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Learning Classifier System for Pattern Evolution of Piecewise Linear Goal-Directed CPPI Trading Strategy

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Abstract: Traders in security market generally create and adapt a trading strategy pool first and choose one to execute according to market states reciprocally. In trading strategy layer, traditional Constant Proportion Portfolio Insurance (CPPI) strategy only considers protecting floor wealth. This study considers a goal-directed strategy to protect goal wealth in advance. Combining the CPPI strategy and the goal-directed strategy, this research adopts a piecewise linear goal-directed CPPI (GDCPPI) strategy to trade securities. In technology layer, this research applies the Learning Classifier System (LCS) to form and adapt the trading strategy pool and choose a suitable trading strategy against the consecutively changed market states. With the help of learning classifier system, this study can deal with the dynamic pattern evolution of the piecewise linear goal-directed CPPI strategy. This study executes many experiments under Brownian motion, GA and LCS technologies to generate the piecewise linear goal-directed CPPI strategies. Experimental results show that the LCS technology outperforms GA technology and GA technology outperforms Brownian motion technology further in generating piecewise linear goal-directed CPPI strategies.

Key words: Learning classifier system, pattern evolution, portfolio insurance, goal-directed strategy, piecewise linear GDCPPI strategy

INTRODUCTION

Security market consists of many traders and securities, where traders transact securities each other in every trading day. According to the demand and supply principle, each security price will be changed after each transaction. When transactions are going on, the price dynamic of each security forms a time series. From technical analysis perspective in security market, traders believe that this price dynamic time series will contain some patterns which can predict the direction of future price dynamics. Therefore, many trading-data-based patterns were proposed, such as head-and-shoulders, cross-moving-average and so on. To formulate, recognize and even evolve the price dynamic patterns are the basic activities for technical traders. Based on pattern recognition, traders can make suitable trading strategies and select one to trade securities for obtaining investment benefit. These pattern activities can form the task of pattern management. However, this is not an easy job.

The difficulties come from many aspects on pattern management. For example, the decision of scale size of a pattern is a hard problem on pattern recognition, i.e., which time range should be taken when comparing the current environment state and the stored patterns. Another difficulty is the problem of deciding the similarity between the current environment state and the stored patterns. In addition, suitable tools or programs to implement the activities of pattern management will affect the success hugely. Moreover, the prediction of any chose pattern still contains prediction risks. This implies that generated trading strategies should have the capability to reduce these risks. Therefore, the purposes of this study are trying to build a good tool to implement activities of pattern management and to adopt a good trading strategy on security markets.

In order to reduce the trading risks, portfolio-insurance-based strategies are likely adopted by investors. Portfolio insurance is a way of investment with the constraint that the wealth can never fall below a pre-assigned protecting wealth floor. The optimal trading strategy for a constant floor turns out to be the popular Constant Proportion Portfolio Insurance (CPPI) strategy (Black and Perold, 1992; Perold and Sharpe, 1988) and can be expressed as:

$$x_t = m_1(W_t - F)$$

where:

x_t = The amount invested in the risky asset at time t.
W_t = The wealth at time t.
m_1 = A constant risk multiplier.
F = The floor.

This optimal strategy states that one should invest more in the risky asset when the wealth increases. In practice, a mutual fund manager generally sets up a performance objective in terms of wealth or return at the beginning of an investment period. If a fund manager follows the CPPI strategy, he will have a greater chance of failing his almost reached goal when current wealth is closed to the goal. The major reason is that CPPI strategy only considers the floor but does not take the goal state into account, while fund managers do have the goal state in mind during the investment process.

Evidences show that an investor will change his risk-attitude under different wealth levels. CPPI strategy demonstrates this phenomenon. In addition, some studies showed that fund managers change their risk-attitudes based on their performance compared to the benchmark. However, there are contradictory observations among these studies. Some studies observed that fund managers take risk-seeking behavior when their performance is worse than the benchmark while some other studies observed that fund managers take risk-averse behavior when their performance is worse than the benchmark.

