Co-Creative Decision Making in Artifactual Systems in Consideration of Bounded Rationality

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1. INTRODUCTION

This study proposes a co-creative decision making method of artifactual systems for creating effective solutions under incomplete conditions by introducing bounded rationality as a characteristic of agents.

A system would deliberate as “rationally” as possible and thereby derive solutions to behave as “optimally” as possible in cases where it makes decisions to attain its purpose.

A “perfectly rational” model or a “perfectly optimal” model has been addressed classically as an agent model not only in the field of economics, but also in engineering. An “agent” is defined herein by its recent usage: an autonomous subject that serves as a system component. Nevertheless, in those fields mentioned previously, limitations or drawbacks of such models have been indicated under imperfect conditions. Numerous studies have been undertaken to propose alternative models.

First, in the economic field, classical economic theories based on a “perfectly rational” agent model have been shown to differ markedly from observed practices of human agents. For that reason, “bounded rationality” is becoming well established as the alternative. The term was coined by Simon to express a human-specific characteristic that is “being partly rational, and in fact being emotional or irrational in the remaining part of his actions [1].”

On the other hand, in engineering field, the qualities of rationality and optimality in designed systems are clearly explained in the literature [2] as: (1) perfect rationality, (2) calculative rationality, and (3) bounded optimality. (1) Perfect rationality is the classical notion of rationality in decision theory, as mentioned above. A perfectly rational agent acts at every instant in such a way as to maximize its expected utility, given the information it has acquired from the environment. Nevertheless, this is not a suitable candidate for the real agent model because perfectly rational agents do not exist for nontrivial environments. (2) Calculative rationality is a notion that we have used implicitly in designing logical and decision-theoretic agents. A calculatively rational agent eventually returns what would have been the rational choice at the beginning of its deliberation. However, that solution has no validity because the computation time is impractical when conditions are complicated. Designers are forced to compromise on decision quality to obtain reasonable overall performance. (3) Bounded optimality is the notion that an agent behaves as well as possible given its computational resources. Among these, most recent studies regarding systems' or agents' decision-making have pursued bounded optimality (3) because of the necessity of solving problems under complex or incomplete conditions.

Ultimately, we can infer from both economics and engineering that there is a necessity for explicit consideration of agents' bounded rationality because of limitations of ability. These limitations impart a negative quality, or use of bounded rationality to resolve agents' inherent deficits.

In contrast, this research proposes that agents' bounded rationality has positive aspects to its use. Bounded rationality can be used for generating effective solutions to decision-making problems. This study provides justifications for its use in imperfect conditions. By way of definition, some terms to express characteristic aside from bounded rationality exist: limited rationality, bounded optimality, and limited optimality. This study uses bounded rationality consistently as its nomenclature because of its familiar characteristics.

A typical example of a system that must produce decisions using incomplete information about its conditions is a manufacturing system. Especially in recent years, situations surrounding manufacturing systems are becoming increasingly complex through diversification of consumer preferences and economic fluctuation. Numerous requirements, such as product type, production amount, due dates, and so on can change radically in response to changing situations. Under such conditions, decision-making must be flexible, robust, and adaptable rather than optimal. In artifactual systems such as manufacturing systems, it has become common sense to eliminate effects of human decisions that are regarded as "the human factor" or "human error" because they might disturb efforts at system optimization. Notwithstanding, actual human beings have the innate ability to produce decisions flexibly, in contrast to artificial agents in the real world.

Humans do so on the grounds of their complexity instead of their ability to derive optimal solutions and act upon them. Making use of that insight, this study presents a decision-making method that allows an artifactual system to derive effective solutions under incomplete conditions by introducing bounded rationality as an agent characteristic. The key concept of our method is “co-creation.”

Co-creation engineering is proposed as “novel engineering for investigating a framework and a methodology to create an effective solution, heretofore unattained by independently-acting agents, as a whole system that allows interaction among acting agents for synthesis of an artifact.” The concept of co-creative decision making is shown in Fig. 1. Co-creative decision making method is based on a multi-agent approach. Such systems must be addressed through a bottom-up approach to gain flexibility, robustness and adaptability; a top-down approach imposes limits [3]. A multi-agent approach is an important bottom-up approach in which effectiveness for situational complexity has been demonstrated in some studies [4]. In an artifactual system, agents who comprise system are not only production machines or autonomous robots, but also human beings such as consumers, designers, and workers.

