Refined Group Learning Based on XCS and Neural Network in Intelligent Financial Decision Support System

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Abstract – **Cooperative learning is widely defined as a process through which a group of individuals interact to achieve a learning goal. In the fluctuating stock market, investors often have various decision-making approaches. This study attempts to exploit computer technology, financial mathematics, and econometrics to make reasonable investment decisions to reduce man-made errors or mistakes and increase profits. This work integrates the eXtended Classifier System (XCS) and neural network modules and incorporates features such as dynamic learning and group decision making. An empirical study is conducted by comparing the profitability of the proposed system with that of investment strategies based on simple rules with single technical indices, individual learning XCS, buy and hold, and six-year term deposit based on the Taiwan Index. The proposed system demonstrates superior performance in terms of accuracy, rate of cumulative return, and variance of return.**

Index Terms – XCS, classifier system, neural network, multi-agent

I. INTRODUCTION

Capturing stock market trends to win extra rewards is a key issue of interest to investors and researchers. Akerlof, Spence, and Stiglitz explained the importance of information collection, as stock information is never symmetrical for most players in the market [8]. This study thus integrates group decision making and machine learning mechanisms eXtended Classifier System and neural network to support quality investment decisions. A model is built by devising trading strategies using XCS and neural network, and by using the concept of multiple agents to make group decisions to raise profitability.

Studies on investment knowledge have been made in artificial intelligence fields such as neural network, fuzzy theory, genetic algorithm, etc. As extended classifier systems are rule-based, active machine learning fits the dynamic nature of the real world, and thus is widely adopted to observe stock trends in an attempt to seek outsize investment profits [2][3][4][10][11][12][15]. This study therefore attempts to combine the advantages of neural network and XCS in stock trend forecast incorporated with the idea of cooperative learning. Our previous work has already shown better group decision making performance than individual learning [16]. Consequently an integrated, enhanced intelligent financial decision support system based on these key concepts is implemented and proposed in this study.

II. BACKGROUND

In literature, Neural networks (NN) have been used extensively in solving financial problems [5][7][26]. NN leads to a satisfying prediction performance when the environment is stable and not complicated. However, if such prerequisites do not hold, NN will be weakened by problems such as over-training, learning rate, and convergent function [11].

To obtain an appropriate solution to the environmental changes, this study integrates Wilson's XCS and neural network to pursue higher profitability performance. XCS combines machine learning and reinforcement learning theories, and it creates a population of rules that form the basis for solving problems via a credit assignment mechanism and genetic algorithms.

A. Extended Classifier System

In 1995, Wilson's eXtended Classifier System (XCS) was first proposed with the Niche-Genetic Algorithm (Niche-GA) to compute fitness and resolve reward oscillation [15]. In XCS, the classifier rule set in the population is randomly generated and all of the related parameters are initialized when this model is executed. If the input rules cannot match the condition parts of the classifiers in the population, new classifiers will be covered by the rules. The classifiers in the XCS model include parameters such as condition, action, prediction error, and fitness. In each stage, the XCS detector transforms the exterior information into input messages, and matched rules are found and collected as the match set by comparing with the rule base. The prediction array is formed by computing the weighted average of fitness for each action in the match set. Action selection is then done by picking the best in prediction array or at random if no classifiers fit the match set and covering rules. Finally, the effector takes the message from the action set. In effector module, the output or action corresponds to the content of the message. Outputs or actions based on the response to the ordinary rules must still necessary to be compared with the exterior environment for feed back. The reinforcement program then renews the related parameters such as expected return, expected return error, accuracy and fitness in the classifier. After the action is completed, possible GA actions include duplication, crossover and mutation on the most fitness outside environment population can be adopted. Fig. 1 shows the XCS model flow.

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Classifier systems have been utilized in the field of financial investment. Mitlöhner labeled economic behaviors as behaviors of adaptation [12]. Because investors make decisions in dynamic environments, it is difficult to apply quantitative mathematical models to support decision making. Therefore, attempts were made to simulate the human decision making process by adopting XCS. XCS observes and explains the environment facilitating better investment decisions. Studies [2][3][4][11] have demonstrated that XCS performs remarkably well compared to other investment strategies such as random walk or buy and hold.

