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Strategy of global asset allocation using extended classifier system

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A R T I C L E   I N F O

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A B S T R A C T

There are several studies about extended classification system (XCS) in past years. XCS model can dynamically learn and adapt to the change of environments for maximizing the desired goals. This paper conducts simulation to apply XCS to global asset allocation in the country-specific exchanged traded funds (ETFs). Since international stock price trend is influenced by unknown and unpredictable surroundings, using XCS to model the fluctuations on global financial market allows for the discovery of the patterns of the future trends. As such, the benefits of international asset diversification can be achieved in a tax-efficient way with country-specific ETFs at a low transaction cost with minimized tracking error. These empirical results indicate that XCS is capable of evolving over time, and thus XCS can provide a good indicator for future global asset allocation decision-making aiming at maximized profit.

1. Introduction

Recently, exchanged 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 closely track the performance of corresponding indices. ETFs 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 listings with assets of USD $1212 billions and 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 affected by 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 (Miffre, 2007). In LCS bibliography, a wide range of resources has been covered (Karpoff & Jonathan, 1987; Kovacs, 2000); however, the applications of XCS on financial issues (Lanzi, Stolzmann, & Wilson, 2000; Leigh, Modani, Purvis, & Robert, 2002) are much fewer when compared with its LCS counterpart. 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, generalized under predefined conditions, can discover generally 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, (Amin & Kat, 2003; Andrea, 1995; Trippi & DeSieno, 1992). This paper continues this investigation by applying an adaptation of a recently developed XCS, Wilson's XCS, to a large multi-class benchmark data set available at the 24 iShares MSCI (Morgan Stanley Capital International) country funds. This paper is structured as follows: Section 1 to introduce the study's motivation and goals, Section 2 to examine the literature, Section 3 to briefly describe XCS in our model, Section 3 to describe the data set and the experimental procedure adopted, Section 5 to present the results, and Section 6 to conclude the result and future study direction.

2. Literature review

On basis of analysis of past studies, we divide the related studies into four parts, which include literature on ETFs, artificial

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intelligence and portfolio, technical analysis and technical indicators and classifier systems.

2.1. International ETFs

In the past, studies by Cumby and Glen (1990); Shukla and Singh (1997), Redman, Gullett, and Manakyan (2000) analyzed mutual fund performance and showed evidence that international mutual funds can outperform the US stock market. Cumby and Glen examined the performance of 15 US-based internationally diversified mutual funds from 1982 to 1988. The findings showed that mutual funds outperformed the US Index. Enu, Kolodny, and Resnick (1991) investigated 19 US-based international mutual funds from 1977 to 1986, and concluded that majority of international mutual funds outperformed the US stock market.

However, Shukla and Singh (1997), Redman et al. (2000), offered distinct conclusions. Shukla & Singh, 1997 evaluated the performance of the US-based global equity mutual funds during 1988–1995 including a total of 20 global and 76 domestic funds. They showed that both global funds and US domestic funds underperformed the S&P 500 Index. Redman also showed that the international portfolio underperformed the US equity portfolio. Bhargava (2001) suggested both the international equity managed funds and mutual funds underperformed the S&P500 Index. Despite the significance associated with their studies, they might have problem making real-time decisions while incorporating traditional models into their models. This paper is thus based on a dynamical and real-time model in order to optimize global asset allocation.

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 are currently 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-specific funds. Like country-specific open and closed-end index funds, country-specific iShares increase mean–variance efficiency. On the other hand, unlike country index funds, which could only be transacted at a cut-off time (such as 4 pm) everyday, the ETFs can be bought or sold at any time during the trading day, offering one or more flexibilities compared to their country-specific index fund counterparts.

2.3. Sharpe ratio

This paper starts by testing whether the returns of 24 iShares MSCI country-specific ETFs are normally distributed and better than the XCS model in the dynamic environment. Skewness and Kurtosis are statistics that very often are used to describe the height and the symmetric of distribution of data test for normality (Amin & Kat, 2003; Wachter & Warusawitharana, 2008). This Sharpe ratio measures are used to test the ETF's performance. Sharpe (1992) proposed the ratio that is mainly used to rank alternative portfolios based on their historic reward-to-variability ratio:

$$SR_i = \frac{R_i - R_f}{\sigma_i} \tag{1}$$

where R_i is the historic mean return on ETF-i over the interval considered, σ_i is the historic standard deviation of the return on ETF-i over the interval considered and R_f is the average risk-free rate over the interval considered.