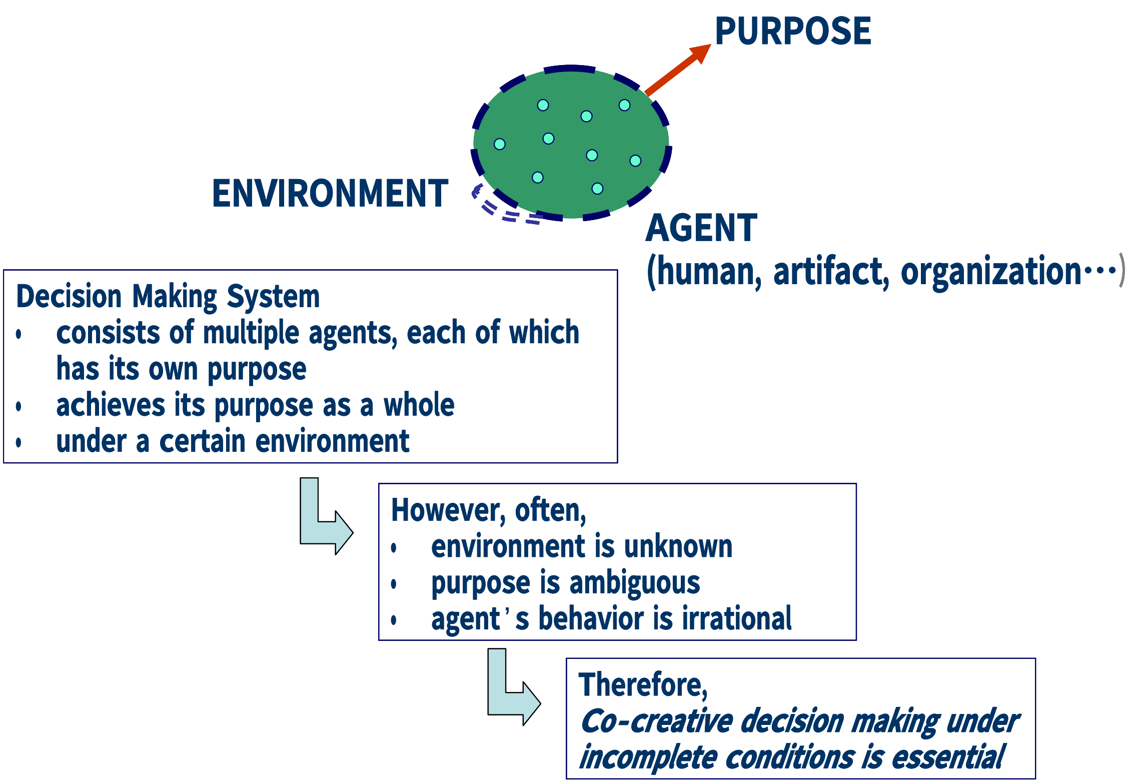


Figure 1: Concept of co-creative decision making

Figure 1 shows the three principal factors of incompleteness of conditions that underpin the necessity of this concept: (1) environmental unknowability, (2) ambiguity of purpose, and (3) agents' irrationality. This research specifically addresses positive aspects of the latter: agents' irrationality.

The next section presents a classification of multi-agent systems from the viewpoint of agents' rationality so that our target system's specifications can be clarified. Section 3 describes bounded rationality to be applied to artifactual systems. Section 4 describes a simulation model for confirming effectiveness of this research and results of computer experiments. Section 5 is the final section. It presents a future strategy fir this research along with a conclusion to the proposition made in this paper.

2. CLASSIFICATION OF MULTI-AGENT SYSTEMS

The target of this research should be systems to which introducing agents' bounded rationality brings important benefits. In this section, specifications of our target systems are clarified by classifying multi-agent systems (MAS).

First, the definition of MAS should be declared. MAS can be characterized as follows [5]:

- It consists of multiple agents.
- Each agent acts in its local environment.
- No special agent controls all agents.
- No special rule determines the whole system.
- Global behavior emerges.
- Individual agents mutually become part of the environment.
- Agent behavior emerges from within a structure.

Classification items by which specifications of the target systems are revealed are the following two:

(1) Presence of the system's purpose: whether the system as a whole has a purpose or not,

(2) An agent's rationality: whether or not an agent behaves perfectly rationally to attain its own purpose.

