Decision-making Model Using XCS in Artificial Market

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***Abstract*—This paper proposes a decision-making model using XCS in the artificial market to analyze an uncertain price fluctuation. We report the price fluctuation created by the interaction of agents using that decision-making models. The revealed the following remarkable implications: (1) the decision-making model using XCS is necessary more than eight ways (action size 3 bits) by action selection to represent the dynamics of price fluctuations in state size 4 bits of XCS; and (2) The increase of the action selection indicates the effect of low market price in big dynamic phenomena.**

I. Introduction

An artificial market is a simulator of the economic system creating phenomena by the interaction of individual autonomic agents [1]. Since Arthur et al. proposed artificial market in the stock market [2] [3], these study develop the artificial markets such as the continuous double-auction market and the financial markets, the emissions trading of carbon dioxide [4] [5] [6].

The autonomic agent is built in a decision-making model with adaptation and the learning by the development of the computer science. How do you build a decision-making model with adaptation and the learning? Arthur defined "Know" and "Learning" of human behavior as "Recognize data from environment" and "Update the data" of model [2]. A learning classification system and genetic algorithm, the reinforcement learning are used as a function of the decision-making model based on this idea.

The previous study proposed a decision-making model using ZCS which is one of the learning classification systems [4]. However, the decision-making model in the artificial market is not discussed enough. In addition, ZCS and XCS indicate a combination of state and action using strings of 0, 1 and $\sharp$ ($\sharp$: only state). Since two methods are different function and update rules, we can not predict an output result by the interaction of individual agents. We can suggest the decision-making model of the agent, but the output result is the uncertain situation.

This paper proposes a decision-making model using XCS [7] which is one of the learning classification systems. In particular, this paper focuses on the number of action selection (action bits) in artificial market. We investigate an output result of market price and a function of XCS based on the action selection.

The rest of the paper is organized as follows. In section 2, XCS as a decision-making model is explained, Experiment results reported in section 3, and are discussed in section 4. Our conclusions are presented in section 5.

[1]This study is called the Agent-based computational economics [1]

II. Decision-making model using XCS

A. XCS

XCS is a learning classifier system using a genetic algorithm and reinforcement learning showing the action based on an input state from Environment [7] [8]. This paper explains brief structure of XCS in Fig. 1. This structure is a system with the input and output to perform in the next procedure.

1) Detectors perceive an information in environmental, and convert information into binary number. In this paper, we define this part in the next section in detail.
2) Population [P] contains the classifier population including state and action of binary number, predictions, predictions err, fitnesses. This population means the set of the rule.
3) Match Set [M] take some matched binary number of detectors from Population [P].
4) If it does not match the classifier population (rule), covering makes a new rule based on binary number of detectors.
5) Prediction Array calculates average of prediction based on the same action of binary number. The maximum prediction uses for the update of the rule and action select.
6) Action Set [A] take out a maximum of the prediction as an action of binary number.
7) Effectors converts action of binary number into a presented information in the environment. In this paper, we define this part in the next section in detail.
8) When the action succeed in environment, the reward feeds back in XCS from environment.
9) Update renew the predictions, predictions err, fitnesses based on the maximum prediction and the reward.
10) Previous Action $[A]_{-1}$ renew the classifier population based on Update.

