Landscape Analysis of Possible Outcomes

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Abstract: The behavior of a complex social system is unpredictable, because both the uncertainties and the complex interactions in the system affect its future behavior. Agent-based social simulation, especially scenario analysis, helps better-informed decisions by increasing their knowledge about the system; the existing scenario-analysis methods focused their attention on the effect of complex interactions of the system on the system behavior rather than the uncertainties of the system. The purpose of this paper is to develop a novel scenario-analysis method that mainly focuses on evaluating a range of possible outcomes of the system under considered uncertainties. The authors validate this method by applying it to a case example, where a configuration of the evaluation system at a sales division is to be selected.

Keyword: scenario analysis, agent-based social simulation, decision support technique, visualization technique

1. Introduction

Agent-Based Social Simulation (ABSS) is used to gain a deeper knowledge about a complex social system of interest rather than to predict the precise behavior of the system in future. The behavior of a complex social system is unpredictable, because both the uncertainties and the complex interactions in the system affect its future behavior. ABSS helps better-informed decisions by increasing their knowledge about the system (North & Macal, 2007). ABSS analysis provides the following two types of knowledge about the system.

- Type 1: Knowledge about the possible outcomes of a complex social system after implementing a policy alternative in the situation under consideration.
- Type 2: Knowledge about the mechanism that results in a notable outcome of the complex social system after implementing the policy alternative in the situation under consideration.

The ABSS approaches that provide such knowledge are called "scenario analyses" (Takahashi, 2008); several studies have been conducted on scenario analysis. Deguchi (2009) emphasized the importance of referring to a landscape that demonstrates a whole bunch of possible outcomes after implementing a large number of policy alternatives. Such a landscape shows a bunch of dots on a two-dimensional plane defined by a vertical performance axis and a horizontal policy axis. The landscape would be helpful in elucidating features of the policy alternatives that satisfy a given performance criterion.

Yang *et al.* (2009) use an inverse simulation technique for searching a set of parameter' values of a complex social system, which results in a notable outcome, from a large parameter space. This technique would be helpful when an outcome of interest has already been identified. Both Deguchi (2009) and Yang *et al*. (2009) focused their attention on the effect of complex interactions of the system on the system behavior rather than the uncertainties of the system.

These uncertainties however do affect the behavior of a complex social system. We define these uncertainties as the concept where modelers of the system do not have sufficient information or knowledge about the elements or the interactions in the system. These uncertainties would generally be faced by ABSS users. For example, we can easily imagine a situation where the modelers of the system assume a distribution of the parameter values but lack a real set of parameter values. In this situation, they generate a tentative set of parameter values, which are consistent with the assumed distribution.

The behavior observed after every run of the simulation using both same and varying sets of the parameter values can vary considerably. The variation using the former comes from the complex interactions in a system, while that using the latter comes from both the complex interactions and the variations in the parameter-value sets itself. As described above, we assume variant sets of parameter values if we consider the uncertainty of the parameters. By reducing the uncertainty in the system, for which the results vary considerably in behavior, we can enhance type 1 knowledge.

The primary purpose of this paper is to develop a novel scenario-analysis method that mainly focuses on evaluating a range of possible outcomes of the system under considered uncertainties; we also validate this method by applying it to a case example. In the following sections, we introduce the developed scenario analysis method, and describe a case example and the results of our method when applied to it. This is followed by a discussion on the results and the conclusion of this study.

2.Landscape Analysis of Possible Outcomes

Figure 1 shows the configuration of the developed scenario-analysis method. Step 1 precedes the three other steps. Steps 2, 3, and 4 are independent of each other. Below, we describe each step in detail.

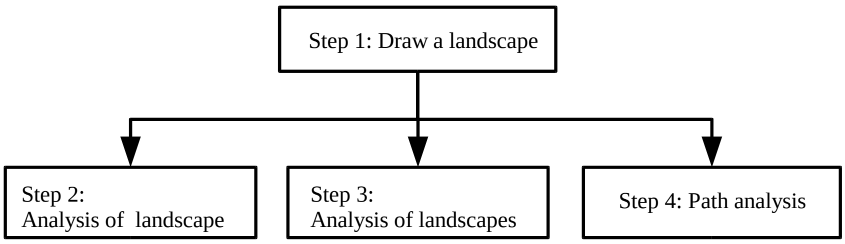

Figure 1. Configuration of landscape analysis of possible outcomes.

