Applying the Extended Classifier System to Trade Interest Rate Futures Based on Technical Analysis

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Abstract

In practice, it is difficult to gain profit in the process of trading interest rate derivative commodities. This could be attributed to the complexity of existing pricing models, which are derived from the term structure and yield curve, both of which cannot adapt well to short-term market dynamics. In this study, we use the Extended Classifier System (XCS) to model the market behavior of interest rate futures, the purpose of which is to provide effective trading decision support. Several technical indicators and their first- and second-order derivatives are selected as the market descriptive variables, which are then used for XCS training. Finally, the adaptive rules of the classifiers, which consist of conditions with relative actions considered helpful for constructing the automatic trading system, are generated from the XCS knowledge discovery process. The market data of the 10-year government bond futures traded in Taiwan are chosen for empirical study to verify the accuracy and profitability of the XCS model. These were also used to conduct a comparative evaluation between the random walk and tendency following models and the XCS model.

1. Introduction

Recently, the subprime mortgage crisis has created an impact on the financial markets of many countries. Thus, people have come to expect that they can hedge the interest rate risk by trading the interest rate futures. Moreover, the interest rate futures can also provide the function of price discovery that could help people effectively evaluate the spot price. Therefore, interest rate derivatives and commodities have become increasingly important in the financial market. According to the investigation of the futures industry association (FIA), there are seven interest rate futures and options among the top 10 futures and option contracts within the trading volume in 2006 [1].

However, it is difficult to identify the price of the interest rate futures. Traditionally, the cost of carry model [2] is the most commonly used evaluation model for stock index futures. However, this model includes too many assumptions inconsistent with the actual trading observed in practice; at the same time, it also overlooks too many market conditions. In addition, especially when considering the interest rate futures, it is quite difficult to forecast spot prices and therefore, the futures prices.

The traditional approach to pricing the interest rate futures is based on the term structure models and the yield curve [3] [4].However, although these traditional models can provide market forecasting, most of which are used for long-term market behavior analysis, they still lack enough information to allow short-term daily trading decisions.

In recent years, many studies have focused on developing the automatic trading system by combining the technical analysis and artificial intelligence techniques [5] [6]. Researchers have proposed many computational forecasting models of financial commodities and used these to generate trading rules that are helpful in generating profit in the financial market. Although most of these models have already been applied to the stock market and stock index futures for empirical study, a few have adopted the interest rate futures market data for the same type of study [7] [8].

We thus propose an automatic trading system of interest rate future. The trading model is derived from the extended classifier system (XCS), which is a revolutionary computing technique for hidden knowledge discovery; it is currently being used for developing a financial investments decision support system [9] [10] [11]. We apply the technical analysis on the interest rate futures to compute the technical

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indicators and their first- and second-order derivatives, and regard them as the market descriptive variables. In the following, we select the variable through the correlation between the next day price change direction (price increase/decrease) of interest rate futures and the sign of the variable's value (positive/negative), after which we construct the classifier system. In this study, market trading data within three years derived from the 10-year government bond futures (GBF) traded in Taiwan are used for the experiments. We also design the trading strategy and assume several market conditions in order to verify the accuracy and profitability of the XCS model.

The rest of the paper is organized as follows. Part 2 presents the details of the proposed XCS model; Part 3 describes the experiment process; Part 4 discusses the experiment results; and Part 5 describes the conclusions drawn from the study.

2. The proposed XCS model

2.1. System framework

The original concept of the classifier system came from Holland [12] in 1976, under the term Cognitive System (CS). The following year, Holland and Reitman [13] jointly published the Learning Classifier Systems (LCS). However, it was not until 1986 when Holland amended the structure proposed in 1977 and introduced a practical version that the system was formally established. Since then, subsequent research conducted by many scholars gradually strengthened the overall operational efficiency and stability of the system. In 1995, Wilson [14] adjusted the fitness of LCS, changing the original use of expected return as a basis for calculating the accuracy of the expected return. He also improved the algorithm for learning and introduced the Extended Classifier Systems (XCS) model.