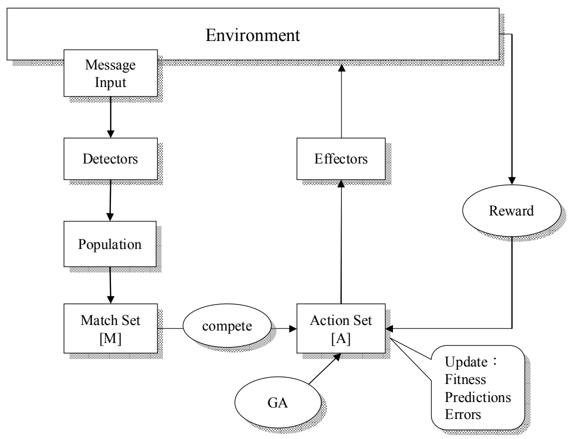

Fig. 1. Wilson's XCS Framework

B. Back-Propagation Neural Network

In a Neural Network, the neurons are organized into layers, each containing numerous weights. The input, hidden and output layers comprise the basis of a neural network. Models without hidden layers are called two-layer networks. Networks containing a hidden layer are called three-layer networks. Every neuron is connected to every neuron in the previous layer. Moreover, the network output is the summation of the input layer neuron multiplied by each weight as the activation function parameter.

$$y_j(n) = \varphi\left(\sum_{i=0}^{P} w_{ji}(n) x_i(n)\right) \tag{1}$$

where φ is activation function.

One of the most widely used activation functions is called the sigmoid function. It is described in detail in the following section. The steps of the back propagation neural network are outlined below.

1. Determine the network topology.
2. Initialize the weight and learning rate.
3. Propagate the inputs forward.

$$y_j(n) = \varphi\left(\sum_{i=0}^{P} w_{ji}(n) x_i(n)\right) \tag{2}$$

4. Back propagate the error.

$$\delta_j(n) = y_j(n)(1 - y_j(n)) \sum_k \delta_k(n) w_{kj}(n) \tag{3}$$

5. Adjust the weight value.

$$w_{ji}(n+1) = w_{ji}(n) + \Delta w_{ji}(n) = w_{ji}(n) + \eta \delta_j(n) y_i(n) \tag{4}$$

6. Convergence testing.

Two conditions can cause the testing to stop. One such condition is when the number of cycles exceeds the preset number, and the other is when the network error remains unchanged.

The weight in every trained neuron reserves for the data to be predicted. The result of this neural network is significantly better than that obtained using traditional statistics.

C. Cooperative learning

The humanistic psychology emphasizes the existence of individual value, and cooperative learning is one of its major representations. Cooperative learning values the interaction between individuals, and it is composed by theoretical frameworks such as constructivist, Vygotsy's scaffolding instruction, and Bandura's cognitive elaboration [17]. Udvari-Solner defines cooperative learning as the process through which a group of students interact to achieve their goal [14]. Every group member cultivates their mutual dependence and social skills by role assignments and job dispatch, and the mission is completed through the devoted participation of all members. Slavin described how students think and resolve problems, and how they integrate and apply knowledge and skills [13].

In 1994, Alavi proposed in [1] that the advantage of IT on collaborative learning lies in improving group process gains. Even without a universal learning theory, collaborative learning remains one of the most important features that increases learning efficacy.

III. Methodology of Study

A. System framework

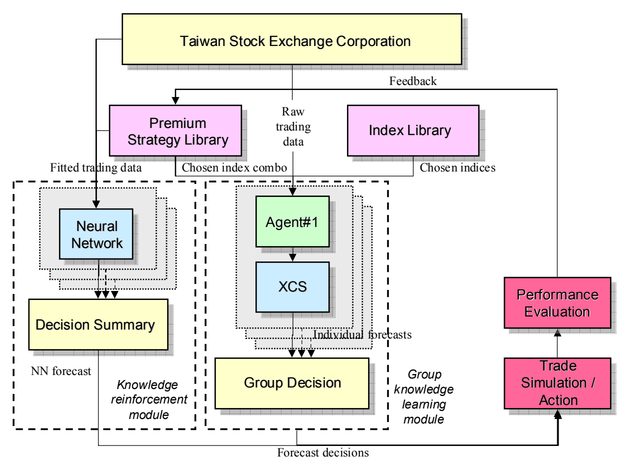

Fig. 2. Framework of the proposed intelligent financial decision support system

As illustrated in Fig. 2, this work simulates transactions in the stock market, and its initial settings and procedures are outlined as follows:

1. This study adopts a multi-agent mechanism, and simulates the behavior of 50 teams of stock traders.
2. The input data of this study are retrieved from January 4, 1986 to September 21, 2005, i.e., 5419 trading days. The training period is 14 years, while the testing period is six years. In the proposed model, training work has two

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parses. The XCS module is trained first. Each training session lasted five years. Through annual application of sliding window shifting, the 14 years of the training period is divided into ten training sessions.