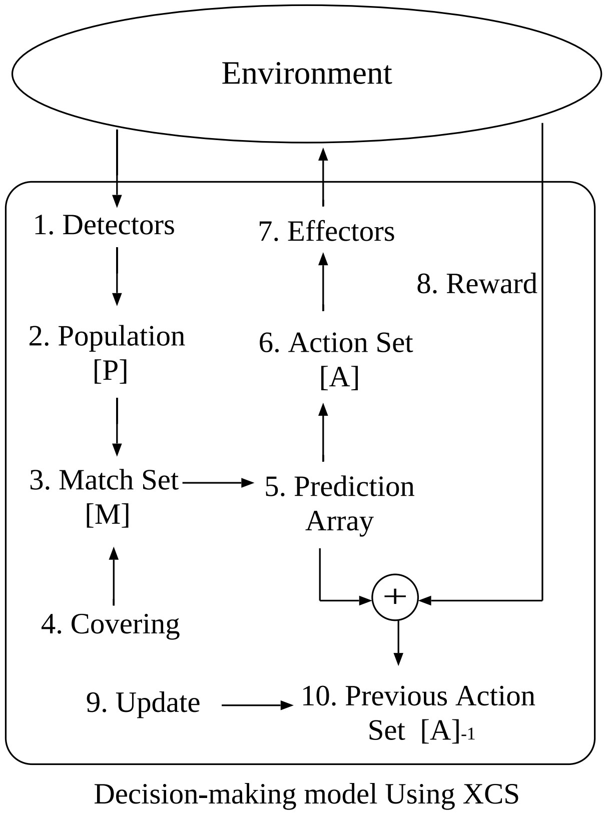

Fig. 1. Structure of XCS: that shows a brief decision-making sequence 1-10.

For more information, other paper explain the detail structure of XCS [9] [10]. Various methods of XCS are suggested and improved. But this paper uses basic XCS as decision-making model.

B. Decision-making model

This paper shows a figure of summary of the agent using XCS in Fig. 2, The individual agents hold one XCS and get a different rule to get a reward in the trading market. The agent shows an action based on state (information) from environment (Trading market). The market price indicates a result of interaction of individual agents.

In the real world and artificial market, a market price indicates a real number. However, XCS design indicates state and action in several bits. In artificial market, it is necessary to argue how you design the input (Detectors) and output (Effectors) of individual agents. To discusses market price fluctuation and population size of XCS, this paper proposes a detectors (State) and effectors (Action) design of XCS in Fig. 3. In this paper, the state fixes four bits. The action defines the designs from one bit to four bits for a comparison experiment.

1) Design of State: The detectors of XCS converts a price of trading market (environment) into binary number. Since this paper sets the action of the agent with 200 from 50, this paper sets the state division into 16 between 50 and 200. This paper defines the relationship between the price and state 4 bits of binary number as follows.

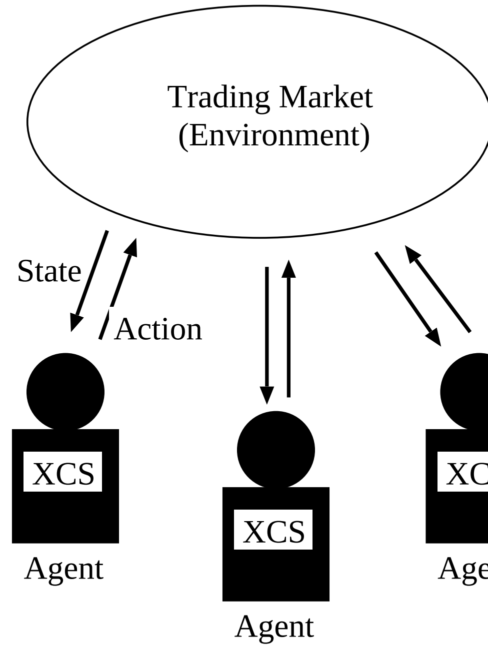

Fig. 2. Trading Market and Agents in XCS

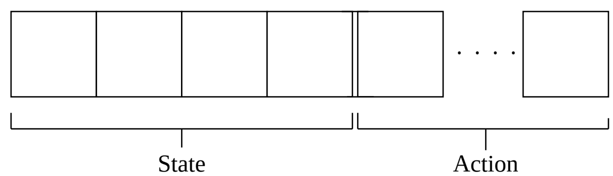

Fig. 3. State-Action Design

2) Design of 1 bit Action: The effectors of XCS converts the binary number into a bid price (or offer price) of agent. In effectors, 1 bit action indicates the buying ”0” and selling ”1” in Table II. To calculate the value of the trading price, buying price and selling price is defined.