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 US Treasury bill is often used as a risk-free rate (Allen & Karjalainen, 1999; Kashima, 2007; Shukla & Singh, 1997). In this study, we also use the US three-month Treasury bill as the risk-free rate. The US three-month Treasury bill historically is obtained from the Board of Governors of the Federal Reserve database. Since we try to view from US investors' standpoints, the US domestic Treasure bill can be used to measure the risk-free rate.

2.5. XCS

XCS is based on the Learning Classifier System (LCS) (Holland, 1992; Karpoff, 1987; Kovacs, 2000), which is a general and independent machine learning system. LCS, which was proposed by John H. Holland (Andrea, 1995; Butz & Wilson, 2000), 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 distinguish suitable or unsuitable rules and solve the rule conflict problem while 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 having the same states and actions. Thirdly, it uses Q-learning-like algorithm to substitute the Bucket brigade algorithm. And lastly, it removes the message board.

2.6. Knowledge integration

Knowledge integration can be considered as a multi-objective optimization problem (Sakai & Masuyama, 2008; Yuan & Zhuang, 1996). Due to the huge searching space, the optimization problem is often very difficult to be solved. A genetic algorithm is usually used to discover a desirable optimal set of rules. The application of a GA in search of the optimal rule set for machine learning is known as Genetic Based Machine Learning (GBML). A well-known GBML architecture is the so-called LCS developed by Andrea (1995); Holland (1986) and Holland, Holyoak, Nisbett, and Thagard (1986). More recent GBML architectures are the Extended Classifier System (XCS) developed by Butz and Wilson (2000), the Anticipatory Classifier System by Lanzi et al. (2000), and EpiCS by Butz and Wilson (2000).

3. System architecture

This paper implements the system architecture shown in Fig. 1. This is based on the Wilson's XCS classifier system (Butz & Wilson, 2000). 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 having the same states and actions. Thirdly, it uses Q-learning-like algorithm to substitute the Bucket brigade algorithm

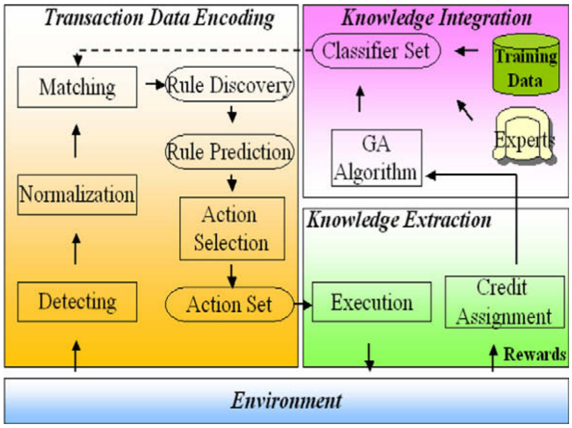

Fig. 1. Architecture of XCS.

in the knowledge extraction module. And lastly, it rewards the result to the knowledge integration module. In this section we tries to elaborate more on the contents of the various models of the architecture as implemented in XCS and illustrated in Fig. 1.

3.1. Transaction data-encoding model

Fig. 1 shows a transaction data-encoding module, a group of financial indices of the country whose stock index is tracked by that country's specific ETF, with same syntax form a classifier population. The group consists of:

1. Detecting condition section

$$C_1 \wedge C_2 \wedge \cdots \wedge C_n, \quad C_i \in \{0, 1, -\}^L, \ 1 \leqslant i \leqslant n \tag{2}$$

That is composed of at least one condition. The condition may include a state of positive (1), negative (0), or do not-care (–). And for the entry of the condition, the associated state must be satisfied. Eq. (2) stands for conditions 1–n are satisfied and in a predetermined sequence. The sequence could be condition 1 is followed by condition 2, which is followed by condition 3, until condition n takes place.

2. Action section

$$A \in \{a_1, \ldots, a_m\} \tag{3}$$

Action section to represent the candidate classifiers action.

3. Rule prediction p to evaluate classifiers utility.
4. Prediction error standing for the difference between actual benefit and prediction p.
5. Fitness F to evaluate the precision of prediction p from prediction error.

