Effect of Communication Error on "Iterated Proposal–Voting Process"

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Abstract. This paper proposes the framework of a multi-agent simulation called "iterated proposal–voting process" and reports the effect of communication error on the decision-making of a relatively small community. The community try to decide on a shared rule via iteration of "propose and vote." In this framework, each agent decides its action based on two criteria: satisfying "physiologically fixed needs" and satisfying "social contextual needs (SNs)," which sometimes conflict with each other. These criteria are derived from a Nursing Theory that puts special emphasis on the relation between subjects and others. SNs are satisfied when such relations are balanced. Employing "Hyder's theory of cognitive balance," SNs are evaluated for whether they are balanced. The simulation yields some interesting phenomena that are not observed by conventional static analyses, e.g. power indices.

1 Introduction

Through the process of decision-making by a community, the final decision should reflect all members' preferences and beliefs, but it is difficult to arrive at such an ideal decision because personal preferences vary with personalities, and the relations among members are not simple [1]. Especially in relatively small communities, it is well known that a personal decision can strongly influence the final decision, leading the so-called "groupthink," "risky shift [2]," and so on. Recently, multi-agent simulations have been applied to analyze such phenomena that emerge in decision-making processes in a bottom up manner, e.g. [3].

The target of our agent-based simulation is a relatively small community that tries to decide a shared rule of community through a process that can be modeled as "iterated proposal and voting." One of the characteristics of our model is the mental model of each agent based on Nursing Theory, especially the Behavioral Systems Model [4], which focuses not only on personal preferences but also on social relationships. The social relationships are assessed by employing Heider's theory of cognitive balance [5].

The preference of voting of each agent is revised through the "iterated proposal and voting" by using Q-learning [6]. Our model is applied to examine the effect of errors on decision-making. The results of simulation are compared with those of conventional methods of analyzing voting systems [7].

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2 Decision Making via "Iterated Proposal–Voting Process"

Decision-making is an interesting topic for Game Theory, Social Psychology, Politics, Sociology, etc., and many research efforts have been carried out. This paper aims to contribute to this research field by considering the notions of "personal needs vs. social relationship" and "iterated proposal-vote process."

2.1 Model of Each Agent and Shared Rule

The iterated process of decision-making by a community is affected by the actions, preferences, and beliefs of each constituent and by the relationships among them. In order to simulate this process, the method of modeling each agent emerges as the main issue. Recent researches has attempted to model agents based not on a simple strategy such as "chasing optimality" but on complex and human-like strategies. For example, some agents are defined by introducing the notion of physiology based on Transactional Analysis, while others are defined by introducing the notion on ethics [8]. This paper defines agents by introducing the notion of Nursing Theory, especially the Behavioral Systems Model [9], which is derived from a tremendous number of observations of "patterns of human behavior." The main feature of this model is its treatment of instincts by considering the motivation of maintaining relationships.

Although the monumental book "Notes on Nursing [10]" by F. Nightingale has not been cited for a long time, various theories motivated by the Notes have been developed since 1950 [4]. These theories vary depending on the basic philosophy. Among them, we employ "system theories [4]" as the basis of modeling agents. The common standpoint of system theories is that a human being consists of several systems, which are categorized into two groups: physiologically personal ones and social ones. For example, the Behavioral Systems Model [9] defines the "behavior system of humans" as an integration of seven subsystems, called "affiliative," "dependency," "ingestive," "eliminative," "sexual," "aggressive," and "achievement" subsystems. Affiliative and dependency subsystems are social while the others are personal. Hereafter, we call the requirement derived from the former "**s**ocial contextual **n**eeds (SN)" and that from the later "**p**hysiologically fixed **n**eeds (PN)."

Each subsystem tends to satisfy its requirements and be in a balanced state. If some subsystem of a person is imbalanced, he/she feels nonconformity and is thus motivated to take certain actions, which lead to subsystems becoming balanced. Furthermore, subsystems sometimes conflict with each other. An action made to balance a subsystem may lead to another subsystem becoming imbalanced.

Physiologically fixed Needs (PN) and Shared Rule. Physiologically fixed Needs (PN) reflect personal and physiologically requirements, e.g., preferable temperature, brightness, and calmness of a room, which are independent of relationships with other people but sometimes conflict with the preferences of other people. Therefore, a community needs a shared rule for governing such requirements.