3. The index library contains 18 indices. Initially, in the "individual learning stage", every agent picks a number of indices using a Roulette Wheel for developing its investment strategy.
4. Based on the selected indices, every single agent simulates the trend for the subsequent trading day using XCS.
5. A general investment decision is formed according to the decisions of the majority of the 50 agents. In accordance with the regulations governing the trading of Taiwanese futures, this work simulates the cumulative return rate calculation (RTN0) and the percentage accuracy to assess the feasibility of the research methodology.
6. Agents put good performing strategies into a premium strategy library following each training session. These indices are referenced by other agents for cooperative learning in the next training session.
7. In each training session, every agent either picks indices from the index library or selects a strategy from the premium strategy library. Steps four to six are repeated for cooperative learning.
8. After premium strategies are collected in the library, the second parse of training is initiated. In the neural network module, every premium strategy maps to a NN network. As each strategy is composed of different number of indices, each neural network module has corresponding different number of input neurons. The NN module adopts the same way of training as the XCS module.
9. In the testing period, actions are taken depending on the number of neural networks which have buy/sell signals over thresholds.

B. Dynamic learning XCS

1) Library indices

Based on the practicality and significance responses to certain features, 18 indices are chosen for inclusion in the index library of this work (see appendix A). The output data of the index formulae are regarded as the input of the proposed XCS system.

2) Action classifiers

From Eqn (5), matched classifiers [M] are calculated to yield action classifiers [9]. ω denotes the average rate of accuracy, γ represents strategy accuracy, and ν is the number of strategies. The classifier with the highest ω is taken as the action classifier in this stage.

$$\omega = \frac{\sum_{i=1}^{\nu} \gamma_i}{\nu} \tag{5}$$

3) Reward/punishment

The accuracy rate of strategy for the action classifiers can be computed by Eqn (6). γ denotes the rate of strategy accuracy, κ represents the number of accurate predictions, and ς is the number actions.

$$\gamma = \frac{\kappa}{\varsigma} * 100\ \% \tag{6}$$

C. Knowledge refinement neural network model

In this study, we adopt the supervised back-propagation network, which has been utilized most widely among other learning rules. This three-layer model has five nodes in hidden layer, and the number of nodes in input layer depends on the number of indices adopted for a certain strategy. The input variables for network training are the indices composed in each of the well-performed strategies, while the output target for neural network is the forecast of whether the index trend goes up or down.

The initial value of the connection weight is a random number between interval [-0.5, 0.5]. The initial learning rate is 1.0, decay ratio is 0.95, and the minimum value is 0.1. Regard as the Sigmoid activation function, the input indices are mapped into interval [-6, 6] and output values interval is [0,1]. The activation function is as followed.

$$sigmoid(x) = \frac{1}{(1+\exp(-x))} \tag{7}$$

This training process takes 100,000 epochs. Learning rate varies within the interval [0, 0.5] according to the number of training that will compose a better forecast model.

D. Transaction simulation

In the action classifier selection stage, individual agents compute the average rate of accuracy ω and generate action classifiers [9] by matched classifiers [M]. The multi-agent mechanism proposed in this study may involve different ωs and strategies, and thus a general strategy is summarized by Eqn (8). η denotes the average rate of accuracy for multi-agent, while ψ represents the number of agents.

$$\eta = \frac{\sum_{i=1}^{\psi} \omega_i}{\psi} \tag{8}$$

E. Premium strategic index

Upon completion of the first round of testing, the better performing indices among those chosen by the 50 agents are entered into the premium strategy library. These indices are references used in cooperative learning for all agents in the following sessions. The steps involved in selecting a premium strategic index are as follows:

1. Compute the average accuracy by Eqn (9) for the strategies predicted by single agents whose accuracy in making uptrend prediction exceeds 50%. Where α denotes the average rate of accuracy in uptrend predictions, γ represents the rate of accuracy, and ν is the number of strategies.

$$\alpha = \frac{\sum_{i=1}^{\nu} \gamma_i}{\nu} \tag{9}$$

2. Compute the average accuracy using Eqn (10) for the strategies predicted by single agents whose accuracy in

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downtrend prediction exceeds 50%. β denotes the average accuracy in uptrend predictions, γ represents the rate of accuracy, and ν is the number of strategies.

