Global Asset Allocation using XCS Experts in Country-Specific ETFs

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Abstract

There are several studies extended classification system (XCS) in past years, the model can dynamically learn and adapt to the change of environments for maximizing the desired goals. This paper conducts simulation the experiment to evolve XCS for global asset allocation in the country-specific Exchanged Traded Funds (ETFs). Since international stock price trend is influenced by unknown and unpredictable surrounding, using XCS to model the fluctuations on global financial market allows for the capability to discover the patterns of the future trends. The benefits of international diversification can be achieved with country-specific ETFs at a low cost, with a low transaction cost, tracking error and in a tax-efficient way. These empirical results indicate that XCS is capable of evolving from generation to generation, and in this way can provide the highest profit for future global asset allocation decision-making.

1. Introduction

Recently, Exchange Traded Funds (ETFs) have become very popular investment products for index trading all over the world since their first introduction at the beginning of last decade. ETFs are the leading financial innovation of the last decade, (Fuhr [2001]). ETFs are shares that closely track the performance of an index. In one ETFs trade offer the benefits of diversification and index tracking at a low cost. The first ETF, SPDR, was launched on AMEX in 1993 and was designed to passively mimic the S&P500 index. Furthermore, at the end of 2007, there were 837 ETFs with 1324 listing, and assets of US$1212 billion, managed by 107 managers on 56 exchanges across the world. Most days, two or three ETFs are on the list of the top five most actively traded stocks on the AMEX.

Additionally, since the trend of fund price is the synergy of many man-made and natural elements, using dynamic machine-learning tool for the fund analysis is more suitable and adaptive than traditional methods. Learning classifier system (LCS) consists of a set of steps and classifiers for discovering rules of genetic and non-genetic operators. [9] In LCS bibliography, a wide range of resources has been covered [10][11]; however, the applications on financial issues [12][13] are so few that are expected to explore. The following are reasons to use XCS on dynamic and noisy environments:

- XCS is capable of making real-time and accurate responses.
- XCS has been shown to properly learn from noisy, complex, and non-linear environments when the outside information continuously changes.
- XCS is able to evaluate rules that are ideal for modeling problems without retraining all data.
- XCS, generalizing under predefined conditions, can discover maximally general, accurate rules to perform on a variety of problem domains.
- XCS can adjust itself to strengthen its inward knowledge step by step.
- XCS assigns rule fitness based on the accuracy of the rule rather than on the reward payoffs.

Recently there have been several investigations into applying LCS to machine learning and data mining classification problems [34], [2], [17], [26]. This paper continues this investigation by applying an adaptation of a recently developed XCS, Wilson's XCS [32], to a large multi-class benchmark data set available at the 24 iShares MSCI(Morgan Stanley Capital International) country funds. The rest of this paper is structured as follows: Section I introduce the study's motivation and goals. Section II examines the literature. Section III briefly describes XCS in our model. Section III describes the data set and the experimental procedure adopted. Section V presents the results and Section VI concludes the result and future study direction.

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2. Literature Review

Analysis past studies, we divide the related studies into four parts, which include literature on ETFs, artificial intelligence and portfolio, technical analysis and technical indicators and classifier systems.

2.1. International ETFs

In the past, there are so much studies by Cumby and Glen [1990], Eun et al. [1991], Shukla and Singh[1997], Redman et al. and Bhargava et al.[2001] analyze mutual fund performance and showed evidence that international mutual funds can beat the U.S. stock market. Cumby and Glen examine the performance of 15 U.S.-based internationally diversified mutual funds from 1982 to 1988. The findings show that mutual funds outperformed the U.S. Index. Enu et al.[1991] investigate 19 U.S.-based international mutual funds from 1977-1986. They approve that majority of international mutual funds outperformed the U.S. market.