These contradictions in fact can be explained by portfolio insurance perspective and goal-directed perspective, respectively. Goal-directed perspective proposes that an investor in financial markets will consider certain investment goal. A goal-directed investor will take risk-seeking behavior when the distance from current wealth to the goal is large and will take risk-averse behavior when the distance from current wealth to the goal is small. Obviously, a CPPI investor's risk-attitude changing direction is opposed to the risk-attitude of a goal-directed investor.

The author of this study, therefore, constructed a Goal-Directed (GD) strategy (Chen and Liao, 2006) $x_t = m_2(G - W_t)$ under constraint $W_t \le G$, where, G is the goal and m_2 is a constant. The concept of GD strategy can also be supported by Browne (1997). In addition, the author of this article combined the portfolio insurance constraint and goal-directed constraint as $F \le W_t \le G$ to construct a piecewise linear goal-directed CPPI (GDCPPI) strategy (Chen and Liao, 2006), $x_t = m_1(W_t - F)$, $F \le W_t < M$ and $x_t = m_2(G - W_t)$, $M \le W_t \le G$. The $M = (m_1F + m_2G)/(m_1+m_2)$, is a wealth position at the intersection of GD and CPPI strategies. This M position guides investors to apply CPPI strategy or GD strategy depending on whether the current wealth is less or greater than M, respectively. In addition, if $m_1 \to \infty$, the piecewise linear GDCPPI strategy reduces to the GD strategy and if $m_2 \to \infty$, the piecewise linear GDCPPI strategy becomes the CPPI strategy. That is, the piecewise linear GDCPPI strategy is a generalization of both CPPI and GD strategies.

Since, the essential structure of Learning Classifier System (LCS) technology (Holland and Reitman, 1978) can contain multiple patterns in each classifier, this study applies this technique to implement the activities of pattern management. This study applies the LCS technique to generate piecewise linear GDCPPI strategies. In order to show, the superiority of LCS technique, this study compares the competence of three techniques, which are Brownian motion technique, GA technique and LCS technique. Experimental results show that LCS technique outperforms GA technique and further GA technique outperform Brownian motion technique in generating piecewise linear GDCPPI strategies.

MATERIALS AND METHODS

Investment strategy: Investment strategies show the investment ways, which basically are selection, timing and allocation strategies. The investment strategies can also be called as trading strategies. Investment strategies can be classified by portfolio insurance perspective and non-portfolio insurance perspective. Typically, investors will face a trade-of between returns and risk. When the risk is not easy to control or predict, to protect investor's wealth becomes very important, which introduces the Portfolio Insurance (PI) strategies in 1980s, such as the CPPI strategy.

CPPI strategy: Assume there are two assets: a risk-free asset such as a T-bill and a risky asset such as a stock. Let the stock price dynamic be:

$$dP_t/P_t = \mu dt + \sigma dZ_t$$

where:

- μ = The mean of return rates.
- σ = The standard deviation of return rates.
- dZ_t = A Brownian motion at time t.

The portfolio wealth dynamic then is:

$$dW_t = rW_t dt + x_t(\mu dt + \sigma dZ_t)$$

where:

- r = The risky-free rate of return.
- x_t = The dollar amount invested in the risky asset.

Suppose an investor tries to maximize the growth rate of expected utility of the final wealth under the portfolio insurance constraint. The problem becomes (Grossman and Zhou, 1993).

$$\sup_{x} \lim_{T\to\infty} \frac{1}{\gamma T} \ln E[\gamma U(W_T)] \quad \text{s.t.} W_t \ge F, \forall t \le T, \tag{1}$$

where x denotes the set of admissible trading strategies, $0 \leq \gamma \leq 1$ and F>0 is the floor. If F is fixed, the optimal strategy to the above optimization problem is:

$$x_t = \frac{\mu}{\sigma^2(1-\gamma)}(W_t - F) \tag{2}$$

Equation 2 can be simplified as:

$$\varsigma_t \equiv x_t = m_1(W_t - F), W_t \geq F, \tag{3}$$

where:

$$m_1 = \frac{\mu}{\sigma^2(1-\gamma)}$$

can be regarded as the investor's risk multiplier, F is the protecting floor. This ζ_t is the popular CPPI strategy. The CPPI strategy directs investors to put more capital into risky assets when current wealth is larger than floor and put less capital into risky assets when current wealth is closer to the floor.

