed the RL agent without a prediction model to help center technical indicators. This may indicate that the prediction model used may not have provided data accurate enough for it to outperform the previous model in this case. Yet, this model still outperformed the full rebalancing approach in the previous experiments which means that the effect of the reduction in NAV by the commission fees is larger than the effect of the RL agent not being able to exploit bullish and protect against bearish trends, similar to the conclusion of the previous experiment.

In conclusion, in this chapter, experiments using a RL agent is conducted and tested. 4 different methods were used in this chapter where there were variations of fully rebalancing and gradual rebalancing with variations to technical indicator centering by using a LSTM model to predict stock prices. The RL agent with gradual rebalancing and no stock prediction model performed the best in the end, as it managed to have the appropriate trading behaviours present in adjusting portfolio composition. Also, the results it achieved in the end has only a 5% difference in performance, which is good considering that it is an online learning algorithm, as compared to GA. As such, it can be concluded that a properly tuned RL agent with and without a prediction model (although one with should in theory provide better results) to center technical indicators can utilise dynamic rebalancing to improve portfolio returns and risk.

Chapter 5

Conclusion and Future Works

In this report, dynamic rebalancing is combined with the concept of Strategic and Tactical Asset Allocation to explore its feasibility and effectiveness. The performance of dynamically rebalanced portfolios are benchmarked with the performance their underlying assets to validate its effectiveness. Two methods were proposed to implement the dynamic rebalancing for a portfolio: by using the Genetic Algorithm (GA) and a novel risk algorithm, and by using Reinforcement Learning (RL).

In the experiments involving the risk algorithm and GA, the algorithm has demonstrated the ability of to dynamically adjust portfolio compositions according to the market trends, risks and returns of each stock/ index throughout the periods tested. Furthermore, it is demonstrated that the algorithm can work well in the global and local market environments, and can work well for both market indexes and individual stocks, as long as the portfolio's underlying assets are not largely correlated to each other as in the case with Goldman Sachs in Experiment 1. It was also found that the algorithm even performs well for portfolio construction, although further tests are needed to verify its results. The effect of the amount of base rates (part of the Strategic Asset Allocation) allowed in each portfolio were also explored and analysed. In conclusion, the algorithm generally is able to outperform all except the highest performing stock/ index in each experiment in spite of commission fees, in terms of returns, while generally carrying less risk.

In the experiments involving RL, the RL agent has also demonstrated the ability to dynamically adjust portfolio compositions according to the market trends, risks and returns of each stock/ index throughout the periods tested, with the added property of the agent being an online algorithm. With exploration into different policies of gradual and immediate changes in portfolio composition, and the inclusion of a better stock prediction model to reduce the time lag introduced by technical indicators, the performance of the RL algorithm could be able to match the performance of the GA and risk algorithm.

Thus, in conclusion, the strategy of dynamic portfolio rebalancing coupled with the concepts of Strategic and Tactical Asset Allocation is shown to work well by using the two proposed methods. Further studies on dynamic rebalancing can explore the use of different models to further improve performance of the portfolio, both in terms of returns and risks. Future works regarding the GA and risk algorithm can further examine the relationship between markets and the base rates optimal for each market, and also further explore the application of the method on portfolio construction as shown in Experiment 4. Finally, future works regarding the RL algorithm can try to improve the stock prediction model that is used to reduce time lag for technical indicators, and experiment on the effectiveness of other techniques of RL such as the Actor-Critic, Experience Replay or Double Q-learning in dynamic portfolio rebalancing.

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Appendix A

Statistics

A.1 Fund comparisons for GIC, JPM and GS

Institution	Funds (Institutional)	Symbol	Start Period	End Period	1 year return (%)	5 year return (%)	10 year return (%)
GIC	GIC	-	04/2017	03/2018	3.40	5.00	9.30
Goldman Sachs	Balanced Strategy Portfolio	GIPIX	01/2018	12/2018	-6.53	2.40	5.73
Goldman Sachs	Equity Growth Strategy Portfolio	GAPIX	01/2018	12/2018	-11.07	4.78	9.62
Goldman Sachs	Growth and Income Strategy Portfolio	GOIIX	01/2018	12/2018	-8.63	3.00	7.23
Goldman Sachs	Growth Strategy Portfolio	GGSIX	01/2018	12/2018	-10.65	3.64	8.32
Goldman Sachs	Satellite Strategy Portfolio	GXSIX	01/2018	12/2018	-10.06	1.32	7.05
JPMorgan	Global Allocation Fund	GAOSX	09/2017	10/2018	-1.58	4.99	-
JPMorgan	Income Builder Fund	JNBSX	09/2017	10/2018	-0.52	4.12	-

