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Constructing a dynamic stock portfolio decision-making assistance model: using the Taiwan 50 Index constituents as an example

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Abstract There are several decisions in investment management process. Security selection is the most time-consuming stage. Tatical allocation is in order to take advantage of market opportunities based on short-term prediction (Amenc and Le Sourd in Portfolio theory and performance analysis. Wiley, 2003). Although it is difficult to keep track of the fluctuations of volatile financial markets, the capacity of artificial intelligence to perform spatial search and obtain feasible solutions has led to its recent widespread adoption in the resolution of financial problems. Classifier systems possess a dynamic learning mechanism, they can be used to constantly explore environmental conditions, and immediately provide appropriate decisions via self-aware learning. This study consequently employs a classifier system in conjunction with real number encoding to investigate how to obtain optimal stock portfolio based on investor adjustment cycle. We examine the constituents of the TSEC Taiwan 50 Index taking moving average (MA), stochastic indicators (KD), moving average convergence divergence (MACD), relative strength index (RSI) and Williams %R (WMS %R) as input factors, adopting investor-determined adjustment cycle to allocate capital, and then constructing stock portfolio. We have conducted empirical testing using weekly and monthly adjustment cycle; the results revealed that this study's decision-making assistance model yields average annual interest rate of 49.35%, which is significantly better than the −6.59% of a random purchase model. This research indicates that a classifier system can effectively monitor market fluctuations and help investors obtain relatively optimal returns. The assistance model proposed in this study thus can provide really helpful decision-making information to investors.

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1 Introduction

Although the opening of Taiwan's financial markets in recent years has led to the gradual diversification of commodities, stocks remain the primary form of investment chosen by people in Taiwan. But due to the cooling world economy, terror attacks, and the domestic political or economic situation, it is difficult to obtain steady profits from the stock market. We therefore chose to make the construction of a dynamic stock portfolio decision-making assistance model the main direction of this study.

Investment management consists of strategic asset allocation, tatical asset allocation, and stock picking three phases (Amenc and Le Sourd 2003). Strategic asset allocation is long-term allocation strategy to assemble an asset level allocation after evaluating risk of each asset class and considering investor's preference. Tatical asset allocation is short-term allocation, regularly adjusts the portfolio in order to take advantage of market opportunities. Stock selection is the most time-consuming stage (Amenc and Le Sourd 2003), and has a greater impact on the return of portfolio (Hensel et al. 1991). In this research, investment portfolio is a single asset portfolio. Therefore, our study was focus on tatical allocation and stock selection of portfolio. Many types of security selection methods using artificial intelligence have been proposed (Butz and Wilson 2002; Venugopal 2004) in recent years, and the use of artificial intelligence for financial market trend analysis and forecasting has been increasing as artificial intelligence gradually comes into favor again. Nevertheless, such artificial intelligence techniques as neural networks, decision trees, Genetic algorithms, and genetic programming all use historical data for learning and training to produce fixed forecasting models. Historical data don't constitute a good representation of the forthcoming period (Amenc and Le Sourd 2003) and historical returns are not only unreliable indicators of future returns but also perverse indicators (Jahnke 1997). Therefore, this type of forecasting model cannot perform very well when the real environment is completely different from the past. For their part, classifier systems absorbed evolutionary computing and reinforcement learning mechanisms based on their dynamic environmental learning concept. These features enhance system accuracy and performance. Thus this study regards the financial market as a continuously changing environment, and consequently employs an XCS in conjunction with a real number encoding scheme to construct a dynamic stock portfolio decision-making assistance model (XCSR decision model). We dynamically construct a stock portfolio after forecasting the future return of each stock, and propose capital allocation strategies corresponding to user-designated adjustment cycle, thereby providing decision-making information to investors. We also perform empirical testing to verify the performance of the model for investor adjustment cycles of week and month, using the Sharpe ratio and annual interest rate as performance assessment criteria. Finally, the model's performance is compared with that of a random purchase stock portfolio model (RP model).

This paper consists of five sections: the first section is an introduction explaining the study's motivation and goals; the second section examines the literature; the third section explains the design of our model; the fourth section consists of empirical results and analysis; and the fifth section presents our conclusions.