Risk attitudes: Evidences show that an investor will change his risk-attitude under different wealth levels. In particular, studies showed that fund managers change their risk-attitudes based on their performance compared to the benchmark. However, there are contradictory observations among these studies. Some studies (Busse, 2001; Chevalier and Ellison, 1997; Tayler, 2003) observed that fund managers take risk-averse behavior when their performance is worse than the benchmark (low wealth risk aversion), while some other studies (Brown *et al*., 1996; Jackwerth, 2000) observed that fund managers take risk-seeking behavior when their performance is worse than the benchmark (high wealth risk aversion). These two types of risk-attitude are described as follows.

Low wealth risk aversion: An investor will become risk-averse when his current wealth is low and will become risk-seeking when his current wealth is high.

High wealth risk aversion: An investor will become risk-averse when his current wealth is high and will become risk-seeking when his current wealth is low.

The goal-less CPPI strategies demonstrate the low wealth risk aversion phenomenon. Goal-directed perspective proposes that an investor in financial markets will consider certain investment goal. A goal-directed investor will take risk-seeking behavior when the distance from current wealth to the goal (goal distance) is large and will take risk-averse behavior when the goal distance is small. Although, low wealth risk aversion can be explained by the CPPI strategy, high wealth risk aversion can not be explained by the CPPI strategy. We argue that these contradictions can be explained from two perspectives: the portfolio insurance perspective and the goal-directed (or goal-seeking) perspective. That is, low wealth risk aversion can be explained by portfolio insurance perspective. High wealth risk aversion can be explained by goal-directed perspective and will be exploited as follows.

Goal-directed strategy: In study Browne (1997), one of the investment problems is to maximize the survival probability in danger zone or to maximize the probability of reaching the goal before reaching the bankruptcy point. The model can be described as following.

$$\max_{X} P(\tau_a > \tau_b), \text{s.t.} a < W_t < b < S, \tag{4}$$

where:

x = The set of admissible strategies.
$P(\bullet)$ = The probability function.
a = The bankruptcy point,
τ_a = The escape time when $W_t = a$.
τ_b = The escape time when $W_t = b$.
s = The safe point and is generally set up to be c/r.

With c being the minimal consumption and r being the risk-free rate of return. This model tries to find an optimal trading strategy which minimizes the probability of reaching the bankruptcy point a before reaching the goal b. The optimal strategy turns out to be:

$$x_t = \frac{2r}{\mu - r}(S - W_t) \tag{5}$$

where, μ is the mean of return rates for the risky asset. If $b \rightarrow s$ in fact can be regarded as the goal G that an investor wants to achieve. Then the author of this article defined a Goal-Directed (GD) strategy (Chen and Liao, 2006) as:

$$\eta_t \equiv x_t = m_2(G - W_t), W_t \leq G, \tag{6}$$

where:

$$m_2 = \frac{2r}{\mu - r}$$

is a constant.

The GD strategy shows that an investor should take a riskier action when goal distance (i.e., the distance from current wealth to the goal) is large and should take less risky activity when goal distance is small. This behavior

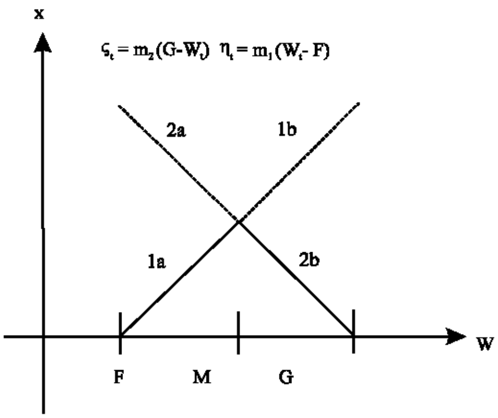

Fig. 1: The piecewise linear GDCPPI strategy (Chen and Liao, 2006)

is consistent with the high wealth risk aversion. In other words, the high wealth risk aversion can be explained by this GD strategy.