3.2. Knowledge extraction model

This model consists of:

- Execution section.
XCS interacts with environment at discrete time t in terms of environment states S_t, utilizes S_t to compare with population $[P]$'s conditions, and copies the matched classifiers to match set $[M]$. XCS further computes the weighted averages of each action in the match set $[M]$, so as to build up a system prediction $\mathrm{PA}(a)$. With $\mathrm{PA}(a)$, XCS further selects an action a_i, and classifiers that have action a_i from match set $[M]$, and puts them in action set $[A]$. The system then executes a_i, and receives a delay reward r_{t-1} in discrete time $t+1$. The same process continues until the objective problem is solved.

- Reinforcement section.
XCS uses reward r to update parameters of strength learning of classifier in action set $[A]$. The update of prediction value p may be as follows:

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

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

C is the classifier, λ is the learning rate ($0 < \lambda \leqq 1$), r_{t-1} is the reward of previous step, E is the max system expected value and τ is the discount factor.
The update of predicted error value ε:

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

The equation of fitness F:

$$C \cdot F \leftarrow C \cdot F + (C \cdot \mu' - C \cdot F) \times \lambda \tag{7}$$

$$C \cdot \mu' \leftarrow \frac{C \cdot \mu}{\sum_{x \in [A]} C \cdot \mu_x} \tag{8}$$

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

ε_0 is the tolerance of predicted error value ($\varepsilon_0 > 0$), α, β is the constant of precision control μ ($0 < \alpha < 1$; $\beta > 0$).
From fitness function F in Eq. (5), we know that the fitness of classifier in XCS evaluates precision of classifier in the same action set $[A]$, and has an invert function relationship with predicted error ε.

```
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 learning performances
  Store the learned classifier set
end procedure
```

Fig. 2. Algorithm of XCS.

3.3. Knowledge integration model

This XCS model focuses on the genetic algorithm (GA) in Fig. 2. Genetic algorithm is used to eliminate unsuitable classifiers in action set [A] rather than the whole population. In doing so, genetic algorithm starts when action set [A] have not been executed by genetic algorithm for an average time value. When genetic algorithm executes, two classifiers and crossover at a χ probability might be randomly selected. Also, it will mutate at probability.

Table 1
Sample data list.

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	2000/5fi
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 2
iShare FTSE/Xinhua China 25 Index (FXI) from 2004/10/12 to 2009/05/30.

Symbol	Date	Open	High	Low	Close	Volume
FXI	2004/10/12	53.6	53.85	53.38	53.7	248,200
FXI	2004/10/13	53	53.31	52.2	52.32	369,100
FXI	2004/10/14	51.96	52.1	51.45	51.62	119,800
FXI	2004/10/15	52.05	52.64	52.03	52.4	234,500
FXI	⋮	⋮	⋮	⋮	⋮	⋮

Table 3
iShare MSCI Japan Index (EWJ) from 2003/1/2 to 2009/5/30.

Symbol	Date	Open	High	Low	Close	Volume
EWJ	2003/1/2	7	7.1	7	7.08	1,529,000
EWJ	2003/1/3	7.05	7.09	7	7.07	360,400
EWJ	2003/1/6	7.15	7.23	7.08	7.2	2,614,900
EWJ	2003/1/7	7.02	7.05	6.96	6.97	890,700
EWJ	⋮	⋮	⋮	⋮	⋮	⋮

4. Experiment

4.1. Data

This paper targets 24 iShares MSCI country-specific ETFs from the iShares web database (http://www.ishares.com). The data include daily opening price, close price, maximum price, minimum price and trade volume over the period from Jan 2003 to June 2009, resulting in 76 monthly observations shown in Tables 2–4. As previously mentioned, the reason for choosing iShares MSCI country-specific ETFs is to achieve international diversification.

Table 1 indicates the basic information of these ETFs including the region, symbol, name, and inception date. The inception date for most of the ETFs is 12 March 1996, and the latest inception date, for iShares MSCI-Xinhua China 25 (FXI), falls on 15 October 2004. Thus, our sample period covers all ETFs historical data. All of these ETFs belong to Barclays Global Investors Group, known as iShares. We use 24 iShares MSCI country funds measured by the MSCI individual country index. These ETFs include eight iShares from Asia Pacific countries (Australia, Hong Kong, Japan, Malaysia, Singapore, South Korea, Japan, and China), 10 iShares from European countries (Austria, Belgium, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, and UK), four iShares

Table 4
Data coded.

