Social Simulation for Analyzing Product Recall Systems Using Co-evolution Model Considering Consumers' Diverse Monetary Sense

Tetsuroh Watanabe, Taro Kanno, and Kazuo Furuta

***Abstract*—In recent years, accidents and product recalls caused by product defects have become major problems in numerous industries worldwide. However, most of existing research studying product recalls adopted empirical approaches. To improve product recall systems, we studied social simulation using a multi-agent system with co-evolution model. This research is important, because empirical approaches are no longer adequate for the complex and diverse modern society. Discussions using quantitative and predictive approaches, including agent-based simulation, are therefore expected. In this study, we propose a new model: Money Importance Factor, for considering consumers' diverse monetary sense. We conducted a simulation experiment, and we discovered the possibility that consumers are willing to buy more expensive and higher-quality products for preventing product accidents, when the products have a large risk of accidents apparently from their attributes. In addition, we have also found that it is important to make an impression or a recognition of product recalls better through improving social systems. We believe this work can contribute to supporting not only government staffs for improving product recall systems, but also executive officers of product companies for deliberating their strategy of recall decisions.**

***Index Terms*—Evolutionary computation, human modeling, multi-agent simulation, multi-objective optimization.**

I. Introduction

In recent years, accidents and product recalls caused by product defects have become major problems in numerous industries worldwide (*e.g.* [1]). Appropriate executions of product recalls are required for keeping the society safe.

Judgment whether or not to conduct product recalls are up to producers in many industries and countries [2]. Therefore, it is important to consider decision-makings by producers and their consumers related to product recalls for improving product recall systems.

Some studies about product recall have been done from a viewpoint of a relationships between product producers and consumers [3] [4] or a viewpoint of an economic aspect [5] [6]. However, most existing studies adopted empirical approaches, *i.e.* based only on facts revealed by case studies or social survey. It can be said that an empirical approach is no longer adequate for complex and diverse modern society. Hence discussions using a quantitative and predictive approach that can predict future events is expected.

As a quantitative and predictive approach, we have proposed and developed a fundamental social simulation model about product recall systems using a multi-agent system [7]. To reflect the real society and achieve effective learning of agents' decision-making, a co-evolution model and an evolutionary computation methodology with producer agents and consumer agents are employed. It was demonstrated that the proposed model was useful for predicting what will happen if various design variables of a recall system are changed.

However, the major shortcoming with the previous study was that there is no consideration about consumers' monetary sense. With respect to modeling the real society, including living humans in particular, it is important to consider cognitive or psychological aspects. Many psychologists have pointed out the difference in people's perception of monetary value [8]–[11]. Consideration of monetary sense is strongly required for improving accuracy of the simulation.

To tackle this problem, the aim of this paper is to introduce a perception model of monetary value into the simulation model, and analyze behaviors of producers and consumers under various consumers' monetary sense. In this study, we propose a new model: *Money Importance Factor* of consumer agents, for implementing diverse monetary sense. Then, we analyze the distribution of agents and transition of agents' evolution, and then obtain suggestions for improving product recall systems in the real world.

II. Simulation Model

A. Assumed category of products

Producer agents sell products and consumer agents buy and use them. In this study, any specific category of products is not supposed, but it is assumed that many producers sell products of the same category and similar specs with various prices. Products are also assumed to possibly cause serious accidents. Home electronics and motor vehicles are typical examples of this class.

B. Co-evolution Model

In the simulation model, *Genetic Programming (GP)* [12] and *the co-evolution model* [13] are applied together as a learning model for producers and consumers. Here, *Layered Co-evolution Model*, an overview of which is shown in Fig. 1, is a unique simulation model adopted in this work.

There are two types of agents in the artificial society in the simulation environment: *producer agents* and *consumer*

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agents, as shown in Fig. 1. Producer agents on the upper layer have their *users* (consumer agents) on the lower layer, and each consumer agent belongs to the *user group* of a certain producer agent. These two types of agents evolve separately for their own convenience, *i.e.* co-evolution.

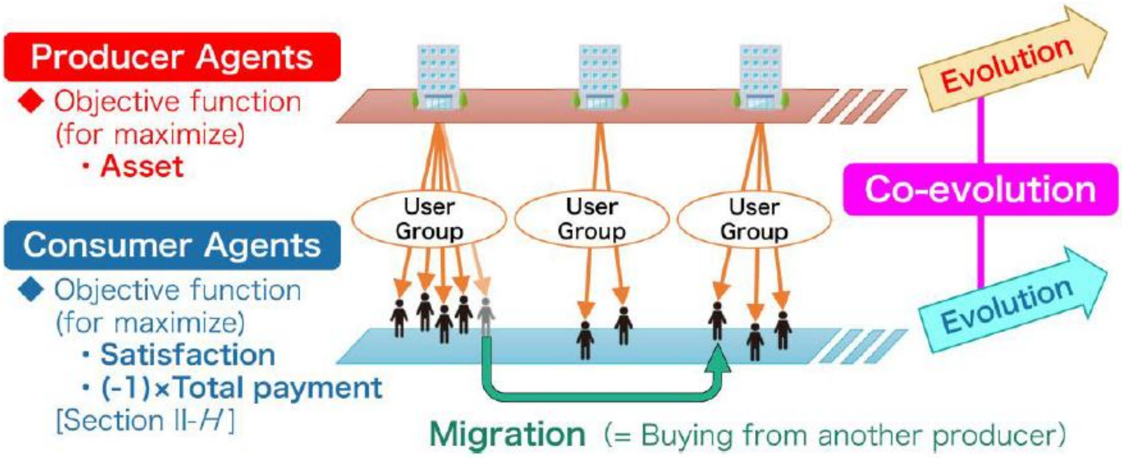

Fig. 1. Overview of Layered Co-Evolution Model. Each consumer agent belongs to the user group of a certain producer agent, and consumer agents can move to the user group of another producer agent: migration.