In XCS, the so-called classifier is composed of many "IF condition/ THEN action" rules to represent the corresponding external state. This is represented by the following formula:

<classifier>：=<condition>/<action> (1)

For the sake of easy application, binary coding is typically used for the condition and the action to represent various parameters of the external state. It is also used as a code for the following set of instructions:

<condition>：= $\{0,1,1\#,0,1,\ldots.\}_L$ (2)

<action>：= {0,1,….,n-1} (3)

Within these codes, L represents the length of the rules, # represents the unimportant characteristics which mean that 0 and 1 can both be matching states, and n represents the classified resulting numbers.

The main structure and application process are represented in Figure 1 below.

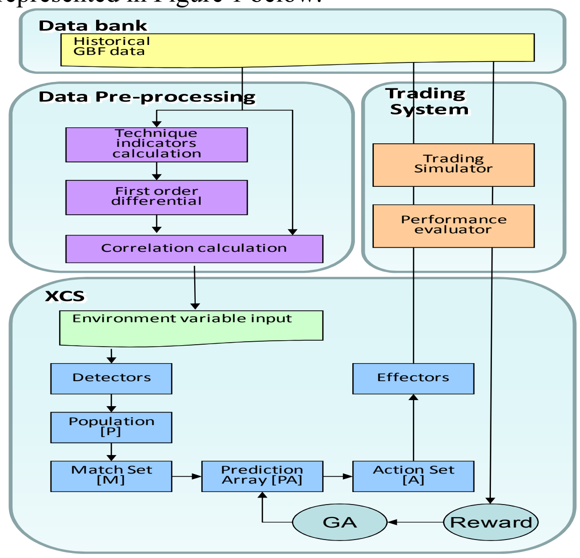

Figure 1. System framework of the XCS model

As can be seen, XCS receives information on the external state through detectors, coding it into chains of rules that can be processed by the system. These chains of rules are called classifiers. These classifiers are then compared to the classifiers identified in the external state's information system and population set [P], and those that match the current imputed state are selected to create a match set [M]. If no matching classifiers are found in the population set, then the cover mechanism is triggered to set up one that contains the set of information as that point in time, and action will be randomly generated thereafter. From the action of each classifier in the match set, the weighted average of each action is then calculated based on the fitness of the classifiers to construct a prediction array [PA] for returns. Finally, the appropriate action is determined through the random exploration or exploitation method. This action is then used to set up an action set [A]. After determining the appropriate action, the system delivers the action to the effector to be sent for execution under the given conditions. Depending on the level of correctness resulting from the execution, the system will then provide internal reinforcement to the classifiers, and the relevant weighting in terms of the strength of each classifier within the action set is thus updated. Afterwards, the evolutionary genetic algorithms mechanism is applied within the action set, which will then eliminate the relatively weak rules. Therefore, after a period of learning, the system can generate the most appropriate action classifier that can adapt to the various states created by various changes within a dynamic environment.

2.2. Data of research

As previously mentioned, data on the interest rate futures traded in Taiwan are chosen for the empirical study. Of the 10-year empirical trading data from the Taiwan Futures Exchange government bond futures (GBF) obtained from January 2004 to December 2006, a total of three years' data are then selected. Data from the first two years are used for the XCS model training, while those from the final year are used for XCS model verification. The data consist of the trading date, expiration month, daily opening price, daily closing price, daily highest price, daily lowest price, daily settlement price, and daily trading volume.

2.3. Data pre-processing

We initially calculated the technical indicators according to the empirical trading data, which describe the conditions of the market at certain times. Many technical indicators have been used for market analysis, and the different parameters for calculating indicators, such as the five-day and 10-day moving averages, exhibited different intervals forecasting. In this study, we adopt 12 technical indicators, which are most commonly used in practice, along with various parameters to represent the long- and short-term market behaviors. These technical indicators and parameters are listed in Table 1.