Step 1: Draw a landscape

In this step, the user draws a landscape of the possible outcomes under the considered uncertainties. This landscape illustrates the possible outcomes after implementing each policy alternative. This step is further divided into the following two sub-steps:

- 1-1: Select the alternatives, a performance index, and a time point for analysis.
- 1-2: Run ABSS and plot the performance index values under the selected alternatives at the selected time point.

In Step 1-1, it is important that the user defines a performance index to effectively capture the system's behavior. In Step 1-2, the user summarizes a simulation log and visualizes both the distributions of performance index values and their averages under the concerning policy alternatives. For each policy alternatives, the user runs ABSS for a given number of times repeatedly under certain conditions. The user records performance index values for each policy alternative at the target time point and plots them on a two-dimensional plane defined by a vertical performance axis and a horizontal policy-alternative axis.

Step2: Analysis of landscape

In this step, the user analyzes the landscape drawn in Step 1 and understands the possible outcomes after implementing the concerning policy alternatives. The user then finds a feature of policy effect under the considered uncertainties. This step consists of the following two sub-steps:

- 2-1: Observe a range of possible outcomes of a policy alternative.
- 2-2: Review the ranges of these policy alternative outcomes.

In Step 2-1, the user focuses on a policy alternative and studies its results such as the highest or lowest performance of the possible outcomes, the mode or average performance of the outcomes, or the ranges of outcomes. In Step 2-2, the user compares the ranges of the possible outcomes of different policy alternatives on the basis of the observations in Step 2-1.

Step 3: Analysis of landscapes

In this step, the user compares a landscape having the considered uncertainties with the one in which the uncertainties have been reduced. If there is a difference in these two landscapes, then it naturally implies that the uncertainties of the parameter affect the performance of policy alternatives. The following two sub-steps are defined:

- 3-1: Draw a new landscape in which uncertainties of a parameter are reduced.
- 3-2: Review the difference between the new landscape and the original one.

In Step 3-1, the user assumes that the set of the concerned parameter values is tentative and runs ABSS using this set. Statistical tests of both average (avg.) and variance (var.) are recommended to compare the new distribution of possible outcomes with the original one in Step 3-2.

Step 4: Path analysis

In this step, the user investigates when and how a notable outcome is produced. Path analysis refers to a kind of time-series log analysis and unveils a mechanism for the outcome. This step is divided into the following three sub-steps:

- 4-1: Select a policy alternative of interest and a notable outcome under the alternative.
- 4-2: Path analysis of the outcome.
- 4-3: Understand the mechanism for the outcome.

In Step 4-2, the comparison between a notable outcome and an ordinary outcome is made to elucidate the differences between the two. However, Step 4 is a highly exploratory process. Therefore, we tentatively mention some viewpoints on analysis.

3. Case Example

3.1 Model

We select a model used by Goto *et al*. (2009), which describes the phenomenon of a change in sales person's behavior with changes in their attitude by organizational learning. A sales manager evaluates the sales persons using an evaluation system in a sales division. The sales persons have their own attitude for sales activities, and their actions are based on this attitude. The attitude of each sales person is different. Basically, the sales person learn their attitude to improve their evaluation by the evaluation system, while some do not because of a lack of interest in their own evaluation. The sales persons learn by exchanging information about their evaluation.

Sales division and sales persons

Consider a sales division which has GN groups having AN sales persons respectively. The sales persons are required to sell goods, and all groups have the same kind of goods to sell. Group i $(=1,2,\cdots,GN)$ initially has m_i customers and can sell goods up to m_i units (one unit for each customer) in a sales period. Let m_i^r be the number of customers who have not yet purchase a good from group i in the current period. At the beginning of the sales period, we set $m_i^r = m_i$. Both m_i and m_i^r will increase or decrease with the activities of the sales persons.

Sales persons have the following four attributes: (1) sales capability cp $(0 \le cp \le 1)$; (2) three kinds of sales attitude: aggressiveness ag, cooperativeness co, and innovativeness in ($ag, co, in \in \{0,1,\cdots,7\}$); (3) learning discriminator $ld \in \{0,1\}$; and (4) learning threshold th (≥ 0). Higher cp values result in higher probabilities of sales success. Aggressiveness ag is connected to the frequency of market cultivation during a sales period, cooperativeness cp to the frequency of instances of educating teammates, and innovativeness in to the frequency of taking training initiatives. A sales person's cp increases or decreases with the sales activity of the sales person, with that of others, and with time. Organizational learning of the attitude can lead to a change in ag, co, and in. Both ld and th are defined initially and fixed.