However, Shukla and Singh [1997], Redman et al.[2000] and Bhargava et al.[2001], propose the other viewpoint. Shukla and Singh[1997] evaluate the performance of the U.S. based global equity mutual funds during 1988 to 1995. They studied a total 20 global and 76 domestic funds observations are included. They show that both global funds and U.S. domestic funds underperformed the S&P 500 Index. Redman[2000] show that the international portfolio underperformed the benchmark and the U.S. equity portfolio. Bhargava[2001] show the international equity managed funds and mutual funds underperformed the S&P500 Index. From their studies, we fund that their transaction has it problem that they cannot real-time to make correct decision due to the traditionally model. This paper is base on these fundamentally conclusions to focused in the international ETFs to try to find out the dynamical, real-time and optimize global asset allocation model.

2.2. Global asset allocation

The country-specific ETFs global asset allocation is an investment strategy that attempts to exploit short-term international market inefficiencies by establishing positions in an assortment of markets with a goal to profit from relative movements across those international markets. These decisions can usually be broken down briefly into two processes. First, select a list of countries that have growth potential or currently being undervalued. The process is called portfolio selection. Secondly, investigate these ETFs price movements of each selected countries, and execute correct trading strategies at appropriate timing.

This paper focuses on 24 iShare MSCI country funds. Like country open and closed-end index funds, country-specific iShares increase mean-variance efficiency. Because the ETFs can be buy or sell at any time during the trading day. Unlike country index funds, just trade at 16:00pm everyday.

2.3. Sharpe ratio

This paper starts by testing whether the returns of 24 iShares MSCI country-specific ETFs are normally distributed and better then the XCS model in the dynamic environment. Skewness and Kurtosis are statistics that very often are used to test for normality (Neil and Webb[1993], Amin and Kat[2003], and Cremers et al.[2004]). This Sharpe ratio measures are used to test the ETF's performance. Sharpe[1966] proposed the ratio that is mainly used to rank alternative portfolios, ex-post, that is based on their historic reward-to-variability ratio:

$$SR_i = \frac{R_i - R_f}{\sigma_i}$$

(1)

2.4. Risk free rate

In theory, the risk-free rate is the minimum return an investor expects for any investment unless the potential rate of return is greater than the risk-free rate. In practice, however, the risk-free rate does not exist since even the safest investments carry a very small amount of risk. The interest rate on a three-month U.S. Treasury bill is often used an the risk-free rate (Shukla and Singh [1997] and Allen and Tan[1999]). In this study the U.S. three month Treasury bill for risk-free rte is also used. The U.S. three-month Treasury bill historic is obtained from the Board of Governors of the Federal Reserve data System web database. Since we stand in U.S. investors' view the U.S. domestic Treasure bill can be used to measure the risk-free rate.

2.5. XCS

XCS is based on the Learning Classifier System (LCS)[10][11], which is a general and independent machine learning system. LCS is found by John H. Holland [2][5], it is an online step-by-step rule base because it includes both genetic algorithm and strength learning. LCS can be classified as an extended genetic algorithm or an algorithm of strength learning. In LCS, strength learning element is used to separate suitable or unsuitable rules, solve the rule conflict problem; genetic algorithm is used to find good and new rules, and eliminate the unsuitable rules. XCS retains the main frames of LCS, but also makes some changes. Firstly, XCS uses precision as the rate of fitness; secondly, it changes the rule discovery component from acting on the whole population to the population have same states and actions; thirdly, it uses Q-learning-like algorithm to substitute the Bucket brigade algorithm; lastly, it removes the message board.

3. System Architecture

This paper implements the system architecture as show in Fig. 1. This is based on the Wilson's XCS classifier system[1965]. XCS retains the main frames of LCS, but also makes some changes. Firstly, XCS uses precision as the rate of fitness in the transaction data encoding module; secondly, it changes the rule discovery component from acting on the whole population to the population have same states and actions; thirdly, it uses Q-learning-like algorithm to substitute the Bucket brigade algorithm in the knowledge extraction module; lastly, it reward the result to the knowledge integration module.

