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Description	

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Agent-based modeling on technological innovation as an evolutionary process

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Abstract
This paper describes a multi-agent model built to simulate the process of technological innovation, based on the widely accepted theory that technological innovation can be seen as an evolutionary process. The actors in the simulation include producers and a large number of consumers. Every producer will produce several types of products at each step. Each product is composed of several design parameters and several performance parameters (fitness components). Kauffman's famous *NK* model is used to deal with the mapping from design parameter space (DPS) to performance parameter space (PPS). In addition to the constructional selection, which can be illustrated by the *NK* model, we added environmental selection into the simulation and explored technological innovation as the result of the interaction between these two kinds of selection.

Keywords: agent-based simulation; technological innovation

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1 Introduction

In recent years, agent-based modeling (ABM) has become increasingly influential in many fields of social science such as economic, political, anthropological, and so on. The examples of such works include [17, 4, 7, 11, 22, 6]. It is widely believed that ABM is not only a new powerful tool for researchers to challenge complex adaptive systems [16], but also a new way of thinking about the world where we live. The main purpose of ABM is to study the macro-level complexities from the interactions in the micro-level, in other words, ABM tries to challenge complexities in a bottom-up way. Researchers doing ABM, especially in social simulations, always keep in mind that "simple patterns of repeated individual action can lead to extremely complex social institutions" [8].

Agents in the ABM can be simply defined as autonomous decision-making entities. From a more theoretical view of artificial intelligence, an agent is a computer system that is either conceptualized or implemented using the concepts that are more usually applied to humans [24]. Simply speaking the purpose of this research is to model and simulate the technological innovation process by ABM.

There are good reasons to view innovation systems as complex systems. The actors of the system interact with each other, learn, adapt and reorganize, expand their diversity, and explore their various options [20]. And one of the obvious features of technological innovation in an advanced industrial society is that it involves the coevolution of marketable artifacts, scientific concepts, research practices and commercial organization [25]. Many researchers suggested that technological innovation should be understood as an evolutionary process [9, 13, 19, 25]. Technological innovation is also featured as a complexity challenge [2].

Based on the above thinking, many different models about technological innovation have been developed. Roughly, those models can be divided into two groups. The first group focuses on industrial firms, treating them as social organizations driven by market forces to adapt to changing technological regimes. Such models abound in literatures of evolutionary economics [23]. The second group focuses on the essence of technologies themselves. Typical models in this group are Arthur's [5] model of the "lock-in" of a single, but potentially sub-optional technology and Kauffman's [12] *NK* model of hill-climbing which predicts potentially different sub-optima in a rugged fitness landscape. The first group tries to capture the features of technological innovation from macro level, while the second group tries to explain technological innovation from micro level. Considering technologies (or its carrier products and services) as species, the first group pays much attention to the environment in which the species live, while the second group pays much attention to how the physical structure of individuals, for example DNA, affects the behavior and future of the species.

This paper presents an agent-based model that integrates the basic ideas of both groups. In our model, there are mainly two kinds of actors (or agents), producers and consumers. Producers design and produce different products. Consumers evaluate and purchase those products. As the carrier of technologies, every product is composed of several design parameters. And as commodities, products have performance parameters which can bring utilities to consumers. The mapping from design parameter space (DPS) to performance parameter space (PPS) is dealt with by using Kauffman's *NK* model. The agent-based model indicates our basic conceptual understanding about technological innovation: an innovation in technology is the result of both constructional selection and environmental selection.

Constructional selection can be seen as a kind of inner selection. In the process of technological innovation, there is some outside pull or pressure, that is to say, the social environment, especially market forces, will play an important role in selection. Corresponding to constructional selection, the impact from the environment is called environmental selection. Constructional selection generates things with high performance, but it doesn't mean these things will be overwhelming in environmental selection. The survivors are the result of both types of selection.

Based on the agent-based model, we developed a platform by using object-oriented programming to simulate the technological innovation process under different situations. The methodology we have adopted accords with Axelrod's description of the value of simulation [9]:

> *Simulation is a third way of doing science. Like deduction, it starts with a set of explicit assumptions. But unlike deduction, it does not prove theorems. Instead a simulation generates data that can be analyzed inductively. Unlike typical induction, however, the simulated data comes from a rigorously specified set of rules rather than direct measurement of the real world. While induction can be used to find patterns in data, and deduction can be used to find consequences of assumptions, simulation modeling can be used to aid intuition* [3].

2 The agent-based model

2.1 Producers, consumers, and mapping from DPS to PPS

Two kinds of actors are included in the model, producers and consumers. Here the producers belong to the same industry, for example the automobile industry. The set of producers can be denoted as:

$$\mathbf{P} = \{P_1, \cdots, P_S\}. \quad (1)$$

The set of consumers can be denoted as:

$$\mathbf{C} = \{C_1, \cdots, C_R\}. \quad (2)$$

In every time step, producer $P_i(i = 1, \cdots, S)$ will produce L_i types of products.

$$\mathbf{A}_{Pi} = \{A_{i1}, \cdots, A_{iLi}\}, i = 1, \cdots, S. \quad (3)$$

As the carrier of technologies, every product is composed of N design parameters, and as a commodity, every product has U performance parameters which can bring utilities to consumers. For consumers, design parameters hide behind performance parameters. For example, when purchasing a digital camera, consumers will consider "compatibility" which can be considered a performance parameter. Most consumers will not consider whether the camera uses a serial or parallel interface because they don't understand what a serial or parallel interface is. But for the technicians who design digital cameras, "interface" is a design parameter they must consider, and "serial" and "parallel" are two design values of this design parameter. The "interface", with other design parameters, will decide the "compatibility" of a digital camera. Also the "interface" will influence other performance parameters, such as the "appearance" of a digital camera. From the above example, we can see that the relationship between design parameters and performance parameters is something like a genotype-phenotype map.