3) Design of 2 bits Action: The effectors of XCS converts the binary number into a bid price (or offer price) of agent. In effectors, 1 bit action indicates the buying ”0” and selling ”1”. Another bit converts the high price and low price. For example, low price is 50, and high price is 200.

Price	State 4 bits	Price	State 4 bits
200 – 190	0000	119 – 110	1000
189 – 180	0001	109 – 100	1001
179 – 170	0010	99 – 90	1010
169 – 160	0011	89 – 80	1011
159 – 150	0100	79 – 70	1100
149 – 140	0101	69 – 60	1101
139 – 130	0110	59 – 50	1110
129 – 120	0111	49 – 40	1111

TABLE I
DESIGN OF STATE

Action 1 bit	Action	Price
0	Buying	50
1	Selling	200

TABLE II
DESIGN OF 1 BIT ACTION

Action 2 bits	Action	Price	Action 2 bits	Action	Price
00	Buying	50	10	Selling	50
01	Buying	200	11	Selling	200

TABLE III
DESIGN OF 2 BITS ACTION

4) Design of 3 bits Action: In effectors, state of XCS is converted to four bits based on price information from the environment. In effectors, action of XCS indicates a total of three bits (1 bit is the buying "0" and selling "1", two bits convert four price). Since the price action of buying and selling sets two bits, the agent selects the price of 50, 100, 150, 200.

Action 3 bits	Action	Price	Action 4 bits	Action	Price
000	Buying	50	100	Selling	50
001	Buying	100	101	Selling	100
010	Buying	150	110	Selling	150
011	Buying	200	111	Selling	200

TABLE IV
DESIGN OF 3 BITS ACTION

5) Design of 4bit Action: In effectors, state of XCS is converted to four bits based on price information from the environment. In effectors, action of XCS indicates a total of three bits (1 bit is the buying "0" and selling "1", two bits convert four price). Since the price action of buying and selling sets two bits, the agent selects the price as follows.

Action 4 bits	Action	Price	Action 4 bits	Action	Price
0000	Buying	50	1000	Selling	50
0001	Buying	70	1001	Selling	70
0010	Buying	100	1010	Selling	100
0011	Buying	120	1011	Selling	120
0100	Buying	140	1100	Selling	140
0101	Buying	160	1101	Selling	160
0110	Buying	180	1110	Selling	180
0111	Buying	200	1111	Selling	200

TABLE V
DESIGN OF 4BIT ACTION

6) Design of Reward: The reward gives to the agent who traded buy and sell. The individual agents compare the trading price of the artificial market with own price as follows.

$$Reward = \begin{cases} TradingP - PriceAagent & \text{if supply} \\ PriceAagent - TradingP & \text{if demand} \end{cases} \quad (1)$$

In the above equation, TradingP indicates trading price in market, PriceAagent indicates selected price of buying or selling based on agent using XCS.

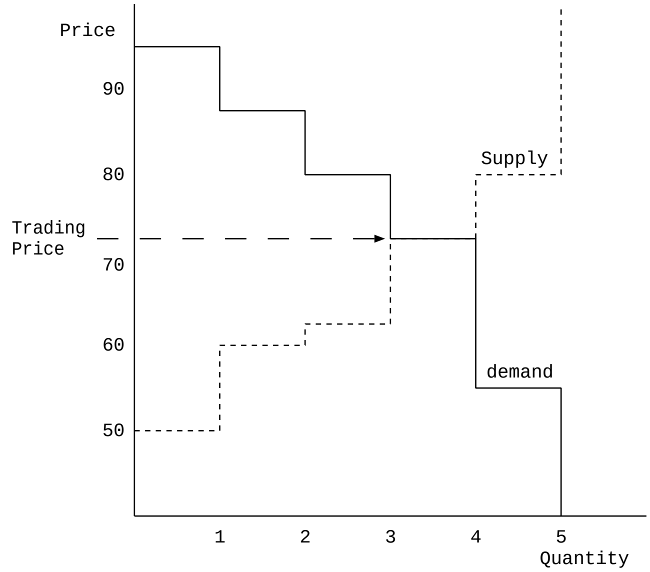

Fig. 4. Trial and size of [P]: the average population [P] of six agents using XCS decreases by trial