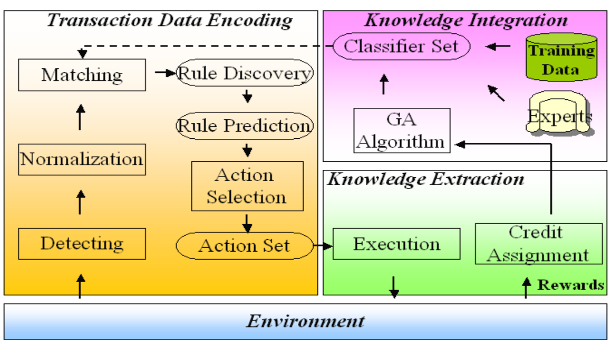

Figure 1. Architecture of XCS

3.1. Transaction data-encoding model

In the transaction data-encoding module, a group with same syntax forms a classifier population. That consists of:

3.1.1. Detecting condition section. That is composed of at least one condition. Each condition matches one state, when one state appears, the rules that have matched condition to compete executive rights.

$$C_1 \Lambda C_2 \Lambda .....\Lambda C_n , C_i \in \{0,1,-\}^L , 1 \le i \le n$$
(2)

3.1.2. Action section. Action section to represents the candidate classifiers action.

$$A \in \{a_1 ,.......a_m\}$$
(3)

3.1.3. Rule Prediction p. evaluates classifiers utility.

3.1.4. Prediction error. It is the difference between actual benefit and prediction p.

3.1.5. Fitness F, evaluates the precision of prediction p from prediction error.

3.2. Knowledge execution model

In this model, that consists of:

3.2.1. Execution section, XCS interacts with environment as: in discrete time t, system detects environment state S_t , use S_t compare with population [P]'s conditions, copy the matched classifiers to match set [M]. Compute the weighted averages of each action in the match set [M], to build up a system prediction PA(a). Use PA(a) and the mechanism to select a action a_i , select classifiers that have action a_i from match set [M], and put them in action set [A]. The system executes a_i , and receive a delay reward r_{t_1} in discrete time t+1. These circulate until the objective problem is solved.

3.2.2. Reinforcement section. In performance component, XCS uses reward r to update parameters of strength learning of classifier in action set [A]. The update of prediction value p :.

$$C.p \leftarrow C.p + (R - C.p) \times \lambda \tag{4}$$

$$R = r_{t-1} + (E \times \tau)$$
(5)

C: Classifier

λ :Learning rate (0< $\lambda \leqq 1$)

r_{t-1} :Reward of previous step

E: max system expected value

τ :discount factor

The update of predicted error value ε :

$$C.\varepsilon \leftarrow C.\varepsilon + (|R - C.p| - C.\varepsilon) \times \lambda \tag{6}$$

The equation of fitness F:

$$C.F \leftarrow C.F + (C.\mu' - C.F) \times \lambda$$
(7)

$$C.\mu' \leftarrow \frac{C.\mu}{\sum_{x \in [A]} C.\mu_x}$$
(8)

$$C.\mu \leftarrow \begin{cases} 1 & if\ C.\varepsilon < \varepsilon_0 \\ \alpha(\varepsilon_0 / C.\varepsilon)^{\beta}, otherwise \end{cases}$$
(9)

ε_0 : tolerance of predicted error value (ε_0 >0)

α , β : constant of precision control μ (0< α <1; β >0)

From fitness function F in equation (5), we know that the fitness of classifier in XCS evaluates precision of classifier in the same action set [A], and it has an invert function relationship with predicted error ε.