Organizational behavior

Sales person have the following four activities during a sales period: (1) sales, (2) market cultivation, (3) education of teammates, and (4) training. Sales refers to the selling of a good to a customer, if $m_i^t > 0$. The probability of sales success is equal to sales person's cp. Market cultivation refers to the process of seeking new customers for a good, and succeeds at a probability of $1 - m_i / (AN \times T)$, where T denotes the number of time units in a sales period. If the market cultivation is successful, then both m_i and m_i^t increase by one. The education of teammates leads to an increase in the cp of all teammates by E_o ($0 \le E_o \le 1$). By the training, the sales person's cp increases by E_s ($0 \le E_s \le 1$).

Both cp and m_i diminish over time. The sales persons' cp decreases by E_d ($0 \le E_d \le 1$) with each time unit. The consumers of group i m_i decrease by one at a probability of P_d ($0 \le P_d \le 1$) with each time unit.

Evaluation system

The evaluation system consists of some evaluation indices and their weights. The sales person's evaluation value ev is defined as the weighted sum of n evaluation indices ($ev_1, \cdots, ev_n$): $ev = w_1 \cdot ev_1 + \cdots w_j \cdot ev_j \cdots + w_n \cdot ev_n$, where w_j is the weight of the *j*th index ($0 < w_1, \cdots, w_n \le 1$, $w_1 + \cdots + w_n = 1$). According to Otomasa (2003) and an interview we conducted with some sales divisions, 40 evaluation indices were found and used in this case example.

Organizational learning

Sales persons learn their attitude for sales activity (ag, co, and in) until their evaluation value ev meets their learning threshold th. Sales persons whose ld is 1 and whose ev is below their th gradually change their attitude to one with which they achieves higher evaluation values. Moreover, all sales persons change their attitude randomly at a very low rate, irrespective of their ld.

3.2 Simulation

Verification and validation

Verification and validation (V&V) techniques in ABSS have been discussed by sereval authors. According to North and Macal (2007), verification refers to confirming whether an implemented model matches to its conceptual specification. Validation is defined as the degree of homomorphism between an implemented model and the real world system (Richiardi *et al*., 2006). Accurate V&V is critical to model development and use.

We performed model-to-model analysis (Hales *et al*., 2003) and parameter sweeping on our model with the objective of V&V. Table 1 shows a list of parameters and their validated values. The behavior of our model, as specified by the parameter values in Table 1, matches the stylized facts of the concerning area. Due to insufficient space, we do not mention the V&V test result here.

Table 1. Parameter setting.

Type	Name	Variable	Value
organizational structure	number of groups	GN	10
	sales persons / group	AN	10
environment	number of customers of group i	m_i	100
	rate of customer decrease	P_d	0.25
organizational behavior	improvement by training	E_s	0.015
	improvement by education	E_o	0.005
	decrease by time	E_d	0.005
time	number of cycles	CN	60
	number of possible actions in a sales period	T	50
organizational learning	mutation rate	P_m	0.001

Experimental design

The sales manager, who is a user of our scenario-analysis method, analyses a configuration of the evaluation system at the sales division. The manager is aware of the distributions of both the sales persons capability and attitude for sales activity and also knows how many persons intrinsically learn their attitude. However, the manager does not know the real set of these parameter values or which person actually learns or does not. The manager examines the effect of such uncertainties. Table 2 shows the uncertainties of sales persons characteristics.

In the experiment, we make the uncertainties operational. Every run starts with a unique set of parameter values, which are consistent with the distribution, as described in Table 2, if the parameter has uncertainties. On the other hand, every run starts with the same set, if the parameter uncertainties are reduced. This operationalization is realized by managing random seeds of our ABSS program.

Table 2. Experimental design.