$$\beta = \frac{\sum_{i=1}^{\nu} \gamma_i}{\nu} \tag{10}$$

3. Compute the overall average accuracy θ by Eqn (11).

$$\theta = \frac{\alpha + \beta}{2} \tag{11}$$

4. Repeat steps 1, 2, and 3 to determine the actual rate of accuracy for all agents.
5. Rank all 50 agents according to θ in descending order, assigning them ranks from 0 to 49, where zero represents the highest ranking, while 49 is the lowest.
6. Formalize the rate of accuracy between area [0,1] as μ.

$$\mu = 1 - \frac{\theta}{49} \tag{12}$$

7. If the μ of an agent equals or exceeds 0.8 ($\mu \geq 0.8$), and the strategy (i.e. a combination of indices) used is not retrieved from the premium strategy library, then this strategy is added into the library. The strategy can then serve as a reference for cooperative learning for other agents.

F. Cooperative learning

The system proposed here enables agents to learn either individually by random selection of technical indices, or comparatively, by taking some strategy from the premium strategy library. If the formalized accuracy μ is between (0.6, 0.8), then the chosen strategy is kept for the next round. When μ is less than 0.6, agents randomly choose to learn either individually or cooperatively. If individual learning is deployed, the agent picks one or more indices from the index library as its strategy. Otherwise the agent retrieves strategies from the premium strategy library.

Regardless of whether individual or cooperative learning is adopted, the predictions given from the 50 agents will be summarized by taking the majority decision as the final decision.

IV. System Design and Implementation

A. Data input

The training data of this study is based on the TaiEX between January 4, 1986 and January 3, 2000, namely 3983 trading days. Each training session lasts five years. By sliding the testing window annually, the 14 years of training period is divided into 10 training sessions. The testing period is from January 4, 2000 to September 21, 2005, i.e. 1436 trading days. Meanwhile, the input items of XCS/NN include date, opening price, highest price, lowest price, closing price, and trading volume. These items are used for computing and encoding XCS/NN input factors.

B. Multi-agent XCS

B

agnet	strategy	accuracy(%)	action no.	cash	agnet	strategy	accuracy(%)	action no.	cash
1	4、5、10、11、13、14、15、16、18	100.00	1	5262.80	2	2、7、8、9、12、14、15、16、18	100.00	1	5000.00
3	1、4、5、7、8、10、14、18	100.00	1	5065.92	4	2、4、5、7、10、13、14、17、18	100.00	1	5065.92
5	5、8、10、11、13、15、16、18	100.00	1	5000.00	6	4、5、7、8、9、10、12、13、17	100.00	1	5000.00
7	5、6、7、8、10、13、16、17	100.00	1	5000.00	8	1、4、7、9、10、11、13、15、16、17	100.00	1	5000.00
9	2、3、6、7、8、9、12、13、15、16...	100.00	1	5053.44	10	1、3、4、5、6、7、9、12、14、17	100.00	1	5000.00
11	1、2、3、5、6、7、8、9、10	100.00	1	5000.00	12	5、6、8、9、11、12、13、14、15、17	100.00	1	5000.00
13	2、4、5、7、8、10、13、14、15、16...	100.00	1	5065.92	14	1、4、6、7、9、11、13、14、15、16	100.00	1	5000.00
15	2、3、6、7、8、9、12、18	100.00	2	5104.33	16	1、3、6、7、8、11、13、16、17、18	100.00	1	5000.00
17	3、7、9、10、11、12、15、16	100.00	1	5103.17	18	3、4、5、7、8、9、11、14、16、18	100.00	1	5000.00
19	3、5、7、8、9、11、12、16、17	100.00	1	5000.00	20	2、5、6、7、8、11、13、15、17	100.00	1	5000.00
21	6、7、8、9、11、15	62.50	32	5505.21	22	10、11、12、16、17、18	100.00	4	5287.31
23	4、5、14、16、17、18	50.00	20	5205.60	24	1、3、10、13、17	50.00	10	5111.92
25	2、5、8、9、10、15、17	100.00	1	5000.00	26	5、7、8、9、11、14、15、16	100.00	1	5000.00
27	1、2、8、11、14、15、16、17、18	100.00	1	5000.00	28	1、4、6、8、14、15	71.43	7	5242.55
29	1、4、5、11、16、17	80.00	10	5247.50	30	1、2、9、16、17	100.00	1	5000.00
31	1、3、5、6、10、17	100.00	1	5000.00	32	6、10、13、15、17、18	50.00	8	5462.16
33	1、6、7、9、14、17	100.00	1	5000.00	34	13、14、15、16、17	51.22	41	5111.31
35	8、9、10、11、15、17	100.00	1	5103.17	36	3、5、6、7、8、10、11、12、13、18	100.00	1	5000.00
37	2、3、4、8、14、16、17	57.14	28	5157.89	38	1、3、4、5、6、8、14、16、18	100.00	1	5000.00
39	5、6、9、10、14、16、17、18	100.00	1	5000.00	40	2、3、11、12、14、18	53.33	15	5360.19
41	2、5、6、8、12、16	100.00	1	5000.00	42	1、6、7、9、10、11	100.00	1	5000.00
43	1、3、4、6、8、11、12	100.00	1	5000.00	44	2、5、6、8、9、14、17	100.00	1	5000.00
45	5、7、11、13、15	57.14	7	5110.40	46	2、5、9、10、11、13、14、16、18	100.00	1	5000.00
47	1、5、6、7、9、13、18	100.00	1	5000.00	48	4、5、6、7、8、12、13、17、18	100.00	1	5000.00
49	1、2、4、6、8	52.63	19	4890.80	50	1、2、3、5、6、9、12、13、16、18	100.00	1	5000.00