3.3. Knowledge integration model

This model is focused in the Genetic algorithm (GA). Genetic algorithm is used to eliminate unsuitable classifiers in action set [A], not the whole population. So, genetic algorithm starts when action set [A] have not execute genetic algorithm for an average time value. When genetic algorithm executes, select two classifiers randomly and crossover at a χ probability. Also, it will mutate at probability.

```
XCS Algorithm
Input RSq<- q rule sets(RS) from different knowldege sources
Output one integrated rule set
procedure XCS
  Initialize classifier set
  While (termination condition of XCS is false)
      Get environment state
      Normalied the state
      Decode the state
      Generate match set
      Generate prediction rule
      Selection action
      Generate action set
      do winner action
          Get rewards
          Update attribute-values of relevant classifiers
          trigger  Genetic Algorithm
                Selection
                Crossover
                Mutation
          end trigger
      end do
  end while
  Report the execution and learining performances
  Store the learned classifier set
end procedure
```

Figure 2. Algorithm of XCS

4. Experiment

4.1. Data

This paper research target consists on 24 iShares MSCI country-specific ETFs from the iShaes web database (http://www.ishares.com). The data include daily opening price, close price, maximum price , minimum price and trading volume over the period Jan 2003 to Dec 2007, resulting in 60 montly observations as Table 3, 4. As said before the reason for choosing iShares MSCI country-specific ETFs is to achieve international diversification.

Table 1 indicates the basic information of these ETFs which includes the region, symbol, name, and inception date. The inception date for most of the ETFs is 12 March 1996, and the lastes inception date, 15 Oct 2004, is for iShares MSCI-Xinhua China 25 (FXI). Thus , our sample period covers all ETFs historical data with no data missing. All of these ETFs belong to Barclays Global Investors Group, know as iShares. We use 24 iShares MSCI country funds as measured by the MSCI individual country index. These include eight iShares from Asian Pacific countries (Australia, Hong Kong, Japan, Malaysia, Singapore, South Korea, Japan, China), ten iShares from European countries (Austria, Belgium, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, and the UK), four iShares form North American countries (S&P500, Dow Jones, Canada and Mexico) and two iShares from the South American country (Brazil and South Africa).

ETFs Region	Extend-Traded Funds Name	Symbol	Inception Date
Asia Pacific	iShares MSCI Australia Index	EWA	1996/3/12
North-American	iShares MSCI Canada Index	EWC	1996/3/12
European	iShares MSCI Sweden Index	EWD	1996/3/12
European	iShares MSCI Germany Index	EWG	1996/3/12
Asia Pacific	iShares MSCI Hong Kong Index	EWH	1996/3/12
European	iShares MSCI Italy Index	EWI	1996/3/12
Asia Pacific	iShares MSCI Japan Index	EWJ	1996/3/12
European	iShares MSCI Belgium Index	EWK	1996/3/12
European	iShares MSCI Switzerland Index	EWL	1996/3/12
Asia Pacific	iShares MSCI Malaysia Index	EWM	1996/3/12
European	iShares MSCI Netherlands Index	EWN	1996/3/12
European	iShares MSCI Austria Index	EWO	1996/3/12
European	iShares MSCI Spain Index	EWP	1996/3/12
European	iShares MSCI France Index	EWQ	1996/3/12
Asia Pacific	iShares MSCI Singapore Index	EWS	1996/3/12
Asia Pacific	iShares MSCI Taiwan Index	EWT	2000/6/20
European	iShares MSCI United Kingdom Index	EWU	1996/3/12
North-American	iShares MSCI Mexico Index	EWW	1996/3/12
Asia Pacific	iShares MSCI South Korea Index	EWY	2000/5/9
South-American	iShares MSCI Brazil Index	EWZ	2000/7/10
South-American	iShares MSCI South Africa Index	EZA	2003/2/14
Asia Pacific	Xinhua China 25 Index Fund	FXI	2004/10/15
North-American	iShares S&P 500 Index	IVV	2000/5/26
North-American	iShares Dow Jones US Industrial	IYJ	2000/7/21

Table 1. Sample data list

Symbole	Date	Open	High	Low	Close	Volume
FXI	2004/10/12	53.6	53.85	53.38	53.7	248200
FXI	2004/10/13	53	53.31	52.2	52.32	369100
FXI	2004/10/14	51.96	52.1	51.45	51.62	119800
FXI	2004/10/15	52.05	52.64	52.03	52.4	234500
FXI	……..					