The *NK* model is used to illustrate the mapping from DPS to PPS because it explicitly shows the epistatic structure of the genotype-phenotype map. In the *NK* model, N represents the number of genes in a haploid chromosome and K represents the number of linkages that each gene has to other genes in the same chromosome [13]. Regarding the design parameters as genes, following L. Altenberg [1], the traditional *NK* model can be described as the following:

- The genome consists of N genes (design parameters) that exert control over U phenotypic performance parameters, each of which contributes a component to the total fitness (performance).
- Each gene controls a subset of the U performance parameters, and in turn, each performance parameter is controlled by a subset of the N genes. This genotype-phenotype map can be represented by a matrix,

  $$\mathbf{M} = (m_{ij})_{N\times U}, i = 1, \cdots, N; j = 1, \cdots, U, \quad (4)$$

  of indices $m_{ij} \in \{0, 1\}$, where $m_{ij} = 1$ indicates that gene i affects performance parameter j. $\mathbf{M}$ is randomly initialized in the simulation. $\mathbf{M}$ will be static unless the DPS or PPS changes.

- The columns of $\mathbf{M}$, called the polygeny vectors, $q_j = (m_{ij})_{N\times 1}\,(i = 1,\ldots,N)$, give the genes controlling each performance parameter j.
- The rows of $\mathbf{M}$, called the pleiotropy vectors, $q_i = (m_{ij})_{1\times U}\,(j = 1,\ldots,U)$, give the performance parameters controlled by each gene i.
- If any of the genes controlling a given performance parameter mutates, the new value of the performance parameter will be uncorrelated with the old. Each performance parameter is a uniform pseudo-random function of the genotype, $x \in \{0,1\}^N$

$$f_i = f(x \circ q_i; i, q_i) \sim \text{uniformon}[0,1]. \quad (5)$$

Where

$$f : \{0,1\}^N \times \{1,\cdots,N\} \times \{0,1\}^N \to [0,1]. \quad (6)$$

Here $\circ$ is the Schur product.

$$x \circ q_i = (x_i m_{ij})_{N\times 1}\,(i = 1,\ldots,N).$$

Any change in i, q_i, or $x \circ q_i$ gives a new value for $f\,(x \circ q_i; i, q_i)$ that is uncorrelated with the old.

- If a performance parameter is affected by no genes, it is assumed to be zero.

$$f_i = 0, \text{ if } q_i = (0\cdots 0)\,. \quad (7)$$

- Total fitness is defined as the normalized sum of the performance parameters:

$$FC = \frac{1}{U}\sum_{i=1}^{U} f_i. \quad (8)$$

We make one change to the traditional *NK* model: the genes are not binary-valued, but H_i-valued, i.e., in our model, the gene i has H_i values, not just the two values 0 and 1. This is acceptable because it is not necessary that every design parameter has only two design values. For example, considering "engine" as a design parameter when designing a new car, technicians can select from dozens of different engines.

Thus the $x \in \{0,1\}^N$ in Eq. (5) and Eq. (7) should be changed into $x \in \{1,\cdots,H_i\}^N (i = 1,\cdots,N)$, and the Eq. (6) should be modified to be:

$$f : \{1,\cdots,H_i\}^N \times \{1,\cdots,N\} \times \{1,\cdots,H_i\}^N$$
$$\to [0,1](i = 1,\cdots,N).$$

We can suppose there is a general DPS [21] $\mathbf{G}$ which includes all the design values of the N design parameters.

$$\mathbf{G} = (\mathbf{g}_1,\cdots,\mathbf{g}_N)^T. \quad (9)$$

Here T means transpose.

For every design parameter $\mathbf{g}_i (i = 1,\cdots,N)$ in $\mathbf{G}$, it has H_{i} values.

$$\mathbf{g}_i = (g_{i1},\cdots,g_{iH_i}), i = 1,\cdots,H_i. \quad (10)$$

For every producer, the values of its design parameters are generated from the $\mathbf{G}$, i.e.

$$\mathbf{G}_{Pi} \subseteq \mathbf{G}, i = 1,\cdots,S. \quad (11)$$

For example, if $N = 4$ and $H_i = 3(i = 1,\cdots,4)$, the $\mathbf{G}$ and the DPS of a certain producer P_{i*} are:

$$\mathbf{G} = \begin{pmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \\ g_{41} & g_{42} & g_{43} \end{pmatrix}$$

and

$$\mathbf{G}_{Pi*} = \begin{pmatrix} g_{11} & 0 & g_{13} \\ g_{21} & 0 & 0 \\ g_{31} & 0 & g_{33} \\ 0 & g_{42} & g_{43} \end{pmatrix}.$$

In $\mathbf{G}_{pi*}$ the 0 means producer P_{i*} has no such design value corresponding to the position in $\mathbf{G}$. Any product is composed of N design parameters. Now we can calculate that with $\mathbf{G}_{pi*}$ the producer