Piecewise linear goal-directed CPPI strategy: As we have noted that investors seem to have two different types of wealth risk aversion: the low wealth risk aversion and the high wealth risk aversion. Intuitively, investors will take different strategy when they posit different risk attitude. That is, if their risk attitude is low wealth risk aversion, they will adopt CPPI strategy. If their risk attitude is high wealth risk aversion, they will adopt GD strategy.

Recall that the constraint of CPPI strategy, $W_t \geq F$, is different from the constraint of GD strategy, $W_t \leq G$. In addition, the objective of CPPI, maximizing the growth rate of certain utility, is different from the objective of GD strategy, maximizing the possibility of reaching the goal first. Combining the 2 constraints $F \leq W_t$ and $W_t \leq G$, a new problem with constraint $F \leq W_t \leq G$ is derived. This new problem can be regarded as containing two objectives, which are composed from the objectives of CPPI and GD strategies. The CPPI and GD strategies are depicted in Fig. 1.

We can see that CPPI strategy only considers the floor and GD strategy only considers the goal. In addition, there is a wealth position M projected from the intersection of these 2 strategies and the value of M can be calculated by:

$$M = \frac{m_1 F + m_2 G}{m_1 + m_2} \tag{7}$$

M seems to be a natural dividing point for changing strategies. Since, CPPI considers only the floor F but not the goal G, an investor can apply CPPI strategy when $W_t < M$. On the other hand, since GD considers only the goal G but not the floor F, an investor can apply GD strategy when $W_t \geq M$. Then the author of this article built a piecewise linear GDCPPI strategy (Chen and Liao, 2006) as:

$$\theta_t \equiv x_t \begin{cases} 0, W_t < F \\ m_1(W_t - F), F \leq W_t < M \\ m_2(G - W_t), M \leq W_t \leq G. \end{cases} \tag{8}$$

It can be seen that the piecewise linear GDCPPI strategy θ_t combines portfolio insurance perspective and goal-directed perspective, as the segments 1a and 2b in Fig. 1. Note that θ_t is a generalization of both CPPI and GD strategies. In particular, if $m_1 \to \infty$, $M = (m_1F + m_2G)/(m_1 + m_2) = F$ and the constraint $M \leq W_t \leq G$ for GD segment will be $F \leq W_t \leq G$. Therefore, piecewise linear GDCPPI strategy reduces to GD strategy. If $m_2 \to \infty$, $M = (m_1F + m_2G)/(m_1 + m_2) = G$ and the constraint $F \leq W_t < M$ for CPPI segment will be $F \leq W_t < G$. Therefore, piecewise linear GDCPPI strategy reduces to CPPI strategy.

Traditional CPPI strategy is based on the assumption of Brownian motion for stock prices. Browne's study (Browne, 1997) for goal seeking objective also made this assumption. When investors try to apply these above strategies, the parameter values are generally obtained by the long-term expectation method. That is, the mean and variance of return rates are the long-term expectations from historical data.

However, the historical data might not follow the Brownian motion (Lo and MacKinlay, 1999). Better m_1 and m_2 parameter values in piecewise linear GDCPPI strategy might be directly obtained using other data driven optimization methods with historical data. Genetic algorithm is the method chosen to search better m_1 and m_2 parameters values in this study due to its success in many applications. In addition, technology of learning classifier system will also be adopted to implement the GDCPPI strategy for the reason of it can fit well for investor's investment process: build a strategy pool first and then choice, execute and adapt suitable strategies.

Investment process: On the essential feature of complicated investment environment, there are many different investment strategies can be applied by investors. However, it seems not to have a universal strategy that can always be a victor under all dynamic environment states. In a logical manner, each strategy has its own features including advantages, drawbacks and suitable application circumstances. This means that, investors should first hold a pool of strategies and choose a suitable strategy after prediction from the pool against different environment states. The strategy

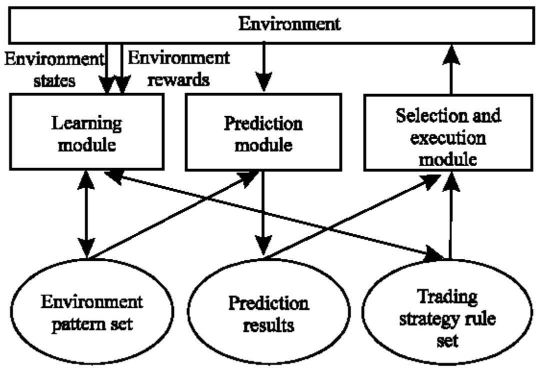

Fig. 2: A Framework of security trading model

building activity in general includes the learning process. Fig. 2 shows a framework of security trading model (Liao and Chen, 2001).