Table 2. iShare FTSE/Xinhua China 25 Index (FXI) from 2004/10/12 to 2007/12/24

Symbole	Date	Open	High	Low	Close	Volume
EWJ	2003/1/2	7	7.1	7	7.08	1529000
EWJ	2003/1/3	7.05	7.09	7	7.07	360400
EWJ	2003/1/6	7.15	7.23	7.08	7.2	2614900
EWJ	2003/1/7	7.02	7.05	6.96	6.97	890700
EWJ	…….					

Table 3. iShare MSCI Japan Index (EWJ) from 2003/1/2 to 2007/12/24

4.2. Data coded and portfolio optimizer

In the experiment, we coded the daily information by the condition part of a classifier consists of 6 comparisons as our input, which is connected by 2 logical operators that are shown in table 4. Each comparison uses one of the differences of different day's moving average and average volume as our input [Brock W]. In order to simply the experiment, the experiment uses 1 for positive and 0 for negative and decided 1 united to buy or sell. In other words, the system will adjust the weight in the global iShares. The daily rules discovery is shown in table 5, as-is is means t-1 day, to-be is means today t.

ETFs Region	Symbol	Date	Open	High	Low	Close	Volume	Coded
Asian Pacific	EWA	2006/3/2	19.91	19.95	19.75	19.91	204,400	-0010
Asian Pacific	EWH	2006/3/2	13.42	13.47	13.36	13.45	392,000	10111
Asian Pacific	EWJ	2006/3/2	13.75	13.75	13.61	13.72	18,600,300	01111
Asian Pacific	EWM	2006/3/2	7.36	7.4	7.33	7.38	497,600	10010
Asian Pacific	EWS	2006/3/2	8.65	8.66	8.59	8.62	467,900	10101
Asian Pacific	EWT	2006/3/2	13.01	13.04	12.9	13.03	2,354,700	11011
Asian Pacific	EWY	2006/3/2	47	47.08	46.57	46.86	762,500	01101
Asian Pacific	FXI	2006/3/2	73.34	73.37	72.8	73.31	379,600	00111
European	EWD	2006/3/2	24.05	24.34	23.98	24.34	49,000	11000
European	EWG	2006/3/2	22.12	22.23	22.01	22.23	603,000	10010
European	EWI	2006/3/2	27.24	27.26	27.04	27.26	66,600	10010
European	EWK	2006/3/2	20.65	20.84	20.62	20.84	90,800	10000
European	EWL	2006/3/2	20.58	20.68	20.4	20.67	71,500	10010
European	EWN	2006/3/2	21.8	21.86	21.61	21.86	86,900	10000
European	EWO	2006/3/2	29.8	30.16	29.62	30.16	158,600	---000
European	EWP	2006/3/2	40.3	40.43	40.02	40.43	28,000	11000
European	EWQ	2006/3/2	27.88	27.99	27.8	27.98	559,000	10010
European	EWU	2006/3/2	19.6	19.76	19.56	19.75	88,400	10100
North American	EWC	2006/3/2	23.72	23.9	23.61	23.88	488,500	10000
North American	EWW	2006/3/2	39.05	39.17	38.8	39.03	459,400	10--00
North American	IVV	2006/3/2	129.04	129.6	128.81	129.48	863,100	10100
North American	IYJ	2006/3/2	61	61.15	60.84	61.06	22,600	11011
South American	EWZ	2006/3/2	42.96	43.18	42.57	43.14	2,135,000	10000
South American	EZA	2006/3/2	19.91	19.95	19.75	19.91	204,400	11011