Type	Name	Variable	Value
sales person's initial characteristics	capability	$cp \sim N(0.4, 0.01)$	
	aggressiveness	$ag \sim N(2.0, 4.0)$	
	cooperativeness	$co \sim N(2.0, 4.0)$	
	innovativeness	$in \sim N(5.0, 4.0)$	
	threshold	$th \sim N(1.1, 0.01)$	
time	number of sales periods	CN	36
organizational learning	number of learning persons	LN	80

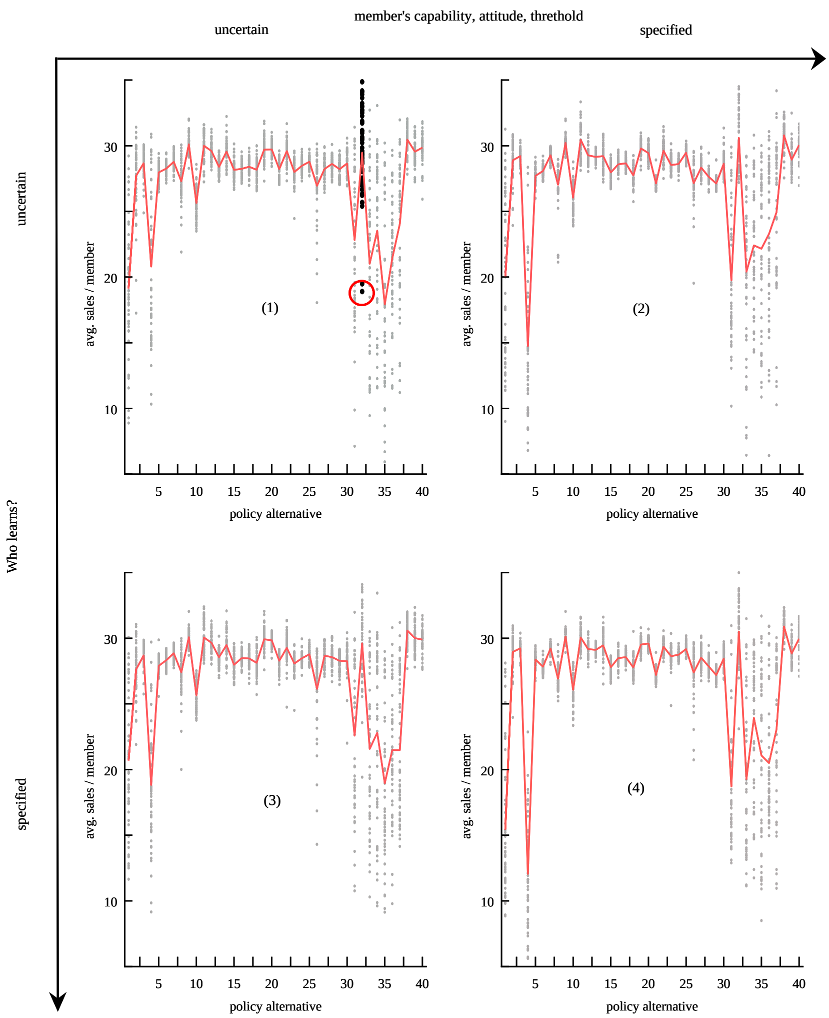

Figure 2. Landscapes of possible outcomes.

Result

The experimental result of ABSS is shown in Figures 2 and 3 and summerized in Table 3. Figure 2 illustrates the four landscapes under different conditions of uncertainties. In Step 2 of our method, the manager analyses the drawn landscape and understands the possible outcomes after implementing the concerning policy alternatives. For instance, in Figure 2 (1), the manager finds the following things about the 1st policy alternative: the best outcome of average sales per member is 29.2, the worst outcome 8.9, and the average outcome 19.1. The manager also finds that the 38th alternative achieves the best average outcome (30.8); the 32nd alternative the best outcome (34.5); the 17th alternative the minimum variance of the outcomes (0.134).

In Step 3 of our method, the manager compares a landscape having the considered uncertainties with the one in which the uncertainties have been reduced. Table 3 shows the occurrence percentages of changes in avg. or var. between two landscapes. The denominator 40 comes from the number of concerning policy alternatives. The result indicates that all three changes in uncertainties make a landscape statistically different.

Table 3. Effect of uncertainties.