Initial shared rule $P = \{4, 4, 1\}$
$PN_0 = \{4, 3, 5\}$
$PN_1 = \{1, 5, 2\}$ zw
$PN_2 = \{5, 3, 2\}$

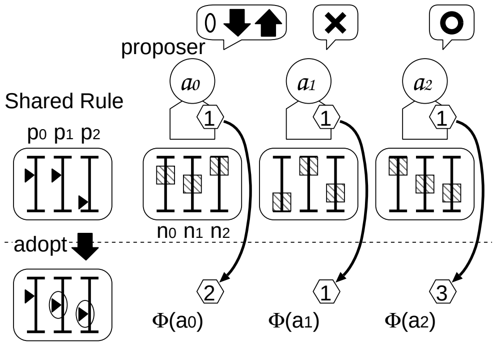

Fig. 1. Example of initial P, PN_i, and "a step of proposal-vote and alteration of $\Phi(a_i)$".

Shared Rule: Deciding the value of a shared rule is the objective of our simulation. A shared rule is represented by a set of values that governs all of the members of the community. Such a rule must be decided through discussion among all members. Our "proposal–voting system" implements a shared rule as a list of integers:

$$P = \{p_0, p_1, p_2, \cdots, p_{R_l - 1}\},$$

where R_l denotes the number of factors that commonly affect all members, and each factor p_j is assigned an integer ($0 \leq p_j < R_s$).

Coding PN: PN of each agent reflect factors of the shared rule. Therefore, each need (n^i_j) of an agent a_i is represented by an integer ($0 \leq n^i_j < R_s$), and each "PN of an agent a_i" is encoded into a list of needs:

$$PN_i = \{n^i_0, n^i_1, n^i_2, ..., n^i_{R_l - 1}\}.$$

An example of a set of a shared rule (P) and PNs is shown in the left part of fig. 1, where $R_l = 3$, $R_s = 7$ and the number of agents $L = 3$. The right upper part of fig. 1 illustrates this situation.

Satisfaction of PN: If the difference between the value of each element of PN (n^i_j) and that of the shared rule (p_j) is within the tolerance range (σ), each element is satisfied. $\Phi(a_i)$ shows the number of satisfied needs under a certain state of shared rule P. We define that PN_i is satisfied as a whole if and only if $\Phi(a_i) \geq R_l/2$, i.e., "more than half of its elements are satisfied."

The Proposal: The objective of each agent is to revise the shared rule to satisfy its own needs. In this revision, one of the agents becomes the proposer and the others are voters. The proposal is uniquely determined by the PN of the proposer. The proposer tries to shift the shared rule toward his PN. The proposal is represented by a set of strings that consists of "stay," "down," and "up" for each p_j. The revision of a shared rule through discussion of members should not be drastic, so the incremental/decremental value is fixed to 1. Figure 1 shows an example. If $\sigma = 1$ and a_0 is the proposer, n^0_1, n^0_2 are

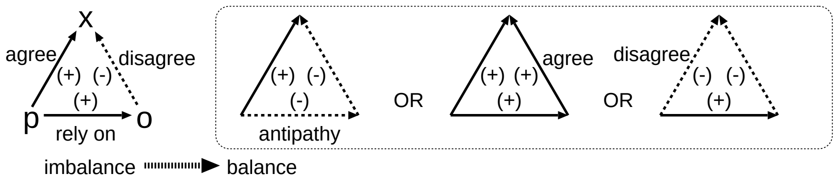

Fig. 2. Heider's cognitive balance and imbalance.

not satisfied by the initial $P = \{4, 4, 1\}$, so a_0 proposes $\{\text{stay}, \text{down}, \text{up}\}$. After a_1 disagrees and a_2 agrees, the number of supporters (a_0, a_2) exceeds that of opponents (a_1), so the proposal is adopted and P becomes $\{4, 3, 2\}$. Finally, $\Phi(a_i)$ is revised to $\Phi(a_0) = 2$, $\Phi(a_1) = 1$, and $\Phi(a_2) = 3$.

Social contextual Needs (SN) and Theory of Cognitive Balance. In contrast to PN, Social contextual Needs (SN) reflect relationships with others, e.g., being close, familiar, dependent. In decision-making by a small community, SN can be interpreted as that which reflects approval/disapproval, sympathy/antipathy, and so on.

In order to analyze whether SN is balanced, we refer to the Naive Psychology proposed by F. Heider [5], especially to his "Theory of Cognitive Balance." He focused his attention on the consistency of these relations in local setting of situations, that is, the cognitive balance of a person (**p**) with another person (**o**) concerning an entity (**x**), as shown in the left part of fig. 2.