MAS are classifiable into the following four types according to (1) presence of the system's purpose and (2) agents' rationality (Table 1).

[A-type]: A system that has an overall purpose and which consists only of rational agents.

[B-type]: A system which has an overall purpose, but which includes several bounded-rational agents.

[C-type]: A system which has no purpose, but which consists only of rational agents.

[D-type]: A system which has no purpose and which includes several bounded-rational agents.

A salient example of the C-type system is a classical economic system. Recent economic systems with consideration of bounded rationality are classifiable as a D-type system. Each economic agent pursues its own profit (i.e. it behaves as rationally as possible) and global behavior emerges, but the system itself has no overall purpose. Incidentally, art by emergent method is also classifiable as a D-type system.

Table 1: Classification of MAS

	All agents are perfectly rational	Not all agents are perfectly rational
System has a purpose	A-type	B-type
System has no purpose	C-type	D-type

A-type and B-type are options for target systems because it is natural that most artifactual systems have a purpose. Here, let the overall purposes of systems be translated as “the global purpose” and the purpose of each agent be translated as “the local purpose”. An A-type system is describable as a system for which the global purpose is equal to the sum of the local purposes because the global purpose can be attained by all agents’ rational behavior. In contrast, a B-type system has no local purpose that can attain its own purpose. It is not necessary for A-type to be considered for bounded-rational agents. However, the global purpose cannot be attained if all agents behave rationally when the target system is classified as B-type. In such a case, the possibility exists of attaining the global purpose by introducing some bounded-rational agents.

For this reason, the B-type of MAS is the target of this research. The novelty of this research lies in its approach by which the decision-making problem of the type-B system, for which the global purpose differs from the sum of the local purposes, can be solved through consideration of agents’ bounded-rationality.

3. DESCRIPTION OF BOUNDED-RATIONALITY

This section presents a specific description of bounded rationality for application to artifactual systems.

First, we define the meanings of rationality and irrationality. “Being rational” means somehow acting optimally in pursuit of one’s goal based on all useful information. “Being irrational” means acting with no intention toward attaining the purpose. Our target is systems with purpose. Therefore, irrationality is beyond the scope of our argument. Conceptualized in this manner, bounded rationality can be the opposite of rationality.

The following three points are inferred to establish a perfect rational model in traditional economics:

(R-1) having unlimited knowledge (information) and unlimited cognitive ability;

(R-2) being under complete self-control; and

(R-3) being completely egoistic.

Correspondingly, being bounded rational can be described as follows:

(BR-1) having limited knowledge (information) and limited cognitive ability;

(BR-2) being sometimes short-sighted and simplistic; and

(BR-3) being sometimes altruistic.

These characteristics are formulated to explicitly consider B-type systems by the following description.

The input of each agent placed in the environment is state s; the output is action a (Fig. 2). Let the decision-making function be represented as f. The formula is:

$$s \xrightarrow{f} a \tag{1}$$

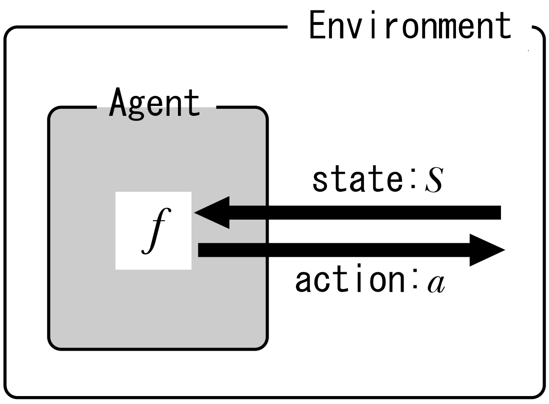


Figure 2: The agent model

The environment s that surrounds the agent may change dynamically. In addition, the agent has limited capability for getting and processing information. Such environmental incompleteness and limitation of recognition of environment are described above as (BR-1). These are only the main characteristics that are indicated as limits of perfect rational models in both economic and engineering fields. Similarly, regarding action a, it is not always possible for the agent to act according to plan. Hence, s and a may include some kind of fluctuation: s would be $s+\alpha$ and a be $a+\beta$ in practice. Both α and β express some sort of fluctuation.

Nothing but the relational expression $s \to a$ can be derived if f is a "perfectly rational" function. Instead, the "bounded-rational" function $f' = f + \gamma$ is determined as "γ". The following properties are listed by interpretation of (BR-2) and (BR-3):

(BR-2)' sometimes selects its action randomly; and

(BR-3)' sometimes gives preference to the purposes of the system over its own purpose.