P_{i*} can produce 8 types of products:

$$\mathbf{A}_{Pi*} = \left\{ \begin{array}{l} A_{i*1} = \{g_{11}, g_{21}, g_{31}, g_{42}\} \\ A_{i*2} = \{g_{11}, g_{21}, g_{31}, g_{43}\} \\ A_{i*3} = \{g_{11}, g_{21}, g_{33}, g_{42}\} \\ A_{i*4} = \{g_{11}, g_{21}, g_{33}, g_{43}\} \\ A_{i*5} = \{g_{13}, g_{21}, g_{31}, g_{42}\} \\ A_{i*6} = \{g_{13}, g_{21}, g_{31}, g_{43}\} \\ A_{i*7} = \{g_{13}, g_{21}, g_{33}, g_{42}\} \\ A_{i*8} = \{g_{13}, g_{21}, g_{33}, g_{43}\} \end{array} \right\}.$$

The U performance parameters of products can be denoted as:

$$\mathbf{F} = \{f_1, \cdots, f_U\}. \tag{12}$$

2.2 Purchasing behavior

A consumer's purchasing behavior can be simply described as: he/she evaluates several types of products, and select one whose utility is the biggest for him/her among those types evaluated by him/her. Now the problem is to model how consumers evaluate products. We consider the following three different evaluation methods. Each method is based on different philosophy, but a discussion of these philosophies is beyond the scope of this paper.

2.2.1 Weighted average method

In this method, for any consumer C_j ($j = 1, \ldots R$), its weights for different performance parameters can be denoted as:

$$\mathbf{W}_{Cj} = \{w_{1Cj}, \cdots, w_{UCj}\}, j = 1, \cdots, R. \tag{13}$$

subject to

$$\left\{ \begin{array}{l} w_{iCj} \in [0, 1], i = 1, \cdots, U \\ \sum_{i=1}^{U} w_{iCj} = 1. \end{array} \right. \tag{14}$$

A consumer's evaluation for a type of product is:

$$E = \sum_{i=1}^{U} w_i f_i \tag{15}$$

Every consumer will select the product which has the biggest E for him/her among those products evaluated by him/her.

2.2.2 Ideal point method

In this method, every consumer has an ideal product in his/her mind. Eq. (16) gives the distance between design performance of products as they are evaluated by a consumer:

$$D = \sum_{i=1}^{U} (f_i - f_i^0)^2 \tag{16}$$

In Eq. (16), f_i is the value of the ith performance parameter of the products evaluated by the consumer, and f_i^0 is the value of the ith performance parameter of the consumer's ideal product. Every consumer will select the product which has the smallest D for him/her among those products evaluated by him/her.

2.2.3 Max-min method

Supposing, before selecting a product, a consumer will evaluate I types of products which can be denoted as:

	Performance Parameter1	$\cdots$	Performance Parameter$U$
Product1	f_{11}	$\cdots$	f_{1u}
$\vdots$	$\vdots$	$\ddots$	$\vdots$
Product$I$	f_{I1}	$\cdots$	f_{IU}

Here $f_{ij}(i = 1, \cdots, I)(j = 1, \cdots, U)$ is the value of ith product's jth performance parameter. If

$$f_{i^*j} = \max_i\{\min\{f_{ij}\}\}, i = 1, \cdots, I; j = 1, \cdots, U. \tag{17}$$

Then product i^* will be selected by the consumer.

Of course, there are many other evaluation methods. Our model and the platform have an open structure, i.e., researchers can define their own evaluation methods, parameters and even agents' behavior to do simulation under different assumptions and conditions.

2.3 Constructional selection and environmental selection

Loet Leydesdorff executed simulation on the complex dynamics of technological innovation by using cellular automata [14]. He explored the innovation process and results from the viewpoint of constructional selection. In our research, we would like to simulate the innovation process by considering the interaction between constructional selection and environmental selection.

Constructional selection means the selection is based on construction and epistatic performance of the product; it does not consider the situation or environment in which the product exists. Environmental selection, on the other hand, means "selected by environment". Here the environment is something like social environment. It refers to consumers, government regulations, and so on. But for the sake of simplicity, we just consider consumers in this paper.

Here we present an example to illuminate constructional and environmental selection by considering a kind of simple vehicle. Supposing there are two design parameters, wheel and container, for designing a vehicle, every design parameter has two design values, as shown in Fig. 1.

Two performance parameters of the vehicles are considered, safety and appearance. Fig. 2 shows a genotype-phenotype map which indicates that the safety is affected by both wheel and container, but the appearance is affected only by the container.

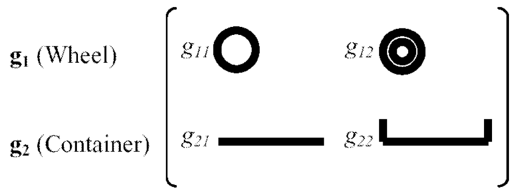

Figure 1: The DPS of a kind of vehicle.

According to the DPS, four types of products can be produced, as shown in the first column of Table 1. The values of f_1 and f_2 (the second and third columns of Table 1) are obtained according to Eq. (5). Then the values of *FC* in the fourth column can be obtained according to Eq. (8), and the type 4 will be selected by constructional selection which is based on *FC*. If, however,

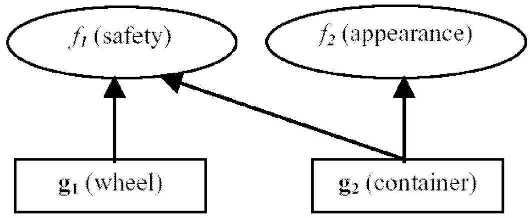

Figure 2: The genotype-phenotype map.

consumers' weight for safety is 0.2 and weight for appearance is 0.8, then according to Eq. (15), the values in the fifth column of Table 1 can be obtained, and type 2 will be selected by environmental selection which is based on E.