EITs region	Symbol	Date	Open	High	Low	Close	Volume	Coded
Asia Pacific	EWA	2003/1/2	19.91	19.95	19.75	19.91	204,400	–0010
Asia Pacific	EWH	2006/3/2	13.42	13.47	13.36	13.45	392,000	10111
Asian Pac&	EWJ	2006/3/2	13.75	13.75	13.61	13.72	18,600,300	01111
Asia Pacific	EWM	2006/3/2	7.36	7.4	7.33	7.38	497,600	10010
Asia Pacific	EWS	2006/3/2	8.65	8.66	8.59	8.62	467,900	10101
Asia Pacific	EWT	2006/3/2	13.01	13.04	12.9	13.03	2,354,700	11011
Asia Pacific	EWY	2006/3/2	47	47.08	46.57	46.86	762,500	01101
Asia 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

form North American countries (S&P500, Dow Jones, Canada and Mexico) and two iShares from countries in Southern hemisphere (Brazil and South Africa).

4.2. Data coded and portfolio optimizer

In the experiment, we codify the daily information of the chosen countries' ETF into a five-code string. The daily information includes opening price ("open"), maximum price ("high"), minimum price ("low"), closing price ("close"), and trade volume ("volume"). The daily information for the chosen ETF on 3/2/2006 and its coded strings are shown in Table 4. It is worth noting that the coded string is configured to represent the differences in the daily information, and we further determine whether the differences fall into predetermined ranges or not before assigning the state code (0, 1, or –) to them. It is also worth noting that the ranges could be open-ended. The difference in daily information could be the differences of different day's averaged price moving and averaged trade volume (Brock, Lakonishok, & LeBaron, 1992). In order to simplify the experiment, the experiment uses 1 for positive and 0 for

Table 5
Daily global asset allocation portfolio.

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 Index	IGM	20O6/3/2	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 E AFE 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 Horn 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 6
Traditional Sharpe ratio asset allocation.

ETFs region	Extend-traded funds name	Symbol	Annual return (%)	Annual std. deviation (%)	Sharpe ratio (%)
Asia Pacific	iShares MSCI Australia Index	EWA	14.72	17.47	63.8237
Asia Pacific	iShares MSCI Hong Kong Index	EWH	2.15	22.06	9.7461
Asia Pacific	iShares MSCI Japan hides	EWJ	11.26	19.45	57.8920
Asia Pacific	iShares MSCI Malaysia Index	EWM	17.96	19.65	91.3995
Asia Pacific	iShares MSCI Singapore Index	EWS	6.95	22.49	30.9026
Asia Pacific	iShares MSCI Taiwan Index	EWT	10.66	34.11	31.2518
Asia Pacific	iShares MSCI South Korea Index	EWY	31.55	33.81	93.3156
Asia 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		

negative in terms of the difference in the daily information. And we further use 1 to associate with "buy" and 0 to associate with "sell." In other words, the system will adjust the weight in the global iShares. The daily rules discovery is shown in Table 5, the column of "as-is" is indicative of information at day $t-1$ while the column of "to-be" is reserved for day t (today).

4.3. Traditionally Sharpe ratio

The traditional portfolio model used the "Sharpe ratio" to evaluate the optimal asset allocation. Hence we compare the monthly Sharpe ratio global asset allocation with the XCS model global asset allocation in Table 6. This Sharpe ratio measures are used to test the ETF's performance (Sharpe, 1992)

4.4. International global asset allocation

In this paper, we implement the integration knowledge model with XCS expert system to study the global markets that include the US, China, Taiwan, Japan, South Africa, and Malaysia. In Fig. 3, the iShares track the indices of international capital markets before any global asset allocation strategies tracking those indices could be implemented for our international global asset allocations. 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 Fig. 4. Fig. 4 shows the profit accumulation result. The average of the cumulated profit is better than the traditional Sharpe ratio, and the highest profit is about 840,888 units after 1300 days, which is about 6.5% per day. Therefore, it is a good performance when the index ended up lower at the end of the 120-day period than the start thereof. Our XCS model is about 74.45% better than the asset allocation strategy on the basis of Sharpe ratio.