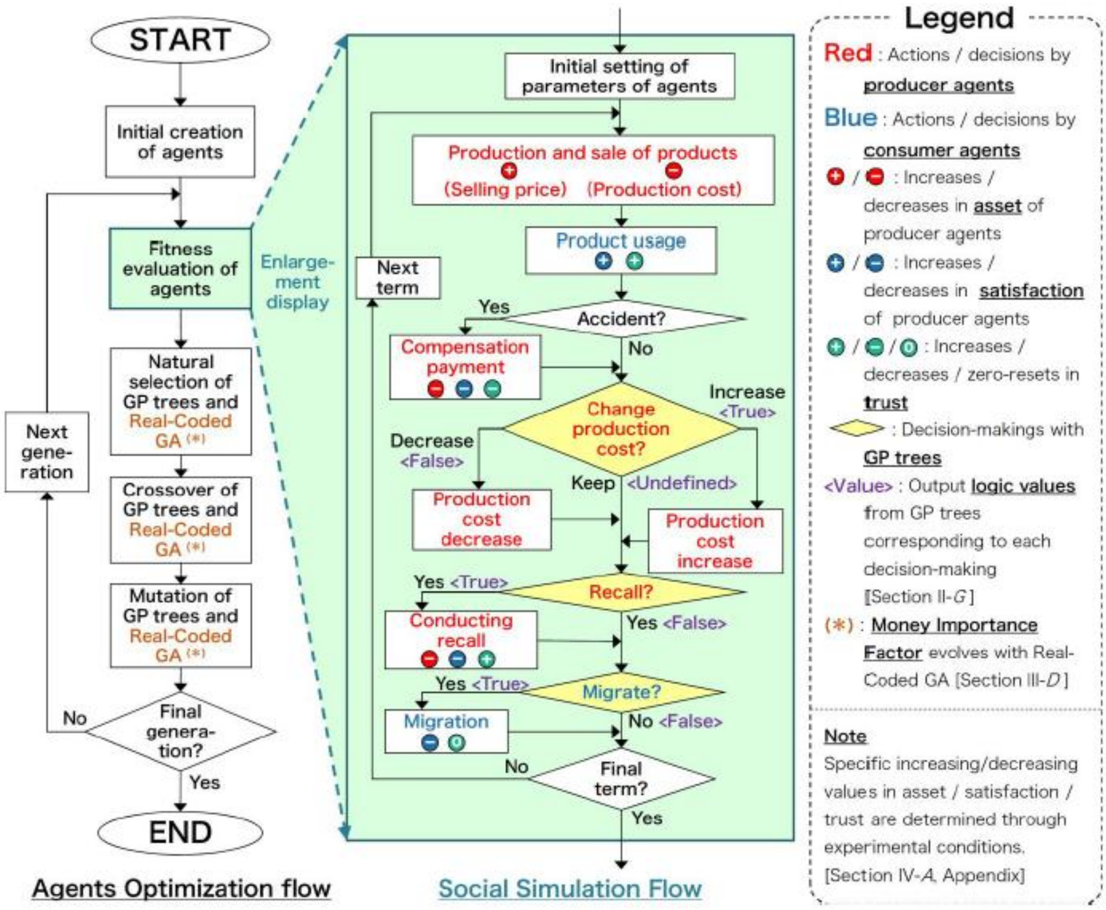

Fig. 2. Simulation flow chart. the simulation flow consists of two parts: Agent optimization flow and social simulation flow, and social simulation flow is the internal loop within agent optimization flow.

Consumer agents can move to the user group of another producer agent. In this paper, we call this action *migration*. The destination producer of migration is chosen probabilistically (as described in Section III-*C*). It is important for producer agents not only to keep royal customers but also increase the probability of being chosen in migration.

There are some existing researches of real-product marketing simulations based on a multi-agent system [14]–[16]. However, either producer agents or consumer agents can move and learn in these studies. Layered Co-Evolution Model has an advantage of enabling both producer agents and consumer agents to take actions and evolve in parallel.

C. Simulation Flow

The simulation flow of this study is described in Fig. 2. The simulation flow consists of two parts: *Agent*

Optimization Flow and *Social Simulation Flow*, and Social Simulation Flow is the internal loop within Agent Optimization Flow. Agent Optimization Flow is similar to the ordinary Genetic Algorithm (GA), promoting agents' learning process toward the direction that agents can optimize the value of fitness function. Social Simulation Flow is the phase where agents take actions and events occur in a time interval, called a term. We abstract factors relevant for discussing product recalls according to the existing studies [3]–[6], and add actions of agents and events into Social Simulation Flow. At the end of Social Simulation Flow, the fitness values evaluated for all agents are fed back to Agent Optimization Flow.