C. Market design

This paper use the model of double auction market [11]. An individual agents present selling price and buying price. When buying price exceeds selling price, a trading price is decided like Fig. 4. Trading price determined as follows:

$$TradingP = \begin{cases} \frac{BuyP+SellP}{2} & \text{if BuyP} > \text{SellP} \\ 0 & otherwise \end{cases} \quad (2)$$

In the above equation, TradingP indicates trading price in market, BuyP indicates buying price of agents, SellP indicates selling price of agents.

III. EXPERIMENT

A. Setting

The parameters set to agent usig XCS as follows. The number of agents: 6, the number of dealing trial: 98, the size of state: 4bits, the size of action: variableness from 1bit to 4bits, the other parameters set table VI in the same way as the previous paper [9]. We conducted ten simulations under these parameters, and we calculated the average of size of population [P] and market price.

B. Experiment Result

Figures 5 and 6 show the average size of population [P] of XCS in all agents and the market price by the interaction of individual agents. In Fig. 5, population of XCS decreases by the function of the macroclassifiers (numerosity). Four results show the stability (Number of trial: 68 - 98) of the rule set of the state and action using a reinforcement learning function. Fig. 6 shows market price of the period from 60 to 98 in Fig. 5. Market price of action size 1 and 2 bits are uniformity of 125 (Note: two lines overlap). Market price of action size 3

Parameter	Value
Population size N	400
Learning rate β	0.2
Discount factor γ	0.71
Threshold of GA θ_{GA}	50
Probability of crossover per invocation of the GA X	0.8
Probability of mutation per allele in an offspring μ	0.03
Value of the fraction used in the second deletion δ	0.1
Probability of a $\sharp$ at an allele position in the condition $P_\sharp$	0.33
Prediction in the initial population P_I	10
Prediction error in the initial population ϵ_I	0.0
Fitness in the initial population F_I	0.01

TABLE VI
MAIN PARAMETERS OF XCS

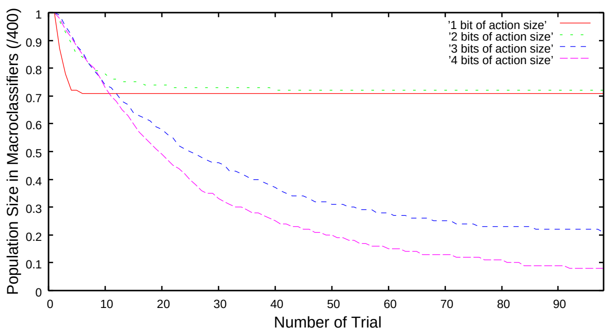

Fig. 5. Trial and size of [P]: the average population [P] of six agents using XCS decreases by trial

bits fluctuated around 120, and showed a small upward trend and a small downward trend. Market price of action size 4 bits fluctuated around 100, and showed a big upward trend and a big downward trend.

Figure 7 shows the relationship between stable time and stability of population size based on the action bits from 1 bit to 4 bits. The stability of population size is inversely proportional to the action bits, the stable time is proportional to the action bits. Each graph change the stable time and stability of population size by increasing the number of the action choice.