4. COMPUTER SIMULATION

This section describes specifications of the computer simulation that verify the validity of the proposed method. The effectiveness of (BR-2)' random action selection is tested in this simulation.

4.1 SIMULATION MODEL

4.1.1 OUTLINE OF SIMULATION MODEL

This simulation is modeled based on the Ant System (AS), which was inspired by observations of actual ant colonies and their inhabitants' complexly structured behavior [6]. In AS, ants are agents with extremely simple capabilities. Consequently, to a degree, they mimic the behavior of real ants. Dorigo et al. applied this system to combinatorial optimization problems [7].

This simulation assumes a discrete two-dimensional space as the environment and a discrete-time model. The system comprises multiple ants. Some food sources exist that are positioned in locations that are initially unknown to the ants. The purpose of the overall system is to gather as much food as possible into the ants' nest.

First, the simulation outline is explained using pattern diagrams like those shown in Fig. 3.

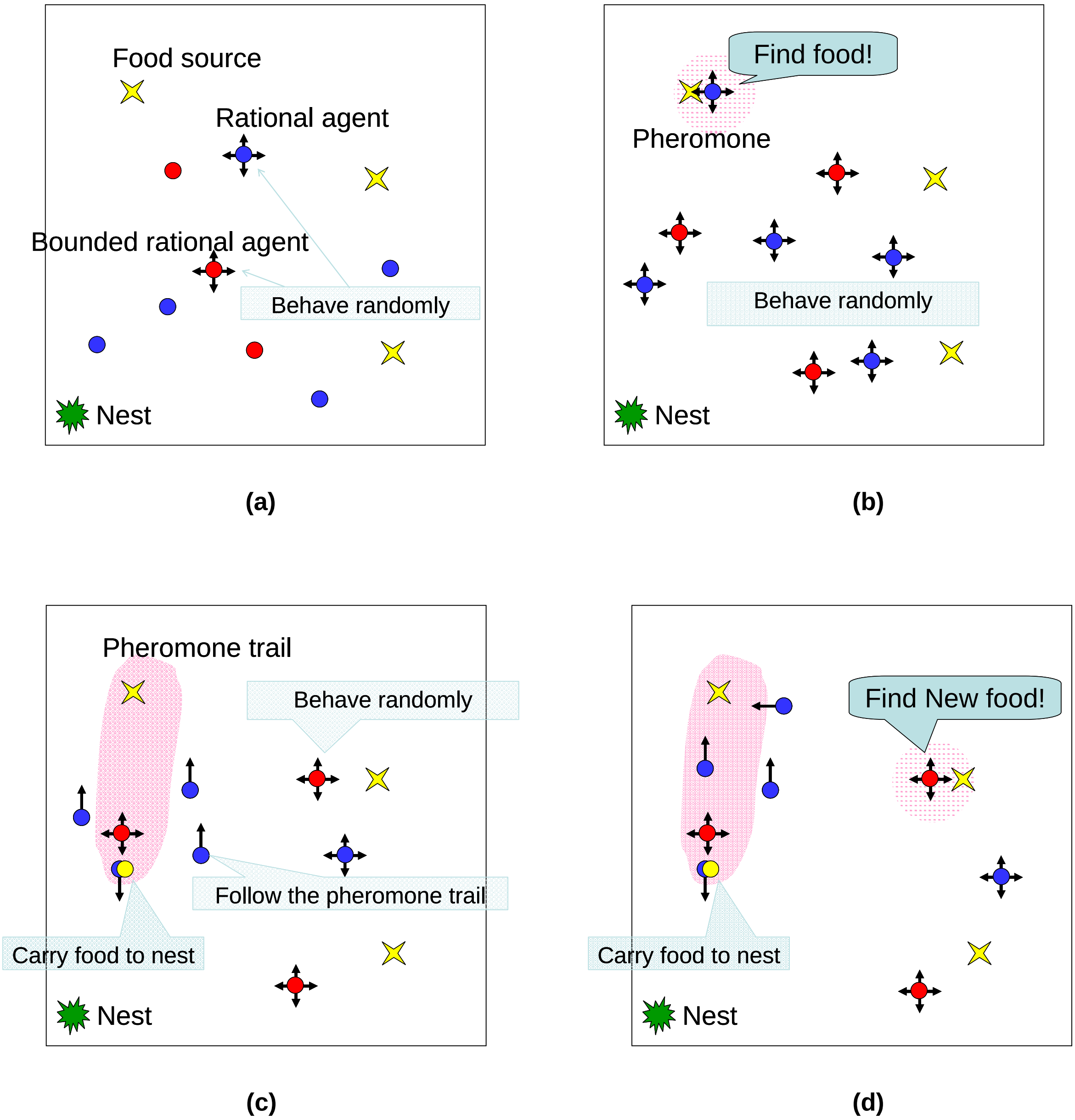


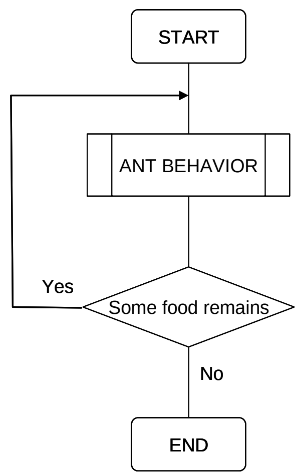
Figure 3: Simulation model based on the Ant System

Initially, all ants are at the nest. Each ant selects one action at every time step from the four decision-branches: move forward, move back, move left, or move right. Each ant's individual purpose is to carry as much food as possible to the nest. They do not know where food sources are. Therefore, they behave randomly for some time (Fig. 3-(a)). At some time, one