For example, let us consider three relations:

- **p** agrees to a proposal **x** (positive $(+)$), and
- **p** relies on a person **o** (positive $(+)$), but
- **o** disagrees with **x** (negative $(-)$).

Accordingly, these relations are imbalanced. The balance of this triangular relation is defined as the sign of the product of the signs of these three relations. In this case, we have $(+) \times (+) \times (-) = (-)$, so the triangular relation is imbalanced.

The balanced situation is accepted by **p** without stress, but the imbalanced situation makes **p** stressful and uncomfortable, and is forced to be altered by emotion of **p** toward restoring its balance. Concerning the above example, if **p** feels antipathy to **o**, we have $(+) \times (-) \times (-) = (+)$; if **o** changes his/her mind and agrees to **x**, we have $(+) \times (+) \times (+) = (+)$, then **p** feels comfort.

Coding SN: The proposed framework interprets **p**, **o**, and **x** as "a voter (a_i)," "another voter (a_j)," and "a proposal," respectively. Therefore, the triangular relation consists of three relations:

- a_i agrees/disagrees with the proposal,
- a_i feels a positive/negative relationship with a_j, and
- a_j agrees/disagrees with the proposal.

Each a_i is required to make each triangle balanced by his/her emotion.

The relations between two agents (a_i, a_j) are assessed by the ratio of agreement by a_i for proposals by a_j. Even though a_j is now a voter, a_i imagines the situation where a_j will be a proposer someday, and all possible situations are evaluated for whether a_i wants to agree to a_j. For this evaluation, Q-table, explained in section 2.3, is employed. Assume the table shows that a_i wants to agree to x cases, we define that the relation between a_i and a_j is positive if and only if $x \geq 3^{R_l}/2$, i.e., "more than half of situations make a_i agree to a_j."

Balance of SN: We define the balance of SN of a_i in terms of Heider's Cognitive Balance. SN of a_i for each voter is represented by the above triangle, and $L-2$ triangles are supposed because the number of agents is L and one of them is the proposer and one of them is a_i itself. We define "the satisfaction of SN of an agent a_i as a whole" as "more than half of triangles of a_i are balanced."

2.2 Framework of the Simulation

The "iterated proposal–voting simulation" is a kind of Multi-agent Simulation. In contrast to methods of static analysis such as power indices [7], this simulation shows sequential shifts of states of agents, relationships among agents, and the effect of the shared rule on agents. This simulation is partially inspired by "a game of self-amendment: NOMIC" [11], which imitates the legislative process. All members of a community propose in turn either "establishing a new rule," "revising a rule," or "abolishing a rule," and for each proposal, members take a vote. If a proposal is approved, it becomes immediately effective and shared by all members.

NOMIC is a game for humans, so rules are described in natural language. On the other hand, our proposed simulator describes a shared rule by a set of integers and confines the proposal to a "revision."

Flow of "Iterated Proposal–Voting Simulation". Our proposed "proposal-voting simulation" shares the basic concept of NOMIC, i.e., it consists of three processes:

– an agent proposes a revision of a shared rule,
– other agents express agreement/disagreement with the proposal, and
– the revised rule affects all agents.

Furthermore, each agent learns preferences of voting by past experiences of voting and its effect on the agent.

First, the values of fixed parameters are determined:

L: the number of agents, R_l: the length of shared rule P,
M: the number of iteration, R_s: the range of the value of "each element of P."

Then, the simulator

1. Initializes a set of agents: $A = \{a_0, a_1, a_2, \cdots, a_{L-1}\}$.
2. Initializes a shared rule: $P = \{p_0, p_1, p_2, \cdots, p_{R_l-1}\}$, where each $p_i(i = 0, 1, \cdots R_l - 1)$ is assigned a random integer ($0 \leq p_i < R_s$).

3. Repeats M times,
   - for $i = 0 \cdots L - 1$
     (a) a_i proposes a revision of P
     (b) for $j = 0 \cdots L - 1; j \neq i$
       - a_j expresses agreement/disagreement with the proposal
     (c) if (agreement exceeds disagreement)
       - the proposal is adopted
       - P is revised
     (d) for $j = 0 \cdots L - 1; j \neq i$
       - a_j learns to revise its preference of voting
4. The final P is the result of the above decision-making.

According to the Behavioral Systems Model, each effect of the shared rule has to affect the learning process of each a_i.