Where, a learning module formulates the environment patterns and the trading strategy rule set, a prediction module applies the learned environment patterns to predict the future trend and a selection and execution module selects and executes the fittest trading rule according to the prediction results.

Pattern management: Pattern is a recurrent structure, where the structure consists of static relationships among elements and dynamic behavior with some processes or procedures. Problem solving by managing patterns includes: pattern formulation/modeling/recognition, i.e., extract the recurrent components first and build the relationships among them, pattern execution, pattern variation/adaptation to fit the dynamic environment states.

A basic pattern modeling and recognition method can be described as following. A pattern generally consists of two parts: the condition state part and the prediction state part. In addition, a real environment state also consists of two parts: the past state part and the future state part. Therefore, we try to find out a suitable pattern that its condition state can match the occurred environment state and then applies its prediction state as the future environment state. Suppose an occurred environment states time series: $x = \{x_1, x_2, \ldots, x_n\}$, where, n is its size and x_n is the state at time n. Now we try to find a most similar pattern: $\eta_q = \{x_{k-u+1}, x_{k-u+2}, \ldots, x_k, x_{k+1}, x_{k+2}, \ldots, x_{k+v}\}$ with size u+v, where its condition state $\eta_c = \{x_{k-u+1}, x_{k-u+2}, \ldots, x_k\}$ with size u and end sate x_k is most similar to the current state $s_c = \{x_{n-u+1}, x_{n-u+2}, \ldots, x_n\}$ with size u and end state x_n. Therefore, the prediction part $\eta_p = \{x_{k+1}, x_{k+2}, \ldots, x_{k+v}\}$ with size v and end state x_{k+v} will be applied as the future environment state $s_f = \{x_{n+1}, x_{n+2}, \ldots, x_{n+v}\}$ with size v and end state x_{n+v}. The way to choose the similar pattern can apply the distance or offset of the distance between past pattern state and current state (Singh, 1999a, b, 2001; Singh and Fieldsend, 2001).

However, the distance calculated by this basic pattern modeling and recognition approach is a hard distance and is not a soft distance. The hard distance in this study means that a distance between 2 real numbers. However, the soft distance in this study means that the distance between two objects that allows some different tolerance. That is, applying soft distance in pattern recognition can allow more patterns to fit the current state and to be the winner candidate further. The learning classifier system is a technique that can provide the similar mechanism of processing soft distance.

Learning classifier system: Since, Holland published his first book about genetic algorithms and then he constructed a cognitive system (Holland and Reitman, 1978), which is the former of the learning classifier systems, there are some difficulties of the Holland's classifier systems (Wilson and Goldberg, 1989), such as the bucket-brigade architecture, the mechanics of bidding and payments and classifier syntax. In the First international workshop on learning classifier systems, the researchers (Smith, 1992) tried to define the field of LCS, in which an LCS equals a combination of a GA and cooperativity. They also defined some major LCS issues include cooperation, discovery, representation, credit assignment and internal processing (for issues of memory usage). After that Wilson (1994) examined the basic level of classifier systems and presented a Zeroth level Classifier System (ZCS). Soon later, Wilson (1995) extended the ZCS into an accuracy-based XCS classifier system which embeds reinforcement learning technique and removes the message list component but adds the prediction array and an action set to improve the effectiveness of classifier systems.