or some agents will find food (Fig. 3-(b)). The ant that finds food picks it up and carries it to the nest while releasing a pheromone. Thus, the path by which the ant passed becomes a pheromone trail and it diffuses around because it is volatile. It is attracted to a pheromone because a rational ant that detects the pheromone will infer, rationally, that the pheromone trail will lead to food (Fig. 3-(c)). However, even if a bounded-rational ant detects the pheromone, it does not always follow the pheromone; it may continue to behave randomly. Although a bounded-rational ant may thereby miss opportunities to find food, it may instead encounter opportunities to develop new food sources (Fig. 3-(d)). Ants will gather around a food source that is already found if they are rational. However, food provided by each source is eventually exhausted. Ants must continually seek new food sources. In such a case, introducing several bounded-rational ants will enhance the system performance.

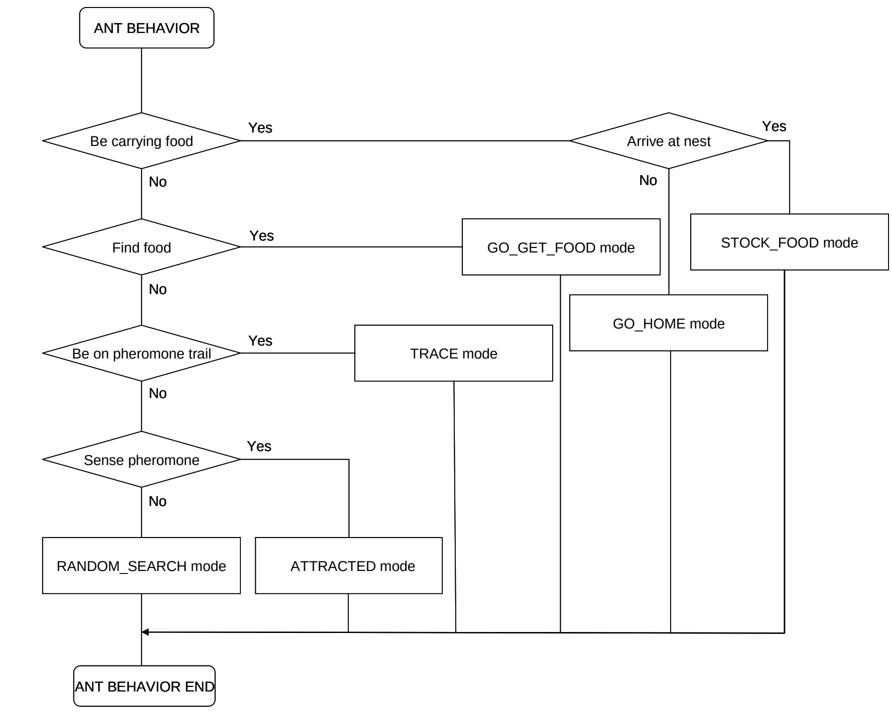
4.1.2 ANT BEHAVIOR MODEL

The ant behavior model of this simulation can be illustrated as the flow-charts shown in Fig. 4. Figure 4-(a) is the main flow; the predefined process of “ANT BEHAVIOR” is shown in Fig. 4-(b) when the ant is rational and in Fig. 4-(c) when the ant is bounded rational. A swarm of ants continues foraging behavior because some food remains in the area. In Fig. 4-(c), P is a “random probability”. When bounded-rational ants search for food randomly even when they detect some pheromone with random probability P.