2 Literature review

This section is divided into four parts which include literature on investment portfolio, artificial intelligence and portfolio, technical analysis and technical indicator, and classifier systems.

2.1 Investment portfolio

The concept behind investment portfolios is to combine several different investment targets to avoid concentrating too much risk on any one target with the aim of dispersing overall investment risk. Any combination of two or more securities or assets can be termed an investment portfolio. Over a half century, the Markowitz mean–variance model has become a universally understood technique within the investment field. However, this model is limited by the uncertainty of the inputs such as expected returns, standard deviations, and correlation matrix. Many asset managers build on the foundation of the Markowitz mean–variance model to construct an Efficient Frontier portfolio. Nevertheless, this approach assumes that the rate of return and variance of each investment target is known, and uses the rate of return and variance to assess overall portfolio performance and risk. Those assumptions are not consistent with the real environment (Michaud 2002, 2004; Pawley 2005) and as a result portfolios created using this method rarely yield significantly positive performance. Arshanapalli et al. (2001) evaluated two static and two dynamic allocation models. Their result revealed that the Markowitz optimization model is the worst-performing model and dynamic allocation model outperforms static allocation model. Jahnke (1997) pointed asset allocation should be viewed as a dynamic process. It should take into consideration both pension obligation and capital market opportunities, including risk, otherwise makes no economic sense. DynaPorte model (Oberuc 2003) sidesteps the required inputs of mean–variance model, using macroeconomic and market-related factors instead. Portfolio changing depends on the future expectation of performance. Therefore, DynaPorte model is a more useful approach which obtains time-varying portfolio by taking into account the influence of macroeconomic factors.

Investment management process has several important decision phases such as strategic asset allocation, tactical asset allocation and stock picking. Strategic asset allocation is long-term allocation strategy, also described as policy asset allocation. This phase is the least amount of time to devote (Amenc and Le Sourd 2003). This phase of allocation involves distributing the different asset class within the portfolio and determining their weights. The consulting community is often behind the idea of separating the asset allocation decision from the investment manager selection decision to the point that tactical asset allocation. Tatical asset allocation is regularly adjusting portfolio in order to take advantage of short-term opportunities. Market timing is the best known method. In tatical allocation phase, there are three steps, including forecasting return, constructing portfolio based on the forecast and performance testing (Amenc and Le Sourd 2003). Investors should increase their location in periods of high expected return, and vice versa. Arshanapalli et al. (2001) suggested that the ability to provide forecast information can add value in a dynamic asset allocation model. Manager generally devote most time to stock picking phase (Amenc and Le Sourd 2003). The portfolio optimization and selection is a complex task (Venugopal 2004) because there are a wide range and variety to choose from. Proportion management and timing of transaction are also major problems affecting portfolio return.

2.2 Artificial intelligence and investment portfolio

The use of information technology for investment portfolio has generally focused on the two aspects of investment target selection and optimal asset proportion management. For instance, Chan et al. (2002) proposed a fuzzy rule-base stock selection model with rate of return, current ratio, and yield rate as input factors. This model uses genetic algorithm to find each company's appraisal grade and employs a multi-period random capital allocation model; empirical results indicate that investment portfolios constructed using this method perform well in terms of predicted rate of return, variance, and utility value. Venugopal (2004) proposed a Genetic Algorithm Model for portfolio selection. This model considers both equity and debt securities and vice versa. The computerized dynamic portfolio has outperformed the sensex throughout the testing period. Kendall and Su (2005) used particle swarm optimization to find the best proportion of risk assets. This method, which was based on the mean–variance model and used the Sharpe ratio as its fitness function; although the performance was slightly different, the Kendall and Su method dramatically shortened solution time. Huang et al. (2002) proposed an optimal portfolio capital allocation model, input factor including RSI, BIAS, psychological line, volume ratio, which employed recurrent neural network to generate decision information and the result discovered about 90% related with the rules extracted by Full-RE algorithm.