Table 4. Data coded

Extend-Traded Fund Name	Ticker	Date	Coded	As-is	To-Be
iShares Dow Jones US Industrial	IYJ	2006/3/2	11011	6%	5%
iShares Goldman Sachs Technology Indx	IGM	2006/3/2	10000	2%	1%
iShares MSCI Australia Index	EWA	2006/3/2	-0010	2%	2%
iShares MSCI Austria Index	EWO	2006/3/2	---000	2%	2%
iShares MSCI Belgium Index	EWK	2006/3/2	10000	2%	2%
iShares MSCI Brazil (Free) Index	EWZ	2006/3/2	10000	1%	2%
iShares MSCI Canada Index	EWC	2006/3/2	10000	2%	2%
iShares MSCI EAFE Index Fund	EFA	2006/3/2	10000	2%	2%
iShares MSCI EMU Index	EZU	2006/3/2	-0111	5%	6%
iShares MSCI France Index	EWQ	2006/3/2	10010	2%	2%
iShares MSCI Germany Index	EWG	2006/3/2	10010	2%	2%
iShares MSCI Hong Kong Index	EWH	2006/3/2	10111	8%	9%
iShares MSCI Italy Index	EWI	2006/3/2	10010	2%	1%
iShares MSCI Japan Index	EWJ	2006/3/2	01111	11%	12%
iShares MSCI Malaysia (Free) Index	EWM	2006/3/2	10010	3%	3%
iShares MSCI Mexico (Free) Index	EWW	2006/3/2	10--00	2%	2%
iShares MSCI Netherlands Index	EWN	2006/3/2	10000	1%	0%
iShares MSCI Singapore (Free) Index	EWS	2006/3/2	10101	2%	2%
iShares MSCI South Africa Index	EZA	2006/3/2	11011	13%	14%
iShares MSCI South Korea Index	EWY	2006/3/2	01101	4%	5%
iShares MSCI Spain Index	EWP	2006/3/2	11000	1%	0%
iShares MSCI Sweden Index	EWD	2006/3/2	11000	1%	0%
iShares MSCI Switzerland Index	EWL	2006/3/2	10010	1%	0%
iShares MSCI Taiwan Index	EWT	2006/3/2	11011	5%	6%
iShares MSCI United Kingdom Index	EWU	2006/3/2	10100	1%	1%
iShares Russell 1000 Index	IWB	2006/3/2	00--10	0%	0%
iShares S&P 500 Index	IVV	2006/3/2	10100	2%	2%
Xinhua China 25 Index Fund	FXI	2006/3/2	00111	9%	10%
NASDAQ 100 Trust Shares	QQQ	2006/3/2	11000	6%	5%

Table 5. Daily global asset allocation portfolio

4.3. Traditionally sharpe ratio

The traditionally portfolio model is used the sharpe ratio to evaluate the optimal asset allocation. Hence we used the monthly sharpe ratio global asset allocation to compare with the XCS model global asset allocation as table 6. This Sharpe ratio measures are used to test the ETF's performance. Sharpe[1966]

ETFs Region	Extend-Traded Funds Name	Symbol	Annual Return	Annual Std. Deviation	Sharpe Rtio
Asian Pacific	iShares MSCI Australia Index	EWA	14.72%	17.47%	63.8237%
Asian Pacific	iShares MSCI Hong Kong Index	EWH	2.15%	22.06%	9.7461%
Asian Pacific	iShares MSCI Japan Index	EWJ	11.26%	19.45%	57.8920%
Asian Pacific	iShares MSCI Malaysia Index	EWM	17.96%	19.65%	91.3995%
Asian Pacific	iShares MSCI Singapore Index	EWS	6.95%	22.49%	30.9026%
Asian Pacific	iShares MSCI Taiwan Index	EWT	10.66%	34.11%	31.2518%
Asian Pacific	iShares MSCI South Korea Index	EWY	31.55%	33.81%	93.3156%
Asian Pacific	iShares FTSE/Xinhua China 25 Index	FXI	56.00%	38.10%	146.9816%
European	iShares MSCI Sweden Index	EWD	10.73%	32.57%	32.9444%
European	iShares MSCI Germany Index	EWG	4.73%	33.69%	14.0398%
European	iShares MSCI Italy Index	EWI	6.89%	22.94%	30.0349%
European	iShares MSCI Belgium Index	EWK	9.12%	23.16%	39.3782%
European	iShares MSCI Switzerland Index	EWL	5.43%	17.71%	30.6606%
European	iShares MSCI Netherlands Index	EWN	2.15%	26.08%	8.2439%
European	iShares MSCI Austria Index	EWO	26.31%	19.91%	132.1447%
European	iShares MSCI Spain Index	EWP	14.21%	24.15%	58.8406%
European	iShares MSCI France Index	EWQ	3.70%	23.90%	15.4812%
European	iShares MSCI United Kingdom Index	EWU	0.74%	16.26%	4.5510%
North American	iShares MSCI Canada Index	EWC	10.61%	16.92%	62.7069%
North American	iShares MSCI Mexico Index	EWW	4.14%	24.62%	16.8156%
North American	iShares S&P 500 Index	IVV	-0.50%	17.90%	-2.7933%
North American	iShares Dow Jones US Industrial	IYJ	2.50%	18.25%	13.6986%
South American	iShares MSCI Brazil Index	EWZ	20.07%	49.14%	40.8425%
South American	iShares MSCI South Africa Index	EZA	27.10%	45.42%	59.6653%
	US T-Bill		3.57%		