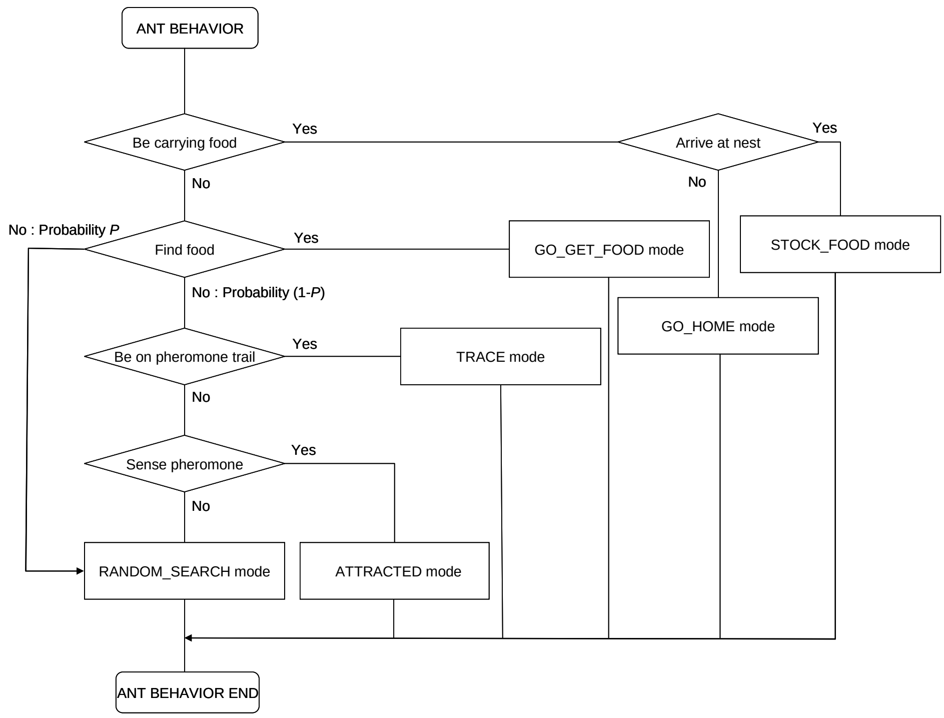
Accounts of several modes that appear in Figs. 4-(b) and 4- (c) are added after Fig. 4.



(a) Main algorithm flow



(b) Predefined process when an ant is rational



(c) Predefined process when an ant is bounded rational

Figure 4: Algorithm flow

[RANDOM_SEARCH mode]: ant moves randomly.

[ATTRACTED mode]: ant moves in the direction for which pheromone concentration is highest in its neighborhood.

[TRACE mode]: ant traces pheromone trail.

[GO_HOME mode]: ant heads toward the nest carrying food and releasing pheromone.

[STOCK_FOOD mode]: ant puts food down at the nest.

4.1.3 PHEROMONE FORMULATION

As mentioned above, the released pheromone evaporates at every time step and the vaporized pheromone diffuses. In this study, the pheromone amount is formulated as stated below based on information from a reference [8].

A food-carrying ant releases a pheromone while returning to the nest. In this simulation, this amount is fixed (=100). This released pheromone forms a trail. Pheromone on a trail evaporates at every time step. The trail density at time step t at position $\left(x, y\right)$ is

$$DT(x,y,t) = DT(x,y,t-1) - \delta \,, \tag{2}$$

where δ is the trail's evaporation rate. The vaporized pheromone diffuses. The process of pheromone diffusion occurs when the pheromone density at time step t at position $\left(x, y\right)$ is $DF(x,y,t)$:

$$DF(x,y,t) = \frac{\delta}{4}\left(\sum_{i,j=-1}^{i,j=1} DF\left(x+i, y+j, t-1\right) \times \rho\right), \tag{3}$$

where ρ is the remaining probability.