2.4 Product evolution

In this paper, the environment mainly refers to market, so environmental selection is also called market selection. In fact, the market selection is very complex, related to each consumers' preferences, cultural background, income, age, sex, and so on. For the sake of simplicity, we assume a simple purchasing model: in every time step, every consumer will evaluate a certain number of product types, and purchase the one that he/she rates the highest. In order to survive, producers must continue to design new products which will better meet consumers' preferences. The products which can have higher utility will be more likely to retain their characteristics in the next generation of products. We use the following genetic algorithm [10] to simulate product evolution.

The set of all product types in the market at a certain time step can be supposed as:

$$\mathbf{A} = \{A_1, \cdots, A_B\}. \tag{18}$$

For every product type A_u (u =1, ..., B) in $\mathbf{A}$, if its sale volume is s_u, then we can get the sale volume set for every type:

$$\mathbf{S} = \{s_1, \cdots, s_B\}. \tag{19}$$

Supposing s_{min} is the minimal value in set $\mathbf{S}$, then for every product type A_u (u =1, ...,B) in

Table 1: Constructional selection and environmental selection

Vehicle types	f_1	f_2	FC	E
1 	0.4	0.8	0.6	0.72
2 	0.5	0.8	0.65	0.74 (max)
3 	0.7	0.5	0.6	0.54
4 	0.9	0.5	0.7 (max)	0.58
weights	w_1 0.2	w_2 0.8		

set $\mathbf{A}$, its probability of being the genome type of the next generation products is:

$$P(A_u) = (s_u - s_{\min})/\sum_{j=1}^{B}(s_j - s_{\min}). \qquad (20)$$

The new products are generated from genome types by crossover and mutation. The crossover process can be described as: for two selected genome types, their chromosome strings are cut at some randomly-chosen position, thus two "head" segments and two "tail" segments are produced, and the tail segments are then swapped over to form two new full-length chromosomes (product types). It is not necessary that crossover be applied to all pairs of genome types selected for generating new types. Users can specify a probability for crossover, which is called crossover rate. In this paper, the crossover rate is:

$$\alpha \in (0, 1). \qquad (21)$$

Crossover makes offspring inherit some genes from each parent, while mutation will enable offspring to have genes that their parents do not have. Each gene (design parameter) of offspring will mutate according to a probability called mutation rate, which is also specified by users. In this paper, the mutation rate is:

$$\beta \in (0, 1). \qquad (22)$$

As shown in Eq. (10), for design parameter $\mathbf{g}_i(i = 1, \cdots, N)$, it has H_i design values. If a mutation happens to $\mathbf{g}_i(i = 1, \cdots, N)$, each design value will have the same probability, which is ${}^1/_{H_i}$, to be selected as the value of this design parameter.

3 Simulation

Based on the model introduced above, we built a platform. On this platform, not only can we set different values for all the parameters mentioned above, but also define different behaviors of the agents. Similar to Nigel Gilbert's statement [9], the role of simulation in this paper is not to create a facsimile of any particular innovation that could be used for prediction, but to use simulation to assist in the exploration of the consequences of various assumptions and initial conditions. In the following we will execute simulations under different situations and discuss the results of those simulations.

Three evaluation methods–weighted average, ideal point and max-min– were mentioned in Section 2.2. Although the following simulations mainly focus on the weighted average method, simulations on the other two evaluation methods are also simply introduced.

The basic initializations for all the following simulations are:

- $N = 6$, $U = 5$, and $H_i = 4$ $(i = 1, \ldots, 6)$, which means every product is composed of 6 design parameters and has 5 performance parameters, and every design parameter has 4 design values. So in total there can be $6^4 = 1296$ types in the industry. The mapping from DPS to PPS , the $\mathbf{M}$ in Eq. (4), is randomly initialized.

- $S = 3$, $L_i = 50 (i = 1, \ldots, 3)$, which means there are three producers, and at each time step, every producer will produce 50 product types. Each producer's initial types are randomly generated from their DPS.
- $R = 1000$, which means that altogether there are 1000 consumers.
- $\alpha = 0.7, \beta = 0.02$, which means the crossover rate is set to 0.7 and the mutation rate is set to 0.02.

The genotype-phenotype map from DPS to PPS is initialized randomly, and in most of the situations, the products evaluated by consumers are randomly selected from the market. Thus the result will be different almost every time we run the program. The absolute values in the output make no sense. What makes sense is the pattern of the output based on the time step. We ran simulations 30 times for each situation. The results shown in the following are typical patterns in different situations.

3.1 Based on weighted average method

We assume that all consumers evaluate products by using the weighted average method. In the simulation, we consider two measures. One is the average evaluation value (*AVE*) of all consumers for all product types, which can be denoted as:

$$AVE = \frac{\sum_{i=1}^{R} \sum_{j=1}^{S} \sum_{l=1}^{Lj} E_{ijl}}{R \times \sum_{j=1}^{S} L_j} \tag{23}$$

Here, E_{ijl} means the evaluation value of consumer C_i to the product type A_{jl} produced by producer P_j. *AVE* can be used to indicate how consumers are satisfied with the industry.

The other is the average performance value (*AVF*) of all products, which can be denoted as:

$$AVF = \frac{\sum_{i=1}^{S} \sum_{j}^{Li} FC_{ij}}{\sum_{i=1}^{S} L_i} \tag{24}$$

Here the FC_{ij} means the constructional fitness of type A_{ij} produced by producer P_i, and it is obtained according to Eq. (8). *AVF* can be used to indicate the maturity of an industry. In the following, we will consider several situations.