Basically, Holland's classifier systems contain three functional components and 2 data/knowledge components. The three functional components are detectors/effectors, bidding and credit apportionment and evolutionary component. The 2 data/knowledge components are message list and a set of classifiers. Each classifier is formed by a bit string with a condition part and an action part, just like a production rule. The bit string of condition part is composed by three codes: 0, 1 and #. The code # means don't care. Suppose a condition part is encoded as 1#. The two real states of 10 and 11 are also matched by this condition part. In addition, if a classifier's condition part is encoded as 1## for a 3-day long price dynamic series. The string of 1## in fact includes 4 price dynamic patterns, which are 100, 101, 110 and 111. If 1 means price up and 0 means price down, Fig. 3 shows the containing ability of classifier structure.

Therefore, the application of the don't care encoding can support the mechanism of soft distance in pattern recognition. This mechanism allows more classifiers (patterns) can match the environment state to participate the following winner competition.

The internal action of learning classifier system can be described as following. Firstly, the classifier system detects the environment stimulus/states, encode them into bit strings and put them into the message list. Secondly, the classifier system produces a matched classifier set in which each classifier's condition part is matched with the environment message. Thirdly, the classifier system starts the iterated bidding and payment process to determine the final action against the environment, execute the action and pay the rewards to the contributive classifiers. Fourthly, when the system's performance could not reach some thresholds, then the classifier systems trigger the evolutionary mechanism (i.e., GA) to generate new classifiers.

The Wilson's XCS system encodes the environment messages into bit strings and produces the matched set of classifiers. The XCS system then produces a prediction array and an action set based on classifier's accuracy. Then XCS system determines the winner action of the prediction array, executes that action against the environment and makes the credit/rewards apportionment process to the classifiers in the action set. When the XCS system's performance could not reach some thresholds, the evolutionary mechanism (i.e., GA) is then triggered. Thus, the XCS system, could handle multiple environment states within a set of classifiers, could improve the Holland's classifier systems and get good performance and embed the reinforcement learning techniques and evolutionary mechanism against the environment states, which get the potential capability of real time or instant learning. Figure 4 shows the architecture of trading learning classifier system (Liao and Chen, 2001).

Financial applications of genetic algorithms have shown promising results in Bauer (1994), Colin (1994) and Deboeck (1994). This study will apply genetic algorithms to search satisfactory m_1 and m_2 strategy parameter values in piecewise linear GDCPPI strategy. In addition, there are

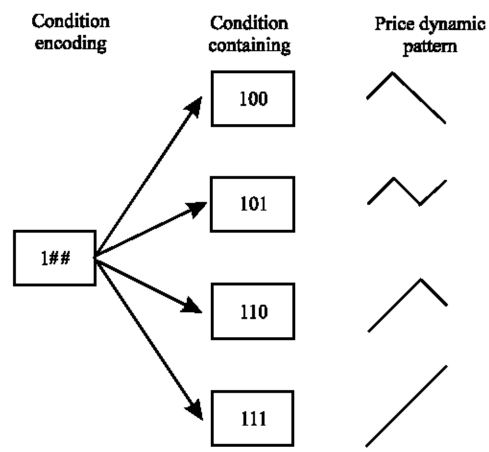

Fig. 3: The containing ability of classifier structure for presenting multiple price dynamic patterns