Each producer agent has *asset* and each consumer agent has *satisfaction* as their own parameters. The parameter values increase or decrease at the points marked + and – in Fig. 2. In regard to satisfaction, we assume consumers' satisfaction is obtained just by using products and satisfaction of other origins is beyond the scope of this paper.

As for producer agents, asset is the fitness function of producer agents, and used for Roulette Selection in the natural selection. In other words, the probability that producer agent p is selected p in the natural selection is proportional to p's asset. If p goes bankrupt, p's asset is evaluated as zero. Selected producer agents are duplicated, and put into the population of the next generation.

As for consumer agents, satisfaction is one of the fitness functions in company with the amount of payment and used in the natural selection (as described in Section II-*H*).

In addition, each product has its lifetime ℓ. In this paper, ℓ is totally fixed as 12 terms. When a consumer agent uses a product through ℓ continuously, he/she has to buy a new product from the current producer even if he/she does not migrate.

Concrete actual data of the real society are not employed into the simulation, because it is unrealistic to obtain detail monetary or strategy data of numerous producers and consumers in the real world. In other words, artificial data are employed in this simulation, *i.e.*, initial parameters of agents are given as experimental conditions that are fixed before starting. The conditions are determined through preliminary experiments, with a view to avoiding poor conditions for completing the simulation (*e.g.* conditions under which all producer agents go bankrupt), and concrete conditions are described at Section IV-*A*-1 and Appendix. In addition, all strategies of agents are generated randomly as GP trees at the first step of the simulation, and the GP trees evolve through Agent Optimization Flow.

D. Trust and Total Trust

Each consumer agent has *Trust* as a parameter value. Trust means the degree of his/her confidence in the producer agent whose product he/she uses. Trust values increase, decrease, or is reset to zero at the points marked +, −, and 0 in Fig. 2.

In this connection, each producer agent has *Total Trust* as a parameter. Total Trust is the summation of users' trust values, and producer agent p's Total Trust $(Trust_p)$ is formulated as follows:

$$Trust_p = \sum_{c \in S_p} trust_c \tag{1}$$

where S_p is the user group of p, and $trust_c$ is a trust value of consumer agent c (user of p).

Total Trust reflects the reputation or word-of-mouth of a producer in the real world. Larger Total Trust results in a larger probability of being chosen in migration (as described in Section III-*B*).

E. Accident Probability Model

Accident probability of products varies from producer agent to producer agent. Producer agent p has the probability of causing a product accident (λ_p) calculated as follows:

$$\lambda_p = \frac{\beta}{Cost_p} \cdot \gamma^{Recall_p} \tag{2}$$

where β and γ are constants assigned as experimental conditions ($\beta > 0$, $0 < \gamma < 1$), $Cost_p$ is the production cost of p ($Cost_p > 0$), and $Recall_p$ is the accumulated times of product recalls by p ($Recall_p \geq 0$).

Producer agents can reduce their accident probability by raising their production cost or conducting product recalls, through their decision-makings with GP tree. Eq. (2) reflects the real world's situation that producers can improve the reliability of their products by increasing production cost or carrying out product recalls.

F. Fixed Cost Rate

To introduce a variable price model into the simulation model, it is assumed that the *cost rate* is fixed constant. Producer agent p can change their production cost $(Cost_p)$ following GP tree output, and the selling price $(Price_p)$ will be changed also in parallel as follows:

$$Price_p = \frac{Cost_p}{R} \tag{3}$$

where R is the fixed cost rate assigned as an experimental condition ($0 < R < 1$).

G. Logic Value Typed GP

All of agents respectively decide how they act at the yellow box in Fig. 2. As for agents' decision-makings, we employ a proposed method: *Logic Value Typed GP*, extended method from Booleanized GP [17]–[19].

Agent has its own GP tree. Each parameter value of each agent is converted into logic values by comparing the value at the current term (v_{now}) with the previous term (v_{prev}) as follows:

$$LV_2 = \begin{cases} \text{True} & (\text{if } \delta \geq 0) \\ \text{False} & (\text{if } \delta < 0) \end{cases} \tag{4}$$

$$LV_3 = \begin{cases} \text{True} & (\text{if } \delta > dm) \\ \text{Undefined} & (\text{if } |\delta| \leq dm) \\ \text{False} & (\text{if } \delta < -dm) \end{cases} \tag{5}$$