Table A.1: Fund comparisons

A.2 Goldman Sachs Portfolio composition

A.2.1 Growth Strategy Portfolio (GGSIX)

GS Growth Portfolio	2018	2017
Emerging Markets Equity Insights Fund	13.3%	16.7%
International Equity Insights Fund	12.3%	7.7%
ActiveBeta U.S. Large Cap Equity ETF	8.0%	7.2%
Tactical Exposure Fund	7.8%	9.5%
Global Real Estate Securities Fund	7.1%	6.9%
Large Cap Growth Insights Fund	7.1%	8.8%
Large Cap Value Insights Fund	7.0%	9.0%
ActiveBeta International Equity ETF	5.7%	1.4%
Financial Square Government Fund	5.5%	2.7%
Small Cap Equity Insights Fund	5.1%	3.5%
ActiveBeta Emerging Markets Equity ETF	4.7%	5.5%
International Small Cap Insights Fund	3.1%	4.9%
Global Infrastructure Fund	2.7%	1.4%
Emerging Markets Debt Fund	2.0%	1.0%
Managed Futures Strategy Fund	1.2%	2.4%
Alternative Premia Fund	1.2%	4.0%
Access High Yield Corporate Bond ETF	1.0%	0.0%
Local Emerging Markets Debt Fund	0.9%	0.0%
High Yield Fund	0.8%	4.0%

Table A.2: Composition of GS Growth Strategy Portfolio (GGSIX)

A.2.2 Growth and Income Strategy Portfolio (GOIIX)

GS Growth and Income Portfolio	2018	2017
International Equity Insights Fund	10.4%	6.5%
Emerging Markets Equity Insights Fund	9.0%	10.5%
Global Income Fund	7.9%	9.2%
Tactical Exposure Fund	7.8%	9.8%
ActiveBeta U.S. Large Cap Equity ETF	7.3%	5.2%

Financial Square Government Fund	7.2%	2.3%
Large Cap Growth Insights Fund	6.0%	7.4%
Large Cap Value Insights Fund	6.0%	7.4%
ActiveBeta International Equity ETF	5.1%	1.9%
Emerging Markets Debt Fund	4.8%	5.3%
Global Real Estate Securities Fund	3.8%	2.8%
Global Infrastructure Fund	3.2%	2.8%
ActiveBeta Emerging Markets Equity ETF	2.6%	3.1%
Managed Futures Strategy Fund	2.6%	4.9%
Alternative Premia Fund	2.5%	4.1%
Small Cap Equity Insights Fund	2.2%	1.4%
Local Emerging Markets Debt Fund	2.0%	1.0%
Access Investment Grade Corporate Bond ETF	2.0%	0.0%
International Small Cap Insights Fund	1.4%	3.4%
Access High Yield Corporate Bond ETF	1.1%	0.0%
High Yield Fund	1.0%	8.6%

Table A.3: Composition of GS Growth and Income Strategy Portfolio (GOIIX)

A.2.3 GS Balanced Strategy Portfolio (GIPIX)

GS Balanced Strategy Portfolio	2018	2017
Global Income Fund	21.3%	30.5%
Emerging Markets Debt Fund	7.8%	4.4%
Tactical Exposure Fund	7.6%	9.7%
Financial Square Government Fund	7.6%	3.0%
Emerging Markets Equity Insights Fund	6.3%	7.8%
International Equity Insights Fund	5.9%	3.0%
Access Investment Grade Corporate Bond ETF	5.2%	0.0%
ActiveBeta U.S. Large Cap Equity ETF	4.2%	1.6%
Local Emerging Markets Debt Fund	3.8%	1.0%
Managed Futures Strategy Fund	3.4%	4.7%
ActiveBeta International Equity ETF	3.0%	0.0%
Global Real Estate Securities Fund	2.7%	2.5%
Access High Yield Corporate Bond ETF	2.5%	0.0%
Large Cap Growth Insights Fund	2.5%	4.0%

High Yield Fund	2.4%	7.6%
Large Cap Value Insights Fund	2.2%	4.1%
Global Infrastructure Fund	2.1%	2.4%
Small Cap Equity Insights Fund	1.7%	80.0%
Alternative Premia Fund	1.6%	4.0%
ActiveBeta Emerging Markets Equity ETF	1.2%	2.2%
International Small Cap Insights Fund	1.1%	2.8%

Table A.4: Composition of GS Balanced Strategy Portfolio (GIPIX)