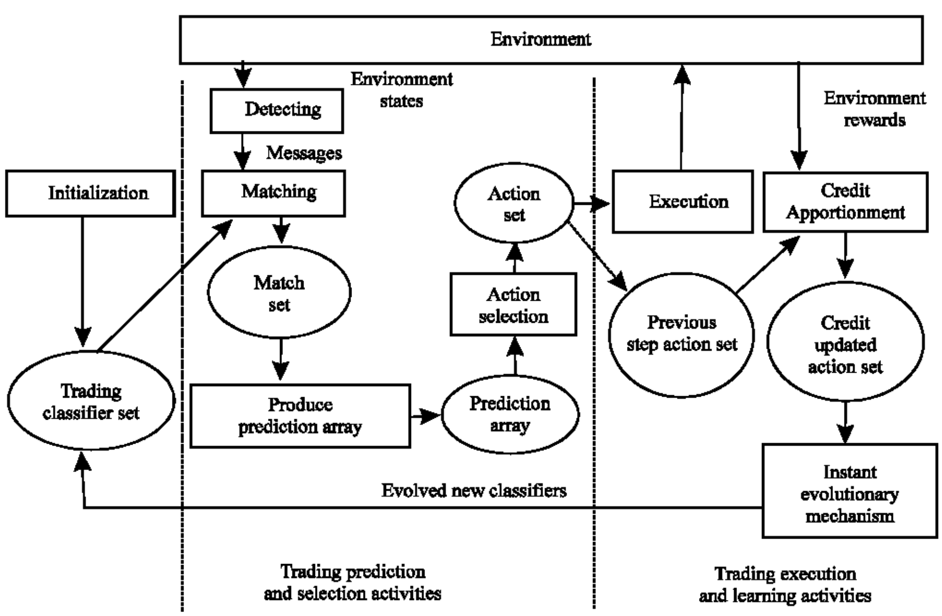

Fig. 4: The architecture of trading learning classifier system

also some financial applications for applying the LCS technique (Beltrametti *et al*., 1997; Liao and Chen, 2001). Basically, an unified pattern can not handle the problem under the dynamic environment. Therefore, a mechanism which can provide the function of pattern evolution or adaptation is most important. Leaning classifier system is suitable to process pattern recognition from its essential structure and also has the capability to evolve or adapt patterns against dynamically changed environment by its essential evolution mechanism. Since, the XCS systems obtains the above capabilities, the study adopts this technique to deal with the pattern evolution for piecewise linear GDCPPI strategy.

RESULTS AND DISCUSSION

The main experimental purpose in this study tries to justify that we can find out better piecewise linear GDCPPI strategy by LCS technique (denoted as LCS strategy) than strategy found by GA technique (denoted as GA strategy) and further better than strategy generated by Brownian technique (denoted as B strategy). This purpose can also show the superiority of LCS for pattern evolution.

Some parameter values are derived by two pretests. The first pretest tries to decide a suitable pair of year length and γ values for Brownian technique, where γ is defined in Eq. 1. The year length is decided to calculate the expected values of return rate μ and variation σ^2. In turn, the μ, σ^2 and γ will be used to calculate the parameters m_1 and m_2 in piecewise linear GDCPPI strategy for Brownian technique, where m_1 is defined in Eq. 3 and m_2 is defined in Eq. 6. The pretest shows that the year length is 8 and γ is 0.1. The second pretest tries to decide the learning length for GA learning and it shows that the better learning length is 100 trading days.

Five stocks are randomly selected as experimental targets from 30 components of Dow Jones Industrial Average (DJIA), namely, American International Group (AIG), IBM, Merck (MRK), HP (HPQ) and Exxon Mobil (XOM). We also randomly select 5 starting learning dates, which are 1999/12/13, 2001/6/6, 2002/2/27, 2003/4/28 and 2004/12/03. Three different floors in the experiments for piecewise linear GDCPPI strategies are pre-assigned and calculated by the ratios of floor to initial wealth, which are 0.7, 0.8 and 0.9. Also, 3 different goals in the experiments for piecewise linear GDCPPI strategies are pre-assigned and calculated by the ratios of goal to initial wealth, which are 1.1, 1.2 and 1.3. The testing length is always 30 days. The risk-free rate of return is 0.0001 per day. There are ($5\times5\times3\times3$=) 225 cases and then generates 225 samples for statistical tests.

Experiment design

GA experiment design: The purpose of applying GA technique in this optimization process is to search satisfactory strategy parameter values m_1 and m_2 to attain better investment performance, i.e, the rate of return in this experiment. In order to show GA's capability, we execute GA searching for 225 circumstances by 5 stocks, 5 testing dates, 3 floors calculated by ratios of floor to initial wealth and 3 goals calculated by ratios of goal to initial wealth as defined above. The training length is 100 days as derived from the above GA pretest.

In addition, each m_1 and m_2 strategy parameter will both be encoded as a 7 bit long gene in a GA chromosome. Therefore, the length of each chromosome is 14 bit long. If the decimal value of each gene is D, each gene will be decoded as values within (1.0, 13.7) calculated by (10+D)/10. Moreover, better m_1 and m_2 values implies better investment performance of piecewise linear GDCPPI strategy. The fitness function is to maximize the investment rate of return. The other important GA parameters are as follows: The population size is 40, each run executes 20 generations, crossover is two-point, mutation rate is 0.001 per bit and selection method is integral roulette wheel selection.