$$\delta = v_{\text{now}} - v_{\text{prev}} \tag{6}$$

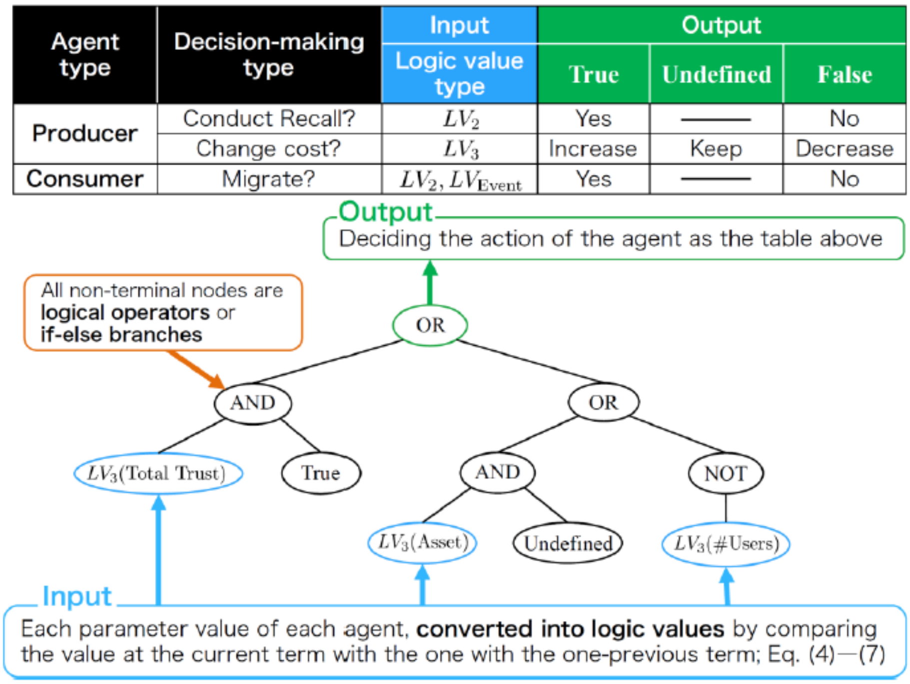

Fig. 3. Overview of logic value typed GP with an example of GP tree.

TABLE I: SUMMARY OF ACTIONS DECIDED BY GP TREES/GA GENES AND EVOLUTIONARY COMPUTATION METHODS

Agent type	Actions decided by GP trees/GA genes	Evolutionary computation methods			
		Gene type	**Crossover**	**Mutation**	**Natural selection**
Producer	Whether or not conduct recall	Logic Value Typed GP (Boolean)	One-edge-cut crossover	One-node mutation	Roulette Selection based on asset
	Change of production cost	Logic Value Typed GP (three logic value)	One-edge-cut crossover	One-node mutation	
Consumer	Whether or not migrate	Logic Value Typed GP (Boolean)	One-edge-cut crossover	One-node mutation	SPEA2 for maximizing two objective functions: 1. Satisfaction 2. $(-1) \times$ Total amount of payment
	Money Importance Factor	Real-Coded GA	BLX-α	Adding random value $\varepsilon \sim N(0, 0.5^2)$	

where LV_2 is the input logic value for decision-making with two options, LV_3 is the one with three options, Undefined is "the third logic value" in the three-valued logic theory [20]–[24], and dm is *Disregard Margin*, which is for avoiding instable fluctuations in the output $(dm \geq 0)$. Disregard Margin is assigned for each parameter type (*e.g.* asset) as an experimental condition.

In addition, one more type of logic value LV_{Event} is used in this method, as follows:

$$LV_{\mathrm{Event}} = \begin{cases} \text{True} & (\text{if the agent encounters an } event) \\ \text{False} & (\text{if the agent does not encounter an } event) \end{cases} \quad (7)$$

where *event* is what agents possibly encounter (*e.g.* product accident, product recall).

Logic values $LV_2, LV_3, LV_{\mathrm{Event}}$ are put into the terminal nodes of GP tree. The logic values are calculated by basic logical operators (AND, OR, NOT, IF-ELSE), and the output logic value, which determines the content of the decision-making, is finally obtained. The correspondence between decisions and the outputs from Logic Value Typed GP are described in Fig. 2 with <Value> format. Fig. 3 additionally shows an overview and an example of Logic Value Typed GP tree and corresponding decisions of agents.

We have discovered that Logic Value Typed GP has advantages over the existing GP method that uses real number values in the previous study [7]. The Logic Value Typed GP is more stable in the evolutionary process and more efficient in terms of agents' learning process in the simulation.

H. Multi-Objective Optimization on consumer agents with MOEA

Selling price of a product varies from producer to producer. It is therefore important to deal with not only satisfaction but also amounts of payment of consumer agents. To optimize both satisfaction and payment at the same time, we employ a *multi-objective evolutionary algorithm (MOEA)* into Agent optimization flow.

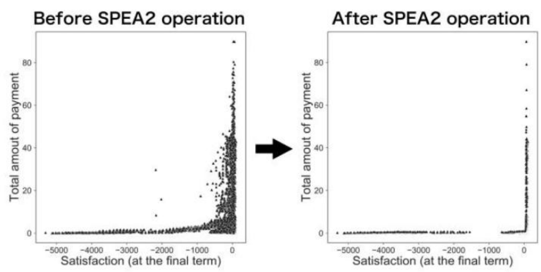

Fig. 4. Example of SPEA2 operation: distribution of consumer agents (satisfaction in x-axis v.s. Total amount of payment in y-axis. ParetoFront boundary is generated by SPEA2 operation.

For adopting MOEA, it is necessary to define the directions of optimization for both satisfaction [25]. In the real world, it is natural to consider that larger satisfaction and smaller payment are better for most consumers. We accordingly assign the objective functions for *maximization* on consumer agents as follows:

1. Satisfaction,
2. $(-1) \times$ Total amount of payment.

We adopt SPEA2 (Strength Pareto Evolutionary Algorithm 2) [26] for the multi-objective optimization on consumer agents. SPEA2 is one of leading MOEA, and can realize fine-grained fitness assignment to each individual. In principle of multi-objective optimization in this simulation, it is also available to use other MOEA, such as NSGA-II [27], MOEA/D [28], and NSGA-III [29]. Fig. 4 shows an example of SPEA2 operation in one of our simulation experiments. In this example, a Pareto Front boundary is generated toward the direction of maximizing satisfaction and minimizing payment.