3.1.1 Situation 1

In this situation, we assume:

- All consumers' weight sets are the same, which means all consumers have the same weight for the same performance parameter.
- All consumers are fully informed about the market, which means when one consumer wants to buy a product, he/she will evaluate all product types available in the market place and select the one which he/she rates the highest.
- The three producers' DPS are randomly generated from the general DPS (the DPS of the whole industry), and will not change during the simulation.

The top part of Fig. 3 shows the sale records (sale volume at each time step) of the three producers. We can see producer 3 monopolizes the market, and producer 1 and producer 2 can sale nothing. This is not to say that producer 3 will always be the monopolist. In almost every simulation, a monopoly appears, and the three producers have an equal chance to be the monopolist. Because all the consumers have the same weight for the same performance parameter, the market will select types which have the maximal E for all consumers. According to the Eq. (8), mostly there is only one type with maximal E, but it is possible that more than two types have the same maximal E by accident. And according to the *NK* model, or Eq. (4), (5), (6), (7) and (8), it is also possible that accidentally more than two producers produce product types with maximal E for all consumers.

The lower part of Fig. 3 shows the *AVE*, *AVF* and *maxFC*, where *maxFC* is the maximal *FC* of all possible product types. We can see *AVE*

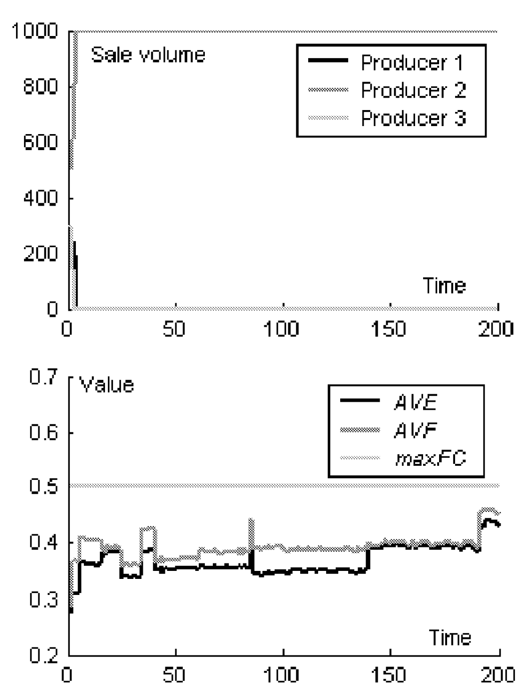

Figure 3: The result of situation 1.

and AVF frequently show large changes. Those changes are caused by the mutation of products. Because the whole market are overwhelmed by one type (or several types with small possibility as discussed above), the mutation of this type will affect all consumers' E, and because all consumers have the same weight for the same performance parameter, the affection is identical for all consumers, that means the affection for different consumers can't be neutralized when calculating AVE. The mutation of the overwhelming type will cause changes to FC of all products in the market place, and those changes also can not be neutralized when calculating AVF. In Fig. 3, the changes of AVE and AVF are not completely synchronous. This is reasonable if we analyze the Eq. (8) and the Eq. (15) more – an increase/decrease in FC does not have to result in an increase/decrease in E. From the view of the market, an improvement of products does not have to result in a business success unless the improvement is what consumers really need and consumers attach importance to the improvement. What we can learn from the simulation and analysis is: it is very important to integrate both the technological knowledge (knowledge about technology) and consumer knowledge (knowledge about consumer) into the new products for getting business success [15].

3.1.2 Situation 2

The assumptions in this situation are the same as those in situation 1 except that consumers are only partly informed about the market, which means when a consumer shops, he/she will evaluate some (5 types), not all, of the products, and those types are randomly selected from all the types available in the market place.

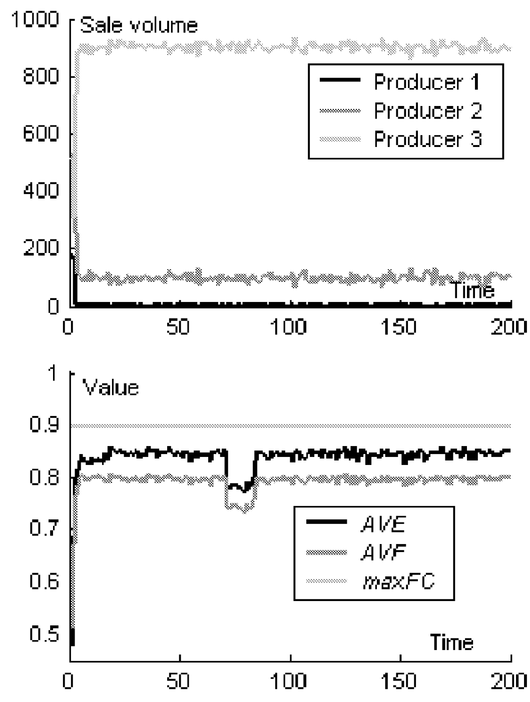

Figure 4: The result of situation 2.

As shown in Fig. 4, although producer 1 occupies most of the market, it can not completely monopolize it. Other producers can sell something, and comparing with the result in situation 1, there is almost no big change to AVE and AVF except at the beginning of the simulation. There are drops in AVE and AVF at about time step 80. The drops were caused by a mutation in products. This mutation decreased both AVE and AVF, in other words, this mutation did harm to the previous technical structure. But we can see producers finally overcame the harm. Such phenomenon can be explained as: technicians apply a new design value without knowing this design value is not good for the current technical structure until the products come into the market. In the real world, a good producer can overcome such bad mutations during the period of test before forwarding the products to the market.