2.3 Technical analysis and indicator

Technical analysis is a method of stock price trend analysis that uses statistics or other quantitative methods to convert data consisting chiefly of historical prices and trading volume to charts or indicators with different implications and forecast future stock price trend according to cyclic tendencies to achieve excess returns. After converting historical price and volume data to various indicators, technical analysis can forecast the direction of stock price fluctuations and trading times. Although many market factors can disrupt price trends, technical analysis can still improve the quality of investor decisions. Blume et al. (1994) incorporated trading volume to examine the relationship between price and volume. Their results verified that the signal transmitted by trading volume can reveal price fluctuation information, which implies that the use of trading volume as an auxiliary signal can significantly increase performance. Technical analysis is not a way to accurate the stock price, but it really help the success probability (Soros 1994). Such as CRISMA system (Pruit and White 1988) used cumulative volume, relative strength index, moving average to do buy and sell decision. With transaction cost or not, CRISMA outperformed the Buy & Hold strategy. Gencay and Stengos adopted price and volume moving averages, investigated Dow Jones index, explored that volume can improve predicting ability (Gencay and Stengos 1988). Mark used 9K, 9KD, 18ADX, 18MACD, and S&P500 etc. as neural network input factors, this model also can predict well (Mark et al. 1991). Our study reference those above mentioned input factors, using moving average (MA), stochastic indicators (KD), moving average convergence divergence (MACD), relative strength index (RSI) and Williams %R (WMS %R) as this research model input factors.

2.4 Classifier systems

In recent years, classifier system techniques have been used in many different fields, including data mining (Barry et al. 2004), electrical machinery control systems (Carse et al. 1996), and financial market analysis, and have demonstrated excellent performance in all of these areas. Classifier systems were introduced by Holland in the form of cognitive systems. The preliminary learning classifier system (LCS) framework was introduced in 1977 (Holland and Reitman 1977). Wilson proposed an extended classifier system (XCS) in 1995 (Wilson 1995) following continuous improvement by many researchers. Wilson's XCS model strives to achieve accuracy in forecasting returns, eliminates message list, adds prediction arrays and action sets in order to improve classifier system effectiveness, and uses Niche-genetic algorithms to implement evolution of rules. Beltrametti et al. (1997) used an LCS model to study the foreign exchange market, the empirical results of this research showed that classifier systems can classify external information and generate suitable predictions, while evolving appropriate trading rules in response to environmental changes. Furthermore, other scholars have used classifier systems to analyze the trading of individual stocks using price indicators as inputs and individual stock sell signals as outputs. For instance, Liao and Chen (2001) used price and volume indicators including closing prices, 6-day average prices, and the OBV indicator as input factors, while Schulenburg and Ross (2002) used average price and volume as input factors; both obtained experimental results significantly better than both Buy & Hold and random trading strategies.

3 Research framework and model design

This study's research framework is as shown in Fig. 1. Data on the constituent stocks of the TSEC Taiwan 50 Index were taken from a historical stock trading database; all constituent