2.3 Learning Preference of Voting

The objective of each agent is to satisfy its needs by revising the shared rule, but the situation for each agent is not simple. It must be concerned about not only its personal needs but also its relationships with others. We employ Q-learning [6] based on the "$\varepsilon-$greedy strategy" as a learning method of agents, using the following parameters.

Range of value Q:	$0.0 \sim 1.0$	zw	Rate of random behavior ε:	0.05
Initial value of Q:	0.5	zw	Learning ratio α:	0.8
Alternatives of action:	agree/disagree	zw	Reduction rate γ:	0.9

Each agent first perceives the current state $q(a_i, \text{current}P)$ and then selects an action v_*. The selection is based on the value of $Q(q, v)$, where v is either agree or disagree.

After voting, the state is revised to $q'(a_{i+1}, \text{new}P)$, and then the value of $Q(q, v_*)$ is revised as follows:

$$Q(q, v_*) = (1 - \alpha)Q(q, v_*) + \alpha\Big(r + \gamma max\big(Q(q', v)\big)\Big).$$

The reward r is determined by how P makes agents comfortable. Namely, it is determined by how PN and SN are satisfied. Humans tend to act to satisfy their own needs. Our system simulates this tendency through learning voting preferences by using rewards that reflect satisfactions of SN and PN.

Size of Q-table The variation of the proposer is $L - 1$, since the number of agents is L and one of them is a_i itself. The value of P is estimated by a_i according to whether each p_j is within a tolerance range σ. The number of p_j is R_l, and each p_j is estimated as "within σ," "too much," or "too small," so the number of all possible estimations is 3^{R_l}. Therefore, each Q-table has $(L-1) \times 3^{R_l}$ cases of states. The alternatives of action are "agree" or "disagree." After all, each Q-table is a matrix of $\{(L - 1) \times 3^{R_l}\} \times 2$.

Revision of Q-value The Q-value is revised by estimation of P. After a_i takes an action, if P satisfies a_i's needs, a_i gets positive rewards, else if P shifts far from a_i's needs, a_i gets negative rewards. Either positive or negative, a_i gets rewards if and only if its vote affects approval/disapproval of a proposal. In this paper, a positive reward is fixed to 0.10, and a negative reward is fixed to -0.02.

3 Result of Simulation with Communication Error

Our simulation focuses on successive changes in the relationships that are important for decision-making by a small community. These relationships are represented by SN. This section shows the possibility of making a decision shift only by altering the relationships, without any enforcements.

3.1 Introducing Communication Error

Misunderstanding the relation with other people affects the state of SN, which reflects the triangular relationship among an agent, a proposal, and another agent. The state of SN affects rewards, which further affects the actions of the agent. This local personal misunderstanding yields, through iterations, global changes such as alteration of a shared rule or the final decision.

Misperceptions of the environment, trouble in the communication route, and other problems sometimes cause misunderstandings. We implement "misunderstandings" by reversing the perception. Namely, if an agent a_i misunderstands the environment, it reversely perceives the votes of all other agents. Hereafter, the character "*" denotes such a misunderstanding. For example, in a community $A = \{a_0, a_1^*, a_2^*\}$, a_1 and a_2 are misperceiving the environment.

3.2 Results of Simulation

We implemented "Proposal–Voting Simulation" in C language and examined all possible combinations of normal and reversed agents. For each combination, simulations were carried out 1,000 times, in which the order of proposals were randomly shuffled. This section reports the mean value of 1,000 trials.

All simulations employ the following settings:

number of agents:	L = 3	zwrange of the value of rules:	R_s = 7
iterations:	M = 500	zwinitial value of shared rule:	P = $\{3, 3, 3\}$
length of rules:	R_l = 3	zw tolerance range:	σ = 1

We confirmed that shared rules are converged before 500 iterations in all simulations. We also confirmed that the result is independent of the initial value of the common rule, so this section only reports the case where initial P is fixed to $\{3, 3, 3\}$.

This section reports three cases, where PN_i varies to a certain degree, PN_i varies drastically, and a dictatorial party exists.

Case 1: PN_i varies to a certain degree: In the case where PN_i varies to a certain degree, we fix the values to $N_0 = \{2, 2, 1\},\ N_1 = \{1, 1, 6\},\ N_2 = \{4, 6, 3\}$.