3.1.3 Situation 3

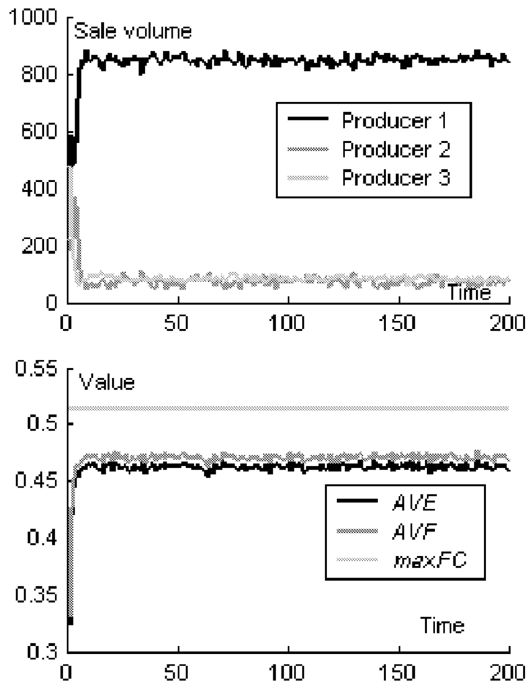

Figure 5: The result of situation 3.

In this situation we assume:

- There are 50 consumer weight sets, which means there are 50 kinds of consumers.
- Consumers are partly informed about the market.
- The three producers' design spaces are randomly generated from the general design space, and will not change during the simulation.

In this situation we find that although one producer (producer 1 in Fig. 5) can occupy most of the market in most of cases, it can not completely monopolize the market, and other producers can have some (small) market share. In Fig. 5, AVE and AVF are more stable than before. This is because the diversity of consumers' demand leads to the diversity of products, thus those changes to FC for individual product and E for individual consumer can counteract each other.

3.1.4 Situation 4

The assumptions in this situation are the same as those in situation 3 except that almost every consumer's weight set is different. That means the diversity of consumers' demand is higher than that in situation 3.

As shown in Fig. 6, there is no monopoly in the market. Because of the high diversity of consumers' demand, it is very difficult for any single producer's products to satisfy all consumers. One thing we have not expected is that AVE almost equals AVF in this situation, which really leads us to think more about the underlying mechanisms. We realize that, in this situation, any single consumer's preference can not dominate the direction of product improvement, and the improvement of products is mainly dominated by products' performance parameters. For a product in the market place, the deviation of different consumers' evaluation will counteract each other, and the final effect is that AVE approximates to AVF.

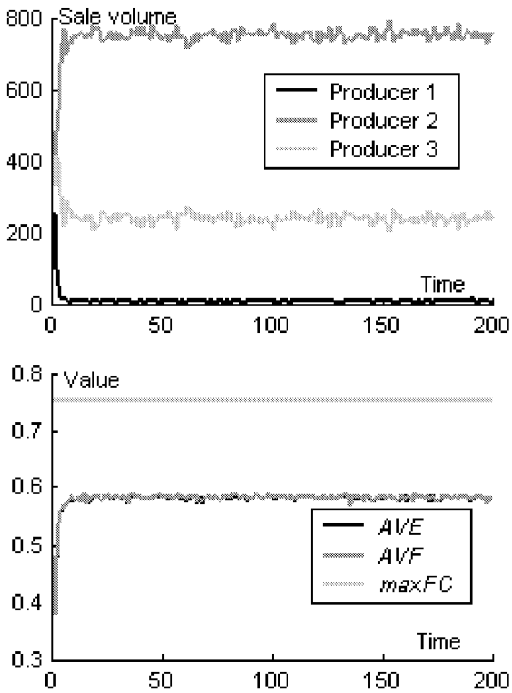

Figure 6: The result of situation 4.

By comparing the results in the above four situations, we find two factors that could protect the market being completely monopolized by producers who make better technological innovation than others. The first factor is consumers' incomplete information. In the first situation, producer 3 (in Fig. 3) occupied all the market because it made better innovation in its products and all consumers realized this innovation; while in the rest three situations, it was possible that a producer made great innovation, but not all of consumers realized it because they were partly informed about the market. The second factor is the diversity of consumers' demand. In the first situation, all consumers' preferences were the same, and there was an apparent monopoly in the market; while in the third situation, the monopoly became weak; and in the fourth situation, we could say there was no apparent monopoly in the market.

A common point in each situation is that AVF is smaller than $maxFC$ that can be looked as the global optimal technological solution in an industry, which means it is most likely that an industry is operated under local optimal technological solutions, not the global optimal solution. We believe two factors contributing to this phenomenon. One is, there are too many peaks in the rugged landscape of PPS, and it is difficult for an industry to find the highest peak. In the above situations, we ran the simulation for 200 time steps. With more time steps, theoretically, producers could find the highest peak. So we could not say it is impossible for an industry to find the global optimal technological solution. But it is really difficult for an industry to find the optimal solution, not only because of the large amount numbers of peaks, but also due to the dynamics of DPS. The other is, technological innovation is the result of both constructional selection and environmental selection. It is not necessary that the global optimal solution (the highest peak) in constructional selection is also global optimal in environmental selection. Table 1 showed a good example of this factor. The type 4 in Table 1 is a global optimal technical solution in terms of constructional selection, but consumers are more like type 2.

3.1.5 Situation 5

The general DPS of the whole industry and the DPS of every producer are dynamic. The dynamics of DPS refers to the expansion of spaces through the addition of new operants and their progressive structuring and articulation [21]. In the real world, the dynamics of DPS are very complex. It makes no sense to study the dynamics of DPS of a certain industry without considering that industry's history and the cultural background. Our aim is not to simulate any real dynamics of DPS, but to reveals the fundamental dynamics of DPS. For our model, the dynamics of DPS has two forms, the change of design values, and the change of design parameters.