III. Money Importance Factor

A. Differences in consumers' monetary sense

In the real society, it can be said that consumers choose what they will buy next considering not only the reputation of producers but also the selling price of products. In addition, the weight between reputation and price varies from person to person, for example:

- Some consumers give priority to a good reputation even if the price is expensive.
- Other consumers give priority to an inexpensive price even if the reputation is poor.

Many psychologists have pointed out the difference in people's perception of monetary value [8]–[11]. It is therefore important to consider consumers' diverse monetary sense in the simulation model for reflecting the real-world situation.

We propose a new model: *Money Importance Factor*, as a parameter of each consumer agent. Using Money Importance Factor, we install the diversity of consumer agents in choosing a new product for purchase.

B. Design policy of Money Importance Factor

Some indicators of people's monetary sense are proposed in existing studies, such as Money Attitudes Scale by Yamauchi *et al*. [8], Money Beliefs and Behavior Scale by Furnham *et al*. [10], Money Ethic Scale by Tang *et al*. [11]. However, these indicators are too complicated as a method for a multi-agent simulation. We consequently propose Money Importance Factor as a single metric for representing monetary sense simply.

In this respect, it is important to consider a tendency of thrift, because most of the existing indicators deal with the tendency. Hence, we design Money Importance Factor to consider a degree of thrift, which will differ from a consumer to another.

C. Money Importance Factor and Likability

Every consumer agent has his/her own Money Importance Factor value $m,\ 0 \le m \le 1$, and he/she evaluates *Likability* of each producer agent except the one whose user group he/she currently belongs to. Then consumer agents choose a producer agent as the destination of migration based on the evaluated Likability.

Likability c of producer agent p $\left(L_{p\leftarrow c}\right)$ evaluated by consumer agent c is calculated as follows:

$$\begin{aligned} L_{p\leftarrow c} &= m_c \cdot Scale\left(-Price_p\right) \\ &\quad + (1-m_c) \cdot Scale\left(Trust_p\right) \end{aligned} \tag{8}$$

$$Scale(x) = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

where m_c is Money Importance Factor of c, $Price_p$ is the selling price of p, $Trust_p$ is Total Trust of p. $Scale(\cdot)$ is the function that scales each parameter value of all agents into the range of [0, 1] using the maximum and the minimum parameter value of all the agents. At this point, we use $-Price_p$, minus value, because a lower selling price is more preferable from a consumers' viewpoint in the real society.

The probability of being chosen as the destination of migration from each consumer is determined by Roulette Selection based on Likability, calculated by Eq. (8). In other words, $P_{p_{\text{dest}}\leftarrow c}$, which is producer agent p_{dest}'s probability of being chosen from consumer agent c belonging to p_{from}'s user group, is proportional to $L_{p\leftarrow c}$, as follows:

$$P_{p_{\text{dest}}\leftarrow c} = \frac{L_{p_{\text{dest}}\leftarrow c}}{\sum_{i\in U^{\text{Pro}}\setminus\{p_{\text{from}}\}} L_{i\leftarrow c}} \tag{10}$$

where U^{Pro} is the universal set of producer agents.

Eq. (10) means that a higher Money Importance Factor has a greater influence of the selling price to Likability. In other words, the larger Money Importance Factor a consumer agent has, the higher priority he/she gives to a low selling price and the more likely he/she tries to reduce payment.

In this model, a larger Total Trust and a cheaper selling price lead to a higher Likability of a producer agent, *i.e.*, a higher probability of obtaining new users. It can be said that this model is appropriate, because it reasonable to think that most consumers in the real world prefer products of a good reputation or a low price.

D. Evolution of Money Importance Factor

In this paper, we apply *Real-Coded GA* to evolution of Money Importance Factor for consumer agents. Real-Coded GA, which is a type of Genetic Algorithm, does not employ binary array chromosome (e.g. *Gray Code* [30]), but directly manipulates real number values using evolutionary operation. This direct value manipulation provides a better efficiency than the binary array method [31]. The evolutionary operation: natural selection, crossover, mutation, of Real-Coded GA are conducted at the same time with the ones of GP tree, as shown in Fig. 2.

We employ BLX-α (blend crossover) [32] as the crossover method for Real-Coded GA. BLX-α generates a child individual from two parent individuals in the range between two parents, distance $= d$, and in the extended range on the both sides of two parents, each distance $= \alpha d$, using the uniform distribution. In this paper, the child individual is not generated outside of [0, 1] because Money Importance Factor is in [0, 1] as described in Section III-*C*. In summary, Money Importance Factor presented by the child individual (m_{Child}) generated from two parent individuals ($m_{\text{Parent1}}, m_{\text{Parent2}}$) as follows:

$$m_{\text{Child}} = u(\max(0, \min(m_{\text{Parent1}}, m_{\text{Parent2}}) - \alpha d), \min(0, \max(m_{\text{Parent1}}, m_{\text{Parent2}}) + \alpha d)) \tag{11}$$

$$d = |m_{\text{Parent1}} - m_{\text{Parent2}}| \tag{12}$$

where $u(x, y)$ is a random variable in a range of $[x, y]$. α is assigned as an experimental condition ($\alpha \geq 0$). Fig. 5 presents the probability density of a child's Money Importance Factor from two parents using BLX-α with Eq. (11) (12). In this connection, we adopted a mutation operator as adding a random variable $\varepsilon \sim N(0, 0.5^2)$ of the normal distribution.