Fig. 3. Index portfolio held by 50 agents

Every agent organizes their own strategy. Based on XCS dynamic learning and auction mechanisms, the agents then propose individual predictions regarding the next trading day. The forecasts of all 50 agents are represented as the red and green cross-outs in Fig. 3, which indicate up and down trends, respectively.

The predictions from 50 agents are summarized afterwards. The dynamic learning XCS model adopts the suggestion predicted by most agents. Average accuracy of agents with same opinion is also calculated respectively as a reference for system users.

C. Knowledge refinement neural network

As mentioned earlier, only strategies with μ >0.8 are put in the premium strategy library. Once the strategies, or index composition, are listed in this library, they are the input factors of the knowledge refinement neural network module. As the number of indices of a strategy may vary from one to 18, the number of input neurons also varies accordingly.

During the XCS training session of this study, 25 strategies are collected in the premium library. In other words, 25 neural networks are trained to offer better quality forecasts. The NN model also adopts the suggestion predicted by most networks.

D. Trading mechanism

This study performs futures transactions based on the XCS/NN module forecasts. If five long signals are identified, the agent makes five purchases. The agents of the proposed system conclude their decision and compare it with the outcome of the neural network module. If XCS and NN have the same trend forecast, the system acts accordingly. Otherwise the system holds. Block E illustrates the summarized trading suggestion.

Owing to the frequent and sharp fluctuations of Taiwan securities market, it is important to consider the use of stop losses as a means of controlling losses. This study sets the following assumptions for profit/loss computation:

1. Targets bought are compared with their lowest prices of that trading day. If the difference between buying price and lowest price exceeds 1% of the lowest price, the target should be sold to take loss. That is, the maximum loss of targets bought in each trading day is 1% of the lowest price.
2. Targets sold are compared with their highest prices of that trading day. If the difference between selling price and highest price exceeds 1% of the highest price, the

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target should be bought back. That is, the maximum loss of targets sold in each trading day is 1% of the highest price.

V. System performance evaluation

A. Comparison with control models

Table 1
RULES OF CONTROL MODELS

Condition	Action
Closing Price > Long-term Average Price	Buy
Closing Volume > Long-term Average Volume	Buy
Closing Price < Long-term Average Price	Sell
Closing Volume < Long-term Average Volume	Sell

Fig.5. Performance chart of single factor XCS (closing price and long-term average price) in the testing period

Fig.6. Performance chart of single factor XCS (closing volume and long-term average volume) in the testing period

Previous works have shown that higher profitability can be achieved using a combination of multiple indices of technical analysis [6]. A comparison is made to evaluate the performance difference among the proposed system, a previous multi-agent XCS model, and simple rule-based models. This comparison chose closing price, long-term (22-day) average price, closing volume and long-term (40-day) average volume as the factors used in the control models. Table 1 lists the trading rules for these models. The performances of these two single rule models are illustrated in Fig.5 and Fig.6.

In Table 2, the performance of the proposed system and other models are evaluated in terms of cumulative profitability, rate of accuracy in buying, and rate of accuracy in selling. The system proposed here shows remarkable performance superior to rule-based models and the multi-agent XCS in terms of profitability.