Table 6. Traditionally sharpe ration asset allocation

4.4. International global asset allocation

In this paper, we implemented the XCS expert system to studied the global markets that include the US, China, Taiwan, Japan, South Africa, and Russia. In Figure 3, the iShares which track indexes of international capital markets, enforce global asset allocation strategies. The global allocation element of ETFs contributes to the global risk diversification and generates sufficient gains in a transparent and low cost manner that is not easily achievable by global index funds.

4.5. Experiment result

The results of the experiments are summarized in Figure 6. Figure 6 shows the profit accumulation result. The average of the cumulated profit is better than the traditional sharpe ratio, the highest profit is about 840888 units after 1300 days, which is about 6.5% benefit per day, it is a good performance when the index is falling in these 120 days. The correct rate is about 70% which is much better than the sharpe ratio asset allocation strategy.

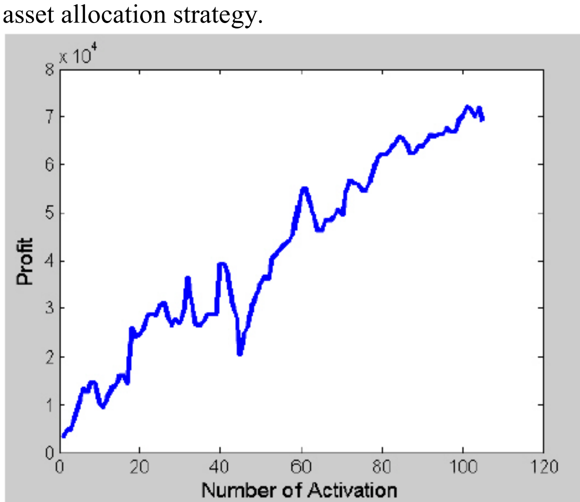

Figure 6. Accumulated portfolio

5. Conclusion

As we know, the country-specific ETFs offer the benefits of international portfolio diversification at a lower cost, with a lower tracking error and in a more tax-efficient way than passive open or closed-end county funds. This paper focused in the soft computing algorithm, XCS, to compare with the traditionally asset allocation model , sharpe ratio. The statistical shows that dynamic artificial intelligence model is better then the non-efficiently monthly sharpe ratio model.

Additionally, using a limited numbers of factors from the real international market, this paper have shown the good performance of country-specific ETFs extended classifier trading mechanism. The XCS experts system consists of Wilson's XCS technique, which provides a good online learning system for our model. In the fast changing security market, Genetic algorithm, rule base, neural network etc. do not satisfy our needs. XCS's online learning is suitable to use. S, XCS can give trader or investor a real-time advise to make right trading activities in the international markets.

In future work, although the experiment have good result, but it can still improve by changing the input factor. Especially, this work has not included the commodities ETF. In the high commodities, it should be included in the future. In addition, this study has no included the short ETF. Hence, the study has so much interesting direction to study. The next step would be to verify XCS in different product just like commodities ETFs, and Actively managed ETF.

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