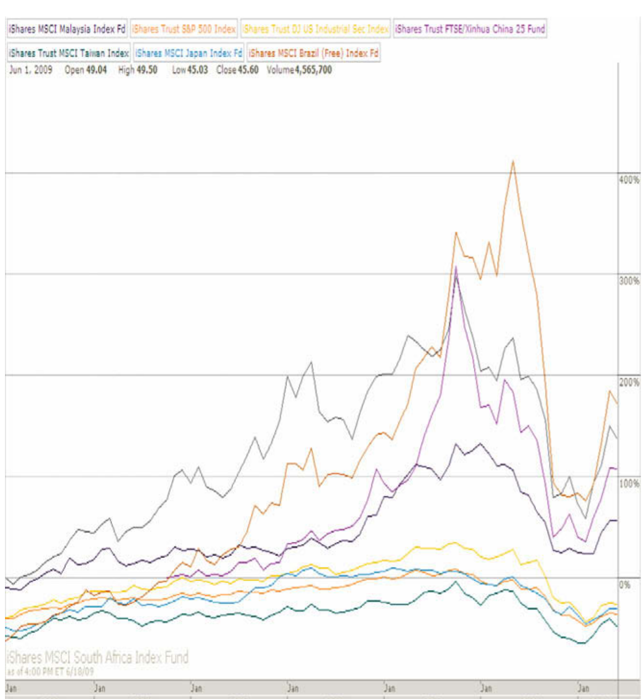

Fig. 3. International markets analysis from XCS exports system.

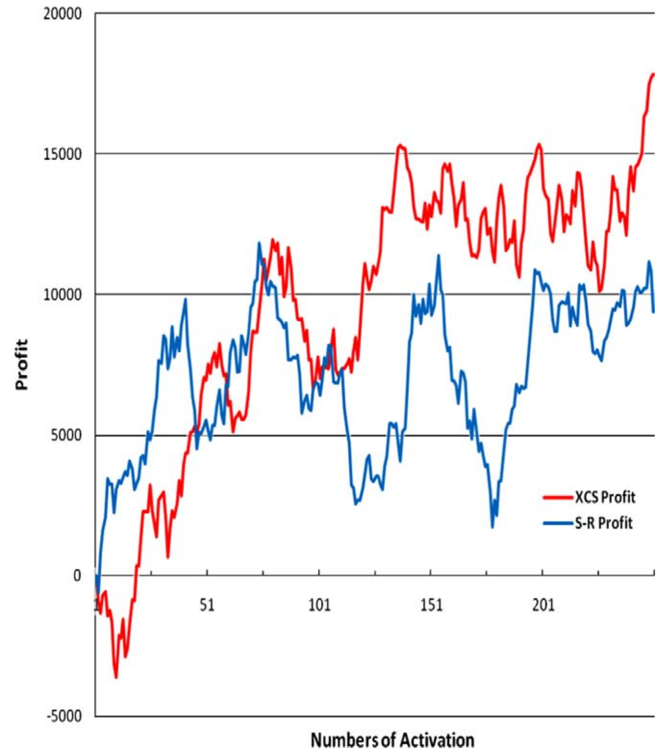

Fig. 4. Accumulated portfolio.

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 in a more tax-efficient way than passive open or closed-end county funds. This paper focuses on the soft computing algorithm, XCS, and compares with the traditional asset allocation model, according to Sharpe ratio. The statistical shows that dynamic artificial intelligence model is better than the non-efficiently monthly Sharpe ratio model. Additionally, using a limited numbers of factors from the real international market this paper has shown some promise using extended classifier trading mechanism in country-specific ETFs. 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. Rather, XCS's online learning is generally perceived as a more suitable option. XCS can give trader or investor a real-time advice to make relatively more accurate trading decisions in the international markets. In the future, although the experiment has shown good results, the model proposed by the current paper may still have some rooms to improve by having the inputted factors changed. Especially, this work does not include the commodities ETF. In addition, this study includes no short ETF either. Hence, the study could be further developed after having the above-mentioned inputted factors considered. The next step would be to verify XCS in different products such as commodities ETFs, and actively managed ETF.

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