Fig.7 and 8 shows the performance chart of the proposed model. The Japanese candles (also called Elliot waves) represent daily quotes. Moreover, the green solid line represents realized profit/loss. In comparison to the control group, the proposed model has the following features:

- No significant loss occurs in the initial execution.
- The overall gain/loss pattern is relatively stable.

Hence the profit and return of the proposed system is relatively stable compared to the other models.

Fig.7 Performance chart of multi-agent XCS module in the testing period

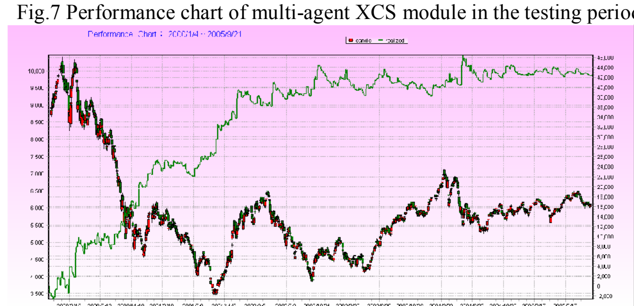
Fig.8. Performance chart of the knowledge refinement neural network module in the testing period

Table 2
PERFORMANCE OF DIFFERENT INVESTMENT STRATEGIES

	Cumulative profitability	Rate of accuracy in buying	Rate of accuracy in selling	Rank of profitability
Proposed group knowledge refinement learning model	943.40%	50.24%	45.85%	1
Multi-agent XCS (cooperative learning)	312.82%	44.76%	34.59%	2
Rule-based decision making (closing price and long-term average price)	236.97%	24.14%	18.87%	3
Rule-based decision making (closing volume and long-term average volume)	128.78%	35.45%	26.46%	4
Buy & Hold	-533.33%			6
Time deposit (at rate of loan interest)	47.54%			5

B. Summary

The TaiEX was 8756 points at the start of the testing period (January 4, 2000), compared to 6056 points at the end of testing period (September 21, 2005). During this fluctuant period, the performance listing, in a descending order, is the proposed group knowledge refinement model, cooperative learning multi-agent XCS model, rule-based model regarding price indices, rule-based model regarding volume indices, term deposit, and lastly buy and hold policy. The buy and hold strategy caused severe losses. Table 5

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compares the results achieved using various investment strategies.

The group knowledge refinement learning model outperforms our previous work of multi-agent XCS and of course the individual learning XCS as well in terms of cumulative profitability, accuracy in buying, and accuracy in selling. Hence in the given training and testing period, the refinement and enhancement of knowledge learning via the cooperation of XCS and neural network has shown the ability in better prediction which leads to its remarkable profitability. Needless to say, both models have better performance than other rule-based models, term deposit and buy and hold strategy. The system proposed in this study brings investors good rewards while keeping the risk at a reasonable level.

VI. CONCLUSION

Technical analysis in stock market is frequently used for devising short-term stock market investment strategy. Therefore, this study focused on the dynamic essence of securities markets, and proposed a system capable of dealing with this issue. A knowledge refinement learning model was proposed and empirical work was performed that supports our primary idea. The proposed system is a combination of Wilson's XCS and neural network. This system includes mechanisms such as group decision making and cooperative learning. Knowledge, or investment strategy with better performance, was first retrieved from the cooperative learning of 50 agents. These agents shared better strategies and applied group decision making to summarize their respective strategies to produce a simple majority decision. Those strategies collected in the premium library were further enhanced using the second stage training. Each strategy was separately trained to maintain its independence. The forecast made by the neural network module is considered the same as a professional offering his expertise. Other agents may also form their personal opinions and see if there is consensus.

Empirical work was conducted to analyze the system performance. This study showed that when considering the trading charge deduction and loss stop mechanism, the proposed system achieved remarkable performance compared with other control models in terms of rate of accuracy in buying/selling, cumulative rate of return, and fluctuation of ROI. This group knowledge refinement learning model is shown to be a practical tool for supporting investment decisions.

In the future, there are issues which can be addressed and further improved to enhance this proposed system. First, the condition handling must be performed when the XCS and NN forecasts conflict with each other. Although the case of unresolved conflict did not happen in our study, such mechanism may further improve system performance. Secondly the number of agents was fixed in the current setting. We are working on a more dynamic model. Lastly, the neural network module can be designed in a more delicate manner which may lead to better learning consequences.

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