Learning classifier system experiment design: The purpose of applying LCS is to evolve a pool of piecewise linear GDCPPI strategies in order to get better investment performance than the performance of GA and Brownian techniques. That the classifier is encoded as 2 parts: the condition part and the action part. In environment level, the condition part is composed of 4-day long price dynamic ratio (i.e., the growth rate in (-12.8~12.7%)) and the action part is composed of m_1 and m_2 parameters of piecewise linear GDCPPI strategy. In internal level of LCS, the condition part is encoded as a 32 bit long (4 day$\times$8 bits) string and the action part is encoded as a 14 bit long (2 parameters$\times$7 bits) string. Each gene in action part will be decoded as value within (1.0, 13.7), the same as in the GA experiment. That is, for each advancing trading day, the LCS system searches qualified previous adjacent 4 day price growth rates and the winner classifier will suggest suitable m_1 and m_2 parameters that investors can attain better investment performance. Therefore, the LCS system here adopts the sliding window (4 day long in this study) approach to continue recognize and evolve the investment patterns with action suggestions. Figure 5 shows the encoding format of each classifier for piecewise linear GDCPPI strategy. The other LCS system parameters are: total runs are 600; max random state lear ning steps are 100; max insample state learning steps are 100; total learning steps are 60,000; population size is 4000; last

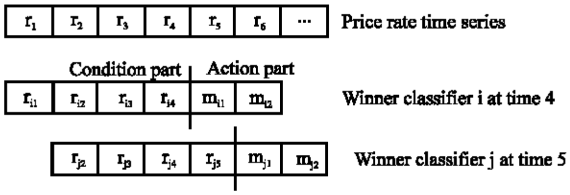

Fig. 5: The encoding format of each classifier for piecewise linear GDCPPI strategy

experiment's GA learning iterations are 18,972 with GA learning rates 0.3162; probability of don't care bit (#) is 0.150; crossover rate is 0.9; mutation rate is 0.03. The other trading setup is the same as the GA experiment design.

Experiment results: We use the paired-samples t-test to validate whether LCS strategy can outperform GA strategy and further GA strategy can outperform B strategy. The null hypotheses are: H_0: $roi_{GA}(\theta) \geq roi_{LCS}(\theta)$ and H_0: $roi_B(\theta) \geq roi_{GA}(\theta)$. The testing results are described as following. For the first hypothesis, the t-value for the whole 225 samples in testing period is -3.924. The significance value (p-value) is 0.000, which is statistically significant. For the second hypothesis, the t-value for the whole 225 samples in testing period is -2.303. The significance value (p-value) is 0.022, which is statistically significant. Therefore, we can reasonably reject these 2 null hypotheses. That is, the LCS strategy can outperform the GA strategy and further the GA strategy can outperform the Brownian strategy.

CONCLUSION

Pattern formulation and recognition are logically applied by most of investors. However, it is hard to handle this job under dynamic changed security markets. Although, applying GA technique in security trading market has remarkable outcome in literature, its essential structure still has drawbacks to handle the dynamic changed environment. For the essential structure of learning classifier system technique, it can generate a pool of trading strategies and can evolve this strategy pool to fit the dynamic changed security market. This study then applies the LCS technique to testify its superiority. This study adopts the piecewise linear GDCPPI strategy as the trading strategy, which this strategy is proposed by the author of this article before. This trading strategy not only tries to protect the floor wealth, but also to protect the goal wealth. In addition, this strategy is a general trading strategy for the CPPI strategy and goal-directed strategy. This study also makes some experiments to show that the LCS strategy can outperform the GA strategy and further the GA strategy can outperform the Brownian strategy significantly. These testing results show the superiority of LCS technique for the pattern management.

Our future research will be on the combination of LCS and Genetic Programming (GP) technique. Since, the essential format of classifier is of fixed length, it therefore has the problem of pattern scaling and flexibility. The essential structure of GP is of dynamic length. Therefore, the combination of LCS and GP is a reasonable approach to enhance the performance of pattern management in trading strategies.

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