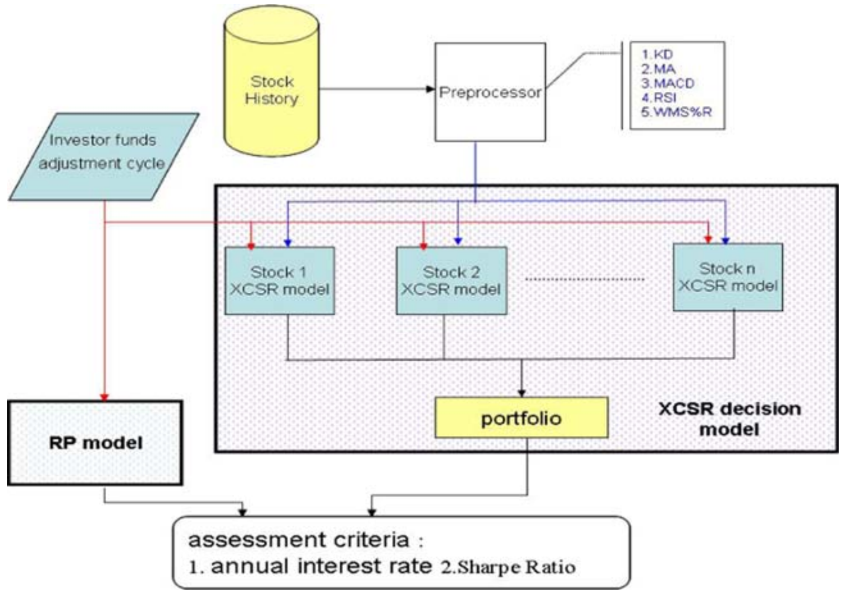

Fig. 1 Research framework

stock was subjected to pre-processing and then submitted to an XCSR sub-model. Each XCSR sub-model forecasts the future return of one stock in accordance with the investor adjustment cycle. All the investment targets forecast to yield good returns were then assembled as a portfolio which will be invested in the succeeding cycle, and capital were allocated according the management strategy so as to complete trading. This process continues until the end of the investing period. While the random purchase model's adjustment cycle and capital allocation method were the same as in the XCSR decision model, the portfolio was assembled randomly and did not reflect forecast price fluctuations.

3.1 Research target

This study's research target consisted of the constituent stocks of the Taiwan 50 Index as of 7 April, 2006. These stocks comprised roughly 70% of the aggregate market value of the Taiwan 50 Index at that time, and comprised an even higher 0.989 of the TSEC weighted stock index linked correlation index (http://www.tw50etf.com/tw50etf/tw50/Introduction/). The stocks chosen as the target of this study are consequently highly representative of the market.

3.2 Data pre-processing

The five technical indicators used in this study were moving average (MA), stochastic indicators (KD), moving average convergence divergence (MACD), relative strength index (RSI) and Williams %R (WMS %R). These technical indicators were used in calculations based on investor adjustment cycle. We converted raw opening price, closing price, maximum price, minimum price, and trading volume into the five technical indicators. Because the technical indicators have different numerical ranges, we used min–max normalization to normalize the five indicators in the range of (0,1).

We also used the proportional increase or decrease percentage in each the five indicators between one day and the before as a strength correlation input factor expressing the strength of correlation between market changes on different days.

The proportional increase or decrease is calculated using formula (1):

$$r_t = \frac{x_t - x_{t-1}}{x_{t-1}} \tag{1}$$

where x_t is technical indicator value on day t and
x_{t-1} technical indicator value on day $t-1$.

3.3 Capital allocation strategy

The portfolio model proposed in this study uses daily trading data as its input. This model is used to determine trends in the investment targets on the basis of daily market information, and the model's price fluctuation forecasts are used to dynamically construct portfolios. We therefore establish corresponding capital allocation strategy to meet the model's needs. Assuming that the investor's adjustment cycle is n days, then capital must be divided into n equal portions at the start of each cycle; one portion of capital is invested on each day (see Fig. 2), and capital are averagely invested in the recommended investment targets. All capitals are invested by n days. On the n+1th day, positions established on the first day are sold at the opening price, and the capital obtained in this way is evenly spread across the investment targets. Onthat day (day n+1) the model forecasts will yield a profit

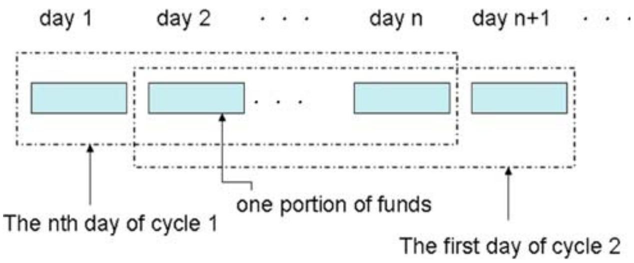

Fig. 2 Capital allocation strategy

after n days (day 2n+1). The new recommended investment targets are purchased at the opening prices, and all portfolio total values are calculated to the day's closing prices. This method is continued until the end of the investment period. Any cash remaining is used to purchase odd lots and after trading is used during the next trading.

3.4 XCSR decision model

Apart from methodological parameters, the use of a classifier system also requires the setting of genetic algorithm parameters when classifier rules evolve. This study sets parameters using the optimal values recommended by Wilson (1995). The following is an explanation of classifier structure, the real number encoding method, reward allocation, and the classifier selection mechanism.