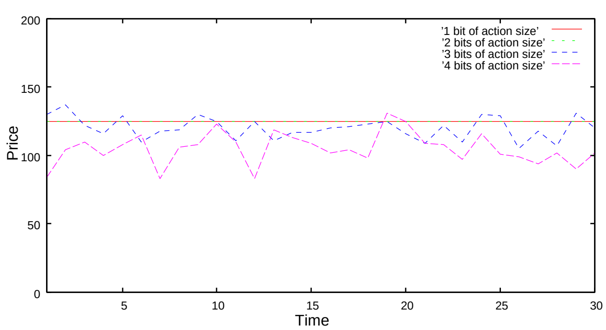

Fig. 6. Price of market: the market price fluctuated by the interaction of six agents using XCS

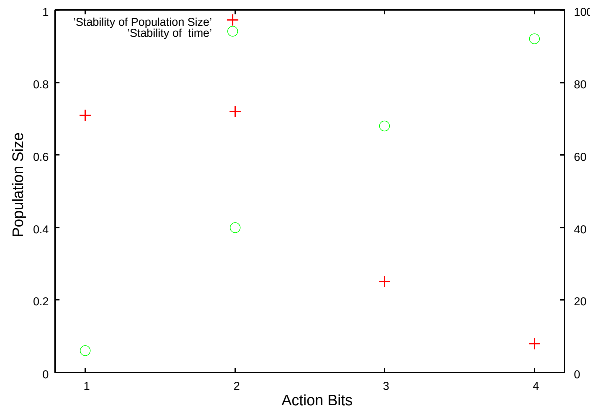

Fig. 7. Relationship between time and population size based on the action bits from 1 bit to 4 bits

IV. DISCUSSION

This paper showed the simulation results of homosexual agent using XCS. Figures 5 stabilize the average population, the design of 1 and 2 action bits are stability of market price in Fig. 6. However, the design of 3 and 4 action bits are fluctuation of market price in Fig. 6. From these results, the decision making model using XCS is necessary more than eight ways (3 bits) by action selection to represent the dynamics of price fluctuations.

The design of 1 bit and 2 bits have different settings. However, the design of 2 bits works the function of reinforcement learning to increase the reward, it converges into a design of 1 bit. The action selects of 2 bits has four ways in table III . To succeed the trading price, the action must select the design of 1 bit. Since Figures 5 and 6 had a similar simulation results, we think the effect of action design and the function of reinforcement learning in XCS. Therefore, it is important to design the action bits.

In addition, the average of the price fluctuation falls down as action bits (action selection) increase in Fig. 6. It shows big market price fluctuation. Many action selection of agent makes the dynamic phenomena.

In Fig. 7, the design of the different action bit affected stable time and converged population size. Since XCS has a function of the reinforcement learning [12], it takes time until stability by increase of the action selection. The agent gets individual learning and adaptation by this function, and the agent selects buyers (bid) and sellers (offer) in artificial market. Since the stability of population size is inversely proportional to the action bits, a subsumption of XCS is functioning by long action bits. From these experiments, the decision-making model using XCS needs a combination of 4 bits state and 3 bit action at a minimum.

We compare the experimental results with previous study [4]. The market price of previous experiment is big fluctuation using 2 bits action of ZCS. The market price of this experiment is stability using 2 bits action of XCS. Since the different decision-making models and the different action bits show different market prices, the function of the decision-making model and the design of the action bit are important.

V. Conclusion

This paper proposed a decision-making model using XCS to analyze an uncertain price fluctuation. Our investigation compared the population size and the price fluctuation by the action selection (from 1 bit action size to 4 bits action size). The revealed the following remarkable implications: (1) the decision-making model using XCS is necessary more than eight ways (action size 3 bits) by action selection to represent the dynamics of price fluctuations in state size 4 bits of XCS; and (2) The increase of the action selection indicates the effect of low market price in big dynamic phenomena.

This paper assumed the human behavior in the artificial market. However, this paper does not investigate to compare the individual human behavior with decision-making model of XCS. It is important to utilize the function of XCS in artificial market. The following issues should be pursued in the near future: (1) an investigation of guideline of the design detail decision-making model of XCS artificial market; and (2) using this decision-making model, we will investigate a phenomenon of the market price in future.

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