It is reported that BLX-α has a weakness for multi-dimensional search because of variable dependencies. However, only one-dimensional search of Money Importance Factor is modeled here by BLX-α, and it is appropriate to employ BLX-α.

Table I summarizes the actions decided by GP trees/GA genes and applied evolutionary computation methods on each agent type, as previously stated in Section II and III.

IV. Simulation Experiment

To confirm usefulness of our proposed method, and to analyze behaviors of producer agents and consumer agents with considering consumers' monetary sense, we carry out a simulation experiment.

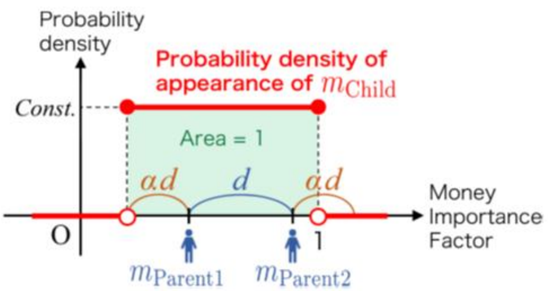

Fig. 5. Probability distribution of a child's Money Importance Factor from two parents using BLX-α.

TABLE II: Main Conditions of The Simulation Experiment

Condition type	Value
Number of generations	300
Number of terms in each generation	120
Number of producer agents (Population size)	200
Number of consumer agents (Population size)	5,000
R (Fixed cost rate)	0.8
α value for BLX-α	0.2
Trust when a consumer agent encounters a product recall	+10
Constant value β in Eq. (2): base value of product accident probability	0.0025
	0.015
Whether or not Money Importance Factor is employed	Employed
	Not employed

A. Preparation of the Experiment

1) Experimental conditions and scenario setting

Table II describes the main conditions of the simulation experiment. The Appendix gives further details about the experimental conditions. The proportion of number of producer agents and the one of consumer agents (1:25) is determined by reference to social statistics in Japan [33].

In addition, we set four scenarios: combination of lower (β = 0.005) and higher (β = 0.015) accident rate, whether or not Money Importance Factor is employed (Employed / Not employed). A simulation experiment using each scenario is conducted respectively. This variation of accident rate reflects different types of products in the market. For example, any product with a keen-edged shape or with use of fire has a higher accident rate. We observed how the difference of accident rate affects evolution of producer agents and consumer agents. The difference whether or not Money Importance Factor is used make it possible to compare the proposed method and the existing method. When Money Importance Factor is not employed, consumer agents choose their destinations of migration based on only Total Trust of producer agents, *i.e.*, selling price is not referred.

2) Method of analyzing the distribution of agents

As a first step of analyzing the distribution of agents at the final term in the final generation, we calculated the mean of Money Importance Factor of the all consumer agents, and classified consumer agents into two classes:

- C^H: class of consumer agents having a higher Money Importance Factor than the mean
- C^L: class of consumer agents having a lower Money Importance Factor than the mean

Next, we tracked the product flows from producer agents to consumer agents, and counted product sales separately based on which class of consumer agents (C^H or C^L) purchased them. Using the result of counting product sales, we categorized producer agents based on whether or not the number of sales is ranked in the top 20 for the each class of consumer agents (C^H and C^L).

B. Results and Discussion

The simulation has been conducted five times for each scenario, and almost the same tendencies have been observed. One set of results is given here due to limitations of space, but referring to another one does not change the following discussions and the conclusion of this paper.

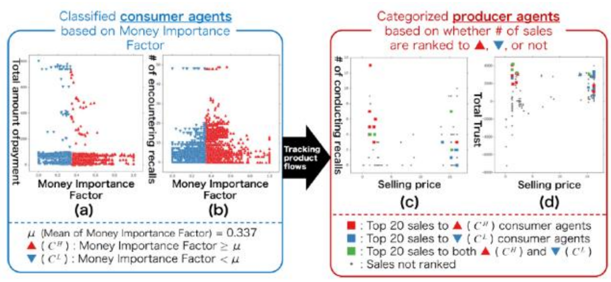

Fig. 6. Classified consumer agents based on Money Importance Factor to C_H and C_L, and categorized producer agents based on whether or not the number of sales are top-ranked for C_H, C_L (β = 0.015).

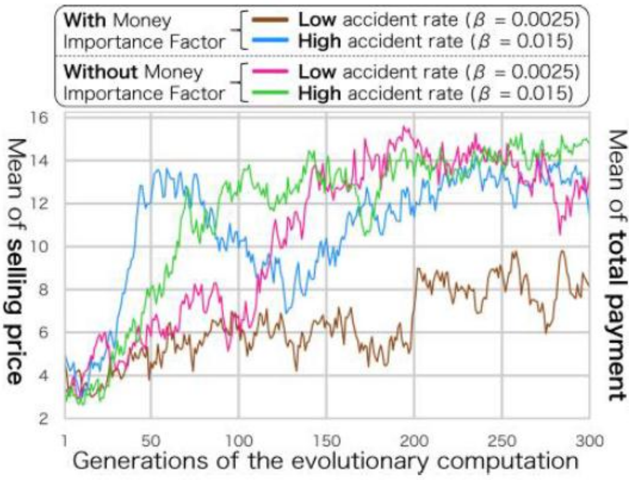

Fig. 7. Transition of evolutionary process: Mean of selling price (producer agents).