4.2 IMPLEMENTATION AND EXECUTION OF A SIMULATION

4.2.1 PARAMETER SETTING

The parameters used in the simulation are listed below:

- Size of the environment:100 × 100 (square spaces)
- Nest position: center of the environment (50, 50)
- Number of food sources: 20
- Amount of food in each food source: 20
- Food source positions: set randomly

- Number of agents: 50

As a preparation, the simulation was executed by changing the pheromone evaporate rate δ and the remaining pheromone probability ρ. The purpose of this pre-simulation is to select the optimal values of δ and ρ when all agents are rational because the main simulation should be executed with the best parameters for rational agents to examine the effect of introducing bounded rationality. Consequently, these parameters were set at:

- δ = 0.005
- ρ = 0.75.

4.2.2 SIMULATION-1

The first simulation was executed by changing the ratio of bounded-rational ants. In this simulation, the random probability P is 1.0: bounded-rational ants behave randomly whenever they detect a pheromone. We counted execution time steps from the start time to the time when all food sources are exhausted. Table 2 and Figure 5 show the average execution time steps of 20 experiments. In Table 2, "R" is the number of rational ants and "BR" is the number of bounded-rational ants.

Table 2 and Figure 5 show that the swarm of rational ants can gather all food in a shorter time than the case in which all ants are bounded-rational, partly because δ and ρ are set appropriately for rational ants. Nevertheless, the swarm with some bounded-rational ants can exceed the swarm of rational ants. In this case, the execution time is shortest when R = 20, BR = 30. The result is affected by the parameters determined in section 4.2.1. Nevertheless, it follows that introducing several bounded-rational agents would improve the system performance.

Table 2: Average execution time steps according to ratio of rational and bounded-rational ants

Number of Ants	R=50 BR=0	R=40 BR=10	R=30 BR=20	R=20 BR=30	R=10 BR=40	R=0 BR=50
Time steps	150466	132250	134617	130076	143389	197284

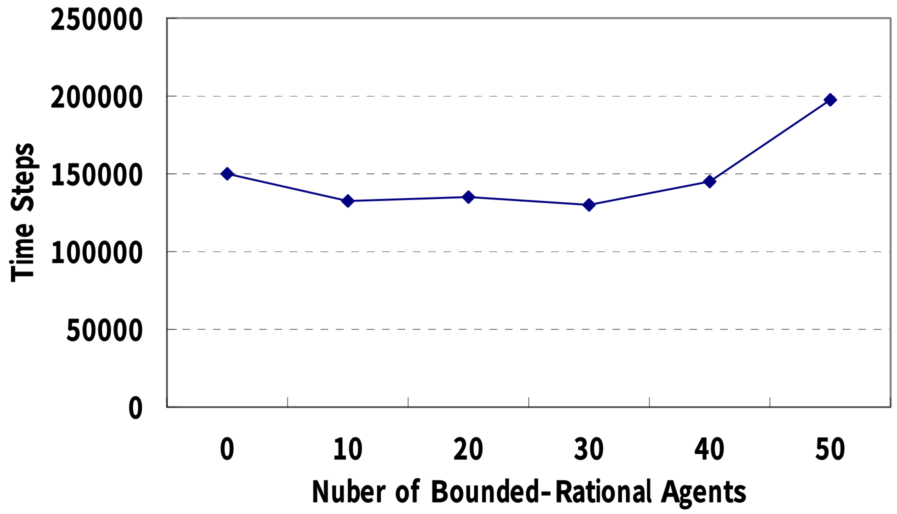


Figure 5: Transition of average execution time steps according to number of bounded rational ants

4.2.3 SIMULATION-2

The second simulation was executed by changing the random probability P when all ants behave according to a bounded-rational mode. The average execution time steps of 20 experiments are shown in Table 3 and Fig. 6, as in the first simulation. In this simulation, the case $P = 0$ is identical to the case of R = 50, BR = 0, and the case where $P = 1.0$ is the same as the case of R = 0, BR = 50 in the first simulation (Table 2). When $P = 0.7$, the number of time steps is similar to that of the case when $P = 10$ (Table 2). In contrast, the performance improved dramatically when $P = 0.1$, 0.3 or 0.5. In this case, the performance is highest when $P = 0.3$. We infer that moderate randomness allows the swarm to avoid entrapment in local solutions.

Results of the first and second simulation allow derivation of the argument that both introducing high level of randomness into several agents and introducing a certain level of randomness into all agents would improve the overall system performance.