The assumptions in this situation are based on situation 4, in addition, producer 1 will expand its DPS by finding new design values at time step 100. As introduced above, every producer's DPS is randomly generated from the general DPS of the industry, in other words, any individual producers' DPS does not contain all design values in the general DPS. In this situation, we let producer 1 get all the design values of the general DPS at time step 100.

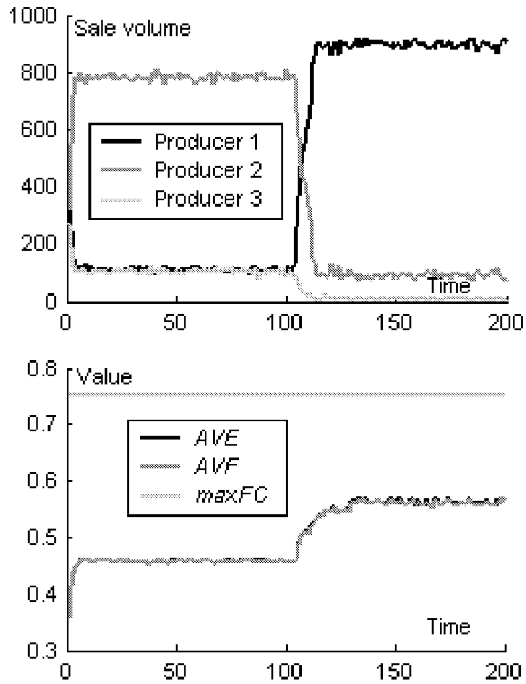

Figure 7: The result of situation 5.

As shown in Fig. 7, after expanding its DPS at time step 100, producer 1 moves from being a poor producer to an excellent one. Its market share increases. And the *AVE* and *AVF* also increase after producer 1 expands its DPS, which means consumers have become more satisfied with the industry and the industry is more mature. The reason why producer 1 can become a successful one is that its expanded DPS provides more deign values for the genetic algorithm introduced in Section 2.4 to find better technical solutions, and the better technical solutions lead to the increase of *AVE* and *AVF*.

In the real world, finding new design values is the main way for producers to reinforce their competitive advantages. Theoretically, not every new design value will benefit the producer. New products are always the result of conscious design. Most of the time, those design values which will not benefit the producer will be filtered out during the research and development process.

3.1.6 Situation 6

Adding new design parameters into DPS will cause big changes in the technical structure of the product. The assumptions in situation 6 are based on situation 4, in addition, a new design parameter is added to the industry at time step 100. When

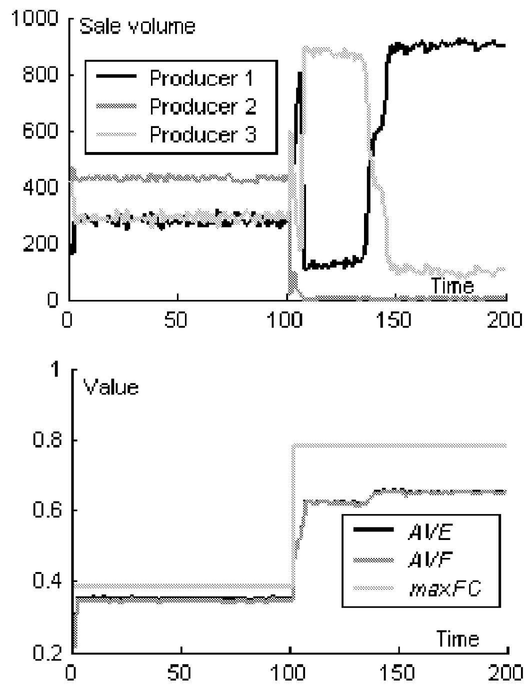

Figure 8: Pattern 1 under situation 6.

we look at *AVE* and *AVF*, we see that three patterns appear under this situation, and we did not find that any pattern appeared more frequently than another two in the simulation. In pattern 1, both the *AVE* and *AVF* increase after adding the new design parameter, as shown in Fig. 8. That means consumers are more satisfied with the industry and the maturity of the industry becomes higher.

In pattern 2, shown in Fig. 9, the *AVE* and *AVF* first decrease sharply, then climb to a level higher than before the new design parameter was added. In other words, when the new design parameter was first added to the industry, the producers knew little about how to integrate it with existing design parameter. It took a little time for the producers to benefit from the new design parameter.

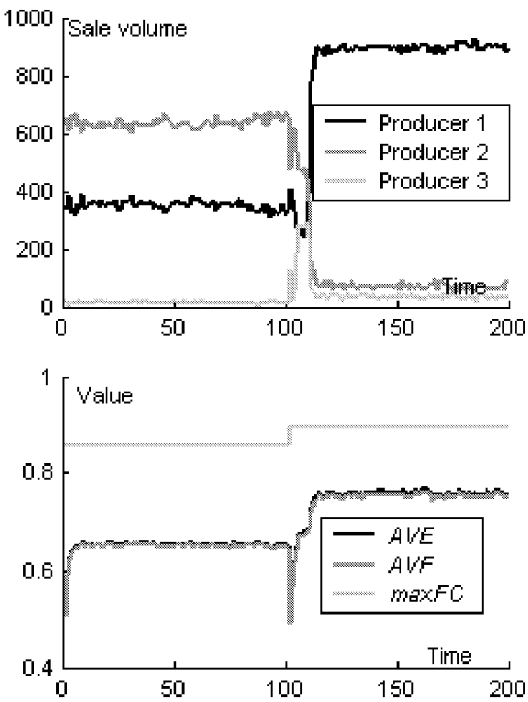

Figure 9: Pattern 2 under situation 6.