Table 1. The XCS variables selection

Technical Indicators	Parameters (intervals)
Trading Volume	1 day
Moving average (MA)	5 and 10 days
Stochastic Indicator (KD)	9 days
Moving Average Convergence/Divergence (MACD)	9 days
Williams Overbought/Oversold Index (WMS%R)	9 days
Relative Strength Indicator (RSI)	14 days
Directional Movement Index (DMI)	14 days
Bull And Bear Index (BBI)	N.A.
Psychological Line (PSY)	5, 10, and 20 days
Momentum (MTM)	5, 10, and 20 days
BIAS indicator (BIAS)	12 days
Volume Ratio (VR)	10 days

However, using only the technical indicators prove to be insufficient in accurately describing the dynamic behavior of the market; as such, more information is necessary. Therefore, we calculate the first- and second-order derivatives of the technical indicators, which represent the tendency and changing momentum, respectively. These are described in Equations (4) and (5) below.

$$\Delta x_t = \frac{x_t - x_{t-1}}{x_{t-1}} \quad \text{and} \tag{4}$$

$$\Delta' x_t = \Delta x_t - \Delta x_{t-1} \tag{5}$$

where x is the technical indicators at the date t.

Upon calculation, we obtained a total of 51 indicator series, including the technical indicators and their derivatives. However, not every time series is correlated with the price increase/decrease of the market. To identify the suitable input variables for the XCS model among the 51 indicator series, we adopt the Pearson Correlation between the indicators and the next day price increase/decrease of the market for measurement. The result of variables selection is shown in Table 2, in which 13 indicators with a significant level of correlation below 0.01 are chosen for the input variables shown below.

Table 2. Input variables of the XCS model

Technical Indicators	Selected variable	Pearson correlation
Moving average (MA)	$\Delta' MA(5)$	-0.076 *
Stochastic Indicator (KD)	$\Delta K(9)$ $\Delta' K(9)$ $\Delta' D(9)$	-0.072 * -0.129 ** -0.111 **
Williams Overbought/Oversold Index(WMS%R)	$\Delta\, WMS\%R(9)$ $\Delta'\, WMS\%R(9)$	0.120 ** 0.096 **
Relative Strength Indicator (RSI)	$\Delta\, RSI(14)$ $\Delta'\, RSI(14)$	-0.147 ** -0.100 **
Directional Movement Index (DMI)	$+DMI(14)$	-0.082 *
Bull And Bear Index (BBI)	$\Delta'\, BBI(14)$	-0.072 *
Psychological Line (PSY)	$\Delta\, PSY(5)$	-0.079 *
Momentum (MTM)	$\Delta\, MTM(20)$	-0.076 *
BIAS indicator (BIAS)	$\Delta\, BIAS(12)$	-0.095 **

Note:
** correlation is significant at the 0.01 level (2-tailed)
* correlation is significant at the 0.05 level (2-tailed)

2.4. Parameters setting

We considered two mechanisms for XCS operation that should be thoroughly explained during the construction of the XCS model, and these are the reward distribution and the parameters of genetic algorithm. In this study, the reward distribution of the XCS model is designed based on the correctness of the price increase/decrease (Positive/Negative) forecasting.

If the next day price increase/decrease forecast by the XCS model is the same as that in the real market (i.e. True Positive and True Negative), the reward is positive; otherwise, if the forecast is different (i.e. False Positive and False Negative), the reward will be negative. Additionally, the parameters of the genetic algorithm, which is used for generating the evolution of the classifier rules, are set at the same best value proposed by Wilson [15]. However, we set the learning iterations with 100 thousand for the purpose of preserving stability. Moreover, the initial prediction, error, and fitness of the XCS model are all set to zero.

2.5. Classifier encoding

The XCS model is composed of many classifiers, each consisting of a condition and an action. The condition component presents the descriptive parameters for the market behavior, while the action component is used to represent the price increase/decrease forecasting. In this study, we use 13 conditions selected from the technical indicators and their derivatives, and one action to represent the classifier. The classifier is encoded in binary and illustrated in Table 3.

Table 3. Binary encode of the classifier

Bit	Encode rule
Condition	
1 ~ 13	$if\ x_i > 0, then\ bit_i = 1,$ $else\ bit_i = 0$ $x: the\ input\ value\ of\ the\ parameter$ $i = 1,2...,13$
Action	
14	$if\ y > 0\ (uptrend), then\ bit_{14} = 1,$ $else\ (downtrend)\ bit_{14} = 0$ $y: price\ change\ of\ the\ tendency\ next\ day$

3. Research method

3.1. Design of Experiments

The trading decision is made according to the next day price increase/decrease forecasting generated by the XCS model. The next day's price is then forecasted using the current day's closing price, a process executed daily after the market has closed.