In the normal case, i.e., there is no misperception ($\{a_0, a_1, a_2\}$), $P = \{p_0, p_1, p_2\}$ converges at $\{2.35, 2.53, 2.88\}$. For the other seven cases ($\{a_0, a_1, a_2^*\} \cdots \{a_0^*, a_1^*, a_2^*\}$), fig. 3 roughly illustrates the differences in final p_i with the normal case and the final number of satisfied PN ($\Phi(a_0)$, $\Phi(a_1)$, and $\Phi(a_2)$).

The results of shared rules are categorized clearly into two types, i.e., whether a_1 is reversed or not. When a_1 is normal, shared rules converge at almost the same value,

	p_0	p_1	p_2	$\Phi(a_0)$	$\Phi(a_1)$	$\Phi(a_2)$
$\{a_0, a_1, a_2\}$	0.00	0.00	0.00	2.28	1.35	1.32
$\{a_0, a_1, a_2^*\}$	-0.03	-0.03	0.15	2.21	1.43	1.28
$\{a_0, a_1^*, a_2\}$	0.02	0.06	0.50	2.16	1.48	1.16
$\{a_0, a_1^*, a_2^*\}$	-0.07	-0.06	0.77	2.08	1.71	1.05
$\{a_0^*, a_1, a_2\}$	0.17	0.04	0.14	2.30	1.00	1.47
$\{a_0^*, a_1, a_2^*\}$	0.16	0.05	0.18	2.25	1.01	1.48
$\{a_0^*, a_1^*, a_2\}$	0.19	-0.07	0.60	2.16	1.03	1.41
$\{a_0^*, a_1^*, a_2^*\}$	0.18	0.08	0.60	2.10	1.03	1.43

Fig. 3. Results of case 1: (PN_i varies).

but in any case where the perception of a_1 is reversed (denoted by a_1^*), the shared rule shifts substantially. Reversing a_1 particularly affects the increase in p_2, as shown the meshed graphs of p_2 in fig. 3. We interpret this phenomenon based on the facts that

1. $n_0^1 \simeq n_0^2 \ \wedge \ n_1^1 \simeq n_1^2$, and
2. $n_2^0 < n_2^2 < n_2^1$.

The first fact implies that p_0 and p_1 are stabilized around "2," with which a_0 and a_1 agree, but reversing the perception of a_1 leads to a_1 agreeing with a_2 instead of a_0. Then the above second fact leads to p_2 shifting toward n_2^1, and p_2 comes to the middle value between n_2^1 and n_2^2.

Focusing on the number of satisfied PN, neither $\Phi(a_0)$ nor $\Phi(a_2)$ varies, and only $\Phi(a_1)$ tends to be small when a_0 is reversed, as shown the meshed graphs of $\Phi(a_1)$ in fig. 3.

Case 2: PN_i varies drastically: In the case where PN_i drastically varies, i.e., for each agent a_i, and for each need, $n_x^i \neq n_y^i$ where $x, y \in \{0..R_{s-1}\}, \ x \neq y$, and $n_j^k \neq n_j^l$ where $k, l \in \{0..L-1\}, \ k \neq l$. We fix these values to $N_0 = \{1, 3, 5\}, \ N_1 = \{5, 1, 3\}, \ N_2 = \{3, 5, 1\}$. Since $\sigma = 1$, no p_i is allowed to satisfy all of agents at the same time.

In this case, all p_i converge at the mean value of the allowed range. The satisfied PN also converge at the same value, but $\Phi(a_i)$ of the reversed agents are slightly higher than those of other agents. These results are just what we expected. Since PN_i varies drastically, agents are symmetrical for any reversion.

Case 3: a dictatorial party exists: In the case where a_0 and a_1 establish a dictatorial party, we fix values of PN_i to $N_0 = \{1, 1, 1\}, \ N_1 = \{1, 1, 1\}, \ N_2 = \{4, 4, 4\}$.

Figure 4 roughly illustrates the differences in final p_i for the normal case and that in the final number of satisfied PN. In this case, both a_0 and a_1 tend to agree/disagree with the same proposal. Therefore, the needs of a_2 are always ignored. In the normal case, i.e., no agent is reversed, the result is just what we expected. The dictatorial party (a_0, a_1) wins a great victory and it's members needs are satisfied. The numbers of satisfied needs, $\Phi(a_0)$ and $\Phi(a_1)$, mark almost the maximal value (3.00). On the other hand, $\Phi(a_2)$ marks almost the lowest value.