In pattern 3 (Fig. 10), *AVE* and *AVF* first decrease sharply, then climb to a level lower than before the new design parameter was added. This is because the new design parameter brought more disadvantages than advantages to the current technical structure, or because the industry sometimes had difficulty in incorporating the new design parameter.

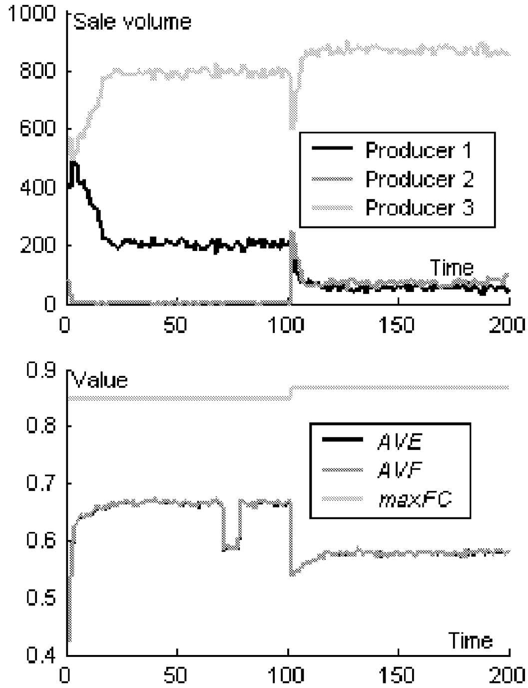

Figure 10: Pattern 3 under situation 6.

In each of these three patterns, there were quakes in the market, as producers changed their position and then after a period of time, became stable again.

Generally, adding a new design parameter to an industry will lead to changes in the industry and changes of producers' standing in the market. It is most likely that the *maxFC* will increase. But that does not mean *AVF* and *AVE* will also increase, although most of the time they will. That is to say, adding a new design parameter will give the industry a chance to increase the *AVF* and *AVE*, but it is possible that the industry will miss this chance and make things worse as in pattern 3.

Mathematically, adding a new design parameter means adding a row to the matrix $\mathbf{M}$ in Eq. (4). In our simulation, the values of this new row are randomly initialized and will not change in the simulation. According to Eq. (5), those performance parameters affected by the new design parameter will get new values which have no relationship with their old values. This is the main reason for the variety of the result in this situation. We also put forward the model in which the new values are related to the old values [15].

3.2 Monopoly Degree

The word "monopoly" has been used in describing the results in from situation 1 to situation 4. Now, we define monopoly degree as:

$$\mu = \frac{\max_s}{S_{all}} \tag{25}$$

Here μ is the monopoly degree, max_s is the maximal sale volume of all the producers at the current time step, and S_{all} is the number of all sold products at the current time step.

We ran the program 10 times for every situation in Table 2, and calculated the average μ at time step 200.

It is also possible to examine the behavior with regard to a time series. But it will result in many lines in a three-dimension space. The randomness, mainly caused by the mutation and crossover of the GA and the consumers' behavior of selecting products for evaluation before shopping, makes those lines rugged. Thus it is not easy to compare the results with regards to a time series. And our purpose is to compare results when market is in relative stable states under different situations, rather than how producers reach those stable states. We found time step 200 is a suitable point for this purpose. We ran simulation under each situation 10 times for reducing the effect of the above randomness.

The results in Table 2 give us the sense that when the consumers are more homogeneous, and the consumers are better informed about the market, there is more possibility that a monopoly will appear in the market place by means of technological innovation. We can see, in the third and fourth columns of Table 2, for the weighted average method and the ideal point method respectively, the μ increases when consumers become more homogeneous. And when the variety of consumers' demand is the same (in the same row

Table 2: Monopoly degree under different situation at time step 200

		Partly informed	Full informed
Weighted average method	All customers are the same	0.904	1
	50 kinds of customers	0.740	0.853
	All customers are different	0.625	0.833
Ideal point method	All customers are the same	0.900	1
	50 kinds of customers	0.420	0.558
	All customers are different	0.400	0.507
Max-min method		0.508	1

in Table 2), the μ in the market with fully informed consumers is higher than that in the market with partly informed consumers. Table 2 also shows that the weighted averaged method can result in higher degree of monopoly than the ideal point method. Other evaluation methods also can be simulated and compared based on the agent-based model introduced in this paper.

4 Conclusions

In this paper, an agent-based model of technological innovation as an evolutionary process has been presented. This agent-based model describes technological innovation as a process of both constructional selection and environmental selection. Several situations were considered and the results of the simulations have been discussed. Through the simulations, this paper identified two factors, consumers' incomplete information and diversity of consumers' demand, which could prevent producers from monopolizing the market by means of technological innovation. In addition, this paper not only intuitively showed that an industry is most likely operated under suboptimal technological solutions, but also suggested two reasons for this issue. The first reason is that there are two many peaks in the rugged landscape of PPS, and the second one is that an innovation in technology is the result of both constructional and environmental selection.

Besides the result and conclusions obtained from the simulations, this paper demonstrates the general fact that agent-based modeling and simulation can be used to aid intuition about technological innovation, which has been featured as a complexity challenge. The agent-based model has an open structure. It can be used as a platform to simulate other problems related to technological innovation.

No single model captures all of the dimensions and stylized facts of technological innovation. The role of simulation in this paper is not to create a facsimile of any particular innovation that could be used for prediction, but to use simulation to assist in the exploration of the consequences of various assumptions and initial conditions.

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