The trading strategy is built based on two criteria: the price change direction and the consistency of two continuous days' forecasting.

When the experiments begin, we do not have any long or short position. If the XCS model forecasts a price increase the next day, then one lot of GBF (build a long position) should be sold. Similarly, if the XCS model forecasts a price decrease the next day, then one lot of GBF should be sold (build a short position). When the initial position has been built, we will do nothing if the prediction of the next day's price change is the same as the previous ones, such as yesterday's price increase prediction and today's continued price increase prediction. Otherwise, if the prediction of the next day's price change is not the same as the previous one, then close the position and build an opposite position.

In order to obtain stable profit and reduce the risks involved, we consider the stop-loss and profit-cap approach. If the profit/loss of the GBF position reaches the threshold, then the position should be closed. We use profit-making investment trading data during the XCS model training as a statistical sample to calculate the distribution of lost dollar value. Afterwards, we then set the stop-loss threshold value to cut the loss at 20% of the maximum loss. On the other hand, the profit-cap threshold value is set according to the profit-making investment trading data for statistical distribution, and is set at 80% of the value as the profit-cap value. At most, the GBF position in our experiments is just one lot. If we hold the GBF until the expiration date, it will be switched automatically. Finally, if the GBF is held until the testing period ends, then the position should be closed.

Furthermore, in order to easily simulate results based on historical data, we make several assumptions in our experiment. We assume that the GBF is traded on the closing price. The transaction cost of one lot of GBF in our experiments is assumed to be at 550 NTD, which is very similar to the summation of the tax and the required fee in the real market situation.

To verify the effectiveness and profitability of the XCS model, two models (i.e., the random walk model and the tendency following model) are considered as the comparison models. The trading strategy and assumptions are the same as those used in the three models. Only the trading decision making is different. When the XCS model determines whether it should provide a prediction to build a long/short position, the random walk model would generate a random trading signal, which corresponds to an action generated from the XCS model. Simultaneously, the tendency following model would also generate a trading signal time according to the last price change direction in the real market. However, the stop-loss and profit-cap mechanism are not considered in the comparison models because it is difficult to determine the threshold value.

3.2. Evaluation scheme

The XCS model is then compared with the random walk and the tendency following models. The evaluation scheme is designed based on two strategies: accuracy and profitability. The accuracy strategy is used to count the correctness rate of the forecasting price change direction (Equation (6)). On the other hand, profitability is measured by the accumulative profit according Equation (7). Both accuracy and profitability are computed during the testing period.

$$\textit{correctness rate} = \frac{\text{number of correct forecasting}}{\text{total number of forecasting}} \tag{6}$$

$$\textit{accumulative profit} = \sum(\text{profit or loss - transaction cost}) \tag{7}$$

4. Experiment results

In this study, we performed a preliminary experiment to illustrate the knowledge discovery ability of the XCS model. The XCS model was trained and tested according to the GBF closing price for the nearest-month contracts. We used 447 records from 2004/3/11 to 2005/12/30 for the XCS training, as well as 232 records from 2006/1/2 to 2006/12/12.. After training 10,000 times, the XCS generated 199 knowledge rules on GBF trading based on the parameters setting in this study, which were then used for testing. The best rules selected by the correctness rate and occurrence times in training and testing are listed in Table 4. From the table, we can see that the correctness rate in training is not consistent during testing. The rule with the highest correctness rate in training does not work during testing, while the highest correctness rate rule during testing does not work as well as that in training. However, the rule which occurs most frequently is consistent in both training and testing.

Table 4. Knowledge rules for GBF trading

rules (cond./act.)	Training		Testing	
	Cor. rate	Occ. times	Cor. rate	Occ. times
0011001111011/1	***0.9999**	27	0.0000	2
0000110100000/0	0.4285	7	***0.9999**	4
0000110000000/1	0.6005	***1890**	0.7272	***44**

Each model in the experiments is tested 10 times in this study, and the evaluation results for model comparison are reported in Table 5. As can be seen, the XCS model demonstrates the best levels of accuracy and profitability, and that using the stop-loss and profit-cap strategies in the XCS model can increase the profit. We also observed that both the random walk and the tendency following models faced difficulty in gaining money in the GBF market. These are manifested by the negative accumulative profit and yield rate.