3.4.1 Design of classifier structure

The structure of a classifier can be divided into condition and action parts. The condition part includes the five technical indicators MA, KD, MACD, RSI, and WMS %R, and the proportional increase or decrease percentage in the five indicators relative to the previous day. These ten data items are used to describe the state of the environment. The action part contains the forecast rise: 1, fall: 0 reflecting price fluctuations n days (the adjustment cycle) in the future. The structure of classifier is as shown in Fig. 3.

3.4.2 Real number encoding method

A classifier system with binary encoding uses a string composed of 0,1,# to express the state of the real world environment. Sometimes a binary variable is taken to represent a pre-thresholded continuous one, but then the thresholding has not been done adequately (Wilson 2000). Thus this study uses a real number encoding method in order to accurately describe the environment states. Center-spread representation (Wilson 2000) is employed to encode input real numbers. It's an interval description method expressing each value c in the classifier's condition, as shown in formula (2):

$$c_i = (l_i, u_i) \tag{2}$$

Here l_i is lower bound, u_i upper bound, and i length of the classifier's condition.

When an input state x possesses the following characteristics, a match occurs between the state and a certain classifier:

$$l_i \leq x_i \leq u_i, \forall x_i \subset x$$

l_i and u_i are calculated as shown in formula (3):

$$\begin{aligned} l_i &= \min[l_{\min}, x_i - rand(0,1)] \\ u_i &= \max[u_{\max}, x_i + rand(0,1)] \end{aligned} \tag{3}$$

Here $l_{\min}$ is value's lower bound, $u_{\max}$ value's upper bound, and *rand*(a,b) generates a random number between a and b.

3.4.3 The GA mechanism

The genetic algorithm acts on the match set of classifier system. This study sets genetic parameters to the optimal values recommended by Wilson (1995). In addition this study employs (Loiacono 2004) Crossover algorithm (see Fig. 4) for the evolution of l_i and u_i and Loiacono's mutate algorithm (see Fig. 5) been used in the calculation of l_i and u_i to ensure that the results do not fall below the lower and upper bounds.

3.4.4 Classifier selection mechanism

XCSR sub-model uses both explore and exploit models for rule selection mechanisms. The explore model uses a randomly-selected prediction array ([PA]) and can be used to select a suboptimal classifier or identify an incorrect classifier. The exploit model selects the classifier in the prediction array with the highest value of fitness in order to obtain

Fig. 3 Classifier structure

condotion										action
KD	MA	MACD	RSI	WMS%R	Increase/decrease percentage					rise/fall forecast
					KD	MA	MACD	RSI	WMS%R	

Fig. 4 Loiacono's crossover algorithm

```
procedure CROSSOVER(cl_i, cl_j)

n ?  number of interval predicates in cl_i;
cp ?  [Random(0,1) * n];                                  ⊕ Chooses a crossover point

if ( Random(0,1) < 0.5 ) then
      swap cl_i.u_cp and cl_j.u_cp;
                    ⊕ fine grained crossover check the interval is well defined or correct it
else
      swap cl_i.int_cp and cl_j.int_cp;                    ⊕Coarse grained crossover
end if

for i = cp + 1 to n do
      switch cl_i.int_i and cl_j.int_i;
end for

end procedure
```

Fig. 5 Loiacono's mutate algorithm

```
procedure MUTATE( cl, s, μ )
  for i=1 to s.length do
      if [ Random(1,0) <  μ ] then                ⊕ Mutates with probability μ
            lower ?  max { cl.l ± Random(0, μ), minimum possible input};
            lower ?  min { lower, cl.u };
            upper ?  min { cl.u ± Random(0, μ), maximum possible input};
            upper ?  max { upper, cl.l };
            cl.li ?  lower;
            cl.ui ?  upper;
      end if
  end for

  if(Random[1,0] <  μ) then
      cl.a ?  a random action;
  end if
  end procedure
```

the greatest return. Explore and exploit are used alternately during the training period to prevent the fitness of a specific classifier from being excessively high and preventing other classifiers from being selected and implemented, which would affect overall system accuracy (Butz and Wilson 2002). Exploit was used as the selection mechanism during the testing period.