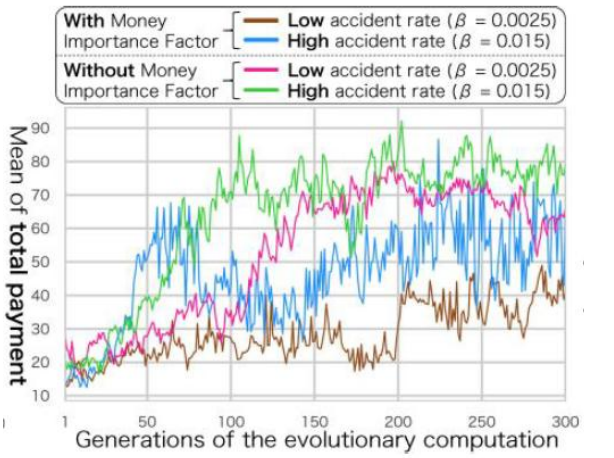

Fig. 8. Transition of evolutionary process: Mean of total amount of payment (consumer agents).

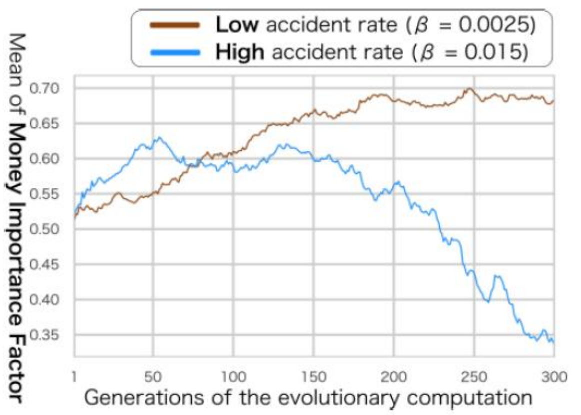

Fig. 9. Transition of evolutionary process: Mean of money importance factor (consumer agents).

1) Relationship between money importance factor and distributions of agents

At first, we analyze the distribution of agents at the final them in the final generation using the method described in Section IV-*A*-2. Fig. 6 shows the result of the analysis, in detail, (a) and (b) indicate the distribution of consumer agents, (c) and (d) presents the one of producer agents. In Fig. 6 (a) and (b), consumer agents are plotted with different markers according to the set, C^H or C^L. About Fig. 6 (c) and (d), producer agents are also plotted with different markers according to whether or not the number of sales is top-ranked.

With respect to Fig. 6 (a), C^L consumer agents are distributed in the area of larger payment than C^H agents. This distribution is explainable on the basis of the definition of Money Importance Factor, that is, C^H agents intend to reduce his/her payment more than C^L in the model. In terms of product recalls, Fig. 6 (b) shows that C^H consumer agents encounter more product recalls than C^L agents. It can be interpreted that consumer agents having a tendency to save money are broadminded about encountering product recalls in this model.

Regarding producer agents, in Fig. 6 (c) and (d), many producer agents that are plotted with a red square marker, top 20 sales producers to C^H consumer agents, are distributed in the area of cheaper selling price. This distribution is also understandable based on the definition of Money Importance Factor, that is, C^H agents prefer cheap products more than C^L in the model.

Fig. 6 describes the result in the scenario with a higher accident rate (β = 0.015), but similar tendencies are observed in the scenario with a lower accident rate (β = 0.005). It can be said that Money Importance Factor, our proposed model, works as expected based on the results mentioned in this section.

2) Effectiveness of money importance factor

Secondly, to verify an effectiveness of the proposed method, Money Importance Factor, we we observe the transition of the evolution through whole 300 generations. Fig. 7 and 8 show evolutionary transitions in the means of parameter values of agents at the final term of each generation. Each figure describes the selling price of producer agents (Fig. 7), the total amount of payment of consumer agents (Fig. 8). Each colored line indicates the corresponding scenario as shown in the legend.

According to Fig. 7, a higher accident probability leads producer agents to sell more expensive products. It can be explained that producer agents learned to raise the production cost and to improve the quality of products for avoiding product accidents. Fig. 8 explains that the total amount of payment of consumer agents accordingly tends to increase because of the increase of selling price.

It should be noted that selling price and consumer's payment under the scenarios where Money Importance Factor is employed tend to be less than the one when Money Importance Factor is not used, as a result of the evolution in Fig. 7 and Fig. 8. When Money Importance Factor is not employed, producer agents do not need to decrease their selling price for attracting new consumers, because consumer agents do not refer selling price for choosing destinations of migrations. In other words, Money Importance Factor restrain an inflation of selling price. In the real society, needless to say, it is not an appropriate situation that producer can raise selling price completely freely. From this result, it can be said that Money Importance Factor can reflect the situation of the real world and improve the accuracy of the simulation model.

3) Evolutionary transition of money importance factor

Next, to check how Money Importance Factor evolves using Real-Coded GA, we observe the transition of the evolution of Money Importance Factor through whole 300 generations. Fig. 9 shows evolutionary transitions in the means of Money Importance Factor of consumer agents.