Table 5. Model comparison results

Model	XCS model: without stop-loss and profit-cap strategy	XCS model: with stop-loss and profit-cap strategy	Random walk model	Trend following model
Correctness rate				
Ave.	***62.04 %**		51.46 %	42.86 %
Std.	2.7		***4.5**	1.4
Accumulative profit				
Ave.	308,139	***380,866**	-87,067	-335,611
Std.	54,730	40,422	***196,779**	48,998
Profit for each trading	2,383	***2,941**	-661	-2,604
Yield rate	102.71 %	***126.96 %**	-29.02 %	-111.87 %

Furthermore, in order to verify the robustness of the XCS model, we randomly divided the three-year experiment data into 10 segments. One segment was used for testing, and the other nine segments were used for the XCS model training. Figures 2 and 3 show the experiment results generated by different testing and training segments. Figure 2 indicates that the standard deviation of accuracy is very small, which is only 0.037. In contrast, the accumulative profits presented in Figure 3 ranged from 18,051 NTD to 203,803 NTD, which constitute quite a large range.

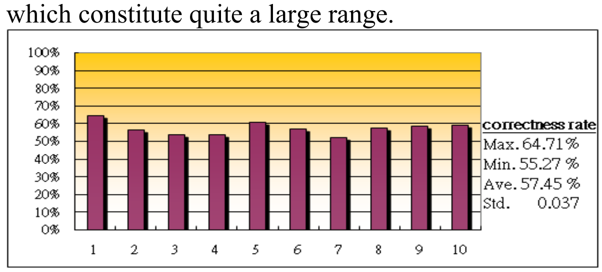

Figure 2. Robustness of XCS model's accuracy

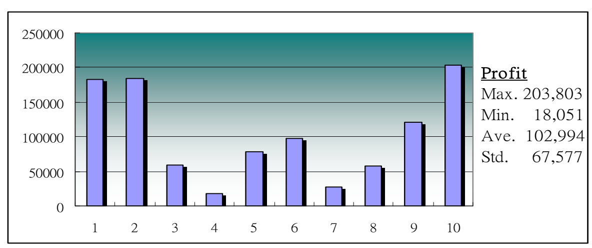

Figure 3. Robustness of XCS model's profitability

The XCS model was also used to study the expiration date of the GBF. The expiration date is an important factor that will affect the futures prices [2]; thus, we applied the XCS model to three different GBF expiration dates (i.e., the 1st, 2nd, and 3rd quarter months following the transaction). The results are listed in Table 6 from which we can observe that the best performance is obtained when the XCS model is applied to the 1st quarter month.

Table 6. Apply XCS model to the GBF of different expiration date

Contract expiration date	1st quarter month	2nd quarter month	3rd quarter month
Correctness rate	*62.04 %	58.01 %	46.75 %
Accumulative profit	*308,139	253,220	99,312
Profit for each trade	*2,382	1,688	735
Yield rate	*102.71 %	84.40 %	33.10 %

5. Conclusion

The prices of interest rate futures are affected by a number of factors, so it is quite difficult to forecast the market behavior. This also makes it difficult to gain exceeding profit. In this study, we adopted the XCS model to construct the interest rate futures trading model and used it to investigate the dynamic market behavior. The subject in this study consisted of the 10-year government bond futures traded in the Taiwan Futures Exchange, of which three years' worth of data from 2005 to 2007 were specifically used for the experiment.

Several technical indicators and their first- and second-order derivatives were considered as the input variables of the XCS model. Thirteen variables were then selected after calculating the correlation of the price change direction and the technical indicators. We also designed the trading strategy and assumed several rules for the experiments.

In order to evaluate the proposed XCS model, we used the historical trading data from the first two years in order to train the XCS model, while data from the final year were used for testing. The experiments results showed that the proposed XCS model could predict the next day's price change direction with high accuracy. The results showed that both random walk and tendency following models demonstrated better profitability. Moreover, the experiments also indicated that the XCS model can be characterized by high robustness with regard to accuracy and is more suitable for trading the nearest-month futures contracts.

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