3.4.5 Reward allocation

Classifier systems are rule-based systems. Each classifier has its fitness strength that shows its usefulness in the current system. After a classifier has been chosen, it receives a reward in case of successful prediction; otherwise, it pays compensation for incorrect prediction. In this research, the reward allocation based on prediction accuracy (Wilson 1995) is shown as Table 1. As a result of manipulation, each classifier has its fitness value varies as prediction accuracy reward is accumulated.

Table 1 Reward allocation

XCSR forecast	Market condition	Reward
Rise	Rise and > transaction cost	+ Reward
Rise	Rise but <= transaction cost	No reward
Rise	Fall	− Reward
Fall	Fall	+ Reward
Fall	Rise	− Reward

4 Empirical result

The empirical part of this study used TSEC data. The trading date, opening price, closing price, maximum price, minimum price, trading volume, and trading value of each of the constituent stocks were extracted from daily trading data.

The testing process used 30 June, 2003 as a dividing date, and performed model training using all daily data from the date each constituent stock was listed to 30 June, 2003. The rule sets established during the training period are used during the testing period as initial rules sets. Testing was performed using daily data from July 2003 to April 2006. A total of 704 data sets were used. The initial investment was NT$10 million. There wasn't short selling of the investment targets, and subscription, redemption, conversion, or dividend activity during the investment period. The cost of each trade was taken into consideration. Service fees were 1.425 thousandths and securities trading tax was 3 thousandths.

Because the capital obtained from each trading session were used for continued trading, the resulting interest rate was expressed as the annual compound interest rate r, which was calculated as shown in formula (4):

$$E = B \times (1 + r)^n \Rightarrow r = \sqrt[n]{\frac{E}{B}} - 1 \tag{4}$$

E is final total value,
B initial amount invested,

Table 2 Comparison of testing results

Adjustment cycle	Model			
	XCSR decision model		RP model	
	Annual interest rate (%)	Annual Sharpe ratio (%)	Annual interest rate (%)	Annual Sharpe ratio (%)
Week	42.16	187.42	−14.13	−83.02
Month	56.54	271.23	0.95	−6.10
Average	49.35	229.33	−6.59	−44.56

r interest rate obtained,
n number of periods, expressed in years.

The Sharpe ratio was used to calculate profitability per unit risk; the risk-free interest rate was set as the post office 2-year CD annual rate of 2.13%.

The random purchase portfolio employed the same capital allocation strategy as the XCSR decision model. The average of ten simulated trades was taken and compared with the XCSR decision model; testing results (Table 2) indicate that the XCSR decision-making assistance model yields much better performance than the random purchase model.

5 Conclusion and future work

In today complex investing arena, many factors influence the stock market, and it is hard for individual and institutional investors to stay abreast of rapid changes in the environment. Classifier system is an on-line learning system and reinforcement from environment based on an evolving set of classifiers (Wilson 2000). Useful classifiers gain strong fitness are selected and propagated over others less useful, thus the system performance increase gradually. Therefore an XCSR model, which is an XCS model together with real number encoding was employed in this study. The input factors consisted of MA, KD, MACD, RSI, and WMS %R and a decision-making assistance model for stock portfolios was constructed on the basis of a user-selected adjustment cycle. The capital allocation strategies this model proposed based on adjustment cycle that could be used to complete trading. Empirical testing was performed by assuming weekly and monthly adjustment cycles and comparing the results of the model with a random purchase model using an identical capital allocation strategy. Testing results showed that the classifier system successfully used its dynamic learning mechanism to keep track of market trends. Regardless of whether the user selects a weekly or monthly adjustment cycle, the dynamic stock portfolio decision-making assistance model will yield an annual interest rate and Sharpe ratio better than those of a random purchase model. This study's decision-making assistance model can consequently be used by stock investors or securities fund managers to guide their decisions.

Risk management is another important issue in portfolio management. Future research should consider incorporating estimated risk values and assess possible portfolio risk. Researchers may further investigate the input factors and select appropriate indicators for different investment periods and adjustment cycles so as to increase profitability. As for trading strategies, stop-loss and stop-profit mechanisms can be used to avoid unnecessary trading costs and bring the model closer to real trading practices. Finally, portfolio insurance policy can be used to construct decision-making assistance models for portfolios with different risk grades.

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