Table 3: Average execution time steps according to random probability of bounded-rational ants

P	0.1	0.3	0.5	0.7
Time steps	84518	52564	64227	171520

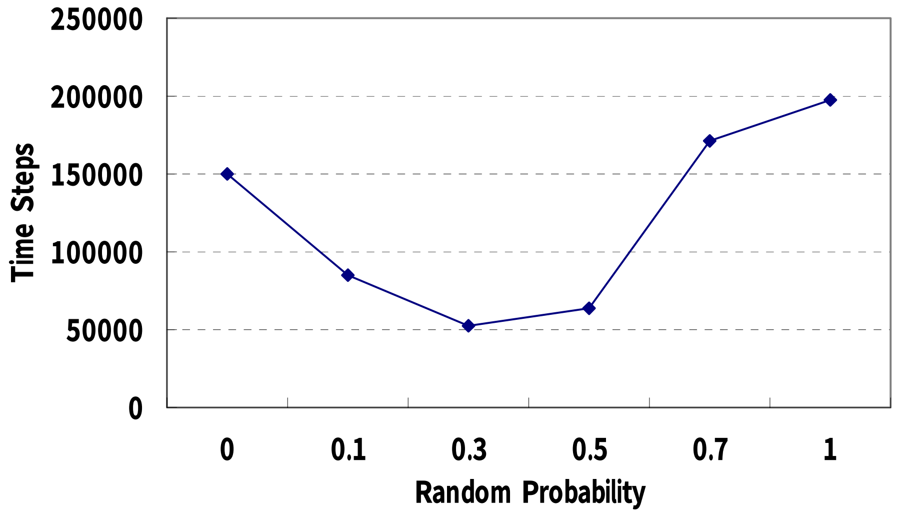


Figure 6: Transition of average execution time steps according to random probability

5. CONCLUSION

This study proposes a co-creative decision making method for creating effective solutions in artifactual systems. Herein, starting with the concept of co-creation decision making, the classification of multi-agent systems was described according to (1) presence of a system purpose and (2) agent rationality. The target of this research is a system that has an overall purpose, but which includes some bounded-rational agents. Subsequently in this paper, the decision-making function for the target system was established through description of bounded rationality. Moreover, we showed a computer simulation for ascertaining the effectiveness of the proposed method. The direction of future research will point to implementation of further simulations to support the proposed method. Application of decision-making problems in real artifactual systems will be developed. Manufacturing systems will be an excellent target as an application because they offer clear purposes despite their difficulty of optimization. Furthermore, the importance of the proposed method will be confirmed through experiments with actual human beings playing the roles of agents.

REFERENCES

[1] Simon, H.A.: “Models of Bounded Rationality,” Vol.2, Cambridge, Mass., MIT Press, 1982.

[2] Russell, S.J., Norvig, P.: “Artificial Intelligence: A Modern Approach,” Prentice Hall, 1995.

[3] Ueda, K., Markus, A., Monostori, L., Kals, H.J.J., Arai, T.: “Emergent Synthesis Methodologies for Manufacturing,” Annals of CIRP, Vol.50, No.2, pp.535 – 551, 2001.

[4] Wiendahl, H.-P., Scholtissek P.: “Management and Control of Complexity in Manufacturing,” Annals of the CIRP, Vol.43, No.2, pp.533 – 540, 1994.

[5] Jennings, N.R., Sycara, K., Wooldridge, M.: ”A Roadmap of Agent Research and Development,“ Autonomous Agents and Multi-Agent Systems Journal, N. R. Jennings, K. Sycara and M. Georgeff (Eds.), Kluwer Academic Publishers, Boston, Vol.1, No.1, pp.7-38, 1998.

[6] Deneubourg, J.L., Pasteels, J.M., Verhaeghe, J.C.: “Probabilistic Behavior in Ants: A Strategy of Errors?” Journal of Theoretical Biology, Vol.105, pp.259 – 271, 1983.

[7] Dorigo, M.: “Optimization, Learning and Natural Algorithms,” Ph.D. Thesis, Politecnico di Milano, 1992.

[8] Nakamura, M., Kurumatani, K.: “Mechanism for Changing the Foraging Behavior in an Ant Colony Model,” Complexity International, Vol.6, http://life.csu.edu.au/complex/ci/vol6/ci6.html, 1999.