	(1) → (2)	(1) → (3)	(1) → (4)
	learning member specified	capability, attitude, and threshold specified	all characteristics specified
avg.	7.5 % (3/40)	55 % (22/40)	55 % (22/40)
var.	10 % (4/40)	37.5% (15/40)	47.5 % (19/40)

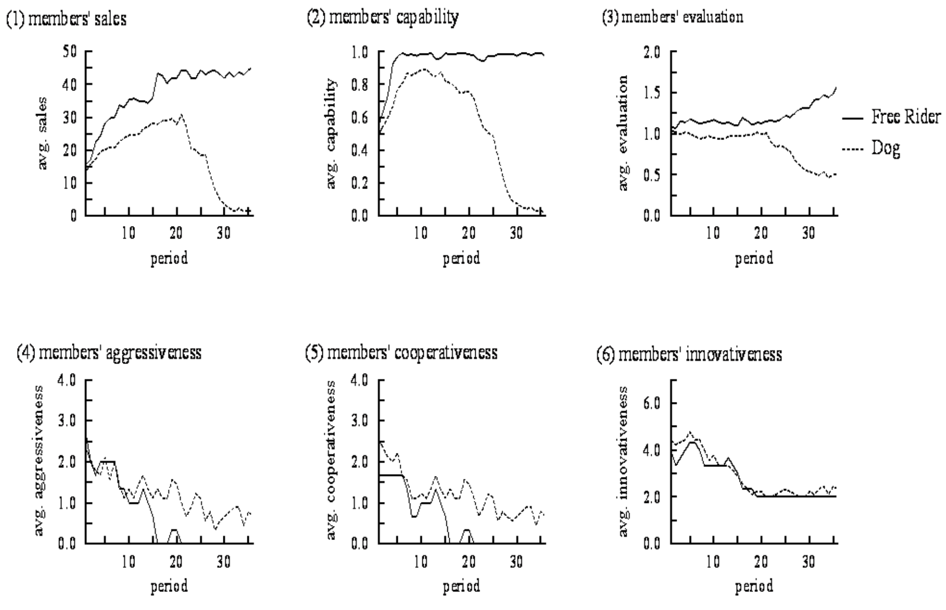

Figure 3. Bifurcation phenomenon in a notable outcome.

Figure 3 illustrates an interesting phenomenon in the 32nd policy alternative, where a bifurcation arising in the sales persons' performance that causes a notable, very low performance outcome; the outcome of this policy is emphasized in Figure 2(1). Through path analysis in Step 4 of our method, the manager finds that the phenomenon follows a specific structure, depending on the sales persons' characteristics.

4. Discussion

Analysis of uncertainties

The simulation result of the case example shows that we can see the difference in both the avg. and var. of the possible outcomes provided the uncertainties of the characteristics of sales persons are different. Path analysis also shows when and how the structure of sales persons' characteristics produces a notable outcome. Therefore, it seems reasonable to conclude that the uncertainties have an impact on the effectiveness of policy alternatives.

In the case example, the reduction of the uncertainties enables a more precise evaluation of the possible outcomes under considered policy alternatives. From the viewpoint of managers, our result implies that the reduction of uncertainties is effective.

Evaluation and scope

We applied our scenario analysis method to the case example in Section 3. The result supports our claim that our method helps gain the two types of knowledge described in Section 1. Although the effectiveness of our method has been demonstrated in only one example, it was effective leastwise. Our scenario-analysis method does not include a concrete and rigid procedure that is restricted to a specific domain of research. Therefore, it is natural to consider it as a domain-free method.

Additionally, our scenario-analysis method and other such methods are rather compatible than competing. The landscape proposed by Deguchi (2009) provides a rough overall image of the possible outcomes under a huge space of policy alternatives. After this analysis, we can focus on a few policy alternatives rather than carrying out further analyses for all the alternatives. Our method provides knowledge about the possible outcomes of the system with considered uncertainties after implementing the focused policy alternatives and the mechanism of obtaining a notable outcome. An inverse simulation technique (Yang *et al*., 2009) may enable the detailed study of the mechanism specified by our method. This comprehensive process of scenario analysis with ABSS is expected to help managers make better-informed decisions.

5. Conclusion

We developed a scenario analysis method, which mainly focuses on evaluating a range of possible outcomes of the system with considered uncertainties. We applied this method to a decision-making example, where a configuration of the evaluation systems at a sales division was to be selected. As the validation of the method, we confirmed the existence of effects that are dependent on the uncertainties of sales persons characteristics and found a mechanism that the specific structure of sales persons' characteristic causes a notable outcome of the system.

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