	p_0	p_1	p_2	$\Phi(a_0)$	$\Phi(a_1)$	$\Phi(a_2)$
$\{a_0, a_1, a_2\}$	0.00	0.00	0.00	2.90	2.90	0.10
$\{a_0, a_1, a_2^*\}$	0.01	0.01	0.01	2.88	2.88	0.12
$\{a_0, a_1^*, a_2\}$	0.08	0.08	0.08	2.67	2.67	0.33
$\{a_0, a_1^*, a_2^*\}$	0.07	0.07	0.07	2.70	2.70	0.30
$\{a_0^*, a_1, a_2\}$	0.13	0.13	0.13	2.52	2.52	0.48
$\{a_0^*, a_1, a_2^*\}$	0.10	0.10	0.10	2.61	2.61	0.39
$\{a_0^*, a_1^*, a_2\}$	0.26	0.26	0.26	2.12	2.12	0.88
$\{a_0^*, a_1^*, a_2^*\}$	0.21	0.21	0.21	2.28	2.28	0.72

Fig. 4. Results of the case 3: (dictatorial party exists).

In the case where the perceptions of more than one agent are reversed, the difference between the number of satisfied needs of the dictatorial party and that of a_2 is slightly narrower than in the normal case. In particular, when a_0 and/or a_1 have reversed perceptions, the results shift far from the normal case. Even though the absolute values are small, in the case of $\{a_0^*, a_1^*, a_2\}$, $\Phi(a_2)$ marks almost nine times the value of the normal case.

4 Discussion and Conclusions

Game Theory has analyzed the effects of the scale of a community on decision-making, the effects of personal preferences on the form of community, and so on [7][12]. Among various approaches, power indices represent the effect (power) of party on a voting system [7]. The Sharpley-Shubik index, Banzhaf index, and Deegan-Packle index are known as representative ones. To compare our simulations in cases 2 and 3, power indices are applied to a community where each of three agents forms its own party, which consists of the agent alone. Therefore, the “voting weight” of each party is “one,” and the approval criterion is “more than half.”

In case 2, PN_i varies drastically, so the interests of agents are symmetrical. The target of analysis by power indices is each voting, which correspond to a set of “a proposal, voting, and the alteration of P.” Interpreting case 2 as a voting game, the major power indices have the values shown in Table 1. On the other hand, the experimental results show that the rate of each $\Phi(a_i)$ against $\sum_{j=0\cdots L-1} \Phi(a_j)$ has nearly the same value as power indices shown in Table 1. This comparison implies that, for a community in which PN_i varies as case 2, the satisfaction of each agents can be predicted by using the power indices.

In case 3, the three indices have the values shown in Table 1. In each index, the dictatorial party $\{a_0, a_1\}$ wins perfectly. As shown in Table 1, the rate of each $\Phi(a_i)$ against $\sum_{j=0\cdots L-1} \Phi(a_j)$ is almost the same as the indices when no communication error is allowed, i.e., the case of $\{a_0, a_1, a_2\}$. On the other hand, these rates drift, especially in the case of $\{a_0^*, a_1^*, a_2\}$ where both members of the dictatorial party contains misperception. This comparison implies that when a dictatorial party exists static analysis,

Table 1. Power Indices and $\Phi(a_i)$ in case 2 and 3.

index	case 2 a_0	a_1	a_2	case 3 $\{a_0, a_1\}$	$\{a_2\}$
Sharpley-Shubik	$1/3$	$1/3$	$1/3$	$2/2$	$0/2$
Banzhaf	$4/12$	$4/12$	$4/12$	$4/4$	$0/4$
Deegan-Packle	$1/3$	$1/3$	$1/3$	$1/1$	$0/1$
Rate of $\Phi(a_i)$ at $\{a_0, a_1, a_2\}$	$178/532$	$175/532$	$179/532$	$290/300$	$10/300$
Rate of $\Phi(a_i)$ at $\{a_0^*, a_1^*, a_2\}$				$212/300$	$88/300$

such as the use of power indices, is not always applicable. In some cases, the behavior following the iterated voting process shows some special phenomena.

Remarkable progress has been made in communication technology to overcome the diverse cases where trivial communication error causes unexpected serious results. This paper reported that some kind of misperception influence the final result of a "proposal–voting system" and that the type of misperception makes a difference in the results. In particular, we investigated three cases: where personal needs vary to a certain degree, where they vary drastically, and where there exists a dictatorial party.

By following the process of iterated proposals and voting, the proposed framework of decision-making can show phenomena that cannot be detected by static analysis methods. We are now planning to extend our simulation to a method for analyzing phenomena related to decision-making by humans, such as risky shifts, cautious shifts, and so on.

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