We would like to emphasize that Money Importance Factor presents completely different evolutionary processes under different accident rate scenarios. According to Fig. 9 Money Importance Factor decreases in the higher accident rate scenario, and on the contrary increases in the lower accident rate scenario through evolution. One interpretation of the phenomena is that consumer agents evolve in a direction toward preventing poor-quality products for protecting themselves from product accidents. Under the interpretation above, it is a reasonable consequence that a higher accident rate results in a stronger tendency for consumer agents to avoid poor-quality products.

At the same time, these results demonstrate an impact of the co-evolution model of producer agents and consumer agents. In other words, Money Importance Factor of consumer agents evolves corresponding to the evolution of selling price of producer agents.

From these results, it is suggested that there is a possibility that consumers are willing to buy expensive but high-quality products for preventing product accidents, when the products have a large risk of accidents apparently from their attributes such as shape or use of fire. This suggestion can assist decision-makings for a sales strategy by executive officers in product companies.

4) Suggestion for improving product recall systems

Finally, we discuss a possibility of improving product recall systems. From the perspective of the distribution of producer agents shown in Fig. 6 (d), many producer agents conduct product recalls honestly not only in the area of a cheap selling price but also in that of an expensive one. Fig. 6 (d) also presents that many producer agents having high Total Trust are distributed in the area of both cheap and expensive price.

It is inferred that these phenomena suggest a possibility of promoting product recall, as follows:

- When a producer agent sells its products with a cheap price, the agent tries to improve the product quality through conducting product recall
- When a producer agent sells its products with a cheap price, the agent tries to raise its Total Trust through conducting product recall

In this way, although the presumed mechanism differs for different price ranges, as a consequence, active product recalls are observed in a wide range of selling price.

This behavior is related to the experimental condition shown in Table II, in particular, that a consumer agent who encounters a product recall adds a positive value to the trust of producer. In other words, the result suggests that, in the real world, if the recognition like "product recalls are desirable if necessary and trustworthy actions by producers for a safer society" is spread in the society widely, product recalls are probably promoted without regard to the price range. We can therefore suggest that it is important to make an impression or a recognition of product recalls better through improving social systems. This suggestion will be helpful for the legislation or risk communication processes relevant to product recall in the real society.

TABLE III: DETAILED CONDITIONS OF THE SIMULATION EXPERIMENT

Condition type	Value
ℓ: Lifetime of products	12 terms
Initial asset of a producer agent	20,000
Initial satisfaction of a consumer agent	0
Initial Trust of a consumer agent	0
Initial production cost of a producer agent	0.5
Minimum production cost	0.05
Changing unit of production cost	0.05
Additional cost for a product recall per product	1
Satisfaction when a consumer agent uses a product normally	+1
Trust when a consumer agent uses a product normally	+1
Compensation cost when a producer agent causes a product accident	200
Satisfaction when a consumer agent encounters a product accident himself/herself	−100
Trust when a consumer agent encounters a product accident himself/herself	−100
Satisfaction when another consumer agent belonging to the same user group encounters a product accident	−5
Trust when another consumer agent belonging to the same user group encounters a product accident	−5
Constant value γ in Eq. (2): reducing rate of product accident probability by a product recall	0.5
Disregard Margin dm (asset)	10
Disregard Margin dm (number of causing accidents)	0
Disregard Margin dm (number of users)	3
Disregard Margin dm (Total Trust)	100
Disregard Margin dm (Z score of selling price)	1.0×10^{-3}
Range of depth of initial GP trees	[0, 3]
Range of depth of GP trees through the simulation flow	[0, 7]
Crossover rate (GP/GA)	0.8
Mutation rate (GP/GA)	0.02
Range of depth of GP trees generated by mutation operation	[0, 2]

TABLE IV: PARAMETERS SELECTED AS CANDIDATE TERMINAL NODES OF GP TREES

Agent type	Parameters selected as candidate terminal nodes (LV_2, LV_3, LV_{Event})
Producer	Asset Total Trust Number of users Number of causing product accidents Z score of selling price
Consumer	Satisfaction Trust Z score of selling price of the producer agents whose user group he/she belongs to Whether he/she encounter an accident himself/herself in the term Whether other user in the same user group encounters an accident in the term Whether he/she encounter a product recall

V. CONCLUSION

In summary, we have constructed a social simulation model for analyzing product recall systems considering consumers' monetary sense and using a proposed parameter: Money Importance Factor. As a result of the simulation experiment, we have discovered the possibility that consumers are willing to buy expensive but high-quality products for preventing product accidents, when the products have a large risk of accidents apparently from their attributes. In addition, we have also found that it is important to make an impression or a recognition of product recalls better through improving social systems.

We believe this work can contribute to supporting not only government staffs for improving product recall systems, but also executive officers of product companies for deliberating their strategy of recall decisions.

In regard to limitations of this research, some problems to be solved still remain. One of the most noticeable issues is difficulties in analyzing micro-level behavior of the agents, i.e., interpretation of GP trees in particular. As a future work, micro-level analysis is required for further validation of the results obtained from the proposed model. Despite the limitations, however, this study opens a new approach for investigating ways to improve product recall systems considering the decision-making and adaptation processes of both producers and consumers from a viewpoint of co-evolution.

APPENDIX

Table III shows the detailed conditions of the simulation experiment and Table IV describes parameters selected as candidate terminal nodes of GP trees. Table III and Table IV are complements of the main conditions described in Table II in Section IV-A-1.

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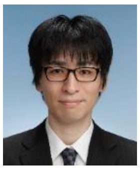

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